Research and Software Implementation of Intelligent Method of Energy Consumption Control

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Abstract

The popular intelligent methods for improving the efficiency of energy consumption in a home automation system have been investigated in this paper. The intelligent method for controlling energy consumption has been developed. It differs from the existing ones in an integrated approach based on predicting electricity generation using a Feedforward neural network, as well as optimizing the schedule for using electrical appliances based on an improved particle swarm optimization algorithm with the proposed system of priorities. The intelligent support subsystem has been created, the integration of which into the home automation system will allow users to control the processes of generation and consumption of electricity, effectively use household appliances and save resources.

Keywords

Home automation system, energy consumption, intelligent method, artificial neural networks, forecasting, schedule optimization

1. Introduction

In recent years, there has been an active development of intelligent technologies, that are actively being implemented in home automation systems (HAS), which allows bringing the standard system to a new level of comfort [1]. The implementation of intelligent methods makes it possible to study the habits of the residents of the house, predict their behavior and create optimal conditions for life [2]-[3]. One of the most important areas of intelligent technologies usage is the saving of resources, in particular electricity, which is currently a significant objective, especially in the conditions of the unstable economic and political situation in Ukraine.

A large number of HASs are offered on the market, in particular, the most popular are: OpenHAB, HomeAssistant, Majordomo, ioBroker, Domoticz, Jeedom. Their functionality is aimed at monitoring and automated management of various processes in houses and apartments. Thus, household equipped with such a system offers more comfort, flexibility and security [4]-[5]. But at the same time, the existing HASs do not provide intellectual support to users from the point of view of organizing the efficient consumption of electricity generated by alternative sources of electricity (solar and wind power plants) based on the optimal usage of various electrical devices. This would allow residents to gain independence from the external power grid and utility tariffs for electricity and significantly save money by using alternative energy sources.

Thus, the objective of developing a subsystem of intellectual support that will allow considering the interests and habits of household residents and saving resources at the same time is urgent.

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The goal of the work is the research and practical implementation of intelligent methods of energy consumption control to increase the efficiency of electrical appliances usage and save electricity in HAS that uses alternative sources of electricity.

2. Related works

As the conducted studies have shown, today the most popular intelligent methods, algorithms and models in the field of efficient energy consumption organization are: particle swarm optimization (PSO) algorithm, genetic algorithm (GA), ARIMA model and artificial neural networks.

In order to reduce electricity costs, researchers suggest using the PSO to optimize the schedule of electrical appliances and solve the objective of minimizing the peak load in the power grid [6]-[10]. The authors of works [11]-[13] use a GA to increase the efficiency of energy consumption in HAS. In the study [14], the authors proposed the usage of the ARIMA method for real-time analysis of electricity consumption in HAS and forecasting of future energy consumption. In works [15]-[22], the authors apply neural networks to predict electricity consumption, in order to use this data in the future to reduce electricity costs and optimize the operation schedule of household electrical appliances. In particular, the authors of [22] investigated the issue of using the main types of neural networks to solve various objectives in HAS. The method for choosing the optimal type of artificial neural network for the same set of historical data was proposed in [22], because of the fact that each artificial neural network has certain features and allows predicting some values and processing various types of data with different accuracy.

Thus, as a result of the review, the existing objectives of organizing efficient energy consumption in HAS and popular methods of solving them were divided into two main groups (Table 1).

Table 1
Objectives and methods for their solution

Objective	Methods
Optimization of the work schedule of household appliances	Particle swarm optimization algorithm [6]-[10] Genetic algorithm [11]-[13]
Forecasting electricity consumption or generation	ARIMA [14], [19] Long Short-Term Memory neural network [15]-[18], [22] Recurrent neural network [19], [20], [22] Feedforward neural network [17], [22] Convolutional neural network [21]

In the considered works, the objective of optimizing the operation schedule of household appliances was solved by automatically scheduling their usage during the period of the day when electricity has a low price. It allows solving the objective of minimizing the peak load in the power grid and reducing utility costs for electricity. The results obtained in studies [6]-[13] showed that the implementation of this approach made it possible to reduce energy costs even up to 55%, which is a fairly high indicator. However, the biggest disadvantage of such scheduling optimization is that the level of comfort of residents can be significantly reduced, because of the fact that it is recommended to use more electrical appliances only at certain times of the day (for example, at night), which is not always convenient. In addition, this approach is not justified if a fixed electricity tariff is set. In the case when the studied HAS uses alternative energy sources (solar and wind power plants), then the objective statement can be changed to optimal planning for the use of electrical appliances during periods when electricity generation from alternative sources is maximum.

Studies have shown that to solve the objective of optimizing the work schedule of household appliances, it is suggested to use the PSO and the GA [6]-[13]. In particular, works [9], [12] compared these two approaches, and the results showed that based on the usage of the PSO it was possible to reduce electricity costs by 8% more than on the basis of the GA, using the same data set. The authors of [23] compared the performance of these approaches and showed that the PSO requires fewer iterations to find the optimal solution and its accuracy is higher. Thus, it can be concluded that the usage of the PSO [24]-[25] is appropriate for achieving the goal of this work.

The objective of analyzing historical data and forecasting electricity generation assumes that the forecasted data will help in the future to develop a plan for economical usage of electrical appliances and to reduce electricity consumption in HAS. Research by the authors [15]-[22] showed that the highest forecasting accuracy that was achieved is 97%, which is a very high indicator and it allows the implementation of the effective energy consumption analysis and forecasting subsystem. If HAS uses alternative sources of electricity, the forecasted data about energy generation will be used by the optimization algorithm to create an optimal schedule for household appliances, which will allow the user to plan the schedule for the upcoming day.

