Electricity Consumption Forecast of Clusters of Buildings Based on Recurrent Neural Networks

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***Abstract*—During the last decade, the relevance of improving the energy efficiency and thus reduce the energy consumption of buildings has gained momentum for many reasons. In addition to economic and sustainability reasons, an important factor is to ensure and maintain comfortable and healthy conditions inside buildings. Indeed, the study of the behavior of users inside buildings is essential to ensure comfortable and healthy conditions in living environments and cannot be avoided when defining energy saving measures. To achieve this goal, this paper presents a simulation framework for the prediction of the electricity consumption of cluster of buildings based on users' behaviors. The framework is based on model-based approaches simulating the energy consumption of buildings and statistical models representing the behavior of users. Simulated energy consumption profiles are then used to train recurrent neural networks that, based on real energy consumption data, can be used to tune the statistical and deterministic parameters of the simulation models. University campuses comprising different type of buildings are used as reference use case in this paper, as representative example of energy cluster of buildings.**

Keywords—Simulation modelling, forecasting system, energy consumption, neural network, Long Short-Term Memory.

I. Introduction

In 2008 half of the world's population lived in urbanized areas but consumed almost 67% of the world's energy [1]. Over time, the situation has become even more contrasting. Buildings in Europe consume a large amount of the primary energy supply. In the European Union (EU), the current demand of thermal energy in the buildings sector (e.g., space heating and domestic hot water) accounts for 40% of the total energy demand in the residential sector [2], and this share is continuously increasing. Worth to note, as the electrification process increases, and fossil fueled heating and cooking equipment is being replaced with electrical equipment, the energy demand of buildings will have an increasing role also in the overall electrical power supply. In this context, the reduction of energy consumption through the application of energy management actions, along with the use of renewable energy sources are important measures to increase the energy efficiency of buildings and reduce greenhouse gas emissions.

While the global targets for saving energy and reducing greenhouse gas emissions are often set at the national level, the main actions can be also taken at the city, or even district scale. For this purpose, groups (i.e., clusters) of buildings connected to the same point of common coupling with utility networks (i.e., gas, district heating, or electrical networks) and under the same administrative management can be identified to identify different consumption patterns and thus proper energy saving and health measures. These consumers include, for instance, university campuses. The electricity consumption in university buildings is usually high, as well as difficult to forecast and reduce due to the variability of building designs, their different ages, and wide range of uses [3]. Indeed, large differences in the thermal and electrical energy consumption of university campuses in different countries have been recorded [4]. The analysis of the electricity consumption in the total energy supply of buildings is gaining an increasing relevance for both economic and environmental reasons [5]. As the use of electricity in building in increasing, following the replacement of fossil fueled systems with electrical equipment providing thermal power supply, the analysis and forecast of electricity consumption is gaining relevance. Accurate consumption forecast could in fact improve both energy efficiency analyses and the planning of energy saving measures, including the efficient operation, and scheduling of energy intensive resources, such as Heating Ventilation and Air Conditioning (HVAC). Indeed, through the analysis of electrical variables, energy saving measures can be applied, and therefore the energy efficiency of buildings can be improved [6]. In this context, the application of advanced analyses of energy consumption data could help to provide a better understanding of the problem, especially if a comparative analysis of various buildings affected by the same (or similar) environmental conditions are combined [7].

Previous research on the topic used two main types of modeling approaches: the black box and the gray box approach [8]. For the black box method, no preliminary information is required, and the models contain formal mathematical relationships between experimentally observed time series. In the grey box strategy, the knowledge of the energy characteristics of the buildings and the dynamic modelling of the processes involved in the energy consumption (e.g., heat transfer models for heating equipment) are considered. However, because of the complexity and (typically) scarcely available information required by the gray box strategies, the black box approach is usually adopted and also more investigated by the literature.

