Medium Term Power Load Forecasting for Java and Bali Power System using Artificial Neural Network and SARIMAX

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***Abstract*—Power load forecasting is an important part of electrical company operations. An accurate forecast can help the company makes various important decisions. Two known models for power load forecasting are ARMA model and its variants and Artificial Neural Network (ANN). The ARMA model has been used for decades while ANN can be considered as a more recent approach. In this paper MLP and SARIMAX are proposed to model the power load of Java and Bali power system. Both models can be used to forecast the load of Java and Bali power system with MAPE of 2.4% for SARIMAX and 2.7% for MLP. The time needed to build a SARIMAX model is shorter compared to MLP. In general, SARIMAX performs better compared to MLP. An application is also developed to facilitate data transformation, model training, and forecasting based on the proposed models.**

Keywords—power load forecasting, artificial neural network (ANN), seasonal autoregressive integrated moving average with exogenous variable (SARIMAX), mean absolute percentage error (MAPE)

I. Introduction

Power load forecasting is an important aspect in electrical company operations and planning. Load forecasting helps electrical company in making important decisions such as purchasing resources and infrastructure planning [1]. In this case, electrical energy can't be stored and must be consumed at once. Hence, overproduction of energy is not effective in terms of resources and underproduction will cause failure in meeting energy demand [2]. One common objective in power load forecasting is to minimalize forecast error which will lead to more accurate energy production. An accurate forecast and accurate energy production will then save costs, increase reliability of the systems, and provide information for decision making [3].

Power load forecasting can be categorized based on its time range. Short term load forecasting ranges up to next 24 hours and mainly used for deciding energy allocations. Medium term load forecasting ranges up to one year and used for maintenance planning and fuel scheduling. Long term load forecasting ranges up to ten years and used for infrastructure planning [4]. This research aims to develop a model which is appropriate for daily maximum load forecasting for Java and Bali power system. An application to develop those models will also be developed to aid model building and forecasting.

The challenge in forecasting problem is how to model the real world (power load). The challenge itself can be decomposed into more detailed problems such as data preparations, determining appropriate model, and increasing model performance. Data preparations might include problems such as determining appropriate data to model power load, scaling data, handling outliers and missing data, etc. The next problem includes determining what model is appropriate including the value of its parameter. This problem also includes the strategy of test and what metrics will be used as deciding factor. The initially proposed model might then need further improvement based on its initial result.

In this paper, ANN and SARIMAX model will be used to forecast daily maximum power load of Java and Bali system. A time series approach like SARIMAX has been used for decades and can be considered more common approach [1]. ANN in the other hand is more recently studied. Both models forecasting performance will be evaluated for Java and Bali system based on their forecast error in forecasting daily maximum load. The time needed to build respective model will also be considered in evaluation. An application to aid forecasting will then be developed based on those models test result.

Section II will see previous work regarding power load forecasting. It will first explain known models for forecasting and then explain previous attempt to forecast power load. Section III contains an explanation of proposed models, the data which will be used, and some test results regarding the proposed models. Section IV contains short explanation regarding the implemented application. Section V contains evaluation of the proposed model and its configuration based on previous test results. Section VI will contain conclusion of the research and suggestion for future work in similar topics.

II. Related Work

A. *Artificial Neural Network and Seasonal Autoregressive Integrated Moving Average with Exogenous Variable*

Artificial neural network (ANN) can be defined as highly connected array of processing unit called neurons [5]. These neurons are located inside neural network layers. Each connection between neurons has certain weight associated with them. A neural network layer can be categorized as input layer, hidden layer, and output layer. A hidden layer is simply a layer between the input layer and output layer. ANN with one or more hidden layers is known as multilayer perceptron (MLP) and ANN without hidden layer is known as single layer neural network (SLNN) [5]. The training of ANN is done by minimizing a cost function which is usually related to the output error [6]. The minimization will change the weight of the connection between neurons. These weights are the component which determine the value passed to a neuron. The value passed will be used as input for a function called activation function which determine the output of a neuron. The main advantage in using ANN for forecasting is its ability to model by itself the functional relationship between input and output through training [2]. ANN does not rely on explicit adoption of functional relationship between input and output.

