Load-shifting in a new perspective

Smart scheduling of smart household appliances using an Agent-Based Modelling Approach

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Abstract – The rapid increase in electricity demand in the Netherlands will continue in the future. Especially during peak hours, the available capacity of the distribution network will be insufficient. Distribution Network Operators traditionally invest heavily in more electricity cables to cope with this problem. Demand-Side Management may provide an alternative, or at least complementary solution, as it shift electricity loads away from peak load periods (Load-shifting). To assess the potential of this load-shifting, we have constructed an agent-based simulation model of a low-voltage network with households that own non-smart appliances and schedulable smart appliances. We have tested the effectiveness of smart scheduling using different demand pattern forecasting methods and scheduling schemes. The results show that the scheduling of smart appliances can reduce peaks by 13% and fill the gaps in the demand pattern resulting in a more levelled demand patterns. In our simulation, 16% of the total load was schedulable, which could almost fill up the major gap (off-peak night time period) in the network demand pattern. An important modelling choice has been the time step of 15 minutes, which allowed only little freedom in scheduling smart cooling appliances, due to their short runtime and many usages per day. However, a smaller time step would not necessarily have produced better results. Even though the variations on the network load will increase, the overall scheduling places’ of smart appliances is expected to stay the same as long as the general demand pattern created by the non-smart appliances stays unchanged. The strategy of scheduling appliances always at the "lowest point" in the projected demand pattern worked very well. We found the model to be insensitive to alternative scheduling schemes, probably because there is no advantage of being first in the scheduler’s queue. We expect that more advanced scheduling algorithms will further increase the effectiveness.

Key words: Demand-Side Management, Load-shifting, Agent-Based Models (ABM), Smart Appliances, Smart Cooling Appliances.

1. Introduction

The electricity demand of households has been growing rapidly for the last decades. In 2009, households in the Netherlands used $87 \cdot 10^{15}$ J of electricity [1]. This is not only by the growing number of end-users [2] but also by the increase in electricity demand per end-user [3]. Both factors will continue to increase in the coming years. This means that the distribution network will have to transport more electricity to the end-users than today.

This is specifically the case during peak hours, when the electricity demand is significantly higher than the average electricity demand. The increase in demand will also increase the peak-demand. The present aging distribution network will not have the
capacity to cope with these future peak loads. The electricity load on parts of the distribution network could then exceed the available capacity, resulting in overloaded network components (assets). This will lead to an excessive reduction in life expectancy of these assets, which will eventually break down [4]. The increase of electricity demand therefore seriously reduces the reliability and safety of the whole electricity distribution, which poses a serious problem for the Distribution Network Operators (DNO’s). DNO’s are responsible for the transport of electricity, and the maintenance and management of the regional electricity distribution networks [5]. The traditional method to cope with capacity availability during peak periods has been to invest heavily in placing more electricity cables. However, upcoming developments such as Distributed Generation (DG) [6-10], Electrical Vehicles (EV) [11-13], Energy Storage (ES) [14, 15], and Demand-Side Management (DSM) [16-18] are changing our entire energy system, which may make the traditional method not the only way nor most effective way to cope with this problem. Especially DSM shows good potential for reducing the peak loads in the network demand pattern [18].

The goal of Demand-Side Management (DSM) is to reduce electricity demand, and to increase the efficiency of the system [16] by “bringing both demand and supply to the best possible low value” [19]. Characteristic for DSM is that it tries to manage the demand on the customer side of the meter and not the supply side.

DSM typically shifts loads from peak periods to off-peak periods. A good measure of DSM performance is therefore the Levelling Effect (LE). From a DNO perspective, the reduction of the peak loads in the network is very important as well. Lower peak loads mean less electricity losses as well as lower thermal strains on the power lines, which will increase the efficiency of transporting electricity and the lifespan of the network [20]. A second performance indicator is therefore the Height of the Peak loads (HP) in the network.

Both the traditional way of improving the network as well as the DSM approach require high investments. To ensure that such investments are economically viable, DNOs should know the extent to which Demand-side Management of households will affect these performance indicators KPIs.