When dealing with the analysis of the energy consumption and the well-being of the users in buildings, it is apparent that the knowledge of the behavior of users using the various types of equipment usually installed in buildings would allow to better understand their energy consumption habits and to better define and implement both health and energy saving measures [9], [10]. However, the knowledge of users' habits requires the collection of several information, some of which cannot be directly measured by sensors (e.g., the level of activity of single users in the same room), also entailing data privacy issues. For this reason, the use of external and publicly available information (e.g., weather conditions or thermostat set points) could be used instead to reconstruct or evaluate the users' energy habits if correlated to energy consumption measurements. Studies published in the literature already demonstrated that there is an obvious positive correlation between energy consumption and average daily temperature [11], as well as characteristics of different days (weekdays, weekends, and holidays). Some extra low consumption occurs during holidays when the number of people inside the building is lower. Electricity consumption at weekends can also be compared to energy consumption during holidays [12]. Finally, the definition of the type of the buildings included in the cluster (e.g., residential, commercial, academic buildings, dorms, labs, etc.) and the definition of a type of energy consumption equipment (e.g., lightning, water heating, cooking, computers, motors, etc.) significantly affects the changes in energy consumption during the day and the volume of annual consumption [13].

By following this research trend, this work presents a methodological framework for the identification of users' energy habits and the prediction of the energy consumption of (cluster) of buildings based only on publicly available information and on the definition of the main energy characteristics of the buildings. The framework is based on the application of model-based approaches simulating the energy consumption of buildings based on statistical parameters representing the behavior of users, combined with artificial intelligence learning methods that are used to tune the statistical and deterministic parameters of the simulation models, based on real energy consumption data.

The rest of the paper is structured as follows. In Section II the main studies in the scientific literature dealing with the energy consumption forecast of buildings is presented and briefly summarized. Section III presents the methodological approach adopted in the present study and describes the structure of the energy forecasting framework. Section IV introduces the definition of the simulation algorithm proposed for the prediction of electrical power consumption of clusters of buildings, by focusing on the use case of university campuses, while Section V provides and discusses some preliminary results of the simulations. Finally, Section VI summarizes the content of the paper and introduces future work on the topic.

II. Related Work

There are two basic approaches to model the electrical energy consumption of buildings at the urban scale: the top-down modeling and the bottom-up modeling [14].

A. *Top-down methods*

Top-down approaches typically compute energy consumption by establishing long-term relationships between the energy consumption in each consumer sector and the related fundamental factors, such as changes in gross domestic product, energy price, population, household size, technology used, and weather conditions. The advantage of this category of models is that it is able to describe the interactions between the energy and economic domains, which allows the use of the energy model under different socio-economic scenarios, i.e., by considering both socio-demographic and economic factors. In addition, top-down approaches tend to use relatively simple implementation techniques, relying on a limited set of inputs such as aggregated socio-economic data. Since the emphasis is on overall energy savings, detailed information on the types of energy-related technologies used in the buildings and detailed energy consumption data is usually not required. Because of their simplicity, top-down approaches are widely used to estimate energy consumption in cities. However, these models are not able to predict the energy consumption of a specific building or type of building, and to catch the relationship between the energy consumption and the habits of users living in the building.

B. *Bottom-up methods*

Bottom-up approaches compute energy consumption based on detailed information about the end users (i.e., as a combination of the type of the building and the behavior of its users) and can be classified into two types: statistical methods and physics-based methods.

The first type of method usually involves the use of energy consumption data from typical buildings to analyze the relationship between end-use and total energy consumption. The statistical approach is similar to the top-down approach in terms of the ability to account for various socio-economic factors. However, this method uses more detailed and often disaggregated information, which is usually provided by energy consumption data for individual buildings. On the other side, model-based methods compute the energy consumption based on the physical characteristics of a building, such as the geometry of the building, and non-geometric elements (such as heating, ventilation, and air conditioning systems), as well as their characteristics of use. In this case, the detailed knowledge and modeling of the building represent the main limitation, concerning both the efforts (and costs) for the realization of the model, and the privacy issues involved in the modelling of end users' habits.

Bottom-up statistical methods use urban construction data and energy consumption data based on long-term historical series. The use of bottom-up statistical methods requires statistical information of the urban areas (i.e., the urban classification, the rate of constructed areas, the size of buildings, etc.) to model the energy consumption of buildings. Information about the past and current state of urban areas, obtained from government sources, can serve as input data for statistical modeling of the total amount of current and future urban energy consumption. The main limitation in this approach is that statistics on urban areas in the future must themselves be modeled since the spatial variation of urban areas cannot be accurately determined. In contrast, a model-based model is not considered suitable for modeling urban areas, given that the model uses detailed information about the technical characteristics of buildings such as type, area, geometry, and other non-geometric information. However, a model-based model can overcome this limitation in a combined approach.