SARIMAX model is a development of AR and MA model by adding seasonal component, integration and differencing, and exogenous variables. This model can be considered as stochastic time series model [7] and assume that the data have internal structures such as autocorrelation, trend, and seasonal component [1]. An AR model of order (p) can be defined as:

$$z_t = \phi_1 z_{t-1} + \phi_2 z_{t-2} + \ldots + \phi_p z_{t-p} + a_t. \tag{1}$$

z_t is value of a time series at a time, a_t is error term or white noise at a time, and ϕ_1 ... ϕ_p are parameters of AR model [8]. To simplify the equation, backshift operation B is introduced [8]. The backshift operation B define z_{t-p} as $B^p z_t$. Equation (1) can then be written as:

$$\phi_p(B) z_t = a_t \tag{2}$$

with $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$. Similar to (1) and (2), MA model of order (q) can be defined as:

$$z_t = \theta_q(B) a_t \tag{3}$$

with $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$ [8]. These two models can then be combined to construct an ARMA model of order (p,q). An ARMA model is only appropriate to model stationary data.

To model data which are not stationary, ARIMA model is used. An ARIMA model can be interpreted as an ARMA model on differenced data which result are then integrated back to get appropriate value (to get the forecast value of original data, not the forecast value of differenced data). The differentiation and integration are done to transform the not stationary data into stationary. An ARIMA model of order (p,d,q) can be defined as:

$$\phi_p(B) \nabla^d z_t = \theta_q(B) a_t \tag{4}$$

with $\nabla^d z_t = (1 - B)^d z_t$ and d is the order of differencing [8]. If a seasonality s is present in the data, a multiplicative SARIMA can be used. The multiplicative SARIMA of order (p,d,q)(P,D,Q) with seasonality s can be defined as:

$$\phi_p(B) \Phi_P(B^s) \nabla^d \nabla_s^D z_t = \theta_q(B) \Theta_Q(B^s) a_t \tag{5}$$

with $\nabla_s^D = (1 - B^s)^D z_t$, D is the order of seasonal differencing, $\Phi_P(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \ldots - \Phi_P B^{Ps}$, and $\Theta_Q(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - \ldots - \Theta_Q B^{Qs}$. The $\Phi_1 \ldots \Phi_P$ are the components of seasonal AR (SAR) and $\Theta_1 \ldots \Theta_Q$ are the components of seasonal MA (SMA).

These models can then be expanded by adding exogenous variables, resulting in SARIMAX model for SARIMA and ARIMAX model for ARIMA. An ARMAX model can be defined as:

$$A(q)y(t) = B(q)u(t) + C(q)e(t). \tag{6}$$

A(q)y(t) is the AR component, B(q)u(t) is the exogenous variable, C(q)e(t) is the MA component, and q^{-1} is a back-shift operator [9]. The *A(q)* component can be expanded as $A(q)=1+a_1q^{-1}+\ldots+a_nq^{-n}$ and $a_1, \ldots, a_n$ are parameters of AR part. The component *B(q)* and *C(q)* can be expanded similarly. Similar components can be added to (5) resulting in SARIMAX model. While only one exogenous variable is used in (6), it is possible to add more exogenous variables.

B. Power Load Forecasting

Reference [2] is an example of an attempt to use ANN to forecast power load. In [2], 63 input neurons are used. The first 48 neurons represent previous 48 hours load. The next eight neurons are input related to temperature. The last seven neurons are input related to day of the week. For the output and hidden neurons, 24 neurons are used for each layer.

It is found that for Greek power system, the number of hidden neurons does not significantly affect forecasting accuracy. Some input variables are also tested. It is concluded that previous load, temperature, and day of the week are three variables which are important to determine forecast result. It is also tested that using single ANN with day of the week as input is better than using seven ANN for each day of the week.

Reference [2] also attempts to handle special load pattern on holidays. There are two known methods, the first one is using specially trained ANN for holiday power load and the second is using the ANN for normal day with special adjustment for the result. The second method is used. The second method initially follows [10] by using normal ANN to initially forecast the normal load for that day which will then be adjusted by looking at the average deviation of normal ANN forecast from the observed value for corresponding holidays in previous years. The adjustment method is then expanded further by adjusting holiday power load when it is used as input for training [2]. The proposed model achieves average percentage error of 2.24% for normal days. For holidays, the initially used method achieves average percentage error of 3.77% while the expanded method achieves average percentage error of 3.56%.

