A Predictive Model for Automatic Generation Control in Smart Grids Using Artificial Neural Networks

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Abstract. This paper presents a predictive model that estimates the load for an Automatic Generation Control (AGC) system. We start by laying the foundation for our system by discussing the AGC, and the benefits of embedding it in a smart power grid. The AGC as a system is discussed with a keen focus on the mathematical relationship between the load on the system and the frequency deviation. Our predictive model is a deep neural network trained on a multivariate time series dataset for energy consumption collected over 47 months. The results show that it is possible to predict to a high accuracy, the total load on the power system within the next minute. The goal of the predictive model is predicated upon the notion that the ability to forecast the future load on the system results in the ability to estimate the frequency deviation as well, and thus giving the AGC the ability to forecast risks such as a system overload.

Keywords: Smart grid · Artificial intelligence · Artificial neural networks Deep learning

1 Introduction

The smart grid power system relies on information technology for the implementation of a system architecture where the major electrical components communicate over an IP network. A typical smart grid architecture consists of generation, transmission, distribution and end user nodes [1]. Each of these components may communicate with each other with a goal of optimizing system performance and reducing risk. In a smart grid power system, one can envision a system design where the end user node through electronic components such as smart meters and smart appliances relays data about energy consumption and load patterns back to the dispatch center. The data is used for instance, to initiate load distribution, just in time to avoid blackouts caused by overloading the system and will therefore save cost due to damage of equipment.

The operational performance of conventional subsystems found in current power grids, such as the Automatic Generation Control (AGC) already benefit from having some form of feedback about the system load [3, 4]. When there is a change in system frequency with respect to an increase or decrease in load, the AGC, based on the corresponding frequency deviation sends control signals to the generator unit to either increase generation or reduce generation to achieve a balance between the system load and system generation. This balance is not always easy to achieve, with sudden peaks

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in system load, the AGC gives up control to an emergency control unit relying on end user load balancing. Over the past decade, researchers have approached the problem of automatic generation through control theory. The literature survey reveals that in general, the AGC problem has been modelled around controller structure and optimization techniques. We review some of these techniques later in Sect. 2.0.

We approach the problem from a relatively different perspective, we observe the direct relationship between the load on the system and the frequency deviation, a key parameter for the AGC. Therefore, the ability for AGC system to forecast the load in the nearest future might serve a huge advantage and solve the problem of handling surprise spikes in load. We propose a neural network based predictive model for the AGC, trained on real energy consumption data that serves the purpose of forecasting the load on the power grid in the next few seconds. Our proposed system design, couples this predictive model to the AGC and the output from the model serves as a parameter for calculating and thus forecasting frequency deviation as well. However, this paper does not present any simulations that determine if truly this proposition improves performance of the AGC or not. We leave such simulations for future work and instead focus on building the ANN model, this paper lays the foundation for the future work. Section 2 lays the theoretical foundations for the proposed system design, in Sect. 3 we present the architecture of the predictive model, the dataset and we report the model performance.

2 Related Work

2.1 Automatic Generation Control

The electric power system, throughout its life cycle, will exists in any of the following four states; normal, preventive, emergency and restorative [4]. These states describe the operational performance of the system with respect to the frequency deviation and the voltage deviation. The normal state is the desirable state where there is a balance between the load and generation [4].

The goal of the control unit in the power system is to keep the system in a normal state. In any case, it is more than likely that contingencies will arise causing frequency deviation and voltage deviations. One of the most common problems is an overload on the power system, resulting in a mismatch between load and generation. Automatic generation control provides an effective mechanism through which the power system can actively balance power by controlling generation to match the load. In a smart grid power system, the AGC is implemented as a software component [3] and is responsible for adjusting the power system generation to minimize frequency deviation.

The AGC achieves generation control by sending signals to control units for the generator. The performance of the AGC system is dependent on how quickly generating units respond to these signals. In general, we can outline the function of the AGC into;

1. Matching an area's generation to it's a load and to control the system frequency
2. Distribute changing loads among available generators so as to minimize costs.

