An Effective Framework For Economic Dispatch Using Modified Harmony Search Algorithm

Advik Kumar, Esmriti Batacharia, Raja Sadana

Abstract: The effects of ever-increasing wind power generation for solving the economic dispatch (ED) problem have led to high penetration of renewable energy source in new power systems. Continuing search for better utilizing of wind turbine associated with thermal sources to find the optimal allocation of output power is necessary in which pro-vide more reliability and efficiency. Dynamic nature of wind energy has imposed uncertainties characteristics in the poser systems. To deal with this problem, an effective probabilistic method to investigate all unpredictability would be a good idea to make more realistic analysis. This paper presents a heuristics optimization method based on harmony search (HS) algorithm to solve non-convex ED problems while uncertainties effects caused by wind turbines are considered. To involve a realistic analysis as a more practical investigation, the proposed probabilistic ED (PED) approach includes prohibited operating zone (POZ), system spinning reserve, ramp rate limits, variety of fuel is considered in this studies. Point Estimate Method (PEM) as a proposed PED model the uncertainties of wind speed for wind turbines to present better realization to the problem. Optimal solution are presented for vari-ous test system, and these solutions demonstrate the benefits of our approach in terms of cost over existing ED techniques.

Index Terms: Probabilistic economic dispatch, Renewable energy harmony search (HS) algorithm, Point estimate method.

1 INTRODUCTION

THE exceptional benefits toward renewable energy sources especially wind power expand rapid growth toward their utilization into existence power systems. At the same time, different characteristics of wind power possess from conventional power generations arise some challenges in terms of their intermittent and probabilistic nature which should be addressed to attain economical and reliable operation of mod-ern power systems. While the advantages such as less dependency on fuels, improving independency and flexibility of distributed power grid; stochasticity of wind behavior and also its probabilistic nature are two main issues which impose more complexity into systematic analysis. Therefore, the appropriate mod-el of wind turbine can play an important role in form of wind's variations into PED model [1]. Aforementioned arising challenges call for proper ED to offer lower cost of power production by allocating operational rules and adequate optimization tools [2]. Hence wind power variation and adoption will have notable impact to economic dispatch of power networks. Practical ED associated with many constraints needs numerical solutions to incorporate with complex and nonlinear characteristics of wind-thermal generators. Prohibited Operating Zones (POZs) of operating units may lead vibration amplification for the generators, so the generators avoided to operates in these region in practical applications [3]. Facing these problems, some heuristics techniques such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO) approach, Decomposition Technique (DT), Cuckoo search Algorithm (CSA), and Integrated Artificial Intelligence (IAI) technique have devoted effort to POZs in the ED problem to improving the existence ED [4-8].

- *Advik Kumar, Esmriti Batacharia, and Raja Sadanaare with the Department of Electrical and Computer Engineering, Shri Jagdishprasad Tibrewala University, India e-mail: kumaradvik3@gmail.com*

