Digital Transformation Using Artificial Intelligence and Machine Learning: An Electrical Energy Consumption Case

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Abstract. Companies nowadays eagerly compete in providing their customers with the best possible services, where the companies in the electrical energy market are no exception. As artificial intelligence and machine learning are considered the fundamental multi-purpose technologies and the innovation entity with the most significant potential for disruption, the companies strive to adopt these technologies and integrate them into their business processes. To test the possibilities for the introduction of AI and ML methods in their information system and business processes, we established a pilot project with a company operating in the electrical energy domain. An electrical energy consumption forecasting model has been developed alongside with some additional components. The obtained results show that a proper use of AI and ML methods can offer means for providing new and advanced services to different kinds of company's customers.

Keywords: Digital transformation · Artificial intelligence · Machine learning · Power engineering · Electrical energy consumption · Prediction

1 Introduction

Efficient processing of business data has always been at the heart of the electrical power engineering industry and its related activities, enabling it to provide secure, reliable and high-quality services and transparent operations [1]. In times of constant growth of both the volume and details of data collected on the one hand, and the desire and need for their best use on the other, we are witnessing extremely rapid development of information technology, software solutions and services. As the overall amount of generated data grows daily, so does the ability of computer systems and approaches to process this mass of data and discover new, more accurate insights. In doing so, modern methods of artificial intelligence (AI) and machine learning (ML) are the ones that enable the designers of information systems and software engineers to develop new services based on in-depth automated processing of the captured data. When properly implemented,

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software solutions based on AI methods and ML algorithms can thus offer a range of functionalities as well as new and improved business solutions which provide customers with a new level of user experience, while offering to provider a competitive advantage.

However, advanced ML methods and the theory behind such increasingly capable intelligent solutions are becoming more and more sophisticated and complex. While bringing ever new functionalities to users, software engineers, IT designers and developers of new systems and solutions on the other hand are faced with a serious challenge from such a development, as they do not have enough time and opportunity to keep up with the technological progress alongside with their everyday operational tasks. In fact, the challenges are all the greater because, as technology evolves, the concepts of their use often change as well. For this purpose, we established a pilot project with the company Informatikad.d., in order to test the possibilities for the introduction and integration of AI & ML methods in their information system and business processes.

The main contributions of this paper are:

– to present a brief overview of the digital transformation using AI and ML,
– to elaborate the digital transformation process with AI and ML on a real-world electrical energy consumption case, and
– to present some general results of a pilot implementation of the electrical energy consumption forecasting model, that has been developed, alongside with possible benefits of such a model for the company adopting it.

2 AI & ML for Digital Transformation

AI is a technology that is transforming businesses as well as our everyday life. It is a wide-ranging tool that enables people to rethink how we integrate information, analyse data, and use the resulting insights to improve decisionmaking.AI is considered the innovation entity with the most significant potential for disruption [2] and the fundamental multi-purpose technology, especially in relation to machine learning [3].

With the proper introduction of intelligent software and services companies can improve product capabilities and service quality, communicate better with customers, streamline operations, and create predictive and accurate business strategies. However, not many companies nowadays have the skills and capacity to adequately address and tackle the whole digital transformation process using AI & ML. For this purpose, they need help from a competent knowledge provider. Such help commonly encompasses three main phases:

– identification phase, with the search for business cases where it makes the most sense to implement AI solutions,
– design phase, where the research is performed on how to design and develop AI & ML methods and solutions, and how to integrate such solution into the company's business model, and
– implementation phase, encompassing a pilot implementation and its evaluation, as well as the transfer of knowledge from a knowledge provider to the company.

If the company decides to fully adopt the tested technologies on the selected, and possibly other, business cases, it will need to build the proper capacity and skills. Thus, it is of vital importance, that counselling and education accompany all these phases.

3 Digital Transformation with AI & ML in the Electrical Power Engineering

The process of digital transformation with the use of AI & ML methods have been established between Informatikad.d. (the company seeking to leverage its business processes with the help of AI & ML) and the Intelligent Systems Laboratory from the University of Maribor (the knowledge provider). The basic purpose of the established cooperation was to implement a digital transformation in a part of the company's business model. AI &ML are certainly tools that can be used to implement digital transformation that helps in gaining a competitive edge with customers at present and in the future. As the company's core business is providing services for electricity distribution companies, the focus of the transformation was analysing and predicting electrical energy consumption. For this purpose, weperformed a pilot project to introduce AI &ML methods in the company's business solutions.

