Dynamic Economic Emission Dispatch Considering Wind Uncertainty Using Non-Dominated Sorting Crisscross Optimization

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ABSTRACT
This paper presents a multi objective crisscross optimization to solve dynamic economic emission dispatch with wind-power uncertainty. The dynamic economic dispatch with combined emission requirements is formulated as a multi-objective optimization problem. The wind power output is predicted as an uncertain model and varies within a bounded limit. Minimizing the wind curtailment is added as an objective to the existing problem objectives of minimizing cost and emissions. Multi-objective crisscross optimization is proposed to solve the problem, utilizing a fast non-dominated sorting principle to obtain the optimal Pareto set of solutions. The proposed non-dominated sorting also ensures diversity, elitism and various complexities due to the high dimensionality of the problem. Exploration for global convergence and exploitation for a better solution is governed by two operators, namely, horizontal crossover and vertical crossover. The proposed solution technique is applied to standard multi-objective benchmark test problems and subsequently to standard dynamic economic dispatch problems with different ratios of wind power penetration.

INDEX TERMS
Heuristic algorithms, nonlinear equations, optimal scheduling, power generation dispatch, wind energy integration.

I. INTRODUCTION
With rapid developments in integrating renewable energy power generation with existing power system networks, complexities also proliferate. Due to sustainability requirements, renewable energy power generation is inevitable and is becoming vital in modern smart power generation [1]. Although modern techniques ensure effective harvesting of renewable energy, uncertainties and complexities mean that more suitable procedures for integrating conventional power systems with renewable energy sources are required. By integrating renewable energy resources, the electricity industry can be regulated according to the Clean Air Act amendments [2], thus reducing the level of emissions dispersed in the atmosphere.

Dynamic economic dispatch (DED) determines the generator output for a forecasted load over a horizon of time (usually 24 hours (h)) [3]. Few methods have been proposed to minimize the pollution dispersed in the atmosphere, but emission dispatch was found to be an effective method, and thus minimizing both fuel costs and emission levels is the objective of solving dynamic economic and emission dispatch (DEED). Ample literature supports the application of diverse methodologies for solving the DEED problem. Solution techniques such as particle swarm optimization (PSO) [4], teaching-learning-based optimization (TLBO) [5], the multi-attribute decision-making approach [6], group search optimization (GSO) [7] and improved bacterial foraging optimization (IBFO) [8] are proposed to solve the DEED problem. In the approaches mentioned, the multi-objective problem is converted to a single-objective function, and the fitness function is minimized. Considering the problem as truly multi-objective, solution methodologies such as the non-dominated sorting genetic algorithm II (NSGA II) [9], the multi-objective differential evolution algorithm (MODE) [10] and the multi objective self-learning...
bat algorithm [11] are used to investigate the problem. A few hybrid techniques have also been proposed to solve the DEED problem. Hybrids of differential evolution, particle swarm optimization and sequential quadratic programming, DE-SQP and PSO-SQP, are presented in [12], and a hybrid of DE with simulated annealing is presented in [13]. A hybrid chemical reaction optimization and differential evolution algorithm was proposed to solve the DEED problem in [14]. Variants of the particle swarm optimization (PSO) technique are applied to solve the DEED problem in [15].

Maximizing the penetration of renewable energy resources into the grid alleviates emission problems better than finding an optimal power dispatch. The inclusion of clean energy greatly impacts the minimization of both costs and gas emissions dispersed in the atmosphere. Thus, environmental degradation due to global warming and air pollution can be controlled. The main drawback of using this clean energy is the inherently variable nature of wind speed and the uncertainty in wind power output. Since the power extracted from a wind farm is not consistent, due to the intermittent nature of wind, various models of it have been investigated in past decades.

The different models of wind power presented in the literature are: the probability density function (pdf), forecasted wind power from wind farms, mathematical models and scenario-based representations of the uncertainty of wind power and load. The cost of overestimation and underestimation of available wind power is based on the Weibull probability density function, and related works are presented in [16–21]. Quantum-inspired PSO [17] and NSGA II [18] are adapted to solve the dynamic economic emission dispatch problem with wind power. Bi population-based chaotic DE is implemented in [19] to solve the wind thermal dispatch problem. In [20], evolutionary optimization is adopted for hybrid dispatch, and in [21], the same is done by gravitational acceleration-enhanced particle swarm optimization. The drawback of implementing a probability density function is that the parameters of the function have to be properly estimated for varying times. For dynamic dispatch, the stochastic nature of wind power varies with varying parameters of the pdf.

The uncertainty of wind power is modeled as a 2-m point in [22] using a modified teaching learning algorithm and in [23] using the honeybee optimization method. The interior-point method is utilized to solve the multi-objective stochastic economic dispatch (MOSED) problem [24]. Using the forecasted wind power from a wind farm for a particular day, the economic emission problem is solved in [25–29]. A scenario-based stochastic programming framework is presented to solve the multi-objective economic emission dispatch problem by integrating wind power in [30–32]. Algorithms such as self-adaptive particle swarm optimization [31] and learning automata optimization [32] are implemented with improvements to their learning strategy. Security-constrained and risk-constrained economic dispatch integrated with load and wind variations are presented in [33] and [34].

From the literature review, it can be seen that a few studies have combined DEED with forecasted wind power for a particular day. All the above studies focus on wind power as an additional power source to meet the power demand. The impact of wind power fluctuation is assumed to have a considerable effect on the power balance constraint. The effects of wind power dispatch on the ramp constraints of thermal units are not considered in any of the above papers.

To address uncertain and complex optimization problems such as DEED, the robust optimization (RO) method has been widely used in recently [35–38]. RO is appealing in two ways. First, decision-makers can form a defined set for the uncertain parameters. In this case, the forecasted upper and lower limits of wind power output from a wind farm are used, rather than speculative probability density functions. Second, the solution obtained by RO does not violate the constraints.

Following [38], in this study, the DEED with wind uncertainty problem is solved based on multi-objective optimization and robust optimization. The effects of the variation of wind power on the ramp constraints of thermal units are considered inequality constraints. Interval reduction in wind power is considered in the dynamic dispatch so that the maximum amount of renewable energy can be accessed. In [38], the wind power is formulated with the above ramp-rate requirements, provided that the methodology of solving the DEED problem is considered as a single objective function by converting two objectives into a single objective using the weighting factor method.

To address this problem, efficient algorithms with simple algorithmic steps are required. Recently, crisscross optimization was developed by Anbo Meng et al., inspired by the Confucian doctrine of the golden mean and the crossover operation in genetic algorithms [39]. This algorithm is efficiently used in power system optimization problems such as economic dispatch and distributed generation allocation [40–42]. The algorithm is constructed with two main operators, namely, the horizontal operator and the vertical operator, to find the moderation solutions of the parent population. The former is employed for global convergence, and the latter performs the work of eliminating the stagnant dimension variables, thus avoiding premature convergence. The main contributions of the paper are listed below:

- An attempt is made to solve the DEED problem as a multi-objective optimization problem considering that the wind power affects the ramp-rate of thermal generating units.
- Multi objective crisscross algorithm is proposed for solving multi-objective optimization based on fast non-dominated sorting principle.
- A modified horizontal crossover operator based on self-adaptive crossover probability is implemented to determine uniform and diverse Pareto fronts.
The rest of the paper is organized as follows: Section 2 describes the problem formulation for dynamic economic emission dispatch with wind power uncertainty. In section 3, an overview of the standard crisscross algorithm is given, and the formation of multi-objective crisscross optimization is described. Section 4 describes the implementation of multi-objective crisscross optimization for dynamic economic emission dispatch with wind uncertainty, and section 5 discusses the results obtained for the benchmark function and various test systems.

