Methods of day ahead load forecasting on the example of a residential area

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Abstract. The work is aimed at identifying the most effective methodology for short-term forecasting of energy consumption concerning intervals of 1 hour to 1 week based on the employment of improved fuzzy recurrence and long short-term memory neural networks. The object of research is a residential area with an uneven consumption of electrical energy. The article discusses methods for forecasting electrical load on the example of a residential area. The existing methods of forecasting were analyzed and the day-ahead and intra-day power forecast were reviewed. The list of relevant sources was presented. On the basis of the reviewed literature in this area, the most effective and modern methods were identified that allow determining the consumption of electrical loads in residential and industrial buildings with an accuracy of 98 percent. Tables were developed reflecting the effectiveness of the considered techniques. The time horizons of the forecast of electric energy consumption are considered. Four categories of load forecasting were identified: long-term forecasting with a forecast interval of more than one year; medium-term forecasting with a forecast interval from one month to one year; short-term load forecasting with a forecast interval from 1 day to several weeks.; operational forecasting, with a forecast interval from 1-2 hours to the end of the day. A comparative analysis of methods for predicting electrical load for intelligent network applications is carried out and its results are presented.

1. Introduction
The number of factors, both systematic and random, affecting the level of consumption is quite large. This is due to the fact that the requirements of the energy market are constantly changing, in addition, the development of the electric power systems themselves is also predominantly stochastic. In this regard, the task of forecasting (in itself not simple) becomes even more complex. And the solution of such problems a priori occurs in the conditions of uncertainty of the initial information.

Methods of artificial neural networks, fuzzy logic, support vectors, etc. (as well as their combined use) are the most actively developing modern technologies that are currently being widely implemented in the energy sector. The validity of using this approach in forecasting is due to the fact that these structures are universal approximators, they are able to model complex dependencies of a nonlinear nature. All this allows us to hope for an accurate forecast of the result. The combination and modification of intelligent computing technologies provide ample opportunities to effectively solve the problem of improving the accuracy of short-term and operational forecasts of energy consumption.

Depending on the time horizon of the forecast, the objectives of the forecasts are also different: long-term forecasting, for example, is required for system planning, medium-term forecasting is used...
for the main work schedules, and short-term and operational load forecasting methods are used for daily and intraday operations. Next, we propose and discuss the current state of short-term load forecasting methods for intelligent networks and intelligent semi-professional applications.

We will look at the main methods used for this purpose, discuss and compare their features, advantages and disadvantages.

2. Methods and materials

Scientific-research methods of short-term load forecasting on the example of a residential area are divided in two main categories: statistical methods and artificial intelligence methods [1]. In statistical methods obtained equations show load-affecting factors relationship, while artificial intelligence methods are copying people's mode of thinking in order to get the information from the past experience and to forecast future load.

A brief characteristics of main Short-term load forecasting methods are presented below.

2.1. Artificial intelligence methods

The use of artificial intelligence methods has great advantages. This is the basic algorithm of a neural network [2], a fuzzy output system [3], genetic algorithms, a swarm of particles [4], chaos theory [5], and others. The foregoing methods of prediction and expert systems belong to artificial intelligence methods.

2.2. Methods based on neural network models

For the first time, they assumed the artificial neural network method for STLF in 1991, Park D.C. developed a neural network for modeling and predicting load [6]. Neural networks are essentially non-linear functions that have the ability to approximate non-linear dependencies. The outputs of an artificial neural network are linear or non-linear mathematical functions of its inputs. Inputs can be outputs of other network elements. The advantage of neural network technology is intellectual processing, which can imitate the work of the human brain. The disadvantage is that the learning process is relatively slow, and this does not guarantee convergence between actual and predicted data. In addition, the determination of the optimal set of input variables and the sizes of hidden layers should be investigated in practice.

Gubsky S.O. [7] developed models of short-term forecasting electricity consumption using the INS for the Rostov University and used air temperature and light as the factors affecting the load.

Hoffman [8] developed an INS model for short-term prediction of electropower for the Samara energy system. Input variables include historical data on hourly load, weather factors, and day of the week. Papalexopoulos et al. [9] also developed and implemented a multi-level rectilinear three-layer ANN for short-term load prediction.

This model uses three type of variables as input data of a neural network: inputs related to the time of year, weather related inputs and historical loads. Khotanzad et al. [10] described an ANN model for predicting workload, which is based on several strategies that reflect different data trends. The predictive model is based on a multilayer perceptron trained in the back-propagation error algorithm. This predictive model can take into account the effect of temperature and relative humidity on the load, and also contains a function that can predict the hourly temperature and relative humidity necessary for the operation of the system. The improvement of this system was described in [11]; this model includes two functions: predicting the base load and changing the load.

