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Prediction based Multiobjective Solution of Economic Emission and Load Dispatch for Solar Integrated Power Systems

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In present day power systems, the conventional thermal generating stations are being interconnected with solar photovoltaic sources to reduce the running cost along with environmental emission. For proper load dispatch, short term forecasting of electric load is essential to avoid overloads, surges and instability because of varying demand. In this work, Improved Multi-Objective Teaching Learning-Based Optimization (IMOTLBO) algorithm has been developed for effective Economic Emission and Load Dispatch (EELD). Here, the predicted load of a real time load center on a test Solar Integrated System (SIS) has been utilized to obtain Pareto solution, considering cost and emission as two objectives. The performance of the proposed IMOTLBO algorithm is compared with four other MOEAs, namely, Non-dominated Sorting Genetic Algorithm-II (NSGA-II), Multi-Objective Particle Swarm Optimization (MOPSO), Modified Multiobjective Cat Swarm Optimization (MMOCSO) and Multi-Objective Differential Evolution with Recursive Distributed Constraint Handling (MODE-RDC). For efficient prediction of the expected electrical load demand, an efficient single layer low complexity neural network i.e. Functional Link Artificial Neural Network (FLANN) model is considered. The weights of FLANN model are optimized by utilizing four different algorithms; one derivative based i.e. Least Mean Squares (LMS), and three others heuristic algorithms, namely Particle Swarm Optimization (PSO), Jaya and TLBO. To compare the performance of the proposed TLBO based FLANN models with the other three models, the Root Mean Square Error (RMSE) has been considered as the performance index. The dominance of the proposed FLANN-TLBO models over others is investigated by conducting non-parametric statistical testing.

Keywords: Constraint handling, Multiobjective optimization, Root mean square error, Short term load forecasting, Teaching learning based optimization

Introduction

Economic dispatch in a multi-unit power system is the scheduling of power generation of the committed thermal generating units to deliver the demanded load at the most economic fuel cost. In view of the growing awareness of environmental pollution and the stringent norms imposed by Government agencies, minimization of emission is also important. But fuel cost and emission are two incommensurable and contradictory objectives that cannot be minimized simultaneously. Thus, the EELD can be considered as being a constraint multiobjective optimization task.[1] The main constraints are the lower and upper limits of the generation of each unit, the power balance criteria, and transmission line capacity.[2–4] It is highly essential to keep both cost and emission under control, for this, a tradeoff between these two conflicting objectives by considering the associated constraints is a challenging and interesting task in solving the EELD problem.

Considering the advancement in the generation of renewable energy, several authors have considered sharing a part of the load demand from renewable sources through interconnected systems to reduce the emission further.[5] One of the major renewable sources is the solar energy which is considered for interconnection with the conventional thermal power systems for lowering the level of pollution.[3,4,6] It is always advantageous if prior information of the expected load demand on the system is available so as to avoid uneconomical scheduling, instability, surges and outages due to overloading.[7,8] To achieve this, various short term load forecasting methods are employed. The predicted load demand may be considered as prior information before taking decisions on the load dispatched by the system efficiently at low operating cost and low environmental emission. The major contributions of this study are as follows:

i) A suitable modification has been made to the traditional Teaching Learning Based Optimization (TLBO) to develop the IMOTLBO technique for solving the constraints multiobjective EELD problem.

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ii) Four different optimization algorithms are implemented for the weight to optimization of the FLANN model for the prediction of electrical load, by testing it on real time data. The efficacy of the models has been evaluated, and the most efficient one is utilized to address the load dispatch problem for a Solar Integrated System (SIS).

iii) An IMOTLBO technique has been developed, and the performance is compared with four other MOEAs to obtain the solution of the EELD problem by utilizing the predicted load of a real time load center on a test Solar Integrated System (SIS). The comparison is carried out by considering four different performance matrices.

iv) The load dispatch problem for an SIS for the duration of the day with significant solar radiation is considered to obtain a tradeoff point between the total cost and emission. The final desired solution is obtained by giving proper importance to the objectives. Comparison between the tradeoff points obtained at various hours of the day is also made.

Related Works

Some significant contribution towards optimization of solar integrated systems has been made by developing a model combining standard thermal and PV units.[3] The work was further extended to include a decomposition framework for solving the problem using a new mixed integer binary programming algorithm.[4] But the authors have mainly relied on the h-index which is the price penalty factor to obtain final solutions through the weighted sum approach giving only one tradeoff solution. The load dispatch problem has been addressed by considering it in a multiobjective framework by various researchers by improving the basic structure of the optimization algorithms.[9,10] However, there is a requirement of further investigation in improving the MOEAs algorithm that can provide better trade-off between cost and emission as two conflicting objectives. Moreover, the EELD task in a multiobjective framework by integrating the grid with renewable sources has been explored in various articles.

All these works are based on a particular load demand on the system. However, the electrical load on a power system is always changing throughout the day and to solve for a particular load is not adequate. Hence, various prediction models for predicting the load have been developed for this purpose.[11–13] An efficient artificial neural network based prediction model named BWO-FLANN has been proposed to predict the future load demand.[14] The dispatch schedule for the predicted demand is achieved using the NS-MOTLBO algorithm. However, a more feasible option is needed to be employed by implementing a less computationally intensive load prediction model. In this research work, the EELD task has been solved in a multiobjective framework by considering the predicted load of a realistic SIS.

