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Modelling and Simulation of Residential Load Profiles as an Approach for Data-Driven Prediction

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***Abstract* — Rapid growth of buildings energy consumption encourages to take measures to improve energy efficiency by actors involved in the field. One of the approaches developed last decades consists in energy management through energy prediction. These approaches engage machine learning algorithms, which focus on predicting energy consumption based on past-observed data. But there are also cases when this information is missing so in this paper, we focus on solving the problem when measured data are not available. Initially, we develop an electrical home appliance simulator, which reflects their energy consumption and occupant behavior. Each of the considered device is modelled using an electrical circuit analogy. Then aggregating single appliance energy consumption from simulator, total power consumption data is generated. Synthetic data are feed to an Artificial Neural Network algorithm to learn consumption pattern and to predict next hour energy consumption.**

***Keywords* — Data-Driven, Electrical Circuit, Energy Management, Electricity Prediction, Neural Networks, Modelling, Simulation, State-Space.**

I. Introduction

Statistics indicate that building energy consumption has increased during last decades in residential and commercial sector according to International Energy Agency (IEA) [1], This indicator has affected other fields like an increase in CO2 emissions, electrical grid difficulties, particularly like energy imbalance especially during peak hours and also affecting system stability. Moreover, according statistics in Albania [2] consumption only residential sector counts for 49% of total consumption.

Most of consumed household electricity goes for water and space heating, food processing, as seen in Fig. 1. As building count for considerable energy consumers, they also can provide opportunities for efficiency measures through building management systems. One approach is the coordination of Building Energy Management Systems (BEMS) [3] with Information and Communications Technology (ICT) through monitoring and intelligent control strategies. BEMS features provide to end users' information regarding their consumption instantly, also they can provide knowledge and suggestions to them to reduce their consumption, including an economic viewpoint.

ICT technologies and BEMS are integrated in a so-called Smart Building environment which helps to reduce building power consumption through the processes: 1- Delivery Optimization, 2- Demand Optimization, and 3- Asset Optimization [4].

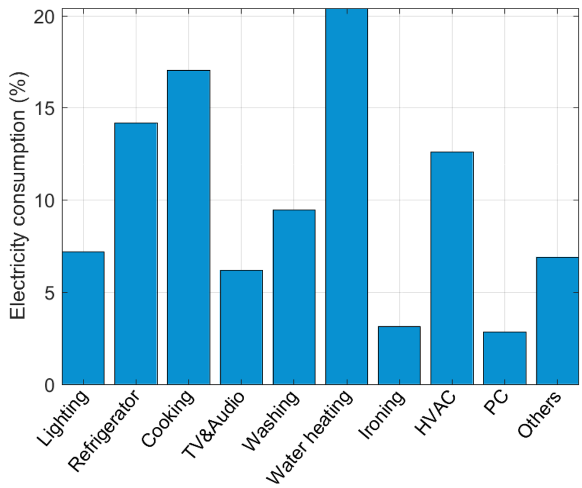

Fig. 1. Statistics of appliance energy consumption [5].

Not only BEMS systems are integrated in buildings, but also emerging technologies in the context of Industry 4.0 like IOT devices are integrated to measure and store data regarding energy consumption [6]. On the other hand, there exist a considerable number of buildings that we do not have past measurements or ICT systems are not installed. Solving this problem synthetic data can be generated and applied for different purposes. Here we have developed a residential load simulator for most consuming electrical appliances according to Fig. 1. Modelling procedure of domestic appliances, is based on our previous works [7],[8]. Power consumption load profiles are generated based on two main factors, first on their nominal power consumption and technology and second based on building occupancy. The majority of devices are modeled based on their direct load profile and simulated in Simulink-MATLAB by adopting their equivalent lumped capacitance electrical circuit. Individual load profiles are aggregated together to obtain total home power consumption. Then simulation results obtained from simulator are used as input data to train an algorithm to predict building energy usage and to validate algorithm performance.