Chen [11] also developed a three-layer rectilinear model of a neural network, which also used the back-propagation algorithm for training. Their INS also considers the price of electricity as one of the main characteristics of the load on the power system. Many published studies use artificial neural networks in combination with other prediction methods, such as time series and fuzzy logic. A recurrent neural network [12] was recently developed and published, which was applied to STLF and positive results were obtained. The artificial neural network does not need human experience and is
aimed at creating links between the input dataset and the observed outputs. This is an advantage when working with non-linear dependencies between the load and the factors affecting it, but there is a drawback in the excessive approximation and duration of training [13]. Kurbatsky proposed the practice of using new information technologies for the prediction and analysis of individual characteristics of network power companies.

2.3. Methods based on fuzzy logic
Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. In [14], the authors describe the use of fuzzy logic for solving forecasting problems. Fuzzy forecasting methods only mimic the reasoning and judgments of experts, they are not intended to determine the exact mathematical model.

Forecasting using expert systems allows you to use rules that are often heuristic in nature, but this increases the accuracy of forecasting. Expert systems include the rules and procedures used by experts in the field of forecasting. Hsu [15] proposed an expert knowledge-based system for short-term load forecasting for the Taiwan power grid. For training, knowledge of operators and hourly monitoring of the system load and weather parameters over the past five years were used.

2.4. Methods based on data mining
Data mining is a process that examines informational data in a large database to discover rules, knowledge, etc. [16]. Mori [18] proposed data mining method for detecting a rule in STLF. The method is based on the use of a hybrid model, including regression and an artificial neural network. In accordance with this method, the range of load variation is divided into several classes and it is determined to which class the predicted load belongs in accordance with the classification rules. Then a multilayer perceptron is used to train each class. The paper focuses on determining the non-linear relationship between input and output variables in the prediction model.

3. Results and discussion
This section is dedicated to identifying the most appropriate energy forecasting methods and comparing existing methods, as well as comparing the most effective forecasting methods for residential area. Vapnik V.N. in 1995 suggested a new type of machine learning algorithms — the SVM support vector method. The support vector method is based on the risk minimization structural principle (SRM) and dimension theory. The ability to generalize the SVM method makes it more effective in model stability than in artificial neural networks [17] and fuzzy logic. The convergence time of the SVM regression algorithm for short-term prediction is less than that of artificial neural networks, the algorithm has a higher prediction accuracy, fewer adjustable parameters and more simply determines the structure of the model. It does not need too much preliminary information and data, which has significant advantages. Applied research in the field of electrical load prediction shows the promise and widespread use of SVM. Hongzhan Niel took advantage of the method autoregressive moving average ARIMA for predicting linear parts of the load. Using this method, it was possible to increase the percentage of forecast efficiency and thereby achieve an update of the forecasting model.

For a clearer definition of the relevance of forecasting methods, a table was developed, which describes the advantages and disadvantages of the main methods of forecasting the load on the example of the considered works.

The literature review on electricity load forecasting modern methods is summarized in Table 1.

| References                     | Technique(s)       | Objectives         | Achievement(s) | Limitation(s)            |
|-------------------------------|--------------------|--------------------|----------------|--------------------------|
| Eapen, R.R.; Simon, S.P.      | Back Propagation   | Short-term Load    | Day ahead Electric | Complexity is increased |
| Title                                                                 | Method                          | Forecasting Period                           | Location/Comments                                      |
|----------------------------------------------------------------------|----------------------------------|-----------------------------------------------|--------------------------------------------------------|
| Combined Similar Day and Day Ahead Short Term Electrical Load Forecasting using Sequential Hybrid Neural Networks. IETE J. Res. 2018 | Neural Networks (BPNN)           | forecasting                                   | Reliability Council of Texas, USA                      |
| Zhang, X.; Wang, J.; Zhang, K. Short-term electric load forecasting based on singular spectrum analysis and support vector machine optimized by Cuckoo search algorithm. Electr. Power Syst. Res. 2017, 146, 270–285. | CS-SSA-SVM                      | Load Forecasting                              | Half hourly, Hourly, Working day and Non-working day (New South Wales (Ten weeks data)) |
| Bouktif, S.; Fiaz, A.; Ouni, A.; Serhani, M. Optimal deep learning LSTM model for electric load forecasting using feature selection and genetic algorithm: Comparison with machine learning approaches. Energies 2018, 11, 1636 | LSTM-RNN                        | Load Forecasting                              | Hourly and monthly Metropolitan France                |
| Jindal, A.; Singh, M.; Kumar, N. Consumption-Aware Data Analytical Demand Response Scheme for Peak Load Reduction in Smart Grid. IEEE Trans. Ind. Electron. 2018 | CC-DADR algorithm and UC-DADR   | Reduce peak load and increase savings of consumer | Pennsylvania-New Jersey-Maryland Interconnection (PJM) |
| Salah Bouktif, Ali Fiaz, Ali Ouni, Mohamed Adel Serhani. Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches. Energies. 2018, 11(7):1636 DOI: 10.3390/en11071636 | LSTM                            | Load Forecasting                              | Electric Load Forecasting using Feature Selection and Genetic Algorithm |
| Wang, Z.; Wang, Y.; Zeng, R.; Srinivasan, R.S.; Ahrentzen, S. Random Forest based hourly building energy prediction. Energy Build. 2018, 171, 11–25 | Random Forest and Support Vector Regression (SVR) | Load Forecasting                              | Hourly Two educational buildings in North Central Florida |
| Lahouar, A.; Slama, J.B.H. Day-ahead load forecast using random forest and expert input selection. Energy Convers. Manag. 2015, 103, 1040–1051. | ANN and SVM                      | Load Forecasting                              | Day ahead Tunisian Power Company and PJM              |

