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COMPARATIVE STUDY OF EFFECTIVE WIND POWER PREDICTION METHODS WITH OPTIMIZATION ALGORITHMS FOR OPTIMAL ECONOMIC DISPATCH OF MULTIPLE FUEL POWER PLANTS

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ABSTRACT

Generally, a major power system problem is dynamic economic dispatch problem (DEDP) for multiple fuel power plants. This problem is a nonlinear and non- smooth optimization problem when multi fuel effects and valve-point effects are considered. In this contribution, Improved Radial Basis Function Network (IRBFN) and Weighted Probabilistic Neural Network (WPNN) are compared and employed to forecast a one-hour ahead wind power for ensuring reliable power supply. Also Teaching Learning Based Optimization (TLBO) and biogeography based optimization is utilized to minimize the overall cost of operation of wind – thermal power system. The above algorithms are integrated with Sequential Quadratic Programming (SQP) for fine tuning the better solutions to reach the optimized minimal level. The proposed hybrid neural network model with the considered algorithms are applied for a test bench DEDP and a practical DEDP wind power forecasted based on real time data from Wind Power Plant. The effectiveness of the approach is also validated with the comparison of the existing methodologies available in the literature.

Keywords: wind power, dynamic economic dispatch problem, improved radial basis function network, weighted probabilistic neural network, sequential quadratic programming.

1. INTRODUCTION

In the growing scenario, there is a tremendous growth in the field of renewable energy resources and utilizing the renewable energy generated in an effective manner. It is well noted and identified that renewable energy are available in plenty, they are reliable in nature and are cost effective i.e., cheap. Considering the notable features and the effective solutions given by renewable energy systems, thisis devised in a manner to effectively utilize one of the most prominent forms of renewable energy – wind energy. The research on various areas of generation of wind energy, its speed, its direction, the temperature and the wind power resulted are analyzed on continuous hour – hour basis in a day for the entire year across the globe. As a result in this problem, steps are taken for the application of the generated wind power from the wind mills to handle dynamic economic dispatch problems (DEDP) and rural electrification. The evolutionary optimization algorithms and neural network architectures are proposed in this research work to solve DEDP and improve the load dispatch solutions.

As presented in [1], multi-objective bacterial foraging with non-dominated sorting procedure is adapted to solve the non-linear constrained environmental / economic dispatch problem. A work carried out in [2],explainsthe efficient hybrid particle swarm optimization algorithm to solve dynamic economic dispatch problems with valve-point effects, by integrating an improved bare-bones particle swarm optimization (BBPSO) with a local searcher named as directionally chaotic search (DCS). The performed evolutionary based approach Evolved Bat Algorithm (EBA) to solve the constraint economic load dispatched problem of thermal plants, piecewise quadratic function is utilized to show the fuel cost equation of each generation unit and the B-coefficient matrix is adapted to address transmission losses [3].

The wind speed data has different patterns which are caused by chaotic and intrinsic complexity of weather parameters and the conversion of wind power to electricity and wind park management depends on the prediction accuracy of wind speed had been pointed out in [4]. The large power prediction errors are caused by wake effect of traditional wind speed models. This approach introduces the new matrix which includes wave effect [5]. As suggested in [6], the stable and reliable operation of wind farm requires accurate forecasting models. Wavelet Neural Network (WNN) to forecast the wind power in which hidden neurons of action function is formed using multi-dimensional Morlet wavelets [7].

As illustrated in [8], two types of rural electrification process carried out in India, 1) Connecting to Grid 2) Renewable Energy. This study is particularly interested in its impacts on local economies such as the creation of new businesses and jobs, agricultural and other productive activities. The best suited hybrid system configuration to overcome the constraints as reliability, availability and continuous generation in India is formulated in [9]. Proposal for a wind –PV battery hybrid system for a small community in the east-southern part of Bangladesh is presented in [10].A refined teaching-learning based optimization (TLBO) was applied by the authors in earlier work to minimize the overall cost of operation of wind thermal power system[11]. The TLBO is refined by integrating the sequential quadratic programming (SQP) method to fine-tune the better solutions whenever discovered by the former method. Improved Radial basis function network (IRBFN) is presented to forecast a one-hour-ahead wind power to plan and ensure a reliable power supply.

