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Explainable needn't be (much) less accurate: evaluating an explainable AI dashboard for energy forecasting

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Abstract. This paper presents the evaluation results of an improved version of an interactive tool for energy demand and supply forecasting, based on the combination of explainable machine learning with visual analytics. The prototype applies a kNN algorithm to forecast energy demand and supply from historical data (consumption, production, weather) and presents the results in an interactive visual dashboard. The dashboard allows the user to understand how the forecast relates to the input parameters and to analyse different forecast alternatives. It provides small utilities not familiar with AI with an easily understandable, while sufficiently accurate tool for energy forecasting in prosumer scenarios. The evaluation of the forecast accuracy has shown our method to be only 0.26%-1.73% less accurate than more sophisticated, but less explainable machine learning methods. Moreover, the achieved accuracy (MAPE 5.06%) is sufficient for practical needs of the application scenario. The evaluation with potential end-users also provided positive results regarding the usability, understandability and usefulness for the intended application context.

Keywords: Explainable AI, Visual Analytics, Energy Forecasting, AI Benchmarking, Smart Energy Management Dashboard.

1 Introduction

The concept of smart grids includes the integration of real-time energy production of renewable sources (e.g. solar power plants) as well as the need for prompt identification of changes in the energy demand [1]. Conventional practices, especially in local or small utilities were focused on heuristic forecasting based on their previous experience or on the application of relatively simple statistical methods to support the operations related to the management of energy supply and demand. However, these practices have become obsolete with the increase of prosumers in the grids as well as the inclusion of additional factors related to renewable energy sources [2]. As a result, utilities are looking for new ways to get accurate forecasts to increase efficiency and productivity.

To improve their energy-related operations, large utilities have relied on the use of sophisticated forecasting systems; however, these tools usually use complex forecasting methods based on “*black-box*” models which are difficult to understand by people with non-technical knowledge [3] [4]. This is particularly challenging for small utilities that commonly don't have the required technical know-how and AI expertise.

In order to address this situation, several investigations suggested the implementation of explainable machine learning methods to develop forecasting systems. These

methods are focused on interpretability and understandability related to promoting users' trust in the obtained results [4]. As a result, the implementation of explainable AI has proven to help users to understand and get access to transparent explanations about the applied algorithms and their obtained results [3] [4]. Common examples of explainable algorithms include rule-based models, decision trees [3] and the kNN [5].

On the other hand, Filz et al. [6] emphasise the role of visual analytics for facilitating the user interaction with massive datasets to understand the data analysis and make informed decisions based on the identification of changes, anomalies and patterns in the data. In this respect, the use of visual tools such as dashboards [7] has demonstrated significant benefits for short-term forecasting in energy grids. According to Miller et al. [8], these benefits can be divided into (i) approaches that focus on finding patterns in energy data and (ii) those focused on energy management. As an example, visualizations help analysts monitor several parameters in the grids to enable them to support their internal planning processes [7] [8].

The first prototype of our approach combining explainable machine learning with visual analytics was previously presented in [9] and provided a proof-of-concept for our application case. In this paper, we present the second, improved version of our solution and the results of its evaluation, in particular regarding the accuracy comparison to other methods. We first give a brief overview of related work in Section 2. Section 3 gives an overview of the system design focusing on the main improvements implemented in this version of the prototype. Section 4 presents the results of the accuracy assessment of our approach and a benchmarking evaluation comparing the performance of our method with other machine learning methods. We also present the results from a user-centred evaluation with end-users regarding the usability and understandability of the prototype. Finally, section 5 presents conclusions and pointers for future work.

2 Related Work

In order to support utility analysts to improve their efficiency in their energy-related operations, many investigations have proposed the implementation of systems based on visual analytics methods to support users in the analysis of complex datasets [6] [10], based on machine learning models. As an example, Kandakatla et al. [10] explain the benefits of using visual analytics-based technologies to enable users to understand the outputs derived from the forecasting models. They classify the benefits into the following categories: a) trust in the data and the prediction generation process, b) trust in the model calibration metrics, c) trustworthy communication in cyber-physical systems and d) trust in inferences from black-box predictions. Therefore, applications focused on enhancing users' trust present the major benefits in the process.

