Electricity price forecasting using hybrid ANN and stochastic approach

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Abstract

This paper purposes efficient approaches for solving indirect electricity price forecasting (EPF) using load and variable renewable energy (VRE) forecasting. The concept is to forecast local renewable generation and consumption, then calculate locational marginal price (LMP). The load at any bus is allocated by region demand. The results of LMP are formulated into trading hub prices (THP) for representing zonal prices. The load and VRE estimation have been taken care by day ahead market, artificial neural network (ANN) and stochastic approach. The LMP consists of energy, congestion and losses components. The previous works on direct EPF are ANN, ARIMA and support vector regression (SVR) which are benchmark. All simulation has been done in NREL 118-bus test system as a result of it provide number of VRE data. The simulation results of the study show that the proposed indirect EPF give better performance compare to direct EPF. Applying load and VRE forecasting into EPF model could drag down the forecasting error. In high volatility of renewable generation, stochastic approach can improve the forecasting's performance. The result shows greatly potential of the proposed solution.

Keywords: electricity price forecasting, LMP, trading hub price, VRE, ANN, stochastic

1. Nomenclature

1.1 Set and Indices

$i \in I$	Set of bus.
$j \in J$	Set of region.
$m \in M$	Set of generator.
$n \in N$	Set of load.
$k \in K$	Set of transmission line.
$u \in U$	Set of minutes in hour

$v \in V$	Set of 15 minutes in hour
$h \in H$	Set of hour in day.
$d \in D$	Set of day in week.
$t \in T$	Sets if time

1.2 Main Parameters

G_m	Generator m.
D_i	Demand at bus i.
RD_i	Demand at region j.
C_{G_n}	Incremental cost of generator n.
P_i	Net active power at bus i.
P_{G_n}	Active power output of generator n.
Q_{G_n}	Reactive power output of generator n.
P_{D_i}	Active power output of demand i.
Q_{D_i}	Reactive power output of generator m.
F_k	Power flow in line k.
V_i^{min}	Minimum voltage limit at bus i.
V_i^{max}	Maximum voltage limit at bus i.
LMP_i	Locational marginal price at bus i.
GSF_{k-i}	Generation Shift Factor to line k from bus i.
DF_i	Delivery factor at bus i.
THP_j	Trading Hub Price at area j.
LP_i	Load participation at bus i.

1.3 Load forecasting parameters

$RD_{j,h}^*$	Forecasted demand in region j at hour h.
$RD_{j,h}$	Demand in region j at hour h.
h	Hour in day (0-23)
d	Day in week (0-6)

1.4 VRE forecasting parameters

$S^{*}_{m,h}$	Forecasted solar PV m at hour h.
$W^{*}_{m,h}$	Forecasted wind m at hour h.
$S^{**}_{m,v}$	Forecasted solar PV m at minute v.
$W^{**}_{m,v}$	Forecasted wind m at minute v.
$S_{m,h}$	Solar PV m at hour h.
$W_{m,h}$	Wind m at hour h.
$SD_{s,m}$	Standard deviation of solar PV m.
$SD_{w,m}$	Standard deviation of wind m.

2. Introduction

The concept of smart grid has been rapidly implemented in power system utilities globally. Theoretical, smart grid transforms conventional grid with smart decisions. Hence, the smart grid consists of communication facilities, effective management strategies, as well as distribution generators (DGs). Following of global environment issues, there are increasing in number of renewable based DGs. There are fast growing green DGs due to resource's obtainable in local area. Hence, ideas of either unit commitment (UC) or economic dispatch (ED) become more difficulty in high penetration on VRE. The association with high capacity fast storage could help to reduce effect of VRE volatility.

Since, there are high fluctuated in electricity supply consisting of high penetration of VRE in deregulated market and electricity is costly to be stored, electricity price is become more volatile. As a result of necessity in Electricity price forecasting (EPF), especially in short time period.

2.1 Previous study on short term electricity price forecasting

In past few decade, the numbers of methods and ideas for EPF is verities with various degree of success (Weron, 2014). Price forecasting is a relatively more difficult task sue to the endogenous characteristic of price time series (Bask & Widerberg, 2009). The main variable that effects the price is the demand. In recent year, several methods have been in use to forecast price in electricity markets. As seen in Table 1, Example are time series (Crespo Cuaresma, Hlouskova, Kossmeier, & Obersteiner, 2004), (Ozozen, Kayakutlu, Ketterer, & Kayalica, 2016), artificial neural network (ANN) (Mandal, Senjyu, & Funabashi, 2006), (Szkuta, Sanabria, & Dillon, 1999) , (Rodriguez & Anders, 2004), (Yamin, Shahidehpour, & Li, 2004), (Chaweewat & Singh, 2017), ANN with weather information (Doulai & Cahill, 2001), price-load correlation (Vucetic, Tomsovic, & Obradovic, 2001), similar day price (Mandal et al., 2006), (Cerjan, Matijaš, & Delimar, 2014), hybrid model (Cerjan et al., 2014), (Chaweewat & Singh, 2017), (Ozozen et al., 2016). (Gupta & Chitkara, 2017) proposed method to predict electricity price using demand forecasting and supply estimation. The data are collected from India market which include demand forecast from DISCO, changes in bilateral contracts, outage, capacity offers, transmission corridor availability.