The first function is achieved by secondary control of the generators to minimize frequency deviation. The frequency of the system is the nominal frequency (usually

50 Hz) of oscillations of the alternating current (AC) being generated by the power system. The system frequency rises when the load decreases and may drop if the load increases. However, it is desirable to keep the frequency constant such that $\Delta f = 0$. We can describe the power-frequency relation for any power system, regardless of the primary source of energy. In Eq. 1, we describe this relation for the turbine-governor control. The power-frequency relation for turbine-governor control [3] is;

$$\Delta p_m = \Delta p_{ref} - \frac{1}{R} \times \Delta f \tag{1}$$

Where Δp_m is the change in turbine mechanical power output, Δp_{ref} is the change in a reference power setting, R is the regulation constant which quantifies the sensitivity of the generator to a change in frequency and Δf is the change in frequency. The first function is also achieved in mutli-area power grid, where each area is connected through a tie-line, by means of load-frequency control (LFC) in which the tie-line power is used. The Area Control Error (ACE) provides each area with an approximate knowledge of the load change and is defined as;

$$ACE = \Delta p_{TL} - \beta \Delta f \tag{2}$$

Where Δp_{TL} is the tie-line power deviation, β is the frequency bias constant and Δf is the frequency deviation, the ACE serves as feedback for the secondary control [4].

The second function is achieved by distributing the load among different unit generators so as to minimize cost of operation and is based on economic dispatch calculation [3].

Frequency Deviations and Associated Controls

The nominal frequency for a typical power system utility is about 50 Hz, with some countries running utility at about 60 Hz. The frequency deviation Δf is a direct indication of the current changes in utility frequency and says something important about the change in the total load on the utility. The frequency deviation in Eqs. (1) and (2) is a crucial variable required for the AGC as shown in Fig. 2 and determines the control signals required to control the generators. The frequency deviation is given by;

$$\Delta f = -\frac{\Delta p_m}{\beta} \tag{3}$$

The symbol Δp_m is known as the change in turbine mechanical power but is actually a ratio of the per unit change in load, β remains the frequency bias constant. For example, if the load on a utility drops by 250 MW, and previously, the generators where running on a base load of 500 MW per unit generator. Then, the unit change in load Δp_m is $\frac{-250}{500} = -0.5$. Take note that the numerator is -250 because there was a drop in the load. From this, using Eq. (3), and a frequency bias constant β of 63.2 per unit, the frequency deviation is given as $-\frac{(-0.5)}{63.2} = 0.0079$ per unit. We can then multiply this by 50 Hz (the nominal frequency) to get the frequency deviation in Hertz $\Delta f(\text{Hz}) = 0.0079 \times 50 = 0.3956\,\text{Hz}$. The purpose of this rather incompletely defined

