CONNECTION SCIENCE
2024, VOL. 36, NO. 1, 2313852
https://doi.org/10.1080/09540091.2024.2313852

Estimating electricity consumption at city-level through advanced machine learning methods

Arpad Gellert[a], Lorena-Maria Olaru[a], Adrian Florea[a], Ileana-Ioana Cofaru[a], Ugo Fiore[b] and Francesco Palmieri[b]

[a]Computer Science and Electrical Engineering Department, Lucian Blaga University of Sibiu, Sibiu, Romania; [b]Department of Computer Science, University of Salerno, Fisciano, Italy

ABSTRACT

An effective energy management system relies on the accurate prediction of electricity consumption, facilitating energy suppliers to optimise energy distribution, reduce energy waste, and avoid overloading the power system. This paper analyses different methods for the estimation of electricity consumption at the level of an urban area. A statistical model based on Trigonometric seasonality, Box-Cox transformation, Auto-Regressive Moving Average errors, Trend and Seasonal components is first presented. Then a model based on fuzzy logic is also proposed. These methods will be optimised and evaluated on a dataset collected by the electric power supply agency of Sibiu, Romania, with the goal of reducing the forecast error. The models are also compared with a Markov stochastic model and with a Long Short-Term Memory neural model. The experiments have shown that our statistical model using a history length of 200 electricity consumption values and a daily seasonality is the most efficient, with the lowest mean absolute error of 3.6 MWh, thus making it a good candidate for integration into a city-level energy management system.

ARTICLE HISTORY
Received 23 October 2023
Accepted 30 January 2024

KEYWORDS
Electricity consumption estimation; energy management system; forecasting; TBATS; fuzzy controller

1. Introduction

With the advancement of technology, the electricity environmental footprint sectors (such as smart buildings, street lighting, data centres, etc.) face a significant number of challenges ranging from trying to meet the constantly increasing electricity demand to reducing costs and losses through the distribution of resources. Massive digitalisation in almost any sector of modern society, together with the Internet of Things (IoT) revolution as the basis for Industry 4.0, and the paradigm changes in the way of working or teaching consequent to the Covid-19 pandemic, led to the continuous generation of huge amounts of data (from 33 ZB in 2018 to 175 ZB in 2025) to be stored and processed (Atoofian et al., 2021). For this reason, companies that store such a large amount of data in their clouds (like Google, Microsoft, YouTube, Amazon or Facebook), invested in bigger and bigger data centres. Nowadays, these data centres use twice the electricity as ten years ago (about 3%) (Andrae, 2020).

CONTACT Arpad Gellert arpad.gellert@ulbsibiu.ro Computer Science and Electrical Engineering Department, Lucian Blaga University of Sibiu, Emil Cioran 4, 550025 Sibiu, Romania

European reports indicate that data centres in the EU consumed 76.8 TWh of energy in 2018, with a projected increase to 98.52 TWh by 2030 (Montevecchi et al., 2020).

Intelligent energy management systems are one of the constantly developing technologies that will not only have a beneficial effect but will also help to improve the operations at the enterprise level as well as the financial judgments. Redefining how IT processes and analyzes real-time information may lead to significant savings in terms of electricity consumption. In addition, awareness of climate change due to the effect of greenhouse gases (GHG) is also providing strong motivations for improving the current ecological footprint by reducing energy waste and maximising the usage of renewable sources.

1.1. Challenges of energy management

Nowadays, energy management is a subject of complexity and major importance. It consists of choosing a source of energy production that will provide this resource to a set of consumers by minimising costs and losses. The choice of resources must be made in real time to avoid system problems like a power outage. At the same time, this type of system has to deal with several problems such as the non-linearities encountered, the behaviour of the hardware components that make up the energy system, or the difficulty of choosing the right energy source. This is a difficult and uneven mechanism. First of all, certain sources do not guarantee continuous energy production (solar, hydro), whereas others are missing in certain areas or countries (wind, biogas, geothermal, etc.). Also, the consumption can be very different in industrialised and populated areas (higher) with respect to other less developed and less crowded ones (lower).

An intelligent electricity management system relies on a series of computer-aided instruments through which electricity operators monitor, optimise and control the performance of the electricity transmission system. Energy management software is used for three main purposes: to report, monitor, and react. Such systems can be designed specifically for building-level automatic control and monitoring of electromechanical equipment that produce high energy consumption such as ventilation, lighting, heating, etc. Data obtained through monitoring can be used to optimise the system and to estimate a forecast of annual consumption. Intelligent electricity management systems aim to provide a range of instruments based on which electricity operators can reduce costs and consumption of energy in a building or a community.

1.2. Industrial significance of electricity consumption forecasting

Forecasting electricity consumption and production is a major energy management issue. For effective energy management, the accurate prediction of electricity consumption is crucial, as it facilitates energy suppliers to optimise energy distribution, reduce energy waste, and avoid overloading the power system (Porteiro et al., 2022). The short-term prediction of electricity consumption is beneficial for consumers, prosumers and suppliers, since it allows for improving energy efficiency policies and the rational use of resources. This is more needed now when a large amount of the energy generated by prosumers accounts for their own consumption.

The role of energy forecasting is to avoid as many as possible energy losses through any source, for any reason. According to Electric Power Supply Agency (AFEE) Sibiu, energy purchase expenses could represent 93% of the company's total expenses. If the forecast is close enough to the actual consumption, then strictly the necessary electricity can be bought from the next day's market to modulate the last part of the load curve so that the losses are as small as possible. If the forecast is not accurate, imbalances appear, and the agency is obliged to buy if there is a deficit, or sell if there is an excess to balance the electricity market. Forecasting contributes to balancing and smoothing the electricity intake from the electricity grid with beneficial consequences on both the operation of the distribution networks and the stability of prices on the daily energy market, improving the process of quality assurance of the electricity distribution and supply service with the adaptability to consumer requirements. Under the current conditions of electricity forecasting at AFEE Sibiu, it is very important to have close communication between the staff who make the energy forecast and the large consumers. For example, a factory producing shoes may start up several sections because it has double the demand compared to the last month and neglects to notify the person in charge of collecting data for energy consumption and the lack of information will result in a wrong forecast leading to imbalances in the delivery of electricity to the system.

Industrial electricity consumption is difficult to be confidently estimated. It differs from residential and commercial consumption where the energy is used mostly for buildings and is reasonably uniform and easily related to household growth and employment. In contrast, industrial electricity demand is extremely varied and tends to be concentrated in fewer extensive uses instead of being spread among many relatively uniform ones.

According to the available statistics (International Energy Agency, 2015), Small and Medium Enterprises (SMEs) generate at least one-third of the global energy demand in industry and service. It can reach 60% of the industrial sector in some countries (Trianni & Cagno, 2011) and 50% of the manufacturing sector in the U.S. (Trombley, 2014). Numerous new enterprises are created constantly worldwide, for which no data on electricity consumption is available, but it could be beneficial for load planning and grid operation. When a new enterprise is founded or a new industrial area is developed in a city, it is relevant for the local utility companies to estimate the upcoming load. The synthetic standard load profiles of typical businesses usually cover only a limited number of consumer types (e.g. general business, shop, bakery, etc.) and focus on the daily load distribution, but do not help to estimate the annual energy consumption of enterprises.

Given that our analysis covers all the electricity consumption in the Sibiu county, including residential consumers (with more than 400,210 inhabitants) as well as SMEs and even large companies (at least 50) in the automotive, manufacturing, extractive industry, food processing (meat, milk), the electrical and electronic equipment industry and IT sectors, an accurate prediction of consumption at the regional level is important for the energy efficiency of AFEE Sibiu.

1.3. Research objectives

This paper presents an analysis regarding the predictability of city-level electricity consumption through a statistical model based on Trigonometric seasonality, Box-Cox transformation, Auto-Regressive Moving Average (ARMA) errors, Trend and Seasonal components (TBATS), and a model based on fuzzy logic. The major contribution of the research reported in this article is the evaluation and comparison of computational intelligence models (both statistical-based and a model relying on fuzzy logic) applied to forecasting the electricity demand at the city-level. The fuzzy controller seems more appropriate for such a purpose, as it is a flexible method of reasoning (allows to add or remove rules) applicable in industrial process control systems, able to model imprecise concepts.

We will optimise and evaluate the proposed methods on a dataset collected by AFEE Sibiu at the city level, in terms of reducing the Mean Absolute Error (MAE). These models will be compared with a Markov stochastic model and a Long Short-Term Memory (LSTM) neural model. The most efficient model will be targeted for integration into a city-level energy management system. The rest of the paper has the following construction: Section 2 reviews relevant and recent related work, Section 3 details the forecasting models used, Section 4 discusses the experiments and their results, Section 5 is a discussion about the limitations of the proposed methods, and Section 6 provides the conclusions and outlines paths for further study.

2. Related work

As a consequence of the recent considerable modernisation of the electrical industry, demand, offer, and pricing have become increasingly irregular and unpredictable. The management, monitoring, and optimisation (in terms of cost and efficiency) of energy systems, whether on the production or the consumption side, all depend on energy prediction, often defined (Gellert & Florea, 2013) as the approximation of future states based on the present and past states. Forecasting the production and consumption of electricity has been the subject of numerous studies. Even though several methods for predicting electricity demand have been published (Ahmad et al., 2020; Bourdeau et al., 2019), addressing hotels (Shao et al., 2020), schools (Mohammed et al., 2021), office buildings (Dong et al., 2021; Ilbeigi et al., 2020; Skomski et al., 2020), campuses (Kim et al., 2020), or entire distribution grids (Wu et al., 2023b), the variability of electricity usage patterns in a residence implies a more challenging prediction at a small level (Falaki et al., 2021).

A long-term goal is the sustainability of the energy sector, so there is a need for research and innovation in forecasting electricity consumption, through the use of advanced technologies such as smart metering, Internet of Things (IoT), big data, digital twins, and artificial intelligence (Ding et al., 2022). The future will also see the start of a new electrification stage, with electricity penetrating virtually all domestic, industrial and transport systems, increasing the importance of being able to control it (Almihat et al., 2022).

