Evaluation of Machine Learning Algorithms for Demand Response Potential Forecasting

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Abstract

This paper focuses on the ability of machine learning algorithms to capture the demand response (DR) potential when forecasting the electrical demand of a commercial building. An actual sports-entertainment centre is utilised as a testbed, simulated with EnergyPlus, and the strategy followed during the DR event is the modification of the chiller water temperature of the cooling system. An artificial neural network (ANN) and a support vector machine (SVM) predictive model, are utilised to predict the DR potential of the building, due to the significant amount of execution time of the EnergyPlus model. The data-driven models are trained and tested based on synthetic databases. Results demonstrate that both ANN and SVM models can accurately predict the building electrical power demand for the scenarios without or with daily DR events, whereas both predictive models are not accurate in forecasting the electrical demand during the rebound effect.

Introduction

Demand response (DR) programs, in which participants change their electricity usage in response to electricity prices or signals, are recently considered as a possible way to enhance renewable energy sources (RES) integration in the electricity grid (Korkas et al., 2016). RES power generation, especially solar and wind, largely depends on the time evolution of weather patterns which are to varying degrees unpredictable. This results in potential imbalances between the power supply and demand on the gird (Thomaidis et al., 2016). As a way to compensate these imbalances, DR is utilised to provide the necessary flexibility to the grid. Additional benefits can be derived to the electricity grid from the implementations of DR programs. Namely, DR can restrict the electricity generation from fossil fuels by adjusting the demand to the present availability of fluctuating resources, so curtailments can be reduced and the overall RES share can be increased (Beil et al., 2015; Gils, 2014).

Among the different demand end use categories, buildings account for almost 50% of the final electricity consumption and thereby can play a significant role in maintain the power supply and demand balance (International Energy Agency, 2013). Commercial buildings, in particular, are of considerable interest for the implementation of DR measures, since they can provide considerable load reduction and offer a range of options for demand management (Gao and Sun, 2016). Heating, Ventilation and Air-Conditioning (HVAC) systems are their largest energy end-use category (Pérez-Lombard et al., 2008), which can also be controlled in order to utilise the building inherent energy storage characteristics and provide demand reduction (Xue and Shengwei, 2012).

In order for commercial buildings to be capable to participate in DR, control strategies which respond and adjust building electricity demand profile are necessary. Forecasting of building electrical power demand under different external and internal conditions when DR measures are applied is of major importance. These forecasts can be utilised from the building energy management (BEM) system to control and select the ideal response to each DR request.

Building energy models have been widely used for performance analysis in the building industry and to demonstrate compliance for codes and standards (Christantoni et al., 2015). Nevertheless, the use of building energy models can be extended beyond that. They can also be used to optimise design solutions or to assist BEM systems during the building operational phase (Zhao et al., 2015). In recent years, different approaches are utilised to model and predict building energy consumption. These methods can be classified as white (physics-based), black (data-driven) and grey box (hybrid) methods (Amara et al., 2015). Detailed physics-based models have been widely used to demonstrate measures for reducing peak loads due to their ability to simulate complex system behaviour and alternative demand response control strategies (Coakley et al., 2016). Black-box models are empirical data-driven models which correlate the energy consumption with the influencing variables, using regression or machine learning algorithms. As they based on historical performance data, they require sufficient historical data to be collected (Amara et al., 2015). Data-driven models can be utilised in real-time control schemes, due to their simplicity to deploy and their fast execution time in comparison with the physics based models. On the contrary, one of the main limitations prior to the implementation of data-driven models in predicting buildings DR potential is the lack of measured data under DR conditions.

The main objective of the current paper is the evaluation of the performance of machine learning algorithms in capturing DR potential of commercial buildings. A building energy simulation model of a multi-purpose commercial building is utilised to obtain a synthetic database and evaluate the DR potential of the current strategy. This evaluation provides insight regarding the suitability of these algorithms for use in real time control when the participation of a commercial building during a DR event is required.

Background

Numerous studies applying machine learning algorithms for forecasting the electrical load of commercial buildings exist in the literature. On the contrary to building energy simulation models, machine learning techniques do not require any physical information of the building as input (Foucquier et al., 2013). Support vector machine (SVM) and artificial neural network (ANN) are among the most common algorithms used in the literature to achieve the prediction of commercial building electricity and thermal loads.

SVM models have been used for predicting energy consumption in buildings relatively recently. They are highly effective models in solving non-linear problems even with small quantities of training data. Regarding the building energy domain, SVM models are mainly used for forecasting heating or cooling energy consumption (Foucquier et al., 2013). These models can be trained utilising data with different time scales (yearly, monthly, hourly) and various nature (instantaneous or space/time averaged).

