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A Refined TLO Based Algorithm and ELMAN NN for DED of Integrated Multiple Fuel and Wireless System

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Abstract: *Dynamic economic dispatch problem (DEDP) for a multiple-fuel power plant is a nonlinear and non-smooth optimization problem when valve-point effects, multi-fuel effects and ramp-rate limits are considered. Additionally wind energy is also integrated with the DEDP to supply the load for effective utilization of the renewable energy. Since the wind power may not be predicted, an ELMAN neural network is presented to forecast a one-hour-ahead wind power to plan and ensure a reliable power supply. In this article, a refined teaching learning optimization based algorithm (TLO) is applied to minimize the overall cost of operation of wind–thermal power system. The TLO is refined by integrating the Sequential Quadratic Programming (SQP) method to fine-tune the better solutions whenever discovered by the former method. To demonstrate the effectiveness of the proposed hybrid TLO-SQP method, 7 unit practical DEDP with wind power forecasted are tested based on the practical information of wind speed. Simulation results validate the proposed methodology is reasonable by ensuring quality solution throughout the scheduling horizon for secure operation of the system.*

Keyword: *Dynamic economic dispatch (DED); ELMAN neural network; Multiple-Fuel; Teaching-learning based optimization algorithm; Valve-point effects; Wind power; Wind speed prediction; Neural network (NN);*

1. INTRODUCTION

A key aspect in power system applications based DEDP is that to effectively dispatch the loads and minimize the cost incurred for the considered power system modules. A work is carried out on implementation of basic and incremental genetic-algorithm techniques for the determination of the global or near-global optimum solution for the economic dispatch (ED) problem, combination of the incremental genetic-algorithm approach and the simulated-annealing technique adapted to minimize the memory requirement [1]. The researcher pointed out genetic algorithm to solve the economic load dispatch (ELD) problem with losses for three thermal plant systems and also one plant as combined cycle cogeneration plant in three thermal plant systems [2].

The work presented in hybrid evolutionary programming and sequential quadratic programming (SQP) methodology to solve the DEDP with non-smooth fuel cost function, evolutionary programming is used to give a good direction to the optimal global region and SQP is adapted to obtain the optimal solution at the final [3]. Particle swarm optimization technique for solving the ED problem and demonstrated for three different power systems [4]. Two parts of evolutionary programming techniques for ELD problems in part I presented the modifications to the basic technique, where adaptation is based on scaled cost and in Part II, evolutionary programs are implemented with adaptation using empirical learning rate [5].

The author performed fuzzy-optimization approach to DEDP, considering the uncertainties in deregulated energy and reserve markets, energy and reserve markets were coordinated by the generator ramp rate limits and also analysed two reserve payment methods such as payment for power delivered and payment for reserve allocated [6]. Unit commitment with flexible generating units on power system operation is adopted in [7]. Simulated annealing technique for DEDP is used in order to determine the global or near global optimum dispatch solution by considering operating limits, load balance constraints, valve point loading, ramp constraints and network losses utilizing loss coefficient [8]. A work on improved differential evolutionary algorithms for solving ED problem that

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takes into account nonlinear generator features such as ramp rate limits and prohibited operating zones in the power system operation. The algorithms and its variants are tested for two test systems consisting of 6 and 15 thermal units and result shows that the presented method outperforms than other prior algorithm [9].

Wind power generation system has lot of glitches such as wind intermittency, independent nature of direction, wind speed variations. The accurate forecasting techniques are needed to solve the problems of wind speed prediction such as reduction in time delay, perfection in speed for short time, reduced error, and model development for effective transformation of wind energy. The aim is to reduce the error and improve the model by hybridizing. [11]. Dynamic models are implemented to calculate the wind speed [12]. Various optimization techniques with quadratic programmes are listed in [10].

