Direct load control for district heating load management using least-squares support vector machine

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Abstract
This study presents a methodology for implementing a Direct Load Control (DLC) scheme for a district of residential dwellings, which aims to minimize peak power in the grid and reduce consumer costs. The study is conducted in three steps: building a dummy residential district as the case study, developing a control-oriented model for the entire district, and casting the DLC scheme as a Model Predictive Control (MPC) problem. The dummy model consists of four residential dwellings, and a surrogate Least-Squares Support Vector Machine (LS-SVM) model is developed for the entire district using a dataset generated from hourly simulations for an entire year of the case study. The DLC scheme is implemented using a centralized control method, with the optimal set-point trajectory determined through solving an MPC problem for the entire district. In order to evaluate the provided flexibility, two main KPIs will be assessed, namely the cost of the consumers, and peak clipping, which denotes how much reduction in peak load has taken place. Utilizing the surrogate model for the DLC scheme leads to 16% of cost saving for the consumers, and reduces the peak demand by 35% as compared to a hysteresis baseline. Moreover, the load profile has become smoother which means a more reliable grid operation.

Highlights
- Building up a dummy district as a case study in Dymola using the IDEAS library.
- Developing a surrogate LS-SVM control oriented model of the case study district.
- Casting a DLC scheme as an MPC problem.
- Deploying the LS-SVM model in the DLC scheme to evaluate the performance.

Introduction
One of the avenues to manage the load on district level and keep the grid operation as smooth as possible is to exercise Demand Side Management (DSM). Demand side management is defined as a series of strategies and technologies used for managing the load on the demand side. It includes very simple yet effective steps such as increasing the energy efficiency - e.g. changing the appliances with more efficient ones - and can go all the way to implementing complex control systems incorporated by the supply side of the grid.

There are different ways for implementing demand side management for achieving energy flexibility and managing the load on the demand side. From a control perspective the energy management on district level could be categorized as centralized, decentralized, and distributed control strategy (Pourbabak et al., 2018). In the centralized scheme all the decisions are made by the central controller for all the dwellings within the district. This method is efficient in terms of optimality and communication, however it suffers from some robustness issues and scalability (Pourbabak et al., 2018). In the decentralized control each of the dwellings will make their decision on their own with an actuator from the supply side, e.g. a price signal. Although this latter method might seem to be more autonomous, due to the lack of communication and the disregarded interconnection of all the elements of the district sub-optimality can be foreseen (Pourbabak et al., 2018). Finally, there is the distributed control scheme where all the elements of the district are capable of making their own decision and communicate at the same time. Despite the increasing performance (optimality of the solution), the soaring computational time and communication equipment is the main drawback (Hua et al., 2021). This study will exploit the centralized control method for exercising DLC on the district. Direct Load Control (DLC) is a method used in Demand Side Management (DSM) to manage peak electricity demand by controlling specific loads at the demand side. DLC involves the utility company remotely controlling specific electrical loads, such as air conditioning units or water heaters, to reduce electricity consumption during peak demand periods. In other words, Direct load control (DLC) or direct load management (DLM) refers to a demand-side management strategy in which utilities control the power consumption of certain appliances or equipment of end-users during peak hours to balance the electricity demand and supply, prevent blackouts, and reduce the peak demand (Salami & Farsi, 2015). It is shown that Direct Load Control (DLC) is more effective than incentive based Demand Response (DR) because of the limited autonomy of the demand side (van Stiphout, 2017), along with the comprehensive oversight of the supply side on the demand side which can take all the interactions within the district into account. There are also other advantages to DLC such as reduced peak energy consumption, preventing blackouts by having less generation units engaged, and making the market price of the electricity cheaper by avoiding the contraction of expensive back up generation.
units (Li et al., 2017; Salami & Farsi, 2015). However, despite the upsides, due to the lost control of the consumers and also General Data Protection Regulation (GDPR) implications the vast implementation of DLC is hindered (Xu et al., 2018).