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Moreover, we are interested on prediction of building energy consumption it is used as a tool integrated in BEMS systems to improve building energy usage through advanced control strategies and operation control [9]. The existence of anticipatory information allows building management personnel to take proactive efforts to reduce consumption and crucially minimize peak consumption. The rapid development of artificial intelligence algorithms that predict time series data can be used also as a tool to predict energy usage. Machine-learning algorithms are one of the most commonly used approaches for predicting energy efficiency, analyzing occupant behavior and provide information.

Many statistical and machine learning models applied: artificial neural networks (ANN), support vector regression (SVR), regression tree (RT), random forest (RF) and other relevant methods [10]-[15]. We have selected to apply ANN as one of the most used approaches in energy prediction context.

This paper deals with literature review of most recent and used approaches on the problem. Followed by methodology used, to continue with experimental results and is closed by the conclusions.

II. Literature Review

In this section we perform with most relevant papers used in the field that deal with similar problems. We have adopted literature review from our previous works [8],[16]. The first part takes into consideration modelling of electrical appliances and second subsection takes into account energy prediction approaches.

A. Appliance Modelling

According to statistics food preparation, shower, lighting, and room heating consume the majority of the residence's energy [2],[5]. As a result, managing such devices may have a significant impact on the power grid as well as the occupant through economic impact. Hart [17] divides residential electrical appliances into three categories: 1- two state (ON-OFF), 2- "three way" lamp, and 3- multi-state devices such as washing machines, dishwashers, and so on. Our primary focus is on modeling two-state appliances with ON/OFF thermostats, as well as multi-state devices (washing machine). Some of these items, such as water heaters, washing machines, and ovens, are adjustable (shiftable), but others, such as refrigerators and water heaters, are not. In the literature, there are several ways that describe interior temperature dynamics and home appliances using lumped parameter circuits.

First, we review used approaches to model building modelling. Modelling and simulation in building design began in 1985 with, “Modelling and Simulation in Building Design” [6], where author combined useful information using different approaches and methods in building simulation. Carbb *et al.* [7] analysed the thermal behaviour of buildings by using a simplified dynamic thermal network consisted of resistances (R) and capacitances (C). Tindale additionally uses third order RC thermal network [18] to simulate thermal behaviour of single zones as well as the behaviour of many zones comparing obtained results using APACHE (finite difference simulation program). Simplified building models were used to model indoor environments by Antonopoulos and Koronaki [19], where they focus on finding optimal values of R and C parameters by taking into consideration effect of different thermal mases on temperature dynamics. Moreover, reducing model complexity are investigated by Gouda *et al.* [20] in order to improve the computational time efficiency. They start with a model of the 20th order and reduce it to a model of the 11th order by adjusting the parameters via Kuhn–Tucker equations. Reduction of modelling complexity is analysed by Fraisse *et al.* [21] whereas they model complete areas by aggregating similar elements of the buildings like walls etc. Thermal modelling of building dynamics using a simplified model is analysed by Nielsen [22]. Moreover, simplified models are used to model single room in order to aggregate them into a building model and then to analyse city energetic behaviour by Kämpf and Robinson [23].

Not only buildings are modelled using RC analogy, but we bring into our focus electrical devices that have been also in our consideration. Starting with water heaters, where selecting best model was investigated in [24]. Here are considered single storage tanks having different volumes and using different nominal electrical power were analysed. hereinafter, authors in [25] apply first order differential equations to model single heating element water heater.

Thermal investigation of domestic oven is also investigated in [26]. They conclude that thermal modelling based on lumped parameters show an accurate model compared to real measurements. A professional oven has been presented in [27], using lumped capacitance method they indicate that this method is capable of accurately forecasting the thermodynamic performances of the oven.

Moreover, temperature dynamics of domestic refrigerator are analysed in [28], they identify model thermal parameters in order to later be used in intelligent control strategies for smart grid power control. Dynamic models of domestic refrigerator using electric circuit analogy were investigated in [29], where investigated different models show their advantages and disadvantages using to model refrigerators. The third order model having three capacitances describes mostly domestic refrigerator.