- Computational time is high
- The risk of over-fitting is not mitigated
- Less fault tolerance rate
- The model is not efficient and robust
- The model is not efficient and robust
- Computational time is high
| Author(s) | Method | Forecasting | Comments |
|----------|--------|-------------|----------|
| Mujeeb, S.; Javaid, N.; Akbar, M.; Khalid, R.; Nazeer, O.; Khan, M. | DNN, LSTM | Price and Load Prediction | Predict both price and load | Price prediction is not accurate |
| Abedinia, O.; Amjady, N.; Zareipour, H. | MI, IG | Feature Selection using Hybrid Algorithm | Improved accuracy by improving feature selection | Optimization of classifier is not considered |
| Ghasemi, A.; Shayeghi, H.; Moradzadeh, M.; Nooshyar, M. | LSSVM, QOABC | Price and Load Forecasting | Price and load forecasting along with conditional feature selection and modification in Artificial Bee Colony | Only suitable of their defined scenario |
| Keles, D.; Scelle, J.; Paraschiv, F.; Fichtner, W. | ANN | Finding Best Parameters for ANN | Optimized parameter for ANN and price prediction | Overfitting problems are not considered |
| Allende, H.; Valle, C. | The Stacking Ensemble Learning Method (SELM) | Performing time series forecasting tasks | The ensemble method is one of the most successful approaches for performing time series forecasting tasks | Small dataset and a small-scale system |
Based on the presented table, we can distinguish that improving short-term forecasting methods power consumption, taking into account the factors affecting it, develops in directions of creating combined models using such methods and models as artificial neural networks (ANN), autoregressive integrated moving average (ARIMA), support vector method (SVM) and Long short-term memory-recurrent neural network (LSTM-RNN). Salah Bouktif, Ali Fiaz, Ali Ouni and Mohamed Adel Serhani developed LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm. The accuracy measured by CV (RMSE) is 0.61% for the short term load forecasting. An artificial intelligence method(ANN) forecasting developed by Lahouar, A. and Slama, J.B.H was able to show high level efficiency. To assess the quality of prediction, the test is performed for a half-year, from 1 January to 30 June 2014. The average obtained MAPE is 2.24%, excepting holidays which are studied apart [17].

Based on the presented review of the literature on the most effective methods for predicting short-term electricity consumption, a diagram was developed showing the percentage of effectiveness of the described methods.

**Diagram 1.** Comparison of short-term forecasting methods.

Based on the analyzed literature, it was possible to create a table showing the quality of prediction for a half-year each of the considered techniques:
Table 2. The quality of prediction for a half-year.

| Technique | RMSE | MAPE  |
|-----------|------|-------|
| RNN       | 3.13 | 6.2%  |
| LSTM      | 1.83 | 1.9%  |
| ARIMA     | 3.25 | 9.8%  |
| ANN       | 2.24 | 2.2%  |

4. Summary

Research methods for short-term load forecasting are divided into two main categories: statistical methods and methods of artificial intelligence [1]. In statistical methods, the resulting equations show the relationship of factors that affect the load, while artificial intelligence methods copy the way people think to get information from past experiences and predict future loads.

In this paper, an overview of the existing methods for predicting the electrical load was carried out on the basis of modern works. The emergence and development of forecasting methods are considered and described. The analysis of the data shown in the table allows you to determine the most suitable area for a particular method. Machine learning is one of the most modern and widely used forecasting methods. Currently, the most effective and popular methods are those that use neural networks (ANS) [17] and models as artificial neural networks (ANN), support vector method (SVM), autoregressive integrated moving average (ARIMA). There are two main types of architecture that allow for the most accurate prediction of electrical load consumption: LSTM and RNN.

This paper provides a brief description and comparative analysis of the main methods for predicting short-term and long-term loads.

5. References

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