II. PROBLEM FORMULATION

The problem is formulated as three objectives optimization problem. Minimizing fuel cost and emissions are existing objectives prevailing in [9] and reduction in wind power curtailment is taken as third objective [38], so that maximum amount of renewable energy is utilized and thereby cost and emission is reduced.

A. MINIMIZATION OF FUEL COST

The fuel cost function curve of a generating unit is approximated as quadratic function. Due to presence of multiple valves in thermal power plant and sequential opening of these valves produces ripple effect in the cost curve. This effect is modeled as rectified sinusoidal component and thus the fuel cost function is expressed as the sum of quadratic and sinusoidal form. For a total T dispatch period the fuel cost function is represented by:

\[
F_1(P) = \sum_{i=1}^{T} \sum_{t=1}^{N} a_i (P_{it})^2 + b_i P_{it} + c_i + e_i \sin \left( f_i (P_{i,t} - P_{it}) \right) \tag{1}
\]

where \(a_i, b_i, c_i\) are cost coefficients; \(e_i, f_i\) are constants from the valve point effect of \(i^{th}\) generating unit; \(N\) is number of generating units; \(P_{it}\) is the power output of \(i^{th}\) generating unit in the time period \(t\); \(P_{i,t}\) is minimum capacity of \(i^{th}\) generating unit and \(T\) is total time period.

B. MINIMIZATION OF EMISSION RATE

The emission rate of a generating unit depends on the power output of the unit. It is expressed as combination of polynomial and exponential function. The emission of \(\text{SO}_2\) and \(\text{NO}_x\) in the atmosphere for a total T dispatch period is represented by:

\[
F_2(P) = \sum_{i=1}^{T} \sum_{t=1}^{N} \alpha_i (P_{it})^2 + \beta_i P_{it} + \gamma_i + \eta_i \exp(\delta_i P_{it}) \tag{2}
\]

where \(\alpha_i, \beta_i, \gamma_i, \eta_i, \delta_i\) are emission coefficients; \(N\) is number of generating units; \(P_{it}\) is the power output of \(i^{th}\) generating unit at time interval \(t\), and \(T\) is total time period.

C. MINIMIZATION OF WIND CURTAILMENT

Wind power available in a particular interval should be utilized entirely and the minimizing the total wind power curtailment for a total T dispatches period is represented by:

\[
F_3 = \sum_{t=1}^{T} (\Delta w_t) \tag{3}
\]

where \(\Delta w_t\) is wind power curtailment at time \(t\), \(T\) is total dispatch period.

D. CONSTRAINTS

1) EQUALITY CONSTRAINT

\[
\sum_{i=1}^{N} P_{t,i} + w_t = P_{D,i} + P_{L,i} \tag{4}
\]

where \(P_{D,i}\) is load demand at \(t^{th}\) dispatch interval, \(P_{L,i}\) denotes the transmission loss at \(t^{th}\) dispatch interval, \(w_t\) is actual wind power at dispatch interval and loss is calculated as

\[
P_{L,i} = \sum_{i=1}^{N} \sum_{j=1}^{N} P_{ij} B_{ij} P_{ij} + \sum_{i=1}^{N} B_{i0} P_{it} + B_{00} \tag{5}
\]

2) INEQUALITY CONSTRAINT

The generation limit of \(i^{th}\) unit and its corresponding ramping limits are given in Eq. (6) and (7).

\[
P_{i,\min} \leq P_{t,i} \leq P_{i,\max} \tag{6}
\]

\[
-d r_i \leq P_{t,i} - P_{i-1,i} \leq u r_i \tag{7}
\]

where \(P_{i,\max}, P_{i,\min}\) are maximum and minimum of \(i^{th}\) generating unit and \(ur_i, dr_i\) are ramp rate limit of \(i^{th}\) generating unit. The relationship between actual and dispatched outputs of thermal units due to wind power fluctuation is given by (8)

\[
P_{t,i} = P_{i,\min} - dr_i \leq P_{i,\max} - ur_i \tag{8}
\]

\[
\sum_{i=1}^{N} e_i = 1 \tag{9}
\]

Substituting (8) into (6) and (7), we obtain

\[
P_{t,i} \leq P_{i,\min} - dr_i \leq P_{i,\max} - ur_i \tag{10}
\]

\[
-d r_i \leq P_{i,\max} - P_{i,\min} \leq u r_i \tag{11}
\]

To make certain the wind power \(\tilde{w}_t\) is within the limit of uncertainty set \((\overline{w}_t, \underline{w}_t)\), Eq.(10) and (11) can be is modeled an optimization problem as shown in (12) by introducing a slack variable \(\Delta w_t\).

\[
\begin{align*}
\min_{\Delta w_t} \left\{ P_{t,i} - e_i (\tilde{w}_t - w_t) \right\} & \geq P_{i,\min} & (a) \\
\max_{\Delta w_t} \left\{ P_{t,i} - e_i (\tilde{w}_t - w_t) \right\} & \leq P_{i,\max} & (b) \\
\min_{\Delta w_t} \left\{ P_{t,i} - e_i (\tilde{w}_t - w_t) - P_{t-1,i} + e_i (\tilde{w}_t - w_t) \right\} & \geq -d r_i & (c) \\
\max_{\Delta w_t} \left\{ P_{t,i} - e_i (\tilde{w}_t - w_t) - P_{t-1,i} + e_i (\tilde{w}_t - w_t) \right\} & \leq u r_i & (d) \\
\text{s.t.} \ w_t \geq \tilde{w}_t \leq \tilde{w}_t - \Delta w_t & & (e)
\end{align*}
\]
The deterministic form of (12) is as follows
\[
\begin{align*}
P_{t,i} - e_i(\bar{w}_i - \Delta w_i - w_i) &\geq P_{t,\text{min}} \quad (a) \\
P_{t,i} - e_i(w_i - w_i) &\leq P_{t,\text{max}} \quad (b) \\
P_{t,i} - e_i(\bar{w}_i - \Delta w_i - w_i) - P_{t-1,i} \\
+ e_i(w_{i-1} - w_{i-1}) &\geq -d_i \quad (c) \\
P_{t,i} - e_i (w_i - w_i) &- P_{t-1,i, i} \\
+ e_i(\bar{w}_{i-1} - \Delta w_{i-1} - w_{i-1}) &\leq u_i \quad (d)
\end{align*}
\]
Thus from (13) the generating capacity limits constraint and ramp rate limit constraints are as follows:
\[
\begin{align*}
P_{t,i} - e_i(\bar{w}_i - \Delta w_i - w_i) &\geq P_{t,\text{min}} \quad (14) \\
P_{t,i} - e_i(w_i - w_i) &\leq P_{t,\text{max}} \quad (15) \\
P_{t,i} - e_i(\bar{w}_i - \Delta w_i - w_i) - P_{t-1,i} \\
+ e_i(w_{i-1} - w_{i-1}) &\geq -d_i \quad (16) \\
P_{t,i} - e_i (w_i - w_i) &- P_{t-1,i, i} \\
+ e_i(\bar{w}_{i-1} - \Delta w_{i-1} - w_{i-1}) &\leq u_i \quad (17)
\end{align*}
\]