C. Artificial Intellingence learning methods

Extensive studies have been carried out to enhance the efficient distribution of electrical energy in power grids. These studies led to a new conceptualization of next generation electrical networks, the so-called smart grids, that make an extensive use of information and communication technologies for the analysis, management, and automated operation of power grids [15]. In smart grids information about consumer behavior is expected to be collected, analyzed, and aggregated to create a context-sensitive system that can distribute power efficiently [16]. Smart grids using artificial intelligence are expected to reduce the need to deploy more power plants to generate electricity [17]. Smart grids also use renewable energy and resources to securely connect to the grid to power consumers. Intelligent systems such as expert systems, fuzzy logic systems [18], systems using machine learning [19], deep neural networks [20], genetic algorithms [21], particle swarm algorithms [22] and chaos theory [23] are revolutionizing the management and operation of power grids. These systems provide powerful tools for designing, simulating, and troubleshooting, as well as enabling diagnostics and fault-tolerant control in today's smart grids. Concerning the forecast of the energy consumption of buildings, extensive research has been carried out in the context of smart grids. The main limitation of this approach is that learning algorithms typically rely only on predefined mathematic relations (depending on the selected method) and are not able to catch the physical- or event-related dependencies of the energy behavior of buildings or end users, respectively.

To overcome this issue, the concept proposed in this study is to consider the forecasting techniques usually applied in the smart grid context, and to implement them, in combination with statistical and model-based approaches, to learn the energy behavior of buildings and to extract the relationship between the energy consumption and the habits of the users.

III. Methodology

In this section, the methodology adopted to develop the proposed forecasting framework is described in detail, by referring to the use case of an university campus.

A. Input data

The aim of the development of mathematical forecasting models is to establish quantitative relationships between the modeled indicators (e.g., power consumption data, rate power consumption of loads, key performance indicators, etc.) and the set of parameters that affect them. Forecasting power and energy consumption of loads using conventional time-based regression models gives a good result in the steady state of energy consumption, but poorly considers significant changes in established trends. Some improvement in the predictive properties of regression and autoregression models can be achieved by using models with variable coefficients, which are themselves functions of time. In addition, the prediction results can be improved using cluster analysis [24]. Clustering consists of dividing data objects into groups or clusters so that objects in a cluster are similar to each other and not similar to objects in other clusters. Cluster analysis in machine learning is an unsupervised learning method that forms the cornerstone of data mining processes and is used to explore relationships between a set of patterns by organizing them into homogeneous clusters. This method is used to identify different types of energy consumption patterns and is applied to individual, industrial, and commercial consumers, or to a large group of residential consumers. The availability of low-cost smart meters with high recording rates (i.e., with recording time intervals in the order of minutes, rather than hours) and good accuracy is however required to ensure the availability of the large amount of data required by this kind of analysis. Large amount of data is in fact required to extract the information used to provide reliable and accurate short-term or long-term forecasting of the consumption of electrical load [25], and also assist energy management teams in developing strategies to reduce the energy consumption in buildings. Worth to note, even though the costs of accurate and reliable smart metering devices are decreasing, their installation costs still remain a concern, particularly in legacy systems that are not equipped with adequate communication infrastructures. In addition, the energy consumption related to the installation of several intelligent devices and the need of large data storage capabilities may represent an issue.

B. System analysis

When considering the possibilities of the simulation of the energy consumption of university campuses, it is necessary to produce a preliminary analysis of the problem in terms of the overall structure and relationships between the system elements under consideration. Following the general approach of system analysis, it is necessary to determine the main internal elements of the system, their hierarchy, as well as external elements, and the most significant interactions inside and outside the system. The definition of the structure itself, the elements of the system, and the characterizing parameters do not only depend on the system but also on the problem to be solved. Despite the use of a comprehensive approach based on the combination of Building Information Model (BIM) with the thermophysical modelling of buildings seems obviously promising, the required detailing of information about all the parameters of buildings and structures could represent an issue, or at least a relevant effort in terms of problem definition and mathematical computation. Since the aim of this study is related to the problem of predicting the electricity consumption, all the parameters defining the structure of the university campus that are essential for the solution of the problem must be first identified, taking into account their (possible) hierarchy.