Moreover, reliability as another concern in ED problem need to consider the available system operating reserve in terms of any disturbances during system operation [4, 9]. Thus, optimal scheduling reserve capacity for dominating these unscheduled outages and load forecast errors would be necessary in ED problem. Decomposition technique [6], the sequential quadratic programming (SQP) PSO [10], Bender's Decomposition (BD) [11] can treat such kinds of problem, but not applicable in large scale systems. In current power system with large steam generators, a ripple heat curve has been produced by sequential opened valves need to address. Due to this, deep investigation such as Evolutionary Programming (EP) [12], modified PSO (MPSO), hybrid PSO (HPSO) [13], GA approach [14, 15], hybrid GA (HGA) [16], improved GA (IGA) [17], hybrid EP combined with SQP [18], and etc. have considered valve-loading effect. On the other hand, vide variety of fuel sources feed the generator units which should be scheduled in economic manner. For this reason, some research inspired of heuristic techniques such as Hierarchical Method (HM) [19], and Taguchi Method (TM) [20] have been considered to provide effective and most economic scenarios for different generators. Taking these problems into account, the parameters such as POZs, spinning reserve, ramp rate limits, alongside multiple fuel source options must consider to formulate a realistic ED problem. The mathematical model developed to deal with the ED problem based on the concept of the Lagrange relaxation [21] and mixed integer programming [22]. Other intelligent methods such neural networks [23] and PSO approach [24] have demonstrated the ED associated to wind power sources. Other relevant works address-ing the multi-fuel option and valve loading effects in the power system with high penetration of renewable sources. A harmony search (HS) algorithm with Multiplier Updating (IGA-MU) [25] and Evolutionary Algorithms (EA) [26] as well as New PSO (NPSO) with Local Random Search (NPSO-LRS) [27] are introduced ED to cope with valve loading effects. Some salient methods called self-tuning Hybrid Differential Evolutionary (self-tuning HDE) [28], hybrid Bacterial Foraging (BF) technique [29] are considered to solve reserve constrained and ramp rate limits ED problem with consideration of POZs and valve loading effects. A GA optimization meth-od based on Real Coded GA (RCGA) [30] with AC and security constraints presented to solve ED prob-lem. However, in most of the mentioned studies no uncertainties impacts of renewable energy sources is considered in the model. Due to high penetration of wind turbines in the promising power networks, pri-mary characteristic that should take into account from conventional generators in ED problem would be stochasticity. To deal with unexpected behavior of wind turbines due to the fluctuation in wind speed, the Primal-dual Interior Point Method has been re-cently reported in [31] to model the spinning reserve constraints for secure system operation. A Monte Carlo Simulation (MCS) method is utilized for generating a large number of scenarios in terms of the wind power volatility based on forecasting error [32]. Authors in [33] has proposed Unscented transform (UT) for ED problem to incorporate with drastic different change of wind power and spinning reserve parameters. This paper provides a PED to determine the optimal operation cost of test systems by incorporating wind-powered generators and to investigate the problem via numerical solutions. Point Estimate Method (PEM) [34] is utilized for modeling of uncertainties rather than well-known stochastic techniques. As an advantage of PEM can points out to low computational burden and time because a smaller amount of data is required compared with MCS method. In particular, the new methodology is based on harmony search (HS) algorithm to explore the search space globally. As discussed before, the practical PED is a sophisticated non-linear optimization problem thus a powerful tool is needed to cope with non-convex equality and inequality constraints. The proposed method will investigate a set of optimal solutions depends upon three sub-modifications according to the system operator decision. The main contributions of this paper are twofold as follows:

1) To introduce a PED based on uncertainties of wind generation. The stochastic method handled uncertainties through PED aim to reach less computational burden.
2) To propose new optimization method rely on modified harmony search (HS) algorithm. The proposed modified HS algorithm provides a more diverse search space and so most optimum solutions in less processing time compared with the former probabilistic search techniques.
3) To evaluate the functionality of proposed PED on different test systems in comparison with several of recent published ED techniques.

2 PROBLEM FORMULATION

This Section describes the problem formulation including the objective function of ED problem incorporating wind turbines. Generation allocation is considered among thermal and wind units in order to attain minimum total production costs associated with satisfying different practical constraints and generators limits. Although the wind generation cost is not same as fossil fuel cost and effect from renew-able energy law regulate so as to simplify the optimization process it is neglected.

2.1 Objective Function

The objective function of ED that is consisted introduce the total cost of generation operate into the power system during a determined time horizon. It can be formulated as an optimization problem as provide in (1).

$$Minimize \quad F_T = \sum_{i=1}^{n} F_i(P_i) \tag{1}$$

Where FT and Pi are the total generation cost of power network and active power output of i^{th} genera-tor (MW), respectively. Mathematically, the thermal generator fuel cost ($F_i(P_i)$) is expressed a polynomial function which is considered in (2) in a second order form. The cost function variations results the nonlinearity of the generator output changes take into ac-counts and is reflected into cost function by (3).

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \tag{2}$$

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + \left| e_i \sin(f_i(P_i^{\min} - P_i)) \right| \tag{3}$$

Where a_i, b_i, c_i, e_i, stand for i^{th} generator cost coefficients. For a generators that supply power by multiple fuel, the type of fuel must be reflected in the objective function (cost). A piecewise cost function considered in [35], is a good model for the operation-al characteristics of thermal units based on their different fuel feeds which is formulate in (4).

$$F_i(P_i) = \begin{cases} a_{i1} + b_{i1}P_i + c_{i1}P_i^2 & fuel\,1, P_i^{\min} \le P_i \le P_{i1}^{\max} \\ a_{i2} + b_{i2}P_i + c_{i2}P_i^2 & fuel\,2, P_{i2}^{\min} \le P_i \le P_{i2}^{\max} \\ \vdots & \\ a_{ij} + b_{ij}P_i + c_{ij}P_i^2 & fuel j, P_{ij}^{\min} \le P_i \le P_i^{\max} \end{cases} \tag{4}$$