Prerequisites

EELD for SIS

The cost of fuel for the i^{th} thermal generator that delivers P_i MW power is,

$$F_i = a_i P_i^2 + b_i P_i + c_i + \left| e_i \sin\left(f_i\left(P_i^{min} - P_i\right)\right)\right| \text{ \$/hr} ; i = 1,2,\dots,n \quad \dots (1)$$

Fuel cost coefficients for the i^{th} thermal generator are a_i, b_i, c_i, e_i and f_i. ; n = number of generators using fossil fuels; P_i has a minimum value of P_i^{min} . The emission from the generator is given as

$$E_i = \alpha_i P_i^2 + \beta_i P_i + \gamma_i + \varepsilon_i exp(\delta_i P_i) \text{ lb/hr}; i = 1,2,\dots,n \quad \dots (2)$$

α_i, β_i, γ_i, ε_i and δ_i are the emission coefficients. The valve point effects are given by the exponential and sine expressions. These emission coefficients have been established by several experimentations on the standard thermal power systems and the amount of environmental pollutants emitted by the power systems is decided by the function E_i. The Output power (MW) of the solar units may be written as

$$P_{gj} = P_{ratedj}\left\{1 + \alpha_{pvj}\left(T - T_{ref}\right)\right\}\frac{Sj}{1000} ; j = 1,2,\dots,m \quad \dots (3)$$

P_{gj} is the power availed from the j^{th} solar unit; P_{ratedj} is the rating of the PV unit; the insolation at temperature T is S_j at reference temperature of T_{ref} and the temperature coefficient is α_{pvj} for the material of PV panel. The cost of operation for the j^{th} solar unit C_j is,

$$C_j = PUC_j \times P_{gj} \text{ \$/hr} ; j = 1,2,\dots,m \quad \dots (4)$$

PUC_j is the value of per unit cost (\$/MWhr) for the j^{th} unit.

The total operating cost is,

$$F_T = \sum_{i=1}^{n} F_i + \sum_{j=1}^{m} C_j ; = 1,2,\dots,n ; j = 1,2,\dots,m \quad \dots (5)$$

The total emission is,

$$E_T = \sum_{i=1}^{n} E_i;\ i = 1, 2, \ldots, n \qquad \ldots (6)$$

The operating cost F_T and emission E_T are considered as two conflicting objectives that need to be optimized simultaneously. The optimization must obey the limits of generation and power balance condition. The power balance condition states that P_G, which is the sum of the generated power produced from all the units equals the load demand plus transmission losses.

$$P_G = \sum_{i=1}^{n} P_i + \sum_{j=1}^{m} P_{gj} = P_D + P_L \qquad \ldots (7)$$

P_D is the total MW demand on the system; P_L is the loss in the transmission network. The transmission loss is represented by Kron's formula as follows:

$$P_L = \sum_{i=1}^{n} \sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{i0} P_i + B_{00} \qquad \ldots (8)$$

The constants B_{ij}, B_{i0} and B_{00} are found from the line parameters. The generation of each thermal power generator should satisfy the lower and upper bounds.

$$P_i^{min} \le P_i \le P_i^{max};\ i = 1, 2, \ldots, n \qquad \ldots (9)$$

The two objectives, cost and emission being conflicting in nature, do not have minimum value simultaneously. Hence, a tradeoff curve between them is obtained for a particular value of load demand P_D and is termed as a Pareto optimal front.

Proposed Work

In this paper, a Functional Link Artificial Neural Network (FLANN) model of short-term load prediction is developed and utilized for forecasting the load. Four different algorithms, such as, Least Mean Squares (LMS), and three others swarm and evolutionary based algorithms, namely Particle Swarm Optimization (PSO), Jaya and TLBO are utilized to update the weights of the FLANN model. The performance of proposed TLBO based FLANN models with the other three models, such as, FLANN-LMS, FLANN-PSO, FLANN-Jaya has been inspected by evaluating the Root Mean Square Error (RMSE) of the forecasted load as the performance parameter. The significance of the proposed FLANN-TLBO models as compared to other is inspected by conducting statistical testing. A possible power pool is formed that consists of thermal and solar units and this pool is simulated to dispatch the predicted load. The TLBO algorithm is suitably modified, and IMOTLBO technique has been developed to obtain all the solutions of the EELD task for the solar integrated system by utilizing the predicted load demand. Instead of finding a single solution to the problem, a flexible Pareto front approach is followed. The priority among cost and emission is given based on the importance to arrive at different optimized solutions. To the authors' knowledge no such work has been done by any other researcher. The flow chart of the introduced IMOTLBO algorithm is depicted in Fig. 1.

IMOTLBO Algorithm for EELD Problem

The IMOTLBO is a proposed improvement on the TLBO[14] for multi-objective framework with the following algorithm steps:

1. Specify the cost and emission functions (objectives), solar per unit costs, irradiance, and temperatures for the working hours.
2. Define the lower and upper generation bounds, loss coefficients for each unit and the total load demand P_D.

