Smart Grid LAB Hessen

WHITE PAPER

Smart Grid AI: Machine Learning in Smart Grid Applications

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1 Introduction

Who has never dreamed of finding the method to predict the future, mitigate uncertainty, get wise information to ensure that big and small projects would lead to success? In ancient Greece, to learn the future, people consulted oracles who were an integral part of their culture and a few of them like the Pythia of Delphi are still very well renowned today.

Today, humanity seems to trust more in science than supernatural abilities and thanks to this our time is being reshaped by technology. Among these technologies is artificial intelligence (AI), which is currently passing through a flourishing period, capturing the extreme interest of almost all scientific communities and business sectors, including electricity system operators.

Think about voice assistants, automatic tags for people in social media, transcription of voice messages, email spam recognition, and weather forecast, artificial intelligence has already reached deep into our lives. How far this technology can further advance and be trusted in tasks requiring a high degree of responsibility, such as handling key tasks for electrical grid operation? How reliable and robust can an AI algorithm be?

Despite these uncertainties, there is still a lot of excitement about AI development. Several renowned companies and institutions, such as IBM and Massachusetts Institute of Technology (MIT) recognize that we are currently at the peak of inflated expectations and that a deeper understanding of the relevance of this technology, as well as a responsible use of it, is of utmost importance for the future.

In this article, we try to answer to some of the questions surrounding AI by looking under the hood of this technology illustrated with a use case: energy forecast based on smart meters and weather forecast. We hope that this article can contribute to expand your understanding on the potentials and disadvantages of artificial intelligence for smart grid

2 Smart Grid AI

2.1 What is Artificial Intelligence, Machine Learning and Deep Learning?

Artificial intelligence is a very active field of research with practical applications that combine computer science and real-world datasets.

Artificial intelligence typically aims to solve prediction or classification problems by using approaches based on hard-coded knowledge, where input and output are programmed by using logical inference rules or by systems based on acquired knowledge, learned by extracting patterns from datasets. The first approach is known as knowledge base approach, while the second is known as machine learning.

In this article we will focus on the machine learning approach. But what machine is learning? In simple words, machine is learning how to incorporate knowledge about the world by correlating input and output data without prior knowledge of their relationships, instead relying on a number of examples. In most cases, the number of the examples can be significantly large, depending on the complexity of the problem and how the input data, often called "features", can describe the output.

A sub-field of machine learning is deep learning, which has been developing to overcome some limitations in the classic machine learning. Deep learning can solve problems that are difficult to formulate in formal language and that may appear to be subjective and intuitive for humans (i.e. image and natural language recognition). The solution of these problems involves knowledge of the real world and usually a large amount of robust data.

A simplified representation of the AI domain with machine learning and deep learning fields is shown in the diagram Figure 1.

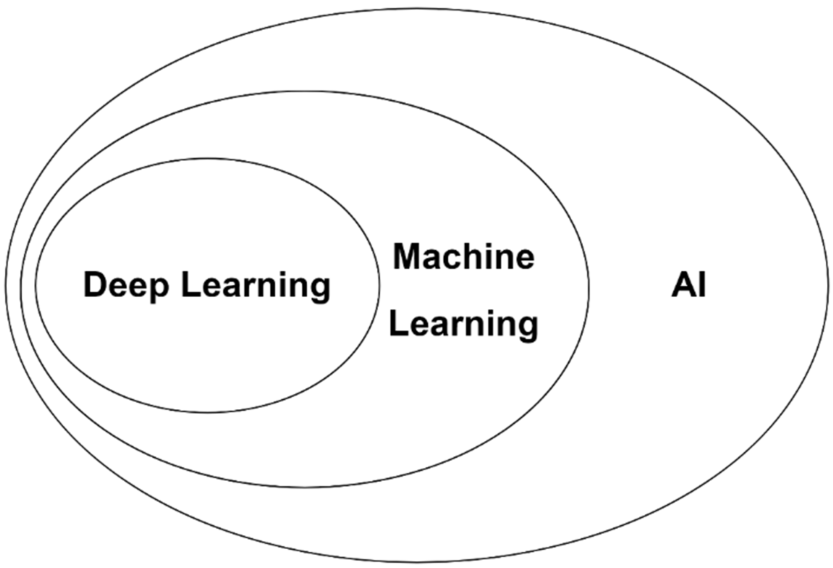

Figure 1 – Venn Diagram defining the field of AI. Machine learning and deep learning are sub-fields of AI. (Based on Ian Fellow 2016 et al.)