2. DSM and Load-shifting

DSM programs in general comprise of policies and measures that try to control, influence and reduce the quantity or pattern of electricity used by the demand side of the electricity system [16, 18]. DSM programs typically uses various techniques, such as peak clipping, gap filling, load shifting, strategic conservation, strategic load growth, and flexible load shapes [17, 21-23].

DNOs cannot directly reduce the demand for electricity by households, but they can try to influence households to shift their demand away from peak periods to off-peak periods. Load-shifting programs (or Demand Responds programs) focus on shifting the electricity load of household appliances, away from peak periods to off-peak periods (see Graph 1) [17, 21-23].

The network load is the sum of all the household loads in the network. These loads are generated by the households’ appliances. The cumulative effect of load-shifting, as seen in Graph 1 above, is
achieved by scheduling household appliances to off-peak periods. The focus is therefore on the household appliances level.

A day-to-day network demand pattern is very irregular and shows many small peaks and gaps. These irregularities occur due to the simultaneous usage of many small power appliances or just a (few) high power appliances. To study the effect of load-shifting a simulation is required that takes into account these irregularities and that enable the scheduling of individual appliances.

3. Assessing load-shifting potential by scheduling smart appliances

3.1. Bottom-up approach

Because the focus lies on the level of household appliances, we have taken a bottom-up Agent-Based Modelling approach has been used. This approach is gaining popularity in the modelling of energy systems [24] mainly because it allows individual modelling of system components, such as consumers, generators, appliances, technologies etc. [25].

The overall systems behaviour then emerges from the simultaneous interaction of individual agents with each other and their environment [26]. Using this approach will capture the irregularities of the demand pattern created by the households’ appliances and enable load shifting at the level of individual smart appliances. The multi-agent modelling program Netlogo [27] has been used to create the simulation model.

3.2. Model Description

To reduce the peak loads in the network by shifting loads from peak periods to off-peak periods, we have constructed simulation model, of a low-voltage network with households connected to it. Each household owns several appliances, which generate the electricity demand of the household.

Appliances

Appliances are divided into two groups: non-smart appliances and smart appliances. Non-smart appliances are appliances that are of direct use to the end-user and can therefore not be scheduled, e.g. lights, TV's, or vacuum cleaners. Because these appliances are non-schedulable, their total electricity usage can be simulated with a single agent (the "other-loads") that represents the combined load of appliances that cannot become smart.

Smart appliances are appliances of which only the end result is useful to the end-user. We included five types of potentially smart appliances in our simulation: washing machines, tumble dryers, dishwashers, refrigerators, and freezers. We excluded other household appliances that can be potentially smart, e.g. air conditioners, heat pumps, and electric heaters, because they have a very low household penetration degree in the Netherlands [28]. Smart appliances are individually simulated to allow scheduling. However, when a potential smart appliance is not appointed as smart, it has not been individually simulated, and its electricity load was incorporated in the “other-loads” of the household.

We made the following assumptions and modelling decisions:

i. The other-loads have a demand profile that depends on the household type and its configuration of smart and non-smart appliances.
ii. For each type of household, we generated a large set of “other loads” profiles. When simulating a day, the demand profiles of the other-loads are defined, by randomly picking demand profiles from these sets. Different types of appliances have different attributes (e.g. wattage), but appliance attributes are the same per type.

Scheduler

The scheduler schedules smart appliances, which can take place at three levels:

i. Appliance level: The appliances are their own scheduler (a very smart appliance).

ii. Household level: The e-meter schedules all the smart appliances owned by the household.

iii. Network level: The network scheduler schedules all smart appliances owned by all the households in the network.

Furthermore, the scheduler uses one of these three types of forecaster to predict the demand pattern of a day:

i. Today’s forecast (assumes perfect knowledge). It aggregates the actual demand profiles of the households of the simulated day.

ii. Yesterday’s forecast uses the network demand pattern of yesterday.

iii. Average forecast, that uses the average of the network demand patterns of the last five days.

Additionally, the scheduler can use three types of scheduling schemes: First Come First Serve (FCFS), Earliest Deadline First (EDF), and Service In Random Order (SIRO). The scheduling schemes determine in which order the smart appliances that are in the schedulers queue, are scheduled.