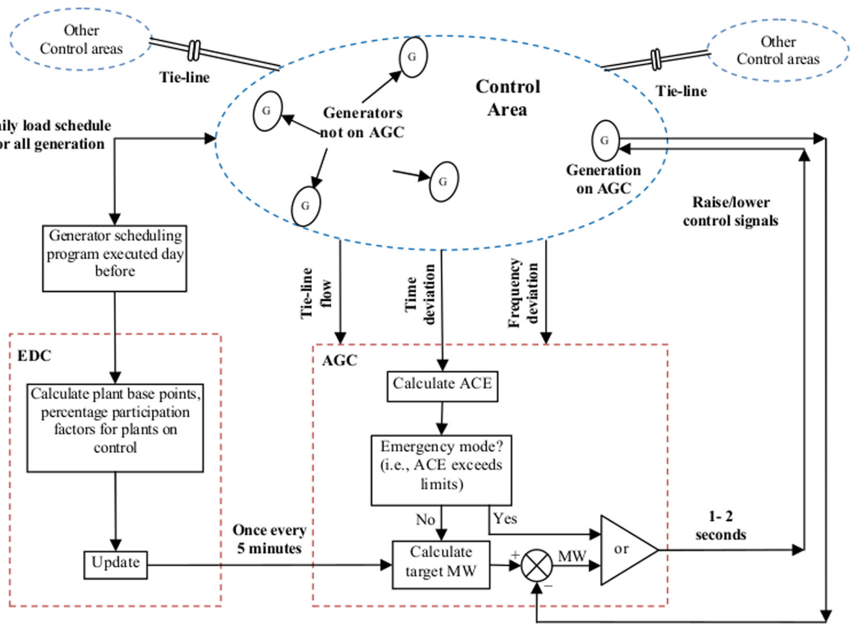

Fig. 1. Typical block diagram for the Automatic Generation Control. The AGC receives input signals including the *frequency deviation*. The input signals are used to calculate the *area control error ACE*, and thus determine the control signals needed to return the utility back to the normal state (image source: Hasan et al.: [4]).

example is to demonstrate symbolically the relationship between the change in load and the frequency deviation, the reader may refer to [15] for a complete example on frequency deviation. The value of Δf along with other parameters, is fed to the AGC and directly influences the type of control signal sent to the utility controllers. The frequency deviation and the corresponding control signal is shown in Table 1.

Table 1. Frequency deviation and associated operating controls.

Range of frequency (f)	Range of frequency at 50 Hz	Types of operation	Types of control
$f^0 - \frac{\Delta f_1}{2}$ to $f^0 + \frac{\Delta f_1}{2}$	50.05 to 49.95	Normal	No controller is required
$f^0 - \frac{\Delta f_2}{2}$ to $f^0 + \frac{\Delta f_2}{2}$	50.20 to 50.05 and 49.8 to 49.95	Normal operation	Primary control
$f^0 - \frac{\Delta f_3}{2}$ to $f^0 + \frac{\Delta f_3}{2}$	50.20 to 51.00 and 49.80 to 49.00	Off-normal operation	Secondary control (AGC)
$f^0 - \frac{\Delta f_4}{2}$ to $f^0 + \frac{\Delta f_4}{2}$	Above 51.00 and Below 49.00	Emergency operation	Emergency control

2.2 Predictive Models for the AGC

Research into various optimization techniques for power systems dates back to the mid 70's and these techniques relied heavily on classical control theory centered around the proportional integral derivative (PID) controller. The nonlinearity of the power system control encouraged researchers to augment the classical controller with optimization strategies and algorithms. Optimization increases the robustness of the PID controller to nonlinearities in parameters such as the load and frequency, however optimization doesn't always lead to successful predictive models. In the literature review, we found that most of the work is centered around optimization techniques, and very little work has been done in predictive modeling for the power system or more specifically the AGC. We classified the work done so far into 2 categories;

1. Optimization

Although reliable to some extent, classical PID controllers and its variants, cannot handle nonlinearities found in power system load and frequency patterns. Thus, classical control theory alone is not sufficient [18]. Modern control theory relies on optimization strategies such as genetic algorithms (GA), particle swam optimization (PSO) and bacteria forging optimization algorithm (BFOA). In [17], the gravitational search algorithm is shown to outperform PID controllers and BFOA. The results show that the optimized control system is quite robust to wide changes in system load conditions and system parameters. The firefly algorithm has been proven to perform well in load frequency control and was demonstrated to outperform PSO, with better response time [16]. Other relevant studies based on optimization strategies such as teaching-learning based optimization [15, 19], have been applied to large scale problems such as the multiarea power system. The Optimization techniques reviewed perform very well and are responsible for the success of modern control applications in power systems. These techniques however have no predictive capabilities.