Domestic heating systems has been in focus of Good *et al.* [30], where they used circuit analogy to model heating elements. To capture the best simulation model, room thermal models and other features such as hot water use are employed throughout this phase.

B. Building Energy Consumption Prediction

Energy consumption in buildings can be related as time series problem since data generated from consumption are related to time and moreover those data have a nonlinear behavior, but there is a strong correlation with outdoor temperature and humidity. Here, we can mention Chou and Tran [31] have investigated household energy consumption as time series prediction phenomena. They review different energy prediction methods applied to real time data installed to a smart grid, concluding with remarks about advantages and disadvantages of used methods to predict next day energy consumption. Moreover, smart building scenario is also presented by Shapi *et al.* [32] considering two different end users they predict energy consumption using three different approaches like ANN, SVR and K-NN concluding that each user creates its consumption profile independently. Despite the fact that energy consumption has a nonlinear behavior there are also similar patterns occurring during time, so Lu *et al.* [33] use this patterns to improve algorithm accuracy. Initially they categorize energy consumption patterns into similar groups then apply a learner to each group in order to increase accuracy compared to traditional method.

One of the best learners used to deal with building energy consumption problems are ANNs due to their success at predicting nonlinear time series. ANNs are used in different areas of analyzing building energy consumption. They are engaged in predicting of total building energy consumption, prediction of sublevel components consumption like heating and cooling system, analyzing occupant behavior, predicting indoor and outdoor temperature variations. Azadeh [34] uses long-term data from Iranian industrial users to train a multi-layer perceptron that predicts long-term energy consumption in high industrial consumers. They compare the capabilities of ANNs to statistical methodologies such as ANOVA. Also a multi-layer perceptron is used Carmona *et al.* [35] to predict monthly electricity demand. ANNs are used also by Wong [36] to study building behavior and predict office energy usage in a subtropical location relative to sunshine and climatic factors. Variables linked to exterior weather conditions, building physical properties, and a weekday indication are used as inputs to the model. They demonstrate the importance of the ANN method by combining and comparing computer-aided simulations with data-driven methodologies. To predict the heating demand of a passive solar building, Gonzales and Zamarreno [37] use a recurrent neural network to predict hourly power usage in buildings. When forecasted air temperature and present load are used as input parameters, a simple model constructed using real-world data produces highly accurate results. But using ANNs in their original approach is not the best approach as Li [38] analyses behavior of traditional ANNs compared to a hybrid genetic algorithm adaptive network-based fuzzy inference system (GA ANFIS). Here, GA is used to find the optimum network parameters and the ANFIS adjusts them to fit better the training data. Resulting that energy consumption predicted by GA ANFIS is more relevant to real data in terms of coefficient of variation (CV). Olofsson [39] use neural networks to forecast space heating needs when just a few performance indicators are known. They suggest a quasi-physical technique to describing building performance using external and internal temperatures, as well as other basic characteristics. Moreover, Qiao *et al.* [40] summarize a systematic approach regarding energy prediction methods.

Neural Networks are also used to model PV modules as an alternative to traditional electric circuit approach in [41].

III. Methodology

The proposed methodology consists of developing e residential load simulator, which considers major electrical consuming home appliances and is simulated in Simulink-MATLAB. Simulator will be used to generate synthetic data regarding electricity consumption. Those data are used to highlight daily peak consumption and as training data for a ML algorithm. Our approach follows those simple steps initially we consider thermal modelling of the particular house, then considered devices are modelled using electric circuit analogy. Then single appliance energy consumption is obtained from simulating ON-OFF transient response of temperature distribution, where during ON interval the appliance draws electricity from grid. The generated data are aggregated to obtain home total energy consumption based on a preloaded occupant behavior selected based on user experience. We use the generated data to predict hourly energy consumption using an ANN model which is trained as described in subsection B.

