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A Data-Driven Modelling Approach for Large Scale Demand Profiling of Residential Buildings

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Abstract

In this paper the traditional use of data-driven models (DDM) as forecasting tools is coupled with parametric simulation to create a building modelling framework for demand profiling of a large number of buildings of the same typology. Most studies to date utilising DDM have been conducted on single buildings, with less evidence of the role that DDM may have as a modelling technique for application at scale. The proposed methodology is based on the use of a simulation-based building energy modelling tool and a parametric simulator to create a large dataset consisting of 4096 different building model scenarios. Three DDM techniques are utilised; Support Vector Machines, Neural Networks and Generalised Linear Models, these are trained and tested using the generated simulation dataset. Results, at an hourly resolution, show that DDM approaches can correctly emulate the outputs of the building simulation software with mean absolute error ranging from 4 to 9 percent for different DDM algorithms.

Introduction

Modelling building energy use at a high spatio-temporal resolution and at large scale is a computational and resource intensive problem. Several issues increase the difficulty in modelling a vast number of buildings, these include but are not limited to: heterogeneity of the built environment, possible lack of building data, high computational requirements for a simulated representation of the building stock, uncertainties related to building information and modelling procedures, linking of structured and unstructured data, complexity in representing interconnected physical phenomena and difficulties in providing scalable and replicable solutions. Overcoming all these issues requires substantial research effort.

Simulating building consumption at different levels of spatial and temporal resolution, facilitates the adoption of a variety of energy efficient technologies and operations, ranging from deep retrofit interventions to demand side management actions. For this reason, different levels of spatial analyses may be required, e.g. national, regional, urban, district and single building level. Based on the objective of the analysis, different time scales may also be appropriate, i.e. annual, monthly, daily, hourly and sub-hourly. On one hand, techniques for modelling and analysing single building energy use are mature and well consolidated; on the other, modelling at fine time resolution and at large scale, such as at district or city level, is an emerging field where there is still a lack of validated procedures and standardisation Reinhart and Davila (2016).

In recent years, different modelling techniques have been proposed for the representation of building energy use at large scale. These methods and techniques, use mostly a bottom-up modelling approach and can be divided into three major categories: the engineering or physical approach, the hybrid approach and the data driven modelling approach Eicker et al. (2015). These techniques, were first used for single building applications but have been recently adopted for studies involving a vast numbers of buildings Swan and Ugursal (2009). In particular the engineering method and the hybrid approach find several applications in the context of large scale modelling Fonseca et al. (2016), Robinson et al. (2009). Other large scale studies employ the use of representative building energy models, usually called archetypes, to represent a portion of the building stock Ballarini et al. (2014). These representative models are usually identified through statistical approaches but more recently through clustering techniques. These techniques aim to isolate building groups sharing similarities and permit the identification of the most representative element of the cluster.

Most of the studies on data driven models (DDM) focus on single building level applications; the majority of these studies investigate DDM as forecasters of individual building electric and heating consumption. In this context DDM are employed for demand side management and demand response analysis Burger and Moura (2015) or in predictive control systems Ferreira et al. (2012). Few studies focus on the use of DDM at large scale and when they do they analyse aggregated groups of buildings or predictive methods for yearly or monthly estimated consumption. Other studies show that DDM can exploit large scale modelling techniques to provide early design consumption information. There are currently no methodologies based on data-driven methods, which are used as building demand profiling techniques at large scale. DDM characteristics could be exploited to alleviate the modelling burdens associated with large scale accurate simulations at district or urban level where simplified methods and computational issues are of interest.

The aim of the current paper is to describe a scalable methodology based on the use of DDM as a demand modelling technique for large numbers of buildings and to test the proposed approach on a case study. The methodology is based on the exploitation of a representative building energy model and the use of parametric simulation to create a database for the training of the DDM. The representative energy model could be representative for example of the outcome of a clustering analysis procedure conducted on an urban case study Ghiassi et al. (2015).

The paper is structured as follows. Initially, a comprehensive review of data driven modelling techniques utilised in the building energy domain is presented; then, the research "gap" is identified and described; following this, the research methodology is discussed and explained in detail as well as the underlining contribution and novelty of the present work; the methodology is then tested on a case study and finally a description of the main outcomes of this approach is provided. The strengths and limitations of the presented approach are discussed and scope for further research is presented taking into consideration the deployment of the technique at an urban or district level.

State of the art

There are many examples of the use of DDM in the building energy sector. Table 1 provides an overview of the main applications of DDM. Specifically, the table provides information regarding the algorithms employed and summarises the main inputs, outputs and resolution of the data. Furthermore, Table 1 provides a useful insight regarding the scale of analysis and level of aggregation of the case studies.