Feilmeier (2015) studied the FENECON Energy Management System (FEMS), an energy management system for a house equipped with photovoltaics and energy storage. Features such as the hour, the weather, the season, and the travel plans of the house occupants are fed to a Multi-Layer Perceptron (MLP) for making short-term predictions of both the production and consumption of electricity in the household. The job of the energy management system incorporating the predictor is to maintain a balance between electricity production and consumption to boost individual consumption and reduce the load on the grid. MLPs have also been used in (Escrivá-Escrivá et al., 2011) to forecast the total energy use at the building level over the next few days. The day type was a significant input that was used when training the MLP, grouping days with similar labour patterns, in addition to meteorological features (temperature coefficient). The model was validated with the consumption of the Polytechnic University of Valencia, an institution with an annual electricity use of around 11.5 Megawatts in more than 60 buildings. Five predictors, one Markovian (Gellert, 2023; Gellert et al., 2019), one using a variant of the Auto-Regressive Integrated Moving Average (ARIMA) method (Gellert et al., 2022), one using LSTM (Bachici & Gellert, 2020; Gellert, 2023), the TBATS algorithm (Gellert et al., 2022), and the last based on the fuzzy controller (Olaru et al., 2022), have all been evaluated using the datasets compiled by Feilmeier (2015).

A predictor based on Markov Chains theory is a contextual predictor. These types of predictors estimate the next value corresponding to a particular context that has been memorised. The context refers to a finite sequence of values with a repetitive appearance. Context-based predictors allow the prediction of any sequence of repetitive values, which can be either incremental or non-incremental. The main limitation of this predictor is that it must have encountered the same context at least once to make a correct prediction. A context-based (Markov) predictor, a stride-based predictor, and a hybrid model (incorporating the functions of both context and stride-based predictors) were evaluated in (Gellert et al., 2019), drawing the conclusion that the stride-based predictor did not perform well, whereas the context-based and hybrid predictors fared better (the Markov model-based predictor being the best overall), with a mean absolute error lower than that of the MLP predictor. The ideal setup for such a model would have an interval of size 1, a context made up of just one value, and a history length of 100.

In (Gellert et al., 2022), statistical forecasting of electricity production and demand was analysed at the household level. Although it performed worse than the Markov model, the analysed ARIMA-based predictor outperformed the MLP. In terms of execution time and computational complexity, this prediction method is more sophisticated. It is worth noting that China uses a form of the ARIMA model among its main forecasting tools for energy consumption. Another statistical predictor, the TBATS model, produced even better results than ARIMA but was still worse than the Markov model. The broad nature of this prediction technique and its capability to extract seasonal trends from the time series were the main factors that led the authors to choose it.

The LSTM, a recurrent neural network (Hochreiter & Schmidhuber, 1997) able to capture long-term dependencies (Fu et al., 2022), was used in (Bachici & Gellert, 2020) to forecast the production and consumption of electricity in households. An LSTM network is organised into layers composed of units. A unit itself is composed of a cell with three gates, called input gate, output gate and forget gate. The role of the cell is to store information, whereas the three gates are responsible for the flow of information through the cell. The memory of an LSTM communicates the knowledge acquired at the current time step to subsequent time steps. It has the ability to discard irrelevant data from the state, sending only the pertinent information to the output. In (Bachici & Gellert, 2020), the sigmoid function was used as an activation function providing nonlinearity. The best hyperparameters were determined as 4 inputs, 10 units in the first and 5 units in the second hidden layer as far as the architecture is concerned, and 50 epochs at a learning rate of 0.01 for training. The LSTM performed far better than the ARIMA and MLP, but it was less accurate than both the Markov and TBATS models.

In (Zhang et al., 2020), a hybrid approach using LSTM and MLP together was presented. More recently, researchers have combined convolutional neural networks (CNNs) for spatial characteristics and LSTM for temporal characteristics to make accurate predictions in various chaotic phenomena. The CNN-LSTM model for electricity consumption outperformed other deep learning models. Time series decomposition with deep learning models has potential for energy consumption prediction and analysis (Rosas et al., 2022). By training a hybrid CNN-LSTM neural network model with available weather and electricity demand data in a region of the study site, relevant results were obtained for the discharging and charging of two ideal energy storage devices, one powered by wind energy and the other by photovoltaics (Rosas et al., 2022). Kim and Cho (2019) used LSTM and CNN to predict the usage of residential electricity demand. The input goes first into the CNN and then into the LSTM component. A fully connected layer uses the output of the LSTM to return the final prediction. Le et al. (2019) employed a similar methodology and bidirectional LSTM. Cai et al. (2019) compared the SARIMAX model with their analysis of gated CNNs for day-ahead power consumption forecasting in buildings. The gated CNNs performed better in their tests. An Elman neural network and an exponential model were suggested by Bedi et al. (2020) as a way to forecast electricity use in buildings with IoT sensors, leveraging upon the relationship between power consumption and, separately, outside temperature and building occupancy. In their experiment, a lab with sophisticated monitoring and control was utilised.

Fumo and Biswas (2015) forecasted power usage in residential buildings for the next hour and day using linear and quadratic regression. The linear model fared better with day-ahead forecasting, while the quadratic regression model performed better for shorter time frames and was effective for predicting electricity one hour in advance. Other machine learning techniques, including a data-driven ensemble model incorporating swarm intelligence (Li et al., 2021), a technique based on deep learning algorithms and rough set theory (Lei et al., 2021), kernel-based algorithms with a linear kernel and tree-based methods (Ding et al., 2021), and a Bayesian regression model (Dab et al., 2022), have been used to predict short-term consumption of electricity at the level of a single building. Zhou et al. (2022) proposed a deep generative model based on a latent stochastic recurrent neural network to forecast the energy generation needs of large-scale hydropower stations. Additionally, generative flows are used to approximate the time series distribution.

Reddy et al. (2023) analysed several machine learning techniques, including linear regression, K-Nearest Neighbours (KNN), extreme gradient boosting (XGBoost), random forest, and artificial neural networks (ANN), to predict power usage. They trained and evaluated these models on a dataset obtained from a power utility business. The data is a year's hourly electricity demand that has been pre-processed to address outliers and missing values. Their experiments have shown that the KNN model outperformed all others. Lazzari et al. (2022) proposed day-ahead electricity consumption forecasting for residential households using Gaussian mixture clustering to identify behaviour clusters and an XGBoost model to predict the day-ahead behaviour pattern. This predicted user behaviour information is used by an ANN to estimate electricity consumption. The efficiency of their method was proved on 500 residential users located in a southeastern region of Spain. Ghimire et al. (2023) proposed a hybrid forecasting model, composed of ANN, Encoder-Decoder Based LSTM (EDLSTM) and Improved Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (ICMD), for estimating daily electricity demand. After data partitioning using ICMD, the most frequent components of electricity demand are predicted with the ANN, and the remaining components being predicted with the EDLSTM. The experiments conducted on the aggregated demand dataset of the State of Queensland have shown the efficiency of the proposed hybrid model with respect to its standalone components. Stingl et al. (2018) show that industrial-level electricity consumption can be forecasted better with linear regression models than with a random predictor, but with high uncertainty.

At the city level, seven data-driven models for the prediction of daily electricity consumption (Wang et al., 2021) were applied and evaluated for the data in three metropolitan areas of the US: Los Angeles, Sacramento, and New York. The models evaluated how city-level electricity usage is influenced by two factors, namely weather conditions and the Covid-19 pandemic. All models achieved a high performance when predicting electricity demand at the city level, with a Coefficient of Variation of the Root Mean Square Error (CVRMSE) of less than 10%. The Gradient Boosting Tree model performed best, with a CVRMSE ranging between 4–6%.

Electricity management companies need to be able to plan optimally the electricity production and supply, in order to prevent electricity surpluses or shortages. A comparative study (Lee et al., 2022) of electricity consumption forecasting in different countries, which aimed to analyze the forecasting accuracy of some machine learning models, specifically compared four models: neural network, fuzzy time series model, adaptive neuro-fuzzy inference system and least squares support vector machine. The variables considered in the study were the monthly electricity consumption over ten years in the target countries. The models were evaluated using different error metrics. The fuzzy time series model was the most efficient for most of the countries studied. A fuzzy controller realises a control strategy that is defined qualitatively. The technology of fuzzy controllers is constantly evolving and it can enhance industrial automation and is appropriate for control operations in complex environments (Wu et al., 2023a). Because the fuzzy controller accepts inputs with linguistic values, it is not constrained by binary statements like "true" or "false." This type of controller can provide empirical guidance by outlining the appropriate course of action given the input. Both simple/straightforward applications and intricate/advanced projects employ this kind of controller. The portability of a system depends on how it is programmed as well as on the system features that we wish to use fuzzy control on.

Fuzzy logic finds use in a range of domains, including the automotive industry for the enhancement of automatic transmission on highways or for controlling speed, in the aerospace industry for controlling the altitude of planes or satellites, in the defense sector for target recognition in underwater circumstances or for the automatic recognition of infrared images. Business uses it in supporting decision making or in personnel evaluation systems in large firms, in medical systems for diagnosing or modelling the neuropathological discoveries in patients presenting Alzheimer symptoms, in the food industry for milk or cheese production, etc. Additionally, it can be used in tandem with other techniques, such as neural networks, to improve artificial intelligence systems. Examples of how fuzzy technology has been used in agent-based systems may be found in (Baloglu & Demir, 2018) and (Walter & Gomide, 2007).

In (Zadeh, 2008), Lofti A. Zadeh, the creator of fuzzy theory, attempts to respond to the question "Is fuzzy logic necessary?" According to him, fuzzy logic formalises two of the most amazing human abilities. First and foremost, the capacity to communicate, think critically, and act rationally in a complex environment when information is incomplete or conflicting, thus, to put it in another way, in a situation where there is imperfect information. The capacity to perform a variety of physical and mental activities without calculation or measurement is the second. Furthermore, according to Zadeh, the linguistic variable mechanism is special to fuzzy logic and plays a crucial part in the conception and design of both control systems and user products. The large universality of fuzzy logic in comparison to bivalent logic is another significant benefit. In his conclusion, he asserts that fuzzy logic is considerably more than a straightforward logic system.

Wang and Mendel (1992) presented a more in-depth approach to build a fuzzy controller, showing a general technique for creating fuzzy rules out of numerical data. The input and output of the numerical data are split into fuzzy regions in the first phase. This operation, which is a part of the data preprocessing, is carried out in the fuzzification block. Fuzzy rules will also be produced by the fuzzification block using the information gathered in the previous step.

In our previous work (Olaru et al., 2022), a particular fuzzy controller is used in the prediction of electricity consumption and production at the household level, presenting the purpose of each block mentioned above and the way the predictor is designed for a certain problem. In the present work, we optimise the fuzzy controller for electricity consumption forecasting at the city level.

The related work is synthesised in Table 1. The forecasting method, the purpose, the dataset lengths, and the data sampling interval are presented.

3. Electricity consumption modelling

In this section, two methods are proposed to predict the electricity consumption at the city level. One is a statistical method and the other one is based on fuzzy logic. Both methods use electricity consumption history to forecast the upcoming electricity consumption levels. Figure 1 illustrates the methodology flowchart.