A. General Appliance Thermal Modelling

Modelling methodology employs thermal electrical circuit analogy, likewise in Fig. 2. There are sources of heat production and sinks (losses), where heat sources are electrical resistances or compressors, so we use thermal analogy to electrical analogy. Particularly, voltage is analogue of temperature, current corresponds to heat flux, resistance correspond s to heat losses and capacitance correspond to thermal capacitance coming from building construction parts or device structure. We model using this analogy the following devices, water heater, oven, refrigerator, domestic heater iron. Moreover, indoor temperature dynamics are a factor that strongly affects device energy consumption as well.

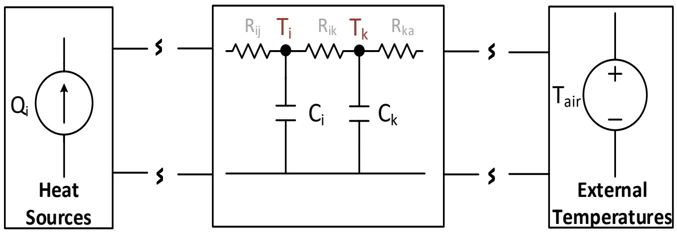


Fig. 2. Appliance electric thermal model.

1) House thermal model

Appliance energy consumption is strongly related to environment temperature, since all electrical devices are placed in an indoor environment it is important to measure or model temperature distribution. Temperature distribution inside house is function of geometry, design and building materials. The house under investigation has single window, balcony door open space living room, where mainly electrical devices are placed. Based on these assumptions we build a house 2R2C circuit thermal model, which has as heating sources the thermal energy released into room from air conditioner system, effects of solar radiation and furniture heat gain are also considered.

2) Water heater modelling

One of the most used devices to heat residential water are Electric Water Heaters (EWH). Their structure at most used market models is constructed as insulated tanks with insulation materials in the middle of two metallic cylinders from the environment, having an electrical resistance as heating element controlled by a thermostat. Tank has two inlets used for the following functions first one to let cold water inside tank and the other for hot water outlet [13].

We have under examination a water heater which is simulated to generate electric power usage, as function of thermostat cycles. During transient simulations using 1R1C equivalent circuit temperature distributions of medium inside tank are considered uniformly distributed. Water heater is modeled with two key aspects in mind: first, the energy required to reduce thermal losses to the outdoor, and second, the energy required to heat the incoming cold water until the desired set point temperature is reached. Parameters considered for this simulation are those used in [7].

3) Oven modelling

Modelling oven there are considered many parameters due to its complexity like heating element, oven cavity and influences of outdoor temperature to its transient response. In our simulations we are considering a 3R3C circuit model whereas there are three temperature zones. Model circuit parameters are found in our paper [7].

4) Refrigerator modelling

One of major energy consumers are also refrigerators, this is due to their time of use not their nominal electrical power, since they operate continuously. Power profiles are obtained from temperature transitions inside cooling compartment.

5) Washing machine modelling

Washing machines are considered as major electrical consumption devices where they mainly consume energy to heat water and then for electric motor operation. A full operation cycle depends on many factors like the selected mode and set point temperature, but they have in common a general operation procedure consisting of three stages [25], they start withdrawing water to pre-wash the clothes with a process that usually last about 15 minutes, then precedes the heating of water done by a controlled On/Off thermostat electrical resistance, to conclude with washing and rinsing.

B. Artificial Neural Network General Learning Scheme

Artificial Neural Networks mimic human brain to process information as basis for developing algorithms. ANNs are structured as multiple layer networks Fig. 3, where there is input layer, output layer and hidden layers. Usually a single layer performs by taking a set of observed inputs $a=(a_1,a_2,...,a_n)$ from input layer, then it to each input is associated with a weight value forming a vector of $w=(\mathrm{w}_1,\mathrm{w}_2,...,\mathrm{w}_n)$. Each input is multiplied with its associated weight to form the pre-activation function.