Informatikad.d. is a company that performs custom information services for most of the Slovenian electricity distribution companies. Their major services include:

- the billing system for electricity distribution (for about 800,000 customers),
- the billing system for selected electricity suppliers (with over 140,000 customers),
- the provision of the electricity market data exchange platform (single entry point), which is used by all Slovenian electricity distributors and all major electricity suppliers (over 30),
- an integration platform based on a service bus, through which over 20 different information systems are already integrated, and
- applications for the management of all consumer-related processes on the side of the distributor (issuing of opinions and guidelines, project consents, connection consents, system use agreements, etc.)

3.1 The Development and Introduction of AI & ML Methods

The basis of the performed pilot project was the development of a prototype back-end software solution for an in-depth analysis of consumer electrical energy consumption data and the use of the results of such an analysis for the implementation of various functionalities. The solution was based on the use of various state-of-the-art AI & ML approaches, methods and techniques. The primary source of data was the captured historical data on measured consumption at individual metering points.

The basic developed functionalities include:

- machine learning models for predicting electrical energy consumption for each consumer (daily, hourly, and 15-min forecasts),

– detection of unusual consumption patterns and identification of deviations in consumption, and
– clustering of users (i.e. consumers) based on their consumption behaviour patterns in groups of similar users regarding the electrical energy consumption behaviour.

The fundamental part of the system is the electrical energy consumption forecasting model. Consumption forecasting is of prime importance for the restructured energy management environment in the electricity market [4]. Despite the increase of smart grids technologies and energy conservation research, many challenges remain for accurate forecasting of electricity production and/or consumption using big data or large-scale datasets [5]. Different approaches have been used recently for electrical energyconsumption forecasting, from various regression methods [6], different probabilistic forecasting techniques [7], all the way to the most advanced ML methods such as artificial neural networks [8] and especially deep learning methods [4].

We designed a hybrid forecasting algorithm, using polynomial regression with regularization for fast generalized long-term forecasting and deep Long Short-Term Memory (LSTM) recurrent neural network for accurate short-term forecasting, which turned out to provide accurate predictions (see an example in Fig. 1).The multivariate LSTM neural network comprised a series of LSTM and Dropout layer pairs with decreasing dropout probability rates, the final Dense layer and the RMSprop optimizer. The network was fed with daily measurements of at least two years to be able to capture seasonal effects. The number of neurons of the LSTM layers was set as 5 times the degrees of freedom in the used data (number of samples multiplied by the dimension of each sample). The LSTM has been commonly trained until the stability of loss rate has been achieved.

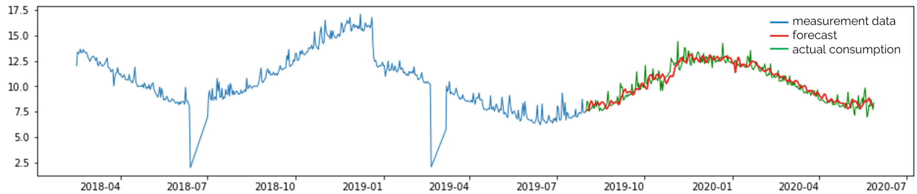

Fig. 1. Electrical energy consumption forecast for one selected household.

The second part of the system is the anomaly detection component, developed for automatic identification of unusual electrical energy consumption and detecting characteristic deviations from the estimated consumption for an individual user. To this end, methods and models for detecting both point (e.g., today's consumption deviates from everyday) and contextual anomalies (e.g., consumption did not increase/decrease as much as would be expected given the circumstances) have been developed. While the point anomalies might represent possible failures, outages, etc., the contextual anomalies might indicate a changed regime of a specific consumer's electrical energy consumption. Figure 2 represents the consumption for a selected household, where both types of anomalies have been detected – the first identified anomaly from the left-hand side represents a point anomaly (a possible measurement error or failure), while the small group of several anomaly points represents a possible concept drift (changed mode of operation, see how the overall consumption has dropped since that point).

The anomaly detection was based on the forecasting model. The exponentially smoothed forecasted values have been used to determine the anticipated “normal” value, with the calculated error (plus standard deviation) on the training set representing the threshold for the “region of normality”. If a real measurement exceeded the anticipated region of normality, it was identified as possible point anomaly. If several consecutive measurements were identified as anomalies, the group was identified as possible contextual anomaly.

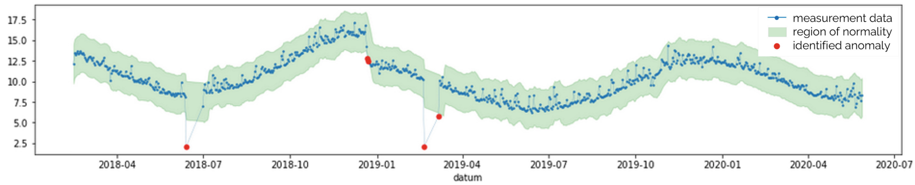

Fig. 2. Identification of anomalies in electrical energy consumption for a selected household.

