

Modelling Transitions in Consumer Lighting



Consequences of the E.U. ban on light bulbs



Maarten Afman

Modelling Transitions in Consumer Lighting



Consequences of the E.U. ban on light bulbs

M.Sc. Thesis

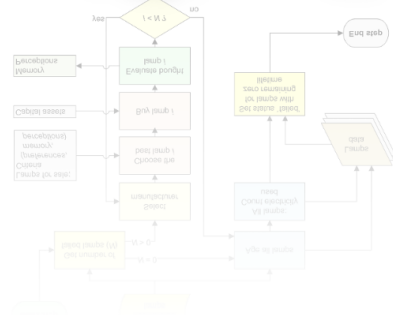
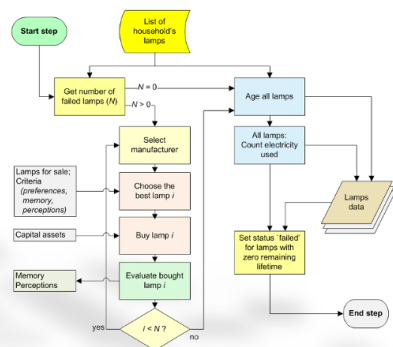
'Final version d.d. 4th February 2010'

Maarten Afman

Graduation committee:

Prof.dr.ir. M.P.C. Weijnen (chair; TU Delft, Energy & Industry section)
Dr.ir. G.P.J. Dijkema (first supervisor; TU Delft, Energy & Industry section)
Dr.ir. C. van Daalen (second supervisor; TU Delft, Policy Analysis section)
ir. E.J.L. Chappin (daily supervisor; TU Delft, Energy & Industry section)
dr. W. Jager (external supervisor; University of Groningen, Marketing department)

Programme	SEPAM – Systems Engineering, Policy Analysis and Management
Graduation	Delft, 18th February 2010
Address	M.R. Afman, v.d. Heimstr. 55, 2613EA Delft, The Netherlands
E-mail addr.	m.afman@gmail.com
Student no.	9006424



Summary

The need for a ban on bulbs?

Energy consumption of the residential lighting sector is high: 3.8 TWh per year for the Netherlands alone, approximately the production of a power plant of 800 MW. Consequently, if 40% of the energy consumption for consumer lighting could be saved, a 320 MW power plant could be taken off the grid. Such a saving would be realistic if consumers would not rely so much on outdated and inefficient lighting technology, i.e. the standard incandescent light bulb and halogen lighting.

The European Union has acknowledged this problem, and is in the process of phasing out the incandescent lamps by removing them from stores. The principle of the 'ban on bulbs'-policy is to *force* consumers to switch to more efficient lighting (such as the compact fluorescent light bulb (CFL), or the LED lamp).

However, as the consumer lighting sector is a complex socio-technical system, the dynamics of the consumer lighting sector, resulting from the E.U. 'ban on bulbs', cannot be predicted.

However, we would like to know whether the ban will be effective, and whether or not there are other policy measures, perhaps more transition-oriented, that are also be effective. Therefore, this research aims to create insight into these ill-understood dynamics and we pose the following main research question: **How can we explore the consequences the E.U. ban on bulbs will have on the electricity demand of the consumer lighting sector?**

The consumer lighting system

The main research question is answered by means of answering three research questions. The first research question deals with defining policy area and characterising the consumer lighting system: *How can the consumer lighting sector and its development be systematically characterised?* (r.q. 1)

The consumer lighting sector is a complex socio-technical system, in which both the social and the technological subsystems have their own dynamics and developments.

From the social subsystem, the consumer is considered the most relevant actor. The consumer's choice in purchasing technological components – light bulbs, luminaires, dimmers – is an important mechanism determining the electricity used for consumer lighting. Consequently, energy consumption by lighting is structurally changed by altering the choice of consumers. Although the price of light bulbs is very important, consumers are heterogeneous in their preferences and have persistent opinions and knowledge on lamps (possibly wrong or outdated), which all influences their purchasing decisions. In addition, consumers have social relationships through which they mutually influence each other over a by means of word-of-mouth and normative adaptation (fashion). Furthermore, consumers are influenced by marketing and promotion activities from manufacturers,

retail stores and government.

Government wants to induce structural changes in the consumer lighting system. For this, a transitions perspective is adopted to come up a way to test the government policy options. Transition management strategies can be tested by performing so-called 'transition experiments' – a simulations approach is used to test assemblages of policy instruments by observing the simulated system's evolution.

An agent-based simulation model of consumer lighting

The second research question is: *What is a suitable modelling approach in order to evaluate the developments in the consumer lighting sector that result from the E.U. 'ban on bulbs'?* (r.q. 2)

The modelling approach best suiting the consumer lighting sector is found to be *Agent-Based Modelling* (ABM). ABM allows for actors to be represented as heterogeneous agents in a social network, making individual decisions on technical objects. In addition, ABM is able to simulate 'word-of-mouth'-sharing of opinions and knowledge. Furthermore, ABM allows for the consequences of technological improvement in the simulated lamps, in the form of performance improvements and declining prices.

An agent-based model is developed that incorporating a network of 250 household agents, representing the consumers in the system. The model also contains a retail store, selling 70 types of lamps of 11 makes (brands). The household agents are implemented with heterogeneous preferences, an evolving memory and opinions (perceptions). Opinions and knowledge are shared with consumers that are close in the social network.

In the model, household agents make purchase decisions involving a number of criteria: criteria about lamp properties (efficiency, purchase price, light output, light colour temperature, colour rendering quality, lamp lifetime); criteria about opinions (on brands, lamp technology types and specific lamps), and a fashion criterion .

Apart from a 'base case' without policy, the model includes three policy strategies to test the different approaches to transition management. These are:

'Ban on bulbs'-policy – phased withdrawal of incandescent lamps; modelled after the E.U. ban on incandescent lamps

'Bulbs-tax'-policy – incandescent lamps are taxed up to €2.00 per lamp (the tax takes effect gradually in the first 5 years)

'Subsidy for LED'-policy – the speed of the switch-over to LED lamps is encouraged by a 33% discount on LED lamps the first 5 years, gradually phased out to zero in the next 5 years.

The main transition indicators for analysis of the results are the adoption levels of the different lamp types, electricity consumption per household and money expenditure for lamp purchases.

Conclusions from the simulation results

The third research question deals with the simulation results: *From the application of the simulation model, what insights can be gained on the effectiveness of the E.U. 'ban on bulbs' in the consumer lighting sector?* (r.q. 3)

The *'ban on bulbs'-policy is likely a very effective way to curb the use of the incandescent lamp*. The number of incandescent lamps in use declines quickly under the ban, and lamp purchases are generally of a more efficient type.

In addition, the ‘ban on bulbs’ is likely very effective at reducing electricity consumption of the consumer lighting sector, and quickly so. In the simulation model, from the moment the ban takes effect, the incandescent lamp is replaced almost one on one with CFL’s, which results in a large reduction of the lighting electricity consumption (see the leftmost graph in fig. 1).

The ‘bulbs-tax’ policy is also likely to be effective to reduce the use of the incandescent lamp. The ‘bulbs-tax’ is likely also effective at reducing electricity consumption of the consumer lighting sector, but it may well take a lot longer to reach similar consumption levels as under the ‘ban on bulbs’-policy. It is unlikely for the ‘subsidy for LED’-policy to have a significant impact. See the centre and rightmost graphs of fig. 1.

Summarising, in the long run, the ‘ban on bulbs’ is the most effective way of achieving a lower electricity usage for lighting, but a tax on bulbs of €2 is also effective.

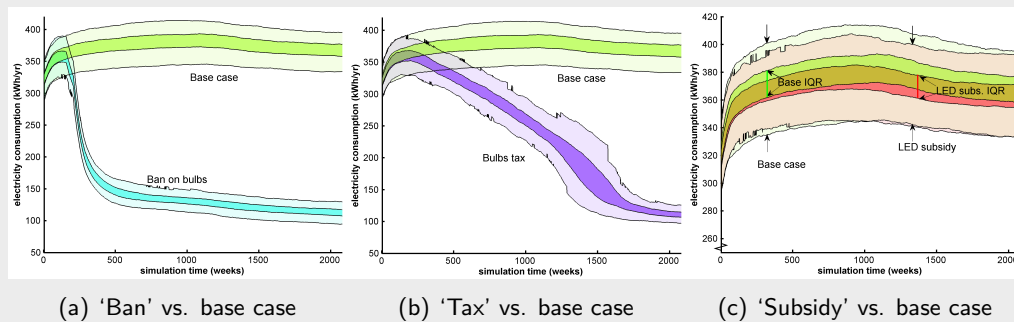


Figure 1 – Average household electricity consumption (kWh/yr) for the ‘ban on bulbs’ ‘bulbs-tax’ and ‘subsidy for LED’-policies, compared against the base case.

Recommendations for policy and future work

For policy makers, it is recommended to pay attention to the upfront cost households incur when purchasing energy efficient lighting, since the policies lead to an increase in the expenditure of households. In addition, new policy options could be implemented, for example, imposing a CO₂ tax as an upfront surcharge on the purchase price of a lamp. This tax will need to be significant: a tax of ~ €2 is effective.

For future work on the model, it is recommended to perform additional experimentation with varying parameter settings and testing to what extent the results hold when model assumptions and parameters are changed. Second, it is recommended to expand the model with luminaire dynamics and consumer heterogeneity. Third, more luminaires for halogen light bulbs and more lamps could be added to the model. Finally, a number of rebound effects of the E.U. ban could be added to the simulation in order to come up with quantitative analysis of their significance.



Preface

In the following hundred-something pages, I present the result of the M.Sc. thesis work that constitute the end of my studies “Systems Engineering, Policy Analysis and Management” at Delft University of Technology. The work was mostly executed from January 2009 onwards, when I had taken upon me the challenge to build an *agent-based* simulation model of the *consumer lighting sector*.

The decision to take up ‘Consumer Lighting’ was made after a discussion with dr. Zofia Lukszo. Zofia pointed out that a master’s thesis project can be the last time in your professional career where you have the opportunity to probe into one subject for a considerable amount of time. So, better choose a project you like! Either choose a project with a subject that has your special interest, or choose a project where the research methodology interests you. With ‘Consumer Lighting’, it was the latter aspect that did it for me. The prospect of being able to do a real simulation modelling project aroused me. I would have the opportunity to do some ‘hard core’-computing, and learn the Java programming language at the same time. . .

And, learning I did! Not only Java, but also L^AT_EX, MATLAB, . . . (see § 10.3.2).

The total process was quite a large amount of work. It turned out to be more than I envisioned at the beginning, more than a year ago. A research project involving the design of a simulation model involves many tasks that all relate to each other and need to be completed. Tasks such as literature research, systems description, software development, validation, analysing results, writing thesis. Timely planning all this work (in advance) I found difficult to do. In the process, I also had to learn how to better handle my procrastination.

Some tasks I considered especially tedious and lengthy: Java debugging (when I did not find the error..), overcoming all sorts of errors and bugs during MATLAB number crunching, overcoming errors with the L^AT_EX-system.¹ Most tasks I liked: Java programming, generating graphs with MATLAB, making the 480-CPU computer cluster perform my experiments. These were the parts I truly enjoyed.

During the process, I developed quite a passion for energy-efficient lighting, up to a budgetary limit however. I did not yet personally dare to invest the ~ €30 needed for one of the high quality LED lamps now available. I did purchase a ‘state-of-the-art’ dimmable CFL for €18 . . . and also some of the last legally available (and very inefficient) 60W, 75W and 100W bulbs!

Wander Jager, of the RUG, eloquently described his fascination with consumers during his presentation in Delft before our half-way meeting (September 28, 2009). Some of his enthusiasm must have spilled over to me, because I now also find consumers to be really interesting. Their behaviour is quite unpredictable. For example: public awareness about global warming peaked after the 2006 release of Al Gore’s ‘An Inconvenient Truth’, yet

¹L^AT_EX is, in its core, a very solid system, having been in daily use by hundreds of thousands of scholars around the world, for more than 20 years now. However, the many additional packages one tends to load in order to achieve some special formatting task, are prone to ‘unsuspected interactions’ and other sorts of software complexity-related problems. . .

British Airways, which has been offering full CO₂ compensation on its flights for the last four years, finds that only 3% of its customers buy these ([The Economist, 2009](#)). Apparent contradictions, such as this one, are really interesting to research further!

In this preface, I would like to express my deep gratitude to all my family and friends who have supported me during my studies... with genuine interest, kind words, love, making it possible financially, sometimes trying if I could push myself perhaps harder, at other times telling me to back off a bit... Martin, you suffered a severe lack of attention during the many evenings and weekend days that I worked on this project and we couldn't do 'more fun' things... You did not always understand my work habits... I realise these times have been frustrating and I think you and I are both very glad this work now comes to a conclusion and we can move on!

Furthermore, I would like to deeply thank all of my supervisors: Prof.dr.ir. Margot Weijnen, Dr.ir. Gerard Dijkema, Dr.ir. Els van Daalen, ir. Emile Chappin and dr. Wander Jager. You have all contributed in many ways to this thesis! Emile, you were my daily supervisor, your very positive and optimistic spirit is your greatest strength! When I could not think of a way to do something, or I was rather frustrated by something (that could happen), your door was always 'open' and you had always kind words ready, stimulating me to find a new approach and try again . . . Gerard and Els, in the studies I always enjoyed your lectures, I am glad you were my supervisors in this project; I always welcomed your feedback very much... thanks for pressing me towards a more speedy progress. Wander, your input contributed much to the social modelling and my understanding of it; I truly enjoyed our conversations and your presentation here, in Delft. Margot, thank you also for your guidance; you are always rather busy but to me you were a very warm person and I think you are inspirational for the section.

And, of course, I also want to thank all other 'colleagues' at the E&I section: staff people, Ph.D. candidates and other M.Sc. students at the E&I section: you always provided a very welcoming work atmosphere, even when desk and chairs were in short supply . . .

Lastly, I would like to especially thank Guido Kuijpers, who, in the summer months of 2009, helped the work greatly by collecting data on lamps from many places in Delft, Zoetermeer, and filling it into the ontology . . . thank you for doing so and working with me on this. I hope your project will come along nicely and you too will be happy with your results!

The work was already well underway when, on 18 March 2009, the European Commission decided to go ahead and implement the ban of non-efficient light bulbs. According to the European Commission, by 2020 the regulations will prevent a yearly 80 TWh² of electricity being generated, causing a yearly stimulus to the E.U.'s economy of 11 billion euros ([CEC, 2009a](#)).

A great day for energy efficient lighting? Let's find out in this thesis. . .

MAARTEN AFMAN
Delft, February 2, 2010

²=1× Belgium

Contents

I	Problem exploration and research framework	1
1	Introduction	3
1.1	Developments in lighting	3
1.2	Electricity usage in residential lighting	4
1.3	Problem statement and research goal	7
1.4	Research questions	8
1.5	Structure of this thesis	9
2	Systems description	11
2.1	Introduction	11
2.2	Description of the consumer lighting system	11
2.3	Marketing simulation perspective	19
2.4	Transitions and their management	24
3	Choice of modelling approach	31
3.1	Introduction	31
3.2	Overview of some modelling techniques	32
3.3	Choice for agent-based modelling	35
II	Development of the consumer lighting model	37
4	Conceptualisation of the consumer lighting model	39
4.1	Introduction	39
4.2	Social system: consumers, market, government	39
4.3	Technological system: lamps and luminaires	42
4.4	Conceptualisation overview	43
5	Implementation of the agent-based model	45
5.1	Model Initialisation	45
5.2	Agent action sequences	47
5.3	Multi-Criteria Analysis: Decision Method for Lamp Purchases	52
5.4	Social Network generation	57
6	Validation	63
6.1	Introduction	63
6.2	Verification	64
6.3	Structural validation	66
6.4	Validating purchase behaviour of household	67
6.5	Validating purchase behaviour – Results	69
6.6	Empirical validation	76
6.7	Conclusion on validation	77

7	Experimental setup	79
7.1	Introduction	79
7.2	Indicators	79
7.3	Policy instruments	80
7.4	Executing the model	82
7.5	Summary	85
III	Results and reflection	87
8	Simulation results	89
8.1	Introduction	89
8.2	Visualising simulation experiments	89
8.3	Simulation results – graphs per output parameter	91
8.4	Conclusions from Simulation Results	103
9	Conclusions and recommendations	107
9.1	Answers to research questions	107
9.2	Recommendations	110
10	Reflection	113
10.1	Introduction	113
10.2	Reflecting on the model	113
10.3	Reflecting on the process	116
10.4	Reflecting on the platform	118
10.5	Overall conclusion	122
IV	Appendices	125
A	Electricity used by Dutch households for lighting	127
B	The E.U.’s ‘ban on bulbs’	129
C	Implementation in Framework for developing ABM’s	131
D	Lamps in the simulation	135
E	Details of model parameters	141
F	Implementing validation testing of household’s lamps purchase	151
G	Power factor of modern efficient lighting	155
H	Results of the first version of the simulation model	157
	Bibliography	163
	Index	171

Part I

Problem Exploration
&
Research Framework



Chapter 1

Introduction

This introductory chapter first concisely give an introduction to consumer lighting; it gives the problem statement; research objective; and the research questions.

1.1 Developments in lighting

Lighting is essential for modern living – it enables humans to do many things otherwise impossible, for both work and leisure. Whereas humanity has used artificial lighting for millennia, the last two centuries have seen dramatic increases in the use of lighting. From medieval times' candles to today's highly efficient gas discharge and solid state lamps, lighting technology has progressed greatly, contributing to a large decline in cost of lighting service (see e.g. Fouquet and Pearson (2006)).

Electric lighting really took off after 1879, when Thomas Edison demonstrated his durable, well-performing incandescent light bulb, by using it to light his Menlo Park laboratory complex (NPS, 2007). In a few years, electric power stations were erected in major cities around the world, supplying current for up to a few thousand incandescent glow-lamps per electric station (e.g. Forbes, 1889).

Gendre (2003) gives a good overview of the early developments in electric lighting. Since Edison's first carbon filament glow bulb (which gave 2 lumens of light per watt of electricity, and boasted a lifetime of 45 hours), many gradual improvements in electric lighting technologies were made. These developments increased the lifetime of the bulbs and the electric efficiency. By 1912, the glow bulb's efficiency had reached 12 lm/W. But from then on, technological progress more or less stopped: almost 100 years later, incandescent lamps still have efficiencies of about 12 lm/W.¹

Nowadays, the efficiency of the incandescent lamp is considered extremely low: circa 98% of the input power is given off as heat and not light². This low efficiency means that the incandescent lamp is not a



Figure 1.1 – Incandescent lamp for general lighting service; banned per 09/09.

¹The most recent innovation in incandescent lighting was the invention of the halogen lamp in the 1950's, which had a filling with halogen gas within a quartz envelope. The temperature of the filament could be increased, and therefore the efficiency could be improved. Halogen lamps can theoretically reach an efficiency of 20 lm/W; although in practice, halogen efficiency is far lower.

²Calculated with an efficiency of 12 lm/W and a theoretical maximum of 683 lm/W (Azevedo et al., 2009).

popular choice if more efficient alternatives are available. In the service sector and industry, fluorescent tube lights (lamp efficiency up to 105 lm/W; 9x better³) are the dominant choice. But there are more alternatives. High intensity discharge lamps (lamp efficiency up to 140 lm/W; 11x better) are popular for flood lighting of sports fields and department stores. Sodium lamps (lamp efficiency up to over 200 lm/W; 17x better), with their characteristic orange colour, are popular for street lighting.

The problem is, however, that in home lighting, the more efficient alternatives never gained much ground. The alternatives were either too expensive, technologically complex, or had other disadvantages, such as colour or the perceived ‘warmth’ of the light.

One efficient lighting technology that did reach the household, from the 1980’s onwards, is the compact fluorescent lamp (CFL). The CFL was introduced by Philips in 1980 (figure 1.2). Technologically, it was a true breakthrough: a complete fluorescent lamp system (tube, ballast) in a very compact package, so that it could be a plug-in replacement for an incandescent light bulb. The CFL was subsequently much improved in the decades afterwards, and became popularly known as the ‘*saving lamp*’. The CFL enables a dramatic increase in the energy-efficiency of lighting while, partly being a screw-in/plug-in replacement, it retains an amount of compatibility with existing luminaires. CFL’s offer clear benefits for many applications, and many governments tried to stimulate their use (see e.g. [Martinot and Borg, 1998](#); [Mills, 1993](#)).

Another exciting development is solid-state lighting: the Light-Emitting Diode (LED). The first commercial LED, following up on advances in semiconductors, was designed by Holonyak of General Electric in 1962⁴.

Since then, the developments in LED technology continued, and these days, LED lamps are a very promising alternative. In the laboratory, LED designs achieve unparalleled electric efficiencies compared to other light sources ([Dupuis and Krames, 2008](#)). Proponents consider the LED as the ultimate lamp of the future, because it is very suitable to a wide range of applications, and because it will continue to achieve significant gains in electric efficiency ([Azevedo et al., 2009](#); [Curtis, 2005](#); [Holonyak, 2005](#); [U.S. Department of Energy, 2009](#)). Figure 1.3 shows an example of a LED spotlight.

A problem is, however, that the inefficient incandescent lamp is the type of lamp that is still predominantly used by households. Despite the fact that the CFL was introduced long ago, it did not fully take over the market. As of 2008, CFL saving lamps are even completely lacking in 45% of all European households ([Bertoldi and Atanasiu, 2006](#)). Therefore, one could say that quite some electricity is wasted in the consumer lighting sector. An estimate of this is calculated in the next section, § 1.2.



Figure 1.2 – The Philips SL*; the first commercially available CFL (1980; 18W, 900 lumen). A technological milestone, but it had some drawbacks (e.g. weight, dimensions).

1.2 Electricity usage in residential lighting

How much electricity is being used in the residential lighting? The sheer number of lamps we use makes lighting responsible for a sizeable part of the total electricity demand. This means lighting is responsible for a significant share of greenhouse gas emissions from power generation. To give an order-of-magnitude overview of the size of lighting’s electricity consumption, we will give some worldwide data, and then focus on the Dutch situation.

³Efficiency data from [Azevedo et al. \(2009\)](#); [Gendre \(2003\)](#)

⁴The Russian scientist Losev discovered, and worked with, Light-Emitting Diodes before Holonyak. Losev published on them in the period from 1927 until his death in Leningrad in 1942. ([Azevedo et al., 2009](#)).

Mills (2002) performed a study on the worldwide cost of lighting. Based on a large number of studies, Mills calculates that 2016 TWh of electricity was produced *worldwide* in 1997, just for electric lighting⁵. Mills also calculates that, within the 28 IEA member countries (countries that constitute a major part of the developed world), lighting consumes 15% of the *total amount* of electricity produced, of which an average of 28% is used for *residential lighting*.

In the Netherlands, each household uses about 500 kWh of electricity per year for lighting (see appendix A). If savings of 40 % would be possible, this would annually save 1.5 TWh, equal to taking a 320 MW power plant off the grid (estimations in appendix A).

Therefore, increasing the efficiency of lighting systems is an important way of achieving lower CO₂ emissions. Not only does it save on CO₂ emission, it is one of the abatement options that also achieves a substantial marginal revenue in doing so: it pays back the investment cost to ultimately both generate a profit *and* reduce CO₂ emissions (Enkvist et al., 2007).

Given the magnitude of the electricity usage by lighting in the residential sector and the large potential for energy savings that exists, it is understandable that the government wishes to promote energy-efficient lighting, like the CFL and the LED lamp.

Over the years, there have been a number of stimulus programs that aim to increase the use of CFL's and, recently, LED lamps (e.g. CEC, 2005; Mills, 1991; Nationale Postcode Loterij, 2009; Taskforce Verlichting, 2008). Stimulus programs typically aim to increase awareness of the possible energy savings and to encourage adoption, by distributing free samples, or giving a rebate on the purchase price of an energy-efficient lamp.

1.2.1 The limited success of energy-efficient lighting technologies

Up to now, these stimulus programs did have some effects, but only to a certain extent: the average European household has about 3 CFL's (Bertoldi and Atanasiu, 2006). Three decades after its introduction, the CFL is adopted, but only partially. This relative lack of success seems remarkable given the clear financial and environmental advantages of using CFL's. Why is the adoption of CFL's so low?

One could think of a number of explanations for this. Smeets (2009), a manufacturer of lamps, thinks that the main barriers to adoption are (1) the purchase price (despite the short payback time), and (2) scepticism about the shape, the dimensions and the light quality (in many cases because of experience with previous generations of CFL's).

The purchase price is important indeed. Consumers are very sensitive to retail price and are (generally) not used to thinking in terms of life cycle cost when deciding on the 'cheapest lamp to buy' (Menanteau and Lefebvre, 2000). Üрге Vorsatz and Hauff (2001) found that, while marketing the associated cost-savings is a crucial success factor in adoption, not all market segments may understand it.

On the scepticism: it is certainly possible that some consumers now withhold from buying CFL's because of disappointing experiences in the past. The first types of CFL's had longer ramp-up times, worse light output, and were far larger than the present designs, posing a compatibility problem for many existing luminaires. Consumers may not know that present designs have improved, or consumers may still feel the CFL is lacking in some respect (see e.g. Martinot and Borg, 1998; Peifer, 2007). In



Figure 1.3 – An example of a modern LED spot (5W, 178 lumen), with sufficient light output to replace a 35 W halogen spot (Ledilight, 2009)

⁵In the figure, transmission and distribution network losses are included. Estimation of these by Mills is 10%, an underestimation for developing countries.

addition, the provided options in shops are limited; consumers may find it too difficult to choose the right ‘alternative’ lamp.

Despite the strengths of LED technology, the success of the new LED lamps in the marketplace is not guaranteed. As of yet, not all LED technology is suitable for general lighting applications. The efficiency of LED, both in terms of electrical efficiency and economic efficiency, is improving year-on-year. Since its invention; prices per lumen produced decrease at a rate of a factor of 10 per decade, while LED chip light output increases a factor of 20 per decade (U.S. Department of Energy, 2009, p. 33).

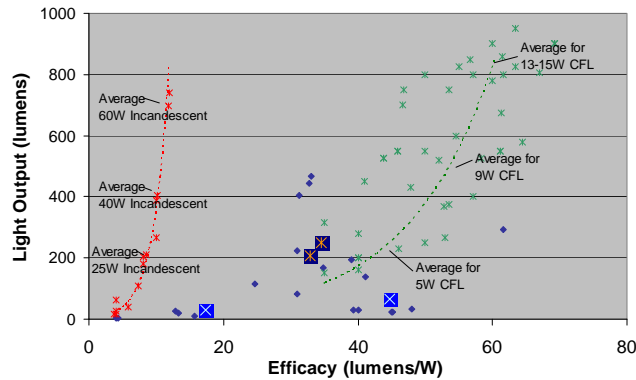


Figure 1.4 – Luminous efficiency vs. light output for LED, CFL and incandescent technology. Values for LED are shown in blue. Measurements from commercially available lamps (from Pacific Northwest National Laboratory, 2009, p. 25).

However, a problem is that efficiency and lifetime claims of LED lamps are exaggerated by manufacturers (Pacific Northwest National Laboratory, 2009; VSL, 2009b); manufacturers claim LED to be better than CFL, while in reality the performance of current LED products on the market is a mixed bag. Figure 1.4 shows the performance of a number of LED products that are now on the market. Most LED products perform somewhat in between traditional incandescent and efficient CFL technology.

Sandahl et al. (2006) give an analysis of lessons that can be learned from the slow and incomplete adoption of the CFL, with recommendations for the introduction of LED lamps. One of the recommendations is that manufacturers do not exaggerate claims on performance. But this is exactly what seems to be happening with LED. Quality-wise inferior LED products appearing on the market are creating negative publicity (see e.g. Maurits, 2009; Oosterbaan, 2009; VSL, 2009a,b). If negative publicity continues, this can have the effect of creating a negative perception of LED technology with the average consumer. This is damaging the future prospects of LED for general lighting, and a worrying situation. Luckily, there is positive publicity on LED’s as well (Lemnis Lighting and Nationale Postcode Loterij, 2009): the LED lamp is now also available in supermarkets.

Given the large market share of inefficient lighting’s in the consumer sector, and the consumer’s reluctance to consider energy-efficient alternatives, it is extremely interesting to research the effectiveness of policy measures to promote energy-efficient lighting.

1.2.2 The ban on incandescent light bulbs

To speed up change in the sector and give energy-efficient alternatives a boost, on 18 March 2009 the European Commission decided to pass regulation (under the EU’s Eco-Label scheme) that forces lighting products available to meet a number of stringent efficiency standards (CEC, 2009b). The regulation is popularly known as the “*ban on bulbs*”. The policy is supported by the lighting industry (European Lamp Companies Federation, 2009).

On a national level, the Minister of the Environment and Spatial Planning, mw. Cramer, initiated a Taskforce Lighting, already in 2007, that aims for similar goals ([Taskforce Verlichting, 2008](#)).

The efficiency requirements mean that traditional non-directional incandescent light bulbs, for which there are more efficient alternatives, will be phased-out, starting this year already. The phase-out means that the applicable light bulbs may no longer be produced in the European Union or imported anymore.

As of now, the regulation entails the phaseout, effective September 1, 2009, of all non-clear (frosted) incandescent light bulbs (depicted in figure 1.1), and the clear ones exceeding 100W; and the phased withdrawal of the remaining clear lamps with lower power ratings in the years to come, up to 2012, when they will all be phased out ([CEC, 2009b,d,e](#)). Halogen lamps are also subject to efficiency regulation, and will be mostly phased out by 2016. See appendix B for a full description of the regulation.

Fig. 1.5 shows an example of a medium-efficiency (energy class 'C') lamp design efficient enough to be allowed in the years 2012–2016.

The regulation is a huge step: it forces consumers to use efficient lighting technologies, by taking away the most popular options (the general service incandescent light bulb). Much opposition exists against the ban, and when the full effects will be felt in the coming years, the opposition can be expected to grow.

In 2013, a functionality review will take place. In this review, the regulation might be altered to allow for more relaxed requirements, or more stringent, depending on progress with alternative technology and the public response to the policy.



Figure 1.5 – Modern Halogen lamp (20W; 370 lumen), for e.g. candelabra. The bulb is a low-voltage halogen, the lamp contains an electronic transformer (image courtesy Philips).

1.3 Problem statement and research goal

The E.U. ‘ban on bulbs’-policy will certainly increase the demand for alternatives to traditional bulbs. But which alternatives will become popular? Consumers’ response to policy measures is often different from the policy maker’s intentions. This can be illustrated, for example, by the slow and incomplete adoption of the compact fluorescent lamps, despite decades of stimulus programs [Ürge Vorsatz and Hauff \(2001\)](#); [Sandahl et al. \(2006\)](#). Therefore, a number of questions can be asked on the consequences of the ban. What will consumers do, which types of lamps will they purchase instead? What alternatives will become popular, and which will not? Will people significantly stock in on specific types of bulbs? And what will be the response of the manufacturers? Could there be pitfalls of this policy? Are there rebound effects, and if so, which can be expected?

A possible pitfall of the policy is, that consumers switch to inefficient technologies that are currently exempt from the ban. Another possible pitfall is that consumers are exposed to products that are technologically or quality-wise too immature. Then, just as with the introduction of the CFL, consumers may have a unsatisfactory experience that will negatively influence their opinions for a long time to come.

The demand for alternatives resulting from the ban will possibly also stimulate new players to enter the market with new products. But these new products may not be the

energy-efficient alternatives aimed for. More consumers will be exposed to alternatives previously not known to them (e.g. LED products). This might cause all sorts of effects: opinions will be formed, people might have negative or positive experiences, and communicate these to others. Through means of principles such as *word-of-mouth*, people might develop negative or positive perceptions, not based on their own, first hand experience, but based on what they hear from others. Some technologies might become successful while the reputation of other technologies might suffer. Public opinion can change to an extent that it forces a change of regulation, which can backfire on industry.

In any case, the E.U. ‘ban on bulbs’ will certainly create a large amount of dynamics in the lighting sector. It is the combined actions of consumers (their objectives, preferences and behaviour), as well as the actions of industry players, that jointly shape the success or failure of lighting systems and thus also the energy efficiency of the lighting system. It is therefore unlikely that the consumer lighting sector will develop exactly as policy makers envision: the dynamics of the sector are not understood in advance. To tackle this problem, this research is proposed.

The research aims to *acquire understanding of the response of the consumer lighting sector, resulting from the E.U. ‘ban on bulbs’*. By developing a simulation model of the consumer lighting sector, we intend to test and evaluate possible reactions of consumer lighting actors, learn to understand patterns that appear, and on the basis of that, achieve insights into what will be necessary to make the E.U. ‘ban on bulbs’ effective in lowering the electricity consumption in the consumer lighting sector.

1.4 Research questions

The main research question is:

How can we explore the consequences the E.U. ban on bulbs will have on the electricity demand of the consumer lighting sector?

This main research question can be answered by means of the the following research questions:

- r.q. 1. How can the consumer lighting sector and its development be systematically characterised?
- r.q. 2. What is a suitable modelling approach in order to evaluate the developments in the consumer lighting sector that result from the E.U. ‘ban on bulbs’?
- r.q. 3. From the application of the simulation model, what insights can be gained on the effectiveness of the E.U. ‘ban on bulbs’ in the consumer lighting sector?

The first research question is important for the design of the simulation model. A socio-technical systems perspective is used for this, incorporating the relevant social and technological components. This is expanded with a transitions-perspective because a transition in consumer behaviour and used technology is aimed for by the government (the E.U.). The perspective is expanded using a marketing simulation perspective, as it will be seen that this is needed to accurately capture what’s important for the consumer in the simulation model.

The second research question then is on the design of a simulation model that can be used in assessing the consequences of the E.U. ban, building on the characterisation of

the consumer lighting system from the combination of the transitions and marketing simulation perspectives.

By the application of the simulation model, insights need to be gained on the consumer lighting sector and the effectiveness of the E.U. ban. This is the topic of the third research question.

The research questions are answered in order; figure 1.6 shows the relations between the research questions and how they relate to the chapters of this thesis (explained in § 1.5).

Determining a complex system's evolution

The research questions should not be taken to suggest that we can positively determine the system's evolution. We cannot, as the simulation model tries to give insights into the evolution of a system that will be found to be complex (§ 2.2).

However valuable the insights gained are, they stem from an attempt to capture the real world's complexity into a computer model. This computer model is in its definition a simple system, yet when the simulation starts, the model behaves in a complex way.

Due to the complex nature of the real world system, any computational approach to 'predict' *the* future evolution of the system is impossible. In a complex system, small disturbances (or rounding errors in recording system variables) can propagate to lead to different system states. This was first discovered by Lorenz (1963) in his work on weather forecasting. In trying to predict future development of a non-linear, complex system with a computer model, there are always inaccuracies involved that make anything but short-term prediction impossible.

What we can do is perform a range of simulation experiments, and sketch a range of possible outcomes, and classify these outcomes. We may see patterns of behaviour that can be characterised as chaotic; stochastic; semi-stable; or stable (Hansell et al., 1997). We may predict some effects, but we cannot predict *the single future* of the consumer lighting system.

Due to the absence of reliable knowledge of the future state of the consumer lighting system, we are also unable to derive policy measures that are certain to be effective; measures that are certain to *guarantee* effectiveness of the E.U. ban. Hopefully the range of possible outcomes of the modelling approach will be insightful and helpful for adopting, changing or creating new policy.

1.5 Structure of this thesis

This thesis is structured in the way visualised in figure 1.6. From the figure, it is clear that the modelling effort undertaken, constitutes the biggest part of the research in this thesis.

This part, **Part I**, deals with the problem exploration and the setting up of a research framework. It develops a system's description, from which essential characteristics are identified. The characteristics are the basis for selecting the modelling approach used for the research.

- ⇒ The next chapter, **chapter 2**, develops a description of lighting system, its components, the occurring and possible transitions and transition management strategies of the actors. The systems description is adapted with learning from an innovation diffusion and marketing perspective.
- ⇒ **Chapter 3** is on the selection of a suitable modelling approach.

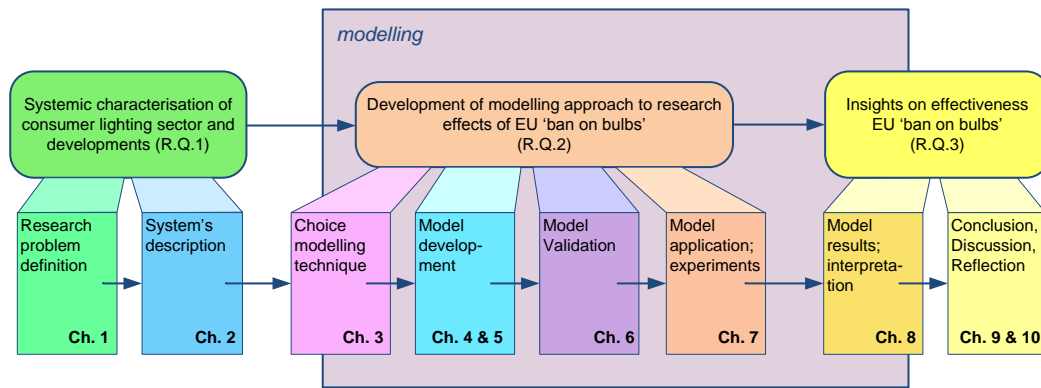


Figure 1.6 – Visualisation of the elements of the proposed research and the structure of this thesis. The elements at the top row corresponds to the research questions. Below these, the different chapters of the thesis are indicated. The blue box shows which part of the work can be considered the modelling part.

Part II deals with the development of the simulation model of the consumer lighting sector, the second research question. The development of the model is spread out over four chapters, dealing with the modelling concept, the implementation, validation and the development of an experimental setup.

- ⇒ First, in **chapter 4** a conceptual implementation of the simulation modelling approach is given. This conceptualisation is the translation from the systems description of chapter 2.
- ⇒ Then, in **chapter 5** the implementation of the modelling approach is described. The chapter contains a detailed overview of the data structures in the simulation model, the decision method used in consumer purchase decisions and a discussion on social network models.
- ⇒ **Chapter 6** is on the validation of the model that was developed. The chapter describes the different tests performed. Results of structure-related tests are presented and discussed.
- ⇒ **Chapter 7** is on the development of the experimental setup used.

(Note: Chapters 5 and 6 contain quite some detail. Readers not interested in the details of model implementation or model validation can skip from chapter 4 directly to 7.)

Part III is the part of the research where we will present, interpret and discuss the model results, observe interesting patterns, and then draw conclusions. We present recommendations for policy, and reflect on the results.

- ⇒ First, in **chapter 8**, the results of the simulation experiments are presented in a series of graphs. Each graphs is interpreted and it is shown what can be learned from it.
- ⇒ In **chapter 9**, the overall conclusions of the research undertaken are presented. This entails answers to the research questions posted in § 1.4. The chapter concludes with recommendations for policy.
- ⇒ In **chapter 10** we reflect on the results and the process in which these have been created. Also courses for future work are subjects of this chapter.

Chapter 2

Systems description

2.1 Introduction

This chapter is about finding a systems description of the consumer lighting sector, to characterise the sector and its development, and the transitions that occur.

A socio-technical systems perspective is taken as a starting point for the description of the system in § 2.2. The systems description means that we will discuss the important elements in the system, subsystems that are present, the delineation of the system boundary, and the interaction mechanisms that occur in the system. As it was found that the systems view did not provide sufficient detail of the behaviour of the lighting consumer, the system's description was expanded with a marketing simulation perspective in § 2.3.

To characterise the developments in the consumer lighting system, in § 2.4 a transitions perspective was introduced. Transition management provides a policy framework for government. This leads to a discussion on how experimentation with simulation models could aid in finding successful transition management strategies for consumer lighting (§ 2.4.5), useful to evaluate alternatives to the E.U. ban on bulbs.

2.2 Description of the consumer lighting system

To start this research we must define what we considered to be the consumer lighting system, and describe what is meant by this. This is the subject of this section. By choosing which elements to include in the analysis and which elements to leave out, the system is delineated.

In describing the system, we will use a socio-technical systems perspective.

Complex and adaptive socio-technical system The consumer lighting sector can be considered a *complex socio-technical system*. The system can be viewed as having a part that comprises social actors and their interaction and development—the social subsystem—and a technological part, with the technological intricacies, compatibilities and developments—the technological subsystem.

With '*complex*', we mean that from a systems viewpoint, the sector is complex, and this complexity arises, among others, from the interdependency of social system components and technical components through many layers of interaction, feedback effects and emergent properties (Dijkema and Basson, 2009).

The system's actors are '*adaptive*': they self-organise adapt to changes in their environment (Macal and North, 2005), they react to what other actors do. The actors in the

social subsystem can be considered as flexible and self-adapting subsystems of the larger system—complex themselves.

The interdependency of the social and the technological system parts result in what is called co-evolution: changes in the technology induce social system changes and vice versa (Geels, 2006; Nikolic, 2009).

Multi-level structures A multi-level description (Chiong Meza and Chappin, 2008) helps to discuss the different aspects of the system. A system concept can either be at one of three levels: the system (macro) level, interaction and governance (meso) level, and the ‘agent’ (micro) level.

If we apply this multi-level framework to the system, then we see that institutional developments, technological development, changes in the energy system, climate change and economic situation are all concepts at the system level. System level concepts and developments all influence, and are influenced by, concepts at the interaction / governance and agent levels.

The agent level is made up by different actors in the consumer lighting sector: households; manufacturers; retailers. Also the technological components are at this level. At the interaction and governance level we find both the government trying to influence individual consumers and other sector actors, as well as the interactions between the different actors, such as consumers learning about lamps in a place of sale; consumers talking to each other about lamps; manufacturers employing marketing strategies; discounting specific lamps, and technological interactions (compatibilities).

A more exhaustive description of the system elements will be given in the following subsections. Technological system components are described in § 2.2.1, social subsystems (actors) are described in § 2.2.2, and interactions between actors and technology are described in § 2.2.3. Findings are summarised in § 2.2.4.

2.2.1 Technological subsystem – technological components

Technical components in the consumer lighting system are the devices related to the lighting service (such as lamps and luminaires), as well as their developments and innovation. It is the technical part of the system that is responsible for providing the needed lighting service but which also generates the emissions.

Main technological components are the range of all the different kinds of lamps (light bulbs¹) suitable for home lighting, the many options for luminaires and lighting fixtures, the light points in the house (these are either the fixed light points at the ceiling / wall of homes, but also include many more locations where people plug in lamps: the desk, locations for standing lamps, etc.), light switches, dimmers, mains voltage coupling apparatus: transformers (electromagnetic, electronic); CFL ballasts; current control modules; and also the electric wiring, power strips, extension cords, and fuses. A schematic overview of this is displayed in figure 2.1.

A free standing luminaire often has an attached electric cable that can contain a switch or a dimmer. A free standing luminaire also contains the needed electronics for the operation

¹In plain English, *lamp* is a broad term reflecting a source of man-made light, which may either be a light bulb, or an the entire device (oil lamp, gas lamp). In this thesis, with *lamp*, we consequently mean the *light bulb*, i.e. the light-emitting component of a lighting system. Thus, *a lamp is the part that is usually user-replaceable, and by switching lamps, a user can influence the quantity, nature, and quality of light, without changing the luminaire.*

If we mean the entire (electrical) apparatus, we will use the term *luminaire*, the technical term for a lighting fixture. A luminaire is the complete unit, including lamp, and (if applicable) reflector, ballast, socket, wiring, diffuser, and housing (Sylvania, 2009).

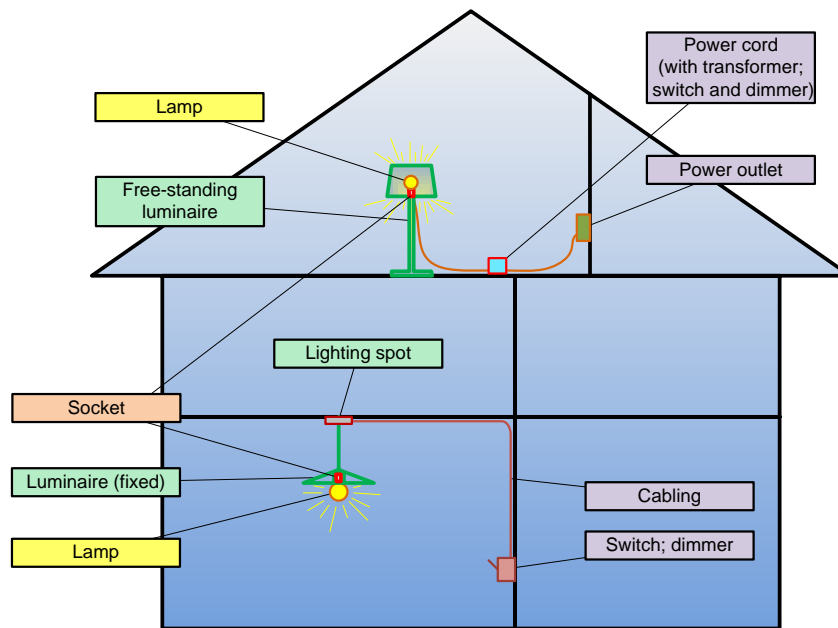


Figure 2.1 – Overview of the main technological components, related to consumer lighting. Two luminaires are shown (free standing and fixed). The free standing luminaire is plugged in a power outlet that delivers electricity at mains voltage. The fixed luminaire is installed at a lighting spot, which is supplied with electric current through installed cabling and a switches, which also may be a dimmer.

of the lamp (transformer for 12V Halogen; ballast for CFL; driver for LED). This electronics is usually dedicated for the luminaire and integrated in it, making it non-replaceable and limiting the choice of replacement lamps.

A fixed luminaire is located at a lighting spot, fixing the location in the house. The lighting spot also largely dictates the hours-of-use, a luminaire in the kitchen is usually switched on during meal preparation et cetera. The luminaire is operated through one or more switches, that can also be dimmers. The compatibility characteristics of the dimmer limit the amount of possible options for replacement lamps.

The technological subsystem in consumer lighting can be considered stable. In lighting, there have been a constant stream of developments, however the incandescent technology that is used in household lighting has hardly progressed in 100 years (see § 1.1).

2.2.2 Social subsystem – relevant actors

In the consumer lighting sector, relevant social actors are consumers, retailers, manufacturers and the government. Consumers are the primary users of the household lighting products, they purchase lamps in retail stores and use them. Social actors are also the (employees of) stores that sell luminaires and/or light bulbs, who give information and influence the lighting consumer. The manufacturers of the different lighting technologies, luminaires, and also providers of informational services (consultancies; environmental pressure groups) and the government are also social actors, who influence each other and the consumer.

Consumers

Consumers are the users of the household lighting products: they have a lighting demand, and therefore go out and purchase lamps. Because of their lamps purchases and their

behaviour in the use of lighting, consumers are very important actors in the consumer lighting system.

In § 1.2.1, the consumer was introduced as being very sensitive to retail price and generally not used to thinking in terms of full life cycle cost when deciding on the ‘cheapest lamp to buy’ (Menanteau and Lefebvre, 2000). Economically viewed, consumers calculate with extremely high implicit discount rates for the upfront cost, meaning they will consider savings measures as unattractive that will, in fact, save them a lot of money in the course of a number of years (Meier and Whittier, 1983).²

Consumers may not always possess the technical literacy to understand the concepts of costs incurred due to energy usage, despite being explained them in marketing and information campaigns (e.g. Ürge Vorsatz and Hauff, 2001). Consumers may have knowledge on lamps that is either correct or incorrect (or outdated).

Furthermore, consumers also have persistent perceptions and opinions on products, technologies and brands; those perceptions and opinions influence the consumer’s actions (see e.g. Martinot and Borg, 1998; Peifer, 2007). Consumers share these perceptions and opinions with other consumers they know from their social network by means of principles such as *word-of-mouth*. In marketing literature, the word-of-mouth interaction between consumers is recognised as one of the leading mechanisms that influences the purchase decision (Johnson Brown and Reingen, 1987; Richins, 1983).

In § 2.3 we focus more in depth on the consumer, when we introduce a marketing-based perspective on the consumer lighting system.

Businesses: manufacturers

Manufacturers of lamps (light bulbs) are important players in shaping the future of the consumer lighting system. The manufacturers are the creator-inventor of new lighting technologies. Manufacturers are largely in a position to direct research & development activities, come up with novel lighting technologies, and market these technologies (marketing is further discussed in 2.3).

Manufacturers generally are quite large multinational corporations. The three biggest manufacturers of lamps (light bulbs) are General Electric; Osram/Sylvania; and Philips. These corporations have manufacturing facilities around the world and have been leaders in the technological innovations in lighting. By shifting their manufacturing resources they may scale up their production in a specific type of bulb, increasing its availability in the marketplace and reducing its price.

There are also many smaller manufacturers specialising in some lighting products. One example is Megaman, a German manufacturer specialising in compact fluorescent lamps, one of the first to market CFL’s that work with an ordinary dimmer.

Smaller companies can be very innovative as well, and can bring innovative products to the market in a short time span. One example is a small Dutch startup company, Lemnis Lighting, which, by a combination of technological innovation and a marketing alliance with a popular lottery and supermarket chain, brought millions of LED lamps to Dutch consumers (Koornstra, 2009). The company was listed by the World Economic Forum as one of its 2009 ‘Technology Pioneers’ (WEF, 2009).

Manufacturers are able to decide on the quality of the products they manufacture. They may decide to go for very cheap production, and take a risk that product quality is not

²To off-load the burden of the upfront cost, options to ‘lease a lamp’ could be envisioned. The financier receives a part of the financial advantage of the realised energy savings as the lease payment. Options for leasing lamps exist for (small) businesses, but these aren’t (yet) available to consumers.

up to scratch or consistent between samples, or opt for a higher quality and a more reliable product (usually more expensive for the same light output level). Small startup companies can be expected to take more (technological) risk than large, well-established ('incumbent') manufacturers are willing to do. The well-established manufacturer is more protective of its brand reputation and has vested interests in continuation of its existing product lines.

Large manufacturers might be reluctant, to an extent, to invest large sums of money needed for a change to novel lamp production processes. When manufacturers do introduce a new lamp technology, the high investment cost of the new production process is one of the causes of the high initial price of new lamps, and also one of the limiting factors of the production rate of the lamps of the novel type (Smithsonian National Museum of American History, 2008).

With new product introductions, a possible consequence of the difference between young and small and large manufacturers is that technology may be pushed beyond its capabilities in the rush to be first. This can result in, for example, a low product lifetime and consumers who ultimately suffer and become disappointed, which may hamper the technology's further proliferation. Recently, the above seems to have occurred: the use of LED lighting has suffered negative publicity on quality aspects (Maurits (2009); Oosterbaan (2009); VSL (2009a,b); see § 1.2.1).

Businesses: lighting retailers

The other type of important businesses are the retail stores. Retailers can be divided in dedicated lighting stores, and stores that deal not exclusively in lighting. Dedicated lighting stores sell mainly luminaires but offer also lamps. Non-dedicated lighting stores sell lamps and/or luminaires, but this is only one of the products they have on offer. Examples are electronics stores; department stores; home decoration, interior design and furniture stores; do-it-yourself (DIY) outlets; and supermarkets.

Dedicated lighting stores are influential in shaping lighting fashion. When a consumer wants to buy a new luminaire, the consumer is influenced by what is for sale; even if he ultimately purchases at a non-dedicated lighting store. What kind of luminaires lighting stores sell is important: the luminaire determines the lamps that fit.

The non-dedicated lighting stores are important because they sell the replacement light bulbs. These stores can decide which type of light bulb to have on stock, or promote. They are important in influencing what the consumer knows about the available lighting options. Retailers in the business of home decoration, interior design, DIY outlets, etc. are also influential in shaping fashion trends, and thus in shaping future demand for lighting products. Examples are Albert Heijn, Bijenkorf, Hema, Ikea, InterGamma, etc.

It is assumed that both manufacturers and other lighting industry players have their own, possibly differing perceptions of the consumer's behaviour (consumer's demand for lighting products, knowledge on lighting, 'rationale' in making purchase decisions).

Government

The government is an important actor in the consumer lighting sector. The government may be taken at a number of levels: the European Union, with the European Commission as its primary executive arm; the Dutch Government; some government ministries. From Dutch ministries, the Ministry of Housing, Spatial Planning and the Environment is the primary relevant actor, as it makes the most policies regarding energy efficient lighting for the built environment (e.g. Taskforce Verlichting, 2008).

Generally speaking, governmental actors on all levels share the same agenda regarding energy-efficient lighting: they try to influence the consumer's behaviour, aiming to reduce electricity consumed in the residential lighting sector. Different governmental actors also have other objectives and interests: government is active in many sectors of society. Governmental policy fields such as industrial policy, or competition policy, will certainly impact lighting manufacturers, and thus also influence the consumer lighting system. However, in this research we will not deal with these other interests different governmental actors might have. From now on we will aggregate all government actors and consider only 'the government', and we will only consider government strategies that directly impact, and are target, the consumer lighting system.

The government employs different strategies to entice the consumer into energy efficient behaviour and thus the use of energy efficient lighting. As these strategies aim for a transition in the lighting system, where the traditional technology is swapped in favour of more efficient alternatives, and these strategies are (partly) based on the learnings from transition management (Rotmans, 2003), we call these strategies *transition management strategies*. Example transition management strategies are incentive programs and publicity campaigns, trying to raise awareness. The E.U. has a mandatory eco-labelling scheme that aims to increase consumer awareness of energy consumption of different lamps (updated in 2009 for lighting: CEC, 2009b,c).