The majority of the studies concerning DDM are related to single building level applications. In this regard, DDM are employed mostly as forecasters of building energy consumption. Edwards et al. (2012) compared seven different machine learning algorithms trained on 15 minute consumption data of a residential case study. Jain et al. (2014) developed a sensor-based forecasting model using support vector regression (SVR), for a multi-family residential building underlining the impact of temporal (i.e., daily, hourly, 10 min intervals) and spatial (i.e., whole building, by floor, by unit) granularity. Fan et al. (2014) developed an ensemble model for a commercial building for predicting next-day energy consumption and peak power demand, using a genetic algorithm for parametric optimisation. Macas et al. (2016) proposed a technique based on artificial neural networks (ANN) to predict total heating energy consumption, internal air temperature and aggregated thermal discomfort 12 hours ahead, for operational cost reduction of an office building. Mai et al. (2014) presented an hourly electric load forecasting model for an office building based on a neural network using outdoor weather data and historical load data as inputs, proposing a simplified parameter tuning procedure. Yang et al. (2014) proposed a model to predict energy consumption for a chiller using historic building operation data and weather forecast information. Paudel et al. (2014) presented a predictive model of an institutional building to predict heating demand with occupancy profiles and operational heating power levels for short time horizon predictions. Kapetanakis et al. (2015) developed DDM for forecasting a commercial building heating loads based building energy management systems variables and weather data, presenting an inputs selection technique. Li and Wen (2014) proposed a methodology to develop building energy estimation models using frequency domain spectral density analysis for a commercial building.

Compared to single building level applications, there are fewer studies which involve the use of DDM on groups of buildings. Consumption data are usually aggregated when the study is performed on more than one building. Data are typically gathered from electric or heating network substations or from building management systems controlling the entire group of buildings. Some relevant examples in this context are studies conducted on university campuses Powell et al. (2014). Escrivá-Escrivá et al. (2011) created an ANN model for short-term prediction of total power consumption for a large group of university buildings. Jurado et al. (2015) proposed a hybrid methodology for three university buildings which combines feature selection based on entropy measures and DDM. Jovanović and Živković (2014) proposed a method for predicting heating energy consumption of 35 buildings using an ANN. Humeau (2013) studied statistical relations between consumption series data by clustering houses according to their consumption profiles and using DDM to estimate aggregate district consumption. Other applications of the use of DDM at an aggregated level are typically performed by utility companies which employ data analysis on smart metering systems and the use of DDM to estimate peak power demand for entire districts. This helps utilities forecast the supply requirements with respect to buying or trading on energy markets at convenient prices or to identify stressed points of the network and to plan ahead network maintenance and upgrades.

At district or city scale, Nouvel et al. (2015)) and Howard et al. (2012) focused on forecasting building consumption for many single buildings at a yearly resolution. Williams and Gomez (2016) proposed an ap-

Table 1: DDM applications from single buildings to large groups: time resolution, algorithms, inputs and outputs

Case studies and models							Inputs										Output
							Weather variables						Time variables		Other		Consumption
Ref.	Case Study	Algorithms				Resolution	Out Air temp	Internal Air temp	Global radiation	Wind speed	Wind direction	Relative humidity	Day type	Hour of the day	Past cons.	Other	Electrical (E) Thermal - Heating (T.H) Thermal - Cooling (T.C.)
		MLR	ANN	SVM	Other												
Edwards et al. (2012)	Residential	X	X	X	X	Hourly	X		X				X	X	X		E
Jain et al. (2014)	Multi family residential			X		Hourly	X		X				X	X	X		E
Fan et al. (2014)	Mixed-use	X	X	X	X	Next day[a]	X		X	X		X	X	X	X[b]	X[c]	E
Macas et al. (2016)	Office building		X			12 hours	X	X	X	X	X	X				X[d]	T.H.
Mai et al. (2014)	Office building		X			Hourly - Daily	X		X	X		X	X	X		X[e]	E, T.C.
Yang et al. (2014)	Commercial			X	X	Annual	X			X	X	X				X[f]	E
Paudel et al. (2014)	School		X			Hourly	X		X				X	X		X[g]	T.H.
Li and Wen (2014)	Campus building		X			Hourly	X		X	X		X	X	X	X		E.
Jurado et al. (2015)	3 Campus buildings		X		X	Hourly							X	X	X	X	E.
Jovanović and Živković (2014)	University buildings		X			Daily	X						X			X[h]	T.H.
Powell et al. (2014)	Campus		X			Hourly	X		X			X	X	X		X[i]	E, T.H., T.C.
Escrivá-Escrivá et al. (2011)	University building		X			Hourly	X[j]						X[k]	X[k]			E
Humeau (2013)	District			X		Hourly							X	X	X[l]		E
Kapetanakis et al. (2015)	Commercial	X	X			15,30 minutes, hourly	X	X	X	X		X				X	T.H.