As the flowchart depicts, the data collection is followed by a data preprocessing step, which includes treating missing values and removing outliers. Then, the preprocessed data is provided to the forecasting method (e.g. fuzzy controller, TBATS, etc.). Finally, the predicted electricity consumption is used by the energy management system for decision making with the following goals: to optimise energy distribution, to reduce energy waste, and to avoid overloading the power system, with financial benefits for AFEE.

3.1. The TBATS statistical method

For the forecasting of seasonal data, statistical models like ARIMA and TBATS can be good candidates. For its better prediction results, we choose the TBATS model which has the following parameters: ω is the Box-Cox value, φ is the dumping value, p and q are the ARMA parameters, $m_1, \ldots, m_T$ are the seasonal periods, and k_i denotes the number of harmonics in the case of the i^{th} seasonal element. The TBATS model has an automated model selection, which makes it simpler to use than ARIMA.

The Box-Cox transformation $y_t^{(\omega)}$ can be determined as follows:

$$y_t^{(\omega)} = \begin{cases} \frac{y_t^{(\omega)}-1}{\omega}, & \omega \neq 0 \\ \log(y_t), & \omega = 0 \end{cases} \tag{1}$$

Table 1. Synthetized related work.

Article	Method	Purpose	Dataset length	Sampling interval
Feilmeier (2015)	Multi-Layer Perceptron	Forecasting electricity production and consumption in a household with solar panels	5 months	5 min
Gellert et al. (2022)	TBATS	Forecasting electricity production and consumption in a household with solar panels	5 months	5 min
Bachici & Gellert (2020)	Long Short-Term Memory	Forecasting electricity production and consumption in a household with solar panels	5 months	5 min
Gellert et al. (2019)	Markov model	Forecasting electricity production and consumption in a household with solar panels	5 months	5 min
Escrivá-Escrivá et al. (2011)	Multi-Layer Perceptron	Short-term prediction of total power consumption in buildings	450 days	15 min
Zhang et al. (2020)	LSTM-ANN hybrid	Short-term prediction of building-level energy consumption	5 months	1 h
Kim & Cho (2019)	CNN-LSTM hybrid model	Prediction of residential electricity demand	4 years	1 min
Le et al. (2019)	CNN-BiLSTM hybrid	Energy consumption prediction at household-level	4 years	1 min
Cai et al. (2019)	Gate CNNs	Day-ahead building-level load forecasting	1 year	1 h
Bedi et al. (2020)	Elman neural network	Prediction of electricity use in IoT-driven buildings	8 weeks	10 min
Fumo & Biswas (2015)	Linear regression and quadratic Regression models	Prediction of residential energy consumption	1 month	5 min
Li et al. (2021)	Swarm intelligence-based ensemble model	Short-term electricity consumption prediction for buildings	6 months	1 h
Zhou et al. (2022)	Latent stochastic recurrent neural network	Prediction of electricity generation demand for large-scale hydropower stations	2 years	1 h
Rosas et al. (2022)	Hybrid CNN-LSTM	Prediction of regenerable energy production and consumption in a public building	1 year	10 min
Wang et al. (2021)	Gradient Boosting Tree model	Prediction of daily electricity consumption at city scale	4 years	1 h
Lee et al. (2022)	Fuzzy time series model	Prediction of electricity consumption at country-level	10 years	1 month
Reddy et al. (2023)	KNN, XGBoost, Random Forest, LSTM	Electricity usage prediction from the power utility provider	1 year	1 h
Stingl et al. (2018)	Linear regression models	Forecasting annual electricity consumption at industrial level	5 years	1 d
Porteiro et al. (2022)	Linear regression models	Day-ahead electricity demand forecasting at industry / city / country level	4 / 2 / 9 years	1 h
Lazzari et al. (2022)	XGBoost-ANN hybrid	Day-ahead electricity consumption forecasting for residential households	1 year	1 h
Ghimire et al. (2023)	ICMD-ANN-EDLSTM hybrid	daily electricity demand prediction at state level	10 years	30 min

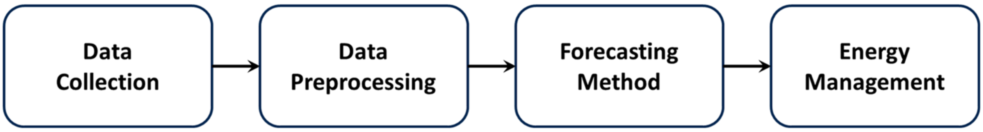

Figure 1. Methodology flowchart

$$y_t^{(\omega)} = l_{t-1} + \varphi b_{t-1} + \sum_{i=1}^{T} s_{t-m_i}^{(i)} + d_t \tag{2}$$

$$l_t = l_{t-1} + \varphi b_{t-1} + \alpha d_t \tag{3}$$

$$b_t = (1-\varphi) b + \varphi b_{t-1} + \beta d_t \tag{4}$$

$$s_t^{(i)} = s_{t-m_i}^{(i)} + \gamma_i d_t \tag{5}$$

$$d_t = \sum_{i=1}^{p} \gamma_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \tag{6}$$

where b is the long-run trend, b_t is the short-run trend in period t, l_t is the level element at time t, $s_t^{(i)}$ is the i^{th} seasonal element at time t, d_t is the prediction error, ε_t is a Gaussian white noise process with zero mean and constant variance σ^2, whereas α, β, s and are γ_i the smoothing values. For more flexibility, we can apply the trigonometric representation of the seasonal elements based on Fourier series, as follows:

$$s_t^{(i)} = \sum_{j=1}^{k_i} s_{j,t}^{(i)} \tag{7}$$

$$s_{j,t}^{(i)} = s_{j,t-1}^{(i)} \cos \lambda_j^{(i)} + s_{j,t-1}^{*(i)} \sin \lambda_j^{(i)} + \gamma_1^{(i)} d_t \tag{8}$$

$$s_{j,t}^{*(i)} = -s_{j,t-1}^{(i)} \sin \lambda_j^{(i)} + s_{j,t-1}^{*(i)} \cos \lambda_j^{(i)} + \gamma_2^{(i)} d_t \tag{9}$$

$$\lambda_j^{(i)} = \frac{2\pi j}{m_i} \tag{10}$$

where $\gamma_1^{(i)}$ and $\gamma_2^{(i)}$ are the smoothing values, $s_{j,t}^{(i)}$ is the stochastic level of the i^{th} seasonal element, and $s_{j,t}^{*(i)}$ is the stochastic growth of the i^{th} seasonal element.

TBATS can decompose seasonal time series into trend, seasonal and irregular elements. The trigonometric terms from TBATS might not be normalised and the overall seasonal element can be decomposed into multiple seasonal elements with different frequencies.

We are forecasting electricity consumption at a granularity of one hour using TBATS on the AFEE datasets.

3.2. Fuzzy controller

The structure of the proposed fuzzy controller is presented in Figure 2. The process of turning the input data into fuzzy sets is called fuzzification. The energy management system's sensors provide accurate, precise data as input. These values have undergone preprocessing so that the fuzzy system can understand them. A membership function is used in this type of transformation to convert every input value to a membership degree within 0 and 1. The partitioning of the mapping region varies depending on the function used.

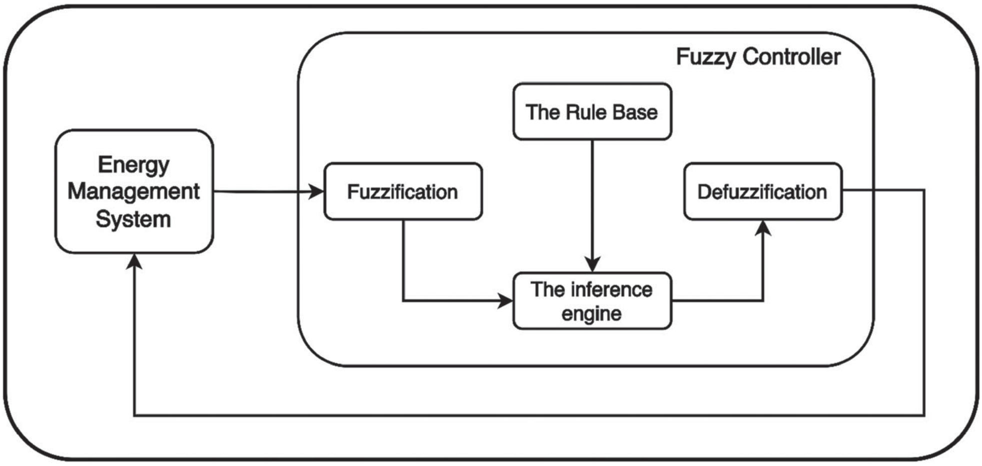

Figure 2. The Structure of the fuzzy controller.

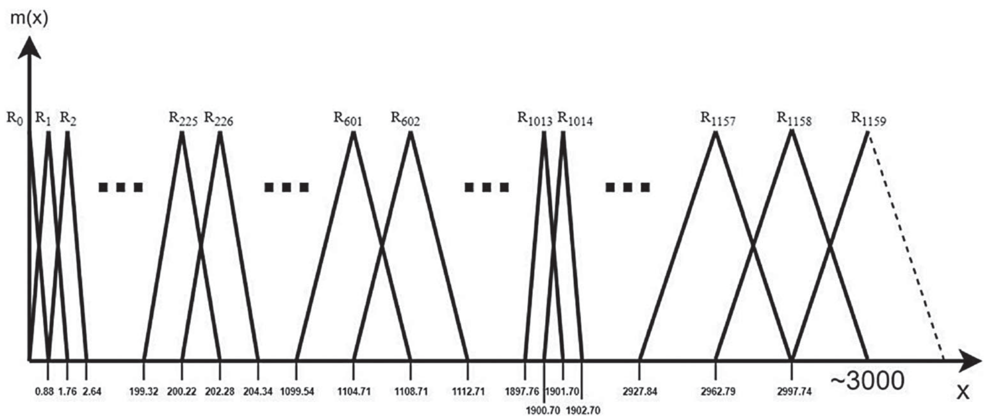

Figure 3. Numerical domain divided into fuzzy regions.

According to Mendel (1995), the triangular, trapezoidal (see Figure 5), and Gaussian membership functions are the most often used.

Figure 3 shows how the numerical domain of one of our research cases was divided into fuzzy regions using the triangular membership function. The numerical domain, shown in the abscissa, ranges from the smallest conceivable value of electricity consumption to the highest number recorded on our benchmarks. The size of the regions varies due to the different behaviours present in the data.