The conducted studies showed that a number of methods are proposed to be used for forecasting electricity generation: ARIMA, Long Short-Term Memory (LSTM) neural network, Recurrent neural network (RNN), Feedforward neural network (FNN) and Convolutional neural network (CNN). The usage of the ARIMA method and CNN is not advisable, because in studies [19], [21] they showed unsatisfactory results in comparison with other methods. Studies [22] show that it is impossible to create a universal neural network that will be suitable for various objectives of HAS. Therefore, it is necessary to conduct a number of computer experiments and choose a neural network model that will provide the highest prediction accuracy for the studied HAS, taking into account its specific features.

3. Main and anticipated findings

3.1 Analysis and selection of a neural network model

The training set comprises the concatenation of input attributes from the weather forecast obtained through a weather API and the output parameter, i.e., electricity generation. The resulting dataset contains 2,160 records and spans the period from August 8, 2022 to November 13, 2022.

In the course of this research, the following models were considered: FNN [26], RNN and a neural network with LSTM. The implementation of FNN is represented as layers in a sequential order, and data is transferred from one layer to another in a given order until they reach the original layer [27]. This model should take four parameters: a set of values for the input features of the weather forecast (solar radiation power, average temperature, wind speed) and the value of the initial feature (the power of electricity generation). Since the original feature is represented as a continuous value, the activation function must return a value in the range $[0, +\infty)$. The selection of this particular activation function was based on the constraint of electricity generation, which can obtain positive and zero values only. The conducted studies have shown that the best forecasting results are obtained by a model with the following added layers:

- Input layer consisting of 3 neurons.
- Dense layer consisting of 128 neurons and having the ReLU activation function.
- Dense layer consisting of 24 neurons.
- Dense (output) layer consisting of one neuron.

The implementation of RNN is represented by recurrent and dense layers. Unlike the FNN, the number of parameters has been increased. Thus, the set of input feature values now includes the de-scaling time, which has been converted to a zero-based integer. The conducted studies of the implementation of this model showed that the best forecasting results are provided by RNN, which has the following layers:

- Input layer consisting of 4 neurons.
- Simple recurrent layer, which includes 200 neurons and has the ReLU activation function.
- Dense layer consisting of 100 neurons.
- Dense (output) layer consisting of one neuron.

The implementation of the neural network with LSTM has a similar set of features as those used for RNN. The conducted studies showed that the best forecasting results are provided by the neural network with LSTM, which includes the following layers:

- Input layer consisting of 4 neurons.

- LSTM layer, which includes 200 neurons and has the ReLU activation function.
- Dense layer consisting of 100 neurons and having the ReLU activation function.
- Dense (output) layer consisting of one neuron.

Also, for forecasting time series, another network of LSTM was implemented, which has only two parameters: date and capacity of electricity generation. Such a model has the following layers:

- Input layer consisting of 2 neurons.
- LSTM layer, which includes 100 neurons and has the ReLU activation function.
- Dense layer consisting of 100 neurons and having the ReLU activation function.
- Dense (output) layer consisting of one neuron.

Each neural network model was trained for 100 epochs using the Keras library written in Python. The input data set was divided into two parts, where the training sample has a share of 80% of the entire set, and the training sample - 20%. The validation set wasn't used because of small dataset. Splitting into three sets may result in insufficient data to train the model effectively.

The sequential model of Keras library was used to implement all the model types, in which the network is represented as layers in a sequential order, and data is transferred from one layer to another in a given order until they reach the original layer.

As a result of the training of neural network models, as well as the application of a test sample to them, graphs of the dependence of accuracy and costs (during training and during validation) of models from epochs were obtained for all types of neural networks. It can be noted that among the investigated models, FNN stands out significantly because of the fact that it has the highest value of accuracy. To increase the accuracy of forecasting, a number of additional experiments using various optimization algorithms were also conducted [26].

As it is known, gradient methods used to optimize neural networks are among the most popular. The used Keras library contains implementations of various algorithms for the optimization of the gradient descent method. Three algorithms (AdaGrad, RMSProp, and ADAM) can be identified that implement different approaches to make gradient descent more efficient in finding optimal weights. However, these algorithms are often used as "black box" optimizers because it is difficult to find practical explanations of their strengths and weaknesses [28]. A comparison of the training results and the work of the created forecasting models is shown in Table 2.

To compare the implemented models, RMSE (Root Mean Square Error) metric was used, which reflects the root mean square deviation [29]. The obtained results indicate that the developed models of RNN and a neural network with LSTM have a rather large forecasting error. Among these models, we can single out the neural network with LSTM with five parameters, since the RMSE value for the test sample is 635 W.

This shows that the neural network with LSTM is better suited for time series forecasting than RNN, however, the accuracy of such models is not satisfactory. This is explained by the fact that the target parameter is based not only on dependent time series, but also on time-independent indicators, that is, weather conditions.

Therefore, to increase the accuracy of forecasting, it is necessary to have a separate set of historical data for electricity generation by solar and wind power plants. Also, another solution can be the accumulation of historical data for several years, which will make it possible to perform time series forecasting depending on the season.

Realized models based on FNN showed good forecasting results. Among the studied models, the one with four parameters and using the ADAM optimizer turned out to be the best. The Z-score method was used to normalize the training sample, as it more accurately preserves significant changes in indicators. The RMSE value for the test sample is 466 W, which is an acceptable indicator. Therefore, it is advisable to use this model to implement a complex intellectual method for increasing the efficiency of using electrical appliances. Among the main advantages, we can also highlight the speed of training and the small file size of the trained model, which will allow the usage of such a model even on low-power computing devices. Since the accuracy of this model is not high enough, to improve its implementation it is necessary to have a larger amount of historical data, at least from one year.

Since the intelligent support subsystem has a mechanism for automatic retraining of the neural network model, the accuracy of power generation forecasting can be increased after a while.