2. IMPORTANCE OF RENEWABLE ENERGY RESOURCES AND DEDP IN POWER SYSTEM APPLICATIONS

Renewable energy resources are available in plenty and are simple. These are forms, which can generate the electricity that is required for every day and are created by the sources naturally existing. The major renewable energy resources include – wind, hydro and solar. These are the resources that are found without human interventions. Wind renewable energy is found to have its vital role for the generation of power around 20149.5 MW annually in India. Thus considering the facts of renewable energy and the effectiveness of wind renewable energy for generation of power, in these attempts is taken to predict the wind power based on the wind speed employing proposed neural network architectures. This predicted wind power is effectively incorporated into the considered load domain and economic load dispatch is carried out for the load centre for which the work is carried out. Further, the steps are taken to include the wind energy as a part of Hybrid PV – Diesel system and perform an efficient rural electrification process reducing the green house emission gases.

Dynamic economic dispatch problem is a real time problem of electric power system application part. The major task of DEDP is to schedule the online generators outputs with the predicted load demands for a certain period of time to operate an electric power system in a very cost effective manner within the considered security limits. The importance and objective of DEDP is to find out the optimal amount of the power generated based on the present generating units in the system and satisfying the specified constraints.

3. PROBLEM DEFINITION AND MATHEMATICAL FORMULATION OF THE DEDP WITH WIND POWER FORECASTED

The objective function of DEDP is to minimize the total production cost of a power system over a given dispatch period, while satisfying various constraints [12]. Mathematically the objective function for this DEDP is given as,

$$Minimize, \quad F_T = \sum_{h=1}^{H} \sum_{i=1}^{N} F_{ih}\left(P_{ih}\right) \tag{1}$$

Generally, the generator cost function is usually expressed as a quadratic polynomial as,

$$F_{ih}\left(P_{ih}\right) = a_i P_{ih}^2 + b_i P_{ih} + c_i \tag{2}$$

Generators with multivalve steam turbines produce ripples like effect on their input-output curves. This effect, known as valve point effect makes, the generator cost function discontinuous and non-convex. For accurate modeling of the cost function, the valve point effect is considered by superimposing it with the basic cost function.

$$F_{ih}\left(P_{ih}\right) = a_i P_{ih}^2 + b_i P_{ih} + c_i + \left| e_i \, Sin\left(f_i\left(P_{ih}^{min} - P_{ih}\right)\right)\right| \tag{3}$$

Many generating units are supplied with multiple fuel sources and the cost functions of these units are represented with a few or several piecewise quadratic functions. Such a cost function is called a hybrid cost function and each segment of the hybrid cost function gives some information about the fuel burned. The hybrid cost function is given as

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

For more accurate dispatch results, the valve point effect and the multiple fuel options are integrated into the basic cost function. Thus the basic quadratic cost function given in (2) with N generating units and N_F fuel options for each unit is given as,

$$F_{ih}\left(P_{ih}\right) = a_{i,k}P_{ih}^2 + b_{i,k}P_{ih} + c_{i,k} + \left| e_{i,k} Sin\left(f_{i,k}\left(P_{ih,k}^{min} - P_{ih}\right)\right)\right|,$$
$$if\ P_{ih,k}^{min} \le P_{ih} \le P_{ih,k}^{max}, fueloption k, k = 1,2,\ldots,N_F \tag{5}$$