The fuzzy rule base is produced once the fuzzy regions have been identified and the fuzzy rules have been constructed. In this N-dimensional space, N stands for the quantity of incoming data. The rule base can be shown as a matrix in Figure 4 for a system with "AND" rules and two inputs and one output (x_1, x_2; y).

The matrix includes two rules as an example. If we were to construct some rules using our datasets and the representation of fuzzy regions from Figure 3, then we would translate the following declaration: "IF at t0 the electricity consumption was equal to 1104 Watts AND

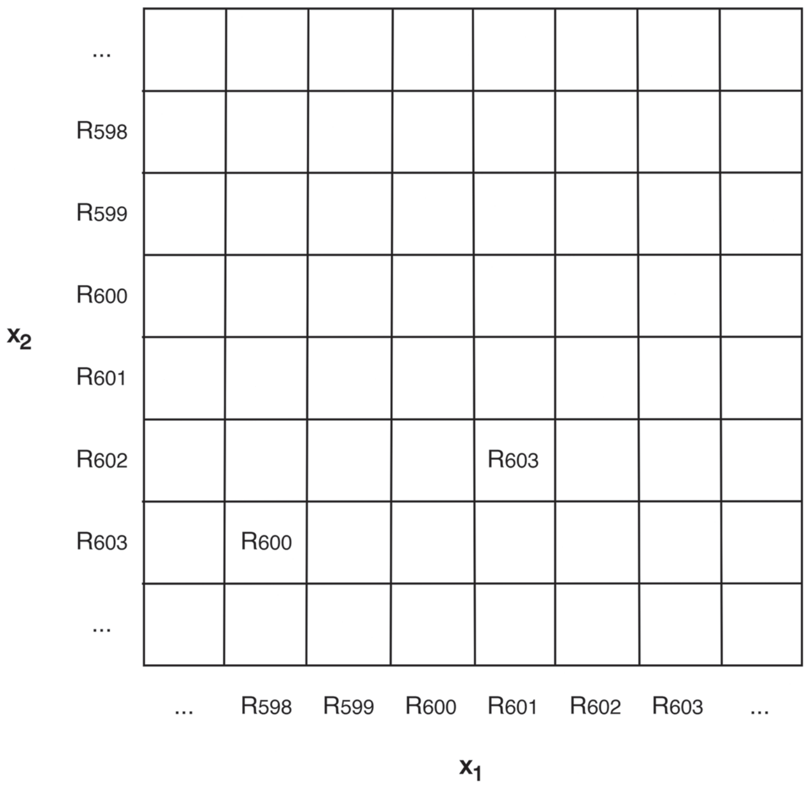

Figure 4. The structure of a fuzzy rule base.

at t1 the electricity consumption value was equal to 1108 Watts, THEN at t2 the electricity consumption value was equal to 1112 Watts" to "R1: IF x_1 is R601 AND x_2 is R602, THEN y is R603". For the sake of representing the rule base we can add a second rule "R2: IF x_1 is R598 AND x_2 is R603, THEN y is R600". The regions related to the input x_1 are vertically represented and the regions corresponding to the input x_2 are represented horizontally. The regions of interest for each rule must be selected, and the position that is chosen will be labelled with the region that corresponds to the output. Conflicts between the existing mapped rules and the newly created rules may arise at this stage. If this occurs, it may be useful to design a mechanism for assessing the level of confidence in that rule, and the more trusted rule should be assigned a position in the matrix based on the level of confidence.

Applying the input data to each rule in the fuzzy rule base yields the final set of rules. As a result, if the rule base contains N rules, it will produce N mappings, each indicating the degree to which the input data is a member of the rule. An illustration of mapping the input data onto two rules is shown in Figure 5. We can see how the inputs are mapped on both rules by considering the set of inputs (x_1: 7 Megawatts, x_2: 26 Megawatts). The two given inputs represent two values of energy consumption levels measured consecutively. For example, for R1, the membership degree of x_1 has a value of 0.5 and the membership degree for x_2 has a value of 0.75, whereas R2 presents the x_1 input with a membership degree of 0.5 and x_2 has a membership degree value of 0.25. The outcome of each mapping is determined by fuzzy operators. The min and max operators are the most used ones for

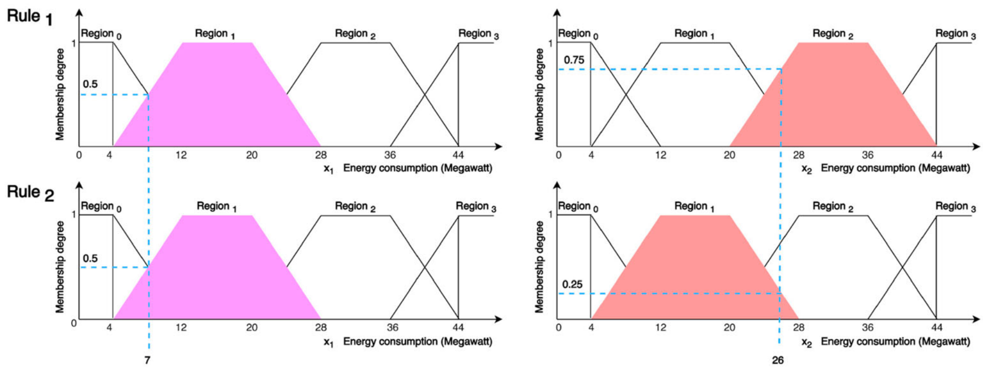

Figure 5. Input data mapping onto fuzzy rules.

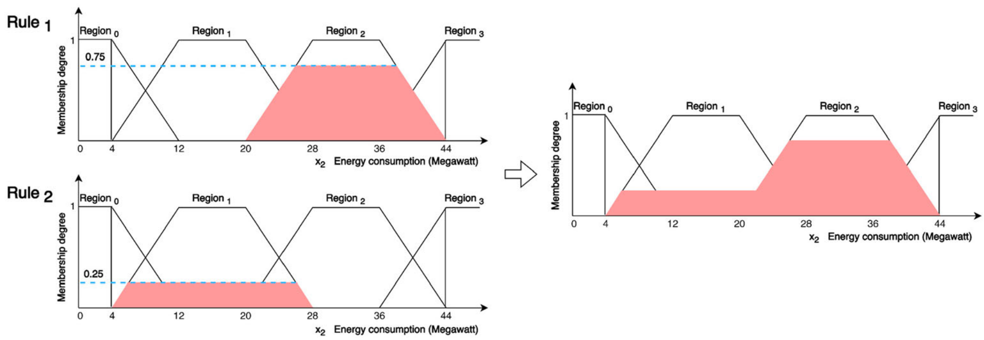

Figure 6. The result of the interference.

"OR" and "AND" rules. The inference engine then combines all the findings. It computes all the mapping results and establishes the defuzzification region using an inference method.

The MIN approach was employed to ascertain each rule's outcomes in the preceding example. This approach entails picking the rule's smallest membership degree. Utilising the maximal algorithm, which presupposes the reunion of the previously established areas, we computed the final area. Figure 6 illustrates the outcome of this entire process, known as inference, which is a fuzzy value. The next step is to convert this fuzzy value into a genuine value by defuzzifying it.

Defuzzification techniques can be applied to the output of the inference block in a variety of ways. Since no single technique would be effective on all systems, it might be one of the system's programmable parameters that can be adjusted to discover the optimal match. The weighted average approach, the centroid method, and the mean of maxima method are the most well-known ones. The membership function, the kind of inference, the fuzzification method, and the defuzzification method are finally selected through this five-step process. We must evaluate each output and replace the variables with the most appropriate ones to determine the system's ideal configuration. Additionally, because each block is interconnected, a change in one block might have an impact on the outcomes of another.

Table 2. Excerpt of electricity consumption from the AFEE dataset.

cc [MWh]	cpt [MWh]	cc_cpt [MWh]
107.971	126.260	234.231
82.731	120.800	203.531

4. Experimental results

The benchmarks used for this purpose are the datasets provided by AFEE Sibiu serving Sibiu county with a total population of 400,210 inhabitants (urban population: 259,337 inhabitants, rural population: 140,873 inhabitants) and an installed power 2020 of 160,915 MW. There are three data collections: the one that indicates the captive consumers (cc), the one that indicates the technological consumers (cpt) and the last one is a sum of the previous two categories (cc_cpt). All these data collections contain the electricity consumption in MWh at a granularity of one hour for six years between January 2014 and December 2019. Because the benchmarks contain measurements with one hour interval between observations, all the predictors are forecasting one hour ahead electricity consumption. Table 2 presents an excerpt from the dataset.

At each predicted value, the computed error is added to the overall error. Thus, after predicting the entire reference file, we will get the total error induced by all the predictions made. Finally, we will use the following formula to compute the mean absolute error:

$$MAE = \frac{1}{N} \cdot \sum_{i=1}^{N} | R_i - P_i | \tag{11}$$

where R_i is the actual value taken from the reference file, P_i is the value predicted by the controller, and N is the total number of predicted values. Precision analysis consists of running multiple simulations with different configurations and on different benchmarks.

4.1. TBATS

The accuracy of this model will be measured using the 80/20 rule. This implies that two sets of data must be generated: one for training and one for testing. The training set accounts for 80% of the total dataset. This portion of the dataset will be used by the model. The testing set accounts for 20% of the whole dataset. This collection of data will be used for the final evaluation. There will be no more changes made to the model to improve its fit to the dataset.

The next step is to decide how the data will be supplied to the model. In order to reduce the magnitude of the spikes, we tried different data transformations. Figure 7 presents the TBATS method applied to the original data, the square root (sqrt), the natural logarithm (ln) and the base 10 logarithm (lg), respectively. We considered a data history length of 500 and a seasonality of 24 (one day).

As Figure 7 depicts, data transformation had no improvement, thus keeping the original untransformed data is the best solution, with an error of 3.85 MWh at average. The second parameter we varied for the TBATS statistical method is the data history length. We considered the original data and a seasonality of 24 (one day).

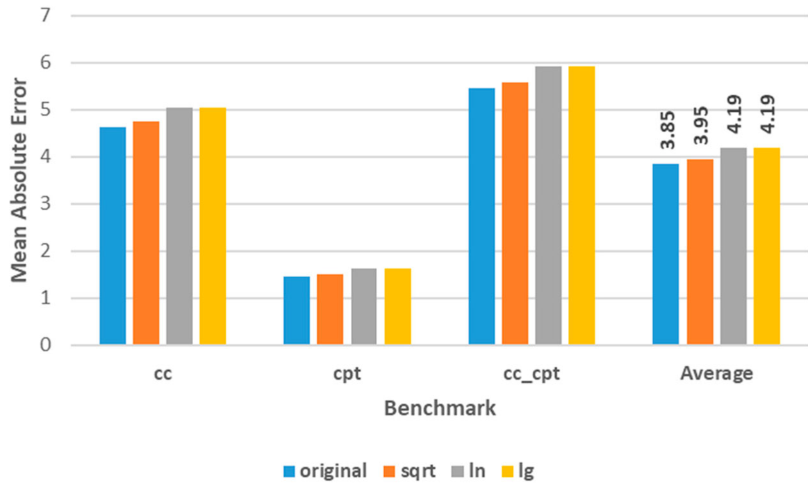

Figure 7. Data transformation.

