An Integrated Framework for Building's Energy Management based on Deep Learning

I. Meintanis, N. Monios, I.E. Livieris, M. Kampourakis, S. Fourakis, N. Kyriakoulis, S. Kokkorikos & A. Chondronasios
Core-Innovation, Kallirois 85, 11745, Athens, Greece

ABSTRACT: Forecasting the building energy consumption constitutes a significant factor for a wide variety of applications including planning, management and optimization. Nowadays, research is focused towards the development of more efficient and sustainable energy management systems which focus on minimising energy waste. These systems are based on intelligent models, which provide accurate predictions of future energy demand/load, both at aggregate and individual site level. In this work, we present a holistic integrated solution for the buildings' energy management systems using deep learning methods. The proposed solution is based on efficient deep-learning forecasting models for short-term local weather parameters and energy load consumption. The developed forecasting models are integrated into the smart energy management system of the building for taking the proper decisions to ensure efficient utilization of energy resources.

1. INTRODUCTION

Nowadays, the economic growth and the increase of human population lead to acceleration of rate energy consumption while building energy consumption accounts for a significant proportion. Worldwide, the building sector is the largest primary energy consumer as well as the largest contributor to the greenhouse gas emission (Pérez-Lombard et al. 2008). For example, in the US and China statistical data reveal that buildings are responsible for more than 40 % of global energy use and one-third of global greenhouse gas emissions (Timoshenko & Berman 2017). To this end, the improvement in the efficiency of building operational performance and its enhancement could save significant amounts of energy, increase indoor comfort, reduce greenhouse gas emissions and reduce stress on the electric grid.

The process of better understanding and improving buildings' energy performance is a critical and significant step towards sustainable mitigation of global climate change. Therefore, the development of an efficient building energy monitoring system is considered essential for improving building operations in order to reduce energy waste and ultimately increase efficiency. Essentially, these systems will provide a deep insight in identifying retrofit opportunities for existing buildings and provide guidelines to improve the design of new buildings. Nevertheless, energy load monitoring and analysis is generally considered as a significantly challenging and complex problem since it is affected by several factors which are characterized by spatio-temporal variability. Buildings' energy monitoring and analysis has a long history in industrial and scientific community. During the last two decades, the advances in digital technology and storage capabilities lead to the enrichment and the accumulation of a large amount of building operational time-series data. This new data-driven era enabled the development of advanced deep learning models for predicting buildings' energy and state.

The main reason for this considerable popularity is their remarkable ability to support decision-making considerations such as ways of reducing energy waste and cost. Additionally, since energy consumption can be considered as a time series problem, deep learning methods constitute the appropriate methodology for dealing with the noisy, highly non-linear and usually chaotic nature of time-series data (Livieris et al. 2020). Li et al. (2017) attempted to exploit the advantages of stacked autoencoders (SAEs) and Extreme Learning Machine (ELM) for the development of a building energy consumption prediction model. More specifically, SAE were utilized to extract the building energy consumption features, while the ELM was used as a predictor for obtaining accurate predictions. Their preliminary experimental analysis presented some promising results. Mocanu et al. (2016) proposed a forecasting model based on Factored Conditional Restricted Boltzmann Machine. They utilized four-year data of one-minute resolution electric power consumption, which were collected from a residential customer. Their experimental results revealed the effectiveness and forecasting accuracy of their proposed model. Fan et al. (2019) investigated the performance of fully connected autoencoders, convolutional autoencoders and generative adversarial networks in automatically deriving high-quality features for building energy predictions. Their motivation was based on the forecasting ability of a prediction model could be improved though feature engineering. Their experiments highlighted the efficacy of their approach and showed that the derived features were able to provide useful information from the original data. Independently, Wang et al. (2015) and Deb et al. (2016) conducted some excellent surveys in which they comprehensively presented buildings' energy prediction models based on data mining methodologies. Furthermore, they highlighted the significance of energy monitoring for planning and energy optimization of buildings and campuses and they attempted to provide a deep insight by identify the factors which affect it. Along this line, Mason and Grijalva (2019) presented a comprehensive review focusing on the application of newly proposed reinforcement deep learning to developing autonomous building energy management systems.