Pre-activation function is transformed by the network using an activation function, which usually it is a nonlinear function (sigmoid or hyperbolic). In case of single hidden layer network, (1) shows the layer output when using a sigmoidal activation function.

$$a_{out} = f(z) = \frac{1}{1+e^{-z}} \tag{1}$$

The ANN model shown in Fig. 3 describes a simple network model with many inputs and a single output.

Network inputs correspond to the number of data features and the output corresponds to the desired output.

Fig. 3 shows a general architecture of neural network, but it is very important to select the proper network architecture like number of hidden layers and number of neurons in hidden layer.

In our case the number of inputs corresponds with dataset number of features and the output will show next hour energy consumption since we are interested to predict next hour energy prediction.

IV. Computational Experiments

In our consideration, there is a small apartment consisting of a living room and two bedrooms, which is heated by an air conditioner with power 2000 W, equipped with 2000 W water heater, 2400 W oven, 200 W cooling refrigerator, 100 W incandescent lamps, 43-inch 100 W television and 1400 W clothes iron and also there are miscellaneous devices but not considered since their power consumption is modest compared to the former devices.

Data generated from the above simulated devices are aggregated over a year period and then feed to ANN model for next hour prediction. Next subsection will explain in detail data processing and fitting neural network to our dataset.

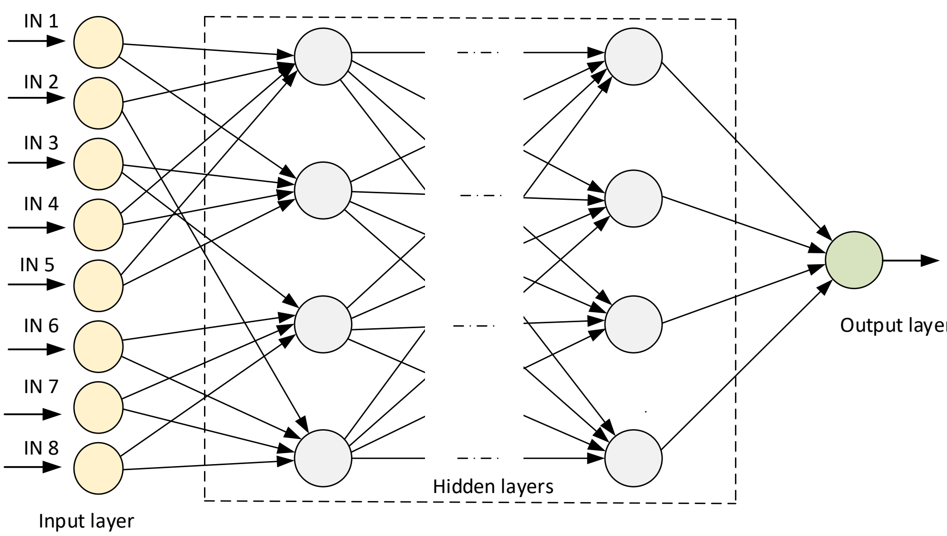


Fig. 3. Artificial neural network model.