[a] daily peak power demand [b] profile information: mean, maximum, minimum, and standard deviation of the standardized daily time series [c] other weather variables [d] Air set point temperature; water set point temperature [e] rainfall,visibility, cloud condition, operation schedule, occupancy space power demand [f] occupancy, water temperatures, ice bank variables [g]Occupancy profiles, operational power level characteristics, pseudo dynamic transitional attributes [h] month of the year [i] month of the year [j]maximum, minimum,average and previous day average [k] considered for the selection of the training days [l]Past consumption at different time steps

proach based on DDM to predict monthly consumption, using regression approaches based on a variety of building features.

Recently, research studies showed the possibility of coupling DDM and parametric simulation. Chou and Bui (2014),Tsanas and Xifara (2012), Catalina et al. (2008) showed that DDM are able to provide early stage design consumption information for a large number of buildings. In addition, these studies underlined the possibility of using DDM not only as a forecasting technique but also as modelling technique.

Another interesting point of the literature review process is that the most employed DDM algorithms are neural networks, support vector machines and multiple linear regression. Regarding input variables, weather data and time variables are among the most common, along with other information such as building energy consumption. The prediction horizon varies dependent on the nature of the application. Usually, forecasting is performed at an hourly or sub-hourly basis. The principal targets of the prediction are electric consumption and thermal requirements both for heating and cooling. In addition, from the literature, it is evident that the use of DDM as an accurate forecasting tool is limited to single building applications or aggregated case studies of groups of buildings. At district or city scale, DDM are employed for single buildings predictions with an annual or monthly resolution. Recently DDM have been employed as large scale modelling techniques for early stage design power demand estimation.

Hence it is evident that there are no applications and methodologies where DDM is used as a modelling technique at large scale to provide accurate profiling information at a low time resolution. Thus, the present paper and the following sections present a scalable methodology associated with the use of DDM as large scale modelling technique to provide estimate building power profiling information at an hourly resolution.

Methodology

The approach adopted in this work couples DDM with a parametric simulation framework for providing demand information of residential buildings at a hourly time resolution. The methodology is based on the use of a representative building energy model and parametric simulation to create a database for the training of a DDM. The parametric simulation allows the creation of a virtual large scale scenario composed of similar but different buildings of the same typology by changing building related parameters such as construction detail, internal gains, glazing surfaces, etc. The representative energy model could, for example, be an urban archetype representative of a large part of the building stock.

Figure 1 provides a concise overview of the research methodology. First, a building energy model (BEM)

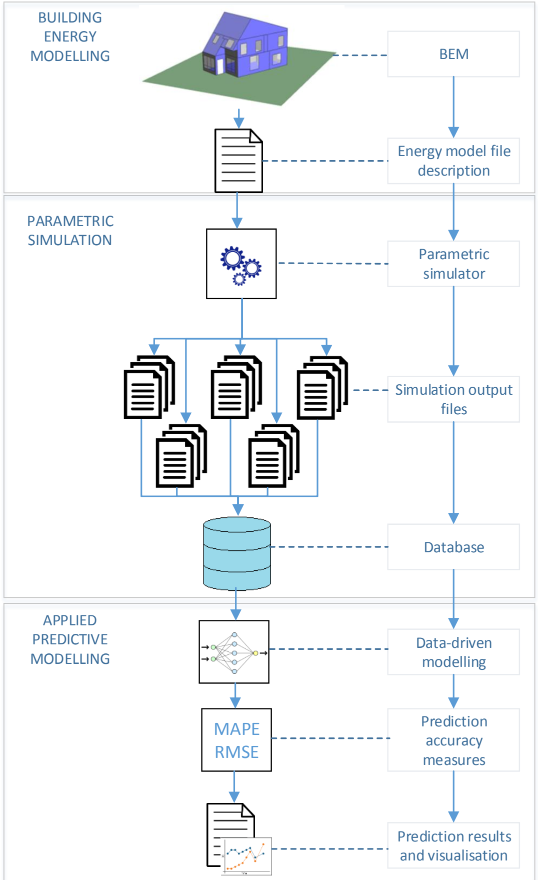

Figure 1: Methodology overview

of a residential building is created, i.e. the baseline model. A file description is then extracted from the energy model and provided as an input to a parametric simulator. A number of energy related input variables are then defined; these are applied to the BEM using the parametric simulator; as a result a large synthetic dataset of BEMs is generated. These BEMs are similar but different variations of the baseline model. Outputs from the synthetic dataset, including hourly power data for both electricity and heating requirements, are then stored in a database. The DDM is then trained with the information from the database and prediction accuracy measures are evaluated. Based on results of prediction accuracy it is possible to evaluate the reliability of the presented modelling framework and to rank different DDM approaches based on their predictive performance on the case study.