In a study by Tasçıkaraoğlu et al. (Tasçıkaraoğlu et al., 2019) a residential building was investigated in terms of the effectiveness of DLC for HVAC systems. The study found that the DLC program reduced the peak demand by 22% and shifted the peak load to off-peak hours without compromising the indoor comfort levels. Mor et al. (Mor et al., 2021) developed a novel methodology for flexibility function estimation within the context of direct load management. They investigated their methodology using three modelling paradigms of white-box (WB), grey-box (GB) and black-box (BB) for three use cases where heat pumps are providing services. WB models are engineering models which are purely based on physical equations. BB models are purely statistical models which are based on mathematical equations with no physical interpretations between then inputs and outputs. GB models are the a combination between WB and BB models. They included a new participant which is responsible for clustering together the local energy systems. This participant acts as a mediator between the aggregator and the end-user. Findings of this study shows the potential of automated demand response in combination with thermostatically controlled heat pumps in providing a maximum of 25% flexibility. Tang et al. (Tang et al., 2018) assessed the demand response of a commercial building to an urgent request from the grid by implementing direct load management by shutting down a number of equipment. Thermal behavior of the building is characterized using heat transfer equations. Occupants incentive to sacrifice of thermal comfort has been considered as well. The findings show that by considering the possibility of acceptable temperature increase rate and deploying appropriate control strategy up to 34% reduction in power demand of the building could be achieved in a DR scheme. Curiel et al. (Rama Curiel & Thakur, 2022) applied direct load management for peak load reduction and energy saving of Air Conditioning (AC) units. The load control method is based on generation of the grid and the related constraints of the supply side. This means that the request is triggered when demand reaches a specific threshold. The results show that when 5% of the households in the study have AC units, the peak demand could be decreased by 2% and the energy bill could be reduced by up to 20% for end-users. Van der Klauw et al. (Van Der Klauw et al., 2016) studied a neighbourhood in Austin, Texas and assessed their flexibility potential for demand side management. They developed linear models of the building’s thermal behaviour and showed the models are reasonably accurate for the prediction of the indoor temperature. They used the home energy management system controller (HEMS), which is a digital system that controls and monitors the energy consumption, generation and storage to communicate with the buildings and subsequently control their HVAC systems. They reported that they managed to steer the load in the desirable direction. The results could have been more promising if more accurate predictive models would have been used.

The more fine grained the climatization load management, the better the results. However, increasing the granularity of the control to the individual building level, instead of building cluster poses critical challenges in terms of developing a control oriented model. Having a district model as the summation of the standalone models of each of the buildings might disregard the interactions among the buildings. Moreover, developing an individual model for each of the buildings by a single entity (the utility company) would be quite time consuming. Developing a unified model of a district for controlling all the individual dwellings can also be challenging specially in terms of the computational assets. Therefore, compact models such as Least Squares Support Vector Machine (LS-SVM) which does not rely on the input space dimensionality (i.e. in this study the number of buildings in the district) are essential. The LS-SVM method, like the normal Support Vector Machine (SVM) technique solely relies on the number of data points and not the input space dimensionality (Suykens & Vandewalle, 1999), which can make it a potent candidate for characterizing the behaviour of systems with a large input space dimensionality to be incorporated in optimization applications.

This study aims to assess the performance of an LS-SVM based district model for minimizing the peak load in the grid while minimizing the consumers cost and maintaining their thermal comfort through a DLC approach. To this end, first, a dummy district is developed in Dymola, using the IDEAS library. Then a dataset is generated which encompasses a comprehensive range of excitation to enrich the data and cover most of the possibilities. Afterwards, this study will make use of the LS-SVM technique for modelling the dummy district. LS-SVM, just like any other black-box methods has its own drawbacks such as generalization issues, which will be investigated and reported in this paper. Finally, the DLC problem will be casted as a Model Predictive Control (MPC) problem, which is an optimal control technique to minimize a cost function through control actions while adhering to the constraints over a finite receding horizon (Drgoňa et al., 2020). The output of the optimization will be the optimal energy and set-point temperature profile for each of the buildings within the district.

