Electric Power Systems Research 173 (2019) 193–201

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Stochastic multi-objective dynamic dispatch of renewable and CHP-based islanded microgrids

Pouya Pourghasem, Farnaz Sohrabi, Mehdi Abapour, Behnam Mohammadi-Ivatloo*

Faculty of Electrical and Computer Engineering, University of Tabriz, Tabriz, Iran

ARTICLE INFO

Keywords:
Stochastic optimization
Economic emission dispatch
Reliability
Combined heat and power
Exchange market algorithm (EMA)
Microgrid (MG)

ABSTRACT

Micro-grids (MGs) are practical solutions for integrating distributed energy resources (DERs) in order to supply electrical and heat demands. In this study, a stochastic model for optimal management of combined heat and power (CHP)-based MGs considering economic, environmental and reliability aspects have been proposed. Two sources of uncertainty including forecast errors of electrical load demand and wind power are considered in scenario generation process using roulette wheel mechanism. Availabilities of units are taken into account to model reliability using capacity outage probability table (COPT). For solving such non-linear, non-convex and complicated stochastic problem, exchange market algorithm (EMA) and the weighted sum method are employed for combining three conflicting objectives and solving multi-objective problem as a single objective problem. Fuzzy satisfying method is applied to choose best compromise solution. The main goal of the stochastic dynamic reliable economic emission dispatch (SDREED) problem is to determine output of each generating unit so that fuel cost and amount of emission are minimized while the electrical demand is provided by more reliable units and operational constraints are met. The output of stochastic problem gives better sight for generation scheduling of MGs. The obtained results show the effectiveness and ability of the proposed method in solving SDREED.

1. Introduction

Micro-grids (MGs) are defined as reasonable solutions for combining distributed energy resources (DERs) for meeting heat and power load demands, which can be operated in grid-connected or islanded modes. Taking into account a MG combined with DERs, such as conventional thermal plants, combined heat and power (CHP) units, boilers, and renewable energy sources, significant improvements in cost saving and pollutant gas emissions can be attained [1,2]. The application of CHP units in supplying power and heat demands takes advantages in both economic and environmental viewpoints, which shows a significant improvement in cost saving of typical 10–40% [3], and reduction in pollutant gas emissions almost 13–18% [4]. Renewable energy sources play an important role in supplying load demand of MGs as natural and continuous sources, which are environmentally friendly and show uncertainty and variability [5].

Optimal scheduling problems absorbed remarkable efforts in recent publications. Solving economic dispatch of CHP-based systems with the aid of an improved genetic algorithm using novel crossover and mutation (IGA-NCM) has been studied in Ref. [6]. Authors in Ref. [7] have proposed a new algorithm by hybridizing Bat Algorithm (BA) and Artificial Bee Colony (ABC) with Chaotic-based Self-Adaptive (CSA) search strategy (CSA-BA-ABC) to solve combined heat and power economic dispatch. The proposed new algorithm eliminates disadvantages of BA and ABC. In Ref. [8], stochastic short-term scheduling of MG, which includes photovoltaic (PV) system, wind turbine and CHP units, is studied considering uncertainties associated with power market price and power generation of renewable energy sources. In this reference, roulette wheel mechanism is used for generating scenarios, and particle swarm optimization (PSO) method is employed for obtaining the minimum operational cost of the MG. Stochastic short-term scheduling of renewable-based MGs is studied in Ref. [9] proposing a new model for battery operating cost, where the efficiencies and cycle lives of batteries are maximized. A two stage framework is proposed in Ref. [10] for obtaining optimal solution of stochastic MG economic dispatch using scenario-based modeling method for uncertainties of wind power, PV system and power market price. In which, the first stage produces scenarios using probability distribution function (PDF) and roulette wheel mechanism, and the second stage employs an adaptive modified firefly algorithm (AMFA) to solve the problem. A home energy system consisting of CHP plant, fuel cell (FC), and energy storage system (ESS) is studied in Ref. [11] in order to provide optimal generation scheduling of the units for supplying heat and power load demand.

In addition, several researches are concentrated on the solution of

* Corresponding author.
E-mail addresses: pouya.pourghasem95@ms.tabrizu.ac.ir (P. Pourghasem), farnaz_sohrabi95@ms.tabrizu.ac.ir (F. Sohrabi), abapour@tabrizu.ac.ir (M. Abapour), bmohammadi@tabrizu.ac.ir (B. Mohammadi-Ivatloo).

https://doi.org/10.1016/j.epsr.2019.04.021
Received 15 May 2018; Received in revised form 10 March 2019; Accepted 16 April 2019
Available online 01 May 2019
0378-7796/

Nomenclature

Indices

i, j, k Power-only, CHP and boiler units indices, respectively
i', j' Indices for members of first and second group of shareholders
l Load demand interval index
m Wind power interval index
OF, p Indices for objective functions and Pareto optimal solutions, respectively
r Index related to COPT states
s Scenario index
t Time interval index
nw Wind turbine index

Constants

$a_j, b_j, c_j, d_j, e_j, f_j$ Cost coefficients of jth CHP unit
a_j' Emission coefficient of jth CHP unit
a_k, b_k, c_k Cost coefficients of kth boiler
a_k' Emission coefficient of kth boiler
C, E Fuel cost and emission functions related to generator units
$g_1, g_{1,max}, g_{1,min}$ Market risk value, maximum and minimum limits of it related to second group, respectively
$g_2, g_{2,max}, g_{2,min}$ Market risk value, maximum and minimum limits of risk value related to third group, respectively
$H_{D,t}$ Heat demand at time t
$H_j^{c,min}, H_j^{c,max}$ Minimum and maximum output heat of jth CHP unit
$H_k^{h,min}, H_k^{h,max}$ Minimum and maximum output heat of kth boiler
$iter_c, iter_{max}$ Current iteration and maximum iterations, respectively
$n_{i'}, n_{j'}$ Total number of members of first and second group of shareholders
N_p, N_c, N_h Total number of power-only, CHP and boiler units, respectively
N_s Total number of scenarios
n_{t_1} Shares of tth member of second group before trading
$n_{t_2}, \Delta n_{t_2}$ Amount of shares after trading and amount of shares must be sold, respectively
N_T Total time intervals
N_w Total number of wind turbines
$OC_r, prob_r$ Outage capacity and respective probability related to rth state in COPT
P Total number of Pareto optimal solutions
$P_{D,t,s}$ Load demand at time t in scenario s
$P_{D,t}^{forecasted}$ Forecasted load demand at time t
$P_j^{c,min}, P_j^{c,max}$ Minimum and maximum output power of jth CHP unit
$P_i^{p,min}, P_i^{p,max}$ Minimum and maximum output power of ith power-only unit
$P_{nw,t,s}$ Output power of nwth wind turbine at time t in scenario s
$P_{nw,t}^{forecasted}$ Forecasted output of nwth wind turbine at time t
P_{nw}^{max} Maximum output power of nwth wind turbine
$pop_{1,i'}^{group\,(1)}, pop_{2,i'}^{group\,(1)}$ The two members of first group of shareholders
$pop_{j'}^{group\,(2)}$ The j'th member of second group of shareholders
$pop_{k'}^{group\,(3)}$ The k'th member of third group of shareholders
rnd Random number between 0 and 1
$S_{k'}$ Share variations of k'th member of third group of shareholders
S_{ty} Shares of tth member
t_{pop}, n_{pop} Numbers of tth and last member in the market, respectively
$V_{nw}^{CI}, V_{nw}^{CO}, V_{nw}^{R}$ Cut-in, cut-off and rated speed of nwth wind turbine
$V_{nw,t}^{forecasted}$ Forecasted wind speed for nwth wind turbine at time t
w_1, w_2, w_3 Weighting coefficients related to weighted sum method
$W_{l,t,s}^{D}$ Binary parameter related to lth interval of load demand at time t in scenario s
$W_{m,t,s}^{w}$ Binary parameter related to mth interval of wind power at time t in scenario s
$\alpha_i, \beta_i, \gamma_i, \varphi_i$ Cost coefficients of ith power-only unit
$\alpha_i', \beta_i', \gamma_i', \lambda_i', \rho_i'$ Emission coefficients of ith power-only unit
$\alpha_{l,t}$ Probability of lth load demand interval at time t
$\beta_{m,t}$ Probability of mth wind power interval at time t
δ Information about market that as equal to sum of shares of second group
η_1, η_2 Risk level for second and third groups members, respectively
μ_1, μ_2 Risk increase coefficients for second and third groups, respectively
π_s Probability of scenario s
$\Delta n_{t_1}, \Delta n_{t_3}$ Amount of randomly added shares to second and third groups, respectively
$\Delta P_{D,t,s}$ Forecast error of load demand at time t in scenario s
$\Delta P_{nw,t,s}$ Forecast error of nwth wind turbine at time t in scenario s

