Hybrid Model for Very Short-Term Electricity Price Forecasting

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***Abstract*—It is expected that more and more grid connected renewable plants, coupled with energy storage, will be added to the Australian grid to meet the grid integration challenges of renewables. With increased penetration of such systems in the grid, optimal daily scheduling of hybrid renewable-storage generation systems has become a topic of interest. The very short-term (VST) electricity price forecasting is one of the key inputs of such optimal scheduling models. This paper presents a hybrid Support Vector Regression (SVR) and Feedforward Artificial Neural Network (FANN) based approach for VST forecasting of electricity prices. The forecast accuracy of this proposed model is demonstrated with real data from the National Electricity Market (NEM) of Australia.**

***Index Terms*—Forecast, Electricity, Price, Renewable, Energy.**

I. Introduction

With growing interest in renewable energy coupled with falling costs of electricity generation from renewable based power generation technologies such as solar and wind, it is expected that more and more variable renewable generation will be added to the Australian grid. However, a high penetration of variable renewable generation, challenges the power system considerably due to the greater variability and uncertainty associated with output from these plants. Energy storage is recognized as a promising enabling technology for solving this problem. In this context, it is expected that more and more grid connected renewable plants, coupled with energy storage, will be added to the Australian grid. The economics of these plants is heavily reliant on being able to optimize the scheduling of output of these energy constrained plants with the aid of storages. Accurate, VST electricity price forecasting is a key input in optimal scheduling of such systems. Although, there are studies on short-term electricity price forecasting, according to our knowledge, there are limited studies on VST electricity price forecasting. To fill this gap, this study presents an approach for very short-term electricity price forecasting.

There are a variety of methods that have been used for electricity price forecasting, most notably for long term, medium, and short-term forecasts [1], [2] [3]. Some of these methods include Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Network (ANN), Support Vector Regression (SVR), Multiple Linear Regression, Time Series Analysis, Fuzzy Logic and Fuzzy Neural Networks. As literature on VST electricity price forecasts is limited, the best methods had to be selected from other applications based on the ability to handle volatile and complex data, and perform accurately on a consistent basis for VST timeframes. We found that the forecasting model outlined by [4], for stock price index forecasting with highly accurate results is a promising model for forecasting VST electricity prices. In the method presented in [4], SVR and ANN are utilized in a two-stage process to forecast the VST stock price indices, illustrating how SVR-ANN forms a more accurate forecasting model than that of a single ANN or SVR in the forecasting of stock prices. Our study demonstrates applicability of this proposed hybrid SVR-ANN approach given in [4] for VST electricity price forecasting using a case study applied to the National Electricity Market (NEM) of Australia. This proposed model can forecast VST electricity prices more accurately by capturing both strongly and weakly correlated parameters. In this study we carried out a comprehensive data pre-processing task to capture both strongly and weakly correlated parameters of electricity prices in the NEM.

The organization of the paper is as follows: Section II presents a detailed methodology for forecasting VST electricity prices using the SVR-ANN based approach. This is followed by an application of the methodology to forecast the VST electricity prices in the NEM given in Section III. Finally, key findings and concluding remarks are presented in Section IV.

II. Methodology

The model for VST electricity price forecasts was developed based on the model proposed in [4] for VST stock price forecasts using SVR and Feedforward Artificial Neural Networks (FANN) in a two-stage process. In our proposed model, the first stage uses multiple SVRs to preprocess a selection of pairs of strongly correlated data. This is done to fully represent the correlations and the

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effect they have on electricity prices, while filtering out extreme outliers that would inaccurately skew the forecast. In the second stage of the model, data that exhibited weak or no correlations are fed directly and independently into the FANN to determine its relevance to the forecast price. The kernel function used for the SVM training is the sigmoid kernel. The overall forecasting model framework is presented in Fig. 1.

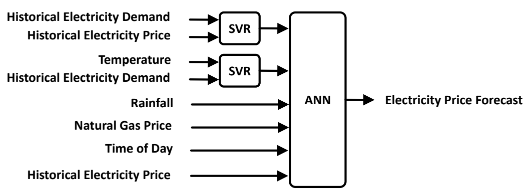

Fig. 1. Forecasting Model Framework

A. Feedforward Artificial Neural Networks

FANNs are one method of forecasting that is popular with many forecasting models and has proven to be effective in a variety of applications. FANNs work through a nodal framework, made up of three types of layers being input, hidden and output. Each node contains an activation function and are connected to other nodes via linkages [5]. Linkages between nodes are assigned a weight which determines how much the node, and its associated variable, affects the output.

FANNs require supervised training in order to become accurate. During this phase the output is compared to actual data or targets to determine the error. As the network is learning the linkage weights are adjusted via using the backpropagation algorithm (BPA) in order to minimize the error [6]. The weights are continually adjusted until the FANN reaches an optimal level of output, with the minimum amount of error. The weights of the neural network are best set when all the data is normalized, to remove the effect of different units and scales. In some cases, where correlation between variables is negligible, neural network linkages can altogether be removed, to allow for a simpler and more computationally effective FANN [7].