Thus from (13) the generating capacity limits constraint and ramp rate limit constraints are as follows:

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P_{t,i} - e_i(\bar{w}_i - \Delta w_i - w_i) &\geq P_{t,\text{min}} \quad (14) \\
P_{t,i} - e_i(w_i - w_i) &\leq P_{t,\text{max}} \quad (15) \\
P_{t,i} - e_i(\bar{w}_i - \Delta w_i - w_i) - P_{t-1,i} \\
+ e_i(w_{i-1} - w_{i-1}) &\geq -d_i \quad (16) \\
P_{t,i} - e_i (w_i - w_i) &- P_{t-1,i, i} \\
+ e_i(\bar{w}_{i-1} - \Delta w_{i-1} - w_{i-1}) &\leq u_i \quad (17)
\end{align*}
\]

### III. MULTI-OBJECTIVE CRUSSCROSS OPTIMIZATION ALGORITHM

#### A. OVERVIEW OF STANDARD CSO

Inspired by the crossover operation of genetic algorithms, Anbo Meng et al. [39] developed an algorithm that enables the candidates to learn in two directions while searching for solutions in the search space, called the crisscross optimization algorithm. One direction is horizontal crossover, where the candidates gain knowledge about the search space from fellow candidates. In the other direction, vertical crossover, the candidates learn from their own knowledge gained from horizontal crossover. After passing through both crossovers, a new candidate is generated, called a moderation solution. In order to survive for subsequent generations, the moderation solutions should be better than the parent solutions. The CSO is described briefly as follows.

Without loss of generality, assume the objective is to minimize

\[
\min F(X) \quad X \in \mathbb{R}^D
\]

The individual represents the solution of optimization problem. The individual solution \(X^m\) is defined as

\[
X^m = (x_{1}^{m}, \ldots, x_{D}^{m}, \ldots, x_{M}^{m}) \quad m = 1, 2, \ldots, M
\]

where \(D\) is the dimension of the problem and \(x_{d}^{m}\) is the element of individual in \(d^{th}\) dimension, \(M\) is the population size.

The search process of CSO is summarized below.

1) HORIZONTAL CROSSOVER

Here, the candidates gain knowledge from various dimensions of the other candidates, to generate moderation solutions as shown below. Assuming that the parent individuals \(X_{d1}^{m1}\) and \(X_{d2}^{m2}\) execute horizontal crossover in the \(d^{th}\) dimension, the moderation solutions are generated as follows.

\[
\begin{align*}
MH_{d1}^{m1} = r_1 \cdot X_{d1}^{m1} + (1 - r_1) \cdot X_{d2}^{m2} + c_1 \cdot (X_{d1}^{m1} - X_{d2}^{m2}) \\
MH_{d2}^{m2} = r_2 \cdot X_{d2}^{m2} + (1 - r_2) \cdot X_{d1}^{m1} + c_2 \cdot (X_{d1}^{m1} - X_{d2}^{m2})
\end{align*}
\]

Here, \(MH_{d1}^{m1}, MH_{d2}^{m2}\) are two newly generated moderation solutions. Furthermore \(r_1, r_2\) are uniformly distributed random values in the range \([0, 1]\) and, \(c_1, c_2\) are expansion coefficients which are uniformly distributed random values in the range \([-1, 1]\). After obtaining the moderation solutions via horizontal crossover, the algorithm must perform the competitive operation between \(MH_{d1}^{m1}\) and \(MH_{d2}^{m2}\). Only the individual with higher fitness can survive. Thus, \(X\) retains a set of personal best solutions called dominant horizontal solutions \((DHS_{m})\).

2) VERTICAL CROSSOVER

This search mechanism performs an arithmetic operation on all dominant horizontal solutions \((DHS_{m})\) to produce a vertical moderation solution \((MV_{m})\). Here, the vertical moderation solutions \((MV_{m})\) are obtained by manipulating all dominant candidates of the horizontal moderation solution. This operation occurs between two different dimensions of same parent. This process is aimed to avoid convergence stagnation so that the algorithm escapes being trapped in local optimum.

Assume that \(d_1\) and \(d_2\) are different dimensions of the individual \(X^m\). The moderation solutions are obtained using equation (20).

\[
MV_{d1}^{m} = r \cdot X_{d1}^{m1} + (1 - r) \cdot X_{d2}^{m2} \quad d_1, d_2 \in D
\]

\[
\begin{align*}
\text{Parent 1} & \quad X_1 \quad X_2 \quad X_3 \quad X_4 \quad X_5 \\
\text{Parent 2} & \quad Y_1 \quad Y_2 \quad Y_3 \quad Y_4 \quad Y_5 \\
\text{Moderation Horizontal Crossover Solution} & \quad (MH_1) \quad (XY_1 \quad XY_2 \quad XY_3 \quad XY_4 \quad XY_5) \\
\text{Moderation Solution} & \quad (MH_2) \quad (xy_1 \quad xy_2 \quad xy_3 \quad xy_4 \quad xy_5) \\
\text{Dominant Horizontal Crossover Solution(MH_1 and Parent 2)} & \quad (DHS_1) \quad (XY_1 \quad XY_2 \quad XY_3 \quad XY_4 \quad XY_5) \\
\text{Dominant Solution} & \quad (DHS_2) \quad (Y_1 \quad Y_2 \quad Y_3 \quad Y_4 \quad Y_5)
\end{align*}
\]

**FIGURE 1. Horizontal crossover.**
B. NON-DOMINATED SORTING CRISSCROSS OPTIMIZATION ALGORITHM

In this section, a new multi-objective crisscross optimization is proposed to solve multi-objective optimization problems. Non-dominated sorting crisscross optimization (NSCSO) is formulated using a non-dominated sorting principle and Pareto dominance, in place of the competitive operator.

The multi objective formulation of CSO adopts a fast non-dominated sorting approach and a modified horizontal crossover operator to obtain uniform and diverse Pareto front. The fast non-dominated sorting approach is adopted from [43]. This approach has also been utilized in other optimization algorithms to tackle multi objective problems [44]. The following sections describes the modified horizontal crossover operator, fast non-dominated sorting principle, the crowding distance calculation and the updating of the new generation.