A new teaching learning optimization based algorithm (TLO) for the process parameter optimization of chosen modern machining processes such as abrasive jet machining, ultrasonic machining and wire electrical discharge machining process [22]. A modified TLBO algorithm for thinning and weighting planar arrays to synthesize the required antenna array factor, optimized the number of active elements and their corresponding excitation weights with reduced main-lobe width, peaks of side lobe level and current taper ratio[23]. A work on a novel self-tuning control method using regulated bi-objective emotional learning controller's structure with TLO to control dynamic voltage restorer compensator, TLO adapted to regulate emotional controller coefficients [24].

Effective TLBO for solving the flexible job-shop problem with fuzzy processing time, decoding method used to move a solution to a feasible schedule in the fuzzy sense and bi-phase crossover scheme; special local search operators are included in TLO in order to balance the exploitation and exploration capabilities. The result reveals that the presented method solves the problem with higher efficiency and effectiveness compared to the other methods [25]. This work also proposes a hybrid method combining TLO and sequential quadratic programming (SQP). For constrained optimization problems SQP is the one of the more powerful method [26]. The SQP method for the economic dispatch problem is adopted in this paper.

To validate the proposed methodology a hybrid system of real time wind power system and thermal power system combination is used. A wind farm data of hundred wind machine each rated at 1.5 MW installed by Suzlon Energy, India is used in this work. This integration of wind and thermal is done at Erode Load Distribution Center (ELDC).

2. MATHEMATICAL MODEL OF DEDP

The grail is to bring down the total production cost for a particular duration. The objective function is given as

$$Minimize,\quad C_T=\sum_{k=1}^{K}\sum_{i=1}^{N}C_{ik}\left(P_{ik}\right) \tag{1}$$

The generator cost function is normally expressed as a quadratic polynomial as

$$C_{ik}\left(P_{ik}\right)=a_iP_{ik}^2+b_iP_{ik}+d_i \tag{2}$$

Where a_i, b_i and c_i are fuel cost coefficients. Generators with many number of fuel options involve frequent opening and closing of a valve. This will produce valve point effect, this is included in the basic cost function.

$$C_{ik}\left(P_{ik}\right)=a_iP_{ik}^2+b_iP_{ik}+d_i+\left|v_i\,Sin\left(f_i\left(P_{ih}^{\min}-P_{ih}\right)\right)\right| \tag{3}$$

If the generating units are supplied with multiple fuel sources then the cost function is called hybrid cost function, now the equation (3) becomes

$$C_{ih}\left(P_{ih}\right)=\begin{cases}a_{i,1}P_{ih}^2+b_{i,1}P_{ih}+d_{i,1}, & fuel\,1,\quad P_{ih}^{\min}\le P_{ih}\le P_{ih,1}\\ a_{i,2}P_{ih}^2+b_{i,2}P_{ih}+d_{i,2}, & fuel\,2,\quad P_{ih,1}< P_{ih}\le P_{ih,2}\\ \vdots & \\ a_{i,k}P_{ih}^2+b_{i,k}P_{ih}+d_{i,k}, & fuel\,k,\quad P_{ih,k-1}< P_{ih}\le P_{ih}^{\max}\end{cases} \tag{4}$$

To get the exact result for the addition of valve point effect the equation (2) becomes

$$C_{ih}\left(P_{ih}\right)=a_{i,k}P_{ih}^2+b_{i,k}P_{ih}+d_{i,k}+\left|v_{i,k}Sin\left(f_{i,k}\left(P_{ih,k}^{\min}-P_{ih}\right)\right)\right|,$$
$$if\;P_{ih,k}^{\min}\le P_{ih}\le P_{ih,k}^{\max},\;fuel\;option\;k, k=1,2,\ldots,N_F \tag{5}$$

