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## Modelling Transitions in Consumer Lighting

Agent-based modelling of transition management policies in the residential lighting sector

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### Abstract

To understand the consequences of the E.U. ban on incandescent lamps, an agent-based model is developed in which consumers are simulated in their behaviour (purchase, sharing of information). Consumers are modelled based on heterogeneous preferences and have memory and perceptions. The results indicate that the ban on bulbs will be effective in realising an energy efficient sector, albeit at significant expense to consumers. Interesting so, a tax on incandescent lamps is also effective given that it is high enough.

**Keywords:** Transition Management, Social Simulation, Agent Based Modeling, Consumer Lighting, Energy

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### 1 Introduction

Lighting is an essential resource 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 \(2006\)](#)).

Since Edison's first carbon filament glow bulb (which gave 2 lumens of light per watt of electricity), 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 ([Gendre, 2003](#)). But from then on, technological progress more or less stopped: almost 100 years later, incandescent lamps still have efficiencies of about 12 lm/W, an efficiency considered extremely low: circa 98% of the input power is given off as heat and not light<sup>2</sup>.

A problem is, however, that the inefficient incandescent lamp is the type of lamp that is still predominantly used by households. A lot of energy is consumed in the residential lighting sector: 3.8 TWh in 2006 for the Netherlands alone ([Afman, 2010](#)). This

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<sup>2</sup>Calculated with an efficiency of 12 lm/W and a theoretical maximum of 683 lm/W ([Azevedo et al., 2009](#)).

amount can be greatly reduced if consumers would switch from inefficient lighting technology (the tungsten filament light bulb and the halogen light bulb) to efficient technology (such as the compact fluorescent lamp (CFL)). Despite the fact that the more energy-efficient alternatives were introduced long ago, they did not take on in the residential market. As of 2008, CFL's are even completely lacking in 45% of all European households (Bertoldi and Atanasiu, 2006).

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 of energy efficient lamps. They also aim to encourage adoption, by distributing free samples, or giving a rebate on the purchase price of an energy-efficient lamp.

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 E.U.'s Eco-Label scheme) that forces lighting products available to meet a number of stringent efficiency standards (CEC, 2009a). The regulation is popularly known as the "ban on bulbs"; it entails the direct phaseout of all non-clear (frosted) incandescent light bulbs, and clear lamps exceeding 100W; and a phased withdrawal of the remaining clear lamps the coming years, after which also halogen lamps will be mostly phased out by 2016 (CEC, 2009a,b,c).

A number of questions can be posed on this attempt to force consumers into energy-efficient lamps purchase: in how far will the ban be effective? Are there other policy measures, perhaps more transition-oriented, that can also have been effective? The consumer lighting sector is a complex socio-technical system. Consumers mutually influence each other through word-of-mouth and normative adaptation, but they are also subject to influences of manufacturers, stores, government and technological options; the dynamics of the consumer lighting sector cannot be understood in advance. A social simulations approach is called for assessing the consequences of the ban on bulbs, as well as from a number of different policy option.