1) MODIFIED HORIZONTAL CROSSOVER

As shown in the original crisscross optimization algorithm horizontal crossover takes place between randomly selected parent pairs and moderation solutions are obtained. In this process the best candidate in the population has only one chance to pair with the other candidate solutions in all iterations. Thus to produce a new improved set of population in the iteration run a modified crossover has been proposed. Here in this scheme a parent candidate perform horizontal crossover either with randomly selected candidate or with the best candidate in the set. A self adaptive crossover probability is proposed in non-dominated sorting crisscross optimization (NSCSO-MH) which determines whether a candidate has to do crossover with other randomly chosen candidate or with the best candidate in the population. Thus the modified horizontal crossover is given as (22), as shown at the bottom of the next page.

Here \( r_1, r_2 \) are uniform random values between 0 and 1, \( c_1, c_2 \) are expansion coefficients which has value of in the range of [-1,1]. \( c_b \) is the expansion coefficient regarding to best candidate. Since \( c_b \) corresponds to the best candidate in the set, the random nature of \( c_b \) is varied in such a way that to maintain the process of exploration and exploitation of the search space. Fig. 3 shows the variation of expansion coefficients \( c_1, c_2, c_b \) with increase in iterations.

Initially the value of \( \rho_{sh} \) is taken as 0.5. After moderation solutions are evaluated, the number of moderation solution entered into the next iteration through randomly chosen scheme is counted as \( n_{cr} \) and the number of moderation solution entered through after crossover with best candidate is counted as \( n_{cb} \). The number of moderation solutions discarded is counted as \( n_{rf} \) and \( n_{fb} \). These two pairs of numbers are accumulated for a period of ten iterations and \( \rho_{sh} \) is updated as given in the Eq. (23). After updating crossover probability the values of \( n_{cr}, n_{cb}, n_{rf} \) and \( n_{fb} \) are made to reset.

\[
\rho_{sh} = \frac{n_{cr} \times (n_{cb} + n_{fb})}{n_{cb} \times (n_{cr} + n_{rf}) + n_{cr} \times (n_{cb} + n_{fb})}
\]  

(23)
2) FAST NON DOMINATED SORTING APPROACH

The fast non-dominated sorting approach is used to categorize the solutions into non-dominated fronts and to obtain the optimal Pareto front. The detailed procedure for this fast non-dominated sorting approach is described in Fig. 4. A graphical representation of the fronts is shown in Fig. 5.

3) CROWDING DISTANCE CALCULATION

To preserve the diversity of solutions in the Pareto optimal front convergence, the crowding distance of the solutions is computed. The detailed steps for calculating the crowding distance are shown in Fig. 6.

Two attributes are assigned to every individual in the population: 1. non-domination rank \( (\text{rank}_i) \) and 2. crowding distance \( (\text{CrowdDist}_i) \).

Two individuals \( i \) and \( j \) are compared, and the better individual is found using the following relation.

\[
(\text{rank}_i < \text{rank}_j) \quad \text{or} \quad (\text{rank}_i = \text{rank}_j \text{ and CrowdDist}_i > \text{CrowdDist}_j)
\]

The choice of individual is based on the individuals’ ranks, and when a conflict of rank arises, the individual with minimum cluster strength will be chosen. This comparison is used as a competitive operator for NSCSO-MH, to find better individuals.

4) UPDATE THE NEW GENERATION

The updated population should consist of the best candidates. It is then processed for the next iteration. To preserve elitism, non-domination rank and crowding distance are utilized, and the comparison of candidates is based on Eq. (24). The procedure for updating the population is represented in Fig. 7.

C. PROCESS OF NSCSO FOR SOLVING MULTI OBJECTIVE PROBLEMS

The following describes the procedure of NSCSO for solving multi-objective problems.

\[
MH_d^{m_1} = \begin{cases} 
 r_1 \cdot X^{m_1}_d + (1 - r_1) \cdot X^{m_2}_d + c_1 \cdot (X^{m_1}_d - X^{m_2}_d) & \text{if rand()} < \rho_{sh} \\
 r_b \cdot X^{m_1}_d + (1 - r_b) \cdot X^{mb}_d + c_b \cdot (X^{m_1}_d - X^{mb}_d) & \text{if rand()} > \rho_{sh} 
\end{cases}
\]

\[
MH_d^{m_2} = \begin{cases} 
 r_2 \cdot X^{m_2}_d + (1 - r_2) \cdot X^{m_1}_d + c_2 \cdot (X^{m_2}_d - X^{m_1}_d) & \text{if rand()} < \rho_{sh} \\
 r_b \cdot X^{m_2}_d + (1 - r_b) \cdot X^{mb}_d + c_b \cdot (X^{m_2}_d - X^{mb}_d) & \text{if rand()} > \rho_{sh} 
\end{cases}
\]
Step 1: A set of initial candidates \( M \) are generated within the search space.

Step 2: Each candidate’s fitness value is evaluated.

Step 3: Based on fitness value a pareto-front is established along with crowding distance of all individuals.

Step 4: Perform horizontal crossover and generate horizontal moderation solutions.

Step 5: Dominant horizontal solutions of size \( M \) are selected from the merging of parent and horizontal moderation solutions and are arranged in a Pareto-front subject to fitness rank and cluster distance.

Step 6: Perform vertical crossover on dominant horizontal solutions and generate vertical moderation solutions.

Step 7: Dominant vertical solutions of size \( M \) are selected from the merging of dominant horizontal solutions and vertical moderation solutions and are arranged in a Pareto-front subject to fitness rank and cluster distance.

Step 8: Repeat the steps 4 to 7 until termination criterion is satisfied. On reaching the stopping condition, the final Pareto set will be the optimal solutions of the multi-objective problem considered.

IV. IMPLEMENTATION OF NSCSO-MH TO DYNAMIC ECONOMIC AND EMISSION DISPATCH WITH WIND UNCERTAINTY

In this section non-dominated sorting crisscross optimization is implemented to solve DEED with wind uncertainty. The detailed steps are as follows:

Step 1: Get the input data of the system which consist of power outputs of thermal generating unit’s cost, emission loss coefficients to calculate cost, emission and loss. Obtain the predicted wind power upper and lower bound from the wind farm.

Step 2: Randomly generate initial population. Each individual in the population is represented as:

\[
P_m = \begin{bmatrix}
P_{1,1} & P_{1,2} & \ldots & P_{1,N} & w_1 \\
P_{2,1} & P_{2,2} & \ldots & P_{2,N} & w_2 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
P_{T,1} & P_{T,2} & \ldots & P_{T,N} & w_T \\
\end{bmatrix}
\]

Initialization of each element of \( P_m \) is given by

\[
P_{t,i} = P_{i,\text{min}} + \text{rand} \cdot (P_{i,\text{max}} - P_{i,\text{min}}) \quad i = 1, 2, \ldots, N
\]

\[
w_t = w_{t-1} + \text{rand} \cdot (w_t - w_{t-1})
\]

Step 3: Constraints handling: To handle the equality and inequality constraints of the problem the following procedure is adopted.

