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Microgrid operation and management using probabilistic reconfiguration and unit commitment

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ABSTRACT

A stochastic model for day-ahead Micro-Grid (MG) management is proposed in this paper. The presented model uses probabilistic reconfiguration and Unit Commitment (UC) simultaneously to achieve the optimal set points of the MG's units besides the MG optimal topology for day-ahead power market. The proposed operation method is employed to maximize MG's benefit considering load demand and wind power generation uncertainty. MG's day-ahead benefit is considered as the Objective Function (OF) and Particle Swarm Optimization (PSO) algorithm is used to solve the problem. For modeling uncertainties, some scenarios are generated according to Monte Carlo Simulation (MCS), and MG optimal operation is analyzed under these scenarios. The case study is a typical 10-bus MG, including Wind Turbine (WT), battery, Micro-Turbines (MTs), vital and non-vital loads. This MG is connected to the upstream network in one bus. Finally, the optimal set points of dispatchable units and best topology of MG are determined by scenario aggregation, and these amounts are proposed for the day-ahead operation. In fact, the proposed model is able to minimize the undesirable impact of uncertainties on MG's benefit by creating different scenarios.

Introduction

Distribution networks are reconfigured in order to power loss reduction, load balancing and service restoration in critical operational conditions [1]. Impact of MG on Distribution Network Reconfiguration (DNR) is discussed in [2–4]. To solve the optimal DNR problem for power loss minimization, the PSO algorithm using some scenarios generated by MCS is presented in [2]. Load Economic Dispatch (ED) and DNR, considering costs of generation and storage in MG, utility and network power loss as OF, are studied in [3,4]. The Distributed Generators (DGs) are considered by the stochastic nature according to forecasting weather data. However, load ED and DNR are not considered within the same time intervals.

MG reconfiguration is analyzed in [5–8]. A new algorithm is proposed to solve MG reconfiguration problem based on an ordered binary decision diagram in order to minimize power loss cost in [5]. A hybrid programming technique to solve MG reconfiguration problem to minimize power loss and service restoration is proposed in [6]. Considering the operational requirements, load maximizing and demand supply priority after fault, some methodologies that are based on genetic algorithm (GA) and graph theory, are used to reconfigure MG in [7]. Neglecting network power loss and line capacity, a scheme to recover much more loads with minimum switching operation is presented in [8]. However, stochastic nature of renewable energy resources and load demand in MGs are neglected in these studies.

MG UC and ED are discussed in [9–14]. A stochastic model for considering wind power uncertainty is investigated in [9]. Different scenarios are generated by MCS and are applied to solve UC problem. A probabilistic approach including point estimate method for handling uncertainties and a self-adaptive optimization algorithm for optimal energy management of MGs is proposed in [10]. The offered mutation technique makes the solution able to meet global optimum. A new algorithm based on an adaptive modified PSO algorithm to optimize multi-objective management of MG is presented in [11]. Three optimization algorithms are developed for optimal MG operation in [12]. A multi-objective optimization, using weight coefficient to coordinate the proportion of generation and environmental costs, is applied to the environmental and economic problem of MG in [13]. A new stochastic method using the probability distribution function of variables and the roulette wheel mechanism is proposed in [14]. Some scenarios

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Nomenclature

x_n	decision variable
OF	objective function
N_{mt}	number of microturbines
$\alpha_{mt}, b_{mt}, \gamma_{mt}, K_{om}, \alpha_{st,mt}, \beta_{st,mt}$	micro-turbine cost coefficients
t_{off}	micro-turbine off time
u_j	on/off state of micro-turbine j at interval t
i	the interest rate
n	unit life time
CF	unit capacity factor
β_{em}	micro-turbine emission coefficient
$T_{j-1}^{on}, T_{j-1}^{off}$	micro-turbine on/off time
MUT, MDT	minimum up/down time
$C_{WC,bat}$	battery wear cost
$C_{rep,bat}$	battery replacement cost
N_{bat}	number of batteries
$Q_{lifetime}$	lifetime throughput of battery
η_{bat}	battery roundtrip efficiency
SOC	battery state of charge
SOC_{in}	battery initial state of charge
$\rho_{buy\text{-}network}$	power cost bought from upstream network
N_{load_out}	number of not supplied loads
$\rho_{penalty}$	power cost paid to vital loads if is shed
$N_{load\_vital\_out}$	number of unsupplied vital loads
$N_{switching}$	number of switching
cv_x	variance coefficient of parameter x
σ_x	standard deviation of parameter x
μ_x	mean value of parameter x
N_s	number of scenarios
$w_1, w_r, w_{cut\text{-}out}$	cut-in, rated, and cut-out wind speed
Pbest, Gbest	best position of each particle until current iteration and best global particle

are generated by using of the proposed probabilistic method. Then similar scenarios are eliminated. A self-adaptive bee swarm optimization algorithm is proposed in [15]. Different uncertainty modeling methods are reviewed and the $2m+1$ point estimate method is used for modeling uncertainties of load demands, market price, WT and photovoltaic systems. UC is investigated on a MG including several grid parallel PEM-fuel cell power plants in [16,17]. The objective is optimal sizing of storage devices and committed units' output power is scheduled with 15 min step over a day. A two stage algorithm is proposed to solve the complexity of the problem imposed by stochastic nature of electrical/thermal load, photovoltaic and WT output power and market price.