Where P_i^{min}/P_i^{max} express the minimum/ maximum active power output of i^{th} generator. It is worth noting that $P_{ij-1}^{max}=P_{ij}^{min}$ equality - $P_{ij}^{max}/P_{ij}^{min}$ defined as maximum/ minimum power output of unit i with fuel option j- considered in the above formulation. Besides inserting all fuel types (N_{fuel}) of thermal units into cost function aims to minimize the ED problem, valve loading effects also must be took into account as summarized as follows:

$$F_i(P_i) = a_{ij} + b_{ij}P_i + c_{ij}P_i^2 + \left| e_{ij} \sin(f_{ij}(P_{ij}^{\min} - P_i)) \right| \quad if \quad fuel j, P_{ij}^{\min} \le P_{ij} \le P_{ij}^{\max}$$
$$\forall_i, i = 1,\dots,n \quad and \quad \forall_j, j = 1,\dots,N_{fuel} \tag{5}$$

2.2 Constraints

In contrast to classical ED model which is depends upon the generators and power balance limits without active loss of the power system, in practice the ED problem [27-29] deal with non-convex and complex characteristics associated with verity of equality and inequality constraints which impact the real power system scheduling. So the following constraints can considered:

(1) Power balance constraints:

$$\sum_{i=1}^{n} P_i = P_D + P_{Loss} \tag{6}$$

As stated previously, P_{Loss} (total active loss of network (MW)) in ED problem is ignored or approximated B matrix loss formula in (7). Also, P_D is the total active power demand of the network.

$$P_{Loss} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \tag{7}$$

Where B stand for transmission loss coefficients matrix.

(2) Ramp rate limits: these limits are considered depends upon the power unit outputs (MW/h) in the previous hour P_{0i} when must be in the range of ramp-up/ramp-down rate limit of unit i (RUP_i/ RDN_i).

$$\begin{cases} P_i - P_{0i} \le RUP_i & if \quad generation \quad increases \\ P_{0i} - P_i \le RDN_i & if \quad generation \quad decreases \end{cases} \tag{8}$$

(3) Generating capacity constraints: The generating capacity unit's upper and lower limits can be adjusted by using the defined ramp rates as expressed in (9).

$$\max(P_i^{\min}, P_{0i} - RDN_i) \le P_i \le \min(P_i^{\max}, P_{0i} + RUP_i) \tag{9}$$

(4) Prohibited Operating Zones (POZ): The operating zones of the *i*th generator can be considered in (10). In addition, for multiple prohibited zones generators (NP_i), a convex set associated with their NP_i+1 disjoint operating regions is presented [3].

$$\begin{cases} P_i^{\min} \le P_i \le P_{i,j}^{LB} & j = 1 \\ P_{i,j-1}^{LB} \le P_i \le P_{i,j}^{LB} & j = 2,3,\ldots,NP_i \\ P_{i,j}^{UB} \le P_i \le P_i^{\max} & j = NP_i \end{cases} \tag{10}$$
$$i = 1,\ldots,N_{GP}$$

Where $P_{i,j}^{LB}$/ $P_{i,j}^{UB}$ denote the lower/upper boundary of POZ *j* of generator *i*; and N_{GP} denoted the number of generators with POZ.

(5) System spinning reserves capacity: The power units with POZs can be considered as units which not contribute in the system spinning reserve as are stated in detail in (11) [36].

$$SR_i = \begin{cases} \min(P_i^{\max} - P_i, SR_i^{\max}) & \forall i \in (\Omega - \Theta) \\ 0 & \forall i \in \Theta \end{cases}$$
$$SR_r = \sum_{i=1}^{n} SR_i \tag{11}$$
$$SR_r \ge SR_R$$

In which spinning reserve contribution of generator *i* (SR_i) is in range of difference between set of all online generators (Ω) and online generators which have POZs (Θ). Of course the system required sipping reserve (SR_R) must be grater or equal than the total sipping reserve contribution of all generators (SR_r).

