A Comparative Study of Energy Load Forecasting Algorithms in Smart Homes

Mohammed Qahtani

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Abstract:

In today's world, the conventional power grid, which relies on non-renewable energy resources, is becoming obsolete and outdated, producing destructive effects on the environment and needing costly repairs and maintenance. Implementing the microgrid, a new decentralised, greener grid, has solved many of these issues but is yet to be perfect. Thankfully, the power industry is in a transition into a newer grid that relies heavily on technology, Artificial Intelligence (AI) and makes use of the smart meter. This device collects immense amounts of data that allow for a process called load forecasting. This paper aims to test and compare four algorithms: linear regression, GaussianProcesses, Sequential Minimal Optimization Regression (SMOreg), and Multilayer Perceptrons. The results will be compared using statistical measurement methods (MAE and RMSE) and deduce the most and least accurate prediction algorithms. After performing the tests, it was concluded that (SMOreg) produced the most optimal results and that the GaussianProcesses algorithm resulted in the least accurate outcomes.

Index Terms: Residential Load Forecasting; Smart Meter; Short-Term Load Forecasting(STLF); Machine Learning

I. Introduction

For the past couple of decades, human dependence on electricity has increased exponentially [5]. Home appliances, smart devices and now electric cars all rely on an efficient power cycle. That increase in energy consumption has to be matched with rapid development in power generation and distribution technologies. All of that spending and attention went towards the conventional power grid, which faces many challenges today [6]. Some of these challenges include the depletion of fossil fuels and the environmental disasters their emissions cause, failing to meet demand at peak hours, leading to costly power outages, and immense amounts of electricity going to waste due to failure in load balancing and management.

Some of these issues were fixed with the use of renewable energy sources and implementing the green microgrid, but many problems still weren't solved, such as load balancing and peak-hour power management. Thankfully a new grid is being studied and implemented today, which is the smart grid. A decentralised grid that revolutionises many aspects of the typical grid by relying on technology for power generation, management and distribution. One of the key components of smart grids is the implementation of smart meters. Standard gas and electric meters only measure the total consumption of a unit, while smart meters show the energy consumption of different appliances in almost real-time, which allows utilities to charge different prices according to the time and season.

Immense amounts of data are collected by smart meters, and they allow for a process called energy load forecasting. It is a method where the data collected is fed into machine learning algorithms that produce predictions of the load needed at a certain point in time, and that can range from a couple of seconds to weeks or even years ahead. These forecasts have become essential for efficient supply, storage and pricing of electric power.

Load forecasting in residential buildings is a vital part of the energy cycle, as residential units' power consumption accounts for almost 50% of all energy expenditure [1]. Minimising energy loss in residential units will save a lot of money and manual labour and reduce pollution caused by this industry.

The load forecasting field still faces many challenges in optimizing the prediction model's accuracy. This paper examines the use of Linear regression, GaussianProcesses, Sequential Minimal Optimization Regression (SMOreg), and Multilayer Perceptrons for short-term load forecasting of a smart home. The accuracy of each algorithm will be measured using statistical performance measurements (MAE and RMSE). For evaluation, the results will be compared to determine the accurate load forecasting algorithm.

The paper is organised into the following sections: Section 2 presents the latest state-of-the-art research in this area, Section 3 explains the experiments applied to the algorithms and the methods of evaluation, Section 4 discusses the results of the tests, and Section 5 concludes the paper.

II. Related Work

Machine Learning has opened the door to countless forecasting methods. However, researchers are still facing problems in predicting load in residential buildings, as residential energy consumption is highly volatile due to the many factors that come into play on the single household level. The authors in this paper [10] have tackled that issue by proposing a hybrid model based on time series image encoding and a Convolutional Neural Network (CNN). Compared to typical forecasting methods such as Support Vector Machines (SVM), Artificial Neural Network (ANN), and (CNN), it resulted in higher accuracy of forecasting, achieving a (MAPE) of 12%.

ANNs are widely used as forecasters because these networks can predict the non-linearities of SGs' load with low convergence time. However, sometimes the achieved prediction accuracy is not up to the mark.

Artificial neural network (ANN) is a subfield of machine learning where the algorithm tries to imitate the biological work of neurons in the brain, where each node or unit represents a neuron, and the connections between nodes mimic that of the signals sent in the brain. Then there are recurrent neural networks (RNN), a class of (ANN), where the output from the previous step is fed as input to the current step, and this method produces more accurate results. In paper [2], Online Adaptive Recurrent Neural Networks (RNN) is used for load forecasting to continuously learn from newly arriving data and adapt to new patterns that improve forecasting. It pointed out that offline methods of (RNN) miss the opportunity of adapting to new data.