2.1 Accounting Wind Power for DEDP

Wind speed prediction plays an important part in determining the power output of a wind farm. There are several methods of forecasting techniques are used. Physical method is one of the method which is used to forecast the wind speed by using past history of data and as well as real time field data. But in actual there are several factors influences the prediction of wind speed. They are wind speed, moisture, humidity, temperature and wind vane direction. Recently many statistical models are used to calculate the wind speed. Neural network is one among the statistical model which is used in this work. [13,14]. Compared to physical model the performance of neural network model in forecasting the wind speed in turn wind power is better [21]. This work proposed the ELMAN neural network for predicting wind speed and power. The useful power can be generated at par-

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ticular wind speed and is given by,

$$w_p = 0,\ \upsilon < \upsilon_{in} \text{ or } \upsilon > \upsilon_{out}$$

$$w_p = w_R(\upsilon - \upsilon_{in} / \upsilon_R - \upsilon_{in}),\quad \upsilon_{in} \le \upsilon \le \upsilon_R \tag{6}$$

$$w_p = w_R,\ \upsilon_R \le \upsilon \le \upsilon_{out}$$

Where, w_R is rated power; υ is the actual wind speed; υ_R is the rated wind speed; υ_{in} is the cut-in speed; υ_{out} the cut-out speed. The total power of the hybrid system power generation is the addition of multiple fuel thermal power system and wind mill.

2.2 Evaluation Function

The valuation practice has to be done to measure the fitness of each prospect in the solution space. It is the union of the production cost function F_{obj} and power balance constraint P_{bnc} as in (1) and (3).

The evaluation function is as follows:

$$Min \quad f = F_{obj} + P_{bnc} \tag{7}$$

$$F_{obj} = F_T / \sum_{h=1}^{H} \sum_{i=1}^{N} \Gamma_{ih} \tag{8}$$

where,

$$\sum_{h=1}^{H} \sum_{i=1}^{N} \Gamma_{ih} = F_{T\max} / F_{T\min} \tag{9}$$

$F_{T\max}$ is the total fuel cost obtained using $P_{ih} = P_{i\max}$ and $F_{T\min}$ is the total fuel cost obtained using $P_{ih} = P_{i\min}$

The power balance constraint is obtained by difference between combination of demand, losses and produced power of wind and thermal

$$P_{bnc} = \left\{ \sum_{h=1}^{H} \left(P_{Dh} + P_{Lossh} - \left(\sum_{i=1}^{N} P_{ih} + \sum_{j=1}^{m} w_{jh} \right) \right)^2 \right\} \tag{10}$$

3. ELMAN NEURAL NETWORK MODEL FOR PREDICTION OF WIND SPEED.

The wind speed is irregular; it is difficult to predict the wind speed. The statistical model considers online measurements of data. By using real time data the statistical model is better than physical model [15, 16]. Recently neural network models are better choice for predicting the wind speed [17-21]. ELMAN neural network classifier proposed in [27] is employed for the prediction of wind speed.

3.1 ELMAN Neural Network

Estimation of calorific value of coals based on BPN and ELMAN NN is forecasted, both BPN and ELMAN NN well reflect the non-linear relationship between consistent cross-validation and various factors of coal quality. The result shows that compared to the BPN, ELMAN NN forecast the consistent cross-validation very accurately with reduced absolute error [27]. The work on an implementation of ELMAN NN for improving reliability of integrated bridge deterioration model is adopted to achieve improved prediction performance. The result shows that the presented approach very effective in handling different situations of condition data quantities and distributions for producing long-term performance curves [28].

The wind speed predication model based on ELMANNN and principal component analysis to avoid the local minimum and lack of dynamic performance existing in forward NN is reported [29]. This is applied to select the feature of wind data and it is used in input parameter optimization of ELMAN NN.

3.2 ELMAN Network Model

For the prediction of wind speed model, the wind direction, temperature and field data of wind speed are taken as input of the network. The predicted wind speed is the output of the network.

