21th International Conference on Renewable Energies and Power Quality (ICREPQ'23)
Madrid (Spain), 24th to 26th May 2023
Renewable Energy and Power Quality Journal (RE&PQJ)
ISSN 2172-038 X, Volume No.21, July 2023

Prediction models and their role in advanced energy management systems supporting energy flexibility services

N. Uremović[1], N. Lukač[1], P. Sukic[1] and G. Štumberger[1]

[1] Faculty of Electrical Engineering and Computer Science
University of Maribor
Koroška cesta 46, 2000 Maribor (Slovenia)
Phone: +386 2220 7075, e-mail: **niko.uremovic@um.si**, **niko.lukac@um.si**, **p.sukic@um.si**, **gorazd.stumberger@um.si**

Abstract. Automated decision tools, such as advanced energy management systems, are required to involve the electrical grid users in energy flexibility services. This paper focuses on the prediction models as a substantial part of decision strategy in advanced energy management systems and on advanced energy management systems as a tool that supports the active involvement of electrical grid users in energy flexibility services. Prediction models' desired properties are self-establishing and self-adaptation, which require new solutions in data selection, filtering, processing and model learning. Some of these properties are investigated within this paper.

Key words. energy management system, prediction models, self-establishment, self-adaptation, energy flexibility services.

1. Introduction

The electrical grid users should be empowered to be involved in energy flexibility services [1], which means they can decide under which conditions they are ready to provide these services. To implement the European green deal [2], [3] the usage of renewable energy should be improved substantially. Unfortunately, the existing electrical distribution grids are typically not oversized, so they can accommodate a limited share of renewable energy sources and additional loads before grid infrastructure is overloaded or the voltage profiles are violated. The active involvement of distribution grid users in grid operation through the energy flexibility services can further extend this share.

Nowadays, grid users are too busy to permanently influence the operating modes of their devices to support grid operation. This process should be automated by introducing advanced energy management systems (EMSs) that are ''smart'' enough to support the grid operation and simultaneously provide benefits for their owners without reducing their quality of well-being and living [4]. Moreover, the advanced EMSs can also support the building up of local nano- or microgrids [5] with at least limited island (off-grid) operation ability.

The question is how EMSs can become ''smart''. They must provide bidirectional data exchange with all devices connected to them, know the actual status of each device in each time instant and predict their operation in the future considering different lengths of the prediction horizon. The owners of EMSs have no expert knowledge and no time to build up prediction models of individual devices. Moreover, the behaviour of individual devices can change over time based on influential external parameters such as climate conditions and ageing. Thus, the prediction models must be capable of self-establishing and self-adaptation. The following section provides a deeper insight into a process that can give prediction models self-establishing and self-adaptation capability [6].

2. Prediction models

The prediction horizon for the prediction models considered in this work is in the range of several minutes to several hours. The models are used as a support for decisions in an advanced EMS, while the procedure that leads to decisions is not in the scope of this work. Suppose the tariffs change (implicit energy flexibility) or a demand response request is received (explicit energy flexibility). In that case, the EMS must know the current status of all devices and systems connected to it. The prediction models are afterwards used to predict the consequences of different EMS actions on operating conditions of all devices, the owner's quality of living in the time horizon of several minutes to several hours, and the benefits that can be provided for the owner. Based on the performed analysis of different scenarios, the EMS decides what level of energy flexibility services will be provided.

Fig. 1 shows how the offline and online data are processed to achieve the self-establishing and self-adaptation capability of applied prediction models. The red blocks mark the offline workflow used for the model establishment and its adaptation, while the green blocks mark the models in an online workflow used in the EMS. In this paper, the models were established and tested for the three simple devices an air-conditioner, a water heater, and a refrigerator. The considered data are the electrical input power, external temperature, internal temperature and target temperature in all discussed cases.

2.1 Data preprocessing through filtering

To alleviate the negative impact of the sampling and quantization noise in the Internet of Things (IoT) data on the forecasting performance [7], we used filtering. Gaussian filter was used to preprocess the data in the offline setting, and Kalman filter in the online (real-time forecasting) setting. We provided the in-depth rationale and analysis of their respective uses and conducted an experiment determining the optimal parametrization in [6]. The effect of the filtering can be seen in Fig 1. in the graph on the bottom left.