Building energy model(BEM)

The first step of the methodology requires the creation or the use of a Building Energy Model (BEM). The case study is a mid-terraced house in Scotland. The house is part of an eco-village and part of a group of similar buildings. The mid-terraced house consists of two floors with a total floor area of $166m^2$ and a total volume of approximately $359m^3$. The total external wall area is approximately $122m^2$ and the external openings area is approximately $29m^2$. A rendering of

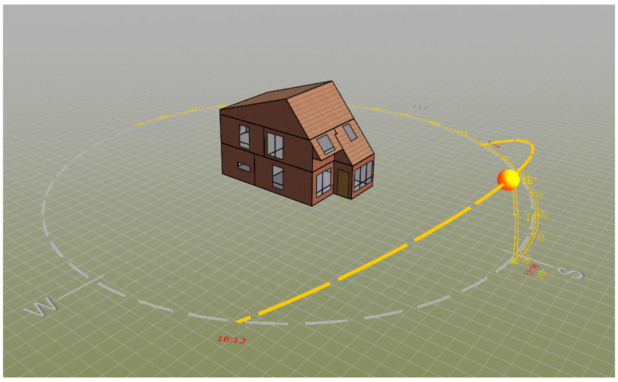

Figure 2: Building energy model: rendering

Table 2: Construction properties

Category	U value (W/m^2K)	Thickness (mm)
External Wall	0.14	359
Internal Partition 1	1.79	75
Ground/Exposed Floor	0.22	268
Door	2.19	37
Internal Ceiling/Floor	1.08	283
Roof	0.09	481
Internal Partition 2	0.77	226
Internal Partition 3	0.14	350
Roof Light	3.10	24
External Window 1	1.24	24
Internal Ceiling/Floor	1.10	113

the energy model is displayed in figure 2.

Opaque surfaces are modelled considering roof, ceiling, external walls, internal partitions, ground floor and doors. Glazed surfaces include roof-lights, external glazing and internal glazing surfaces. Table 2 summarises construction properties and the thermal transmittance assigned to the construction components.

The heating system is characterised by an air source heat pump (air to water system) with an average seasonal coefficient of performance (COP) of 3.1. The heat pump is connected to a solar heating system with a surface area of $2.6m^2$. The overall system provides domestic hot water and the thermal requirements for the building. An underfloor heating system distributes heat in the house. Electric heaters are available as auxiliary source of heat acting as a surplus, directly controlled by the occupants. Room set points have been defined using information from thermometers when available. Heating set point is set at $20°C$. The heating system is modelled to run continuously during the period of simulation. Cooling systems are not present in the building; if required, cooling is provided by natural ventilation in summer periods. Occupant presence is modelled defining a value of 22 $m^2/person$ and an occupant presence profile for the period of simulation. Equipment and lighting gains are modelled considering sensor data when available to create variation profiles and assigning a peak value in W/m^2. For lighting and equipment, values in W/m^2 are assigned: $2W/m^2$ and $34W/m^2$, respectively. Furthermore, the energy model is developed taking into account information regarding floor plans, sections, elevations, construction, internal temperature sensors, flow and return temperature of heat pump, solar system and underfloor heating, flow measurement of heat pump, solar systems and underfloor heating, electrical meters data from lighting, ground floor sockets, first floor sockets, heating and main feed.

Parametric simulation

The building simulation model is incorporated in a parametric simulation framework. Parametric simulation is applied to a number of parameters which have significant impact on building requirements and these include: transmittance of external walls, transmittance of glazing surfaces, orientation of the building, infiltration rates, internal gains due to occupancy, lighting and equipment; the internal gains due to occupancy, lighting and equipment are grouped together and considered as a single parameter. Percentages of variation are applied to each of the six selected variables. No assumptions are made on the distributions of percentage of variations of the parameters and their values are decided on the basis of a range of realistic values for the typology of the building. The total number of simulations created by the process is equal to the product of the number of variations considered for each variable. Equation 1 provides the mathematical description of the process:

$$Ns = \prod_{k=1}^{K} n_k \tag{1}$$

$$Ns = n^K \tag{2}$$

where Ns is the number of simulations, K is the total number of variables, n is the number of values the variable k can have. Equation 1 becomes equation 2 if the number of values is the same for all the parametric variables. In this study a total number k of 6 variables is considered with $n_k = 4$ variations expressed as percentage of the baseline model. Table 3 summarises the variables considered in this study. Four possible variations are associated to each variable. Therefore, with reference to equation 2 the total amount of simulations Ns is : 4096.