The government also employs transition management strategies to steer *technological developments* in lighting, and how lighting businesses market their products. For example, the E.U. has a voluntary CFL Quality Charter (CEC, 2005), that encourages manufacturers to improve the quality of their CFL products (ramp-up time, mercury content, etc). We will discuss the government's transition management strategies separately in § 2.4, where we focus on transition management.

The government itself is part of the consumer lighting system: it is influenced by developments in the energy system (e.g. the developments of electricity demands) and developments in the technological sphere (the development of energy efficient lighting solutions, and the adoption of these). The government has a specific view of the consumer's rationale and of the primary mechanisms underlying the consumer's behaviour. These views are the starting point for government action and transition management strategies.

2.2.3 Interactions

The consumer lighting system also has important interactions, between actors; technological components; and also between social subsystem and technological components. These are described in this section.

Social interactions

A first type of social interactions (interactions between actors) are interactions between consumers. Consumers communicate with one another in a social network structure. The consumers sharing their knowledge, opinions, and perceptions on lamps; technology-related matters and brands, through principles such as word-of-mouth (§ 2.2.2).

Other interactions are the interactions between a government and other social actors. The government is trying to influence the consumer to switch to energy efficient lighting. For this the government conducts information and awareness campaigns. The government also tries to influence the manufacturers, the government wants the manufacturers to increase production of energy-efficient lamps, and improve the technology.

Businesses (manufacturers, retail stores) also interact. They try to entice the consumer

into purchasing products using a number of marketing strategies (e.g. pricing, promotion). Marketing is further discussed in 2.3.

There are also interactions between social system components and technology: **social-technological interactions**. A first example is when social actors need to make purchase decisions regarding lamp products. Actors may not be able to understand the intricacies of the technology involved. The technological characteristics and requirements may be difficult to understand, causing people to purchase the wrong product for their situation. Another, more indirect, example of a social-technological interaction arises due to improvements in LED technology. These technological developments, with the many lamp products appearing on the market makes changes political processes: the push to end the use of incandescent technology (e.g. the EU's ban on bulbs) is made possible by the range of alternatives being available or around the corner.

Technological interactions

There are also strong interactions between technological components. The technical subsystem consists of an assemblage of components that interact in a number of ways, increasing the complexity of the technological system.

The nature of a technological interaction is determined by different physical and electronic properties of the components. Components can be designed to be compatible with one class of other components or technological parameter, or be designed with a more universal compatibility in mind. The compatibility relationships between different components are the most important, as they are the most restrictive.

Example technological relationships:

- A specific luminaire has a specific socket, with a specific voltage (12V, 230V, etc.), that only allows certain specific lamps to be fitted. The lamps need to match in socket, in dimension, in voltage, et cetera.
- A luminaire can be a free standing luminaire, being autonomous in the sense that the only coupling with the residence is through a 230V (for Europe) power outlet. A luminaire that is in a fixed location in the house, integrates with one or more switch(es) that operate the luminaire.
- Switches to operate a luminaire can be simple binary on/off-switches, or they can contain active electronics that are compatible with only some specific options for lamps and/or luminaires. Dimmers only work in some nominal wattage range. There are different types of electro-magnetic or electronic (touch) dimmers, with/without memory; posing different limitations on allowed lamps. Lamps themselves react in different ways to dimmers, causing different effects, e.g. on the mains power (reactive power requirements).
- A luminaire can contain electronics that are specific to one type of bulb. Examples are: the electromagnetic or electronic ballast and starter modules for a fluorescent light tube, an external ballast for some CFL's, or a transformer for a 12V Halogen (electro-magnetic; electronic; with/without 'touch-dimmer'-functionality), a driver for LED arrays (with/without dimming capabilities, etc).

2.2.4 Conclusions from social-technical systems description

The following characteristics can be concluded on the basis of the system description presented in this section. These characteristics are need to be translated as modelling

assumptions to be incorporated in a simulation model. The list of characteristics are input for the choice of modelling technique in chapter 3.

- S.t. concl. 1. Important **technological components** of the consumer lighting system are the lamps, luminaires, dimmers, and sockets.
- S.t. concl. 2. The technological subsystem contains a number of **linkages and interactions** (voltage level, lamp socket, presence of a dimmer or normal light switch). These interactions are important in restricting and shaping behaviour of consumers (and other actors).
- S.t. concl. 3. **The individual purchase decision**, made by consumers when purchasing technological components (lamps, luminaires, dimmers) is the main mechanism by which, lastingly, the energy use in consumer lighting can be reduced. Together with the usage by the consumers (hours-of-use), the technological components are the main **determinants of the energy use**.
- S.t. concl. 4. The **social** part of the consumer lighting system consists of a number of involved **actors**: consumers, retailers, manufacturers, and the government, of which (in consumer lighting) the **consumer** is the most important (the consumer buys the lamps).
- S.t. concl. 5. The government, retailers and manufactures have **strategic objectives** and actively try to influence the consumer's behaviour. the manufacturers and retailers have more commercial motifs.
- S.t. concl. 6. The government wants consumers to reduce electricity consumption and for this instigate a **transition** in consumer lighting, away from old and inefficient technologies to modern and efficient alternatives. For this it
- S.t. concl. 7. The consumers partly have **strong preferences and persistent perceptions (opinions and beliefs)**, and they share these with other consumers they know, influencing the purchase behaviour of other consumers.

We conclude that the consumer is especially important if we want to influence the system, we must change the behaviour of the consumer. In order to do so, we need to find out more about the consumers preferences, opinions and beliefs (the last characteristic). To do this, in § 2.3, we will apply a 'marketing simulation perspective' to the systems description.

Systems diagram

An overview of the described system components is displayed in figure 2.2.

At the centre of the diagram is the core of the system: the social actors, the government who implements policy, and the technical assets with their characteristics. The actors buy; sell; operate and dispose of lamps and luminaires. The bottom box contains the interactions of actors and technology, which are important in shaping the system's behaviour. (The government's policy could also be thought of as an activity at this level).

The government is the principal agent to influence the systems development, this is reflected by the top item '*Transition management strategies*' (see also § 2.4.4). *Scenario*'s, at left, can be seen as inputs for the system. Scenario factors are exogenous from the standpoint of the system's actors. *Transition indicators* (Chappin and Dijkema, 2010) are used to observe the pace of change in the sector. They are further discussed in § 2.4.5.

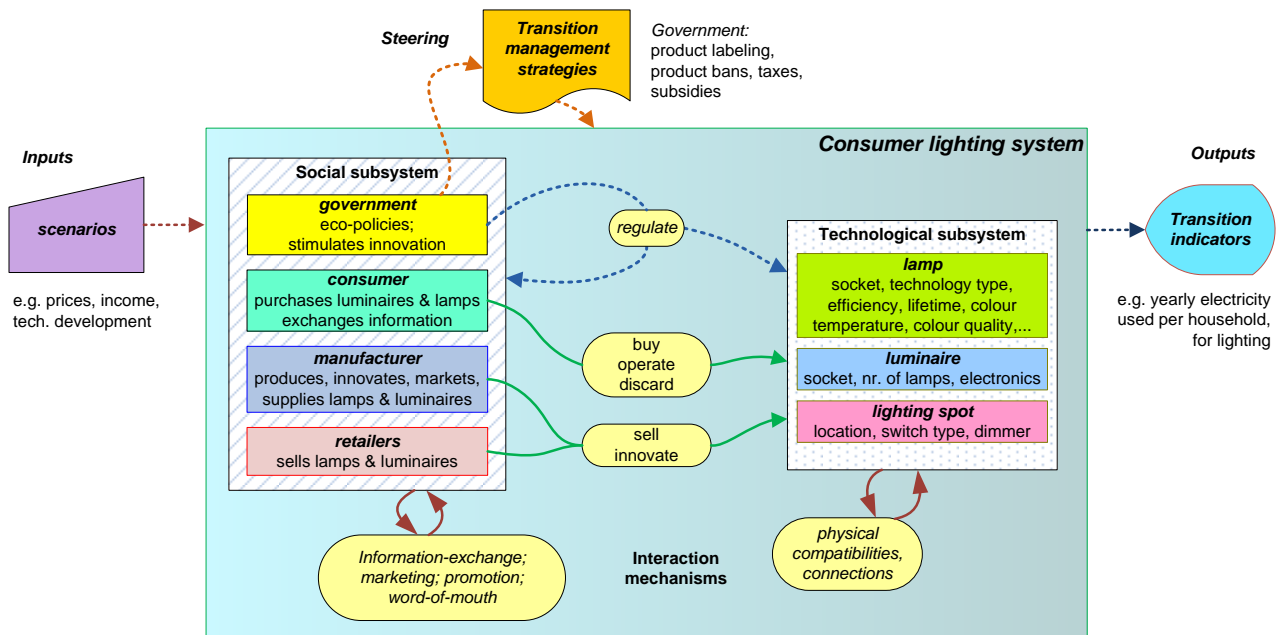


Figure 2.2 – Diagram of the consumer lighting system.

2.3 Marketing simulation perspective

2.3.1 Introduction

In § 2.2 we described the consumer lighting system from a socio-technical systems perspective. Would the system's description change, or need to change, if we focus on the system in a different way, and we use a marketing simulation perspective to focus more on the consumer, which was found to be very important?

Marketing learns us aspects of what consumers' purchase behaviour drives. Marketing is a business process, used to “create the customer, to keep the customer and to satisfy the customer”³. *Marketing science* is the quantitative approach to market research and analysis, using data analysis to deliver greater precision and direction to marketing and sales decision-making (Hewitt, 2008).

Topics of marketing include *pricing, new products, channels, promotions, buyer behaviour, product lines, forecasting, advertising, competitive strategy, services marketing, salesforce management, targetability, and segmentation* (INFORMS, 2009). All of these topics are applied by manufacturers in their attempts to persuade households of buying products; for our understanding of the lighting consumer, ‘pricing’ and ‘buyer behaviour’ are the most relevant.

In § 2.2.2 a number of things already were said about pricing and buyer behaviour. Product pricing is a critically important aspect for a consumer, furthermore, consumer behaviour is shaped by a number of other mechanisms.

Crosbie et al. (2008) show that nowadays, mood lighting is becoming increasingly significant. A desire for stylish interiors can override environmental principles. There is a very weak correlation between environmental consciousness and environmentally efficient behaviour and product purchases (Nationale DenkTank, 2009, p.25).

With fashion a key driver for what consumers decide, and consumers influencing each

³<http://en.wikipedia.org/wiki/Marketing>

other and being influenced by the promotional messages in the media, what can we learn more about the adoption decisions consumers make on energy efficient lighting? For this, in the § 2.3.2 we will introduce innovation diffusion theory and apply it to the consumer.

2.3.2 Innovation diffusion

Innovation diffusion gives us an approach focussing on the drivers and limiting factors with the adopters of ‘new’ efficient lighting technologies vs. the perseverance of the use of the ‘old’ technology. Diffusion of innovations is a social science discipline that is one of the main fields that influence transition studies (Yücel and van Daalen, 2008).

Elements of diffusion

Diffusion is defined by Rogers (2003, p. 5) as *the process by which an innovation is communicated through certain channels over time among the members of a social system*. Elements in this definition are the innovation, communication channels, time, and the social system (as described in Rogers, 2003, pp. 11–31). All of these are relevant in the diffusion of new lamp technologies.

The *innovation* itself is, of course, important. The perceptions consumers have on the characteristics of lighting innovations determine the initial probability to adopt it. These key perceptions are: *relative advantage, compatibility, complexity, trialability* and *observability to others*. A product that is perceived badly on any of these perceptions will suffer lower adoption rates.

Communication channels refer to the channels through which individuals acquire knowledge on, and through which they mutually share knowledge on the innovation. The communications process is important because some key information on aspects of the technology is acquired and processed when a decision is made whether or not to acquire energy saving lamps. Communication channels are both mass media as well as interpersonal. Interpersonal communication is most effective if the subjects are alike each other, in a number of aspects (e.g. social background, intelligence level, level of proficiency with technology, et cetera).

Time is involved in diffusion research in the rate of adoption, the length of the innovation diffusion process, see § 2.3.2, and the characterisation of adopters with regards to their innovativeness. Some typical characteristics of people eager to innovate (as compared to laggards) are: progressive attitude, above-average education level, commercially thinking (adapted from Rogers, 2003, p. 194).

The *social system*, and its *structure*, is also very relevant. In the consumer lighting system, the social system refers to the consumers. People adopting a product are not the same, some people are more keen to take risks than other people. There are key influencers, the opinion leaders and change agents, whose adoption behaviour truly matters because they have more influence on others.

Innovation decision process

When a consumer decides to implement a lamp technology that is new to him, he goes through an innovation-decision process. The actual purchase of the new lamp is just one moment in this process.

The innovation-decision process is described by Rogers (2003, p. 168) as *a process through which an individual [...] passes from gaining initial knowledge of an innovation, to forming*

an attitude toward the innovation, to making a decision to adopt or reject, to implementation of the new idea, and to confirmation of this decision. Rogers models this process as consisting of five stages (knowledge formation – persuasion – decision – implementation – confirmation), depicted in figure 2.3:

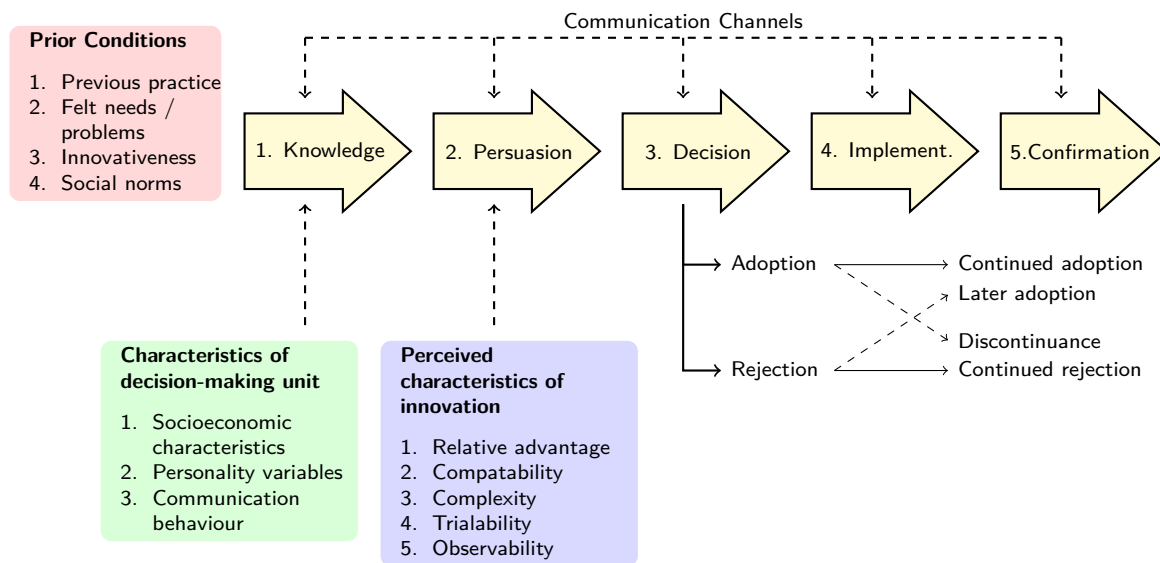


Figure 2.3 – Steps from the innovation decision process (from Rogers, 2003).

For the consumer’s adoption of novel lighting products, the first steps are important. During the knowledge acquisition stage, mass media communication channels are important, during the persuasion stage, peer-to-peer communications are more effective.

However, according to [Nationale DenkTank](#), in social psychology one usually considers different stages not to be linked; there is a weak correlation between consciousness of energy usage, and energy-efficient behaviour ([Nationale DenkTank, 2009](#), p.25).

2.3.3 Implications for the consumer lighting system

Innovation diffusion of the CFL—from continued rejection to adoption For innovations that are truly perceived as ‘new’, the steps in this innovation decision process occur in order of figure 2.3: it starts with knowledge acquisition, then persuasion, and then a decision.

If we study the present situation of the non-adoption of the CFL, we see that most people have already been familiar with it for quite some time. People are generally well aware of the innovation and of its energy savings, yet they have decided to not adopt it. Thus, at present, people are at various stages of adoption, and the households that do not have CFL’s, belong to the ‘continued rejection’ group. This is true for the Netherlands as well as many other western countries ([Bertoldi and Atanasiu, 2006](#)).

People already have informed opinions on them: in many cases, consumers who have not implemented the CFL have made conscious decisions to not adopt. The consumer went through the innovation decision process, but decided to reject the technology. Changing the outcome to a later adoption is only possible if some opinions, perceptions or beliefs, or the circumstances that form a barrier to adoption, change.

Encouraging previous rejectors of the technology to re-consider and adopt later on, is perhaps more challenging a task than if no previous innovation decisions were made. For these groups of consumers, it can be postulated that marketing efforts should focus not

on knowledge spreading, but more on changing the confirmatory process that individuals undertake. If the individuals knowledge is wrong, it may be corrected by promotional campaigns that give correct information.

It becomes harder if the products available are simply out of line with consumer preferences, or with fashion. In this case, the preferences need changing in order for the consumer to choose the efficient lighting product. Promotional activities are less effective in changing these kinds of preferences, and it is more difficult for government to do this. Promotion activities for efficient lamp technology should at least try to focus on actors that are key influencers in the social network (Delre et al., 2007a). If important influencers change around, this may change the fashion principles.

Marketing and communication on low-involvement products Following on the discussion of innovation diffusion theory, two remarks can be made.

The first is that spread of lamp technology may be slower than many other technology products because lamps are a low-involvement product. A lamp product a consumer buys in a store is usually a replacement purchase for a lamp that failed. During ordinary peer-to-peer communication processes, low-involvement products like lamps are not discussed frequently. Marketing can change this, frequently marketing is used successfully in changing a low-involvement product into something people have informed attitudes on (e.g. specific brands of dishwasher detergent have become very strong).

Of course, this doesn't hold for the luminaire. Being one of the cornerstone pieces of interior design, for some consumers, the luminaire is a (very) high-involvement product. In the replacement of luminaires incompatible with energy-efficient lighting by luminaires that are compatible, innovative, or even are inherently energy-efficient (LED designs), there lies real opportunity for increasing the penetration of energy-efficient lighting technology.

Another important remark is that, generally, attention is more easily obtained if there is some negative aspect / negative perception that one wants to discuss. In the communication that people undertake on energy-efficient lamps, *negative aspects* usually are more dominant than the positive aspects. This is an important barrier for the adoption of lamps like the CFL that have quite different characteristics than what people were used to. If there are sufficient people to focus on the negative points, this blocks the spread of adoption of it. Marketing can change this. There are quite a number of interest groups and companies that try to change the dominant negative perceptions.

Mass media channels (e.g. television, radio, magazine and newspaper articles) are important in creating awareness and knowledge about the innovation, while interpersonal communication channels with peers are most important in persuading a person to actually try the innovation (Rogers et al., 2008).

Therefore, we see that in studying the diffusion dynamics of innovative lighting technologies the mass media are important, but in order for people to actually try the lamps for themselves, that they need to be mentioned and recommended by peers.

Social network—relevant for adoption decision The consumer's preferences, perceptions and opinions can differ greatly from person to person, but in a sense that is also limited: people influence each other. This mutual influencing happens by means of information sharing, word-of-mouth, over a **social network structure**. The social network structure are the communication channels depicted in figure 2.3 Innovation diffusion theory tells us that these communication channels are important in all stages of the innovation decision process.

The information sharing can either have a *normative influencing character*. Fashion is one of the normative mechanisms: people adopt some energy saving lamps because one ‘should’ have them. Fashion is a key driver for what consumers want. People want stylish interiors, mood lighting, and this overrides environmental concerns (Crosbie et al., 2008).

The information sharing can also have a more *informative influencing nature* (e.g. a person telling someone else about the energy savings of LED lamps) (for the effect of normative and informative influence see Jager and Jansen, 2008). People also influence each other purposefully. Especially if people have a specific interest or a strong opinion, they are likely to engage in exchange of information. This informative influence happens through mechanisms such as word-of-mouth (see e.g. Gilbert et al., 2007; Goldenberg et al., 2001; Johnson Brown and Reingen, 1987; Lau and Ng, 2001; Richins, 1983).

The social network **structure** is very relevant: the composition of actors and actor-groups matter, it has the potential to alter the pattern of transition processes (Yücel and van Daalen, 2008, p. 915). The diffusion of lighting products is helped or hampered by the network structure. The more heterogeneous the preferences of consumers are, the faster the **spreading** of information in the network (Delre et al., 2007b).

2.3.4 Conclusion marketing perspective

The behaviour of individual consumers determines the way the system evolves on an aggregate level. The consumer’s individual behaviour is shaped by a number of mechanisms and interactions. These are important to incorporate when one wants to choose a modelling approach. For these mechanisms and interactions, a list of characteristics of the consumer, can be made, input for the development of a simulation model.

The characteristics entail:

- Mkt. concl. 1. People are **heterogeneous** in their *preferences, perceptions, beliefs and knowledge* on lamps. Veitch and Gifford (1996) studied lighting perceptions/beliefs by comparing CFL and incandescent; the conclusion is that negative perceptions/beliefs are a problem for the CFL’s acceptance. Knowledge may be factually correct, incorrect, or outdated.
- Mkt. concl. 2. The consumer behaves autonomously, but consumers are influenced by **marketing messages** communicated through different media.
- Mkt. concl. 3. In addition, many consumers do as their neighbours do. If their friends adopt a certain product, they want the same product. This is called **normative influencing** (Jager and Jansen, 2008), **fashion** is an example of this.
- Mkt. concl. 4. People also influence each other purposefully. Especially if people have a specific interest or a strong opinion, they are likely to engage in exchange of information. This **informative influence** happens by principles such as **word-of-mouth**.
- Mkt. concl. 5. Consumers exist in some **social network structure**. Some consumers have many connections, meaning they are key for spreading of (normative and informative) information. Other not so ‘important’ people have fewer connections. The diffusion of lighting products is helped or hampered by the network structure. The more heterogeneous the preferences of consumers are, the faster the **spreading** of information in the network.
- Mkt. concl. 6. Consumers more readily share information or convictions if they have **strong opinions**, and **negative information** is shared more easily than positive (Lau and Ng, 2001; Richins, 1983).
- Mkt. concl. 7. Consumers differ in their **willingness to adapt** new ideas. The consumer’s resistance or readiness to accept lighting innovations is essential

in shaping developments. Earlier adopters are more innovative. Five adopter categories could be envisioned: innovators, early adopters, early majority, late majority and laggards (Rogers et al., 2008). However, the transition to CFL does not seem to follow an S-shaped curve out of its own.

Mkt. concl. 8. If the ‘important’ people in a social network structure, the **opinion leaders**, are adopting a product, then this has more effect than if an ‘ordinary’ person adopts it. Opinion leaders, in addition to having a more central network position, possess more accurate product knowledge. They are also less susceptible to norms, and are more innovative van Eck et al. (2009).

Mkt. concl. 9. Consumer **preferences** may change slowly, or may experience a radical shift (Tripsas, 2008). In lighting, the new lighting effects that are made possible by LED technology may contribute to such a preference shift.

Ideally these conclusions should be further substantiated by real world data from the consumer lighting system or an equivalent consumer market.

2.4 Transitions and their management

The research is on the possible consequences of the E.U. ban on bulbs. The ban is one example of a government policy measure to instigate change in the lighting sector. In § 2.2.2 the government’s transition management strategies were already introduced. To elaborate on this, in this section we will apply a transitions perspective to the consumer lighting sector. The transitions research question that goes along with this is: “*how can we steer transitions that occur in consumer lighting?*”

2.4.1 Definition of ‘transition’

Up to now, the word ‘transitions’ was used without it being defined. What exactly is meant by it? Rotmans defines a ‘transition’ as a

“structural societal change that is the result of developments, having an effect on and reinforcing one another, in the areas of economy, culture, technology, institutions, and nature & environment” (Rotmans, 2003, p. 14)

This definition is quite broad and encompasses many aspects that – at first sight – seem beyond the consumer lighting sector. Another definition is given by Chappin and Dijkema. They define a system transition as a *structural change in both technical and social subsystems* of a large-scale socio-technical system (‘ λ ’-system) (Chappin and Dijkema, 2010, p. 2). This definition is more narrow in that it focusses on change in social and technical subsystems.

A *radical* transition is a transition that is not only fundamental but also happens quickly. Perrels (2008) splits the term ‘radical’ in a product and a process aspect. In this definition, the change of the product aspect means a shift to something fundamentally different, change of the process aspect means that the change happens in a relatively short amount of time.

One important aspect from these definitions is that the change is *structural*, meaning that the change is more than just an incremental improvement, it *fundamentally* changes both the technological and the social systems. As an example, when in some manufacturing industry a totally new process is employed, this may mean that e.g. the unit cost price

of the product may decrease sharply. This can lead to change in both related manufacturing industry and its consumers: it may be that some competing options are no longer competitive anymore; some firms or customers may benefit, others lose out.

If a change is merely a ‘significant’ improvement over the old situation, one does not speak of a transition. A single incremental change is not a transition as it has no structural implications. Generally speaking, all firms competing in some market continuously try to find incremental innovations to improve their processes.

The continuation of a long series of incremental improvements, can (and often will) result in fundamental transitions. When these transitions involve discontinuities, e.g. technological discontinuities, that may arise from smaller incremental innovations (Funk, 2008), the process of continuous improvement can even result in radical transitions. For example, the continuous improvements in micro-lithography in the semiconductor industry (e.g. Bruning, 2007) have resulted in the rise of an IT industry that has profoundly changed and is changing, society.

2.4.2 Transitions in consumer lighting

Past decades, the technological situation in consumer lighting sector can be considered quite stable: traditional technology (standard incandescent; halogen) is dominant, and due to the slow adoption of more efficient lamps, the average luminous efficiency of the sector increases only slowly (§ 1.1).

We can speak of a ‘lighting transition’ if this dominance of traditional, ‘incumbent’ technology is broken, and more efficient technologies, such as CFL and LED, are the prevalent choices.

The case of the halogen torchiere (described by Page and Siminovitch (1998) and Calwell and Mills (1997); see box 1) serves as an illustration of a market introduction of a new lighting product (luminaire employing a specific type of bulb), that became very successful in a short time-span and had a pronounced effect on the sector and its energy use.

The case of the halogen torchiere (box 1) makes clear that it is the combined actions of consumers (their objectives, preferences and behaviour), as well as the actions of industry players, that jointly shape the success or failure of lighting systems and thus also the energy efficiency of the lighting system.

The invention of the light emitting diode in 1962 and the many incremental improvements and innovations that followed it, result in solid-state lighting now having a good electric efficiency, making it suitable for many lighting applications and starting to change the consumer lighting sector (Azevedo et al., 2009). If technological progress in solid-state lighting continues as in the past, a fundamental switch over to LED for many applications seems likely; we conjecture a ‘lighting transition’ will occur once LED has matured in price and performance to the level of incandescent technology.

2.4.3 Emergent transitions and complexity

Government aims for a fundamental change in energy consumption in residential lighting. At the minimum, this will require the increased use of radically more efficient technology. For this to be possible, structural change in *both* the social and the technological subsystems needs to happen. In the technological subsystem, more efficient alternatives must become competitive (if they are not so already); in the social subsystem the different actors involved need to act in a way that stimulates the adoption of the more efficient lighting alternatives.

Halogen torchieres are elegant luminaires that give an upward light. They were created by Italian designers in the 1980's to provide a novel lighting effect: a large amount of light, beamed upwards to be defused by the ceiling. This lighting effect complemented new trends in interior design of the 1980's (brighter and lighter colours; spacious living). The torchieres give out a very large amount of light, enough to illuminate an entire room. For this they are typically employed with a 300W tubular halogen bulb (500W lamps is also possible), making them very energy intensive.

As mass production commenced in factories in Asia, average purchase price of a halogen torchiere collapsed to less than \$20. Sales of the luminaires skyrocketed: at the end of the 1990's, their penetration rate was around 40% of households, with multi-million unit sales per year (Calwell and Granda, 1999; Page and Siminovitch, 1998), up from almost zero at the start of the decade.

Because the torchieres put out a lot of light, they are typically equipped with a dimmer and are frequently operated in a dimmed state, worsening their luminous efficiency, which was already low due to it being used for indirect lighting (reflection of the ceiling surface). Despite being sometimes marketed as 'energy-efficient', in practical use, the torchieres clearly are not. Because of their inefficiency and their widespread adoption, in many countries the introduction of the halogen torchiere did undo any energy savings realised by implementation of energy-efficient lighting.

The decline off the luminaire's popularity started when they were identified as the cause of hundreds of house fires and numerous deaths (Vine et al., 2000), a reason for them to be banned for certain applications. A safer and more energy-efficient torchiere alternative is provided with a 65–80W CFL, instead of halogen / incandescent bulbs (Chen, 1997).



Box 1 – Case of the halogen torchiere.

The interaction between social and technological system parts is important. If the consumer lighting sector is to change, both the social and the technological parts and subsystems must evolve. As these developments will be occurring in all system parts and subsystems, and these will then be mutually influencing one another, we speak of co-evolution (Nikolic, 2009).

A transition arises due to the joint actions of different autonomous actors; a transition is emergent (Chappin and Dijkema, 2008a). The dynamics of such emergent transitions are not known in advance: they can be slow or fast, technology may spread rapidly or may stop spreading, consumers may choose certain technologies or not. The notion that transitions are emergent is important for the need of a simulation modelling approach (approach chosen in chapter 3).

2.4.4 Strategies for managing transitions

Transition management is the assemblage of practices attempting to either instigate a transition process that one deems beneficial, or to change a transition process that one already sees occurring (see Chappin and Dijkema (2008c); Rotmans (2003)). The government uses strategies based on transition management to steer developments in consumer lighting.

Loorbach (2007) pose the 'transition management approach' as a new complexity based mode of governance useful for achieving long-term change in societal systems.

Transition management practices are policy practices where the following characteristics are important (Chappin and Dijkema, 2008b, p. 1):

- Long-term thinking for framing short-term policy;
- Focus is multi-domain, multi-actor, multi-level;
- Focusing on learning;
- Use innovation for system improvement;
- Keeping many options open.

Given the emergence of transitions from co-evolution of technology and social processes, understanding how governments and businesses can develop successful strategies is difficult. The success of a policy or strategy cannot *ex ante* be guaranteed.

Many actors actively try to instigate and change the development of the sector. The EU's 'ban on bulbs' (appendix B) is one example of a transition management initiative in the consumer lighting sector. It was formulated to directly impact consumer's choice by taking away options, forcing people towards a different behaviour. Businesses also try to change the developments in the sector. The U.S. Department of Energy, also has a transition approach, it carries out focussed solid-state lighting research (Pacific Northwest National Laboratory, 2009), and also holds an innovation contest to stimulate lighting manufacturers to develop high-quality, high-efficiency LED lighting products to replace the incandescent lamp (?).

Businesses may have agendas that differ from the government (more short-term focussed), but they can effectively co-operate in the transition management practices of other actors (as evidenced by for example businesses are willing to cooperate with government in energy steering groups, such as the Dutch Lighting task force (Taskforce Verlichting, 2008)).

2.4.5 Using simulation modelling to help managing transitions

In order for true management of transitions to take place, there is a need for performance indicators of transitions (transition indicators), that one can use to develop as well as assess the effects of transition management practices (Chappin and Dijkema, 2010).

Combinations of transition management practices may be called transition assemblages and can be defined as follows: *a transition assemblage is the all-inclusive set of transition instruments. This means that a transition assemblage is a coherent combination of transition instruments such as policies, regulations, R&D strategies, financing schemes / financial aid, etcetera* (adapted from Chappin and Dijkema, 2010).

To help in establishing the success of transition assemblages, one would like to be able to observe the evolution of occurring transitions; one would like to test the effects of alternative transition assemblages under different scenarios. For this, experimentation with a simulation model is a very useful technique because it gives many opportunities in observing the evolution of transitions in environments one can control.

A generic approach for developing models for transition research consists of the following steps:

1. Find a suitable representation of the system.
2. Design transition assemblages
3. Develop exogenous scenarios
4. Perform the experiment: let the system evolve; observe the occurring patterns and behaviour
5. Assess the impacts of the transition instruments.

The above generic approach is followed in this research on transitions in the consumer lighting sector.

The system representation should be developed after a careful description of a system, which is the focus of this chapter (§ 2.2 and § 2.3). The systems description should be developed in a way suitable and useful for a modelling approach. The modelling approach, in turn, should be chosen to optimally suit the characteristics of the studied system (chapter 3). The design of the transition assemblage is part of the general research question, which tests a specific transition instrument (the ‘ban on bulbs’), but other transition instruments can be envisioned. The observation of the system evolution, and assessing the impacts of the transition instruments are all done with a simulation modelling approach (part II).

Transition experiments

With the simulation model, we want to perform *transition experiments*: experiments to test the performance of transition assemblages. In transition experiments, we evaluate the performance of sets of transition management practices, from different actors, with specific settings for exogenous scenarios.

In a transition experiment, actors (the government and/or the manufacturer) display specific combinations of transition management practices and other behaviour, together called a *behaviour-case*. The simulated system is then let to evolve to analyse the performance of the behaviour-case under a specific sets of parameters for influences from the system’s exogenous environment (*exogenous scenarios*) and sets of structural parameters characterising the system (*system parameters*).

The sets of actor behaviour-cases and scenario/systems parameters are developed partly using the transition design framework from Chappin and Dijkema (2010). Included strategies are, for the government and the manufacturers:

Government strategies	Manufacturer (retailer) strategies
A ban on specific kinds of lamps	Innovate to introduce a new lamp
Price regulation of specific kinds of lamps	Marketing by price strategies
Public information campaigns	Other promotional activities
Requirements for information on packaging	
Subsidies for manufacturers, or on technology	

Then there are the structural and scenario parameters. The structural parameters revolve around the way the model (Part II) is developed, and mainly have to do with the nature of the consumer.

Structural parameters	Scenario parameters
Division of preferences among consumers	Electricity price
Way consumers influence each other	Household income
Type of agent-interaction network	...

The system behaviour in the different cases can be analysed by observing the system’s evolution and looking at transition indicators, see the next subsection.

Assessing the impact — transition indicators

In order to establish the success of transition management strategies, it is important to be able to observe the developments in the consumer lighting system. For this, transition indicators need to be developed.

The transition indicators need to show the nature of the occurring transition (is it *'significant'*, or is it perhaps *'structural'*, *'fundamental'* or *'radical'*?)

From a sustainability perspective, the indicators need to show progression towards reduced energy use in the consumer lighting sector, meaning both the actual use (hours of use, etc.) and technological components' efficiency need to be incorporated in the indicators.

Indicators for a transition in lighting are:

- Number of lamps per household
- Average wattage of a household's lamps
- The adoption of lamps of a technology type (e.g. CFL; LED; halogen; incandescent)
- Electricity consumed for lighting (yearly average per household)
- Money spent on replacement lamp purchases (yearly average per household)

These indicators will be used in quantitatively and qualitatively analyse the performances of transition experiments.

2.4.6 Conclusion from systems description

In this chapter, we concluded that, from the actors in the consumer lighting system, the consumer is the most relevant one. The consumer's purchase choice of technological components (lamps, luminaires, dimmers) is the most important mechanism by which, lastingly, the energy use in consumer lighting can be reduced. Furthermore, consumers are found to have persistent opinions and knowledge on lamps. Knowledge may be wrong or outdated. The opinions and knowledge are relevant to purchase decisions, as is purchase price.

To focus more in depth on the consumer, a marketing simulation perspective was applied to the system, and we used innovation diffusion theory to focus on the adoption behaviour of the consumer. Fashion is a key driver for consumers. In shaping fashion, marketing-promotion is important, but mutual social adaptation is also key. Furthermore we learned that consumers share negative and positive experiences with other consumers, using the word-of-mouth principle. Consumers exist in a social network structure; the social network structure hampers or increases the spread of information in the network.

A transitions perspective was used to analyse options for shaping the development of the consumer lighting system, from which we concluded that transition experiments are a way of assessing system development using a simulations approach. In transition experiments, assemblages of related policy measures of government are tested, and evolution of the system can be assessed using transition indicators. From the range of transition indicators, the most important transition are the average electricity consumed for lighting, per household per year; and the money spent on replacement lamp purchases, per household per year.

To actually implement transition testing using transition experiments, a simulation modelling approach is needed; in the next chapter we will make a choice for the modelling approach to use.



Chapter 3

Choice of modelling approach

3.1 Introduction

In the preceding two chapters we developed a description of the consumer lighting system, using a transitions perspective (chapter 2), and adapted with a marketing simulation perspective that involves innovation diffusion theory (section 2.3). From the systems description it was concluded that a simulation modelling approach is useful for analysing the range of possible developments in the consumer lighting system that are possible consequences of different policy measures.

The development of a modelling approach with an experimental setup is the focus of this chapter. Requirements for the simulation modelling approach are described in § 3.1.1. An overview of available modelling techniques is given in 3.2. A modelling technique for implementing the model is chosen in § 3.3.

3.1.1 Requirements for a simulation model

For each simulation task there are a number of modelling approaches that can satisfy the needs. What is needed for making a model of the consumer lighting system, is a modelling approach that is suitable for tasks such as: researching market introductions and adoption rates of new products; calculating the energy consumption of the sector under policy changes; and for researching the effects of social interaction and limited knowledge on lamps. For all this, arguably a number of modelling techniques can be used.

The modelling technique chosen should be compatible with a number of requirements that can be derived from the system description in the preceding two chapters. From § 2.2.4 and 2.3.4, we are able to construct a list of main requirements for the simulation model. These main requirements are:

- req. 1 The modelling technique should be suitable to represent social actors (households) and technological artifacts (lamps, fixtures) with sufficient accuracy.
- req. 2 Decision processes of social actors should be accurately modelled: actors should have perceptions, memory and be able to form opinions.
- req. 3 Actors should have a place in a social network structure and should be able to change their perceptions, opinions through interaction. Actors should update memory and beliefs through mutual interchange of information and word of mouth.
- req. 4 The modelling technique should allow for the consequences of innovations in the simulated technologies, performance improvements and declining prices.
- req. 5 The model should allow for experimentation with government policy. We should be able to assess the impacts of the influence of the ban on bulbs.

- req. 6 The simulation model should be conceptually as simple as possible, yet it should still be able to capture as much broadness and depth of the real world’s system as possible, without being overly complex itself.

The modelling approach should enable us to say something about the development of the complex system, it must capture the occurring non-linearities in a computer simulation.

With a simulation model we attempt to perform simulation experiments. The experiments should be designed to lead to insights into the possible consequences of policy. Possible simulation experiments include the different policy measures themselves and different types of reactions on policy measures. Policy measures can be incorporated in a number of policy scenarios, with different model parameters. The modelling approach must be able to incorporate these experiments as well.

3.2 Overview of some modelling techniques

Which computer simulation modelling technique should be used for the development of transition models of consumer lighting?

From the available modelling paradigms, we should choose a technique that provides the means necessary to best model the autonomous actions and preferences of consumers in accordance with the requirements set above.

3.2.1 Top-down approach — Equation based modelling

Modelling techniques that use equations to calculate on a system aggregate level are techniques that can be used to build high-level models of the consumer lighting system ‘economy’. An example of such an approach is System Dynamics.

Capturing (some of) a system’s most striking behaviour, by means of modelling a limited number of important mechanisms, is a powerful strength of these kind of models. The strength of equation-based models lies there in that with few equations, relationships and parameters, one can create insight into systems that would otherwise have been considered as quite complex. With equation-based modelling techniques one can choose a high aggregation level. This enables the modeler to broaden the scope of the model at the expense of some depth (Yücel and Chiong Meza, 2008).

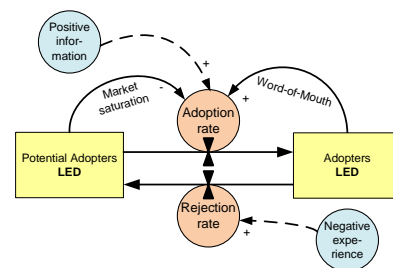


Figure 3.1 – Detail of how an equation-based System Dynamics model would look like. This detail highlights the generic innovation adoption for one type of lamp, made dependent on two variables.

These kind of modelling techniques are very well suitable to adoption rate studies if it is workable to capture the system evolution in variables, equations and/or concepts such as stocks and flows. See figure 3.1 for an example of such a mechanism: with only a limited number of concepts one can capture essential system characteristics (e.g. the model depicted in the figure could result in the familiar S-shaped adoption curve, depending on parameter settings; a full system model will be many times more complex than is illustrated).

The top-down nature of this approach is problematic however, and the modelling paradigm is not suitable to model what is occurring on an individual level. Especially if there are many actors, that need to have heterogeneous properties and share these, this becomes a problem.

For some policy questions, capturing the aggregate behaviour of groups of actors would be sufficient. But because in the consumer lighting sector, interaction between individual consumers is thought to be an essential system property, and we want to learn what that interaction means, what the consequences of this interaction are. Therefore we conclude the top down modelling approach incompatible with our modelling goals for the lighting consumer.

3.2.2 Bottom-up approach — Event-driven modelling

Instead of opting for a top down modelling approach, a bottom-up approach can do justice to the heterogeneity of preferences, opinions and attitudes that exist in the system, and focus on the emerging effects that the interaction at that level provides.

One class of bottom-up modelling is discrete-event simulation. Discrete-event modelling techniques are able to cope with large numbers and kinds of different objects, on which then many different actions can be performed, altering the different kinds of properties of the simulated objects (see e.g. Cather, 1992; de Swaan Arons and Boer, 2001; Takus and Profozich, 1997,

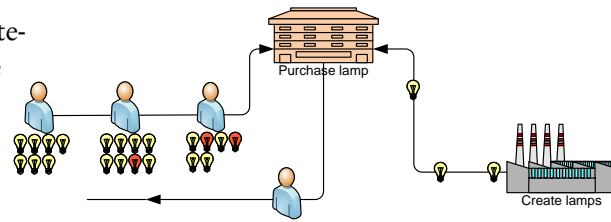


Figure 3.2 – Illustration of how an event-based model would look like, visually, in event-driven simulation software such as Arena (Rockwell Automation, 2009).

for a description of event-based modelling concepts). Theoretically, this offers a workable simulation platform for a model of the consumer lighting system.

In event-driven simulation, the subjects of event-driven simulations are rather passive ‘objects’, on which in some sequence some set of operations is performed, often making use of stochastic distribution functions. Simulated objects could be the lamps and households. The simulation objects are ‘processed’ by system modules, rather than that they are free to share information with their peers.

Discrete modelling techniques are very well suitable if the focus lies more on the logistics of the retail store visits by consumers. Also events like random breakdown of lamps, changing technological properties over time, can be included in such a model. The modelling of concepts like informational influence; word-of-mouth; normative influence, is difficult, however, and will require perhaps complicated modules that are not easy to implement.

Because we want to find a way to accurately model the behaviour of consumers and are looking for a good modelling tool to do this, we deem discrete event simulation as not optimally suited to the development of the model.

3.2.3 Bottom-up approach — Agent-based modelling

Agent-Based Modelling (ABM) is a bottom-up modelling approach especially suitable when it is advantageous to model the behaviour of actors at the individual level, if, at least, its behaviour can be captured in algorithms (van Dam, 2009, pp. 31–33).

In agent-based modelling, real world actors from the studied system are modelled as computer agents that are capable of autonomous action. A definition for an agent is given by (Jennings, 2001, p. 36):

“An agent is an encapsulated computer system that is situated in some environment and that is capable of flexible, autonomous action in that environment in order to meet its design

objectives”

An important characteristic of agent-based modelling is that agents have their own memory, characteristics, and implement their own decision making behaviour. This causes agents, even while they may be identically defined or share the same structural features, to display behaviour that differs from each other. The study of the interaction of a number of heterogeneous agents may lead to a number of patterns of outcomes that can be observed. If the model allows, then by varying the model parameter settings over a number of experiments, possible dominant patterns can be established.

Because of the autonomy the agent has in its behaviour, agent-based modelling is well-suited to incorporate social and behavioural aspects of the system entities that need to be studied (Chappin et al., 2007).

The key to developing useful agent-based models is capturing the essential characteristics of the actors and the modelled system, so that in the computer model, the computer agents are capable of displaying their autonomous behaviour and have the freedom in making their decisions that are like decisions real world actors would make.

It is important to note that the autonomy of the agent, referred to in the definition of Jennings above, is a special kind of limited autonomy. With the autonomy it is meant that the agents are responsible for their own state and memory, and might have a number of decision rules by which to live by. However all this happens within the boundaries of the agent specification. The agent only has autonomy in so far as is allowed by the specification created by the model-designer.

Some important questions that appear when agent-based modelling is used for modelling social processes and where the agents represent people, are (e.g. Macal and North, 2005):

- How much do we know about credibly modelling people’s behaviour?
- How much do we know about modelling human social interaction?
- Can we codify this in algorithms?

In comparing agent-based techniques with differential equation based modelling techniques, Rahmandad and Sterman conclude that:

Agent-based models can capture heterogeneity across individuals and in the network of interactions among them. Agent-based models relax aggregation assumptions, but entail computational and cognitive costs that may limit sensitivity analysis and model scope. (Rahmandad and Sterman, 2008, p. 2)

Some critiques and pitfalls of designing agent-based computational systems are described by Wooldridge and Jennings (1999). One of the conceptual pitfalls Wooldridge and Jennings describe is that, where developing an agent-based systems is experimental in nature, it is in fact a software development project, requiring thorough software engineering tasks such as requirements analysis, specification, design, verification, and testing; tasks which are readily forgotten.

In figure 3.3, some concepts of a possible agent-based model are shown. The illustration depicts consumers, with heterogeneous properties in a social network structure and a retail store that supplies many different lamps. Information flows between the store and consumers, and consumers also share information over their social network structure.

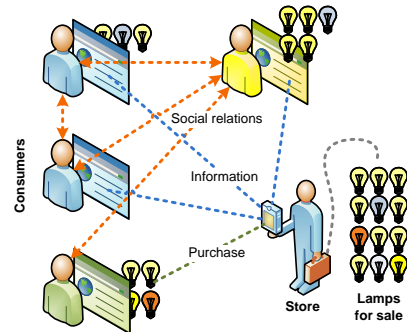


Figure 3.3 – Visual illustration of some of the agent concepts if we were to develop an agent-based model.

3.3 Choice for agent-based modelling

The requirements on the modelling technique of § 3.1.1 are depicted in table 3.1, where we score the different modelling approaches on their suitability in meeting the requirements.

Table 3.1 – Decision matrix on the choice of modelling approach. The requirements from § 3.1.1 are in the leftmost column. The ‘+’ and ‘-’ signs are indicative of how good the alternative modelling options are fitting the requirement. The scores are calculated in the bottom row

<i>Requirements</i>	<i>Equation-based</i>	<i>Event-driven</i>	<i>Agent-based</i>
Req. 1 Social actors, technological artifacts	+	+/-	++
Req. 2 Decision processes—perceptions, opinions	+/-	-	++
Req. 3 Social network	-	-	++
Req. 4 Changing technology, innovation, declining prices	+	+/-	+
Req. 5 Government policy	+	+	+
Req. 6 Conceptually simple	++	+	-
<i>Score</i>	4	0	7

Agent-based modelling makes it possible to model the adaptive nature that arises due to interaction effects between individual consumers (word-of-mouth, fashion), combined with the intricacies of the technological components of the system (interactions, compatibilities of technologies, and so on). The more adaptive a system or the more the system evolves over time, the greater the opportunity to learn more about the adaptive system using ABM’s (Garcia, 2005).

In event-driven modelling techniques the objects themselves cannot have any kind of autonomous (in AI-sense) behaviour, which makes it necessary to circumvent this using different programming concepts. This is the reason for the ‘-’ for event-driven in table 3.1.

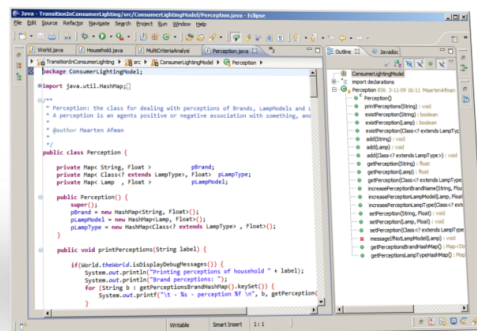
Out of the discussed modelling approaches, in agent-based modelling one has the greatest freedom to implement the behaviour of the consumer, with all its heterogeneous properties (preferences, opinions, perceptions) and other peculiarities. Especially the demand for a social network structure almost necessitates using the agent-based approach.

The next Part, II, is where we shall start developing the simulation model.



Part II

Development of the Consumer Lighting Model



```
package ConsumerLightingModel;

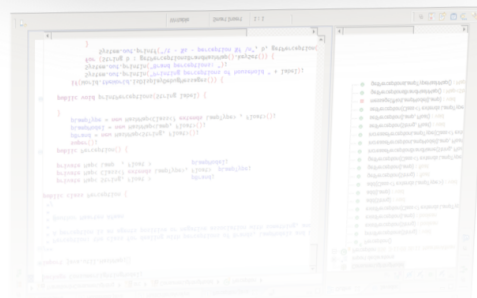
import java.util.HashMap;

/**
 * Perception: the class for dealing with perceptions of brands, lampModels and
 * a perception is an agents positive or negative association with something, and
 * another instance of them
 */
public class Perception {
    private Map<String, float> brand;
    private Map<Class<? extends LampType>, float> lampType;
    private Map<String, float> lampModel;

    public Perception() {
        brand = new HashMap<String, float>();
        lampType = new HashMap<Class<? extends LampType>, float>();
        lampModel = new HashMap<String, float>();
    }

    public void printPerceptions(String label) {
        if (label.charAt(0) != 'l') {
            System.out.println("Printing perceptions of " + label);
            System.out.println("Brand perceptions:");
            for (String b : brand.keySet()) {
                System.out.printf("%s = %s - perception %f\n", b, getPerception(

```



```
    }

    /**
     * @param agent the agent
     * @param brand the brand
     * @param lampType the lamp type
     * @param lampModel the lamp model
     */
    public void setPerception(String label, float value) {
        if (label.charAt(0) != 'l') {
            brand.put(label, value);
        } else {
            String[] parts = label.split(" ");
            Class<? extends LampType> lampType = null;
            for (Class<? extends LampType> lt : LampType.values()) {
                if (lt.getSimpleName().equals(parts[1])) {
                    lampType = lt;
                }
            }
            if (lampType != null) {
                lampType.put(lampType, value);
            }
        }
    }

    /**
     * @param agent the agent
     * @param brand the brand
     * @param lampType the lamp type
     * @param lampModel the lamp model
     */
    public void setPerception(String label, float value, String lampModel) {
        if (label.charAt(0) != 'l') {
            brand.put(label, value);
        } else {
            String[] parts = label.split(" ");
            Class<? extends LampType> lampType = null;
            for (Class<? extends LampType> lt : LampType.values()) {
                if (lt.getSimpleName().equals(parts[1])) {
                    lampType = lt;
                }
            }
            if (lampType != null) {
                lampType.put(lampType, value);
            }
            lampModel.put(lampModel, value);
        }
    }
}
```


Chapter 4

Conceptualisation of the consumer lighting model

Following the results of the system's description and the choice for a modelling approach in the preceding part (I) of this thesis, we can now focus on devising a representation of the system in a simulation model. This is done in this part of the thesis, where we develop the simulation model.

4.1 Introduction

In this chapter the focus lies on the conceptual development of the simulation model of consumer lighting. The model is explained conceptually in terms of its building blocks: agents, structure, technology, and its behaviour and interactions.

The model is implemented in an object-oriented software framework. Concepts from the social system and from the technological system, are considered to be objects that have data structures (fields) and to have behaviour (methods). The conceptualisation is based on the consequences for the system description of chapter 2 and the requirements of § 3.1.1.

In § 4.2, concepts from the social system are discussed, followed, in § 4.3 with those from the technological system. An overview is given in § 4.4.

4.2 Social system: consumers, market, government

For the social system, the most important actors are the *consumers*. Other actors are *retailers*, *manufacturers* and the *government*.

4.2.1 Market – retailers and manufacturers

In the simulation model, we focus on dynamics in the market for replacement light bulbs, i.e., lamps. By replacing lamps with more efficient ones, a household can reduce the electricity it uses for lighting.

In the consumer lighting system, there are a many kinds of places of sale of replacement lamps. There are dedicated lighting stores selling mostly luminaires, and non-dedicated lighting stores, e.g. interior design, furniture stores; supermarkets (§ 2.2.2).

Replacement lamps are usually purchased in retail stores like home improvement retailers, electronics stores, D-I-Y outlets, supermarkets. These retailers are supplied with the product of the manufacturers.

To simplify all this, in the model implementation, the *retailer* and the *manufacturer* are taken as one, from here on called **manufacturer** agent, of which there is one. The manufacturer should be thought of as the ‘lamps market’.

The manufacturer creates the different lamps; sells them, and determines the sale prices. The manufacturer has an unlimited supply of lamps. In § 2.4.5 we introduced a number of strategies for the manufacturer, but we will not implement these as such.

It can be expected that energy-efficient lighting technologies will improve as time progresses. This *innovation* in lamp technology is implemented through the market (manufacturer) by means of declining prices: as technology progresses, sale prices of lamps gradually decline, making previously expensive technology more attractive and thus more widely used.