1. Initialize \( t = 1 \).
2. Calculate the power deviation of period \( t \) as

\[
delp_t = \sum_{i=1}^{N} P_{t,i} + w_t - P_{D,t} - P_{L,t}
\]

3. If \( delp_t = 0 \), then go to step 9, otherwise distribute \( delp_t \) in a random percentage to every unit.

4. Set \( \text{count} = 0 \) and initialize \( \text{iter}_{\text{max}} \) which denotes maximum number of iteration to distribute random proportion and \( \text{delpviolmt} \) is maximum allowable violation.

5. While \( \text{count} \leq \text{iter}_{\text{max}} \& \& \ |delp_t| < \text{delpviolmt} \), modify each unit power allocation as

\[
P_{t,i} = P_{t,i} + \left( \frac{delp_t}{N} \right)
\]

\[
w_t = w_t + \left( \frac{delp_t}{N} \right)
\]
| Problem   | Dimension | Variable Bounds | Objective Function |
|-----------|-----------|-----------------|--------------------|
| SCH       | 1         | $[-10^3, 10^3]$ | $f_1(x) = x^2$     |
|           |           |                 | $f_2(x) = (x - 2)^2$ |
| FON       | 3         | $[-4, 4]$       | $f_1(x) = 1 - \exp \left(- \sum_{i=1}^{3} \left( x_i - \frac{1}{\sqrt{3}} \right)^2 \right)$ |
|           |           |                 | $f_2(x) = g(x) \left[ 1 - \sqrt{x_i / g(x)} \right]$ |
| ZDT1      | 30        | $[0, 1]$        | $g(x) = 1 + 9\left( \sum_{i=2}^{n} x_i \right) / (n - 1)$ |
|           |           |                 | $f_1(x) = x_i$     |
|           |           |                 | $f_2(x) = g(x) \left[ 1 - (x_i / g(x))^2 \right]$ |
| ZDT2      | 30        | $[0, 1]$        | $g(x) = 1 + 9\left( \sum_{i=2}^{n} x_i \right) / (n - 1)$ |
|           |           |                 | $f_1(x) = x_i$     |
|           |           |                 | $f_2(x) = g(x) \left[ 1 - (f_1(x) / g(x))^2 \right]$ |
| ZDT3      | 30        | $[0, 1]$        | $g(x) = 1 + 9\left( \sum_{i=2}^{n} x_i \right) / (n - 1)$ |
|           |           |                 | $f_1(x) = 1 - \exp(-4x_i \sin^6(6\pi x_i))$ |
|           |           |                 | $f_2(x) = g(x) \left[ 1 - (f_1(x) / g(x))^2 \right]$ |
| ZDT6      | 10        | $[0, 1]$        | $g(x) = 1 + 9 \left[ \left( \sum_{i=2}^{n} x_i \right) / (n - 1) \right]^{0.25}$ |
|           |           |                 | $f_1(x) = x_i$     |
|           |           |                 | $f_2(x) = g(x) \times h(f_1(x), g(x))$ |
| ZDT1 with linear front | 30   | $[0, 1]$        | $g(x) = 1 + 9\left( \sum_{i=2}^{n} x_i \right) / (n - 1)$ |
|           |           |                 | $h(f_1(x), g(x)) = 1 - f_1(x) / g(x)$ |

6. If $P_{t,i}$ and $w_{t,i}$ are violating the capacity limits following procedure is done to handle inequality constraint

$P_{t,i} = \min(P_{t,i}^{\max} - P_{t,i})$,  
$w_i = \min(w_{t,i} - w_i)$  
$P_{t,i} = \max(P_{t,i}^{\min} - P_{t,i})$,  
$w_i = \max(w_{t,i} - w_i)$  

7. Increment count and calculate $P_{L,t}$ and $delp$, using (5) and (26).

8. Until the stopping condition is satisfied, continue with the steps 5 to 7, else go to step 9.

9. Calculate the output limits of next period according to (14)-(17) as follows:

$P_{t+1,i}^{\min} = \max \left( P_{t,i}^{\min} + \varepsilon_i \left( w_{t+1} - w_i \right), P_{t,i} - d_{t,i} + \varepsilon_i \left( w_{t+1} - w_i - w_{t,i} + w_i \right) \right)$  

$P_{t+1,i}^{\max} = \min \left( P_{t,i}^{\max} + \varepsilon_i \left( w_{t+1} - w_i \right), P_{t,i} + u_{t,i} - \varepsilon_i \left( w_i - w_{t,i} + w_{t,i} + w_{t+1} \right) \right)$  

$\varepsilon_i \left( w_{t+1} - w_i \right) = 1 - f_1(x) / g(x)$
FIGURE 8. Flowchart of proposed methodology.
TABLE 2. Statistical results of multi objective problems for 30 trials.

| METHOD | METRICS | SCH | FON | ZDT 1 | ZDT 2 | ZDT 3 | ZDT 6 | ZDT 1 with linear front |
|--------|---------|-----|-----|-------|-------|-------|-------|------------------------|
| NSCSO-MH | GD MEAN | 1.411E-04 | 0.00342 | 0.00551 | 0.00234 | 0.00781 | 0.0091 | 0.00190 |
|        | SD 6.892E-05 | 2.241E-04 | 6.895E-04 | 7.124E-04 | 0.00212 | 0.00187 | 0.00218 |
|        | DIVERSITY MEAN | 0.001915 | 0.00101 | 0.00382 | 0.00432 | 0.18121 | 0.00321 | 0.00187 |
|        | SD 2.8812E-04 | 3.441E-04 | 2.678E-04 | 3.218E-04 | 0.00279 | 3.212E-04 | 2.891E-04 |
| NSCSO | GD MEAN | 1.425E-04 | 0.00512 | 0.00575 | 0.00221 | 0.00615 | 0.0104 | 0.00241 |
|        | SD 7.362E-05 | 4.234E-04 | 7.199E-04 | 7.225E-04 | 0.00153 | 0.00198 | 0.00312 |
|        | DIVERSITY MEAN | 0.002215 | 0.00121 | 0.00419 | 0.00411 | 0.17461 | 0.00385 | 0.00224 |
|        | SD 2.9976E-04 | 3.421E-04 | 2.703E-04 | 3.884E-04 | 0.00298 | 3.442E-04 | 3.241E-04 |
| NSGA II | GD MEAN | 6.950E-04 | 0.00725 | 0.05805 | 0.05223 | 0.04841 | 0.02451 | 0.06214 |
|        | SD 7.431E-04 | 0.00031 | 0.00591 | 0.00586 | 0.00699 | 0.00712 | 0.00512 |
|        | DIVERSITY MEAN | 0.004581 | 0.00348 | 0.00813 | 0.00623 | 0.66721 | 0.00745 | 0.00521 |
|        | SD 3.984E-04 | 0.00252 | 0.00135 | 0.00152 | 0.00526 | 0.00235 | 0.00217 |
| MOPSO | GD MEAN | 6.574E-04 | 0.00415 | 0.02342 | 0.03521 | 0.05428 | 0.02104 | 0.02746 |
|        | SD 4.733E-04 | 0.00589 | 0.00499 | 0.00227 | 0.00181 | 0.00254 | 0.00521 |
|        | DIVERSITY MEAN | 0.004687 | 0.00241 | 0.00751 | 0.00784 | 0.54271 | 0.00721 | 0.00623 |
|        | SD 0.001165 | 0.00228 | 0.00342 | 0.00183 | 0.00442 | 0.00261 | 0.00216 |

FIGURE 9. Pareto fronts obtained by NSCSO,NSGA II, MOPSO for bench mark test functions SCH,FON, ZDT 1, ZDT 2.

