Forecasting Locational Marginal Prices in Electricity Markets by Using Artificial Neural Networks

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ABSTRACT

Electricity price forecasting is an important tool used by market players in decision-making and strategizing their participation in the electricity market. In most studies, market-clearing price is forecasted as it gives an aggregated overview of system price. However, locational marginal price (LMP) gives better outlook of the price particular to the customer location in the electrical power grid. This study utilizes Artificial Neural Networks to forecast weekday LMP of generator and load nodes. Various inputs such as historical prices and demand, and temporal indices were used. Using data for selected nodes of the Philippine Wholesale Electricity Spot Market, forecast Mean Average Percentage Error (MAPE) of 6.8% to 6.9% were obtained for generator and load node forecasts, with better prediction intervals than ARIMA models. The results showed that the proposed method of using the LMP of adjacent generator nodes in forecasting load node LMP results in significant improvement of forecast accuracy.

Keywords: *short-term forecasting, electricity markets, locational marginal price, artificial neural networks*

Introduction

In recent years, the traditionally regulated and monopolistic electric power industry has undergone deregulation and restructuring to reduce electricity costs and ensure a reliable energy supply through competition. Competitive electricity markets were introduced to promote long-run gains in efficiency and stimulate technical innovation, leading to efficient capital investments. Like other commodities, market participants trade electricity through bids and offers that would maximize their profits under market rules using spot and derivative contracts. The Electric Power Industry Reform Act of 2001 initiated the development of the electricity market dynamics in the Philippines, allowing customers and suppliers to participate actively in the market. Load customers may strategize their use of demand to save operational costs, while power-generating suppliers may strategize their bids for dispatching power in the network.

However, electricity is a special commodity type. It is non-storable, and therefore it must be consumed as soon as it is produced (no inventory) to maintain a balance between production (generation) and consumption (load) that is critical in maintaining power system stability. The generation of and demand for electricity is highly dependent on weather, while demand is dependent on the intensity of business and daily activities exhibited by residential, commercial, and industrial consumers. These features result in electricity prices that have the following

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characteristics: high volatility, sharp price spikes, mean-reversion, and seasonality in different frequencies. Due to these idiosyncratic characteristics, accurate forecasting of electricity prices becomes a challenging task. Generator companies, distribution companies, or large industrial customers require an accurate short-term forecast of the volatile wholesale prices so that they can adjust their bidding strategy and their own production, consumption, or pool purchase schedules to reduce financial risk or maximize profits in real-time or day-ahead trading. In the Philippine Wholesale Electricity Spot Market (Philippine Electricity Market Corporation [PEMC] 2019), there are two different types of electricity prices: Market Clearing Price (MCP) and Locational Marginal Price (LMP). MCP refers to the price cleared once the total generation meets the total demand of the network, as seen in Figure 1. LMP, on the other hand, refers to the price at the node where the customer or supplier is connected (Shahidehpour, Yamin, and Li 2002). This is different from MCP as MCP is the clearing price applicable to the whole system, whereas LMP is the price particular to the location of the customer or supplier, considering the added cost in the delivery of power due to the difference in locations.

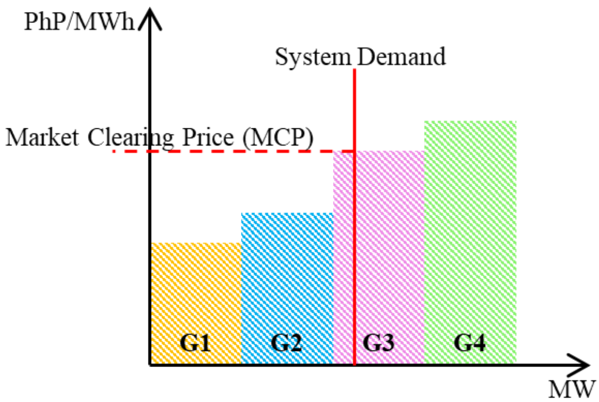

Figure 1. Market clearing price determination for four generators (G1 to G4)

Under perfect competition, marginal cost pricing will result in economic efficiency or social optimality. This is the price of the last unit of a commodity that balances supply and demand. However, the oligopolistic nature of electricity generation leads to imperfect competition Furthermore, electricity demand is also inelastic as the usage of power is more affected by the need to use electricity than by its price. Actual consumer use of electricity (in the industrial, commercial, residential sectors) is driven less by market prices but rather by other factors such as commercial product or service contracts dictated by the demand/supply of these products/ services, preferences in the timing or intensity of usage of electric appliances, and operating business hours or work shift schedules.

Locational marginal pricing is designed to achieve two economic objectives simultaneously: (a) minimize the cost of generating enough electricity to meet load by using the least-cost set of available generators given various constraints, through what is known as a least-cost, security-constrained dispatch; and (b) produce the instantaneous price of electricity (LMP), at every point in the system, which reflects the instantaneous short-run marginal cost of serving one incremental unit of load at that location. The LMPs are the shadow prices of the power balance equality constraints of an optimization problem that maximizes the total social welfare function subject to the constraints of the physical power system, based on the offer and bid functions of the sellers and buyers, respectively, for a specified point of time (Singh, Padhy, and Sharma 2010).