**Methodology**

The methodology of this study takes place in 3 main steps. First, a dummy district is built up in Dymola which is both simple and representative of non-renovated and renovated residential dwellings; afterwards this model of the district is used to generate an academic dataset. In the second step, using the dataset generated in the first step, a model is developed for the entire district which is control oriented. Finally, in the third step the direct load control scheme is casted in the form of a Model Predictive Control problem (MPC) and then formulated.
Case study and dataset

A simple dummy district which is made out of 4 residential dwellings is modeled and developed in Dymola using the Modelica language and the IDEAS library (Jorissen et al., 2018). The dwellings are divided into 2 archetypes based on envelope properties and airtightness to represent different renovation and insulation levels. Also, each of the dwellings has their distinct occupancy profile. Dwellings 1 and 2 represent the 2010s dwellings (renovated 1980s dwellings) with a thicker insulation layer (Rockwool with a thickness of 13 cm), a thick rooftop insulation layer (Glass-wool with a thickness of 26 cm), a thick ground floor insulation layer (EPS with 15 cm of thickness), a window frame with a U-value of 2.6 W/(m²K), an Argon filled double glazing window with a U-value of 1.1 W/(m²K), and an airtightness at 50 Pascal (n50) equal to 2.5 ACH. Dwelling 3 and 4 represent the 1980s dwellings with a thin outer wall insulation layer (Expanded Polystyrene or EPS with a thickness of 1 cm), a thin rooftop insulation layer (Glass-wool with a thickness of 4 cm), a thin ground floor insulation layer (EPS with 3 cm of thickness), a window frame with a U-value of 4.5 W/(m²K), an air filled double glazing window with a U-value of 2.9 W/(m²K), and an airtightness at 50 Pascal (n50) equal to 4 ACH. The rest of the properties are identical, including the volume and surface area. It is worthwhile to mention that the total surface area of each of the dwellings is 128 square meters. Moreover, the internal walls of all the dwellings are the same, therefore the structure is not enlisted in the table, however included in the simulation. Table 1 summarizes all the properties in which the dwellings differ.

With having the district model available, the next step is to generate the dataset from the district’s white box-model. For this step all the dwellings are equipped with a PID controller trying to track a semi-random sinusoidal set-point temperature with a non-diurnal period so as to avoid a bias towards the time-of-the-day for the predictive model training phase. The input to the controller is the error from the target value and the output is the load of the heating system. The dataset consists of 8760 data points, which represent the hourly simulation of the dwellings for an entire year. Later on, this dataset will be used for training a control oriented model of the district.

Table 1- dwelling properties

<table>
<thead>
<tr>
<th>Insulation thickness [cm]</th>
<th>Dwellings</th>
<th>2010s</th>
<th>1980s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Outer wall</td>
<td>Rock-wool, 13</td>
<td>Rock-wool, 13</td>
<td>EPS, 1</td>
</tr>
<tr>
<td>Roof</td>
<td>Glass-wool, 26</td>
<td>Glass-wool, 26</td>
<td>Glass-wool, 4</td>
</tr>
<tr>
<td>Ground</td>
<td>EPS, 15</td>
<td>EPS, 15</td>
<td>EPS, 3</td>
</tr>
<tr>
<td>Frame U-value</td>
<td>2.6</td>
<td>2.6</td>
<td>4.5</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Glazing filling U-value [W/(m² K)]</th>
<th>Argon, 1.1</th>
<th>Argon, 1.1</th>
<th>Air, 2.9</th>
<th>Air, 2.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>Airtightness (n50)</td>
<td>2.5</td>
<td>2.5</td>
<td>4</td>
<td>4</td>
</tr>
</tbody>
</table>