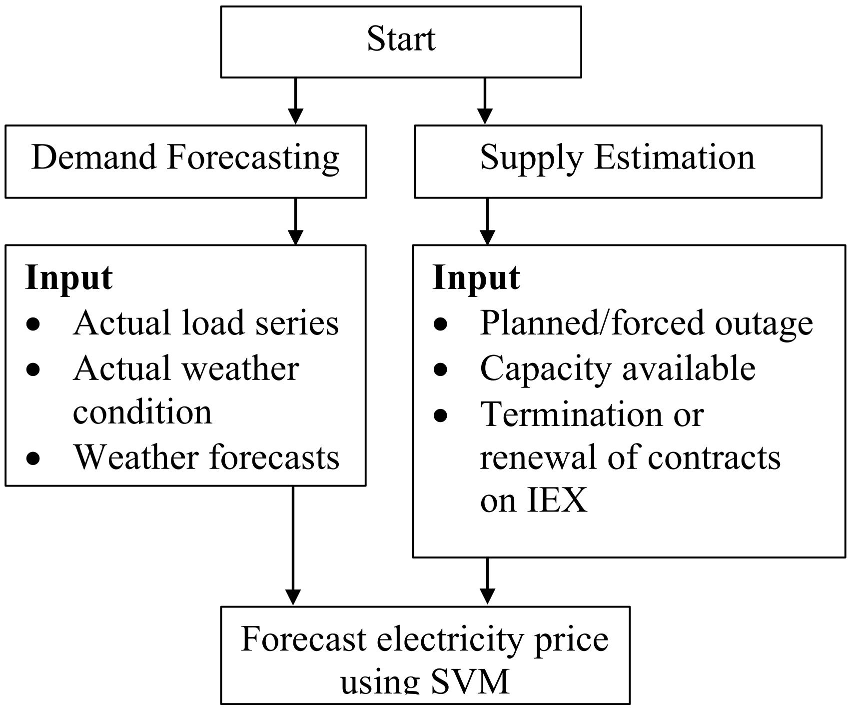

Figure 1 Framework of Multivariate Model (Gupta & Chitkara, 2017)

TABLE 1. Selective bibliography focusing on hour ahead price forecasting

Ref.	Model	Market/system	Performance (MAPE%)
(Mandal et al., 2006)	ANN	Victorian Electricity Market	9.75-10.69%
(Szkuta et al., 1999)	ANN	Victorian Electricity Market	27.95%
(Rodriguez & Anders, 2004)	ANN	Ontario Electricity Market	26.52%
(Yamin et al., 2004)	ANN	IEEE 118-bus	8.12%
(Doulai & Cahill, 2001)	ANN	Australian National Electricity Market	8.3%(summer), 10.2%(winter)
(Vucetic et al., 2001)	Price-load correlation	California's electricity market	R-sqaure = 0.75
(Cerjan et al., 2014)	SD	European Energy Exchange(EEX)	10.63%
(Cerjan et al., 2014)	SD-ANN	European Energy Exchange(EEX)	8.49%
(Chaweewat & Singh, 2017)	ANN-ABC	New South Wales, Australia	15.85 – 35.61%
(Crespo Cuaresma et al., 2004)	ARMA	Leipzig Power Exchange	5.354%
(Ozozen et al., 2016)	SARIMA	Turkish power market	13.8%
(Ozozen et al., 2016)	SARIMA-ANN	Turkish power market	10.2%

2.2 Previous study on short term VRE forecasting

The power output from variable renewable energy resources such as solar PV and wind turbine is non-dispatchable and more fluctuated than others renewable resources such as hydro, biomass and geothermal. Many research has developed forecasting tools of DGs' output, especially VRE. Similar to wind and solar, the forecasting tools can be categorized into two types; indirect and direct forecasting method. The indirect method requires predicted solar irradiation and wind velocity and other weather data such as temperature, humidity, cloudy index, etc. Then, those predicted values are convert to solar PV and wind output. In case of direct method, solar PV and wind output are predicted based on their historical data with weather information. Examples of techniques has been used to in those methods are support vector regression (SVR) (Shi, Lee, Liu, Yang, & Wang, 2012), wavelet (Zhang, Takano, & Murata, 2011), ANN (Oudjana, Hellal, & Mahamed, 2012), hybrid ANN method (S. Wang, Zhang, Zhao, & Zhan, 2011), fuzzy logic (Tanaka et al., 2011), learning vector quantization (Yang, Huang, Huang, & Pai, 2014). Furthermore, wind and solar PV is predicted using stochastic model (Liu, Lee, Chen, & Mehrotra, 2016) on power system optimization. In summarize, ANN and ARIMA method give better performance over SVR, wavelet, fuzzy logic and other methods, but the flexibility of an ANN as universal non-linear approximation make it more preference than classical ARIMA (Voyant et al., 2017). To address with volatility on VRE power, Monte Carlo simulation generated hourly random wind output (J. Wang, Shahidehpour, & Li, 2008) from forecasted wind power in order to ensure security constraint UC.