There are various factors that affect the price of electricity like market characteristics, system uncertainties, market behavior, and temporal effects (Aggarwal, Saini, and Kumar 2008, Li *et al.* 2005, Muñoz *et al.* 2010, Weron 2014). In most cases, the behavior of electricity price follows the same behavior as the electricity demand (Muñoz *et al.* 2010), especially for forecasting the MCP. Compared to MCP forecasting, LMP forecasting is more challenging because it may be affected by different factors that are particular to the bus/node location, requiring more information about the system. This may be observed in Figure 2, where the behavior of one week-LMP of the load node considered in this study exhibits a different behavior compared to the load demand, especially for price spikes and dips.

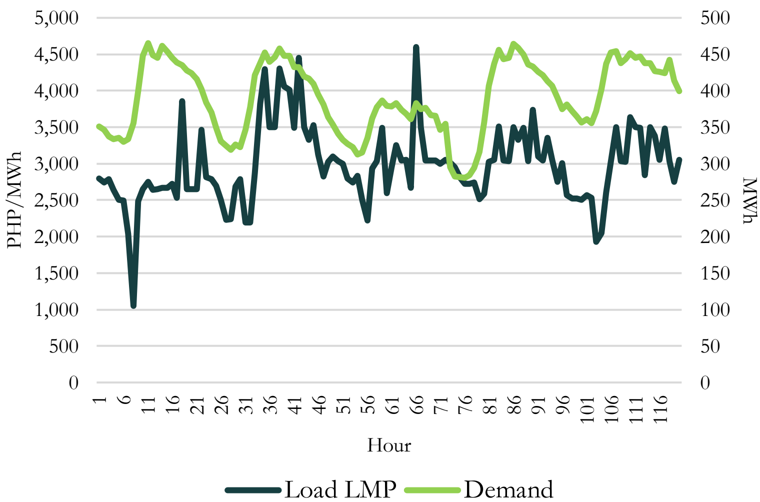

Figure 2. One-week load LMP vs. load demand

In addition to being load-dependent, LMP is also influenced by renewable generation and transmission constraints. Consequently, LMPs can become highly volatile and undergo unpredictable price spikes. The best results may be obtained from optimal power flow solutions that consider generation and transmission constraints, however, without extensive knowledge of the system state or its network model – which is usually not available to the customer, this will not be possible. LMP forecasting has previously been done using the behavior of historical data associated with the node, including node demand, through Artificial Neural Network (ANN) and time series methods. ANN utilizes a set of data and learns the behavior of that data by "training" (doing iterative simulations) the network structure to best represent the data. In some cases, modifications to the training models were also done to improve the results (Hong and Wu 2012, Ji *et al.* 2013, Kim 2015).

LMPs provide market participants with a clear and accurate signal of the price of electricity at every location on the power grid. These prices reveal the value of locating new generation, upgrading the transmission network, or reducing electricity consumption. In a well-functioning market, these elements are needed to alleviate constraints, increase competition and improve the systems' ability to meet power demand. In electricity markets, the purpose of marginal cost pricing is to differentiate consumption by time of use and geographical area so that costs could be conveyed to consumers in a clear and fair manner. Consumers can then make an informed decision about the appropriate economic level and timing of their use of electricity. Therefore, it is imperative that an accurate forecast of LMPs be available for market participants to make informed market and investment decisions.

MCPs are usually forecasted like forecasting electricity demand because they behave almost the same way. LMP, however is better forecasted using more input variables in addition to demand because the location of the node in the electrical network greatly affects the price. ANNs usually produce better performance in dealing with nonlinearities and difficulties encountered in time series forecasting methods (Aggarwal, Saini, and Kumar 2009, Kim 2015). Compared to MCPs, LMP forecasting are more complex because they are affected by the node location. Artificial Neural Networks will be used in this study to forecast the LMP in an electrical network by studying the behavior of different input variables such as historical price and demand, time of the day, day of the week, and electrical price of adjacent generators. The main contribution of this study is the use of the LMPs of adjacent generator nodes in forecasting the LMPs of consumer load nodes, which results in significant improvement in forecast accuracy over previous works that utilized only historical price and demand. Forecast performance will be measured using Mean Average Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) from the actual electricity price. Autoregressive Integrated Moving Average (ARIMA) will be used to benchmark the accuracy of the ANN forecast model through prediction intervals. The rest of the paper is organized as follows: methodology to define the terms and methods used in the study, results and discussion of the study, conclusion from these results, and recommendations for future work.

Methodology

In this study, power system nodes, or buses, are classified as being either a generator node or a load node. A generator node is a node that has a connected generator or has both load and generator connected but with the generated power greater than the load. A load node is a node that has a connected load or has both load and generator connected but with the generated power less than the load. Due to the limited data available, generator node prices will be forecasted using only its historical price. Generators are assumed to be oligopolistic in nature, as they usually set the prices for the node. Therefore, the assumption for this study is that generator bid offers have a certain pattern that resemble their previous bids. Load node prices are affected by various factors, including time and prices of adjacent generator nodes.