To determine at what time a smart appliance must turn-on, the schedule uses a “lowest-point” principle. For each appliance, the scheduler creates an operation window (the period in which the appliance must turn-on). In this operational window, the scheduler searches the lowest point in the forecasted demand pattern and schedules the appliance use to begin in that timeslot. The dispatcher finally turns on the appliance at the correct time.

Key assumptions:

i. Scheduler always plans in every appliance in its queue (clears its list)

ii. Appliances cannot be rescheduled, stopped or paused once scheduled or turned on.

3.3. Operationalizing the KPI

To assess the effects of the smart system, we used the KPI’s that we mentioned in the introduction, i.e. Levelling Effect (LE) and Height Peaks (HP).

Levelling Effect (LE) is defined as the sum of the deviation to the average load of the current network. When the peaks in the demand pattern decrease and the gaps are filled, the deviation to the average load of the network will reduce. The sum of these deviations is an indication for the effectiveness of the smart system. To enable comparison with other networks, the sum of the deviation is then divided by the average load of the network.

\[
LE = \frac{\sum_{t=0}^{T} \left| network.load_t - \mu \right|}{\mu}
\]

with \( t \) in quarters and \( \mu \) representing the average demand of the network.

LE makes no distinction between which peaks are reduced and which gaps are filled. To also measure this aspect, we used a squared deviation value \( LE^2 \), which gives lower gaps and higher peaks higher deviation values. To enable comparison with other networks, these values are then divided by the squared average load of the network.
\[
LE^2 = \frac{\sum_{t=0}^{96}(\text{network load}_t - \mu)^2}{\mu^2}
\]

with \( t \) in quarters and \( \mu \) representing the average demand of the network.

**Relative Height of Peaks (R.HP)** is defined as the maximum peak of the network divided by the average of the network load. Load-shifting will reduce the peak loads in the system. To measure this reduction, the maximum peak of the network demand is measured.

\[
R.HP = \frac{\text{MAX}_{t=0}^{96}(\text{load}_t)}{\mu}
\]

with \( t \) in quarters and \( \mu \) representing the average demand of the network.

To see if the shape of the peak loads changes, the duration \( (d) \) of a demand above a certain percentage of the maximum network load is measured. In our simulation, we set this a percentage to 80%.

\[
d = \sum_{t=0}^{96} \text{if load}_t > \alpha \cdot HP, \quad \text{then 1 else 0}
\]

with \( t \) in quarters and \( \alpha \) in percentages.

To give an indication of the number of gaps that are still available for filling (D.HP) with smart loads, \( d \) is then divided by the number of time steps and subtracted from 1.

\[
HP.D_a = 1 - \frac{d}{96}
\]

3.4. Validation

We validated the simulation model by performing the following checks:

1. The share of electricity consumption and demand patterns of the network and of individual households comes close to the share of actual electricity consumption and demand patterns of a similar network and individual households.
2. The percentage of smart loads of the total appliances load of a household made-up about half of the percentages found in the literature.
3. The demand pattern shows the peak irregularities caused by simultaneous usage of appliances.
4. A load shift occurs when households have smart appliances.

3.5. Experimental Design

**Simulation Setup**

We used a time step of 15 minutes, making a trade-off (based on literature and the available data), between the required accuracy and the computational time needed. Furthermore, only one day has been simulated, because the focus lies on reducing the peak load in the day-to-day demand pattern. In addition, we made no distinction between different days, e.g. working or weekend days or special event days (holidays). Furthermore, we excluded other external influences like weather or seasons.

A warm-up time of six days is required to fill-up the memory of the scheduler for the average forecaster. Furthermore, to ensure the variability of the data, the number of replications required is derived from the moment the standard deviation of the main output (LE) no longer shows irregular or chaotic behaviour. This method allows the use of different replications for different networks sizes, i.e. bigger networks require fewer replications than smaller networks.

**Scenarios**

We examined the effectiveness of the smart system in a network of one hundred households for the following scenarios.

**Base scenario:** This network has no smart appliances and is used as a base line to compare the effects of the smart network with.
**Perfect Conditions scenario:** this network has a 100% penetration of smart appliances and perfect conditions for all smart systems used: Toda's (perfect) forecast, and a horizon of 80 quarters (20 hours) for operational window.