2. Predictive models

Predicative models for the AGC should be able to estimate with an acceptable accuracy, at least one parameter needed in some aspect of power system control. Predicting parameters for the AGC for instance is not as straight forward as one might assume, again these parameters tend to be highly nonlinear. One technique which has been proven to be quite successful is the model predictive control (MPC). The predict unit of the MPC estimates the AGC system's future output based on its current state, over a finite prediction horizon [22]. The estimated prediction is fed to the control unit to minimize an objective function. The MPC is able to reduce the area control error in multiarea automatic generation control and also provide robustness and faster response [23, 24].

So far, we have reviewed optimization and predictive models that attempt to optimize the whole system response or estimate a set of system parameters. Some interesting studies have focused only on estimating the load of a power system, of the AGC. In [27], a systematic approach for feature selection for predictive modelling of the power system is presented, this is relevant because the features have a direct effect on the predictive potential of a machine learning model. An indirect approach to the load forecasting problem is demonstrated in [25], here the authors predict the state parameters of the system then derive a prediction of the load from the previous estimates, using the support vector regression algorithm. Recurrent neural networks (RNN) have been used for load estimation from a timeseries dataset, RNNs are powerful tools for timeseries forecasting and is quite rightly applied to the load estimation problem, although the accuracies were not too impressive [26]. RNN regression estimates the future load based on previous or past load readings.

From the review, one can infer that there is potential in studying the effects of predictive models for the power system. The issue of nonlinearity is not too big a problem for a robust multilayer deep neural network, these neural networks can be trained on multidimensional datasets to accurately estimate key parameters for power systems. Finally, one can also study the effect of combining deep learning with the optimization techniques reviewed, comparative studies with the MPC strategies are definitely worth looking into.

2.3 Smart Grid Architecture

In this section, we briefly introduce the smart grid in an attempt to consolidate the reason why predictive models in AGC systems are better suited for smart power grids. The main components of a Smart Grid (Fig. 1) are electric power controllers, smart meters, collector nodes, distribution and transmission control generators, electric power substations, transmission and distribution lines, and control centers [6]. Power generators and electric power substations use electronic controllers to control the generation and the flow of electric power.

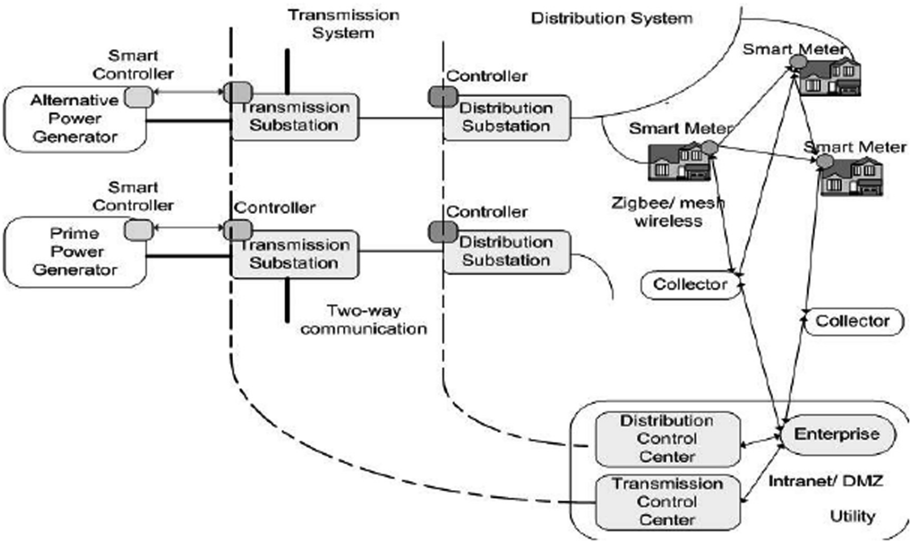

Fig. 2. Typical smart grid architecture (image source: Mavridou et al. [1])

End consumers and collector nodes may communicate through a Zigbee or similar mesh wireless two-way communication network [1]. Two-way communication paths are also used between collectors and the utility. Collector nodes communicate with the utility mostly using the Advanced Metering Infrastructure (AMI) [1, 7] possibly via the Internet. Communication between the transmission and distribution substations and the control center guide the operational process. Like existing power grids, a Smart Grid includes a control system that accommodates intelligent monitoring mechanisms and keeps track of all electric power flowing in a more detailed and flexible way [1]. The fact that as a system, the smart grid relies heavily on information technology makes it more suitable to implement modern innovative solutions that can benefit from online data streams and can exist as a software component embedded within any smart grid electronic component.