B. Support Vector Regression

Support Vector Machine (SVM), is another effective and popular forecasting method in literature. SVM is a supervised machine learning method and is mainly used for classification [8]. It does however have the ability to perform regression to forecast data, being Support Vector Regression (SVR) [9]. SVR maps the data and then fits a function to the data and introduces an error margin, epsilon (ϵ). This is a value which sets up a zone around the function in which errors are ignored [8]. In order to prevent this from creating unnecessary constraints, a soft margin loss, or cost factor, is introduced to allow some points to exist outside of the ϵ-margin.

There are two ways to make support vector functions non-linear. The first is achieved by pre-processing the training patterns by a map into a feature space [8]. This method works well but becomes computationally impossible for functions of higher orders. The second is through the use of kernel functions. A kernel function is a dot product function that is used to optimize the support vector function [8] and are selected based on the requirements of the model. The result is the fitting of a non-linear function to the data. In our model, demand and price, and temperature and demand, are filtered using SVR, as they were the two pairs of variables that demonstrated the strongest correlation. This is consistent with extensive literature that recognizes that electricity price is highly dependent on demand, and demand is highly dependent on temperature [5].

C. Data pre-processing and Error Measurement

To ensure that the magnitudes of the different data sets have no effect on the weights trained within the neural network, all of the FANN input data is scaled using a z-transform prior to entering the FANN. The z-transform is calculated as follows $z{=}(x - mean(x))/std(x)$. This scales all of the data into values within [-1,1], ensuring that the neural network can learn properly off the input data. Targets are assigned to the neural network while training to ensure the FANN is training to recognize future trends off historical data. The targets are the price for the $(t{+}1)th$ time step at every timestep, t. This trained the neural network to recognize the relationship between the current inputs at time t, and the future electricity price at time $t{+}1$.

Mean Absolute Percentage Error (MAPE) was one measurement of the forecast error chosen for this project. MAPE is a widely accepted form of error measurement that is used for electricity price forecasts. MAPE is calculated using the following formula [4]:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|A_t - F_t|}{|A_t|} \times 100. \tag{1}$$

Another important measure of error is variance of the error from the actual value. To calculate this, the relative Root Mean Squared Error (rRMSE) is used. rRMSE is calculated using the following formula [4]:

$$rRMSE = \sqrt{\sum_{t=1}^{n}\left(\frac{A_t - F_t}{A_t}\right)^2}. \tag{2}$$

Other forms of error measurement include Mean Absolute Error (MAE) and Mean Squared Error (MSE). In this study, MAPE and rRMSE were chosen for error measurement instead of these alternatives as they provide easily interpretable values.

III. Results and Discussion

In the present study, we illustrate the application of the hybrid method of SVR and FANN, for forecasting VST electricity prices in the NEM. Data was collected for the year 2014, with all weather data sourced from the Bureau of Meteorology (BOM), and electricity market data from the Australian Energy Market Operator (AEMO). SVR was implemented with the statistical programming language R as it allows for graphical representations, data handling and storage and is a simple programming language that allows for a multitude of applications [10]. The FANN was implemented using the MATLAB Neural Network toolbox. The MATLAB Neural Network toolbox provides a consistent and reliable means for creating and training FANNs and also allows for importing large data sets. This combined with the its flexibility and ease of use was the reason MATLAB was chosen to develop the FANN for the forecasting model. The model uses data input from the prior 100 days to train each progressive timestep.

As described in Fig. 1, SVR was used to pre-process strongly correlated data before supplying them into the FANN in a two-stage process. In order to ascertain the accuracy of the SVR-FANN method, the results were compared to a single SVR model prediction and a single FANN model prediction. The errors were compared using MAPE and rRMSE to determine the models' ability to represent price spikes, an important aspect of VST electricity price forecasting. Comparing the different methods in this way will allow a conclusion to be drawn on whether there are any benefits to a hybrid model of electricity price forecasting. It will then be investigated whether an average of two separate forecasts, that display strengths in predicting different aspects of the electricity price, can provide a more accurate forecast, than by one alone.

A. Variable Correlations

The six variables used in this forecasting model were date/time, historical price, historical demand, rain, temperature and natural gas prices. These six variables were chosen based on the availability of data, given the scope of the project, and their relevance to VST time frames. Scatterplots were generated for all of the variable pairs, giving a visual representation of their correlation for this forecasting model. The correlation determined from these scatterplots were used to determine which pairs of data would benefit from pre-processing in SVR and which would not. Correlation was visually checked on scatterplots to determine which pairs demonstrated strong correlation. Two pairs of data demonstrated strong correlation with each other, which were demand and price, and temperature and demand. These two pairs of data are commonly recognized throughout literature as having the strongest correlations for VST electricity price forecasting [11], [12]. The other pairs of data, while showing small amounts of correlation, did not show enough correlation to be of any added benefit. The scatterplots for demand and price, and temperature and demand can be seen in Fig. 2.