The software architectural style selected for the deployment of the prediction tools is based on microservices. Such Service-Oriented Architecture (SOA) offers great abilities in a Continuous Integration (CI) / Continuous Delivery (CD) environment, such as: (i) deployment, (ii) increased modifications, and (iii) strong resilience to architectural erosion. Unlike traditional monolithic application architecture, where all the functionality is into a single process and it is scaled by replicating the application on multiple servers, the utilized microservices architecture puts each element of functionality into a separate service and it is scaled by distributing the services across servers, replicating as needed. The advantages of such architecture are the shorter deployment times, simpler deployment procedures, zero-downtime releases and easier modifiability (as defined by Chen 2018, Chen & Ba 2014) which translates to shorter cycle times for small incremental functional and quality changes.

In this work, we propose a new and complete framework for building's energy monitoring based on deep learning methodologies. The proposed framework is based on efficient prediction models which forecast key short-term weather parameters (temperature and insolation) as well as energy load demand. The rationale behind our approach is that short-term weather forecasting and analysis constitute a key role for estimating the future energy demand and hence the efficient management of energy resources, respectively. The developed forecasting models are going to be integrated into the smart energy management system of the ENERGETIKUM demo-site building for taking the proper decisions to ensure efficient utilization of energy resources. Our aim is that the proposed approach could be used as a reference for efficient decision-making in the context of PVadapt Project, but also can be adapted to new use-cases (pilot buildings) as well.

The remainder of the paper is organized as follows. Section 2, presents the proposed weather and energy load foresting models including the data preparation and pre-processing for each model as well as the detailed experimental analysis and the evaluation of proposed models. Section 3 presents the microservices architecture used for gathering data from online services and sub-systems and preparing them for feeding the models in order to get real-time predictions. Finally, Section 5 presents our conclusion and the findings of this work.

2. PROPOSED WEATHER AND ENERGY LOAD FORECASTING MODELS

In this section, we present the two forecasting models for the prediction of short-term local weather conditions and energy load based on deep learning methodologies.

For determining the network structure and hyper-parameters for both prediction models, we conducted an exhaustive experimentation, namely utilize different number of the LSTM and dense layers, different number of neurons in each layer, etc. The selected loss function was Mean Square Error (MSE) while the Adaptive Moment Estimation (ADAM) algorithm (Kingma & Ba 2014) was used as the optimizer together with schemes for adapting the learning rate through the epochs of training. Finally, the implementation code was written in Python 3.7 while using the Tensorflow-Keras backend (Chollet 2018).

2.1 WEATHER FORECASTING MODEL

2.1.1 Modelling

For the prediction of short-term weather conditions (temperature and insolation), we developed a forecasting model based on Deep Recurrent Neural Networks (RNNs), which was trained with historical (local) weather data and provide hourly temperature and insolation predictions for the next 24 hours. More specifically, the historical data concerns Burgenland location in Austria and were collected by online weather service (www.meteo.com), covering the period from Jan-01, 1985 to Dec-31, 2018. This results in more than 300,000 hourly observations of weather variables including: temperature (°C), relative humidity (%), pressure (hPa), cloud coverage (%), shortwave radiation (W/m^2), sunshine duration (min.), total precipitation (mm), and wind speed (m/s). The data were divided into approximately 80 % samples for training and the rest 20 % for testing the generalization performance of the model. More specifically, the training samples cover the period from Jan-01, 1985 to 31-Dec 2012, whereas the testing set consist of observations from the last 6 years of the given dataset. Finally, the data were pre-processed to eliminate outliers and fill any bad values.

The architecture of the forecasting model consists of:

- LSTM layers with 50 units using ReLU as activation function.
- Pooling layers (for downscaling feature maps).
- Two fully connected layers of 64 and 32 neurons, respectively using ReLU as activation function.
- Output layer of 48 neurons with a linear activation.

Finally, weight regularization (L2) was added to our model in order to reduce the difference between the bias error and the validation/testing error, and hence the model was able to better generalize in unseen data. The model output consists of 24 nodes, i.e. one node for each hour to predict ahead, for each target variable (temperature and insolation).

2.1.2 Numerical experiments

For evaluating the prediction efficiency of the forecasting weather model, we plot the distribution of prediction errors, i.e. true(i) - prediction(i) for each test observation(i) (Fig. 1). Clearly, the prediction error is considerably low regarding both target values; thus, we can easily conclude that the model's prediction and generalisation performance are considered successful. Fig. 2, show snapshots of temperature and insolation predictions for 24 hours ahead. The interpretation of the results reveal that the model provides accurate predictions for both target variables (temperature – left plot, insolation – right plot), although temperature predictions show a slightly higher error than insolation.

