A Stochastic Mid-Term Scheduling for Integrated Wind-Thermal Systems using Self-Adaptive Optimization Approach: A Comparative Study

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Abstract

In the optimal and economic operation of the power system, generation scheduling is an essential task. Conventional short-term generation scheduling does not regard the huge important operational issues related to the generators, such as initial enterprise costs, maintenance costs, fuel availability, monthly load, etc. Hence, due to the time horizon scheduling of the daily short-term generation scheduling, it is not optimal in the long-term operation while considering the mentioned effects. In this context, this paper proposes a stochastic higher level of scheduling named Stochastic Mid-Term Generation Scheduling of Wind-Thermal systems by considering fixed and variable maintenance costs of generators units. In the proposed model, the $2m+1$ Point Estimate Method is applied to accurately evaluate the uncertainty related to the operation cost wind power and the load uncertainties for the proposed problem. To effectively solve it, a heuristic algorithm named Adaptive Modified Cuckoo Search Algorithm is employed with a novel self-adaptive Wavelet mutation tactic. To assess the performance of the proposed algorithm on solving the problem, the results are compared with the latest algorithms presented in the literature. Numerical results confirm the efficiency and superiority of the $2m+1$ point estimate method model and stability of the novel adaptive modified cuckoo search algorithm on solving the stochastic mid-term generation scheduling of wind-thermal systems problem.

Keywords: Generation Scheduling; Stochastic; Point Estimate Method; Wind Power; Cuckoo Search Algorithm; Self Mutation.

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Nomenclature

Indices

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b	Index for Dimension
c	Output variable with uncertainty
d	Input variable with uncertainty
FE	Index for function evaluation
g	Index for thermal unit
k	Index for Generation
p	Index for concentration location in the Point Estimate Method
t	Index for time interval in the scheduling
u	Index for Moment
w	Index for Wind farm

Constants

FE_{max}	The function evaluations maximum for the Adaptive Modified Cuckoo Search Algorithm
fp_{gk}	Fuel price of thermal unit group k ($/MBtu)
$H(\ )$	Production cost function in the PSWTGS problem
H_{gk}^{max}	Upper bound of fuel consumption for thermal unit group k in the scheduling
H_{gk}^{min}	Lower bound of fuel consumption for thermal unit group k in the scheduling
Ng	Thermal unit numbers in the power system
Nh	Hour numbers in the horizon scheduling
Nt	Hours numbers at time t.
Nw	Wind farms numbers
OMFCT(g)	Fixed cost of operation and maintenance for thermal unit g $(\$/MW.yr)$
OMFCW(w)	Fixed cost of operation and maintenance for wind farm w $(\$/MW.yr)$
OMVCT(g)	Variable cost of operation and maintenance for thermal unit g $(\$/MW.yr)$

OMVCW(w) Variable cost of operation and maintenance for wind farm w ($\$/MW.yr$)

$PG_{\max,g}$ Generation upper bound for thermal unit g (MW)

$PG_{\min,g}$ Generation lower bound for thermal unit g (MW)

$PL_{\max,l}$ Upper bound for power flow of transmission line l (MW)

$PL_{\min,l}$ Lower bound for power flow of transmission line l (MW)

$PW_{\max,w}$ Maximum wind power generation for wind farm w (MW)

T Number of periods under horizon scheduling

Variables

$a_{d,p}$ Uncertain input variables vector for pth concentration location of dth random variable in the Point Estimate Method

$J(\;)$ Total operation cost function of SMGSWT problem

$\tilde{P}_{load}(t)$ Expected value of load at time t (MW) for system scheduling

$\tilde{PGD}_g(t)$ Load shared expected value for thermal unit g at time interval t (MW)

$\tilde{PGR}_g(t)$ Reserve shared expected value for thermal unit g at time interval t (MW)

$PL_l(t)$ Line Power flow on line l at time interval t

$\tilde{PW}_w(t)$ Generation wind power expected value for wind farm w at time t (MW)

$u(g,t)$ Decision variable of unit g at time interval t for PSWTGS problem

$U_g(t)$ State variable of unit g at time interval t (on = 1, off=0)

$V_w(t)$ State variable of wind farm w at time interval t (on=1, off=0)

$\tilde{W}_{av,w}(t)$ Maximum available wind power expected for wind farm w at time interval t (MW)

$x(g,t)$ State variables for unit g at time interval t

Superscript

$\sim$ Expected value of random variables in the Point Estimate Method strategy

1. Introduction

The generation scheduling problem plays a considerable role in the operational planning and scheduling of all generation units in the power systems. The objective of the Generation Scheduling (GS) problem is to obtain the optimal strategy for the operation of the generating units in order to satisfy the equality and inequality constraints at the minimum operation with respect to the scheduling horizon. Generation scheduling is the process of determining optimal schedule of generating units over a set of scheduling horizon subject to system operating constraints.

1.1. Background

In the scheduling problem, the time horizon usually ranges from one day to some years. The GS problem from time perspective is divided into three stages [1] consists of 1) short-term scheduling, 2) mid-term scheduling, and 3) long-term scheduling.

1- Short-Term generation scheduling

The short-term generation scheduling is a significant task in a daily operation of the power systems [2]. The short-term generation scheduling is defined as the optimal scheduling of generators over one day or one week while maintaining various generators and system constraints. The objective function of the mentioned problem includes energy production costs, start-up costs and shut-down costs. In the short-term generation scheduling, unit commitment is one of the best available ways for supplying electric power of customers in a secure and economic manner. The unit commitment determines a day-ahead or weekly schedule for minimizing the cost of fuel and starting-up/shutting-down generating units while satisfying the system constraints consists of hourly load balance, operating reserve requirements, ramp rate limits of units, generating capacity constraints, minimum up and down time limits, startup and shutdown limits of units [3]. Ref. [4] presents a method to incorporate the wind power generation into the short-term GS of the power system. Ref. [5] reports the impact of high penetration of wind power on the day-ahead GS of the system. Ref. [6] presents a stochastic cost model for short-term scheduling of the thermal, wind and solar units in a wind integrated power system regarding the uncertainty of the solar radiation and the wind generations.

2- Mid-Term generation scheduling

In the scheduling of the power units, conventional daily short-term generation scheduling problem does not regard the huge important operational issues related to the generators such as initial enterprise costs, maintenance costs, fuel availability and monthly load and etc. Hence, due to the time horizon scheduling of the daily unit commitment is short, it is not optimal by considering the mentioned effects. Therefore, we need a higher level of scheduling named mid-term generation scheduling. The mid-term generation scheduling problem is an operation-planning problem consists of the optimal allocation of natural resources, enhance the power systems security based on limited generation and transmission equipment, prolong investment costs for adding new facilities, extend the life span of generating and transmission units, reduce operation costs for supplying competitive loads. The optimal allocation of the natural resources includes available fuel and emission allowance for the thermal units, water inflows for hydro units, and solar and wind conditions for renewable energies in the power system. The mid-term generation scheduling results are coordinated with the short-term generation scheduling solutions for system security purposes and operational effects. In the mid-term generation scheduling problem, the time horizon of the scheduling is seasonal or yearly scheduling. Moreover, the decision intervals of horizon scheduling for the GS problem, is monthly or weekly [7]. [8].

3- Long-Term generation scheduling

The principle of the long-term generation scheduling is the least-cost operation of the system within a pre-specified level of system security [9]. The long-term generation scheduling consists of fuel availability and transportation accessibility to generating plant sites, annual load growth, different financial loan incentives, construction costs, transmission rights availability and congestion constraints, as well as load curtailment costs. The long-term generation scheduling solution determines physical sites and markets for new generating units with various unit types and capacities, best timing for the addition of new generation and transmission units into power system, best timing for the closure or retrofitting of old units, and strategies for the timely returns on investment. Ref. [10] introduces a method for efficiently long-term combining of the GS of the power system. However, the important constraint such as network and fuel constraint are overlooked. Ref. [11] proposes a yearly GS formulation for a power system with significant levels of wind power generation. The yearly operation cost of the power system is computed by the sum of the daily UC costs of the system. However, many important problems such as maintenance units cost, yearly/seasonally fuel available, fuel cost fluctuation and etc. cannot address in this approach.