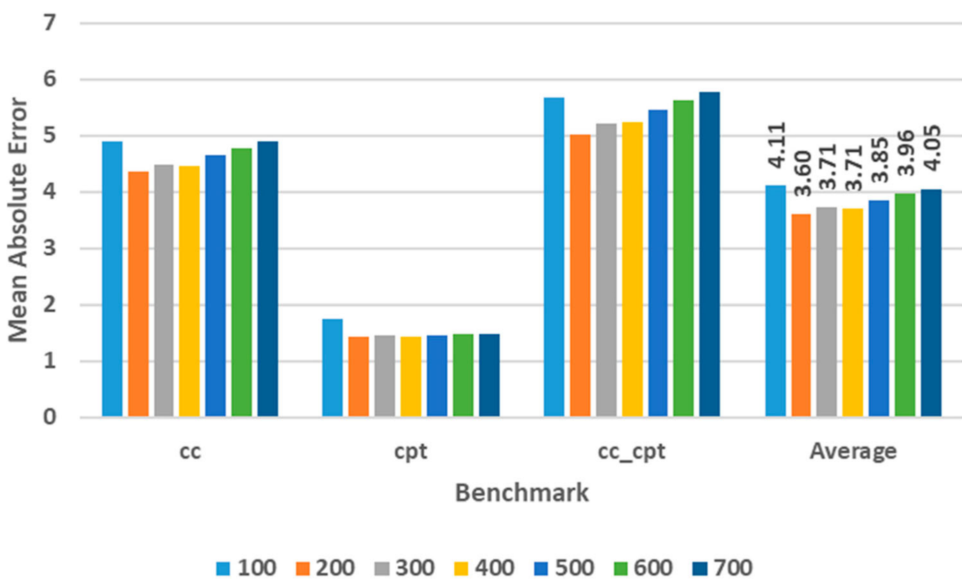

Figure 8. The influence of the data history length over the mean absolute error.

As Figure 8 shows, a data history length of 200 provides the best results, the error decreasing to 3.60 MWh with this history lengths. Either a lower or a higher history length makes TBATS less performant. Next, we have varied the seasonality. Besides the seasonality of 24 (one day), we also tried 168 (one week) and 720 (one month).

As Figure 9 illustrates, the seasonality of 24 (one day) provides the lowest error in all the three datasets, 3.6 MWh at average. Consequently, the optimal TBATS configuration is based on untransformed data, a history of 200 values and a seasonality of 24.

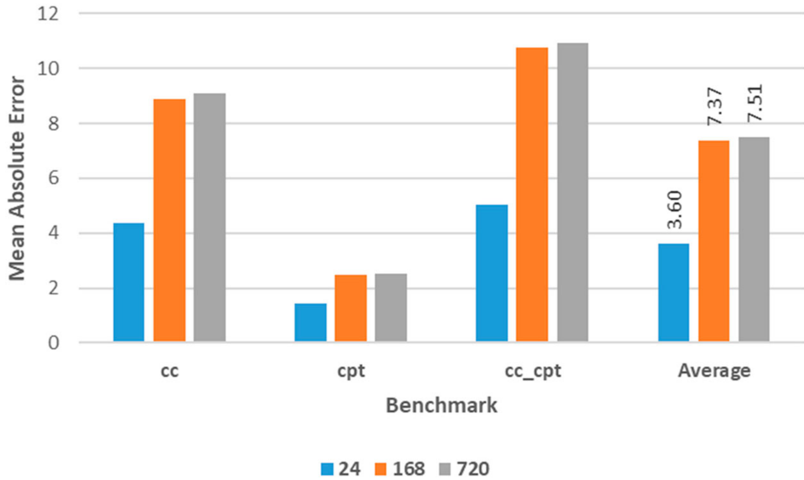

Figure 9. Varying the seasonality.

4.2. Fuzzy controller

In the fuzzy controller case, the parameters that can influence the accuracy of the prediction are: the number of fuzzy inputs, the number of training values, the method through which the rules from the fuzzy rule base are chosen in case of a conflict, the error threshold and the number of states related to the saturated counter method and lastly the defuzzification method.

The first step in configuring the fuzzy controller was to vary the number of inputs for the fuzzy rules, meanwhile, all the other parameters were set to a random static value which is maintained onwards for the parameters not configured yet.

In Figure 10, it can be seen that a number of 4 inputs gives the best results for the cc and cc_cpt benchmarks and by increasing it onwards, the mean absolute error increases as well. The cpt benchmark did not respond to the changes in the number of inputs, maintaining its error during the variations. The number of inputs for the fuzzy rule is an important parameter because it helps the controller detect certain patterns in the benchmarks.

After determining the number of input values that resulted in a configuration with an average absolute error of 7.1 MWh, the second parameter to be adjusted was the number of values utilised for the training phase. The training set of values helps build the first set of rules in the fuzzy rule base and train the controller for its next predictions. Figure 11 depicts the desired size for the training set, 5,000, which results in a mean absolute error of 6.89 MWh. Even though the mean absolute error tends to decrease with a bigger set of training values such as 20,000, the number of predicted values decreases. Interestingly, this behaviour applies to the cc and cc_cpt benchmarks, while the controller is more efficient on the cpt benchmark with smaller sets of training values. The purpose of this controller is to learn by prediction which led to selecting a smaller set for the training phase instead of pursuing the one which created a smaller error. It is noticeable that by adjusting this parameter, the absolute error has slightly decreased as we increased the number of inputs. A size of 5,000 values for the training set represents 10% of the whole benchmark, the remaining 90% will then be predicted by the controller. With each value predicted, the rule base

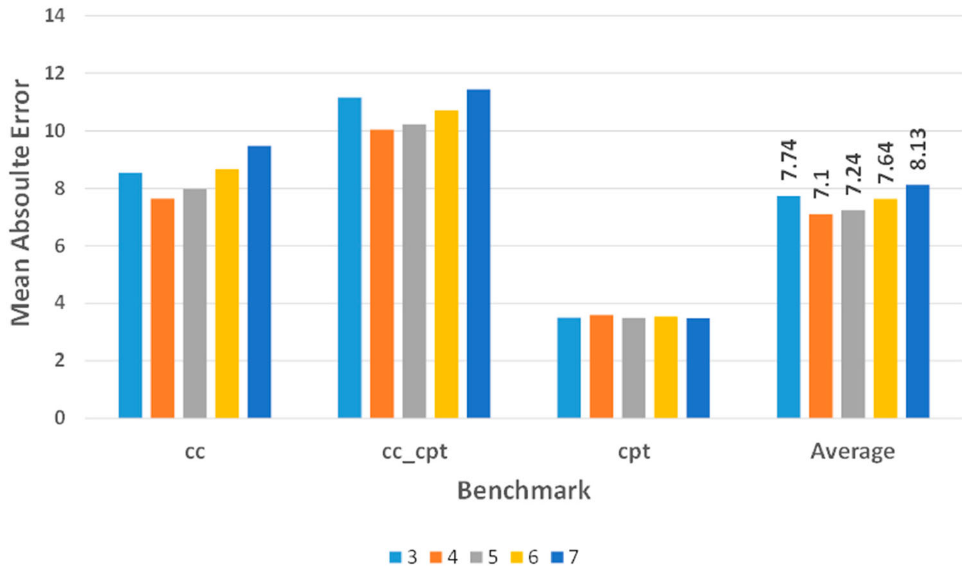

Figure 10. The influence of the number of inputs for the fuzzy rules.

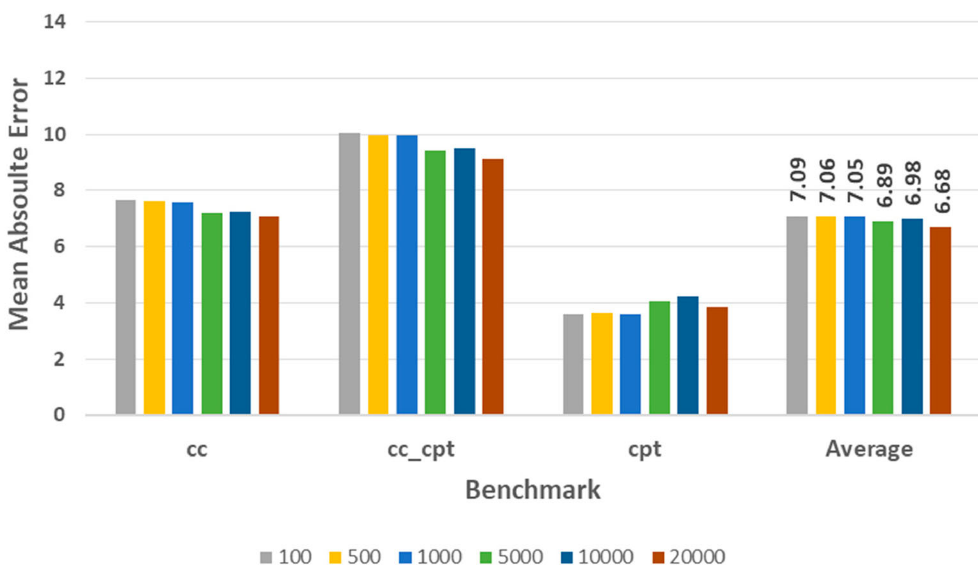

Figure 11. The influence of the number of training values.

is updated with new rules if needed. This size will be maintained at this value for the next simulations.