2.3 2m point estimate method

Forecasting of renewable energy sources such as wind turbine is a challenging task and its randomness needs to analyze in a stochastic environment. There are three different categorizes to solve optimization problem involving uncertainties such as analytical methods, MCS method, and approximate methods. Although MCS offers more accuracy with cost of much more runs to converge to the optimal point, analytical methods produce reasonable precision with less computational burden [6]. Point estimation methods as one of well-known approximation methods can be useful in which wide variety of classes arise based on the number of input uncertain variables for ED problem. Among these different classes, 2m point estimate method (2*m* PEM) evaluate uncertainty in which are treated randomly at the specific points in search spaces. For the sake of simplest algorithm, the original PEM [7] determine the statistical moment of random variables. For multivariate problems involving *m* number of uncorrelated random variables with known mean value and standard deviation of μ_Y and σ_Y , $Y=\{y_1, \ldots, y_k, \ldots y_m\}$ state as a random vector. The random output variable (*Z)* is related to random input variable of PEM (*Y*) by the known function *h*, i.e. *Z*=*h*(*Y*). Each individuals of the variables y_k as location of estimating points of PEM can be expressed as a pair consisted of location and a weight. By evaluating *h* function *s* times for each random input variable y_k and the mean of the remaining input variables, the total number of evaluation would be 2*m* which reflected in the name of the method. The location $y_{k,s}$ is formulated depends upon mean value of random variable *Y* (μ_Y) in (12).

$$y_{k,s} = \mu_{k,s} + \zeta_{k,s}\sigma_{k,s} \tag{12}$$

where $\zeta_{k,s}$ stand for y_k standard location. Then all standard locations and weights (w) associated with random variable of y_k for number of estimating points in PEM (*m*) are calculated by (13), and (14).

$$\zeta_{k,1} = \frac{\lambda_{k,3}}{2} + \sqrt{m + \left(\frac{\lambda_{k,3}}{2}\right)^2} \quad , \quad \zeta_{k,2} = \frac{\lambda_{k,3}}{2} - \sqrt{m + \left(\frac{\lambda_{k,3}}{2}\right)^2} \tag{13}$$

$$w_{k,1} = \frac{-\zeta_{k,2}}{m(\zeta_{k,1} - \zeta_{k,2})} \quad , \quad w_{k,2} = \frac{\zeta_{k,1}}{m(\zeta_{k,1} - \zeta_{k,2})} \tag{14}$$

Where $\zeta_{k,s}$ stands for standard location of the random variables in PEM, and $\lambda_{k,3}$ denotes the skewness of the random variable y_k based on standard deviation of random variable (σ_Y) as follow:

$$\lambda_{k,3} = \frac{E[(y_k - \mu_{y_k})^3]}{\sigma_{y_k}^3} \tag{15}$$

A deterministic ED must be run for each individual and the results is:

$$Z_{k,s} = h(y_{k,1}, \ldots, y_{k,s}, \ldots, y_{k,m}) \tag{16}$$

where $Z_{k,s}$ denoted the vector of random output variables associated with the s^{th} individuals of random input variable. The origin moment of the output random variables can be obtained from (17).

$$E(Z) \cong E(Z) + \sum_{s} w_{k,s} Z_{k,s} \tag{17}$$

3 SOLUTION PROCEDURE

3.1 Modified Harmony search (HS) Algorithm

The HS algorithm was inspired by musical search process for an ideal state of harmony. HS algorithm was first introduced in 2001 by Xiang et al. [17] to mimic the harmony among the musicians for producing a powerful optimization algorithm. In the original HS algorithm, each candidate solution named a "harmony" which expressed by an n-dimensional vector. It is a population based optimization algorithm which is consisted of a set of harmony which generated and stored in a harmony memory (HM). Each note in HM is played by a musician to get to the highest harmony based on three subsets [38]:

1) Memory consideration
2) Pitch adjustment
3) Random search

Based on above definition, HM is n-dimensional solution vectors which a store new candidate harmony (solution) by using memory consideration, pitch adjustment, and random search rules. The HM is updated by comparing harmony candidates and the worst harmony vector through HM. The process repeated to stopping criterion met. Musician choose a notes depends upon their memories (HM) in form of random search through memories to improve their proper harmony. Thus, HM constant variable considering this rate is defined.