The objective function as given in(1) is subject to following equality and inequality constraints: i) The power output from all the generating units must satisfy the total demand and the transmission losses of the system. So the equality constraint is given as,

$$\sum_{i=1}^{N} P_{ih} = P_{Dh} + P_{Loss,h} \tag{6}$$

ii) The transmission loss is expressed in a quadratic form as,

$$P_{Loss,h} = \sum_{m=1}^{N} \sum_{n=1}^{N} P_{mh} B_{mn} P_{nh} \tag{7}$$

iii) The real power output of each generating unit is limited by the maximum and minimum power limit of the units. It is given as,

$$P_i^{\min} \le P_{ih} \le P_i^{\max} \tag{8}$$

iv) The operating range of the generating units is restricted by their ramp rate limits. This is given as,

$$\begin{cases} P_{ih} - P_{i(h-1)} \le UR_i & \text{if generation increases} \\ P_{i(h-1)} - P_{ih} \le DR_i & \text{if generation decreases} \end{cases} \quad (9)$$

Thus the (8) is modified as,

$$\max\left(P_i^{\min}, P_{i(h-1)} - DR_i\right) \le P_{ih} \le \min\left(P_i^{\max}, P_{i(h-1)} + UR_i\right) \quad (10)$$

The wind power is estimated from the forecasted wind speed using the following expressions, as well known the wind power can be harvested only at a particular wind speed, thus, the wind power 'w' is given by,

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

$$\mathrm{w} = \mathrm{w_R}(\upsilon-\upsilon_{in}/\upsilon_R-\upsilon_{in}), \qquad \upsilon_{\mathrm{in}} \le \upsilon \le \upsilon_R \quad (11)$$

$$\mathrm{w} = \mathrm{w_R}, \qquad \upsilon_{\mathrm{R}} \le \upsilon \le \upsilon_{\mathrm{out}},$$

Where, w_R is the wind turbine rated power; υ is the actual wind speed; υ_R is the wind turbine rated wind speed; υ_{in} is the wind turbine cut-in speed; υ_{out} the wind turbine cut-out speed. Thus (6) is rewritten as,

$$\sum_{i=1}^{N} P_{ih} + \sum_{j=1}^{m} \mathrm{w}_{jh} = P_{Dh} + P_{Loss,h} \quad (12)$$

$$0 \le \mathrm{w}_{\mathrm{jh}} \le \mathrm{w}_R$$

Where, $W_{jh}$is the wind power generated at time h, and the total power generated from the entire wind farm containing 'm' wind mills is the summation of the wind power generated by the individual wind turbine. Thus the DEDP will then be solved for economically dispatching the remaining demanded power using the multiple-fuel power plant.

4. PROPOSED APPROACHES FOR DEDP IN POWER SYSTEM APPLICATIONS

This section presents the various approaches proposed to solve DEDP for considered power system models.

A. Proposed Refined Teaching-Learning Based Optimization (RTLBO) algorithm with Improved Radial Basis Function Neural Network (IRBFN) to solve DEDP

A new improved version of traditional Radial Basis Function (RBF) network architecture for forecasting the wind power by modifying the one designed in [13] is proposed, called as IRBFN. In this research, three different data of temperature and wind vane directions for the range of wing speed is used to train the proposed IRBFN. This improves the accuracy in predicting the wind speed and thereby the wind power with a chance of increasing the reliability of the installed wind power generation. The wind power from the IRBFN is incorporated into the proposed hybrid RTLBO – Sequential Quadratic Programming (SQP) algorithm to perform the load dispatch solutions. The following steps enumerate the step-by-step procedure of the Teaching learning based optimization algorithm refined using the SQP method;

Step-1: Initialize the number of students (population), range of design variables, iteration count and termination criterion.

Step-2: Randomly generate the students using the design variables.

Step-3: Evaluate the fitness function using the generated (new) students.

// Teacher Phase //

Step-4: Calculate the mean of each design variable in the problem.

Step-5: Identify the best solution as teacher amongst the students based on their fitness value. Use SQP method to fine-tune the teacher.

Step-6: Modify all other students with reference to the mean of the teacher identified in step 4.

// Learner Phase //

Step-7: Evaluate the fitness function using the modified students in step 6.