Now that the number of training values and the number of inputs have been set, the next parameter to be varied is the method of solving the fuzzy rule base conflicts. As mentioned before, with each prediction, the fuzzy rule base is being updated. Sometimes, while updating, the new rules to be added create conflicts that need to be resolved and decide which rule gets to take the selected position in the rule base. Figure 12 depicts the results of

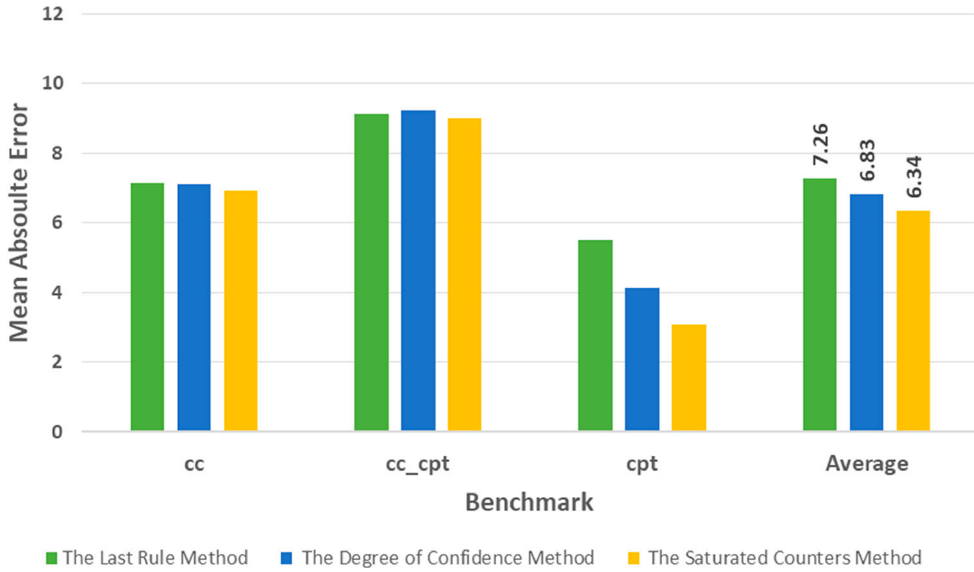

Figure 12. The influence of the method of solving the fuzzy rule base conflicts.

three different approaches to solving conflicts. The last-rule method implies that the newly created rule gets the position in the rule base, while the old one is erased. This method might lead to erasing good rules that would have benefited the controller, hence the higher error of 7.26 MWh. In the second method, the degree of confidence is computed for each rule with the help of the membership function, but as it can be seen in the diagram, the mean absolute error of 6.83 MWh for this approach is still higher than the one produced by the saturated counters method, which is an error of 6.34 MWh. Clearly, the third method brings the best results because each rule has its own saturated counter which increases or decreases based on the last prediction. If the prediction was below a certain threshold, the counter for the fuzzy rules used for the prediction increases, which means the confidence level for those rules increases, otherwise the counters for those rules are decreased. The error threshold and the upper limit of the confidence counters associated with the rules decide which rule wins the place in the rule base in the case of a conflict.

The choice of the saturated counters method as the approach for solving the fuzzy rule base conflicts, brings two more parameters to be varied: the number of counter states and the error threshold. The first one to be varied is the number of states that the saturated counter can take. For this, we need to maintain the error threshold at a certain value to determine which configuration outputs the best results. So, the error threshold will be set to 100 for the next set of simulations.

The influence of the number of counter states can be seen in Figure 13. It can be seen that the only benchmark that responds to this parameter variation is cpt, while in the other two benchmarks, the error variation is almost unnoticeable. The best value for this simulation will be chosen by observing the cpt benchmark behaviour. So, by increasing the number of states up to 10, the error is visibly decreasing, reaching a point where increasing the number even more, does not help the results to improve. Consequently, a number of 10 states for the saturated counter is the best configuration for this set of benchmarks as well.

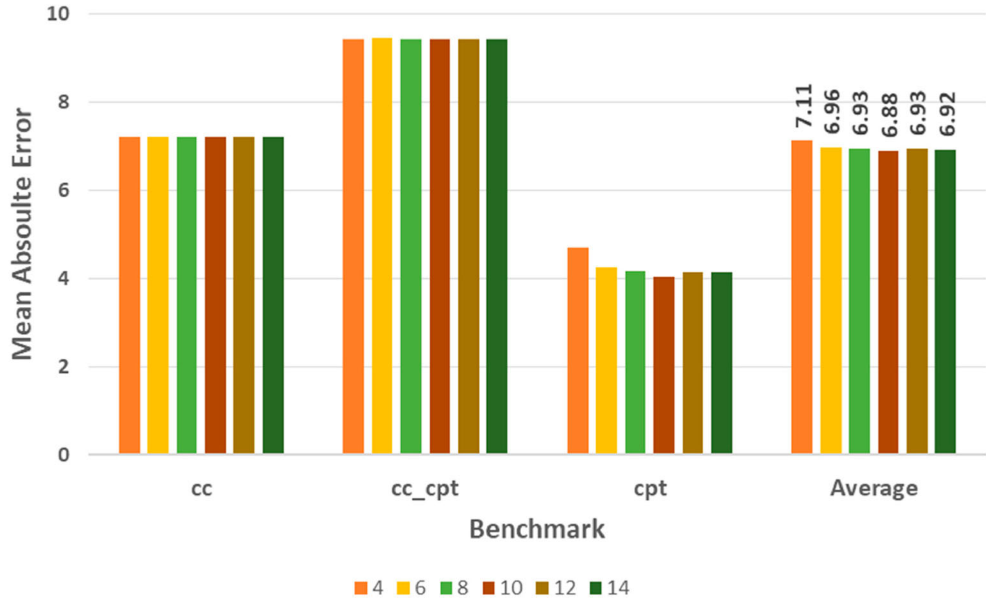

Figure 13. The influence of the number of counter states.

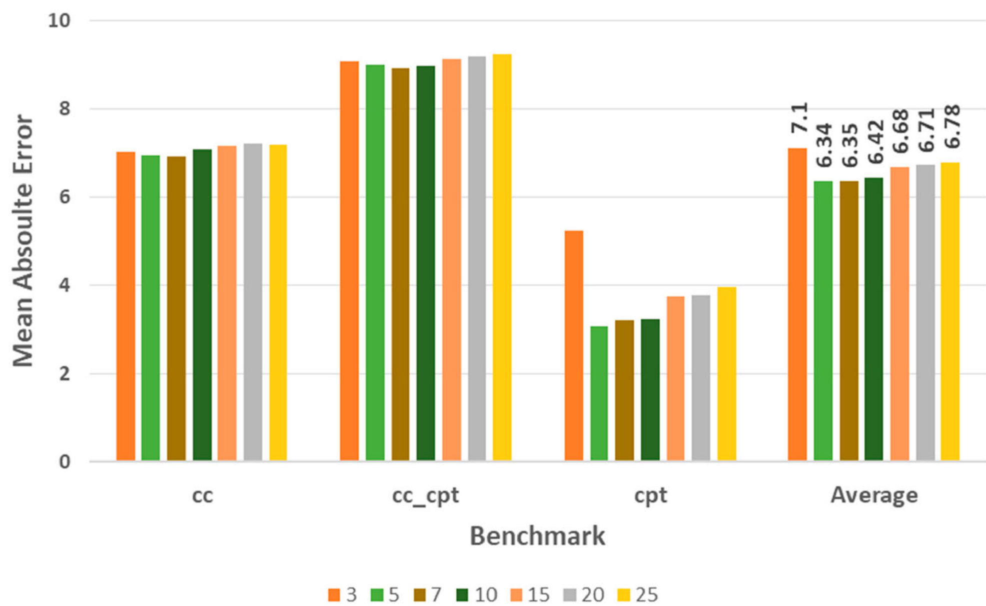

Figure 14. The influence of the threshold error value.

Now that the desired number of states has been determined for each of the benchmarks, we can continue with the variation of the second parameter which is the error threshold. The same scenario will be followed for this parameter as well.

The number of the counter states has to be fixed to 10 and the threshold will be varied. In Figure 14, we can see that on the cpt file the mean absolute error decreases once

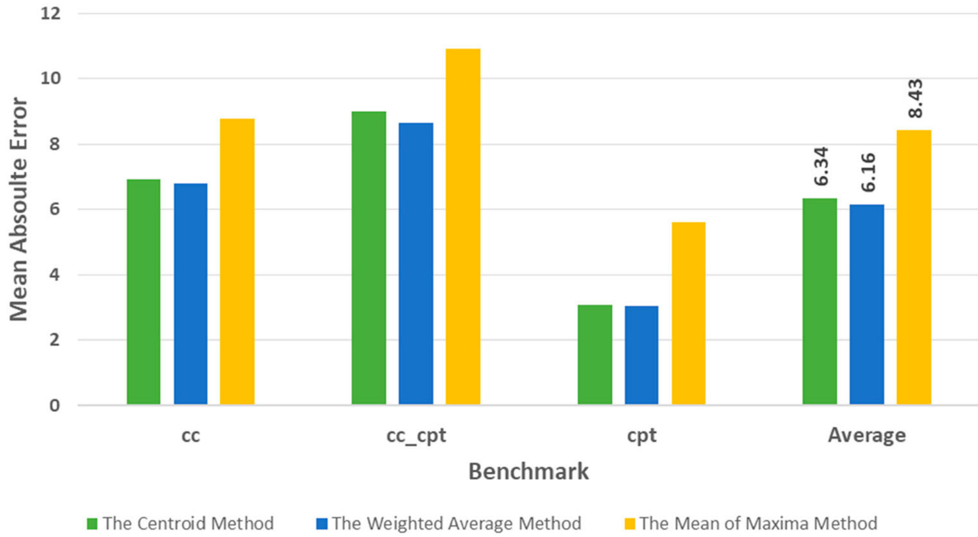

Figure 15. The influence of the defuzzification method.

the threshold increases while on the cc and cc_cpt benchmarks it is slightly affected by the change. In order to determine the best value for the threshold parameter, we analyze the averages to see what configuration had the smallest error as output. While varying the number of states, the absolute error increased with almost half of MWh. This is because during that configuration, the error threshold was set to 100, which meant that a lot of bad predictions were taken into consideration. Afterwards, while varying the error threshold we tested out the controller with the parameter varying from a 3 MWh accepted error to a maximum of 25 MWh of accepted error. So, the best configuration for this category of benchmarks would be a counter with 10 states and an error threshold of 5. The number of states and the error threshold are strongly connected.

Lastly, the defuzzification method was varied. Figure 15 depicts the results provided by each method. The mean of maxima approach has the least desired error results of 8.43 MWh, while the weighted average method and the centroid method had similar results. In order to choose the best one, we need to look at the average section of the diagram where we can clearly see that the weighted average method gives the best results overall, with a mean absolute error of 6.16 MWh.

4.3. Comparison

Now, we can compare the studied predictors with several other predictors that have been used for the mentioned sets of benchmarks (see Figure 16). We considered the optimally configured TBATS and fuzzy controller, as well as the best configurations of LSTM (Bachici & Gellert, 2020) and Markov model (Gellert et al., 2019).