Variables

$F_{EENS}, EENS$ Amount of expected energy not supplied (EENS)
$F_{emission}$ Amount of pollutant gas emission
$F_{generation}$ Cost of electricity generating
$F_{OF}^{min}, F_{OF}^{max}$ Minimum and maximum values of objective function OF
$H_{j,t,s}^{c}, H_{k,t,s}^{h}$ Output heat of jth CHP unit and kth boiler unit at time t in scenario s, respectively
$P_{i,t,s}^{p}, P_{j,t,s}^{c}$ Output power of ith power-only unit and jth CHP unit at time t in scenario s, respectively
$\Phi_{normalized}^{p}$ normalized membership function for pth solution
Φ_{OF}^{p} Fuzzy membership function for objective function OF in pth point of Pareto set

multi-objective MG economic dispatch with different competing objectives considering operational cost, pollutant gas emissions and reliability aspects. The authors studied multi-objective economic emission dispatch of MG including micro turbines, PV unit, wind turbine, fuel cell (FC), and electrical energy storage system in Ref. [12]. In this study, the normal boundary intersection (NBI) is employed for obtaining Pareto optimal solutions, and a fuzzy satisfying concept is used in order to obtain the best compromise solution. Multi-objective combined heat and power unit commitment problem is studied in Ref. [13]. Economic and environmental aspects are considered in objective function in the above mentioned paper. In Ref. [14], a modified bacterial foraging optimization method is proposed for optimal economic environmental solution of a MG consisting of DERs, CHP units, energy storage system. An intelligent energy management system is introduced in this reference for optimal operation of the MG, where a fuzzy satisfying method is applied to obtain a compromise solution. Daily multi-objective scheduling of CHP-based MGs is studied by using firefly algorithm (FA) in Ref. [15], where valve-point effects of thermal plants, ramp-rate limits, and spinning reserve are considered. The authors studied the multi-objective economic emission dispatch of MGs consisting of electric vehicles (EVs) in Ref. [16] using an improved particle swarm optimization algorithm. Multi-objective dispatch of CHP-fuel cell (FC)-based MGs is studied using ε-constraint technique and a fuzzy satisfying method in Ref. [17]. Authors of Ref. [18] implemented cuckoo search algorithm (CSA) into multi-objective problem considering fuel cost, emission and reliability functions. In this reference, capacity outage probability table (COPT) is used to calculate expected energy not supplied (EENS) as reliability index and Fuzzy set theory is applied to select the best compromise solution.

A series of uncertainty parameters associated with MGs and CHP-based systems have been studied in recent publications, which include electrical energy price, power and heat demands, and power generation output of renewable energy sources. Stochastic scheduling of CHP-based MGs is accomplished using scenario-based modeling method in Ref. [19], where the uncertainties of wind turbine power output, power price, and MG load are studied. In Ref. [20], information gap decision theory (IGDT) approach is utilized for solving the unit commitment problem of CHP units considering the uncertainty of electrical energy transfer of market. Optimal design of CHP-based energy hubs is studied in Ref. [21] employing a two-stage stochastic mixed-integer linear programming based on Monte Carlo simulation method. A new modified bacterial foraging optimization (MBFO) is applied in Ref. [22] for studying the stochastic energy management of MGs considering wind speed uncertainty, where the wind speed is forecasted using artificial neural network and probabilistic method of confidence interval is used for using the forecasted parameters. A robust optimization-based framework is proposed in Ref. [23] to insure optimal operation of a CHP-based system in the presence of load uncertainties. In addition, robust optimization has been utilized in Ref. [24] to solve optimal power and heat generation scheduling of a CHP-based MG considering power market price uncertainty.

Optimal scheduling of CHP-based MGs with regard to economic, environmental and reliability aspects by considering uncertainties related to electrical load demand and wind power is not investigated in the literature. Due to the importance of uncertainties in MGs, stochastic dynamic reliable economic emission dispatch (SDREED) of a CHP-based MG is studied in this paper. Additionally, a scenario-based method is applied for handling uncertainties associated with electrical load demand and power generation of wind turbine. COPT is employed in order to deal with availability of CHP units and conventional thermal plants. Also, it has been used to calculate EENS as reliability index. Weighted sum method is used to obtain single objective problem.

The SDREED is a large scale, non-linear, non-convex and complicated problem. Due to inability of mathematical methods in solving such complicated problems [7], Meta-heuristics algorithms have been proposed. In this paper, exchange market algorithm (EMA), which is based on the behavior of shareholders in the stock market, is utilized for optimization purpose due to its approved capability in solving non-linear, non-convex, non-smooth and complex optimization problems. EMA is successfully applied for obtaining the optimal solution of power system problems such as capacitor bank placement [25], CHP economic dispatch (CHPED) problem [26,27], economic load dispatch [28], economic and emission dispatch in electrical energy systems [29], optimal chiller loading [30] and reactive power dispatch [31]. EMA is utilized to solve optimization problem including minimization of the generation cost, pollutant gas emission, and EENS. Pareto optimal solutions are provided using different weighting coefficients. Finally, the best compromise solution is obtained using Fuzzy satisfying method. The main contributions of this research are listed as follow:

- Considering generation cost, pollutant gases emission and reliability terms in the objective function of a CHP-based MG scheduling.
- Solving multi-objective stochastic dynamic reliable economic emission dispatch for a CHP-based MG.
- Reliability analysis of a CHP-based MG dispatch is accomplished considering EENS index.
- Taking into account the uncertainties of load demand and wind power in the multi-objective CHP-based MG scheduling problem.
- Implementing EMA into the SDREED problem.