Dong et al. (2005) were the first to introduce the use of SVM for prediction of the building energy consumption. The objective of their work was to examine the feasibility and applicability of SVM in building load forecasting area. Four commercial buildings, of the Central Business District, in Singapore were selected as case studies. The input variables were the mean monthly outdoor dry-bulb temperature, the mean monthly relative humidity and the mean monthly global solar radiation. The kernel function used was the radial basis function kernel. The obtained results were found to have coefficients of variance less than 3% and percentage of error within 4%. Li et al. (2009a) used the SVM model in regression to predict hourly building cooling load for an office building in Guangzhou, China. The outdoor dry-bulb temperature and the solar radiation were the input parameters for this model. Results indicated that the SVM method can achieve accurate predictions, with mean relative error of 1%, and that it is effective for building cooling load prediction. A comparison of the newly developed SVM model against different artificial neural networks was published by the same research group later the same year (Li et al., 2009b). The SVM model was compared with the traditional back propagation, the radial basis function and the general regression ANN. All predictive models were applied at the same office building in Guangzhou, China. The SVM and general regression ANN methods achieved better accuracy and generalisation than the back propagation neural network and radial basis function ANN methods. Hou and Lian (2009) also used an SVM model for predicting cooling load of an HVAC system in a building in Nanzhou, China. The performance of the SVM with respect to two parameters, C and ε, was explored using stepwise searching method based on radial-basis function kernel. Actual prediction results showed that the SVM forecasting model, whose relative error was about 4%, may perform better than autoregressive integrated moving average ones. Zhao and Magoulès (2012) developed SVM predictive models of office buildings, in France, to forecast their hourly electricity consumption using as possible inputs; weather variables, occupancy, internal heat gains and indoor variables. The datasets were generated using EnergyPlus and two input variable selection techniques, correlation coefficient and gradient guided selection, were applied. Results indicated that the selected subset of input variables was valid and provided acceptable predictions. More recently, Jung et al. (2015) combined a genetic algorithm with an SVM model to forecast the daily building energy consumption of the Telecommunication Corporation building in Korea. In this study, historical data of building energy consumption for the previous four weekdays were considered as input parameters in order to predict the daily quarter-hourly weekday building energy consumption. The average root mean square error (RMSE) of the developed model varied from 7.59 to 11.13.

ANN predictive models have been utilised to analyse commercial buildings energy demand, such as heating and cooling load, under different conditions. The datasets implemented for the development of ANN models contain data with different time scales varying from hourly up to yearly. The completeness of the learning dataset is the main and most essential condition for applying the ANN technique (Foucquier et al., 2013).

Dombayci (2010) developed an ANN model in order to forecast hourly heating energy consumption of a single-storey building, in Denizli, Turkey. The hourly heating energy consumption of the building was calculated using the degree-hour method. The model was trained with heating energy consumption values of years 2004-2007 and tested with values for the year 2008. Input data of the ANN model were the month, day of the month, hour of the day and energy consumption values at certain hours. Best estimate was found with 29 neurons and a good coherence was observed between calculated and predicted values. The RMSE value of the models was 0.988 for the testing period. Massana et al. (2015) created a method to forecast the electric load in commercial buildings. An analysis was performed regarding which type of data (such as weather, indoor ambient, calendar and building occupancy) was the most relevant in building load forecasting. The newly proposed method was tested with three different models, such as regression, ANN and SVM. The results, from an actual case study in the University of Girona, indicated that the developed method had high accuracy and low computational cost. Chitsaz et al. (2015) suggested a new prediction method, in which a Self-Recurrent Wavelet Neural Network was applied as the forecast engine. Moreover, the LevenbergMarquardt learning algorithm was implemented and adapted to train the ANN model. The proposed method was examined on real-world hourly data of an educational building, in British Columbia Institute of Technology (BCIT), Vancouver, within a micro-grid. The results showed that the proposed ANN model generated more accurate forecasts when a volatile time series prediction was of interest. Burger and Moura (2015) formulated an ensemble machine learning method that performs model validation and selection in real time using a gating function. The ensemble models was designed to forecast building electricity demand, by learning from electricity demand data streams, while requiring little knowledge of energy end-use. The models was tested both on commercial and residential buildings. In particular, eight commercial buildings were used and the generated electricity demand forecasts had a mean absolute percent error (MAPE) of 7.5%. Chae et al. (2016) proposed a short-term building energy usage forecasting model based on an ANN model with Bayesian regularization algorithm. This study investigated the effect of the network design parameters such as time delay, number of hidden neurons, and training data on the model capability and generality. The results demonstrated that the proposed model with adaptive training methods was capable to predict the electricity consumption with 15-minute time intervals and the daily peak electricity usage reasonably well in a test case of a commercial building complex.

The utilisation of machine learning algorithms, such as SVM and ANN, for the prediction of commercial building electrical and thermal loads is an active research topic for the last two decades. However, the suitability of these algorithms in capturing the DR potential of commercial buildings has not been fully evaluated. Hence, the performance of machine learning algorithms on datasets that include DR events is examined in the context of the current paper.

Methodology

A four-stage methodology was developed to assess the effectiveness of SVM and ANN machine learning algorithms to capture the DR potential of commercial buildings. The sequence of the steps followed in this paper is the following:

1. Development of a virtual testbed capable of capturing dynamic DR effects;
2. Implementation of a selected DR strategy;
3. Machine learning algorithms utilisation for electrical power demand prediction, and;
4. Assessment of machine learning algorithms accuracy.

Development of Virtual Testbed

EnergyPlus (U.S. D.O.E., 2015) was used to develop a virtual DR testbed, based on a mixed-use commercial building. This building is the new Student Learning Leisure and Sports Facility (SLLS), located on the University College Dublin campus, and it was selected since it exhibits a strong commercial profile including a wide variability of HVAC systems, space usage and occupancy patterns.