1.2. Aim and motivation

In the scientific literature, the short-term generation scheduling and long-term scheduling have been investigated pleasantly. However, less attention is allocated to the mid-term generation scheduling problem. On the other hand, because the wind power is pure, indigenous, fast to deploy and economically competitive with the other power generation types, within the last two decades, the integration of the wind farms with the power system has occurred in the large-scales [12]. For system operators planning of the wind power generators in the mid-term scheduling of power system has a lot of challenges in spite of various advantages of wind power. The Mid-term Generation Scheduling of Wind-Thermal (MGSWT) system is concerned with the seasonal commitment and dispatch of the wind and the thermal units in the integrated system. In the horizon of one year or one season the power output of a wind farm and load demand could be extremely intermittent and volatile. Hence, it is possible that the actual wind power of a wind-thermal system and the load demand would be different from its forecasted values. In a large-scale wind integrated power system, due to that the wind power and the load demand are difficult to predict and highly intermittent, the MGSWT problem is a very complex task. Since, the load and the wind power are uncertain parameters; the performance of MGSWT can be seriously caused weak in terms of fuel consumption and the level of reliability in supplying loads. Therefore, in the operational planning analysis of the system, the wind power and the load uncertainties of the system should be appropriately modelled in the final model. Moreover, the intermittency of the wind farms generation and load forecasting errors should be taken into account in the proposed MGSWT in order to ensure that the transmission and fuel constraints and other wind-thermal system constraints are satisfied. In this regard, a sophisticated technique must be utilized to overcome with the effects of the wind power and the load demand uncertainties on the mid-term generation scheduling problem.

1.3. Literature review

Ref. [13] studies the mid-term impacts of PHEV charging patterns and the large-scale wind power scheduling by stochastic Unit Commitment (UC) model. This study considers the uncertainty of the load and the wind power. However, the essential constraints in the long term such as network constraint, maintenance cost and seasonally available fuel are neglected. Ref. [14] proposes the deterministic mid-term generation scheduling of the Portuguese system without regarding the uncertainty of the wind power and load. Hence, the proposed approach is not a realistic approach. In addition, the impact of the variable and the fixed maintenance cost on the mid-term generation scheduling problem is not considered. Ref. [15] presents the optimal seasonal planning and scheduling of batteries in the distribution grid considering uncertainties of the wind power and the load. Ref. [16] evaluates the effective load carrying capability of wind and solar via the stochastic long-term hourly based security-constrained UC. This work does not regard the effects of variable and fixed maintenance costs which is an important task in the long-term operation of the power system. These uncertainties are simulated via the scenario tree using the Monte Carlo simulation. Ref. [17] proposes a type-2 fuzzy method to model the load demand and the wind power uncertainties associated with scheduling of a Genco. In this paper, the effects of variable and fixed costs of mid-term generation scheduling are regarded. However, the important constraints such as network or available fuel constraints have been neglected which can cause the weak performance of the mid-term scheduling of the thermal units. Since the horizon scheduling of the mid-term generation scheduling problem is long, it is necessary to consider the fixed and variable maintenance costs in the objective function.

1.4. Contributions

To the best of authors' knowledge, none of the few publications dealing with the mid-term generation scheduling problem have successfully suggested a general framework that considers the effects of the fixed and the variable maintenance costs of generation units, as well as simultaneously regarding the network constraint and seasonal fuel availability in the power system when the uncertainty of the system is taken into account. The network constraints and seasonal fuel availability in the power system are essential constraints in the MGSWT problem, which are mostly not regarded in the MGSWT problem. Hence, this paper presents the general framework for the mid-term generation scheduling of a wind-thermal system by considering the essential effects of fixed and variable maintenance costs of generation units, the network constraint and seasonal fuel availability. In addition, the intermittency of wind farms generation and load forecasting error are taken into account in the proposed SMGSWT in order to ensure that the transmission and fuel constraints and other wind-thermal system constraints are satisfied.

In this regard, the probabilistic optimization $2m+1$ Point Estimate Method (PEM) strategy is implemented to surmount the uncertainties of the wind power and demand in the wind integrated power system [18]. The PEM is a fast and accurate probabilistic uncertainty analysis that utilizes the approximated lower-order probability moments to cope with the uncertain parameters. Compare with the other schemes of the PEM, $2m+1$ scheme is more accurate. Hence, in this paper the stochastic reserve for the thermal units is proposed to accommodate the volatility of the wind power based on the PEM. Hence, this stochastic reserve is not a pre-determined value.

Due to the MGSWT problem under uncertainty has a large number of thermal/wind units and decision intervals, it is a large-scale, mixed integer combinatorial and nonlinear problem which needs a powerful method to solve it. Therefore, in this study, an Adaptive Modified Cuckoo Search Algorithm (AMCSA) is applied to solve the SMGSWT problem under uncertainty. The Cuckoo Search Algorithm (CSA) is a new meta-heuristic optimization algorithm which is based on the exceptional lifestyle of Cuckoo birds and their characteristics in egg laying [19], [20]. The attempt to survive among cuckoos establishes the basis of the CSA. Unfortunately, the performance of the original CSA depends on its parameters such as the maximum laying distance from their habitat and the migration factors. These dependencies have caused that the algorithm to get trapped in local optima in the search procedure. Hence, a novel Self Adaptive Wavelet Mutation (SAWM) tactic is utilized to increases the robustness of algorithm to solve the SMGSWT problem and efficiently amend the performance of the original CSA. The self-adaptive Wavelet mutation tactic dynamically changes the mutation for Cuckoo search algorithm along the search procedure which causes the intelligent search. Moreover, the SAWM prevents the algorithm from falling into the local optima.

In this paper, a comparative study of the different uncertainty analysis methods and the proposed 2m+1 PEM uncertainty analysis to overcome the system uncertainties is presented. Moreover, a detailed analysis of the various optimization methods including the proposed AMCSA algorithm to solve the mid-term generation scheduling is investigated. Analytic analysis has been applied to reveal the performance and the efficiency of the optimization and the uncertainty analysis methods on solving the mid-term wind-thermal generation scheduling.

The main contributions and the novelty of this paper can be briefed as below:

(i) Improving the general formulation of the mid-term generation scheduling of a wind-thermal system by regarding the effects of maintenance cost, fixed preliminary budgets and important constraints including network and fuel constraints.

(ii) Employing the stochastic 2m+1 PEM strategy to cope with the mid-term effects of the intermittency of wind power and load demand.

(iii) Proposing a novel self-adaptive Wavelet mutation tactic for the AMCSA algorithm to attain an efficient and robust algorithm to solve the SMGSWT problem.

(iv) Successfully validating of the performance and the potential of the proposed algorithm by the numerical results and the empirical distribution success performance figure.

The rest of this paper is organized as follows: In section II, the general formulation of the SMGSWT problem under uncertainty is described. In section III, uncertainty analysis methods and solving approaches for SMGSWT problem are presented. Section IV expresses the proposed stochastic framework based on 2m+1 PEM. In section V, the proposed AMCSA optimization algorithm and the corresponding self-adaptive Wavelet Mutation tactic are described. The simulation and numerical results are shown and discussed in section VI. Finally, section VII shows the main conclusions and remarks about the proposed method.

2. SMGSWT Problem Formulation

In this section, the formulation of the SMGSWT problem with system constraints is described. The objective function of the stochastic seasonal wind-thermal generation scheduling problem is the minimization of the total expected operation cost of the power system with regard to scheduling horizon, while the system constraints are satisfied. The operation cost consists of the variable cost for the electricity production of the units and the operation and maintenance expenditure of them.