The ability of selecting individual elements in a complex system is associated with their relative independence and functional isolation [26]. From this point of view, the largest building elements (subclusters) in the campus are the large construction objects (buildings) included in it, and the integral parameter of interest to us is the total electrical power $P_c(t)$ consumed by the campus at a given time, i.e., the sum of the power consumed by each object at time t, so that:

$$P_c(t) = \sum_{j=1}^{N} P_j(t), \tag{1}$$

where N is the total number of facilities on the campus. In turn, the energy consumption of individual objects is made up of different components, depending on their purpose, so that

$$P_j(t) = \sum_m n_{jm} P_{jm}(t), \tag{2}$$

where n_{jm} is the number of consumers of the same type, numbered by index m, inside the object j.

To determine the contribution of individual objects to the total electricity consumption, the objects are classified according to their purpose, i.e., by using the following classification: 1) Campus dormitory, 2) Educational and laboratory buildings, 3) Auxiliary buildings and structures (garages, warehouses, boiler repair shops), 4) Sports facilities (pools, stadiums, sports complexes), 5) Catering facilities (canteens, cafes), and 5) Campus territory.

The characteristic of the type of electrical load for each object is also set, by considering specific classifications. For the campus dormitory, for instance, the following classification has been considered: 1.1) Public power systems, supporting pumps and lighting in common areas; 1.2) Total electricity for heating and air conditioning; 1.3) Laundries, ironing; 1.4) Electric stoves; 1.5) Electricity consumption in student rooms; 1.6) Computers and chargers; 1.7) Lift equipment. Similar classifications have been adopted for all the other objects of the model.

The behavior of electricity consumers depends on a number of factors, which are defined here as power consumption modes, namely mode P, D, S, and V, that depend on the frequency of the action triggering the power consumption, i.e.:

- P. Permanent consumption of electricity (e.g., for security systems and emergency lighting);
- D. Electricity consumption with daily variation;
- S. Seasonal modes of electricity consumption;
- V. Electricity consumption during vacation, weekends, and holidays.

The presented decomposition can be displayed as a graph having a tree structure. The external environment is determined by weather conditions, including outdoor temperature, solar radiation, air humidity, and wind speed [27]. These factors can be included in the model directly, or they can be presented indirectly as the result of the measurements of the electricity consumption in the different climatic seasons of the year. In the simulation model presented in this study, these factors are considered indirectly along with random processes representing the behavior of people inside the buildings of the campus.

C. Proposed model

The following assumptions have been considered for the design of the proposed forecasting model:

- the model considers only the type and number of electrical loads, without considering the details of the physical processes involved in the transmission and distribution of electrical energy;
- the model is dynamic since it is designed to reproduce the change in electricity consumption over time;
- the model is constructed as a stochastic process since it describes the behavior of a large number of consumers, most of which are turned on and off at non-strictly defined times;
- the model is based on pure mathematical formulations and does not describe the physical processes occurring in electrical equipment during power consumption;
- the model is discrete, as the events are described as switch-on and switch-off of electrical equipment or types of electrical loads with a certain probability as a function of time, that changes with a constant step Δt according to the model time clock.

Existing experience in the realization of similar simulation models with an agent-based approach to consumers [28], gives reason to expect success.

IV. Simulation Model

This section presents the mathematical modelling and the algorithms used in the proposed simulation model.

When advancing in time by step

$$t_{i+1} = t_i + \Delta t, \tag{3}$$

each event (corresponding to the activation of a given electrical load) occurs with a certain probability $P_{jm}(t)$. The duration of the time interval from switching on to switching off the electrical equipment is a random variable $\tau_{jm}(t)$. The power consumed by an individual consumer has an interval character: in the on state, it is a constant value W_{jm}, and that is zero in the off state:

$$P_{jm}(t) = W_{jm}, \tag{4}$$

$$P_{jm}(t) = 0. \tag{5}$$

The duration of the on the state of the consumer $\tau_{jm}(t)$ may also be a random variable.