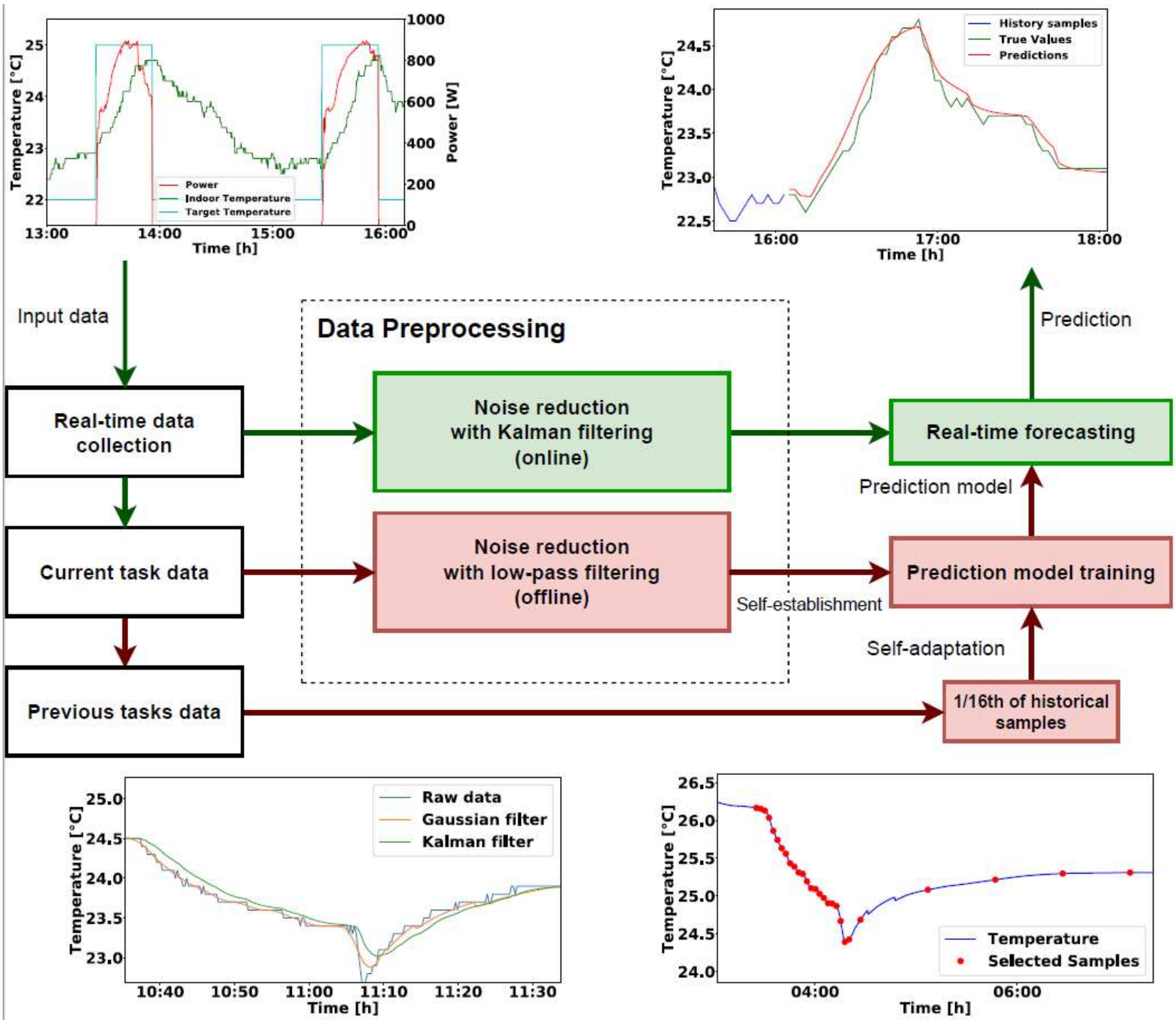

Fig. 1. Online and offline workflow in establishing, adapting and exploiting the prediction model.

2.2 Prediction model architecture

The greatest challenge of developing a forecasting model suitable for lifelong autonomous operation is achieving a reliable and efficient self-establishment and self-adaptation. To that end, we propose an architecture based on a neural network (NN). The advantage of NNs over traditional approaches, such as autoregressive or exponential smoothing models, is that they do not require expert knowledge for their initialization or correction [8], allowing us to develop automatable algorithms for prediction models' initialization and adaptation.