2.1. Objective function of the SMGSWT

The equation described the objective function of the mid-term wind-thermal generation scheduling problem under uncertainties is as follows:

$$\begin{aligned} Min\ \ & J\left(x(g,t), u(g,t), a_{d,p}\right) \\ = & \sum_{t=1}^{T}\sum_{g=1}^{Ng}\left\{H\left(\mathrm{PGD}_{\tilde{g}}(t)\right).\mathrm{Nt}\right\}\mathrm{U}_{g}(t) + \sum_{t=1}^{T}\sum_{g=1}^{Ng}\left\{\left(\mathrm{PGD}_{\tilde{g}}(t)+\mathrm{PGR}_{\tilde{g}}(t)\right).\mathrm{OMVCT(g)}.\ \mathrm{Nt}\right\}\mathrm{U}_{g}(t) \\ & + \sum_{t=1}^{T}\sum_{g=1}^{Ng}\left\{\mathrm{PG}_{\max,\ g}.\mathrm{OMFCT(g)}\ .\frac{\mathrm{Nt}}{\mathrm{Nh}}\right\} + \sum_{t=1}^{T}\sum_{w=1}^{Nw}\left\{\mathrm{PW}_{\tilde{w}}(t).\mathrm{OMVCW(w)}\ .\mathrm{Nt}\right\}V_{w}(t) \\ & + \sum_{t=1}^{T}\sum_{w=1}^{Nw}\left\{\mathrm{PW}_{\max,\ w}.\mathrm{OMFCW(w)}\ .\frac{\mathrm{Nt}}{\mathrm{Nh}}\right\} \end{aligned} \tag{1}$$

A quadratic cost function is assumed for the power of the thermal generator in the stochastic seasonal wind-thermal generation scheduling problem which is gained by:

$$H(\mathrm{PGD}_{\tilde{g}}(t)) = A_g + B_g.\mathrm{PGD}_{\tilde{g}}(t) + C_g.(\mathrm{PGD}_{\tilde{g}}(t))^2 \tag{2}$$

where A_g, B_g, C_g are the cost coefficients of the g-th thermal units.

Eq. (1) represents the total operation cost of stochastic mid-term wind-thermal generation scheduling. This equation consists of five cost terms. The first term represents the fuel cost of the thermal generators *g*-th if it is on. The second term is the mid-term effect of variable operation and maintenance cost of thermal generator *g*-th if it is on in the operation of the system. The third term represents the mid-term effect of fixed operation and maintenance cost of thermal generator *g*-th if it is on in the operation of the systems. The fourth term consists of the mid-term effect of variable operation and maintenance cost of wind generator *w*-th if it is on. Moreover, the mid-term effect of fixed operation and maintenance cost of wind generator *w*-th if it is on has been represented in the fifth term.

2.2. Constraints of SMGSWT problem

1-Power balance constraint

In the stochastic seasonal wind-thermal GS problem the equilibrium between the generation and demand is indispensable. Hence:

$$\sum_{g=1}^{Ng} \mathrm{PGD}_{\tilde{g}}(t)\cdot \mathrm{U}_{g}(t) + \sum_{w=1}^{Nw} \mathrm{PW}_{\tilde{w}}(t)\cdot V_{w}(t) = P_{\widetilde{load}}(t),\ t = 1,2,\ldots,T \tag{3}$$

2-Span limits of generators

For each thermal units, the minimum and maximum limitations of unit generation capacity must be regarded in the SMGSWT:

$$PG_{\min,g} \le \mathrm{PGD}_{\tilde{g}}(t) + \mathrm{PGR}_{\tilde{g}}(t) \le PG_{\max,g} \tag{4}$$

3- Reserve allocation for system

In the proposed model, the stochastic reserve allocation in each interval for the power system includes two parts. A constant percentage of the total load demands ($P_R(t)$) in respective time interval is regarded for the first part. Moreover, the constant percentage of the total wind power production (SRW) in respective time interval is considered for second part. The SRW is regarded as an additional reserve required for the power system to compensate the mismatch power between the forecasted wind power and the generation actual wind power generation. The formulation for reserve constraint is as follows:

$$\sum_{g=1}^{Ng} \mathrm{PGR}_{\tilde{g}}(\mathrm{t}).\mathrm{U}_{\mathrm{g}}(\mathrm{t}) \geq SRW \times \sum_{W=1}^{Nw} \mathrm{PW}_{\tilde{w}}(\mathrm{t}).V_{w}(\mathrm{t}) + P_{R}(t) \ , t=1,2,...,T \tag{5}$$

4- Available wind power limit

Due to primary source of the wind energy is uncontrollable; the wind power is intrinsically non-dispatchable. Hence, the following constraint which is described the relation between the available wind power and the actual wind power generation in each interval must be satisfied:

$$\mathrm{PW}_{\tilde{w}}(\mathrm{t}) \leq W_{\widetilde{av,w}}(t) \ , \ t=1,2,..,T \tag{6}$$

5- Transmission lines constraints

The stochastic seasonal wind-thermal GS problem without considering the transmission constraint is worthless. So, in order to consider this constraint and decrease the computation time, the transmission lines constraints will be modeled based on DC load flow model by:

$$PL_{\min,l} \leq PL_{l}(t) \leq PL_{\max,l} \tag{7}$$

6- Fuel availability constraint

Another important constraint in the SMGSWT is fuel constraint. Hence, the following constraint must be satisfied:

$$\mathrm{H}_{\mathrm{gk}}^{\min} \leq \sum_{g=1}^{Ng} \sum_{t=1}^{NT} \left[H\left(PGD_{\tilde{g}}(t)\right).U_{g}(t) \right] / fp_{gk} \leq H_{gk}^{\max} \tag{8}$$

It is worth to note that the non-linearity and non-smoothness of the SMGSWT problem are ignored to linearize the objective function and constraints, which may lead to large errors in the final dispatch of the thermal generators in the linear programming method. For the effective usage of the Non-linear programming and mixed linear programming, the objective function requires being differentiable. Thus, some approximations of problem formulation are needed when non-linear programming and mixed linear programming are implemented to solve the SMGSWT problem, which may generate a large error in the final results. The Evolutionary algorithms like CSA impose no restrictions on the non-smoothness and non-convexity of the SMGSWT problem. Indeed, in recent years, there has been a surge of interest toward heuristic methods which put no limitation on problems and consider real characteristics of the problems, accordingly many published research is done to present modern meta-heuristic optimization algorithms which could cope with the difficulty of the mathematical programming ones. Accordingly, CSA algorithm has been used in this paper to consider the large-scale, mixed integer combinatorial and nonlinear characteristic of the SMGSWT problem. In addition, we presented a novel Self Adaptive Wavelet Mutation (SAWM) tactic to increases the robustness of algorithm to solve the SMGSWT problem and efficiently amend the performance of the original CSA.

3. Uncertainty Analysis Methods and Solving Approaches for SMGSWT Problem

3.1. Uncertainty Analysis Methods

There are several uncertainty analysis methods in the literature to deal with the wind power and the load demand uncertainties of the mid-term generation scheduling problem. These approaches include robust optimization, interval analysis and probabilistic approaches. The fundamental aim of the mentioned uncertainty analysis is to measure and evaluate the effects of the uncertain input variables on the operation cost of the mid-term generation scheduling problem. The details of these methods are explained as follows:

1-Robust optimization

Soyster initially presented the robust optimization [21]. In the robust optimization method, the uncertainty ranges are utilized to describe the uncertainty associated with the input random variables. The obtaining of a decision that remains optimal for the worst-case investigation of the uncertain variables within a specific range is the basic of the robust optimization. In [22], the robust optimization is used for analyzing the uncertainties of the generation scheduling problem.

2- Interval analysis

Interval-based uncertainty analysis relies on utilizing recognized intervals to model the uncertain variables, based on a possibility distribution received from experience and historical data [23]. The interval analysis is slightly similar to the probabilistic uncertainty analysis with a uniform Probability Density Function (PDF). The interval analysis finds the bounds of output variables.

3- Probabilistic methods

The probabilistic uncertainty analysis techniques model uncertainty as random variables with a certain probability distribution function. They are based on the statistical data to obtain the probability distribution of the input variables. These techniques assumed that the PDF of input random variables are pre-determined. Probabilistic methods can be classified into two main groups: numerical and analytical uncertainty analysis. Monte Carlo Simulation (MCS) [24] and scenario-based method [25] are the most common an accurate stochastic method in the field numerical probabilistic uncertainty analysis. In [26] a model of wind-hydro-thermal generation scheduling problem along with the pumped storage plant is established. Combination of proposed weighted-improved crazy particle swarm optimization along with a pseudo code based algorithm and Monte Carlo simulation is utilized to solve above problem. The disadvantage of the MCS is that it needs the determination of the marginal distributions of input random variables.