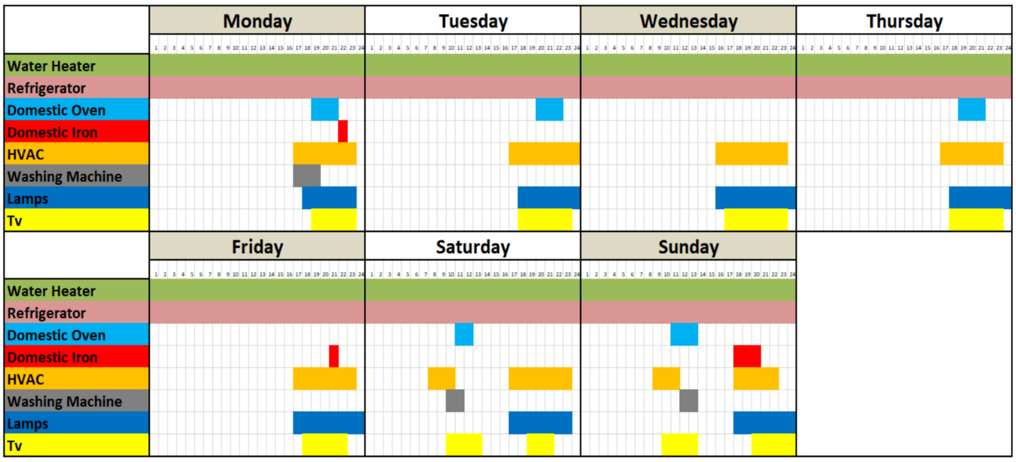


Fig. 4. Gantt chart for electrical appliances working.

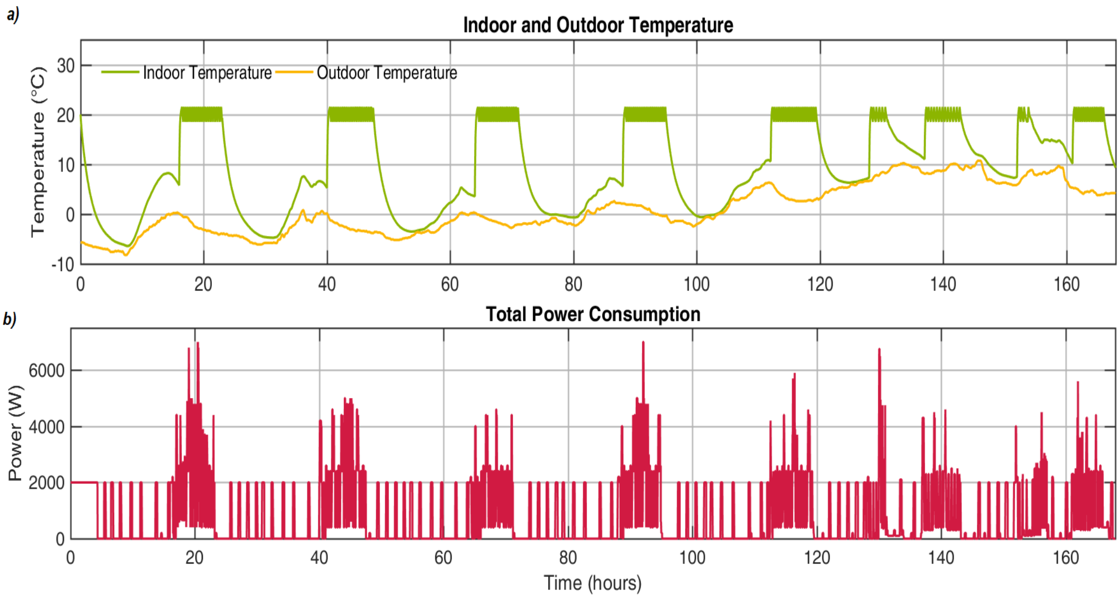


Fig. 5. Household weekly simulations a) weekly indoor and outdoor temperature variation and b) weekly electrical aggregated power consumption.

A. Data Generation

This part gives a detailed description for the proposed simulator considering a real case scenario, running them in Simulink MATLAB. The outdoor temperature variation for year in Tirana Albania data are taken from NASA [42] database and occupancy profile for a typical working day and weekends. Usual working period is 08:00-16:00 from Monday to Friday, and weekends are off. Considering that 17:00 time when occupants are home from work, and the number of occupants is two (young couple), we are running simulations for each of the considered appliances. In Fig. 4 there are reflected considered working periods for appliances for a typical week. Simulated water heater, refrigerator, oven, iron and air conditioning system use thermal parameters as in [8] and models are described in section III-A. The first step we take is to model the internal living space temperature dynamics. The considered house located in a multi-story building has dimensions (l = 12 m, w = 8 m, h = 3 m), has two openings facing southeast (one window and balcony door), walls consist of bricks and are isolated by outer and inner plaster layers.