The third major part of the system is the clustering component, aimed at the analysis and segmentation of consumers into groups of similar users based on electrical energy consumption patterns (Fig. 3 shows two very different profiles, each quite typical for a group of consumers with similar monthly consumption behaviour). Such clustering may provide means for better user management, advanced consumption statistics, and more accurate forecasting, to name a few.

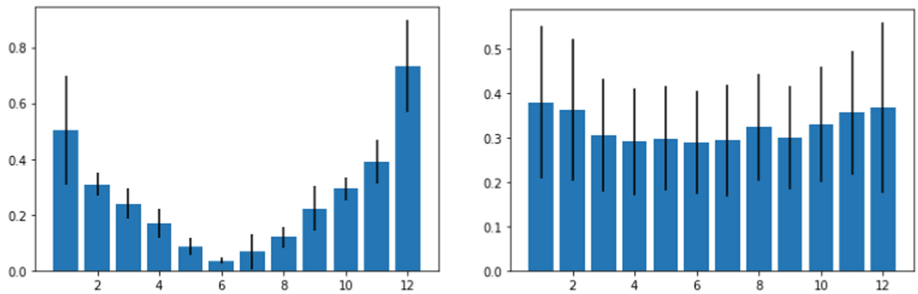

Fig. 3. Two typical monthly user consumption profiles, indicating two different groups of users.

3.2 Electrical Energy Consumption Forecasting Results

The developed forecasting models have been tested on a set of electrical energy consumption measurements. The results of the short-term forecasting using recurrent neural networks (RNN) turned out to be very good (see Fig. 4), achieving less than 10% mean-absolute error (MAE) on average, and around 12% rootmeansquare error (RMSE) – both metrics are calculated on normalized scales and thus expressed as percentages. As the consumption may be very dispersed on some occasions, the standard deviation of predictions is unfortunately quite large (around ± 10% for MAE, and ± 12% for RMSE).

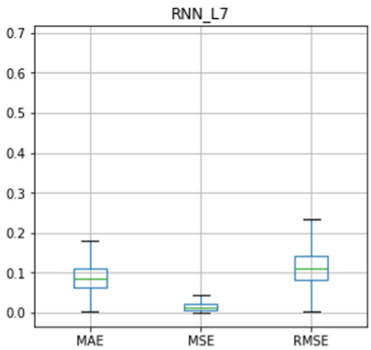

Fig. 4. The predictive performance results of electrical energy consumption forecasting.

3.3 Possible Benefits for the Company

By providing an efficient and accurate forecasting model for the electrical energy consumption (together with other components), the company may be able to offer a set of advanced new services to its various customers:

– for distributors and suppliers: optimization of the amount of electricity, optimization of alternative sources, planning of the electricity distribution network development and investments in the electricity network, …
– for external stakeholders (e.g., regulators): visualization and analysis of consumption by regions, municipalities,…, analysis of consumption behaviour habits, determination of the tariff system and new billing rules,…
– for end-users (e.g., consumers): better monitoring and planning of consumption, detection of faults on devices, more optimal consumption of electricity,…

In this manner, we helped the company to identify, design, and implement (currently in a pilot setting) advanced AI & ML based solutions, which can enable new and advanced services directly to their business users as well as end consumers.

4 Conclusion

In this paper, we provided an overview of the digital transformation based on AI and ML methods, algorithms and tools. We briefly explained how a knowledge provider could help a company, operating within the electrical energy market, when engaging in the adoption of AI and ML methods for their business operations and services. A case of such a pilot project, aimed at providing new advanced services based on an efficient and accurate electrical energy consumption forecasting model, has been provided.

Although the developed forecasting model shows very promising results, the challenging task of providing a production-ready electrical energy consumption forecasting technology is by far not finished. No specific learning model outperforms other learning models for every forecasting problem. Thus, the best algorithm choice depends on specific forecasting tasks and challenges. Even then, there is an enormous space of possibilities for fine-tuning the chosen algorithms' parameters and settings, as they can significantly influence the results, both from the predictive performance point of view, as well as regarding their computational complexity.

Finally, the development of accurate and efficient ML models alone is not even remotely enough to achieve all the benefits the proper digital transformation can offer. However, it is definitely a very good and promising start in this direction, which we will certainly pursue in the future.

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