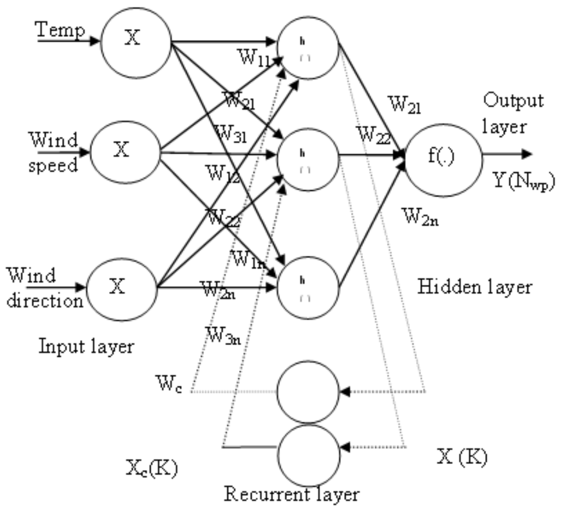

Figure 1 ELMAN network architecture

The architecture for fixing number of hidden neurons in ELMAN network is shown in Figure 1.The input and the output target vector pairs are (X_1, X_2, X_3: Y) = (Temperature, Wind Direction, and Wind Speed: Predicted Wind Speed)

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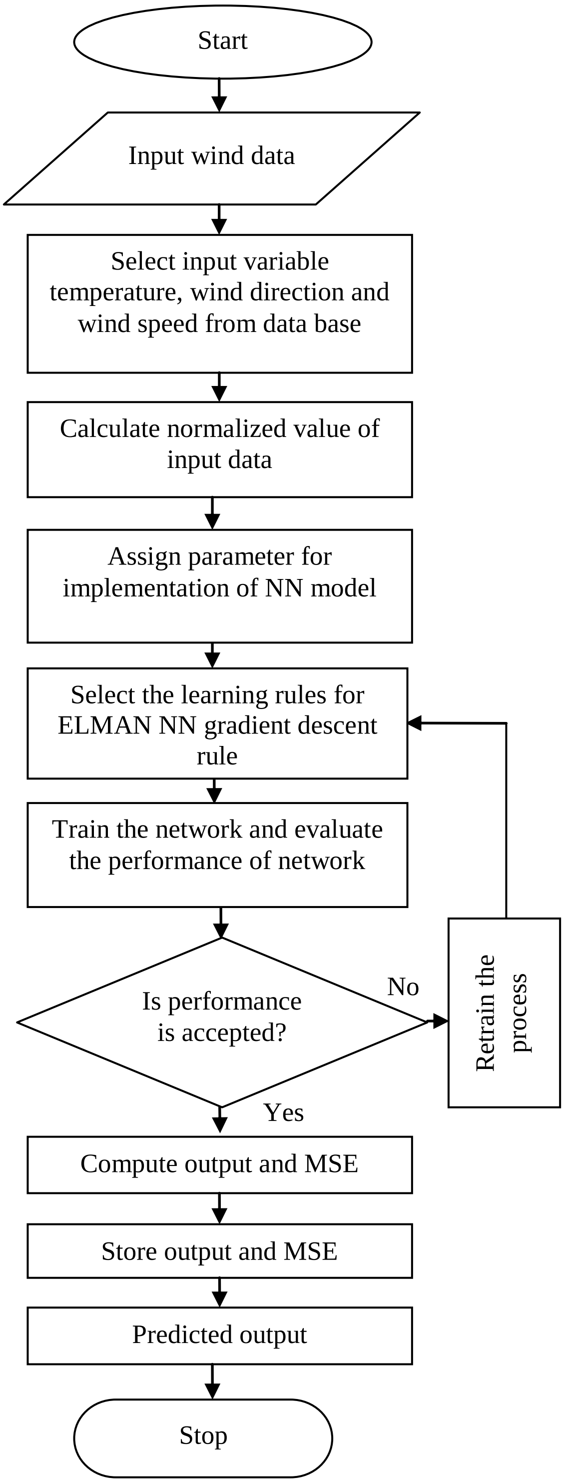

Figure 2: ELMAN flowchart

The dimensions like number of input, hidden and output neuron are to be designed. The numbers of hidden neurons are assumed. The input is transmitted through the hidden layer that multiplies weight by hyperbolic sigmoid function. The network learns function based on current input plus record of previous state. Further, this output is transmitted through second connection multiply with weight by Purelin activation function. The stopping criteria are reached until the existence of minimum error is noted.