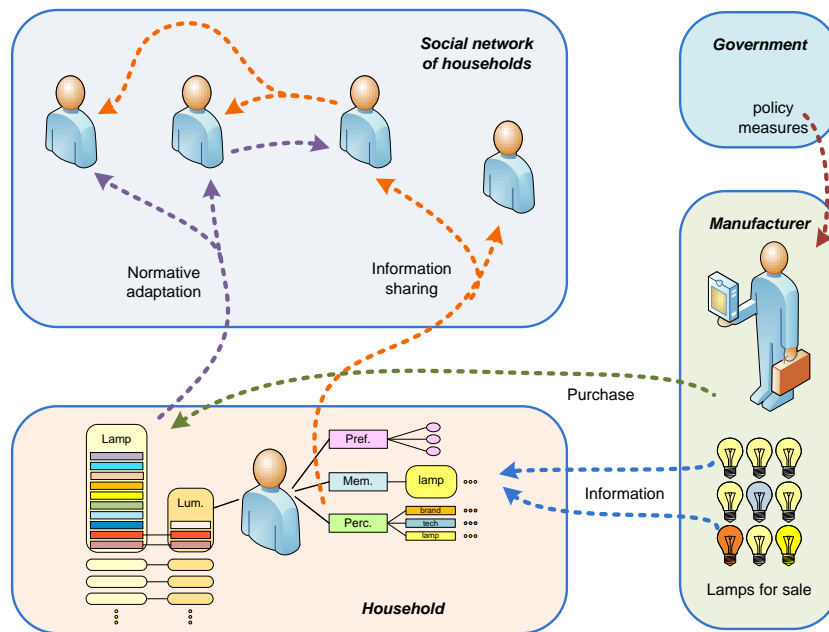
## 2 Model

Agent-based modelling was selected as the best suitable social simulations approach. 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). Agent-based modelling also allows for the consequences of innovations in the simulated technologies (e.g. performance improvements and declining prices of some newer technological lamps).

An agent-based model is developed, incorporating 250 consumers as households agents; as well as technology. A conceptual overview of the model components and mechanisms is presented in figure 1.

Key features of the model:

- Households are implemented with heterogeneous preferences, evolving memory (knowledge) and perceptions.
- Households exist in a social network structure.
- Households acquire knowledge and form opinions on lamps, brands, lamp technology, and share these over its social network structure ( 'word-of-mouth')
- Households have a distribution of luminaires (lighting fixtures), with lamps in them.
- Lamps fail, causing household to go out and purchase replacement lamps.
- Technology forms interactions: a lamp with a specific socket/voltage will only fit in a specific luminaire.



**Figure 1** – Overview of the modelled social and technological entities, and how they relate.

- The lamps market is implemented as one retail store, the ‘manufacturer’, selling 70 simulated types of lamps of 11 makes (brands).
- The 70 lamps include compact fluorescent lamps (CFL’s), LED lamps, halogen lamps, as well as incandescent lamps (the type that will be banned).
- The lamps are modelled with gradually declining prices, depending on the relative newness of the technology.

### 3 Implementation details

This section presents the implementation details of the model. The model is implemented in Java, and expands on a Repast-3 based modelling framework developed at TU Delft (Nikolic, 2009; van Dam, 2009).

#### 3.1 Technology

The technological system consist of all the modelled hardware.

The **luminaire** (displayed at right side of figure 3), 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.

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 right side of figure 3).

Lamps are specified in an ontology, and have parameter values 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* (€).

### 3.2 Initialisation of agents

During model initialisation, agents are created. The manufacturer initialises its lamps for sale.

Households are created and given a number of luminaires with a specific distribution of lamps as a starting portfolio. The number of luminaires, and their location properties differ for all households. These are calculated from random distributions based on student's survey data of Delft citizens (unpublished). 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), using a uniform distribution. For some locations in the house, luminaires are used for a longer duration, on average, than on other locations. The initial distribution of lamps assigned to each household depends on the starting percentage of CFL lamps, a starting percentage for halogen lamps, and a factor for the number of households without any CFL's.

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). This makes the households heterogeneous. Preferences and thresholds are displayed in table 1; the values assigned are randomised (between 90% and 110% of the values shown).

The households start with an empty memory, and neutral perceptions, however, in their initialisation they already form opinions on lamps they have at  $t=0$ . 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, we implemented the scale free network algorithm for this parameters: minimum degree = 15; initial agents: 4)

**Table 1** – Parameters for heterogeneous preferences and thresholds for the household

<b>Preferences for households</b>		<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 ( $700 \text{ lm} \approx 60W \text{ incand.}$ ).
Threshold Light Colour	300	. . . no light that is too yellow ( $2400K$ ); or too white ( $3200K$ ).
Threshold CRI	20	. . . colour rendering not worse than 80.
Threshold Light	650	. . . light output not below 50 lumen ( $\approx 5W \text{ bulb}$ ) and not above 1350 lumen ( $\approx 100W \text{ bulb}$ ).