Table 2
Results of training of implemented models

Criterion of comparison	FNN			RNN	Neural network with LSTM	
Total number of layers	4	4	4	4	4	4
Number of parameters	4	4	4	5	5	2
Optimizer	ADAM	RMSprop	AdaGrad	ADAM	ADAM	ADAM
Error on training set (RMSE)	446,9633	425,1278	812,8156	183,9365	499,6775	1066,8383
An error on the test set (RMSE)	466,1486	492,0719	831,0850	672,0999	635,0425	1066,8383
Size of training set	1728	1728	1728	1728	1728	2112
Size of test set	432	432	432	432	432	48
The file size of the trained model	153,9 Kb	153,9 Кb	153,9 Кb	773,52 Кb	344,8 Кb	166,79 Кb
Study time	21 s	22 s	21 s	1 min 20 s	4 min 36 s	18 min 22 s
Number of batches	24	24	24	24	24	24
Number of epochs	100	100	100	100	100	100

3.2 Complex intelligent method

On the basis of the research of popular intelligent methods in the field of organization of optimal electricity consumption, a complex intelligent method of energy consumption control was developed, using FNN and a basic variant of PSO with some improvements.

The algorithm of the complex method is given in the form of the UML activity diagram (Fig. 1) and involves two main stages: forecasting of electricity generation and creating an optimal hourly schedule for the usage of electrical appliances.

In order to implement a complex intelligent method, the neural network is first trained based on the historical data obtained from HAS. They should include the date and time, information on electricity generation, as well as data on weather conditions. After successful training, the neural network is able to predict the generation of electricity. The input data for the operation of the neural network is the hourly weather forecast for the next day, which can be obtained using a weather service (for example, Visual Crossing). Thus, the forecasted generation information will help to estimate the available electricity for usage and to develop a plan for the efficient application of appliances for the next day, making maximum use of alternative sources of electricity.

The next stage of the implementation of the complex method is the creation of an optimal hourly schedule for the usage of electrical appliances using the PSO. The idea is to automatically plan the use of electrical appliances during the next day, considering the habits of residents, during periods when electricity generation is maximum. However, the operating time of the devices is not limited for the comfort of users. The goal of optimization is to create a schedule that will use as much electricity as possible from alternative power sources to ensure the operation of all planned household appliances, and minimize the consumption of electricity from the external power grid.

Thus, the user will be able to save money significantly and be less dependent on electricity suppliers. Input data for the operation of the optimization algorithm are the forecasted data on electricity generation, as well as the list of household appliances that are planned for usage the following day. The description of available devices includes the following data: name, nominal power (W), planned duration of operation. The user can choose from the list of electrical appliances that he plans to use, as well as specify the time intervals of their usage that are convenient for him.

