A Comparative Study of Energy Load Forecasting Algorithms in Smart Homes

Problem Statement

Utilities face a massive challenge in balancing energy supply and demand in smart homes, as residential power consumption is highly volatile. So they rely on a process called "energy load forecasting", a method where past load data is used to predict future load. Nevertheless, the load forecasting field still faces many challenges in optimising prediction model accuracy.

Objectives

The purpose of this project is to test, measure, and compare a selected set of load forecasting algorithms.

This research aims to :

- Predict energy load one, two and three hours ahead
- Apply various algorithms to actual data
- Evaluate results using statistical measurements (MAE and RMSE) and deduce the most and least accurate prediction algorithms.

Related Work

- There are three types of load forecasting [1], mainly short-term load forecasting (STLF) ranging from a few hours to a couple of 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.
- 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, and it pointed out that offline methods of (RNN) miss the opportunity of adapting to new data.

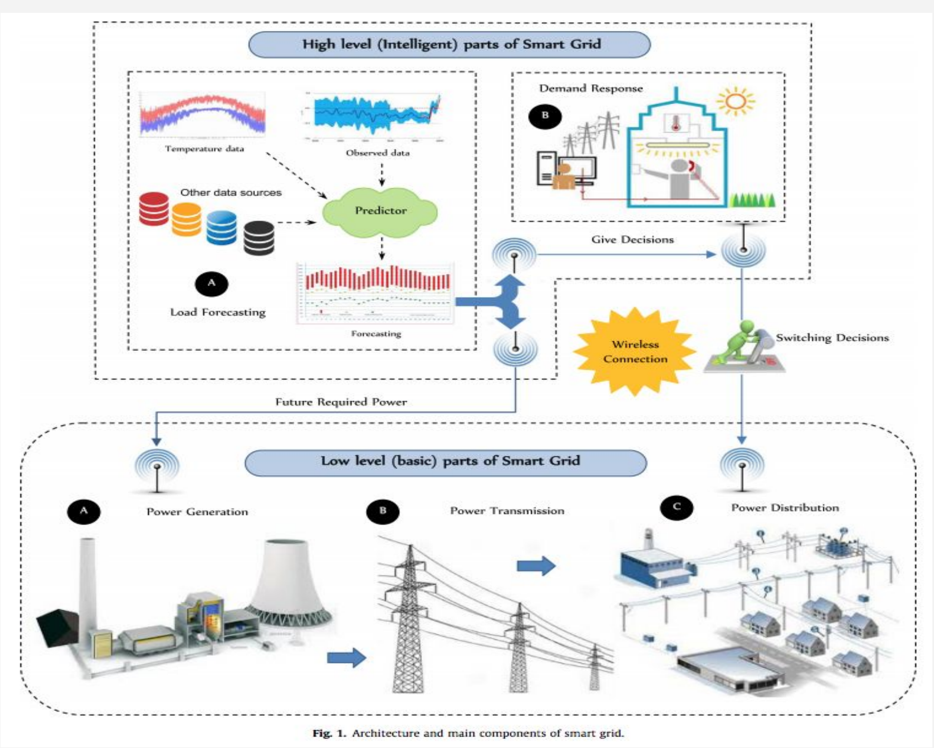


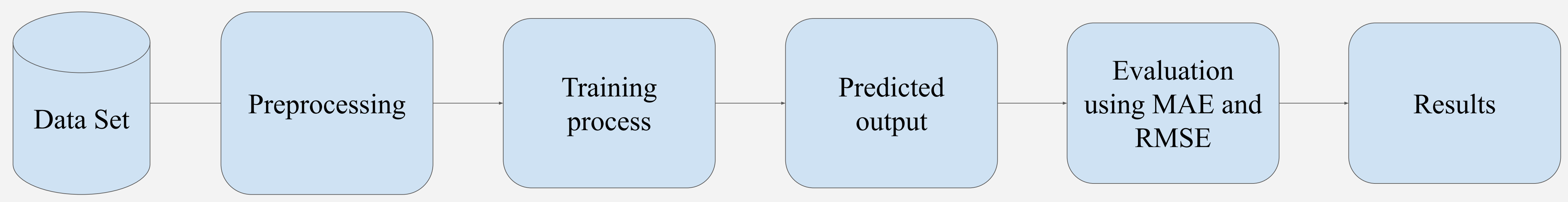
Fig. Main components of smart grid [3]

Hypothesis and Variables

We hypothesized that with the an increase in periodicity, there will be a significant decrease in forecasting accuracy.