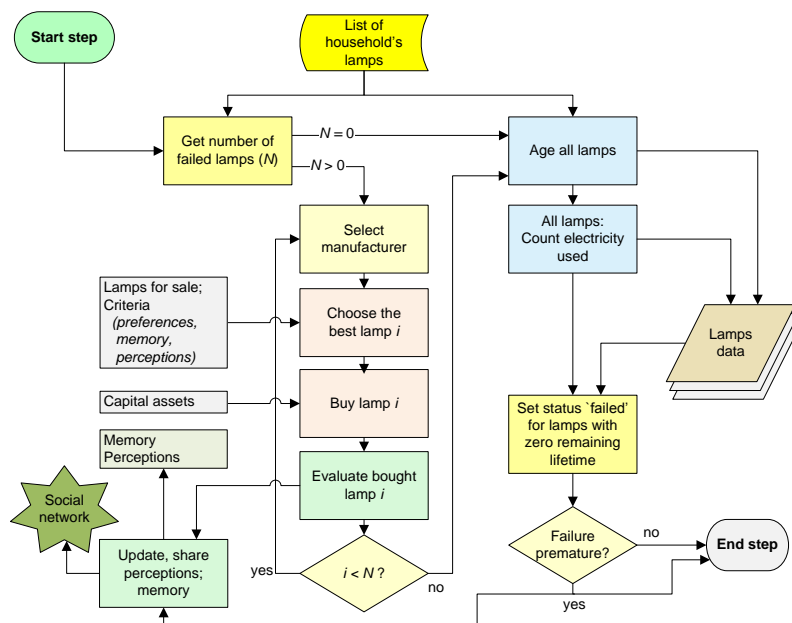
### 3.3 Schedule

Each simulation tick, the manufacturer performs a step. A manufacturer's step consists of limited actions, it alters the sale prices of lamps; as time progresses, lamps become cheaper. Depending on the selected policy ('ban on bulbs'), the manufacturer removes lamps from those available for sale, or there can be taxes or subsidy on different types lamps; the manufacturer implements these.

Each simulation tick, all households also do one 'step', one after another. A household step consists of the following actions, see also figure 2:

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

- 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.
- 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.
- 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). If a lamp failure is considered prematurely, this negatively affects the households perception of it, and the household communicates this to one other random agent of its social network.



**Figure 2** – Flow chart representing the sequence of actions during the household's step

### 3.4 Household behaviour

**Purchase** Household's lamps purchase decision is taken to be a multi-criteria decision problem. The household's preferences, perceptions, and knowledge on lamp aspects can be considered to be different criteria, to use in selecting one lamp for purchase, from the many for sale by the store. The way this can be implemented is 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)<sup>3</sup>).
5. Normalise the scores of the alternatives on a 0–1 scale, using a normalisation algorithm.
6. Multiply scores by the criteria weight factors.

<sup>3</sup>Not implemented as such. Thresholds for preferences are in the model, they are used in updating perceptions, not in multi-criteria analysis.

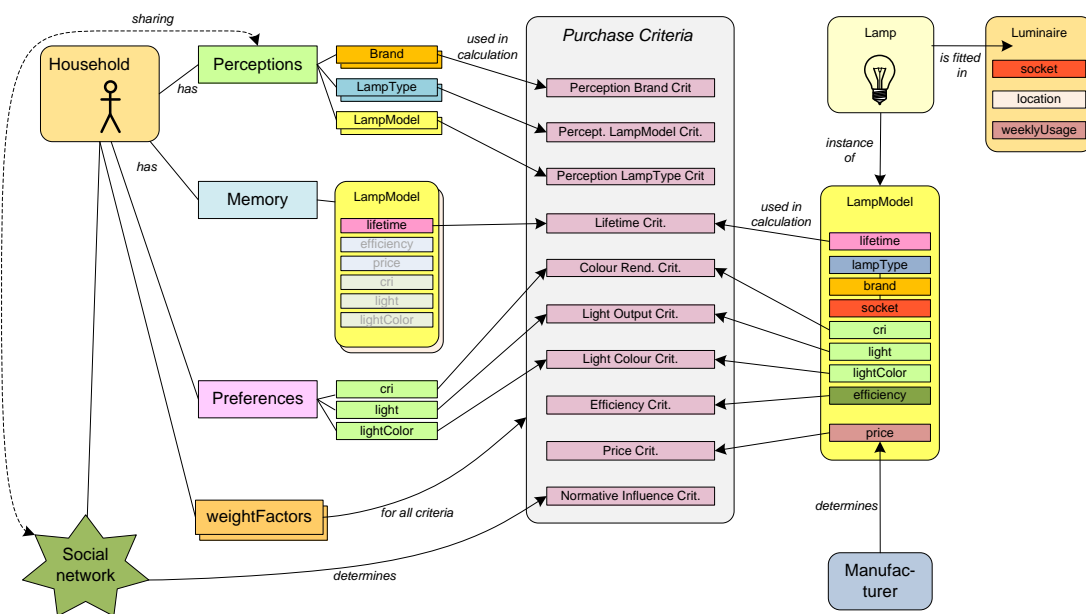
7. Obtain a ranking of the alternatives, and choose the single best alternative.