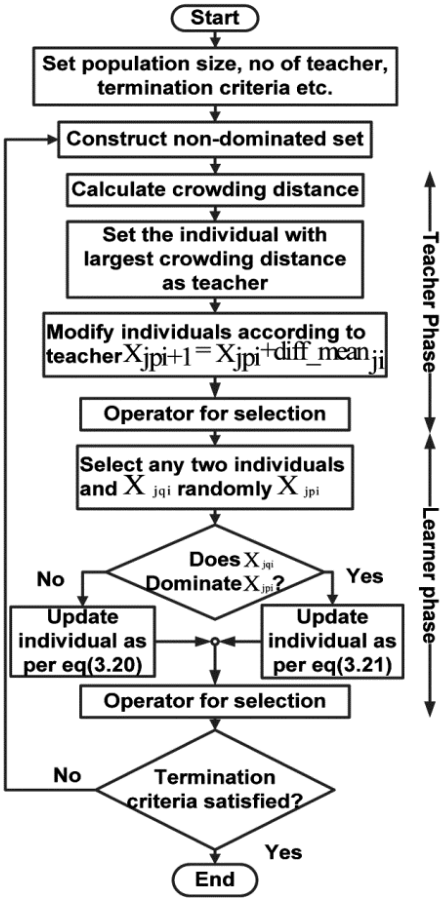

Fig. 1 — Flowchart of IMOTLBO algorithm

3. Specify the size of population (*n*), and teacher count (*T*). Initiate a random population taking the upper and lower bounds.
4. Evaluate the performance of all the individuals (learners) with respect to the objective functions.
5. Consider the best *T* learners as teachers based on larger crowding distance. Find the best among the teachers as

$f(X_{T1}) = f(X)_{best}$ where, X_{T1} is the learner assigned as the best teacher. Other teachers are found as

$f(X)_{Ts} = f(X)_{best} + rand * f(X)_{best}$ where, $Ts = 1, 2, \dots, T$, and *rand* stands for random number in between 0 and 1.

6. The teachers are attached to a group of learners according to their fitness. Also, the teachers are arranged in terms of decreasing fitness. The teacher T is assigned as the best teacher.

```
$for\ p = 1:(n - Ts)$
    $if\ f(X)_2 \geq f(X_p) > f(X)_1$ ; teacher 1 attached to learner $p$
    $else\ if\ f(X)_3 \geq f(X_p) > f(X)_2$ ; teacher 2 attached to learner $p$
    $else\ f(X)_T \geq f(X_p) > f(X)_{T-1}$ ; teacher T-1 attached to learner $p$
end
```

7. Update the positions of learners following the teachers in the teacher phase, this is done for all the populations.
8. Evaluate for each group the learner's phase. The modified correction for learner phase is as follows:

```
$if\ f(X_{jqi}) < f(X_{jpi})\ \ then\ \ X_{jpi+1} = X_{jpi} + rand * (X_{jqi} - X_{jpi}) + rand * (X_{jTsi} - E_F X_{jpi})$
$else\ if\ f(X_{jpi}) < f(X_{jqi})\ \ then\ \ X_{jpi+1} = X_{jpi} + rand * (X_{jpi} - X_{jqi}) + rand * (X_{jTsi} - E_F X_{jpi})$
end
```

where, $E_F = round(1 + rand)$ is called the exploration factor which is because of tutorials and self-learning.

9. Construct the non-dominated set and store the same.
10. Check for termination criteria. If satisfied draw the Pareto front and find the best tradeoff solution using fuzzy decision system. If not satisfied repeat steps 5 to 9.

The performance evaluation of the algorithms is carried out taking spacing (S), Diversity (Δ), Spread Diversity (SD), and Mean Ideal Distance (MID) as parameters as mentioned in references 15 and 16, and have been utilized to investigate the performance analysis.[15,16] The mathematical formulation of these performance indices is as follow:

The spread of Pareto solutions is measured by Spacing (S) matric.[16]

$$S \triangleq \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\bar{d} - d_i\right)^2} \quad \dots (10)$$

where, $d_i = \min_j\left(\left|f_1^i(\vec{x}) - f_1^j(\vec{x})\right| + \left|f_2^i(\vec{x}) - f_2^j(\vec{x})\right|\right)$ and $i, j = 1,2, \dots n$ … (11)

Diversity (Δ) matric indicated the evenly distribution of solutions in the search space.[15] Euclidean distances is utilized to find this matric.

$$\Delta = \frac{d_f + d_l + \sum_{i=1}^{n-1}|d_i - \bar{d}|}{d_f + d_l + (n-1)\bar{d}} \quad \dots (12)$$

Spread Diversity (SD) matrix that estimates the diversity among the solutions by considering the Pareto optimal front extreme ends. Higher the *SD* better is the performance.[16]

$$SD = \sqrt{\sum_{i=1}^{N_{OF}}\left(OF_i^{max} - OF_i^{min}\right)^2} \quad \dots (13)$$

Mean Ideal Distance (MID) specifies the evenly spreading of the non-dominated solutions in the search space. The lower the *MID* value better the performance.