The general framework of the study will be as follows:

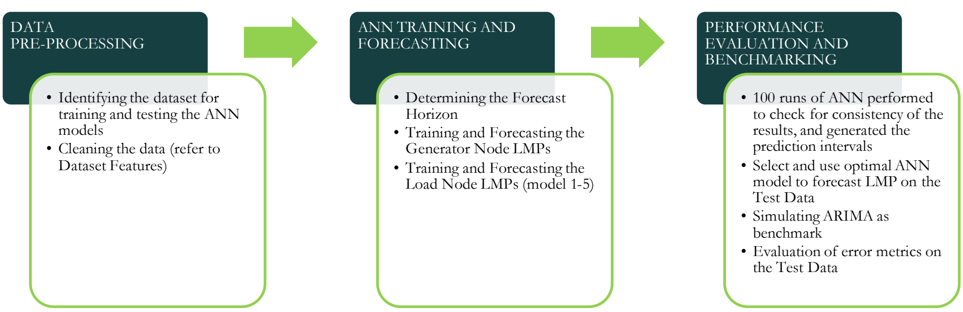

Figure 3. The general framework of the study

The dataset is divided into a training dataset and a test dataset. The training dataset will be used to train the forecast models through ANN. Training will find the best fit of the input and output parameters. Out-of-sample data were reserved through the test dataset to measure the forecast performance of the generated models when predicting future values.

ANN Structure

The general ANN structure that will be used for this study is shown in Figure 4. In the neural network[1], training starts with the feed forward pass, which produces the output of the network (right) from the normalized[2] inputs (left) through a set of neurons in the hidden layer (middle) as determined by corresponding weights in the model (Thomas 2017).

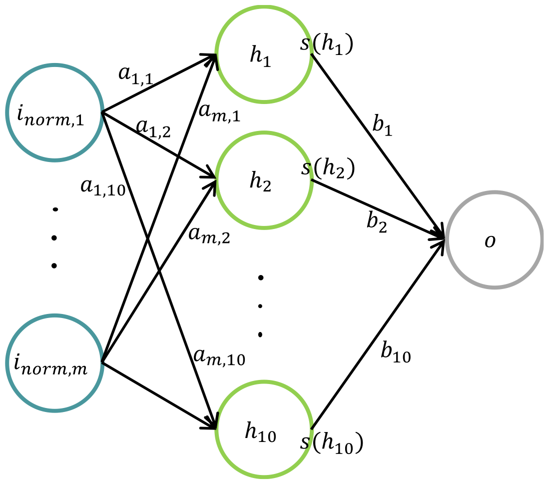

Figure 4. General ANN structure to be used in the study

Using the normalized input, the hidden neuron values are obtained using a weight[3] matrix A, as shown below:

$$\mathrm{I}_{norm,1\times m} \times \mathrm{A}_{m\times 10} = \mathrm{H}_{1\times 10} \tag{1}$$

where I_{norm} = normalized input
A = weights between the input layer and the hidden layer
H = hidden layer output
m = number of inputs

The training starts with a random set of weights A (and B), which will be refined throughout the training process. Once H is determined, the effect of the input parameter on the output is determined by how much it 'activates'[4] the neuron. The activation of each neuron is determined through the sigmoid function *s(H)* (Hyndman and Athanasopoulos 2018). From the activated hidden layer, the output O of the network can be obtained, using the weight matrix B:

$$s(\mathrm{H})_{1\times 10} \times \mathrm{B}_{10\times 1} = O \tag{2}$$

[1] The ANN structure is composed of three layers: input layer which accepts normalized input, hidden layer that processes these inputs towards the output layer. This is illustrated in Figure 4.
[2] Because the ANN structure usually accepts input that are of different data types (like demand [kWh], day, [Monday through Sunday], and electricity rate [PhP/kWh], it is important that the input variables are scaled properly first through data normalization before proceeding with the ANN.
[3] The weights A (and B) serve as coefficients of the structure that relates the input to the hidden layer, and the hidden layer to the output.
[4] ANN is inspired by the activation of biological synapses through a stimulus. This behavior of the synapses is imitated by the ANN through a sigmoid function.

The error E of the output from the target T is also computed using the sigmoid function of the output s(O) as follows:

$$\mathrm{E} = \mathrm{T} - s(\mathrm{O}) \tag{3}$$

where B = weights between the hidden layer and the output layer
O = output
T = target values
E = output error

The model is optimized by determining the weights that have minimal error. Most methods use the square-of-error as the cost function to refine the weights, which is done through the process of back-propagation. This then concludes a training run. After the back-propagation, the necessary adjustments, $\Delta\mathrm{A}$, and $\Delta\mathrm{B}$, were determined and applied on A and B for the next training run. This will eventually result in a better model with minimal error E.

$$\mathrm{C} = \frac{1}{2}\mathrm{E}^2 = \frac{1}{2}(\mathrm{T} - s(\mathrm{O}))^2 \tag{4}$$

$$\frac{\partial \mathrm{C}}{\partial \mathrm{B}} = \frac{\partial \mathrm{C}}{\partial s(\mathrm{O})} \times \frac{\partial s(\mathrm{O})}{\partial \mathrm{B}} \tag{5}$$

$$\frac{\partial \mathrm{C}}{\partial \mathrm{B}} = -(\mathrm{T} - s(\mathrm{O})) \times [s(\mathrm{O}) \times (1 - s(\mathrm{O}))]s(\mathrm{H}) = \mu\Delta\mathrm{B} \tag{6}$$

$$\frac{\partial \mathrm{C}}{\partial \mathrm{A}} = \frac{\partial \mathrm{C}}{\partial s(\mathrm{O})} \times \frac{\partial s(\mathrm{O})}{\partial s(\mathrm{H})} \times \frac{\partial s(\mathrm{H})}{\partial \mathrm{A}} \tag{7}$$

$$\frac{\partial \mathrm{C}}{\partial \mathrm{A}} = -(\mathrm{T} - s(\mathrm{O})) \times [s(\mathrm{O}) \times (1 - s(\mathrm{O}))]\mathrm{B} \times [s(\mathrm{H}) \times (1 - s(\mathrm{H}))]s(\mathrm{H}) = \mu\Delta\mathrm{A} \tag{8}$$