3.3 Flow chart of ELMAN Model for Prediction of Wind Speed

The ELMAN NN model is necessary to get the accurate output. The flow chart of ELMAN network is shown in Figure 2.

3.4. ELMAN Network Methodology

The proposed methodology in ELMAN Network is given:

Step 1: Data collection From Suzlon Energy Ltd., India the field data is collected for the year 2012.

Step 2: Data Normalization It is done with the help of Min-Max technique.

Step 3: ELMAN network design

The number of neurons has to be found out for each layer. The design is shown in Figure 1. Figure 3 shows the various input data used in this model. Mean square error (MSE) factor is used to validate the results. In Table 1 statistical error for various trials is listed.

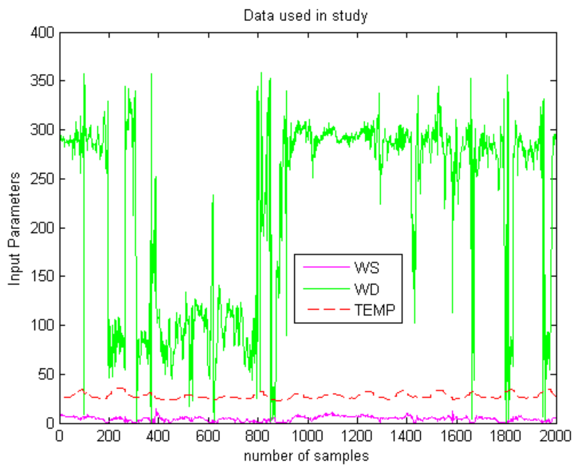

Figure 3 Variation of input data used in proposed study

TABLE 1 VARIOUS COMBINATIONS OF TRAINING AND TESTING FOR 12000 SAMPLES

Training data	Test data	Elman network – MSE Value
7000	5000	0.00374
9000	3000	0.0032
8000	4000	0.00079
10000	2000	0.00183
6000	6000	0.00188

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4. TEACHING LEARNING OPTIMIZATION BASED ALGORITHM (TLO)

TLO is used in this paper. [22, 23] based on this the teacher and learner in a class is used for various optimization processes. This algorithm is adopted in this paper. The best value is treated as teacher.

5. WIRELESS COMMUNICATION

The approved operating frequency range for 3G and 4G technology is 894MHZ/1900MHZ [30] and the data transmission rate is 60-240kbps [31]. This cellular network is framed by cells which are developed by multiple low power wireless transmitters. The non interrupted data flow has been facilitated through transmission of data between cell to cell. This way the point to point architecture is achieved. The fast improving data rate and quality of service in 3G/4G is used in the field of power systems. Cellular technology shown in Figure 4 helps in monitoring the power generation and transmitting the data in wind and thermal systems. The monitoring using general packet radio service of remote station is reported in [32]. This technology is suggested for non interrupting data transmission in power systems. Finally the control centre located in dispatch centre will take the necessary action about the data.

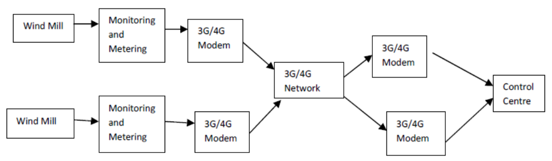

Figure 4 Cellular technology for power generation monitoring

6. NUMERICAL EXPERIMENTS

Integrated wind power with DEDP is used in this paper. The result of DEDP with wind is validated for the real systems in 2 different cases,

- The wind speed is predicted by using the ELMAN NN. The necessary data's were collected from suzlon wind energy is given in Table 2.
- Solving a 7 unit multiple fuel DEDP with wind
- The simulation is done in MATLAB.