$$MID = \sum_{j=1}^{N_S}\left(C_j / N_S\right) \quad \dots (14)$$

where, $C_j = \sqrt{\sum_{i=1}^{N_{OF}}\left(OF_i^j - OF_i^{min}\right)^2}$ … (15)

Short-term Load Prediction

Functional Link Artificial Neural Network (FLANN)

FLANN can generate nonlinear decision boundaries and can be used for predicting time series data with a high degree of accuracy. It is a single layer Artificial Neural Network (ANN), where the inputs are expanded into higher order through function expansion to avoid the necessity of hidden layers as present in the multilayer perceptron (MLP).[12] The inputs of the FLANN model are expanded using the function expansion; the weighted sum of the expanded input is added to obtain the output; the output is applied to the activation function to achieve the output of the model.[11] The difference between the output and the desired value is considered to be error, and it is utilized for the updation of the weights of the FLANN model in each iteration.

$$X = F(x) \quad \dots (16)$$

$$h = \sum X * w^T \quad \dots (17)$$

$$y_o = \varphi(h) \quad \dots (18)$$

where, F is the function for expansion, X is the output from expansion function of input of x; φ is the activation function. The structure of FLANN model is shown in Fig. 2.

Expansion Function

The function expansion block in the FLANN creates a set of expanded functions from the inputs. For example, the expanded function X from a two-input sample $x = [x1x2]^T$is formed using algebraic polynomial expansion as:

$$X = [x1\ x2\ x1^2 x2^2\ x1 * x2]^T \quad \dots (19)$$

For a three-input function $x = [x1x2\ \mathrm{x3}]^T$, the enhanced function will be represented as:

$$X = [x1\ x2\ x3\ x1^2 x2^2 x3^2\ x1 * x2\ x1 * x3\ x2 * x3]^T \quad \dots (20)$$

Optimization Techniques used for FLANN

For prediction purposes, the MSE is taken as the cost function in the FLANN model and is minimized through the following optimization techniques:

Least Mean Squares (LMS)

It is a gradient based algorithm, and is suitable for the updation of the weights of single layer ANN models.[15] The weights are updated in the LMS algorithm as:

$$w_{new} = w_{old} + 2 * \mu * x * error \quad \dots (21)$$

where, μ is the learning rate which controls the rate of convergence. For lower values of μ converges are slower, and may not converge within the last iteration even. Higher values of μ can lead to improper adjustments and the predicted output may not follow the actual input properly. Hence, an adaptive value is always better.

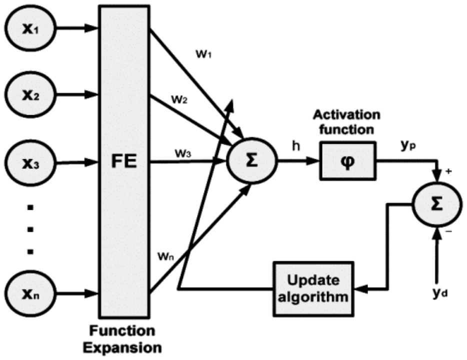

Fig. 2 — Structure of the FLANN model

Particle Swarm Optimization (PSO)

The heuristic algorithm for optimization inspired by the behavioral pattern of birds in a flock or fish in a group is called PSO.[16] Everyone in the swarm is assigned a position and velocity and is called as a particle. The swarm of population may be represented as follows:

$$V_i(k) = \left(v_{i1}(k), v_{i2}(k), \dots, v_{iD}(k)\right); i = 1,2, \dots, N \quad \dots (22)$$

$$X_i(k) = \left(x_{i1}(k), x_{i2}(k), \dots, x_{iD}(k)\right); i = 1,2, \dots, N \quad \dots (23)$$

where, the epoch count is k, space vector dimension is D and population size is N.

The particle with the best fitness value in the current population is p_{best}; whereas that with the best fitness from all the populations is called the g_{best}. The position and velocity of each particle in the population will be updated following the best particles in the next iteration as follows:

$$v_{id}(k+1) = w * v_{id}(k) + c_1 * r_1 * \left(p_{id}(k) - x_{id}(k)\right) + c_2 * r_2 * \left(g_{id}(k) - x_{id}(k)\right) \quad \dots (24)$$

$$x_{id}(k+1) = x_{id}(k) + \chi * v_{id}(k+1) \quad \dots (25)$$

where, $d = 1, 2, \dots, D$ and $i = 1, 2, \dots, N$; $p_{id}(k)$ is the particle with the best fitness value in the population p_{best} and $g_{id}(k)$ is the global best, g_{best} in the k^{th} iteration; χ is the constriction factor; weight is w; c_1 represents the acceleration coefficient to follow the pbest; c_2 represents the coefficient of acceleration towards the g_{best}; r_1, r_2 are random numbers in the range [0,1] termed as acceleration constants.