The rest of this paper is organized as follows: Section 2 introduces uncertainty model used in this paper. Section 3 studies problem formulation of SDREED. The proposed solution method is described in Section 4. Simulation results and discussions are reported in Section 5. Finally, the paper is concluded in the last section.

2. Stochastic model

In order to implement stochastic model in this paper, scenario generation and scenario reduction approaches are implemented. The principles of these techniques are explained in the following.

2.1. Scenario generation

Electrical load demand of MG and output power of wind turbine are two sources of uncertainty. Hence, forecast errors of load demand and wind power are taken as random variables with specific probability density functions (PDF). Afterwards, roulette wheel mechanism is used to generate scenarios [32]. The associated load demand and wind power for each scenario is as follows:

$$P_{nw,t,s} = P_{nw,t}^{forecasted} + \Delta P_{nw,t,s};\ nw = 1, \ldots, N_w;\ t = 1, \ldots, N_T;\ s = 1, \ldots, N_s \tag{1}$$

$$P_{D,t,s} = P_{D,t}^{forecasted} + \Delta P_{D,t,s};\ t = 1, \ldots, N_T;\ s = 1, \ldots, N_s \tag{2}$$

In this research work, the PDF function of the load forecast error is considered as normal distribution function, while Weibull distribution function is selected for the wind power forecast error. The PDF of each random variable is discretized into seven intervals as shown in Fig. 1 for normal PDF.

As shown in this figure, intervals are centered on zero mean, width of each interval is equal to σ, the standard deviation of forecast error for each random variable and probability of interval l is equal to $\alpha_{l,t}$. Probability of each interval is normalized in such a way that the sum of the probabilities becomes equal to 1. After that, accumulated probability for each interval is calculated as depicted in Fig. 2.

Therefore, we have a binary vector for each scenario comprising of binary parameters of intervals for each random variable:

$$Scenarios = [W_{1,t,s}^{D}, \ldots, W_{7,t,s}^{D},\ W_{1,t,s}^{w}, \ldots, W_{7,t,s}^{w}]_{N_S \times (14 \times N_T)} \tag{3}$$

In order to generate a scenario, for each random variable a random number in the interval $[0,\ 1]$ is generated and the binary parameter of first interval with accumulated probability less than or equal to the random number becomes equal to 1 while the others are equal to 0. The probability of each scenario is calculated using:

$$\pi_s = \frac{\prod_{t=1}^{N_T} (\sum_{l=1}^{7} (W_{l,t,s}^{D} \times \alpha_{l,t}) \sum_{m=1}^{7} (W_{m,t,s}^{w} \times \beta_{m,t}))}{\sum_{s=1}^{N_s} \prod_{t=1}^{N_T} (\sum_{l=1}^{7} (W_{l,t,s}^{D} \times \alpha_{l,t}) \sum_{m=1}^{7} (W_{m,t,s}^{w} \times \beta_{m,t}))} \tag{4}$$

2.2. Scenario reduction

In order to achieve better modeling of uncertainties, a large number

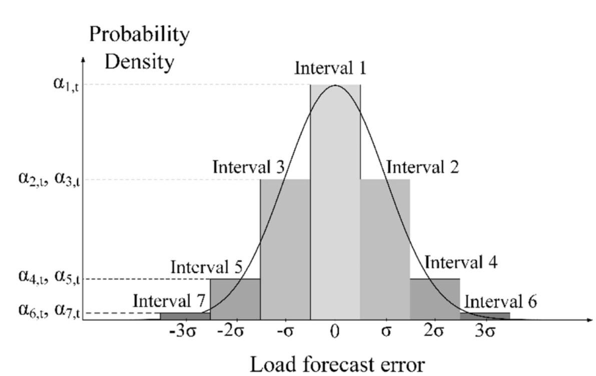

Fig. 1. Discretized PDF for load forecast error.

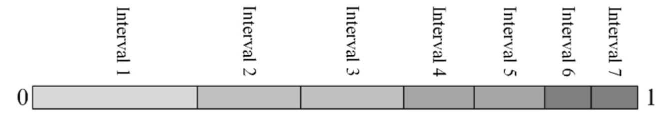

Fig. 2. Accumulated normalized probabilities for roulette wheel mechanism.

of scenarios should be generated that increases the time of computation. Thus, scenario reduction techniques are employed to decrease total number of scenarios by omitting repetitive or low probable scenarios [10]. In this paper, simultaneous backward method is used as scenario reduction technique. To explain principles of this method consider a scenario set Ω_s containing N_s scenarios, each with probability of occurrence (π_s), that distance between two scenario pairs (s, s') is indicated by $DT_{s,s'}$ [33]. In this method scenarios are omitted until desired number of reduced scenarios are achieved using these steps:

Step 1: Consider Ω_d as deleted set of scenarios. The distances between all scenario pairs should be computed using: $DT_{s,s'} = \sqrt{\sum_{i=1}^{all\ scenario\ pairs} (v_i^s - v_i^{s'})^2}$

Step 2: For each scenario k, find the scenario r that has minimum distance with scenario k:

$r = \arg\{DT_{k,r}{=}\min DT_{k,s'}\};\ k, s' \in \Omega_s,\ s' \neq k$

Step 3: Calculate $PD_{k,r} = \pi_k \times DT_{k,r}$ for all $k \in \Omega_s$ and find $d = \arg\{PD_d{=}\min PD_{k,r}\};\ k \in \Omega_s$

Step 4: $\Omega_s = \Omega_s - \{d\}$, $\Omega_d = \Omega_d + \{d\}$, $\pi_r = \pi_r + \pi_d$.

Step 5: Repeat steps 2–4 until desired number of reduced scenarios are achieved.

3. SDREED problem formulation

In this section, the formulation of SDREED problem is presented.