It is worth noting that such definition of adjustment might not be necessary. It is previously stated that ANN can learn by itself the functional relationship between input and output variables [2]. This means that providing corresponding holiday data as input variables might be enough for the ANN to learn and adjust forecast for holidays. The question is then what kind data should be used so that ANN can learn to adjust power load for holidays.

III. Proposed Model

It is proposed that MLP and SARIMAX models which take previous load, day of the week, and holiday types are used to forecast daily maximum power load in Java and Bali system. The temperature variable is also an interesting input variable but because historical temperature data are not available, it is not used.

The data initially available consist of three time series, the daily maximum, minimum, and average power load of one of the Java and Bali system subarea. Those data span across two years starting from 1 January 2016 until 31 December 2017. Those data contain some missing values found on 1st day of both years (1 January 2016 and 1 January 2017). Those data are then omitted resulting in 2016 data which have 365 records and 2017 data which have 364 records. It is then decided that the 2016 data will be used for training and the 2017 data will be used for testing.

Day of the week and holiday data are then added to both years data. Eight type of holiday are considered. Those eight types are working day, Saturday, Sunday and other public holidays, Eid al-Fitr, Eid al-Adha, Indonesia Independence Day, Christmas, and New Year. Previous years load for those holidays can't be used due to limitation in amount of data available. The holiday data used only denote if a certain date is considered one of those holiday types. If a date can be considered as two types, a more specific holiday is chosen. For instance, if a date can be considered as Sunday and Eid al-Fitr, that date will be denoted only as Eid al-Fitr. There's no case of overlapping specific holiday in the data used. Similar approach is used to incorporate day of the week information, each data will have indicator which tell a certain date is considered which day of the week. At this point the data used will have five columns for each timestamp (maximum, minimum, average daily load, type of holiday, day of the week). The type of holiday and day of the week are then encoded using one hot encoding technique, resulting in seven Boolean columns representing day of the week and eight Boolean columns representing type of holiday.

After the one hot encoding process, SARIMAX model can be fitted using one time series column (the maximum daily load in this case) and the 15 columns which are the result of the one hot encoding as exogenous variables. For the seasonality of the SARIMAX model, weekly seasonality will be used. monthly and yearly seasonality can also be used but weekly is chosen because it is the span of time which is closest and expected to be more relevant to daily pattern. The order of the model will be determined based on test result, except for the order of exogenous variables which value is determined to be one. This means based on (6), only an exogenous variable at the current time is considered. It is worth noting that the proposed model considers 15 different exogenous variables at time. Using exogenous order of two or more is not necessary because for each date there will only be one exogenous variable, amidst the seven, with true value (it is impossible for a date to be both Monday and Wednesday) and the previous values are indirectly contained. While for holiday types, knowing previous value might provide some information, it is not used in the proposed model. No scaling is needed for SARIMAX input data.

For MLP, the three time series values will be first scaled to value between zero and one. This scaling process is done by subtracting a value by the minimum value of the series and then dividing it by the range (maximum value minus minimum value) of the series. The scaled time series with one hot encoding results are then transformed into a form which are suitable for MLP. This form will be referred as supervised problem form. In this form every record from the data will contain the input for every input neuron and the expected output of the output neurons. These data can then be used to train the proposed MLP model.

The proposed MLP will have (3x+15) input neurons with x representing last x days to be used as input variables, 3y output neurons with y representing next y days to be forecasted. The three in input and output neuron represent the maximum, minimum, and average daily load. The other 15 input neurons represent Boolean input indicating day of the week and holiday types. Each layer is densely connected with the next layer and bias is used for every neuron. The number of hidden layers and hidden neurons will be determined based on test result.

As an example, for 2016 data, if represented in tabular form, these data will be represented as 365 rows and 18 columns (maximum, minimum, average load and 15 Boolean variables representing day of the week and type of holiday). If five last power loads are used as input and one day ahead forecast is desired, the MLP will have 30 input neurons and 3 output neurons. The supervised form of the data will be represented as 360 rows and 33 columns.

For activation functions, sigmoid is used for input and hidden layer and rectifier with alpha value of 0.4 is used for output layer. The alpha value is arbitrarily chosen. The sigmoid function will map its input to a value between zero and one. The rectifier function output will be the same as its input if the input value is greater than or equal to zero or its input multiplied by alpha if the input is less than zero. In this case, the Rectifier is chosen to make it possible for the output to be greater than one, resulting in forecast which is greater than maximum value in the data.