There are three types of load forecasting [8], mainly short-term load forecasting (STLF), ranging from a couple of seconds to a few hours or days; medium-term load forecasting (MTLF), which varies from several days to several months, and finally there is long-term load forecasting (LTLF) which is one year or more.

Utilities generally use short-Term Load forecasting (STLF) for economic energy dispatch, unit commitment, and energy trade in the competitive market [11]. A multi-model forecasting ANN with a supervised architecture is used in [3], improving the forecast accuracy of DALF models to 98.76% without increasing their execution time. Mohammed et al. [4] proposed a hybrid of Convolutional neural network (CNN) and Gated recurrent unit (GRU) electricity consumption prediction model in residential buildings for short-term future electricity consumption prediction and achieved state-of-the-art results. One of the issues when constructing a (STLF) model is limited data sets, and it's called Cold-starting the authors in [5] proposed a novel STLF model that combines random forest (RF) models while considering two cases (i.e., weekdays and holidays) to solve the cold-start problem. This study focuses on STLF, which is a particularly challenging problem because decisions need to be made within a very short span of time, and there is less room for error.

III. Methodology

Finding an accurate prediction algorithm for energy load is crucial for saving money, scheduling maintenance, and decreasing stress on the grid at peak hours. In this section, an experiment has been applied to choose the most precise forecasting algorithm. The evaluation among (Linear regression, GaussianProcesses, Sequential Minimal Optimization Regression (SMOreg), and Multilayer Perceptrons) is investigated for more reliable forecasts.

Dataset:

The dataset used is data provided by the French grid [7]. It includes 720 instances of hourly historical load data from a smart home listed in the LOAD attribute. The goal is to use the various prediction algorithms; Linear regression, GaussianProcesses, SMOreg and Multilayer Perceptron to predict load for the next three hours. Choosing the most accurate model is based on Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) evaluation methods. For this experiment, Waikato Environment for Knowledge Analysis (WEKA) [9] machine learning program was used. In addition, the time-series load forecasting package was installed and used for regression.

Linear Regression:

After installing the time-series load forecasting package, the WEKA tool is opened, and the (LOAD) is chosen as the selected attribute. The periodicity is set to (Hourly) and then the (Number of time units to forecast) is set to three (next 3 hours). Then the *Linear regression* algorithm is applied to the data. The performance measurements show an MAE of 4.4024 one hour ahead, 5.521 two hours ahead, 7.6365 three hours ahead, and an RMSE of 5.7648 one hour ahead, 7.2572 two hours ahead, and 10.2958 three hours ahead.

Figure 1 shows the actual and predicted load of the trained data using *Linear Regression.*

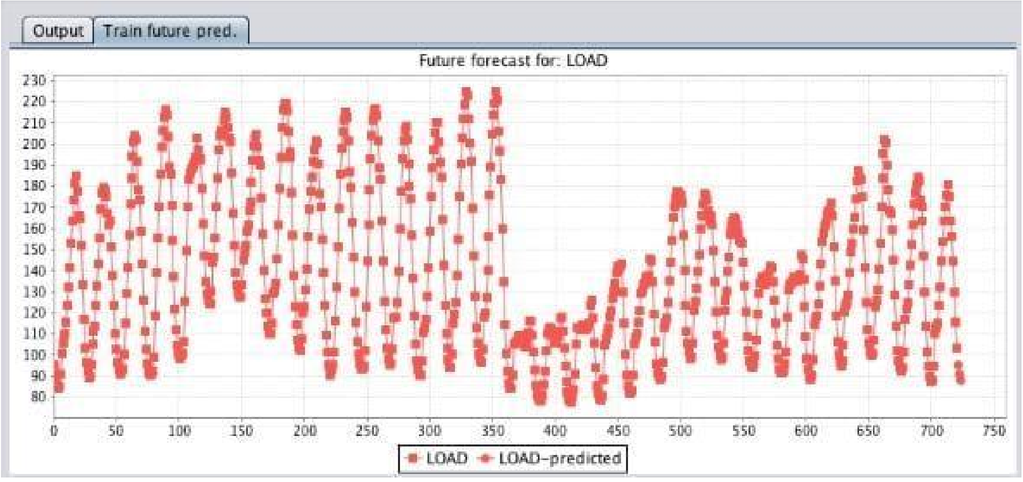

Figure 1: The Actual and Predicted Load (*Linear Regression*)

GaussianProcesses:

Then, the *GaussianProcesses* algorithm was applied with the same attribute and periodicity. The performance measurements for the first step in *GaussianProcesses* show an MAE of 7.3419 and RMSE of 9.2627. The second step resulted in an MAE of 12.4834 and an RMSE of 15.5226. Finally, the third step produced an MAE of 17.0836 and an RMSE of 21.1742. Figure 2 shows the actual and predicted load of the trained data using *GaussianProcesses.*

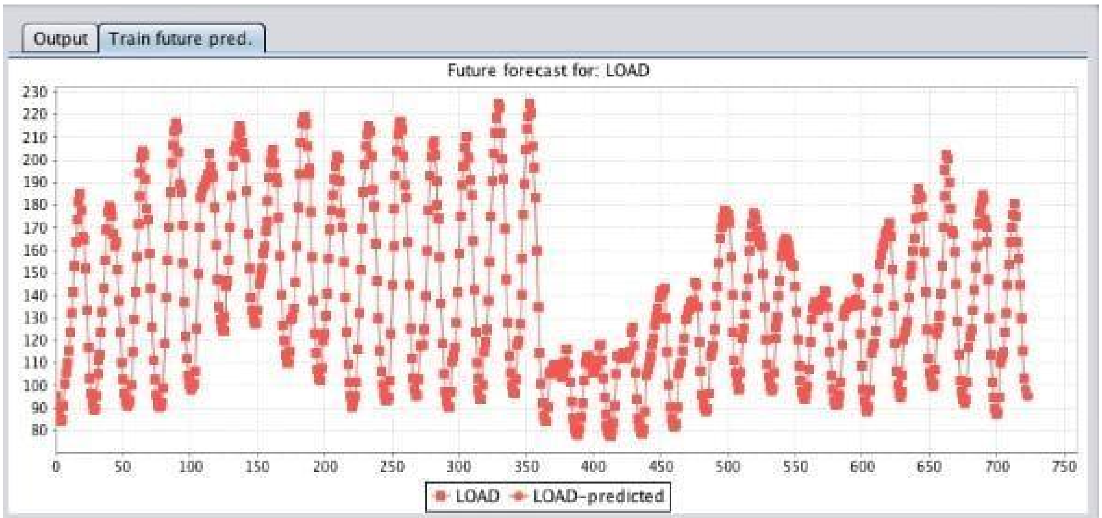

Figure 2: The Actual and Predicted Load (*GaussianProcesses*)

Sequential Minimal Optimization Regression (SMOreg):

The *(SMOreg)* was tested using the same package and settings as the other algorithms. The performance measurements were: an MAE of 2.4574 one hour ahead, 4.699 two hours ahead, 6.342 3 hours ahead, an RMSE of 3.5395 one hour ahead, 6.515 two hours ahead, and 8.9004 3 hours ahead. Figure 3 shows the actual and predicted load of the trained data using *(SMOreg)*.

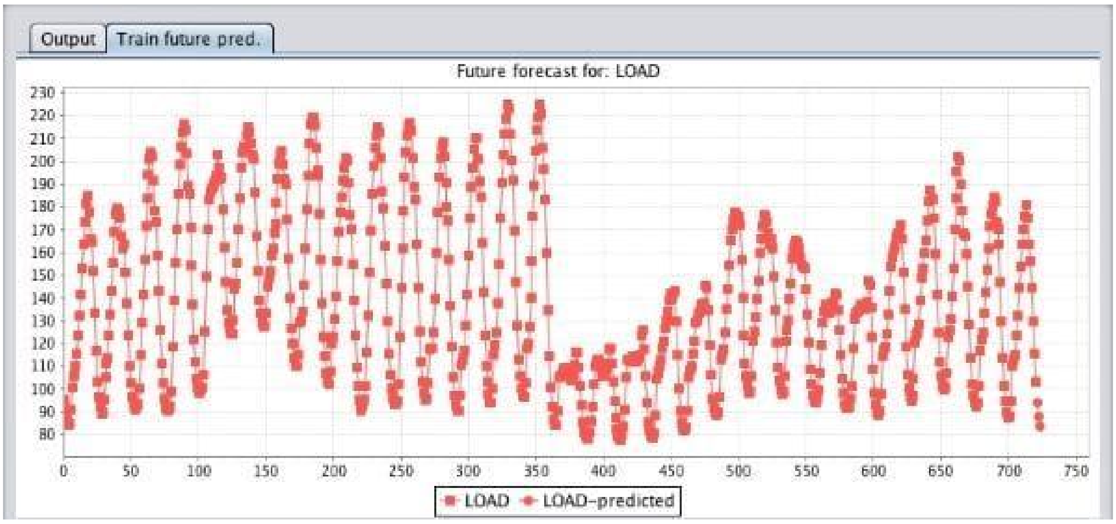

Figure 3: The Actual and Predicted Load (SMOreg)