The selection of informative and independent baselines is a preparatory stage of modeling [29]. To build a discrete-event simulation model of electricity consumption the following components must be defined:

- *the system state*: is the set of variables indicating the state of the system at a certain time t;
- *the model time*: is the variable indicating the current value of time;
- *the list of events*: is the list containing the time of occurrence of each of the events;
- *the statistical counters*: are variables containing statistical information about the system, the probability of switching on the electrical load, and the duration of electricity consumption;

The initialization program sets the state of the simulation model at the initial time, then the event generation program sequentially generates the events with a given probability depending on time. A passive stochastic agent model is proposed in which individual aggregate consumers of electrical energy have statistical characteristics that change over time according to their own rules, as well as under the influence of external conditions, but which do not interact directly with each other and make an additive contribution to the total electricity consumption. The choice of this model among other agent-based models [30] is determined by the considered general forecasting problem.

In this study, the model is limited to the simulation of the time series of the total electricity consumption of a university campus, based on the aggregated energy consumption of the objects of the system (i.e., buildings and related electrical loads) [31]. The paper proposes a bottom-up simulation method based on statistical data from energy consumption surveys. The proposed model considers the characteristic dynamics of electricity consumption during the day [32], also including seasonal changes.

Electricity consumption most significantly depends on the behavior of students living in the campus. This can be taken into account by building a multi-agent behavior model [33], or by introducing appropriate statistical characteristics based on empirical studies. Expected campus occupancy drives many components of the model, although climatic conditions further affect electrical load, and daylight availability can also affect the load of lightning equipment. Peak demand for electricity in most commercial buildings occurs on hot summer days (except in cold climates dominated by electric heating) when buildings are full and cooling costs are highest.

To take into account for randomly distributed events related to users' behavior, a random component in modeling the energy consumption was introduced, based on the Poisson distribution of events. In the simulation process, the occurrence of the events is set for different intervals using a random number generator. The Poisson distribution is:

$$p(k) = \frac{\lambda^k}{k!} e^{-\lambda}, \tag{6}$$

where k is the number of events, λ is the mathematical expectation of a random variable (the average number of the activation of the electrical load for a fixed period of time). Thus, the simulation model of a random number of inclusions in a given period was obtained, based on average data of the number of inclusions, and the average consumption per consumer. From the data sample, which is equal to the number of iterations, the maximum and minimum consumption is selected, and the average consumption value of the simulation model is also calculated.

As the simulation starts, the main program calls the initialization program, which sets the starting time, initial state, statistical counters, and event list. Next, the event generation program is called, which changes the state of the system at each step with given probabilities. The simulation consists in computing random experiments, and then ensembles of implementations must be analyzed in order to isolate the average behavior and determine the error corridor.

V. Results and Discussion

This section describes the simulation modeling results which are obtained by implementing the proposed models to the energy-related data generated by the simulation agents.

Based on the statistical data obtained by surveying consumers, the activation times of monitored electrical loads in the different periods and their energy consumption were determined. From the input data, electricity consumption is recorded in the given interval with a given step. Thus, data were obtained in which the total power consumption in each generated time interval with a given step. Further, the average power consumption was extracted from this type of data by dividing the total power by the number of consumers participating in the calculation. Fig. 1 shows the basic simulation of the electricity consumption pattern of a student living in the dormitory of the electricity campus, based on real data surveys. The expected electricity consumption of a student living in the dormitory for one day, computed by taking into account stochastic components, is shown in Fig. 2.

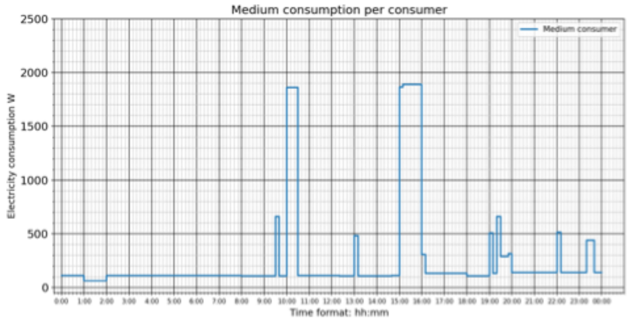

Fig. 1. Example of the average consumption of a student living in the dormitory of the university campus for one day.