Various model parameter values are then tested based on those general models to find good enough configuration. The test uses Mean Average Percentage Error (MAPE) of maximum daily power load to determine which parameter value is better. MAPE can be defined as:

$$\mathrm{MAPE} = (1/n)\, \Sigma_{i=1}^{n} \left(|y(t) - \hat{y}(t)| / y(t)\right) \quad (7)$$

with y(t) is the actual value at time t, ŷ(t) is the predicted value at time t, and n is the number of data records used [3]. à y

Each model is trained or fitted using the 2016 data and its performance is then evaluated by using the 2017 data. The evaluation is performed by using the model to forecast the next day maximum load for every possible day and then calculating the percentage of error based on the forecasted value and actual value recorded. For example, if the number previous daily load used is five (five last load data is used) and one day ahead prediction is desired, the earliest possible day to be forecasted is 7 January 2017. It is previously stated that the data for 1 January 2017 contain missing values and is omitted, hence for the example above, the earliest possible forecast will use the data from 2 January 2017 until 6 January 2017 to make a load forecast for 7 January 2017. The last possible forecast will be for 31 December 2017. The percentage of error for every possible day is then averaged resulting in the MAPE value for a model. This MAPE value is then compared between models with different parameters.

The test for MLP use "one variable at a time" approach which try to find the best value for each parameter without considering their combination. Table I is the result summary of the test for MLP.

For MLP, the use of the day of the week and holiday as input variable is deemed appropriate as it greatly decrease the train and test MAPE. Based on this result, the effect of these variables for SARIMAX model will not be tested.

It is concluded that using a lot of previous load will overfit the model. This conclusion is drawn since increasing previous load used as input decrease the train MAPE but increase the test MAPE. Such pattern suggests that further training will likely fit the model only for the train data, resulting in less general model.

For the number of hidden layers, it is observed that the train MAPE and test MAPE tend increase by each addition of hidden layers. The only exception is when one hidden layer is used which shows improvement in forecast error compared to model without hidden layer. It is then concluded that one hidden layer is appropriate for the model.

The test result suggest that the number of hidden neurons does not significantly affect forecasting accuracy. This result corresponds to previous work which also state similar result [2]. Nine hidden neurons are then chosen as appropriate parameter configuration for the model. Smaller number of neurons is chosen to simplify the model while the value nine is chosen based on smallest test MAPE even if the difference is not significant.

The use of three time series (daily maximum, minimum, and average) as input variable is also deemed appropriate. It is decided by observing the decrease of test MAPE. The model which use three time series as input also performs better in forecasting daily minimum and average load compared to the model which only use minimum or average load.

The test for SARIMAX model revolves around finding if seasonal model is needed and finding the appropriate order of SARIMAX model. The SARIMAX model is tested with "grid search" approach because SARIMAX fitting is faster compared to the time needed to train a good enough MLP. Based on the difference in time needed, a grid search for SARIMAX order is considered feasible. The minimum order of SARIMAX model is then arbitrarily determined to be (1,0,0) (0,0,0) and the maximum order is arbitrarily determined to be (3,1,3) (3,1,3). The complete result will not be shown. The best train MAPE is found on SARIMAX (3,0,2) (1,0,1) with value of 2.38%. This model has test MAPE of 2.46%. The best test MAPE is found on SARIMAX (1,1,0) (0,0,0) with value of 2.35%. This model has train MAPE of 2.52%. The use of seasonal model is deemed appropriate as the lowest train MAPE is found on model with seasonal component. From the grid search result, it is found that a lot of SARIMAX model share similar MAPE and is concluded that no specific order is significantly better than the others except for the order of seasonal difference. It is observed from the grid search result that model with order of seasonal difference of one tends to have significantly higher MAPE.