JAYA

Jaya is a Sanskrit word meaning success or victory that defines the principle of this algorithm. A fighter always strives to achieve success or get close to the desired (best) and endeavors to eliminate failure or move away from the worst situation.[17] The population-based algorithm starts with a random population initialized within the boundaries. The best and worst individuals are identified through the evaluation of their fitness. The weight of each input is updated as

$$z = w_i^n + rd1 * \left(best_{value} - abs(w_i^n)\right) - rd2 * \left(worst_{value} - abs(w_i^n)\right) \quad \ldots (26)$$

$$w_i^{\boldsymbol{n+1}} = z \quad \ldots (27)$$

where, $rd1$ and $rd2$ are random numbers in the range [0,1], the $best_{value}$ is the weight corresponding to the lowest value of the cost function and the $worst_{value}$ is the weight that leads to the highest cost function value. If the updated weight yields a lower cost function value, then it is selected for the next iteration, otherwise it is rejected, and the original weight is carried to the next iteration.

Teaching Learning Based Optimization (TLBO)

It is a metaheuristic optimization technique having no algorithm specific control parameters. It is considered better than Jaya because of the two phase search; the global search in one phase called as the teacher phase, and other local search named as the learner phase.[14]

Simulation Study

Test System

The test system considered here is a standard IEEE 30 bus system with six thermal units interconnected with five PV units the details of which are borrowed from standard sources.[3] The coefficients for emission and cost functions, and the upper and lower limits of generation of the units are given in Table 1.(2) Here, the one-line diagram of the test system has been considered as depicted in Fig. 3. The thermal units are represented by G and all the PV units are connected to bus 15 represented by S. For simplicity, compensation devices and transformers are not shown; the orientations and lengths of the lines are not as per scale. All the generating units are committed all the hours of operation. The solar hour with significant radiation is considered; i.e., from 10AM till 3PM on hourly basis as shown in Table 2.

The real time data of the load demand is collected from the State Load Dispatch Center (SLDC), Odisha for the SOUTHCO Distribution Company (DISCOM) for a period starting from 1st July 2019 to 12th July 2019. The company provides the load demand for every 15 minutes of a day. The demand of load data for the first three consecutive instants is used to train the FLANN model to forecast the load demand for the 4th instant. A total of 1070 such instants are considered out of which 900 instants are taken as the training set and the rest 170 as the testing set. The four algorithms for updating the weights of the FLANN model i.e., LMS, PSO, JAYA and TLBO are alternatively applied for prediction. The performance of the weights updating algorithms used for prediction in the FLANN model is analyzed by taking the amount of error between the desired and predicted outputs. The error can be either positive or negative,

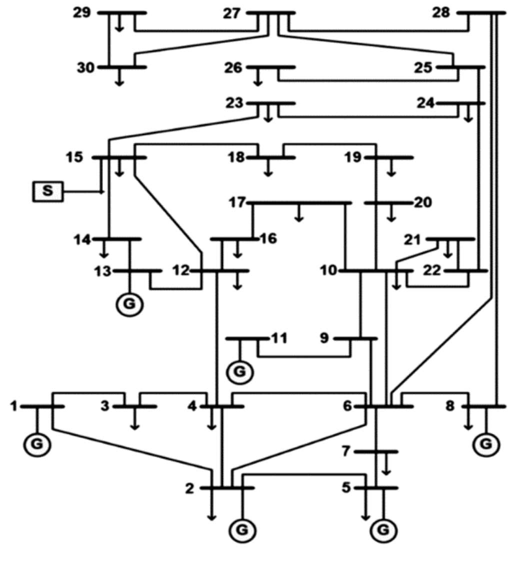

Fig. 3 — Single line diagram of the test system

Table 1 — Cost and emission coefficients of the thermal generating units[2]

Thermal unit No.	1	2	3	4	5	6
Max MW	200	80	50	35	30	40
Min MW	50	20	15	10	10	12
γ	0.0126	0.02	0.027	0.0291	0.029	0.0271
β	−0.9	−0.1	−0.01	−0.005	−0.0004	−0.0055
α	22.983	25.313	25.505	24.9	24.7	25.3
a	0.00375	0.0175	0.0625	0.00834	0.025	0.025
b	2.0	1.7	1.0	3.25	3.0	3.0
c	0	0	0	0	0	0

Table 2 — Ratings of the solar units and solar radiation data

Unit No	Prated (MW)	PUC ($/MWh)	Time	Global radiation (W/m^2)	Temperature (°C)
1	20	0.22	10:00 AM	793.9	34
2	25	0.23	11:00 AM	1078	35
3	25	0.23	12:00 N	1125.6	36
4	30	0.24	1:00 PM	1013.5	37
5	30	0.24	2:00 PM	848.2	37
			3:00 PM	726.7	37