4.2.2 Government

The *government* is not explicitly included in the simulation model as a separate actor-agent. Its policy is modelled as the different policy instruments that can be performed. Policy instruments of the government are described in chapter 7.

4.2.3 Consumer

The *consumer* is represented as the *household* agent, as this is the useful level for the analysis. So from here on, when we speak of consumers, also ‘households’ could be read, and vice-versa. The household’s main tasks are the purchasing of lamps when there is a need to do so, evaluating the lamps purchased; and the sharing of its information with neighbours.

The most important activity of the household is the purchasing of lamps. In deciding which lamp to buy, a household will need information on the different existing alternatives and on his own preferences and ways of how these different alternatives are to be compared. For this decision problem, the household is equipped with a set of preferences for different aspects of lamps; with memory for lamp characteristics and with perceptions of different lamps, technology types and brands. This is schematically shown in figure 4.1.

The household’s preferences, memory and perceptions will be further detailed below.

Preferences

A household has preferences. A preference can be a qualitative aspect of light, such as the light’s colour temperature (warm / cold / daylight). In this case the household prefers lamps that emit light close to the preferred performance level. A lamp that closely matches the household’s preferred performance level scores ‘good’ on that preference, and this improves the lamp’s chances of being selected for purchase. Preferences are heterogeneous between households, which means that households differ in their preferred performance level.

Preferences can also be maximising or minimising in nature. This means that a lamp scores ‘best’ if it maximises or minimises its performance on the preference aspect. For these types of preferences, all households are alike.

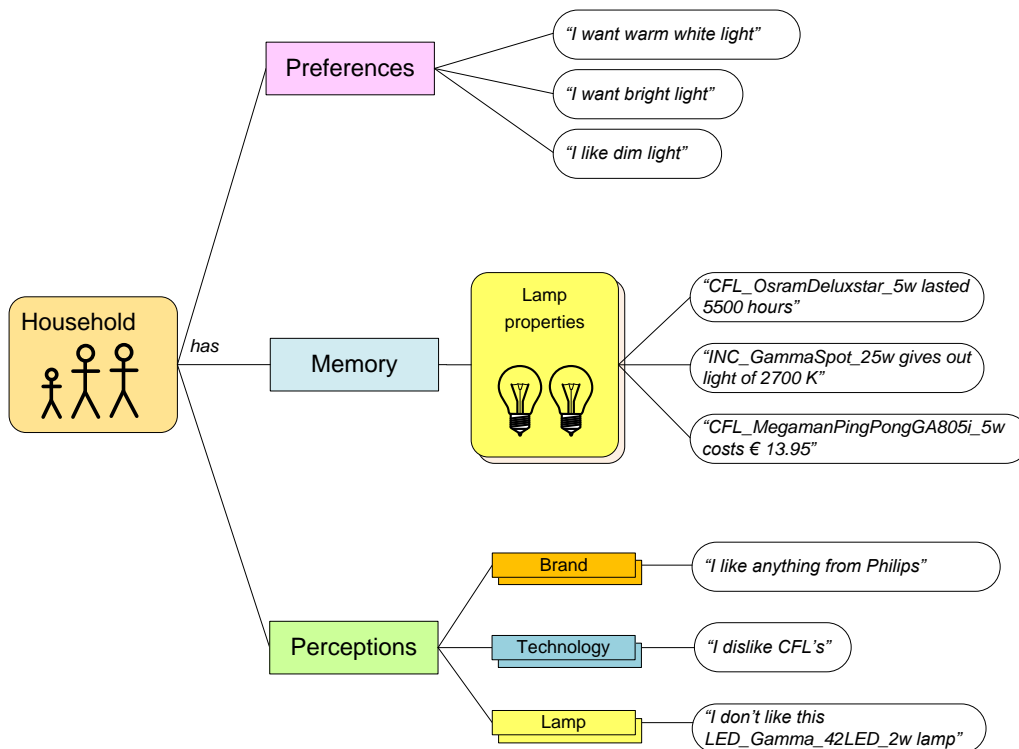


Figure 4.1 – Conceptual view of a household's data structure concerning lamps.

Economic preferences of households are of the latter type: the purchase price and the efficiency of the lamp (how much electricity does it need to output an amount of light) are minimising and maximising preferences, respectively, and this holds for all households.

Memory

The household has the ability to use its memory in its purchase decision. One way the household has some learning ability is through the use of memory that contains its 'knowledge' on lamps. A household's memory stores information on the lamps it has ever had, both working and non-working. By consulting this memory, the agent can recall his own experience, and does not have to go blind on what the manufacturer 'says'. If a manufacturer states on the packaging of a lamp product that the lifetime is L , then, if the household already had purchased a lamp of that type, and the household experienced, historically, a value of, say, $\frac{1}{3}L$, then the household can use the stored values to improve the purchase decision, and perhaps avoid buying this specific type of lamp.

The household can have memory on many different aspects of a lamp: retail price; lifetime; light colour; light output, and so on¹. The memory is updated twice during a lamp's lifetime: when a lamp is evaluated (which is after its purchase and at its end-of-life).

Perceptions

The household also has perceptions of different lamps, technology types and brands. Perceptions are opinions that can vary from neutral on a sliding scale. The household retains perceptions for brands and technology type, even if it has no working lamps of these types any more.

¹Many kinds of memory are implemented in the simulation model, as of now, only memory for lifetime is actually used by the agent to improve its purchase decision.

Household social network

The household has a number of people it knows and communicates with, it exists in a social network structure. The number of other households it knows (its ‘friends’), can range from 1 to far more (depending on the algorithm used to generate the network). In this way, all households are linked together in a social network.

Behaviour of the household

The household's main activities are the purchasing of lamps; the evaluating of lamps; and the sharing of its information with neighbours. The purchase is the most important for what happens with the technological system

The *purchase* is made using multi-criteria analysis, in which the different preferences and characteristics of the lamps are weighed. When a household purchases a lamp, it updates its information stored in memory using the characteristics of the lamp purchased.²

Also, after purchasing a lamp, the household *evaluates* the lamp and updates memory and perceptions, accordingly. If, for example, a lamp breaks down and the failure is ‘too soon’, the perceptions decline and memory is updated incorporating the newly experienced value.

An household might engage in *sharing* of negative or positive perceptions on lamp-models, brands, and technology types with its peers in the social network. By means of this information sharing, the ‘word-of-mouth’ effect is implemented.

In deciding which lamp to buy, a household may be influenced by the types of lamps their neighbours have. This *normative adaptation* implements principles of fashion.

4.3 Technological system: lamps and luminaires

The technological system consist of all the modelled hardware.

The **luminaire**, displayed at right in figure 4.2, is the device that ties the lamp to a *location* in the house, and also determines which lamp can be placed by means of the compatibility with the *socket*. In their choice for replacement lamps, consumers are restricted by the kind of luminaires they have. Each of a household’s luminaires has a *weekly usage*, which also determines how long the lamps operate.

We focus on dynamics in the market for replacement light bulbs (i.e. lamps), in the model we will keep the luminaires fixed, we do not consider luminaire dynamics. It is the energy consumed by lamps that, structurally, impacts the electricity usage of the sector. The luminaire is certainly important for the energy use through the restrictions it poses on the replacement lamps used (evidenced by the case of the halogen torchiere; see box 1 on p. 26).

The **lamp** is the most important technological object in the model: the different alternative lamps are the objects of the household’s purchase decision. Lamps have a set of extensive properties defining qualitative aspects and defining the interactions and compatibility restrictions with luminaires. See the left part of figure 4.2.

One of the main properties of a lamp is its technology type (CFL, LED, Halogen, Incandescent), which we will call ‘*lamp-type*’ from now on. Furthermore, a lamp has a *brand*, a *light output* and *electricity input*. By combining the last two, we can calculate a lamp’s efficiency.

²When an household visits a lighting store, it can learn and update its knowledge on lamps. This acquiring of knowledge on lamps not in possession and not purchased, is presently not incorporated in the model.

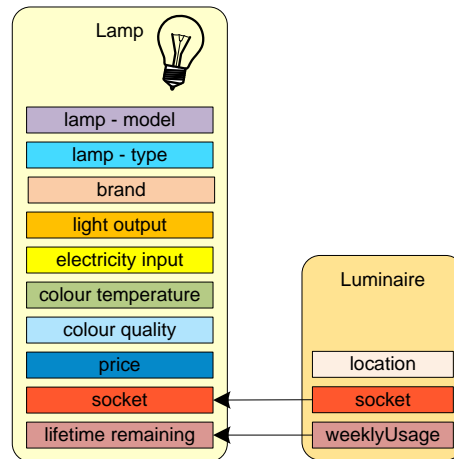


Figure 4.2 – Concept of the luminaire's and the lamp's data structures

Important for the experience of a lamp are properties that relate to the qualitative nature of the light it produces, these are the light's *colour temperature* (warm, neutral, cold light) and *colour quality* (how accurately colours are represented under the light source). Very important for an household's purchase decision is the sale *price* of a lamp. The *socket* (E27 screw fitting, pin-based fitting, ...) also is important, it restricts the options for the purchase decision.

A lamp counts its *remaining lifetime*, updated by the weekly usage of the lamp. When the remaining lifetime has reached zero, the lamp fails, and needs to be replaced by a new one. The topmost field, '*lamp-model*', has to do with the implementation in the model, the field records, for an actual instance of a lamp (i.e. a lamp that has been sold to a consumer) a reference to the specific lamp-model (of the manufacturer) from which the lamp was created.

4.4 Conceptualisation overview

The conceptualisation of the Consumer Lighting Model, as described in the above sub sections, is visualised in figure 4.3. The households form a social network structure (displayed top-left), through which they share information and adapt mutually. One household is expanded (bottom-left), with its the data structure concerning lamps, and its technological 'possessions' (lamps; luminaires). The manufacturer, with its lamps for sale, is displayed at right. The manufacturer is influenced by government policy measures (such as a ban on bulbs).

The next chapter focusses on the implementation details of the simulation model.

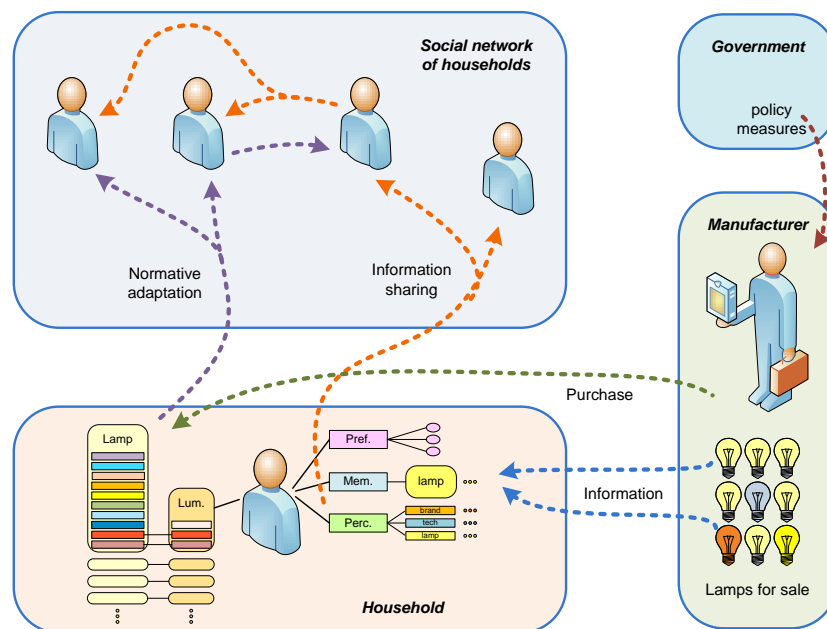


Figure 4.3 – Overview of the modelled social and technological entities, and how they relate

Chapter 5

Implementation of the agent-based model

In this chapter the focus lies on the development and implementation of the consumer lighting simulation model. First, in section ?? the model is explained conceptually in terms of its building blocks: agents, structure, technology, and its behaviour and interactions. Then, in section 5.1 the implementation details of the model are given. These are the key algorithms, program data structure and assumptions on a more lower level.

5.1 Model Initialisation

When the simulation is started, the simulation is first initialised. This initialisation occurs only at the start of a model run, or, when the simulation was halted, parameters are adjusted, and the simulation is reset.

Initialisation first entails clearing up any previous simulation runs (destroying all existing simulation values and the existing agents). After this, the parameters that the experimenter specified are applied, the agents are created with their properties and the household social network is built. Then a series of graphs for selected output parameters are displayed on the screen (and/or the model is setup to output parameters to a file on disk) and the schedule of agent actions is created.

After being initialised, the model can commence its simulation run. During the execution of the simulation, in each time step all agents perform one action sequence. The aggregate of the many action sequences from the agents constitute the system's evolution and developments that can be observed. The action sequences the agents perform during the model execution are discussed in § 5.2

When the simulation is first started, the agents are created, and initialised. This is described in the next two subsections (§ 5.1.1, § 5.1.2).

5.1.1 Initialisation of the manufacturer and its lamps for sale

During model initialisation, the manufacturer creates the lamps for sale. The manufacturer puts the lamps in a 'showcase', i.e. an inventory of lamps for sale. The manufacturer also calculates the initial sale prices of the lamps in its inventory, which will be updated during model simulation execution (incorporating the policy settings).

The manufacturer creates the lamps based on lamps specified in the 'ontology', which is the knowledge base part of the modelling framework used. The ontology is described further in the discussion of the agent-based modelling framework in appendix C.

The ontology contains, for each lamp, a parameter value for: *Lamp-model name* (a string, e.g. ‘lampIncandescentIkeaGloda_40w’; *Lamp-type* (type of technology: CFL, LED, halogen, or incandescent); *Average lifetime* (hours); *Uncertainty lifetime* (fraction); *Light output* (lumen); *Power consumption* (Watt); *Colour rendering index* (CRI); *Colour temperature* (K); *Voltage* (V); *Shape* (tubular, pear, reflector, tiny bulb); *Socket* (E27, E14, R7S, G24D2, GU10, G9, MR11, MR16); *Energy label* (A++, A, . . . G); and *Price* (€).

The above parameters are further explained in appendix D. The appendix also shows the parameter values for each lamp specified in the ontology.

5.1.2 Initialisation of the household

In total, there are 250 households agents that need to be created. Each household is given a number of luminaires with a specific distribution of lamps as a starting portfolio. The number of luminaires with their location properties differs for all households. The number of luminaires is assigned to each household in a random way, on the basis of a triangular distribution; see table 5.1 for the values. More details are in appendix E.

For each luminaire, the number of burning hours per week is calculated (the duration of a lamp’s operation in a week is determined by the luminaire to which the lamp is attached). The calculation is done using a random distribution (uniform distribution), see table 5.1.

For some locations in the house, luminaires are used for a longer duration, on average, than on other locations. This is incorporated using the ‘Longer Factor’ shown in table 5.1; more details of the implementation are in section E.4 in appendix E. During initialisation of an household, its luminaire locations are assigned in accordance with the distribution in section E.5 (appendix E).

Table 5.1 – Parameters for lamps distribution and a luminaire’s hours of use per week

Initial distribution of lamps		
Households without CFL’s	40%	Starting percentage (Bertoldi and Atanasiu, 2006).
Starting percentage CFL’s	20%	Calculated as follows: the average number of CFL’s per household in the Netherlands is 4, and rising (Taskforce Verlichting, 2008). CFL’s are in 60% of households (Bertoldi and Atanasiu, 2006). This means that a ‘CFL-household’ has 8 CFL’s, on average; with 40 lamps → 20%
Starting percentage Halogen	20%	Assumed to be the same as the percentage of CFL’s...
Number of luminaires per household		
Nr. luminaires, lower boundary	5	Parameters for triangular distribution. See E.3.
Nr. luminaires, median	20	
Nr. luminaires, upper boundary	65	
Weekly hours-of-use per luminaire		
Lamps usage p/wk (low)	0	For the hours-of-use per week, we use a uniform distribution between 0 and 20.
Lamps usage p/wk (high)	20	From Bartlett (1993) (data on the average lighting demand in Dutch households, measured January 1988 [Kemna e.a. (1991)]), we derived that lamps in living; dining; and kitchen areas burn ~ 30% longer than lamps in sleeping areas; stairs and hallways; bathroom; garage; and other rooms.
Lamps usage ‘LongerFactor’	30%	

Also important during agent initialisation is the distribution of the types of lamps an agent has. The lamps are distributed using a starting percentage of CFL lamps, a starting percentage for halogen lamps, and a factor for the number of households without any CFL's. These are also shown in table 5.1.

To be able to purchase lamps, each household's is assigned a starting capital of €1,000,000. This is a value chosen high enough to prevent households ever running out of money for lamps purchases.

The households are given preferences, thresholds, and weight factors. These are based on parameter settings in the simulation model, made heterogeneous by randomising them to a certain extent, using a uniform distribution, see table 5.2. This makes the households heterogeneous.

The households start basically with an empty memory, and neutral perceptions, however, in their initialisation they already form opinions on lamps they have.

Table 5.2 – Parameters for heterogeneous preferences and thresholds for the household

Preferences for households		<i>Generally, consumers want ...</i>
Preference Light Colour	2800	... a warm light colour, of $\sim 2800K$
Preference CRI	100	... the best colour quality ($CRI_{max} \equiv 100$).
Preference Light	700	... medium bright light (700 lm \simeq 60W incand.).
Thresholds for households		
Thresholds are normally used to eliminate alternatives from a decision process. But we use them for the calculation of negative and positive perceptions. Thresholds are coded as the maximum allowed difference relative to the preference value.		
Threshold Light Colour	300	Not warmer than 2400K; not cooler than 3200K
Threshold CRI	20	CRI not worse than 80...
Threshold Light	650	Light output not below 50 lumen (\simeq 5W bulb) and not above 1350 lumen (\simeq 100W bulb)
Randomisation interval for preferences and thresholds		
Randomisation is done with a uniform distribution, characterised by an interval that has lower and upper boundaries. The boundary values below are multiplied with the preference/threshold value to create the interval for the uniform distribution.		
Lower interval boundary	0.9	<i>(factors)</i>
Upper interval boundary	1.1	

During model initialisation, after the households have been created, they are placed in a *social network structure* to represent the social system they are part of. This social network needs to be generated.

For the social network of households, two methods have been implemented: the algorithm for a *small world network*, and the algorithm for a *scale free network*. A choice for one of the two has to be made. The algorithms are described in detail in section 5.4. Parameters are in table 5.7.

5.2 Agent action sequences

The execution of the simulation model consists of the agents all performing their action sequences, or '*steps*', in turn.

The steps are executed in sequence: first the manufacturer performs a step, and then all of the households, one after another. After the last household has completed its step, the

simulation time is incremented one unit value (a ‘tick’), and the action sequences start again. Model execution goes on until the simulation is stopped/paused, or reaches the specified duration.

The action sequences for the manufacturer is first described first (subsection 5.2.2), and then the sequence of the households (subsection 5.2.3).

During the action sequence, an agent performs some specific behaviours, like the buying of lamps, or not. The specific behaviours of the agents are detailed in the remainder of this section.

5.2.1 Simulated time

The agent steps are executed each simulation tick, but how long should a simulation tick be, in simulated time? For how long should the simulation be run?

This choice of the duration of the ‘tick length’ is not entirely self-evident. Retail store visits and updates of knowledge on lamps is arguably not a daily activity for the household agent. Many agents might even visit a dedicated lighting store only a couple of times a year, or less. However, lamps can break more often, and when a lamp is broken, one does not wait a year before purchasing a replacement bulb.

All this considering, a time step of one week was chosen. This is quite detailed, and thus should lead to sufficient data.

The duration of the simulation length was set at 40 years, equal to 2080 time steps of one week.

5.2.2 Manufacturer’s step

Each simulation tick, the manufacturer performs a step. A manufacturer’s step consists of a number of actions:

- Altering the price setting of lamps. As time progresses, lamps become cheaper (see appendix E.1), and the manufacturer implements this.
- Depending on the selected policy (‘ban on bulbs’, see section 7.3), the manufacturer removes lamps from those available for sale.
- Depending on the selected policy, there can be taxes or subsidy on different types lamps; the manufacturer implements these.

5.2.3 Household’s step

Each simulation tick, all households do one ‘step’, one after another. A household step consists of the following actions, see also figure 5.1:

- The household checks if any of its lamps have failed (by counting its operational lamps).
- The household purchases a new one for each broken lamp. For this the household agent needs to visit a retail store (the manufacturer). The steps are as follows:
 1. Choose a manufacturer to go to
 2. Choose a lamp that is for sale
 3. Buy the lamp of the chosen type
 4. Repeat the process as needed

The choice of manufacturer is trivial: there is only one manufacturer.

Deciding which lamp to choose is done means of multi-criteria analysis (MCA), a decision method where a number of alternatives are compared on a number of criteria, which may have different weights attached to them. The multi-criteria analysis decision method is discussed in § 5.3. Details of the implementation of the criteria are discussed in § 5.3.2.

The household spends a certain amount of *money* on the lamp purchases, this is counted.

- If the household has bought a new lamp, it evaluates it to see what it thinks of it. This updates the household's memory and perceptions. The perceptions are **shared** with a random other agent from the household's social network.
- In the course of a simulation time step (one week), the household uses its lamps for some duration (different for each lamp and each household), causing the lamps to age. Therefore, per lamp, the *remaining lifetime* is decreased for the number of burning-hours of the past week. Also the *electricity* used is counted for each lamp.
- Furthermore, if the remaining lifetime of any lamp of a household is zero or below zero, the lamp is broken, and the lamp's status is changed to 'failed' (and next time step it will be replaced). For each failed lamp, the household assesses whether it has failed prematurely. If so this negatively affects the households perception of it, and the household communicates this to one other random agent of its social network.

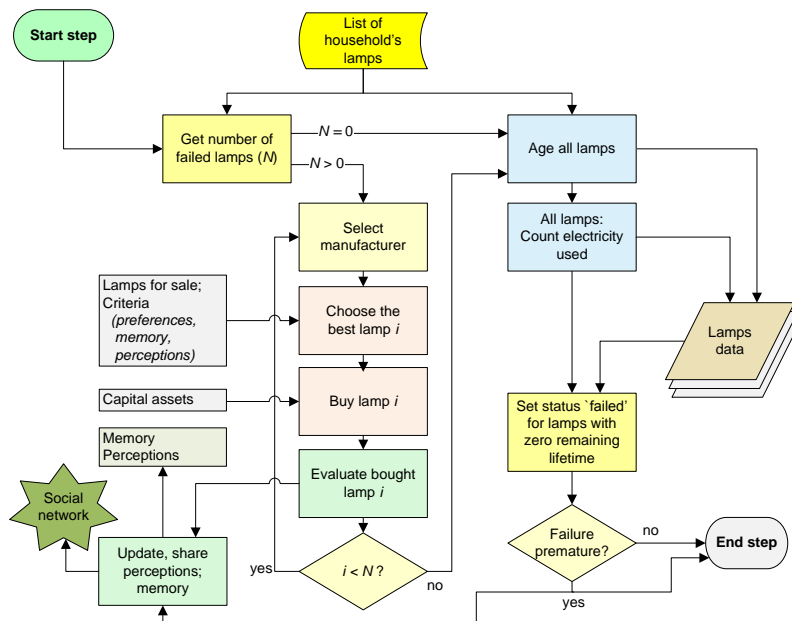


Figure 5.1 – Flow chart representing the sequence of actions during the household's step

How the above actions relate to each other is visualised in the flow chart of figure 5.1.

5.2.4 Implementation of household's memory and perceptions

The memory is updated at **two moments**: (1) when a household purchases and evaluates a lamp, and (2) when a lamp breaks down.

If no memory exist, the memory value is set to the observed value, and when a memory already exists, the new memory value is an average of the memory and observed values. This allows for the gradual averaging of memory as time passes on. There is no separate

‘memory loss’, or fading of memory with time in the model, memory is overwritten using the averaging of old and new values (smoothing).

An household’s perceptions are updated at the same moments, but is more complicated, we will discuss this in the remainder of this subsection. Households also engage in *sharing of perceptions*.

Updating perceptions when evaluating a lamp that was bought After a lamp was just bought, the agent evaluates the lamp and updates its perceptions of it. The agent assesses whether the operating characteristics reflect its preferences; the agent asks: “*How does my lamp actually perform, compared to my preferences?*” Perceptions are updated for: *brand; lamp-type* and *lamp-model*; the characteristics that are tested are *colour rendering index, light output* and *light colour temperature*.

A **negative** perception arises when the observed qualities of the lamp evaluated, compared to the agent’s preferences, are so different that they exceed the agent’s threshold value (preferences and thresholds are displayed in table 5.2).

Example: For colour rendering index, if the agent has a preference of 100, a threshold value of 20, and the lamp-model to evaluate has a value of 85, then the difference with my preference value is 15, which is lower than my threshold, so no reason to lower my perceptions for this lamp-model.

A perception increases for the **positive** if any of the following two conditions occur:

- The memory value for the aspect is worse than the actual value – a surprise factor.
- The properties of the lamp are *very close* to the agents’ preferences. This is also calculated with the threshold values, but now we take half of the threshold value as a boundary for ‘very close’.

Example: For CRI, if the agent has a preference of 100, a threshold of 20 and the lamp to evaluate has a value of 91 for CRI, then the difference with the agent’s preference value is smaller than $0.5 * \text{threshold}$, so there are grounds for a positive perception.

Table 5.3 – Parameters for perceptions

Changing perceptions		
Perceptions Increment	0.1	Increment value
Perceptions Negative Factor	3	How many times stronger is a negative perception compared to a positive?
Perceptions Surprise Factor	2	How many times stronger is a an experience that is contrary to what’s expected ?
Changing perceptions related to a lamp’s early failure/breakdown		
Lifetime Minimum Expectation	0.5	Factor to be multiplied with designLifetime, negative perception of if lamp fails earlier.
Lifetime Sceptical Factor	0.8	If households have no memory on lamp’s lifetime, do they trust the packaging information? Consumers may be suspicious about the value and don’t trust the packaging label. (1.0 if they are not suspicious).

The amount the perceptions are changed is dependent on the context. Perceptions are incremented using an increment value: ‘Perceptions Increment’ (table 5.3).

- Negative perceptions are stronger in general, and multiplied by ‘Perceptions Negative Factor’ (table 5.3).

- Negative perceptions are *stronger* when the lamp-model was more *expensive*. That is why they are multiplied with the *memory on the price* of a lamp-model.
- Positive perceptions are multiplied with the ‘Perceptions Surprise Factor’ if the existing perception is negative (table 5.3).

Updating perceptions when a lamp fails prematurely A lamp fails *prematurely* when the failed lamps actual realised lifetime is less then the lamp-model’s design lifetime multiplied by ‘Lifetime Minimum Expectation’ (e.g. half the design lifetime that is ‘claimed on the box’). When this is the case, the perceptions for brand, lamp-type and lamp-model are decremented using the increment value of table 5.3.

Sharing of perceptions An agent shares its perceptions with a random neighbour from its social network after a lamp was purchased, or after perceptions are updated following a *premature* lamp failure.

1. Select one random other agent from neighbours
2. For all my brand perceptions, check if the other agent has a perception of the brand, and if so, set the other agent’s brand perception as the average of my own and the other agent’s old value.
3. idem for the lamp-type perceptions.

5.2.5 Household’s lamp aging and failure

Each household step, the number of burning hours per week is subtracted from the lamp’s remaining lifetime. The number of hours a lamp operates each week is an important variable, influencing the electricity consumption; the lifetime of the bulbs and the amount of money needed to be spent on replacement lamps.

Lamps that have zero lifetime remaining (or a negative value) have reached the end of their lifetime. They are assigned a status of ‘failed’, and during the next step of the household, the household will notice this ‘failed’ status and replace them ¹.

When a household purchases a lamp (in a household’s step), then the actual lamp instance for the household is ‘manufactured’ from the specific inventory lamp of the manufacturer. At the moment of the lamp purchase/manufacture, the manufactured lamp is given a specific initial lifetime, calculated from the average lifetime and uncertainty parameters, specified in the ontology for the different lamps. The implementation is described in § E.2 in appendix E.

As incandescent lamps have relatively short lifetimes, they are the first to fail, and will need to be renewed frequently. LED lamps have the longest lifetime.

¹There is a small inaccuracy, related to the counting of the electricity consumed, in the assignment of a lamp as ‘failed’. The inaccuracy is that, realistically, failure will not occur at the end of a week, but somewhere between the start and end of a week. However, the full electricity usage, for a whole week, is counted. Of course, related to the total number of burning hours of a lamp, and total household electricity consumption, the error is small.

5.3 Multi-Criteria Analysis: Decision Method for Lamp Purchases

How do household judge the available lamps, which alternative do they choose? The household purchase decision is the crucial decision-making problem in the simulation model. In chapter 2 it was established that, in purchasing lamps, households have different preferences, perceptions/opinions on lamps and differ in their knowledge on them.

If the household's purchase decision is viewed as a multi-criteria decision problem, then the household's preferences, perceptions, and knowledge on lamp aspects can be considered to be different criteria. Incorporating these in the purchase decision can be done using multi-criteria analysis (MCA).

Multi criteria analysis involves the following steps (e.g. Jahanshahloo et al., 2006):

1. Establish criteria to be used for judging alternatives on performance.
2. Find the alternatives that need to be considered.
3. Calculate the scores of each alternative on the criteria.
4. (Optionally: eliminate alternatives that do not exceed some specific threshold value for some preference, to account for non-substitutable attributes (Jager, 2007, p. 871)²).
5. Normalise the scores of the alternatives on a 0–1 scale, using a normalisation algorithm.
6. Multiply scores by the criteria weight factors.
7. Obtain a ranking of the alternatives, and choose the single best alternative.

An household may not be consciously aware of the lamps purchase process being a decision problem requiring a formal multi-criteria decision method such as MCA to solve. Still the implementation can be realistic for many groups of consumers, if MCA parameters are chosen in the right way. E.g. to model consumers for whom only upfront purchase price is important, and the rest of the aspects of lamps are not incorporated in the decision problem, MCA is a valid approach if all weight factors except purchase price are put at zero.

Criteria measure different things, that are not quite comparable. In order to be able to weigh them and rank the outcomes, criteria scores need to be translated to a comparable scale, this is called normalisation.

In this section, first, a number of methods for normalisation of the alternative scores on the criteria are discussed in § 5.3.1. The criteria implementations themselves (how the alternatives score on them), are discussed in § 5.3.2. The weight factors (determining the relative importance of the criteria) are discussed in § 5.3.3, and, finally, choosing the top ranking alternative is discussed in § 5.3.4

5.3.1 Normalisation methods

The challenge with multi-criteria decision methods (MCDM's) is that, generally, criteria measure different things, so in order to compare criteria scores on a comparable scale to be able to weigh them and to be able to rank them, the criteria need to be *normalised*. There are a number of ways this can be done.

Normalisation algorithm: 'interval' The simplest way, which we call 'interval normalisation', is by, for each criterion $c = 1..n$, establishing the scores of the best and worst

²Not implemented as such. Thresholds for preferences are in the model, they are used in updating perceptions, not in multi-criteria analysis.

performing alternatives $a = 1..m$. The worst score is then given a normalised score n_{ac} of 0, the best score is then given a normalised score of 1, and the other scores are given values in between.

Normalisation algorithm: ‘sum-of-squares’ Another simple way can be using a sum of squares approach, from Jahanshahloo et al. (2006); for criteria $c = 1..n$:

$$n_{ac} = x_{ac} / \sqrt{\sum_{a=1}^m x_{ac}^2} \quad (5.1)$$

Both these methods suffer from a methodological problem: it is possible that the outcome of the MCDM *is changed by the addition of an uncompetitive alternative* which has an exceedingly bad score for at least one criterion. The extreme score on that criterion changes the normalised values of the other alternatives on that criterion, altering the ranking and thus the outcome of the MCDM, see table 5.4.

Table 5.4 – Illustration of the methodological problem of multi-criteria normalisation using the interval normalisation algorithm, where the best score is normalised as ‘1’, and the worst as ‘0’. The ranking changes with the removal or addition of a very bad scoring alternative.

altern.	crit. c_1 w.factor = 2	crit. c_2 w.factor = 1	ranking
<i>scores:</i>			
a_1	1	2	4
a_2	2	1	5
a_3	-100	0	-100
<i>normalised (interval):</i>			
a_1	0.99	2	3.98
a_2	1	1	3
a_3	0	2	2
<i>idem, without a_3:</i>			
a_1	0	1	1
a_2	1	0	2

Normalisation algorithm: ‘good-neutral’ A third way is using a normalisation with a *good and a neutral alternative*. This algorithm normalises not on the lowest performing and best performing alternative, or on the least squares distance from the mean, but on an alternative known to score average (‘neutral’), and an alternative that is known to score ‘good’. This achieves methodologically-wise better, but we have to supply a neutral value ($x_{c,neut}$) and a good value ($x_{c,good}$) for each criterion. The algorithm:

$$n_{ac} = \begin{cases} \frac{x_{ac} - x_{c,neut}}{x_{c,good} - x_{c,neut}} & \text{if } x_{c,good} > x_{c,neut} \\ \frac{x_{c,good} - x_{ac}}{x_{c,neut} - x_{c,good}} & \text{if } x_{c,good} < x_{c,neut} \end{cases} \quad (5.2)$$

The normalised results, with $x_{c_1,good}; x_{c_2,good} = 2$ and $x_{c_1,neut}; x_{c_2,neut} = 1$ are displayed in table 5.5. Clearly, with this normalisation; the removal of the third alternative does no longer change the outcome.

Table 5.5 – Normalised outcome when an algorithm employing a good and a neutral alternative is used. The ranking does not change with the removal or addition of a very bad scoring alternative. The good and neutral values are $x_{c_1,good}; x_{c_2,good} = 2$ and $x_{c_1,neut}; x_{c_2,neut} = 1$.

altern.	crit. c_1 w.factor = 2	crit. c_2 w.factor = 1	ranking
a_1	0	1	1
a_2	1	0	2
a_3	-101	-1	-203

The discussion on normalisation methods is presented for completeness. Both interval normalisation and good–neutral normalisation are implemented in the simulation model. Despite the methodological problems, the interval normalisation method was used to eliminate the requirements to describe ‘neutral’ and ‘good’ alternatives for all criteria. Using interval normalisation is not a problem in the model, as all alternative scores are within reasonable ranges, for all criteria, and all households.

5.3.2 Criteria details

Households make lamps purchase decisions on the basis of ten criteria. The criteria are displayed in figure 5.2 where the household’s surrounding data structure is also visualised.

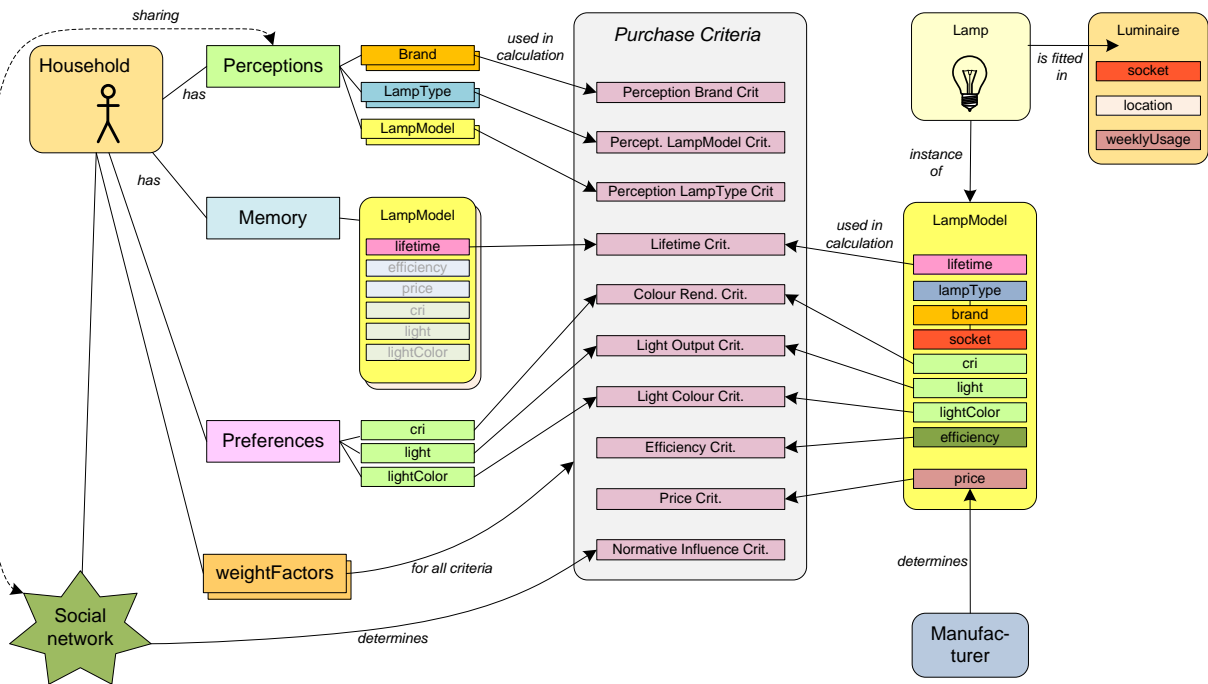


Figure 5.2 – Representation of the data structure of the household, relating to the purchase decision. The figure shows the relationship between the different objects and concepts, as implemented in the simulation model.

Lamp-model parameters criteria Six criteria have directly to do directly with parameters of lamp-models, as specified in the ontology (appendix D). These are the criteria related to *efficiency*, *purchase price*, *light output*, *light colour temperature*, *colour rendering quality (CRI)* and the lamp’s *lifetime*.

Efficiency and purchase price criteria The *efficiency* and the *purchase price* criteria are relatively straightforward. The criterion for *efficiency* should be maximised (each household prefers it if a lamp offers maximum efficiency), and the *purchase price* criterion should be minimised. Efficiency of the lamps is calculated from the values on light output relative to electricity input specified in the ontology. The purchase price is taken from the manufacturer's list of lamp sale prices.

Criteria with preferences For criteria that work with preferences (the *CRI*, *light output* and *light colour temperature* criteria), the household has some *preference* value. A household prefers it if a lamp-alternative scores approximately close to its preference value.

Criteria with memory For the lifetime criterion, the household consults its *memory*. If it remembers a lamp to offer really low lifetime (from previous experience), the lamp-model scores less on this criterion.

Criteria related to perceptions Then there are three criteria related to *perceptions*. These work in the same way as a memory, but are more like an opinion (the memory is a facts-memory). A perception can have a value of -1 to 1. There are perceptions on manufacturer *brand*, *lamp-type* and *lamp-model*, and all of these are also included as criteria.

Perceptions are updated negatively/positively based on buying lamps, experiences with lamps, and are also shared in the social network (see § 5.2.4).

Normative influence criterion The *social network* is responsible for the last criterion, the normative social influence criterion. This criterion is a measure to mimic the normative influence posed by concepts such as fashion and the tendency of an consumer to mimic the behaviour of others—'to do as others do'. On high involvement products it is clearly an important driving factor (evidenced by the quick rise to dominance of specific brands or products in markets for sneakers (Nike); cell phones (Nokia); media players (Apple); and so on). On low-involvement products normative influence is shown to exist as well (Jager and Jansen, 2008).

The implementation is based on counting the number of adopters of the lamp's lamp-type (Jager, 2007). In this criterion, the 'neighbours' in the social network are used as the 'friends' to imitate. The social network used is discussed in § 5.4).

First, all neighbours of the household in the social network are queried. For all neighbours, their lamps are 'read'. The neighbours give as answer a list of their true lamp possessions: what they say they have, is what they have. Then, for every neighbour i , the amount of lamps with a technology type that matches the alternative under question (a) is counted, and this is converted to a percentage $f_{a,i}$, relatively to the neighbour's total number of lamps.

$$f_a = \frac{\text{number of bulbs of lampType eq. to } a}{\text{neighbour's total number of bulbs}} \quad (5.3)$$

If $f_{a,i} \geq 0.5$; count the neighbour as an adopter of a : i_a . Then, after the above is complete, calculate the adoption percentage p_a of all neighbours, as follows:

$$p_a = \frac{\sum i_a}{\sum i} \quad (5.4)$$

This adoption percentage acts as the normative influence criterion.

5.3.3 Criteria weight factors

Criteria differ in how important they are to different consumers. Therefore, *weight factors* are attached to the criteria. These weight factors are very interesting to experiment with. To make the weight factors heterogenous with respect to the consumer, the weight factors are randomised.

The default assignment of weight factors is done in a manner loosely based on literature discussed in § 2.2.2 and § 1.2.1 as well as study project reports of students of the 2008 course ‘SPM9521’ that analysed Delft citizens on their lighting preferences. Assumptions:

- Purchase price is the most important criterion, therefore this weight factor is given the highest value, of 4
- After this, the efficiency, normative influence, colour rendering, light colour and lamp-type perception criteria are given a value of 2
- Least important are the remaining criteria (lifetime, light output, brand perception, and lamp-model perception).

The values attached to these weight factors can be taken also as modelling assumptions. In general, the model contains quite a number of these assumptions (see also the other sections of this chapter). It is most important that the *behaviour of the simulation model is right*, given some choice of parameters for assumptions.

The default values of the different weight factors for the household’s criteria are displayed in table 5.6.

Table 5.6 – Weight factors for household’s criteria

Weight factors for multi-criteria analysis	
wf Price	4
wf Efficiency	2
wf Lifetime	1
wf Normative Influence	2
wf Preference CRI	2
wf Preference Light	1
wf Preference Light Colour	2
wf Perception Lamp-type	2
wf Perception Brand	1
wf Perception Lamp-model	1
<i>(Default values; base case)</i>	
Randomisation interval for weight factors	
The weight factors are made heterogeneous for all households using a uniform distribution, an interval defined by lower and upper boundaries. The uniform distribution boundary values are created by multiplying the values for the weight factors (above) with the boundary factor values below.	
Lower interval boundary	0.5
Upper interval boundary	1.5
<i>(factors)</i>	

5.3.4 Choosing the top-ranking alternative

The last step of MCA is that, after ranking the alternatives, the top-ranking alternative is the one that is selected. If alternatives score exactly equal, a random selection is made.

However, one could argue that, for low-involvement products, like lamps, it is not entirely satisfactory that a consumer will always choose the single-best alternative, given his preferences, perceptions, opinions and so on. Especially for low-involvement products, the

time and amount of effort that is invested in the decision making is often quite low. So, it would be realistic to incorporate an amount of arbitrariness in which of the high-ranking lamps are selected.

Especially in cases where the top-performing alternatives are very close to each other, many consumers will not single out the alternative that scores the very best, all the alternatives are put on a ‘short list’, and in many cases quite arbitrarily one of these alternatives is selected. Given the limited nature of the rationality of consumer choice, it is more realistic if sometimes an alternative is selected that scores just a little worse than the ‘very best’.

This can be improved in two ways:

- Implement an addition to multi-criteria analysis algorithms so an alternative is selected depending on some probability, if it falls say within 10% of the very best alternative.
- Or, more simple: introduce another criterion, that is completely random, and assign it a weight factor that is not too high. In this way, decision after decision a small number of alternatives perform very similarly, then due to the random criterion, the outcomes will display more heterogeneity.

5.4 Social Network generation

The households are part of a network of social relationships. Social processes that occur through these relationships are one of the main elements of diffusion processes (§ 2.3). It matters who is acquainted with people that adopt novel lighting systems or have strong opinions. How communication messages travel; how the word-of-mouth communication with peers (neighbours, friends, relatives) work; and also how normative social influence occurs, is all depending on the social network. Therefore the household agents in the computer model need to be part of some social network configuration that needs to be created for the agents.

To generate a social network for the households we need to know the characteristics of the real consumer network. Two network generation algorithms, the Small-World algorithm and the Scale Free algorithm were implemented, which are discussed in § 5.4.2 and § 5.4.3, after a treatment of important parameters of social networks in § 5.4.1.

5.4.1 Network parameters

There are a number of parameters relevant to the study of social networks. These are the *network size*, the *average shortest path length*, the *clustering coefficient* of the nodes and the *degree distribution* of the nodes.

The *network size* N is the number of nodes (vertices) in the network. For the simulation, this is equal to the number of households, specified through the user interface of the simulation.

The *average shortest-path length* of a network is the mean distance between two nodes, averaged over all node pairs. An interesting property of real world social networks is that the the average shortest path length turns out to be rather small. This is called the ‘*small-world*’ effect after Stanley Milgram’s experiments in the 1960’s trying to establish the average path length for people in the United States (“six degrees of separation”) (Watts and Strogatz, 1998). For the simulation model, the average path length needs to be not too large, otherwise the social network in the simulation would not be realistic.

The *clustering coefficient* C is the average fraction of pairs of neighbours of a node that are also neighbours of each other. $C = 1$ for networks where every node is connected to every other node. These kind of networks are not often observed in practice. Completely randomly connected networks (random graphs) have clustering coefficients of around $C \approx 1/N$ (Wang and Chen, 2003). Thus for large random networks the clustering coefficient is tiny. However, in real-world social networks have rather high clustering coefficients; they range from a few percent to 40–50%, or even higher. The network of movie actors, which is a surrogate for a social network, has a clustering coefficient of 79% (Newman, 2001; Newman et al., 2002; Watts and Strogatz, 1998).

If the clustering coefficient is high enough and the average shortest path length is short enough, then propagation of information through the network, through effects like word-of-mouth, informational exchange, sharing of norms and customary behaviour (normative informational influence), is facilitated.

The *degree* is probably the most important characteristic of a node. The degree k of a node is the total number of its connections. The degree distribution is the distribution of the degrees of all the nodes in the network. Completely random networks have degrees k according to a Poisson distribution. It turns out, that for most big networks, the degree distribution is significantly different from the Poisson distribution. If the degree distribution $P(k)$ follows a power law, $P(k) = k^{-\gamma}$, with $P(k)$ the chance that a randomly selected node has degree equal to k , then the network is called scale free. For most networks, the degree exponent $\gamma \geq 1$ lies between 2 and 3. For example, for movie actors, $\gamma = 2.3$ (Dorogovtsev and Mendes, 2002; Wang and Chen, 2003).

There are a number of algorithms for generating a network of social relationships between household agents. Both the small-world network (Watts-Strogatz algorithm) and the scale free network (according to the BA algorithm) were implemented, so that a choice can be made for either type. In the model, the scale-free algorithm is the default choice. Default parameters used are in table 5.7.

Table 5.7 – Parameters for Social Network generation

Parameters for Social Network generation.		
Degree	15	Number of relationships of an agent. Small-World network: degree = the average degree. Scale Free network: degree = minimum degree.
Rewire Probability	0.20	The chance p that an edge is rerouted.
Scale Free Initial Agents	4	The initial number of agents for the scale-free network algorithm.

5.4.2 Algorithm for a small-world network

The small-world network is built according to the Watts and Strogatz algorithm (Wang and Chen, 2003). First the average degree (connectivity of a node) and the rewire-probability need to be specified. The degree k must be chosen even number ($k \bmod 2 = 0$), and $k \geq 2$. The rewire-probability p needs to be smaller than one: $0 \leq p \leq 1$.

The neighbour relationships are specified as “knows”- relationships in the ontology. The relationships are formed between the N nodes in a way that the nodes form a ring topology. How many relationships are created depends on the degree. Each node is given a relationship to its neighbour nodes at distances $i = 1, 2, \dots, k/2$, until every node has relationships equal to k . The relationships are assumed to be bi-directional: if a household knows someone else, the reverse is assumed to be the case as well.

After the creation of $k * N$ relationships, a randomisation step takes place. In this step all relationships are scanned, and depending on the rewiring-probability p , one node of the relationship is changed to a randomly selected different node. The probability p is chosen so that the resulting network structure resembles something between complete order ($p = 0$) and complete randomness ($p = 1$).

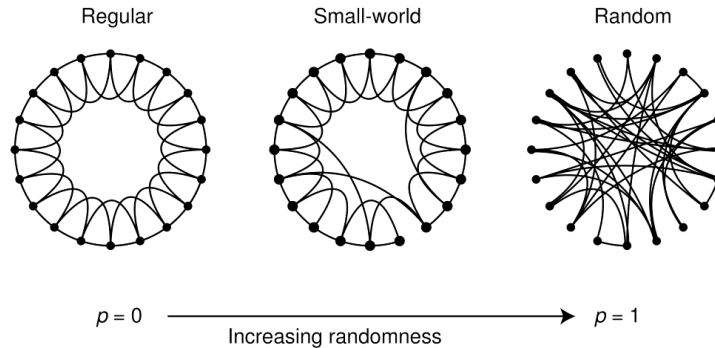


Figure 5.3 – A small world-network resembles in structure to a perfectly ordered ring topology (at left). After a randomisation step, the average path length drops dramatically, the small-world effect is observed (centre). The completely random network structure, for $p = 1$, is displayed at right. From [Watts and Strogatz \(1998\)](#).

The interesting property of the small-world network is that it is both highly clustered, like a regular lattice network structure, and displaying short average path lengths. For small values of p , the average path length decreases very quickly to the low values representative of random graphs and real world networks. This is due to some important 'short-cuts' being formed in the network structure ([Watts and Strogatz, 1998](#)). Note that there are different ways of generating networks that exhibit these properties, the Watts and Strogatz algorithm is just one way to generate a 'small world' (see e.g. [Dorogovtsev and Mendes, 2002](#)).

Figure 5.4 shows an example of a small-world network, generated by the simulation model. It can be observed that the nodes all have approximately the same degree; quite a number of nodes have relationships with nodes at a greater 'distance', the average path length will therefore be shorter than in a regular lattice structure.

5.4.3 Algorithm for a scale free network

The 'scale free' network is generated by the algorithm from [Barabási and Albert \(1999\)](#). The algorithm generates a scale free network through two mechanisms: *growth* and *preferential attachment*.

The preferential attachment mechanism is a way to explain how natural networks self-organise into scale free structures: if a node wants to form a link with another node, there is a tendency to link with a node that already has more links to it, for it could be advantageous to connect to an already 'popular' node. The network of scientific citations is found to be scale free ([Barabási et al., 2002](#)). Rumours spread well in scale free network. Even with some nodes inhibiting the rumour from spreading, in scale free networks rumours spread and reach the entire network ([Nekovee et al., 2007](#)).

The algorithm to construct a scale free network consists of a set of starting nodes, with some limited connections (edges), and then growing the network by adding nodes one at a time and connecting them to the existing nodes. Parameters that are to be specified are the initial number of nodes m_0 and a minimum degree of nodes m ($m \leq m_0$).

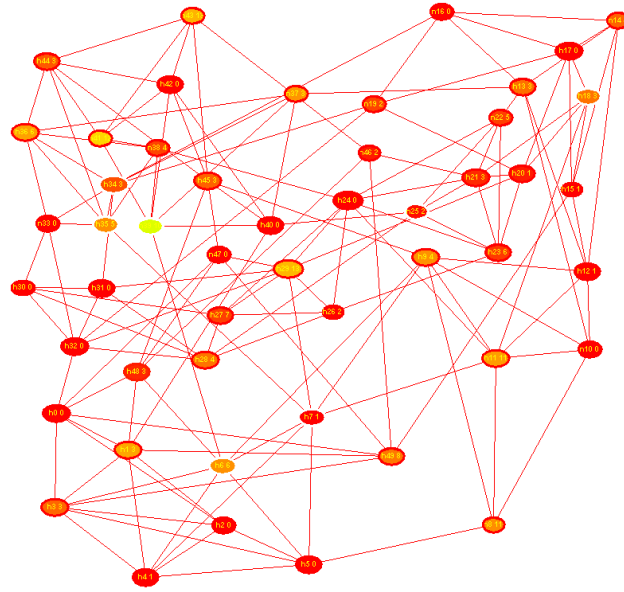


Figure 5.4 – Small-world network of households, for 50 households, with an average degree of 6. The size of the node corresponds to the node degree; the colours differ according to the household's lamps' energy efficiency.

The algorithm is in its simplest form as follows (Barabási and Albert, 1999; Wang and Chen, 2003):

1. First we start with a small number of households, e.g. $m_0 = 6$ nodes.
2. Then, on at a time, add a new node, and give it an m edges to another nodes.
3. The new edges connect to a node depending on the 'popularity' of that node, so that the probability that a node connects to node i with degree k_i is: $\Pi(k_i) = \frac{k_i}{\sum_j k_j}$.

This model gives a network with a degree distribution following a power law, with exponent $\gamma \approx -3$. The probability of finding a node with k connections is proportional to k^{-3} .

In the simulation model, the algorithm was slightly adopted: the m_0 initial nodes all have a connection to one other node, completely randomly selected. So there are also m_0 edges before new nodes are added.

When generating large networks of consumers, we should choose parameters so that all nodes have a degree of say at least (say) 10, or 20. People differ in how big their social network is, but there are not much people who really know more than a hundred (or so) people: man's cognitive and social capacities limit the amount of relationships with other people.

While creating large scale free networks, with quite high m , there is a definite possibility that there will be consumers with very many connections (e.g. 1000). Practically, depending on the interpretation of the relationship that is modelled, this could be unrealistic. If the relationship is taken to be of the 'friendship' nature, how many people are your friends? A solution would be to modify the algorithm to limit the amount of connections to some value, e.g. 50, or 100. On the other hand, due to mass media and modern popular culture, in real life there or quite a lot of people who have extremely high one-way connectivity and are highly influential. For the consumer model the choice was made not impose an upper degree limit.