For the criteria, we use the ten criteria displayed in figure 3. The data structure used in calculating scores on the criteria is also visualised. Six criteria relate to lamp parameters (efficiency, purchase price, light output, light colour temperature, colour rendering quality, lamp lifetime). For three of these, the household has preferences, and threshold values (light output, light colour temperature, colour rendering quality; see table 1). Three criteria relating to perceptions (on brands, lamp technology types and specific lamps). The last criterion, for ‘normative influence’, relates to fashion: consumers tend to adopt products their neighbours in the social network use.

After normalization on a 0–1 scale, the relative importance of different criteria is established using weight factors. All criteria have weight factors; default values (table 2) have been derived from a number of assumptions, data sources from student surveys, and literature. Purchase price is assessed to be the most important. Weight factors are made heterogeneous for all households by multiply it with a random number from a uniform distribution out of the [0.5 – 1.5] range. Weight factors remain static during the simulation.

**Table 2** – Weight factors for multi-criteria analysis

Price	4	Preference Light	1
Efficiency	2	Preference Light Colour	2
Lifetime	1	Perception Lamp-type	2
Normative Influence	2	Perception Brand	1
Preference CRI	2	Perception Lamp-model	1



**Figure 3** – 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 are implemented in the simulation model.

**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. 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. A perception increases for the **positive** if any of the following two conditions occur: (1) The memory value for the aspect is worse than the actual value – a ‘surprise’ factor. (2) 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’.

Perceptions are incremented using an increment value that is dependent on a number of things. Negative perceptions are stronger in general (increment value is multiplied with a ‘Perceptions Negative Factor’. Negative perceptions are also *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. See table 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’. When this is the case, the perceptions for brand, lamp-type and lamp-model are decremented.

**Sharing of perceptions** An agent shares its perceptions for brands and lamp-technology with a random neighbour from its social network after a lamp was purchased, or after perceptions are updated following a *premature* lamp failure. For the agent’s perceptions, the agent checks if the other agent has a perception for that instance of brand or lamp technology type, and if so, it sets the other agent’s brand perception as the average of my own and the other agent’s old value.

**Table 3** – Parameters for perceptions

Perceptions Increment	0.1	Lifetime Minimum Expectation	0.5
Perceptions Negative Factor	3	Lifetime Sceptical Factor	0.8
Perceptions Surprise Factor	2		

### 3.5 Structural validation tests

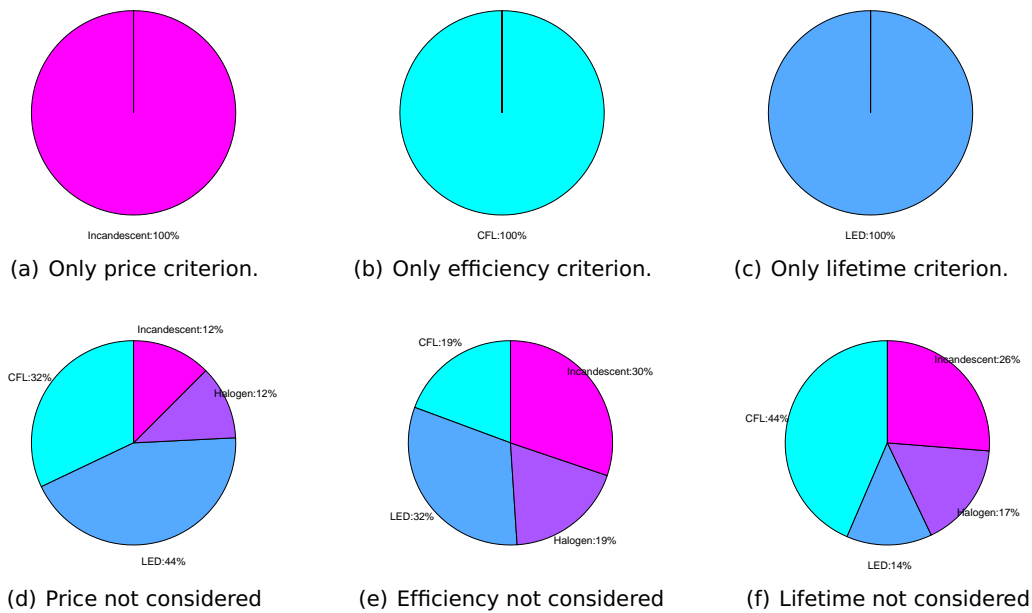
The results of the household’s purchase decision were validated using structure oriented tests. In a great number of validation experiments, the household’s purchase decision was tested under elaborate combinations of settings for preferences, weight factors and values for perceptions (full-factorial); with the limitations that we only tested the buy behaviour of a single household. Therefore, normative influence criterion was left out of these tests. Also, the influence of luminaire/socket distributions was not incorporated, nor is memory on lamp qualities included. The results are displayed in figure 4.