More specifically, we propose a model based on the Long Short-term Memory (LSTM) architecture [9]. LSTM is a type of a recurrent neural network (RNN), which are specifically designed to model the temporal correlation within the timeseries data. We described the proposed architecture, training details and conducted experiments determining the optimal hyperparametrization of the forecast model and the training process in [6].

2.3 Prediction model self-adaptation

The adaptation of the prediction model to changes within the data is key for maintaining the desired forecasting accuracy, needed for successful operation of the EMS. Physical properties of the electrical devices are subject to change due to material deterioration, as well external conditions may change (such as ambient temperature). Furthermore, we cannot assume the training data for the establishment of the prediction model to be complete, considering all possible operating conditions. It is desirable that the model can be established on the minimal training data, which may not include all operation modes of the device, and will definitely not include different climate seasons, or even weather conditions.

When adapting the model to the changes, we wish to fulfil the following criteria:

- Model should achieve accurate prediction on the new patterns.
- Model should retain good forecast accuracy on the old patterns.
- Adaptation should be time and space efficient.

One naïve approach to adapt the model would be to simply train it on the new patterns. While this approach minimizes the training costs and model does achieve accurate prediction on the new patterns, it "forgets" the previous patterns, which is often referred to as "catastrophic forgetting" [10]. The latter naïve approach of training the model, based on old and new data, mostly solves the problem of forgetting. However, it requires storage for all historical data and maximizes the training costs, which is often unforgivable in the setting of EMSs, which should be implemented on the low performance hardware to reduce the initial costs, operational costs and footprint required for mass implementation.

Fortunately, we can achieve the benefit of the second approach already by only repeating the model training on the small subset of the samples from previous patterns (historical data). We have found out, that for most device models, by randomly selecting at least $1/16^{th}$ of the historical samples can practically completely alleviate the effect of catastrophic forgetting. Furthermore, we have developed an algorithm of selecting this smaller subset of samples from historical data, which further improved the forecasting accuracy both on old and new patterns, compared to the random selection. An in-depth description of the algorithm and the evaluation of adaptation approaches is presented in [6].

3. Examples of use in the EMS

The experimental EMS used for testing the prediction models consists of fully controllable units in the form of 3.5 kW PV systems, 5kW and 10 kWh LTO battery storage, 1.8 kW water heater, 300 W refrigerator, and three air conditioners (1 kW electrical power). The discussed experimental system is capable of limited island operation. This work focuses on the prediction model of the water heater.

Following is the description of the scenario in a simple EMS, demonstrating the use of the prediction models in the autonomous decision logic. We demonstrate the use of prediction model in the example, containing the following constraints:

- Assuring user comfort and quality of living by controlling the temperature within predefined bounds.
- Utilizing the PV system production - as much as possible.
- Scheduling the electrical devices to control peak consumption (peak shaving).
- Demand response activation. Sharing the energy from the battery and PV system with the grid.
- Prediction model adaptation to changes in the device behaviour.

The example is demonstrated in Fig 2. and Fig 3. The former depicts the measured and predicted temperatures within the water heater, whereas the latter depicts the water heater energy consumption and solar energy production. The data displayed in graphs was collected from the sensors over the period of eight hours, while the data used to establish the models for each device spanned over four weeks. The forecast horizon used on the graph is two hours. The user predefined rules on the interval were that the temperate may not fall below 50°C or exceed 60°C.

Finally, we provide and discuss the example of prediction model adaptation.

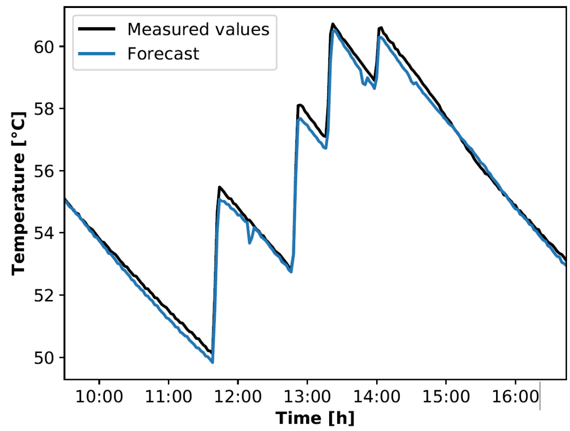

Fig. 2. Measured values and forecasts for water heater temperature.