Indoor temperature dynamics are used as input parameter for each of modelled devices. Simulations for each of the devices are used to gain overall building energy consumption shown in Fig. 5. Results are contribution of two factors, first time that is required to reach device set-point and second is the user intervention (switching on and off device).

Moreover, electricity consumption data are compared to real measured data form electricity bills of electricity provider in Albania. We have taken into consideration that starting from April the heater is turned off and only during hot days the cooling air conditioning is turned on and in August the habitants are on vacation so only refrigeration is on, and no other devices are turned on.

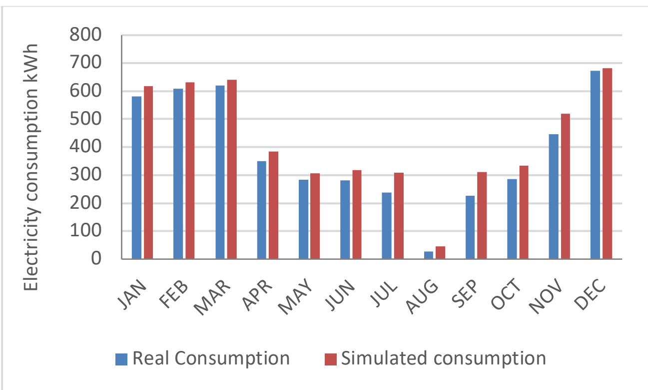
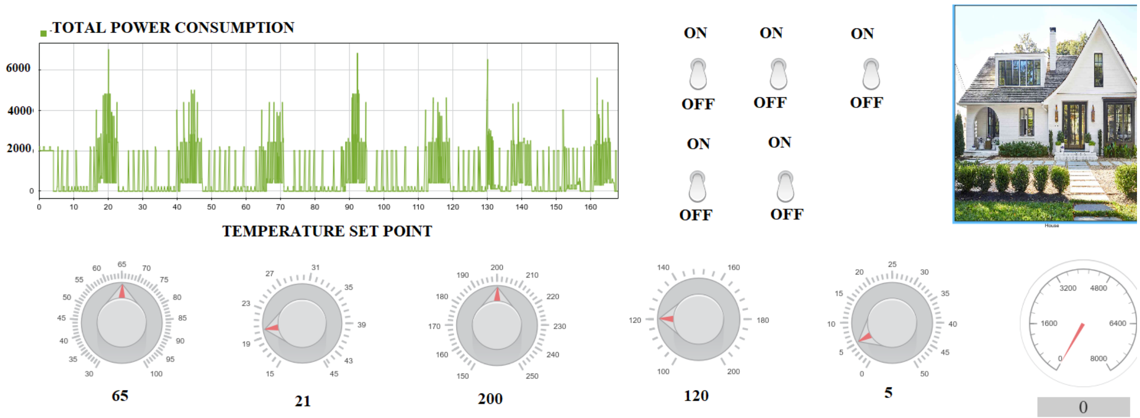


Fig. 6. Household monthly electrical power consumption.



APPLIANCES	MONDAY		TUESDAY		WEDNESDAY		THURSDAY		FRIDAY		SATURDAY		SUNDAY	
OVEN	ton	toff	ton	toff	ton	toff	ton	toff	ton	toff	ton	toff	ton	toff
HVAC	tonH 16	tdH 7	ton1H 16	td1H 7.5	ton2H 16	td2H 7	ton3H 16	td3H 7	ton4H 16	td4H 7.5	ton5H 8	td5H 3	ton6H 17	td6H 6
IRON	tonh 21	tdh 1	td1h 0	td1h 0	ton2h 21	td2h 1	ton3h 0	td3h 0	ton4h 20	td4h 1	ton5h 0	td5h 0	ton6h 0	td6h 0
LIGHTS	tonll 17	tdll 6	ton1ll 17	td1ll 6.5	ton2ll 18	td2ll 5	ton3ll 17	td3ll 6	ton4ll 17	td4ll 6.5	ton5ll 0	ton5ll 0	ton6ll 17	td6ll 6
TV	tonT 17	tdT 6	ton1T 17	td2T 5	ton2T 18	td2T 5	ton3T 17	td3T 6	ton4T 17	td4T 6.5	ton5T 10	td5T 4	ton6T 19	td6T 2
WASHING M.	tonL 17.5	tdL 1.4	tonL1 0	tdL1 0	tonL2 0	tdL2 0	tonL3 0	tdL3 0	tonL4 0	tdL4 0	tonL5 10	tdL5 1.4	tonL6 0	tdL6 0