2.3 Previous study on short term load forecasting

The short-term load forecasting has been done in transmission and distribution system (Chen & Jain, 1994). 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. The forecasting input consists of day of week index, similar day, previous day load and forecast weather (Chen & Jain, 1994). Example of techniques has been used to in theses method are most widely used in ANN (Sun et al., 2016), regression (Sun et al., 2016), wavelet neural network (Chen & Jain, 1994), SVM (Sun et al., 2016), ABC (Cevik, Harmancı, & Çunkaş, 2016).

2.4 Problem statement

The recent studies show that the variations on wind power could have the largest effects on the power system reliability and cost of operation in hourly and daily timeframe (Smith, Milligan, DeMeo, & Parsons, 2007). During real time operations, the generation and load must be matched. Despite of the controllable conventional generator, the load and VRE generator must be forecasted. With precisely forecasted values, the operators can estimate reserved capacity of the system, then reliability and frequency control requirement.

2.5 Research gab and contribution of this paper

Since, previous study on half-hour, hour ahead electricity price prediction considers only historical price data, demand, changing in demand but not consider in transmission congestion and transmission losses, the electricity price forecasting in this paper consider those values. This paper integrates renewable generation and demand forecasting to improve hour ahead electricity price forecasting.

3. Data acquisition

To tackle with volatility on wind and solar, we assume the solar PV power and wind is subject to a normal distribution N(u,SD) with forecasted solar PV and wind power as its expected value (u) an a percentage of u is its volatility (SD). In each hour, a 15-minutes based random solar PV power minute based random wind powers are generated based on forecasted solar PV and wind power.

Load demand in any bus is formulated from load participation factor of regional demand (RD) as provide in NREL IEEE-118 bus system. Both day ahead and real time RD and VRE historical data are provided in NREL IEEE-118 bus system (Peña, Martinez-Anido, & Hodge, 2018).

4. Proposed Problem formulation

4.1 The general ACOPF model

In transmission system can be formulated as minimize:

$$\sum_{n=1}^{N} C_{G_n} \times P_{G_n} \tag{1}$$

Subject to:

$$P_{G_n} - P_{D_m} - P(V,\theta) = 0 \tag{2}$$

$$Q_{G_n} - Q_{D_m} - P(V,\theta) = 0 \tag{3}$$

$$|F_k| = F_k^{max} \tag{4}$$

$$P_{G_n}^{min} \leq P_{G_n} \leq P_{G_n}^{max} \tag{5}$$

$$Q_{G_n}^{min} \leq Q_{G_n} \leq Q_{G_n}^{max} \tag{6}$$

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{7}$$

where, C_{G_n} is generation cost of generator G_n (\$/MWhr). P_{G_n} and Q_{G_n} are real and reactive power output of generator G_n (MW, MVar). $P_{G_n}^{min}$ and $P_{G_n}^{max}$ are minimum and maximum limit of P_{G_n}. $Q_{G_n}^{min}$ and $Q_{G_n}^{max}$ are minimum and maximum limit of Q_{G_n}. P_{D_m} and Q_{D_m} are real and reactive power demand of load D_m (MW, MVar). $|F_k|$ and F_k^{max} are line flow and its maximum limit at line k. V_i^{min} and V_i^{max} are minimum and maximum voltage limit at bus i.

4.2 The general formulation of LMP and THP

The LMP at bus i can be written as follows:

$$LMP_i = LMP^{\text{energy}} + LMP_i^{\text{congestion}} + LMP_i^{\text{loss}} \tag{8}$$

$$LMP^{\text{energy}} = \lambda \tag{9}$$

$$LMP_i^{\text{congestion}} = \sum_{k=1}^{M} GSF_{k-1} \times \mu_k \tag{10}$$

$$LMP_i^{\text{loss}} = \lambda \times (DF_i - 1) \tag{11}$$

LMP^{energy} illustrates system λ or system marginal cost which represent marginal unit's cost. $LMP_i^{\text{congestion}}$ appears when there is congestion in system. LMP_i^{loss}can only be calculated using ACOPF. In DCOPF, LMP_i^{loss} is equal to zero. The LMP at any bus i for demand variation at bus i can be calculated in Equation (12). The derivation of Equation (12) is shown in (Bo & Li, 2011).

$$LMP_i = \sum_{m=1}^{M} C_{G_m}^{T} \times \frac{\partial P_{G_m}}{\partial P_i} \tag{12}$$

Where; P_i is net active power at bus i. Equation (12) can be explained by LMP at any bus i is calculated by summation of incremental cost at changing in all generators with respected to changing in demand at bus i.