District modelling

The modelling of the district relies on the application in which it is being used. Therefore, in this study, the surrogate district model should be a unified model of the entire district, which is simple, fast responsive, real-time control oriented and yet accurate. Grey-box models of the entire district which are capable of considering all the interactions are difficult to develop, topology dependent, and sophisticated; whereas, black-box models which can easily consider all the interactions in the district are less complicated. Nevertheless, having a heavily detailed unified black-box model of the entire district, which is control oriented depends on the district’s size. There are several black-box modelling techniques available for modelling the entire district. Since the models are used for the individual control of each of the buildings within the district - meaning no aggregation is in place - many of the choices will be ruled out due to the lack of accuracy and development implications. Jafarinejad et al. (Jafarinejad et al., 2021) conducted a study on the accuracy and development of three of the most prevalent black-box modelling techniques for identifying the thermal behavior of a district for further utilization in optimization applications. They illustrated that Auto-Regressive with exogenous inputs (ARX) models, despite their linearity and a fair training time, suffer from the lack of accuracy even when the district is small. On the other hand there are the Artificial Neural Network (ANN) models, which require a huge training time (including neuron sweeping) to achieve a desirable accuracy. Finally, there is the Least Squares Support Vector Machine (SVM) method, which is both quite accurate and less computational demanding when it comes to training. Therefore, in this paper Least-Squares Support Vector Machine (LS-SVM) is chosen. The main difference between LS-SVM and SVM is the use of a squared loss function instead of an $\varepsilon$-insensitive loss function. Another important reason for using this method is its reliance on the number of data points rather than the input space dimensionality. Imagine a district of a few thousands buildings to be developed by an ANN model; it would be devastating in terms of Random Access Memory (RAM) since the weight matrix would be extremely large in size. Apart from the memory issues it will also lead to computational barriers since the model wouldn’t be as fast responsive as the LS-SVM one. Despite the merits of the LS-SVM modelling technique in terms of dealing with large input space dimensionality as in a DLC application implemented for all the individual dwellings in a district, one should investigate if the developed model can also
perform well within the application or not. Such an evaluation might further lead to opting for other modelling techniques or revising the training dataset.

SVM/LS-SVM is actually a machine learning technique for classification and regression based on Vapnik’s revolutionary statistical learning theory (Vapnik, 2013). The way SVM works is to bring the input and output space to a higher (infinite) dimension, namely the feature space, using the feature map, or in other words, a Kernel function. Afterwards, classification or regression is carried out in that feature space in a linear way through using a hyperplane. For the regression applications, SVM finds a decision boundary at a distance from the original hyperplane such that the data points closest to the hyperplane, i.e. the support vectors, are within that boundary line (De Brabanter et al., 2002). The SVM regression output is expressed as in Equation (1).

\[ y = \omega^T \varphi(x) + b \]  

(1)

Where, \( x \) is the inputs vector, \( \omega \) and \( b \) are the model parameters that would be obtained by solving a convex optimization problem in the primal representation (Suykens & Vandewalle, 1999).

Over the course of a recursive (backwards) input feature selection along with a lag sweeping technique, the optimum inputs for the LS-SVM model and their respective time lags are concluded as follow: the boundary condition (ambient temperature and solar radiation), internal heat gains, lagged energy consumption until the 6th previous time steps, lagged indoor temperature of each of the dwellings until the 4th previous time-steps, and finally the set-point temperature at the current time-step (the next time-step indoor temperature). The output of the model is the energy needed to meet the set-point temperature trajectory (set-point). It is worthwhile to mention that prediction uncertainty is not taken into account in this study. Moreover, the ToU price is extracted from a Belgian electricity supplier day ahead electricity tariff and assumed to have a repetitive pattern for the simulation period (Belgian Bidding Zone Day-Ahead Reference Price, n.d.).