Although visualizations simplify the analysis of complex datasets, Markus et al. [11] recommend the implementation of explainable processes to contribute to user trust and facilitate their decision-making. In addition, Guidotti et al. [12] conducted an exhaustive survey on the analysis of explainable black-box models and according to their findings, decision tree, and linear models are considered easily understandable and interpretable for humans. Furthermore, in an attempt to identify explainable algorithms,

Dam et al. [13] classified several machine learning methods based on their accuracy and explainability. According to that analysis, the kNN and decision tree-based algorithms are the most explainable. They found that in general the higher the accuracy, the less explainable the algorithm tends to be, and vice-versa. Furthermore, recent research has suggested that explainable algorithms needn't necessarily be less accurate than black-box models [13].

As discussed in [14], the similar-day approach and regression methods are popular approaches for short-term load forecasting due to their simplicity. In a related study, Dong et al. [15] measured the accuracy of a kNN-based algorithm with different datasets related to energy load forecasting to verify the robustness and effectiveness of the model. They presented high accuracy results of the method without sacrificing simplicity. However, in contrast to our work, they didn't evaluate the explainability of their method and didn't use visual elements to specifically support the explainability of the results for the users. In a more general context, Shin [4] conducted an end-user evaluation of several explainability parameters (e.g. trust, performance). According to the results, users like understanding how algorithms work and how the data are analyzed to understand to what extent the results are fair. When the users trust in the results, they tend to believe that content is useful and therefore, user satisfaction increases too. The findings from related work thus support our choice of the kNN method as a suitable candidate for short-term energy demand and supply forecasting in a way that could support understandability and user satisfaction.

3 System design and implementation

The first implementation of our solution approach was previously reported in [9], however, for reasons of comprehensibility we present a brief overview in sections 3.1 and 3.2. In section 3.3 we then focus on the main functionalities of the improved prototype whose evaluation is presented in Section 4.

3.1 Method

Our proposal is based on combining the explainable machine learning method (kNN) with visual analytics methods to implement what we term a Smart Energy Management Dashboard for energy forecasting and analysis. We choose the kNN method as the best candidate with intuitive explainability for users without technical knowledge and AI know-how. The main objective is to support utility analysts to obtain reliable and understandable short-term forecasts of energy demand and supply. The implemented algorithm works with predefined weather input parameters (temperature, wind speed, air pressure and sunshine duration) from a day ahead which are used to identify the most similar days in the historical data. The forecasting results presented to the user are based on calculating the average consumption and production values of the k most similar days identified.

To facilitate the understanding of the forecast, the prototype presents visualizations of the forecasted day, as well as of the k most similar days and the related weather parameters. In this way, the analyst can inspect and compare the visualized information to understand the reasons for the forecasted demand and supply.

3.2 Architecture

The architecture of the Smart Energy Dashboard is presented in Fig. 1. The application uses a MySQL database to store the datasets required for calculating the forecasting results (historical consumption, production and weather conditions) which are also used to create the visualizations. A python script pre-processes and prepares the data in the format needed by the forecasting process. In order to calculate the forecasting results, a modified implementation of the kNN-algorithm developed in python is used to calculate the most similar days regarding the input parameters which are initially pre-loaded in the tool (average weather conditions). The algorithm is based on comparing the average weather input parameters from a day-ahead weather forecast with historical weather data to obtain the k most similar days. To produce the forecast, the algorithm calculates the average energy supply and demand on the most similar days and this result is presented in the dashboard. The visualizations are created by a web-application (implemented with dash and plotly¹) that displays the results obtained from the forecasting process. By default, the application presents the forecasting for the next day, however, the user can modify the input parameters to make a customized forecast (e.g. forecasting a “what-if” scenario for a day with more sun hours).