In classical machine learning, the system is based on mathematical algorithms often borrowed from the field of statistics, such as linear regression, logistic regression, naïve Bayes, random forest, gradient boosted, trees, etc.

Classical machine learning does not require high computational power and its outcomes are relatively easy to interpret. However, as a downside, it requires a significant effort for the right preparation of the data – feature engineering – and algorithms may face difficulties to learn large datasets or complex functions.

Deep learning can overcome the downsides of classical machine learning by using neural networks, which can better handle complex functions and large data sets, but at the price of higher computational costs and the use of more empirical strategies that make results harder to explain.

The simplest deep learning neural network is the feedforward network. A representation of feedforward network is showed in Figure 2. Feedforward networks are generally composed by (i) an input layer, (ii) one or more hidden layers and (iii) one output layer. The role of hidden layers is to better approximate more complex functions. In theory, a single hidden layer with enough nodes can approximate any function, but the computational effort and complexity of the problem may be so high that in practice the algorithm may not find a solution. For this reason, more than one hidden layer can be used to split a single complex computational task in multi simpler computational tasks. The number of hidden layers is often used also to describe the degree of deepness of a neural network.

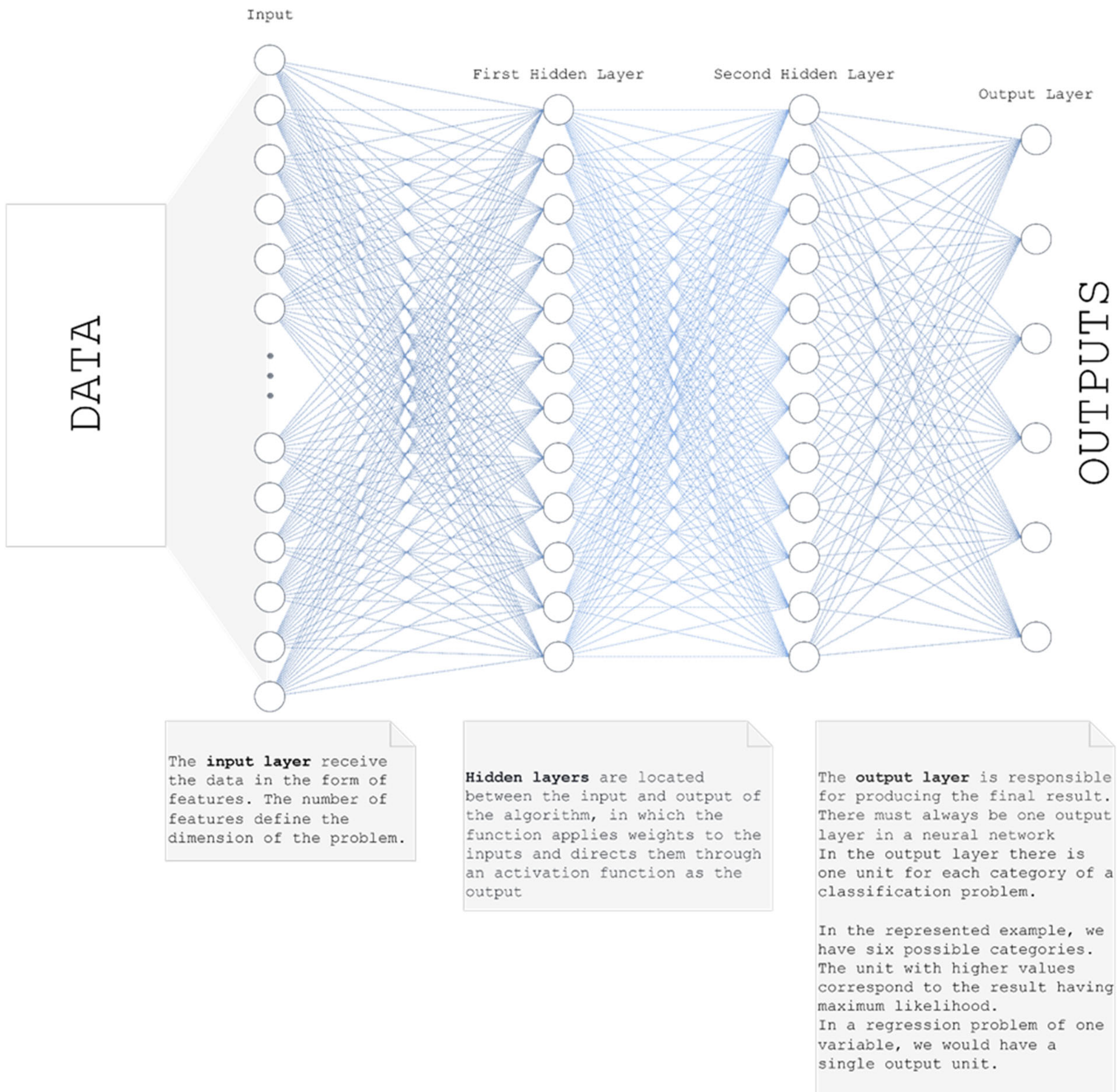

Figure 2 – Example of Feedforward neural network with two hidden layers

Alongside the feedforward neural networks, other well-known and commonly used neural networks are the Convolutional Neural Network CNN, recurrent neural networks RNN (sometime used in combination) and autoencoders. These have been created to better fit specific problems, like image and text recognition, natural language processing and time series predictions. These are the basis of deep learning. In practice, it comprises much more, and researchers are continuously exploring new models and solutions.

Now we know a little more about machine learning, but how does it work and how can we use it for smart grid applications?

2.2 How Machine Learning Works

We can think of machine learning as an iterative process of estimation, evaluation, and optimization, repeated until the desired accuracy of the model is satisfied. This is known as model training. A model must also go through a process of validation and testing, to check if the model also performs well on previously unseen datasets (test data).