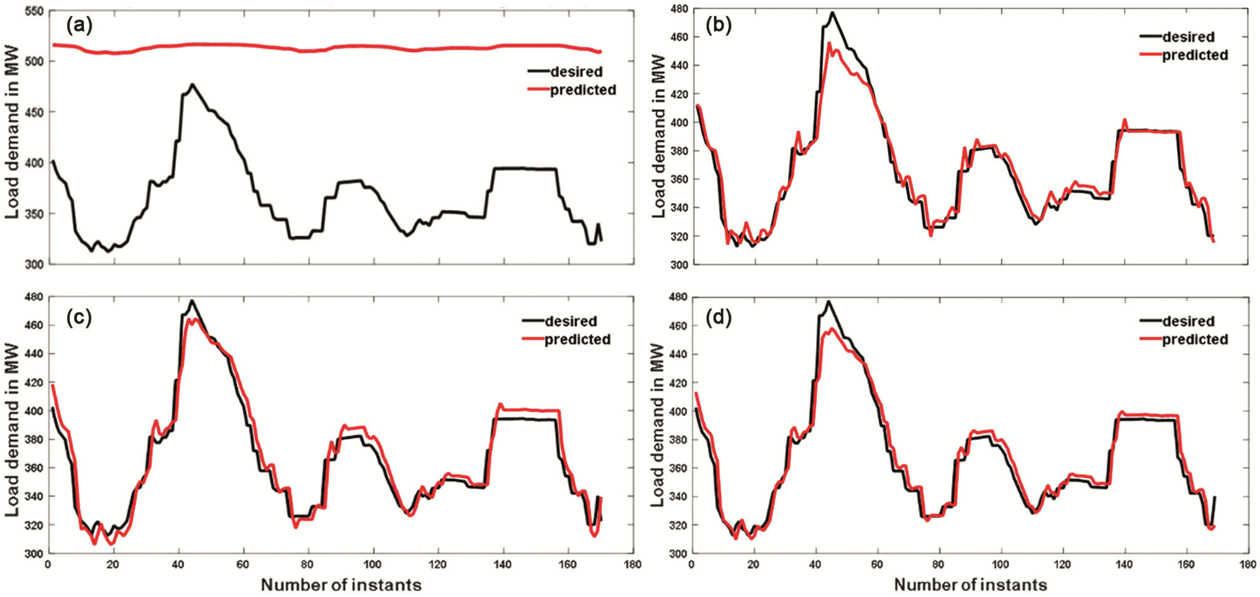

Fig. 4 — Comparison between predicted load with the desired load using: (a) the FLANN-LMS, (b) the FLANN-PSO (c) the FLANN-JAYA (d) the FLANN-TLBO

so a comparison is made with respect to the value of the Root Mean Square Error (RMSE).

$$RMSE = \sqrt{\frac{\sum_{i=0}^{N}\left(y_{p_i} - y_{d_i}\right)^2}{N}} \qquad \dots (28)$$

where, N is the total number of tests, y_p is the predicted output and y_d is the desired output. A lower value of RMSE means a better accuracy in prediction, so the model with lowest RMSE value is the best. The graphical results are shown in Fig. 4. Which indicates the best match between the predicted load with the actual load for the TLBO algorithm. Graphical representation of the RMS error values of the desired and predicted load for 20 runs of the algorithms is shown in Fig. 5. The RMS errors for the TLBO show lower values indicating better accuracy.

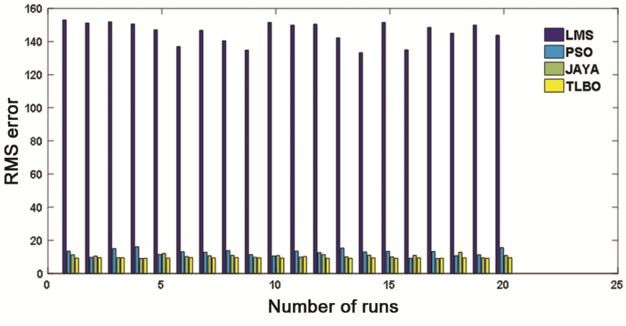

Fig. 5 — RMS errors obtained from the algorithms for 20 runs

A pair-wise sign test is performed to assess the efficacy of the algorithms.[12] The higher number of wins indicates the supremacy of the TLBO algorithm as shown in Table 3. The results are further validated through the Friedman Test as shown in Table 4; a lower rank ensures better accuracy.[8]

The Friedman Test shows the lowest rank for TLBO and a low critical value is depicted in Table 5, reinforcing the supremacy of the algorithm. The Wilcoxon sign rank test has been performed and the results are enumerated in Table 6. These results further emphasize the performance of the algorithm.

The comparison of the performance of the proposed IMOTLBO technique is carried out with four other MOEAs, namely, NSGA-II, MOPSO, MMOCSO and MODE-RDC.[15] Four performance indices, such as, Spacing (S), Diversity (Δ), Spread Diversity (SD), Mean Ideal Distance (MID) have been considered for investigating the performance of the proposed IMOTLBO with the other four competitive multiobjective optimization algorithms as shown in Table 7.

The EELD problem for the standard IEEE 30 bus system is solved using these algorithms, and the comparison of results is shown in the following Table 8.

The Pareto front obtained by MODE-RDC, MMOCSO, IMOTLBO for IEEE 30 bus system for a load demand of 283.4 MW is depicted in Fig. 6.

As the performance of IMOTLBO is found to be the superior one, the EELD solution for the predicted load has been achieved in the form of a tradeoff as the Pareto front for different hours of the day by applying the IMOTLBO algorithm as depicted in Fig. 5. From this tradeoff curve a single point is achieved through the fuzzy inference system as presented in Table 9. The results reveal that at the peak solar radiation time of 12N, the solar share of power being the maximum, the thermal share is pushed to the minimum thus keeping the thermal units' generation closer to their minimum values. The fuel cost as well as the emission under this condition remains very low. On the other hand, at the minimum solar radiation time of 3PM, the solar power share falls causing higher thermal share and higher fuel cost as well as a higher emission level.