Although still theoretical for the most part, many can agree that current and proposed smart grid systems are highly reliable and efficient and secure, [2, 5, 8]. Other features of the smart grid include;

- Flexible network topology: the smart grid architecture has been shown to allow bidirectional energy flow, where the grid can generate energy sources as well receive energy from other sources [11].
- Load balancing/adjustment: the total load on a grid varies highly and is dependent on variables with high uncertainty. When the load on the grid indicates a spike in demand it is essential to redistribute the load or to call on standby generators to support the increase in demand. Smart grid can solve this problem with real-time communication with appliances to efficiently redistribute the load [12].
- Demand response support: Demand response support allows generators and loads to interact in an automated fashion in real time, coordinating demand to flatten spikes. Eliminating the fraction of demand that occurs in these spikes eliminates the cost of adding reserve generators, cuts wear and tear and extends the life of equipment, and allows users to cut their energy bills by telling low priority devices to use energy only when it is cheapest [13].
- Sustainability: the improved flexibility of the smart grid allows for the implementation of more renewable sources of energy. This is due to fact that the smart grid architecture allows for a more distributed feed-in networks.
- Security: The exposure of Supervisory Control and Data Acquisition systems (SCADA) in such an open network introduces security risks. Therefore, the security of smart grids is paramount when designing the architecture. The security of smart grids is a thriving research area, several institutions have proposed cybersecurity protocols for smart grids [9, 10, 12, 14].

3 Proposed System Design

The success of the AGC is guaranteed only when the frequency deviation is still within the range of $49\,\text{Hz} \le f \le 51\,\text{Hz}$ as shown in the Table 1. When the frequency and thus the frequency deviation is suddenly increased or decreased beyond that range, the utility is at the risk of a blackout and a resulting damage in equipment costing millions.

The problem with current models of the power system and the AGC is that the control systems cannot deal effectively with the non-linearity of the load patterns on a utility. This is why there is an emergency control to take over from the AGC in worse case scenarios. The load on a utility at any given point in time is subject to fluctuations that are difficult to predict. Based on this problem, we present a predictive model for the automatic generation control. At the heart of our design is the regression model, in the form of an artificial neural network (ANN) trained on electric consumption data (i.e. the load) collected over 47 months. The goal is to be able to predict the total base load in the next minute. The predicted load should then be used to estimate the frequency deviation, which is then fed to the AGC for processing the output control signals.

3.1 Data Analysis and Feature Engineering

The dataset used for the training is a multivariate time-series dataset collected from a single household over 47 months [20]. The data attributes include the date, time (in minutes), global active power (kW), global reactive power (kW), voltage and sub meter readings 1, 2 and 3. Each of the electrical readings are collected per minute, the result of this a large dataset of 2075259 instances. The date attribute is split into day and month attributes, all attributes except the sub meter readings are used as input attributes. The desired output label for the supervised learning required is the total energy consumption, the total load. Since the total load was missing, we had to derive the output label using the formula (Fig. 3);

$$Total\,load = \frac{Global\,active\,power \times 1000}{60} \tag{4}$$

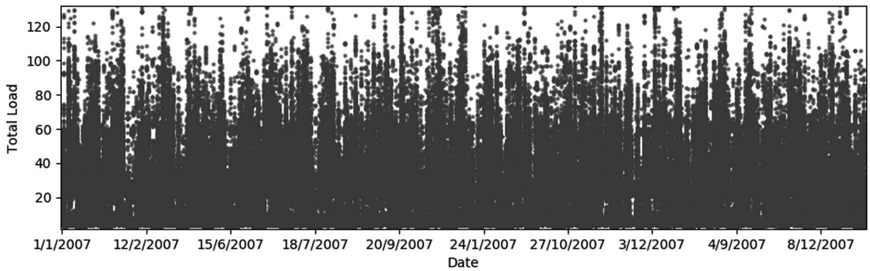

Fig. 3. Scatter plot of the *total load* for just one year. *Total load* is in Kilowatt.