**Direct load control**

The direct load control (DLC) optimization application is casted as a Model Predictive Control (MPC) problem which is essentially an Optimal Control Problem (OCP). The point of view of this problem is the supply side (from a DSO all the way downwards to an aggregator) and the target is to reduce the peak load, while reducing the consumers cost and maintaining their thermal comfort. The MPC’s control and prediction horizon is 24 hours, and each time-step is one hour in duration. Therefore, the objective function of this optimization problem is written as the minimization of having peak power, which will alleviate the stress on the grid, reinforcement costs, costly backup generation unit contraction and also expensive storage systems. This objective function directly corresponds to reducing the consumers’ cost (Equation (2)), or in other words maximizing their benefit from taking part in the DLC scheme. The reason for such a direct relation is that the peak load probability in grid is almost the same the normalized Time of Use (ToU) price of the electricity. Therefore, the Time of Use price (ToU) is used to represent the desirability of having peak load (inversely proportionate), or the probability to have peak power demand in the grid. The decision variable of this optimization problem is the set-point temperature – the rise and fall in each of the dwellings indoor temperature - which will be held constant for an entire hour. Manipulating the rise and fall of the temperature will eventually activate the thermal mass of the dwellings and provide flexibility for steering the load. However, the rise and fall in the temperature should be constrained since not all values are reasonable and technically feasible for HVAC systems and the dwellings to cope with. Therefore, at each time step, the HEMS of each of the dwellings will send a signal to the supply side, using an individual model of the building, defining their feasible rise and fall in temperature. For the fall, once the HEMS’ individual model will predict the drop in temperature given no heat input at the lower margin of thermal discomfort band and once at the higher margin of the thermal comfort band. The smaller value is taken as the maximum feasible fall in the indoor temperature. For the rise in the indoor temperature, once the HEMS’ individual model will predict the rise in the indoor temperature given maximum heat input at the lower margin of thermal discomfort band and once at the higher margin of the thermal comfort band. The smaller value is taken as the maximum feasible rise in the indoor temperature. In this way the dynamic constraints (equation (6)) will be overwritten at each time step and held constant throughout the control horizon at that time-step. Obviously governing such a decision variable comes at a cost of losing some optimality due to the feasible solution space truncation. This means that maybe at a given time step the dwellings could have more rise or fall, yet we considered a smaller value just to stay on the safe side and avoid infeasibility. The mathematical representation is expressed in Equation (2) to (6).

\[ f = \min(\text{thermal discomfort} + \beta \times \text{energy cost}) \]  

(2)

s.t.  

\[ \text{Energy}_k = f(T_k, \text{boundary condition, occupancy}) \]  

(3)

\[ T_{\min} < T_{k,...,k+n} < T_{\max} \]  

(4)

\[ T_{k+n} = T_k + \alpha_1 + \cdots + \alpha_n \]  

(5)

\[ \alpha_{\min,1,...,n} < \alpha_1,...,n < \alpha_{\max,1,...,n} \]  

(6)

Equation (3) represents the LS-SVM model, where the output is the heating energy of the entire district. Equation (4) defines the thermal comfort band, Equation (5) describes that the temperature at a given time step is the result of the summation of the initial indoor temperature plus all the rises and falls at previous time-steps (positive values for rise and negative values for fall). Finally, Equation (6) represents the dynamic constraint that is updated for the next 24 hours at the beginning of each time-step by the HEMS internal model of each of the dwellings. By solving this MPC problem and finding the optimal rise and fall in temperature for each of the
dwelling over the control horizon at each time-step, the set-point temperature of the dwellings will be set by the supply side.

Figure 1 depicts the entire framework in the Matlab Simulink environment. The entire DLC framework is casted in the Matlab Simulink environment.

The DLC is written in a Matlab user defined function. Since the objective function is a nonlinear and nonconvex function, the Genetic Algorithm (GA) function is used for finding the (local) optimal solution. As MPC approach is used, it means that at each time-step the real response of the system should be obtained. This means that there should be a connection between Matlab Simulink and the Dymola model. One of the main pathways to establish such a connection is co-simulation. Co-simulation is a simulation technique in which multiple simulation models are executed simultaneously while passing data through predefined interfaces. Co-simulation will streamline the simulation of a larger system composed of multiple subsystems, each modelled separately using different simulation tools or programming languages. To this end, Functional Mock up Unit (FMU) is used. FMU (Functional Mock-up Unit) is a standard interface for model exchange and co-simulation of dynamic system models. It facilitates the integration of different models developed in different simulation tools and programming languages into a single simulation environment (in this case Simulink). An FMU is a self-contained executable file that is comprised of a dynamic model, including the internal states, inputs and outputs. The plant model (emulators) in the framework are exported as Functional Mock up Units (FMU) from the individual buildings which were initially developed in Dymola. Afterwards those FMUs are integrated in the Simulink environment for commencing the optimization framework.

Results and discussion

Before discussing the simulation results, the accuracy of the LS-SVM model should be reported. With the given inputs and output in the previous section, the coefficient of determination (R²) for the district’s LS-SVM model is equal to 0.99, which sounds quite promising. Nevertheless, the main question is, does an accurate model lead to an extraordinary application performance?