The SLLS building is used as a sports / entertainment centre and consists of three storeys with total floor area of 11,000 m^2. It contains a gym, a 50 m x 25 m swimming pool and additional facilities such as offices, meeting rooms, retail units and a cinema (Christantoni et al., 2015). The building electrical and space conditioning requirements are provided by two combined heat and power (CHP) units (506 kW thermal and 400 kW electrical output), two gas boilers (each 1146 kW) and an air cooled water chiller (865 kW). Moreover, heat is also provided by the campus district heating installation (500 kW). The building operates from 06:00 to 23:00 on weekdays and from 08:00 to 18:00 on weekend days.

The building geometry was created using the 3D modelling software Google SketchUp 8.0, depicted in Figure 1, while the EnergyPlus model consists of 63 zones (Christantoni et al., 2015). The model was created utilising building design and operational parameters including: building orientation, building fabric, occupancy loads, HVAC equipment schedules, ventilation rates, as well as indoor control setpoints. The weather file used was compiled from 2014 actual measured weather data from the UCD campus weather station. A simulation time-step of 15 minutes was

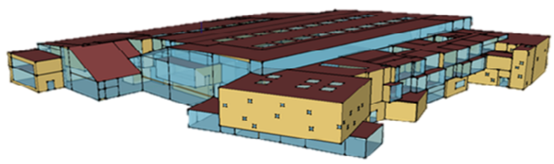

Figure 1: EnergyPlus model of SLLS (Christantoni et al., 2015).

defined in order to produce detailed results that can be validated against the BEM system archived data. Furthermore, this time-step enables building electric loads to be controlled over different timeframes from real-time to 24-hour horizons.
A building energy simulation model built for DR analysis should be able to model building response to aggregator/utility requests for electric load curtail/shift in a time range from 15 minutes to several hours (up to 24 hours). For this reason, the model was calibrated utilising archived data by the BEM system for 2014 on a 15 minutes basis (Christantoni et al., 2015). The mean bias error (MBE) and the coefficient of variation of the RMSE (CV-RMSE) indexes were used as calibration metrics. The criteria, set by ASHRAE, for a model to be considered as calibrated are 5% for MBE and 15% for CVRMSE when calibrating using monthly data (ASHRAE, 2002). The calibration results using monthly and 15 minutes intervals data are presented in Table 1.

Table 1: Building total electricity consumption calibration results.

	Monthly	**15 minutes**
MBE	-1.6%	5.5%
CV-RMSE	10.5%	7.8%

Introduction of a DR Strategy

The development of the building energy simulation model addresses the lack of historical data, by enabling a wide permutation of DR strategies to be evaluated in an effective manner (Christantoni et al., 2016). The average electrical power demand of the weekdays for the hottest month (July) in 2014, at fifteen minute intervals, is depicted in Figure 2. As shown, the building demand exhibits a peak at 06:00 when the building starts to operate. A DR strategy targeting the chiller load was developed to curtail this peak. Specifically, the chilled water temperature (CWT) setpoint, which was set at 6 ^{o}C for normal operation, was increased to 12 ^{o}C (upper operational temperature limit) during the event (Christantoni et al., 2016). This increase results in the rise of the chiller COP during a DR event as the chiller performs better at higher water temperatures. The main advantage of this strategy is that energy savings can be achieved without a significant impact on occupant comfort, so long as the delivery equipment can maintain the supply air temperature setpoints.

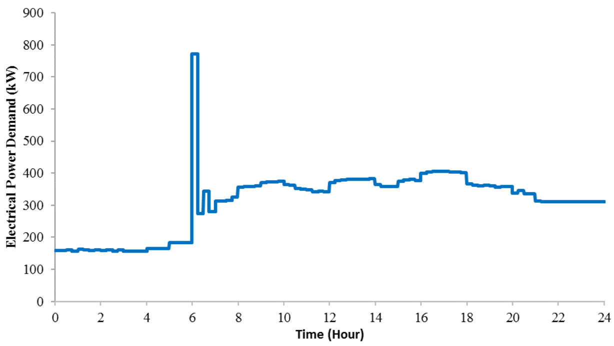

Figure 2: Average weekday total electrical power demand profile in July in 15 minute time-step.

A synthetic database was created for the CWT increase strategy in July, by considering DR events occurring daily and weekly. The events were commenced at 06:00 and lasted for one hour. The duration of the DR event lies within the range of durations specified by EirGrid (2015) for demand side resources, which varies from half an hour to two hours. The CWT setpoint values are returned to their initial settings, following the one-hour DR event.

Machine Learning Algorithms

Once the synthetic database is generated, SVM and ANN data-driven models are utilised and assessed regarding their ability to predict the electrical power demand of the testbed building, with and without DR events. The data-driven models are developed taking into account only the weekdays of July, since weekend days have different electrical power demand profiles.
The synthetic datasets are divided into training and testing partitions, which are used to train and test the developed predictive models, respectively. The training partition consists of eleven weekdays, from 3rd to 17th of July, while the testing partition consists of ten weekdays, from 18th to 31st of July. Ambient temperature, ambient relative humidity, solar radiation, wind speed, zone air temperature of the building and time of the day are the input variables of the data-driven models. The output of the predictive models is the total electrical power demand and the cooling electrical power demand of the testbed building. Furthermore, when daily and weekly DR events are included in the dataset, separate predictive models are developed for predicting the cooling electrical power demand.
A machine learning regression algorithm that maximizes the predictive accuracy without overfitting the training data, is implemented for the SVM predictive models. The kernel function selected is the polynomial one, implemented when applying the SVM algorithm in order to overcome the presence of nonlinearity relationships between input and output variables.
Moreover, ensemble models developed using boosting are the ANN predictive models used in the context of this research. A sequence of models is generated to obtain more accurate predictions. Boosting produces a succession of models, each of which is built on the same training partition of the dataset. The input variable measurements are weighted prior to building each successive model, based on the residuals of the previous model. Measurements with large residuals

are given relatively higher analysis weights, so that the next model is focused on predicting better these records. Additionally, the input to the output variable are connected through the hidden layers using the multilayer perceptron (MLP) structure and the sigmoid activation function.