The trading hub price (THP) delineates overall price in area with local aggregate load. THP calculation requires a set of network node, a set of allocation factors or weighting factor or load participation factors and nodal prices (Treinen, 2005). THP is calculated from the weighted average of the nodal prices using the load participation factors in equation (13).

$$THP_j = \sum_{i=1}^{I} (LP_i \times LMP_i) \tag{13}$$

Where THP_j is trading hub price at area j, LMP_i and LP_i locational marginal price and load participation at bus I which are located in area j. The Equation (13) is shown in (Treinen, 2005).

4.3 Artificial Neural Networks (ANN)

Generally, Feed Forward Neural Network is the basic of ANN. It consists of one input, one output and one hidden layer (Guo, Zhao, Lu, & Wang, 2012). The hidden layer can be increased to multilayer in order 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 Figure 2.

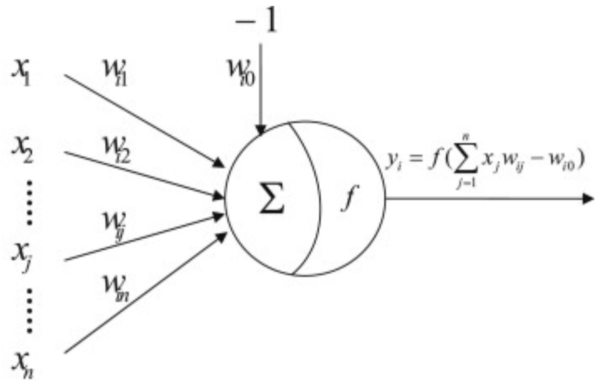

Figure 2 ANN

where; f is the transfer function. The weight between layer j to layer i is denoted by w_{ij}. Bias value at i is denoted by w_{i0}

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 in order to minimize the error (Chen & Jain, 1994). The half of total square of error is calculated in Equation (14):

$$error = \frac{1}{2}\sum_{t=1}^{n}(desired_t - calculated_t)^2 \qquad (14)$$

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.

4.4 NREL IEEE 118-bus system

NREL IEEE 118-bus test system was published in (Peña et al., 2018). The NREL IEEE 118-bus test system is extended from IEEE 118-bus test system which include high renewable energy resource penetration. The generation mix and load profiles of three regions of the WECC 2024 common case database. The network consists of three areas, 118 buses, 186 transmission lines and 327 generators. This network is providing the opportunity to researchers to conduct renewable integration studies. In this paper, this network will be presenting hour a head price forecasting. The NREL 118-bus test system is developed using Pandapower library based on python language.

4.5 Benchmark EPF

In this study, ANN, ARIMA (5,1,0) and SVR approach are selected as benchmark to evaluate the result of proposed approach. The input of benchmark approach is shown in Figure 3. The historical data is formulated from (8), (12) and (13) with real-time VRE and load data.

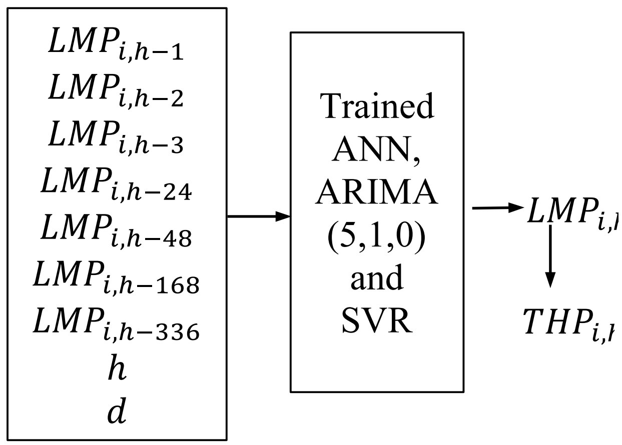

Figure 3 Benchmark EPF

4.6 Proposed ANN-stochastic electricity price forecasting

In this paper, EPF is formulated under load and VRE estimation using ANN and stochastic. As mentioned above, load in any bus is formulated from RD estimation. The estimated RDs are allocated into any bus using load participation factor as shown in Equation (15).

$$D_i = RD_j \times \mathrm{LP}_i \tag{15}$$

Hence, RD will be predicted in this paper. The VRE forecasting has been done using historical data of solar and wind generation.

All scenarios are explained below:

<u>Model I</u>

The hour-ahead electricity price ($LMP_{i,h}$) simply forecasted using by market clearing based on economic dispatch with $RD^*_{j,h}$, $S^*_{m,h}$ and $W^*_{m,h}$ in day ahead (DA) market. The conceptual of Model I is illustrated in Figure 4.