In this study, the ANN is composed of one hidden layer with ten neurons, trained by minimizing the squared errors and weights to find the best fit for the model[5]. The ANN is used to perform the simulations. The input variables used vary for the different models that will be proposed in the study. For each ANN model, 100 training runs were done to observe the forecast precision of each model.

Forecast Horizon

Different forecast horizons (from day-ahead to week-ahead forecasts) will be tested to determine the best forecast horizon applicable for the quantity of available data. An ANN that will generate the LMP forecast for a generator node by using only the historical prices of the node as an input variable will be used for this purpose. The oligopolistic nature of generators in electricity markets assumes that the forecast price is mainly a function of past prices possible. This will be done for a selected generator node, and forecast performance will be evaluated using the above-mentioned error measures.

[5] This is known as Bayesian regularization.

Generator Node Forecast

Forecasts of generator nodal prices were simulated using a generator ANN model for 100 runs with the following input data: Day of the week, Time of the day, and the LMP of the chosen load node. The generator nodes used in this study are those electrically adjacent to the load node considered. An illustration of this is shown in Figure 5. In this study, directly adjacent nodes are termed as primary adjacent, while generators adjacent to the load through another node are termed as secondary adjacent.

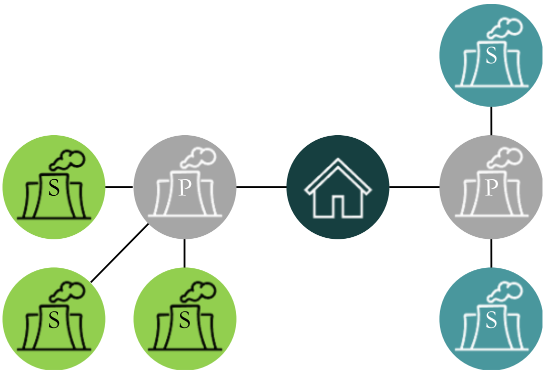

Figure 5. Node adjacency diagram

Load Node Forecast

Unlike generator nodes, nodal prices at load nodes are highly sensitive to the nodal prices of adjacent generator nodes. To observe the effect of adding adjacent generator prices on the LMP forecast, models were designed to take in the historical load demand, historical load price, and historical generator price, aside from the time of the day and day of the week input parameters. In this study, four different ANN models using various combinations of input variables, each to be done for 100 runs, will be used to forecast the LMP of the load node:

Model 1: Time *t(d-k)*, Day *D(d-k)*, and Load *L(d-k)* *k*-day before forecasted day *d*

Model 2: Time *t(d-k)*, Day *D(d-k)*, and Load LMP $P_L(d\text{-}k)$ *k*-day before forecasted day *d*

Model 3: Time *t(d-k)*, Day *D(d-k)*, Load *L(d-k)*, and Load LMP $P_L(d\text{-}k)$ *k*-day before forecasted day *d*

Model 4: Time *t(d-k)*, Day *D(d-k)*, Load LMP $P_L(d\text{-}k)$, and Primary Adjacent Generator Price *Pgp(d-k)k*-day before forecasted day *d*

Model 5: Time *t(d-k)*, Day *D(d-k)*, Load LMP $P_L(d\text{-}k)$, and Secondary Adjacent Generator Price *Pgs(d-k)* *k*-day before forecasted day *d*

Models 1, 2, and 3 are composed of a combination of historical load demand and load LMP. It aims to forecast the LMP using these load characteristics, as used by most literature.

Models 4 and 5 will incorporate the adjacent generator prices to show how these parameters affect the forecast of the LMP in comparison to the models that only consider load characteristics.

All the input variables are *k*-day before the forecasted day *d* (i.e., for a day-ahead forecast, the input variables are all *d-1* data, for a two-day ahead forecast, *d-2*, and so on). The forecast horizon of the final model will be the same as what will be previously determined in the first part of the methodology, based on the quantity of available data.

Dataset Features

Typical data for the LMP of the load node used in this study is shown in Figure 6. From the figure, the volatility of the prices can be observed. Since weekends generally have a different load profile compared to weekdays, this study limits the forecast to weekday forecasts to avoid distortion in the training of the models. There are instances when the prices are negative, where generators pay the customers to consume power, particularly when there is an over-generation in the network. This happens sometimes but is not the normal behavior for the market. Therefore, negative prices are replaced with a price of zero. This study only used publicly available data, which is the last 3-months data from the Philippine Electricity Market Corporation (PEMC 2019) website.