All predictive models were developed using the IBM SPSS Modeler 14.2 software (IBM Corp., 2011) utilising a computer with an Intel Core i7-3630QM processor and 8 GB of DDR3 RAM. The settings of the ANN and the SVM models are selected automatically from the software with the objective to enhance the models accuracy. The ANN model structure can not be extracted from the software when the boosting option is selected, while the details of the most accurate SVM algorithm are as follows:

- degree of complexity set to 4;
- regression precision epsilon (ϵ) equal to 0.1;
- regularization parameter (C) equal to 10;
- gamma (γ) equal to 1, and;
- bias parameter equal to 0.4.

Assessment of Machine Learning Algorithms

The accuracy of the data-driven predictive models is assessed based on their performance compared to the testing partition of the synthetic datasets. Two error indexes are used to calculate the overall accuracy of each predictive model, the CV-RMSE, as given in Equation 1 and the MAPE, as given in Equation 2.

$$CV-RMSE \quad = \quad \frac{\sqrt{\frac{\sum_{i=1}^{n}|y_i-\hat{y_i}|^2}{n}}}{\bar{y}} \qquad (1)$$

$$MAPE \quad (\%) \quad = \quad \frac{\sum_{i=1}^{n}\left|\frac{y_i-\hat{y_i}}{y_i}\right|}{n} \times 100 \qquad (2)$$

In Equations 1 and 2, y are the actual values, $\hat{y}$ are the predicted values of the electrical power demand of the testbed building, $\bar{y}$ is the mean of the actual values and n is the total number of time-steps summed up at the testing partition period.

In addition to the overall accuracy of the predictive models, certain days of the testing dataset are monitored, in order to assess whether the predictive models capture the occurring DR events and sudden changes to the electrical power demand of the building.

Results and Discussion

After the generation of the synthetic database, ANN and SVM data-driven models are assessed regarding their ability to predict the total and cooling electrical power demand of the testbed building, with and without DR events. Tables 2 and 3 summarise the overall results concerning the accuracy of the data-driven models when predicting the total electrical power demand and the cooling electrical power demand of the testbed building, respectively. It is observed that for all the scenarios examined, the accuracy achieved from the ANN and SVM predictive models is maintained at the same level regardless of the existence or not of DR event in the dataset. To provide more insight regarding the developed predictive models their accuracy during training, when predicting the cooling electrical power demand of the testbed building, is given in Table 4. It is noted that when comparing the results of Tables 3 and 4, the models are marginally over-fitted due to the slightly higher accuracy achieved during training.

Opposite results regarding the most accurate machine learning algorithm are obtained from the two error indexes utilised, when predicting the total electrical power demand, as seen in Table 2. Based on the CV-RMSE, the ANN predictive models are more accurate than the SVM models for all the scenarios under examination. On the contrary, when using the MAPE as an error index, the SVM models are performing

Table 2: Accuracy of data-driven models predicting the total electrical power demand.

Error index	Scenario	ANN	SVM
CV-RMSE	Without DR event	0.271	0.318
	Daily DR event	0.272	0.317
	Weekly DR event	0.267	0.316
MAPE (%)	Without DR event	6.135	3.066
	Daily DR event	7.934	2.803
	Weekly DR event	7.271	3.028

Table 3: Accuracy of data-driven models predicting the cooling electrical power demand.

Error index	Scenario	ANN	SVM
CV-RMSE	Without DR event	0.138	0.068
	Daily DR event	0.123	0.100
	Weekly DR event	0.146	0.087

Table 4: Accuracy of data-driven models for the training partition predicting the cooling electrical power demand.

Error index	Scenario	ANN	SVM
CV-RMSE	Without DR event	0.009	0.014
	Daily DR event	0.010	0.028
	Weekly DR event	0.009	0.025

better compared to the ANN models. This paradox could be caused due to the fact that the CV-RMSE index is influenced by the existence of outliers as well as the bias of the MAPE towards favouring underestimates (Tofallis, 2015). Thus, the SVM models are generating, in general, predictions closer to the actual total electrical power demand but at the same time the forecasts from these models contain bigger outliers than the ANN models. The most accurate predictive models, for both ANN and SVM, based on the CV-RMSE error index are the ones developed with the dataset containing weekly DR events. Moreover, based on the MAPE index, the most accurate ANN model is the one developed without DR event present in the dataset, while the most accurate SVM is the one developed with daily DR events in the dataset.

Furthermore, when focusing on the prediction of the cooling electrical power demand of the testbed building, results indicate that SVM models can achieve higher accuracy in predictions for all the scenarios examined, as illustrated in Table 3. The most accurate SVM model is the one developed without DR event present in the dataset, while the most accurate ANN model is the one developed with the dataset containing daily DR events. It is noted, that the predictive models forecasting the cooling electrical power demand could not be evaluated based on the MAPE index, because zero values of the cooling demand occur during the DR event period leading to a mathematical indeterminacy.