It can be observed that a model fitting too tightly to a training dataset, may not have a good performance with the test data. This is known as overfitting, and it is detrimental in machine learning. There are numerous regularization techniques to avoid overfitting, but in principle, all are aiming, with different approaches, to equilibrate the performance of the model on train and test examples. This process is also known as generalization.

However, due to differences between train and test data, it is impossible to fully generalize a model and make our predictions 100% accurate, even when the model is trained with very large datasets. This means that even very well performing models can produce erroneous results. A profound understanding of the model behaviors and the possible errors in the outcomes, as well as the impact on real-world applications shall be responsibly meditated. Whenever this error may have serious consequences, either in terms of human safety or damages to property or ecosystem, machine learning processes shall include humans-in-the-loop.

When responsibly implemented, machine learning can be very useful and significantly improve operations in multiple sectors. Sage Journals reported that AI will automate 57% of today's traditional jobs by 2025 with an increasing of data volume of 530%. Can we image a similar impact on smart grid systems?

Let's have a look at the real AI applications scenario for smart grids, covering the current and most promising use cases.

2.3 Application of Machine Learning in Smart Grid

"Climate change is not on pause". This is the statement of United Nations after acknowledging that the year 2019 was the second warmest year at the end of the warmest decade ever recorded (2010-2019).

Experts say that the drop in carbon dioxide emissions caused by travel bans and economic slowdowns of last two years (2020-2021), make no significant difference to long-term climate change.

In the decarbonization programs of the energy sector, renewables play a key role and electricity utilities are working on new strategies to push forward the sharing of renewables, engaging even more the distribution level of the electrical grid.

In this setting, there is the need to leverage smart technologies, enabling the electrical grid to deal with the expected growth of electric vehicles, further increase of renewable generation, and new energy storage technologies.

Machine learning has already been found to be a good ally of smart grid technologies in several applications and ongoing research shows interesting application fields to be further developed.

