Effects of High Penetration of Solar Rooftop PV on Short-Term Electricity Pricing Forecasting by Using ANN-ABC Hybrid Model; Case Study of South Australia

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***Abstract*— This work focus on short-term electricity price forecasting in deregulated market. Short-term electricity pricing forecasting becomes more difficulty due to high penetration of uncertainty renewable energy resources. Moreover, high level of solar PV rooftop's is one of portions in price spike due to its uncertainty and intermittent. The historic data is collected from New South Wales, Australia electricity market. This paper proposed artificial neural network (ANN) integrated with artificial bee colony (ABC) based on particle swarm optimization provide highest R-square comparing to conventional ANN method. In the prediction for future electricity price, ANN and ANN-ABC has excellent performance.**

Keywords-Artificial Bee Colony, Artificial Neural Network, Hybridge method, Electricial pricing forecasting, Smart Grid

I. INTRODUCTION

Nowadays, electricity markets are more complex and became more sophisticate since rapidly change of biding on electricity prices and exchanging structures. The incorporation of pool and bilateral, or two-sided, contract became more important role tools in energy business sector [1]. In the pool contract, examples are the Californian pool, the Australian national power market, the mainland Spain, both the power producers and customers submit offers and biding prices which gets cleared by the market operators. These market operators state the costs, examples are production cost, congestion cost and maintenance cost, for the following day or called "day-ahead". The organizations may likewise need to utilize respective contacts for support against the risk of price instability due to fuel prices, weather condition and regulation.

For both these instruments, day-ahead electricity price forecasting or next couple of months is key factor for market operator who schedule blackout, design load response and different decision making process. Moreover, hour ahead can offer to both producer and customer to increase the benefits on financial aspect. The market clearing costs or local marginal price are freely accessible for all the power showcase as it is the situation of the day-ahead and hourly-ahead pool of mainland Spain (www.omel.es), the Californian pool (www.caiso.com), or the Australian national power market (www.aemo.com.au) [2].

The rest of this paper is organized as follows. The reviews on real time electricity price and forecasting tools is explained in section II. Section III discusses on similar day data collection, the mechanism to predict electricity price and evaluation. Simulation results are shown in Section IV. A discussion and conclusion of this paper are represented in Section V and VI.

II. LITERATURES REVIEW

A. Electricity pricing

The electricity spot market is operated by submission of agent's bids for hour and half hour which come from both producer and consumer or only producer which is difference from other energy markets. Typically, electricity spot market is done in day-head and the price is created by system operator with information of transmission constraint, available of generations, prices of fuel and other variables which is call market clearing price (MCP). MCP denotes the balanced pricing of aggregated supply and demand for delivery electricity in power pool. Usually, MCP is created before market closing time in day-ahead using intersection between aggregated supply curve and aggregated demand curve from producer and consumer or retailer. In Australian or Spain electricity market, one side auction, system operator estimated forecasted demand to create MCP. Increasing and reducing in MCP comes from buy and sell order until total supply and demand are balanced. In case of no congestion in transmission network, the MCP is introduced to the entire system's price, it is suitable for small or medium sized electricity market. Nodal prices are created due to the electricity value based on where it is generated and how far its delivered which creates transaction cost. The nodal prices are different for different bus in same location area. This concept is proposed in [3]. Nodal prices are more complexity compare to LMP. On the other hand, the nodal prices are slightly differed in difference zone due to low-congestion management cost. The nodal prices' structure in the European network is more complexity comparing to North America where transmission system is highly meshed and Australia where the network construction is simpler.