Fig. 4 shows one example of a series of structure tests. In pie charts (a), (b) and (c), a clear single-best outcome can be observed. 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. When that criterion is left out of the purchase decision (by giving it a weight factor of zero), a more mixed outcome is obtained, as shown in pie charts (d), (e) and (f): no single criterion is really determining of all results. All technology types appear to have strengths.

## 4 Experiments

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)



**Figure 4** – Purchase outcomes in validation experiments in terms of the **purchased lamp’s lamp-type**. Top row: *only one criterion* (indicated) is used for the purchase decision. Bottom row: the criterion indicated is left out of the purchase decision by putting its weight factor at zero. Top row  $N = 2376$ . Bottom row  $N = 2,598,156$ .

**‘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.

These alternative policies are varied in an experimental setup, incorporating different settings for the price and normative influence weight factors. The evolution of the system will be observed using a number of indicators.

The simulation time step was put at one week, and the simulation was run for a duration of 40 years, equal to 2080 weeks. The number of runs that will be performed per experiment is put at 100. This value was chosen to limit the size of the data set produced, but still allow for quite a bit of repetition.

As each experiment needs about an hour to compute, and the experimental setup consists of 1600 experiments, a choice was made to compute the experiments using the High Performance Computing cluster (HPC) of the Energy & Industry section and the Next Generation Infrastructures foundation (enabling ~480 runs to compute in parallel).

## 5 Results

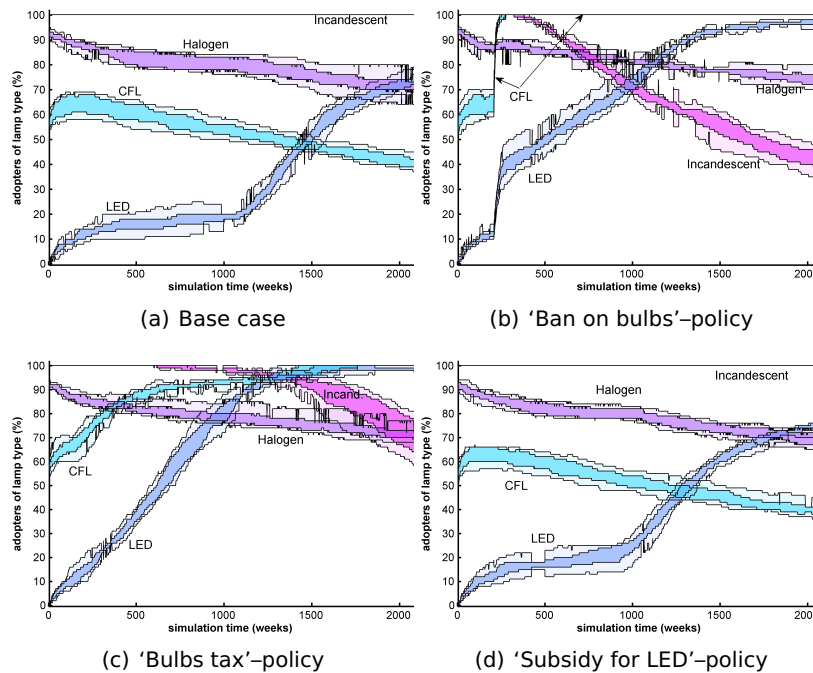
Results will be generated on a number of indicators. The main indicators are the adoption levels of the different lamp types, electricity consumption per household and money expenditure for lamp purchases. For a proper assessment of the results on the indicators, we will, for each indicator, plot a number of descriptive statistics derived from the box-plot statistical tool. These statistics help us assess the spread and average values of the different simulation runs, as well as assess apparent skewness.