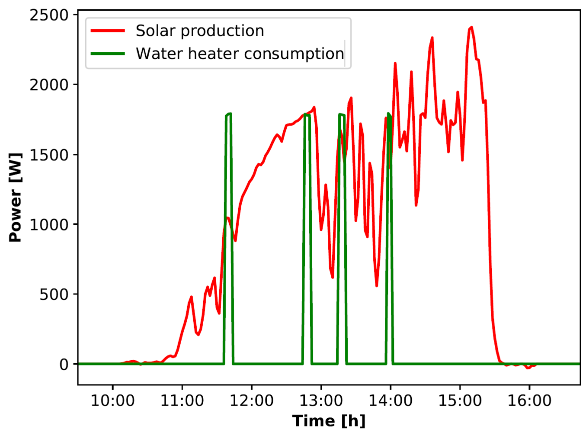

Fig. 3. Solar production and water heater consumption.

3.1 Managing user predefined rules

Essential feature of the EMS is ensuring the comfort and quality of living of the user. This is most commonly managed by defining the boundaries of allowed temperature (room temperature for air conditioners, water

temperature for water heater, etc.). Predicting when the temperature will either fall below the permitted boundary or exceed it is key for all following use cases of the forecasting models.
The example of this is seen on Fig 2. between 11 and 12am. The forecast model predicts that the temperature will fall below the desired threshold ahead of time, allowing EMS to appropriately react to possible demand response activations.

3.2 Utilizing the PV production

Converting solar energy to fill the battery introduces considerable energy loss, as well as the battery discharging itself over time. Instead, we aim to use the solar energy directly to heat up water, control the room temperature etc., when possible.
This is seen at 12:45, 13:15 and 13:55 on Fig. 3, where solar energy production reaches the required to supply power the water heater. Despite the fact, that the forecasted water heater temperature would not fall below the threshold, water heater is activated to take advantage of the solar production. In the case of multiple devices, at such scenario, EMS can use forecasts for all connected devices and assign them priorities based on the importance of individual devices and how far from the threshold their forecast is. The priorities can then be used to schedule devices' activities within the solar production capacity.

3.3 Scheduling the electrical devices to control peak consumption

In the case that multiple devices' temperatures would reach the permitted boundaries at the same time, EMS can use the prediction models to detect this event in the future and schedule the devices' activity pre-emptively to prevent peak consumption (peak shaving).

3.4 Demand response activation

In the case of demand response request, EMS can, based on forecasts of controlled appliances, decide what is acceptable reduction of load power and in some cases even how much power can be transferred to the grid and how long can it support the grid operation.
This can be seen on Fig. 2 after 14:00, where forecasts provide EMS with information, that the water heater's temperature will not drop under the permitted threshold.

3.5 Prediction model adaptation

Proper adaptation of prediction models is essential for proper operation of EMS. This subsection demonstrates superiority of the proposed model adaptation model in comparison with the methods based on the catastrophic forgetting. The results obtained by the proposed model adaptation method described in section 2.3 are compared with the ones obtained without adaptation and those obtained using a naïve approach to model adaptation that leads to catastrophic forgetting.
The example depicts a scenario, in which the model was established on the (incomplete) training data, including temperature range from 40°C to 50°C. The water heater's operation then changed with the changed user rules, influencing the EMS controlling the water heater. The temperature ranges then changed to 50°C to 60°C and the device's activity became more sporadic. An interval from the model establishment period is depicted in Fig. 4 (temperature range from 40°C to 50°C), and the interval from the latter period in Fig. 5 (temperature range from 50°C to 60°C). The intervals of observation in Figs 2, 3 and 5 are identical.
In Fig. 5, which depicts the model predictions based on new patterns, that were not present in the data used for model establishment, we can see, that the model's accuracy without any adaptation (blue) is very poor. While the naïve method of adaptation does improve the accuracy on the new patterns, it drastically worsens model's accuracy on the old patterns, which is evident in the Fig 4. where we can observe the effects of catastrophic forgetting (orange). Finally, we can observe that the proposed adaptation method (green) performs well on both new and old patterns.