The analytical approaches evaluate the uncertainty of the output variables based on the PDF of uncertain inputs variables. The analytical methods consist of the PDF approximation methods. One of the well-known methods in the PDF approximation method is Point Estimate Method (PEM). The PEM is an approximate method based on the Taylor series with an acceptable level of accuracy and efficiency to evaluate moments of output random variables [27]. The PEM was initially introduced by Rosenblueth [28]. The Rosenblueth's method needs the 2^m number of simulations where m is the number of input random variables. However, several new methods have been presented in the literature to decrease the number of simulations [29], [30]. Finally, an efficient PEM is presented by Hong which consists km and $km+1$ schemes (K is a parameter depending on the type of Hong's PEM schemes) [31]. The $2m+1$ scheme is more accurate than $2m$ scheme due to its use the Kurtosis of the input random variables. Moreover, the standard locations of $2m$ depend on the number of input random variables. Hence, the accuracy of $2m$ scheme is decreased when the total number of input variables is increased in the system.

4. Evaluating Operation Cost of SMGSWT Based on the *2m+1* PEM

The point estimate method is a numerical method exerted to calculate the true unknown value [31], [32]. In this study, the point estimate method calculates the statistical information of the operation cost value of the power system by converting the stochastic MGSWT problem with m input random variables into 2m+1 equivalent deterministic MGSWT problem by specific probabilities. Point estimate method estimates the information about a random variable S which is a function (F) of m uncertain input variables (z_d).

$$S = F\left(z_1, z_2, \ldots, z_d, \ldots, z_m\right) \tag{9}$$

In the above equation, with regard to the SMGSWT problem the variable S is equal to the seasonally or yearly operation cost value of power system and the corresponding input random variable *m* is related to the value of wind power and load demand and function F is related to Eq. (1) with constraints (2)-(7). For each random variable, PEM utilizes three concentration locations to replace Probability Distribution Function (PDF) of input variables. Each random input variable consists three concentration locations with the *p*-th location $(z_{d,p})$ $,p=1,2,3$ and the weighting factor $(\omega_{d,p})$. The impact of the corresponding location in evaluating the expected operation cost is revealed by the weighting factors. By the following equations, the three concentration locations and the weighting factors for each wind farm and load demand in each time interval with the corresponding mean (μ_{zd}) and standard division (σ_{z_d}) are calculated:

$$z_{d,p} = \mu_{z_d} + \xi_{z_{d,p}} \cdot \sigma_{z_d} \qquad p=1,2,3 \tag{10}$$

$$\xi_{z_{d,p}} = \frac{\lambda_{z_{d,3}}}{2} + (-1)^{3-p}\sqrt{\lambda_{z_{d,4}} - \frac{3}{4}\lambda_{z_{d,3}}^2} \quad \textit{for}\ \ p=1,2\ \ \&\ \xi_{z_{d,3}}=0 \tag{11}$$

$$\lambda_{z_{d,3}} = \frac{E\left[\left(z_d - \mu_{z_d}\right)^3\right]}{\left(\sigma_{z_d}\right)^3}\ ,\quad \lambda_{z_{d,4}} = \frac{E\left[\left(z_d - \mu_{z_d}\right)^4\right]}{\left(\sigma_{z_d}\right)^4} \tag{12}$$

$$\omega_{z_{d,p}} = \frac{(-1)^{3-p}}{\xi_{z_{d,p}}\left(\xi_{z_{d,1}} - \xi_{z_{d,2}}\right)} \quad p=1,2\ \ \&\ \omega_{z_{d,3}} = \frac{1}{m} - \frac{1}{\lambda_{z_{d,4}} - \lambda_{z_{d,3}}^2} \tag{13}$$

where E is the expectation operator. For each concentration locations, the operation cost is calculated. In this procedure, one of the load demand and the wind power is fixed to one of its corresponding concentration locations and the other input random variables are fixed to their mean or forecasted points.

$$Cost_{(d,p)} = F\left(\mu_{z_1}, \mu_{z_2}, \ldots, z_{d,p}, \ldots, \mu_{z_m}\right) p=1,2,3 \tag{14}$$

Accordingly, the expected value of the operation cost is attained by Eq. (15):

$$E(Cost) = \sum_{d=1}^{m}\sum_{p=1}^{3}\omega_{z_{d,p}}.\left(Cost(d,p)\right) = \sum_{d=1}^{m}\sum_{p=1}^{2}\omega_{z_{d,p}}.\left(Cost(d,p)\right) + \left[F\left(\mu_{z_1}, \mu_{z_2}, \ldots, \mu_{z_d}, \ldots, \mu_{z_m}\right)\right]\sum_{d=1}^{m}\omega_{z_{d,3}} \tag{15}$$

5. Adaptive Modified Cuckoo Search Algorithm

5.1. Standard Cuckoo search algorithm

The Cuckoo Search Algorithm (CSA) is a new meta-heuristic population-based optimization method inspired by the survival laws for society of Cuckoos in the ecological system [19], [20]. In the CSA algorithm, each Cuckoo' habitat in the ecosystem represents a solution and a cuckoo' egg represents a new solution. The superiority and the proficiency of CSA in comparison to the other heuristic methods have been illustrated in [33] on a benchmark functions. To elucidate the CSA, consider a space with initial a NP cuckoos (solution). In this context, the habitat of the *i*-th Cuckoo is located as:

$$X_i = \left(x_i^1,\ldots, x_i^k, \ldots x_i^r\right) \ for \ \ i = 1,2,\ldots, NP \tag{16}$$

Then, some fortuitously procreated number of eggs is allocated for each of initial Cuckoo habitats. The number of the eggs dedication to each Cuckoo is between Eggs-min to Eggs-max. One of the real habits of Cuckoos is that this bird lays eggs within a maximum distance from its habitat. This maximum range will be called Egg Laying Radius (ELR) and defined in an optimization problem with the upper limit of var_{hi} and lower limit of var_{low} for variables by:

$$ELR = \alpha \times \frac{Number\ \ of\ \ current\ \ Cuckoo\text{'}s\ eggs}{Total\ \ number\ \ of\ \ eggs} \times (\mathrm{var}_{hi} - \mathrm{var}_{low}) \tag{17}$$

where α is an integer, supposed to handle the maximum value of ELR. Another special real habit of Cuckoos is that Cuckoos employ the obligatory brood parasitism by laying their eggs in the nests of other host birds. Unfortunately, if host bird senses that the eggs are not its own, it will either throw them away. These eggs have no chance to grow but rest of the eggs will hatch in the host's nest. In the original CSA [20], 10% of all eggs with less profit values, will be killed but in this paper, a probability technique is applied.

In this technique, Alien eggs which are away from optimal value are detected by host birds with a probability Pa ε [0, 1]. If a random number be smaller than relevant Pa, the target Cuckoo's egg is substituted by a new randomly generated one. Otherwise, the egg grows up and survives for the next generation.

$$\mathrm{Pa} = \left(0.9 \times \mathrm{Fit}_{\mathrm{i}} / \max\left(Fit\right)\right) + 0.1 \tag{18}$$

The Cuckoo eggs hatch slightly earlier than host' eggs. When the first Cuckoo chick is hatched, the initial natural tendency action which it will do, is to drive out the host' eggs by blindly moving the host' eggs outside the nest. Ergo, after a couple of days only Cuckoo' chick stays in the nest because the host bird's own chicks die.

As time passes, the new Cuckoos become mature. Approached this time, Cuckoos migrate to a new better place with more food and more similarity of eggs to host birds. Due to mature Cuckoos exist in all over the ecosystem; it's difficult to distinguish which Cuckoo belongs to which society. To overcome this problem, the K-means clustering technique is applied to extract the categories of all Cuckoos [34]. Now that the Cuckoo groups are constituted, the mean profit or fitness function value for each group is calculated. Then the maximum value of mean profits for Cuckoo groups determines the destination habitat for migrant Cuckoos.

When Cuckoos move toward the goal habitat, they do not fly the whole way. Each Cuckoo flies only L% of the way and also has φ deviation. After all Cuckoos migrated toward the goal habitat, each Cuckoo has got a number of eggs. Hereafter, new egg laying process begins.

5.2. Self-Adaptive Wavelet Mutation Tactic (SAWM)

In order to improve the performance of the original CSA, a novel mighty SAWM tactic is applied. The SAWM tactic provides a balance between exploration and exploitation of the CSA and prevents it to get trapped into the local minima. The SAWM dynamically varies the mutation of population along the search based on the Wavelet theory [35].