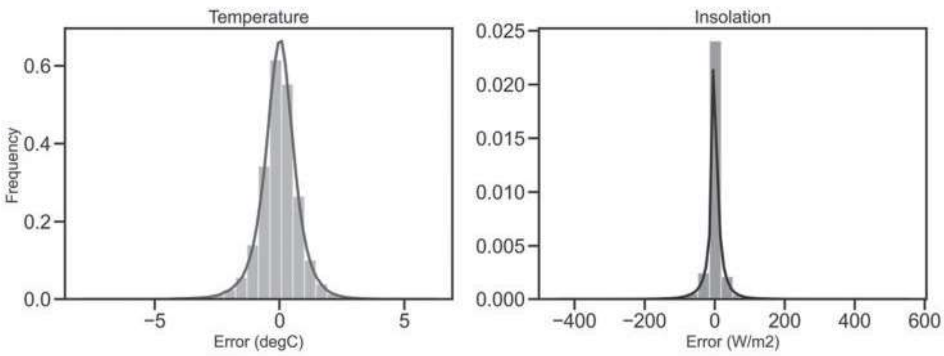

Fig. 1: Prediction error distributions for the weather model in test set.

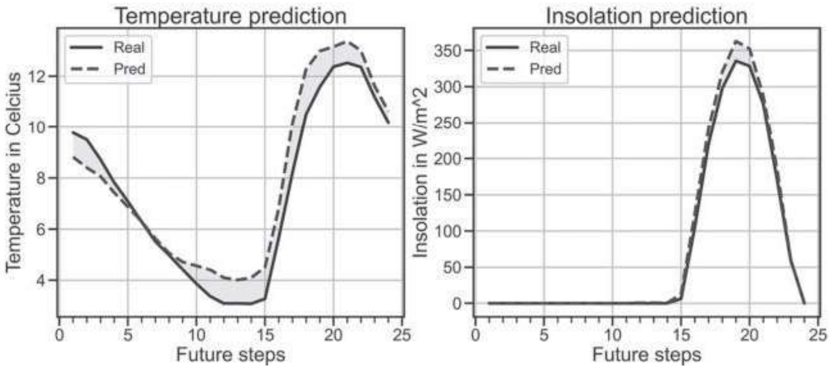

Fig. 2: Temperature and insolation predictions for a random 24-hour interval in UASB building.

2.2 ENERGY LOAD FORECAST

In the sequel, we present the development of short-term load forecasting model for a single lab building (ENERGETIKUM, UASB) that is served as demo-site in the context of PVadapt project.

2.2.1 Modelling

The collected data concern historical energy observations from the living lab ENERGETIKUM, referring to the electrical indoor consumption and covering a period of 2 years (from Mar-2018 to Mar-2020). The sampling rate of the energy meter is approx. 10 seconds, however in order to synchronize it with the weather forecast system (Section 3.1) we resampled the raw data into hourly observations. This results in 24 data points per day, or 8760 data points within a year. Fig. 3, presents a snapshot of the yearly electrical load profile of the living lab ENERGETIKUM (from Mar-2018 to Mar-2019) and the corresponding outside temperature for the same period.

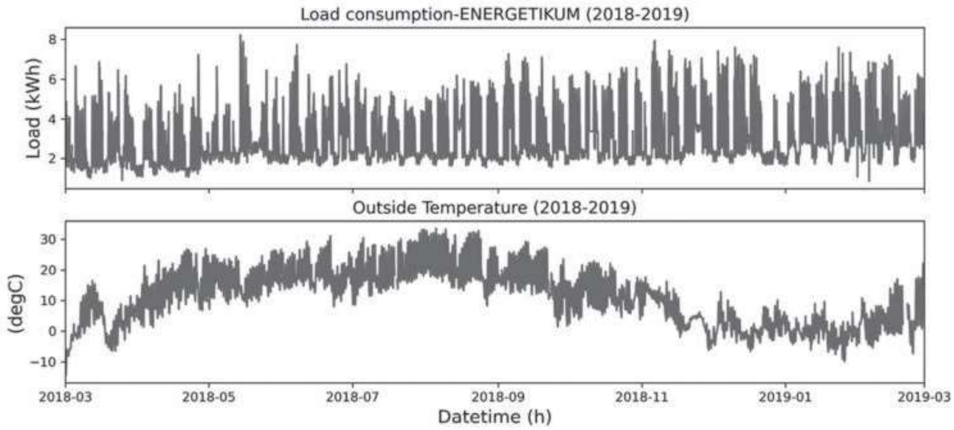

Fig. 3: Electrical load consumption of Lining Lab ENERGETIKUM based on historical measurement data.