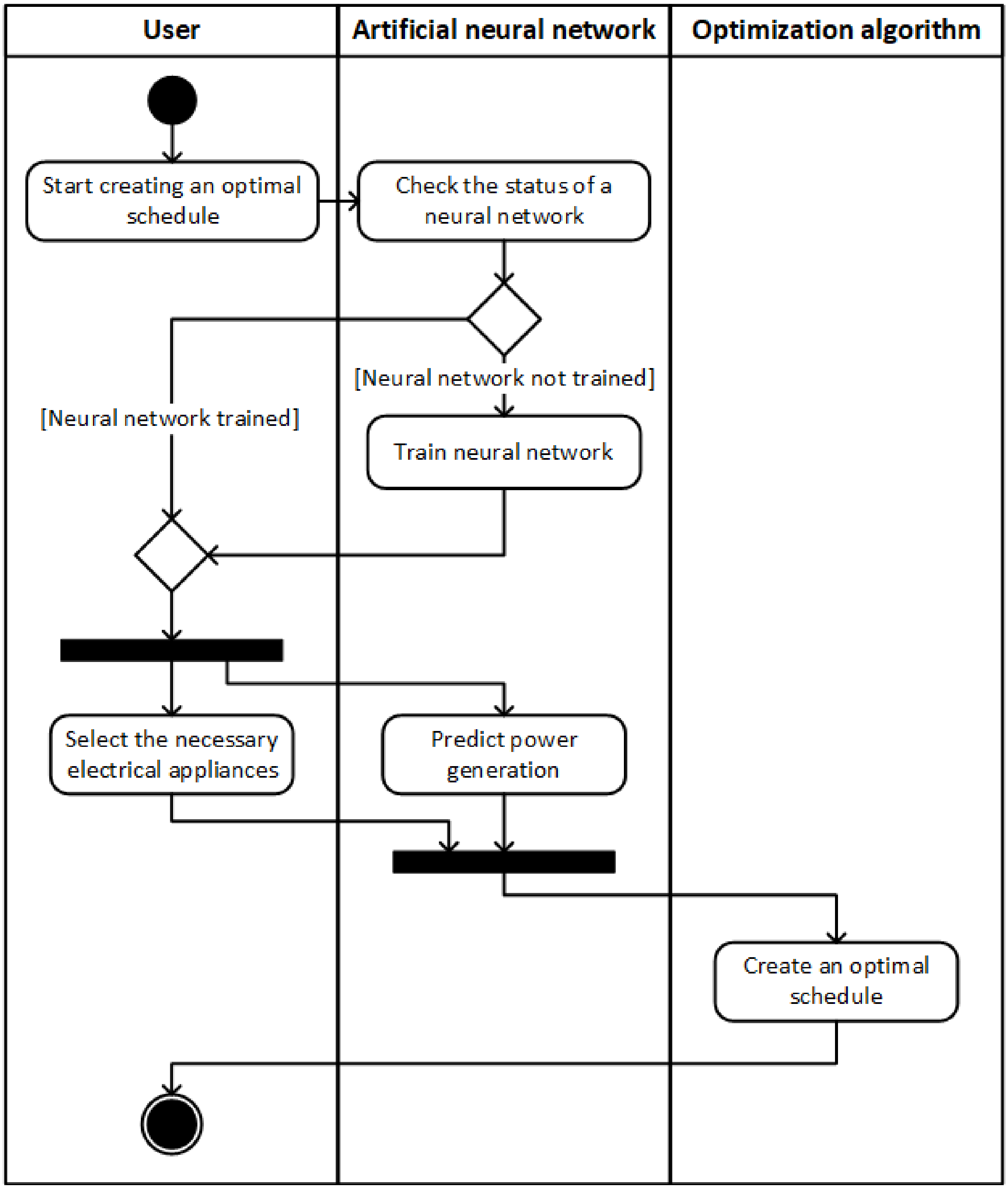

Figure 1: UML diagram of the developed complex intelligent method

Since solar and wind power plants provide the generation of a limited amount of electricity, it was proposed to improve the PSO by introducing a priority system (Fig. 2).

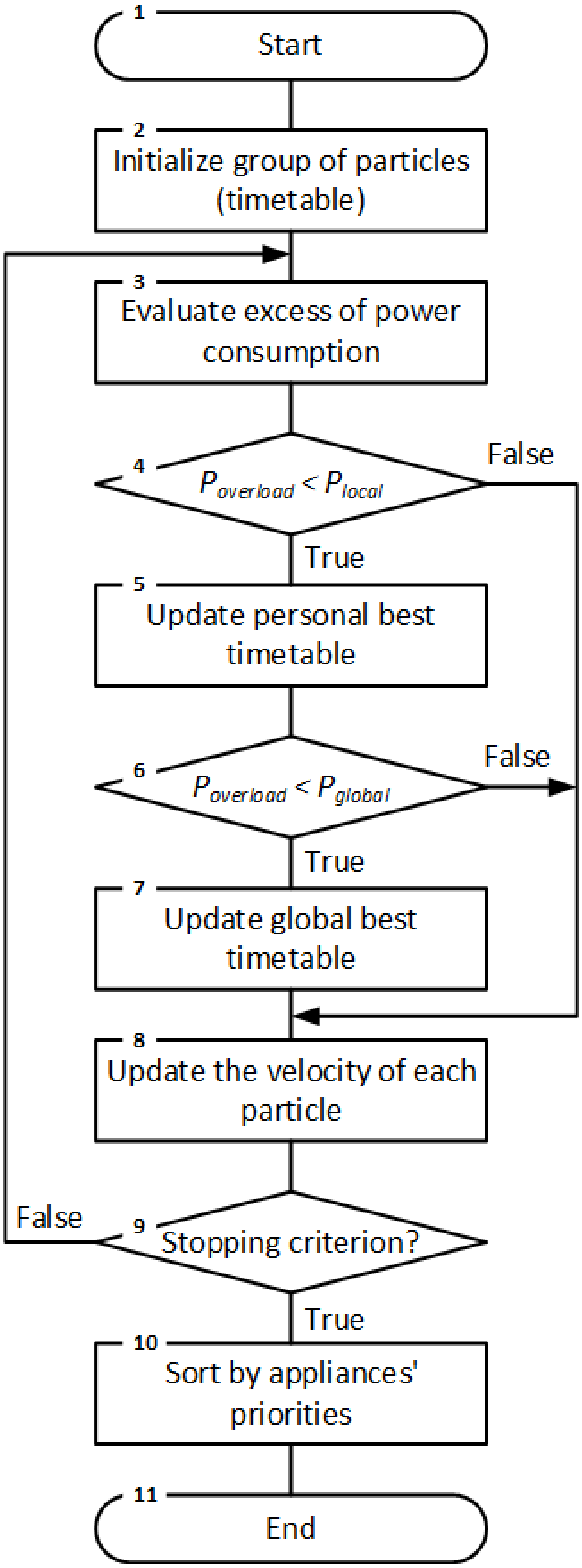

Figure 2: Particle swarm optimization algorithm with priority system

Priority is a number that can take a value from one to five, where five means the highest priority. This will allow the user to choose the most important household appliances for him, and in case of insufficient electricity generation, the algorithm will suggest not to use those with the lowest priority.

The input data of the PSO is the predicted electricity generation for the next 24 hours and a list of household appliances. For each of them the time intervals of use, the number of operation hours and the priority are indicated. The PSO also includes some tuning parameters which influences the performance of this algorithm. These parameters were set as follow: particle numbers m = 100, the max iteration number T_{max} = 10000, cognitive parameter c_1 = 1.49618, social parameter c_2 = 1.49618, inertia weight w = 0.7298. As a result of the work, the optimization algorithm will offer the best schedule for the use of electrical appliances, adjusting to the requirements and habits of the resident, but considering the generation of a certain amount of electricity from alternative sources.

The developed algorithm for monitoring the operation of the power grid provides round-the-clock monitoring of the consumption of electricity generated in the household, as well as supplied from the external power grid, which allows the owner to instantly react to situations and take measures to improve the energy efficiency of HAS.

3.3 Software implementation of the intelligent support subsystem

Based on the developed method and algorithms, an intelligent support subsystem was created, which integrates with the OpenHAB home automation platform and is designed to provide recommendations to the residents of the house on the efficient usage of electrical appliances with the maximum use of energy from alternative sources, as well as with minimal dependence on the external power grid. The developed structural/functional diagram of the subsystem includes the following modules (Fig. 3):

- Module of indicators monitoring, which analyzes energy consumption data in real time and sends a message to the user in case of exceeding electricity consumption.
- Module of electrical appliances editing, that allows the user to add, modify, and delete electrical appliances from the list of HAS.
- Module of schedule optimization, that allows to create an optimal hourly schedule for the operation of household appliances, using the list of electrical appliances that the user plans to use, as well as the forecasted electricity generation.
- Module of forecasting of electricity generation for the next day using the weather forecast downloaded from the weather service and historical energy consumption data stored in the system database. The forecasting module is called when necessary, and the forecasting results are used during the generation of the optimal schedule.