3.1. Objective functions

A CHP-based MG is considered comprising of conventional power-only units, boilers, CHP generators and wind turbines. Generation cost, pollutant gas emission and EENS related to above mentioned units as three objectives of this problem can be formulated as follows:

$$F_{generation} = \sum_{i=1}^{N_p} C_i(P_{i,t,s}^p) + \sum_{j=1}^{N_c} C_j(P_{j,t,s}^c, H_{j,t,s}^c) + \sum_{k=1}^{N_h} C_k(H_{k,t,s}^h) \tag{5}$$

$$F_{emission} = \sum_{i=1}^{N_p} E_i(P_{i,t,s}^p) + \sum_{j=1}^{N_c} E_j(P_{j,t,s}^c, H_{j,t,s}^c) + \sum_{k=1}^{N_h} E_k(H_{k,t,s}^h) \tag{6}$$

$$F_{EENS} = EENS \tag{7}$$

3.1.1. Generation cost functions

The cost of the power-only unit i at time t in scenario s is considered as a function of the generated power [34]:

$$C_i(P_{i,t,s}^p) = \varphi_i(P_{i,t,s}^p)^3 + \alpha_i(P_{i,t,s}^p)^2 + \beta_i P_{i,t,s}^p + \gamma_i \tag{8}$$

The generation cost of CHP units is a function of generated heat and electrical powers. The operation cost function of CHP unit j at time t considering the sth scenario is as follows [34]:

$$C_j(P_{j,t,s}^c, H_{j,t,s}^c) = a_j(P_{j,t,s}^c)^2 + b_j P_{j,t,s}^c + c_j + d_j(H_{j,t,s}^c)^2 + e_j H_{j,t,s}^c + f_j P_{j,t,s}^c H_{j,t,s}^c \tag{9}$$

The cost function of boilers can be formulated as [34]:

$$C_k(H_{k,t,s}^h) = a_k(H_{k,t,s}^h)^2 + b_k H_{k,t,s}^h + c_k \tag{10}$$

3.1.2. Emission functions

Pollutant gas emission functions for power-only, CHP and boiler units can be respectively formulated as:

$$E_i(P_{i,t,s}^p) = \alpha_i'(P_{i,t,s}^p)^2 + \beta_i' P_{i,t,s}^p + \gamma_i' + \lambda_i' \exp(\rho_i' P_{i,t,s}^p) \tag{11}$$

$$E_j(P_{j,t,s}^c, H_{j,t,s}^c) = a_j' P_{j,t,s}^c \tag{12}$$

$$E_k(H_{k,t,s}^h) = a_k' H_{k,t,s}^h \tag{13}$$

3.2. Expected energy not supplied

In this research work, EENS is considered as reliability index to study the effect of availability of units in the dispatch problem. In order to calculate amount of EENS, COPT is computed and the amount of reliability index is obtained using (14) [18]:

$$EENS = \sum_{r \in COPT} OC_r \times prob_r \tag{14}$$

3.3. Constraints

The total generated electrical and heat powers should satisfy the electrical and heat power balance constraints as in (15) and (16), respectively:

$$\sum_{i=1}^{N_p} (P_{i,t,s}^p) + \sum_{j=1}^{N_c} (P_{j,t,s}^c) + P_{w,t,s} = P_{D,t,s} \quad \forall\ t,\ \forall\ s \tag{15}$$

$$\sum_{j=1}^{N_c} (H_{j,t,s}^c) + \sum_{k=1}^{N_h} (H_{k,t,s}^h) = H_{D,t} \quad \forall\ t,\ \forall\ s \tag{16}$$

Moreover, the minimum and maximum limits for output electrical and heat powers related to power-only, CHP and boiler units should be considered:

$$P_i^{p,min} \leq P_{i,t,s}^p \leq P_i^{p,max} \tag{17}$$

$$P_j^{c,min}(H_{j,t,s}^c) \leq P_{j,t,s}^c \leq P_j^{c,max}(H_{j,t,s}^c) \tag{18}$$

$$H_j^{c,min}(P_{j,t,s}^c) \leq H_{j,t,s}^c \leq H_j^{c,max}(P_{j,t,s}^c) \tag{19}$$

$$H_k^{h,min} \leq H_{k,t,s}^h \leq H_k^{h,max} \tag{20}$$

It should be noted that the produced power and heat by the CHP units have mutual dependency. Fig. 3 shows and example of dual dependency between generated power and heat by a CHP unit.

3.4. Wind turbine modeling

Power generation of wind turbine is a function of wind speed, which is formulated as follows [35]:

$$P_{nw,t}^{forecasted} = \begin{cases} 0 & V_{nw,t}^{forecasted} > V_{nw}^{CO} \text{ or } V_{nw,t}^{forecasted} < V_{nw}^{CI} \\ P_{nw}^{max} \times \left(\dfrac{V_{nw,t}^{forecasted} - V_{nw}^{CI}}{V_{nw}^{R} - V_{nw}^{CI}}\right) & V_{nw}^{CI} \leq V_{nw,t}^{forecasted} < V_{nw}^{R} \\ P_{nw}^{max} & V_{nw}^{R} \leq V_{nw,t}^{forecasted} < V_{nw}^{CO} \end{cases} \tag{21}$$

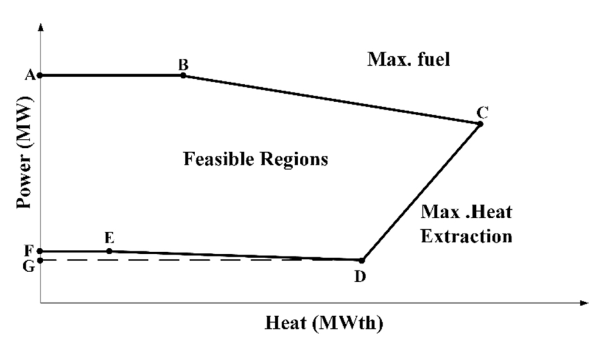

Fig. 3. Heat-power feasible operation region for a CHP unit.

4. Solution methodology

The SDREED is a multi-objective optimization problem. Among different proposed methods for solving multi-objective problems, the weighted sum method is used in this paper. Due to different range of objective functions variations, all of them should be normalized [36]. The objective function of SDREED problem can be stated as:

$$\min OF = \sum_{s=1}^{N_s} \pi(s) \sum_{t=1}^{N_T} (w_1 \times F_{generation} + w_2 \times F_{emission} + w_3 \times F_{EENS}) \tag{22}$$

where the multi-objective SDREED problem is converted to single objective problem using weighted sum method and is solved by Exchange market algorithm. It should be noted that sum of the weighting coefficients is equal to 1:

$$w_1 + w_2 + w_3 = 1 \tag{23}$$

In the next step, different Pareto optimal solutions are obtained for different weighting coefficients. To select the best compromise solution among all Pareto optimal solutions, the Fuzzy satisfying method is employed.

4.1. Exchange market algorithm

EMA is an effective optimization method that is inspired of selling and purchasing shares in the stock market [37]. EMA is widely used in the literature [26,28] due to better performance compared to other heuristic methods. In this algorithm, the decision variables of the problem are assumed as shares of shareholders. There are three groups of shareholders that participate in the market by purchasing and selling their shares using specific equations. First group consists of 10–30% of total shareholders. Members in this group are the best solutions and do not trade their shares. Second group comprises 20–50% of total population. These shareholders try to improve their shares considering share values of members of the first group. Hence, they are responsible for finding local optimal points. Finally, the rest of shareholders are placed in the third group. Members in this group take more risks to search in a wider space. Thus, they are looking to find global optimal points.