For the sake of first step note improvement, HM constant parameter construct for memory consideration through (18).

$$x_{kh}^{new} = \begin{cases} x_{kh}^{HM} & rand \prec HMCR \\ x_{kh}^{rand} & otherwise. \end{cases} \tag{18}$$

Where x and rand stand as input sample point and a uniform random number through [0, 1] rang. Hm considering rate in HS algorithm express with HMCR. New harmony vector generated by (18) will be updated and store in memory by competition between the new value and the worst harmony in the HM.

$$x_{kh}^{new} = \begin{cases} x_{kh}^{HM} \pm rand \times BW & ; \quad rand < PAR \\ x_{kh}^{rand} & ; \quad Otherwise \end{cases} \tag{19}$$

Wherein the *BW* parameter as the bandwidth is updated in each iteration (*g*) as follows:

$$BW(g) = BW_{\max} \times e^{\rho g} \tag{20}$$

$$\rho = Ln(\frac{BW_{\min}}{BW_{\max}}) \times NI^{-1} \tag{21}$$

Initially, all algorithms parameters such as HM, BW and PAR were defined. However, by adopting varying PAR, search capability of the algorithm can be improved for total number of improvisation (*NI*). Dynamic updates value of PAR is compute in (22).

$$PAR(g) = PAR_{\min} + \frac{g}{NI} \times (PAR_{\max} - PAR_{\min}) \tag{22}$$

Where *PAR(g)* is the pitch adjustment rate in generation *g* at population. $PAR_{\max}$ and $PAR_{\min}$ stand for maximum and minimum tolerance of adjustment rate. While HS algorithm take advantages of the best candidate harmony vector to update and generate a new vector, the pitch tuning rule may cannot adjust the harmony note structure good enough for being the best among the population. As a results, modification stages are needed to modify the search ability of proposed algorithm for optimizing the nonlinear constrained problem. In this paper a novel modification method is proposed to enhance the total search ability of the HS as well to avoid the premature convergence. The proposed modification method is folded in two sub-modification techniques as follow:

First modification stage: In this step, the diversity of population increases by benefiting the Lévy flight method. A Lévy flight defines a random walk which model various distance steps. The step-lengths are distributed depends upon to a heavy-tailed probability distribution [39] which is modeled by Lévy flight as bellow:

$$Le'vy(\omega) \sim \tau = t^{-\omega} \quad ; \quad (1 < \omega \leq 3) \tag{23}$$

$$X_n^{new} = X_n^{old} + \varphi_1 \oplus Le'vy(\omega) \tag{24}$$

Where *Le'vy(.)* is Levy flight function which equal to approximation of the levy flight (τ). X_w^{new} as new position of the notes is updated by old position of note (X_w^{old}) and random variable in the range of [0, 1] multiple by Levy function. If the new solution is better than the last one then replace it.

Second modification step: This modification method utilizes the crossover and mutation operators from genetic algorithm for the diversity increment of the notes' population. In this way, for each new produced note X_n, three notes X_{n1}, X_{n2}, and X_{n3} are selected from population in random such that $n1 \neq n2 \neq n3$. Then, by using the mutation operator, two new test notes are created by (25).

$$X_{Mut,1} = X_{n1} + \Im_1 \times (X_{n2} - X_{n3}) \tag{25}$$

4 SIMULATION RESULT

The proposed approach is evaluated for solving realistic ED and PED by applying the method on three different case studies. To show effectiveness of the proposed algorithm, test systems with 10, 15, and 40 units are tested with different dispatching and undisptaching units. The first tests system with 10 generators [40] considers valve-point effects and multi-fuel options simultaneously. The proposed ED problem are comprised for 15 dispatching units with 2630MW load demand addressing POZs. The detail characteristics of thermal units in this case can be found in [41]. Moreover, power loss analysis of the system is considered in the second case study. In order to demonstrate the feasibility and performance assessment of the proposed framework for large power plant third test system is studied ED problem with valve-point effects for 40 units [42]. As stated previously, the wind turbines generation output can be model by utilizing the wind turbine power curve. However, wind power generation volatility is taken into account based on predefined power curve and model. This model characteristics are denoted in Table 1.

TABLE1

THE WIND TURBINE MODEL CHARACTERISTICS

Parameter	Value	Parameter	Value
$s_{1,w,f}$ (MWs/m)	0.0667	$v_{co,w,f}$ (m/s)	25
$s_{2,w,f}$ (MWs/m)	0.1520	$v_{1,w,f}$ (m/s)	7
$s_{3,w,f}$ (MWs/m)	0.02	$v_{2,w,f}$ (m/s)	12
$v_{ci,w,f}$ (m/s)	4	$v_{r,w,f}$ (m/s)	14

The results of the proposed MHS are shown in Tables 2-4 for aforementioned test systems, respectively. For the purpose of comparison the attained results, several applied well-known ED solution methods are also summarized in these tables to show functionality effectiveness of the proposed method.