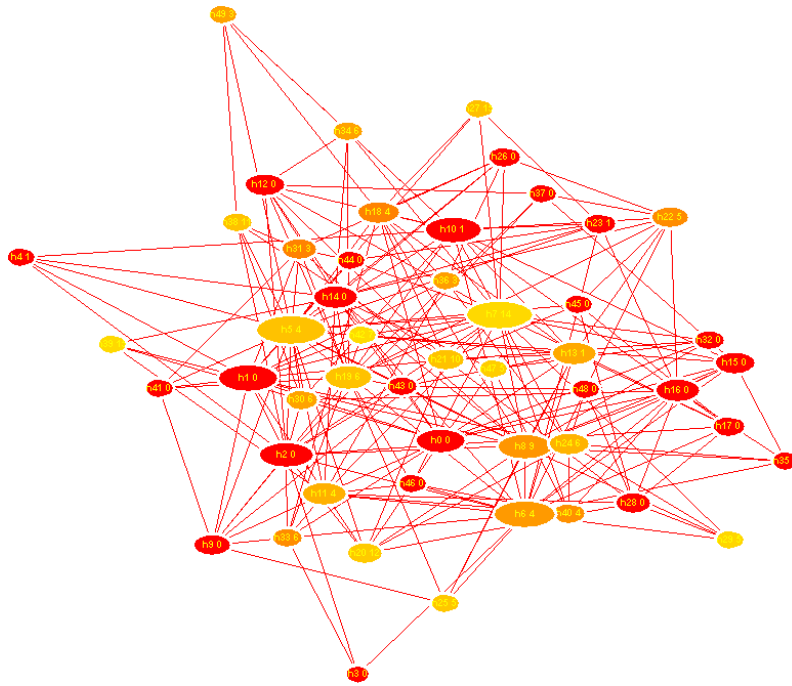


Figure 5.5 – Scale free network of households, for 50 households, with degree parameter $k = 6$. The size of the node corresponds to the node degree; the colours differ according to the household's lamps' energy efficiency.

An example of a scale free network, generated by the simulation model for 50 households, is displayed in figure 5.5. As the dimensions of the ellipse of the node indicate the degree of that node, one can easily observe the small number of highly connected nodes.

Choice of Algorithm for Household Social Network

A choice can be made for either type of network. The important difference of the scale free network is the presence of a few nodes with a large number of links. These are largely absent in the Watts-Strogatz small-world network, but do appear in the scale free model, where they dominate the network's connectivity (Barabási and Albert, 1999).

The different characteristics of the networks are clearly observed by looking at the degree distributions resulting from the two network algorithms, see figure 5.6. In the case of the small-world network; the nodes are really evenly distributed in connectivity; in the scale free network, there are quite some well-connected nodes, with a degree many times higher than the specified minimum. Such nodes are important hubs in the network. In social networks, these are the opinion leaders. If these people switch in their technology, this is an important event, influencing many others to do the same.

For choice of which network algorithm: Nekovee et al. (2007) did a study on rumour spreading in social networks. Their conclusion is that a scale free network structure is properly for information sharing like this.

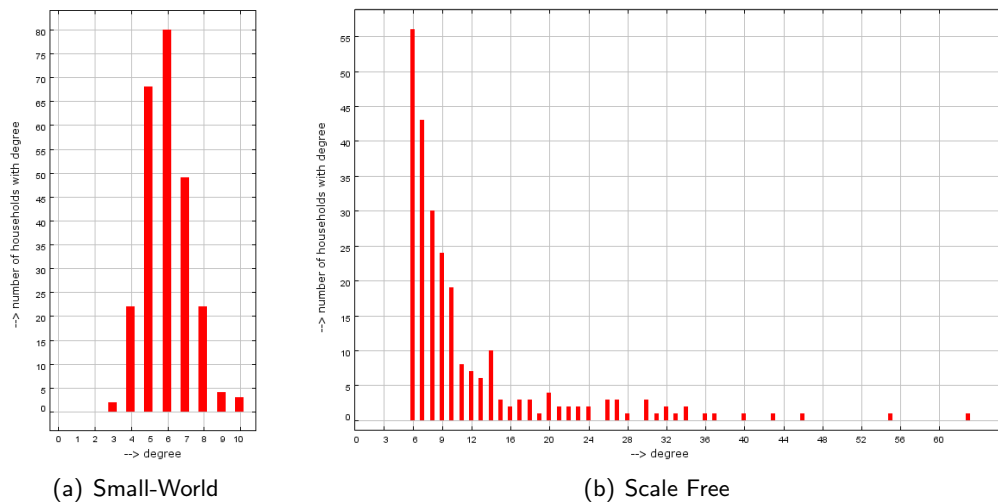


Figure 5.6 – Comparison of the degree distribution resulting from the implementation of the two network generating algorithm: small-world at left, and scale free, at right. For both networks, the degree parameter $k = 6$, and the rewiring probability $p = 0.20$.

Chapter 6

Validation

6.1 Introduction

After model development, an important test is in how far the model is correct, and where its limitations lie. Questions that may be asked are: is the model ‘right’? How can the internal logic and the internal consistency of the model be verified? Is the model useful to say something about the real world problem that we have? These questions are part of the task of validation of a simulation model. Only if the outcomes of the testing process are positive, we can have confidence in that the computer simulation model can meet its purpose.

In validating computer simulation models one can do this at any or all of three levels: verification, validation and certification; see table 6.1 (Küppers, 2005, p. 2).

Table 6.1 – Levels of standardisation (adapted from Küppers, 2005, p. 2)

Validation level	Description
Verification	Transformational accuracy. Are concepts in the model correctly formulated, does the model work correct, logically?
Validation	Representational and/or behavioural accuracy. Does the model correspond with the real world system, in terms of structure, parameters, and/or output, behaviour?
Certification	Independent assurances of sufficient credibility. Are the results of the model correct and useful to such an extent, so that an independent standardisation body that reviewed the model is willing to give its approval?

The certification step is not something that is aimed for with the consumer lighting model. The certification option is very case specific: there must be a party willing to perform the tests, and a problem owner that demands the quality assurances from the certification step (and that is willing to pay for it).

According to van Dam, validation is “*a continuous process, not a single test to check if the model output matches its ‘real world’-system. During the validation step, modelers and domain experts evaluate if the model is useful and convincing*” (van Dam, 2009, p. 72)

Useful & convincing The results may not be able to predict the future, but we will have failed in the simulation undertaking if we cannot learn anything from the model. Apart from what already can be said about this in the present chapter, the usefulness and the

convincing qualities of the model results will be further dealt with in chapters 8 (results), 9 (Conclusions) and 10 (Reflection).

The notion of usefulness of the model implicates that the possible use base of the model is important in the validation process. A model may be valid for a specific group of users, but not so for another group of users, because that group has different objectives or criteria. If a model has many different potential audiences, validation becomes complicated (Forrester, 1980).

Target group For the consumer lighting model the audience are considered to be everyone interested in the main research question: the nature of the effects of the ban on bulbs. In addition, the audience includes fellow researchers and academics.

Confidence in the model results is established by testing the appropriateness of model structure, and by comparing simulation model results and outputs with independent data. In the validation process one can distinguish *structure-oriented validation tests* that tests different aspects of the model in a structural way, from *empirical validation tests* where one compares data with data from the real world.

The first part of validating the model is verification of the model, this is done in § 6.2. The second set of tests are structure-oriented tests, described in § 6.3. A specific set of structural test that were performed to verify the household's parameters and data structure is the testing of the household *purchase method*. This is done in § 6.4, where we also present the validation results. The empirical validation method is discussed in § 6.6.

6.2 Verification

In verification of the model, the model is checked on consistency, whether concepts and relations are coded correctly. Verification asks “does the model do what it is intended to do”, or “is it programmed according to the specification”.

The intention is that the items from the conceptual design, all relevant entities, concepts, and relationships, are correctly translated into the simulation model.

For this, it is important to continuously test, during programming, that the source code produced, is (1) well-written, (2) well-behaved and (3) does what it is intended to do. One checks the source code for errors, logically or grammatically (usually the compiler outputs error messages if it is grammatically incorrect). Secondly, one checks if the source code works alright with a number of input parameters, e.g. negative values, zero, very large values. The last step, does what it is intended to do, is the most difficult. Using e.g. ‘print’-statements, one observes the results of the code. If these are according to expectations, confidence in the source code is increased. It also helps to work with a peer to (co-)review the source code, e.g. when writing a new software module from scratch.

These procedures were followed, day-to-day during model development. The co-review with a peer was done mainly when an obnoxious bug was feared to be present. As an illustration of this verification, an example of the verification procedures used is displayed in the box of figure 2.

One of the advantages of working with an object oriented programming language is that the modularity of the source code facilitates the testing of code. This is a major advantage, as this testing can take place *during* model development. Whenever a new module is implemented, one can test the modules, without the need for the rest of the model to be finished. This was done constantly during model development.

When a bug (software coding error) was feared to be present and I could not see why or where, I would consult with peers / supervisors. In these circumstances source code was

When the module was written that allow for gradually declining prices of lamps, allowing for recent technology to evolve to cheaper prices over time, a complex algorithm was programmed to do this. The module was complicated by the fact that there also had to be a selective government subsidy scheme. To do this, the algorithm was first created into MATLAB, where graphs could be made of the price sequences. Then the algorithm was implemented in Java. By visualising the workings of the simulation model into a Repast graph, it could be verified that it worked ok. And finally, when the model was run on the high performance cluster, the exported data sequences (in the SQL server) were queried, these data could be fed to a MATLAB graph, and again it could be established that the values match.

Box 2 – Description of the implementation of a module, as an example of how the correct working of a module is verified

either co-reviewed, or discussions took place that had the effect of pointing me in the right direction regarding a solution.

Implementation of a module The approach that was undertaking during the implementation of concepts into computer code:

1. Think about how the concept can be implemented in the existing model structure
2. Implement it, by designing new java classes, concepts in ontology, and writing code.
3. Test it, e.g. by select some key indicators and printing their values for a number of runs.
4. Clean up the code and document it.

During the first step, one carefully thinks not only about the new concept, but in thinking about ways to implement it, the existing structure of the model, what is already in place, is also reviewed. It is during this step, that improvements are envisioned for the existing structure. In a number of cases, also inadequacies of the existing structure or implementation were discovered.

After implementation of the piece of new functionality, the new functionality is carefully tested to see that it behaves all right. With reading and writing computer code, my experience is that one generally is able to understand quite easily how code works when one sees it, however when one actually starts writing code, a beginner would write very bad code that is obviously lacking in a number of aspects, but even an experienced programmer can really easily introduce bugs that can be quite subtle. Therefore testing of whether the code behaves all right is really mandatory.

During testing, in many cases the first attempt at some algorithm did not succeed, and a number of times one has to go back-and-forth between revising code and testing it.

At some point one can conclude that the implementation is as it should be, and does not need more modification. At this point one could stop, which is what many programmers do: they are satisfied, it works.

However, stopping now means that the code will contain many lines of debug comments, pieces of non-functional or alternative algorithms that are commented out, at cetera. This does not ‘look good’ and it also does not make the maintenance of the code easier, nor does it facility future understanding of the code if one has to revisit the code a couple of months later, or if someone else needs to look at the code.

Therefore, at this point, I always went back to the piece of code that was implemented, and removed all non-relevant things, commented-out lines of software, non-useful

print statements, and wrote a new piece of documentation for the module/method implemented. The documentation written includes the purpose of the module/method and if applicable key behavioural assumptions or the workings of its main algorithm. The documentation part is important; it functions to reflect on the source codes purpose in a way more abstract.

I also see the software development undertaking as a learning project, source code should not only function all right, but it should also be easy to understand and ‘look good’.

6.3 Structural validation

The structural validation means verifying whether a simulation model is found to match in structure to a real world system. Different types of models traditionally use different validation techniques. Validation of agent-based models is a research field in progress (e.g. Moss, 2008; Windrum, 2007). We will base the structural validation that we perform on Forrester (1980), who gives a range of structure and behaviour tests to perform, advised for validating System Dynamics models. These are: (1) verification of the model structure; (2) boundary adequacy of structure; (3) verification of model parameters; (4) extreme conditions tests; (5) dimension analysis of equations.

In agent-based modelling of socio-technical systems, one is codifies the ‘internal logic’ of agents, and not the larger system structure. Therefore, structural tests that focus explicitly on the system structure are less useful for agent-based models. From the above list of structure-oriented tests, boundary adequacy testing, the most applicable to SD models, was not performed, and neither was the structure ‘verified’ by looking at it using a top down approach.

Structural tests were carried out on the consumer lighting model are verification of model parameters; extreme conditions tests and dimension analysis; we will detail them concisely in the remainder of this section.

The internal logic of the agent should also be validated, however. As an agent has both structure and behaviour, it can change as simulation progresses, and is adaptive in this respect. This makes validation difficult. What we did do was execute a range of *structural-behaviour tests*. This is detailed in § 6.4, where we focussed on validating the agent’s buy behaviour given a wide range of settings (including extreme values).

Verification of model parameters When one codifies the agent, it was found that this was a non-trivial task. Many parameters are required in the model to quantify relationships. Validating these is very difficult.

Küppers (2005) argues that models in the social sciences cannot be tested for their model structure in a meaningful way as causalities of social processes are ambiguous in the sense that competing theories exist for most phenomena. This remark certainly applies to the consumer lighting model, where it was only possible to model key components by making a list of behavioural assumptions, of which only for a few a theory exists. Therefore, for the parameters defining the agent-based model, these are certainly different from the real world system.

A different (agent-based) simulation model of the consumer lighting model could be built by using different parameters. **What matters is that the behaviour of the simulation model is right, given the choice of parameter.**

Extreme conditions tests & Dimension analysis As described in § 6.2, these test were carried as part of model development. When input parameters were varied into

extremes, it was observed that model behaviour matched this. During the construction of the algorithms, dimensions were checked (note, there is quite limited algorithmic ‘power’ in the model)

6.4 Validating purchase behaviour of household

To test the purchase function, an experimental setup is developed to test the buy behaviour of the household agent.

In this testing-mode, the simulation model is started up using a special parameter setting. In this testing-mode, in the simulation model there exists **one household** and the manufacturer are created. The household agent is instructed to **buy a single lamp**, which is undertaken by the household agent under an elaborate range of parameter settings for its data structure. Where possible, parameter settings are given to all relevant model parameters that directly influence the household’s buy decision.

In these validation experiments, we test the household’s purchase decision under all possible combinations of settings, with the limitations that we can only test the household *in so far as is possible in a model with only one household, making one purchase decision*.

The following things are left out:

- Making a decision based on lamps other people have (normative influence).
- The influence of existing luminaires and sockets distributions.
- Memory of lamp-models and perceptions for lamp-models.

The effect of the aspects of the purchase process that are not included in the validation testing are expected to be neutral. If there is no memory on anything, it is not included as a purchase criterium, and not of influence to purchase (Perceptions for lamp-types and brands are included in the experimental setup). The resulting experimental setup used for the purchase validation experiments is displayed in table 6.2.

Weight factors and *preferences* are varied in a full factorial manner¹. Because there are so many *lamp-types* (4) and *brands* (11), it is not doable to test all possible combinations of *perceptions* for these. Doing so would result in multiplying the number of experiments by 16 for lamp-type (2^4) and by 2048 (2^{11}) for brand, excluding the weight factors for these perceptions (which are varied using three values).

Therefore, it was chosen to vary the testing of *brand perceptions* in a mutually exclusive manner: the household is given only one perception for some specific kind of brand (perception value = 1), and the perception values for the other brands remain zero. This significantly reduces computational time: the number of experiments is multiplied by a factor of 11 for perceptions for brands, instead of 2048. *Perceptions for lamp-type* are varied in a full factorial manner.

The resulting total number of experiments to perform is high (10 million), but manageable.

Aspects of the buy process that were left out, due to computational constraints, are *perception values for individual lamp-models* and the weight factor for the corresponding criterium. As there are 70 lamp-models and (for reasons of symmetry) three possible values for the weight factor for the criterium, if these perceptions would be included then the number of experiments would be a factor of $70 * 3 = 210$ higher in the mutually exclusive

¹A single experiment test was found to be very quick. If a single experiment would not have been very quick, a different algorithm to compute the experiments would have to be used; e.g. Latin hypercube sampling, or random sampling (Nikolic, 2009, app. E).

Table 6.2 – Parameters varied in experimental setup for the testing of the purchase of lamps. The rightmost column displays the cumulative number of experiments, which results from the cumulative multiplication of the number of experiments per parameter to vary.

<i>Parameter to vary</i>	<i>Experiment</i>	<i>Nr. experiments</i>
preference light colour	2400 – 2700 – 3100	3
preference light output	400 – 700 – 1110	9
weight factor price	0 – 1 – 5	27
weight factor efficiency	0 – 1 – 5	81
weight factor life time	0 – 1 – 5	243
weight factor prf. light colour	0 – 1 – 5	729
weight factor prf. CRI	0 – 1 – 5	2,187
weight factor prf. light	0 – 1 – 5	6,561
weight factor perc. lamp-type	0 – 1 – 5	19,683
lamp-type perception CFL	0 – 1	39,366
lamp-type perception LED	0 – 1	78,732
lamp-type perception Halogen	0 – 1	157,464
lamp-type perception Incand.	0 – 1	314,928
weight factor perc. brand	0 – 1 – 5	944,784
brand perception (x 11)	0 – 1	10,392,624

experimental setup (or hypothetically $2^{70} * 3$ in a full factorial setup). Also left out was the influence of neighbours and of sockets and luminaires.

Appendix F further details how the experiments were implemented, what issues were encountered and how the data were processed into useful results (graphs and tables). The results of the purchase testing are given in the next section (§ 6.5).

6.5 Validating purchase behaviour – Results

The winning lamp-models, aggregated over all experiments, are displayed in figure 6.1. The general outcome that can be observed is that there are some lamps who are clearly very popular. Chiefly among these are some LED lights and some high efficiency CFL's. A number of questions arise when looking at figure 6.1: why are some lamps clear winners? What can we say about the validity of the buy function, based on these results?

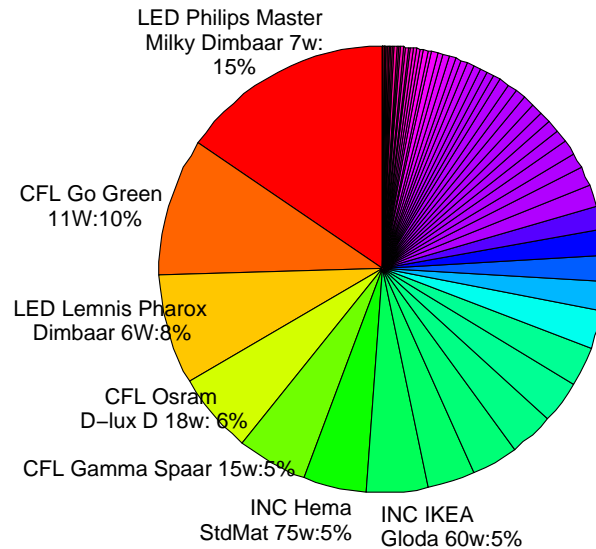


Figure 6.1 – Pie charts showing the distribution of the purchase outcomes for the 10,392,624 experiments of the setup of table 6.2

To answer these questions, we need to explore the result further. Exploring these validation results will be done by making subsets, using the criteria weight factors.

In § 6.5.1 we will first present results for the data subset where we only look at one criterion at a time. We make the subset by selecting, from all experimental cases, only the cases where the single criterion we include, can have a *weight factor of 1 or 5, but not zero*; and where all the other criteria weight factors have a value of zero. This gives back 2376 cases out of the 10+ million.

in § 6.5.2 we will do the reverse, and look at results for subsets of the data where we eliminate the cases where the weight factor for the criterion has a value *other than zero*. This gives back more cases: 2,598,156 to be precise.

In both sections, we show pie charts giving a distribution in terms of the most frequently selected **lamp-models**, and their **lamp-types**.

6.5.1 Outcomes: only one criterium included

The experimental outcomes where all weight factors are put at zero, except for one weight factor, which can take either 1 or 5, is given in figure 6.2 for lamp-types, and 6.3 for lamp-models (page 71).

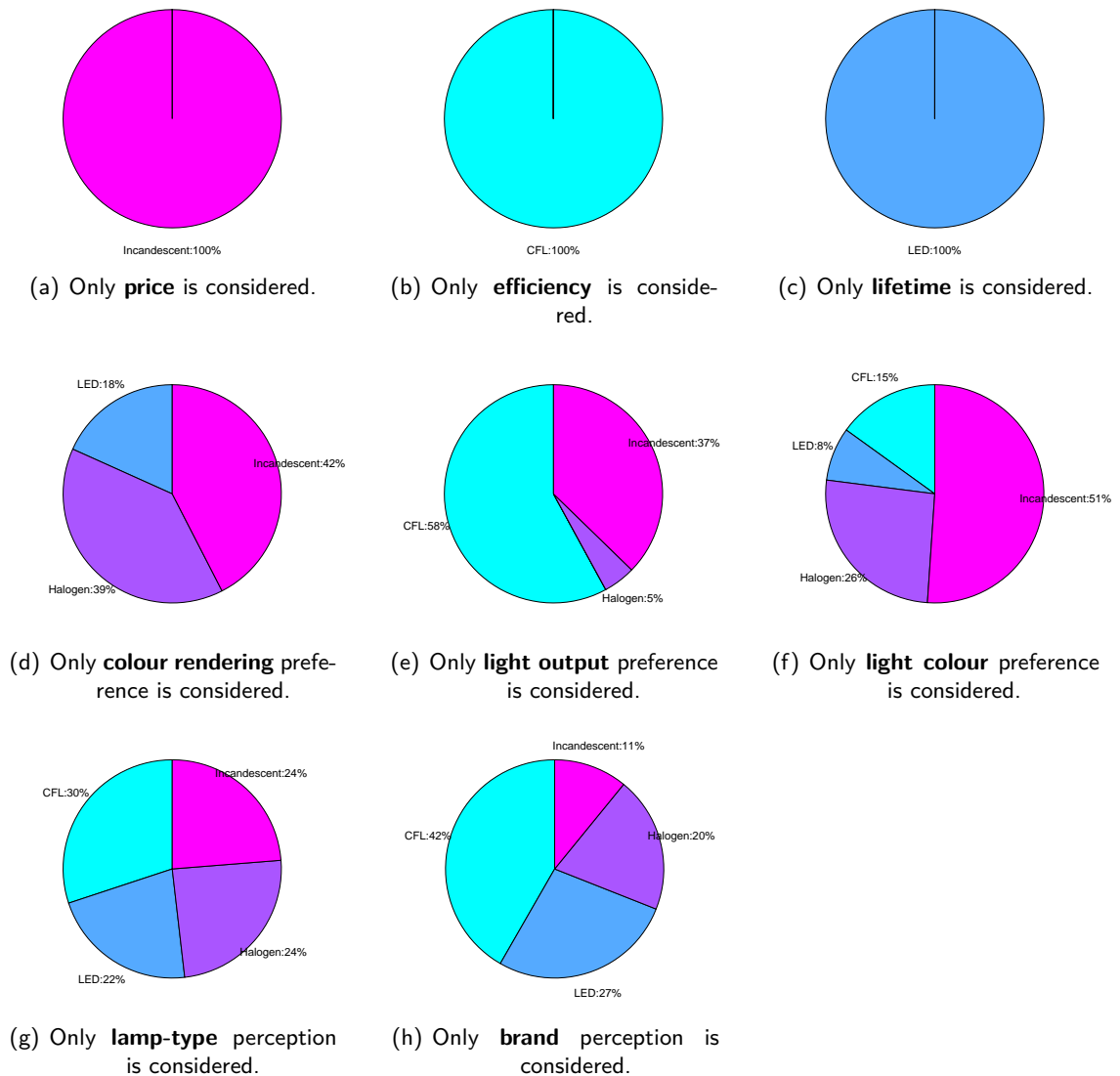


Figure 6.2 – Pie charts showing the distribution of the purchase outcomes, in terms of the **purchased lamp’s lamp-type**, when *only one criterion* is used for the purchase decision. The other criteria are left out of the purchase decision by putting their weight factors at zero. For each of the graphs, the number of included cases is 2376.

Observations What can be observed in figures 6.2 and 6.3 is that in pie charts (a), (b), and (c); for price, efficiency and lifetime; that some specific lamp-types being very strong on these respects. In the case of efficiency, 6.3 (b), only one lamp-model is winning; in (a) and (c), two lamp-models score about equal.

In the charts 6.2/6.3 (d)–(h), a more mixed approach is seen. Figures 6.3 (e), (g) and (h) show a very ‘even’ / ‘gradual’ output, with all lamps being selected in some cases, a few lamps being relatively popular and then many lamps of declining popularity. Charts 6.2/6.3 (d) and (f) do so as well, except for the presence of one single lamp-model with

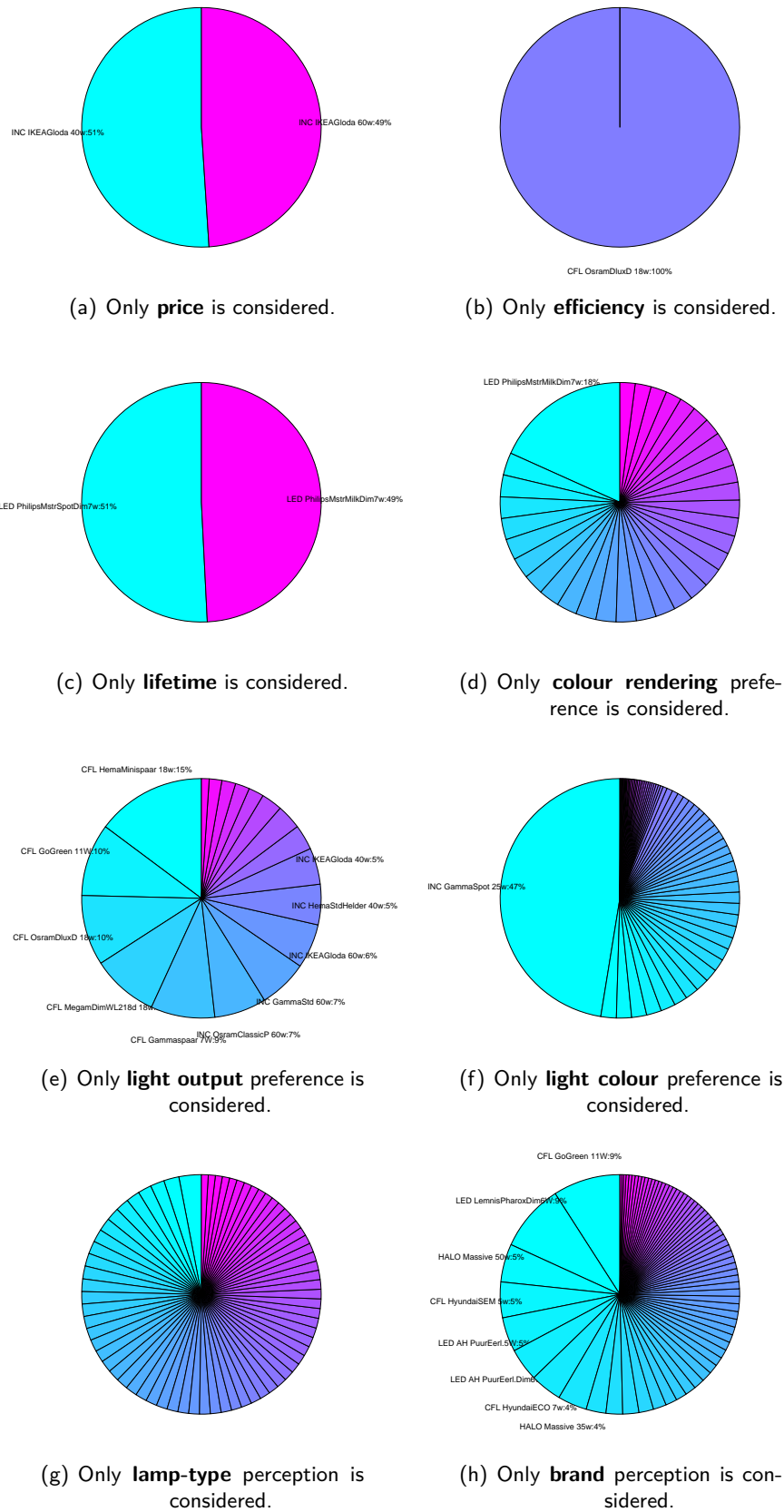


Figure 6.3 – Pie charts showing the distribution of the purchase outcomes, in terms of the **purchased lamp-model**, when *only one criterion* is used for the purchase decision. The other criteria are left out of the purchase decision by putting their weight factors at zero. For each of the graphs, the number of included cases is 2376.

significant occurrence, which poses some sort of anomaly.

Interpretation How should this be interpreted? In the outcomes of figures 6.2 and 6.3, supposedly *only one criterion* is incorporated in the purchase decision. Therefore, we expect that, from the available lamps (appendix D), lamps that are selected very frequently, score exceptionally well on *that tested criterion*.

In the pie charts where a ‘*single best*’ winner-effect can be observed, in others a *more ‘even’* approach is observed, or there may be true *anomalies*, as in the case of (d) and (f). This will be detailed below.

Single best winners In figure 6.3 (a), (b) and (c), a clear single-best outcome can be observed, as expected: the winning lamp models score the best on the aspect related to the criterion: incandescent lamps are the cheapest, CFL’s have the highest efficiency and LED lamps have the longest lifetimes.

In (a) and (c), the dual outcome is caused by the lamps scoring equally on the criterion, they are just as cheap, or have exactly the same lifetime, respectively, and in those cases, multi-criteria analysis (§ 5.3) reverts to randomly selecting one of the best-performing alternatives.

‘Gradual’ distribution of lamp-models The typical distribution in figures 6.2/6.3 (d)–(h), where all lamps and lamp-types are present, is caused by a large number of lamps performing similarly, and almost all lamps being favoured by the household in some case. E.g. many lamps have a warm white light colour (e.g. 2700 K), causing them all to be selected with closely the same frequency, explaining the even / gradual outcome, except from the anomaly described below.

The distribution of lamp-models with the lamp-type perception and brand perception criterions (charts (g) and (h)) are also quite even/gradual, with very many lamps having some frequency of occurrence that is about the same.

In these cases, the distribution in lamp-type outcomes (fig. 6.2), is more indicative of *the amount of lamps with a specific lamp-type* are included in the simulation per instance of brand / instance of lamp-type. For example, 25 out of the 70 lamps in the simulation are of the CFL lamp-type (appendix D). If randomly a lamp would be chose, this would in $25/70 = 36\%$ of cases be a CFL. The proportion of CFL’s in (g) is 30% and in (h) 42%. It is probably higher in (h) because there are a number of brands in the simulation that only have CFL’s.

Anomalies Another anomaly is shown in 6.3 (f): the ‘GammaSpot 25W’ is winning 47% of experiments where the households only consider light colour. This has to do with this lamp-model being the only lamp, with 2600K, offering a warmer light than 2700K. So when the household’s preference is for extremely warm light (2400 K), it is the only lamp being able to ‘score’. This would explain some 33% of the outcomes. The remaining 14% can be explained by the notion that a household’s preference values are randomised. This will be discussed below, in the case of the ‘PhilipsMasterMilkyDimbaar7W’. When a household has a preference value of 2700K, if it is randomised, also with this preference value the ‘GammaSpot 25W’ can be a closest match.

An interesting anomaly can be seen in the figure 6.2 (d). In this chart, LED is significant (18%), caused by the lamp-model ‘PhilipsMasterMilkyDimbaar7W’, which has a CRI of 87 (see appendix D). This is strange, because the halogen and incandescent lamp-types are superior technology in this respect, their CRI is 100. How can this be?

It turns out that this anomaly occurs due to the randomisation of preferences of a household, performed to make the household's preferences heterogeneous. In the experimental setup, after preferences and criteria weight factors are assigned to an household, the household makes them somewhat heterogeneous by randomising them using a randomisation interval. The randomisation algorithm is displayed in the pseudocode box 1. The randomisation interval $[a,b]$ used is $[0.9 - 1.1]$ for preference values (table 5.2; p. 47), and $[0.5 - 1.5]$ for weight factors (table 5.6; p. 56).

```
function randomise(oldV, a, b)
    new RandomNumberGenerator.Uniform
    r = createRandomNumber(a, b)
    return newV = oldV * r
```

Pseudocode 1 – Randomisation algorithm.

Thus, we can deduce why the aforementioned lamp-model is selected in 18% of cases: the true preferences for CRI for households are from the interval $[90-110]$. As the score for the colour rendering criterion is taken as the absolute value of the difference between a lamp-model's CRI value and the preference value, all incandescent and halogen lamps, with a CRI of 100, are generally preferred indeed. Except when the preference is randomised to something close to 90%, in these cases the 'PhilipsMasterMilkyDimbaar7W' is a better choice. A CRI-preference value precisely in the middle of this lamp-model's CRI and that of halogen/incandescent, is a preference value of 93.5. From the uniform distribution follows that the probability of achieving a preference value lower than that value is equal to 17.5%, which is the frequency of the 'PhilipsMasterMilkyDimbaar7W' being selected.

Another source of anomalies could arise through the way numbers are stored in computers. The fact that in MATLAB and Java, weight factors are stored as floating point numbers, which could possibly sometimes cause strange effects, like a value that is put at zero being turning out to differ from zero (Bedford, 2009)². This effect can be expected to be unnoticeably small, however.

6.5.2 Outcomes: one weight factor kept at zero

A different set of experimental outcomes is where all weight factors are allowed values of 1 or 5, but one parameter is put at zero. Results are given in figure 6.4 for lamp-types and figure 6.5 for lamp-models (page 75).

These pie charts of figure 6.4, and especially figure 6.5, all show a gradual division of outcomes.

This is nice, as now worrisome patterns and anomalies are absent, certainly when comparing with the results of § 6.5.1. With each criterion that is left out, a slightly different pattern emerges. This leads us to conclude that no single criterion is really determining of all results. Apparently all technology types and/or lamp-models appear to have some (different) strengths.

²In computers, if floating point calculations are applied, small inaccuracies can occur when data is stored that is a repeating sequence in binary format. These small differences may build up, causing results to deviate from what could be expected. In computers, $1.0 - 0.90 - 0.10 \neq 0$ (Bedford, 2009). This principle may be the cause of why criteria, put at zero, are not precisely zero, but have a value from the range $0 * [-0.5 - +0.5] \neq 0$.

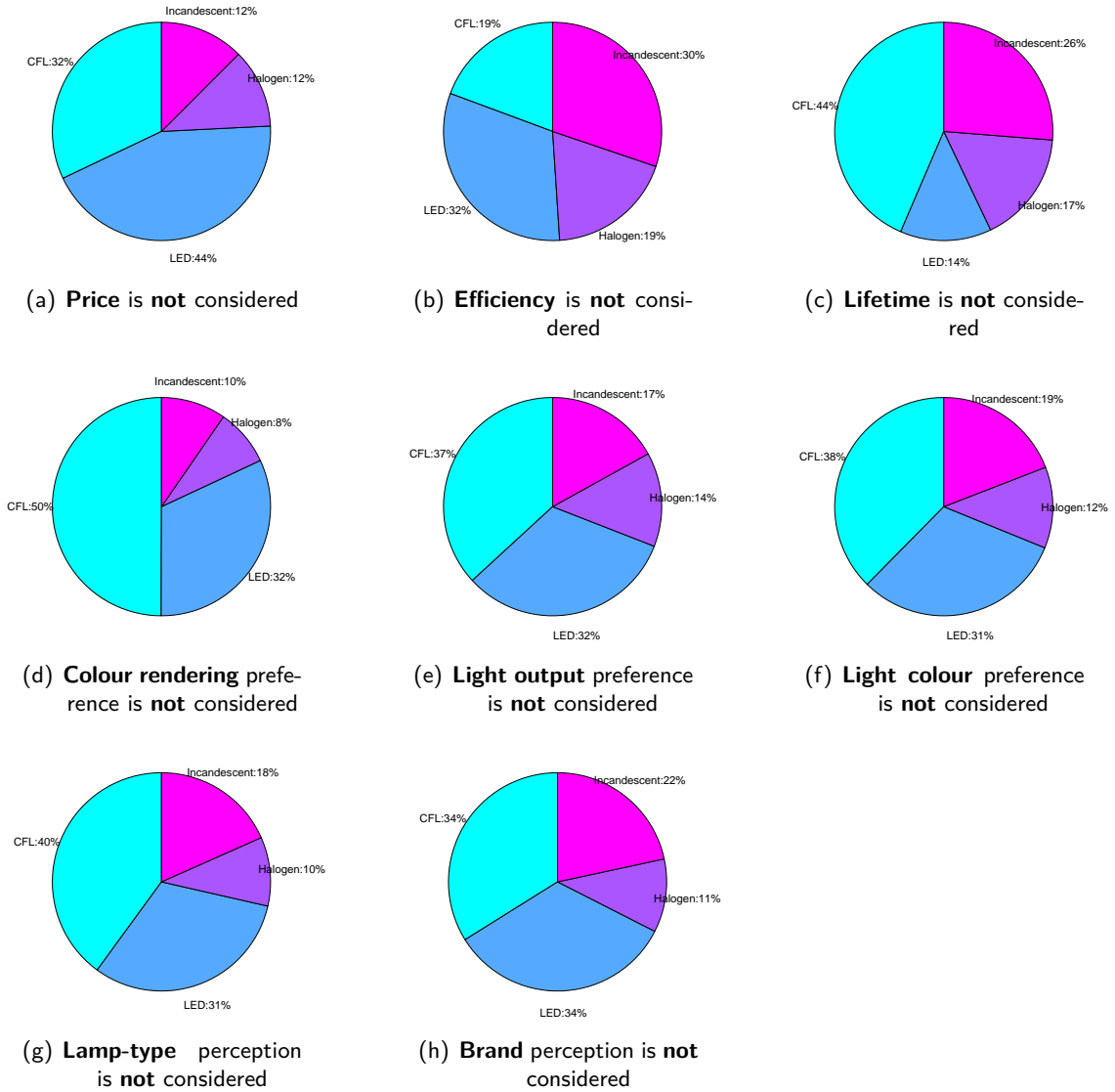


Figure 6.4 – Pie charts showing the distribution of the purchase outcomes, in terms of the purchased lamp's lamp-type, when, one at a time, a criterion is left out of the purchase decision (by putting its weight factor at zero). The number of included cases in each of the graphs is 2,598,156.

6.5.3 Summary of validating purchase behaviour results

Based on the results in § 6.5.1 and § 6.5.2, we can draw conclusions of why the lamps of figure 6.1 are clearly the most frequently selected.

The winning lamps are displayed in table 6.3, where the reasons for them winning are also given.

We can conclude a number of things from this. First of all, LED has a relative lifetime advantage that, compared to other lamps, is quite big. This makes LED lamps frequent winners, despite scoring less on price and less on light output/light quality aspects.

Furthermore, lamps with a high / highest luminous efficiency are also winners. Other lamps are winning due to a close match with the preference values in the experimental setup. This says nothing about the validity of the simulation model per sé, it is more an artefact of the validation's experimental setup. This also holds for the lamp-model 'PhilipsMasterMilkyDimbaar7W', which has a CRI of 87 that turns out beneficial. However,

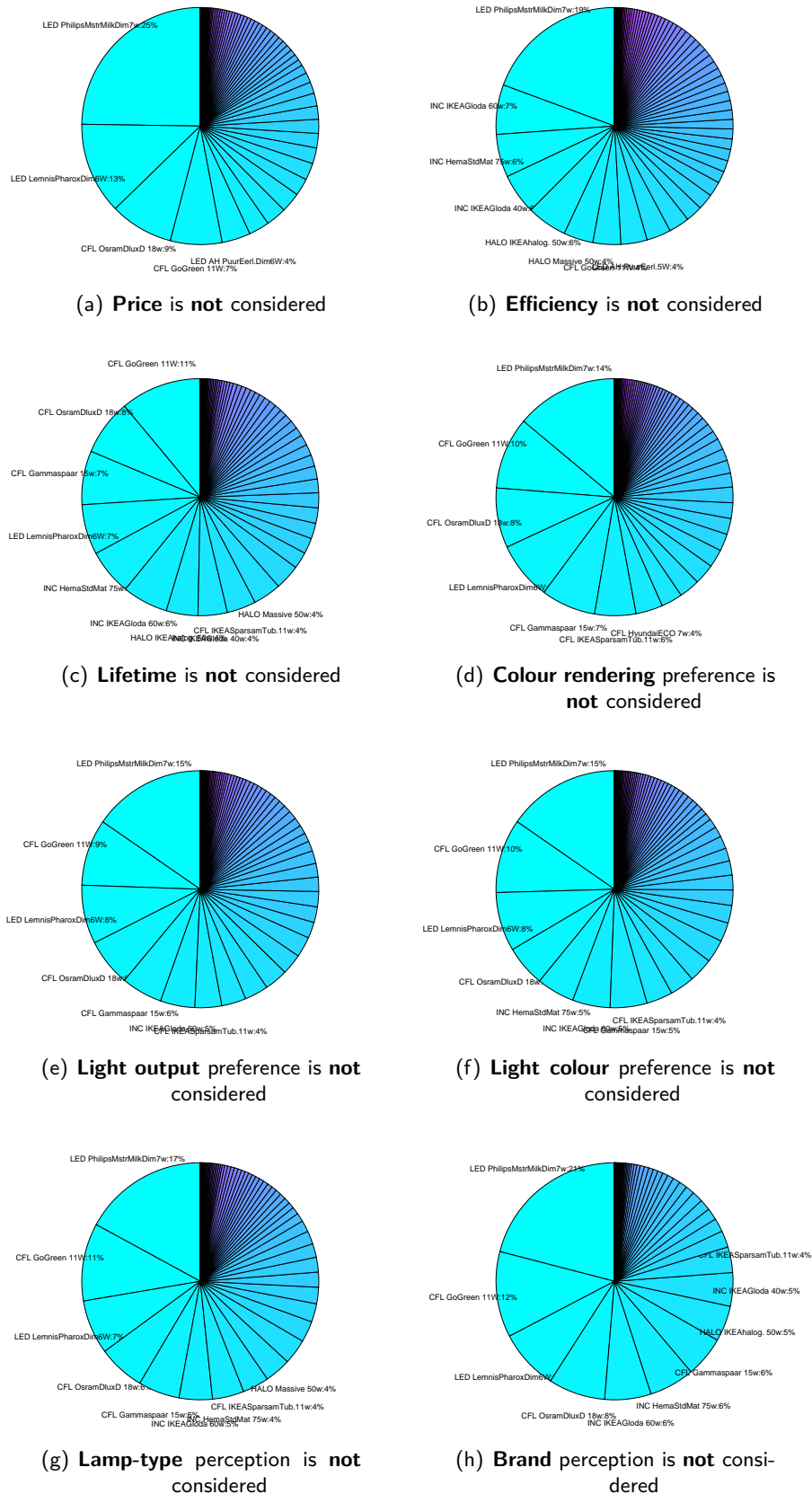


Figure 6.5 – Pie charts showing the distribution of the purchase outcomes, in terms of the **purchased lamp-model**, when, one at a time, a *criterion is left out of the purchase decision* (by putting its weight factor at zero). The number of included cases in each of the graphs is 2,598,156.

Table 6.3 – The most frequently occurring lamp-model outcomes; the 10 most frequently selected lampmodels are displayed, with, shown as a percentage, the number of times the lampmodel is selected in the experimental setup.

Pop. Name	Type	Fract. of outcomes	Reasons for popularity
1 Philips MasterLED Milky Dimbaar 7w	LED	15.5 %	Very long lifetime; CRI anomaly
2 Go Green 11W 60Weq	CFL	10.0 %	High efficiency
3 Lemnis Pharox Dimbaar 6W	LED	8.0 %	Long lifetime (and light output matches to an extent)
4 Osram DeluxD 18w	CFL	5.7 %	High efficiency
5 Gamma Spaarlamp 15w	CFL	5.1 %	Low price
6 Hema StandaardMat 75w	Incand.	4.6 %	Light output ~ matches + low price
7 IKEA Gloda 60w	Incand.	4.5 %	Light output close match + low price
8 IKEA SparsamTubular 11w	CFL	3.4 %	Low price
9 IKEA halogen 50w	Halogen	3.3 %	Light output matches + low price
10 Massive 50w	Halogen	3.2 %	Light output matches

in practical use, when this lamp's price is included in the equation, it will not be so attractive anymore.

Frequently selected lamps are from all lamp-types. Therefore, with the given experimental setup, we conclude that there is clearly **no significant purchase bias** in the model towards any of the four lamp-types.

6.6 Empirical validation

Empirical validation entails comparing model outputs with what can be derived from the real world. [Küppers \(2005\)](#) makes the case that in computer simulation, focus should lie on performance of the model, i.e. predictive quality of the model results, and not on structure. [Küppers](#) gives interesting examples where some models, deliberately being less structurally matching to the real world system, achieved superior predictive results to models that were structurally more 'valid'.

For social simulation models, the adequacy of a simulation model cannot be theoretically deduced, it must be derived from the performance of the model in terms of correspondence to real world observation, the models need to be validated against independent data. As independent data we have a survey of Delft citizens (although this is limited).

Empirical validation for agent-based models is hard. [Nikolic \(2009\)](#) even argues that it is impossible for models of complex systems that aim to predict likely possible future states of the complex system. This remark also applies partly to the consumer lighting model, the outcomes are quite wide ranging.

A number of methods for validation testing of agent-based models are in development ([Moss, 2008](#); [Windrum, 2007](#)). Some scholars see testing agent-based models for validity as not so very different from testing theories in the natural sciences. The key assumption for empirical validations tests are that different features of the model's behaviour should be valid in the real world.

For the consumer lighting model, the main things to check if the social network structure and the consumer's behaviour, corresponds to real world data; e.g. are in agreement with what can be derived from data on Delft citizens (left for future work).

6.7 Conclusion on validation

In validating the consumer lighting model, we performed a range of tests: verification: structural validation; and did not do real empirical testing.

What we did do, was perform elaborate structural-behavioural testing of lamps purchases by households.

Whilst looking at subsets of data from these structural-behaviour tests, some anomalies were identified. These anomalies were partly due to some specific testing artifacts and these are not expected to be of significant concern in the real experiments to perform (chapter 7), or in interpreting the model results.

One other anomaly found to exist. One lamp-model (PhilipsMasterMilkyDimbaar7W) has a CRI of 87. Despite being worse than 100, in some cases, households will prefer this lamp-model over lamps with CRI 100: incorrect. However, this was when looking *only* at CRI testing. In practical use, when, for example, this lamp's price is included in the equation, it will not be so attractive anymore. Therefore this will not be a concern with the real simulation experiments.

From the structural-behaviour testing of lamps purchases, we conclude that there is clearly **no significant purchase bias** in the model towards any of the four lamp-types. To the best of our ability, this underscores the validity of the model.

Steps could be taken to further validation of the model. Especially empirical validation would be desirable and something that is recommended to pursue. Also face validation with experts the lighting industry and government would add value to results.



Chapter 7

Experimental setup

7.1 Introduction

The aim of the research, formulated in chapter 1, is to come up with a way of analysing the consequences that the E.U. ‘ban on bulbs’ might have. This means that we want to perform experiments with the simulation model in such a way that we can judge the consequences of the E.U. ‘ban on bulbs’: we want to find out whether the ban on bulbs is effective. In addition, we also want to find out if there aren’t any other policy measures that could also be effective, or could increase effectiveness of the E.U. ‘ban on bulbs’. To perform these experiments, an experimental setup needs to be developed. This is the subject of this chapter.

In § 7.2 we will first derive a list of indicators which we will judge in assessing the development of a batch of simulation experiments. In § 7.3 we will describe the policy instruments that we test in the experimental setup. § 7.4 is then on how these experiments are to be performed, with what model settings, the number of runs, execution on a high performance computing cluster, and a discussion on the size of the experimental data that the experiments will result in. A summary is given in § 7.5.

7.2 Indicators

The simulation model generates a number of output parameters that are interesting to use in assessing the evolution of what is happening in the simulation model.

Model output parameters that can be used in assessing the progression of the simulated system towards more or less efficient lighting system, i.e. that are useful as *transition indicators* (§ 2.4.5), are:

- ⇒ Adoption of the different lamp technology types;
- ⇒ Development of purchase prices of the different lamps;
- ⇒ Money spent on lamps purchases;
- ⇒ Electricity consumed for lighting by households.

In addition, a number of out parameters are useful in trying to understand why the observed developments are occurring:

- ⇒ Adoption of the different lamp-models;
- ⇒ Perceptions of the different lamp-models;
- ⇒ Perceptions of the different technology types;

⇒ Perceptions of the different brands.

The perceptions of brands is not directly relevant to the understanding of the adoption of efficient lighting products. As there are 70 lamp-models, and 11 brands, we will not be presenting results of these in this thesis, it would be too much data to be able to present these as graphs. They are all output to file, however, so analysis is possible if deemed necessary.

7.3 Policy instruments

For this the policy measures need to be compared with each other in different policy scenario's. Policy scenario's are a form of fractional factorial designs where groups of parameters are varied in concert; if there are three independent groups of factors in a scenario, then a hypothesis can be tested in 8 distinct scenario's (Chappin and Dijkema, 2010).

Table 7.1 – The policy scenarios implemented in the simulation model

<i>Scenario</i>	<i>Name</i>	<i>Description</i>
0	Base case	All model parameters are at their default values; no specific policy has been implemented. This is the 'laissez-faire' approach.
1	Ban on bulbs	In five years time, all ordinary incandescent light bulbs are banned, which means they are not available for sale anymore.
2	Bulbs tax	In five years time, a significant tax is imposed on incandescent technology, making the more efficient technologies more cost-competitive from a consumer's point of view.
3	LED subsidy	The purchase price of LED lighting is lowered considerably by a large discount: 33%, in the first 5 years of simulated time, and then gradually declining to zero.

In the base case scenario, the settings are at their default values (described in chapter 5), and no policy is implemented.

7.3.1 Phased ban of incandescent lamps

The phased ban on incandescent lamps is modelled after E.U. policy, as described in § 1.2.2. The distinction between non-clear (frosted) and clear lamps is not made: in the 'ban on bulbs'-scenario, all incandescent lamps are gradually phased out, depending on their wattage.

Because the incandescent bulbs are gradually becoming unavailable as a replacement purchase, the households have no other option than to purchase lamps of a competing lamp-type that is more efficient: either a CFL, LED, or Halogen technology. Implementation details are given in table 7.2.

Table 7.2 – Implementation details of the ‘ban on bulbs’-scenario.

Phase	Start at	Phase-out of:
Phase 1	$t = 1$ year	incandescent lamps $P > 75 W$
Phase 2	$t = 2$ years	incandescent lamps $P > 60 W$
Phase 3	$t = 3$ years	incandescent lamps $P > 40 W$
Phase 4	$t = 4$ years	incandescent lamps $P > 5 W$

Effects of the EU’s ban on halogen are not included. The simulation model includes only a very limited number of halogen lamps that would be subject to the current regime of the EU’s ban (i.e. halogen lamps with a general purpose socket, E27/E14; see appendix D).

Furthermore, as the luminaires are fixed in the model, and for many luminaires the only allowed technology type is halogen, banning halogen would mean that households would need to replace luminaires. This would be interesting to implement, but it is something that hasn’t been incorporated in the simulation model yet, see 10.

7.3.2 Tax on incandescent lamps

As an alternate policy scenario, a tax on incandescent lamps has been implemented. As we have seen in part I of this thesis, consumers are very sensitive to the upfront cost of products they want to purchase. Generally speaking, energy-efficient lamps are significantly more expensive than the traditional incandescent light bulb (which is a rather simple technology that, due to low material usage and a simple manufacturing processes, is available at a very low purchase price, measured in cents and not euro’s).

By gradually taxing the incandescent light bulb to make it more expensive, the advantage of cheapness of the incandescent lamp disappears. The implemented details are given in table 7.3. To be effective, the tax level is set ultimately at €2.00, where it remains for the remainder of the simulation run.

Table 7.3 – Implementation details of the ‘bulbs tax’-scenario.

Phase	Start at	Tax level on incandescents:
Phase 1	$t = 1$ year	€ + 0.20
Phase 2	$t = 2$ years	€ + 0.50
Phase 3	$t = 3$ years	€ + 1.00
Phase 4	$t = 4$ years	€ + 2.00

7.3.3 Transition by means of a subsidy for LED

This scenario follows more of a transition-oriented approach, by stimulating the purchase of LED lamps by giving a discount on the purchase price. By doing so, the government hopes to stimulate more players to enter the market, and as a result accelerate the improvement of LED which can hopefully entail a quicker switch over.

The subsidy-scenario consists of three ‘stages’:

I. Steady and high purchase price discount For the first 5 years, give 33% subsidy on the retail purchase price of LED lamps. This is quite a big subsidy. The subsidy needs to be considerable in order to be effective.

II. Phase-out of the price discount For the 5 years afterwards, linearly phase this subsidy out towards zero. It is important to phase-out the subsidy linearly to prevent a sudden market disruption.

III. Accelerated LED technology development. The subsidy scheme does not only lower prices for consumers, it will have the effect to increase the demand for LED earlier on. This increased demand means that manufacturers are able to ramp up production sooner and as a result the innovativeness and learning by the manufacturers are stimulated. In the scenario we therefore assume that the cost decline curve (see appendix E.1) is shifted, so that LED's are made less expensive earlier on in the simulation, by two years. The acceleration of the price decline happens in the first ten years of the simulation (as that is when there is extra demand for LED due to the subsidy).