Due to the fact that the data was collected per minute, the data points are highly dense, we show a scatter plot for the total load for just one week and a day in Figs. 4 and 5 respectively.

The scatter plots in Fig. 4 illustrate the times at which there is a peak load in the system, which is at about 9.30pm, this is the time at which electricity consumption is highest. Some studies have shown that peak loads usually occur in the evening. Some primary reasons for this are the need for more electric bulbs because of the darkness, evening Tv shows and higher number of people are indoors during the evening. Finally, we show a histogram of frequency of total load in kilowatt.

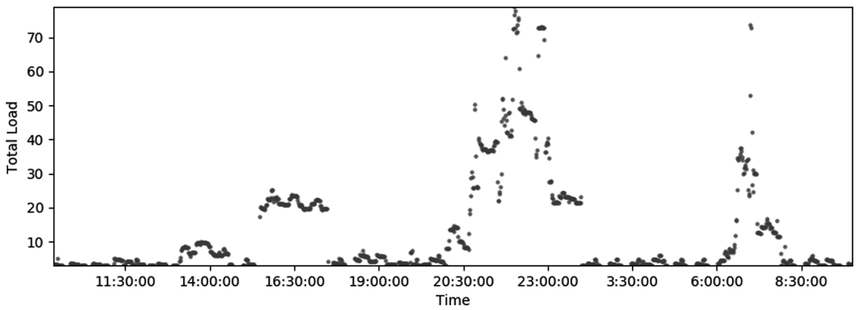

Fig. 4. Scatter plot of the *total load* for one day. *Total load* is in Kilowatt.

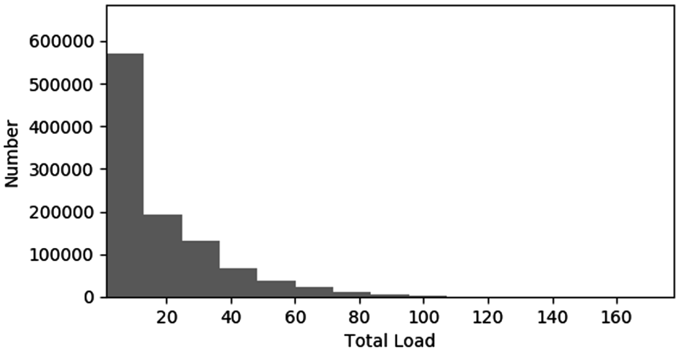

Fig. 5. Total load and their frequency.

3.2 ANN Architecture

The regression model is a simple model that has two fully connected hidden layers with 7 input attributes. The model is built using the Keras deep learning framework [21]. The network weights are uniformly initialized (Fig. 6).

The rectified linear unit activation function is used for the hidden layer. No activation function is used for the output layer because it is a regression model and we are interested in predicting the numerical values directly without an affine transform. The efficient ADAM optimization algorithm is used and a mean squared error (MSE) loss function shown in Eq. (5) is optimized. This will be the same metric used to evaluate the performance of the model. The MSE gives us an error value we can directly understand in the context of the problem. We also include dropout in the hidden layers to reduce overfitting.

$$MSE = \frac{1}{n}\sum\nolimits_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2 \tag{5}$$

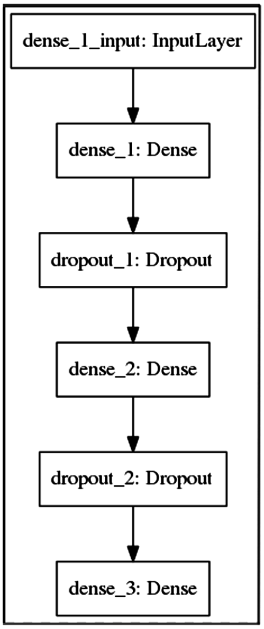

Fig. 6. Model architecture showing the input, hidden and output layers

3.3 Training and Validation

The training data contains a sample of 21,992 instances spread over the period of 2006 to 2007 (Fig. 7).