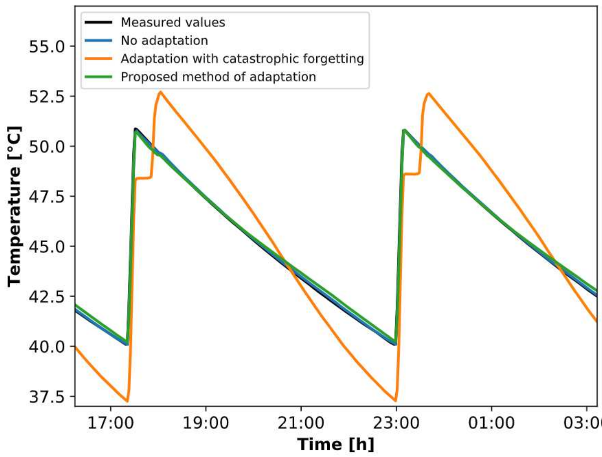

Fig. 4. Comparison of the different adaptation modes based on historical data (old patterns)

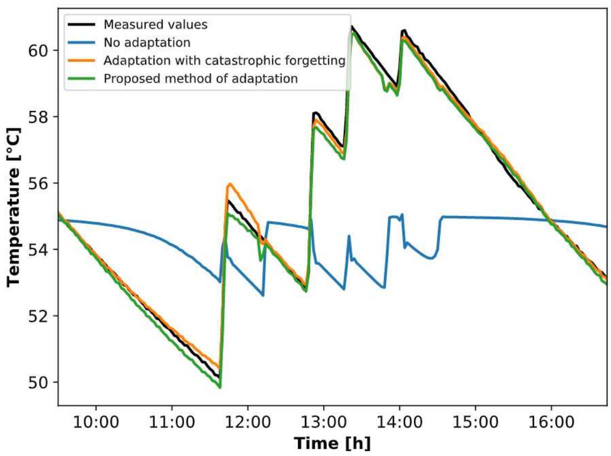

Fig. 5. Comparison of different adaptation modes based on recent data (new patterns)

4. Conclusion

The paper discusses the importance of energy management systems for the involvement of electrical grid users in electricity flexibility services and the role of

prediction models inside energy management systems as a part decision-making procedure.
Presented is the workflow for self-establishment and self-adaptation for lifelong function of prediction models in the energy management system. The use cases for the predictions are presented on real-world examples.
The comparison of predicted temperature time behaviour obtained by the proposed model adaptation with the measured ones shows a good agreement. This agreement is not good when model adaptation is not used, or a naïve approach to model adaptation is applied.
In future work, authors intend to research the extended usage of prediction models in EMS autonomous decision algorithms and the possibilities of taking advantage of transfer learning to improve and accelerate the self-establishment of the models and reduce the need for model self-adaptation.

Acknowledgement

The authors acknowledge the financial support from the Slovenian Research Agency (Research Core Funding P2-0041 and P2-0115, as well as Research Project No. J2-1742). The authors acknowledge financial support for Young Researcher Funding No. 0796-56898 under Research Core Funding P2-0041.

References

[1] European Commission, Directorate-General for Energy, Clean energy for all Europeans, Publications Office, 2019.
[2] European Commission, Communication from the Commission: The European Green Deal, Brussels, 11.12.2019, COM (2019) 640.
[3] M. Sztorc, The Implementation of the European Green Deal Strategy as a Challenge for Energy Management in the Face of the COVID-19 Pandemic, Energies 2022, 15(7), 2662.
[4] G. Štumberger, Energy management: the introduction of flexible energy consumption, storage, and generation in smart grids, smart buildings, and smart communities, Conference proceedings. 7th Symposium on Applied Electromagnetics SAEM'2018, Podčetrtek, Slovenia, 17-20 June, 2018.
[5] S. Ali, A Review of DC Microgrid Energy Management Systems Dedicated to Residential Applications, Energies 2021, 14(14), 4308.
[6] N. Uremović, M. Bizjak, P. Sukič, G. Štumberger, B. Žalik, N. Lukač, A new framework for multivariate time series forecasting in energy management system, IEEE Transactions on Smart Grid (Early Access).
[7] S. Wheelwright, S. Makridakis, and R. J. Hyndman, Forecasting: methods and applications. John Wiley & Sons, 1998.
[8] F. M. Bianchi, E. Maiorino, M. C. Kampffmeyer, A. Rizzi, and R. Jenssen, “Recurrent neural networks for short-term load forecasting,” SpringerBriefs in Computer Science, 2017.
[9] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural computation, vol. 9, pp. 1735–80, 12 1997.
[10] S. Sodhani, S. Chandar, and Y. Bengio, “Toward training recurrent neural networks for lifelong learning,” Neural computation, vol. 32, no. 1, pp. 1–35, 2019.