The parametric procedure is performed with the software IES-VE and its associated parametric simulator. The parametric simulator allows the management of batch simulations and to collect output data of each simulation. Scripting is performed in the programming language Lua. Thus, data is generated for 4096 different simulations for a two month period (November and December, 2014). Simulations are run with

Table 3: Parametric simulation: variables and values

	baseline	units	variations			
U-values (external walls)	0.14	W/m^2K	0.11	0.17	0.21	0.25
U-values(glazing surfaces)	1.24	W/m^2K	0.93	1.55	1.85	2.17
Orientation	-	deg	90	180	270	0
Infiltrations	0.15	ach	0.3	0.45	0.6	0.75
Glazing surface	32.3	m^2	25.5	28.7	35	38.2
Internal gains						
Occupancy	22	$m^2/person$	17.6	26.4	28.6	33
Lighting	2	W/m^2	1.6	2.4	2.6	3
Equipment / miscellaneous	34	W/m^2	27.2	40.8	44.2	51

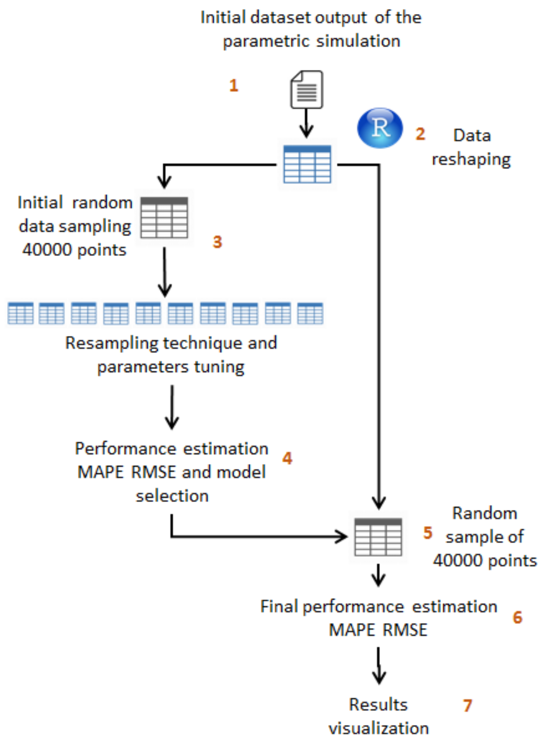

Figure 3: Predictive modelling methodology

at an hourly time step resolution. The selection of 2 months of simulations is due to limit the very large output dataset obtained from the parametric study. A total of 5,996,544 simulation results regarding average electric demand of the building are collected and merged together with the weather data. This dataset acts as the input to the data-analysis process for the creation of a predictive model.

Applied predictive modelling

Figure 3 shows the methodology regarding the creation of the applied predictive modelling. Initially, data output of the parametric simulation (1) are organised and reshaped in a data-base structure (2). The statistical software R is employed for the following steps. An initial random sample is selected from the overall dataset for the purpose of model training and model selection. In addition, randomly sampling the dataset may artificially recreate conditions of data scarcity and sparsity: a possible condition in large scale modelling. The selected subset is of 40,000 output values corresponding to 40,000 different hourly simulation outcomes (3). Three common predictive models found in the literature (support vector machines (SVM), neural networks (NN) and generalised linear models (GLM)) are used for predicting average hourly electric demand. Inputs to the models are weather variables and values of the parametric simulations. Parameter tuning and the selection of the most accurate predictive model is then performed adopting a re-sampling technique, the k-fold cross validation method. The procedure creates k groups of samples of equal size called folders. A model is trained using all the folders except one. Thus, the model is used to predict values of the hold-out folder and to compute performance measures. The procedure is repeated several times, shuffling training and testing folders, to perform an algorithm parameter tuning procedure. In this study, a total number of 10 folders is created to perform parameter tuning and best model selection. As a result, accuracy measures are evaluated for each model. The best model is the one that produces the minimum value of the two indices: mean absolute percentage error (MAPE) and root mean square error (RMSE)(4). Thus, in order to test the effective performance of the models on an unseen dataset, another large sample (40,000 points) is selected randomly from the remaining initial data (5). MAPE and RMSE are evaluated again on the total unseen dataset (6). Finally, results are visualised in different ways to help the modeller to understand which model performs best (7).

Results

Predictive models performance

Predictions of the three models (SVM, NN, GLM) are compared with the parametric simulation results to assess the capability of DDM for emulating outputs of the building simulation software. Figure 4 represents the comparison between simulated and predicted outputs. The output variable compared in Figure 4 is the