Real-time market, the transmission system operator (TSO) operates in very short time period before delivery. For this situation, the electricity price is deviated from day-ahead prices or long-term contracts. Due to unbalancing in supply and demand, the TSO run ancillary services market which call for extra production to warranty the balance in system. However, there is not only this technique. The spinning and non-spinning reserve services for real and reactive power is another option of ancillary services market. TSO has different purposes to use day-ahead balancing and ancillary services markets. Example of real-time market are the Ontario Electricity Market (OEM) and the Australian National Electricity Market (NEM). In those system, producers and consumers make biding to market operator in day-ahead but the volume is revised up to 5 and 10 minutes for NEM and OEM before electricity dispatching without any limit. The spot prices are set in half-hourly and hourly interval in NEM and OEM which are computed from average of 5 and 10 minutes' prices. The researches show that the electricity price in OEM and NEM include more fickler and high number of spike comparing to other markets [4], [5] and [6].

B. Forecasting tools

One of the most popular standard EPF model is similar day method. The idea is finding characteristic in historical data for previous day to predict the same day [3] and [7]. For example, historical data of Monday is used to predict the next Monday. The characteristics include day of the week, holiday type, weekend, weather condition and demand statistics. The several number of similar days is used in linear regression to predict more accurately.

Dubbed the naïve method was introduced to EPF by [8]. Nicholas, 2011, purposed that same rule of Monday can be applied to Mondays, Saturdays and Sundays. The same rule of Tuesday, if it like previous Monday, can be applied to Wednesdays, Thursdays and Fridays.

CI is the combination of learning, evolution and uncertainty components in computational techniques [9]. CI has been adapted to solve complex and dynamic questions. CI give better result comparing to traditional method, for example statistical approaches. CI can be adapted with artificial intelligence (AI) approaches due to learning component of CI.

The main classification of CI techniques is artificial neural networks (ANN), fuzzy systems, support vector machines (SVM) and evolutionary computation. Example of evolution computation are genetic algorithms, particle swarm intelligence. With integrating of probabilistic approaches AI has been changed from traditional AI. Example are artificial life techniques and wavelets techniques. The scale of CI is widely. It can be from soft computing up to machine learning, data mining and even cybernetics [10] and [11].

In literature, modeling of CI can easily flexible and suitable for complex and non-linear equations. So, the excellent prediction performance comes from CI model on short term EPF comparing to other methods. The most popular CI techniques in load forecasting is artificial neural network [3] and [12]. However, hybrid method of fuzzy logic, genetic algorithm and swarm intelligence are widely used to predict load forecast.

C. Hybridge forecasting tools

The combination techniques from two or more of the modeling and EPF is called hybrid EPF [13]. The prediction of the improved hybrid models is more excellent comparing to the results from the traditional model [14]. The wavelet-ARIMA can serve higher performance over original ARIMA in day ahead EPF [15]. The ARIMA model generates a linear forecast. Then, the differ between target and prediction create error which can correct on wavelet-ARIMA using a radial basis function (RBF). Conejo, et al., 2005, proposed a wavelet-ARIMA technique for EPF in Spanish electricity market procedure which are; I) a discrete wavelet transformation (DWT) used to decompose the component in electricity price, II) ARIMA are model and predict 24 hours' electricity price, and III) multiply inverse a discrete wavelet transform to result from ARIMA [16]. The result from wavelet-ARIMA provides better results comparing to pure ARIMA. Moreover, the fuzzy neural network, represent as 'mixed model', also give good results [17]. An artificial intelligent hybrid based forecasting model show effective performance on hourly forecasting in [6]. The hybrid model of ARMAX and Least Square is in [2]. The optimization the neuron connections weight in Artificial Neural Network (ANN) using Artificial Bee Colony (ABC) is develop for short term load forecasting. The forecasting result on transmission electricity price can perform efficiently [18].

In general, the difference between this paper and the studies in the literature include the following:

- ANN-ABC approach is used to forecast electricity prices,
- Connection weight and bias is optimized using ABC,
- High volatility on electricity price due to high number of price spike.

The contributions of work are summarized as follows:

- The R-square test shows better improvement in training data in ANN using ABC,
- The impact of price spike on EPF using ANN and ANN-ABC approach.