TABLE2

COMPARED RESULT OF BEST, AVERAGE, AND WORST COSTS FOR ED OF FIRST TEST SYSTEM

Method	Cost of generation ($/h)			CPU (min)
	Best	Average	Worst	
DE [40]	624.5146	624.5246	624.5458	0.04706
RGA [40]	624.5081	624.5079	624.5088	0.0689
PSO [40]	624.5074	624.5074	624.5074	0.05642
PSO-LRS [20]	624.2297	624.7887	628.3214	0.01467
NPSO[20]	624.1624	625.218	627.4237	0.00583
NPSO-LRS [20]	624.1273	625.9985	626.9981	0.00867
RCGA [43]	623.8281	623.8495	623.8814	NA
MHS	**623.82231**	**623.8553**	**623.8255**	**0.09266**

** Not Available in the respective reference*

TABLE3

COMPARED RESULT OF BEST, AVERAGE, AND WORST COSTS FOR ED OF SECOND TEST SYSTEM

Method	Best	Average	Worst
GA[41]	33113.0	33228.0	33337.0
PSO[41]	32858.0	33039.0	33331.0
MHS	**32680.5956**	**32687.3305**	**32693.2641**

TABLE 4

COMPARED RESULT OF BEST, AVERAGE, AND WORST COSTS FOR ED OF THIRD TEST SYSTEM

Method	Cost of generation ($/h)			CPU time (min)
	Best	Average	Worst	
IFEP[42]	122624.3500	123382.0000	125740.6300	19.45
MPSO[44]	122252.2650	NA	NA	NA
ESO[45]	122122.1600	122558.4565	123143.0700	0.000435
PSO-LRS[27]	122035.7946	122558.4565	123461.794	0.2625
Improved GA[17]	121915.9300	122811.4100	123334.0000	NA
HPSOWM[13]	121915.3000	122844.4	NA	0.42317
IGAMU[15]	121819.2521	NA	NA	0.4505
NPSO[27]	121704.7391	122221.3697	122995.0976	0.05867
HDE[28]	121698.5100	122304.3000	NA	0.101167
NPSO-LRS[27]	121664.4308	122209.3185	122981.5913	0.0655
BF[29]	121423.6379	121814.9465	NA	NA
RCGA[36]	121418.5425	121814.9465	121628.5987	NA
MHS	**121412.5355**	**121412.9482**	**121412.7863**	**0.12274**

Simulation are carried out for 200 iterations foe three case studies. The best, average, worst solutions of the proposed method among the results are less than the other approaches which shows the proposed MHS is pioneer to find optimum solution. It is noteworthy to mention that the worst solution of MHS method is far-off better than the others methods best solution. Moreover, the CPU time taken by the processor to attain to optimum point is 22% less than the other methods computational time. To determine the impacts of proposed method in solving PED, the uncertainty associated with wind generation is involved to the problem for case studies. To show the uncertainty effects compare deterministic analysis, three different scenarios include without wind generation, with deterministic wind generation consideration, and stochasticity of wind generation are considered, respectively. In first scenario, no wind generation considered in PED model. In the second scenario, wind turbine output power supposed to be deterministic. Finally, in third scenario, a stochastic analysis of wind generation is considered to optimize ED problem by using proposed MHS to minimized operational cost of generators by dedicating their output economically. For the first and second case studies, the generation cost for three scenarios are depicted in Fig. 1 and 2. Fig. 3, and 4 give more details about power generation units output for both first and second case studies.