Multilayer Perceptrons:

Finally, the *Multilayer Perceptrons* algorithm was tested and evaluated using the same methods stated before. The results showed an MAE of 3.0333 one step ahead, 5.9787 two steps ahead, 8.5811 three steps ahead, and an RMSE of 3.8065 one step ahead, 7.5499 two steps ahead, and 10.9644 three steps ahead. Figure 4 shows the actual and predicted load of the trained data using *Multilayer Perceptrons.*

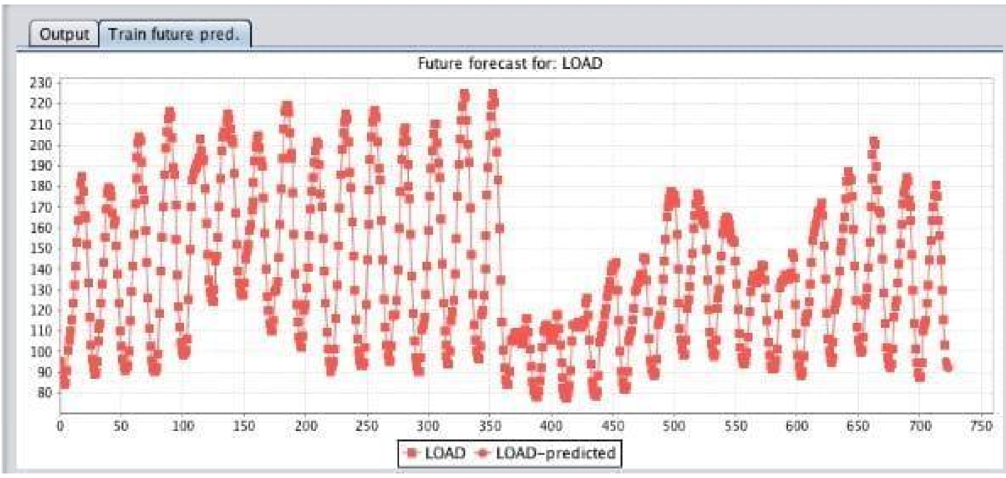

Figure 4: The Actual and Predicted Load (*Multilayer Perceptrons*)

IV. Discussion

It was noticed that prediction accuracy is affected negatively with each instance. The further in the future a prediction is, the less precision it has. The results conclude that the (SMOreg) has been shown to produce the most reliable forecasts one, two and three hours ahead. It is also shown that the GaussianProcesses resulted in the least accurate predictions using all evaluation models. The experiment results are compared in Table 1.

	Linear regression			Multilayer perceptrons		
Periodicity	1-hour-ahead	2-hours-ahead	3-hours-ahead	1-hour-ahead	2-hours-ahead	3-hours-ahead
MAE	4.4024	5.521	7.6365	3.0333	5.9787	8.5811
RMSE	5.7648	7.2572	10.2958	3.8065	7.5499	10.9644

	GaussianProcesses			(SMOreg)		
Periodicity	1-hour-ahead	2-hours-ahead	3-hours-ahead	1-hour-ahead	2-hours-ahead	3-hours-ahead
MAE	7.3419	12.4834	17.0836	2.4574	4.699	6.342
RMSE	9.2627	15.5226	21.1742	3.5395	6.515	8.9004

Table 1: Comparing the MAE and RMSE of the Algorithms, one, two and three Steps Ahead

V. Conclusion

Predicting the load of smart homes, using smart meter data, is an essential part of a smart grid, affecting all parties in the energy cycle. It is still a developing field that faces many challenges, but through the reviewed literature it becomes clear that there are countless ways to tackle these problems, from basic Machine Learning algorithms to complex, hybrid Deep Learning techniques. In this paper, the WEKA tool was used in addition to the time-series load forecasting package. Four prediction algorithms were applied to the data: Linear regression, GaussianProcesses, Sequential Minimal Optimization Regression (SMOreg), and Multilayer Perceptrons. MAE and RMSE were used as evaluation models, and it was concluded that the (SMOreg) algorithm produced the most accurate results, while the (GaussianProcesses) algorithm was deemed as the least accurate. It is also noticed that with an increase in periodicity, there was a decrease in outcome accuracy. The Load Forecasting field is a rapidly developing one with many opportunities for improvement. As for future work, studying larger data sets that include more effective attributes can result in higher prediction accuracy. In addition, a hybrid forecasting model can be proposed and compared with SMOreg for evaluation.

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