For each agent in the SAWM tactic, a mutation probability (P_{mut}) has been allocated and with respect to it, all the elements of each agent in the population will have a chance to be mutated. A mutation on the corresponding agent will be applied if the random number between zero and one is less than P_{mut}. The basic of SAWM tactic is the actuality that the total number of agents in the population tend to move in a similar way with $best\,(k)$ and avoid the route of $worst(k)$ in order to promote their performance. Accordingly, a mutant agent $\left(x^b_{mut,i}(k+1)\right)$ is proposed as:

$$x^b_{mut,i}(k+1)=\begin{cases} x^b_{new,i}(k+1)+\varpi\left(best(k)-x^b_{new,i}(k+1)\right) & if\ \varpi>0 \\ x^b_{new,i}(k+1)+\varpi\left(worst(k)-x^b_{new,i}(k+1)\right) & if\ \varpi\le 0 \end{cases} \tag{19}$$

$$\varpi = \psi_{h,0}(\varphi) = \frac{1}{\sqrt{h}}\psi\left(\frac{\varphi}{h}\right) \tag{20}$$

where $\psi(\varphi)$ is Morlet wavelet and defined as:

$$\psi(\varphi) = \exp\frac{-(\phi)^2}{2}\cos(5\varphi) \tag{21}$$

$$\varpi = \frac{1}{\sqrt{h}}\exp\frac{-\left(\frac{\varphi}{h}\right)^2}{2}\cos\left(5\left(\frac{\varphi}{h}\right)\right) \tag{22}$$

Accordingly, large searching space with large changes in the mutation of agents is caused by a larger value of $|\varpi|$, vice versa. The mutant agent tends to move toward the position of the global best solution if ϖ is positive and withdraws from the position of the worst solution if ϖ is negative.

From this point that over 99% of the total energy of the wavelet function is placed in the interval [−2.5, 2.5], φ located in the interval [−2.5h, 2.5h] and can be randomly procreated. In order to fine-tuning of SAWM, the value of the dilation parameter (h) is varies with respect to time. Hence, the mutation operator for an agent carry outs an extensive search at the early function evaluations and the search is surrounded around the global position at the later function evaluations. Particularly, at the early steps of SAWM, the value of h is small and the maximum value of ϖ is large. Moreover, with the going time the value of h become larger and the maximum value of parameter ϖ will become very small. Accordingly, the value of h is given as:

$$h = \exp^{-\ln(\eta)\times\left(1 - FE\,/\,\mathrm{FE}_{\max}\right)^{\beta} + \ln(\eta)} \tag{23}$$

where, η is the upper bound and β is the shape parameter for the parameter h. The efficiency of the AMCSA is seriously influenced by the parameter β. Hence, in order to create a suitable balance between the exploitation and exploration potency of the proposed adaptive modified Cuckoo search algorithm, the value for parameter β should be selected accurately. Accordingly, in the initial steps of the search, in order to increase the step size of the search, a small value of β should be applied. Moreover, at the end of the search, a large value of parameter β is utilized to fine-tune faster. So, the fowling equation describes the β :

$$\beta = \beta_{\min} + \frac{\beta_{\max} - \beta_{\min}}{\mathrm{FE}_{\max}} \times FE \tag{24}$$

At the end, if the new mutant agent with the fitness value $\left(x_{mut,i}(k+1)\right)$ is less than the fitness value of the existing vector $\left(x_{new,i}(k+1)\right)$, the existing vector should be replaced with a new mutant agent in the SAWM tactic procedure by the following equation:

$$x_{new,i}(k+1) = \begin{cases} x_{mut,i}(k+1) & if \;\; Fit\left(x_{mut,i}(k+1)\right) \le Fit\left(x_{new,i}(k+1)\right) \\ x_{new,i}(k+1) & otherwise \end{cases} \tag{25}$$

5.3. Implementation of AMCSA and 2m+1 PEM on the SMGSWT problem

In this sub-section the step-by-step procedure of the applying the AMCSA algorithm and the proposed *2m+1* PEM to solve the stochastic mid-term generation scheduling problem is presented as follows:

Step 1: Input the initial data of the stochastic seasonal wind-thermal GS problem.

Step2: Apply *2m+1* point estimate method in order to reveal the three concentration locations with their corresponding weighting factors of the wind power generation and the load demand.

Step3: Characterize the set of concentration locations of wind power generation and the load demand for function F with respect to Eq. 1.

Step4: Randomly initialize the habitats for all Cuckoos and their eggs in the population. All agents must satisfy the equality and inequality power system constraints for stochastic seasonal wind-thermal GS problem.

Step5: Lay eggs of Cuckoos in a different location.

Step6: Compute the operation cost for each Cuckoo based on the Eq. (1).

Step7: keep the maximum number of best solutions.

Step8: Employ the *K*-means clustering technique to determine the solution groups.

Step9: Move all solution towards the best solution group.

Step10: Perform self-adaptive Wavelet mutation tactic for all existing Cuckoos. The new agent set must satisfy all constraints of the power system for SMGSWT problem.

Step11: Until the current function evaluation number attains to the pre-determined maximum number of function evaluations, repeat step 5 to step 10.

Step12: Until the whole random input variables are regarded go to step 3.

Step13: Compute the expected total operation cost of power system based on *2m+1* point estimate method.

6. Numerical Examples and Discussions

In this section, three test case studies, which include the 10- unit power system and the modified IEEE 30-bus and the modified IEEE 118-bus system, are studied to demonstrate the effectiveness of the uncertainty analysis and heuristic optimization methods on the proposed SMGSWT model. The simulations for tests cases have been performed on MATLAB 7.10 utilizing a Pentium P4, Dual-core 2.21-GHz personal computer with 6 GB of RAM. The parameters NP, L and α for the adaptive modified Cuckoo search algorithm are selected to 10, 60 and 2, respectively. Moreover, in order to find the convergence of the AMCSA, the mutation probability and parameters η, $\beta_{\max}$ and $\beta_{\min}$ of SAWM tactic are set to 0.01, 1000, 5 and 0.5, respectively. For the entire above mentioned test systems, the AMCSA perform 10 independent runs. The maximum number of Function Evaluations (FE) for AMCSA is set to 10000. The PDFs of the load demand and the wind power generation are taken in to account as a normal distribution. The probability distribution functions of the load demands have been assumed to be normal distribution. Moreover, the probability distribution functions of the wind power generations have been assumed to be normal distribution [36].

6.1. The 10-unit system

For the first test system, a system which has 10 thermal units and two wind farms located on units 11 and 12 is employed. The system is planned for a year. The total load for this test system in the SMGSWT problem is 1500 MW. The data about the 10-unit system is shown in [37]. For the stochastic reserve, the parameter $P_R(t)$ is assumed to be 5% of the total load for each time. Moreover, the parameter SRW is 10% of the total wind power generation for each time interval. The uncertainty of wind power and load demand is evaluated by the 2m+1 point estimate method. Two cases are studied to illustrate the impact of the wind power and the load uncertainty on planning the power system:

Case 1: Deterministic—without network and fuel constraints;

Case 2: Stochastic—without network and fuel constraints;

The commitment and the dispatch of Case 1 are based on the forecasted wind power and load demand data. The operation cost for Case 1 is displayed in Table 1. From this figure in the case 2, the expected operation cost of the proposed *2m+1* PEM is less than 2m and scenario-based methods. The results for dispatching and commitment of the thermal units gained by AMCSA are presented in Table 2. The results demonstrate that without considering the wind power and the load forecasting uncertainties, large and economic coal-burning units are committed and generate the power as much as possible to supply the load in each time interval while the more expensive thermal units are committed and dispatched to balance the system load. In this context, the available wind power in each time interval is fully employed because the wind farms are price-takers.

In Case 2, the variability and uncertainty of wind power generation and the demand, is compensated by the thermal generation units in each time interval. Table 1 shows the operation cost of system in the horizon scheduling for four uncertainty analysis methods including two-stage scenario generation method, 2m and proposed 2m+1 PEM and Monte-Carlo methods. In the two-stage scenario generation method, the first refers to the mid-term scheduling in the commitment and the dispatch of thermal units considering deterministic (mean points) prediction of wind power generation and load demands. The second stage refers to the redispatching of the thermal units for satisfying all operational constraints under the uncertainty of the wind power generation and load demand (represented by a scenario). Comparing to Case 1, the total operation cost of the power system in Case 2 is increased from M$241.87 to M$242.03 by 2m+1 PEM. This is expected due to the fact that deterministic optimization approach call on and use economic coal-burning units more which- cause less robust schedule. Moreover, the case with deterministic approach needs less replacement reserve than the case with a forecast error since the uncertainties in this case are disregarded. In other words, the difference in operating costs between Cases 1 and 2 is the cost of maintaining the power system constraints when taking into account the fluctuations of the wind power and the load in the system. The comparison time results of 2m+1 PEM with other methods reveal the superiority of it than other methods. Addition, the accuracy of the 2m+1 PEM is close to the Monte Carlo method and is better than 2m PEM and two-stage stochastic scenario generation method.