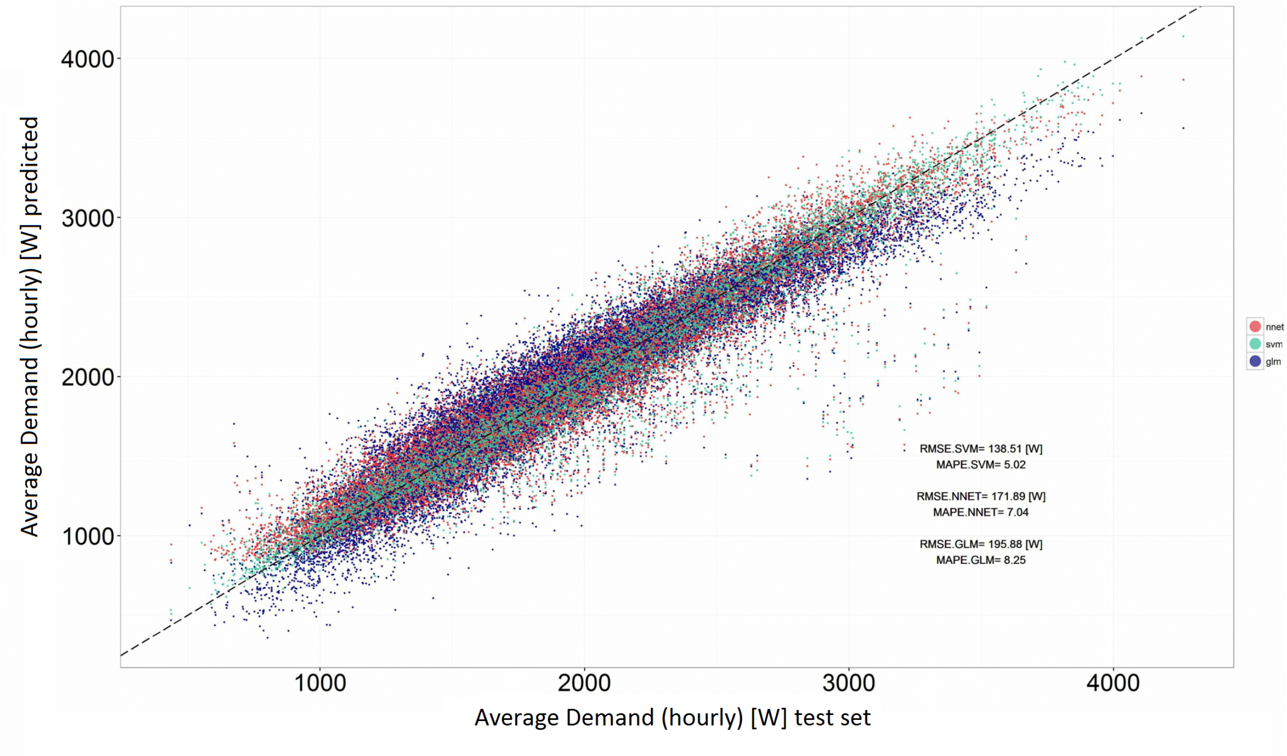

Figure 4: Predictive modelling: simulated vs predicted outputs(Nov-Dec 2014)

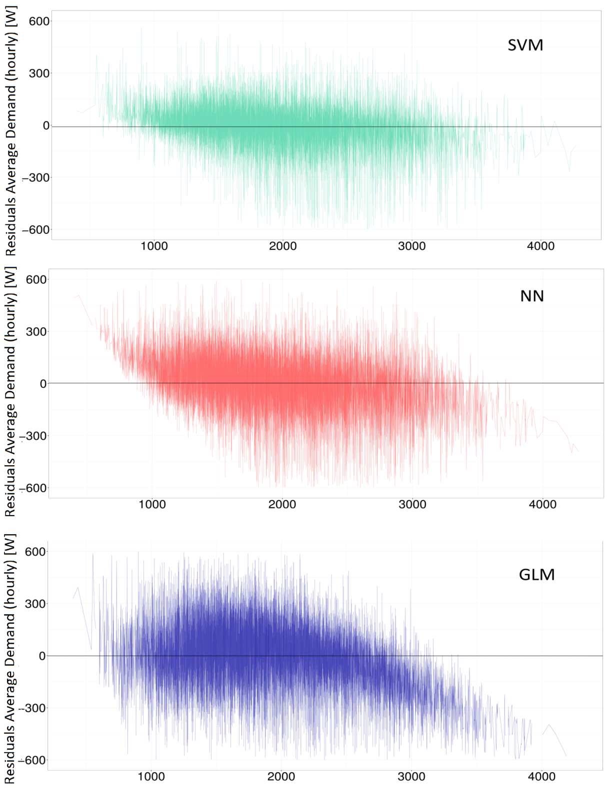

Figure 5: Predictive modelling: residuals (Nov-Dec 2014)

average electricity demand, averaged over 60 minutes. Another way to assess the accuracy of the predictive models is to graph predicted and simulated data in terms of residuals defined in equation 3

$$r = s - p \tag{3}$$

where s are outputs of the parametric simulation, p outputs of the predictive models. Figure 5 shows the results of this visualisation technique; if the oscillation of the results is close to 0, it means that simulation and prediction data are similar. Residuals help the modeller to understand if the model performs particularly well or not in defined situations (e.g. prediction capability for low or high demand values).