The subsystem is implemented as a web application using the Java programming language and the Spring framework. The electricity generation forecasting module is developed in the Python programming language using the Keras library. All necessary data is stored in the MongoDB database, which is suitable for storing large volumes of information. Storage of historical weather forecast data, as well as forecasted electricity data, is implemented using CSV files.

The web application provides the users with a graphical interface through which they can access and control all subsystem functions and receive important messages using a browser. Web pages for the Spring framework were developed using JSP technology. In the process of creating web pages, the jQuery library was used, which provides a wide range of functions for convenient development. The Bootstrap library was used to implement an adaptive design that will display well on all devices. The FontAwesome library allows to add various icons, which makes the graphical interface more understandable and attractive.

Thus, the developed intelligent support subsystem provides the user with the opportunity to create an optimal schedule of household appliances, adapting to the requirements and habits of residents, using the forecasted electricity generation for the next day.

In addition, the subsystem performs round-the-clock control of energy consumption indicators and, in case of high consumption of electricity from the external power grid, sends a message to the user using a graphical interface.

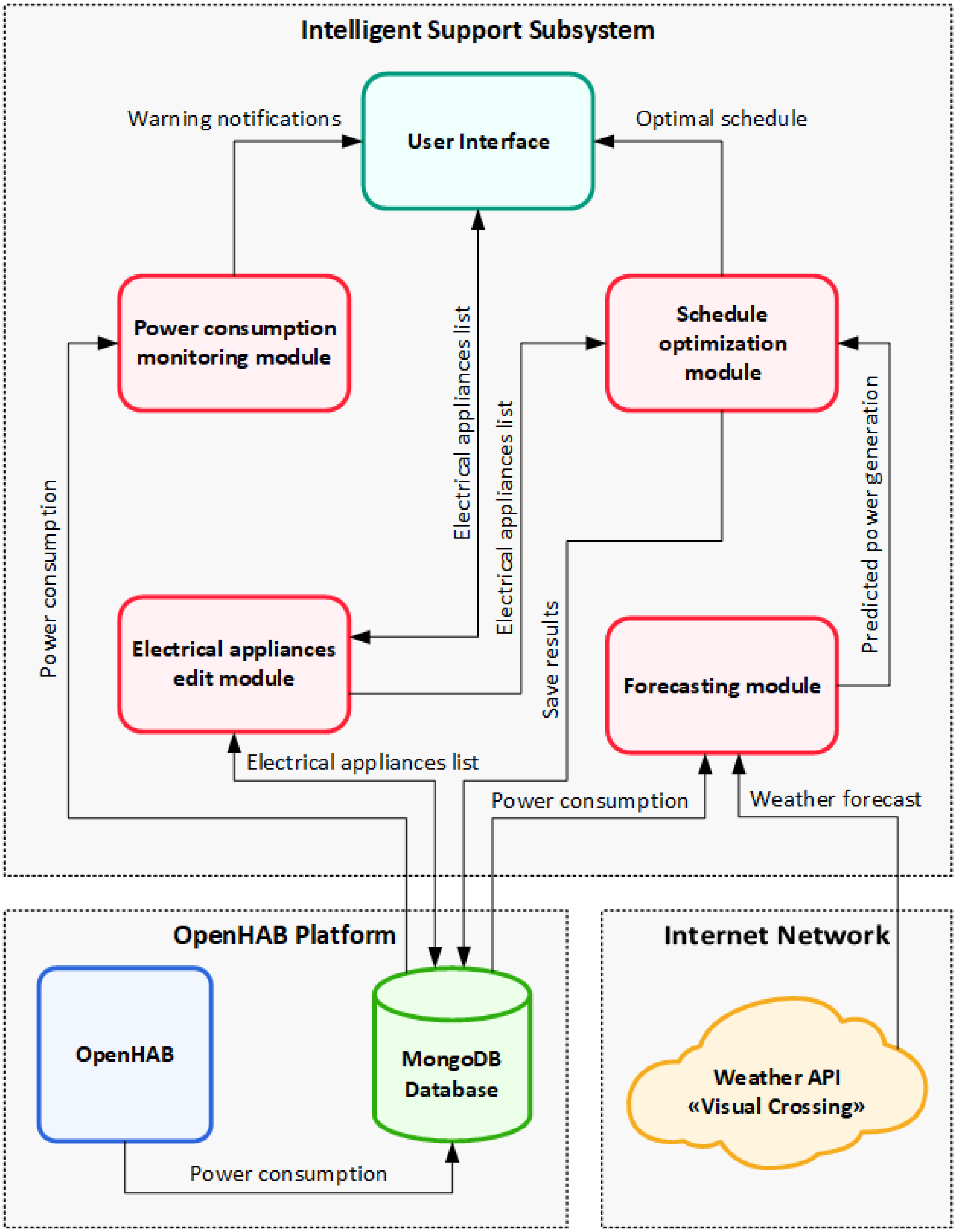

Figure 3: Structural/functional diagram of the developed subsystem

4 Discussion

To date, the developed intelligent support subsystem is at the stage of experimental operation in a real HAS and is integrated with the OpenHAB platform [2].

The studied real HAS is a hybrid system with a hybrid inverter, connection to an external power grid, batteries, as well as alternative energy sources (solar and wind power plants).