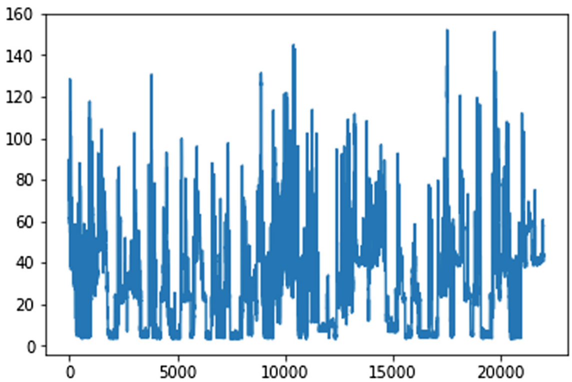

Fig. 7. Scatter plot showing output label y in training set.

The kfold cross validation technique is used for training and validating the model. A batch size of 10 and epochs of 100 was used for cross validation scoring. The mean square cross validated score is shown below (Table 2).

Table 2. Mean square error for cross validated scoring.

Mean square error (MSE)	Mean absolute error (MAE)
0.0014	0.0121

4 Results

The model is tested on an isolated test data from the period between 2008 and 2009, a sample size of 18,100 is used for testing (Fig. 8), (Table 3).

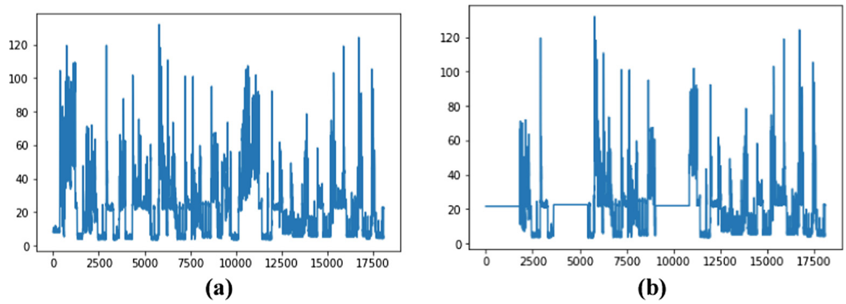

Fig. 8. (a) Scatter plot for test data output label (b) Scatter plot showing predicted output results on the test set.

Table 3. Mean square error for cross validated prediction on test data.

Mean square error (MSE)	Mean absolute error (MAE)
0.0076	0.0111

Although we observe some bias in the first 5000 instances, it can be observed that the variance is in general, relatively low on the test data. The results show that the predictive model performs quite well on the test data and is able to correctly predict the total load given an instance of the input parameters for the date, time, global active power and reactive power, and the voltage.

5 Future Work and Conclusion

The work presented here lays the foundation for a more intensive design for a predictive automatic generation control system. Future work presents the opportunity of training the model on larger training and test samples. The dataset for energy consumption from an area (a state for instance) should be used and the input attributes may be increased to accommodate for some social events such as “festive season or not”, which may directly influence total base load. From here, simulations should be run using the predictive model in conjunction with the AGC software so as to consider the effect of other parameters.

In conclusion, a predictive model for the AGC model was developed and trained on a dataset for energy consumption from a single household. The mean square error from the test set shows that there is a tolerable balance between the bias-variance tradeoff. The model provides evidence that it is possible to train a deep neural network to predict the total load on a power grid at any given time and day with a very high accuracy.

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