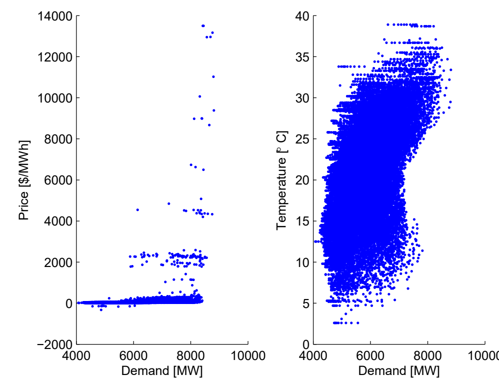

Fig. 2. Highly correlated input pairs

B. Stage 1 – SVR

Stage one of the forecasting model is a SVR filtering of data with strong correlations. SVR was performed in RStudio and its performance was tuned with regards to the error factor ϵ, and the cost factor, which determines how strict the model is on allowing outliers to exist outside ϵ's range. Fig. 3 gives the SVR for one day for price and demand. SVR was tuned with a range of ϵ values of [0, 0.5], and a cost factor of 2^c, with a $c \in [2, 9]$. After tuning, the model with the best performing combination of ϵ value and cost factor was selected. Once the best performance was found, these SVR outputs were used as inputs into

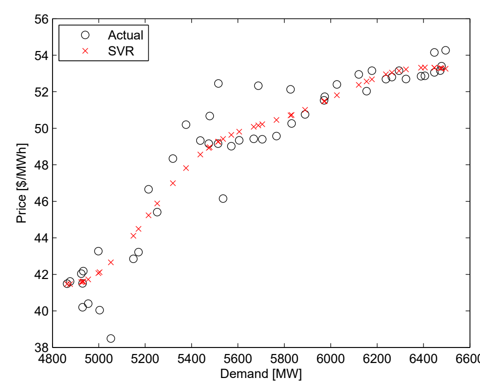

Fig. 3. SVR Pre-tuned

the FANN. Fig. 4 shows the tuned SVR results for the same day as Fig. 3 for price and demand. As can be seen from the Fig. 4, the tuning gives a more accurate filtering and fitting to the data than what is initially performed, allowing for more accurate data to be passed to the neural network, while ignoring the extreme outliers.

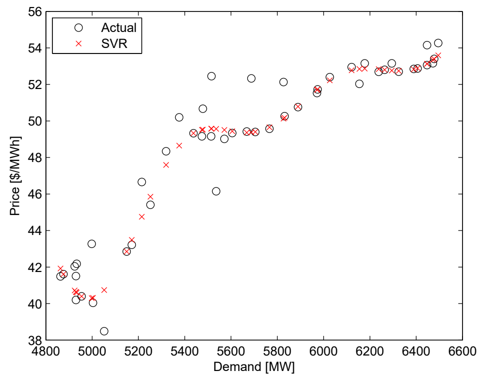

Fig. 4. SVR Tuned

C. Stage 2 – FANN

The FANN was initialized using the tanh function as the activation function. This utilizes the normalized data to increase the sensitivity of the FANN. The neural network was first initialized with 10 hidden nodes. However, while experimenting with network sizes, the network was found to perform better when the number of nodes was equal to the number of inputs. This meant that the final neural network had 6 inputs, 6 nodes in a hidden layer and 1 output, which was the final price forecast.

To train the network, the data division was set as MATLAB command "dividerand" and the training algorithm command "trainlm" (the Levenberg-Marquardt algorithm). Performance was determined using the default "Mean Squared Error", and calculations were undertaken in MEX, which is the most memory efficient option in MATLAB. Due to the use of "dividerand", a random seeding is used to initialize the weightings of the nodes while training. This meant that a bias value had to be included in the network and a constant seed for the random number generator had to be provided before training, to ensure that the network was trained consistently every time. This random seeding was found by repeating the training with different seeds, until the best training of the network was found.