The efficiency of the proposed AMCSA on solving the SMGSWT problem is compared with the performance of original CSA, Teaching Learning Based Optimization (TLBO) [38], Gravitational Search Algorithm (GSA) [39] and the Particle Swarm Optimization (PSO) [37]. The statistical comparative results in the important parameters such as standard deviation, mean, worst, best solutions and the Deviation of the Best (DB) and Deviation of the Worst solutions (DW) [40] for the AMCSA versus the results of other algorithms in solving Case 1 is displayed in Table 3. It is notable that the best results in this table are typed in bold. The supremacy of the AMCSA algorithm is vouched when the mean solutions of the proposed AMCSA are compared with the mean solutions of the other algorithms. Table 3 demonstrates that the AMCSA is capable of attaining a lower cost (M$242.68) with lower SD, DB and DW than the other algorithms. The best solution of the proposed AMCSA without any exception in Table 3 is better than the other algorithms. The corresponding results of AMCSA, CSA, TLBO, GSA and PSO in terms of the SD for case 1 are M$0.038, M$0.167, M$0.319, M$0.364 and M$0.531. Referring to exclusivity of the Wavelet theory reveals the concept of this superiority of the AMCSA in terms of SD. In the Wavelet theory when the number of samples is large and ϕ is randomly produced cause that the summation of the positive values of ϖ and the summation of the negative values of ϖ in the procedure is equal. Thus, in the self-adaptive Wavelet mutation tactic, the total number of positive and the total number of negative generated mutations are approximately equal which causes the low standard deviation value of proposed AMCSA. Comparing the smaller SD of the algorithms, the quality and stability of SAWM tactic to promote the proposed AMCSA on solving the SMGSWT is realized. Ergo, the capability and robustness of the proposed AMCSA to solve the stochastic mid-term wind-thermal GS problem are completely unveiled by these comparisons in Table 3. In order to reveal the capability of AMCSA, a numerical comparison between the proposed AMCSA algorithm and linear programming, nonlinear programming and mixed integer programming is presented in Table 4.

6.2. The IEEE 30-bus system

The IEEE 30-bus system consists of 6 generators and 41 transmission lines in its topology. The more accurate details for this case are given in [41]. It is assumed that a wind farm is located at bus 27. The total system load is 284MW in this system. The system is evaluated in a season with 13 weeks. The following three cases are considered to assay the impact of wind farm on the optimal seasonal generation scheduling of power systems:

Case 1: Deterministic—without network and fuel constraint;

Case 2: Deterministic—with network and fuel constraint;

Case 3: Stochastic—with network and fuel constraint.

For case 1, the load and the wind power generation are taken into account as deterministic quantities and perfected forecasted data is used. In this case, no congestion or fuel constraint and uncertain variables is regarded. . Table 1 shows the operation cost of system in the horizon scheduling for four uncertainty analysis methods including two-stage scenario generation method, 2m and proposed 2m+1 PEM and Monte-Carlo methods in three cases. The total system operation cost for case 1 is K$2,526.782. It is important to say that the solution of deterministic MGSWT is optimal only to a particular mean point and this strategy is not actually optimal for the other points that may occur in the system. Hence, with the huge uncertainties in power generation of the wind farms and high forecast errors of load demand, scheduling power system based on deterministic strategy is not a reliable schedule. If there is congestion in the system, the expected operation costs in Cases 2 would be K$2,557.388. The increasing cost in this case demonstrates the effects of the system congestion. In this regard, due to congestion of the network, the lower cost generation units cannot generate power as much as possible. Hence, the operation cost of the system increases regarding the network constraint. The total operating costs of the power system in horizon scheduling are K$2,572.169 for Case 3. It is evident that $2m+1$ scheme can reach optimal cost with the low SD. It illustrates the high efficiency and the accuracy of $2m+1$ scheme than 2m scheme. Comparison of Cases 2 and 3 shows the effects of demand and wind power uncertainties in the operation costs. Table 6 shows the expected consumption of fuel for the planning of power system in Case 2 and 3 obtained by $2m+1$ PEM. Due to the stochastic strategy sees more points than deterministic approach it should use the more expensive units including oil and gas units.

The stochastic strategy tries to find a solution near optimal deterministic solution when all probable events are taken into account. The stochastic strategy may not be a global optimal solution for perfected forecasted wind power and load demand. However, this strategy is a robust and reliable solution over all probable realizations of the uncertain variables. The scheduling based on $2m+1$ PEM method increases the operation cost of system, since this method sees more points with low wind power and convexity in the supplying demand than the perfected forecast wind power and load points seen by the deterministic method. Moreover, the stochastic generation scheduling with higher cost is more reliable than the deterministic scheduling in the real-time operation of the power system. Table 4 shows the numerical comparison between the proposed AMCSA algorithm and linear programming, nonlinear programming and mixed integer programming. It can be seen that the proposed AMCSA has better performance than other optimization methods.

In this paper, in order to evaluate the remarkable difference between AMCSA and the other optimization algorithms on solving the SMGSWT problem, the t-test approach is applied [42]. In this context, when the first algorithm is better than the second algorithm on solving problem, the t-value will be positive and vice versa. In Table 7, the t-values with 24° of freedom at a 0.05 level of significance are shown for IEEE 30-Bus test system obtained by *2m+1* PEM. Considering the t-values between the AMCSA and the other algorithms, it is realized that the t-values are enormously higher than 1.96. Hence, the AMCSA is significantly better than other algorithms with a 95% confidence level on solving SMGSWT problem.

6.3. The IEEE 118-bus system

A modified IEEE 118-bus test system is used to test the SMGSWT model. The IEEE 118-bus system has 54 units, 186 transmission lines, and 91 demand sides. The power system peak load is 6000 MW. The more accurate details for the IEEE 118-bus case are given in [43]. Five 150 MW wind generation farms are taken into account for this case on buses 12, 31, 66, 72, and 100, respectively. The system is scheduled for a season with 13 weeks. The data for fuel consumption of system and the fuel constraint over thirteen weeks, which are the same for different cases, are given in [44]. The simulations search space has 1339 dimensions for this test system, namely the 49 thermal generators, 5 wind farm and 49 reserve allocation for thermal units in each 13 weeks. The cases under study are same with the IEEE 30-bus system cases.

Table 8 shows the operation cost for assumed cases obtained by all uncertainty analysis methods. Comparing Cases 2 and 1, the system scheduling cost in the case with transmission constraint is higher than one. Moreover, the operation costs of Case 3 are higher than Case 2 due to considering uncertainties of wind power and load demand. Although, considering the uncertainties of wind power and load demand imposes an extra cost on the scheduling of system, it provides a more realistic condition for the scheduling of power system. The comparison time result of 2m+1 PEM is lower than other uncertainty analysis methods. Addition, the accuracy of the 2m+1 PEM is close to the Monte Carlo method and is better than 2m PEM and two-stage stochastic scenario generation method. By this Table the superiority of the 2m+1 PEM than other uncertainty analysis methods is revealed.

Fig. 1 shows the changes in the reserve requirement of the power system over the horizon scheduling for the Case 2 and Case 3. In the proposed SMGSWT model the committed thermal units for stochastic reserve allocation to compensate the uncertainties make the scheduling of system more robust. The difference in the level of reserve allocation considered in the system displays the risk of the power system scheduling in the deterministic strategy. It should be kept in mind that the deterministic and the stochastic strategies for the scheduling use the same forecast wind power and load demand data but the only difference of two strategies is in how they evaluate them to schedule system. In this regard, the deterministic strategy schedules the system with mean point of forecast data, whereas the stochastic strategy schedules the system by the average expected value of variables.