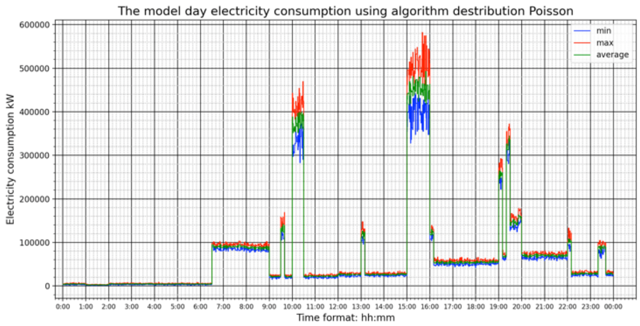

Fig. 2. Example of the expected electricity consumption of a student living in the dormitory of the campus for one day, including stochastic components.

If additional data related to external parameters (such as weather conditions) are considered along with simulation results, a Long Short-Term Memory Model (LSTM) neural network could be trained to predict the daily power consumption profile depending on environmental conditions.

VI. Conclusions and Future Work

In this paper, a simulation model was proposed to compute the expected energy consumption of cluster of buildings. The proposed simulation model is based on the analysis of the problem from the point of view of the general structure of objects and their relationships, the main internal elements of the system, their hierarchy, as well as external elements and the most significant interactions inside and outside the system.

To complete the forecasting problem, a unified scheme based on deep learning and recurrent neural networks was proposed [34]. Recorded data of the energy consumption of the university campus are pre-processed and then LSTM is applied. The LSTM-based regression model is expected to yield minimum mean square and mean absolute percent error values compared to other methods described in the literature. A detailed discussion of the method, the features of its application, and the results obtained are planned to be carried out at the next stage of the work. Like any model based on supervised machine learning, LSTM requires a large number of training examples, while the corresponding data may be incomplete or missing. Collecting them and integrating them into a smart energy system may require additional time and funding. To solve this issue, the use of a simulation model of electricity consumption has been proposed, which performs two functions. Firstly, the simulation model itself makes it possible to predict electricity consumption. Secondly, the data generated by the model will allow the training and testing of a forecasting system based on recurrent neural networks [35].

REFERENCES

[1] B. K. Sovacool and M. A. Brown, "Twelve metropolitan carbon footprints: A preliminary comparative global assessment," *Energy Policy*, vol. 38, no. 9, pp. 4856–4869, Sep. 2010, doi: 10.1016/J.ENPOL.2009.10.001.

[2] A. Dahash, F. Ochs, M. B. Janetti, and W. Streicher, "Advances in seasonal thermal energy storage for solar district heating applications: A critical review on large-scale hot-water tank and pit thermal energy storage systems," *Appl Energy*, vol. 239, pp. 296–315, Apr. 2019, doi: 10.1016/j.apenergy.2019.01.189.

[3] C. Lodi, V. Malaguti, F. M. Contini, L. Sala, A. Muscio, and P. Tartarini, *University energy planning for reducing energy consumption and GHG emissions: The case study of a university campus in Italy*, vol. 35, no. Special Issue 1. 2017. doi: 10.18280/ijht.35Sp0104.

[4] Y. T. Ma, M. Y. Lu, and J. T. Weng, "Energy Consumption Status and Characteristics Analysis of University Campus Buildings," 2015. doi: 10.2991/iccet-15.2015.232.

[5] D. Vasenin, M. Pasetti, O. Sotnikova, and T. Makarova, "Justification of the Choice of the Generation Capacity," 2021, pp. 258–265. doi: 10.1007/978-3-030-57453-6_22.

[6] O. Rewthong, B. Eamthanakul, S. Chuarung, S. Sansiribhan, and N. Luewarasirikul, "Status of Total Electric Energy Consumption in University," *Procedia Soc Behav Sci*, vol. 197, pp. 1166–1173, Jul. 2015, doi: 10.1016/j.sbspro.2015.07.373.