Specifically, the input variables of the model are: i) total electrical load (kWh), ii) outside temperature (°C), iii) solar irradiation (W/m^2), iv) datetime inputs (hour of day, weekday etc.) and v) holidays and weekends indicators. To capture the daily and weekly patterns of the electricity demand, the input layer's time step was set to 96 hours.

The architecture of the energy load forecasting model consists of:

- Two RNN layers with 50 units each, using sigmoid-type activation function for the input, forget, and output gates, whereas for the activation gate a hyperbolic tangent function was used.
- A fully connected layer of 32 neurons, using ReLU as activation function.
- Output layers of 48 neurons with a linear activation

The performance of the proposed model for forecasting short-term electricity demand (24 hours ahead) was tested using the last 3 months of the available historical observations.

2.2.2 Numerical experiments

Fig. 4, presents a graphical comparison of the true electricity demand during Jan-2020 and the electricity demand forecasted by the proposed RNN model. For better visualization weekly and 3-day periods are presented in Fig. 5 and Fig. 6, respectively.

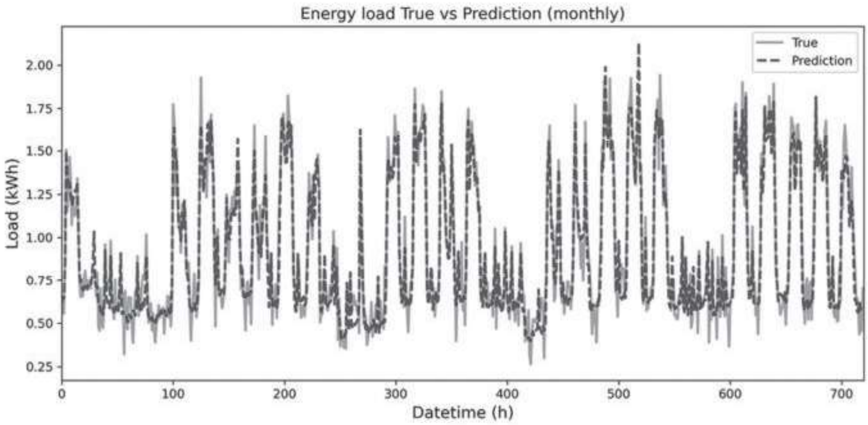

Fig. 4: True consumption vs. model predictions for whole month (January 2020).

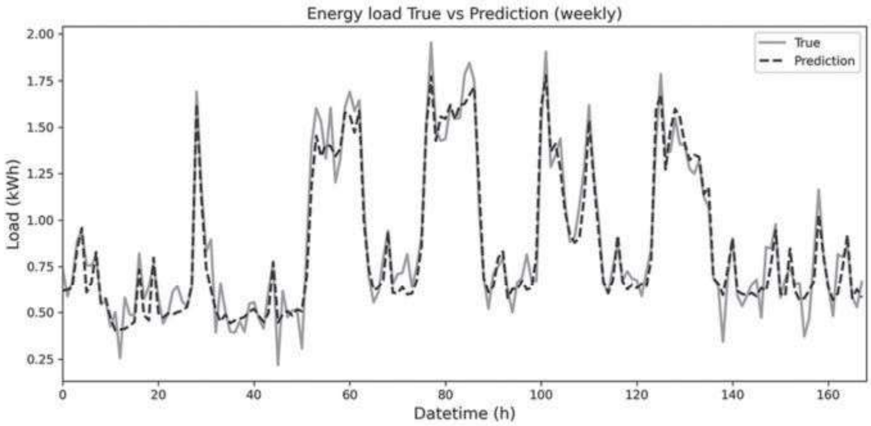

Fig. 5: True consumption vs. model predictions for a week in January 2020.

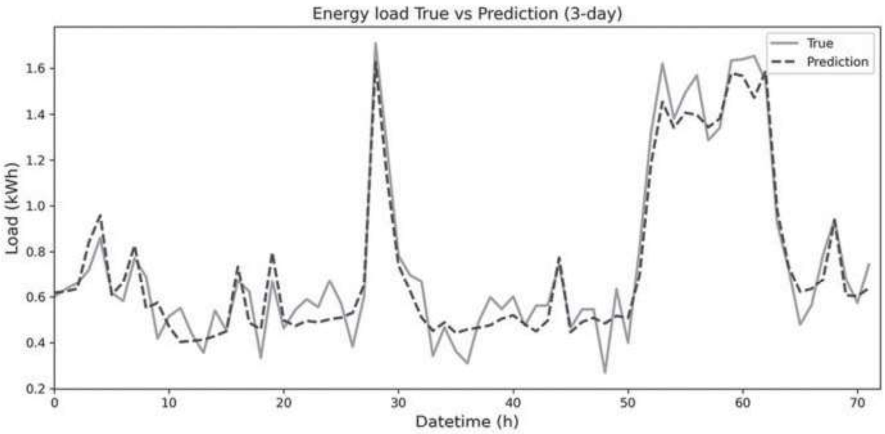

Fig. 6: True consumption vs. model predictions for 3-days in January 2020.