7.3.4 Effects of policies on prices of lamps

The different scenarios have an effect on the prices of some lamps. Prices of lamps are declining as time progresses (see appendix E.1 for a discussion of this, including algorithms and implementation). The consequences of the different scenarios on the average prices of lamps is plotted in figure 7.1. This is plotted for each lamp-type (CFL, LED, halogen, incandescent). The prices of LED are largely reduced by the subsidy, the average of the prices of the simulated LED lamps is plotted as the blue dotted line. The LED lamp reaches price equality with the other types a couple of years earlier, as specified in 7.3.3.

The impact of the policies for incandescent bulbs are also clear. The lower dot-dashed red line is what happens when the ban on bulbs is in full effect: the average price of incandescent lamps becomes zero, as there aren't no incandescent lamps for sale anymore. The tax level (upper red dashed line) means that the price point of incandescent lamps is brought far more closer to the competing technologies. After $t \simeq 15$ years, thanks to the tax, efficient lamps are cheaper.

7.4 Executing the model

7.4.1 Settings for weight factors

Apart from the experimentation with the four policy scenarios, there are a number of weight factors for the purchase decision that are interesting to experiment with.

The weight factor for normative influence is the primary mechanism to determine how important the influence of the social network is in determining what households purchase. Its default value is 2.0, but it is interesting to see what the results would be if it was put at 4.0. The weight factors for price is also very relevant for experimentation, as it is by far the single most important weight factor, the only one with a value of 4.0. As an alternate experiment, a value of 6.0 was included. See table 7.4.

For each of these policy scenarios, the two weight factors are varied in the above manner using a full factorial setup. The resulting combination of scenarios and parameters results in $E = 16$ different experiments.

7.4.2 Number of runs

Theoretically, it could be possible that a single model run gives a reasonable appreciation of the general pattern of outcomes of the simulation experiment. However, this will be "more luck than skill".

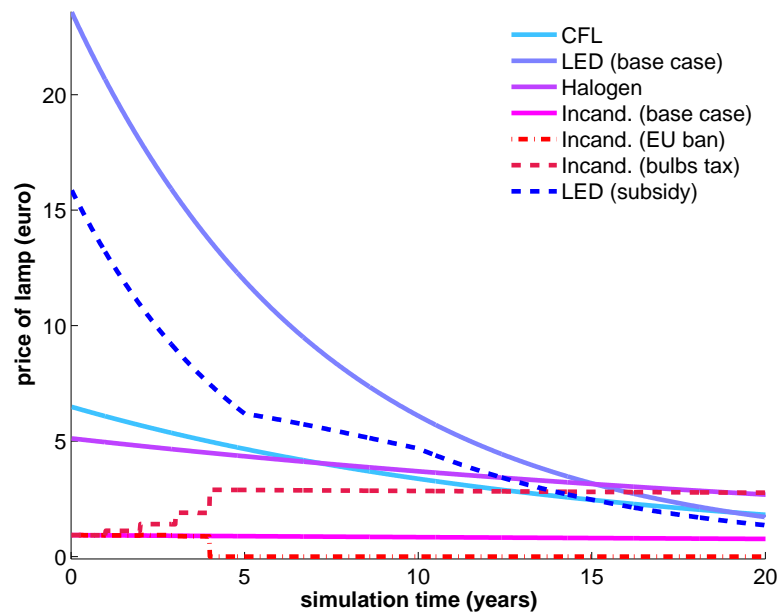


Figure 7.1 – Output of the simulation model: average prices of lamps, per lamp-type, for the four different scenarios. The solid line represents the prices in the base case scenario, the colours correspond with those used in chapter 6. The dashed curves correspond to scenarios ban on bulbs (lower red; dot-dashed), bulbs tax (upper red dashed), and LED subsidy scenarios (blue dashed). For clarity, only the first 20 years of the simulation are displayed; the lines continue to converge in the years afterwards.

Table 7.4 – Overview of the experimental setup. There are four policy cases. In addition, two weight factors are varied in the manner shown.

Exp.	Policy	Weight factor variation		runs
		Price	Normative influence	
1	Base case	4	2	100
2		6	2	100
3		4	4	100
4		6	4	100
5	Ban on bulbs	4	2	100
6		6	2	100
7		4	4	100
8		6	4	100
9	Bulbs-tax	4	2	100
10		6	2	100
11		4	4	100
12		6	4	100
13	Subsidy for LED	4	2	100
14		6	2	100
15		4	4	100
16		6	4	100
Total runs:				1600

More likely, a single simulation run mainly indicates the coincidental effects of stochastic events during the simulation run, more than that it really shows the general pattern of what is going on. During agent initialisation and model execution, in a number of routines, use is made of pseudo-random number generator. These pseudo-randomisation steps were added to make the agent's behaviour and state heterogeneous and allow for meaningful experimentation by making parts of the model less deterministic. The consequence of the randomisation, however, is that we can not use only a single model run in drawing conclusions.

It is better to use a large amount of runs. This will give a broader spectrum of model outcomes, and then, by observing the aggregate result of a large amount of runs, patterns of system behaviour can be observed. In order to obtain a full range of possible simulation outcomes, it would be ideally if the number of runs is very large, thousands of runs.

However, practically, one is limited in computational time and data processing capabilities. Therefore, the number of runs that will be performed per experiment is put at $R = 100$. This value was chosen to limit the size of the data set produced, but still allow for quite a bit of repetition. The repetition gives a chance to possible simulation outcomes that are not so very likely to occur.

A pseudo-random number generator uses a 'seed' to generate a sequence of numbers that statistically behave much like random numbers. To see whether the seed has influence on the patterns of outcomes, we can vary the random number 'seed', and do a large number of simulation experiments. In the present experimental setup, the seed is varied each run.

7.4.3 Execution using *high performance computing*

It is not possible to perform the calculations of the experimental setup of table 7.4 on a single-CPU machine. Each experiment needs about an hour to compute, so if only one machine would be used, you would have to wait for more than a month to get results.

A better solution exists. Especially for the purpose of performing parallel computations of agent-based models, the Energy & Industry section and the Next Generation Infrastructures foundation purchased a High Performance Computing cluster, HPC.

The HPC cluster is specifically designed to be able to quickly carry out many simulation experiments in parallel. For this, the HPC consists of 60 nodes, which are blade servers. The nodes offer lots of processing power and RAM in a space saving design. Each node has two quad-core Opteron CPU's¹. The nodes have 16 GB of RAM and each core can access this memory directly. Because each of the 60 nodes has eight processor cores (two Opteron CPU's per node; four processor cores per Opteron CPU), 480 simulation runs can be performed in parallel. Each of the simulation runs has access to 2 GB of memory, sufficient for the model execution with 250 households.

Scripts were written to perform the simulations and distribute the runs on the cluster, and to concatenate the results into a single file.

7.4.4 Simulation data

Executing a simulation run generates one sequence of comma separated values per time step, for all of the $L = 2080$ time steps. Each of these lines consists of $C = 227$ columns for the different simulation fields. The average field takes a number of bytes, s , to be written to an ASCII-formatted output file. The number that it takes mainly depends on the data type (floating point vs. integer). It turns out that, on average, $s \simeq 10$.

¹Quad-Core AMD Opteron(tm) Processor 2347 HE: energy saving; processor speed is 1.9 GHz; each processor core has 512 kB of L2 cache memory and the four cores share 2 MB of L3 cache

Combining the above, the experimental setup of table 7.4, results in an output data size of:

$$L * E * R * C * s \simeq 7.3 \text{ GB}$$

This data size is too big to fit into memory all at once. Therefore, subsets of data need to be analysed. For this, the output data was loaded into a SQL database server (PostgreSQL). The database server makes data retrieval efficient, because using SQL ‘select’ statements, subsets of the data (e.g. only policy instrument ‘bulbs tax’) can be retrieved relatively quickly.

After the execution of the simulation experiments was completed, the data was loaded into SQL server, analysis of the results with the MATLAB software could commence. This leads to the *results* of the experiments, which will be presented in the next Part (III) of this thesis.

7.5 Summary

This chapter details the experiments to perform. Apart from a ‘base case’ without policy, the model includes three alternative policy instruments to test the different approaches to transition management: ‘Ban on bulbs’-policy (phased withdrawal of incandescent lamps); ‘Bulbs-tax’-policy (incandescent lamps are taxed up to €2.00 per lamp); and ‘Subsidy for LED’-policy (a 33% discount on LED lamps the first 5 years, gradually phased out).

Apart from the policy measures, the weight factors for normative influence will be alternated, between 2.0 (default) and 4.0; and the weight factor for price, between 4.0 (default) and 6.0. This adds up to 16 different experiments to perform. For each experiment, the number of runs is put at 100.

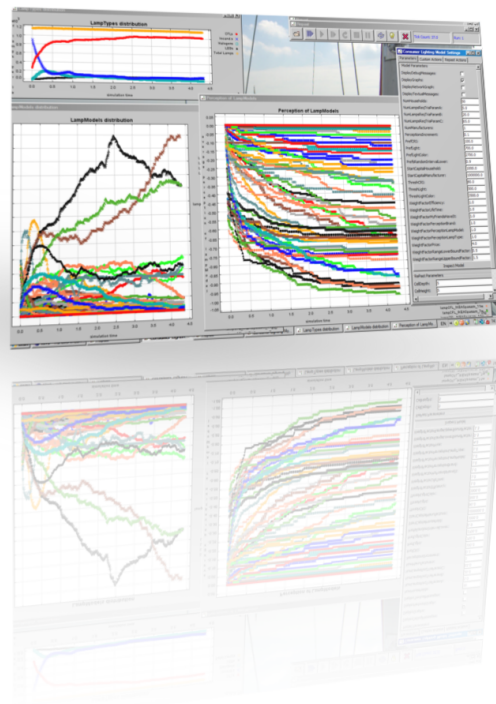
The simulation’s output can be observed using transition indicators. The main transition indicators for analysis of the results are the adoption levels of the different lamp types, electricity consumption per household and money expenditure for lamp purchases.

Results of the experimental setup will be given in the chapter 8, in Part III of this thesis.



Part III

Results & Reflection



Chapter 8

Simulation results

8.1 Introduction

In this chapter, we will present the results of the simulation experiments, carried out to test the different policies (no policy; ‘ban on bulbs’; ‘bulbs tax’; ‘subsidy for LED’), according to the experimental setup detailed in chapter 7.

First, in section 8.2, we will introduce how we will visualise the simulation output. Then, in section 8.3 we will present the simulation output in a series of graphs per output parameter. Finally, section 8.4 concludes this chapter with an overview of the results.

8.2 Visualising simulation experiments

Each of the simulation experiments detailed in chapter 7 consists of a number simulation runs. A single simulation run gives, for each output parameter, a sequence of values: one value per simulation time step. As a single simulation run has 2080 time steps (one time step per week of simulated time), a single output parameter can be considered a column vector of 2080 rows. This vector may be plotted against the values for the simulated time, also in 2080 steps from $t = 0$ to $t = 40$ years. This will show the evolution of the parameter over time, and in this way, one would think we can observe the system’s evolution.

However, a single run of a simulation experiment is—in itself—not so meaningful in drawing conclusions. This is because, during agent initialisation and model execution, in quite a number of routines use is made of pseudo-random number generation. This is done, e.g., to make different agents heterogeneous in some respect, or to give lamp failure a stochastic nature. The thus introduced stochasticity makes the system’s behaviour and development over time different each simulation run, as a result of sequences of coincidental events.

To be able to say something about patterns that can be observed in the simulated system’s evolution, we will need the average result of many runs for a realistic assessment of what happens in the simulation experiment. This is why, in 7.4.2 we introduced a number of 100 runs to be performed per experiment, so that we are able to compute an average result of a number of runs. Plotting averages values of a large number of simulation runs for the output parameters, lessens the impact of a single stochastic process.

However, only the average itself doesn’t tell all. If we perform a great number of simulation runs, we are interested in the spread of the outcomes around the average, and the skewness, if any. If we were to only look at one single average, then we would miss out

on developments of patterns that happen relatively infrequently compared to a more dominant pattern. This is why we want to plot a *series of 'descriptive statistics'* per output parameter.

We don't know the underlying statistical distribution of the output parameter. In these cases the '*box plot*' is a useful way of graphically depicting numerical data through a small number of summary statistics (Wikipedia, 2010).

The descriptive statistics that we will graph to display the spread and average values of the simulation runs, we will plot a number of lines, derived from the statistics used in the box plot. These are:

Median (2nd Quartile) 50% of the data lie below the line; 50% lies above.

1st Quartile line 25% of the data lie below the line; 75% lies above it.

3rd Quartile line 75% of the data lie below the line; 25% lies above it.

Lower whisker line This line is plotted $1\frac{1}{2} * IQR$ below the 1st quartile. (IQR = Inner Quartile Range; the distance between the 1st and the 3rd quartiles). This means that, for data that distributed according a normal distribution, only $\sim 0.7\%$ of the data points lie below this line.

Upper whisker line This line is plotted $1\frac{1}{2} * IQR$ above the 3rd quartile. From data following a normal distribution, $\sim 99.3\%$ will lie below this line.

These statistics are displayed in the figure 8.1. In the figure, the corresponding normal distribution is placed at the right of the diagram. Note that the distribution doesn't need to be normally distributed. The normal distribution is only plotted to show how the IQR and whisker lines relate to data that are.

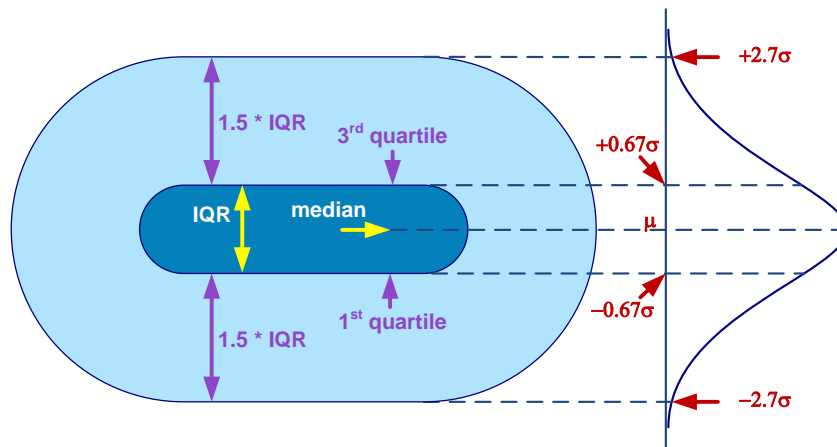


Figure 8.1 – Schematic illustration of the different statistics that are plotted as curves in the figures that show the results of the experiments with the simulation model. At the left are the median, 1st and 3rd quartiles; lower and upper whiskers, and the Inner Quartile Range, explained in § 8.2 . At the right is shown how these statistics relate to a normal distribution function, with its mean μ and its standard deviation σ (the comparison holds for normally distributed data).

The statistics described above are the primary ways we will use in visualising simulation results in the most of the result-graphs of this chapter: § 8.3.

8.3 Simulation results – graphs per output parameter

In this section, we will present the results of the simulation experiments. For each output parameter we will show a series of graphs.

The following results are given in this section:

- ⇒ Total number of lamps, per lamp-type, in the simulation — § 8.3.1
- ⇒ Adoption of lamp technology types in the simulation — § 8.3.2
- ⇒ Perception of lamp technology types, aggregated for all households — § 8.3.3
- ⇒ Evolution of electricity consumption — § 8.3.4
- ⇒ Money spent by households on the purchases of lamps — § 8.3.5
- ⇒ Perception of lamp technology types vs. their adoption — § 8.3.6
- ⇒ Changing normative influence — § 8.3.6

In the subsections indicated, results of the model “base case” are given, as well as results for the model with the three different kind of policy-instruments (‘ban on bulbs’; ‘bulbs tax’; ‘subsidy for LED’). In the base case, all model settings are at their default values (described in chapter 5) and no specific policy is active. In the policy cases, the only thing that is changed, relative to the base case, is the activation of the policy instrument.

Note on what will be plotted per output parameter:

- The graphs of § 8.3.1 – § 8.3.4 and § 8.3.6 are graphs where we plot the inner quartile range and the lower and upper whisker lines. In these graphs we omit to plot the median for clarity.
- The graphs of the ‘money spent on lamps purchases’ (§ 8.3.5) is a single graph with only the medians. This is done for easy comparison of all policy cases.
- Graphs of ‘perception vs. adoption of lamp-types’ (§ 8.3.6) are graphs that display raw data of a number of simulation runs (none of statistics discussed in § 8.2).

In each of the following results subsections, we will first describe what it is, precisely, that is *shown*. Then, under ‘observations’, we describe what can be observed in the graphs and what is remarkable to note. Based on this, under ‘interpretations’, we then interpret the remarkable observations. Finally, under ‘conclusions’ we will then draw conclusions that can be learned from the output parameter and graphs.

In the following results subsections, where we list observations, interpretations and/or conclusions with small-case Latin numbering (e.g. (iv)), then these numbers are used to indicate correspondence of the applicable remarks on the output parameter.

8.3.1 Results – Total number of lamps in the simulation

The first series of graphs that we will show for the experiment's results are graphs that show the development of the relative 'popularity' of lamp technology-type (lamp-type), by looking at the *total number of lamps* in the simulation of each lamp-type. The 70 lamps in the ontology are all being purchased by different households, but it can be expected some lamps are more popular than other lamps. The development, over time, of the different lamps in the simulation is displayed in figure 8.2.

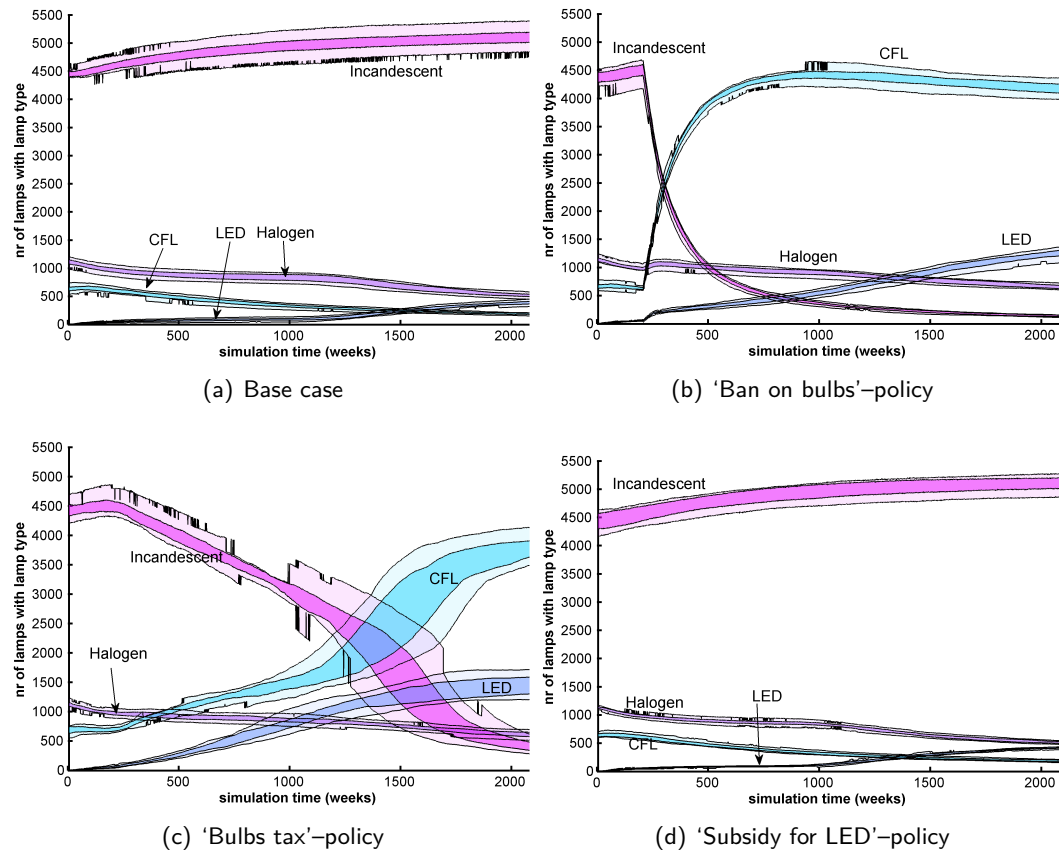


Figure 8.2 – The total number of lamps in the simulation, for each of the lamp-types. There are four graphs corresponding to the four policy instruments. The statistics displayed (per lamp-type: first and third quartiles, lower and upper whisker) are for 10 consecutive runs. The colours correspond with those used in chapter 6.

Observations

- (i) In the base case and with the 'subsidy for LED'-policy (fig. 8.2 (a); (d)), there is not much development. In these cases, the *incandescent* lamp is, by far, the most popular lamp. the number of *CFL*'s diminishes over time; and the number of *LED* lamps is slowly increasing (leading to a takeover, after 1500 weeks (about 30 years) of the *CFL* by the *LED* lamp).
- (ii) In the 'ban on bulbs' and the 'bulbs tax' cases (figs. 8.2 (b) and (c)), *CFL*'s are quickly increasing, in the 'ban on bulbs' case (fig. 8.2 (b)) very quickly indeed.
- (iii) *LED* lamps are only slowly making inroads, never becoming the dominant lamp. Their popularity is smallest in the base case and with the 'subsidy for LED'-policy (fig. 8.2 (a); (d)), bigger with the 'ban on bulbs'-policy (fig. 8.2 (b)) and greatest in the 'bulbs tax'-policy (fig. 8.2 (c)).
- (iv) *halogen* is declining, in all policy cases, but never reaches zero.

Interpretation

- (i) First, we see that, in the base case, without policy (fig. 8.2 (a) and the ‘subsidy for LED’-policy (fig. 8.2 (d)), the popularity of the incandescent lamp means that that lamp is preferred greatly by consumers, given their set of criteria. The market share is increasing. The takeover of the CFL by the LED lamp means that, if the price has lowered sufficiently, the LED lamp is preferred more than the CFL.
- (ii) Why does the CFL rise so quickly?
 - (a) In the ‘ban on bulbs’-policy (fig. 8.2 (b)), the ban has the effect of letting the amount of working incandescent lamps exponentially decline after $t = 5$ years. At that point, there are no incandescent lamps available for purchase anymore. The alternatives, and then mainly the CFL, are quickly taking the place of the incandescent lamp. The main alternative is the CFL, so incandescent lamps are almost being replaced by CFL’s on a 1:1 ratio.
 - (b) In the case of the ‘bulbs tax’-policy (fig. 8.2 (c)), after the bulbs tax comes into force in the first couple of years, when it reaches its maximum value of €2, this certainly has effect on the purchase behaviour. From that time on, more and more incandescent lamps are replaced by different technology.
- (iii) The lack of popularity of LED lamps means that their drawbacks (more expensive, less brightness) are a reason why households purchase alternatives. Interestingly, LED fares best under the ‘bulbs tax’-policy (fig. 8.2 (c)). Apparently, making incandescent lamps more expensive works to stimulate LED.

The fact that LED lamps, discounted 33% under the ‘subsidy for LED’-policy (fig. 8.2 (d)), are not being purchased in that case, while a tax on the incandescent lamp—with a price €0.35–1.95 by far the cheapest option—has a bigger effect, means that the absolute price of LED is less important than the relative price difference.
- (iv) From the halogen lamp-models included in the simulation, the large majority have dedicated sockets. These lamps cannot be used as a replacement for a E27/E14 socket incandescent lamp. Only two halogen technology lamp-models in the ontology are E27/E14 compatible, but these are relatively expensive; see appendix D. This is the possible interpretation of the lack of really significant change with halogen.

Conclusion

In the model, both the ‘bulbs-tax’ and ‘ban on bulbs’ policies are very effective ways to curb the number of incandescent lamps in use. The ‘subsidy for LED’-policy has no significant impact on changing the distribution of lamps in the simulation.

Under the ‘ban on bulbs’-policy, a clear switch over between incandescent and CFL can be observed from the curves for the CFL and Incandescent lamp types (fig. 8.2 (b)). This means that, once banned, incandescent lamps are being replaced almost 1:1 with CFL’s. This can be expected to have a high effect on the expected electricity consumption.

Interestingly, a ‘bulbs tax’-policy (fig. 8.2 (c)), also works to stimulate demand for CFL and LED lamps. The adoption of LED lamps is even bigger, after 10 years, than what is the case in the ‘subsidy on LED’ policy.

8.3.2 Results – Adopters of lamp technology-types

The second series of results graphs measure the same sort of adoption of lamp technology-types as the graphs of § 8.3.1 displayed, but in a different metric. Instead of looking at

the total number of lamps in the simulation, we now look at the adoption of technology types in terms of the percentage of households that have *one or more lamps of the specific lamp-type in a working state*. Thus, a household is counted as an adopter of a lamp-type if it has **one lamp of that type**. The results are displayed in figure 8.3.

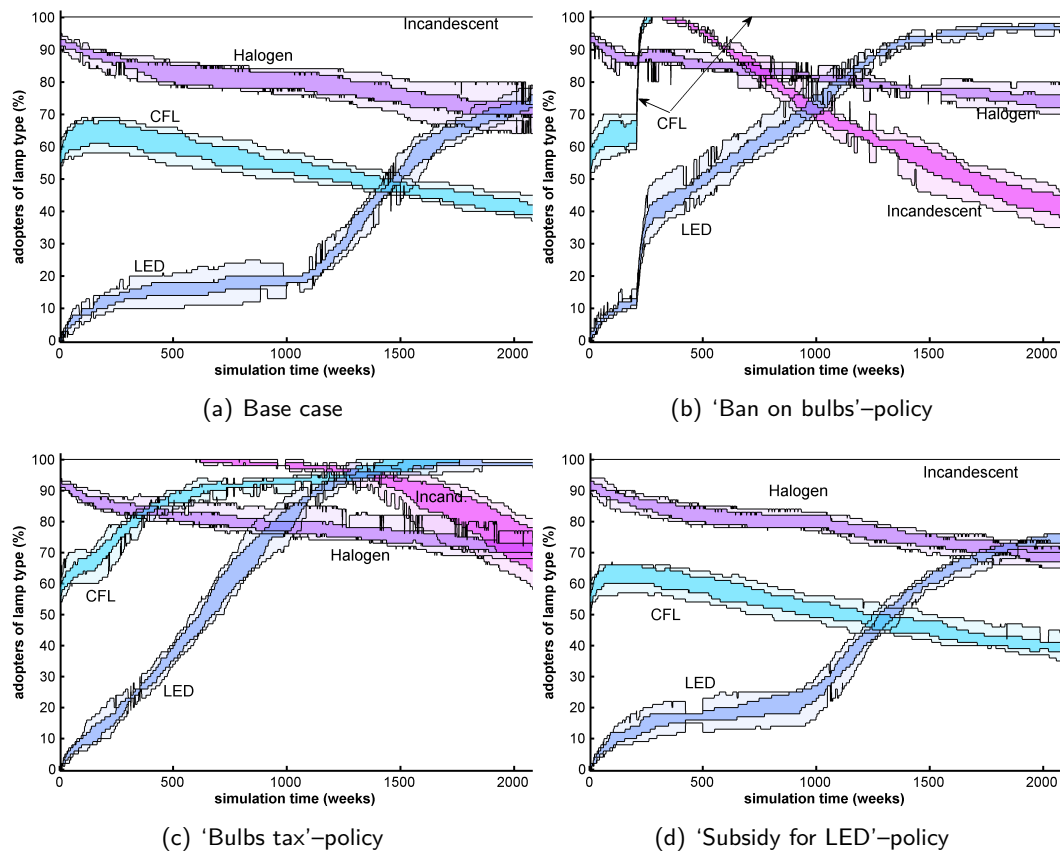


Figure 8.3 – The development over time of the **percentage of adopters of a lamp-type**, for the four policy cases. The statistics (per lamp-type: first and third quartiles, lower and upper whisker) are for 10 simulation runs per policy case.

Observations

- (i) In the base case and the ‘subsidy for LED’-policy (figs. 8.3 (a); (d)), the *incandescent* lamp stays in 100% of households. In the ‘ban on bulbs’ and ‘bulbs tax’ cases (figs. 8.3 (b); (c)) it is declining.
- (ii) In the ‘ban on bulbs’ case (figs. 8.3 (b)), when the ban on bulbs takes full effect at around 5 years/250 weeks, adoption of CFL quickly rises to 100%. At the same moment, LED also jumps from 10% to ~40% adoption.
- (iii) Adoption of CFL rises in the ‘bulbs-tax’ case (fig. 8.3 (c)), reaching 90% adoption. In the base case and the ‘subsidy for LED’-policy (figs. 8.3 (a), (d)), a clear decline of the popularity of CFL’s can be observed.
- (iv) In all cases, LED is gaining adoption, with its best performance in the ‘bulbs-tax’ case (fig. 8.3 (c)), where it starts to rise linearly with time until it reaches 100% adoption after circa 1400 weeks (27 years), which is earlier than the CFL.
- (v) In the base and ‘subsidy for LED’ cases (figs. 8.3 (a); (d)), the adoption of LED first grows quickly to reach ~20% adoption, then lags, after which from ~1000 weeks popularity starts to rise again, after which it apparently starts to stabilise around 70% adoption.

- (vi) Halogen is steadily declining in all scenarios. This was also already observed in the previous section.

Interpretation

These graphs measure the same kind of adoption as those of § 8.3.1; only the unit of measure is different. This difference results in the above adopters graphs (fig. 8.3) being more ‘sensitive’ than the graphs on the number of lamps (fig. 8.2). This means that the adopters graphs more clearly show developments in adoption of lamps with low market share.

- (i) The decline of the incandescent lamp’s adoption under the ‘ban on bulbs’ and ‘bulbs tax’ policies cases is steady, but never complete. After 40 years, in the ban case (fig. 8.3 (b)), still over 40% of households have one or more incandescent lamps. This is caused by the longevity of its life time when it is only used for a short duration per week, as will be the case for some luminaires.
- (ii) Fig. 8.3 (b) clearly shows how quickly the ‘ban on bulbs’-policy results in 100% adoption for the CFL. Clearly, when households need to purchase a replacement lamp, the CFL is an attractive option for all households.
- (iii) The decline of the CFL in the base and ‘subsidy for LED’ cases (figs. 8.3 (a); (d)) is clear and steady, after first a couple of years of rising popularity. Apparently something is happening in the model causing a sizeable fraction of the household to abandon all their CFL’s.
- (iv) The linearly increasing adoption of LED under the tax (fig. 8.3 (c)) clearly shows that the tax-policy is more effective than the ‘subsidy for LED’-policy (fig. 8.3 (d)). This was already noted in the preceding section (interpretation ‘(iii)’ of § 8.3.1).
- (v) Apparently something is happening why adoption of halogen lamps is dropping over time: in the course of a simulated 40 years it drops some 20%.

Conclusion

The conclusions are partly the same as the in section 8.3.1.

Both the ‘bulbs-tax’ and ‘ban on bulbs’ policies seem very effective to promote energy efficient lighting; both policies cause a steady decline of the households that own one or more incandescent lamp. The percentage of households that have one or more incandescent lamps declines to approximately 40% under the ‘ban on bulbs’-policy, and to approximately 70% with the bulbs tax policy.

Interestingly, in the ‘bulbs tax’-policy, the adoption of LED lamps increases quicker than under the ‘subsidy on LED’ case. Even at $t=250$ weeks, when the full 33% discount on LED’s has been in effect of 5 years, and tax on bulbs has only been at a high level of €2.00 for two years, adoption of LED is already *higher* in the ‘bulbs tax’ case. A tax on incandescent lamps of €2 appears to be *more effective* than a LED discount of many times more (\sim €3–10, depending on the lamp-model).

To answer question why the adoption of halogen steadily declines in all policy cases, and that of the CFL in the base and the ‘subsidy for LED’ cases, we look at the *perceptions*, underlying the purchase behaviour, in the next section.

8.3.3 Results – Perception of lamp technology-types

The previous two sections showed adoption results of the different lamp technology types. To understand this further, in this section we display some results for perceptions.

The perception for a lamp-type is one criterion a household uses in its purchase decision (§ 5.3.2). Each household can have a perception, a value between -1 and +1, for all of the four lamp-types.

In figure 8.4, we show the results for the **perception of each lamp-type**, averaged over all the 250 households in the simulation, for the base case and the three policy cases. Each of the figures consists of the aggregate data of 25 simulation runs.

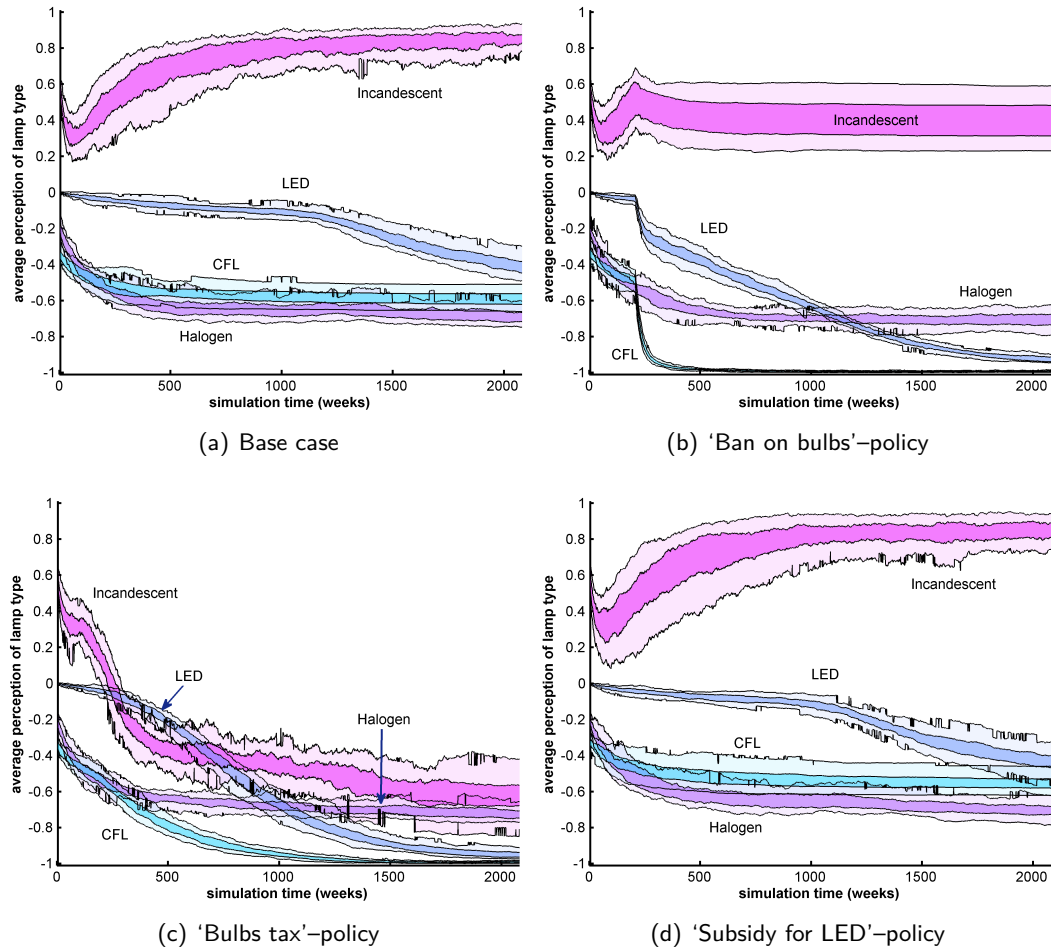


Figure 8.4 – The development over time of the **perception** that the average household has of a **lamp-type**, for the four policies. The perception is the average of all the 250 households in the simulation run. The statistics (first and third quartiles, lower and upper whisker for each lamp-type) are for 25 simulation runs per policy setting.

Observations

These graphs of perceptions of lamp-types show a number of things.

- (i) The incandescent lamp-type is the only type that has an increasing perception in any graph. With the exception of the 'bulbs-tax' case, it has either a positive and/or an increasing perception. In the 'bulbs-tax' case (fig. 8.4 c), the perception suffers a sharp decline to negative from the moment the tax takes effect (after $t = 250$ weeks).
- (ii) Perceptions generally are **declining** and below zero for other lamp-types. In the 'ban on bulbs' case (fig. 8.4 b), at $t = 250$ weeks, suddenly the perception of CFL declines sharply and hits the floor value of -1 at $t \simeq 500$ weeks (a perception value must be in the range of $[-1 \dots 1]$). LED suffers from the same moment on.

- (iii) Stable perceptions: in the base case (fig. 8.4 a) and the ‘subsidy for LED’ case (fig. 8.4 d), LED perceptions remain rather neutral for a long duration. In the ‘ban on bulbs’ case (fig. 8.4 b), perceptions of incandescent lamps remain stable after $t = 500$ weeks.
- (iv) With Incandescent, CFL and halogen, generally the lines don’t seem to start at a specific point where the average perception is zero.

Interpretation

How can we interpret the development of the lamp-type perceptions?

- (i) Firstly, we conjecture that the rather positive perception (close to the maximum value of 1) of the *incandescent* lamp-type is one of the factors of its lasting popularity and high adoption in the base case and in the subsidy for LED policy (figs. 8.2 (a), (d); 8.3 (a), (d)).
We interpret the sudden decline of the perception of incandescent in the ‘bulbs tax’-policy (fig. 8.2 (c)) to mean that perceptions quickly change for the negative when lamps are more expensive.
- (ii) Households apparently develop negative perceptions of the halogen, CFL and LED lamp-types *from the moment they adopt them*. The sudden jump to negative for LED and CFL perceptions at $t = 250$ in fig. 8.4 (b) coincides with their adoption taking off (compare with fig. 8.3 (b)).
- (iii) Perceptions remain fixed if the no new lamps of the types are being purchased. Also, if adoption is low, perceptions don’t change.
- (iv) This is strange, as households start the simulation with neutral perceptions (zero) for all lamp-types. It turns out this is due to model initialisation: at the start of the simulation, the households start with a distribution of lamps of all types. Mostly these are incandescent lamps; roughly 20% will be halogen and 20% will be CFL, see § 5.1.2. During this initialisation, already perceptions are formed of the lamps the household has initially, so perceptions will already form at $t = 0$ (see § 5.2.4).

Conclusion

We can conclude three things on the perceptions.

First of all, the development of lamp-type perceptions seems strongly related to the price of lamp-models. When lamps become more expensive, perceptions are more negative and decline more quickly. This happens with the incandescent lamp under the ‘bulbs tax’-policy: the only thing that is changed is the purchase price; this causes perceptions to drop quickly.

Perceptions’ price sensitivity is implemented explicitly in the simulation model, see § 5.2.4: perceptions are updated with an increment value that is larger if the memory for price is higher, this is apparently what we see here.

Furthermore, for most lamp-types, apparently the perceptions algorithm (§ 5.2.4) is slightly biased towards making lamptype perceptions negative.

And lastly, perceptions change more as a result of the evaluation of lamps after lamps purchase, rather than due to lamps failure. This explains the perceptions remaining stable in the ‘ban on bulbs’-policy when they aren’t bought anymore (but they *are* still in use).

8.3.4 Results – Impact on electricity consumption

The previous sections gave results showing the relatively adoption, importance, and perceptions of the different lamp technology types a household can have. These are important, as lamp technology can be considered to be a proxy for the energy efficiency of a household's lighting technology: within lamp-types, energy efficiency (in terms of luminous efficiency) does not differ very much.

However, in order to truly observe the development of the energy efficiency of household lighting, we are interested in the electricity households consume for their lighting needs. This is a true and direct transition indicator. The results are displayed in figure 8.5 below.

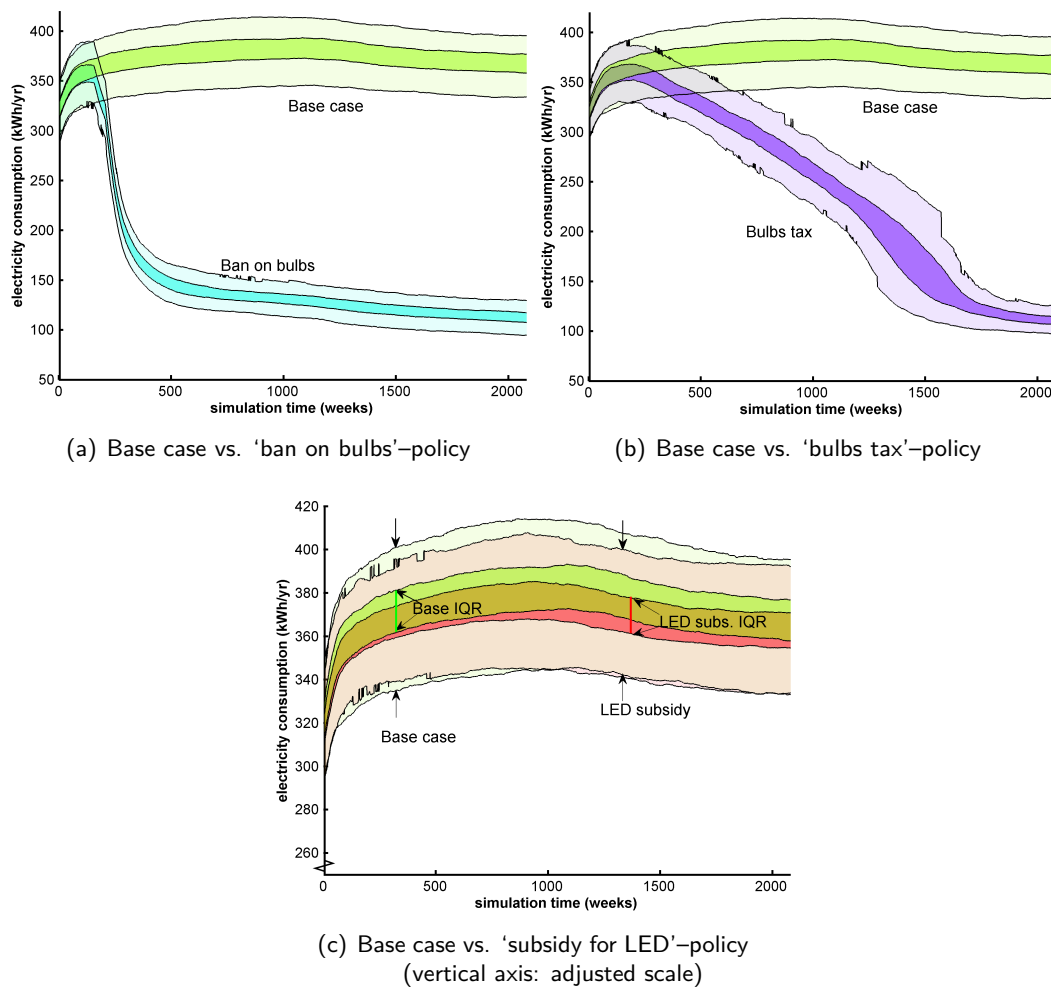


Figure 8.5 – The development over time of the **average yearly electricity consumption** for households (kWh/yr), for the different policy cases, compared against the base case. The graph shows the first and third quartiles, and the lower and upper whisker lines, for 100 simulation runs per policy.

Observations

- (i) In the 'ban on bulbs'–policy (fig. 8.5 a) and the 'bulbs tax'–policy (fig. 8.5 b), electricity consumption declines, from around 350 kWh/yr at the start of the simulation to about 125 kWh at the end, after 40 years.
- (ii) The reduction of the electricity consumption happens far quicker under the 'ban

on bulbs’-policy than under the the ‘bulbs tax’-policy. At $t = 500$ (~ 10 years), the electricity consumption is already only 150 kWh/year in the the ‘ban on bulbs’ case, vs. more than 300 kWh/year in the ‘bulbs tax’ case

- (iii) In the base case, electricity consumption rises somewhat. The effects of the ‘subsidy for LED’-policy are marginal, compared to the base case. While it can be observed (fig. 8.5 c) that the electricity consumption of the ‘subsidy for LED’-policy lies a slightly below the electricity consumption of the base case, the difference is not expected to be significantly different.

Interpretation

- (i) The switch to efficient lighting technology in these cases clearly impacts the electricity consumption: it declines due to the ban.
- (ii) The rate and completeness of a switch over are both needed for large reductions in electricity consumption to materialise quickly. Only in the case of the ‘ban on bulbs’, the incandescent lamps are relatively completely replaced by efficient ones in a short amount of time, this is needed to realise large savings in energy consumption.
- (iii) In the base case (as well as in the ‘subsidy for LED’ case), the popularity of the incandescent lamp rises (figs. 8.2 (a); (d)), this causes an increase in electricity consumption. We already saw that adoption of LED is not significant, so a reduction of electricity consumption is not expected on that ground.

Conclusion

Overall, we can conclude that both the ‘ban on bulbs’ as well as the ‘bulbs-tax’ *are effective at reducing electricity consumption* of the consumer lighting sector, albeit on totally *different time scales*: the ban achieves the results quickly, within 10 years.

The effect of the ‘subsidy for LED’-policy is negligible in reducing the electricity demand.

8.3.5 Results – Money spent on lamps purchases

When lamps break down, households purchase a replacement lamp. For this, they need to spend money. When a policy measure involves taxation or subsidy, this can be expected to directly impact the ‘money spent’-indicator. This indicator is relevant socially and politically, when a certain policy needs to be implemented.

The number of lamps a household purchases depends on the number of luminaires they have, the usage per luminaire, and the lifetime of the lamps they have. When the household has more luminaires, uses them for a longer time each week, and have a larger proportion of their lamps as lamps with a lower lifetime (incandescent/halogen), they will purchase a replacement product more often. In these cases, they can be expected to spend more on lamps purchases per year than households who have fewer lamps, especially if these households have lamps that last longer.

The amount of money spent on lamps purchases is plotted as an average for all households, for the four scenarios, in figure 8.6, for 25 simulation runs per scenario.

Observations

What we can observe is that, for the base case and ‘subsidy for LED’-cases, the amount of money spent is similar, from around an average €10 per year in the first years, to an asymptotic €3–4 euro per year after 15 years.

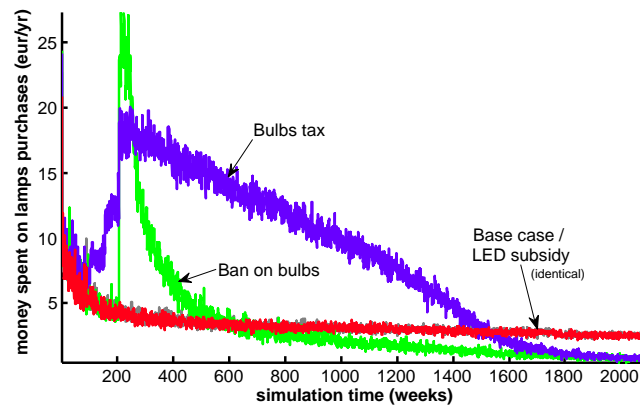


Figure 8.6 – The development over time of the average yearly amount of **money spent on lamps purchases** by households (€/year), for the different policy cases, compared against the base case. The graph shows the results for all four policy cases. Only the *medians* of the data sets are plotted. The data are from 25 simulation runs for each policy.

In the ‘regulatory’ scenarios (ban and tax) the amount goes up at the moment the ban or tax takes effect, to a steep peak of an average of about €30 per year in the ‘ban on bulbs’ case, and a high of about €18 per year for the ‘bulbs tax’-policy.

In the ‘bulbs tax’ case the amount stays high for quite some time. In the ‘ban of bulbs’ case, the spike is the steepest, but afterwards, from about 13 years (700 weeks), the amount households spend each year on lighting is lower.

Interpretation

In the ‘regulatory’ scenarios (ban and tax), households who mainly relied on incandescent lamps for their lighting applications, are either spending more per incandescent lamp, or are switching over to more efficient technology, with a larger upfront cost.

Under the ‘ban on bulbs’-policy, the households spend less on lighting products than in the other cases after some 700 weeks (13 years), due to the long lifetimes of the CFL and other efficient lamps they purchase. However, they have to do an upfront investment for this, which occurs after the ban is implemented.

Conclusions

For drawing conclusions on the money spent, we will need to separate effects at a specific moment in time and the effects in the long run.

For the **effect in the long run**, that is the cumulative cost of lighting purchased during the 40 years of simulation, we need to assess the total area under the curve. However, in this discussion, it is important to note that the energy costs are not incorporated in this graph of purchase cost.

By means of a visual assessment of the area under the curve, from $t = 0$ to $t = 2080$ weeks, we conclude that the ‘bulbs tax’-policy is the most expensive option for households. In this case, a large proportion of households continue to buy incandescent lamps, which are now taxed. So this money spent is transferred to government, which is free to redistribute it as it sees fit. Regarding the other cases (‘base case’, ‘ban on bulbs’, ‘subsidy for LED’) a definite conclusion is not easy. By looking at the graphs, one could conclude that slightly less money is spent on lamps purchases in the base and ‘subsidy for LED’ cases, however, as energy costs are not included in this graph, these alternatives, with their high use of inefficient incandescent lamps, are not really cheaper.

The **peak costs** differ strongly between policy cases: in the ‘regulatory’ scenarios (ban and tax) the money spent on replacement lamps increases sharply at the moment the ban or tax takes effect. The highest peak occurs in the ‘ban on bulbs’ case, the peak averages about €30 per year. This peak is an average of 250 households and 25 simulation runs. Therefore, there will certainly be households with a higher cost (with the worst case for an household that has very many incandescent lamps that all fail shortly after the ban takes effect).

The amount seems certainly high enough to be a reason for policy makers to take notice, it can be a problem for social acceptability of the ‘ban on bulbs’ and the ‘bulbs tax’. Although the amounts of money spent are arguably not enormous, especially for poorer households, it can pose a problem.

8.3.6 Results – Perception vs. adoption (base case)

The above graphs all show the development of output parameters over time. What we can also do is make a different kind of plot. If we directly plot two output parameters against each other this can shine light on possible correlations that could exist, and perhaps this can shed some more light on what is really happening in the simulation model.

In order to show some possible correlations between the perception of a lamp-type and its adoption, we can plot the average perception of the lamp-types of all households, against the percentage of adopters of a lamp-type. The result is displayed in figure 8.7.

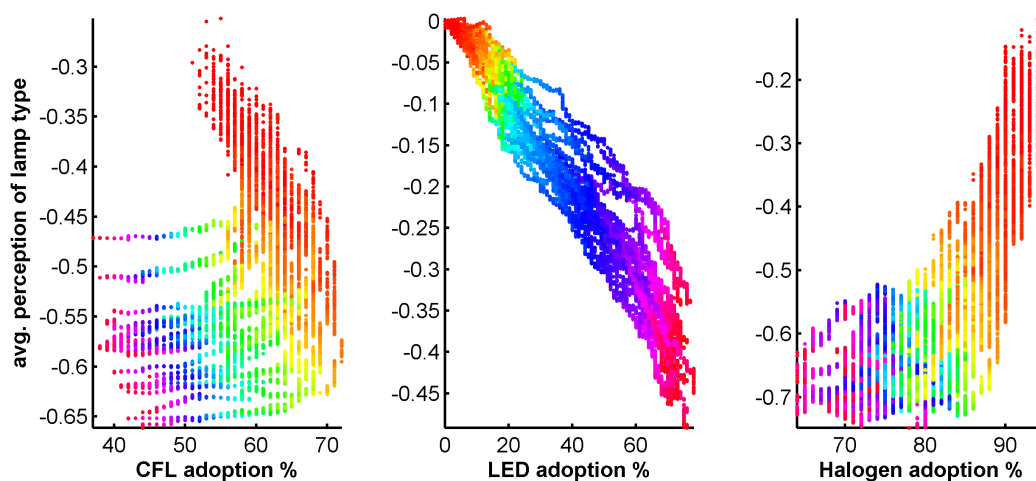


Figure 8.7 – The percentage of **adoption** of a lamp-type (horizontally) plotted against the 250-household-average **perception** of that lamp-type, for CFL, LED and halogen. This figure is for the **base case – no policy**. Per graph, 25 lines are plotted, showing average lamp-type perception and adoption for 25 simulation runs. The line **colour** shows the progression of time; approximately: red – first years of the simulation; green: $t \sim 12$; blue: $t \sim 22$; purple: $t \sim 30$; dark pink: last years.

Observations

Each subgraph of the figure shows lines that represent combinations of adoption percentages and average perception for a lamptype, there are 25 lines in each graph, one line for each simulation run. So these graphs show actual simulation results, not averages of runs, or ‘box plot’-statistics. The lines have been given a colouring to indicates the passing of time, each colour represents a time step. Incandescent lamps are not plotted in the figure as their adoption is a continuous 100% in the base case making the graph of incandescent lamps is not interesting.

What we can see:

- (i) The lines show a clear ‘J-shape’ in the case for the CFL: while the perception is continuously falling, adoption first increases in the beginning and then reaches a point where it starts to decline.
- (ii) Halogen also has some sort of similar ‘J-shape’.
- (iii) LED adoption seems to deviate from this pattern and is more or less a straight line, where as adoption rises, perception falls.
- (iv) The lines diverge as time progresses.