Step-8: Randomly select any two students and compare their fitness. Modify the student whose fitness value better than the other and use again the SQP method to fine-tune the modified student. Reject the unfit student.

Step-9: Replace the student fitness and its corresponding design variable.

Step-10: Repeat (Test equal to the number of students) step 8, until all the students participate inthe test, ensuring no two students (pair) repeating the test.

Step-11: Ensure that the final modified student's strength equals the original strength, ensuring there is no duplication of the candidates.

Step-12: Check for termination criterion and repeat from step-3.

The above procedure is used to solve the DEDP once the wind power is forecasted by the proposed IRBFN Network. Here the SQP method will be used to fine-tune to improve (better fitness) the solution. This will ensure the better solution region will not be over run and will also aide in converging faster towards the possible best solution of the DEDP.

B. Proposed RTLBO algorithm with ELMAN neural network to solve DEDP

This section introduces the applicability of ELMAN neural network for predicting the wind speed and results in increased wind power generation. The output wind power predicted from the ELMAN neural network is hybridized with that of the proposed RTLBO algorithm to solve the DEDP and find solutions and achieve minimal cost incurred. In this case also the ELMAN network is applied to forecast a one-hour-ahead wind power to plan and to ensure a reliable power supply. The applicability of the proposed hybrid RTLBO – SQP and ELMAN network is implemented for a standard DEDP and one practical DEDP with wind power forecasted based on the practical information of wind speed. The proposed ELMAN architecture for determining wind speed is as shown in Figure-1.

C. Proposed Hybrid Weighted Probabilistic Neural Network (WPNN) and Biogeography Based Optimization (BBO) algorithm to solve DEDP

In this contribution, a modification of the basic Probabilistic Neural Network (PNN) is developed; WPNN is employed to forecast a one-hour ahead wind power for ensuring reliable power supply. Also, BBO algorithm is utilized to minimize the overall cost of operation of wind power system, wherein the wind power computed from WPNN aids for the processing of BBO. The proposed methodology involves the integration of BBO with SQP for fine tuning the better solutions to reach the optimized minimal level. The proposed hybrid WPNN – BBO – SQP method is applied for a test bench DEDP and a practical DEDP wind power forecasted based on real time data from wind power plant. The following steps present the step-by-step procedure of the BBO algorithm modified by employing the SQP method;

Step-1: Initialize the population *P* randomly.
Step-2: Evaluate the fitness and sort the population from best to worst.
Step-3: Initialize species count probability of each habitat
Step-4: While the termination criteria is not met do Step 1
Step-5: Save the best habitats in a temporary array.
Step-6: For each habitat, map the HSI (Habitat Suitability Index) to number of species S, λ and μ
Step-7: Probabilistically choose Immigration Island based on μ
Step-8: Migrate randomly selected SIV (Suitability Index Variable) based on the selected island in Step7.
Step-9: Mutate the population probabilistically.
Step-10: Evaluate the fitness and sort the population from best to worst and use again the SQP method to fine-tune the modified population. Reject the unfit population.
Step-11: Sort the population.
Step-12: Check for feasibility and similar habitat
Step-13: Stop

The above discussed hybrid BBO and SQP algorithms are used to solve the DEDP once the wind power is forecasted by the proposed WPNN with modified weighting factors.

D. Numerical results of the proposed approaches to solve DEDP

This effectiveness of the proposed solution methodology for DEDP with integrated wind power by solving the following test systems as three different cases,

Table-1. Comparison of MSE for various approaches.