The interpretation of Fig. 5 shows that the electricity demand exhibits rapid fluctuations daily and follows a weekly pattern with very low consumption in the weekends. This can be also verified from Fig. 6 where we can see that between hours ~60 – 110 (~48 hours) the load consumption is at lowest levels. From the model evaluation analysis, we deduct that the proposed forecasting model exhibited few deviations, especially when we have rapid fluctuations within the day, however, it appears that captures the short-term load consumption pattern with high accuracy.

Fig. 7, presents the forecast error distribution for the whole test set, i.e. the deviation between the actual and forecasted values. As it can be observed the majority of the error values are within +/- 0.2 kWh with very few error points with amplitude ~0.7-0.9 kWh.

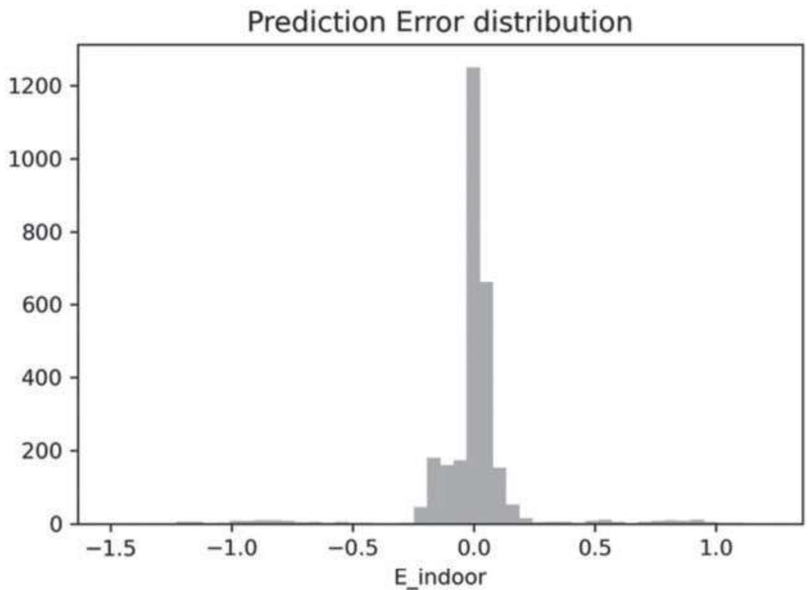

Fig. 7: Forecast error distribution for the validation/test sets.

4. INTEGRATION & DEPLOYMENT FOR REAL-TIME INFERENCE

In the context of this work, the microservices architecture was used in order to gather data taken from online services and sub-systems, prepare them for feeding the models, cast predictions or detect anomalies, transmit the predictions to remote servers or to the cloud, and store them in an external database for future calibration. Fig. 8, presents the utilized microservices architecture.

The Data Receiver block is a containerized (Docker) application that is responsible for receiving data from an external database via a Publish-Subscribe (e.g. MQTT, Orion context broker, etc.) method or from an online service via REST API using HTTPS protocol. In the case of the Publish-Subscribe method, the endpoint of the Data Receiver is hidden behind a proxy, in order to secure it. Upon received, the data are stored to a docker-based local database. Periodically, every 1 hour, the Data Preprocessing block, which again is a Docker-based application, queries the database for all the data that have been received for the past one hour. The queried data pass through statistical processes for filtering and in order to fill possible missing values (using extrapolation) and are then stored as timestamped data frames to the database.

The Model Input/Output Forwarder block also works periodically. This block is again a Docker-based application. Its purpose is to query the database for the processed timestamped data and send them to the appropriate ML models, which are hosted as servables in a TensorFlow Serving container. The communication between the two blocks is achieved through REST API. Once the outputs of the ML models have returned to the Forwarder, they can be transmitted to remote servers or services via REST API. The outputs are also saved to the database for future use.