Interpretation

- (i) The shape is the result of the adoption of CFL increasing a little bit in the beginning of the simulation (fig. 8.3 (a), from $\sim 57\% \rightarrow 64\%$), and then starts to decline. The perception starts to decline very quickly in the beginning of the simulation, and then levels out (fig. 8.4 (a)). This together creates the appearance of a J-shape.
- (ii) The J-shape exists for similar reasons; halogen adoption is declining quite steadily where halogen’s perception declines rapidly in the beginning of the simulation and then stabilises between $\sim 55\text{--}75\%$.
- (iii) The straight line is indicative of a correlation between adoption and perception. From the previous conclusions we know that a jump in adoption can cause a worsening perception, this may be observed here as well. The increase in adoption has the effect of lowering the perception. In the case of the LED, contrary to the CFL and halogen, a low perception might not lead to increased non-adoption. This can be explained by the long lifetime of LED lamps—an adopter can have a low perceptions and still be an adopter of the lamp.
- (iv) This shows the propagating effects of small deviations in the model’s methods and functions between each simulation run (e.g. small deviations in random number generation).

Conclusion

On the basis of a qualitative assessment, we could conclude that indeed, in general, *a lower adoption level is associated with a lower average perception* of the technology type, as was also concluded in § 8.3.3.

There seem some notable exceptions. First, while CFL adoption quickly rises in the beginning of the base scenario, the perception lowers. Then, at one point in time, adoption begins to fall while perceptions development flattens out. Perhaps this is because, as also was concluded in § 8.3.3, the perceptions don’t change anymore if adoption is low.

Interesting in these graphs is the strong spread of the results. The above graphs display the nature of the agent-based modelling technique. Surprising patterns and results can occur due to the interaction of a number of effects, on a high number of agents.

8.3.7 Results – Normative influence varied

The experimental setup of § 7.4 includes a number of settings for normative influence of price. Up to now, results that we presented are only for the default weight factors, but we also computed experiments with different weight factor settings.

To research the effects of varying the importance of the social network, the graphs of figure 8.8 (‘ban on bulbs’ scenario) are from the experimental setup where the normative influence is made twice as important by giving it a weight factor of 4, and the price is *also* made more important, giving it a weight factor of 6. The figures may be compared to that of the ‘ban on bulbs’ case of fig. 8.3 (b) on page 94.

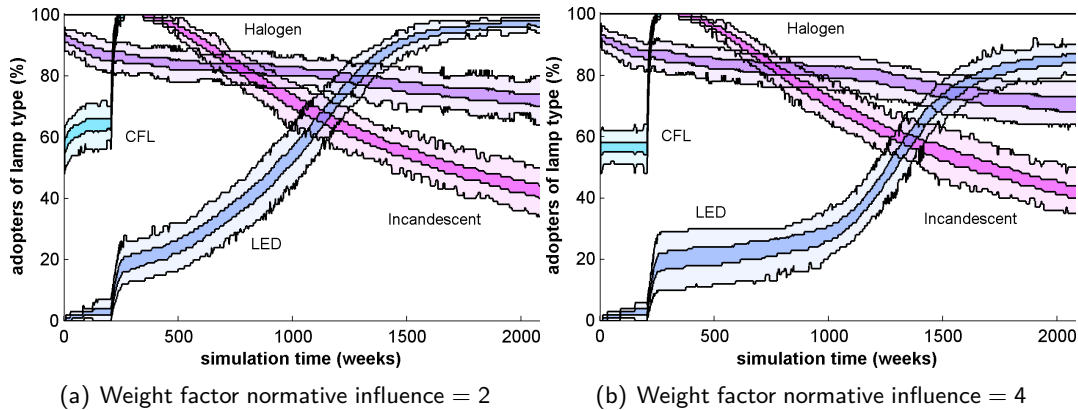


Figure 8.8 – The adoption of the lamp-types with different settings for the weight factor for normative influence in the ‘ban on bulbs’ scenario. In both cases, the weight factor for price is set at 6, from the default of 4.

Observations Compared to the ‘ban on bulbs’ case of fig. 8.3 (b), we can see that, as a result of the higher weight factor for price, LED adoption is already slower in fig. 8.8 (a).

In fig. 8.8 (b), we observe that the development of LED is significantly slower, even compared to fig. 8.8 (a). In fig. 8.8 (b), adoption takes off at the same time $t = 250$, but it is slower: more flat until $t = 1000$. After that, it starts to increase again (S-shaped) but it flattens out before reaching 100%.

Interpretation & conclusion Making the normative influence more important changes the shape profoundly; adoption of the LED lamp is clearly hampered by this normative adaptation.

Rather than stimulating adoption of new lighting products, the way normative adaptation is implemented in the model stimulates the ‘status quo’ – it helps the already widespread technologies. To paraphrase this: the model’s households do not think “a LED lamp is cool, I want to have it, too”, they seem to think “most of my neighbours don’t have that LED lamp, therefore I am not interested.”. This can be realistic for some real world consumers, but a further differentiation is perhaps recommended.

8.4 Conclusions from Simulation Results

Both the ‘bulbs-tax’ and ‘ban on bulbs’ policies seem effective ways to curb the use of the incandescent lamp. The ‘subsidy for LED’-policy has no significant impact.

Both the ‘ban on bulbs’ as well as the ‘bulbs-tax’ are effective at reducing electricity consumption of the consumer lighting sector, albeit on totally different time scales: the ban achieves the results quickly, within 10 years, the bulbs-tax reaches these levels after 30 years.

The ‘bulbs tax’-policy works better to stimulate the adoption of LED lamps than the ‘subsidy on LED’-policy. A tax on incandescent light bulbs of €2.00 works better than a 33% discount on the sale price of LED lamps (\sim €3–10, depending on the lamp).

The ‘bulbs-tax’ and ‘ban on bulbs’ policies cases both cause an increase in the amount of money households need to spend, upfront, on lighting products, compared to the base case and the ‘subsidy for LED’ scenario. This is an aspect relevant for policy making. For the average household, will incur a peak investment of about €30 per year, in the ‘ban on bulbs’ case. In the long term, the ‘bulbs tax’-policy is a more expensive option for households, but the revenues accrue the government, which is free to re-distribute them.

The simulation results also show the development of average perceptions from the agents in the model. Perceptions have their own dynamics and specific implementation in the simulation model; they are not necessarily comparable to ‘real world’ positive/negative opinions. We found out that the development of our model’s perceptions is strongly related to both the adoption of lamps of specific lamp-types and their sale price.

Also the influence of normative influence was researched. It was shown that, rather than stimulating adoption of new lighting products, in the model, normative adaptation stimulates the ‘status quo’. Normative influence acts to counter the proliferation of ‘novel’ lighting technologies with a very small market share.

8.4.1 Recommendations for future work

Observing the results and interpreting them leads to a number of recommendations. There are a number of recommendations and courses for future work.

The first recommendation is to increase the amount of parameters that are varied in the experimental setup. The model has many parameters that can be given different values; it would be recommended to perform a different range of experiments to do additional parameter sweeps and observe the system’s behaviour in those cases, and assess to what extent of parameter variation the results stay unchanged.

Secondly a remark on the halogen lamp-type. From the model results, it is apparent that, with halogen technology, not a lot of development occurs. This is probably not entirely realistic. Arguably much of this has to do with the lack of halogen lamps that are socket-compatible with the majority of luminaires. We could perhaps add extra halogen lamps that are compatible with the generic sockets (E27/E14) to overcome this, these types of lamps have become quite popular the last years, and will be probably remain important in the marketplace as incandescent lamps are phased out, and we should also add the CFL and LED-alternatives that are socket-compatible with halogen (GU10, MR11, MR16, etc.). A totally different course of action, that also will change halogen lamp-type dynamics, is implement changeable luminaires (but this will require more work)..

Thirdly, a note on the visualisation of simulation data. These graphs are mainly time series. This is easily interpretable, but many other ways of visualising data from the runs are possible and should be found. An essentially different view is obtained by looking at individual runs, and then observing – in-depth – the inner workings of a household and its purchase decision. This has not really done in this thesis, it was performed semi-continuously during model implementation as a verification of the implemented algorithms.

Lastly, a way should be found to assess the impact of network metrics on purchase decisions. Right now, the simulation model outputs only the parameters discussed in § 7.2,

but more should be derived that really shows some network effects other than the effect normative influence is shown to have.



Chapter 9

Conclusions and recommendations

9.1 Answers to research questions

The research aimed to acquire understanding of the response of the consumer lighting sector, resulting from the E.U. ‘ban on bulbs’, with as main question: “*How can we explore the consequences the E.U. ‘ban on bulbs’ will have on the electricity demand of the consumer lighting sector?*”

To answer this question, the system was analysed and found to be rather complex. Based on insights from a socio-technical perspective as well as from marketing and innovation diffusion theory, a simulation modelling approach was developed to assess the possible transitions in consumer lighting.

From this, the overall conclusion is that the E.U. ‘ban on bulbs’ *will likely be very effective at curbing the use of the incandescent lamp, and reducing the electricity demand of the consumer lighting sector.* A ‘bulbs tax’-policy is *also likely to be effective* in a longer time frame and, on average, at a higher cost to consumers.

The research addressed three questions (§ 1.4), answers will be given in the paragraphs below.

Consumer lighting: complex sector, consumer is paramount

In answer to the first research question, *how can the consumer lighting sector and its development be systematically characterised?*, the consumer lighting system was described using a socio-technical systems view and a marketing-innovation diffusion perspective. We could conclude that:

- The consumer is the most relevant actor out of the range of actors involved in the system.
- The consumer’s choice in purchasing technological components (lamps, luminaires, dimmers) is an important mechanism determining the electricity consumption of the consumer lighting system. This is also the area through which, energy use in consumer lighting can be structurally changed.
- Consumers have persistent opinions and knowledge on lamps, but their knowledge may be wrong or outdated. The opinions and knowledge are relevant to purchase decisions. Purchase price was found to be important as well.
- Consumers engage in sharing of their opinions and knowledge with other consumers (over a social network), influencing their adoption behaviour (word-of-mouth). The consumers adapt to one another through mutual social adaptation. Fashion is

important in this mutual social adaptation (and the willingness to adapt), and is possibly influenced by marketing and promotion activities.

Agent-based modelling: approach for researching transitions

Consumer markets are, due to their inherent complexity, not predictable: the interactions of the many consumers; producers; and retailers determine how the effects of government policies take shape in practice, and whether transition(s) will occur or not.

To analyse options for instigating a transition in consumer lighting, we concluded that a simulations approach was needed to test government strategies. This is the subject of the second research question—*what is a suitable modelling approach in order to evaluate the developments in the consumer lighting sector that result from the E.U. ‘ban on bulbs’?*

From a range of modelling techniques, it was concluded that **agent-based modelling** is a modelling approach that best suits the consumer lighting sector, as it allows for actors to have a place in a social network structure, and for actors to be heterogeneous and able to engage in ‘word-of-mouth’-sharing of opinions and knowledge.

The agent-based model was developed incorporating 250 heterogeneous households that exist in a social network structure; and one retail store, selling 70 simulated types of lamps of 11 makes (brands). The households are implemented with heterogeneous preferences, evolving memory and perceptions, which are updated by interactions in the social network. The model was verified and validated (using a.o. structure-tests).

The model includes three policy strategies to test the different approaches to transition management. These are: a **‘ban on bulbs’** (phased withdrawal of incandescent lamps; modelled after the E.U. ban on incandescent lamps); a **‘bulbs-tax’** (incandescent lamps are gradually taxed up to €2.00 per lamp) and a **‘subsidy for LED’** (where the speed of the switch over LED is encouraged by a 33% discount on LED lamps the first five years, gradually phased out to zero in the next 5 years).

By means of performing a great number of simulation runs (a sweep) of these different policy cases against a number of settings for model parameters, we could test the consequences of policies. With this approach, we have found a suitable way to assess possible developments of the complex consumer system and the effects of the government policies.

Effectiveness of the E.U. ‘ban’

On the basis of the experiments, answers on the third research question (*from the application of the simulation model, what insights can be gained on the effectiveness of the E.U. ‘ban on bulbs’ in the consumer lighting sector?*) can be given.

We concluded that the *‘ban on bulbs’-policy is likely a very effective way to curb the use of the incandescent lamp*. The number of incandescent lamps in use declines quickly; after lamp failure they are replaced with more efficient lamps of different types.

The *‘ban on bulbs’ is likely very effective at reducing electricity consumption of the consumer lighting sector, and quickly so*. In the simulation model, from the moment the ban takes effect, the incandescent lamp is replaced almost 1:1 with CFL’s, which leads to a large reduction of the lighting electricity consumption. See figure 9.1.

Part of the analysis of the effectiveness of the E.U. ban is researching whether other policies would also be effective. It turns out that the *‘bulbs-tax’ policy is also likely to be effective to curb the use of the incandescent lamp*, whereas the ‘subsidy for LED’-policy likely has no significant impact (i.e. it is very similar to the base case).

The *‘bulbs-tax’ is likely also effective at reducing electricity consumption of the consumer lighting sector, but it likely takes a lot longer than with the ‘ban on bulbs’-policy to achieve*

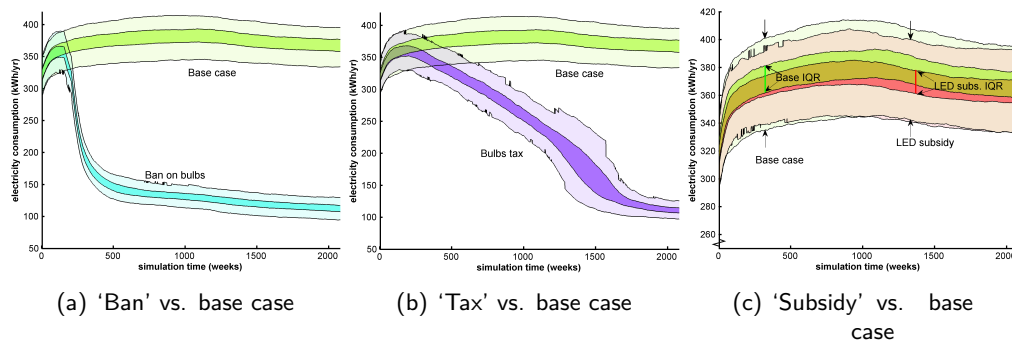


Figure 9.1 – Average household electricity consumption (kWh/yr) for the ‘ban on bulbs’ ‘bulbs-tax’ and ‘subsidy for LED’-policies, compared against the base case.

roughly the same results (~ 30 years instead of ~ 10 years in the case of the ban). The ‘subsidy for LED’-policy likely has no significant impact on electricity consumption. So, taken over a 40 year time span, the ‘ban on bulbs’ is the most effective way of achieving a lower electricity usage for lighting, but a tax on bulbs of €2 is also effective.

Level of the tax on incandescent lamps – CO₂ price

Interestingly, in the ‘bulbs tax’-policy, the adoption of LED lamps increases more quickly than in the ‘subsidy on LED’ case, we conclude that *a tax on incandescent lamps of €2 seems more effective than a LED discount of \sim €3–10* (depending on the lamp-model). The main reason a tax on incandescent lamps is effective is that the relative price difference between inefficient incandescent lamps and efficient alternatives shrinks by the largest amount as a result of tax. The subsidy for LED scheme, of which the monetary cost is uncertain (depending on how many LED’s will be bought), does nothing to change the relative price difference between other options (e.g. CFL vs. incandescent), enabling the cheap incandescent lamp to stay a consumer’s favourite.

The tax policy included in the simulation model works with a fixed amount of €2 per incandescent lamp. For an incandescent lamp, the number of burning hours is relatively short, enabling a rapid turnover. This means that, compared to many other consumer products, lifetime energy use can be quite accurately calculated. This means it is also relatively easy to devise a policy where the tax level can be set according to the lifetime CO₂ emissions of the lamp—making lamps a product where the full cost of lifetime emissions of CO₂ is integrated in the products *retail price* as compared to the *electricity consumption*. A quick calculation learns that a 60W incandescent lamp emits 36 kg of CO₂ during its 1000h lifetime, of which the current CO₂ cost only is about €0.54¹. The consumer pays for this in its electricity bill, but such a small amount will go unnoticed. Interestingly, the research shows that it is likely that the CO₂ policy of emissions will be effective in changing consumers behaviour if

- Consumers are charged for full lifetime CO₂ cost up front.
- The CO₂ cost will be high enough (indicatively \sim €60 per tonne)

This is expected to work better as consumers are highly sensitive to upfront costs and generally do not pay much regard to lifetime usage costs.

¹Assumptions: CO₂ price €15 per tonne (www.emissierechten.nl); CO₂ emissions: 0.6 tonne/MWh (based on indicatively natural gas CCGT \sim 0.3 ton/MWh; coal \sim 0.9 ton/MWh)

9.2 Recommendations

Disadvantages of efficient lighting

Compared to the incandescent lamp people are familiar with, quite some efficient lighting products suffer from a number of drawbacks (i.e. ramp-up time of the CFL, colour rendering, etc.). These were largely discussed already. We will now discuss two disadvantages not noticed by consumers. First we discuss the power factor that is generally not ideal; following this we discuss the mercury CFL's contain.

The electronics in the modern, efficient consumer lighting products cause some system inefficiencies in the electricity transport network. This is caused by their low power factor, arising from the electronic circuitry that drives the lamps; see appendix G. Indicatively, many CFL's have power factors in the range 0.5–0.8, and LED lamps have a power factor of around 0.5–0.6 (sometimes better and possibly worse—for one lamp I even measured less than 0.2).

The impact of the low power factor on the network is that current flows are increased relative to the power produced at power generating stations, which need to supply more reactive power. Although as of now the problem seems limited in practice (van der Zee, 2010), it is recommended that a policy maker pays attention to this, especially as some renewable electricity generation techniques (wind power) are less suited to meeting reactive power demands.

Another aspect is on mercury pollution. CFL's contain some mercury in their gas fillings, integral to their operation (EPA, 2008). Improperly disposed CFL's will release their mercury into the environment. As CFL's become more popular, it is important to limit the mercury-content of CFL's as much as possible, and give clear handling and recycling instructions. Another aspect of the mercury problem arises in the manufacturing stage. Poor working conditions in mercury mines and some CFL bulb factories in China have recently been subject to discussion with reports of mercury poisoning (Sheridan, 2009).

Policies generate upfront costs for households

It is recommended that policy makers look at the upfront costs the policies create for households.

The amount households spend on lighting products differs between the policy options: the 'ban on bulbs'-policy will create higher upfront costs for consumers, as the incandescent lamps need to be replaced by more expensive lamps when they fail, mainly in the first few years after the ban's implementation. The more efficient lamps, bought as a replacement, offer longer lifetimes that compensate the higher investment cost in the long run, but the initial upfront cost can be significant.

The 'bulbs tax'-policy, by its very nature, involves higher costs for consumers. The results show that in the 'bulbs tax' case, after the tax takes effect, consumers continue to purchase incandescent lamps, and henceforth incur the extra costs. In the tax-case, the taxes imposed on light bulbs generate revenue for the imposer (the government). These revenues can be re-distributed at will, allowing for consumers to be compensated with lower taxes in other policy areas. The 'bulbs tax'-policy is different from the 'ban on bulbs' case in this respect: in the latter policy case, the higher upfront costs accrue the retail stores and the manufacturers of lamps, and it is not up to the government to redistribute these.

Rebound effects of the ban on bulbs

There are a number of rebound effects that were not explicitly incorporated in the simulation model. As these rebound effects potentially negatively affect the results achieved by policies such as the ban on bulbs, it is advised that they are taken into account when developing and adjusting policies.

- Energy consumed by lighting is not only dependent on wattage but also on the hours of use. Energy efficient lamps such as the CFL generally have a significant warm-up time, which consumers consider annoying and causing them to be left burning for longer stretches of time. Furthermore, lamps are left burning for a longer duration when they are believed to be efficient: people are aware of the lower energy consumption of the CFL / LED lamps, and think it doesn't matter to leave them burning. The end result is that energy savings can be partly undone.
- In the E.U.'s 'ban' policy, ordinary incandescent lamps are banned, but *dedicated-socket halogen lamps are not* (as of 2009). The consequence is that, if people genuinely prefer incandescent and halogen technology (e.g. because of its light's colour), then luminaire manufacturers will provide more designs based on halogen bulbs. A transition to halogen is a problem because, while halogen technology theoretically offers a higher efficiency, many halogen bulbs are inefficient².
- The proliferation of luminaires with dedicated halogen sockets, is likely to lower prospects for a changeover to CFL's and LED lamps, because technologically it is more difficult to make these compatible with the small physical dimensions of halogen bulbs. The majority of CFL and LED replacement lamps are available for the generic E27 and E14 screw based sockets.
- In advance of the ban, some people will stockpile large amounts of bulbs. This can mitigate energy savings. A scarcity of bulbs can make them undergo a transition from a low involvement product and that there will not develop a 'black market' for ordinary bulbs.

Future research

For future research on consumer lighting, and policy impacts, it is recommended that the effects of the above considerations be further quantified, so policy makers can take action on them.

Especially the options for introducing a tax incorporating lifetime CO₂ emissions seems an interesting avenue to do more research; not only for consumer lighting but also for other consumer markets.

The simulation model developed in this research allows for many more experimentation, and expansion with some additional features.

The experimental setup designed in chapter 7, is not the only way the model can be executed. Many more settings can be varied, e.g. the number of households, lamp parameters, purchase criteria weight factors, social network parameters, and so on. About 60 model parameters can be set directly using the Repast user interface controller. In future research it is very interesting to perform a different set of experiments to assess the consequences of network assumptions, weight factor settings, and so on.

Interesting suggestions to expand and improve the simulation model are given in § 10.2.1.

²E.g. for 230V halogen: less than 10 lumen/W for omnidirectional 230V; 4-5 lumen/W for directional bulbs. Manufacturers lower the efficiency on purpose in order to give the halogen light a warmer appearance (van Agt, 2009). High efficiency halogen light is cooler in appearance.



Chapter 10

Reflection

10.1 Introduction

This last chapter is on reflecting on the work performed in this M.Sc. thesis research project. In § 10.2, we reflect on the simulation modelling approach and address whether we can find it both useful and convincing. After this, § 10.3 focusses on the work process—positive and negative aspects, and learning points of *how* the work was carried out. § 10.4 reflects on the software platform used in the modelling approach, with remarks on their advantages and disadvantages. § 10.5 concludes.

10.2 Reflecting on the model

At this point, we can ask the principal questions:

Is the model useful?

Is it convincing?

Can we say something about developments in the real world human-technological system, that is the Consumer Lighting System? With our very limited computer model, did we find a way to capture and mimic the broadness of human’s behaviour as a lighting consumer?

Gödel’s theorem (Gödel, 1931; Hofstadter, 1985) shows the limitations of axiomatic formal systems: either they contain unprovable truths, or they contain inconsistent statements. This has far reaching implications for use of formal systems, such as computers, in creating artificial intelligence (Feferman, 2009). In the debate whether humans are somehow superior to computers or not, Lucas (1961) stated:

No machine can be a complete or adequate model of the mind ... minds are essentially different from machines

Agent-based modelling does deliberately not attempt to be a complete formal description of a system (the world). It doesn’t even attempt to make a formal model of the complete workings of an agent itself, only parts related to some functions and behaviour of an agent are modelled. This deliberate incompleteness means that, at least, ABM does not suffer from Gödel’s incompleteness, which is a promising start.

But, what can we say about the approach in this thesis? Have we included sufficient depth and broadness of the consumer’s behaviour? Are the results convincing or have we

been too limited? Could the same result have been reached with a far simpler modelling technique? The answer should lie in the users of the model, and in the audience of the thesis.

Personally, I think this has been an interesting attempt at elucidating the impact of the ban on bulbs and of other possible policies, but, yes, there are some limitations.

- Government policies implemented are quite ‘rigid’ and narrow target one series of lamps. This is probably not realistic.
- The 70 models of lamps included in the model is only a subset of the available types. Perhaps with more types of general-purpose socket halogen lamps (E14/E27 socket), more dynamics with halogen could have been observed.
- The implementation of luminaires in the model is simple—one lamp attaches to one luminaire, and the luminaire remains fixed during simulation. Initially the plan was to include more luminaire dynamics; due to time constraints these were not implemented.
- Also the impact the presence of dimmers has on the developments of the lamps people purchase was not included. If people put non-dimmable lamps in luminaires that contain dimmers, the efficient lamps will either not work, flicker, or will be damaged (some effects of a dimmer on the power factor of dimmable CFL’s/LED lamps are discussed in § 9.2 and appx. G).
- We have chosen one way of modelling the consumer’s behaviour and rationale, using preferences, perceptions, memory, and multi-criteria decision making involving a number of criteria for these preferences to which weight factors are attached. We don’t know if this is the right way — there are simply no adequate data on aspects like the sharing of perceptions and information about lamps.
- Originally, the idea was to also research the effects of a number of rebound mechanisms of the ban. This was not executed, also due to time constraints. This is a very interesting area for follow-up research.

A number of these limitations could be improved upon with an possibilities to expand the model, discussed in the next section.

10.2.1 Possibilities to expand and improve the model

There are a number of possibilities to expand the model. These are interesting areas to venture into, as by incorporating these features, the realism will be enhanced and some limitations that were experienced with the model can be solved.

Some ideas for a more elaborate model, and how these can be added in conceptual / implementation terms, are described below.

More dynamics in technology The option to add more dynamics to luminaires is very interesting. In the present model, luminaires are fixed, households cannot change them.

The fixed luminaires mean that households are inflexible, they cannot switch to new technology if that new technology requires a different luminaire (e.g., because of socket or voltage voltage). This is one of the causes of the slow developments with halogen in the model results presented in chapter 8. If a household would be able to replace luminaires, more interesting developments with halogen lamps can be expected.

Furthermore, the LED lamps included in the simulation model have ordinary sockets (e.g. screw-based E27; E14), meaning they are drop-in replacements for traditional technology. However, with LED technology there are also interesting developments that depart from

the traditional concept of a luminaire that has a user-replaceable lamp. These novel concepts integrate the LED module and the luminaire, made possible by LED chips offering a very long life time. One example of such a novel lighting product is given in figure 10.1. Replaceable luminaires can be implemented in a simple way by randomly removing luminaires from households after a specific amount of time.

It would also be interesting to have multiple lamps per luminaire. This can capture the increase in energy consumption if households move from a luminaire with e.g. one 75 W incandescent bulb, to a halogen fixture with many 20W bulbs, as depicted in figure 10.2.

It would also interesting to add more technological innovation in the sale of lamps. The present model reduces lamp cost price, but does not improve the technological properties. Mainly for LED it would be interesting to see to what extent this would make a difference. As of now, LED is generally less bright than other alternatives. Of course, doing this will require doing assumptions on the pace of technological change, or introduce ‘imaginary’ lamp products at specific moments in simulated time.



Figure 10.1 – Philips LivingColor: LED-based colour changing accent lighting (courtesy Philips).



Figure 10.2 – Halogen ceiling luminaire with many 20W halogen lamps ('7 days more light', Voldersgracht, Delft).

More heterogeneous consumers; different consumer rationalities We have tried to implement a mechanism based on what we know of other consumer markets. What matters most is that the behaviour of the consumer is realistic. To investigate how robust the results are when our modelling assumptions are different, we can research different ways the consumers are modelled. Within the implemented framework, we can do this the easiest by increasing the **heterogeneity** in the household consumers and see how households behave in that case.

What we can also do is introduce **different classes of households**, with some households that actively try to influence others, other households that are quite illiterate on technology and not understanding anything about cost savings associated with energy efficient lighting.

One could also incorporate different **rationalities** for the consumer, for example different discount rates when thinking about upfront costs ((e.g. [Azevedo et al., 2009](#); [Menanteau and Lefebvre, 2000](#))), or totally eliminating the cost criterion.

Interesting option is to use **good-neutral normalisation** method in MCA (§ 5.3.1), and give the household agents good and neutral alternatives, and then make these alternatives rather strongly heterogeneous. What kind of model outcomes would then be established? This situation would arguably mimic the modelling of a consumer market where

either *product involvement and/or knowledge on alternatives* is low; or a market where consumers *strongly differ in opinion* (e.g. such as the automobile market?).

Add rebound effects A number of rebound effects that were presented in § 9.2 can be added to the simulation model. It is quite simple to implement these rebound effects in the simulation model.

That people are more inclined to keep their CFL's burning for a longer duration (either because they find the ramp-up time of the CFL annoying, or they think it doesn't matter given that CFL's are energy efficient), can be implemented by lengthening the hours of use of luminaires that contain CFL's or energy efficient lamps.

Another feed-back effect is that CFL's might premature failure (i.e. lifetime is shorter than advertised) when they are switched on/off in short cycles. This effect can be implemented by shortening the lifetime of CFL's for e.g. a certain percentage of households, or a certain percentage of CFL's of a certain percentage of households.

10.3 Reflecting on the process

10.3.1 Steps of the work

The total process of the work presented in this thesis consisted of many steps:

- ▷ *literature research*
- ▷ *conceptual modelling*
- ▷ *case / systems description*
- ▷ *software development for model*
- ▷ *more software development for experiments*
- ▷ *validation experiments*
- ▷ *policy experiments*
- ▷ *processing & analysis of data; making graphs*
- ▷ *writing thesis.*

There were many iterations between these steps. The total process was quite a large amount of work, with retrospect, it is quite a lot more than I would have envisioned at the start, more than a year ago; the total amount of hours put into it exceeded what is normal for a SEPAM M.Sc. thesis project.

Personal reflection on the work process

When the work started in January 2009, I had some planning difficulties: overseeing all of the work that was to do. Only after the work on the case description and initial model development, presented at the kick-off meeting in June 2009, I realised where I was and what had to be done to complete it, and I truly grasped what the thesis work would entail. In the months of January—June I think I can say that I 'wasted time' on non-focussed literature research, aggravated by learning a programming language (Java) and \LaTeX . The advantage of this 'wasted time', of course, is that now I know both Java and \LaTeX . Having learned Java will turn out advantageous when I will work professionally in fields involving software development. This, I consider to be a personal target that I fulfilled with this work. Learning \LaTeX may not be a true advantage if I will only do work outside of the scientific field, but who knows what the future has in store?

The model was further implemented from June till August 2009. From the summer onwards, I realised it would be very difficult to finish before the end of the year (given the level of detail and quality of software and thesis I felt were needed), so I started working under more time pressure, working evenings and weekends. At times it was a wrong decision to work evenings skip weekend breaks. I had to learn to plan my free time very consciously. However, in the last months of the work, I was simply unable to do otherwise, given the length of tasks still needed to be completed.

10.3.2 Complexity of simulation software tools

The model is conceptually quite simple, the algorithms used are simple, yet the software engineering task in getting the simulation model to work is quite complex.

The ‘consumer lighting model’ and the related packaging for creating graphs, writing to file, and so on, contain some 4400 source lines of code, mostly written from scratch, of which 2700 lines are within methods (code that is actually doing things)¹.

This is annotated and documented with 2700 lines of comment code, which is relatively elaborate, to make certain in the future other users of the model could understand the models design and workings².

Software tools There are many layers of software tools that all work together to do a research like this. For the majority of the software used, a conscious choice was made. A list of the tools used is displayed in table 10.1. Each of these tools has its own way-of-use, file format(s), documentation, keyboard shortcuts and peculiarities (also known as bugs). The most important software was Eclipse, a fully featured open source Java integrated development environment, and \LaTeX , used for writing this thesis.

Table 10.1 – Many different software tools were used in this research.

Category	Software applications
\LaTeX	MiKTeX; WinEdt; SumatraPDF; BibTeX; JabRef ...
Graphics	Visio; muPDF; PGF/TikZ; The Gimp; UnFREEz ...
Editors	WinEdt; TextPad; TeXnicCenter ...
Programming	Eclipse IDE; Java; Repast; Protégé ...
Data collection	Excel; SPSS; calc.exe ...
Data processing	MATLAB ...
Shell scripting	Bash; AWK; SED; Perl; CMD; CygWin ...
Connectivity	SSH; Putty-SCP; Xming X11R6; Cisco VPN ...
File management	TortoiseSVN; Subclipse ...

The complexity of the software effort undertaken is both fascinating and fun viewed at it from one perspective, but it is also a disadvantage; it easily lowers productivity of the work when one has to learn all these tools.

Using these software programs was mostly fun. Some tasks were tedious and lengthy, and sometimes difficult (Java debugging, getting MATLAB to work all right given the memory constraints, overcoming all sorts of errors and bugs in these software tools, learning

¹Figures exclude white space and comments. Largest classes are: ‘World’ – 1470 lines; ‘Household’ – 899; ‘Lamp’ – 235; ‘Perception’ – 204; ‘SocialNetwork’ – 196; ‘KnowledgeBaseImportFilter’ – 177; ‘Manufacturer’ – 175; and ‘Memory’ – 136

²Model documentation, based on JavaDoc, was generated and is available at <http://gux.tudelft.nl/svn/MaartenAfman/Model/doc/index.html>

and overcoming errors with L^AT_EX). Other tasks I found very nice: Java programming, designing experiments, generating graphs using MATLAB, making the HPC cluster to work properly, ... These were the parts I truly enjoyed.

The software minimally needed to develop an agent-based simulation model can probably be reduced to less than the above list. It is recommended to incorporate this as a separate goal during the ‘design’ stage of a new modelling exercise (especially for M.Sc. thesis projects).

10.4 Reflecting on the platform

10.4.1 Using the high computing cluster – Processing of simulation data

To perform the simulation experiments, we used a high computing cluster (HPC) (§ 7.4.3). This cluster has an extreme amount of parallel computational power. It consists of 60 nodes, that each have 1.9 GHz * 8 CPU’s per node of processing power. One can do 480 simulations in parallel, which can be used to do large parameter sweeps of the simulation model, where one tests the effects of all the parameters.

The amount of data this generates is, consequently, enormous. The simulation data is output using ‘writers’ that were created for the model. The ‘writers’ generate 230 data fields per time step. Because there are 2080 time steps (for a simulation duration of 40 years), one simulation run will ‘produce’ 478,400 fields of data. (And then not every data that could potentially be interesting is plotted!)

These data fields are mainly stored as integer and as single or double precision floating point numbers in the execution environment. The output ‘writers’ write to a comma-delimited ASCII text file, where each field is separated by a comma. In this format, integers are quite efficient, but floating point numbers can take up to 19 bytes in this format. It turns out that an average of ~ 11 bytes are used per field, a single simulation run has an ASCII output file of about 5.0 MB.

To perform a meaningful analysis, a number of runs have to be performed, say 100 per model setting. This translates to 1600 runs in total. The combined size of all the data is ~ 8 GB, residing in an ASCII file of 230 columns x $3.3 * 10^6$ rows. This is too much for workstation software like MATLAB to load directly into memory.

Data in a database server The solution we employed was to throw more software-technology on it. The data file was loaded into an SQL database server. The SQL (Structured Query Language) programming language can then be used to fetch blocks of data into MATLAB for processing and the creation of the graphs displayed in chapter 8.

Unfortunately the data processing of the large amounts of data was still not without problems, it was real slow. Trying to find out why, after timing each step, we discovered that it was the SQL query that took very long:

```
tic
% ask the SQL server to look up the data.
cursor.exec(SQLdb, "SELECT data1..n FROM table WHERE restr1..n")
toc

tic
% transfer data
data = fetch(cursor).data
toc
```

Pseudocode 2 – SQL timing in MATLAB

This would give results like:

```
Elapsed time is 935.773726 seconds.
Elapsed time is 0.810693 seconds.
```

It were the SQL queries that would take a long time in processing. One would consider that the limited nature of the capabilities of the database server hardware came to light ³, however this was not the case. The data size is simply too big to be stored in one big table, it will reside largely on disk and not in memory. The solution was to add ‘indices’ to the most important columns of the SQL table.

Memory in MATLAB Apart from the long query times, at times I would be plagued by memory errors like:

```
??? Error using ==> compute. Out of memory.
Type HELP MEMORY for your options.
```

These memory errors meant that, depending on the operation’s complexity, I had to decide to not use a part of my simulation data in generating the final results.

The results in chapter 8 were mainly from aggregating only 10-25 runs. Still, it would take hours to graph only one output parameter. It may not be immediately clear, but the result graphs contain really large amounts of data, they stretch the limits of what is possible (anno 2009) with the MATLAB software.

10.4.2 Improvements for data processing

I could think of a number of points that I could have done better:

Experimental setup I did two sets of experiments: validation testing, using a parameter sweep with a special routine in the simulation model, described in chapter 6, and an analysis of four scenarios with a limited sweep of two parameters (2x2 settings), chapters 7 and 8.

The validation parameter sweep I could optimise in a way so that, in the end, I was able to perform the many millions of experiments without major difficulty. The experimental setup for the scenarios testing, I used the full computational power, generating so much data that I was not able to overcome the limitations of the data processing capabilities and could not process all of it.

It is better to not combine any different parameter settings whilst analysing scenarios. The scenarios should be evaluated with many many simulation runs per scenario (e.g. minimum 100) in order to explore the range of possible pathways of the developments in the system, and trying to analyse the scenarios for different parameters in the same batch of simulation runs, just takes really really long, and will generate that much extra data that one will really easily run in data processing limitations, diminishing the quality of the end result.

But what then, if we do want to vary many parameters in the full model, not just in the validation step? Three things could be done:

³The SQL server, PostgreSQL resides on test.eeni.tbm.tudelft.nl, which is a beefed-up desktop system.

- Aggregate to a lesser extent: e.g. not 100 simulation runs per parameter setting, but e.g. only 10 runs. However, in reducing the number of runs at which one looks, one generally is at risk of looking at more or less random patterns that are not so much related to model variable settings.
- Lower the resolution of the data; e.g. use the ‘month’ as a time step instead of the ‘week’ (this would reduce data requirements by 75%).
- Simulate for a shorter amount of time. Find a way to adjust the model in a way so that it reaches a more or less stable state, at which you can terminate the simulation.
- Go very deep and look at key points in time, at individual runs. Look at the state of the actors, look at what their preferences, perceptions, attitudes are, and find out why and how they have been changed.

Model implementation & optimisation One should find ways to be able to say interesting things about the model without having to generate too many fields of data per simulation. If one generates 478,000 fields, one has to process many data. A smarter ‘model’ could save on this.

Optimisation It may be that I underestimated the data processing task. I think it is only natural to only realise after having gone through the whole process of *conceptual modelling* ▷ *software development* ▷ *validation* ▷ *experiments* ▷ *processing & analysis*, to realise that decisions, undertaken in an early stage, strongly affect what one has to work with in a later stage.

In software development, one generally optimises a piece of software once it has been implemented and the impact of design choices are fully understood. (If one optimises too early on, one does not understand the software/algorithms/data structures completely, and as a result the optimisation might either take too much time, but may also lead to code that is not good, that is hard to understand and debug).⁴

For the data analysis, the above means that, now I have ‘completed the circle’, I can now go back to the model, and change or implement routines to alleviate the data processing task. It is better to compute aggregate results for groups of lamps and groups of consumers, rather than to feed all data as simulation output data to be analysed externally of the model (in MATLAB).

10.4.3 Working with the shared ontology

Strengths / Benefits

The ontology is a shared language for dealing with concepts from the socio-technical domain. It is the core of the modelling framework in use at the E&I-section, and arguably used by every agent-based simulation model developed at the section. The ontology is a collection of data structures, and is accompanied by a library of Java source code.

The use of a shared ontology helps in developing an agent-based model of a socio-technical system, given that the system representation is shared (van Dam, 2009).

The advantage of the shared ontology is that all models that use it, at the very core employ in its data structures similar concepts. Because of this, code sharing and re-use is encouraged, which improves the efficiency of programmers. This a real strength and a big opportunity for quickly developing agent-based models.

⁴http://en.wikipedia.org/wiki/Program_optimization

Weaknesses

However there are also weaknesses.

In my perception, the main weaknesses, especially applicable for someone quite new to agent-based modelling and java programming in general, are:

- (1.) Steep learning curve, terminology.
- (2.) When working with it, the many instances of the many other models are confusing.
- (3.) Not so efficient for storing data.

I will clarify these points in the following subsections.

Learning curve Thinking in terms of ontological relationships can be quite a different task from capturing the essential system characteristics. Not everybody is good at this kind of thing. Especially from the perspective of a user who is, at the same time, new to agent-based modelling, new to java programming.

Furthermore, if the system definition is only partly shared, then the use of a shared ontology is not helpful anymore. This is what I found out during the initial stages of my modelling attempt. I could only come up with a meaningful way to use the ontology for the technological subsystem. By considering the lamps and lighting components to be some sort of a technical chain of interactions, the use of the ontology was useful here.

The ontology and the relationships in its class structure have been designed with industrial networks in mind. When one is attempting to develop an agent-based model that does different things, then this becomes a problem: the definition of concepts in the ontology subtly different from what one would like to have, and large chunks of the ontology will not be useful anymore.

Ontology terminology choices can be confusing. I wanted to store information on lamps in the memory of an household. Looking in the ontology, I would ask: “*what, precisely, is a 'Data ▷ DataTuple ▷ Component Tuple'?*”; “*How does it relate to 'Data ▷ DataTuple ▷ CompositionTuple'?*” and “*Do these fit my model?*” (No, I implemented the data structure of the consumer in Java, independent of the ontology). It is not clear out of the naming itself why the structure is as it is: only during discussions with experienced users one can achieve familiarity with the meaning and implications of the concepts.

An example of a terminology choice that was somewhat confusing is the subtle difference between the ‘industrial / energy network’-meaning and the ‘social network’-meaning is the term ‘Edge ▷ SocialEdge ▷ Knows’. From social science, this is of course a suitable term for people knowing each other. However, in the ontology, ‘Knows’ was designed to go strictly from an ‘Node ▷ SocialNode ▷ Agent’ to a ‘Node ▷ DecisionMaking’. So out of the box this term can’t be used for two household consumers knowing each other. The solution, of course, was to change the ‘Knows’ so that it now also allows to go to another Agent, which was possible in this case.

To make it conceptually easier to ‘learn to understand’ the relationships between the concepts in the ontology, especially for someone new to java programming, one of the ways this could be resolved is by improving the documentation for beginners.

Large size of the ontology (many classes, many instances) When one is just starting the modelling task, the large numbers of classes and instances of the classes that are visible once the ontology editor is opened up, can be confusing. An inherent disadvantage of a shared ontology for new users is that ever more instances of classes are created. As of now the ontology has more than 5000 instances in it, and these have to be loaded every

time the knowledge base is read. There are now 360 instances of 'Node ▷ PhysicalNode ▷ Technology', 70 of which are lamps. These lamps are not relevant for modelers not using any of these, but they have to scroll through an ever longer list if they want to locate their own technology.

A risk of a shared ontology is that if models are developed with it that use a slightly different system description, then the addition (or change) of a large number of classes becomes necessary, which could cause the ontology to be more complex and thus confusing (or that would break older models).

Storing data in the ontology The addition of the 70 lamps was quite a lot of hours of work: it took days, in all. Many fields have to be filled with instances: per lamp to do, about 20 clicks of the mouse are required. And after it was complete, data import errors caused bugs. This is why I wrote my own specific `KnowledgeBaseImportFilter.java` (200+ lines of code) that checks if the lamps had been specified correctly in the ontology. Otherwise the model could crash during execution because of an incomplete specification of a some lamp in the ontology.

This leads me to conclude that a any approach with a table-based database, for example a comma separated text file (.CSV file), would have been quicker in specifying the lamps with their properties. This would also have been easier to check for completeness, and if modifications of properties are required, this would also be far easier. The disadvantage is that lamps are not in the ontology.

I think it would structurally be better, if there are to be many instances of a class, that the ontology should not be used to store all the instances, but just be used to say something *about* the data, and not *contain* data itself. However this line is vague, when we started modelling we did not assessed that even 70 lamps is barely adequate to do the simulation with...

Concluding on the ontology

I used the ontology for the lamps, these were specified for 100% in the ontology. The luminaires, the households were not specified in the ontology, as was 99% of the data structure of the agents themselves. This basically evolved out of itself. Starting learning the ontology I found that I could easily put technologies, like lamps, in the ontology, but the somehow it didn't feel right to add the lighting consumer to it, with its peculiar memory, perceptions and other properties.

Apart from the time needed to develop this in a generic way, it would have been highly uncertain if it would be possible to develop this in the ontology in a way usable for other models. But perhaps it is an effort worth trying as some follow-up. Or perhaps adding it now, in a generic way, using experiences from the past simulation model development.

10.5 Overall conclusion

At this point we conclude this chapter reflecting.

On the model the research shows that the ban works, with the caveat that we have not quantified rebound effects. It is unfortunate that we couldn't delve deeper into this. On the other hand, simply banning a product is perhaps the right answer for cases of low-involvement products that are clearly needlessly damaging to the environment. I am very happy, however, to show policy makers that a tax could also have worked, the results on

the tax case are significant in the sense that it shows a richness of the agent-based modelling approach, we could not have argued up front that it would work.

The model is created for consumer lighting, but due to the fact that the ban was already a fait accompli when I was programming, I implemented the model to be as generic as possible. Apart from lighting-specific implementation details, the concepts of the model I created and the way they are implemented are largely applicable to *any* consumer market. Therefore, I hope this opens up possibilities to reuse (parts of) the model in a simulation of a different product case.

On the process and platform The amount of work was larger than I expected at the start (already described in the preface and in § 10.3).

When the model was largely ‘feature frozen’ around August, 2009, it took me five full months to do the validation, distributed simulation, simulation results processing, creation of graphs, and interpreting / reporting work in the thesis. I worked quite hard during this time, but did not keep track of the hours I worked (in any case more than 40 per week). During this time, where applicable, I followed instructions on the ‘wiki’ to the best of my ability and I was quite ‘clever’ with the software tools at hand.

For future agent-based modelling work to be done in a time-efficient manner by people who are making a first attempt at it, something should be done to shorten the time required. If a graduation project should be doable in five months (SEPAM), in total, then results generation and interpretation should not take more than one–two months, which I did not manage to do.

I think it would be an excellent idea to provide some good documentation for ‘beginners’, e.g. how to do data analysis, how to properly design for data-acquisition and results generation on the cluster, how to do data analysis in the easiest manner, and so on. I think a great opportunity lies here.

On the case This research work was already underway when the E.U. council of ministers decided to go ahead and implement the ban of bulbs. The case of the quick adoption and implementation of the ban shows the sheer regulatory power of the E.U.’s institutions. The E.U.’s institutions and offices only have a limited budget and limited political power, but they can still act with great effects through these kinds of regulations.

The ban was given its go-ahead without a great deal of public debate, reflecting the low-involvement nature of incandescent glow lamps – many people did not care enough to voice an informed opinion. There were some comics, it was an item on national television, some popular articles appeared. We are now 6 months further, the phase out can be clearly seen when visiting a place of sale of lamps: the display of lamps has changed profoundly. Matte bulbs are completely removed from sale, what is left are the clear bulbs, very many halogen bulbs, but clearly space reserved for CFL’s seems to have doubled, and there is a larger selection of LED lamps.

It could be argued the lighting industry is rather happy with the present situation: coming years, halogen and the CFL will become a popular option. This will making some handsome profits for manufacturers due to the increased margins on these types of lamps.

Personally, I am quite happy with it as well. In my opinion, the ordinary incandescent lamp is a product that has partly outlived its time in history; given the range of alternatives and the pace of development in energy-efficient technology, incandescent technology simply has no place anymore in the majority of use cases. Having said this, there are also cases where alternative technologies are not (yet) suitable, e.g. very dim ‘mood lighting’ (operating in a very dimmed state), as well as in locations with very few hours of use per year.

Much can be expected of LED technology. It will become more cost-competitive, and better suited to replace halogen, even in dedicated sockets. LED seems optimally suited to provide the warm colour temperatures of the light Northern Europeans enjoy, while achieving a high efficiency (that will only be improving as time progresses!). LED can be dimmed, and offers exception directionality of the light, making it a good replacement candidate for the halogen-reflector lamps in the halogen luminaires that proliferated the last decade.

Part IV

Appendices



Appendix A

Electricity used by Dutch households for lighting

How much electricity do Dutch households use for lighting?

Wajer and Kemna (1991) developed a model to accurately assess this. Their NOVEM-model, which is based on empirical studies, so-called ‘residual analysis’ (see Kemna et al., 1991), as well as market data and technical analysis, gives a total electricity consumption for lighting of 498 kWh per household per year (in 1987). This figure compares well with the figure for the Netherlands of 524 kWh per household per year, derived by Bertoldi and Atanasiu (2006) on the basis of questioning E.U. energy efficiency experts.

It is interesting to note that the electricity Dutch households use for lighting has increased since 1987, despite a high CFL penetration ratio today (now an average of 4 CFL’s per household (Bertoldi and Atanasiu, 2006))¹. The relatively high adoption of CFL’s did not compensate for the increased number of light points per household, popularity of electricity-hungry halogen uplights, increased welfare, etc.

As of 2009, there are 7.2 million households in the Netherlands (CBS, 2009). Combining this with the figure of 524 kWh per household–year, the total amount of electricity for Dutch household lighting turns out to be a considerable amount: 3.8 TWh per year. This figure is the same as what can be derived from Mills (2002)².

How large could the possible savings be, for the Netherlands alone? Mills (2002) gives estimates of 40–60% for the savings potential for residential lighting. If we take the lower percentage limit, 40%, of 3.8 TWh, then we could save 1.5 TWh. Taskforce Verlichting (2008) even targets a 50 % reduction in Dutch residential lighting, to be achieved in 2013. To get a grasp of the order-of-magnitude of this, this would equal to taking a (hypothetical) power plant of 320 MW off the grid. Calculation:

$$1.5 \cdot 10^6 / 8760 / 0.6 / 0.9 \simeq 320 \text{ MW} \quad (\text{A.1})$$

The 0.6 and 0.9 factors are for the power plants capacity power factor, and electricity grid losses.

¹There is indication that in 2008 the number of CFL’s per household increased to 7 (Taskforce Verlichting, 2009, p. 2).

²Mills gives the following data for the Netherlands in 1996: fraction of electricity consumption for lighting, sum of all sectors ~ 15%. Total electricity consumed for lighting 14.24 TWh. Total electricity consumed for residential lighting, two values: 2.97 TWh and 3.38 TWh, average is ~ 3.18 TWh. Fraction for residential as a share of the total for lighting: 3.18/14.24 ~ 22%. Then, with the figure for the total electricity consumption (in 2006) of 115 TWh (IEA, 2008): $115 * \frac{15}{100} * \frac{22}{100} \simeq 3.8 \text{ TWh}$. That the calculation gives the same number strengthens the validity of the figures mentioned, although it is possible that the different calculations share some data.

[Bertoldi and Atanasiu \(2006\)](#) estimate how much electricity could be saved when households would adopt more CFL's. The authors estimate that 12.8–18.4 TWh could be saved yearly in the entire EU-27. The lower figure is if every household would replace one of its higher-wattage lamps with a CFL, the higher estimate is when a household uses a CFL in a quarter of lighting points. This way, for the Netherlands the authors estimate savings of 0.23–0.43 TWh. These savings potentials are clearly more conservative than our own calculation.

However, [Bertoldi and Atanasiu](#) use a rather simple model, in which the parameters for the Netherlands are such that the savings in GWh from adding a million CFL's turn out lower than the average of the EU-15 (by a factor of 2 resp. 3). Part of this might be due to a first-mover disadvantage: the Netherlands already has somewhat higher CFL penetration, but partly it is unrealistic, savings continue beyond the first few CFL's that a household has. Furthermore, with electricity prices of about 15 ct. / kWh and today's low CFL prices (a pack of two for €2.99), it is now cost-effective to replace all 40W and above incandescents that only burn 15 minutes per day with a CFL, so it is economically rational to adopt more CFL's than [Bertoldi and Atanasiu](#) assume.

Appendix B

The E.U.'s 'ban on bulbs'

To speed up change in the sector and give energy-efficient alternatives a boost, on 18 March 2009 the European Commission decided to pass regulation (under the EU's Eco-design framework) that forces lighting products available to meet a number of stringent efficiency standards (CEC, 2009b). The regulation is popularly known as the "ban on bulbs".

As of now, the regulation entails the following (CEC, 2009b,d,e):

Non-clear (frosted) lamps These lamps are required to be energy class "A", from September 1, 2009 onwards. This means that all *matte* incandescent lamps (energy class "E", "F" or "G") are phased out already (although in practice, they are still available in many retail stores).

Clear lamps These need to first reach energy class "C" (2013) and then class "B" (2016). In the years 2009-2012, the less efficient lamps will be gradually phased out, depending on their light output (luminous flux Φ), as follows:

Date	Lamps with $\Phi \geq$	E.g. phased-out lamps:
1 September 2009	950	100 W bulb
1 September 2010	725	75 W bulb
1 September 2011	450	60 W bulb
1 September 2012	60	15 W, 25 W, 40 W bulbs

And from 2016 onwards, these lamps need to be class "B" at minimum (only the most efficient type of halogen allowed).

Directional lamps Are currently exempt, but regulation will probably follow in 2010.

Halogen technology lamps Non-directional conventional halogen lamps at mains voltage are at the "D", "E" or "F" energy class. These need to be "C" class, the scheme is the same as for general clear lamps. Generally, low voltage halogen is already at "C". Mains voltage halogen can be at "C" by using a xenon gas filling.

For 230V-halogen, there are two types: the special socket halogen lamps (e.g. G9 pin-based; R7S tubular sockets). These lamps will need to be energy class "C". The other type of halogen lamps are those with general purpose socket (E27, E14 etc). For this type of socket, from 1 September 2016, only B-class halogen (low voltage; infrared coating) will be available.

In 2013, a review of the regulation will take place.