[7] S. Alonso, M. Domínguez, M. A. Prada, M. Sulkava, and J. Hollmén, "Comparative Analysis of Power Consumption in University Buildings Using envSOM," 2011, pp. 10–21. doi: 10.1007/978-3-642-24800-9_4.

[8] T. Ahmad, H. Chen, Y. Guo, and J. Wang, "A comprehensive overview on the data driven and large scale based approaches for forecasting of building energy demand: A review," *Energy and Buildings*, vol. 165. Elsevier Ltd, pp. 301–320, Apr. 15, 2018. doi: 10.1016/j.enbuild.2018.01.017.

[9] W.-H. Hong, J.-Y. Kim, C.-M. Lee, and G.-Y. Jeon, "Energy Consumption and the Power Saving Potential of a University in Korea: Using a Field Survey."

[10] Y. Han, X. Zhou, and R. Luo, "Analysis on Campus Energy Consumption and Energy Saving Measures in Cold Region of China," in *Procedia Engineering*, 2015, vol. 121, pp. 801–808. doi: 10.1016/j.proeng.2015.09.033.

[11] A. A. Chowdhury, M. G. Rasul, and M. M. K. Khan, *Modelling and simulation of building energy consumption: A case study on an institutional building in central queensland, australia*, no. Krarti 2000. 2007.

[12] M. Jafary, M. Wright, L. Shephard, J. Gomez, and R. U. Nair, "Understanding Campus Energy Consumption - People, Buildings and Technology," in *IEEE Green Technologies Conference*, Apr. 2016, vol. 2016-April, pp. 68–72. doi: 10.1109/GreenTech.2016.20.

[13] S. O. Oyedepo *et al.*, *A Study on Energy Demand and Consumption in Covenant University, Ota, Nigeria*. 2015.

[14] W. Li *et al.*, "Modeling urban building energy use: A review of modeling approaches and procedures," *Energy*, vol. 141. Elsevier Ltd, pp. 2445–2457, Dec. 15, 2017. doi: 10.1016/j.energy.2017.11.071.

[15] S. Howell, Y. Rezgui, J. L. Hippolyte, B. Jayan, and H. Li, "Towards the next generation of smart grids: Semantic and holonic multi-agent management of distributed energy resources," *Renewable and Sustainable Energy Reviews*, vol. 77, no. September 2017, pp. 193–214, 2017, doi: 10.1016/j.rser.2017.03.107.

[16] M. Alazab, S. Khan, S. S. R. Krishnan, Q. V. Pham, M. P. K. Reddy, and T. R. Gadekallu, "A Multidirectional LSTM Model for Predicting the Stability of a Smart Grid," *IEEE Access*, vol. 8, pp. 85454–85463, 2020, doi: 10.1109/ACCESS.2020.2991067.

[17] S. M. Miraftabzadeh, M. Longo, F. Foiadelli, and M. Pasetti, "Advances in the Application of Machine Learning Techniques for Power System Analytics : A Survey †," *Energies (Basel)*, vol. 14, no. 16, p. 4776, 2021, doi: 10.3390/en14164776.

[18] C. Wang, Z. Cui, and Q. Chen, "Short-term Load Forecasting Based on Fuzzy Neural Network," in *Workshop on Intelligent Information Technology Application (IITA 2007)*, Dec. 2007, pp. 335–338. doi: 10.1109/IITA.2007.17.

[19] S. Seyedzadeh, F. P. Rahimian, I. Glesk, and M. Roper, "Machine learning for estimation of building energy consumption and performance: a review," *Visualization in Engineering*, vol. 6, no. 1, p. 5, Dec. 2018, doi: 10.1186/s40327-018-0064-7.

[20] M. Kalimoldayev, A. Drozdenko, I. Koplyk, T. Marinich, A. Abdildayeva, and T. Zhukabayeva, "Analysis of modern approaches for the prediction of electric energy consumption," *Open Engineering*, vol. 10, no. 1. De Gruyter, pp. 350–361, Jan. 01, 2020. doi: 10.1515/eng-2020-0028.

[21] E. Lee and H. Bahn, "A genetic algorithm based power consumption scheduling in smart grid buildings," in *International Conference on Information Networking*, 2014, pp. 469–474. doi: 10.1109/ICOIN.2014.6799726.