Two market modes are considered that increase the efficiency of the algorithm and its convergence speed. First, the oscillations are not considered in the market. So, shareholders of the second group try to change their shares using:

$$pop_{j'}^{group\,(2)} = rnd \times pop_{1,i'}^{group\,(1)} + (1 - rnd) \times pop_{2,i'}^{group\,(1)} \qquad i' = 1, \dots, n_{i'},\ j' = 1, \dots, n_{j'} \tag{24}$$

According to this equation, each member of the second group tries to improve its fitness value by using experiences of two members of the first group. The equations for share trading in the third group can be stated as:

$$S_{k'} = 2 \times rnd_1 \times (pop_{1,i}^{group\,(1)} - pop_{k'}^{group\,(3)}) + 2 \times rnd_2 \times (pop_{2,i}^{group\,(1)} - pop_{k'}^{group\,(3)}) \tag{25}$$

$$pop_{k'}^{group\,(3),\,new} = pop_{k'}^{group\,(3)} + 0.8 \times S_{k'} \tag{26}$$

Members in the third group use the differences of theirs shares with the shares of two members of the first group. Additionally, as stated in (26), they utilize their own shares to improve their fitness values.

In the second market mode, oscillations are taken into account. In this situation, members try to take more risks. Equations for the second group members are as follows:

$$\Delta n_{t_1} = n_{t_1} - \delta + (2 \times rnd \times \mu_1 \times \eta_1) \tag{27}$$

$$\mu_1 = \frac{t_{pop}}{n_{pop}} \tag{28}$$

$$n_{t_1} = \sum_{y=1}^{n} |S_{ty}| \tag{29}$$

$$\eta_1 = n_{t_1} \times g_1 \tag{30}$$

$$g_1^k = g_{1,max} - \frac{g_{1,max} - g_{1,min}}{iter_{max}} \times iter_c \tag{31}$$

$$\Delta n_{t_2} = n_{t_2} - \delta \tag{32}$$

According to these equations, risk is taken into account in the oscillation mode. In (28), μ_1 is a constant for each shareholder which increases as the algorithm moves toward lower ranked shareholders. As a result, these shareholders take more risks to improve their rank. In addition, as the iteration number increases, the market risk value (g_1) decreases and shareholders take less risks. It should be noted that total shares of members in the second group are constant as mentioned in (32). Members in the third group also try to buy and sell shares using following equations:

$$\Delta n_{t_3} = 4 \times (0.5 - rnd) \times \mu_2 \times \eta_2 \tag{33}$$

$$\eta_2 = n_{t_1} \times g_2 \tag{34}$$

$$g_2^k = g_{2,max} - \frac{g_{2,max} - g_{2,min}}{iter_{max}} \times iter_c \tag{35}$$

In (33), μ_2 is the risk coefficient related to each member in the third group and it is defined similar to (28). In contrast to the second group, share values of members of the third group are not constant.

4.2. Fuzzy satisfying method

As mentioned before, Fuzzy satisfying method is used as decision maker to select best compromise solution among all Pareto optimal sets in this paper. Fuzzy membership function for objective function OF in pth point of Pareto set is formulated as [38]:

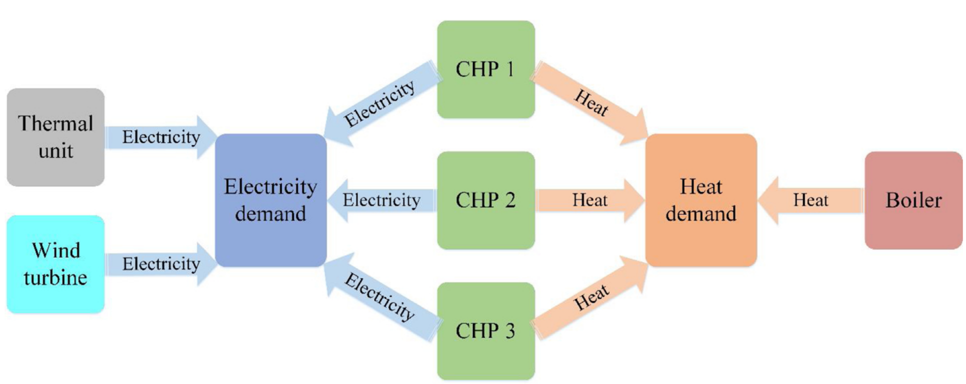

Fig. 4. Schematic of case 1.

Table 1
Cost coefficients for test system 1.

Power-only unit							
Unit	φ_i ($^{\$}/_{MW^3}$)	α_i ($^{\$}/_{MW^2}$)	β_i ($^{\$}/_{MW}$)	γ_i ($)	P^p_{min} (MW)	P^p_{max} (MW)	
1	0.000115	0.00172	7.6997	2.5489	0.35	1.35	
CHP units							
Unit	a_j ($^{\$}/_{MW^2}$)	b_j ($^{\$}/_{MW}$)	c_j ($)	d_j ($^{\$}/_{MWth^2}$)	e_j ($^{\$}/_{MWth}$)	f_j ($^{\$}/_{MW.MWth}$)	Feasible operation region $[P^c,\ H^c]$
2	0.0435	36	12.5	0.027	0.6	0.011	[0.44, 0], [0.44, 0.159], [0.4, 0.75], [1.102, 1.356], [1.258, 0.324], [1.258, 0]
3	0.1035	34.5	26.5	0.025	2.203	0.051	[0.2, 0], [0.1, 0.4], [0.45, 0.55], [0.6, 0]
4	0.072	20	15.65	0.02	2.3	0.04	[0.35, 0], [0.35, 0.2], [0.9, 0.45], [0.9, 0.25], [1.05, 0]
Boiler unit							
Unit	a_k ($^{\$}/_{MWth^2}$)	b_k ($^{\$}/_{MWth}$)	c_k ($)	H^h_{min} ($MWth$)	H^h_{max} ($MWth$)		
5	0.038	2.0109	9.5	0	0.6		

Table 2
Emission coefficients for test system 1.

Power-only unit					
Unit	$\alpha_i^{'}$ ($^{kg}/_{MW^2}$)	$\beta_i^{'}$ ($^{kg}/_{MW}$)	$\gamma_i^{'}$ (kg)	$\lambda_i^{'}$	$\rho_i^{'}$
1	$10^{-4} \times 6.490$	$10^{-4} \times 5.554$	$10^{-6} \times 4.091$	$10^{-4} \times 2$	0.02857
CHP units					
Unit	$a_j^{'}$ ($^{kg}/_{MW}$)				
2	0.00165				
3	0.0022				
4	0.0011				
Boiler unit					
Unit	$a_k^{'}$ ($^{kg}/_{MWth}$)				
5	0.0017				

Table 3
Wind turbine characteristics.