Appendix C

Implementation in the framework for developing agent-based models

In the E&I section a framework has been developed to facilitate the creation of agent-based models of diverse socio-technical systems. The framework consists of a simulation engine for agent-based models, a shared knowledge base to make the the system representation easier and more structure, and a hardware platform to execute the simulation runs. The framework is described by [van Dam \(2009\)](#) and [Nikolic \(2009\)](#).

C.1 Shared ontology for a system representation

To help with the system representation, use is made of the framework for agent-based modelling developed by Nikolic, Van Dam, Chappin and others at the E&I section [Nikolic \(2009\)](#); [van Dam \(2009\)](#). This framework includes a knowledge base and an ontology shared between the different simulation models. The ontology helps with capturing concepts from the real world system. Data about the real world system is captured in a knowledge base that defines classes and instances, with some of their properties. The ontology consists of an hierarchical class structure, with the definitions of objects and properties used for representing things from the world in network models. To use the concepts from the ontology in software models, the framework also includes source code in the Java programming language that defines the actual properties and behaviours of agents and other concepts from the ontology.

Using a ontology that is partly shared between simulation models is useful because agent-based models developed for different complex socio-technical systems turn out to have a quite similar representation of the world in the simulation model. Formalising this similar representation in an ontology means that it saves programmer's time and lowers the amounts of errors. Another advantage is that having a well tested and 'proven' data structure saves time in developing new simulation models, and it facilitates the communication about the development process with other researchers.

The ontology defines classes and interfaces, makes it clear how objects interact, and forces programmers to think precisely about the relationships between objects. The combination of a shared ontology with useful generic implementations in Java source code shortens the development time of new models.

Description of the ontology The Energy and Industry ontology is a network-view of the world. All things in the E&I ontology are either thought of as *Node*, *Edge*, *Data*, or *Knowledge*, which are the four main classes. From that, the E&I ontology makes a

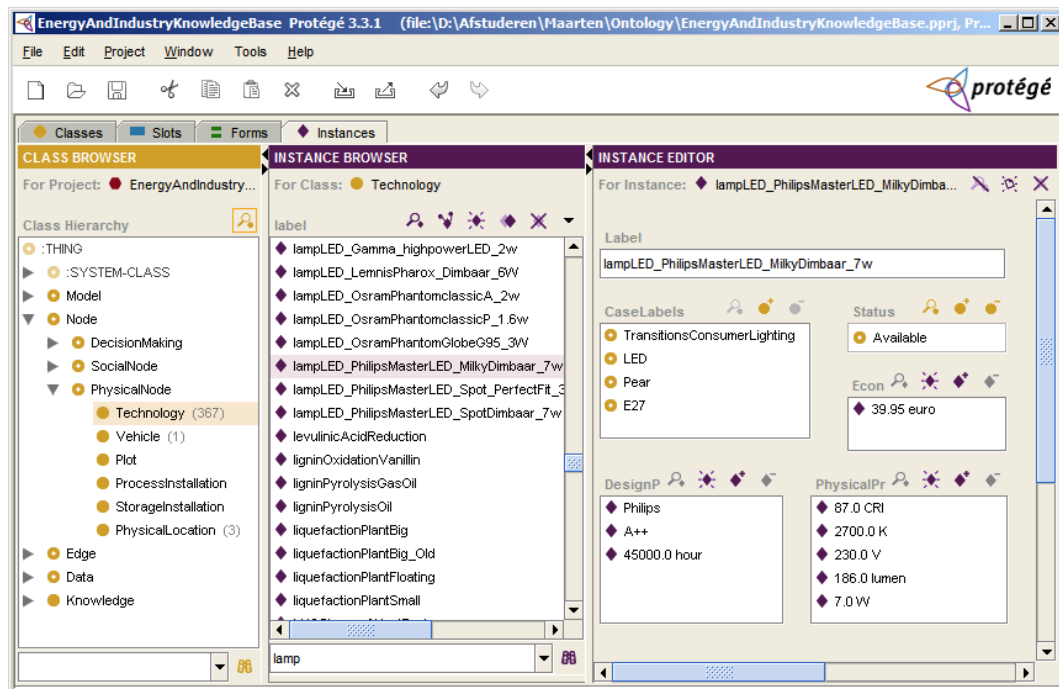


Figure C.1 – Protégé Ontology Editor, showing, from left to right, the ontology class structure, lamps as instances of the class ‘technology’, and values of properties of the lamp selected. The properties displayed are instances of other classes in the ontology (not shown).

distinction among technical artifacts and social things: a Node can be either a *PhysicalNode* or a *SocialNode*. Edges form the relationships between node, and these can be social and physical as well.

C.2 Java programming language and platform

The actual behaviour of the simulated agents is represented in computer language through the Java programming language. To define the actual behaviour of agents, many lines of code need to be written for each type of agent or for each simulated concept. The code needs to be written from scratch, but if available, already existing code may be adapted. The advantage of using Java as programming language for the simulation model is that it offers a flexible and robust approach for object-oriented software development. Because of the modular and object-oriented properties of the Java programming language, once the code is written, this code can then be easily shared and re-used for other purposes (Flanagan, 2005). Java code written for the simulation of the consumer lighting sector may be easily be reused for — say, a simulation of consumer automobile purchases. The Java platform refers to the assemblage of libraries of classes that Java programs can use. The simulation is implemented using the Java platform version 5.0.

C.3 Repast agent-based simulation toolkit

Repast J is a Java based platform for developing agent-based simulations. Repast is an implementation of a large number of routines that one can use to build agent-based models. Repast provides a user interface for specifying input parameters, tools for displaying graphs, a simulation engine that involves a time sequence in which agents perform their routines. In addition, Repast provides a number of libraries useful in programming agent’s

behaviour (e.g. mathematical libraries and random distributions). An overview of Repast 3's features and workings is given in [North et al. \(2006\)](#).

What Repast does not help with is the system representation, the 'agent architecture' itself (see [Wooldridge and Jennings, 1995](#), pp. 23-35 for a discussion on agent architectures). One is completely free to develop the way the agent is internally composed, and how its modules, methods, behaviour and data structure are built and function. This is left to the developer.



Appendix D

Lamps in the simulation

In table D.1 the lamps used in the simulation are displayed, along with their properties.

The bulk of the data were collected by selecting lamps that were on prominent display in different shops (Gamma, Ikea, Bouwhof, Hema, Blokker, Albert-Heijn) in the cities of Zoetermeer and Delft¹. To complement the range of lamps in the simulation model, a number of lamps not for sale in any of the above retail stores were added. This holds for e.g. the Philips LED lamps, these were not yet seen in stores, but are relevant (or will be in the near future). The LED lamps from Lemnis Lighting and Albert-Heijn only became commercially available just in time to be incorporated in the simulation model.

The data on the parameters of each lamp were taken from the packaging, or from specifications on the lamp manufacturer's web site. The EU's energy labelling directive requires specification of a number of lamp characteristics related to lamp energy use on the lamp packaging, see figure D.1. These energy labels were used for the lamp parameters light output, wattage, rated lifetime, and energy class (A-G).

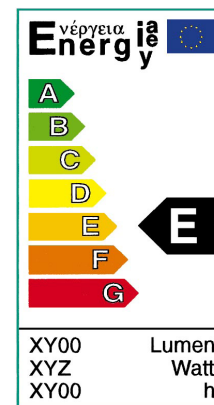


Figure D.1 – The energy label that needs to be present on lamps packaging (CEC, 1998).

Explanation on the columns in table D.1 is shown below. The model source code also checks whether the parameters and values are completely specified.

ID An identifier of the lamp-model (used in calculations, MATLAB, e.g.)

Lamp-model name Name of the lamp-model, reflective of how the lamp is specified in the ontology. Included in the lamp-model name are technology type, brand, model, and power rating (in the ontology, **brand** is also specified as a separate parameter).

Lamp-type The technology used by the lamp, e.g. CFL / LED / Halogen / Incandescent

Average lifetime Value used as the expected lifetime L_E . This is the manufacturer's rated lifetime (adapted for some LED's). See section E.2 in appendix E.

Uncertainty lifetime Value used for the uncertainty of the expected lifetime L_E (see section E.2 in appendix E).

Light output Measure for the luminous flux, the amount of useful light emitted by the lamp, in lumens. Usually the light output, in lumens, is specified on the lamp packaging (as part of the energy label logo, see figure D.1). A difficulty arises with

¹The bulk of the data collection effort was undertaken by Guido Kuijpers, B.Sc. student Technische Bestuurskunde, as part of his Bachelor's project. Thank you, Guido!

directional lamps: for these, the packaging does not contain the lumen output (directional lamps are exempt from both energy-label requirements as well as the ‘ban on bulbs’ (CEC, 1998, 2009b)). In these cases, values were taken based on what is available from lamp catalogues on manufacturers’ websites, and, if needed, assumptions were made based on the values of similar lamps combined with values taken from the lamps measurements site Olinio (Olinio, 2009b).

Power consumption Power consumption is almost always specified on the lamp / packaging. For traditional bulbs, the measure of lamp power consumption is a proxy for the light output, people relate to lamp power when buying an incandescent bulb, and not the lumens of light produced. For modern / efficient lamps, a lamp packaging might indicate its true power and also an ‘equivalency rating’ to compare it with a traditional bulb. These ratings are almost always inflated.

Colour rendering index The colour rendering index (CRI) is a measure for how colours appear under some light source compared with a reference light source (a black radiant body like the sun). A value of 100 is achieved when there are no difference. This is achieved by traditional incandescent and halogen lamps. A value of 80 or above is generally regarded as ‘good’, although it may not be good enough for specific lighting applications (museums, shop displays etc.). A value below 80 is will be noticed by the average person, the shift of the colours is then large enough to be perceived (a red meat can look brownish, green pies can look radiantly vivid green, etc.). CRI is not specified on packaging. Sometimes it is specified on product data sheets, if so, we used this value is used. Based indicatively on the measurements at Olinio (2009b), we took values of 80 as a standard for CFL, 70 for low quality LED, and 100 for Incandescent. CRI is not an absolute measure of colour fidelity, only 8 colours are used in its calculation, so it is easy for a manufacturer to optimise for just these colours so that the lamp looks good on paper.

Colour temperature Also the colour temperature is important for the colour perception. An incandescent lamp emits warm light of a colour temperature of around 2700 - 2800K, depending on lamp power. This kind of warm light is what most people prefer in their homes, therefore most lamps for house lighting have this temperature, including CFL’s. Efficient halogen light, such as 12 V Halogen, has a higher temperature of the glowing filament, and consequently emits cooler² light. We took 3000 K as value for all Halogen lamps. Daylight-type lamps have a colour temperature that is even higher, around 5500 K. These lamps are not popular for home lighting. Only some specific cold white LED’s (cheap LED lamps) have this temperature.

Voltage Most lamps are 230V. For G24d2, this value is taken although the voltage that is on the CFL itself is not 230V.

Shape This parameter characterises the physical shape of the lamp. This parameter was added to be able to determine compatibility with luminaires (in terms of aesthetics and dimensions). As of now, this parameter is not used in the model.

Socket There are many different kinds of sockets for lamps. With the popularity of halogen lamps, the amount of sockets has increased, and due to introduction of LED

²The colour temperature is determined by comparing a lamps light to a reference light source, a black body. A black body that is heated to some temperature emits light with a specific spectrum. The spectrum can be characterised by its dominant wavelength. The higher the temperature of the black body is, the shorter the dominant wavelength becomes, and the ‘cooler’ the light appears, as the blueish colours gain strength relative to the reddish colours. Therefore, a high colour temperature equates to a lamp giving ‘cool’ light, and light of a low colour temperature, is ‘warm’ light.

the same could happen. The general-purpose Edison screw-fitting (E27 / E14) is the most common, and this socket has the greatest choice of lamps available, which is reflecting in the lamps included in this research. Some sockets are quite dedicated, e.g. the G24d2 and the R7S socket. G24d2 is one of the sockets designed for CFL's that have an external ballast (the kind that is more present in offices than in homes). R7S is the tubular halogen fitting, which exists in many different lengths for different lamp power ratings (up to thousands of Watts). For these rather dedicated sockets we have not incorporated many alternative lamps to choose from because a switch-over to a different lamp technology for these sockets is not possible.

Energy label The energy label is taken of the packaging. If unspecified, it is assigned according to the type of lamp and its efficiency.

Price Price data are the real purchase prices of the lamps, as observed in the retail store(s). For lamps not for sale in any of the above shops, price data were taken from online stores. If lamps were sold in bulk packaging, the price is the unit price, obtained by dividing the package price by the amount of lamps in the package. A lamp is usually cheaper if it can be bought in a bulk packaging. Lamps are modelled with gradually declining prices, see [E.1](#) in appendix E.

Table D.1 – The data on lamps

ID	lamp-model name	lamp-type	Average life-time (hours)	Uncert. life-time	Light output (lumen)	Power consumption (W)	Colour rendering index	Colour temperature (K)	Voltage (V)	Shape	Socket	Energy label	Price (€)
1	LED Osram PhantomGlobeG95 3W	LED	25000	0.55	50	3	80	2700	230	Pear	E27	A++	24.95
2	CFL Gamma spaarlamp 7W	CFL	5000	0.5	377	7	80	2800	230	Tubular	E27	A	1.99
3	CFL Gamma Spaarlamp 11w	CFL	5000	0.5	612	11	80	2800	230	Tubular	E27	A	1.99
4	CFL Gamma spaarlamp 15w	CFL	5000	0.5	928	15	80	2800	230	Tubular	E27	A	1.99
5	CFL Gamma SpaarlampBol 9w	CFL	5000	0.5	358	9	80	2700	230	Pear	E27	B	5.49
6	CFL Gamma SpaarlampBol 11w	CFL	5000	0.5	450	11	80	2700	230	Pear	E27	B	5.49
7	INC Gamma Gloeilamp 25w	Incand.	1000	0.4	210	25	100	2700	230	Pear	E27	E	0.45
8	INC Gamma Gloeilamp 40w	Incand.	1000	0.4	359	40	100	2700	230	Pear	E27	E	0.45
9	INC Gamma Gloeilamp 60w	Incand.	1000	0.4	675	60	100	2700	230	Pear	E27	E	0.45
10	INC Gamma Gloeilamp 75w	Incand.	1000	0.4	880	75	100	2700	230	Pear	E27	E	0.45
11	INC Gamma Spot 25w	Incand.	1000	0.4	240	25	100	2600	230	Reflector	E27	F	1.50
12	INC Gamma Spot 50w	Incand.	1000	0.4	600	50	100	2700	230	Reflector	E27	F	1.50
13	INC Gamma Spot 75w	Incand.	1000	0.4	900	75	100	2800	230	Reflector	E27	F	1.50
14	LED Gamma highpowerLED 2w	LED	25000	0.65	70	2	75	5000	230	Pear	E27	A++	23.95
15	LED Gamma 42LED 2w	LED	25000	0.65	50	2	70	5000	230	Pear	E27	A	22.95
16	LED Gamma 15LED halogen shape 1w	LED	10000	0.65	16	1	70	5000	230	Pear	GU10	A	6.49
17	LED Gamma 1.2w	LED	25000	0.65	20	1.2	70	5000	230	Pear	E27	A	9.99
18	CFL Hyundai SEMI 5w	CFL	8000	0.5	180	5	80	2800	230	Tubular	E14	A	2.95
19	CFL Hyundai ECO 7w	CFL	8000	0.5	310	7	80	2800	230	Tubular	E27	A	2.95
20	LED Osram PhantomclassicA 2w	LED	25000	0.55	30	2	75	2700	230	Reflector	E27	A++	13.95
21	LED Osram PhantomclassicP 1.6w	LED	25000	0.55	40	1.6	75	2700	230	Reflector	E27	A++	13.70
22	HALO Osram Halopar20ALU 50w	Halogen	2000	0.35	600	50	100	3000	230	Reflector	E27	D	13.00
23	HALO Osram HaloluxT 60w	Halogen	2000	0.35	790	60	100	3000	230	Tubular	E14	D	12.00
24	HALO Osram Decostar 20w	Halogen	2000	0.35	200	20	100	3000	12	Reflector	G53	C	4.05

(Continued on Next Page...)

Table D.1 – Continued

ID	lamp-model name	Type	Life time	Uncert. lifet.	Light outp.	Power cons.	CRI	Col. temp.	Voltage	Shape	Socket	E-label	Price
25	HALO Osram Halopar16ALU 50w	Halogen	2000	0.35	400	50	100	3000	230	Reflector	GU10	E	5.55
26	INC Osram ClassicP 40w	Incand.	1000	0.35	400	40	100	2700	230	Pear	E14	E	1.45
27	HALO Osram Haloline 200w	Halogen	2000	0.35	3400	200	100	3000	230	Tubular	R7S	D	6.75
28	INC Osram ClassicP 40w	Incand.	1000	0.35	400	40	100	2700	230	Pear	E27	E	1.45
29	INC Osram ClassicP 60w	Incand.	1000	0.35	660	60	100	2700	230	Pear	E27	E	1.95
30	INC Osram ClassicP 15w	Incand.	1000	0.35	90	15	100	2700	230	Pear	E27	F	1.95
31	CFL Osram DeluxELLonglife 5w	CFL	15000	0.4	240	5	80	2700	230	Tubular	E14	A	13.95
32	CFL Osram Deluxstar 5w	CFL	6000	0.4	250	5	80	2700	230	Tubular	E14	A	4.95
33	CFL Osram DeluxD 18w	CFL	8000	0.4	1200	18	80	2700	230	Tubular	G24d2	B	10.00
34	HALO IKEA halogen 35w	Halogen	2000	0.4	138	35	100	3000	230	Reflector	GU10	E	1.25
35	HALO IKEA halogen 50w	Halogen	2000	0.4	343	50	100	3000	230	Reflector	GU10	E	1.25
36	HALO IKEA halogen 20w	Halogen	1000	0.4	100	20	100	3000	230	Reflector	GU10	F	1.60
37	INC IKEA Gloda 25w	Incand.	1000	0.4	210	25	100	2700	230	Pear	E14	E	0.50
38	INC IKEA Gloda 40w	Incand.	1000	0.4	415	40	100	2700	230	Pear	E27	E	0.35
39	INC IKEA Gloda 60w	Incand.	1000	0.4	710	60	100	2700	230	Pear	E27	E	0.35
40	CFL IKEA SparsamGlobe 11w	CFL	10000	0.5	530	11	80	2700	230	Pear	E27	B	3.50
41	CFL IKEA SparsamGlobe 7w	CFL	10000	0.5	260	7	80	2700	230	Pear	E27	B	3.50
42	CFL IKEA SparsamTubular 11w	CFL	6000	0.5	600	11	80	2800	230	Pear	E27	A	1.00
43	CFL IKEA 7w	CFL	8000	0.5	260	7	80	2800	230	Reflector	E14	A	5.39
44	CFL Megaman LiliputSLU111 11w	CFL	10000	0.4	600	11	80	2800	230	Tubular	E14	A	9.35
45	CFL Megaman SLU100 8w	CFL	10000	0.4	400	8	80	2700	230	Tubular	E27	A	9.36
46	CFL Megaman PingPongGA805i 5w	CFL	15000	0.4	200	5	80	2700	230	Pear	E27	A	13.95
47	CFL Megaman DimmerableWL218d 18w	CFL	10000	0.4	1008	18	80	2800	230	Tubular	E27	A	22.95
48	HALO Massive 35w	Halogen	2000	0.4	138	35	100	3000	230	Reflector	GU10	D	2.50
49	HALO Massive 50w	Halogen	2000	0.4	343	50	100	3000	230	Reflector	GU10	D	2.10
50	CFL Hema Sfeer 5w	CFL	8000	0.5	190	5	80	2700	230	Pear	E27	A	6.25
51	CFL Hema Sfeer 12w	CFL	8000	0.5	610	12	80	2700	230	Pear	E27	A	6.25
52	CFL Hema Spaarlamp 16w	CFL	10000	0.5	900	16	80	2800	230	Tubular	E27	A	9.25

(Continued on Next Page...)

Table D.1 – Continued

ID	lamp-model name	Type	Life time	Uncert. lifet.	Light outp.	Power cons.	CRI	Col. temp.	Voltage	Shape	Socket	E-label	Price
53	CFL Hema SuperSpaarlamp 8w	CFL	8000	0.5	500	8	80	2800	230	Tubular	E27	A	6.25
54	CFL Hema Minispaarlamp 5w	CFL	8000	0.5	230	5	80	2800	230	Tubular	E27	A	4.25
55	CFL Hema Minispaarlamp 18w	CFL	8000	0.5	1100	18	80	2800	230	Tubular	E27	A	4.25
56	INC Hema StandaardHelder 40w	Incand.	1000	0.4	415	40	100	2700	230	Pear	E27	E	0.50
57	INC Hema StandaardMat 75w	Incand.	1000	0.4	935	75	100	2700	230	Pear	E27	E	0.50
58	INC Hema Standaard 15w	Incand.	1000	0.4	120	15	100	2700	230	Pear	E27	E	0.50
59	CFL Go Green 11W 60Weq	CFL	8000	0.5	726	11.3	81.3	2800	230	Tubular	E27	A	5.00
60	HALO Philips EcoHalo 20w	Halogen	5000	0.35	240	20	100	3000	12	Reflector	G53	C	6.22
61	HALO Osram Haloline 150w	Halogen	2000	0.35	2500	150	100	3000	230	Tubular	R7S	D	6.75
62	HALO Osram Haloline 300w	Halogen	2000	0.35	5300	300	100	3000	230	Tubular	R7S	D	6.75
63	LED Philips MasterLED MilkyDimbaar 7w	LED	45000	0.5	186	7	87	2700	230	Pear	E27	A++	39.95
64	LED AH Puur&Eerlijk 5W	LED	25000	0.65	200	5	85	3000	230	Pear	E27	A++	16.49
65	LED Lemnis Pharox Dimbaar 6W	LED	25000	0.65	336	6	85	3000	230	Pear	E27	A++	29.95
66	LED AH Puur&Eerlijk Dimbaar 6W	LED	25000	0.65	300	6	85	3000	230	Pear	E27	A++	24.99
67	LED Philips MasterLED SpotDimbaar 7w	LED	45000	0.5	180	7	85	2700	230	Reflector	GU10	A++	39.95
68	HALO Philips TwistLine 35w	Halogen	2000	0.35	165	35	100	3000	230	Reflector	GU10	D	3.50
69	HALO Philips TwistLine 50w	Halogen	2000	0.4	349	50	100	3000	230	Reflector	GU10	D	3.50
70	LED Philips LED Spot PerfectFit 3w	LED	22000	0.5	105	3	80	3000	230	Reflector	GU10	A++	39.95

Appendix E

Details of model parameters

E.1 Lamps — Gradually declining prices

Lamps are modelled with declining prices. To come up with a formula to model the declining cost of lamps, we use the formula for exponential decay. The results are shown in figure E.1

Exponential decay for the price P as a function of time t can be expressed as:

$$P(t) = P_0 e^{-t\lambda} = P_0 * e^{-t \ln 2 / t_{1/2}}$$

Here, λ is the decay constant and $t_{1/2}$ is the ‘half-price time’. With P_0 the price at the start of the simulation, $P(t_{1/2}) = \frac{1}{2} * P_0$.

We refine the equation to include a asymptote $p_{lim} = \text{€}0.25$ for the price different from zero, as follows:

$$P(t) = p_{lim} + (P_0 - p_{lim}) * e^{-t \ln 2 / t_{1/2}}$$

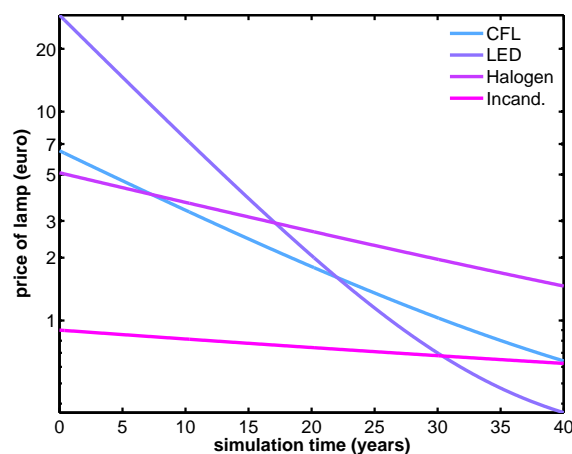


Figure E.1 – The gradually declining prices of lamps, visualised semi-logarithmic. The curves are computed averages per lamp-type.

To calculate the declining prices we assume the following half-price times:

lamp-type	Price half-time $t_{1/2}$
CFL	10
LED	5
Halogen	20
Incandescent	50

For LED lamps we have assumed a short half-price time: 5 years. LED replacement bulbs are just now starting to appear on the market, for a price that has been hovering around the € 20–30 range for a 40 W replacement bulb. This is a fairly high price, more expensive than the CFL ever was. Therefore, the price may go down rapidly as manufacturing is scaled up.

Since the invention of the red LED, the purchase price of a LED chip, in the dollars per unit of emitted red light, decreased at a rate of a factor of 10 per decade (U.S. Department of Energy, 2009, p. 33); see the red line in figure E.2. This historic price decrease is stronger than with our assumed half-price time of 5 years (factor of four decrease per decade). However, in our study we include the retail price of the complete lamp package, including electronics, and so on. It may be that we have been conservative with the estimate used in the study, but real long-term extrapolations are always uncertain. Furthermore, the price decline, in \$ per lumen of light, is made possible by advancements in luminous output. When fundamental physical limitations limit the further improvement of the luminous output per LED chip, price will decline less fast.

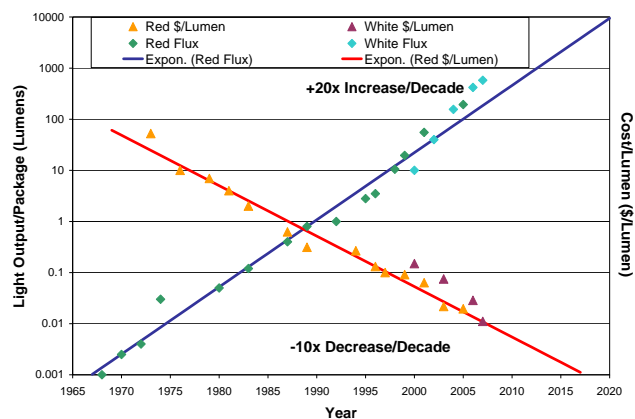


Figure E.2 – LED technology's historical progression (from U.S. Department of Energy, 2009, p. 33). The blue line shows the light output realised by a LED chip; the red line shows the price per unit of light.

For CFL's we have observed a gradual price decline in the last decades. In the simulation model, CFL's are modelled with an average price starting at over € 6. This leaves considerable room, realistically, to assume that prices will halve each decade. Again, as they will become more popular, and production numbers go up, prices will also come down.

The value for Halogen, 20 years, is put somewhat higher. The technology will become more popular as standard incandescent is phased out, but the possibilities for production process improvements are not as great as with CFL and LED, because Halogen can be considered an adapted version of a very well-established technology: incandescent.

Because standard incandescent glow-lamps have been in production in large quantities for the last 100+ years, possibilities for dramatic price decreases or not considered great. Therefore the long price half time of 50 years.

E.1.1 Subsidy for LED

Subsidy for LED was implemented as follows:

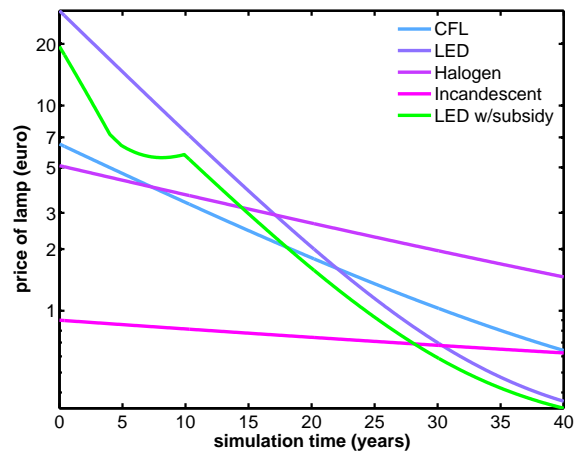


Figure E.3 – The gradually declining prices of lamps, visualised semi–logarithmic. The curves show the computed averages per lamp-type. The curve in green shows the price consequence of the subsidy for LED’s.

- For the first 5 years, give 33% subsidy on the retail purchase price of LED lamps.
- For the 5 years afterwards, linearly phase this subsidy out towards zero.
- The subsidy scheme does not only lower prices for consumers, it will have the effect to increase the demand for LED earlier on. Therefore the cost decline curve is shifted towards the left: the price of LED with subsidy P_{sub} , at time t , is equal to $P(t + 2)$ when no subsidy would have been given.

The development of the average cost of LED, with subsidy, is displayed in figure E.3, alongside the development without subsidy and the development of the other lamp types (vertical axis is on a logarithmic scale).

E.2 Lamps — Expected lifetime

The expected lifetime of a lamp is the cumulative total time that the lamp can usually be in operation before it fails. It is an important parameter in the simulation model.

There are two reasons why this lamp parameter is important in the simulation model. Firstly, when a lamp fails, a new lamp need to be bought as a replacement, so it is the start of a purchase decision. Secondly, if a bulb fails *prematurely* (‘a lot’ earlier than can be expected), this influences a household’s perception of that lamp, and possibly also of the brand and lamp technology type (see § 5.2.4).

To quantify the expected lifetime, two parameters are used: *lifetime* and *uncertainty*. We calculate for *each manufactured lamp* an initial lifetime based on a normal distribution characterised by a mean (=expected lifetime) and a standard deviation (=uncertainty). This gives all lamps in the simulation a unique lifetime.

An interesting property is that some lamps will have a negative expected lifetime. This is a consequence of using the normal distribution in calculating the expected lifetime: all values are possible. This is not unrealistic however: it means simply that some lamps are broken when purchased, which can happen to any product in real life.

The values used are displayed in table E.1, the rationale for the values chosen is discussed in sections E.2.2 and E.2.3.

Table E.1 – Overview of the parameters used for the expected lifetime and the uncertainty of the lifetime, for the different technology types

Technology type	Lifetime L_E [hours]	Uncertainty u [fraction of L_E]
Incandescent	1000	0.35–0.40
Halogen	2000	0.35–0.40
CFL	5,000–15,000	0.40–0.50
LED	10,000–45,000	0.50–0.65

E.2.1 Calculation

Each lamp gets a LifeTimeRemaining L_r , in burning-hours, during construction. This lifetime might even be negative, which means that the lamp is broken from the start. The lifetime is calculated by taking a number from a normal distribution.

A lamp has a expected lifetime L_E , specified in the ontology, see table E.1. The expected lifetime depends mainly on the lamp's technology type. From the range of values, for the CFL's a value of $L_E = 8,000$ is the most common, and for LED most lamps this is our estimation of $L_E = 25,000$ (see E.2.2).

The actual value of L_r at the manufacture of a lamp is calculated by selecting a number from a normal distribution, characterised by mean L_E and standard deviation $L_E * u$, where u is the uncertainty, also specified in the ontology.

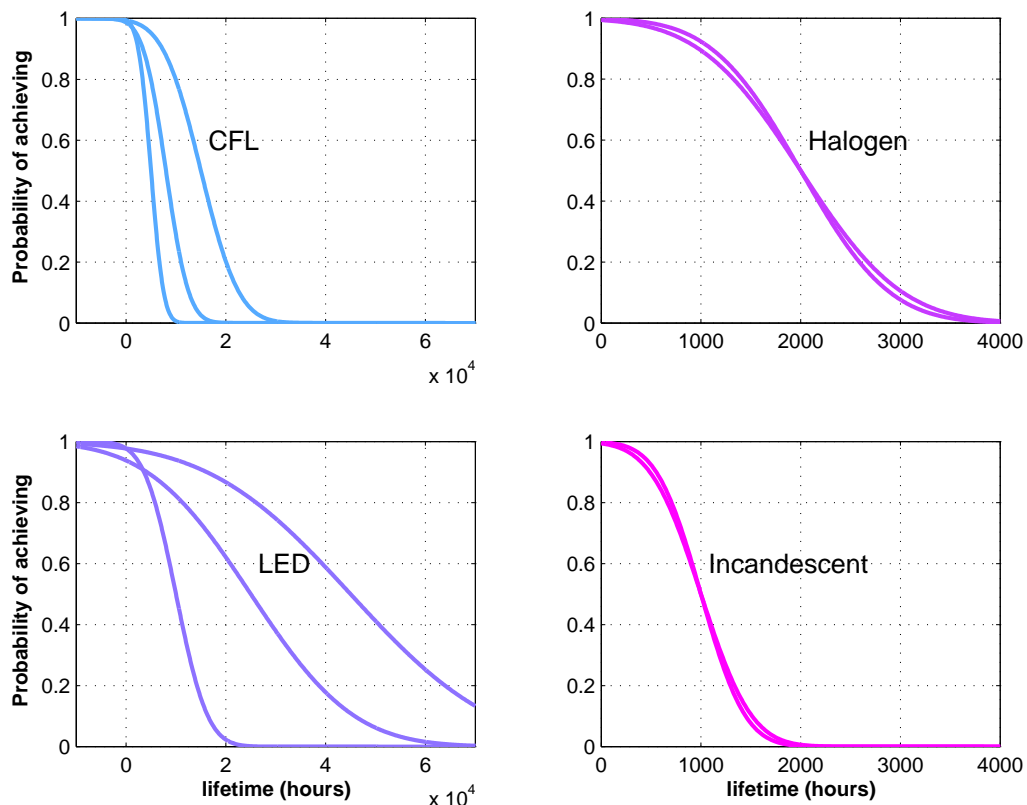


Figure E.4 – The probability that a lamp achieves a certain lifetime, plotted for different lamp-types. The values plotted correspond to the average values shown for each lamp-type in table E.1.

E.2.2 Values for the Expected Lifetime

The values used for the lifetime of a lamp were, where possible, taken from manufacturers' specifications: these values can typically be found on the packaging of the lamp product, and otherwise they could be found on manufacturer data sheets, web sites, etc. In the case of CFL and LED, manufacturers often use the longer lifetime in comparison to incandescent bulbs as a marketing message.

Generally, tungsten-filament incandescent light bulbs have a lifetime about 1000 hours, halogen lights 2000 hours, fluorescent lamps 8000 hours, and LED unparalleled 10.000 - 50.000 hours.

How manufacturers come up with their estimated life time figures is generally not clear. They should be calculated in accordance with some industry-agreed testing / quality assessment procedures, but independent supervision is not clear (there are a number of independent assessments, quality charters, voluntary schemes in which manufacturers can participate if they want to prove the quality of their products (see e.g. the E.U. CFL Quality Charter [CEC, 2005](#))). The values that can be found on LED products are extremely high and probably not realistic. See section [E.2.2](#) below.

Incandescent

The value of 1000 hours for incandescent lamps is a traditional value that is quite accurate and is the result of the conflicting demands of luminous efficiency and lifetime. A thinner filament design would burn hotter at the same drive current and voltage, and thus give more light, but would have a shorter lifetime. A thicker design has the opposite effect.

Halogen bulbs have a lifetime that is at least twice as long, as the addition of halogen gasses to the gas mix allows tungsten that evaporates from the filament during operation to be redeposited to the metal thread, which makes a longer lifetime possible, and at the same time allowing for higher operating temperatures of the filament and thus enhanced efficiency.

CFL

The lifetime of fluorescent light bulbs is determined for a large part by the electrodes, which become nonfunctional at some point due to degradation of materials. The lifetime is dependent on both the number of burning-hours and the number of start and stop cycles. If a CFL lamp is only used for extremely short durations, the lifetime is even reduced to the same order of magnitude of an ordinary incandescent lamp. This fact is relatively well-known, leading to recommendations of only using CFL's in light spots where the lamps will be used for some duration at a time. Compared to an incandescent light bulb, the CFL is more complicated technology-wise, as it has an electronic ballast that consists of a number of electronic components. Competitive pressures in the manufacture of CFL's drives down the budget for sourcing the electronics components. The consequence is that a proportion of lamps will fail after only being used for a short amount of time. This limits the lifetime of the CFL as well.

LED

The lifetime of the LED lamp is quoted as one crucial advantage of solid-state technology. Values of 50.000 hours are commonly put on the box. It is true that an individual LED chip can achieve really high lifetimes.

Values for lifetime of LED chips are derived through lumen degradation measurements in laboratory conditions, with precise control over factors like thermal management.

The actual lifetime is very much dependent on accurate controlling the operation of the LED chip itself (especially the temperature at the junction in the semiconductor, which in many cases may not exceed 125°C (Seoul Semiconductor Co., Ltd., 2005), but also operating parameters like drive currents are crucial).

Efficient as LED's may be, a lot of heat is still produced in a small area. A 10W LED lamp may only generate 2W of light, and 8W of heat (20% efficient, (Seoul Semiconductor Co., Ltd., 2005)). This heat needs to be removed if the LED needs to reach its lifetime. However, accurate control over thermal conditions in the LED chips in LED lamps is problematic for two reasons. Firstly, manufacturers can decide to not fully optimise the thermal management, pay exceeding amount of attention to the problem, because their expectation is that it is not necessary for them to reach the lifetime of 50,000 operating hours. Present generations of LED lamps will be replaced by more powerful and more efficient designs in a couple of years time, more advanced LED lamps that consume a less electricity but generate more and better light. Manufacturers can think that it is sufficient to last only 10,000 hours, even if the their lamp is marketed at a lifetime of 50,000 hours. Secondly, thermal issues cannot be expected to be controlled that well in many real life applications, and may severely shorten the LED's lifetime in (for example) secluded or recessed fixtures. This aspect of thermal control is outside of the manufacturer's sphere of influence.

Regarding the LED bulb 'as-a-system', as with the CFL, the bulb is more complex due to number of components can be made. Due to the weakest-link effect, this is expected to be a limiting factor for the lifetime of many LED bulbs. The complexity of a LED bulb is even greater than the CFL: the LED's require a precise control of drive currents, or otherwise they will be used outside their designed operating range and fail prematurely.

All of this leads us to presume that for a very large part, LED lamps in use by consumers, the LED lamps will not reach the 50,000 hour operating time.

E.2.3 Values for the Uncertainty of Lifetime

Also the uncertainty the lifetime is important. From a batch of lamps, not all samples will have the same lifetime due to small but significant differences in manufacture, and because of different usage. The uncertainty value is probably dependent on technology type and brand, with established technologies performing better (i.e. less uncertain), just as established brands/manufacturers¹.

Exact figures for uncertainty are not easily obtained however: in the public domain, no real hard statistics quantifying unreliability of lamps were found. Therefore assumptions have been made. In determining the values to use, it was guessed that the values chosen are reasonable. With an uncertainty (standard deviation) of 0.5, 2.3 % of lamps will be broken.

Incandescent/Halogen

These technologies are well established. Therefore we choose values of 0.35 for the uncertainty of the A-segment brands (Philips and Osram) and 0.40 for brands that aim for cost leadership (Massive, IKEA).

¹N.B. the actual lifetime of a bulb is also influenced by many other factors: environmental factors, usage characteristics, numbers of power off/on cycles, et cetera. None of these was incorporated in the simulation model, they are not accounted for.

CFL

We chose a value of 0.40 for the A- brands (Philips, Osram) and 0.50 for the other brands. There is some confusion over the causes for premature failure, but generally speaking the cheaper a product, the more important the cost-cutting during manufacture, causing a larger number of defective products in a sample.

LED

We included a limited sample of LED products, from Philips, Osram, Lemnis and Albert-Heijn. Lemnis Lighting is a younger and smaller company, who is now entering the consumer LED bulb market and apparently also supplies Albert-Heijn. Lemnis (Albert-Heijn) and the included Osram products are directed at consumers. These products quote high lifetimes and are ambitious in energy efficiency. Philips' 'Master LED' products are mainly aimed at the business/service sector, are somewhat more expensive and somewhat less ambitious in energy efficiency than competitors. But for these reason we consider Philips' quoted figures for lifetime as more reliable. Philip's LED lifetime values were given a lower uncertainty of 0.50, and as a mean we use Philips values. Osram (also a technology leader) was given a higher uncertainty of 0.55 (due to lower price) and Lemnis an uncertainty of 0.65. We halved the quoted figures for the lifetime of Lemnis and Osram's consumer products.

E.3 Household — Number of luminaires

The number of luminaires per household was computed from a survey of 600 Delft citizens, conducted in the autumn of 2008 in Delft. This data was collected as a second year-project by students Technische Bestuurskunde who interviewed the consumers. The students asked questions on the amount of lamps the respondents have, we equate these values to their numbers of luminaires.

In the data set, the household with the lowest amount of lamps had 5 lamps (quite a small number, meaning this figure is probably about a student) and the household with the largest number of lamps had 101 lamps / light bulbs (quite large number, perhaps representative of a larger canal house with chandeliers and many lights).

Data from other scholars (see survey by [Bartlett, 1993](#)) seem to indicate that households typically average around 20-30 lamps per household. The average number is higher for single family dwellings, lower for multi family dwellings, and still lower for 1-room dwellings.

A triangular distribution with parameters as in eq. [E.1](#) seems to be reasonable to capture the distribution of lamps in the sample.

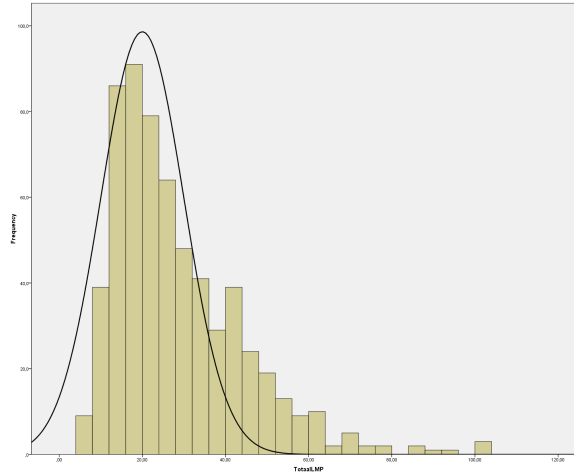
$$\begin{aligned} a &= 5 \\ b &= 20 \\ c &= 65 \end{aligned} \tag{E.1}$$

The expected value E of this distribution needs to equal the average number of lamps per household. E is calculated as follows:

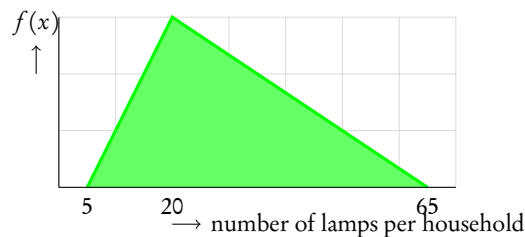
$$E = \frac{a + b + c}{3} \tag{E.2}$$

With the above parameters, the average number of lamps becomes $E = 30$. This is quite reasonable, given the value of 25 from [Bartlett \(1993\)](#) and 40 from [Bertoldi and Atanasiu](#)

(2006). Of course, we may also choose a different distribution, e.g. an uniform distribution. But, as can be seen by in figure E.5 comparing the subfigures (a) and (b), a triangular distribution offers a reasonably good fit to the data, better than if a uniform distribution were used. If a uniform distribution were chosen, it would have to be symmetrical around the same mean $E = 30$.



(a) Frequency of households with the number of lamps as specified in the x-categories, the observed frequency vertically. (The x-axis range is approximately -5–125; y-axis 0–105)



(b) Triangular distribution.

Figure E.5 – Distribution of the number of lamps per household. (a) shows data from the Delft population. The histogram shows the frequency of households with specified number of lamps (x-categories). The smooth line is a normal distribution with $\mu = 28$ and $\sigma = 15.8$. $N = 618$, plotted to show the skewness of the observed distribution. (b) shows the triangular probability density function for the number of lamps per household, with parameters $a = 5$, $b = 20$ and $c = 65$. The mean $E = 30$.

Azevedo et al. (2009) model the number of lamps per household also with triangular distributions. Based on data from a 2001 survey into energy consumption from USA residents, they model the number of lamps per household with separate distributions for CFL and incandescent, as follows:

Incandescent		CFL	
a	$= 0$	a	$= 0$
b	$= 37$	b	$= 6$
c	$= 80$	c	$= 15$

The total number of lamps per household is higher in this case, the combined mean will be the sum of the means: $E = \frac{0+37+80}{3} + \frac{0+6+15}{3} = 46$. Azevedo et al. truly make a distinction between light-bulbs and fixtures, and the numbers given are for light-bulbs. The studies

on Delft citizens, as well from Bartlett and from Bertoldi are vague about this distinction, therefore it is not completely clear what is meant by lamp. which means that implicitly it is assumed that a one fixture equals one light bulb (which is not the case!). For simplicity, we follow this assumption in the first model version, and don't use the numbers from Azevedo et al.

E.4 Household — Duration of lamp use per week

The duration of lamp use is an important factor influencing a household's electricity usage.

Wall and Crosbie (2009) did a study of illuminance data from 18 UK households during 1-week periods in the spring of 2007. The authors of the study wanted to establish when luminaires were used and calculate the electricity consumed for lighting (Wall and Crosbie, 2009). The adapted data is given in table E.2.

We assume that the data on the number of burning hours per lamp per week is assumed to follow a triangular distribution.

The hours lamps are used per day or week is a crucial variable in determining the cost-effectiveness of lighting stimulus programs. However the values that can be derived from different studies are hard to compare (Vine and Fielding, 2006), who did an elaborate desk study evaluating a large number of studies in which the hours-of-use, per day, of a CFL was used. There are quite a lot of differences between the studies, but the average value for the hours-of-use of a CFL seems to lie in the range 2.0–3.0 (for the studies done usage monitoring). This would translate to weekly figures greater than used in the model (14–21 hours per week). Most households would place their CFL's at the locations in the house where they will be used the most, thus maximising the energy savings from the use of the CFL's.

A triangular distribution with parameters values of $a = 2$, $b = 10$ and $c = 30$ gives a reasonable starting amount of electricity consumed for residential lighting. These values are a lot higher than the values derived from Wall and Crosbie.

The duration of the hours of use of different luminaires in the different lighting spots inside the house is varied: on some locations (living room, kitchen), the duration is longer. See section E.5

(add)

Table E.2 – Frequency of households with average lamp duration as specified in the leftmost column (adapted from Wall and Crosbie, 2009).

hours per week	number of households
[0 – 2]	1
[2 – 4]	6
[4 – 6]	3
[6 – 8]	1
[8 – 10]	2
[10 – 12]	1
[12 – 14]	1
[14 – 16]	0
[16–]	1

A different way a figure may be obtained for the hours of use of household lamps, that is more tailored to the Netherlands, is by looking at the number of lamps and the average household electricity consumption for lighting. The average number of lamps per Dutch household N was 24.5 in 1987.² and the average lighting electricity consumption $E = 498$ kWh/year (Wajer and Kemna, 1991). With assumptions that the average lamp is $P = 45$ W Bartlett (1993), and $d = 300$ the number of days per year that people are home and lighting is used, then the following relation holds for E :

$$E = \sum_d N * P * T_d \simeq 498 \text{ kWh per household per year,} \quad (\text{E.3})$$

where t is the average number of hours a lamp burns per day. The above may be written for T_d :

$$T_d = \frac{E}{d * N * P} \simeq 1.51 \text{ hour per day} \quad (\text{E.4})$$

Thus we see that an average number of burning hours can be derived. Weekly this becomes $T_w \simeq 10.5$. The average value of the triangular distribution used ($a = 1$, $b = 3$, $c = 16$), is equal to $(a + b + c)/3 \simeq 6.67$. So the derived average is higher the value used in the simulation model. This needs to be investigated further. Part of it is offset by the higher number of lamps assumed in the simulation (section E.3), but as of yet the results for the electricity usage per household in the simulation model will lower than in reality.

E.5 Household — Luminaire locations

The distribution of the luminaires over the locations in the house is calculated from data on Delft citizens.

Luminaires are assigned locations in the house making use of the percentages displayed in table E.3.

Table E.3 – Luminaires locations

Part of a house	Perc. of luminaires
Living area	30.1%
Kitchen	13.3%
WC & Bathroom	12.1%
Sleeping room(s)	21.9%
Study / Hobby room	6.8%
Hallway / Corridor(s)	10.8%
Miscellaneous	5.0 %

The luminaire locations are a determining factor in the hours of use of a luminaire.

Bartlett (1993), presents an analysis of lighting data on residential consumers from an number of E.U. countries. The data may be somewhat old, but in the composition of a typical house (number of light-hours etc) the changes since then are arguably not that big. From this source, we derive that lamps in living; dining; and kitchen areas burn $\sim 30\%$ longer than lamps in sleeping areas; stairs and hallways; bathroom; garage; and other rooms. See table 5.1 in § 5.1.2.

²The number of lamps per household is dependant on the number of rooms in the dwelling. An apartment with only one room has 12 lamps; a single family dwelling with more than five rooms has 32 lamps (Wajer and Kemna, 1991).

Appendix F

Implementing validation testing of household's lamps purchase

The experimental setup developed in § 6.4 consists of the execution of a great number of experiments. In this appendix, the approach of how these experiments are executed is detailed.

The experimental setup of table 6.2 (p. 68), for convenience reprinted below (table F.1), consists of 26 parameters, which can have either three or two values. Each experiment is given such a set of 26 input parameters. In 'validation-testing mode', each experiment result in an ID number for the selected lamp-model¹, which is added as a 27th column to the matrix. The results in an experimental matrix consisting of 10,392,624 rows and 27 columns, posing some memory problems, see § F.3.1.

Table F.1 – Parameters varied in experimental setup for the testing of the purchase of lamps. The rightmost column displays the cumulative number of experiments, which results from the cumulative multiplication of the number of experiments per parameter to vary.

<i>Parameter to vary</i>	<i>Experiment</i>	<i>Nr. experiments</i>
preference light colour	2400 – 2700 – 3100	3
preference light output	400 – 700 – 1110	9
weight factor price	0 – 1 – 5	27
weight factor efficiency	0 – 1 – 5	81
weight factor life time	0 – 1 – 5	243
weight factor prf. light colour	0 – 1 – 5	729
weight factor prf. CRI	0 – 1 – 5	2,187
weight factor prf. light	0 – 1 – 5	6,561
weight factor perc. lamp-type	0 – 1 – 5	19,683
lamp-type perception CFL	0 – 1	39,366
lamp-type perception LED	0 – 1	78,732
lamp-type perception Halogen	0 – 1	157,464
lamp-type perception Incand.	0 – 1	314,928
weight factor perc. brand	0 – 1 – 5	944,784
brand perception (x 11)	0 – 1	10,392,624

F.1 Computing input matrix

The input-matrix was computed using MATLAB scripts.

¹These are displayed in table D.1, appendix D

To speed up execution, the input-matrix was split up into 8 pieces of 1,3 million rows. Manually 8 instances of MATLAB were started up on some nodes of the high performance computing cluster to execute a part of the input matrix. This way computation could be done in parallel and memory usage and total time was limited. Each instance took 45 minutes of time to complete its experiments, so total computing power needed for this experiment was about 6 hours².

The resulting tables were saved, concatenated into a results file, which are processed in a data analysis package, for which a choice has to be made.

F.2 Choice of data analysis package

In starting to use a program to analyse the results of the above detailed experimental setups, one has to invest effort into getting things to work, even with software that one is familiar with, like MS Excel. During my studies I already had used, among others, Excel, SPSS and MATLAB³. Each data analysis application has its own strength, weaknesses, and limitations. Personal observations on these are in table F.2; see also Connor (2009).

Table F.2 – Advantages and Disadvantages of some data analysis tools

<i>Software</i>	<i>Advantages</i>	<i>Disadvantages</i>
Excel	Graphing	Limit on number of rows, unreliable with large data sets
SPSS	Robust and easy generation of statistics	No command line, poor scripting.
MATLAB	Fast computation, distributed computation, good scripting possibilities.	Memory requirements with large data sets

Excel is software that is surprisingly versatile. It is quick, has a very polished user interface, and offers scripting and programmability. Time to develop models and perform calculations is really short if one knows how to use the software. However, for processing large data sets it unfortunately still lacks. Previous versions had low limits of around 65k rows, the current version is a big improvement, increasing the number of rows allowed to one million. However this limit is still a problem for the experimental setup detailed above, and it is unsure if all computations and functions work properly with these large Excel files.

SPSS can handle large data sets easily, it is smart to only load the parts of the file in memory that it needs. This makes SPSS well-suited to work with large data sets. However SPSS is lacking in graphing and scripting possibilities. SPSS has un-elegant scripting that is hard to work with⁴. SPSS is very much focussed on statistics, but we will not be generating many: in this experimental setup, the outcomes are nominal numbers, of which we are mainly interested in the frequency of occurrence.

MATLAB is a robust computational platform strong in working with matrices and arrays. It is not so much focussed on statistics as SPSS. MATLAB is versatile enough to perform the computations and create the graphs we need, and all this can be scripted. Another

²Using a previous run with 7.8 million experiments (25 % less) and double precision floats, computational time was $7\frac{1}{2}$ hours (25 % longer). This shows the importance of reducing data load and thinking about optimising code where possible: large savings can be made.

³Excel was used intensively in many study-projects at TBM; SPSS was used in some TBM courses involving statistics; MATLAB wasn't used at TBM but I had used it for an elective course at the L&R faculty

⁴The syntax of SPSS .SBS style files seems awkward, and is hard to get used to if one also works with programming languages such as Java and scripting languages such as UNIX shell, DOS, and MATLAB at the same time.

advantage is that MATLAB also runs on Linux and is installed on the cluster, and it can distribute large arrays into smaller pieces and execute computation on them in local or distributed separate worker processes. This can greatly speed up computation on multi-core machines. These capabilities mean that the choice was made for MATLAB.