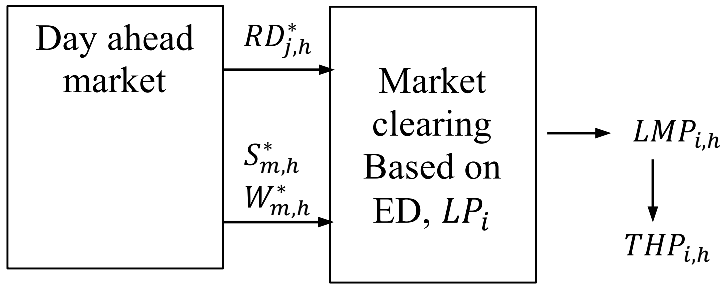

Figure 4 Day ahead data is used in Model I

Model II

The hour ahead EPFs in model II are formulated from forecasted RD in each region and VRE in day ahead market. The RDs forecasting, $RD^*_{j,h}$, is done by trained ANN models where input data are historical RD, hours of day, day of week. There are 3 trained ANN models represented for each 3 regions as shown in Figure 5.

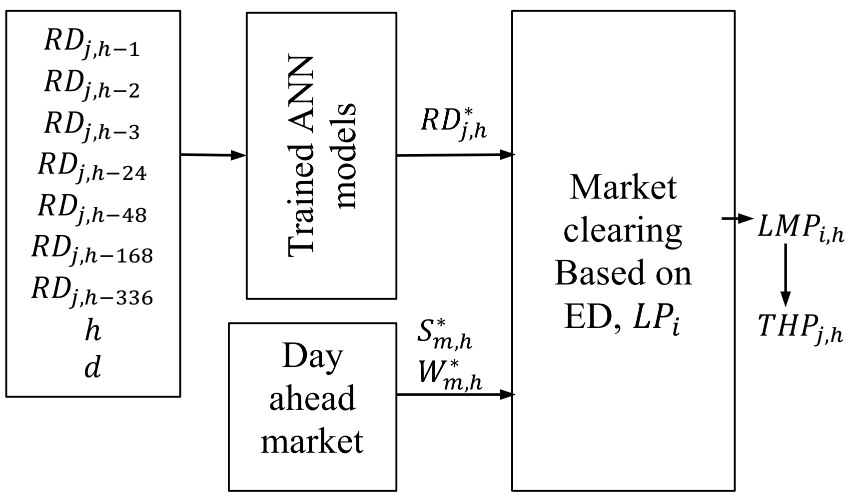

Figure 5 Demand forecasting and VRE day ahead market are used in Model II

Model III

The hour ahead EPF in model III are formulated by forecasted RDs ($RD^*_{j,h}$) and VRE ($S^*_{m,h}$, $W^*_{m,h}$) using trained ANN. Each ANN models represented each RD and VRE generation. Hence, there are 3 ANN models for 3 RD, 17 ANN models for wind and 75 ANN models for solar as shown in Figure 6.