- Independent variable : Forecasting periodicity
- Dependent variable : Forecasting accuracy

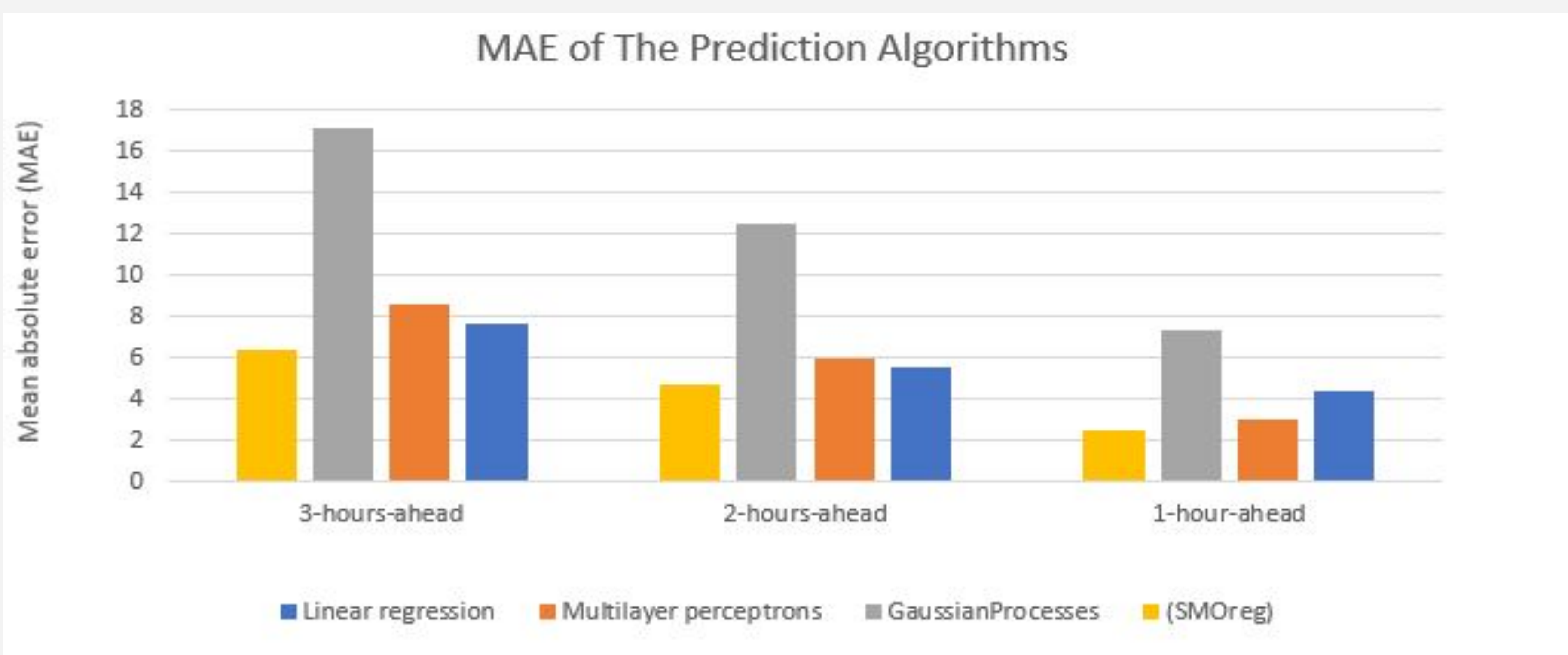
Methodology

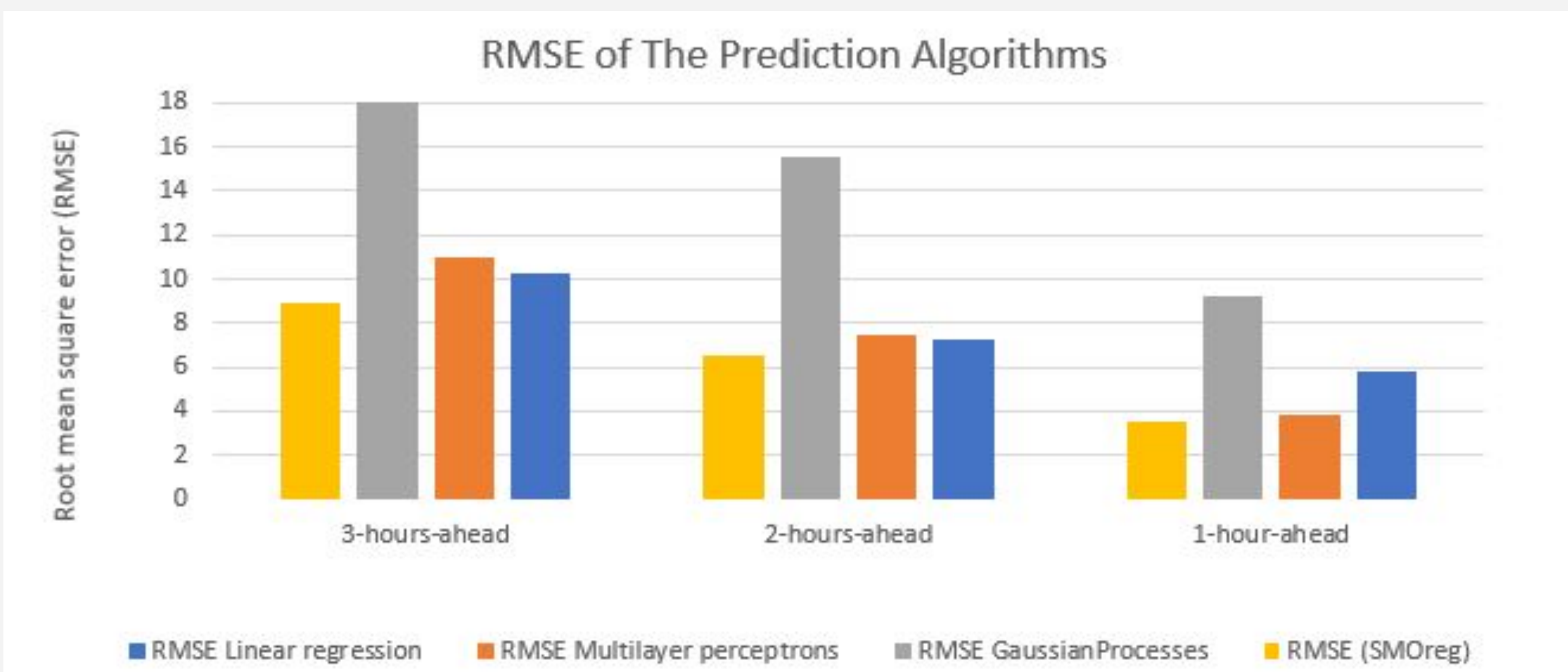


- Program used: Waikato Environment for Knowledge Analysis (WEKA) [4] machine learning program
- Install the time-series load forecasting package
- Choose algorithms; Linear regression, GaussianProcesses, SMOreg and Multilayer Perceptrons
- Upload the data-set and choose the (LOAD) column as the selected attribute
- Predict the load one, two and three hours ahead
- Evaluate the output using: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics.

➢ The used dataset was provided by the French grid [5]. It includes 720 instances of hourly historical load data from a smart home listed in the (LOAD) attribute.

Results and Graphs





	Linear regression			**Multilayer perceptrons**		
Periodicity	**1-hour**	**2-hours**	**3-hours**	**1-hour**	**2-hours**	**3-hours**
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**	**2-hours**	**3-hours**	**1-hour**	**2-hours**	**3-hours**
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**

Discussion

- In this study, the predicted outcome proved that prediction accuracy is affected negatively with each instance. The further a prediction is, the less precision it has.
- The results concluded that the (SMOreg) had been shown to produce the most reliable forecasts one, two and three hours ahead. The GaussianProcesses resulted in the least accurate predictions using all evaluation models.

Conclusion

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.

Applications