On top of the assessment of the overall accuracy of the predictive models, specific days of the testing partition of the dataset are plotted, in order to visualise and evaluate the ability of the predictive models to capture the occurring DR events at the testbed building. The days selected for each scenario are the 20th of July, when no DR event is included in the dataset and the 26th of July, when daily and weekly DR event are included. As a result of the large magnitude of the total electrical power demand of the building (in the order of 800kW, as shown in Figure 2), it is hard to capture the effect of the DR event when plotting the profile of the total electrical demand. Hence, only the cooling electrical power demand is utilised to perform

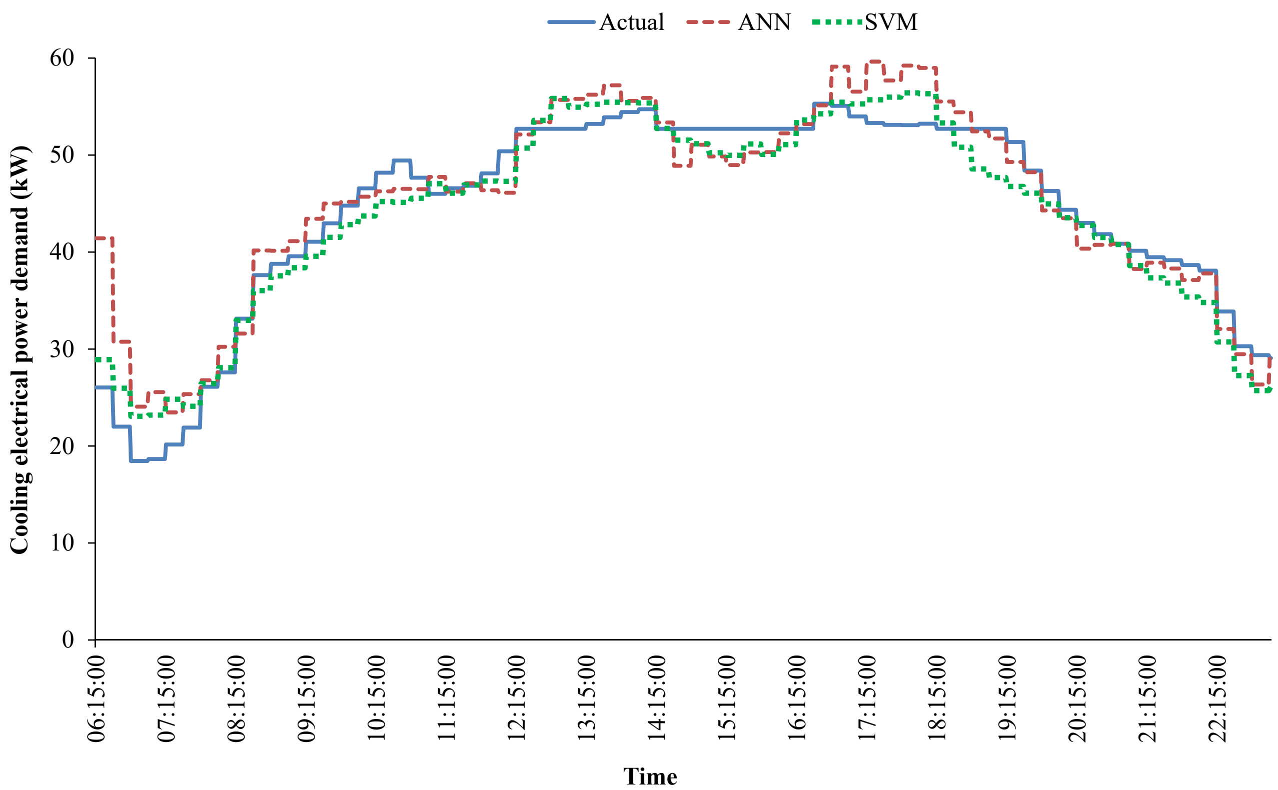

Figure 3: Prediction of cooling electrical power demand without DR event, on July 20th.

this evaluation of the predictive models.

Figure 3 presents the performance of the ANN and SVM predictive models for the scenario without DR event. Some useful observations can be made based on the visualisation of the prediction of the data-driven models. Initially, it is noted that overall both ANN and SVM models are generating predictions quite closely to the actual cooling electrical power demand of the testbed building. During the early morning hours both predictive models are overestimating the cooling demand of the buildings, while the ANN is overestimating the demand more than the SVM model. The predictions are following accurately the actual demand profile from 08:00 to 14:00. A slight underestimation period of the actual demand from both models is noticed from 14:00 to 16:00 and a second overestimation of the cooling demand is observed during the early evening hours (from 17:00 to 18:00). Subsequently, the predictions are once again following accurately the actual demand profile until the end of the day. In regard to the evening overestimation period, both predictive models are again forecasting higher cooling demand than the actual values and the ANN is the model with the biggest overestimation. These forecasts, where the ANN predictive model overestimate the cooling load with higher predictions than the SVM model, are the ones that lead the overall CV-RMSE of the SVM to be better that the ANN one.