Rated power (MW)	Cut-in speed (m/s)	Rated speed (m/s)	Cut-off speed (m/s)
0.5	3	13	25

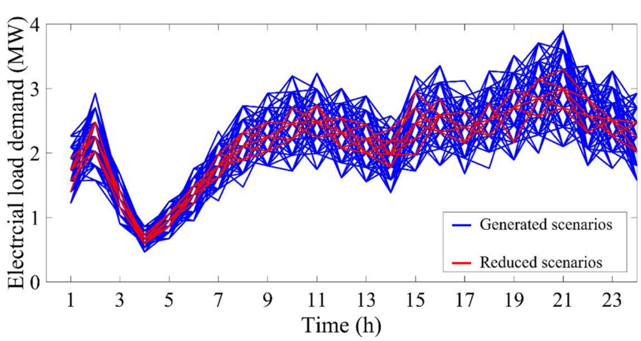

Fig. 5. Generated and reduced scenarios for electrical load demand in cases 1 and 2.

$$\Phi^p_{OF} = \begin{cases} 1 & F_{OF} \le F^{min}_{OF} \\ \dfrac{F^{max}_{OF} - F_{OF}}{F^{max}_{OF} - F^{min}_{OF}} & F^{min}_{OF} < F_{OF} < F^{max}_{OF} \\ 0 & F_{OF} \ge F^{max}_{OF} \end{cases} \tag{36}$$

The normalized membership function for pth solution is calculated using:

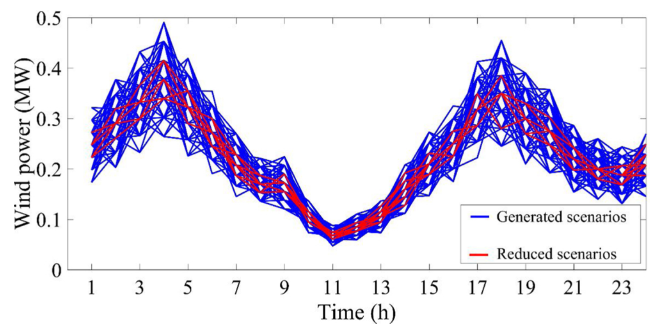

Fig. 6. Generated and reduced scenarios for wind power in cases 1 and 2.

$$\Phi^p_{normalized} = \frac{\sum_{OF=1}^{3} \Phi^p_{OF}}{\sum_{p=1}^{P} \sum_{OF=1}^{3} \Phi^p_{OF}} \tag{37}$$

Considering the definition of membership function in (36), the best compromise solution will have the maximum amount of $\Phi^p_{normalized}$.

5. Case studies and simulation results

The proposed method has been implemented on three case studies. Test systems are adopted from literature and modified in order to show the performance of the method. For the first case study, deterministic dynamic reliable economic dispatch (DDREED) is solved and after that, SDREED problem which is the main goal of this paper is investigated in order to compare with deterministic problem. In the second case study, the impact of reliability index is studied and in the third case, the proposed method is implemented into a large scale test system. The range of adjustable parameters of EMA are chosen from Ref. [26]. Afterwards, numerous simulations have been executed to select the best values of them to find optimum solution in minimum iterations. The chosen parameters of EMA are as follows for all case studies:

$g_{1,max} = 0.05,\ g_{1,min} = 0.04,\ g_{2,max} = 0.04$ and $g_{2,min} = 0.03$

It should be mentioned that choosing higher values for the risk parameters, cause convergence problems. On the other hand, lower risk values decrease convergence speed of the algorithm. Thus, a trade-off should be made.

5.1. Case study 1

The test system is taken from Ref. [34] and modified that comprises of one thermal unit, three CHP units and one boiler. Schematic of this case study is presented in Fig. 4. Cost and emission coefficients are

Table 4
Results of deterministic problems for case 1.

Problem	Generation cost ($)	Emission (kg)	EENS (MWh)
Deterministic dynamic economic dispatch	2468	0.0576	5.9647
Deterministic dynamic emission dispatch	2494.1	0.0433	6.1775
Deterministic dynamic reliable dispatch	2808.7	0.0735	5.9646
Deterministic dynamic reliable economic emission dispatch	2468.1	0.0434	5.9655

Table 5
Results of stochastic problems for case 1.

Problem	Generation cost ($)			Emission (kg)			EENS (MWh)		
	Best	Mean	Worst	Best	Mean	Worst	Best	Mean	Worst
Stochastic dynamic economic dispatch	2564.3	2627.9	2663.2	0.0595	0.0613	0.0629	6.2600	6.8604	8.0891
Stochastic dynamic emission dispatch	2629.3	2663.2	2706.4	0.0479	0.0502	0.0526	6.4125	7.1004	7.7889
Stochastic dynamic reliable dispatch	2756.5	2780.4	2813.2	0.0677	0.0701	0.0718	5.9111	6.1659	6.2922
Stochastic dynamic reliable Economic emission dispatch	2603.5	2651.3	2689.2	0.0490	0.0539	0.0575	6.1148	6.6425	7.6898

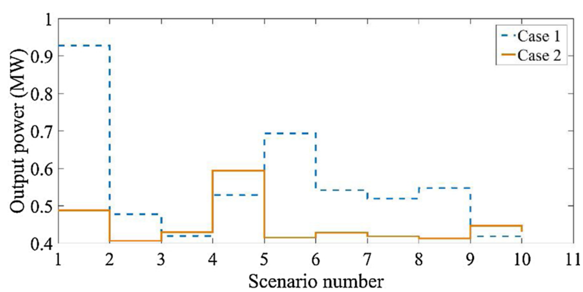

Fig. 7. Output power of unit 2 in cases 1 and 2 for different scenarios at time = 10 h.

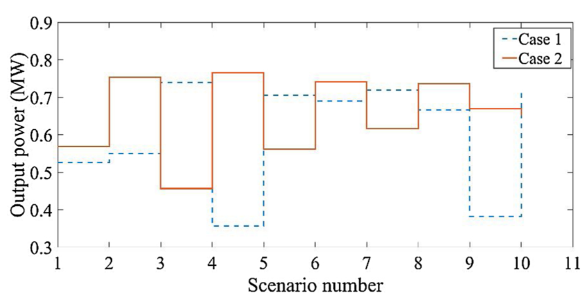

Fig. 8. Output power of unit 4 in cases 1 and 2 for different scenarios at time = 10 h.

provided in Tables 1 and 2, respectively. Also a wind turbine is added to this test system. The wind turbine characteristics is provided in Table 3 and forecasted wind speed profile can be found in Ref. [35].