10. Increment $t = t + 1$, if $t \leq T$ go back to step 2, otherwise stop the process.

Step 4: After this constraint handling process, some individual may not be feasible solutions, so constraint violation of them is calculated.

Step 5: Calculate the objective cost and emission of each individual and also the wind curtailment according to equations (1-3). The violation is added as penalty function to cost, emission and wind curtailment.

Step 6: Perform non-dominate sort and obtain initial Pareto front.

Step 7: Horizontal crossover: Perform horizontal crossover on two different individuals to learn from all dimensions.

The steps of horizontal crossover operation are summarized as follows:

a. Take $P$ as parent population. $P$ will be the randomly generated initial population, and it will be replaced by the dominant solutions in the subsequent iterations.

b. Choose $M/2$ pairs without repetition form $P$.

c. For each paired individuals $P^{m_1}$ and $P^{m_2}$ ($m_1 \neq m_2$), the horizontal crossover operator is performed according to (35), as shown at the bottom of the next page.

Step 8: Due to introduction of expansion coefficients, the moderation solutions may not be in feasible region. To tackle generation capacity and ramp rate constraints,
constraint handling procedure is executed on horizontal modifications.

Step 9: Parent solutions and horizontal modifications are merged and non-dominated sort is performed and crowding distance is calculated.

Step 10: Based on the comparison criteria M solution is selected for vertical crossover operation.

Step 11: Vertical Crossover: To overcome premature convergence, vertical crossover is performed on \( P_{t,m} \). The following describes the steps of vertical crossover.

a. Since each unit has different boundary limits, normalizing element of \( P_{t,m} \) is done by (36)

\[
NP_{t,i} = \left( p_{t,i} - p_{\text{min}} \right) / \left( p_{\text{max}} - p_{\text{min}} \right) \quad (36)
\]

b. For each normalized individual \( NP_{t,1}, \ldots, NP_{t,N} \), \( (N \times T) / 2 \) pair of elements is generated.

c. For each paired \( NP_{t,1} \) and \( NP_{t,2} \), \( (t_1, i) \neq (t_2, i_2) \), the vertical crossover operation is performed according to vertical crossover probability.

\[
MV_{t_1,i_1}^m = \begin{cases} 
    r \cdot NP_{t_1,i_1} + \left( 1 - r \right) \cdot NP_{t_2,i_2} & \text{if rand()} < P_v \\
    NP_{t_1,i_1} & \text{otherwise}
\end{cases} 
\]  
\( m = 1, 2, \ldots, M \)  (37)

4. As discussed earlier, moderation solutions are obtained using (38) called reverse normalization

\[
MV_{t,1}^m = MV_{t,1}^m (P_{t,1}^\text{max} - P_{t,1}^\text{min}) + P_{t,1}^\text{min} \quad (38)
\]

Step 12: Apply constraint handling techniques for infeasible solutions.

Step 13: Parent solution of vertical crossover and vertical crossover moderations solutions are merged and non-dominated sorting is performed and crowding distance is calculated.

Step 14: Based on the comparison criteria M solution is selected for next iteration and Pareto set of solutions is obtained. Fuzzy decision principle is used to find best compromise solution.

Step 15: Repeat step 3 to 14 until maximum number of iteration is satisfied.

The flowchart of the methodology is shown in Fig. 8.

V. SIMULATION RESULTS AND DISCUSSION

In this section, the solution technique is initially investigated for multi-objective benchmark test functions, and the optimal Pareto front is obtained. Secondly, a five-generator system and a 10-generator system are investigated, and the corresponding cost and emissions obtained are compared with...
previous studies. Finally, 10-generator system with large-scale wind penetration is investigated with two different ratios of wind power, and a comparison with other techniques is performed. This technique has been developed using MATLAB, and simulations are carried out on a personal computer with an Intel Core i5 2.5 GHz processor, with 16 GB RAM.

A. IMPLEMENTATION TO BENCHMARK TEST FUNCTION

To demonstrate the applicability of the proposed non-dominated sorting crisscross optimization and to illustrate its effectiveness, a comparison of NSGA II [43], MOPSO [45] and the proposed NSCSO, NSCSO-MH was conducted on standard benchmark test functions. Table 1 describes the seven benchmark problems [43], [46], which are multi-objective and difficult to solve. The results obtained by techniques should be compared between themselves and the true front of the problem. In this regard, convergence, diversity of Pareto front is analyzed.

The performance metric generational distance (GD) is evaluated to determine the convergence of the multi objective algorithm and expressed as (39).

\[
GD = \left( \frac{1}{|Q|} \sum_{i=1}^{|Q|} d_i^p \right)^{\frac{1}{p}}
\]  

(39)

For \( p = 2 \), \( d_i \) is the Euclidean distance between solution \( i \in Q \) and the nearest member of \( \text{P}^* \). \( f_m(i) \) is the \( m^{th} \) objective function of the \( k^{th} \) member of \( \text{P}^* \).
The spread metric measures the diversity achieved among the obtained solution. It is given by (41)

\[
\Delta = \frac{\sum_{m=1}^{M} d^e_m + \sum_{i=1}^{Q} \left| d_i - \bar{d} \right|}{\sum_{m=1}^{M} d^e_m + \sum_{Q} \bar{d}}
\]

where \(d_i\) is the distance the distance between neighborhood solutions and \(\bar{d}\) is the mean value of distances of all Euclidean distance \(d_i\). \(d^e_m\) is the distance between the extreme solutions of \(P^*\) and \(Q\) corresponding to \(m^{th}\) objective function.

The algorithm parameters for solving multi objective problems are population size, horizontal crossover probability and vertical crossover probability, and the corresponding values are 80, 1 and 0.8 respectively. The parameters of NSGA II and MOPSO are adopted as in [43] and [45]. Among the test functions, problems such as ZDT 1, ZDT 2, ZDT 3, ZDT 6 and ZDT 1 with linear fronts are highly complex problems. To have a fair comparison, the maximum number of function evaluations (NFEs) was varied for each problem. The NFEs of SCH and FON are kept at 4000 and 5000, respectively. For ZDT 1 and ZDT 1 with a linear front, the NFE value is taken as 10000. For the other problems, ZDT 2, ZDT 3, and ZDT 6, the NFEs are set as 12000. The corresponding value of the NFE for NSGA II and MOPSO is 25000. The proposed algorithm was found to obtain the real Pareto front within a minimum number of function evaluations.