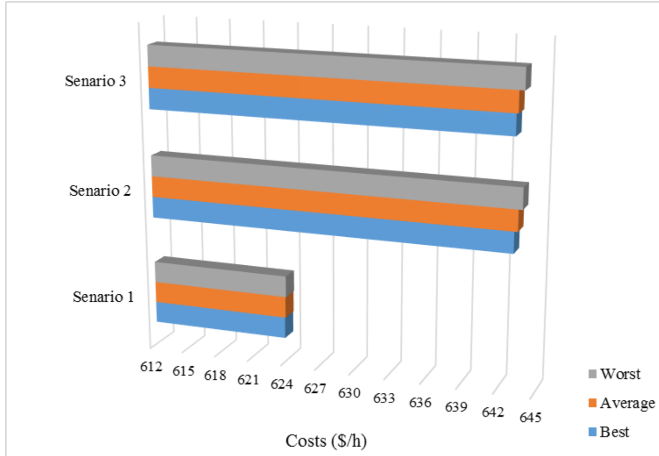

Fig. 1. *Compared result of best, average, and worst costs for PED of first test system.*

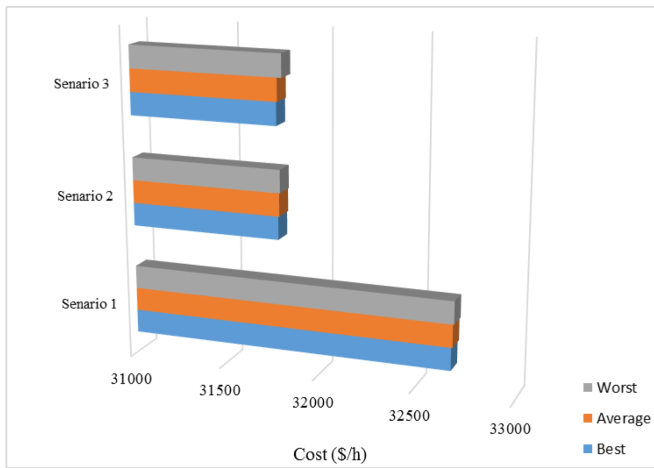

Fig. 2. *Compared result of best, average, and worst costs for PED of second test system.*

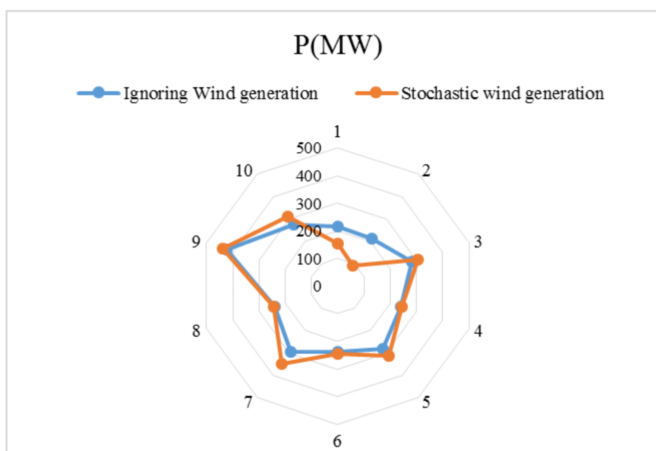

Fig. 3. *PED results of the proposed MHS for first case*

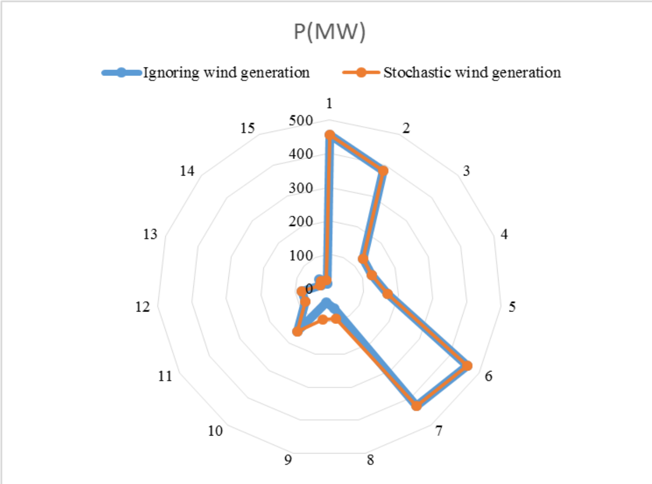

Fig. 4. *PED results of the proposed MHS for second case study.*

It can be observed from results that the 10-units generation costs in third scenario is higher than first scenario. The attained results from Fig. 3 and 4 reveal the reason of increase on cost based on the power generation of units in both first and second case studies. In first case study (10-units) two units (1 and 2) were considered as wind turbines which tend to supply less power in the third scenario (stochastic wind generation). As result of this reduction in these wind turbines, the rest of units should generate higher level of power to meet the power balance requirement between demand and supply. Similarly, for the second case study (15-units) three units were assumed to be wind turbines (unit 13, 14, and 15) which decrease the total network costs. Results demonstrate that the robustness of the proposed algorithm (MHS) through different PED characteristics for variety of power networks which in none of former studied investigated. A main factor of the optimization tools can be capability of them in solving PED problem when the intermittency and randomness of the concerned variables take into account. Numerical results of third case study associated with stochasticity of wind generation in large-scale are summarized in Fig. 5 and Table 5.