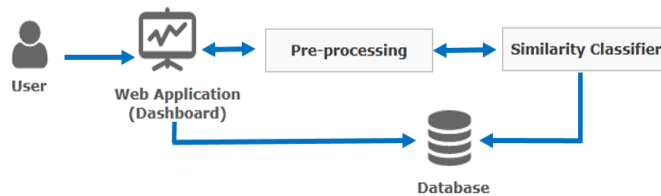


Fig. 1. The architecture of the Smart Energy Management Dashboard.

3.3 Dashboard Design

The prototype includes different visualizations related to the forecasted day as well as the most similar days to support the analysis and understanding of the results. To facilitate the interaction, the dashboard automatically calculates and fills in the input parameters (Fig. 2a) from a connection with an external weather API. However, the user can change these parameters manually to forecast a customized scenario.

The visualizations include different types of charts such as bar charts, line charts, etc. to inform the forecasting analysis (Fig. 2). However, the user can filter the dates to create customized visualizations to perform a more specific analysis (e.g. selecting two days with the most similar temperature). In addition, Fig. 2c shows the results of the

¹ <https://dash.plotly.com/>

expected consumption of the predicted day as well as the amount of energy consumed on the most similar days. This information is complemented with hourly consumption (Fig. 2d) to perform a more detailed analysis and also to help users to identify the peak consumption time (a typical use case for the analysts).

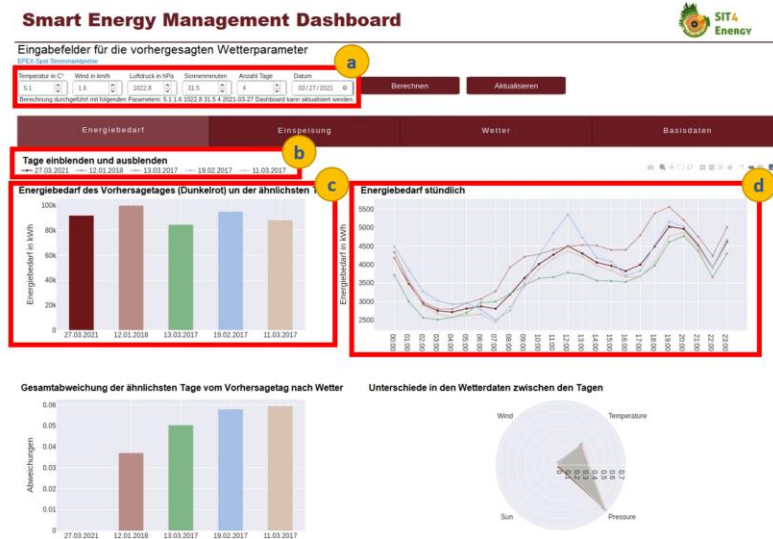


Fig. 2. Smart Energy Management Dashboard: a) Weather input parameters for the forecast b) Filter (toggle) with the forecasted day and most similar dates and c) Forecast of the total energy demand on the forecasted day (dark red) and the most similar days d) Hourly energy demand for the forecasted day and the most similar neighbours.

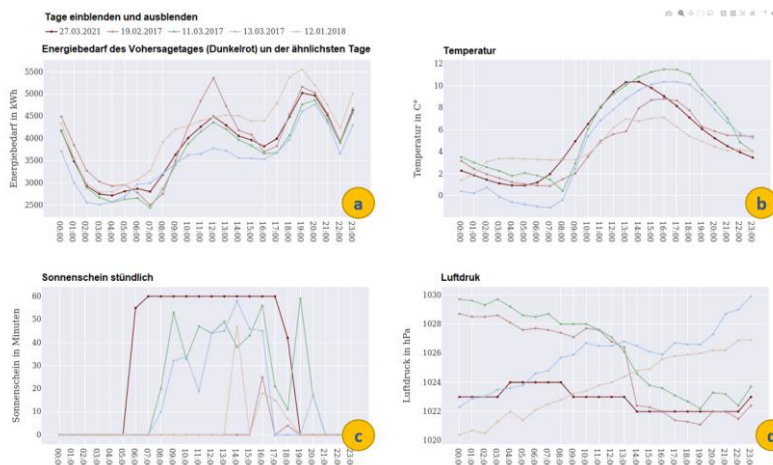


Fig. 3. Detailed weather information in the Smart Energy Management Dashboard: a) Hourly energy demand, b) Temperature, c) Hourly sunshine (in minutes), d) Hourly air pressure.