Looking at the averages, it can be seen that overall the TBATS model provided the lowest error, 3.6 MWh. The TBATS is followed by the LSTM and the fuzzy controller, the Markov model being the weakest on these datasets. However, when we examined each benchmark, TBATS predicted the cc best, while the fuzzy controller and LSTM had similar lower

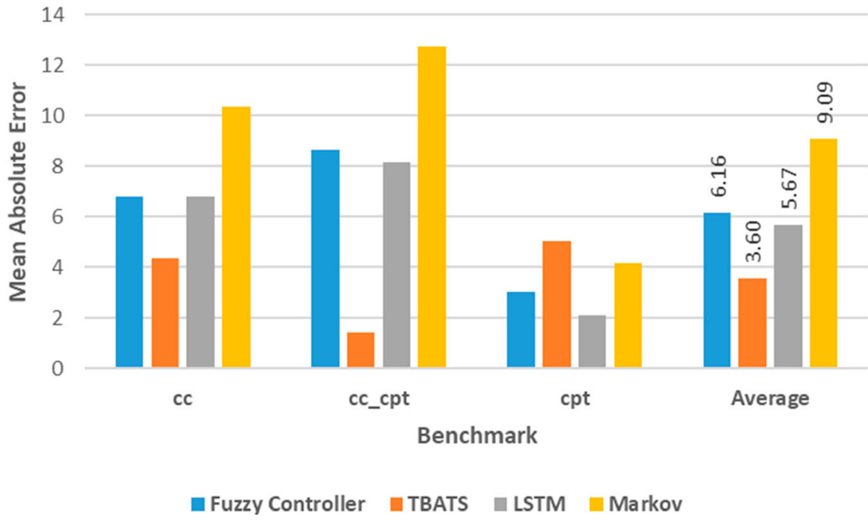

Figure 16. Comparison of the mean absolute error between different predictors.

performance. While predicting the electricity consumption for cpt, the TBATS model had the worst performance out of all the other benchmarks, while the fuzzy controller and LSTM performed better than they did on the cc or cc_cpt benchamrks. Lastly, the cc_cpt benchmark seems to have been harder to predict for the fuzzy controller and the LSTM, but the TBATS' performance was the best out of all the benchmarks.

Focusing on the two models described in this paper, we can state that even though the TBATS model outperformed all the others, it is much slower than the fuzzy controller. Because of this constraint and due to the fact that it had better results on the cpt benchmark, we can suggest that the fuzzy controller may be a better model to employ for the supplied city-level dataset.

Regional agencies might maintain an average monthly deviation of the electricity consumption forecast below 5% for economic reasons. As an example, for a small city with a monthly consumption of approximately 120,000 MWh, a prediction accuracy increased by only 0.13% results in an economy of 1,500 Euros. The average monthly deviation D can be computed as follows:

$$D = \frac{1}{M} \cdot \sum\nolimits_{i=1}^{M} \frac{|R_i - P_i|}{P_i} \cdot 100[\%] \tag{12}$$

where M is the number of months, R_i is the real electricity consumption in month i and P_i is the predicted electricity consumption in month i. The average monthly deviation on all the 72 months was 0.07% (without exceeding 0.27% per month) for the TBATS model on the cc_cpt dataset which includes both captive and technological consumers.

5. Discussion

Despite the valuable results produced, our method is limited by the lack of using external factors that can influence the fluctuating energy consumption. Determinant factors influencing consumption must be identified and observed over time. These will be taken into account as a further step of our research. Below, we briefly emphasise some of them:

- Outdoor temperature: this factor is the most important of all factors because it depends on making a forecast as good as possible, as close as possible to the actual consumption to be measured. During 2–3 weeks in the summer, directly proportional to the increase in environmental temperatures, the energy consumption also increases by 30–40%, this aspect being observed on the load curve when the temperature increases from 29°C to 33°C. For this difference of 4°C, the increase in electricity consumption is very high in such a short time.
- Cloudiness means the degree to which the sun and by implication the sky is covered with clouds, both during the day and at night: partial cloudiness and full cloudiness of the sky in which it covers all types and aspects of the visual nature of clouds.
- Precipitation also has its importance in the oscillation of consumption observed on the load curve because it can start instantly and stop in the same way.
- Official holidays that are free from government: they have a very big influence on household consumption because people have time off these days. Compared to another day when they would normally spend at work and household consumption is lower, on the day when it is a holiday, consumption increases considerably.
- Energy efficiency of buildings: numerous factors influence and even limit the energy performance of buildings, in addition to these are added environmental conditions, building architecture, character and degree of occupancy, habitation behaviour and the regime of lighting and HVAC system utilisation.
- Unexpected breakdowns in stations or on low and medium voltage power lines require quick recovery measures, including that the surplus energy be sold on the balancing market.

The two models presented in this study are set up to produce the best outcomes for the benchmarks provided. In case the models are to be used in different scenarios or use-cases, a recalibration must be done. Paragraphs 4.1 and 4.2 should be used as a guide to determine the optimal parameters for the new scenario. For instance, we use data measured in MWh, if any user wants to use data measured in KWh, then it is clear that the models provided in the article need to be re-configured.

6. Conclusions and further work

In this paper, the TBATS statistical model and the fuzzy controller were optimised to forecast the electricity consumption at the city level. These proposed methods were also compared with the LSTM and Markov models. The experiments have shown that TBATS is the best model for electricity consumption prediction at the city level. The optimal TBATS configuration is using untransformed data, a history length of 200 values and a seasonality of 24 (meaning one day). This optimal TBATS model had a mean absolute error of 3.6 MWh (averaged on all the datasets). To put it all together, TBATS is a time-consuming model and was outperformed by the fuzzy controller on the cpt dataset. If time is favoured over accuracy, then the best choice would be the fuzzy controller. The average monthly deviation was 0.07% for the TBATS model on the cc_cpt dataset, which includes both captive and technological consumers.

At the household level, the profit offered by a correct prediction (or the loss from an incorrect one) will economically affect the owner of the building (individual / local level). In the case of the AFEE approach at the city level, a wrong forecast leads to high economic losses for the energy supplier which will later affect the entire population. The role of electricity consumption forecasting is to avoid as much as possible energy losses from any source, for any reason. If the forecast is not precise, imbalances can occur, and the energy company is obliged to buy electricity when there is a deficit or sell when there is a surplus. In Sibiu, energy purchase expenses (in case of wrong estimation of daily energy demand) represent 93% of the expenses of electricity supply companies.

As further work, we intend to implement a voter predictor that aggregates the best performing predictors presented in order to exploit their particular advantages. In addition, an analysis of the uncertainty of the predictions would be useful for risk managers. Indeed, quantifying the uncertainty in the predictions made by machine learning models is one of the most active areas of research in machine learning (see, among others, the survey of Abdar et al. (2021) and the work of Sbailò and Ghiringhelli (2023) on epistemic uncertainty). A full-fledged investigation of the confidence that can be put in the predictive power of models is in the plans for a subsequent study and will be undertaken when the techniques and models are sufficiently mature. This will be complemented by a detailed analysis of the explanatory capabilities of the models, another property that is much needed in practice, as it facilitates, among other things, validation and what-if analysis.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

Project financed by Lucian Blaga University of Sibiu through the research grant LBUS-IRG-2022-08.

Data availability statement

The code and excerpts from the dataset are available upon request.

References

Abdar, M., Pourpanah, F., Hussain, S., Rezazadegan, D., Liu, L., Ghavamzadeh, M., Fieguth, P., Cao, X., Khosravi, A., Rajendra Acharya, U., Makarenkov, V., & Nahavandi, S. (2021). A review of uncertainty quantification in deep learning: Techniques, applications and challenges. *Information Fusion*, *76*, 243–297. https://doi.org/10.1016/j.inffus.2021.05.008

Ahmad, T., Zhang, H., & Yan, B. (2020). A review on renewable energy and electricity requirement forecasting models for smart grid and buildings. *Sustainable Cities and Society*, *55*, 102052. https://doi.org/10.1016/j.scs.2020.102052

Almihat, M. G. M., Kahn, M. T. E., Aboalez, K., & Almaktoof, A. M. (2022). Energy and sustainable development in smart cities: An overview. *Smart Cities*, *5*(4), 1389–1408. https://doi.org/10.3390/smartcities5040071

Andrae, A. S. (2020). New perspectives on internet electricity use in 2030. *Engineering and Applied Science Letters*, *3*(2), 19–31.

Atoofian, E., Shaikh, Z., & Jannesari, A. (2021). Reducing energy in GPGPUs through approximate trivial bypassing. *ACM Transactions on Embedded Computing Systems*, *20*(2), 1–27. https://doi.org/10.1145/3429440

Bachici, M.-A., & Gellert, A. (2020). Modeling electricity consumption and production in smart homes using LSTM networks. *International Journal of Advanced Statistics and IT&C for Economics and Life Sciences*, *10*(1), 80–89. https://doi.org/10.2478/ijasitels-2020-0009

Baloglu, U. B., & Demir, Y. (2018). An agent-based pythagorean fuzzy approach for demand analysis with incomplete information. *International Journal of Intelligent Systems*, *33*(5), 983–997. https://doi.org/10.1002/int.21908

Bedi, G., Venayagamoorthy, G. K., & Singh, R. (2020). Development of an IoT-driven building environment for prediction of electric energy consumption. *IEEE Internet of Things Journal*, *7*(6), 4912–4921. https://doi.org/10.1109/JIOT.2020.2975847

Bourdeau, M., Zhai, X., Nefzaoui, E., Guo, X., & Chateller, P. (2019). Modeling and forecasting building energy consumption: A review of data-driven techniques. *Sustainable Cities and Society*, *48*, 101533. https://doi.org/10.1016/j.scs.2019.101533

Cai, M., Pipattanasomporn, M., & Rahman, S. (2019). Day-ahead building-level load forecasts using deep learning vs. traditional time-series techniques. *Applied Energy*, *236*, 1078–1088. https://doi.org/10.1016/j.apenergy.2018.12.042

Dab, K., Agbossou, K., Henao, N., Dubé, Y., Kelouwani, S., & Hosseini, S. S. (2022). A compositional kernel based Gaussian process approach to day-ahead residential load forecasting. *Energy and Buildings*, *254*, 111459. https://doi.org/10.1016/j.enbuild.2021.111459

Ding, Y., Fan, L., & Liu, X. (2021). Analysis of feature matrix in machine learning algorithms to predict energy consumption of public buildings. *Energy and Buildings*, *249*, 111208. https://doi.org/10.1016/j.enbuild.2021.111208

Ding, Z. K., Fu, Q. M., Chen, J. P., Wu, H. J., Lu, Y., & Hu, F. Y. (2022). Energy-efficient control of thermal comfort in multi-zone residential HVAC via reinforcement learning. *Connection Science*, *34*(1), 2364–2394. https://doi.org/10.1080/09540091.2022.2120598

Dong, Z., Liu, J., Liu, B., Li, K., & Li, X. (2021). Hourly energy consumption prediction of an office building based on ensemble learning and energy consumption pattern classification. *Energy and Buildings*, *241*, 110929. https://doi.org/10.1016/j.enbuild.2021.110929

Escrivá-Escrivá, G., Álvarez-Bel, C., Roldán-Blay, C., & Alcázar-Ortega, M. (2011). New artificial neural network prediction method for electrical consumption forecasting based on building end-uses. *Energy and Buildings*, *43*(11), 3112–3119. https://doi.org/10.1016/j.enbuild.2011.08.008

Falaki, F., Merabtine, A., & Martouzet, D. (2021). A Spatio-Temporal Analysis of electric appliance end-use demand in the residential sector: Case study of Tours (France). *Sustainable Cities and Society*, *65*, 102635. https://doi.org/10.1016/j.scs.2020.102635

Feilmeier, S. (2015). *Loads management based on photovoltaic and energy storage system, MSc thesis*. Lucian Blaga University of Sibiu.