Table 9 shows the expected consumption of fuel in the power system for scheduling horizon obtained by *2m+1* PEM. Fig. 2 shows the change in the number of committed thermal units when using both stochastic and deterministic strategies. It is obvious from this figure that the stochastic and the deterministic strategies would act differently in terms of the number of committed thermal units when the system is scheduled. Thus, when the number of thermal committed units is increased, caused that the system cost will increase due to increasing the operation and maintenance variable costs of system. The optimal system scheduling gained by the AMCSA, is based on that in some weeks the thermal units would be turned on and turn off more frequently to decrease the system cost. It can be seen from Fig. 2 that regarding the wind power and load demand uncertainties causes all thermal units to start-up more frequently in the scheduling.

The statistical indexes which demonstrate the quality analysis of stochastic scheduling strategies such as expected value, the standard deviation of results, the relative error, the 95% confidence intervals, the Value of the Stochastic Solution (VSS) and the coefficient of variation for the operation cost in case 3 are displayed in Table 10. The 95% confidence interval would reflect the uncertainty of power system operation in the scheduling of system. Hence, when the confidence interval is the smaller value, the expected value is more accurate. Also, when this index is smaller we expect that the real-time solution to be closer to the expected value of operation cost. On the other hand, the relative error express the efficiency of the *2m+1* PEM stochastic strategy and a lower rate of the relative error causes the higher efficiency of the *2m+1* PEM stochastic strategy. When no more information about the future can be found, a more useful value may be the difference between the result of using an expected value solution and the recourse problem solution. The parameter VSS allows us to obtain the goodness of the expected solution value when the expected values are replaced by the random values for the input variables. The value of the stochastic solution has been presented as a measure of the benefit received from solving the stochastic recourse problem instead of the deterministic expected value problem. The value of the stochastic solution is normally used to measure the importance of using a stochastic model. The VSS index is defined as how much the operator of system should spend to obtain the occurrence of the wind power and load uncertainties in the future by the stochastic point estimate method when makes seasonal system scheduling. For example, to reveal the load and the wind power generation uncertainties, the system operator would be desired to pay 1.056% more than the deterministic cost when the system is scheduled by SMGSWT model. Table 4 shows the comparison between the proposed AMCSA algorithm and other optimization methods. It can be seen that the proposed AMCSA has better performance than other optimization methods.

The convergence characteristics of the adaptive-modified Cuckoo search algorithm and the other algorithms on solving the Case 2 for IEEE 118-bus system are displayed in Fig. 3. It is obvious from this figure that the adaptive modified Cuckoo search algorithm has the capability to relax the stagnation and skip the local optima on solving SMGSWT. Accordingly, the proposed AMCSA has better efficiency than the other algorithms for SMGSWT problem.

6.4. Empirical distribution of normalized success performance

In this sub-section a figure named the empirical distribution of normalized success performance is presented in order to conclusively compare the overall efficiency of all algorithms on the all test systems [45]. In order to plot this figure the successful runs for all algorithms on solving each test system are initially calculated. Then, based on the Successful Performance (SP) of each algorithm, the ranking of the algorithms on solving SMGSWT problem is computed as follows:

$$SP = mean\,(NFE\ of\ successful runs) \times \frac{Total\ number\ of\ all\ runs}{Number of\ successful runs} \tag{26}$$

If at least one algorithm is successful in at least one run to solve a test system, the results and outcomes of corresponding test systems are utilized on plotting the empirical distribution of normalized success performance figure. Fig. 4 demonstrates the curve of the empirical cumulative distribution for all the test systems on solving SMGSWT problem. In the end, small values of the successful performance and the large values of the empirical distribution in this figure are desirable and higher-ranking on solving SMGSWT problem. An algorithm is the best algorithm with higher proficiency if firstly reaches to the top of the graph than other algorithms. It is obvious from this figure that the empirical distribution of adaptive modified Cuckoo search algorithm reaches digit one with smaller successful performance value. Accordingly, for solving the SMGSWT problems adaptive modified Cuckoo search algorithm has the higher efficiency.

7. Conclusions

The general framework for the mid-term generation scheduling of a wind-thermal system was presented by considering fixed and variable maintenance costs, network and fuel constraints. In the mid-term generation scheduling problem, the intermittent and volatile nature of the wind power and the load uncertainties request for a sophisticated GS formulation in mid-term operation of the wind integrated power system. In this regard, this paper presented a $2m+1$ point estimate method for the mid-term wind-thermal generation scheduling formulation. In order to efficiently solve the probabilistic mid-term wind-thermal generation scheduling problem, the adaptive modified Cuckoo search algorithm was reinforced with the new SAWM tactic based on Wavelet theory. The solution advantages of the stochastic method are that it provides better performance and more reliable decisions on seasonal fuel consumption, reserve allocation, and seasonal usage of thermal units when the uncertainty of the wind power and the load is taken into account. To help operators choose the optimal and realistic operation tool for the mid-term generation scheduling problem, a comprehensive overview and detailed analysis for several uncertainty analysis and optimization methods was presented in this paper. The proposed $2m+1$ PEM indicated that for solving the SMGSWT problem had lower cost than the scenario-based and $2m$ PEM methods. Compared with the other optimization algorithms, the performance of AMCSA was more efficient with better quality solutions.

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FIGURES

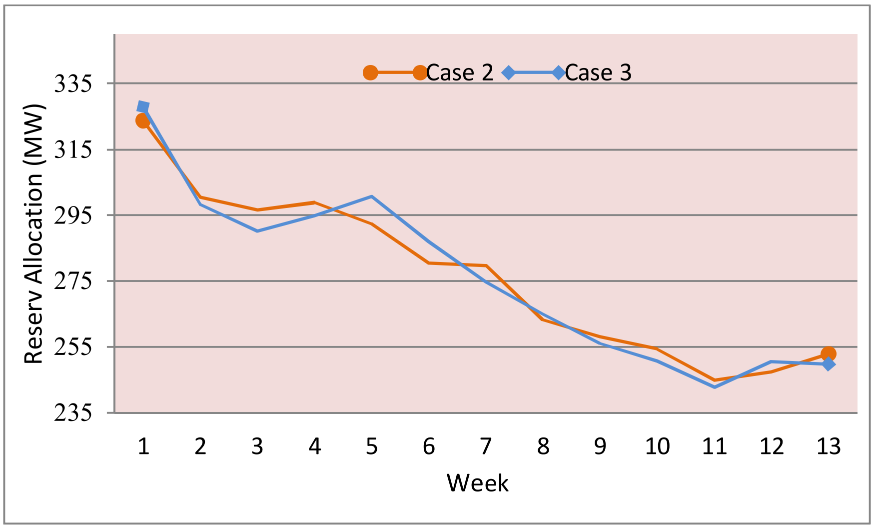

Fig. 1. Reserve allocation for the case 2 and case 3 in IEEE 118 –bus system.

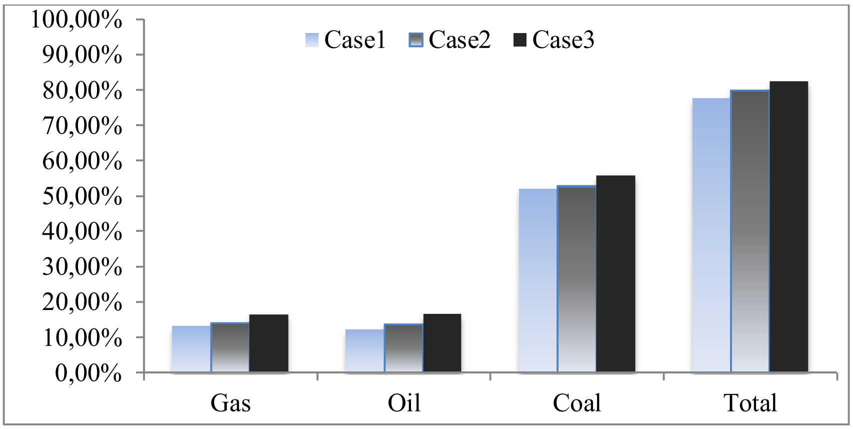

Fig. 2. Percentage change in start units compared to all Cases for 118-bus system