Table 3 — Results of pair-wise sign test on RMSE obtained from different algorithms taking RMSE as winning factor

TLBO	LMS	PSO	JAYA
Wins (+)	20	19	15
Loss (−)	0	1	5
α factor	α=0.05	α=0.05	α=0.01

Table 4 — Ranks obtained from Friedman Test on RMSE obtained from the algorithms

Algorithms	TLBO	JAYA	PSO	LMS
Mean Ranks	3.3	6.4	9.8	14.5

Discussion

It is observed that the FLANN-TLBO network (represented in yellow color) provides the lowest RMSE values as compared to other networks as depicted in Fig. 4. The results have been confirmed by the pair-wise sign test as listed in Table 3, the TLBO algorithm for updating the weights wins over LMS, PSO and JAYA algorithms 20, 19 and 15 times respectively out of 20 runs each time. This is further validated through the Friedman test results shown in Tables 5 and 6. A lowest rank of 3.3 is obtained having a very low critical value of 3.5837×10^{-12} indicating better prediction accuracy compared to the other algorithms. Therefore, the predicted short term load by FLANN-TLBO network of the test system is dispatched by the solar integrated power system considered using the IMOTLBO algorithm. The Pareto solutions obtained at six different hours in a day are depicted in Fig. 7. The light blue curve corresponds to 3PM where the solar radiation decreases to the lowest, and hence, the share of thermal power becomes the highest. It can be observed that, at 12N, the solar irradiance is highest (1125.6W/m^2) among the six hours considered as shown in Table 9. Therefore, less thermal and high solar power leading to low value of cost, as well as emission is depicted by the yellow curve in Fig. 7. The best fit points of these two curves found using the fuzzy decision making system show the total fuel cost of 457.0385 $/hr and 613.9038 $/hr respectively. The corresponding emission values are 197.2196 lb/hr and 271.1919 lb/hr respectively. As the power contribution by the thermal plant is less at 12N, the loss due to transmission is also low i.e., 2.6193 MW on the other hand, at 3PM it is 4.7161 MW.

Table 6 — Wilcoxon sign test results on FLANN-TLBO model with RMSE as winning parameter

Evaluation	p-value	h-value
TLBO based FLANN vs LMS based TLBO	0.0001	1
TLBO based FLANN vs PSO based TLBO	0.0015	1
TLBO based FLANN vs JAYA based TLBO	0.0035	1

Table 5 — Friedman Test on RMSE

Source	SS	DOF	MS	Chi-square	Critical value (p)
Columns	1381.8	3	461.933	61.02	3.5837e-12
Error	295	60	4.932		
Total	1701	79			

where, SS is the Sum of Squares, DOF is the degree of freedom, MS is the Mean squares

Table 7 — Performance analysis of algorithms for IEEE 30 bus system

Performance Index ↓ Multiobjective optimization technique→		NSGA-II	SP-MOPSO	MMOCSO	RDC-MODE	IMOTLBO
Spacing (S)	Minimum	0.43	0.47	1.07	0.76	0.51
	Maximum	0.66	1.87	1.07	1.84	0.51
	Average	0.51	0.86	1.07	1.09	**0.51**
	Std Deviation	0.06	0.35	0.01	0.34	0.01
Diversity (Δ)	Minimum	0.33	0.422	0.59	0.56	0.46
	Maximum	0.61	0.70	0.59	0.83	0.46
	Average	0.46	0.53	0.59	0.66	**0.46**
	Std Deviation	0.07	0.07	0.01	0.07	0.01
Spread Diversity (SD)	Minimum	72.36	101.28	103.77	96.21	109.25
	Maximum	110.99	118.87	103.77	123.48	109.24
	Average	85.97	106.67	103.77	110.74	**109.24**
	Std Deviation	8.28	4.13	0.01	6.6798	0.0001
Mean Ideal Distance (MID)	Minimum	33.40	40.57	47.67	40.2758	41.96
	Maximum	42.40	45.37	47.67	47.3751	41.96
	Average	37.76	42.81	47.67	43.8901	**41.96**
	Std Deviation	2.44	1.36	0.0001	1.7781	0.01

Table 8 — Results of EELD on IEEE 30 bus system

Algorithm→	NSGA-II	MOPSO	MMOCSO	MODE-RDC	IMOTLBO
Gen1 in MW	132.85	140.84	136.99	135.14	139.64
Gen2 in MW	51.54	50.34	51.35	53.88	51.87
Gen3 in MW	26.67	25.04	25.53	25.33	26.07
Gen4 in MW	31.08	29.66	31.07	28.69	29.94
Gen5 in MW	24.85	22.58	22.55	24.68	22.32
Gen6 in MW	23.68	22.58	23.41	23.12	21.17
Total generation	290.69	291.05	290.92	290.84	291.02
Loss in MW	7.29	7.65	7.52	7.45	7.62
Run time in sec	222.39	178.45	10.80	11.04	**10.44**
Fuel Cost ($/hour)	821.31	815.14	817.44	818.72	814.98
Emission (lb/hour)	379.29	388.07	384.15	382.68	387.76