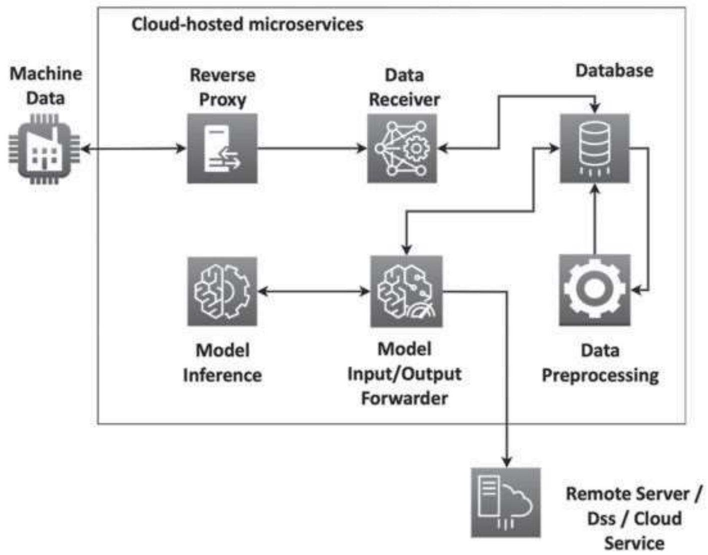

Fig. 8: Microservices-based cloud implementation.

5. CONCLUSIONS

In this work, a new holistic integrated solution for the buildings' energy management systems using deep learning methods was presented. The proposed approach is based on efficient deep-learning forecasting models for short-term local weather parameters, energy load demand and energy generation from PV arrays. The developed models were integrated via a micro-services architecture with the smart energy management system of the demo-site building for supporting the decision-making.

It is worth mentioning that short-term weather forecasting is a crucial contributing factor for estimating future energy demand in buildings, while forecasting short-term electricity demand in residential buildings is considered essential for efficient power-system planning and energy management. To this end, the proposed forecasting tools constitute necessary components for planning in energy system and play a significant role in the operational decision making.

Our main objective and expectation is that the proposed approach could be adapted also outside of the scope of PVadapt Project, as a reference for efficient decision-making and provide better services by offering customized assistance according to predicted energy performance.

ACKNOWLEDGEMENTS

This work has received funding from the Innovation and Networks Executive Agency (INEA), European Commission H2020 under Grant Agreement No.: 818342, PVadapt project (www.pvadapt.com).

REFERENCE

Chen L. (2018) Microservices: Architecting for Continuous Delivery and DevOps, IEEE International Conference on Software Architecture.

Chen L., Babar M.A. (2014) Towards an Evidence-Based Understanding of Emergence of Architecture through Continuous Refactoring in Agile Software Development, in Software Architecture (WICSA) IEEE/IFIP Conference, pp. 195-204

Chollet F. (2018) Deep Learning mit Python und Keras: Das Praxis-Handbuch vom Entwickler der Keras-Bibliothek. MITP-Verlags GmbH & Co. KG.

Deb C., Zhang F., Yang J., Lee S. E., Shah K. W. (2017) A review on time series forecasting techniques for building energy consumption. Renewable and Sustainable Energy Reviews, 74, 902-924.

Fan C., Sun Y., Zhao Y., Song M., Wang J. (2019). Deep learning-based feature engineering methods for improved building energy prediction. Applied Energy, 240, 35-45.

Kingma D. P., Ba J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Li C., Ding Z., Zhao D., Yi J., Zhang G. (2017) Building energy consumption prediction: An extreme deep learning approach. Energies, 10(10), 1525.

Livieris I. E., Stavroyianni S., Pintela E., Pintela P. (2020) A novel validation framework to enhance deep learning models in time-series forecasting. Neural Computing and Applications, 1-19.

Mas K., Grijal S. (2019) A review of reinforcement learning for autonomous building energy management. Computers & Electrical Engineering, 78, 300-312.

Moca E., Nguy P. H., Gibes M., Kli W. L. (2016) Deep learning for estimating building energy consumption. Sustainable Energy, Grids and Networks, 6, 91-99.

Pérez-Lombar L., Orti J., Po C. (2008) A review on buildings energy consumption information. Energy and buildings, 40(3), 394-398.

Timoshen A., Berm M. (2017) The United Nations Environment Programme and the United Nations Development Programme. In Greening international institutions (pp. 38-54). Routledge.

Wan Z., Srinivasa R. S. (2015) A review of artificial intelligence-based building energy prediction with a focus on ensemble prediction models. In 2015 Winter Simulation Conference (WSC) (pp. 3438-3448). IEEE.