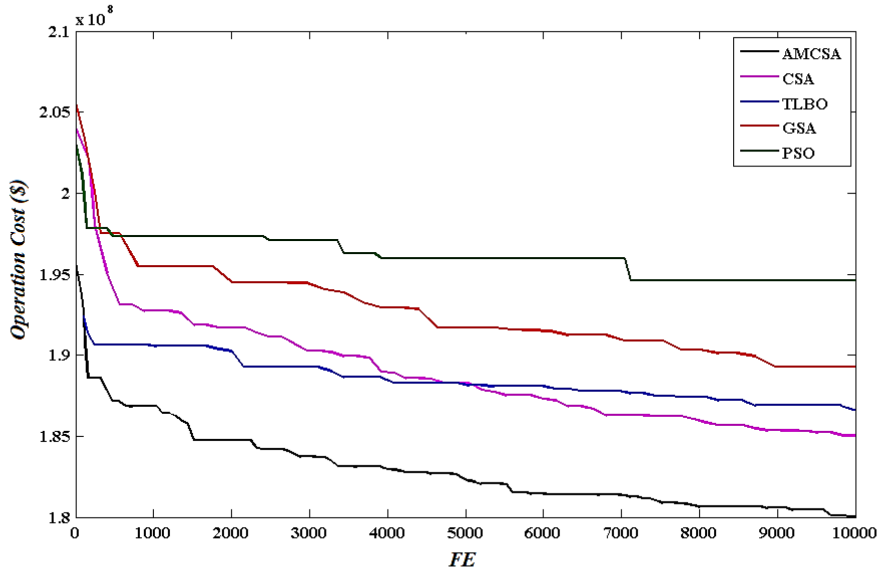

Fig. 3. Convergence characteristics of AMCSA, CSA, TLBO, GSA and PSO for 118-bus system in Case 2

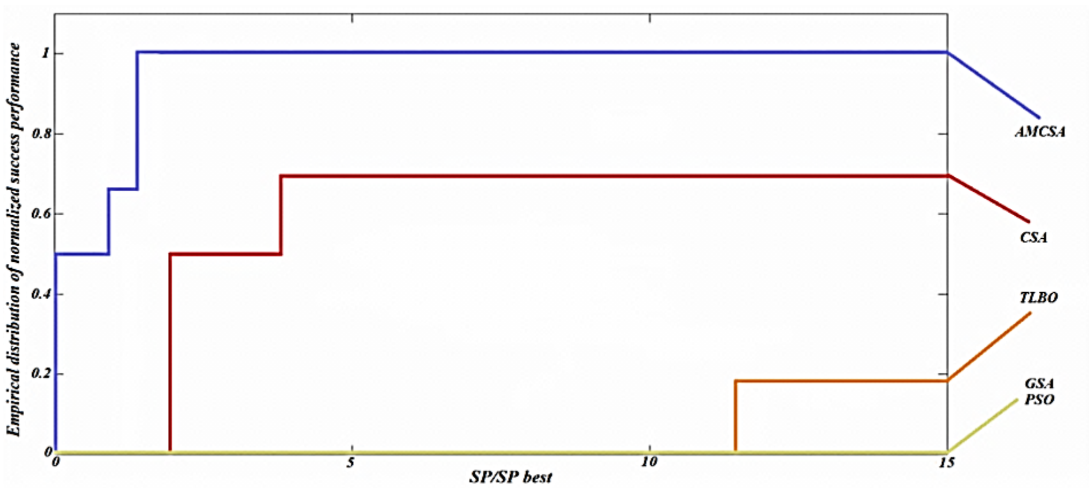

Fig. 4. Empirical distribution of normalized success performance of algorithms

TABLES

Table 1. Total costs for 10-unit system

	Case 1	Case 2							
		Uncertainty Analysis Method							
		Two stage scenario generation		2m PEM		2m+1 PEM		Monte Carlo	
		Expected	%SD	Expected	%SD	Expected	%SD	Expected	%SD
Operation Cost (M$)	241.87	243.94	3.23	242.71	1.24	242.03	0.83	241.92	0.75
Time Computational (Minutes)	4	52		31		36		135	

Table 2. Optimal scheduling result for 10-unit system in Case 1 found by AMCSA (MW)

Time	Power Generation of Units (MW)									
	Unit 1	Unit 2	Unit 3	Unit 4	Unit 5	Unit 6	Unit 7	Unit 8	Unit 9	Unit 10
1	455	340	126	112	32	78	50	55	33	22
2	454	351	130	130	159	21	0	0	0	54
3	454	292	104	129	43	70	0	0	0	0
4	394	453	91	124	12	0	0	33	0	0
5	454	455	130	114	98	0	0	55	0	0
6	410	455	129	130	97	0	44	0	0	55
7	455	442	129	95	111	52	0	0	0	15
8	454	454	39	21	60	24	83	24	0	0
9	407	449	130	130	25	0	0	0	0	0
10	455	455	129	130	95	0	0	35	0	0
11	453	342	28	128	155	80	84	55	54	0
12	455	343	130	130	162	73	0	55	54	55

Table 3. Algorithm results for 10-unit system in Case 1

Solution Technique	Total Operation Cost (M$)					
	Best	Mean	Worst	SD	DB (%)	DW (%)
PSO-IWA [14]	251.37	254.37	257.39	0.531	1.17	1.18
GSA	250.73	253.23	255.48	0.364	0.98	0.88
TLBO	246.91	247.95	249.33	0.319	0.41	0.55
CSA	245.35	246.09	247.43	0.167	0.30	0.54
AMCSA	**242.03**	**242.68**	**243.64**	**0.038**	**0.26**	**0.39**

Table 4. Comparison results between optimization methods for various test systems

Optimization method	Test system 1		Test system 2			Test system 3		
	Operation Cost (M$)		Operation Cost (K$)			Operation Cost (M$)		
	Case 1	Case 2	Case 1	Case 2	Case 3	Case 1	Case 2	Case 3
Linear programming	241.93	242.09	2,526.789	2,557.392	2,572.173	178.4272	180.3299	182.240
Nonlinear programming	241.97	242.15	2,526.793	2,557.396	2,572.178	178.4279	180.3304	182.244
Mixed integer programming	242.103	242.19	2,526.798	2,557.399	2,572.182	178.4283	180.3308	182.249
Proposed AMCSA	**241.87**	**242.03**	**2,526.782**	**2,557.388**	**2,572.169**	**178.4267**	**180.3294**	**182.235**

Table 5. Total costs for 30-bus system

	Case 1	Case 2	Case 3							
			Uncertainty Analysis Method							
			Two stage scenario generation		2m PEM		2m+1 PEM		Monte Carlo	
			Expected	%SD	Expected	%SD	Expected	%SD	Expected	%SD
Operation Cost (K$)	2,526.782	2,557.388	2,585.394	24.35	2,581.523	18.45	2,572.169	15.34	2,569.43	9.34
Time Computational (Minutes)	2	3	37		23		26		96	

Table 6. Fuel consumption for IEEE 30-bus system obtained by 2m+1 PEM

Fuel (MBtu)	Coal	Oil	Gas
Case 2	1,2440,880	1,746,289	174,628
Case 3	1,220,880	1,764,976	180,341

Table 7. t-value between AMCSA and other algorithms for IEEE 30-bus system obtained by 2m+1 PEM

Case	t-value Between AMCSA and PSO	t-value between AMCSA and GSA	t-value between AMCSA and TLBO	t-value between AMCSA and CSA
Case 2	76.18	38.25	30.55	24.86

Table 8. Total costs for 118-bus system obtained by *2m+1* PEM.

	Case 1	Case 2	Case 3							
			Uncertainty Analysis Method							
			Two stage scenario generation		2m PEM		2m+1 PEM		Monte Carlo	
			Expected	%SD	Expected	%SD	Expected	%SD	Expected	%SD
Operation Cost (M$)	178.4267	180.3294	185.634	3.235	184.750	2.853	182.235	1.548	181.874	1.023
Time Computational (Minutes)	8	10	93		69		74		246	

Table 9. Fuel consumption for IEEE 118-bus system obtained by 2m+1 PEM

Fuel (MBtu)	Coal	Oil	Gas
Case 2	111,543,623	9,651,490	8,454,933
Case 3	108,475,858	9,672,767	8,704,335

Table 10. Statistical results of stochastic scheduling strategy for IEEE 118-bus system obtained by 2m+1 PEM

Test Case	Total Operation Cost (M$)				Relative Error (%)	Coefficient of Variation (%)
	Expected	SD	0.95% Confidence Intervals	VSS (%)		
Case 3	182.235	1.09	1.23	1.056	0.674	0.598