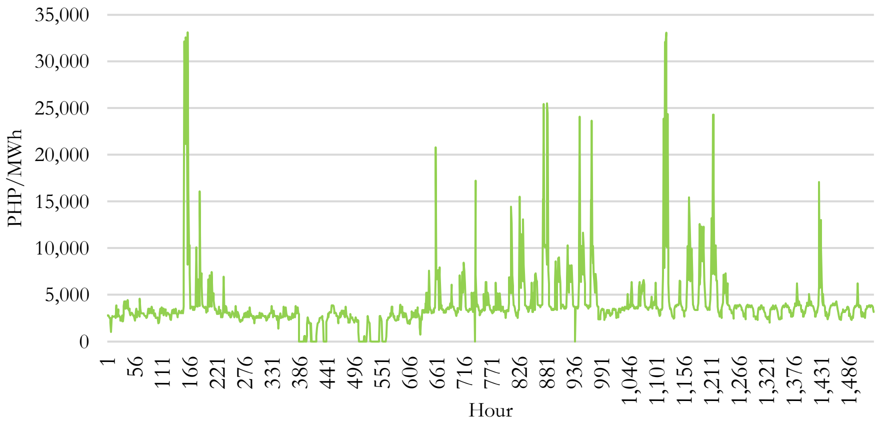

Figure 6. Load node LMP from November 2018 to February 2019

Results and Discussion

Forecast Horizon

Using the historical data for the nodal price at a generator node, the performance of using different forecast horizons in a single-input ANN model was measured and compared to get the best forecast horizon suitable for the quantity of data available. The results for 100 training runs of the ANN for each candidate forecast horizon are shown in Table 1.

Table 1. Performance of the five different forecast horizons on 100 simulation runs

	MAPE (%)	RMSE (PHP/MWh)	MAE (PHP/MWh)
Week-ahead	24.42	1,817.84	971.95
Four-day ahead	24.58	1,406.80	809.88
Three-day ahead	27.00	1,415.41	891.42
Two-day ahead	7.39	397.36	263.26
One-day ahead	13.98	644.13	493.22

From the results in Table 1, a two-day ahead forecast performed best among the different forecast horizons. Though the one-day ahead forecast is closer to the present day, the removal of the weekends adversely affects the ANN training as Mondays were trained to be forecasted using data from Fridays. The two-day ahead forecast trained the model to account for this error because all the days are trained with a one-day gap between the forecasted and forecasting data, resulting in better training performance for the chosen input data and biases on the hidden layer of the ANN.

Generator Node Forecast

Generator nodal prices are forecasted using three ANN input variables: Day, Time, and Generator LMP from *d-2* day (based on the chosen forecast horizon). To simplify the presentation of the results, only the forecasts for the primary adjacent generator nodes, G1 and G2, are presented in this paper. The other generator nodes show similar behavior as the two. The two-day-ahead forecast for G1 and G2 are shown in Figure 7, with the forecast performance tabulated in Table 2.

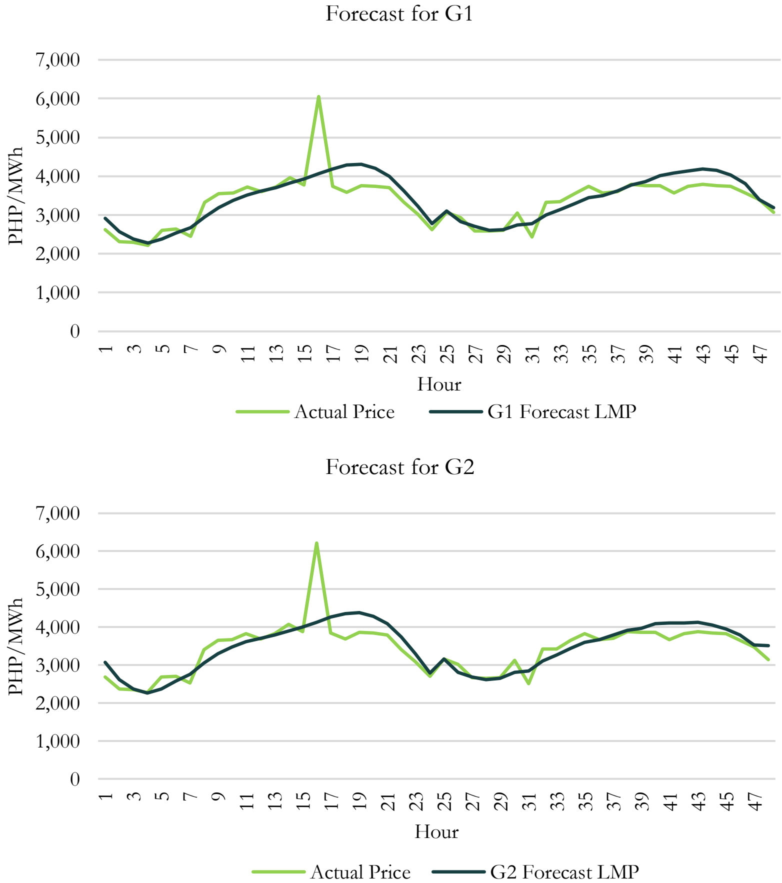

Figure 7. LMP two-day ahead forecasts for G1 (top) and G2 (bottom)

Table 2. Two-day ahead LMP forecast performance for generator nodes, G1 and G2

Generator Node	MAPE (%)	RMSE (PHP/MWh)	MAE (PHP/MWh)
G1	7.39	397.36	263.26
G2	6.90	397.51	252.09

From these results, one prominent observation is that the shape of the forecast imitates the shape of the actual generator LMP. This shows that the model was able to mimic the behavior of the price using the input variables chosen in the study. However, there are spikes in the actual values that this model was not able to predict. Comparing the two graphs for G1 and G2, the behavior of the LMPs are almost identical, suggesting that the LMP, though different, follow a certain common behavior (i.e., the market-clearing price).