The statistics are: inner quartile range (50% of the data) and lower / upper whisker lines. (For normally derived data, 98.6% of the data will lie between the whisker lines. For clarity, the median and outliers are not plotted.)



## 5.1 Adopters of lamp technology

The first results are results for 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*. The results are displayed in figure 5.



**Figure 5** – 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** A number of patterns can be observed:

- In the base case and the ‘subsidy for LED’-policy (figs. 5 (a); (d)), the *incandescent* lamp stays in 100% of households. In the ‘ban on bulbs’ and ‘bulbs tax’ cases (figs. 5 (b); (c)) it is declining.
- In the ‘ban on bulbs’ case (figs. 5 (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.
- Adoption of CFL rises in the ‘bulbs-tax’ case (fig. 5 (c)), reaching 90% adoption. In the base case and the ‘subsidy for LED’-policy (figs. 5 (a), (d)), a clear decline of the popularity of CFL’s can be observed.
- In all cases, LED is gaining adoption, with its best performance in the ‘bulbs-tax’ case (fig. 5 (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.
- In the base and ‘subsidy for LED’ cases (figs. 5 (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.

### Interpretation

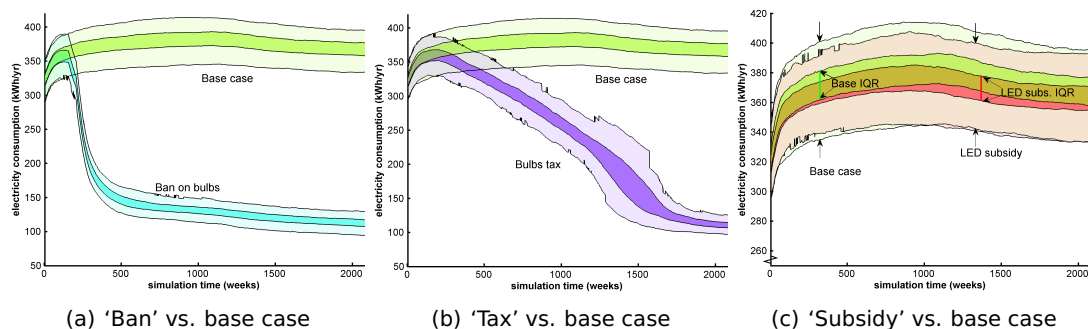
1. The decline of the incandescent lamp’s adoption under the ‘ban on bulbs’ and ‘bulbs tax’ policies cases is steady, but never complete. After 40 years, in the

ban case (fig. 5 (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.

2. Fig. 5 (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.
3. The decline of the CFL in the base and ‘subsidy for LED’ cases (figs. 5 (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.
4. The linearly increasing adoption of LED under the tax (fig. 5 (c) ) clearly shows that the tax-policy is more effective than the ‘subsidy for LED’-policy (fig. 5 (d)).

## 5.2 Results – Impact on electricity consumption

The results for the electricity households consume for their lighting needs, are displayed in figure 6.



**Figure 6** – Average household electricity consumption (kWh/yr) for the ‘ban on bulbs’ ‘bulbs-tax’ and ‘subsidy for LED’-policies, compared against the base case.

**Observations** First of all, in the ‘ban on bulbs’-policy (fig. 6 a) and the ‘bulbs tax’-policy (fig. 6 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. 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. 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. 6 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** Clearly, households are switching to efficient lighting technology, impacting their electricity consumption. 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. In the base case (as well as in the ‘subsidy for LED’ case), the popularity of the incandescent lamp rises, causing 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.

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.