III. METHODOLOGY

A. Simillar Day Approach

1) Data collecting

This study collect historical half hour price and load demand during 2nd January 2017 to 26th February 2017, these data are separated in to similar day from Monday to Sunday. Figure 1. to Figure 7. illustrate half hour price on Monday to Sunday in every half hour point of the day. The price spikes appeared on 30th January 6th, 9th and 10th February, see details in Table I.

TABLE I. PRICE SPIKE

Date	Prices spike
Monday, 30th January 2017	p(34) = 2346.05
Monday, 6th February 2017	p(31) = 2741.78, p(32) = 4686.56, p(33) = 11692.09, p(34) = 6392.31
Thursday, 9th February 2017	p(33) = 2558.96, p(34) = 7822.25, p(35) = 2829.62
Friday, 10th February 2017	p(31) = 549.57, p(32) = 2088.32, p(33) = 3747.48, p(34) = 12914.63, p(35) = 13966.67, p(36) = 14000, p(37) = 4738.51

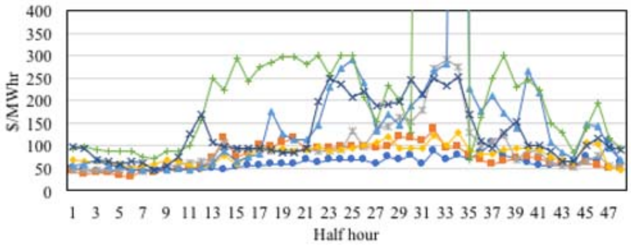

Figure 1. Historical half hour price on Monday

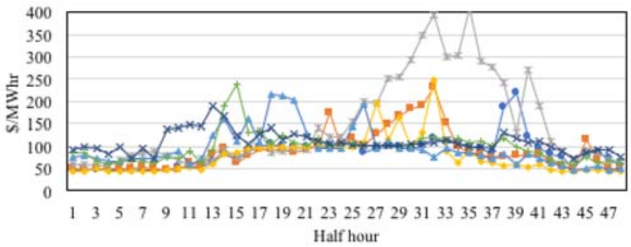

Figure 2. Historical half hour price on Tuesday

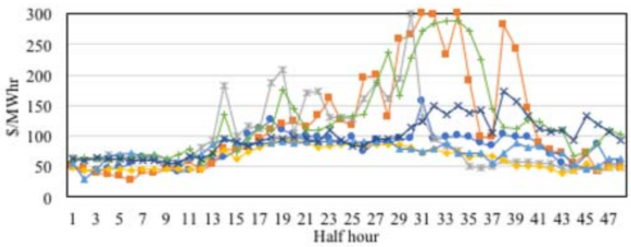

Figure 3. Historical half hour price on Wednesday

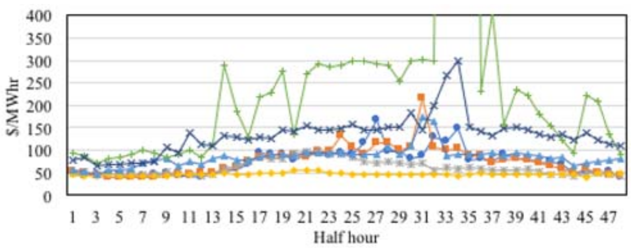

Figure 4. Historical half hour price on Thursday

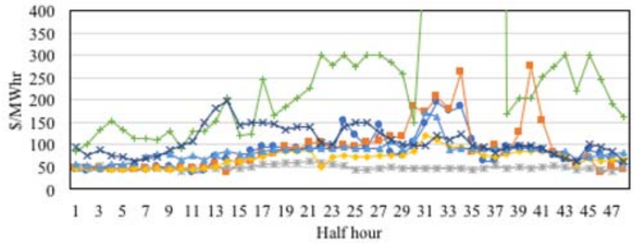

Figure 5. Historical half hour price on Friday

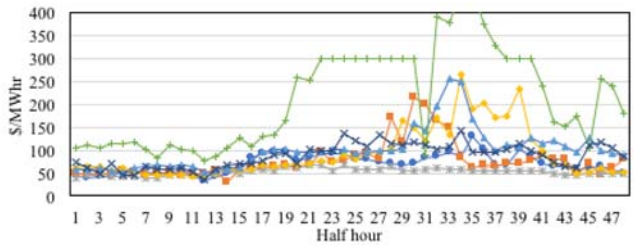

Figure 6. Historical half hour price on Saturday

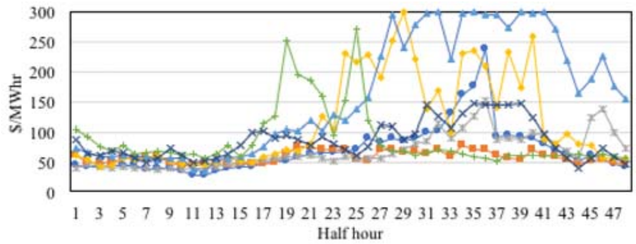

Figure 7. Historical half hour price on Sunday

B. *Forecasting tools*

1) ANN

As mention above that Artificial Neural Networks (ANN) are the most widely used in load forecasting due its high performance to find the relationship between historical (inputs) and prediction (output) data. Generally, Feed Forward Neural Network is the basic of ANN. It consists of one input, one output and one hidden layer [19]. The hidden layer can be increased to multilayer to improve performance of ANN. Node connects to other node between layer with weight value. Example are input weight between input to layer, layer weight between layer to other layers. The result from each node is produced from transfer or activation function. Output from node is shown in

$$y_i = f_i\left(\sum_{j=1}^{n} w_{ij}x_j + \theta_i\right) \tag{1}$$

Where; f_i is the transfer function. The weight between layer j to layer i is denoted by w_{ij}. Bias value at i is denoted by θ_i.