TABLE I. MLP TEST RESULT SUMMARY

Variables	Value	Train MAPE	Test MAPE
Features	With day and holiday data	3.06%	3.37%
	Without day and holiday data	2.14%	2.97%
Previous Load	5	2.51%	2.71%
	12	2.38%	2.82%
	19	2.36%	2.90%
	26	2.27%	2.94%
	33	2.21%	2.96%
	61	1.95%	3.31%
Hidden Layers	0	2.49%	2.78%
	1	2.45%	2.71%
	2	2.39%	2.75%
	3	2.49%	2.79%
	4	2.54%	2.79%
	5	2.56%	2.82%
Hidden Neurons	61	2.50%	2.71%
	57	2.51%	2.72%
	49	2.47%	2.71%
	33	2.47%	2.70%
	17	2.48%	2.70%
	9	2.45%	2.69%
	5	2.49%	2.72%
Time Series	Max, min, and average	2.45%	2.69%
	Max only	2.36%	2.83%

IV. APPLICATION

An application is developed based on the test result on MLP and SARIMAX model. The application in general facilitate data transformation, model training, and forecasting. The application can receive a dataset containing three time series, day of the week, and holiday information in certain format and store those files and record them in database. The uploaded dataset can then be transformed to a form which can be used by MLP. The transformed dataset is stored in new file and recorded in database. The SARIMAX can be fitted using the uploaded data without any further transformation while MLP can only be trained using transformed data. The uploaded and processed dataset might function as input data for building the model and input data for making a forecast.

User can choose to build either MLP or SARIMAX model based on specific datasets. Some parameters like previous load and amount of forecasted output can be customized while some parameter like hidden layers are set based on the result of the previous test. The resulting model is then saved as a file and recorded in database.

User then can choose from the list of stored models which model will be used for forecasting. After a model is chosen, user can specify a previously uploaded dataset as input for the selected model. The application will then use the selected model and the specified dataset to make a forecast. The result is then shown as a line graph showing the actual maximum load if it is available in the data and forecasted load.

V. EVALUATION

The configuration of MLP and SARIMAX based on test result is summarized on table II. For further evaluation SARIMAX (1,0,1) (1,0,0) is arbitrarily chosen from the SARIMAX with small total order and both train and test MAPE around 2.4%. For MLP, a model with 30 input neurons with 15 representing five last power load data for three time series, seven Boolean input variables representing day of the week, and eight Boolean input variables representing holiday types are used. The MLP model use one hidden layer with nine neurons on its hidden layer. The evaluation will focus on the forecast error of both models and time needed to build the model.

TABLE II. CONFIGURATION BASED ON TEST

Model	Parameter	Value	Description
MLP	Input Neuron	30	15 previous load and 15 day of the week and holiday data
	Hidden Layers	1	-
	Hidden Neurons	9	-
SARIMAX	Orde of AR	1-3	No specific order significantly better
	Orde of difference	0-3	No specific order significantly better
	Orde of MA	0-3	No specific order significantly better
	Orde of SAR	0-3	No specific order significantly better
	Orde of seasonal difference	0	Seasonal difference tends to increase MAPE
	Orde of SMA	0-3	No specific order significantly better

The chosen SARIMAX model has train MAPE of 2.42% and test MAPE of 2.39% while the MLP has train MAPE of 2.46% and test MAPE of 2.74%. Fig. I is the plotted line chart for the actual value and predicted value of MLP and SARIMAX from 1 June 2018 to 1 September 2018. Based on the MAPE, the proposed SARIMAX model not only has lower error rate, it is also more general which can be inferred from similar error rate between the train and test. Further evaluation based on standard deviation also shows that the proposed