Sl. No.	Comparison of approaches	MSE
1	BPN [13]	0.0397
2	RBFN [13]	0.00133
3	Proposed Improved RBFN	0.00092
4	Proposed method using ELMAN	0.00079
5	Proposed WPNN with weighting factors	0.00018

i) Case (i) Results for wind speed and wind power predictions: In this case, the data for the wind power prediction is provided by the Suzlon Energy Ltd., India as they play key role in predicting the wind power for the Load Dispatch Centre, Erode (LDCE) which is controlling the Neyveli Thermal Power Station (NTPS). The wind farm consists of 100 wind turbines of 1.5 MW each. The LDCE forecasts wind power using Naive method as a generalized method for further scheduling the thermal units to fulfill the balance power demand requirements.On carrying out the necessary simulations, Table-1 shows the results of the proposed model (IRBFN, ELMAN, and WPNN) for statistical errors in comparison with other existing models. Table-2 shows the wind power estimated using (11), from the wind speed predicted using various methods including the proposed method using ELMAN and WPNN model. The next step is to compute the DEDP solutions based on the methods proposed in this research for a standard 10-unit test system.

ii) Case (ii) Validating the proposed Hybrid RTLBO – IRBFN, Hybrid RTLBO – ELMAN and BBO- WPNN method for solving DEDP:This research is carried out for a 10-unit test system proven as a complex test bench for several solution methods for validating the proposed three Hybridized models: RTLBO – IRBFN, RTLBO – ELMAN and BBO [14] – SQP – WPNN methods for solving the DEDP.Also the results are compared with the existing solutions reported in [15]. Table-3 shows the production cost distribution as best, worstand the average production cost obtained for a 40 different trial runs.From Table-3, it is proved that the proposed method is

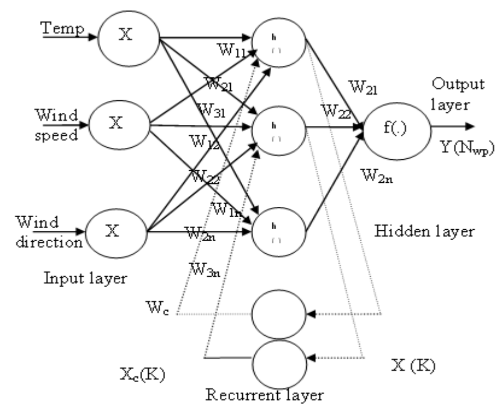

Figure-1. Proposed Elman network architecture model.

consistent in reaching the best optimal solution and best suitable for solving the DEDP with valve-point effects.

ii) Case (iii) A practical 7-unit multi-fuel DEDP with integrated wind power: A practical system where 7-thermal units are supplying the power demand and controlled by LDCE is considered for applying the proposed approach. During 2010, wind power generation is penetrated into the system with an installed capacity of 150 MW. The proposed methodologies in section IV (A, B, C) are applied for this case (iii) module In Table-4, the proposed hybrid BBO - SQP with wind power from

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WPNN method obtains the better total fuel cost and best total fuel cost compared to CSADHS method [15] and the methods proposed in section IV B and section IV A, thus resulting in the higher quality solution. Moreover, in all the 30 different trial runs, the proposed hybrid BBO – SQP –WPNN resulted in almost less total fuel costs, thus conforming a better quality solution and convergence characteristic. From Figure-2, it is revealed that the convergence characteristic of the proposed hybrid BBO-SQP with WPNN algorithm is steady and fast.

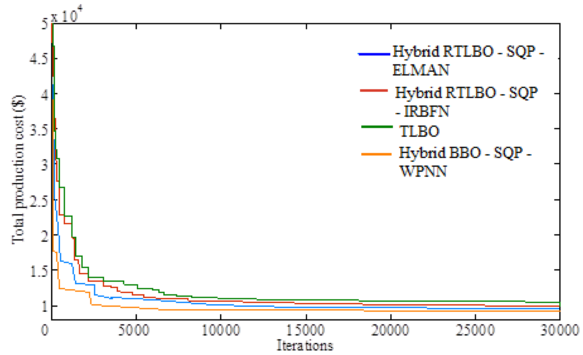

Figure-2. Convergence plot for the proposed methods for case (iii).

Table-2. Wind power (for a particular trial) estimated from the wind farm for the predicted wind speed using proposed neural network models.