Additionally, the dashboard includes detailed weather charts (e.g. temperature, sunshine time; see Fig. 3), because they are of paramount importance to understand the forecasted and visualized demand. In this way, the dashboard also contributes to identifying energy-consumption patterns to support the energy planning process.

4 Evaluation

In order to expand the preliminary evaluation reported in [9], we conducted additional tests. The first one focused on an additional accuracy evaluation of the forecasting with respect to different “ k ” values with an improved division of the test and training data. In the second one, we conducted a benchmarking evaluation to compare the performance of our implemented algorithm with other machine learning methods. Finally, a user evaluation was conducted to collect feedback from target users regarding the usefulness and understandability of the prototype.

4.1 Accuracy Evaluation

In order to verify the preliminary accuracy evaluation reported in [9], we improved the method to prepare the datasets to be used in the assessment. In contrast to the first evaluation where the training and test data were obtained by cutting the dataset straight in two halves, in this evaluation, the data were randomly assigned to the training and testing datasets (keeping the 50%-50% proportion). The data set included one full calendar year of historical data for consumption and production in a small municipality of ca. 13.500 inhabitants (from a utility participating in the project) and weather data from a commercial weather service. The evaluation was based on measuring the accuracy error values of MAE (Mean Absolute Error) and MAPE (Mean Absolute Percentage Error) of the average results of 2 to 10 neighbours. As depicted in Table 1, the best accuracy result with a MAPE of 5.06% was obtained from the average of the 4 most similar neighbours (since the averages from 6 to 10 neighbours did not show any better results, they are not presented in the table).

This is a better result compared to our previous evaluation (MAPE of 5.77% reported in [9]). However, the change in measured accuracy suggests that it is important to conduct additional assessments with additional data sets to understand how the accuracy might change under different conditions (e.g. different amounts of historical data).

Table 1. kNN accuracy evaluation of different k-values.

kNN Average Neighbours	MAE (kWh)	MAPE(%)
2	2148.434	5.25
3	2263.809	5.56
4	2057.771	5.06
5	2200.683	5.46

4.2 Benchmarking Evaluation

To assess the relative accuracy of our method with respect to other machine learning methods, we performed a benchmarking evaluation. This consisted of comparing the results of the forecasting based on using our implemented algorithm to the forecast performed with different machine learning methods on the same data. The forecast with the other methods was performed with RapidMiner². As well as in the above evaluation, we measured MAE and MAPE from a dataset from the year 2015 (consumption, production and weather) provided by a local utility. The data were randomly split into training and testing (50%-50%) to be used for each method. The *Gradient Boosted Tree* produced the best results with a MAPE value of 3.3% compared to 5.06% for the *kNN*. However, the accuracy of our method is very close to all methods evaluated, differing only between 0.26%-1.73% (Table 2). Interestingly, the decision tree that is also considered an explainable method [3] performed slightly better than kNN (0.48% better). It would be interesting to perform a more detailed assessment of these two methods regarding their accuracy and explainability trade-off for our application case.

Table 2. Benchmarking comparison with other AI methods.