## 6 Conclusion and outlook

From the model results, we conclude that the E.U.’s ‘ban on bulbs’-policy is likely a very effective way to curb the use of the incandescent lamp. The adoption declines; lamp purchases are generally of a more efficient 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 one on one with CFL’s, which results in a large reduction of the lighting electricity consumption (see the leftmost graph in fig. 6).

The ‘bulbs-tax’ policy is also likely to be effective at reducing the use of the incandescent lamp and decrease household’s electricity consumption; however, it may well take a lot longer to reach similar consumption levels as under the ‘ban on bulbs’-policy. The ‘subsidy for LED’-policy is unlikely to achieve much effect. See the centre and rightmost graphs of fig. 6.

Summarising, the simulation model leads us to believe that, 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.

### Discussion and outlook

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. What matters most is that the behaviour of the agents is right, realistic and credible. As long as that is the case, the underlying agent mechanisms are no issue. For this, we seek additional options for validating the model results. A student’s survey of Delft citizens is a first start, but we are actively seeking additional validation options, e.g. insights from the lighting industry and government.

The experimental setup used is not the only way the model can be executed. Many more settings, for 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 do additional structured testing of combinations of these settings, to try to see to what extent the conclusions hold up when these settings are altered.

Furthermore, it is recommended to expand the model in a number of ways. First of all, the 70 models of lamps included in the model is only a subset of the types available in stores. Perhaps with more types of general-purpose socket halogen lamps (E14/E27 socket), more dynamics with halogen can be observed. We could also opt for more dynamics in technological innovation, not only reduce lamp cost price, but also improve technological properties (mainly interesting for LED, which is, as of now, generally less bright than other alternatives). Secondly, as the implementation of luminaires in the model is presently quite simple (one lamp attaches to one luminaire, and the luminaire remains fixed during simulation), it would be interesting to add more luminaire dynamics, such as the ability to replace a luminaire. Lastly, it would be interesting to add a number of rebound effects of the E.U. ban (e.g. stockpiling; change of usage; power factor; impact of dimmers) to the simulation, in order to come up with quantitative analysis of their significance.

## References

- Afman, M. (2010). Modelling transitions in consumer lighting – consequences of the E.U. ban on light bulbs. Master's thesis, Delft University of Technology, Faculty of Technology, Policy and Management.
- Azevedo, I., Morgan, M., and Morgan, F. (2009). The transition to solid-state lighting. *Proceedings of the IEEE*, 97(3):481–510.
- 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/>.
- CEC (2005). European compact fluorescent lamps quality charter. Technical report, European Commission.
- CEC (2009a). 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 (2009b). FAQ: phasing out conventional incandescent bulbs. Memo, 1 September 2009. Available from: <http://europa.eu/rapid/pressReleasesAction.do?reference=MEMO/09/368>.
- CEC (2009c). 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>.
- 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.
- Garcia, R. (2005). Uses of agent-based modeling in innovation/new product development research. *Journal of Product Innovation Management*, 22(5):380–398.
- Gendre, M. F. (2003). Two centuries of electric light source innovations. Available from: [http://www.einlightred.tue.nl/lightsources/history/light\\_history.pdf](http://www.einlightred.tue.nl/lightsources/history/light_history.pdf).
- 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.
- 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.
- Mills, E. (1991). Evaluation of european lighting programmes – utilities finance energy efficiency. *Energy Policy*, 19(3):266–278.
- Nationale Postcode Loterij (2009). Miljoenen gratis led-lampen tegen klimaatverandering. Website. Accessed: October 2, 2009. Available from: <http://www.postcodeloterij.nl/StandaardMediabankpagina/MiljoenenGratisLEDlampenTegenKlimaatverandering.htm>.
- Nikolic, I. (2009). *Co-Evolutionary Method for Modelling Large Scale Socio-Technical Systems Evolution*. PhD thesis, Delft University of Technology.
- 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](http://www.senternovem.nl/mmfiles/Eindrapport%20Taskforce%20Verlichting%20-%20Groen%20licht%20voor%20energiebesparing_tcm24-297801.pdf).
- van Dam, K. H. (2009). *Capturing socio-technical systems with agent-based modelling*. PhD thesis, Delft University of Technology, Delft, the Netherlands.