All computational tools can use data from a SQL database, either using ODBC (MS Excel), or some other method. If data were to be loaded into an SQL database, Excel's row count limit may be circumvented. SQL technology was not used at this stage.

F.3 Generating the results graphs with MATLAB

As results, we generate a series of pie charts, as follows.

- The most frequently selected **lamp-models**, in all of the 10,392,624 experiments.
- For each criterium varied, if only one criterium is relevant, which **lamp-model** is then the most frequently selected lamp-model (8 charts).
- For each criterium varied, if only one criterium is relevant, which **lamp-type** is most frequently selected (from all lamp-model outcomes) (8 charts).
- If all criteria are relevant, **except one** of all the varied criteria, which **lamp-model** is then the most frequently selected lamp-model (8 charts).
- If all criteria are relevant, **except one** of all the varied criteria, which **lamp-type** is most frequently selected (from all lamp-model outcomes) (8 charts).

The charts are shown in § 6.5, pp. 67–77

These charts were generated by processing the results data file in MATLAB:

- (1.) For lamp-model pie charts, count the occurrences of each lamp-model selected
- (2.) Alternatively, for lamp-type charts, get the lamp-type of each lamp-model outcome and count that one
- (3.) Sort and rank the occurrences
- (4.) Plot and annotate the pie chart

After this the pie charts were saved to vector-based PDF and cropped.

Algorithm for counting lamp-models:

```
results = get column 'results' of 'data table'
frequencies = new column vector(70,1)    % for 70 lamps

for all rows of results:
    idValue = row value
    frequencies(idValue) = frequencies(idValue) + 1;
end
```

Pseudocode 3 – Counting lamp-models algorithm in one pass

F.3.1 Overcoming memory issues with MATLAB

Working with the input matrix posed some memory issues.

MATLAB computes with its data in RAM, and when loading a data file, it allocates the full amount theoretically needed for the array, and it needs a sequential (non-fragmented) part of RAM memory for this. This limits the amount of usable memory, e.g. to about 500-1200 MB for my 32-bit Windows system, depending on other programs running and how MATLAB is started up (without Java etc).

When each cell of the matrix is stored as a floating point double (8 bytes), then the resulting table needs about 2 GB of RAM to be loaded by MATLAB:

$$8 * 10.4 * 10^6 * 27 = 2.25 * 10^9 \simeq 2.1 \text{ GB}$$

This turns out to be beyond the capabilities of my 32-bit Windows Vista system with only 2 GB of RAM. The Linux computers of the HPC, with 16 GB each, were able handle this, so the experiments were performed on Linux. By conversion of the values to 2-byte signed integers, where 16 bits are used per field (allowing for values of -32,768 to 32,767) the memory requirement were reduced to 535 MB, which would also be manageable on a 32-bit system.

Troublesome is that, apart from optimising the data set as done above, it was found that MATLAB memory issues are not easily overcome. Adding memory to a 32-bit computer cannot solve the limit as processes limited at 2 GB size. Therefore a switch to a 64-bit operating system would be advantageous and recommended for anyone doing work like this in the future.

Appendix G

Power factor of modern efficient lighting

G.1 Power factor

The ‘power factor’ PF is a dimensionless figure for the ratio between the real power P used by a device (measured in Watt), and the apparent power S (measured in Volt*Amperè, or VA), the power apparently taken from the electricity grid in order for the device to function.

$$PF = \frac{P}{S}$$

Lamps such as CFL and LED are inherently not suitable to be dimmed with a traditional incandescent lamp dimmer that works with *phase cut* or *pulse width* modulation. The electronic circuitry will not function properly, and in the CFL or LED will not burn, flicker, and possibly also fail.

CFL and LED lamps can be made to work on traditional dimmers by a clever design of the electronic transformer and/or ballasts the lamp, at a cost. The disadvantage is that, in these cases, the *power factor* is lowered (discussion at [Olino, 2009a](#)).

For the ‘Lemnis Pharox 300’ dimmable LED lamp, of $P = 6\text{W}$ input power, I measured a $PF \sim 0.20$ when it was connected to a luminaire equipped with a cord dimmer. The power factor remained ~ 0.20 whether the lamp was in a dimmed state, or the dimmer was in the ‘full-on’ position.¹

Ideally, a lamp would have a power factor of $PF = 1.0$. In this ideal case, the apparent power would equal the real power, and conversion / transmission losses would be minimised.

At lower values of the power factor, more apparent power needs to be transferred to get the same real power. To get 6 W of real power at 0.20 power factor, $S = P/PF \simeq 30$ VA of apparent power needs to be produced and transmitted through the transmission/distribution system. Only the real power is converted into light and heat, but the full apparent power needs to be generated and transmitted, where it is subject to the usual distributed losses in the production and transmission processes ([Wikipedia, 2009](#)).

The effects of the low power factor will be mainly felt by distribution network operators.

G.2 Current demands

Apart from the power factor of modern lighting, high apparent power requirements can also result from the high current demands that can occur. Especially when modern, effi-

¹Without a dimmer, this lamp’s power factor is 0.50 ([Olino, 2009a](#)).

cient lamps are made to be backwards compatible with a conventional incandescent lamp dimmer, peak inrush currents can become quite high for some lamps, e.g. reportedly up to 2 Ampère; equal to 460W incandescent (discussion at [Olino, 2009a](#)).

The combined effects of the high apparent power requirements and the peak current demand mean that, when many of these or similar lamps would be used, network constraints can be experienced that lower the efficiency of the lamps in the entire electrical system.

Appendix H

Results of the first version of the simulation model

A good approach to the development of a simulation model is to first develop a simple version of the model that captures only a few important aspects from the real world, and then to expand that model to include more concepts from the real system in the simulation model.

So first a first version of the model was developed that is the most simple, minimal design that captures all components. This model was subsequently run to test the key assumptions, sensitivities to the main input parameters and so on. Results from the first version of the simulation model are presented in this appendix for reasons of completeness.

H.1 First model: "Rational agent; Fashion-sensitive agent; Access to complete information"

This first version of the model involves a number of consumers (households), a manufacturer of lamps and *two types of lamps*: an *incandescent* and a *compact fluorescent lamp*. The households have a certain number of lamps (assigned randomly from a triangular distribution from Delft citizen's data, § E.3), and have a certain behaviour in the sense that the lamps are all used a specific duration per week.

The lamps have a couple of properties, of which lifetime and electricity input are the most important. During the manufacture of a lamp, lifetime is assigned a random value, based on a lamp technology dependent interval (§ E.2).

Each simulation step, lamps age. After expiration of the preassigned lifetime, the lamp stops functioning, and a household needs to purchase a new lamp.

In the beginning of the simulation, the household already possesses a number of lamps. An agent is given a specific percentage of the number of lamps it requires as a CFL, and the rest as incandescent lamps. This percentage varies between households because it is a random value, chosen from a uniform distribution with lower and upper boundaries. These two boundary parameters are very interesting to experiment with. Some interesting switch-over behaviour is displayed if the fraction of CFL's is from the interval $[10 - -30]\%$.

A decision on which lamp to buy is made using multi-criteria analysis. This decision resolves around three aspects, which are the **criteria**, see also § 5.3.2:

- What is the purchase price of the lamp (*price criterion*)
- What is the efficiency of the lamp (this is a proxy for running / operating costs, environmental performance) (*efficiency criterion*)
- How many of the neighbours are adopters of the technology type (CFL/Incandescent). Relatives' / friends' choices for lamps influence a consumer to have a preference for the same lamp (*normative influence criterion*)

The third aspect means that, if enabled, agents tend to mimic what other agents do. So this is a '*fashion*'-element.

The model is called a "*complete information*" model, because the consumer has perfect information on price, efficiency, and what kinds of lamps the neighbours have; the model does not deal with information asymmetry or illiteracy on lamp technology aspects. In this version of the model, the household doesn't have preferences, perceptions nor memory of results from past lamps.

The criteria above differ in how important they are to different consumers. Therefore, *weight factors* are attached to the criteria. These weight factors are very interesting to experiment with. Interesting behaviour is displayed by, for example, the following weight factors:

$$\begin{aligned} w f_{\text{efficiency}} &= 2.0 \\ w f_{\text{normative influence}} &= 1.0 \\ w f_{\text{price}} &= 1.0 \end{aligned} \tag{H.1}$$

The lamps are sold at a place called "the manufacturer", which creates the lamps and sells them. There is only one manufacturer/store. The sale transaction resolves around deciding which of the lamps offer the highest score, taking into account the three criteria mentioned above.

A lamp is created by the manufacturer the moment the sale transaction takes place. During the sale transaction, money exchanges between the household and the manufacturer. Because the household agents spend money on lamps and have no income, if their starting budget is set too low, they run out of money and can't buy any lamps anymore. Therefore, they are given a high starting budget of 10000 euro, sufficient for the entire simulation run.

H.2 Results

H.2.1 Influence of the number of households

The simulation seems sensitive to the number of households. If this number is too little, then different changeover behaviour takes place.

The following two simulation runs show the results of increasing the number of households, from 12 to 800. The runs display a switch-over to a new stable situation. The first is for 12 households, the second for 50 households and the third for 800 households. The settings are:

$$\begin{aligned} w f_{\text{efficiency}} &= 2.0 \\ w f_{\text{normative influence}} &= 1.0 \\ w f_{\text{price}} &= 1.0 \\ \text{rand}_{w f} &= (0.5 - 1.5) \\ \text{rand}_{\text{CFL}} &= (0.1 - 0.3) \end{aligned} \tag{H.2}$$

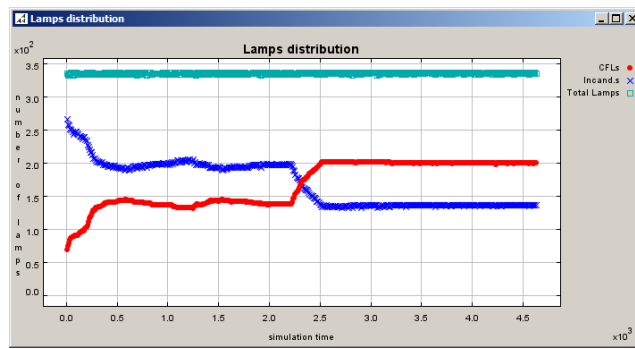
The simulation results are displayed in figure H.1. The figure shows the total number of lamps in the simulation, and those of the CFL type and the incandescent type.

What one observes is that, when the number of households increases from sub figure (a) to (c), this has the effect of making the ‘switch over’ to CFL’s happen *earlier and quicker*. Also the apparently stable situation is reached sooner, and the number of CFL’s that are in use in that stable situation is, as a percentage, also higher.

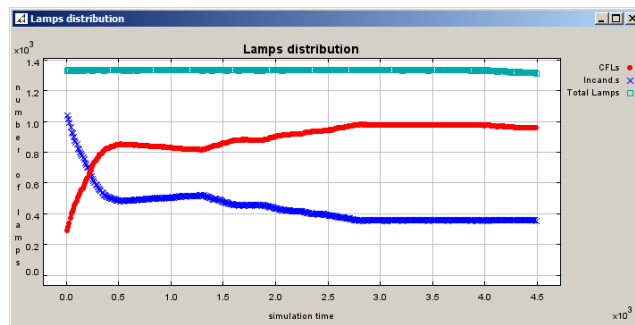
Therefore, one has to conclude that the number of agents must not be taken too small.

Note that the decline in total lamps, which may be observed after 4000 simulation ticks, is due to some households running out of money. This can be averted by giving the households a higher starting budget.

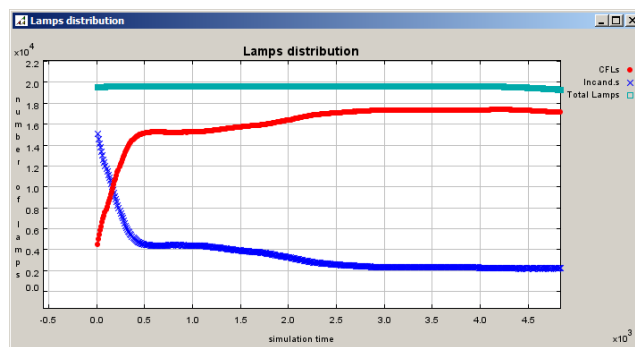
Note: the graphs shows the result of a single run. As described above, the distribution of CFL’s per household is made dependent on the pseudo-random distributions. The pseudo-random distributions employ a random seed, which was not varied in these runs. If a different random seed is chosen differently, then the patterns are (somewhat) different.



(a) Simulation result for 12 households



(b) Simulation result for 50 households



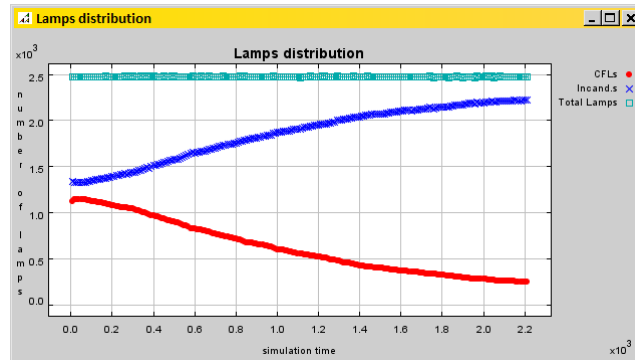
(c) Simulation result for 800 households

Figure H.1 – Influence of the number of households

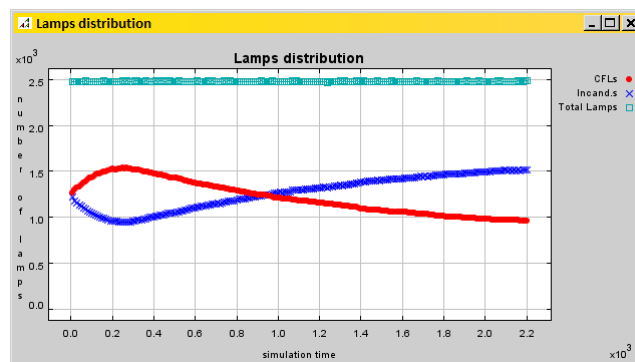
H.2.2 Influence of the initial fraction of CFL lamps

The three runs depicted in figure H.2 show the effect of changing the initial numbers of CFL lamps the households have. The settings are the same as in the previous section (H.2.1), except that we now fix the number of households ($N_{hh} = 100$), and alter the initial fraction of CFL's. Also, the efficiency weightfactor was lowered, $w_{efficiency} = 1.0$.

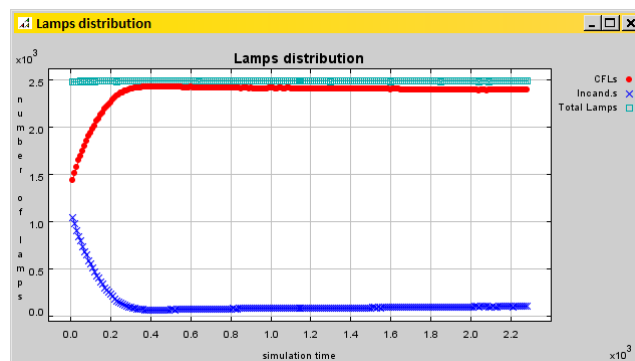
It turns out that, with the above settings, the model is extremely sensitive to the initial distribution of CFLs. This is due to the normative influence criterion. Once sufficient neighbours adopt a CFL, the switch over rate accelerates.



(a) Simulation result for 100 households, start CFL fraction between 30–60 %



(b) Simulation result for 100 households, start CFL fraction between 40–60 %



(c) Simulation result for 100 households, start CFL fraction between 40–70 %

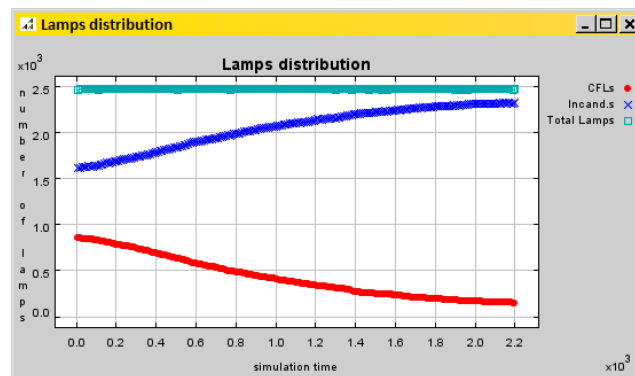
Figure H.2 – Influence of the initial fraction of CFL lamps

H.2.3 Other results from this model version

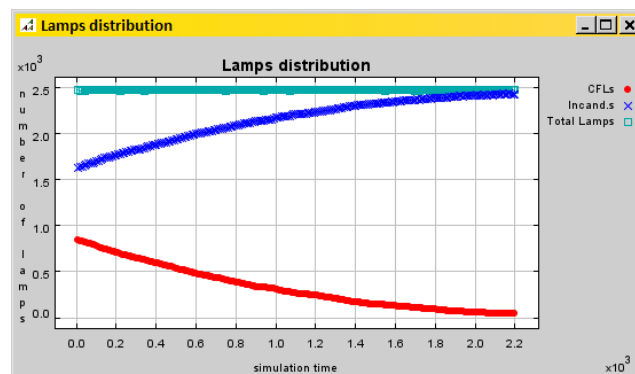
Some other results from this model version:

The normative influence criterion has the effect of making the alternative that is currently higher in market share, more favourite. See the results in figure H.3. Settings used were:

$$\begin{aligned}
 w_{\text{efficiency}} &= 1.0 \\
 w_{\text{normative influence}} &= 0.0/2.0 \\
 w_{\text{price}} &= 4.0 \\
 \text{rand}_{w_f} &= (0.5 - 1.5) \\
 \text{rand}_{\text{CFL}} &= (0.3 - 0.4)
 \end{aligned}
 \tag{H.3}$$



(a) Simulation result for 100 households, without normative influence ($w_f=0$)



(b) Simulation result for 100 households, with normative influence ($w_f=2$)

Figure H.3 – Effect of the normative influence weight factor

Some other remarks:

- Without normative influence ($w_{\text{normative influence}} = 0$), the model behaves especially sensitive to the criteria weight factors.
- In general, the model ought to behave sensitive to weigh factors, which is found to be true. The model also behaves sensitive to the range an individual's weightfactors are allowed to be randomised.
- As of yet, it is remarkable that results such as depicted in figure H.4 occur. The market share of CFL's starts to first starts to rise, and then fall, all this with the normative influence criterion switched off. It is not yet understood why this is the case. Settings in eq. H.4.

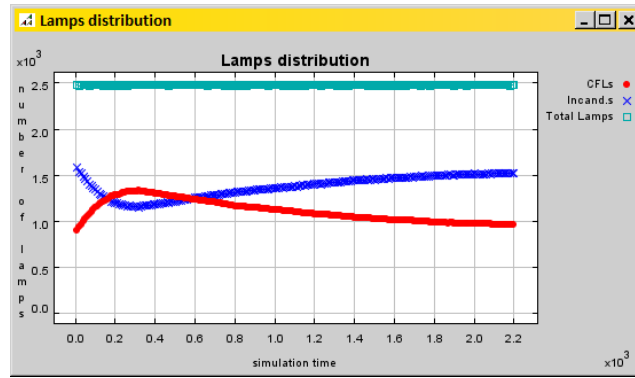


Figure H.4 – With the efficiency and price criteria balanced to an extent, the CFL's market share starts to rise, and then fall. Without normative influence.

$$\begin{aligned}
 w_{\text{efficiency}} &= 4.0 \\
 w_{\text{normative influence}} &= 0.0 \\
 w_{\text{price}} &= 5.0 \\
 \text{rand}_{w_f} &= (0.1 - 1.9) \\
 \text{rand}_{\text{CFL}} &= (0.3 - 0.4) \\
 N_{hh} &= 100
 \end{aligned}
 \tag{H.4}$$

Bibliography

- Azevedo, I., Morgan, M., and Morgan, F. (2009). The transition to solid-state lighting. *Proceedings of the IEEE*, 97(3):481–510.
- Barabási, A. b., Jeong, H., Néda, Z. b. c., Ravasz, E., Schubert, A., and Vicsek, T. e. (2002). Evolution of the social network of scientific collaborations. *Physica A: Statistical Mechanics and its Applications*, 311(3-4):590–614.
- Barabási, A.-L. and Albert, R. (1999). Emergence of scaling in random networks. *Science*, 286(5439):509–512.
- Bartlett, S. (1993). Shedding light on residential consumers. *Energy*, 18(2):171–183.
- Bedford, M. (2009). Why computers suck at maths—how simple calculations can be a matter of life and death. Website. Accessed October 31, 2009. Last viewed January 12, 2010. Available from: <http://www.techradar.com/news/computing/why-computers-suck-at-maths-644771>.
- Bertoldi, P. and Atanasiu, B. (2006). Residential lighting consumption and saving potential in the enlarged EU. In *Proceedings of EEDAL'06 Conference, London, UK, 21-23.06.2006*. European Commission, Institute for Energy. Available from: <http://re.jrc.ec.europa.eu/energyefficiency/>.
- Bruning, J. (2007). Optical lithography... 40 years and holding. *Proceedings of SPIE - The International Society for Optical Engineering*, 6520(PART 1).
- Calwell, C. and Granda, C. (1999). Halogen torchiere market transformation: A look at progress to date and future strategies. Technical report, Prepared for the Natural Resources Defense Council (NRDC). Available from: http://www.iaeel.org/iaeel/Archive/Downloads/US_torchiere_paper.doc.
- Calwell, C. and Mills, E. (1997). Halogen torchieres: A look at market transformation in progress. *IAEEL Right Light 4 Conference. Proceedings.*, pages 41–47.
- Cather, H. (1992). Using SIMAN in simulating manufacturing systems. In *Discrete Event Dynamic Systems - A New Generation of Modelling, Simulation and Control Applications, IEE Colloquium on*, pages 5/1–5/3.
- CBS (2009). Gemiddeld inkomen; particuliere huishoudens naar diverse kenmerken. Electronic data. Available from: <http://statline.cbs.nl/StatWeb/publication/?DM=SLNL&PA=70843ned&D1=a&D2=0&D3=0&D4=a&HDR=G1,G2,G3&STB=T&VW=T>.
- CEC (1998). Commission Directive 98/11/EC of 27 January 1998 implementing Council Directive 92/75/EEC with regard to energy labelling of household lamps. *Official Journal of the European Union*, L 71:1–8. Available from: <http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:1998:071:0001:0008:EN:PDF>.
- CEC (2005). European compact fluorescent lamps quality charter. Technical report, European Commission.
- CEC (2009a). Commission adopts two regulations to progressively remove from the market non-efficient light bulbs. Memo, 18 March 2009. Available from: <http://europa.eu/rapid/pressReleasesAction.do?reference=IP/09/411>.

- CEC (2009b). Commission Regulation (EC) No 244/2009 of 18 March 2009 implementing Directive 2005/32/EC of the European Parliament and of the Council with regard to ecodesign requirements for non-directional household lamps. *Official Journal of the European Union*, L076:3–16.
- CEC (2009c). Commission Regulation (EC) No 245/2009 of 18 March 2009 implementing Directive 2005/32/EC of the European Parliament and of the Council with regard to ecodesign requirements for fluorescent lamps without integrated ballast, for high intensity discharge lamps, and for ballasts and luminaires able to operate such lamps, and repealing Directive 2000/55/EC of the European Parliament and of the Council. *Official Journal of the European Union*, L076:17–44.
- CEC (2009d). FAQ: phasing out conventional incandescent bulbs. Memo, 1 September 2009. Available from: <http://europa.eu/rapid/pressReleasesAction.do?reference=MEMO/09/368>.
- CEC (2009e). Frequently asked questions about the regulation on ecodesign requirements for non-directional household lamps. Memo, 18 March 2009. Available from: <http://europa.eu/rapid/pressReleasesAction.do?reference=MEMO/09/113>.
- Chappin, E. J. L. and Dijkema, G. P. J. (2008a). Agent-based modeling of energy infrastructure transitions. In *International Conference on Infrastructure Systems - Building Networks for a Brighter Future*, Rotterdam, The Netherlands. NGInfra.
- Chappin, E. J. L. and Dijkema, G. P. J. (2008b). On the design of system transitions - is transition management in the energy domain feasible? In *IEEE IEMC: International Engineering Management Conference*, Estoril, Portugal. IEEE.
- Chappin, E. J. L. and Dijkema, G. P. J. (2008c). Towards the assessment of policy impacts on system transitions in energy. In *31st IAEE International Conference, Bridging Energy Supply and Demand: Logistics, Competition and Environment*, Istanbul, Turkey. IAEE.
- Chappin, E. J. L. and Dijkema, G. P. J. (2010). Agent-based modeling of energy infrastructure transitions. *International Journal of Critical Infrastructures*, 6(2):106–130.
- Chappin, E. J. L., Dijkema, G. P. J., Dam, K. H. v., and Lukszo, Z. (2007). Modeling strategic and operational decision-making - an agent-based model of electricity producers. In Sklenar, J., Tanguy, A., Bertelle, C., and Fortino, G., editors, *The 2007 European Simulation and Modelling Conference*, St. Julians, Malta. Eurosis.
- Chen, A. (1997). Alternative to energy-hogging halogen torchieres invented here. Berkeley Lab Research News, website. Available from: <http://www.lbl.gov/Science-Articles/Archive/fluorescent-torchiere.html>.
- Chiong Meza, C. M. and Chappin, E. J. L. (2008). Modelling energy infrastructures: Where transition theory meets agent-based modelling. In *5th Conference of The European Social Simulation Association*, Brescia, Italy. ESSA.
- Connor, B. O. (2009). Comparison of data analysis packages: R, Matlab, SciPy, Excel, SAS, SPSS, Stata. Website. Accessed: November 16, 2009. Available from: <http://anyall.org/blog/2009/02/comparison-of-data-analysis-packages-r-matlab-scipy-excel-sas-spss-stata/>.
- Crosbie, T., Stokes, M., and Guy, S. (2008). Illuminating household energy demand and the policies for its reduction. *Energy and Environment*, 19(7):979–993.
- Curtis, S. (2005). Efficiency gains boost high-power LED performance. *Compound Semiconductor*, 11(11):27–30.
- de Swaan Arons, H. and Boer, C. A. (2001). Storage and retrieval of discrete-event simulation models. *Simulation Practice and Theory*, 8(8):555 – 576.
- Delre, S., Jager, W., Bijmolt, T., and Janssen, M. (2007a). Targeting and timing promotional activities: An agent-based model for the takeoff of new products. *Journal of Business Research*, 60(8):826–835.

- Delre, S., Jager, W., and Janssen, M. (2007b). Diffusion dynamics in small-world networks with heterogeneous consumers. *Computational and Mathematical Organization Theory*, 13(2):185–202.
- Dijkema, G. P. J. and Basson, L. (2009). Complexity and industrial ecology: Foundations for a transformation from analysis to action. *Journal of Industrial Ecology*, 13(2):157–164.
- Dorogovtsev, S. and Mendes, J. (2002). Evolution of networks. *Advances in Physics*, 51(4):1079–1187.
- Dupuis, R. and Krames, M. (2008). History, development, and applications of high-brightness visible light-emitting diodes. *Journal of Lightwave Technology*, 26(9):1154–1171.
- Enkvist, P., Nauclér, T., and Rosander, J. (2007). A cost curve for greenhouse gas reduction. *The McKinsey Quarterly*, (1).
- EPA (2008). *Frequently Asked Questions – Information on Compact Fluorescent Light Bulbs (CFLs) and Mercury*. Available from: http://www.energystar.gov/ia/partners/promotions/change_light/downloads/Fact_Sheet_Mercury.pdf.
- European Lamp Companies Federation (2009). European lighting manufacturers welcome EU decision to phase out incandescent and less energy efficient lamps in European homes. Available from: <http://www.elcfed.org/documents/05ELC%20Quarterly%204.pdf>.
- Feferman, S. (2009). Gödel, Nagel, minds, and machines. *Journal of Philosophy*, 106(4):201–219.
- Flanagan, D. (2005). *Java in a Nutshell, Fifth Edition*. Sebastopol, CA: O'Reilly Media Inc.
- Forbes, G. (1889). Electric-lighting stations in Europe, and their lessons. *Science*, ns-13(326):337.
- Forrester, J.W., S. P. (1980). Tests for building confidence in system dynamics models. *TIMS Studies in the Management Sciences*, 14:209–228.
- Fouquet, R. and Pearson, P. J. G. (2006). Seven centuries of energy services: The price and use of light in the United Kingdom (1300-2000). *Energy Journal*, 27(1):139–177.
- Funk, J. (2008). Components, systems and technological discontinuities. Lessons from the IT Sector. *Long Range Planning*, 41(5):555–573.
- Garcia, R. (2005). Uses of agent-based modeling in innovation/new product development research. *Journal of Product Innovation Management*, 22(5):380–398.
- Gödel, K. (1931). Über formal unentscheidbare Sätze der Principia Mathematica und verwandter Systeme I. *Monatshefte für Mathematik und Physik*, 38(1):173–198.
- Geels, F. W. (2006). Co-evolutionary and multi-level dynamics in transitions: The transformation of aviation systems and the shift from propeller to turbojet (1930-1970). *Technovation*, 26(9):999–1016.
- Gendre, M. F. (2003). Two centuries of electric light source innovations. Available from: http://www.einlightred.tue.nl/lightsources/history/light_history.pdf.
- Gilbert, N., Jager, W., Deffuant, G., and Adjali, I. (2007). Complexities in markets: Introduction to the special issue. *Journal of Business Research*, 60(8):813–815.
- Goldenberg, J., Libai, B., and Muller, E. (2001). Talk of the network: A complex systems look at the underlying process of word-of-mouth. *Marketing Letters*, 12(3):211–223.
- Hansell, R., Craine, I., and Byers, R. (1997). Predicting change in non-linear systems. *Environmental Monitoring and Assessment*, 46(1-2):175–190.

- Hewitt, K. (2008). Opinion: Putting the science back into marketing. Website, accessed November 27, 2009. Available from: <http://www.amsrs.com.au/index.cfm?a=detail&id=2968&eid=152>.
- Hofstadter, D. R. (1985). *Gödel, Escher, Bach: een eeuwige gouden band*. Amsterdam : Contact. vert. [uit het Engels] door Ronald Jonkers.
- Holonyak, Jr., N. (2005). From transistors to lasers and light-emitting diodes. *Materials Research Society Bulletin*, 30:509–515.
- IEA (2008). Key world energy statistics. Technical report, International Energy Agency. Available from: http://www.iea.org/textbase/nppdf/free/2008/key_stats_2008.pdf.
- INFORMS (2009). About marketing science. Website. Accessed Nov 27, 2009. Available from: <http://mktsci.journal.informs.org/misc/about.dtl>.
- Jager, W. (2007). The four P's in social simulation, a perspective on how marketing could benefit from the use of social simulation. *Journal of Business Research*, 60(8):868–875.
- Jager, W. and Jansen, M. A. (2008). Normative and informative social influence on sales and the effect of a discount. In *5th Conference of The European Social Simulation Association*, Brescia, Italy. ESSA.
- Jahanshahloo, G., Lotfi, F. H., and Izadikhah, M. (2006). An algorithmic method to extend TOPSIS for decision-making problems with interval data. *Applied Mathematics and Computation*, 175:1375–1384.
- Jennings, N. R. (2001). An agent-based approach for building complex software systems. *Communications for the ACM*, 44(4):35–41.
- Johnson Brown, J. and Reingen, P. H. (1987). Social ties and word-of-mouth referral behavior. *The Journal of Consumer Research*, 14(3):350–362.
- Kemna, R., Couvee, H., and Vonk, C. (1991). Verlichting in gezinshuishoudens, modelvorming en mogelijkheden voor energiebesparing (lighting in family households, models and potential for energy conservation). Technical report, NOVEM.
- Koornstra, R. (2009). *Wat LED je - Met een lampje de wereld redden*. Nieuw Amsterdam.
- Küppers, G., L. J. (2005). Validation of simulation: Patterns in the social and natural sciences. *JASSS*, 8(4).
- Lau, G. and Ng, S. (2001). Individual and situational factors influencing negative word-of-mouth behaviour. *Canadian Journal of Administrative Sciences*, 18(3):163–178.
- Leditlight (2009). PowerPro V2 3 x 2W CREE LED GU10 spot. Website. Accessed 20 september 2009. Available from: <http://www.leditlight.net/?menu=article&categoryID=49502&articleID=8223873>.
- Lemnis Lighting and Nationale Postcode Loterij (2009). De natuur in haar waarde laten. Wat LED je? Website. Available from: <http://www.watledje.nu>.
- Loorbach, D. A. (2007). *Transition Management - new mode of governance for sustainable development*. PhD thesis, Erasmus Universiteit Rotterdam. International Books, Utrecht.
- Lorenz, E. N. (1963). Deterministic nonperiodic flow. *Journal of the Atmospheric Sciences*, 20(2):130–141.
- Lucas, J. R. (1961). Minds, Machines and Gödel. *Philosophy*, 36(137):112–127. Available from: <http://users.ox.ac.uk/~jrlucas/Godel/mmg.html>.
- Macal, C. M. and North, M. J. (2005). Tutorial on agent-based modeling and simulation. In *WSC '05: Proceedings of the 37th conference on Winter simulation*, pages 2–15. Winter Simulation Conference.
- Martinot, E. and Borg, N. (1998). Energy-efficient lighting programs. experience and lessons from eight countries. *Energy Policy*, 26(14):1071–1081.

- Maurits, P. (2009). Informatie over ledlamp is te rooskleurig. *Trouw*, 1 april. Available from: http://www.trouw.nl/nieuws/economie/article2068630.ece/Informatie_over_ledlamp_is_te_rooskleurig_.html.
- Meier, A. and Whittier, J. (1983). Consumer discount rates implied by purchases of energy-efficient refrigerators. *Energy*, 8(12):957–962.
- Menanteau, P. and Lefebvre, H. (2000). Competing technologies and the diffusion of innovations: The emergence of energy-efficient lamps in the residential sector. *Research Policy*, 29(3):375–389.
- Mills, E. (1991). Evaluation of european lighting programmes – utilities finance energy efficiency. *Energy Policy*, 19(3):266–278.
- Mills, E. (1993). Efficient lighting programs in europe: Cost effectiveness, consumer response, and market dynamics. *Energy*, 18(2):IN1,131–144.
- Mills, E. (2002). The \$230-billion global lighting energy bill. *Proceedings of the Fifth European Conference on Energy-Efficient Lighting*, pages 368–385.
- Moss, S. (2008). Alternative approaches to the empirical validation of agent-based models. *JASSS*, 11(1).
- Nationale DenkTank (2009). Eindrapport Nationale DenkTank 2009. Technical report, Nationale DenkTank.
- Nationale Postcode Loterij (2009). Miljoenen gratis led-lampen tegen klimaatverandering. Website. Accessed: October 2, 2009. Available from: <http://www.postcodeloterij.nl/StandaardMediabankpagina/MiljoenenGratisLEDlampenTegenKlimaatverandering.htm>.
- Nekovee, M., Moreno, Y., Bianconi, G., and Marsili, M. (2007). Theory of rumour spreading in complex social networks. *Physica A: Statistical Mechanics and its Applications*, 374(1):457–470.
- Newman, M. (2001). The structure of scientific collaboration networks. *Proceedings of the National Academy of Sciences of the United States of America*, 98(2):404–409.
- Newman, M., Watts, D., and Strogatz, S. (2002). Random graph models of social networks. *Proceedings of the National Academy of Sciences of the United States of America*, 99(SUPPL. 1):2566–2572.
- Nikolic, I. (2009). *Co-Evolutionary Method for Modelling Large Scale Socio-Technical Systems Evolution*. PhD thesis, Delft University of Technology.
- North, M., Collier, N., and Vos, J. (2006). Experiences creating three implementations of the repast agent modeling toolkit. *ACM Transactions on Modeling and Computer Simulation*, 16(1):1–25.
- NPS (2007). Edison biography. Website. Accessed: May 19th, 2009. Available from: <http://www.nps.gov/edis/historyculture/edison-biography.htm>.
- Olino (2009a). Lemnis PharoX III milkwhite glass. Web site. Last viewed: Dec 30, 2009 (See comments nr. 20–27 for discussion on power factor). Available from: <http://www.olino.org/articles/2009/02/13/lemnis-pharox-iii-milkwhite-glass>.
- Olino (2009b). Overzichtsartikel lampmetingen. Web site. Accessed: May 13, 2009. Last viewed: Dec 29, 2009. Available from: http://www.olino.org/articles/2007/08/11/overzichtsartikel_lampmetingen.
- Oosterbaan, W. (2009). Gebreken van een ‘wonderlamp’. *NRC Handelsblad*, 15 january. Available from: http://www.nrc.nl/wetenschap/article2121203.ece/Experts_hou_gloeilamp.
- Pacific Northwest National Laboratory (2009). DoE Solid-State Lighting CALiPER Program – Summary of results: Round 9 of product testing. Report, U.S. Department of Energy. Available from: http://apps1.eere.energy.gov/buildings/publications/pdfs/ssl/caliper_round-9_summary.pdf.

- Page, E. R. and Siminovitch, M. J. (1998). The energy case against halogen torchieres. *Energy Engineering: Journal of the Association of Energy Engineering*, 95(2):34–43.
- Peifer, D. (2007). The cfl myth. *Lighting Design and Application: LD and A*, 37(10):87–90.
- Perrels, A. (2008). Wavering between radical and realistic sustainable consumption policies: in search for the best feasible trajectories. *Journal of Cleaner Production*, 16(11):1203–1217.
- Rahmandad, H. and Sterman, J. (2008). Heterogeneity and network structure in the dynamics of diffusion: Comparing agent-based and differential equation models. *Management Science*, 54(5):998–1014.
- Ürge Vorsatz, D. and Hauff, J. (2001). Drivers of market transformation: analysis of the Hungarian lighting success story. *Energy Policy*, 29(10):801–810.
- Richins, M. L. (1983). Negative word-of-mouth by dissatisfied consumers: A pilot study. *The Journal of Marketing*, 47(1):68–78.
- Rockwell Automation (2009). Arena simulation software – value-driven solutions to solve industry challenges. Web site. Accessed: November 24, 2009. Available from: http://www.arenasimulation.com/Arena_Home.aspx.
- Rogers, E. (2003). *Diffusion of Innovations*. New York: Free Press, fifth edition.
- Rogers, E. M., Singhal, A., and Quinlan, M. M. (2008). Diffusion of innovations. In Stacks, D. W. and Salwen, M. B., editors, *An integrated approach to communication theory and research.*, chapter 27. New York: Routledge, second edition. Available from: <http://utminers.utep.edu/asinghal/Reports/EMR-Singhal-Quinlan-june19-07-DOI-Word-file-Stack-Salwen%5B1%5D.pdf>.
- Rotmans (2003). *Transitiemanagement: Sleutel voor een duurzame samenleving*. Van Gorcum, Assen.
- Sandahl, L., Gilbride, T., Ledbetter, M., Steward, H., and Calwell, C. (2006). Compact fluorescent lighting in america: Lessons learned on the way to market. Technical Report PNNL-15730, Pacific Northwest National Laboratory; The U.S. Department of Energy. Prepared by Pacific Northwest National Laboratory for U.S. Department of Energy. Available from: http://apps1.eere.energy.gov/buildings/publications/pdfs/ssl/cfl_lessons_learned_web.pdf.
- Seoul Semiconductor Co., Ltd. (2005). *Z-PowerLED Thermal Management Guide*. 148-29, Kasan-Dong, Keumchun-Gu, Seoul, Korea. Available from: <http://www.acriche.com/en/product/prd/zpowerLEDp7.asp>.
- Sheridan, M. (2009). ‘green’ lightbulbs poison workers. *Times Online*. Available from: <http://www.timesonline.co.uk/tol/news/world/asia/article6211261.ece>.
- Smeets, R. (2009). Philips lighting. Personal Communication.
- Smithsonian National Museum of American History (Last Updated: August 2008). Inventing six modern electric lamps. Website: ‘Lighting A Revolution’. Available from: <http://americanhistory.si.edu/lighting/20thcent/invent20.htm#in4>.
- Sylvania (2009). Business products: Glossary. Website. Accessed: November 2009. Available from: <http://www.sylvania.com/BusinessProducts/Glossary/>.
- Takus, D. A. and Profozich, D. M. (1997). Arena software tutorial. pages 541–544.
- Taskforce Verlichting (2008). Groen licht voor energiebesparing – eindrapport van de taskforce verlichting. Report, SenterNovem. Available from: http://www.senternovem.nl/mmfiles/Eindrapport%20Taskforce%20Verlichting%20-%20Groen%20licht%20voor%20energiebesparing_tcm24-297801.pdf.
- Taskforce Verlichting (2009). Voortgangsrapportage uitvoering taskforce verlichting. Report, SenterNovem.

- The Economist (2009). The green slump. *The Economist – A special report on the carbon economy*, 393(8860):10–11.
- Tripsas, M. (2008). Customer preference discontinuities: A trigger for radical technological change. *Managerial and Decision Economics*, 29(2-3):79–97.
- U.S. Department of Energy (2009). Multi-year program plan fy'09-fy'15 – solid-state lighting research and development. Technical report, Prepared for: Lighting Research and Development, Building Technologies Program, Office of Energy Efficiency and Renewable Energy, U.S. Department of Energy. Prepared by: Navigant Consulting, Inc., Radcliffe Advisors, Inc., and SSLS, Inc. Available from: http://apps1.eere.energy.gov/buildings/publications/pdfs/ssl/ssl_mypp2009_web.pdf.
- van Agt, J. (2009). Vervanging van 5 x 35W halogeen door LED spots in mijn huiskamer. Website. Accessed: December 23, 2009. Available from: <http://www.olino.org/articles/2009/07/27/vervang-ing-van-5-x-35w-halogeen-door-led-spots-in-mijn-huiskamer#more-6100>.
- van Dam, K. H. (2009). *Capturing socio-technical systems with agent-based modelling*. PhD thesis, Delft University of Technology, Delft, the Netherlands.
- van der Zee, T. (2010). Lage power factor LED's kan goed worden ondervangen. *Energie-Gids.nl*, 3(1):28–29.
- van Eck, P., Jager, W., and Leeflang, P. (2009). Opinion leaders' role in innovation diffusion: A simulation study. *Journal of Product Innovation and Management*, (in press).
- Veitch, J. and Gifford, R. (1996). Assessing beliefs about lighting effects on health, performance, mood, and social behavior. *Environment and Behavior*, 28(4):446–470.
- Vine, E. and Fielding, D. (2006). An evaluation of residential CFL hours-of-use methodologies and estimates: Recommendations for evaluators and program managers. *Energy and Buildings*, 38(12):1388–1394.
- Vine, E., Mills, E., and Chen, A. (2000). Energy-efficiency and renewable energy options for risk management and insurance loss reduction. *Energy*, 25(2):131–147.
- VSL (2009a). LEDs in opschudding. Website. Accessed: December 15, 2009. Available from: <http://www.vsl.nl/nieuws/leds-in-op-schudding/312>.
- VSL (2009b). OpgeLED minder opbrengst dan verwacht. Technical report. Available from: http://www.vsl.nl/files/VSL_meetrapport_OpgeLED_minder_opbrengst_dan_verwacht_31_maart_2009.pdf.
- Wajer, B. H. and Kemna, R. (1991). Electricity consumption for lighting in the average Dutch household. In Mills, E., editor, *Proceedings of Right Light Bright Light, 1st European Conference on Energy-Efficient Lighting*. IAEEEL.
- Wall, R. and Crosbie, T. (2009). Potential for reducing electricity demand for lighting in households: An exploratory socio-technical study. *Energy Policy*, 37(3):1021–1031.
- Wang, X. F. and Chen, G. (2003). Complex networks: small-world, scale-free and beyond. *Circuits and Systems Magazine, IEEE*, 3(1):6–20.
- Watts, D. and Strogatz, S. (1998). Collective dynamics of 'small-world' networks. *Nature*, 393(6684):440–442.
- WEF (2009). Technology pioneers 2009. Available from: <http://www.weforum.org/pdf/techpioneers/brochure.pdf>.
- Wikipedia (2009). Power factor. Website. Accessed December 30, 2009. Available from: http://en.wikipedia.org/wiki/Power_factor.
- Wikipedia (2010). Box plot. Website. Accessed January 31, 2010. Available from: http://en.wikipedia.org/wiki/Box_plot.
- Windrum, P., F. G. M. A. (2007). Empirical validation of agent-based models: Alternatives and prospects. *JASSS*, 10(2).

- Wooldridge, M. J. and Jennings, N. R. (1995). Intelligent agents: theory and practice. *Knowledge Engineering Review*, 10(2):115–152.
- Wooldridge, M. J. and Jennings, N. R. (1999). Software engineering with agents: Pitfalls and praftalls. *IEEE Internet Computing*, pages 20–27.
- Yücel, G. and Chiong Meza, C. M. (2008). Studying transition dynamics via focusing on underlying feedback interactions: Modelling the Dutch waste management transition. *Computational and Mathematical Organization Theory*, 14(4):320–349.
- Yücel, G. and van Daalen, C. (2008). When does it really make a difference? experimenting with the actor-heterogeneity in modeling socio-technical transitions. In *Conference Proceedings - The 2008 International Conference of the System Dynamics Society*. System Dynamics Society.

Index

- Actors, 13, 18, 39
 - Consumers, *see* Consumer
 - Government, *see* Government
 - Manufacturers, *see* Manufacturers
 - Retailers, *see* Retailers
- Adaptive, 11
- Adoption (of CFL), 5, 6
- Agent, 33
- Agent-based modelling (ABM), 33, 35, 66, 84, 102, 108, 113, 117, 120, 131
- Albert-Heijn, 147
- Ban on bulbs, *see* E.U. Ban on bulbs
 - Policy case, 80
 - Simulation results, 91–104, 108–109
- Base case
 - Policy case, 80
 - Simulation results, 91–104
- Boundary adequacy of structure, 66
- Box plot, 90
- Bulbs tax
 - Policy case, 80, 81
 - Simulation results, 91–104, 108–109
- Certification, 63
- CFL Quality Charter (EU), 15
- CO₂ emissions, ix, 5
- CO₂ price, 109
- Colour rendering index, 45, 136–141
- Colour temperature, 45, 136–141
- Communication channels, *see* Social network
- Complex, 11, 107, 117
- Complex system, 9
- Consumer, ix, 5, 7, 13, 18, 40, 107
- Cost, 5, 13, 15, 81, 99, 108, 141
 - Upfront cost, 13, 81, 99, 110, 115
- Database server, 118
- Dimension analysis of equations, 66
- Disadvantages of efficient lighting, 110
- E.U. Ban on bulbs, 6, 7, 80
 - Effectiveness, 9, 108, 111
 - Rebound effects, *see* Rebound effects
- Edison, Thomas, 3
- Electricity consumption, 4, 8, 17, 51, 98, 107, 108, 111
- Empirical validation, 76
- Energy label, 45, 137–141
- Environmental consciousness, 19
- European Commission, 6, 7
- Experimental setup, 119
- Extreme conditions tests, 66
- Fashion, 15, 19, 21–23, 35, 42, 55, 107, 157
- Fixture, *see* Luminaire
- Floating point, 73, 84, 118, 154
- Framework for developing ABM's, 131
- Future research, 111, 114
- General Electric, 14
- Government, 15, 39
- Halogen not banned, 111
- Halogen torchiere, 25
- Heterogeneous (preferences perceptions etc.), 22, 23, 33, 35, 40, 47
- High performance computing cluster (HPC), 84, 117, 118
- IKEA, 146
- Information, 22, 23, 41, 42, 57, 107, 157
- Informative influence, 22, 42, 57
- Inner Quartile Range (IQR), 90
- Innovation
 - Decision process, 20
 - Diffusion, 20–23
 - Diffusion of the CFL, 21
 - Elements of diffusion, 20
 - Social network, 22
- Inputs and outputs (of system), 18
- Integer, 84, 118, 154
- Interaction mechanisms, *see* Interactions
- Interactions, 16, 18
- Java, 116, 117, 132

- Knowledge (on lamps), 23, 41, 42, 107
- Lamp, 12, 42
 - Compact Fluorescent Lamp (CFL), 4
 - Halogen lamp, 4
 - Incandescent lamp, 4
 - LED lamp, 4
 - Saving lamp (CFL), 4
- Lamp-model name, 45, 135–141
- Lamp-type, 45, 135–141
- LaTeX, 116, 117
- LED subsidy, *see* Subsidy for LED
- Lemnis Lighting, 14, 147
- Life cycle cost, 5, 13
- Lifetime, 74
 - Expected, 45, 135–141
 - Uncertainty, 45, 135–141
- Light
 - Bulb, *see* Lamp
 - Output, 6, 45, 135–141
- Lighting
 - Electricity, *see* Electricity consumption
 - Energy, worldwide, 4
- Lighting components
 - Ballast, 12, 17
 - Cabling, 12, 17
 - Dimmer, 12, 17
 - Driver, 12, 17
 - Fuse, 12, 17
 - Lighting spot, 12, 17, 150
 - Power outlet, 12, 17
 - Switch, 12, 17
 - Transformer, 12, 17
- Lighting technology, 3
 - Fluorescent, 3
 - HID (High-Intensity Discharge), 3
 - Incandescent, 3
 - LED (Light Emitting Diode), 4
 - Sodium, 3
 - Solid-state lighting (SSL), 4
- Lines of code, 117
- Luminaire, 12, 42, 111, 114
 - Fixed, 12
 - Free-standing, 12
 - Halogen torchiere, 25
 - LED lamps, 114
 - Locations, 150
- Luminous efficiency, 6, 74, 98
- Manufacturers, 14, 39
- Market, 39
- Marketing
 - Low-Involvement Products, 22
 - Science, 19
 - Marketing message, 23
 - Marketing simulation perspective, 8, 19–24
 - Massive, 146
 - MATLAB, 117, 118
 - Megaman, 14
 - Memory, 41, 42, 49–51
 - Mercury, 110
 - Model
 - Conceptual, 39–45
 - Implementation, 45–61
 - Modelling approach, 8
 - Agent-Based (ABM), *see* Agent-based modelling (ABM)
 - Bottom-up, 33
 - Equation-based, 32
 - Event-driven, 33
 - Requirements, 31
 - Software tools used, 117
 - System Dynamics (SD), 32
 - Top-down, 32
 - Modelling techniques, 32
 - Mood lighting, 19
 - Multi-Criteria Analysis, 52–57
 - Multi-level, 12
 - Normalisation method, 52
 - Normative influence, 22, 42, 55, 57, 82, 103, 104, 157, 161
 - Number of runs, 82, 84
 - Ontology, 45, 58, 120–122, 131–132, 135–141
 - Opinions, *see* Perceptions
 - Osram, 14, 146
 - Perceptions, 18, 22, 23, 35, 41, 42, 47, 49–51, 107
 - Philips, 4, 5, 14, 146
 - Power consumption, 45, 136–141
 - Power factor, 110
 - Preferences, 18, 22, 23, 35, 40, 42, 47, 107
 - Premature lamp failure, 51
 - Price, 45, 137–141
 - Pricing, 19
 - Process, 116
 - Pseudo-random number generation, 82, 89, 102, 158
 - Publicity (on LED), 6, 14
 - Purchase decision, 18, 42
 - Purchase price, 5, 81, 82, *see* Price, 141

- Random number generation, *see* Pseudo-random number generation
- Rebound effects, 111, 114, 116
- Reflection, 113–124
- Repast, 111
- Repast (simulation toolkit), 64, 132
- Research
 - Aim, 8
 - Problem statement, 7
 - Questions, 8
 - Results, 9, 89–105
- Retailers, 15, 39
- Runs (Simulation –), 82
- Scale free network, 59
- Scenario's, 18
- Scenarios, 27
- Shape, 45, 136–141
- Shared ontology, 131
- Simulation
 - Visualisation, *see* Visualising simulation experiments
- Simulation model, *see* Model
- Simulation modelling approach, *see* Modelling approach
- Small-world network, 58
- Social network, 13, 16, 22, 23, 35, 42, 47, 57–61
- Social system, *see* Actors
- Socket, 12, 17, 45, 136–141
- Software tools, 117
- SQL, 118
- Steering and control (of system), 18
- Stimulus programs, 5
- Strategic objectives, 18
- Structural validation, 66
- Subsidy for LED
 - Policy case, 80, 81
 - Simulation results, 91–104, 108–109
- System representation (in model), 27, 39–45, 131
- System's diagram, 17
- Systems description, 11–18
- Systems perspective, 8, 11
- Taskforce Lighting, 6
- Tax level, 109
- Tax on bulbs, *see* Bulbs tax
- Technological components, 18
- Thresholds, 47
- Total number of lamps in the simulation, 92
- Transition, 15, 18
 - Assemblage, 27
 - Experiments, 28
 - Indicators, 29
 - Management, 11, 15, 26, 108
 - Management practices, 27
 - Management strategies, 11, 15, 18, 27, 108
 - Transitions perspective, 8, 24–29
- Validation, 63–77
 - Purchase behaviour, 67–76
- Verification, 63, 64
 - Model parameters, 66
 - Model structure, *see* Structural validation
- Visualising simulation experiments, 89
- Voltage, 45, 136–141
- Weight factors, 47
- Whisker, 90
- Willingness to adapt, 23, 107
- Word-of-mouth, 7, 13, 16, 22, 35, 42, 57, 107