Next month prediction

In order to test the potential of the presented approach in predicting building requirements in different scenarios, the procedure is repeated considering only the month of November as the training month and the month of December for testing phase. Hence, training is performed providing, in addition to the input explained in the methodology, the electric and heating requirements of the baseline building. Hourly average electric and heating demand are the target variables. The results are visualised in Figure 6 and Figure 7 both in terms of predicted against simulated results and in terms of residuals. Thus, MAPE and RMSE are evaluated.

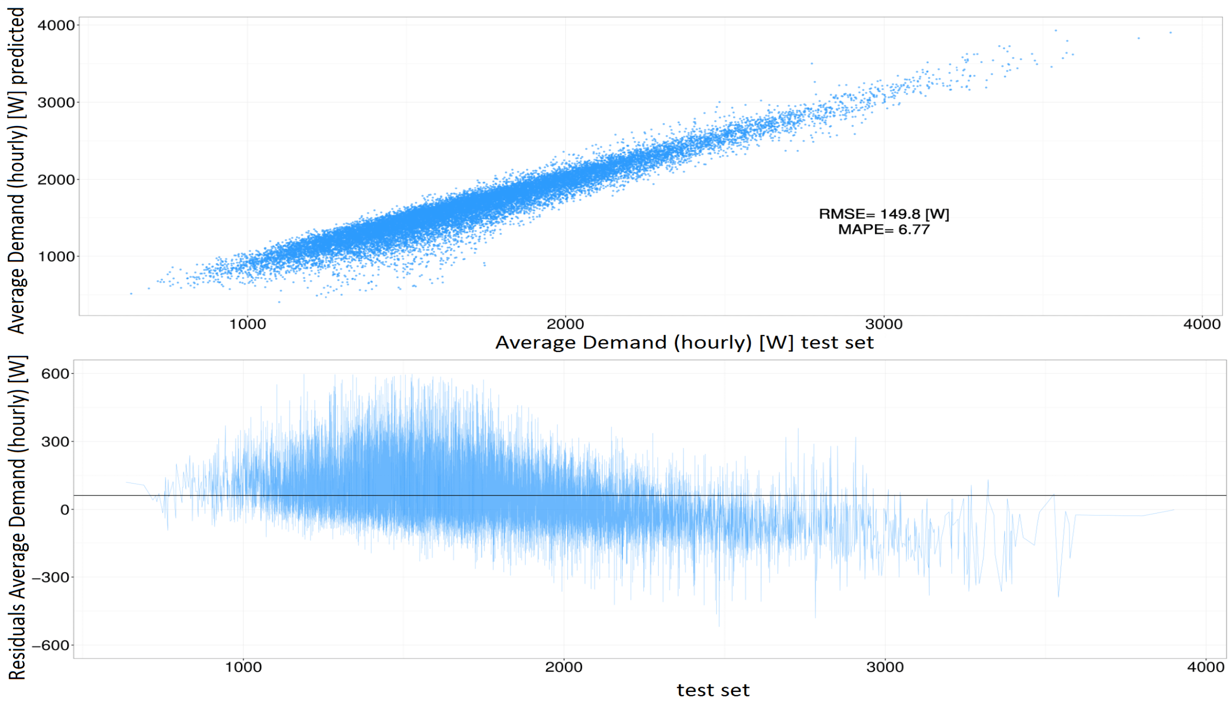

Figure 6: Predictive modelling (SVM): next month prediction, simulated vs predicted outputs (total electricity)