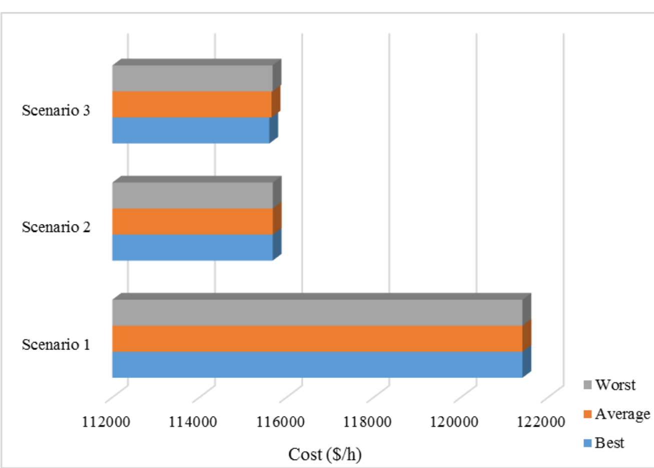

Fig. 5. *PED results of the proposed MHS for third case study.*

TABLE 5

PED RESULTS OF THE PROPOSED MHS FOR THIRD CASE STUDY.

Unit	P(MW) Ignoring wind generation	P(MW) Stochastic wind generation	Unit	P(MW) Ignoring wind generation	P(MW) Stochastic wind generation
1	112.2460	113.9744	21	523.2798	523.6334
2	112.3141	113.9922	22	523.2793	523.7420
3	97.8202	119.9975	23	523.2804	523.2932
4	179.7331	179.7510	24	523.2796	523.3504
5	91.7458	97.0000	25	523.2796	523.2888
6	140.0000	140.0000	26	523.2798	523.2819
7	259.6055	263.5208	27	10.0000	48.0257
8	284.6495	291.4401	28	10.0001	70.1485
9	284.6061	288.7307	29	10.0002	91.9978
10	130.0000	204.8045	30	92.3796	96.9979
11	243.5996	94.0000	31	190.0000	190.0000
12	168.7997	94.0147	32	190.0000	190.0000
13	125.0000	125.0000	33	190.0000	190.0000
14	304.5195	304.5176	34	200.0000	199.9997
15	394.2796	304.5213	35	192.1066	200.0000
16	304.5196	304.5267	36	200.0000	200.0000
17	489.2798	489.2996	37	109.9999	110.0000
18	489.2794	489.2891	38	109.9996	110.0000
19	511.2794	511.2899	39	109.9999	110.0000
20	511.2792	511.2831	40	511.2794	511.2877

In the third tested system, three wind turbines placed as 27-29th units into the power plant which integrated with the rest of thermal units. The total cost of third test system is decreased as it can be seen from Fig. 5. As the size of tested system increase, the PED problem complexity increase as well as computational time regard probabilistic analysis. In this case, wind turbines generation level increase and also so the rest of units force to decrease their level of generation to satisfy the network balance requirements. This justify the total costs decrement of the tested system in third case. In other words, the most important effects of wind turbines integration to the power network would be thermal unit's output power decrease that it would be helpful from environmental points of view.

5 CONCLUSION

This paper presented a self-adaptive modified harmony search (MHS) algorithm in application ED and realistic PED model involving several characteristics such as ramp rate limits, POZs, valve loading effects, spinning reserve, and multiple fuel options under wind turbine generation stochasticity. The proposed MHS method applied a different designed scenarios to demonstrate its effectiveness so as to benefit from inherent characteristics of evolutionary techniques for practical PED. Simulations are carried out to three tested systems, comprising 10, 15, and 40 units, and correspondence results compared to other methods such as PSO, GA, RCGA, and etc. show better optimum solutions, low computational burden, and easier implementation code. PEM is also considered to address the uncertainty effects imposed by wind turbines integration to power networks which offer more accurate and realistic results.

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