**Smart Cooling Appliances Only scenario:** Refrigerators and freezers turn on about 24 times a day for short periods. Sequencing these appliances can decrease the peaks and gaps caused by the simultaneous use of these appliances. Furthermore, since they turn on so often, and have a short operational time, they are excellent for filling small gaps in the network, which has a smoothening effect on the network demand pattern. These smaller gaps are difficult to fill with the other smart appliances as their operational time is longer. This scenario studies the impact of only smart cooling appliances.

4. Results

We measured the load-shifting effectiveness of the smart system by calculating the Key Performance Indicators for each of the scenarios presented in the previous section.

**Base vs. Perfect Conditions**

As expected, the Perfect Condition scenario results in lower KPIs, as can be seen in Table 1. Smart appliances are effectively scheduled to off-peak periods (lower LEs) and peak loads are reduced (lower HPs).

Table 1: KPIs of scenario's

<table>
<thead>
<tr>
<th>KPI</th>
<th>LE</th>
<th>LE²</th>
<th>HP</th>
<th>HP.D</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base</td>
<td>22.7</td>
<td>7.95</td>
<td>1.63</td>
<td>0.83</td>
</tr>
<tr>
<td>Perfect conditions</td>
<td>13.9</td>
<td>2.92</td>
<td>1.42</td>
<td>0.76</td>
</tr>
<tr>
<td>Maximum gap filling</td>
<td>8.12</td>
<td>1.05</td>
<td>1.29</td>
<td>0.76</td>
</tr>
<tr>
<td>Only smart non-cooling appliances</td>
<td>14.7</td>
<td>3.38</td>
<td>1.49</td>
<td>0.81</td>
</tr>
<tr>
<td>Only smart cooling appliances</td>
<td>22.6</td>
<td>7.91</td>
<td>1.56</td>
<td>0.79</td>
</tr>
</tbody>
</table>

To reach a completely level load pattern (LE = 0), the smart load should represent around 35% of the total load. In our model, the smart load is about 16%. As can be seen in Graph 2, this is enough to almost fill the first gap.

![Graph 2: Network demand pattern incl. different load-shifting situations](image)

If the entire smart load is scheduled to fill the gaps, even lower KPIs values are reached. However, this also includes the cooling appliances. These appliances are bound by repetitive usage throughout the day of roughly once per hour. They cannot (yet) be turned off for long periods without warming up too much. Not all the smart load is therefore schedulable freely throughout the day. In our simulation, the non-cooling appliances represent about 50% of the entire smart load, or about 8% of the total network load. As can be seen in Graph 2, the smart load shifting of non-cooling appliances already fills up the entire first gap (off-peak nighttime period).

When the peaks in the network demand pattern are reduced (lower HP values), and the gaps are filled, the demand pattern becomes more level (lower LEs). The lower HP.D values in (Table 1), reflect that the off-peak period (and hence the number of timeslots available for scheduling) is reduce.

Examining the load patterns in more detail, we found numerous short (one time step), but very
high peak loads. These peaks were caused by those smart appliances that start with a low demand load, followed by a much higher load (e.g. washing machine). Since our scheduler does not consider appliances load profiles, it schedules these appliances to start at the lowest point in the operational window. Because of the low starting load, this point remains a low load point, so the scheduler will continue to schedule appliances to this point. Graph 3 illustrates this effect.

![Graph 3: Peak forming by appliance with low start demand](image)

**Graph 3: Peak forming by appliance with low start demand**

### Sensitivity of smart variables

As expected, Today’s memory forecast (perfect knowledge) gave the best result (lowest KPIs) followed by the Average and Yesterdays forecast. Likewise, longer operational horizons also resulted in lower KPIs. Unexpectedly however, using different scheduling schemes did no lead to different results.

### Smart Cooling appliances only

The sequencing of smart cooling appliances can reduce peak forming caused by the simultaneous use of these appliances. We therefore expected that an increase in penetration percentage of smart cooling appliances would reduce the KPIs values. This however did not occur; they actually increase. The scheduler appears not to cope very well with appliances that have a short runtime, a short switched-off period and a narrow operational window.

Although the individual cooling appliance cannot be scheduled to the deepest gaps, the scheduling does produce a "smoothing" effect: a layer of smart cooling loads that lays on top of the demand pattern emerged and absorbed all the small irregularities in the demand pattern (see actual.network.load in Graph 4 but note that Graph 2 also clearly shows this effect).