Load Node Forecast

Using the five different models for load node ANN structure, the two-day ahead forecasts for each model are shown in Figure 8, with their performance tabulated in Table 3.

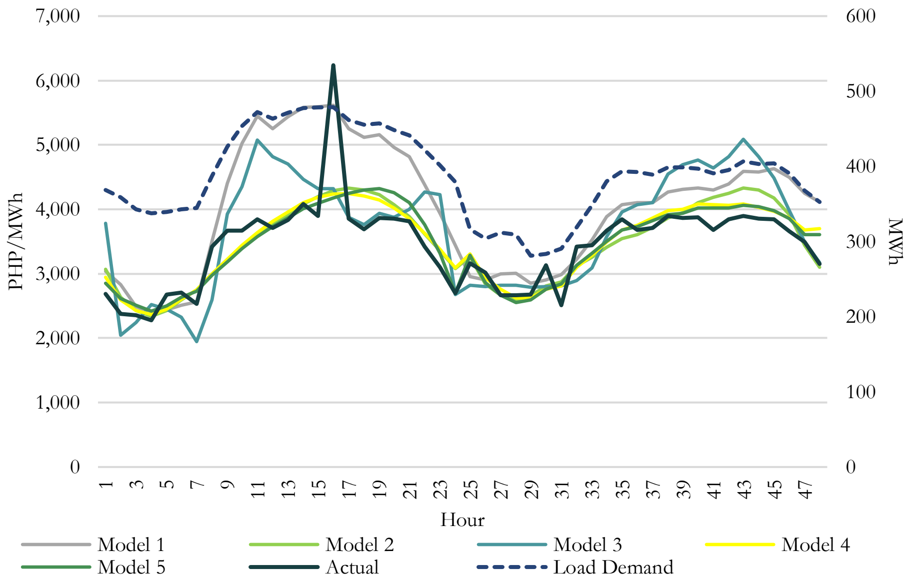

Figure 8. Comparison of different models for the load node forecast

Table 3. Two-day ahead LMP forecast performance of the different models for the load node

Model	**MAPE (%)**	**RMSE (PHP/MWh)**	**MAE (PHP/MWh)**
1	18.50	817.52	659.44
2	7.33	392.87	265.21
3	14.09	652.42	499.50
4	6.86	376.87	246.93
5	6.76	387.55	246.41

The first three models (models 1, 2, and 3) combine different parameters specific to the load (i.e., day of the week, time of the week, load LMP, load demand). Among these three, model 2 performed best on 100 runs of the ANN. This shows that the LMP of a load node at a given instant is greatly affected by its LMP in preceding time instants. Since model 1 is trained using the load demand as an input, the behavior of the forecast of model 1 follows the variation of the load demand as shown on the graph. This behavior is also visible in model 3.

The last models (models 4 and 5) combine different parameters specific to the load and the adjacent generators of the load (i.e., day of the week, time of the week, load LMP, primary and secondary adjacent generator LMPs). Generally, an improvement in the forecast can be observed if, instead of just the load parameters, LMPs from the adjacent generators are also included as ANN inputs in the forecast training. A better forecast MAPE is obtained from model 5, which may be attributed to the number of training inputs that model 5 has compared to model 4. Both models performed better than the first three suggesting that the addition of generator LMPs as ANN inputs can improve the model performance.

Prediction Intervals

Prediction intervals were used to identify the area in which the forecast values will likely fall (i.e., forecast distribution). ANNs train models according to activation functions, hence prediction intervals were not calculated similar to stochastic models. In this study, prediction intervals for ANN were generated from 100 training runs, producing 100 forecasting models. These were compared to Autoregressive Integrated Moving Average (ARIMA) models with prediction intervals to compare the model accuracy.

ARIMA models produced good estimates using the 3-month data, with the ACF and PACF plots suggesting seasonality every 24 hours, hence seasonal ARIMA (i.e., ARIMA (*p, d, q*)(*P, D, Q*)) was used. The data used first-order trend differencing for stationarity. Using different orders for *p* and *q* simulated on MatLab, the best fit ARIMA model was obtained. Shown in Figure 8 are the ARIMA parameters used in modeling and the ARIMA LMP forecast.