The performance of the predictive models for the scenario when a DR event is occurring daily, is illustrated in Figure 4. As mentioned in the methodology, the DR event is targeting to reduce the chiller load by changing the CWT setpoint in order to curtail the morning peak of the electrical power demand of the building. The DR event is set to commence at 06:00 and last for one hour and it is noticed that both ANN and SVM models manage to capture the reduction of the cooling electrical power demand. It is noted, that during the event the predictions of the ANN model are really close to the actual values of the cooling electrical power demand compared with the ones from the SVM model. Moreover, both predictive models attempt to capture the rebound effect caused to the cooling demand due to the DR event, but both underestimate the magnitude of the effect. For the reminder of the day it is observed that the ANN model overestimates the actual cooling electrical power demand of the building from 10:00 in the morning until 16:00 in the afternoon. In addition, it is detected that the SVM models is underestimating the actual cooling demand from 15:00 until the end of the day.

Concerning the scenario when a DR event is occurring weekly, the performance of the predictive models is depicted in Figure 5. Once again, it is noticed that both predictive models realise that there is a decrease at the cooling electrical power demand of the building during the DR event, but the SVM model does not manage to fully capture this reduction of the de-

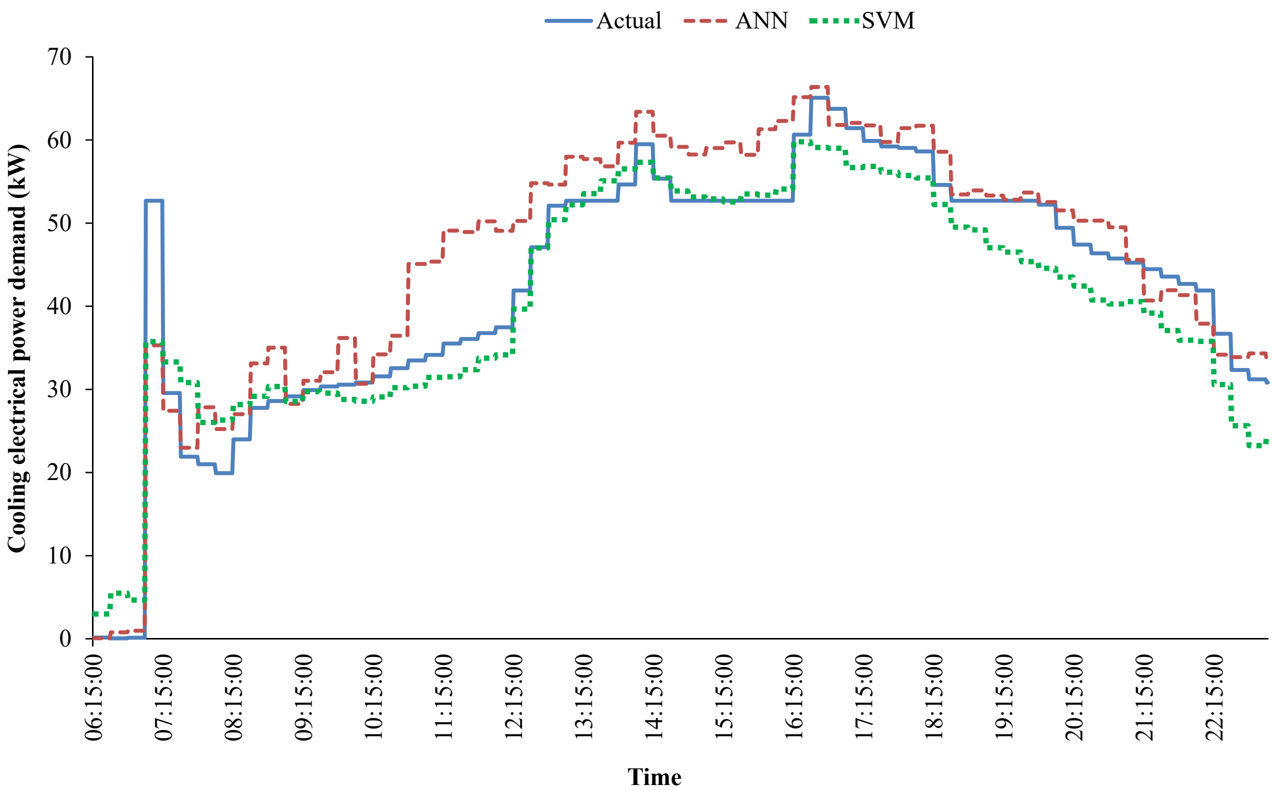

Figure 4: Prediction of cooling electrical power demand with daily DR event, on July 26^{th}.