Batteries are used as a backup for situations when there is no own generation of electricity, or it is impossible to use an external power grid. The rest of the time they are in a charged state in a buffer mode.

In this operating mode, the analysis of consumption from the external power grid, the values of the charge/discharge currents of batteries and other parameters related to the consumption of electricity is performed.

The main objective of the developed intelligent support subsystem is to minimize consumption from the external power grid, as well as the number of charge / discharge cycles of batteries while maximizing the usage of internally generated energy.

With this mode of operation, there is no deep discharge of the batteries and, accordingly, there is no decrease in the number of working cycles of their work.

However, the system will provide power consumption optimization even in the case when the power consumption from the external power grid is zero, and it is also possible to obtain and analyze the batteries charge/discharge currents.

The improved architecture of the real HAS and its interaction with the integrated intelligent support subsystem is shown in Fig. 4.

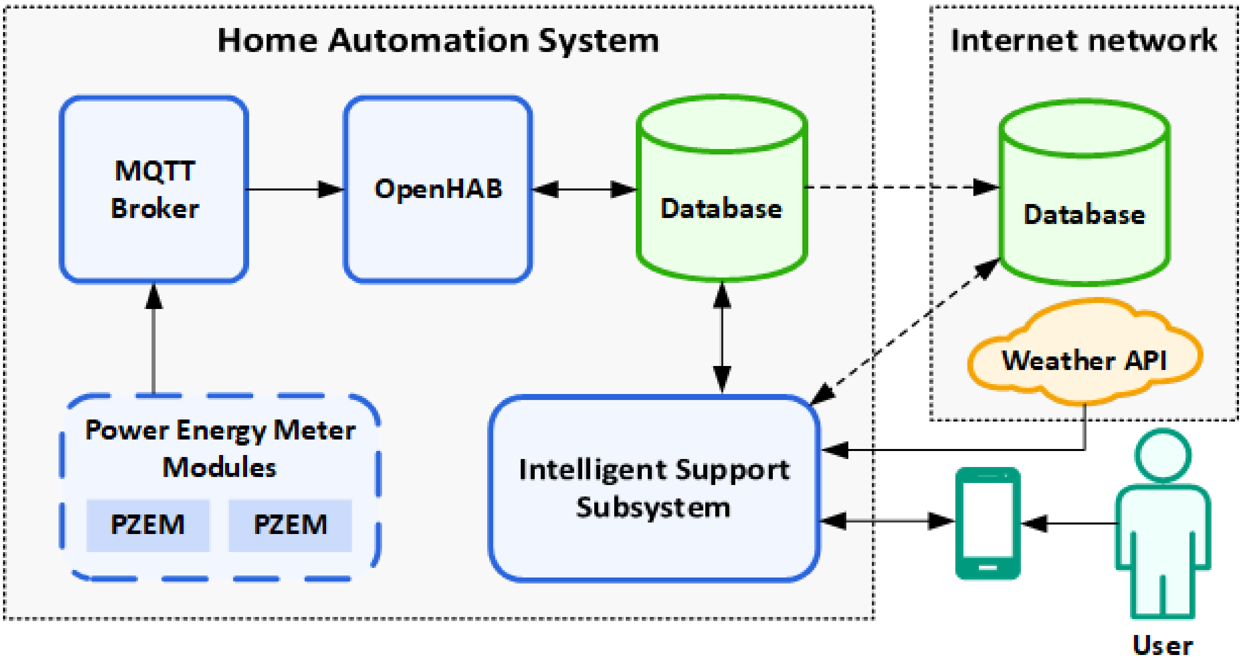

Figure 4: Improved architecture of real HAS

The main component of the investigated real HAS is the OpenHAB platform. Data from the PZEM-004T modules, which are designed to measure input voltage, current load consumption and calculate power consumption in real time, are received by the MQTT broker, which sends them to OpenHAB, which in turn writes them to the database.

The developed intelligent support subsystem interacts with the local database included in HAS and receives all the necessary indicators from the electricity measurement modules, analyzes them in real time, and also uses them for neural network training. The list of the used most powerful electrical appliances is stored in the same database.

The remote database uses a replication mechanism and is an optional element of the architecture, although it is required to perform subsystem performance testing.

Using any device, the user can connect to the intelligent support subsystem using only a browser to create an optimal hourly schedule for using appliances, monitor energy consumption and generation, edit the list of the most powerful electrical appliances, and receive important messages (Fig. 5).

The conducted software testing showed that the developed software functions correctly and meets all the requirements.