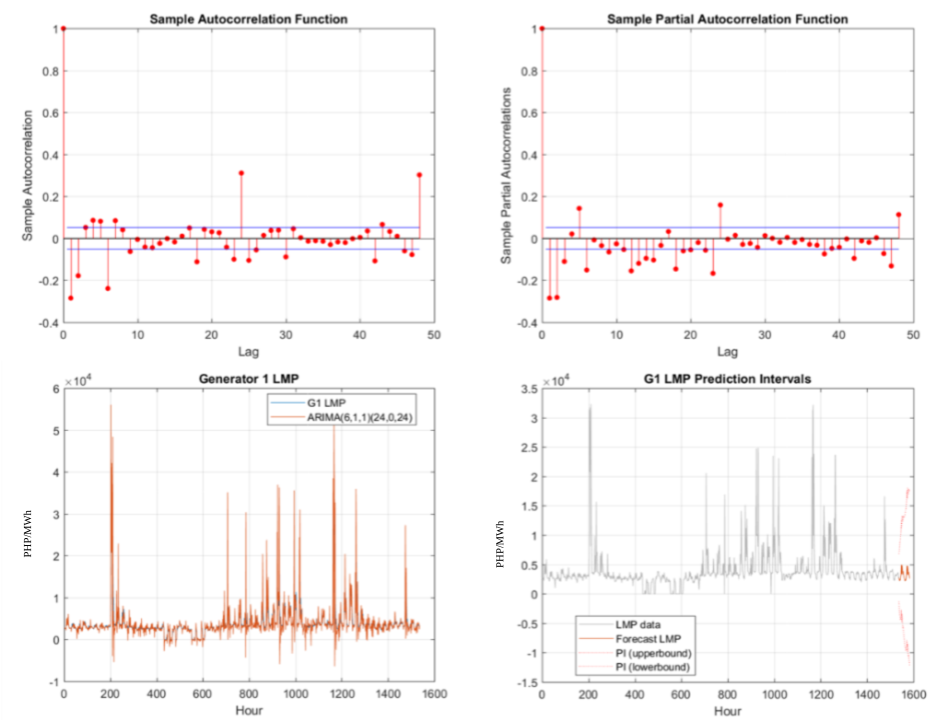

Figure 8. ARIMA model forecasting (from top left to bottom right): ACF, PACF, ARIMA model fitting, ARIMA model forecast with 95% prediction intervals

Looking closely at the ARIMA forecast, there is a broad range of values that the forecast may fall at 95% prediction interval of this model. This is because of the huge price spikes present in the three-month training data that cause large residuals. Shortening the training to only one-week data improved the prediction accuracy, and introducing a price cap (in this case, PHP 5.00/kWh) improved this further, as shown in Figure 9. The results showed that price spikes, even in low frequency, significantly affect the prediction interval.

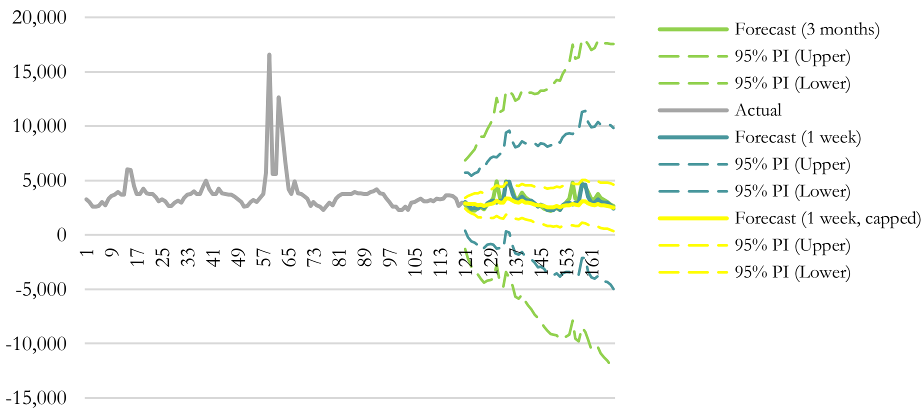

Figure 9. Comparison of prediction intervals of ARIMA models trained using 3-month data vs. 1-week data

On all models of ARIMA, the forecast distribution widens as the forecast step goes farther from the last known data. This shows that the accuracy of the model decline as the forecast horizon increases. This is different from ANN as ANN was trained to capture the behavior of the price at any specific time for a specific forecast horizon. This results in a forecast that is consistently precise even the step forecast increase, as shown in Figure 10 and Figure 12.