One important instrument of ANN is back propagation algorithm which measure feedback from output and compare to the expected target. The error is fed back to weight of network to minimize the error [20]. The half of total square of error is calculated in

$$E = \frac{1}{2}\sum_{t=1}^{n}(desired_t - calculated_t)^2 \tag{2}$$

In evaluation part, two set of data are used in learning algorithm or call “training” and testing algorithm or call "validating". During training part, weights and biases are repeat updated until the error reaches to minimum value.

2) ABC

Artificial Bee Colony (ABC) algorithm, which is introduced by Karaboga, is used as an optimization technique with based on swarm optimization which the relationship between food and bees. The inspiration of this model is behavior of bee colony. Generally, structure of ABC consists of three artificial honey bees which are onlooker bees, employed bees and scout bees. The employed bees play an important role for collecting and searching new food sources with memorize. Scout bees acts different from employed bees due to no memorization and may provide better resources [21]. Artificial observer bees consider quality of food source (fs) or call fitness value fit_i based on the probability value (p_i) as shown in

$$p_i = \frac{fit_i}{\sum_{n=1}^{fs} fit_n} \tag{3}$$

The high number of p_i means that fs_i has good quality. fit_i denotes quality of fs_i or call fitness value of food sources of the calculated solution as shown in

$$fit_i = \begin{cases} \dfrac{1}{1+x} & if\ x \geq 0, \\ 1+abs(x) & if\ x < 0 \end{cases} \tag{4}$$

The duty of scout bees is to initialize food sources using lower and upper limit of data set with random value as shown in

$$x_i^j = x_{min}^j + rand(0,1)(x_{max}^j - x_{min}^j) \tag{5}$$

Where; x_i^j is food source number i for variable j, x_{min}^j is lower limit of variable j and x_{max}^j is upper limit of variable j. The employee bees report better food source to hive then new food source is memorized. The duty of employee bee is to search new food source using its memory and co-worker' memory. The reported food source is calculated and compared with previous value. The new food source is update when fitness value of new food source is higher than previous one.