AI Algorithm	MAE (kWh)	MAPE(%)	Accuracy difference (w.r.t. kNN)
kNN	2057.711	5.06	-
Decision Tree	1861.409	4.58	0.48
Deep Learning	1967.011	4.80	0.26
Generalized Linear Model	1893.497	4.61	0.45
Gradient Boosted Tree	1378.596	3.33	1.73
Random Forest Tree	1532.055	3.76	1.3
Support Vector Machine	2104.956	5.24	-0.18

4.3 User Evaluation

Finally, we conducted a usability and understandability evaluation with five potential users from a municipal utility in a user workshop. The users were between 21 to 70 years old. Although all participants considered themselves to be highly experienced in the use of computers, all of them reported having no experience in using forecasting tools. Two participants stated a medium level of experience with energy forecasting in general, and three participants stated little experience with that. After the dashboard was introduced and briefly explained, participants answered open questions regarding the current forecasting process and the typical use cases in the company (to verify that the requirements haven't changed from the original analysis [16]). Subsequently, they performed several tasks with the dashboard corresponding to the main use cases (e.g. find out the expected consumption and supply for the next day, identify the peak consumption hours for the next day). During the workshop, participants were asked to

² <https://rapidminer.com/>

“*think-aloud*” to get insights on how they were using the dashboard. At the end, they answered a questionnaire focused on evaluating the usability and understandability of the prototype. The items regarding usefulness i.e. performance expectancy (Table 3) and ease of use (Table 4) were derived from the well-known UTAUT model (unified theory of acceptance and use of technology [17]). The understandability questions were formulated specifically for our case (Table 5). After the questionnaire, we also elicited user feedback in a group discussion. We can summarize the main findings as follows:

Usefulness: All participants stated that the dashboard helps them to make the forecasting process quicker, easier and more effective (Table 3, items 1-3). All participants also considered the dashboard to increase their forecasting productivity (item 5). Four participants considered the dashboard to improve their performance and one was neutral (item 4). All but one participant found the dashboard overall useful for forecasting (item 6; the one exception was neutral). Further, during the interaction with the different charts, they expressed their interest in the analysis of hourly charts. This type of analysis allowed them to solve not only the requested tasks but also additional insights such as the identification of outlier conditions generated mainly by weather changes that could represent important facts for their planning.

Table 3. Answers to questionnaire items regarding usefulness: (1) do not agree at all, 2) rather disagree, 3) neutral, 4) rather agree, 5) fully agree.

Statements	1	2	3	4	5
1. I can use the dashboard to make energy demand and supply forecast more quickly	0%	0%	0%	60%	40%
2. Using the dashboard increases my effectiveness in forecasting energy demand and supply	0%	0%	0%	60%	40%
3. Using the dashboard makes it easier to forecast energy demand and forecast	0%	0%	0%	60%	40%
4. Using the dashboard improves my performance in forecasting energy demand and supply	0%	0%	20%	60%	20%
5. Using the dashboard increases my productivity in forecasting energy demand and supply.	0%	0%	0%	40%	60%
6. The dashboard was easy to use	0%	0%	60%	40%	0%

Ease of use: All but one participant found that it was easy to learn to use the dashboard and that the interaction was clear and understandable (item 6-7). Thus, it is surprising that the overall ease of use of the dashboard has been positively assessed by two participants with three being neutral. Feedback from the discussion suggests that this is largely due to different screen sizes used by the participants and that the dashboard should be optimized to better deal with this situation. Most participants interacted with the dashboard on their own computers from their homes (one from the office). As some screens were smaller than others, for some participants it was necessary to increase the zoom in the browser to facilitate the interaction with the charts. The same situation has

occurred with some titles and legends in the interface that appeared too small. Also, one user had connection issues during the workshop and it took him a little bit longer to launch the application. Based on these observations we can implement the corresponding improvements in the next version of the prototype.

Table 4. Answers to questionnaire items regarding ease of use: (1) do not agree at all, 2) rather disagree, 3) neutral, 4) rather agree, 5) fully agree.

Statements	1	2	3	4	5
7. The interaction with the dashboard is clear and understandable	0%	0%	20%	80%	0%
8. I find it easy to learn how to use the dashboard	0%	0%	20%	80%	0%
9. The dashboard was easy to use	0%	0%	60%	40%	0%

Understandability: The participants were asked to identify the expected forecast for the day ahead. By interacting with the first screen (Fig. 2), they found the expected consumption in the first bar chart (Fig 2c) and complemented the understanding with the hourly data in the first line chart (Fig 2d). Three participants explicitly mentioned that “.. *the interaction with the line charts helps to understand better the expected consumption..*”. As the results in Table 5 show, the use of visualizations to support the understandability of the forecast has been positively affirmed (one participant was neutral). A “control” question asking specifically about the helpfulness of charts for understandability of the forecast had a slight deviation (one neutral, one negative). This suggests that more investigation should be given to the role of specific charts.