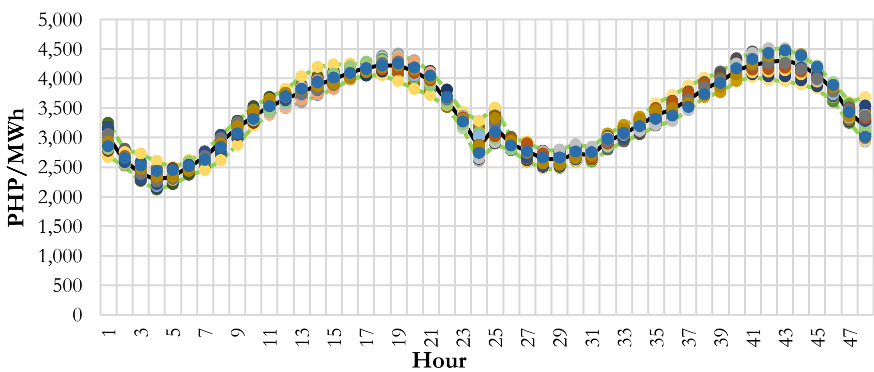

Figure 10. ANN 100-run forecasts: 2-day ahead hourly forecast

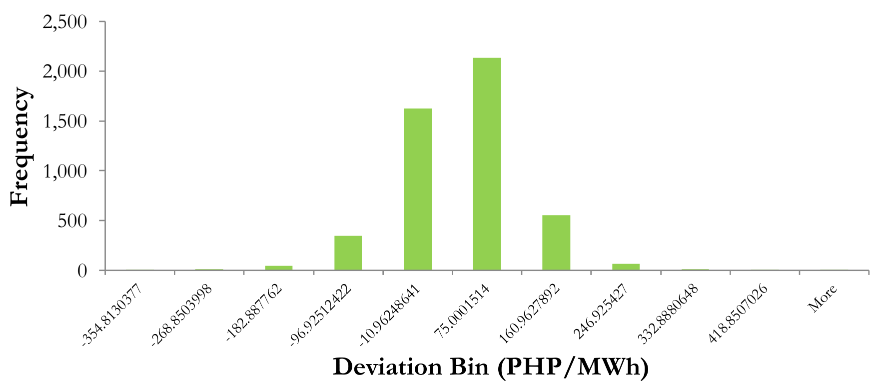

Figure 12. ANN 100-run forecasts: forecast deviation histogram

The presence of price spikes also did not affect the prediction interval of ANN too much compared to ARIMA, where even a single spike causes the prediction interval to widen by a significant value. This makes the selection of price caps crucial in improving the ARIMA model. ANN, however, can learn this and adjust the model accordingly based on the time (and day) the price spike happens (or usually happens). Therefore, the ANN model is more vulnerable to sudden spikes and returns a more normal model for the LMP. It is also interesting to note that comparing the ARIMA model trained using a 3-month data and the ARIMA model trained using 1-week data with a price cap, the ARIMA model trained using a 3-month data has a better resemblance to the actual LMP than the other model, despite having the worse prediction interval. The ARIMA model trained with 1-week data with price capped may have a narrower prediction interval, but it also loses more information about the shape of the LMP through the process. This is not the case for the ANN-trained model, as this model captured the price behavior without too much intervention on the input variables. The comparison of the different forecast models is shown in Figure 13.

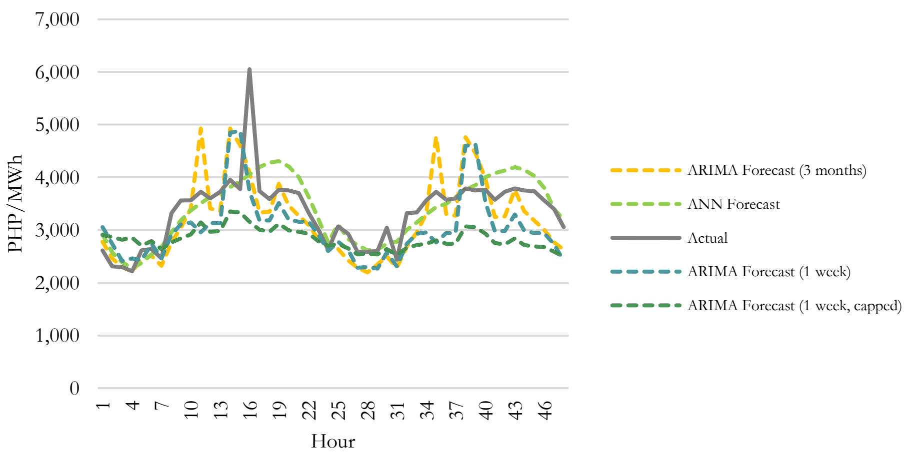

Figure 13. Comparison of actual LMP vs. various forecasts between ARIMA and ANN models

Summary and Conclusion

Locational Marginal Cost Pricing (LMP) is an important information that players may use in participating in a competitive electricity market. LMP is a decision factor that might affect resource allocation and network operations. Unlike Marginal Cost Pricing (MCP), LMP is more local and is more difficult to forecast. This study presents a novel Artificial Neural Networks (ANN) based methodology for forecasting the LMP of generation and load nodes in a market-based power system. To forecast generator node LMP, an ANN that uses generator historical LMP as inputs is proposed. A preferred forecasting horizon can initially be determined for the given quantity of available LMP historical data by using an ANN that forecasts generator node LMP. Load node LMP forecasting is performed by ANNs that use a combination of time, day, historical load power, historical load LMP, and historical adjacent generator nodes LMPs as inputs. Results show that the inclusion of the LMPs of adjacent generator nodes as inputs to the ANN for load node LMP forecasting is found to produce a significant improvement in forecast accuracy that has not been previously investigated in the existing literature. Prediction intervals generated by ANN are also better than those generated by other stochastic models such as ARIMA. ANN was able to precisely model the behavior of the LMP and maintain this precision through the whole forecast horizon.

Recommendations

The artificial neural network models used in this study have successfully forecasted the behavior of the nodal electricity prices in the market. However, the availability of data limits the forecast horizon to only two days. Longer dataset may improve the forecast and forecast horizon. Other exogenous variables may be considered to predict spikes in prices on the generator nodes. Load nodes, however, were trained well with the incorporation of generator node prices as input variables. Further improvement in the generator node forecast may also help improve the load node forecast.

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