The simulation is taking place in the city of Uccle, Belgium and from January 2nd to the January 10th (9 days) and the simulation time-step is one hour. Given the optimization problem, the time-step length is adopted in a way not to sabotage the real-time response of the controller. Hereinafter, all the results are only illustrated for the first 5 days for a clearer view but the peak clipping and cost saving are reported for the 9 days of simulations. This period is chosen to have typical winter conditions. It is logical to assume the demand would be at its highest during this time period and peak demands are more pronounced. This way, the potential of conducting DLC would be put in exercise and the benefits in terms of peak clipping can be assessed. The start of the simulation is at 00h00. Figure 2 (a) shows the temperature profile and Figure 2 (b) the power consumption versus the normalized price for a typical dwelling of 2010s archetype, namely dwelling 2. The reason for using the normalized ToU price is to make it more sensible on a scale of 0 to 1 and make a more compressible comparison between the ToU price and the probability of having peak load in the grid. As it could be seen in Figure 2 (a), the set-point temperature trajectory obtained by the DLC is being tracked in somewhat an accurate manner, which accentuates the agreement between the prediction and reality. The emulator temperature as mentioned before is the plant (dwelling) actual thermal behaviour. For having a better grasp on what is really happening one should make an eye on Figure 2 (a) and (b) at the same time, while having a close look at the normalized energy cost, which denotes the probability of having peak demand in the grid. As could be elicited from Figure 2, before the rise of the set-point temperature, the dwelling’s temperature starts to rise when the price is low, i.e. when there is a higher probability of having peak demand in the grid. Results are more accurate in higher temperatures, which could be due to the fact that the lower the temperature, the closer the model to its training dataset margins. Machine learning based black-box models perform somewhat inaccurate when they are supposed to interpolate close to their training margins or extrapolate out of the training margins. The reason the 2010s dwelling operates in high temperature ranges is the fact that their training data was also in that range due to the high insulation level (low Heat Loss Coefficient (HLC)). This could be solved by generating more enriched datasets which cover a larger range of temperatures, especially low ranges. Another reason for such a high temperature operation of the 2010s dwelling might be the underestimation of the LS-SVM model over the control horizon, which always tries to keep the temperature high so as to avoid pushing the dwelling in to the under-heating phase.
Another support for that claim is the 4th day, when the temperature is going out of the upper comfort band. Right before that incidence, it could be seen that the price is low and the DLC is trying to store as much as energy via the thermal mass of the building, however, due to the higher ambient temperature and the solar gains the temperature rises significantly and exceeds the upper band. This is yet another reason for concluding that the LS-SVM model is underestimating. On the two final days when the ambient temperature goes as low as -5℃, it can be seen that the heating system is almost performing on maximum capacity and trying to avoid thermal discomfort. Looking at the power consumption it could be elicited that the DLC is perceiving the extreme cold weather and yet suffering from underestimation. Still, the DLC attempts to use the energy when it is cheaper. Finally, it can be concluded that the DLC has a high tendency to activate the thermal mass of the renovated dwellings with a lower HLC value to store more energy for providing flexibility.