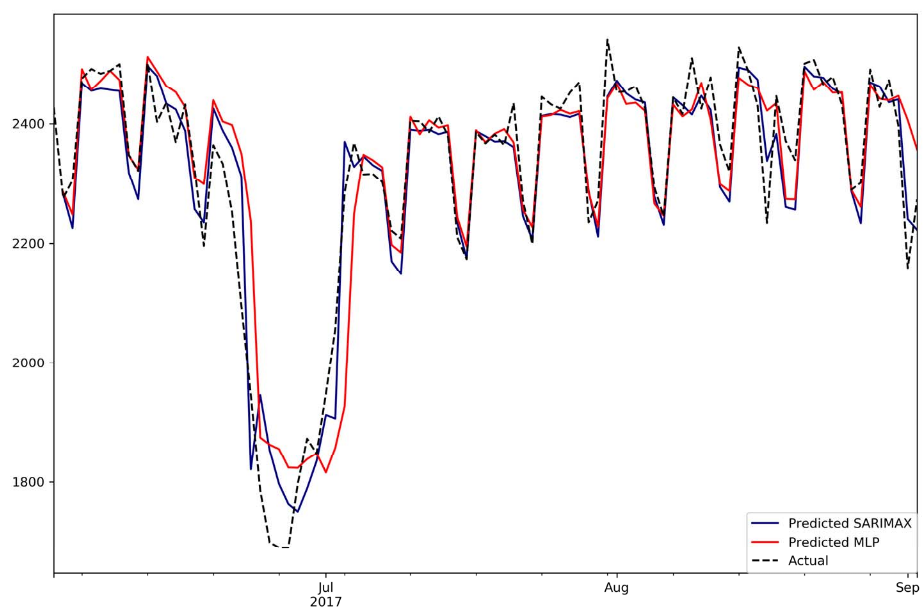

Fig. 1. Actual and predicted value from 1 June to 1 September

SARIMAX model is better compared to the proposes MLP model. The percentage of error from the SARIMAX model has standard deviation of 1.94% while the percentage of error from MLP model has standard deviation of 2.57%. The standard deviation of MLP can be considered quite high as it is close to its mean value. The maximum error of SARIMAX is less than 11% while the maximum error of MLP is less than 16%.

Based on the model building time, the SARIMAX model has significantly faster speed in building the model. The SARIMAX model needs around four seconds to finish building model while the MLP model needs around 44 seconds to obtain a good enough model. It is worth noting that adding more data might have more impact on SARIMAX fitting compared to MLP train. For a far larger dataset, building SARIMAX model might not be feasible compared to building an MLP model.

Another important result founds is that the forecast of holiday power load tends to have above average error rate. While table I suggest that using day of the week information and holiday data decrease error rate of forecast, it might be still insufficient to model holiday power load accurately. Another conjecture is that the data used are not enough for the model to accurately model the adjustment needed for holiday. Fig. II is the scatterplot based on train percentage of error for SARIMAX model. It can be seen from fig. II that most error for holidays are greater than 2.4%, the average percentage error (MAPE) of SARIMAX model.

If roughly compared to [2], the proposed MLP model performs worse. For normal days including weekend, the proposed MLP model achieves test MAPE of 2.62% while [2] achieves MAPE of 2.24%. For holidays only, the proposed MLP model achieves test MAPE of 4.38% while [2] achieves MAPE of 3.56% with the extended method. For 2-days consecutive holidays, the proposed model achieves test MAPE of 6.96% while [2] achieves MAPE of 4.00%. The proposed SARIMAX model also performs worse compared to [2] but performs better compared to the proposed MLP model. It achieves test MAPE of 2.28% for normal days and weekends, 4.97% for holidays, and 5.04% for 2-days consecutive holidays. One thing to remember is that these comparisons only provides rough comparisons because the data, input, and expected output used to train the proposed models and [2] are totally different.

VI. Conclusion and Future Work

The proposed MLP and SARIMAX model for forecasting the electrical load of Java and Bali power system. Both models can be used to forecast power load. In term of forecast accuracy and time needed to build a model, the proposed SARIMAX model is better compared to the proposed MLP model. The proposed SARIMAX can achieves MAPE of 2.4% while the proposed MLP can only achieves MAPE of 2.7%. The percentage of error in SARIMAX also has lower standard deviation compared to MLP. While in general SARIMAX model performs better, both models still lack the capability to model power load on holidays accurately. An application is also developed to facilitate data transformation, model training, and forecasting based on the proposed models.

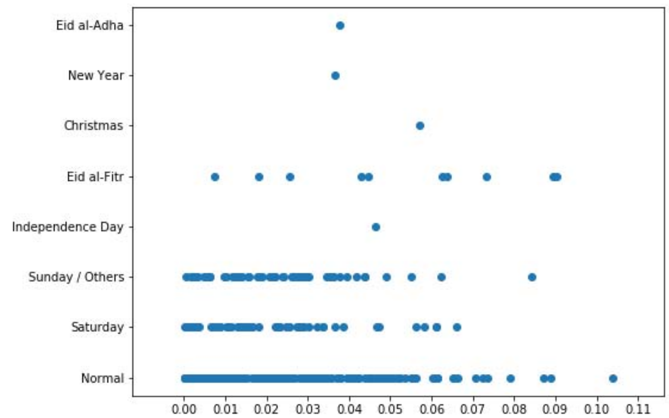

Fig. 2. Train percentage of error scatterplot (SARIMAX)

Future work seeks to improve the proposed model can try to incorporate more variables as inputs. It is suggested that temperature data and similar holiday load in previous year are used as input.

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