Fu, L., Ding, X., & Ding, Y. (2022). Ensemble empirical mode decomposition-based preprocessing method with Multi-LSTM for time series forecasting: a case study for hog prices. *Connection Science*, *34*(1), 2177–2200. https://doi.org/10.1080/09540091.2022.2111404

Fumo, N., & Biswas, M. A. R. (2015). Regression analysis for prediction of residential energy consumption. *Renewable and Sustainable Energy Reviews*, *47*, 332–343. https://doi.org/10.1016/j.rser.2015.03.035

Gellert, A. (2023). *Prediction-Based modeling and estimation in advanced computing systems, habilitation thesis*. Lucian Blaga University of Sibiu.

Gellert, A., Fiore, U., Florea, A., Chis, R., & Palmieri, F. (2022). Forecasting electricity consumption and production in smart homes through statistical methods. *Sustainable Cities and Society*, *76*, 103426. https://doi.org/10.1016/j.scs.2021.103426

Gellert, A., & Florea, A. (2013). Investigating a New design pattern for efficient implementation of prediction algorithms. *Journal of Digital Information Management*, *11*(5), 366–377.

Gellert, A., Florea, A., Fiore, U., Palmieri, F., & Zanetti, P. (2019). A study on forecasting electricity production and consumption in smart cities and factories. *International Journal of Information Management*, *49*, 546–556. https://doi.org/10.1016/j.ijinfomgt.2019.01.006

Ghimire, S., Deo, R. C., Casillas-Pérez, D., & Salcedo-Sanz, S. (2023). Efficient daily electricity demand prediction with hybrid deep-learning multi-algorithm approach. *Energy Conversion and Management*, *297*, 117707. https://doi.org/10.1016/j.enconman.2023.117707

Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural Computation*, *9*(8), 1735–1780.

Ilbeigi, M., Ghomeishi, M., & Dehghanbanadaki, A. (2020). Prediction and optimization of energy consumption in an office building using artificial neural network and a genetic algorithm. *Sustainable Cities and Society*, *61*, 102325. https://doi.org/10.1016/j.scs.2020.102325

International Energy Agency. (2015). *Accelerating energy efficiency in small and medium-sized enterprises*. Retrieved January 02, 2024, from https://c2e2.unepccc.org/wp-content/uploads/sites/3/2016/03/sme-2015.pdf.

Kim, M. K., Kim, Y. S., & Srebric, J. (2020). Predictions of electricity consumption in a campus building using occupant rates and weather elements with sensitivity analysis: Artificial neural network vs. linear regression. *Sustainable Cities and Society*, *62*, 102385. https://doi.org/10.1016/j.scs.2020.102385

Kim, T.-Y., & Cho, S.-B. (2019). Predicting residential energy consumption using CNN-LSTM neural networks. *Energy*, *182*, 72–81. https://doi.org/10.1016/j.energy.2019.05.230

Lazzari, F., Mor, G., Cipriano, J., Gabaldon, E., Grillone, B., Chemisana, D., & Solsona, F. (2022). User behaviour models to forecast electricity consumption of residential customers based on smart metering data. *Energy Reports*, *8*, 3680–3691. https://doi.org/10.1016/j.egyr.2022.02.260

Le, T., Vo, M. T., Vo, B., Hwang, E., Rho, S., & Baik, S. W. (2019). Improving electric energy consumption prediction using CNN and Bi-LSTM. *Applied Sciences*, *9*(20), 4237. https://doi.org/10.3390/app9204237

Lee, M. H. L., Ser, Y. C., Selvachandran, G., Thong, P. H., Cuong, L., Son, L. H., Tuan, N. T., & Gerogiannis, V. C. (2022). A comparative study of forecasting electricity consumption using machine learning models. *Mathematics*, *10*(8), 1329. https://doi.org/10.3390/math10081329

Lei, L., Chen, W., Wu, B., Chen, C., & Liu, W. (2021). A building energy consumption prediction model based on rough set theory and deep learning algorithms. *Energy and Buildings*, *240*, 110886. https://doi.org/10.1016/j.enbuild.2021.110886

Li, K., Tian, J., Xue, W., & Tan, G. (2021). Short-term electricity consumption prediction for buildings using data-driven swarm intelligence based ensemble model. *Energy and Buildings*, *231*, 110558. https://doi.org/10.1016/j.enbuild.2020.110558

Mendel, J. M. (1995). Fuzzy logic systems for engineering: a tutorial. *Proceedings of the IEEE*, *83*(3), 345–377. https://doi.org/10.1109/5.364485

Mohammed, A., Alshibani, A., Alshamrani, O., & Hassanain, M. (2021). A regression-based model for estimating the energy consumption of school facilities in Saudi Arabia. *Energy and Buildings*, *237*, 110809. https://doi.org/10.1016/j.enbuild.2021.110809

Montevecchi, F., Stickler, T., Hintemann, R., & Hinterholzer, S. (2020). Energy-efficient cloud computing technologies and policies for an Eco-friendly cloud market. *Final Study Report. Vienna*.

Olaru, L., Gellert, A., Fiore, U., & Palmieri, F. (2022). Electricity production and consumption modeling through fuzzy logic. *International Journal of Intelligent Systems*, *37*(11), 8348–8364. https://doi.org/10.1002/int.22942

Porteiro, R., Hernández-Callejo, L., & Nesmachnow, S. (2022). Electricity demand forecasting in industrial and residential facilities using ensemble machine learning. *Revista Facultad de Ingeniería Universidad de Antioquia*, *102*, 9–25.

Reddy, G. V., Aitha, L. J., Poojitha, C., Shreya, A. N., Reddy, D. K., & Meghana, G. S. (2023). Electricity consumption prediction using machine learning, 4th international conference on design and manufacturing aspects for sustainable energy, Hyderabad, India, May 2023.

Rosas, M. A. T., Pérez, M. R., & Martínez Pérez, E. R. (2022). Itineraries for charging and discharging a BESS using energy predictions based on a CNN-LSTM neural network model in BCS, Mexico. *Renewable Energy*, *188*, 1141–1165. https://doi.org/10.1016/j.renene.2022.02.047

Sbailò, L., & Ghiringhelli, L. M. (2023). Uncertainty quantification in deep neural networks through statistical inference on latent space. arXiv preprint arXiv:2305.10840.

Shao, M., Wang, X., Bu, Z., Chen, X., & Wang, Y. (2020). Prediction of energy consumption in hotel buildings via support vector machines. *Sustainable Cities and Society*, *57*, 102128. https://doi.org/10.1016/j.scs.2020.102128

Skomski, E., Lee, J.-Y., Kim, W., Chandan, V., Katipamula, S., & Hutchinson, B. (2020). Sequence-to-sequence neural networks for short-term electrical load forecasting in commercial office buildings. *Energy and Buildings*, *226*, 110350.

Stingl, C., Hopf, K., & Staake, T. (2018). Explaining and predicting annual electricity demand of enterprises – A case study from Switzerland. *Energy Informatics*, *1*(S1), 149–166. https://doi.org/10.1186/s42162-018-0028-0

Trianni, A., & Cagno, E. (2011). Energy efficiency barriers in industrial operations: evidence from the Italian SMEs manufacturing industry. *Energy Productivity in Industry: Partners and Opportunities*, *12*, 189–200.

Trombley, D. (2014). *One small step for energy efficiency: Targeting small and medium-sized manufacturers*. American Council for an Energy Efficient Economy.

Walter, I., & Gomide, F. (2007). Genetic fuzzy systems to evolve interaction strategies in multiagent systems. *International Journal of Intelligent Systems*, *22*(9), 971–991. https://doi.org/10.1002/int.20234

Wang, L.-X., & Mendel, J. M. (1992). Generating fuzzy rules by learning from examples. *IEEE Transactions on Systems, Man, and Cybernetics*, *22*(6), 1414–1427. https://doi.org/10.1109/21.199466

Wang, Z., Hong, T., Li, H., & Piette, M. A. (2021). Predicting city-scale daily electricity consumption using data-driven models. *Advances in Applied Energy*, *2*, 100025. https://doi.org/10.1016/j.adapen.2021.100025

Wu, H., Wang, F., Mei, X., Liang, L., Han, B., Han, D., Weng, T. H., & Li, K. C. (2023a). A novel fuzzy control path planning algorithm for intelligent ship based on scale factors. *The Journal of Supercomputing*, 1–24.

Wu, J., Hu, J., Chen, S., Xu, W., Tang, B., & Wen, X. (2023b). Demand-side adjustable resources unified data model study. *Journal of Computational Methods in Sciences and Engineering*, *23*(5), 2275–2289. https://doi.org/10.3233/JCM-226944

Zadeh, L. A. (2008). Is there a need for fuzzy logic? *Information Sciences*, *178*(13), 2751–2779. https://doi.org/10.1016/j.ins.2008.02.012

Zhang, C., Li, J., Zhao, Y., Li, T., Chen, Q., & Zhang, X. (2020). A hybrid deep learning-based method for short-term building energy load prediction combined with an interpretation process. *Energy and Buildings*, *225*, 110301. https://doi.org/10.1016/j.enbuild.2020.110301

Zhou, F., Wang, Z., Zhong, T., Trajcevski, G., & Khokhar, A. (2022). HydroFlow: Towards probabilistic electricity demand prediction using variational autoregressive models and normalizing flows. *International Journal of Intelligent Systems*, *37*(10), 6833–6856.