The issue of the high temperature operation of the 2010s dwellings and the low temperature operation of the 1980s dwellings can be addressed by generating richer datasets which can cover a larger range of temperatures. Another remedy is to use other modelling techniques which are better at performing close to the training margins. This means that the PID controllers of all the dwellings should be retuned and also the semi-random sinusoidal set-point temperature that was fed to the PID controller for the dataset generation should be revised. Although generating a richer dataset may alleviate such issues, one should consider that a richer dataset means drifting away from reality and stepping into a more academic realm, which is not always the case and will not happen in real life when it comes to practical implementation.
In order to have a fair comparison of the performance of the LS-SVM model within the DLC framework, a baseline should be considered. In this study, the baseline is defined as the case in which all the dwellings are equipped with a hysteresis controller tracking the lower comfort band. The hysteresis controller is in fact a price unaware controller which is purely tracking a predefined set-point trajectory regardless the price of the electricity (peak demand probability). Figure 4 (a) shows the DLC framework’s aggregated power consumption for all the dwellings within the district and Figure 4 (b) depicts the aggregated power consumption of the hysteresis scenario for all the dwellings within the district. As it can be seen in the figure, the DLC framework power consumption for the entire district mostly takes place when the price is low, or the peak load probability is low. The only case that it doesn’t follow the trend is on the two final days, when the boundary condition is at its most extreme. Taking a look at Figure 4 (b), it can be realized that the hysteresis scenario is not sensitive to the price at all, and shows elevations when the set-point is rising or the temperature is going out of the hysteresis band. Another important take from the figure is that for the hysteresis case, there are huge power peaks of roughly 28 kW, coinciding with the times that the peak load probability is at its highest; whereas, for the DLC case, the peaks are less than 18 kW and they rarely coincide with the times that there is a high probability of peak demand in the grid. This outcome shows that the DLC framework managed to clip the peak load by almost 35%. The other interesting point is that we observe the DLC’s power consumption is smoother than the hysteresis scenario one. Although by increasing the size of the district the hysteresis power profile will also get smoother, it is important to see how on a small scale the DLC proved to be a potent remedy for flattening the load curve, which is turn will lead to a smoother and more reliable local grid operation. In order to have a better idea on how much benefits the DLC has brought about, the cost of the entire district will be studied for both scenarios. The total cost of the district for the simulation period when applying the DLC scheme in comparison to the hysteresis scenario has been reduced by 16%. This drop in the cost signifies a 16% cost reduction when implementing the direct load control scheme for the district.

Finally, Figure 5 shows the stacked power consumption of the entire district. It is clear that the 1980s dwellings consume more energy than the 2010s, even though they are operating at a lower temperature. The power consumption for each of the archetypes doesn’t necessarily follow the same trend since as mentioned earlier each of the dwellings has a distinct occupancy behaviour. It can also be elicited that the power demand on the last 2 days for the entire district is higher which is on the ground of more extreme weather conditions at that time, along with some under estimation issues.

**Conclusion**

This study describes simulation based methodology used for the implementation of a direct load control (DLC) scheme for an entire district of residential dwellings. The study is carried out in three main steps: building a dummy district model in Dymola and generating an academic dataset, developing a control-oriented model for the entire district (the main focus of the study), and casting the DLC scheme in the form of a Model Predictive Control (MPC) problem. The dummy district model consists of four residential dwellings divided into two archetypes based on their renovation and insulation properties. A dataset of hourly simulations for an entire year is generated from the generated dataset an LS-SVM model is developed for the district model using a PID controller tracking a semi-random sinusoidal set-point temperature. Using the generated dataset an LS-SVM model is developed for the entire district which is able to foresee how much energy power will be used is each of the dwellings in the district are supposed to follow a specific set-point trajectory. Finally, the DLC scheme is implemented using a centralized control method, where the set-point temperature trajectory of each of the dwellings is
suggested by a central controller. The dwellings’ HEMS will update the DLC constraints on the set-point at each time step. The optimal set-point trajectory will be obtained through solving an MPC problem for the entire district, aiming to minimize the peak power in the grid, i.e. minimizing the consumers cost. The findings could be concluded is follows:

- Thermal mass of the dwellings is activated by increasing or decreasing the set-point temperature trajectory.
- Compared to a baseline, in which every dwelling is following the lower comfort band as a set-point, the DLC reduces the peak load by 35% as compared to the baseline.
- The DLC scheme leads to 16% cost saving for the consumers.
- When temperature gets close to the lower margins of the training range, the LS-SVM model should interpolate (in some cases extrapolate) around those margins, which in turn decreases the accuracy.
- For both the 1980s and 2010s dwellings when the price (peak load probability) is low the DLC strives to consume more power.
- The MPC favours the 2010s dwellings for providing flexibility through storing energy within their thermal mass.

Finally, it is concluded that the choice for the generated dataset wasn’t the best one and richer and more elaborate datasets could have improved the performance and the prediction accuracy. Moreover, other modelling techniques should be also deployed for making a fair comparison between different modelling techniques.

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References