To achieve a statistical precision on each problem, 30 independent trials were carried out to evaluate the performance of solution methodologies. Table 2 presents the mean and standard deviation (SD) of generational distance metric and spread metric of multi objective problems obtained by NSCSO, NSCSO-MH, NSGA II and MOPSO. Fig. 9 shows the Pareto front obtained by NSCSO, NSCSO-MH, NSGA II and MOSPO for bench mark test functions SCH, FON, ZDT 1, and ZDT 2. The Pareto front of ZDT 3, ZDT 1 with linear front, ZDT 6 is show in Fig 10. It is observed that NSGA II could not able to achieve true Pareto front for ZDT 1, ZDT 2 and ZDT 1 with linear front. Also MOPSO optimal set of solutions are not uniformly spaced for FON and ZDT 1 problems. From the simulation results it could be observed that NSCSO-MH has superior performance over the other two algorithms in terms convergence and spread metrics.
1) STATISTICAL ANALYSIS

To compare the proposed algorithm with existing techniques in the literature, a non-parametric statistical hypothesis test is conducted. Wilcoxon’s signed rank test is used in this paper to determine the difference between the algorithms. The algorithms are implemented in each test problem, and the performance scores that measure the difference between them are calculated as ranks. \( R^+ \) and \( R^- \) are the sums of positive and negative ranks, and the \( \rho - value \) is obtained through normal approximation. Considering the level of significance as 0.05, if the \( \rho - value \) is less than the level of significance, then there is a difference between the two algorithms. Table 3 shows the results of Wilcoxon’s signed rank test to analyse the four algorithms’ generational distance and diversity performance measures on all benchmark functions. From the statistical analysis, it can be seen that the proposed NSCSO-MH has better performance than NSCSO, NSGA II and MOPSO.

B. IMPLEMENTATION TO TEST SYSTEMS

In this section the proposed non-dominated sorting crisscross optimization is demonstrated to solve DEED problems of sizes 5 & 10 units, along with wind power considered and neglected. Four cases have been considered and are listed below. The descriptions of the test cases are also shown in Table 4.

Case 1 Five generator system with valve point effects considering transmission loss

Case 2 Ten generator system with valve point effects considering transmission loss

Case 3 & 4 Ten generator system with valve point effects considering loss and wind power uncertainty.

The algorithm parameters such as population size, number of iterations, horizontal crossover probability and vertical crossover probability are assigned as 30, 500, 1 and 0.8 respectively for all test cases.

1) TEST CASE 1

This test system consists of a 5 generator system with a non-smooth valve point effect cost function and emission function. Ramp-rate limits and transmission losses are included. The dispatch horizon is set at 24-h dispatch intervals. Cost coefficient data and emission coefficient data for the generating units are adopted from [4]. The power output of each generator at every dispatch interval, with losses, is shown in Table 5.

The parameter which influences the convergence in meta-heuristic algorithms is the initial population size. To analyze the algorithms NSGA II, MOPSO, NSCSO and NSCSO-MH are implemented in the case study consisting of 5 units and Fig. 12 shows the variations cost and emission obtained by the algorithms. Four different population sizes of 30, 50, 60 and 80 are considered and shown as 1 to 4 in the Fig 12. In all cases the proposed methodology has better performance in determining the best compromise solution. An observation regarding population size and time complexity has been noted. Time complexity of fast non dominated approach is where the number of objectives is and is the population size. The proposed method has obtained superior results comparing to NSGA II, MOPSO and NSCSO in all cases. The test results are based on the simulation results obtained after 30 trial runs for each algorithm. From the trial run results, it was observed that population size of 30 since the computational and time complexity was high when comparing with other population size.

The power output of each generator at every dispatch interval, with losses, is shown in Table 5. Table 6 shows the best compromise solution obtained by NSCSO-MH and other techniques. The cost obtained by NSCSO-MH is $47,497, and emissions total 18,172 lb. The fuel cost and emission level obtained is less than for PSO and PS. The MODHE-SAT technique has a lower value of emissions, but the cost is higher than for the NSCSO-MH technique. The Pareto front obtained by NSCSO-MH for case 1 is shown in Fig. 13.

2) TEST CASE 2

This test system consists of a 10-generator system with non-smooth valve point effect cost function and emission function. Ramp-rate limits and transmission losses are included. The dispatch horizon is set at 24-h dispatch intervals. Cost coefficient data and emission coefficient data for the generating units are adopted from [9]. The power outputs of generators at every dispatch interval, with losses, are shown
in Table 7. Initially the test case is simulated by treating the problem as single objective. The bi-objective problem is converted in single objective problem using weighting factor approach. By assuming the value of weight $w = 1$, the fitness function is cost objective function and with $w = 0$, the fitness function is emission objective function. By varying the value of best compromise solution can be obtained. Table 8 shows the results of optimizing cost and emission as single objective and best compromise solution obtained by CSO and CSO-MH algorithm. Then the test system is solved using proposed NSCSO-MH algorithm. Table 9 shows the comparison of fuel costs and emission levels for the NSCSO-MH technique and other techniques. The total fuel cost determined is $2,515,011.2456$ and the emissions total 300,294.4943 lb. This result is superior to those of NSGA-II [9], RCGA [9] and CRO [14]. MOHDE-SAT [13] obtained a lower value of emissions, but the cost obtained was higher than in all the other techniques. The Pareto front obtained by NSCSO-MH for case 2 is shown in Fig. 14.
3) TEST CASE 3

In this case, a 10-unit DEED is assumed to be penetrated by wind power generation at a level of 9.06%. For this purpose, unit 6 is replaced with a 200 MW wind farm. Wind power prediction interval data are adopted from [38]. Fig. 15 summarizes the upper bound, lower bound and dispatched wind power obtained by the proposed NSCSO-MH. The outputs of thermal generators and the wind farm are given in Table 10. The cost, emissions and wind curtailment are given in Table 11. From Table 11 it can be seen that NSCSO-MH obtained minimum values compared with other techniques. Fig. 16 describes the output of each generator and wind farm for every dispatch interval. The Pareto front obtained by NSCSO-MH for case 3 is shown in Fig. 17.

4) TEST CASE 4

In this case, a 10-unit DEED is assumed to be penetrated with wind power generation at a level of 27.17%. For this purpose, unit 6 is replaced with a larger wind farm of 600 MW. Wind power prediction interval data are adopted from [37]. Fig. 18 summarizes the upper bound, lower bound and dispatched wind power obtained by the proposed