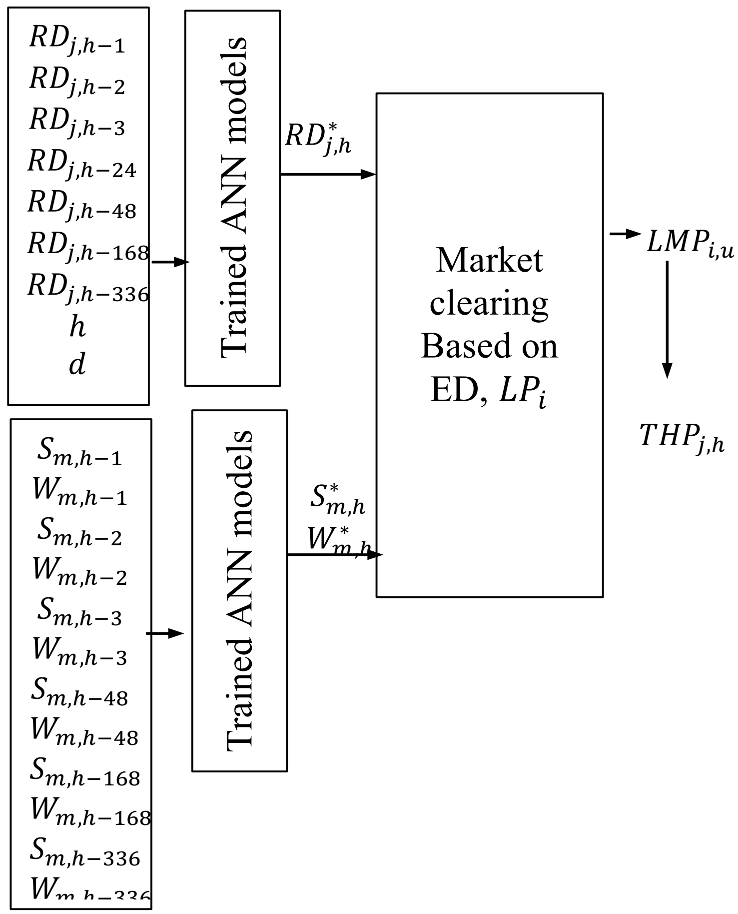

Figure 6 Demand and VRE forecasting are used in Model III

<u>Model IV</u>

The hour ahead EPFs in model IV are extended from model III. Therefore, solar and wind characteristic fluctuated due to its intermittency on fuel sources. The forecasted VRE from trained ANN in each hour generates minutely forecasted VRE values for each minute within that hour. The forecasted solar values, $S^{**}_{m,v}$, are generated in every 15 minutes and forecasted wind values, $W^{**}_{m,v}$, are generated in every 1 minutes. These values are generated by apply normal distribution function where standard deviation is 10% of predicted value. An example of minutely forecasted wind output in one hour are shown in Figure 7.

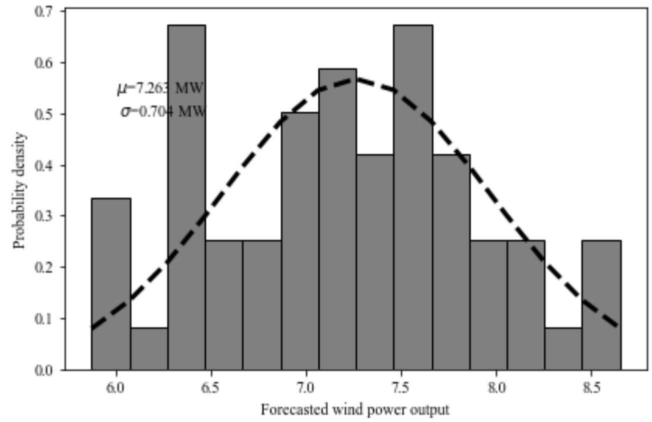

Figure 7. Output power of wind with NDF

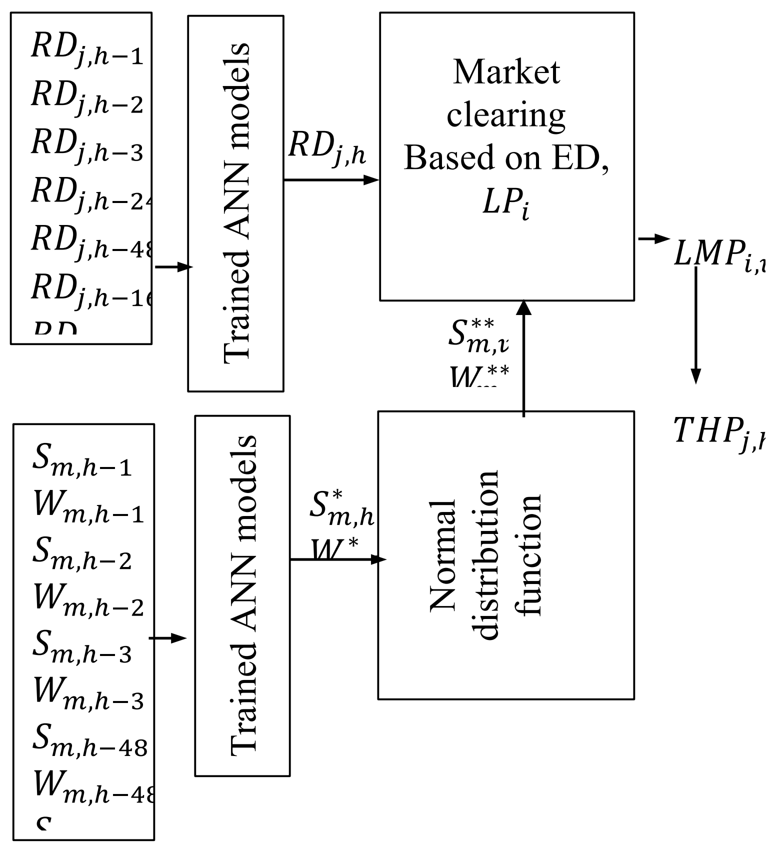

Figure 8. Demand forecasting with hybrid VRE forecasting are used in Model IV

This paper four scenarios of EPF on NREL 118-bus system based on data and training model as shown in Table 2.

Table 2. Scenarios

Model	RD forecasting	VRE forecasting
I	Day ahead market	Day ahead market
II	ANN	Day ahead market
III	ANN	ANN
IV	ANN	ANN+NDF

4.7 Evaluation

Comparison between results from actual EPF and proposed EPF is done by using Equations (16).

$$\text{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{p_i - \hat{p}_i}{p_i}\right| \tag{16}$$

where; p_i and $\hat{p}_i$ are THP_jvalues from actual EPF and propose EPF approach. N is number of THP_j values where is 24 hours in this study.