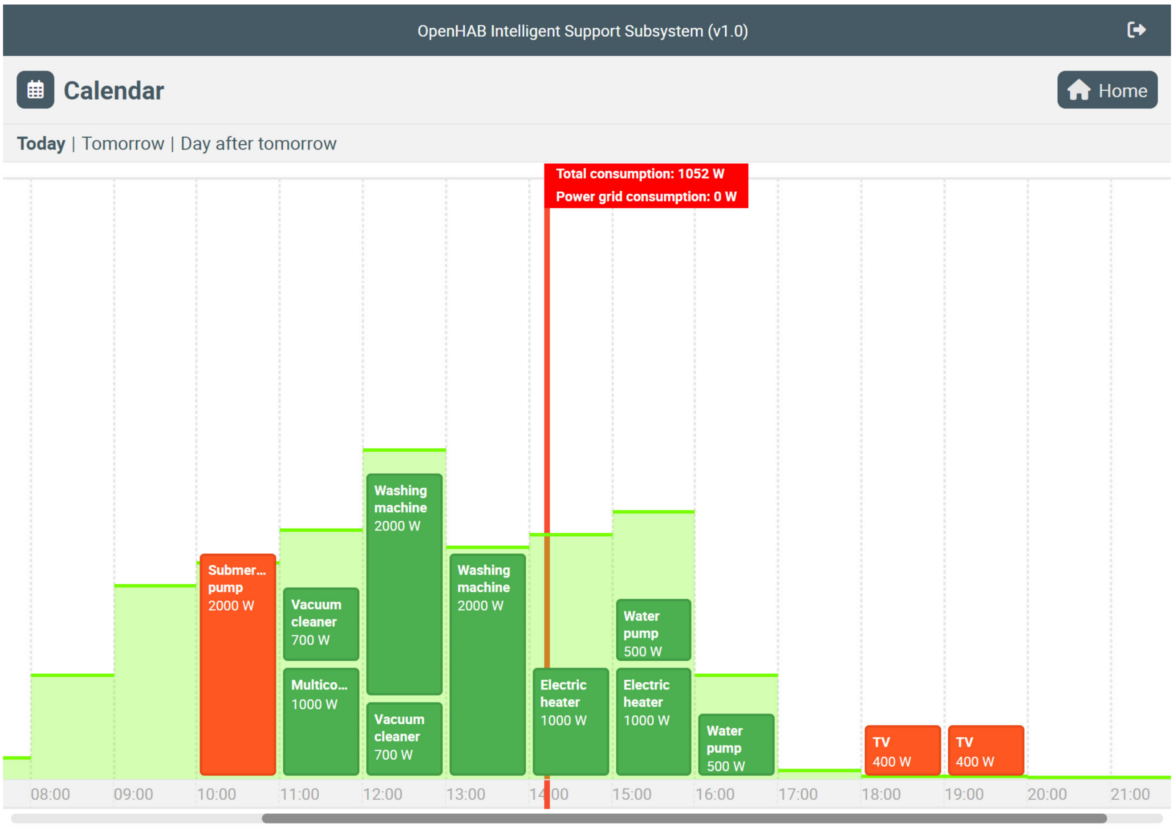

Figure 5: The interface of the intelligent support subsystem

5 Conclusion

As a result of the conducted research, a complex intelligent method of controlling energy consumption in HAS was developed based on forecasting electricity generation with maximum use of alternative sources, as well as optimizing the schedule of use of electrical appliances to minimize electricity consumption from the external power grid.

The conducted computer experiments made it possible to choose the best neural network model for forecasting electricity generation, as well as to analyze the factors that affected the accuracy of the forecast. To train neural network models, a set of historical data of electricity consumption, which was accumulated in a real HAS on the OpenHAB platform, was used.

The developed intelligent support subsystem is designed to provide recommendations to the residents of the house on the effective use of electrical appliances in order to minimize energy consumption from the external power grid.

The scientific novelty of the work consists in the development of an intelligent method of energy consumption control, which differs from the existing ones by a comprehensive approach based on forecasting electricity generation using a Feedforward neural network, as well as optimizing the schedule of electrical appliances usage based on the improved PSO with the proposed system of priorities.

The practical significance of the work is that the integration of the developed intelligent support subsystem in HAS will allow controlling the processes of electricity generation and consumption, increasing the efficiency of using household appliances and saving resources.

In future work it's planned to enhance the learning algorithms by combining multiple neural networks that can improve the overall accuracy of power generation prediction to create a more optimized schedule in order to electricity consumption.

In future work, it is planned to improve the learning algorithms by combining several neural networks, that can improve the overall accuracy of electricity generation forecasting to create a more optimized schedule to maximize electricity saving. Also, in the future development of this work, it is planned to consider more promising architectures of neural networks for solving problems of time series forecasting.

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7 References

[1] C. Bruhathireddy, G. N. Kodandaramaiah, M. Lakshmipathy, Design and implementation of home automation system using Raspberry Pi, International journal of science, technology & management 03(12) (2014) 94-98.

[2] M. Zadoian, Y. Horichenko, A. Tulenkov, A. Parkhomenko, Data mining to achieve quality of life for home automation users, in: Proceedings of 11th IEEE International conference on Intelligent data acquisition and advanced computing systems: technology and applications, Cracow, Poland, 2021, pp.55-59. doi:10.1109/IDAACS53288.2021.9660836.

[3] A. Tulenkov, Y. Yaremchenko, A. Parkhomenko, Ya. Zalyubovskiy, A. Parkhomenko, M. Kalinina, Adaptation of Smart House system for people with special needs based on wireless technologies, in: Proceedings of 5th IEEE International symposium on smart and wireless systems within the International conference on Intelligent data acquisition and advanced computing systems, Dortmund, Germany, 2020, pp.12-17. doi:10.1109/IDAACS-SWS50031.2020.9297072.

[4] A. Arhipov, A. Tulenkov, A. Parkhomenko, Ya. Zalyubovskiy, A. Parkhomenko, Remote monitoring of electrical equipment for Smart House system safe exploitation, in: Proceedings of 5th IEEE International symposium on smart and wireless systems within the International conference on Intelligent data acquisition and advanced computing systems, Dortmund, Germany, 2020, pp.260-265. doi:10.1109/IDAACS-SWS50031.2020.9297103.

[5] A. Parkhomenko, A. Tulenkov, A. Sokolyanskii, Y. Zalyubovskiy, A. Parkhomenko, A. Stepanenko, The application of the remote lab for studying the issues of Smart House systems power efficiency, safety and cybersecurity, in: Smart Industry & Smart Education, volume 47 of Lecture Notes in Networks and Systems, Springer, Cham, 2018, pp. 395-403. doi:10.1007/978-3-319-95678-7_44.

[6] J. Zhu, F. Lauri, A. Koukam, V. Hilaire, Scheduling optimization of Smart Homes based on demand response, in: Proceedings of the 11th IFIP International conference on Artificial intelligence applications and innovations, Bayonne, France, 2015, pp. 223-236. doi:10.1007/978-3-319-23868-5_16.