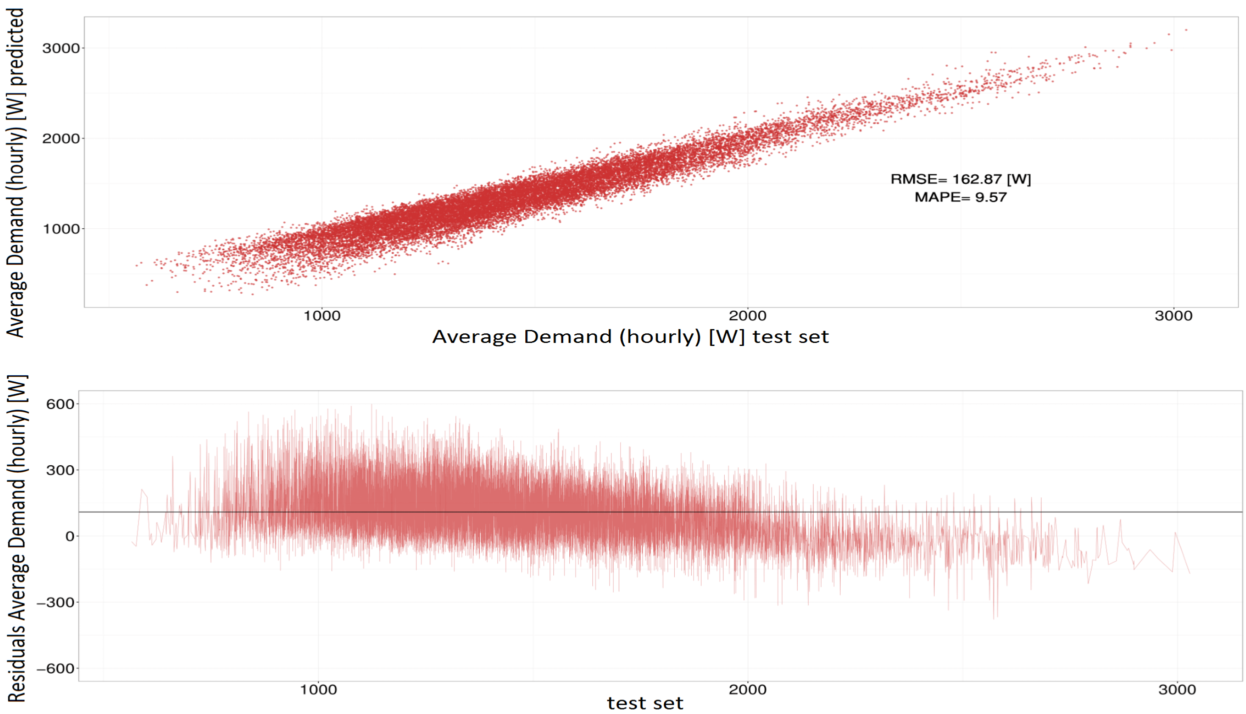

Figure 7: Predictive modelling (SVM): next month prediction, simulated vs predicted outputs (heating)

Discussion

Prediction algorithms

Comparing the three predictive models underlines different accuracy and prediction capabilities. From the analysis of the predicted against simulated results it is evident that quantitatively all the algorithms perform well. Predictions are well aligned to the diagonal line meaning that the algorithms generalise well on the testing set. Model comparison can be performed by the means of quality indices such as MAPE and RMSE. The RMSE ranges from 195 W, 171 W, and 138 W for SVM, NN and GLM approaches, respectively. The MAPE values range from 5 for SVM, 7 for NN and to 8.20 for GLM. As such, it is evident that the SVM is the model which performs best. Visualisation of the residual between predicted and actual results helps to understand if the models perform well with respect to a determined range of outcome. Both generalised linear model and neural network do not have good performances for low and high demand values. This is easily understandable looking at the prediction results which are averagely skewed for low and high requirements. SVM seems to perform with a constant accuracy on average in all the range of possible outcomes. This confirms that its performance are the best of the three models for this analysis.

Next month prediction

The previous analysis showed that SVM out performs the other algorithms, hence, it will be deployed as the predictive approach in this analysis. In this case, the model is required to predict unknown conditions such as the one generated from next month weather variables. Output targets are average electricity and heating demand, averaged over 60 minutes for all the simulated buildings. The results show that by increasing the prediction horizon and testing the predictive capabilities for unknown conditions, the model is still able to perform well with a MAPE of 6.77 for the electricity demand and 9.57 on the heating requirements.

Conclusion

Possible uses of the predictive model

DDM integrated within a parametric framework are able to accurately predict outputs of large sets of different building simulations. This could lead to further research in investigating the use of DDM as a modelling technique in studies involving a vast number of buildings. A trained DDM could be employed for investigating different building scenarios. For example it may be employed to assess the effect of changing total transmittances, internal gains magnitudes, glazing surface options, orientation, changes in building air tightness of the baseline model. Most of the variables, appropriate in retrofit analysis, may be evaluated using a trained DDM. A similar approach may be assumed for characterising and to predict the demand of a group of buildings of the same typology of the baseline model. The level of detail of the outcomes allows investigation at different level of aggregation commencing with single buildings and extending to entire groups.

Advantages and limitations of the proposed approach

A trained predictive model can produce fast and reliable results (in the range of identified errors). This may be beneficial in large simulation studies with similar building typologies (e.g. district or city level), where a large number of constructions affect the simulation time and modelling complexity. However, the proposed approach presents a series of limitations due to modelling assumptions that must be taken into account in order to define important improvements. In particular, a series of assumptions must be relaxed. Geometry is typically not homogeneous in an urban environment. The heterogeneity of construction defines volumes, areas, adjacencies and shading effects: all of these variables highly influence modelling outcomes. Heating, cooling and electricity systems and their efficiencies change from building to building due to different configuration and operations. Occupant behaviour is highly unpredictable, it defines internal gains schedules and operation of a building, thus it is an important factor in determining the demand pattern especially in the residential sector. All the aforementioned issues must be considered for improving the reliability of the presented approach. On the other hand, the scalability of the proposed technique may play a key role in improving its ability to represent realistically an urban environment. The flexibility of the parametric approach guarantees the possibility to increase the number of relevant parameters in the analysis and enhance the capability of DDM to represent more realistically a large scale context.

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