The item about the helpfulness of visualizing the similar days for understanding the forecast was positively affirmed by all. Overall, this suggests that the implemented combination of the kNN forecast with accompanying visualizations to facilitate understandability is a viable approach for our application case. Finally, we identified some insights to further enhance the understandability of the forecast: (i) include additional charts regarding additional weather conditions (e.g. wind speed), (ii) include the numeric value for the total consumption forecast in a visible place on the first screen, for a quick reference immediately after the application has been launched.

Table 5. Answers to questionnaire items regarding understandability: (1) do not agree at all, 2) rather disagree, 3) neutral, 4) rather agree, 5) fully agree.

Statements	1	2	3	4	5
10. Based on the analysis of the visualizations, I can understand the forecast results presented in the dashboard	0%	0%	20%	80%	0%
11. The similar days presented in the dashboard help me to understand how the forecast was calculated	0%	0%	0%	80%	20%
12. The charts in the dashboard help me to understand the forecast of energy demand and supply.	0%	20%	20%	20%	40%
13. Using the dashboard allows me to understand how the expected forecast comes about					

5 Conclusions and Future Work

In this paper, we presented the design and evaluation of an explainable AI dashboard for energy forecasting that combines explainable machine learning and visual analytics to enable small utilities to forecast energy demand and supply in an easily understandable way. The presented improved prototype (compared to a previous version [9]), was developed by using open source software (dash, python). This makes the deployment of our solution more accessible, especially for small utilities. The focus on providing an explainable application developed from a user-centred design perspective also facilitates the transition from their traditional forecasting practices to the use of a more sophisticated analytical tool.

The improved evaluation setup has demonstrated a higher accuracy than in the previous test (MAPE 5.06% vs 5.77% presented in [9]). This shows the importance of choosing the appropriate test design with respect to training and test data sets. But it also highlights the potential sensitivity of the method to different data conditions. Therefore, additional evaluations with more extensive and varied datasets should be performed for a final accuracy assessment in future work.

The results of the benchmarking evaluation comparing the accuracy of our method with other machine learning methods confirm the viability of our approach. Although most of the other methods showed a somewhat better accuracy, the difference was very small (0.26-1.73%). Moreover, all but one of the better performing methods are much more complex and difficult to explain to users without profound AI expertise. The decision tree, as the only method with potentially comparable explainability to kNN, has performed with only 0.48% better accuracy than our solution. This suggests that this could be another candidate algorithm to further improve the accuracy while potentially retaining explainability.

However, this is only a hypothesis that should be investigated in future work, in particular, because decision trees can grow quite complex while the kNN mechanism and its results are intuitively easily explained to non-technical users. We consider this intuitive understandability and the simplicity of the kNN implementation to be a major advantage for achieving the goals of our approach: providing an easily implementable and understandable forecasting solution for small utilities with no AI expertise.

This choice is supported by the results of the user-centered evaluation where both the usefulness and the understandability of the implemented forecasting solution have been positively assessed. However, these results need to be taken with caution, since the number of test participants was small (5 participants) and all of them were from one utility. We aim to repeat this evaluation with a larger group of users from different utilities, although for this some organizational and technical challenges need to be solved (e.g. obtaining historical data from different utilities).

The dashboard is currently being tested in a pilot trial with the same participants to gain more insights from everyday use. We will further improve the dashboard design by including the recommendations provided by the users during the evaluation (e.g. increasing the font size to adapt to different screen sizes). The explainability evaluation could also be performed in more detail (e.g. the role of specific visualizations) and with additional metrics, such as interpretability and fidelity [11] in future user studies.

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