To work well, machine learning needs good features, which means sufficiently large datasets able to describe the observations. Smart grid technologies can provide such large and accurate data. However, from the point of view of electricity system operators, machine learning solutions shall be also robust, resilient, and reliable and eventually perform as good as humans. This statement is more complex than it seems, because the evaluation of performance can be very tricky. Let us take a model with almost all correct predictions. It would score a very high accuracy, but if this model is hypothetically used to automate a very critical task, the very few wrong predictions could jeopardize the whole system. On the contrary, a human being could be less accurate than the algorithm, but they may solve unexpected situations or doubts more wisely, for example by conducting further investigation or by consulting other experts. Of course, there are also activities that machines conduct objectively better than humans. For example, the recognition of equipment failures based on continuous streaming of measurements with sampling of about one second. This would be very complicate or impossible for humans, but quite easy for a machine.
Machine learning is a good tool to support smart grids in maintenance, system operation and forecast, such as early detection of system failures, islanding detection, assistance to system re-synchronization, load shedding management, optimization of generation-load management, prediction of renewable power and energy generation, recognition of electric vehicle charging patterns, energy price forecast, etc.

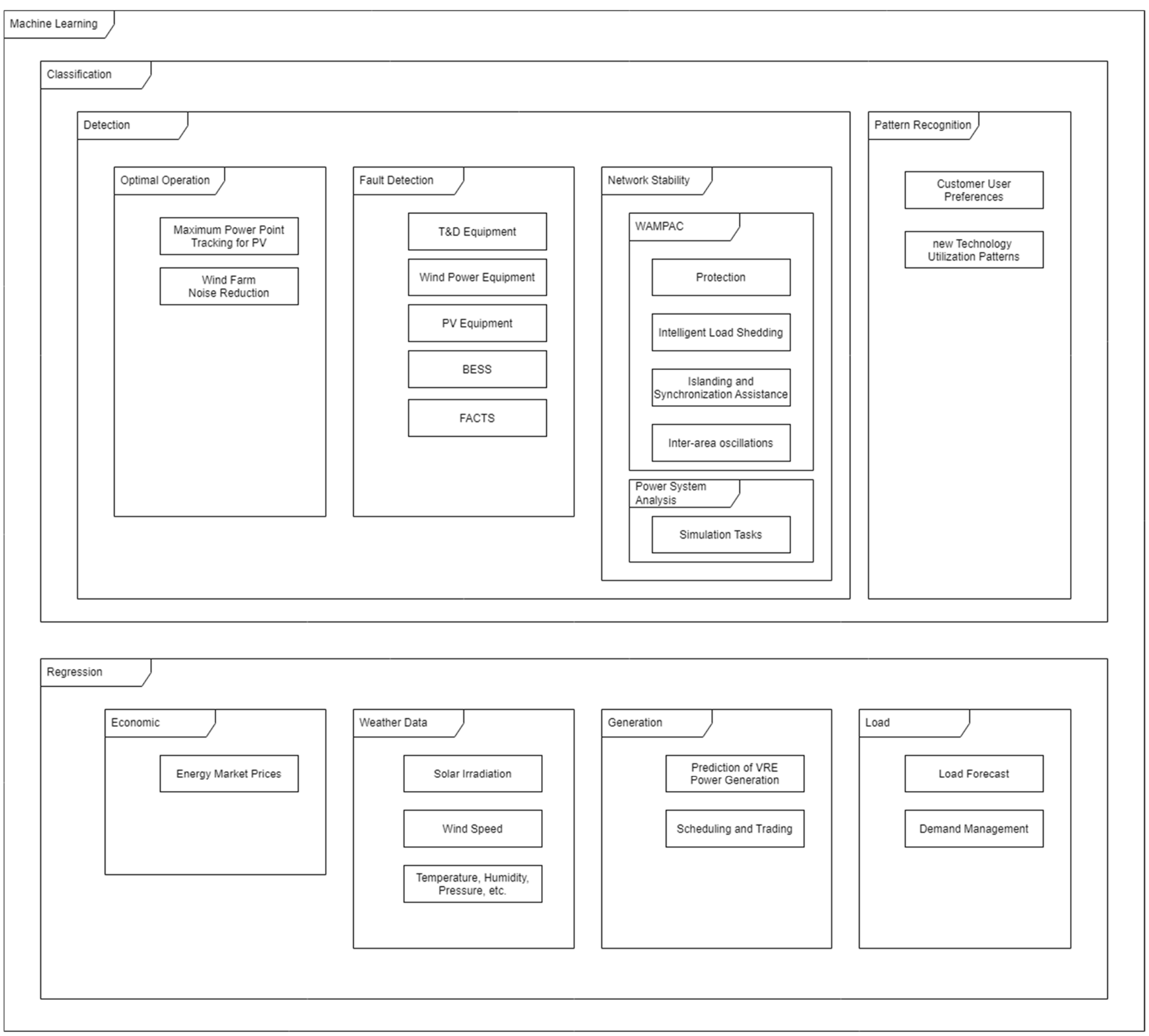

Figure 3 – Overview of machine learning applications for smart grid. The results are not exhaustive, but a condensed summary of about 250 research papers, available on IEEE data base.