3) ANN-ABC

Employed bees of ABC use weight, bias in transfer function to produce solution in artificial bee colony inputs as parameters in particles. ABC produce weight and bias using error of predicted data and target data. On the other hand, weight and bias in hidden layers are trained by ABC. The flow chart of this method is shown in Figure 8.

In this study, ANN is constructed with one input layer, one hidden layer (10 hidden layers) and one output layer. Activate functions of the hidden layers are Sigmoid function and linear function is used in the output layer.

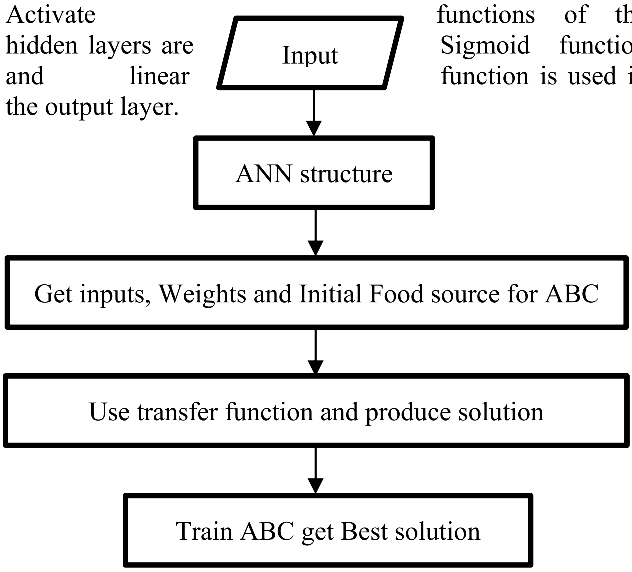

Figure 8. The flowchart of trained ANN by ABC [16]

4) Evaluation

The measurement of forecasting accuracy is accomplished by Mean Absolute Error (MAE) and Mean Relative Error (MRE), which is computed as

$$MAE\ [\$] = \frac{1}{N}\sum_{i=1}^{t}\left|P_A^i - P_F^i\right| \tag{6}$$

$$MRE\ [\%] = \frac{1}{N}\sum_{i=1}^{t}\frac{\left|P_A^i - P_F^i\right|}{P_A^i} \times 100 \tag{7}$$

where; P_A is the actual price, P_F is the forecasted price, N is the number of data point.

IV. Simulation Results

This section presents simulation results for training process which calculate electricity pricing based on historical data for each day and testing process which forecast future hour-ahead electricity pricing.

A. Training process

This study consists training period to and test period to develop the ANN and ANN-ABC. The train data consist of electricity price and load demand between Monday, 2nd of January 2017 to Sunday, 19th February 2017. The algorithm is developed using validation set of Mondays, 13rd February 2017 to Sunday, 19th February 2017 to tune parameter to find optimum point.

TABLE II. R-SQUARE TEST FOR ANN AND ANN-ABC RESULT

	R-square	
Day	*ANN*	*ANN-ABC*
Monday	0.867	0.965
Tuesday	0.766	0.912
Wednesday	0.933	0.970
Thursday	0.974	0.993
Friday	0.863	0.964
Saturday	0.842	0.938
Sunday	0.948	0.963