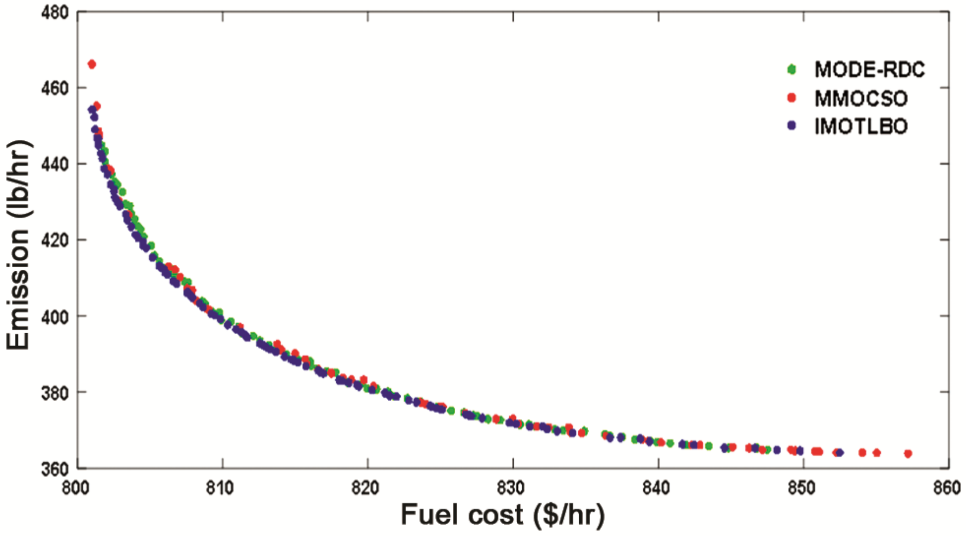

Fig. 6 — Pareto front obtained by MODE-RDC, MMOCSO, IMOTLBO for IEEE 30 bus system for a load demand of 283.4 MW

Table 9 — Result of EELD on solar interconnected system taking the predicted load demand

	Time →	10:00 AM	11:00 AM	12:00 N	1:00 PM	2:00 PM	3:00 PM
Generation by Thermal Plant in MW	Generator-1	107.08	85.34	82.42	89.82	103.14	111.30
	Generator-2	39.05	31.66	30.43	33.02	38.58	41.35
	Generator-3	21.10	18.30	17.62	19.07	20.44	21.10
	Generator-4	17.70	14.37	13.35	14.48	17.41	20.10
	Generator-5	16.01	12.58	12.08	13.31	14.16	15.30
	Generator-6	15.39	13.44	12.48	13.79	13.40	15.35
Solar Generation in MW	Solar Generator	107.57	146.73	153.89	139.18	116.48	99.79
Cost	Fuel Cost ($/hr)	565.92	443.58	421.16	466.26	535.70	590.64
	Solar Cost ($/hr)	25.07	34.19	35.87	32.44	27.15	23.26
	Total Cost ($/hr)	590.99	477.78	457.03	498.70	562.85	613.90
Others	Emissions (lb/hr)	257.97	204.70	197.21	213.85	246.21	271.19
	Power Loss (MW)	4.33	2.83	2.62	3.09	4.03	4.71

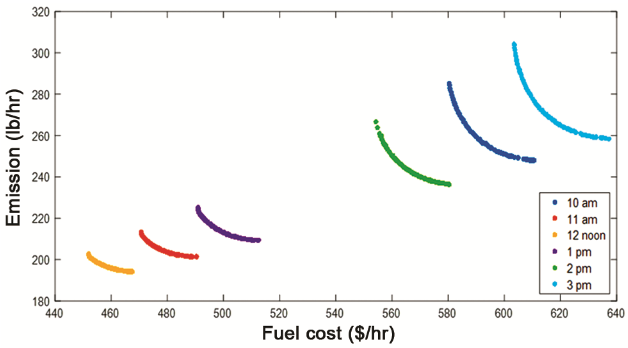

Fig. 7 — Pareto fronts of the EELD on the solar integrated test system using the forecasted load condition: MOP predicted load using solar integrated system II

Conclusions

The short-term electric load has been effectively predicted by utilizing the FLANN model, where the weights are optimized using the LMS, PSO, JAYA and TLBO algorithms. It has been observed that the TLBO based FLANN model is found to be superior among them as it yields a lower RMS error. Non-parametric statistical testing shows the significance of the proposed FLANN-TLBO network as compared to the other three. Real time data collected from the SLDC has been suitably used for training and validation of the FLANN models. The predicted value of load is considered for taking decision on dispatch from the solar integrated test system. The proposed IMOTLBO algorithm is successfully find the solutions by considering the cost and emission as two objectives for an effective dispatch of load utilizing the predicted value. The solar share of power is the highest at the peak solar radiation hour; i.e., 12N. So, the running cost is low (457.0385 $/hr) along with the emission (197.2196 lb/hr) at that time. The generation schedule during that hour leads to lower transmission loss (2.6193 MW). The future scope of this work may be the solution of the unit commitment in the solar integrated power system. Other renewable energy sources like wind, biomass etc. may be integrated and the Pareto solution for the cost and emission may be further investigated. The solution of the EELD problem for larger power pool can also be explored by taking other practical constraints like stability, line losses etc.

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