Fig. 7. Household electricity power consumption simulator.

B. *Data Preprocessing*

Electricity consumption data are provided residential building, the data simulated from 1st of January 2022 until 31st December 2022. Observed information within a frequency of one hour contain power consumption and air temperature values taken from NASA site as we have mentioned above. This dataset is used to predict hourly building energy consumption by use of ANN model in order to make the learning process more efficient.

Attributes that represent the problem are outside air temperature and power consumption, an extraction of additional information taken from data is applied to improve algorithm accuracy and the input vector to be more informative.

$$X(t) = \{t, D, M, T_t, P_{t-168}, P_{t-24}, P_{t-3}, P_{t-2}, P_{t-1}, \overline{P_{t-24}}\} \quad (2)$$

As it can be seen from (2), X is the input vector represented by: T_t temperature at time t, D is day of the month (M), P_{t-24} power consumption at same hour one day before, P_{t-168} power consumption at same hour a week before and $\overline{P}_{(t-24)}$ average power consumption the day before prediction takes place. Other time lagged energy consumption measurements respectively measured for three(P_{t-3}), two (P_{t-2})and an hour (P_{t-1}) before prediction starts.

C. *Prediction Results*

Conducting experiments for trained neural network, the architecture used as described in above section, using backpropagation neural network using as training algorithm Levenberg–Marquart and nonlinear sigmoid activation function of ten hidden neurons in hidden layer. Proposed network is compared to one of the most competitive baseline learners, known in literature as target mean, which predicts the mean value of energy consumption for current batch training dataset. The results are evaluated using accuracy measurement as in (3) coefficient of variation of root mean squared error (CV-RMSE).

$$CV - RMSE = \frac{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(P_p - P_r)^2}}{\overline{P_r}} \quad (3)$$

Analyzing the data statistics we have the following results standard deviation is 850, data range is 6400 and mean value is 600 for 8760 data point which correspond to yearly total hours. Table I shows prediction results for trained ANN.

TABLE I: PREDICTION RESULTS

Training period	Learner	CV-RMSE
01.01.2022-31.03.2022	ANN	44.17
	BaseLearner	44.26
01.01.2022-31.06.2022	ANN	22.62
	BaseLearner	28.7
01.01.2022-31.09.2022	ANN	17.07
	BaseLearner	25.026

Results obtained show an increase of prediction accuracy for ANN learner as the training data size increases. On the three different training sizes the ANN learner performs better than base learner. According to ASHRAE guideline 14 [43]. The CV-RMSE error for hourly predictions should be less than 30%, a value which is obtained from two training periods. Results are repeated five different times and the results show the average values.

V. CONCLUSION

This paper deals with the problem of generating residential electricity consumption data using a simulator built in Simulink. Model used to describe on off power consumption use electrical circuit analogy. Using occupancy for a particular home we generate hourly consumption data for the year 2022 based on outdoor temperatures. The results were compared to monthly electricity bills from electricity provider showing accurately results. Those data then were used to train a Neural Network to predict next hour energy consumption. Obtained results are satisfying ASHRAE guideline, but there is also a space for improving those results. From our current results we have concluded that the necessity of more available data is mandatory, since the data are generated ad not measured this will be not a problem. But in our case the monthly bills were not available for previous years so in near future those data will be gathered in order our results to be comparable to real data. Moreover, different ML learners will be used as our future work.

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