5. Results and Discussions

In this section, all results will be descripted and discussed. The results of EPF will be evaluated using Equation (16) with actual price. The actual electricity price is formulated from real time load and VRE via Equation (12) and formed into THP via Equation (13). In addition, all result will be compared with previous with other method in literature review. Examples are ANN, ARIMA (5,1,0) and SVR. All results are shown in Table 3. All method is test with weekday and weekend in summer and winter period. Middle of June and December represents forecasting period in this study.

Table 3

MAPE (%) Results for Trading Hub Price forecasting in NREL IEEE-118 bus system

Season	Day type	Area	Previous study			Proposed in this study			
			ANN*	ARIMA (5,1,0)**	SVR ***	Model-I	Model-II	Model-III	Model-IV
Summer (mid-Jun)	Weekday	1	4.18	4.51	9.27	5.59	1.41	1.27	1.24
		2	3.75	4.65	10.27	5.60	1.31	1.20	1.17
		3	4.12	5.25	9.27	5.82	1.49	1.24	1.19
	Weekend	1	5.57	4.24	10.41	5.57	3.86	2.16	2.17
		2	4.16	4.24	6.98	5.56	3.68	2.05	2.07
		3	4.82	4.52	8.34	5.76	3.85	2.11	2.17
Winter (mid-Dec)	Weekday	1	4.04	4.72	4.96	2.72	2.24	0.96	0.96
		2	3.15	4.62	5.01	2.38	2.14	0.82	0.82
		3	4.40	4.84	7.56	2.53	2.32	0.85	0.86
	Weekend	1	6.23	4.92	13.42	6.35	4.29	3.89	3.78
		2	4.92	4.86	6.46	6.13	4.27	3.72	3.69
		3	5.74	5.24	8.93	6.47	4.79	4.00	3.90

*(Panapakidis & Dagoumas, 2016), **(Contreras, Espinola, Nogales, & Conejo, 2003), ***(Mohamed & El-Hawary, 2016)

As seen in Table 3, overall results can be descripted that the average MAPE of benchmark approaches are 4.59 %, 4.72 % and 8.41 % for ANN, ARIMA (5,1,0) and SVR, respectively. For the proposed method, the average MAPE are 5.04 %, 2.97 %, 2.02 % and 2.00 % for Model-I, II, III and IV, respectively.

The analysis of integrated load forecasting into EPF can be shown by comparison between Model-I and II, since Model-II include load forecasting into model-I. the average MAPE drop by 2.07 %.

The analysis of impact of VRE forecasting to EPF can be explained by comparing results between area 2 with area 1 and 3. Since, the least total generation capacity of VRE in area 2 is 444 MW comparing to area 1 and 3, which are 1,535 and 2544 MW. The MAPE in area 2 is less than area 1 and 3 in every period. In addition, integrating VRE forecasting into forecasting model could improve forecasting performance as seen in results from Model-II and III. The averaged MAPE drops by 0.95 %.

The analysis of include stochastic approach can be explained by comparing results between Model-III and IV. The averaged MAPE drops by 0.02 %.

Seasoning also impact to EPF. In Winter, MAPE results are higher than Summer. Figure 9 illustrates average MAPE of Model I, II, III and IV by seasoning. It can be notice that Model-I can perform better performance in Winter period. Despite of Model-II, III, and IV, they can provide better performances in summer than winter. In model II, III and IV, the MAPE results in Summer are less than Winter approximately by 0.7 %, approximately. The VRE generation in winter is more fluctuated comparing to summer, consequently, the EPF can be improved in model IV.