The basic concept is that machine learning work well for classification and forecast problems. Starting from these two macro fields, other sub-fields can be found and detailed. In Figure 3, a summary of the most favorable use cases of machine learning for smart grid applications is presented, indicating the related domains and sub-domains.

2.4 Risk and Challenges of AI Application on Smart Grids

The fundamental goal of smart grids is to achieve energy efficiency optimization and to manage complex scenarios that classic T&D technologies are unable to handle. The journey is not free from risks. Cyber-attacks, software bugs, unpredictable scenarios shall be carefully considered in the design and planning of smart grids, especially in combination with machine learning. Strong grids and communication infrastructure are a prerequisite for the implementation of these new technologies. Other challenges are data security, data scalability and latency. Latency is here defined as the gap between the data generation time and the data availability time for applications.

Development of new technologies, exponential growth of computer computation power and infrastructure suitable for big data analysis are helpful in overcoming these challenges.

But how much can machine learning help grid operation? Let's try to answer this question by doing a deep dive in a real use case for energy forecast.

Why energy forecast as a use case? Because energy forecast is already an important practice in the operation of the system and it will be even more important in the future, due to the increasing deployment of electric vehicle charging stations and renewable energy generation at the distribution level. In this context, the available data from the power equipment, smart meters and weather stations will be essential.

2.5 Machine Learning Aided Energy Forecast based on Smart Meters and Weather Forecast – The Case of London, UK

About ten years back, the UK government wanted energy providers to install smart meters in every home in England, Wales, and Scotland. There were more than 26 million homes, with the goal of every home having a smart meter by last year (2020).

The dataset we used in this analysis is a refactored version of the data from the London data store, which contains the energy consumption readings for about two years for a sample of 5,567 London Households that took part in the UK Power Networks led Low Carbon London project.

Classical machine learning and deep-learning models have been defined, trained, and evaluated with the aim to compare their performance on the prediction of daily energy consumption and to compare their results with a naïve prediction, which simply assumes the energy consumed in a specific day will be equal to the energy consumed the day before.

The aim of our study was also to identify the best performing model, providing an energy forecast with a mean absolute percentage error below 2%.

Linear regression, gradient boosted trees and random forest classical machine learning algorithms have been analyzed. A deep learning recurrent neural network named Long-Term-Short-Memory (LSTM), which fit very well for time series predictions has also been implemented.

The architecture of an LSTM recurrent neural network is quite different than feedforward neural network. An LSTM unit is constituted by a cell, carrying information over time intervals and by gates (input gate, output gate and forget gate), which are regulating the flow of information between successive units. With this architecture, unlikely the simpler form of feedforward neural network, LSTM can process entire series of data, improving the accuracy of predictions.

Among the tested algorithms, the LSTM deep learning model performed best (on test data), as evident from the results of Figure 4.