6.1 Case 1: Wind Power Predictions

The data collected from Suzlon Energy Ltd., India is used to predict the wind power for the LDCE which is controlling the Neyveli Thermal Power Station (NTPS).

The wind farm consists of 100 wind turbines of 1.5 MW each. The dispatch centre using Naive method for wind speed prediction, the remaining generation can be done from thermal units. The range of parameters used in this model is given in Table 3.

TABLE 2: SAMPLE DATA FROM WIND FARM

Wind speed(m/s)	Wind Direction (degree)	Temperature (degree. C)
4.2	341.7	28.8
4.6	338.9	28.8
5	326.2	28.8
4.8	322	28.2
4.2	324.8	28.2
4.6	317.8	28.2
4.9	316.4	28.2
4.7	327.7	28.2
4.7	323.4	28.2
4.4	323.4	27.5
3.8	323.4	27.5
4	320.6	27.5
3.8	310.8	27.5
3.8	300.9	27.5
4.2	282.7	27.5
4.2	285.5	26.7
4.4	312.2	26.7
4.4	293.9	26.7
5.1	212.3	26.7
5.2	270	26.7
6.1	306.6	26.7
5.1	310.8	26.6
5.4	296.7	26.6
5.6	292.5	26.6

TABLE 3 RANGE OF INPUT PARAMETERS

S. No	Input Parameters	Units	Range of the Parameters
1	Wind speed	m/s	4-6.5
2	Wind direction	Degree	212-342
3	Temperature	Degree. C	26-28

TABLE 4: MSE OF VARIOUS METHODS

Sl. No.	Comparison of various approaches	MSE
1	BPN (Sheela&Deepa, 2013)	0.0397
2	RBFNN(Sheela&Deepa, 2013)	0.00133
3	Proposed IRBFNN	0.00092
4	Proposed method using ELMAN NN	0.00079

From MSE listed in Table 4, the ELMAN proposed in this research predicts closer wind speed compared to the other method. The prediction of wind speed is used to calculate the wind power listed in Table 5. The result proves ELMAN is suitable than others. This network is used in practical power system.

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6.2 Case 2: Validating the Hybrid TLBO-SQP Method for Solving DEDP

TABLE 5: COMPARISON OF PREDICTED POWER WITH EXISTING METHOD

Hour	Actual Wind power (Suzlon) (MW)	Naive method (MW)	Proposed model using ELMAN (MW)
1	129.9336	126.287	130.1220
2	130.5483	134.9044	130.2596
3	129.6927	131.6120	130.1213
4	130.3383	133.7114	130.4927
5	130.5251	127.5346	129.9997
6	130.5604	130.0561	130.4926
7	132.4563	128.2020	132.8593
8	140.1752	143.6834	141.0673
9	142.3433	142.9024	141.0032
10	144.4042	142.5835	144.1908
11	146.2464	144.9367	146.1199
12	146.9441	146.5454	147.0001
13	146.4430	145.1807	146.3021
14	147.0039	142.7703	146.9945
15	144.1318	141.0621	144.2612
16	141.6287	137.0738	141.2092
17	134.4697	135.0275	134.8875
18	134.4699	130.6500	134.2915
19	132.3468	132.5606	132.0216
20	132.2144	128.3965	132.1695
21	131.5594	134.1488	131.0321
22	130.1897	128.8190	129.7624
23	130.3156	133.5282	129.9108
24	130.1835	125.5980	130.0024