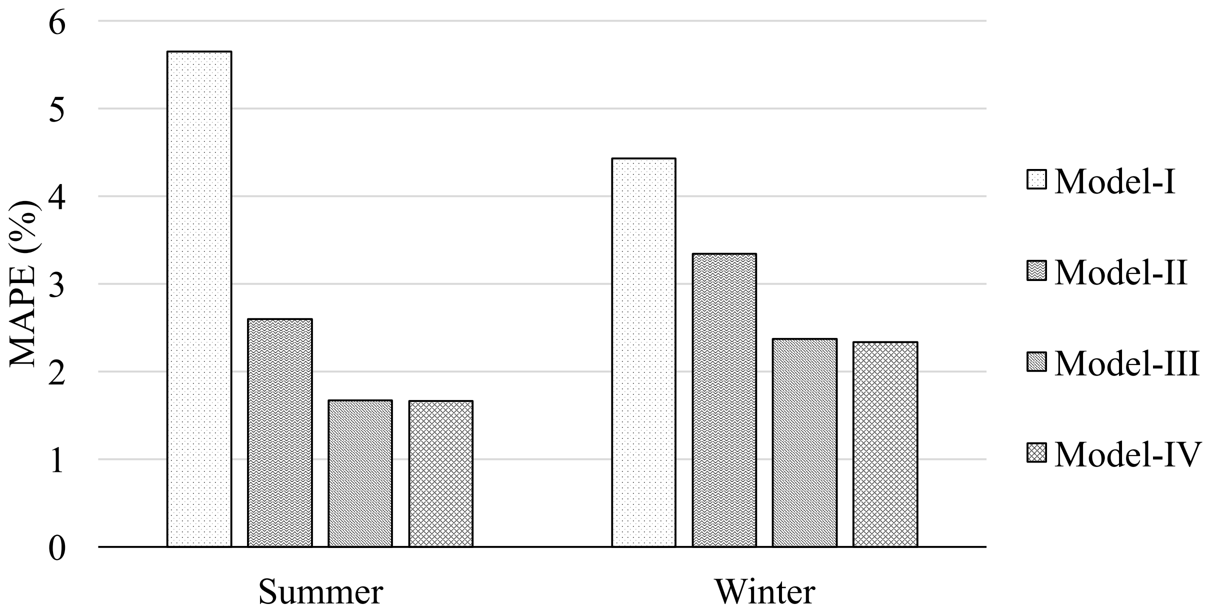

Figure 9. Seasonal analysis

The analysis of day type, weekday and weekend, can be represented in Figure 10. All results indicated that EPF in weekday can perform better than weekend. The MAPE results in weekday are less than weekend by 2 %, approximately.

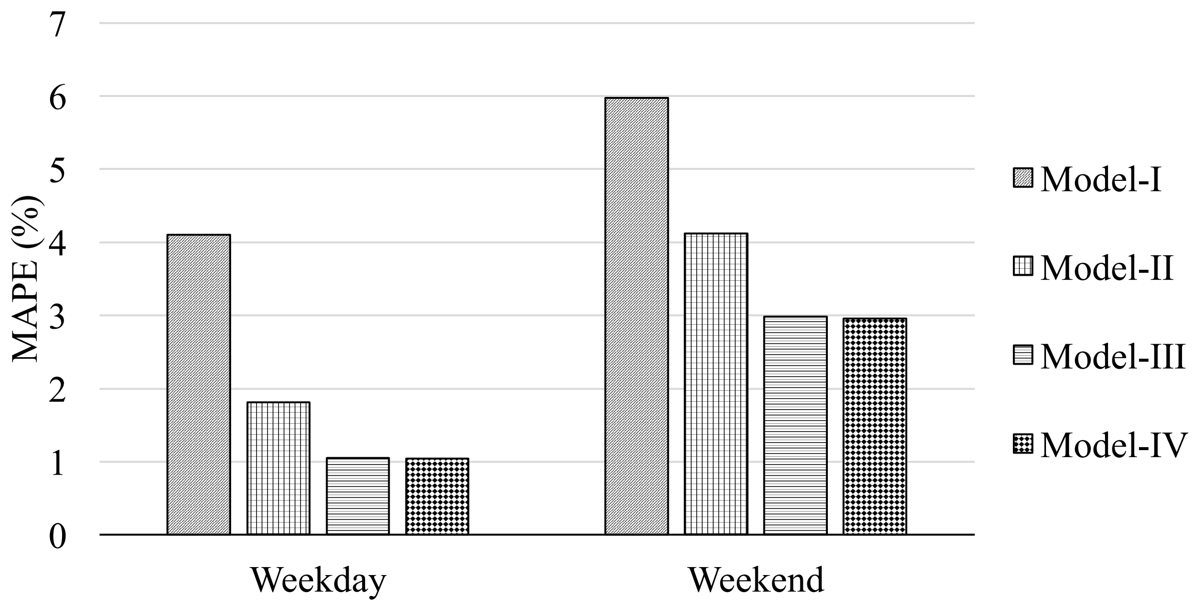

Figure 10. Day type analysis

6. Conclusion

In this paper EPF methods are proposed including with load and VRE forecasting and mathematic equations. All data are collected from NREL IEEE-118 bus test system. The main algorithm of load and VRE forecasting are ANN and stochastic approaches. The results of testing method are evaluated with previous study. The main conclusions from simulation results are:

- EPF can be done by direct and indirect forecasting model. The direct forecasting model collects historical electricity price and fed into trained model to predict future values. However, the indirect forecasting model collects historical load and generation data. Then, it's fed into forecasting model to predict future load and generation values. Those predicted values are fed into mathematic model to compute electricity price signal. The overall results conclude that indirect forecasting model provide better results than direct forecasting model.
- The direct forecasting models are represented by benchmark method which were done in previous works. ANN and ARIMA (5,1,0) perform better than SVR since they can handle time series values.
- In model I, the day ahead market load and VRE data, in summer, give about 5 % error on THP comparing to real-time market.

- Adding load forecasting to model I, model II gives the better performance on real-time THP forecasting. The MAPE drops down by 2-3 % in summer.
- The EPF using load forecasting can be improved further by integrate VRE forecasting into the EPF model. The average MAPE is improved by 0.95 %.
- Applying normal distribution function into VRE forecasting to compute THP by minutes could slightly drop down the MAPE, since high volatility in VRE generation.

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