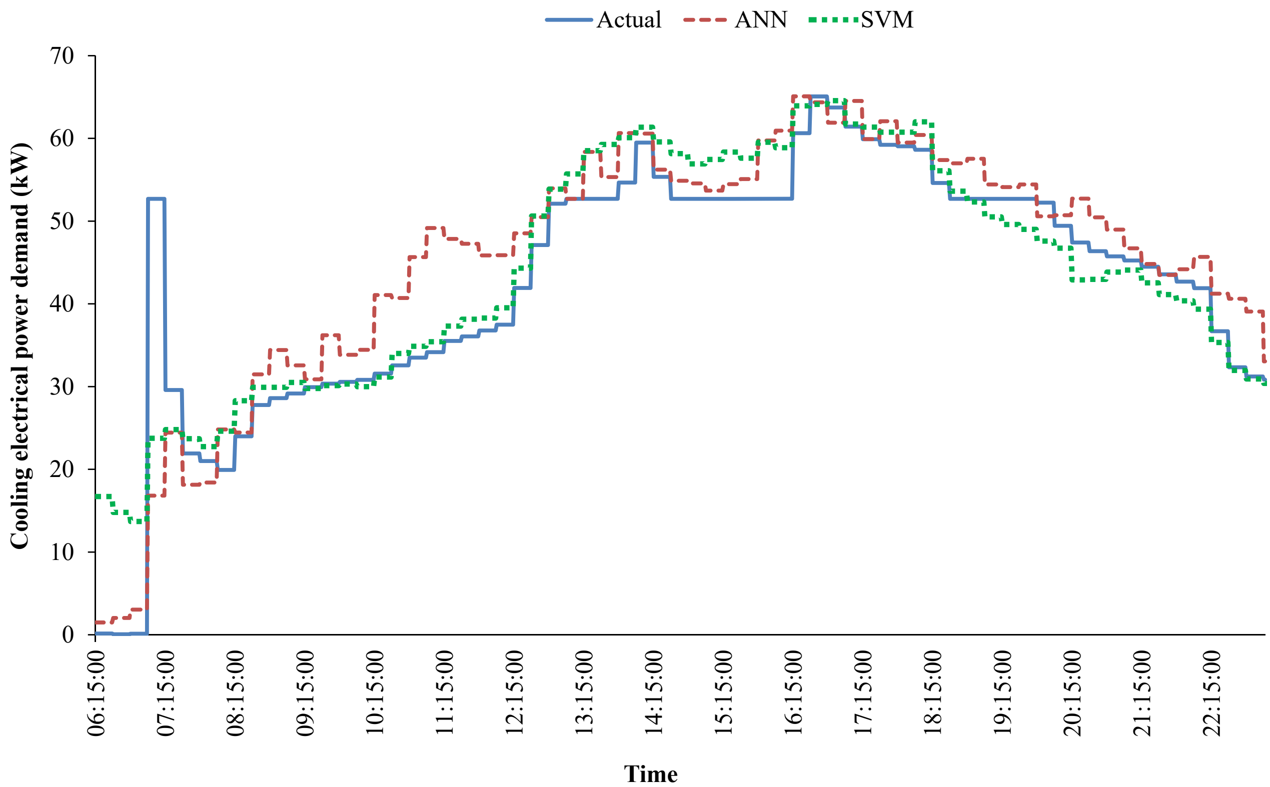

Figure 5: Prediction of cooling electrical power demand with weekly DR event, on July 26th.

mand. On the contrary, the ANN model once more is generating quite accurate predictions compared to the actual values of the cooling electrical power demand during the DR event. After the end of the DR event none of the predictive models is able to capture the rebound effect that follows. This is an indication that with the presence of only few DR events in the training dataset, it is possible that the predictive models either will not be able to fully capture the reduction on the cooling demand during the DR event, or entirely miss the existence of a rebound effect after the event. Furthermore, the ANN model is overestimating the cooling electrical power demand of the building from 09:00 in the morning until the end of the day with the exemption of few more accurate instances. On the other hand, the SVM model is forecasting accurately the actual cooling demand of the building, after the rebound effect of the DR event, for the reminder of the day, with an exception of an overestimation period between 14:00 and 16:00 in the afternoon.

Conclusions

To summarise, the results of this research work highlight that both ANN and SVM models can generate accurate predictions of the total and cooling electrical power demand of the building, when none or daily DR events are included in the training and testing datasets. However, when including weekly DR events in the datasets, the SVM model cannot accurately capture the reduction of the cooling demand during the event, and both predictive models are not accurate in forecasting the electrical demand during the rebound effect.

Overall, it is illustrated that machine learning algorithms are able to capture the DR potential of a commercial building provided that DR events are included into the training and testing datasets. Moreover, it is shown that ANN and SVM algorithms could have a great potential for use in real time control of HVAC systems commercial buildings participating in DR schemes with regular DR events.

Future research work includes the evaluation of other machine learning algorithms regarding their ability to capture DR events. Additionally, the application of the methodology presented in this paper with different types of DR strategies, such as changing the air temperature setpoints or shutting down fans in unoccupied rooms, will be examined. The implementation of the machine learning algorithms in the context of a real time control will also be investigated. Finally, through this future research work, it will be examined whether the conclusions drawn herein can be generalised, as well as the reasoning for the performance of the predictive models.

References

Amara, F., K. Agbossou, A. Cardenas, Y. Dubé, and S. Kelouwani (2015). Comparison and Simulation of Building Thermal Models for Effective

Energy Management. *Smart Grid and Renewable Energy 6*(4), 95–112.

ASHRAE (2002). Measurement of Energy and Demand Savings. American Society of Heating, Refrigerating and Air-conditioning Engineers Inc.

Beil, I., I. Hiskens, and S. Backhaus (2015). Round-trip efficiency of fast demand response in a large commercial air conditioner. *Energy and Buildings 97*, 47 – 55.

Burger, E. M. and S. J. Moura (2015). Gated ensemble learning method for demand-side electricity load forecasting. *Energy and Buildings 109*, 23 – 34.