**TABLE 10.** Compromise result of dispatch (MW) obtained by NSCSO-MH for case 3.

| Hours | $P_1$ | $P_2$ | $P_3$ | $P_4$ | $P_5$ | Wind Farm | $P_7$ | $P_8$ | $P_9$ | $P_{10}$ | Loss |
|-------|-------|-------|-------|-------|-------|-----------|-------|-------|-------|---------|------|
| 1     | 152.1141 | 136.4725 | 100.1700 | 89.7883 | 157.8696 | 114 | 113.6237 | 89.7303 | 59.3606 | 42.5366 | 19.6654 |
| 2     | 150.112 | 145.1844 | 126.4302 | 95.9168 | 180.8187 | 108 | 111.4037 | 113.3967 | 62.5827 | 38.6863 | 22.5316 |
| 3     | 158.6247 | 139.7965 | 192.1761 | 144.2441 | 185.6691 | 96 | 128.8944 | 114.1973 | 73.731 | 53.526 | 28.8859 |
| 4     | 227.762 | 135.9115 | 207.1787 | 176.0416 | 234.2351 | 94 | 129.86 | 115.5078 | 76.1844 | 46.0845 | 36.7659 |
| 5     | 151.9999 | 167.1789 | 283.4338 | 188.2158 | 242.6006 | 106 | 129.7244 | 119.7445 | 77.2707 | 53.9781 | 40.1467 |
| 6     | 208.6848 | 231.8154 | 271.868 | 237.2894 | 242.1223 | 105 | 129.0458 | 119.1218 | 78.8543 | 53.8352 | 49.637 |
| 7     | 188.2968 | 251.4941 | 299.6347 | 285.5741 | 242.4834 | 106 | 129.4834 | 119.3828 | 79.4834 | 54.4834 | 54.3161 |
| 8     | 234.0098 | 270.9353 | 303.1152 | 297.5145 | 242.1077 | 107 | 128.5739 | 119.5463 | 79.158 | 53.906 | 59.8666 |
| 9     | 291.5964 | 316.0511 | 339.0645 | 299.1975 | 242.1066 | 126 | 129.0671 | 119.1311 | 79.0682 | 54.2207 | 71.4968 |
| 10    | 353.4096 | 347.6339 | 339 | 299.32 | 242.32 | 138 | 129.32 | 119.32 | 79.32 | 54.32 | 80.2887 |
| 11    | 378.8509 | 401.6665 | 339.2875 | 299.3011 | 242.2875 | 152 | 128.7203 | 118.5273 | 79.2875 | 54.32 | 88.2487 |
| 12    | 402.5468 | 412.4796 | 339.0502 | 299.0424 | 242.0681 | 166 | 129.0682 | 119.0692 | 79.0686 | 54.0338 | 92.4263 |
| 13    | 367.0999 | 379.3526 | 339.15 | 297.5363 | 242.15 | 150 | 129.1479 | 119.15 | 79.15 | 54.15 | 84.8859 |
| 14    | 302.4558 | 339.9867 | 314.2035 | 299.43 | 237.3927 | 122 | 129.0325 | 117.5542 | 79.43 | 54.43 | 72.0155 |
| 15    | 235.2551 | 273.7641 | 319.8254 | 274.1421 | 242.42 | 111 | 127.9522 | 118.8467 | 79.0768 | 53.6258 | 59.9082 |
| 16    | 157.8197 | 226.9956 | 297.6557 | 234.2639 | 219.3969 | 98 | 127.9556 | 116.6539 | 76.7389 | 43.7687 | 44.8889 |
| 17    | 179.5259 | 147.7183 | 219.1303 | 265.1551 | 242.33 | 89 | 129.33 | 119.33 | 79.0545 | 49.6908 | 40.2651 |
| 18    | 179.4713 | 225.6738 | 298.7405 | 241.9321 | 241.9321 | 66 | 128.8542 | 118.9596 | 79.242 | 54.3608 | 49.8236 |
| 19    | 231.7968 | 298.9268 | 318.0853 | 297.1574 | 240.4947 | 71 | 127.5107 | 119.4799 | 78.7001 | 53.5377 | 60.6894 |
| 20    | 307.9439 | 377.7912 | 338.9673 | 298.9871 | 241.9867 | 102 | 129.4199 | 118.7624 | 78.8065 | 53.9332 | 76.5982 |
| 21    | 283.2767 | 298.3712 | 338.3791 | 297.2075 | 239.7392 | 161 | 127.2404 | 119.9439 | 78.4928 | 53.1286 | 70.7775 |
| 22    | 221.908 | 226.7793 | 262.3917 | 248.3871 | 206.8131 | 150 | 128.8224 | 117.9012 | 78.5242 | 35.788 | 49.3132 |
| 23    | 150.1397 | 147.8193 | 183.4317 | 231.3482 | 176.8243 | 126 | 126.916 | 102.9265 | 69.4239 | 49.2384 | 32.0682 |
| 24    | 150 | 138.2712 | 156.7411 | 184.884 | 151.3049 | 137 | 98.1612 | 97.7593 | 74.9791 | 20.1484 | 25.2492 |
NSCSO-MH. The output of thermal generators and the wind farm are given in Table 12. The cost, emissions and wind curtailment are given in Table 13. From Table 13, it can be seen that NSCSO-MH obtained minimum values compared with other techniques. Fig. 19 describes the output of each generator and wind farm for every dispatch interval. The Pareto front obtained by NSCSO-MH for case 4 is shown in Fig. 20.

From Tables 11 and 13, it can be observed that the dispatch result obtained by NSCSO-MH is lower in terms of cost, emissions and wind power curtailment. In [38], the multi-objective problem is converted to a single-objective problem using the weighting method, and linear programming is utilized to minimize the reduction in prediction interval. The authors do not use three-objective models with the same weighting factor because the choice of assigning the same weights for all the three objectives may not reflect the maximum utilization of wind power. To avoid this difficulty, the fuel production cost, emissions and minimal interval reduction all are treated as non-commensurable objectives and solved simultaneously, rather than converting to a single-objective problem. By taking the minimal reduction interval as one of the objectives, the maximum utilization of renewable energy is possible, and therefore fuel cost and emissions are reduced drastically. In case 3, the total wind curtailment weighting factor because the choice of assigning the same weights for all the three objectives may not reflect the maximum utilization of wind power. To avoid this difficulty, the fuel production cost, emissions and minimal interval reduction all are treated as non-commensurable objectives and solved simultaneously, rather than converting to a single-objective problem. By taking the minimal reduction interval as one of the objectives, the maximum utilization of renewable energy is possible, and therefore fuel cost and emissions are reduced drastically. In case 3, the total wind curtailment...
is zero and all the power available from the wind farm is utilized, but in case 4 the safe upper bound does not coincide with the upper bound and falls below the predicted upper bounds during time periods 22-24. The differences between the lower and upper bounds are high, due to wider prediction intervals, and the system is not able to utilize all the power available.

VI. CONCLUSION
Dynamic economic emission dispatch with wind power uncertainty is considered as a robust and multi-objective optimization problem, in which both fuel cost and emissions are simultaneously minimized with minimization of wind curtailment, taking into account various system constraints. A multi-objective crisscross optimization algorithm is proposed to solve the problem. In the proposed method, fast non-dominated sorting is employed to select the dominant solutions and preserve the Pareto optimal front. The proposed method preserves the required features of maintaining diversity in the solution space, elitism in the new population and the capability of solving high-dimensional problems. Several multi-objective benchmark functions are handled using this technique and it was found that they could obtain diverse and even Pareto fronts. Systems with five and 10 generating units were solved for dynamic economic and emission dispatch. A further 10-generator system with wind power penetration was studied, with different ratios of wind power, to test the applicability and feasibility of the approach. Comparison of the results shows that the proposed methodology has superior performance with respect to producing solution quality over other existing techniques, and it can be effectively applied in solving real-time dynamic dispatch problems. Future work will focus on maximizing the utilization of generated wind power using effective demand response programs and sufficient storage units.

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