Electrical power and heat demand profiles as forecasted values are taken from Ref. [17] and scaled to 3 MW and 1.5 MWth at the maximum. The availability of units are equal to 95% in this case. First, 1000 scenarios have been generated and after scenario reduction process, 10 scenarios have been selected. Figs. 5 and 6 show the generated and reduced scenarios for load demand and wind power, respectively. Results of generation cost, emission and EENS for different deterministic problems are provided in Table 4. According to this table, the minimum amount for each objective function is obtained in the related dispatch problem. As an example, the minimum amount of pollutant gases emission for this case study is 0.0433 kg which is obtained by solving the deterministic dynamic emission dispatch (DDED) problem. By considering generation cost and reliability term in the objective function and solving deterministic dynamic reliable economic emission dispatch (DDREED), the amount of emission is slightly increased and a compromise solution is obtained. In the following, results for the stochastic problems are reported in Table 5. As reported in this table, the proposed method is able to find best solution for each dispatch problem. In addition, it is capable to find a compromise solution for the multi-objective problem. As an example, in the SDREED, the mean of generation cost is increased by $23.4 in comparison with the stochastic dynamic economic dispatch (SDED) problem. Results show that by including emission and EENS in economic dispatch problem, greater achievements can be reached for longer dispatching horizons.

By comparing the results of deterministic and stochastic problems, it can be inferred that modeling the intermittent nature of load demand and wind power increases the generation cost, amount of emission and EENS. For more explaination, the best value of each objective function in the SDREED has been increased in comparison to the solutions of the DDREED problem. On the other hand, stochastic programming provides more precise solutions encountering different unpredicted situations. Solving stochastic problem gives better sight to system operators by considering the most probable scenarios in comparison with deterministic approach.

5.2. Case study 2

In order to investigate the impact of the reliability index on the outputs of the units, availability coefficients should be changed. Thus, the outputs of the units with lower availability coefficients will decrease and the algorithm must supply load demand with more reliable units. To investigate the effect of availability coefficients, the test system of case 1 is modified and the availability coefficient of unit 2 is decreased

Table 6
Results of deterministic problems for case 3.

Problem	Total generation cost ($)	Amount of emission (kg)	EENS (MWh)
Deterministic dynamic economic dispatch	7569.8	0.1617	12.8371
Deterministic dynamic emission dispatch	7652.7	0.1354	14.0838
Deterministic dynamic reliable dispatch	8365.1	0.2086	12.8166
Deterministic dynamic reliable economic emission dispatch	7601.4	0.1353	12.8441

Table 7
Results of stochastic problems for case 3.

Problem	Generation cost ($)			Emission (kg)			EENS (MWh)		
	Best	Mean	Worst	Best	Mean	Worst	Best	Mean	Worst
Stochastic dynamic economic dispatch	8291.7	8337.4	8402.8	0.2055	0.2089	0.2130	28.2752	29.1517	30.6468
Stochastic dynamic emission dispatch	8388.1	8457.6	8541.5	0.1767	0.1818	0.1873	31.8584	29.7137	28.3405
Stochastic dynamic reliable dispatch	8765.7	8816.8	8844.5	0.2357	0.2368	0.2383	21.6327	22.5157	24.2974
Stochastic dynamic reliable Economic emission dispatch	8297	8364	8413.7	0.1861	0.1924	0.1976	26.3326	27.5745	29.5813

from 95% to 50%. The output power of unit 2 at time = 10 (h) is shown in Fig. 7. As mentioned before, it can be seen that output power of this unit is decreased in must of scenarios due to lower availability coefficient of this unit. On the other hand, the change in the availability coefficient of unit 2, affects outputs of the other units. As an instance, the output power of unit 4 is depicted in Fig. 8. It is shown in this figure that the output of unit 4 is increased for seven scenarios due to reduction in the output power of unit 2.

5.3. Case study 3

The main aim of this case study is to investigate the performance of the proposed method in a larger problem. The test system for this case study is obtained by tripling the test system of case 1. Thus, the maximum load and heat demands are 9 MW and 4.5 MWth, respectively. The availability coefficients are considered 95% for all of the generating units. 1000 scenarios generated and reduced to 10 scenarios using scenario reduction algorithm. Table 6 is representing results for deterministic problems. As reported in this table, the proposed method is able to find best solution for each deterministic problem. Also, the minimum value of each objective is gained by solving the respected dispatch problem which approves the performance of the proposed method. Results for stochastic problems are reported in Table 7. As mentioned in this table, the algorithm is able to find best and compromise solutions for large scale and stochastic problems. For the sake of comparison, the minimum amount of EENS for deterministic problem is equal to 12.8166 MWh. By considering generation cost and amount of emission in the objective function, in the compromised solution, the amount of EENS is increased by 0.0275. In addition, by presuming different probable scenarios for load demand and wind power, the best amount of EENS in the stochastic problems, which is equal to 21.6327, is increased by 7.5489 in comparison to the worst EENS value in the deterministic problems. This comparison shows the importance of the stochastic programming in planning and operation of power systems.

6. Conclusion

In this paper, scheduling of a CHP-based microgrid considering three conflicting objectives is investigated. EENS as reliability index as well as pollutant gases emission and generation cost of the units are considered in the objective function. The multi-objective problem is solved using stochastic programming method. Uncertainties of load demand and wind power are taken into account. Scenarios are generated using roulette wheel mechanism and weighted sum method is applied to solve multi-objective problem. By considering non-linearity, non-convexity and complexity of the problem and incapability of mathematical methods, an evolutionary optimization method, namely exchange market algorithm is utilized. Obtained results demonstrate the effectiveness and capability of the proposed method in solving SDREED problem. Results of the stochastic problem provide a better sight for planners and operators of power systems coping with different possible scenarios. This can lead to better efficiency in using available energy resources. As future work, the dynamic dispatch problem can be extended by considering robust and opportunity functions. Also, other renewable energy sources and energy storage systems can be considered in the problem.

Acknowledgment

This project is supported by a research grant of the University of Tabriz (Number S-821).