[7] C. Deng, S. Zhang, W. Yang, W. Yao, J. Tan, Z. Liu, Two-stage optimization model for Smart House daily scheduling considering user perceived benefits, in: Proceedings of the International conference on Mathematics, modelling, simulation and algorithms, Chengdu, China, 2018, pp. 64-68. doi:10.2991/mmsa-18.2018.15.

[8] Z. Qu, N. Qu, Y. Liu, X. Yin, C. Qu, W. Wang, J. Han, Multi-objective optimization model of electricity consumption behavior considering combination of household appliance correlation and comfort, Journal of electrical engineering and technology 13(5) (2018) 1821-1830. doi:10.5370/JEET.2018.13.5.1821.

[9] I. Gupta, G. N. Anandini, M. Gupta, An hour wise device scheduling approach for demand side management in smart grid using particle swarm optimization, in: Proceedings of the 19th National power systems conference, Bhubaneswar, India, 2016, pp. 1-6. doi:10.1109/NPSC.2016.7858965.

[10] Y. Zhou, Y. Chen, G. Xu, C. Zheng, M. Cheng, Home energy management in smart grid with renewable energy resources, in: Proceedings of the 16th International conference on Computer modelling and simulation, Cambridge, United Kingdom, 2014, pp. 351-356. doi:10.1109/UKSim.2014.46.

[11] F. Iqbal, K. Iqbal, Optimal load scheduling using genetic algorithm to improve the load profile, ADRRI Journal of engineering and technology 4(9(3)) (2021) 1-15. doi:10.55058/adrrijet.v4i9(3).621.
[12] A. Thivy, K. Thamini, P. Narmadha, I.S. Vishaka, K.R. Vairamani, Demand side management in smart grid using heuristic algorithm, in: Proceedings of the 2nd International conference on Emerging enhancement in engineering and technology, Tiruchirappalli, India, 2016, pp. 361-365.
[13] E. Lee, H. Bahn, Electricity usage scheduling in Smart building environments using smart devices, The scientific world journal (2013) 11 p. doi:10.1155/2013/468097.
[14] P. B. Gopikrishna, J. A. Mathew, Power consumption analysis and prediction of a Smart Home using ARIMA model, Rochester, SSRN, 2021, 9 p. doi:10.2139/ssrn.3819512.
[15] M. Taksir, S. Aktar Data-driven time series-based prediction in smart home appliance energy consumption, International journal of computer applications 178(15) (2018) 41-46.
[16] R. E. Alden, H. Gong, C. Ababei, D.M. Ionel, LSTM forecasts for Smart home electricity usage, in: Proceedings of the 9th International conference on Renewable energy research and application, Glasgow, UK, 2020, pp. 434-438. doi: 10.1109/ICRERA49962.2020.9242804.
[17] W. Kong, Z. Y. Dong, D. J. Hill, F. Luo, Y. Hu, Short-term residential load forecasting based on resident behaviour learning, IEEE Transactions on power systems 33(1) (2017) 1087-1088. doi: 10.1109/TPWRS.2017.2688178.
[18] Y. Wang, N. Zhang, X. Chen, A short-term residential load forecasting model based on LSTM recurrent neural network considering weather features, Energies 14(10) (2021) 1-13. doi:10.3390/en14102737.
[19] O. D. Diaz-Castillo, A. E. Puerto-Lara, J. A. Saenz-Leguizamon, V. Ducon-Sosa, Prediction of electrical energy consumption through recurrent neural networks, in: Proceedings of the workshops at the 4th international conference on Applied informatics, Buenos Aires, Argentina, 2021, 174-182.
[20] M. Beigi, H. B. Harchegani, M. Torki, M. Kaveh, M. Szymanek, E. Khalife, J. Dziwulski, Forecasting of power output of a PVPS based on meteorological data using RNN approaches, Sustainability 14(5) (2022) 1-12. doi:10.3390/su14053104.
[21] K. Amarasinghe, D. L. Marino, M. Manic, Deep neural networks for energy load forecasting, in: Proceedings of the IEEE 26th International symposium on Industrial electronics, Edinburgh, UK, 2017, pp. 1483-1488. doi:10.1109/ISIE.2017.8001465.
[22] V. Teslyuk, A. Kazarian, N. Kryvinska, I. Tsmots, Optimal artificial neural network type selection method for usage in Smart House systems, Sensors 21(1):47 (2021) 1-14. doi:10.3390/s21010047.
[23] F. D. Wihartiko, H. Wijayanti, F. Virgantari, Performance comparison of genetic algorithms and particle swarm optimization for model integer programming bus timetabling problem, IOP conference series: Materials science and engineering 332:012020 (2018) 1-6. doi:10.1088/1757-899X/332/1/012020.
[24] J. Kennedy, R. Eberhart, Particle swarm optimization, in: Proceedings of the International conference on Neural networks, Perth, Australia, 1995, pp. 1942-1948. doi: 10.1109/ICNN.1995.488968.
[25] C. Li, D. C. Coster, Improved particle swarm optimization algorithms for optimal designs with various decision criteria, Mathematics 10 (13) (2022) 1-16. doi:10.3390/math10132310.
[26] S. O. Subbotin, Neural networks: theory and practice, Zhytomyr, 2020, 184 p.
[27] Keras – Models, 2023. URL: https://tutorialspoint.com/keras/keras_models.htm/.
[28] A. Oppermann, Optimization in deep learning: AdaGrad, RMSProp, ADAM, 2023. URL: https://artemoppermann.com/optimization-in-deep-learning-adagrad-rmsprop-adam/.
[29] Root-mean-square error in R programming, 2020. URL: https://geeksforgeeks.org/root-mean-square-error-in-r-programming/.