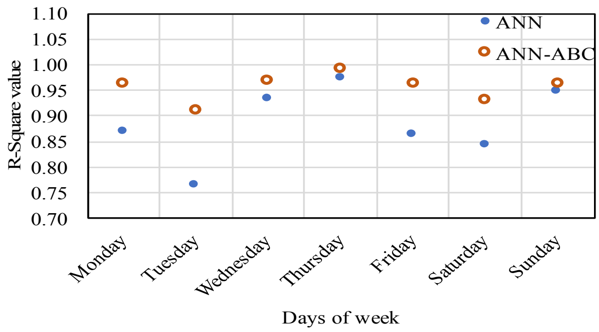

Figure 9. R-squre test on 19th to 26th, February, 2017

TABLE II. and Figure 9 represent comparison on R-square

		Day	*Method* *ANN*	*ANN-ABC*
MAE ($)	Train	Monday	8.35	4.70
		Tuesday	4.67	2.78
		Wednesday	2.97	2.03
		Thursday	4.00	1.61
		Friday	5.27	2.65
		Saturday	5.29	3.34
		Sunday	3.03	2.58
	Test	Monday	35.04	39.09
		Tuesday	57.51	20.92
		Wednesday	14.18	31.31
		Thursday	18.50	19.57
		Friday	23.68	25.90
		Saturday	13.92	9.80
		Sunday	28.54	16.99
MRE (%)	Train	Monday	6.24	4.72
		Tuesday	4.51	2.72
		Wednesday	3.46	2.20
		Thursday	3.09	1.42
		Friday	5.15	2.54
		Saturday	6.11	3.93
		Sunday	3.84	3.21
	Test	Monday	33.44	35.61
		Tuesday	49.49	18.66
		Wednesday	16.84	34.25
		Thursday	15.15	17.21
		Friday	20.85	22.75
		Saturday	21.81	15.85
		Sunday	71.93	34.36

value from ANN and ANN-ABC during 19th to 26th, February 2017. We can observe that R-square values are improved for every day.

Figure 10. and bias value optimization using ABC. Point A represent MAE value, 5.29 $/MWhr, which is resulted from ANN approach. Then, the ABC starts optimizing connection weight and bias value. From point A to B and C to D, employee bee is searching for their local best food sources. Then, scout bee starts randomly to undiscovered food sources from Point B to C and D to E. At 2,000 iteration, Point E, MAE value is 2.65 $/MWhr.

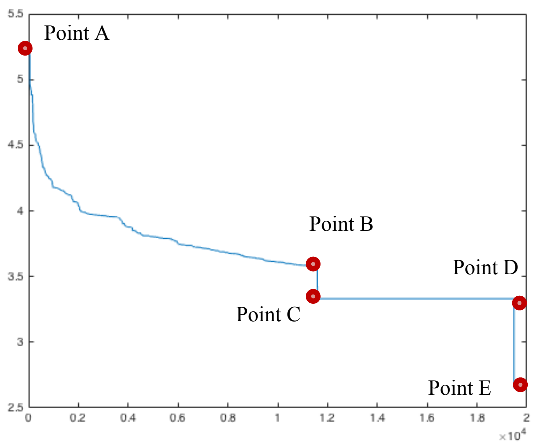

Figure 10. Improved MAE in training ANN result using ANN-ABC on Friday, 23rd February, 2017

B. *Forecasting process*

In this section, the fully-trained is used to predict the future value of electricity price during Monday, 20th February 2017 to Sunday, 26th February 2017 or called testing period. The calculated MAE and MRE values are shown in **Fehler! Verweisquelle konnte nicht gefunden werden.**Figure 11. and Figure 12. illustrates predicted electricity price values using trained data. Figure 13. and Figure 14. shows predicted electricity price values using test data.