References

[1] Q. Jiang, M. Xue, G. Geng, Energy management of microgrid in grid-connected and stand-alone modes, IEEE Trans. Power Syst. 28 (2013) 3380–3389.
[2] Y. Zhang, N. Gatsis, G.B. Giannakis, Robust energy management for microgrids with high-penetration renewables, IEEE Trans. Sustain. Energy 4 (2013) 944–953.
[3] A. Rong, H. Hakonen, R. Lahdelma, A dynamic regrouping based sequential dynamic programming algorithm for unit commitment of combined heat and power systems, Energy Convers. Manage. 50 (2009) 1108–1115.
[4] Y. Wu, X. Wang, Y. Fu, Y. Xu, Difference brain storm optimization for combined Heat and power economic dispatch, International Conference in Swarm Intelligence, (2017), pp. 519–527.
[5] L. Che, X. Zhang, M. Shahidehpour, A. Alabdulwahab, A. Abusorrah, Optimal interconnection planning of community microgrids with renewable energy sources, IEEE Trans. Smart Grid 8 (2017) 1054–1063.
[6] D. Zou, S. Li, X. Kong, H. Ouyang, Z. Li, Solving the combined heat and power economic dispatch problems by an improved genetic algorithm and a new constraint handling strategy, Appl. Energy 237 (2019) 646–670.
[7] R. Murugan, M. Mohan, C.C.A. Rajan, P.D. Sundari, S. Arunachalam, Hybridizing bat algorithm with artificial bee colony for combined heat and power economic dispatch, Appl. Soft Comput. 72 (2018) 189–217.
[8] M. Bornapour, R.-A. Hooshmand, A. Khodabakhshian, M. Parastegari, Optimal coordinated scheduling of combined heat and power fuel cell, wind, and photovoltaic units in micro grids considering uncertainties, Energy 117 (2016) 176–189.
[9] T.A. Nguyen, M. Crow, Stochastic optimization of renewable-based microgrid operation incorporating battery operating cost, IEEE Trans. Power Syst. 31 (2016) 2289–2296.
[10] S. Mohammadi, S. Soleymani, B. Mozafari, Scenario-based stochastic operation management of microgrid including wind, photovoltaic, micro-turbine, fuel cell and energy storage devices, Int. J. Electr. Power Energy Syst. 54 (2014) 525–535.
[11] H. Karami, M.J. Sanjari, S.H. Hosseinian, G.B. Gharehpetian, An optimal dispatch algorithm for managing residential distributed energy resources, IEEE Trans. Smart Grid 5 (2014) 2360–2367.
[12] M. Izadbakhsh, M. Gandomkar, A. Rezvani, A. Ahmadi, Short-term resource scheduling of a renewable energy based micro grid, Renew. Energy 75 (2015) 598–606.
[13] H. Anand, N. Narang, J. Dhillon, Multi-objective combined heat and power unit commitment using particle swarm optimization, Energy (2019).
[14] M. Motevasel, A.R. Seifi, T. Niknam, Multi-objective energy management of CHP (combined heat and power)-based micro-grid, Energy 51 (2013) 123–136.
[15] T. Niknam, R. Azizipanah-Abarghooee, A. Roosta, B. Amiri, A new multi-objective reserve constrained combined heat and power dynamic economic emission dispatch, Energy 42 (2012) 530–545.
[16] H. Liu, Y. Ji, H. Zhuang, H. Wu, Multi-objective dynamic economic dispatch of microgrid systems including vehicle-to-grid, Energies 8 (2015) 4476–4495.
[17] M. Nazari-Heris, S. Abapour, B. Mohammadi-Ivatloo, Optimal economic dispatch of FC-CHP based heat and power micro-grids, Appl. Therm. Eng. 114 (2017) 756–769.
[18] K. Chandrasekaran, S.P. Simon, N.P. Padhy, Cuckoo search algorithm for emission reliable economic multi-objective dispatch problem, IETE J. Res. 60 (2014) 128–138.
[19] M. Alipour, B. Mohammadi-Ivatloo, K. Zare, Stochastic scheduling of renewable and CHP-based microgrids, IEEE Trans. Ind. Inform. 11 (2015) 1049–1058.
[20] J. Aghaei, V.G. Agelidis, M. Charwand, F. Raeisi, A. Ahmadi, A.E. Nezhad, et al., Optimal robust unit commitment of CHP plants in electricity markets using information gap decision theory, IEEE Trans. Smart Grid (2016).
[21] A. Dolatabadi, B. Mohammadi-ivatloo, M. Abapour, S. Tohidi, Optimal stochastic design of wind integrated energy hub, IEEE Trans. Ind. Inform. (2017).
[22] M. Motevasel, A.R. Seifi, Expert energy management of a micro-grid considering wind energy uncertainty, Energy Convers. Manage. 83 (2014) 58–72.
[23] M. Majidi, B. Mohammadi-Ivatloo, A. Anvari-Moghaddam, Optimal robust operation of combined heat and power systems with demand response programs, Appl.

Therm. Eng. 149 (2019) 1359–1369.
[24] M. Nazari-Heris, B. Mohammadi-Ivatloo, G.B. Gharehpetian, M. Shahidehpour, Robust short-term scheduling of integrated heat and power microgrids, IEEE Syst. J. (2018) 1–9.
[25] P. Farhadi, N. Khandoozi, N. Ghorbani, Practical installation of capacitor banks by exchange market algorithm, Fundamentals of Electrical Engineering (ISFEE), 2016 International Symposium on, (2016), pp. 1–6.
[26] N. Ghorbani, Combined heat and power economic dispatch using exchange market algorithm, Int. J. Electr. Power Energy Syst. 82 (2016) 58–66.
[27] P. Pourghasem, F. Sohrabi, B. Mohammadi-Ivatloo, M. Abapour, Reliable economic dispatch of microgrids by exchange market algorithm, 2017 Smart Grid Conference (SGC), (2017), pp. 1–5.
[28] N. Ghorbani, E. Babaei, Exchange market algorithm for economic load dispatch, Int. J. Electr. Power Energy Syst. 75 (2016) 19–27.
[29] A. Rajan, T. Malakar, Optimum economic and emission dispatch using exchange market algorithm, Int. J. Electr. Power Energy Syst. 82 (2016) 545–560.
[30] F. Sohrabi, M. Nazari-Heris, B. Mohammadi-Ivatloo, S. Asadi, Optimal chiller loading for saving energy by exchange market algorithm, Energy Build. 169 (2018) 245–253.
[31] A. Rajan, T. Malakar, Exchange market algorithm based optimum reactive power dispatch, Appl. Soft Comput. 43 (2016) 320–336.
[32] J. Aghaei, T. Niknam, R. Azizipanah-Abarghooee, J.M. Arroyo, Scenario-based dynamic economic emission dispatch considering load and wind power uncertainties, Int. J. Electr. Power Energy Syst. 47 (2013) 351–367.
[33] T. Niknam, R. Azizipanah-Abarghooee, M.R. Narimani, An efficient scenario-based stochastic programming framework for multi-objective optimal micro-grid operation, Appl. Energy 99 (2012) 455–470.
[34] M. Nazari-Heris, B. Mohammadi-Ivatloo, G. Gharehpetian, A comprehensive review of heuristic optimization algorithms for optimal combined heat and power dispatch from economic and environmental perspectives, Renew. Sustain. Energy Rev. (2017).
[35] M. Mazidi, H. Monsef, P. Siano, Robust day-ahead scheduling of smart distribution networks considering demand response programs, Appl. Energy 178 (2016) 929–942.
[36] S. Nojavan, M. Majidi, K. Zare, Stochastic multi-objective model for optimal sizing of energy storage system in a microgrid under demand response program considering reliability: a weighted sum method and fuzzy satisfying approach, J. Energy Manage. Technol. 1 (2017) 61–70.
[37] N. Ghorbani, E. Babaei, Exchange market algorithm, Appl. Soft Comput. 19 (2014) 177–187.
[38] R. Arul, S. Velusami, G. Ravi, A new algorithm for combined dynamic economic emission dispatch with security constraints, Energy 79 (2015) 496–511.