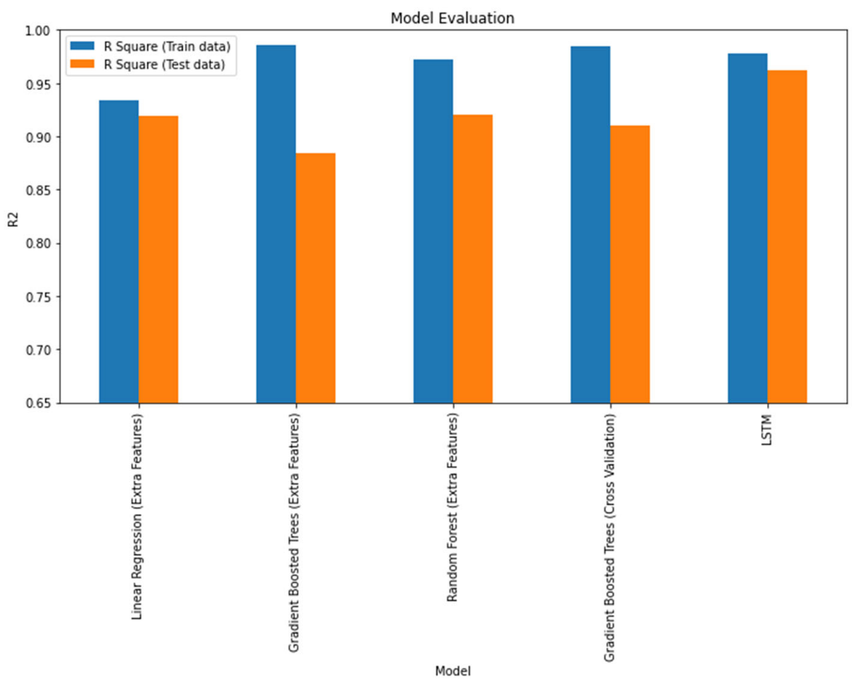

Figure 4 – Comparison of performance (R2) of machine learning models in energy forecast

A comparison of the prediction of energy vs true data for the GBT and LSTM models is plotted in Figure 5 and Figure 6.

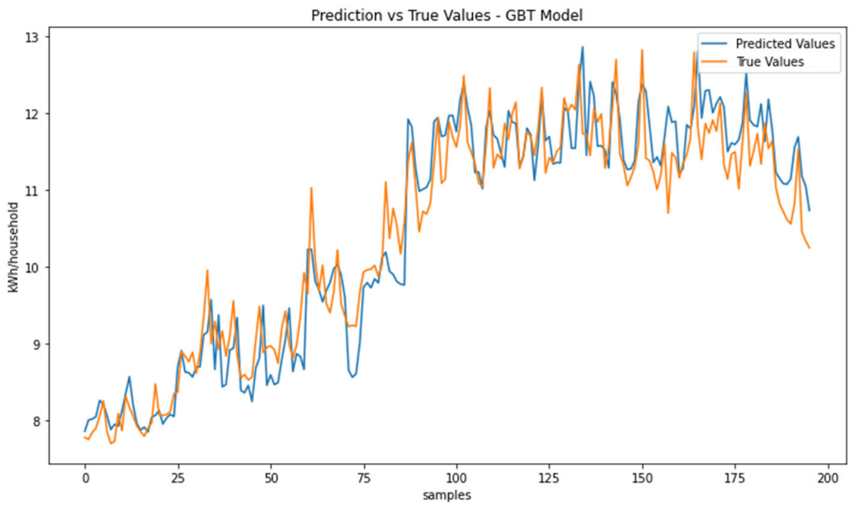

Figure 5 – Prediction vs true value – GBT model (test data)

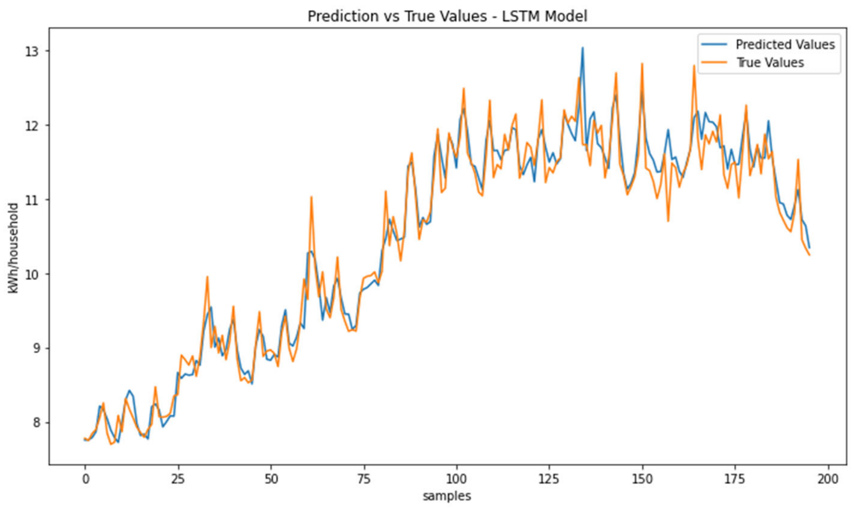

Figure 6 – Prediction vs true value – LSTM model (test data)

As can be seen in the diagrams above, the LSTM model demonstrates the best performance.