TABLE III. MAE AND MRE VALUES

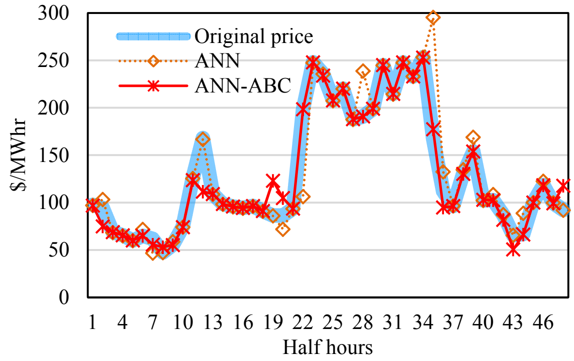

Figure 11. Training result on Monday 13rd, February, 2017

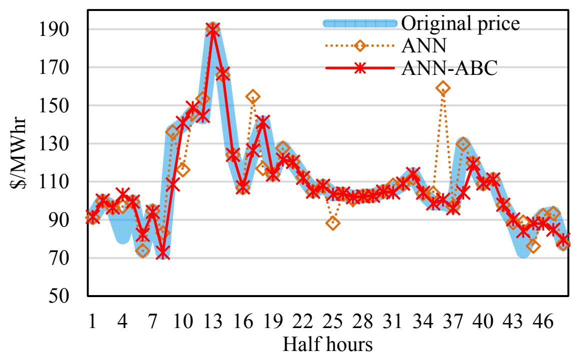

Figure 12. Training result on Tuesday 14th, February, 2017

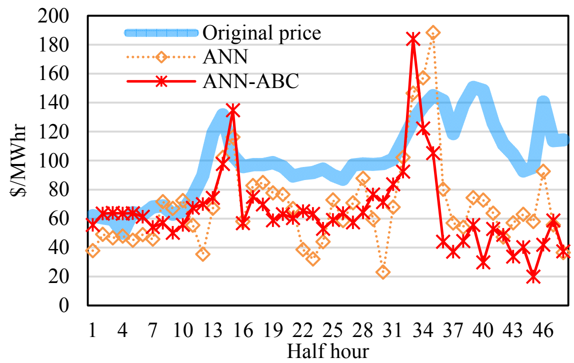

Figure 13. EPF on Monday 20th, February, 2017

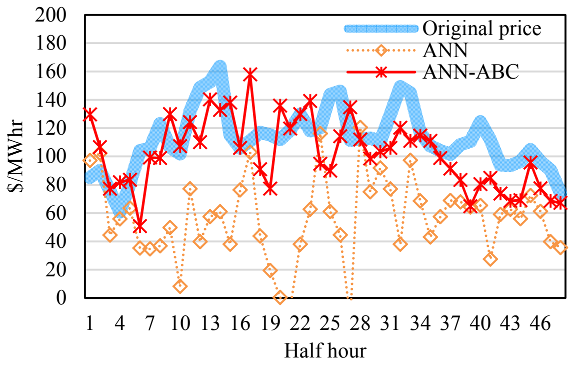

Figure 14. EPF on Tuesday 21st, February, 2017

V. DISCUSSION

This section compares and discusses the results of training and forecasting period using ANN and ANN-ABC. During training process connection weights and biases of ANN's structure are optimally updated to reduce R-square value. The mean relative (percentage) error (MRE) from ANN process are reduced which are comparing to ANN-ABC for 1.52%, 17.9%, 1.26%, 1.67%, 2.61%, 2.18% and 0.63% for Monday to Sunday data, respectively. In forecasting process, ANN-ABC slightly give bad results on forecasting future electricity price due to high number of price spike in history. MRE increased for 2.17%, 2.06% and 1.90% on Monday, Thursday and Friday data. Despite of without price spike in historical data, ANN-ABC can reduce MRE in EPF for 30.83%, 5.96% and 37.57 on Tuesday, Saturday and Sunday data. On Wednesday, ANN-ABC gives poorer performance comparing to ANN due to price spike occurs in forecasting period.

VI. CONCLUSITON

In the study, artificial intelligence forecasting model were developed and predict future short-term electricity prices from New South Wales, Austrian during 19th February to 26th February 2017. The historical data on 2nd January to 18th February 2017, i.e. half-hour prices and half-hour load demands, is fed to train ANN and ANN-ABC models. There are two major benefits using ANN-ABC comparing to ABC. First benefit is ANN-ABC performs excellency on EPF on the day which has no price spike in history. Second, ANN-ABC can reduce R-square from pure ANN.

VII. RECOMMENDATION

Since ANN-ABC has excellent performance on tuning the forecasting model to match validate with train data, this method can use to forecast a change in price with changing in input parameters. For example, renewable energy resource can be an additional input for forecasting model. The model can show how a change in renewable energy resource effects to short-term electricity prices.

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