D. Model Accuracy

For each of the three prediction models that were investigated, an output was generated and compared to the actual price for the period specified. The overall performance was measured using MAPE and rRMSE. The summary of the MAPE and rRMSE results of the three forecasting methods can be in Table I. Based on the MAPE outlined in Table I, SVR provides the most accurate forecast. However, this only represents how well the model approximates the average of the price. In order to determine whether the model represents the price spikes, rRMSE was calculated. Based on rRMSE, the SVR-FANN provides the most accurate forecast. Using a combination of the two measurements it can be determined that SVR-FANN provides the most reasonable forecast, as its MAPE is not significantly high and the rRMSE is low, meaning that the spikes are represented the most accurately. The results of the three models can be seen in 5. Fig. 5 shows that

TABLE I
MODEL ACCURACY COMPARISON (10/04/2014)

Method	*MAPE*	*rRMSE*
SVR	3.4826%	0.2596
FANN	10.0750%	4.5847
SVR–FANN	8.6165%	0.1348

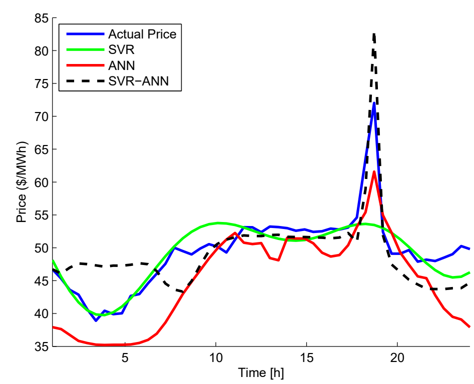

Fig. 5. Comparison of hourly price forecasts of day 10/04/2014 from different models

the SVR follows the average of the actual price very well, which is reflected by its low MAPE value. However, SVR fails to properly recognize the price spike. The SVR-FANN model tracks a better approximation of the actual price average than the FANN, and recognizes the magnitude and duration of the price spike the most accurately out of the three models, which is reflected by its low rRMSE. Accurately representing the duration of the price spike is especially important, even more so that the precise magnitude, as the duration of the higher prices it what is used for the scheduling of operations and maintenance. If the duration of the price spike is incorrect, it could lead to incorrect scheduling and unnecessary profit losses.

After these results were obtained, it was further investigated whether an average of the SVR prediction and the

SVR-FANN prediction would result in a low MAPE and low rRMSE, with the ability to more accurately predict price spikes to give a more accurate overall forecast. The average of the two predictions of SVR and SVR-FANN was calculated and resulted in a MAPE very similar to the SVR prediction, being 4.157%. As seen in Fig. 6, the magnitude and duration of the price spike in the averaged model, provides the best forecast so far regarding both duration and magnitude of the price spike. By averaging out the SVR and SVR-FANN predictions, the best traits from each are combined. These results have confirmed that

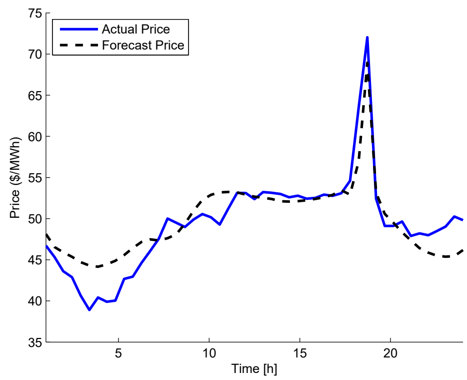

Fig. 6. Hourly price forecasts of day 10/04/2014 form combined average of SVR and SVR-FANN

a hybrid SVR-FANN model demonstrates higher accuracy than that of individual SVR or FANN forecasting models. The averaging results have also demonstrated that the accuracy of any given forecast can be improved by combining multiple predictions that each display strengths in certain aspects of forecasting. This means that combining the current model with more complex methods, as outlined in [11], [12], can result in overall improved accuracy. These more complex methods could be implemented in further research in order to improve model accuracy and increase the accuracy of price spike prediction. These more complex methods, as outlined in [11], [12] include:

- Wavelet Transform
- Compound Classifiers (Relevance Vector Machine, Bagged decision trees, Probabilistic Neural Network)

As the investigation into developing an accurate electricity price forecast proves, combining multiple methods in a relevant manner, leads to an increase in accuracy. Incorporating these other methods would also go towards predicting the price spikes more accurately, which when combined with an accurate average prediction, would predict the overall actual price in a more accurate manner.

IV. Conclusion and Recommendations

As seen from the results obtained from the investigation, a hybrid model, combing SVR and FANN, does lead to an improvement in forecasting VST electricity prices. An improvement to the accuracy of the SVR-FANN model was also achieved by combining the low MAPE SVR prediction with the SVR-FANN, which performed the best predicting price spikes and rapidly changing trends, while still maintaining a respectable MAPE value. Averaging the two resulted in lowering the MAPE to that of the SVR prediction, while even more accurately forecasting the magnitude and duration of the price spike.

Further research to be undertaken in this area could include accurate price spike forecasting, implementing some of the improvements as outlined by [12], [13]. It would be recommended that more variables be investigated into their usefulness in VST price forecasting, such as bidding and rebidding strategies and generator availability. Determining other variables which have an effect in electricity prices would mean that other significant factors not able to be taken into account in this project could be used to further increase the accuracy of the VST electricity price forecast.

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