Chae, Y. T., R. Horesh, Y. Hwang, and Y. M. Lee (2016). Artificial neural network model for forecasting sub-hourly electricity usage in commercial buildings. *Energy and Buildings 111*, 184 – 194.

Chitsaz, H., H. Shaker, H. Zareipour, D. Wood, and N. Amjady (2015). Short-term electricity load forecasting of buildings in microgrids. *Energy and Buildings 99*, 50 – 60.

Christantoni, D., D. Flynn, and D. P. Finn (2015). Modelling of a Multi-purpose Commercial Building for Demand Response Analysis . *Energy Procedia 78*, 2166 – 2171. 6^{th} International Building Physics Conference, IBPC.

Christantoni, D., S. Oxizidis, D. Flynn, and D. P. Finn (2015, December 7-9). Calibration of a Commrcial Building Energy Simulation Model for Demand Response Analysis. In *14th Conference of International Building Performance Simulation Association, Hyderabad, India*, pp. 2865–2872.

Christantoni, D., S. Oxizidis, D. Flynn, and D. P. Finn (2016). Implementation of demand response strategies in a multi-purpose commercial building using a whole-building simulation model approach. *Energy and Buildings 131*, 76 – 86.

Coakley, D., G. Aird, S. Earle, B. Klebow, and C. Conaghan (2016). Development of Calibrated Operational Models of Existing Buildings for Real-Time Decision Support and Performance Optimisation. In *CIBSE Technical Symposium, Edinburgh, UK*.

Dombayci, Ö. A. (2010). The prediction of heating energy consumption in a model house by using artificial neural networks in Denizli Turkey. *Advances in Engineering Software 41*(2), 141–147.

Dong, B., C. Cao, and S. E. Lee (2005). Applying support vector machines to predict building energy consumption in tropical region. *Energy and Buildings 37*(5), 545–553.

EirGrid (2015). EirGrid Grid Code. Technical Report Version 6.0, EirGrid Group, Dublin, Ireland.

Foucquier, A., S. Robert, F. Suard, L. Stéphan, and A. Jay (2013). State of the art in building modelling and energy performances prediction: A review. *Renewable and Sustainable Energy Reviews 23*, 272–288.

Gao, D. and Y. Sun (2016). A GA-based coordinated demand response control for building group level peak demand limiting with benefits to grid power balance. *Energy and Buildings 110*, 31 – 40.

Gils, H. C. (2014). Assessment of the theoretical demand response potential in Europe. *Energy 67*, 1 – 18.

Hou, Z. and Z. Lian (2009, May). An Application of Support Vector Machines in Cooling Load Prediction. In *Intelligent Systems and Applications, 2009. ISA 2009. International Workshop on*, Wuhan,, pp. 1–4. International Workshop on Intelligent Systems and Applications.

IBM Corp. (2011). IBM SPSS Modeler 14.2. `http://www-01.ibm.com/software/analytics/spss/products/modeler`.

International Energy Agency (2013). *Transition to Sustainable Buildings*. Paris: IEA.

Jung, H. C., J. S. Kim, and H. Heo (2015). Prediction of building energy consumption using an improved real coded genetic algorithm based least squares support vector machine approach. *Energy and Buildings 90*, 76 – 84.

Korkas, C. D., S. Baldi, I. Michailidis, and E. B. Kosmatopoulos (2016). Occupancy-based demand response and thermal comfort optimization in microgrids with renewable energy sources and energy storage. *Applied Energy 163*, 93 – 104.

Li, Q., Q. Meng, J. Cai, H. Yoshino, and A. Mochida (2009a). Applying support vector machine to predict hourly cooling load in the building. *Applied Energy 86*(10), 2249–2256.

Li, Q., Q. Meng, J. Cai, H. Yoshino, and A. Mochida (2009b). Predicting hourly cooling load in the building: A comparison of support vector machine and different artificial neural networks. *Energy Conversion and Management 50*(1), 90–96.

Massana, J., C. Pous, L. Burgas, J. Melendez, and J. Colomer (2015). Short-term load forecasting in a non-residential building contrasting models and attributes. *Energy and Buildings 92*, 322 – 330.

Pérez-Lombard, L., J. Ortiz, and C. Pout (2008). A review on buildings energy consumption information. *Energy and Buildings 40*(3), 394 – 398.

Thomaidis, N. S., F. J. Santos-Alamillos, D. Pozo-Vázquez, and J. Usaola-García (2016). Optimal management of wind and solar energy resources. *Computers and Operations Research 66*, 284 – 291.

Tofallis, C. (2015, August). A Better Measure of Relative Prediction Accuracy for Model Selection and Model Estimation. *Journal of the Operational Research Society 66*(8), 1352–1362.

U.S. D.O.E. (2015). EnergyPlus Energy Simulation Software. `http://apps1.eere.energy.gov/buildings/energyplus`. accessed on 28.02.16.

Xue, X. and W. Shengwei (2012). Interactive building load management for smart grid. In *Power Engineering and Automation Conference*, pp. 1–5.

Zhao, H.-X. and F. Magoulès (2012). Feature selection for predicting building energy consumption based on statistical learning method. *Journal of Algorithms and Computational Technology 6*(1), 59–78.

Zhao, J., K. P. Lam, B. E. Ydstie, and O. T. Karaguzel (2015). EnergyPlus model-based predictive control within designbuildoperate energy information modelling infrastructure. *Journal of Building Performance Simulation 8*(3), 121–134.