[22] O. C. Ozerdem, E. O. Olaniyi, and O. K. Oyedotun, "Short term load forecasting using particle swarm optimization neural network," *Procedia Comput Sci*, vol. 120, pp. 382–393, 2017, doi: 10.1016/j.procs.2017.11.254.

[23] Z. Yuan, S. Liu, L. Xue, and X. Yuan, "Notice of Retraction Short-term load forecasting based on chaos theory and RBF neural network," in *2011 Seventh International Conference on Natural Computation*, Jul. 2011, pp. 526–529. doi: 10.1109/ICNC.2011.6022118.

[24] B. Nepal, M. Yamaha, A. Yokoe, and T. Yamaji, "Electricity load forecasting using clustering and ARIMA model for energy management in buildings," *Japan Architectural Review*, vol. 3, no. 1, pp. 62–76, Jan. 2020, doi: 10.1002/2475-8876.12135.

[25] D. N. Vasenin, T. v Makarova, T. v Bogatova, and E. E. Semenova, "Methods of day ahead load forecasting on the example of a residential area," *J Phys Conf Ser*, vol. 1926, no. 1, p. 012007, May 2021, doi: 10.1088/1742-6596/1926/1/012007.

[26] S. Pan *et al.*, "Cluster analysis for occupant-behavior based electricity load patterns in buildings: A case study in Shanghai residences," *Build Simul*, vol. 10, no. 6, pp. 889–898, Dec. 2017, doi: 10.1007/s12273-017-0377-9.

[27] K. P. Amber *et al.*, "Energy consumption forecasting for university sector buildings," *Energies (Basel)*, vol. 10, no. 10, Oct. 2017, doi: 10.3390/en10101579.

[28] T. Zhang, P.-O. Siebers, and U. Aickelin, "Modelling Office Energy Consumption: An Agent Based Approach."

[29] J. Xu *et al.*, "Clustering-based probability distribution model for monthly residential building electricity consumption analysis," *Build Simul*, vol. 14, no. 1, pp. 149–164, Feb. 2021, doi: 10.1007/s12273-020-0710-6.

[30] A. González-Briones, F. de La Prieta, M. Mohamad, S. Omatu, and J. Corchado, "Multi-Agent Systems Applications in Energy Optimization Problems: A State-of-the-Art Review," *Energies (Basel)*, vol. 11, no. 8, p. 1928, Jul. 2018, doi: 10.3390/en11081928.

[31] H. Lin, Q. Wang, Y. Wang, R. Wennerstern, and Q. Sun, "Agent-based Modeling of Electricity Consumption in an Office Building under a Tiered Pricing Mechanism," *Energy Procedia*, vol. 104, pp. 329–335, Dec. 2016, doi: 10.1016/j.egypro.2016.12.056.

[32] B. Akbar, K. P. Amber, A. Kousar, M. W. Aslam, M. A. Bashir, and M. S. Khan, "Data-driven predictive models for daily electricity consumption of academic buildings," *AIMS Energy*, vol. 8, no. 5, pp. 783–801, 2020, doi: 10.3934/ENERGY.2020.5.783.

[33] D. Saba, H. E. Degha, B. Berbaoui, F. Z. Laallam, and R. Maouedj, "Contribution to the modeling and simulation of multiagent systems for energy saving in the habitat," in *2017 International Conference on Mathematics and Information Technology (ICMIT)*, Dec. 2017, pp. 204–208. doi: 10.1109/MATHIT.2017.8259718.

[34] D. Kaur, R. Kumar, N. Kumar, and M. Guizani, "Smart Grid Energy Management Using RNN-LSTM: A Deep Learning-Based Approach," in *2019 IEEE Global Communications Conference (GLOBECOM)*, Dec. 2019, pp. 1–6. doi: 10.1109/GLOBECOM38437.2019.9013850.

[35] I. Petri, S. Kubicki, Y. Rezgui, A. Guerriero, and H. Li, "Optimizing Energy Efficiency in Operating Built Environment Assets through Building Information Modeling: A Case Study," *Energies (Basel)*, vol. 10, no. 8, p. 1167, Aug. 2017, doi: 10.3390/en10081167.