By how much does the LSTM perform better than the naïve prediction of assuming the energy consumed in a specific day equal to the energy consumed the day before?

The answer is shown in the diagram of Figure 7.

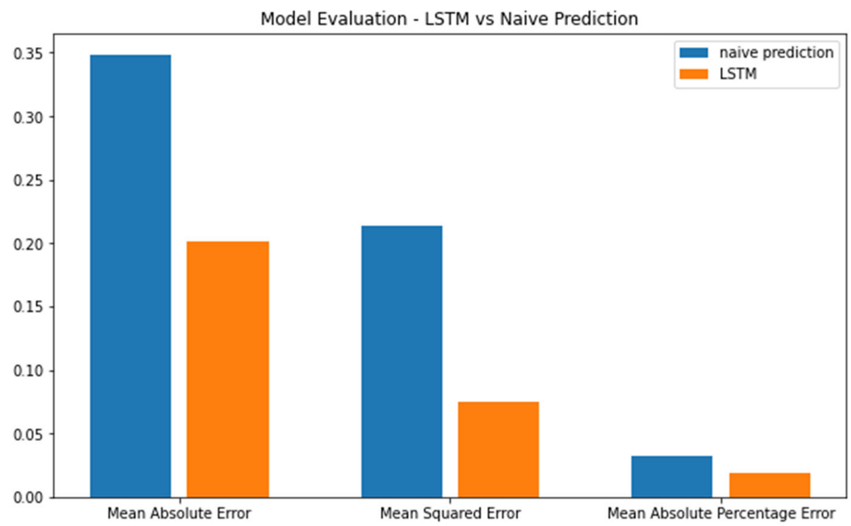

Figure 7 – Performance of LSTM model compared to naïve prediction. A significant improvement is provided by LSTM, compared with naïve prediction, where energy consumption of a specific day is assumed to be equal to the day before.

The LSTM largely outperforms a naïve forecast in all calculated performance indexes. In case of mean squared error, the improvement is quite impressive, from about 0.213 to 0.075. This means that LSTM limits quite well large errors, which are penalized by the square operation of the index. The mean absolute percentage error is also significantly lower from about 3.3% to 1.9%.

In this use case, we found quite stunning improvements of the predictions by using deep learning algorithm, even without a full optimization of the model. The risk of overfitting has been mitigated quite well by some basic hyperparameter tuning, such as learning rate, batch size and number of epochs.

The gap between naïve prediction and deep learning model would probably be even higher in an electricity environment with high penetration of renewables, electric vehicles, and storage systems.

More information on the study is available in a dedicated article of ENGIE Impact.

2.6 Conclusions

The combination of AI and specifically machine learning and deep learning with smart grid applications is going to provide a fundamental contribution to improving the operation of electrical systems that are facing core transformations in terms of architecture and complexity. AI is already widely used in smart grid systems, but its presence is expected to grow further, and more innovations are anticipated in both technologies.

In this article we presented a successful use case of AI for energy forecasting, which we believe is a theme of growing interest.

Finally, the successful deployment of machine learning for smart grids requires robust, secure and scalable data and high computational power.

With the widespread adoption of new communication technologies (i.e. 5G), Internet of Things (IoT) and visionary download speeds of up to 10Gb/s, the levels of data available is expected to grow rapidly. Fast growth is also expected in computational power. This will also require robust, secure, and scalable digital infrastructure connecting distributed data centers.

At the same time, these infrastructures will require more power from the grid, which may be a tread for climate change. Therefore, a significant effort should be dedicated to further improve machine learning algorithms and best practices, aiming to optimize computational costs, keeping machine learning a sustainable solution for the future.

About the Author:

Dr. Luca Pizzimbone is a key expert for power system analysis, active in energy transition and evolution of electrical transmission and distribution grids worldwide. He holds a Diploma in Electrical Engineering from the C.I.T.I. G. Galilei of Genova (Italy), a Doctor degree (Laurea di Dottore) in Electrical Engineering from the University of Genoa and he is an IBM certified advanced data scientist.

Being part of the Power Transmission and Distribution Department of Tractebel Engineering GmbH, he has been leading projects in network planning, renewable energy, hybrid systems and smart grids in Africa, Asia, Europe and Middle East.

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