![Graph 4: Network demand pattern of only smart cooling appliances](image)

Graph 4 highlights in particular that the combined demand pattern of the smart cooling appliances is the mirror image of the irregularities of the other-load pattern.

### 5. Discussion

First we will discuss the implications of our decision to use a 15 minute time in order to keep computing time low. We will then discuss the surprising insensitivity to the choice of scheduling algorithm, and finally consider how our selection of smart appliances may have influenced the findings of this study.

### Simulation time step

A time step of 15 minutes turned out to constrain the scheduling of cooling appliances. Their short runtime, short switch-off periods and narrow operational window leaves but few eligible timeslots for the scheduler. Improving the scheduler for the smart cooling appliances however was not possible due to the simulations time step used. Using a shorter time step in combination with a more advanced scheduling algorithm should improve the scheduling of smart cooling appliances.
The time step also limits the impact of variety in the appliances attributes. Small differences in attribute values of appliances of the same type (e.g. washing machine with a power of 1000 or 1200 Watt), will not have had any significant effect. Furthermore, the time step also limits the duration that the appliances are active. Now appliances have been turned on in a multiple of 15 minutes, which leads to higher loads per household.

The question is whether a smaller time step would have significantly changed our main findings, i.e. that scheduling smart appliances has a strong levelling effect. A shorter time step would increase the impact of variety in the appliances’ attributes and allow a better representation of the profiles of the other-loads. This would result in more variation in irregularities on the demand pattern (see Graph 5).

However, although the scheduler does make a distinction between the small irregularities on the demand pattern, the overall pattern of peak and off-peak hours would stay the same. This is because the “other-loads” are the main contributors to the demand pattern. Even when this pattern becomes more irregular as in Graph 5, the scheduler will shift smart loads first to the low points in the overall pattern (the gaps in Graph 2).

This leads us to conclude that, a smaller time-step would probably not have altered the general results of this research.

Scheduler algorithm

Our model turned out to be insensitive to the choice of scheduling scheme. A first explanation is that under every scheme the non-cooling appliances will be scheduled in the big gaps.

The scheduling schemes differ in the way they determine which appliances are scheduled first. Appliances first in queue have a advantage over the other appliances. However, in our model the scheduler always plans in every appliance in its queue, which reduces the advantage of being first in queue. In addition, in our model appliances cannot be rescheduled. This limits the possibility for more optimal alternative positions for the appliances to emerge while the appliances are in standby mode.

As we observed, peak forming can occur in subsequent timeslots because the scheduler does not take into account the entire demand profile of the appliances. More advanced scheduling algorithms that take into account the appliances demand profile, and allow appliances to be re-scheduled or not to be scheduled at all, may increase the effect of the scheduling schemes and create better solutions for the filling of the gaps.

Smart appliances used

In our simulation we used only five different smart appliances, because their penetration degrees are very high in the Netherlands. The use of other less common appliances, such as air conditioners and heat pumps, may however increase in the near future. Furthermore, with the introduction of the electric vehicles (EVs) the burden on the network will significantly increase. Smart recharging of their batteries may help to reduce the added burden on the network. In addition, new developments in smart and non-smart appliances themselves (e.g. fitting small batteries in appliances that load during off-peak periods and can be used during peak load periods) could contribute to a more optimal scheduling and thus a more optimal use of electricity. The increase of possible other smart appliances and
their developments should therefore also be taken into consideration in following studies.

6. Conclusions

Our study has shown that load shifting by scheduling smart appliances is likely to produce more levelled demand pattern. Peaks in the network demand pattern can be reduced by 13% and the gaps are filled resulting in a more levelled demand pattern.

A time step of 15 minutes works well for non-cooling appliances, but it limits the effective scheduling of (the present) smart cooling appliances. But a shorter time step would not necessarily have produced better results. The overall network demand patterns, and thus the overall scheduling places of the smart appliances, will most likely stay the same.

What potentially could make a difference is a more advanced scheduler. Allowing rescheduling and the possibility for smart appliance not to be scheduled could result in a higher effectiveness of the scheduling schemes and more optimal scheduling of the smart appliances.

References


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