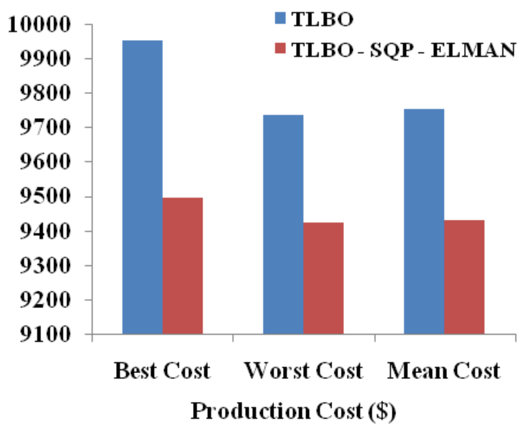

Figure 5 Various production costs of TLO and TLO-SQP-ELMAN

To formalize the DEDP, this research adopts a 7 unit practical system as reported in [10]. The best, worst and mean production cost according to the proposed model is compared with TLO and is shown in Figure 5.

TABLE 6: POWER PRODUCTION OF 7THERMAL UNITS

Hours	U1 (MW)	U2 (MW)	U3 (MW)	U4 (MW)	U5 (MW)	U6 (MW)	U7 (MW)
1	50.2	246.9	110.2	201.5	253.5	451.9	132.0
2	50.5	246.9	110.0	200.0	250.0	450.5	132.7
3	50.2	249.1	110.5	200.3	252.0	393.8	132.5
4	50.3	248.5	110.1	200.1	251.5	394.6	131.2
5	51.0	248.9	229.4	200.0	249.9	393.5	131.2
6	51.3	248.2	229.7	300.0	149.4	492.1	431.8
7	152.6	249.0	228.6	302.0	202.0	492.0	432.0
8	153.9	249.0	228.0	401.0	253.8	493.5	427.9
9	203.6	248.6	229.6	400.0	253.5	492.3	428.0
10	200.6	249.0	228.1	284.9	251.0	492.5	427.7
11	151.9	248.9	227.9	285.0	251.0	424.0	377.5
12	151.5	249.1	228.0	231.5	251.0	416.9	377.0
13	114.4	207.0	188.3	231.6	250.0	367.9	374.0
14	56.5	246.0	110.2	199.0	171.6	450.0	133.2
15	53.2	247.9	110.1	199.7	169.8	393.9	131.4
16	53.5	248.9	224.5	198.5	249.9	360.9	130.5
17	103.9	249.5	225.0	199.5	250.9	405.0	193.9
18	101.5	249.2	223.5	198.9	247.7	400.8	250.0
19	151.0	249.7	223.8	281.3	248.0	421.6	420.4
20	151.2	248.7	223.7	230.8	247.6	386.4	421.1
21	151.9	249.2	221.8	201.9	240.9	332.5	400.9
22	151.9	246.8	221.5	201.6	190.6	326.4	403.0
23	151.7	245.9	221.7	200.7	191.4	285.5	302.6
24	151.1	241.9	200.5	201.0	190.9	286.5	250.8

7. DISCUSSION

The key objective of the proposed population based optimization approach is to minimize the fitness function – cost incurred in this problem with the satisfactory guarantee on specified constraints for the considered power system application modules. After forecasting the wind speed and wind power, the difference in power is scheduled from 7-unit thermal system. Based on the results in case 2 from Figure 5, the better solution is arrived by the use of hybrid TLO-SQP method. On that account hybrid TLO-SQP is used to meet the balance power from thermal system.

8. CONCLUSION

In this paper, the numerical simulation studies were carried out and results revealed that the proposed ELMAN model predicted the wind power in a better manner than the existing methods used in LDCE. Based on the predicted wind power, the hybrid refined TLBO-SQP algorithm was used to solve the DEDP to source the remaining power demand with the available thermal generation. The performance of the proposed approach has been tested for a practical 7-units multiple-fuel DEDP with valve-point effects with practical data from wind farm. Wireless communication system is used to collect the data from the generating side

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