- Short-term load forecasting can be used in home energy management systems (HEMS) to give consumption data and feedback for smart home residents.
- It can also be used by utilities to avoid overloading, to make daily decisions regarding maintenance and operations, and to balance energy supply and demand.

Future work

- Short-term : Apply deep learning algorithms for time series forecasting.
- Long-term : Apply the previous algorithms to existing projects involving more data to work with

Phase	Feb 2022			Mar 2022				April 2022			
	W2	W3	W4	W1	W2	W3	W4	W1	W2	W3	W4
Find out real data from an existing case study											
Cleaning the collected data											
Select the appropriate algorithms											
Running the experiments											
Evaluate the results against the defined metrics											

References

[1] Anwar, Tahreem & Sharma, Bhaskar & Chakraborty, Koushik & Sirohia, Himanshu. (2018). Introduction to Load Forecasting. International Journal of Pure and Applied Mathematics. 119. 1527-1538.

[2] Fekri, M. N., Patel, H., Grolinger, K., & Sharma, V. (2021). Deep learning for load forecasting with smart meter data: Online adaptive recurrent neural network. Applied Energy, 282, 116177.

[3] Saleh, A. I., Rabie, A. H., & Abo-Al-Ez, K. M. (2016). A data mining based load forecasting strategy for smart electrical grids. *Advanced Engineering Informatics*, *30*(3), 422-448.

[4]Waikato Environment for Knowledge 'Available [Online] https://waikato.github.io/weka-wiki/downloading_weka/ Accessed: July 2021'.

[5] Hong, T., Pinson, P., Fan, S., Zareipour, H., Troccoli, A., & Hyndman, R. J. (2016). Probabilistic energy forecasting: Global energy forecasting competition 2014 and beyond. *International Journal of forecasting*, *32*(3), 896-913.