Hour	Actual wind power (Suzlon) (MW)	Proposed IRBFN method (MW)	Proposed model using ELMAN (MW)	Proposed model using WPNN (MW)
1	129.9336	131.317	130.122	130.0951
2	130.5483	131.5846	130.2596	130.1263
3	129.6927	131.3064	130.1213	129.7124
4	130.3383	130.5666	130.4927	130.4001
5	130.5251	128.5235	129.9997	130.4999
6	130.5604	130.8185	130.4926	130.5109
7	132.4563	133.6588	132.8593	132.4278
8	140.1752	142.0634	141.0673	140.0926
9	142.3433	141.182	141.0032	142.3125
10	144.4042	145.2115	144.1908	144.2600
11	146.2464	146.2729	146.1199	146.2133
12	146.9441	148.6656	147.0001	146.8942
13	146.443	147.2728	146.3021	146.4123
14	147.0039	145.9053	146.9945	147.0126
15	144.1318	143.8849	144.2612	144.1569
16	141.6287	140.2092	141.2092	141.5923
17	134.4697	136.2793	134.8875	134.6675
18	134.4699	133.8301	134.2915	134.3154
19	132.3468	130.4664	132.0216	132.2999
20	132.2144	133.237	132.1695	132.2096
21	131.5594	133.032	131.0321	131.4927
22	130.1897	129.2422	129.7624	130.1942
23	130.3156	129.387	129.9108	130.2934
24	130.1835	131.8266	130.0024	130.1791

Table-3. Summary of best, worst and mean production cost produced by the various methods for case (II).

Methods	Max. Cost ($)	Min. Cost ($)	Average Cost ($)	Average Time (min)	Min. Time (min)
TLBO	1037842	1031746	1035748	5.62	5.21
BBO	1036942	1029787	1034521	4.96	4.74
CSADHS [14]	1018760	1018681	1018718	2.72	--
Proposed Hybrid RTLBO – SQP	1018842	1018679	1018702	2.63	2.61
Proposed Hybrid BBO – SQP	1018654	1018592	1018629	2.59	2.57

Table-4. Summary of best, worst and mean production cost produced by the various methods for case (III).

Methods	Max.Cost ($)	Min.Cost ($)	Average Cost ($)	Average Time (min)	Min. Time (min)
TLBO	9952.2471	9736.1471	9754.2321	4.21	4.18
Hybrid RTLBO – SQP with IRBFN	9588.2141	9538.1851	9551.3271	2.53	2.51
Hybrid RTLBO – SQP with ELMAN	9497.1625	9425.6721	9432.5183	2.17	2.12
Proposed Hybrid BBO – SQP with WPNN	9362.1098	9341.8902	9357.6814	2.01	1.99

5. CONCLUSIONS

DEDP is always one of the most important research problems in the current growing scenario of power system engineering domain and as well as the case of rural electrification in renewable energy system domain. This research focused on developing certain nature inspired evolutionary algorithms and neural network architecture models for solving dynamic economic dispatch problems in power system environment. In power system modules, it is very important to have intelligent mechanisms in order to obtain the optimal load dispatch solution for the test beds considered. As a result, in this research work steps are taken to obtain an optimal load solution with a satisfactory output on cost factor. Evolutionary optimization algorithms are proposed in order to obtain near optimal solutions. Also, the contribution on a hybrid renewable energy system constituted of photovoltaic (PV)-wind-diesel-battery-converter systems was found to meet the power requirement of rural area educational institution.

All these proposed approaches aim to solve power system application problems and can be used as a helping tool for the user to compute the feasible load dispatch solutions. Each of the proposed approach follows its own mechanism for exploring and exploiting the search space to compute the better solution with reaching the best fitness point. All the approaches perform their search process in a supportive and co-operative manner rather than an aggressive manner. The computed results are more intelligent and robust in nature providing better solutions in comparison with that of the existing conventional techniques.

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