Some novel aspects in DNR studies are represented in [18–24]. Time varying data characteristic is considered in [18,20]. A method to determine annual reconfiguration scheme, considering switching cost and time-dependent variables such as load profiles, is proposed in [18]. The best topology for each hour is determined in [19], aimed at minimizing power loss and switching cost. Considering time-varying loads, a probabilistic approach for optimal DNR to reduce the total cost of operation, including power loss and switching cost, is presented in [20]. The proposed method can obtain an optimal balance between the number of switching and the power loss.

Reconfiguration with different kinds of uncertain data is presented in [21,22]. Different kinds of uncertainty are modeled in [21], in order to assess stochastic distribution feeder reconfiguration in the presence of fuel cell power plants. Interval analysis is used in [22], to deal with imprecision and uncertainties in reliability input, electrical parameters and load data to present a reliability oriented reconfiguration method in order to enhance distribution network performance. A methodology to convert a distribution network to an autonomous MG is presented in [23]. The methodology determines number, site and size of DGs and structural modifications in distribution network. Multi-scenario analysis handled with decision theory concepts is applied in [24], to determine intra-day distribution configuration. The determined configurations are then used to formulate a demand response scheme, aimed at demand reduction to further decreasing in distribution network losses.

However, none of the above-mentioned papers has considered the reconfiguration and UC simultaneously. As the review shows, probabilistic reconfiguration and UC for MG optimal management, is a novel operation scheme. Considering wind power and load demand uncertainties, simultaneous reconfiguration and UC for hourly scheduling is used to estimate MG's benefit in the uncertain environment. The paper includes five sections. In section 'Problem formulation', problem formulation is introduced. In section 'Proposed algorithm', proposed algorithm is described. Section 'Simulation results' indicates simulation results and section 'Conclusion' is dedicated to conclusion.

Problem formulation

One of the most involving problems that MG owner faces is how to increase the benefit. There are two methods to achieve this goal: UC and reconfiguration. UC has been regarded very much. However, reconfiguration has been ignored for this purpose. Reconfiguration provides MG with more benefit by changing the topology. Topology changes can cause loss reduction or line allocation with more power transfer capacities. Uncertainties of wind power and load demand are taken into account in this paper. The MG under study includes WT, battery, MTs, vital and non-vital loads. The MG's structure is shown in Fig. 1 [25]. In the following subsections problem formulation is described.

Decision variables

The three MTs output power (P_{mt}), battery charge or discharge (P_{bat}), power exchange with upstream network (P_{grid}) and switches status ($n\_topology$) are considered as decision variables for each hour. So, there are six vectors of decision variables for each hour and 144 variables for day-ahead, which must be determined.

$$x_n = \begin{bmatrix} P_{mt1}(1) & P_{mt2}(1) & P_{mt3}(1) & P_{bat}(1) & P_{grid}(1) & n\_topology(1) \\ P_{mt1}(2) & P_{mt2}(2) & P_{mt3}(2) & P_{bat}(2) & P_{grid}(2) & n\_topology(2) \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ P_{mt1}(24) & P_{mt2}(24) & P_{mt3}(24) & P_{bat}(24) & P_{grid}(24) & n\_topology(24) \end{bmatrix} \tag{1}$$

Objective function

MG's benefit, which is defined as the difference between revenue and cost, is considered as OF and defined as follows [26]:

$$Max: \; OF = \sum_{t=1}^{24} (revenue(t) - cost(t)) \tag{2}$$

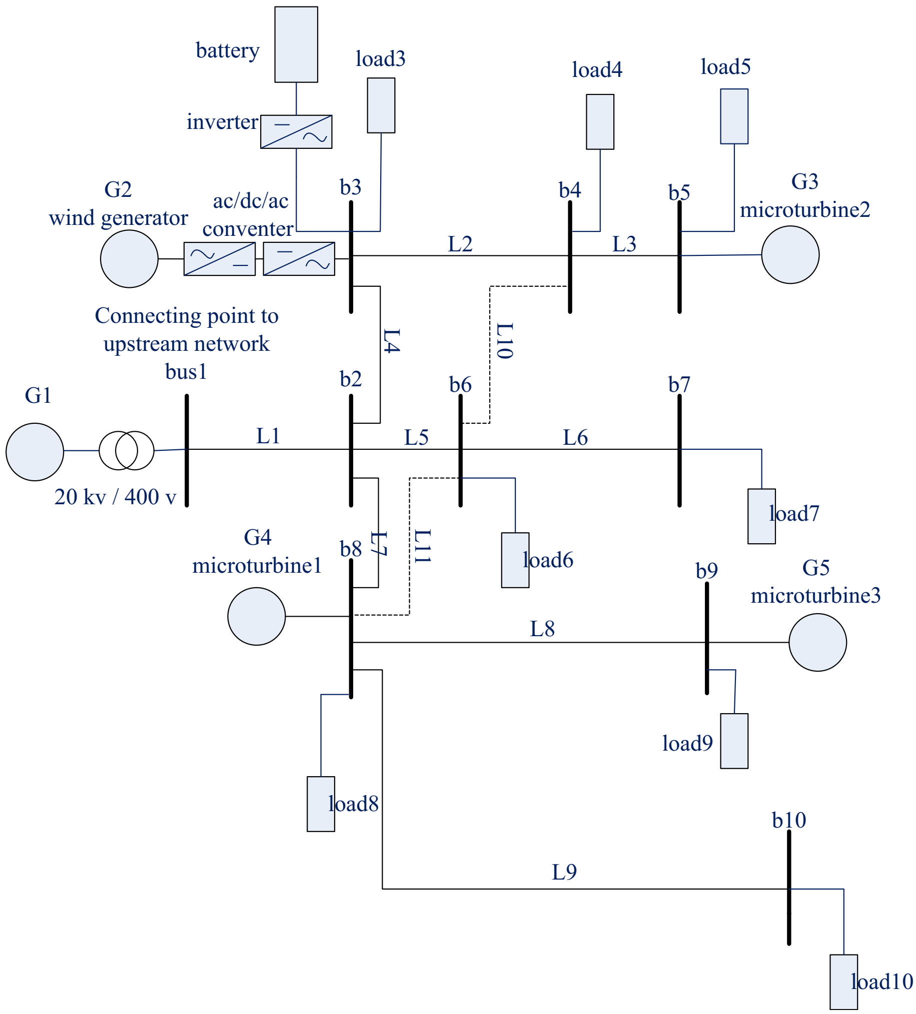

Fig. 1. MG structure scheme.

revenue includes the price of power sold to MG's loads (R_{load}) as well as to the upstream network ($R_{network}$).

$$revenue = R_{load} + R_{network} \tag{3}$$

$$R_{load} = \sum_{k=1}^{N_{load}} (\rho_{load,k} \cdot p_{load,k} \cdot t) \tag{4}$$

where R_{load} depends on the k-th load demand ($p_{load,k}$), and power price ($\rho_{load,k}$) at that hour. t is set as one hour and $R_{network}$ is calculated as follows:

$$R_{network} = \rho_{sell\text{-}network} \cdot p_{sell\text{-}network} \cdot t \tag{5}$$

Cost includes costs of MTs (C_{mt}), WT (C_{wind}), battery (C_{bat}), power bought from upstream network ($C_{network}$), power loss cost (C_{loss}) and switching cost ($C_{switching}$).

$$cost = \sum_{j=1}^{N_{mt}} C_{mt}(j) + C_{wind} + C_{bat} + C_{network} + C_{loss} + C_{switching} \tag{6}$$

MT cost

MT's cost (C_{mt}) includes fuel ($C_{Fuel,mt}$), maintenance ($C_{o\&m}$), startup ($C_{st,mt}$), capital ($C_{capital,mt}$) and emission cost ($C_{em,mt}$). It is formulated in (7)–(12).

$$C_{mt} = C_{Fuel,mt} + C_{o\&m} + C_{st,mt} + C_{capital,mt} + C_{em,mt} \tag{7}$$

$$C_{Fuel,mt} = \left(\alpha_{mt} + b_{mt}P_{mt} + \gamma_{mt}P_{mt}^2\right) \tag{8}$$

$$C_{o\&m} = K_{om}P_{mt} \cdot t \tag{9}$$

$$C_{st,mt} = \left(\alpha_{st,mt} + \beta_{st,mt}\left(1 - e^{-(t_{off}/\tau)}\right) \times u_j(u_j - u_{j-1}\right) \tag{10}$$

$$C_{capital,mt} = \frac{I \times \frac{i(1+i)^n}{(1+i)^n - 1}}{P_{mt,rated} \times CF_{mt} \times 8760} \times P_{mt} \times t \tag{11}$$

$$C_{em} = (\beta_{em})P_{mt} \tag{12}$$

$P_{mt,rated}$, P_{mt} are rated and hourly power of MT respectively.

WT probabilistic model

A doubly fed induction generator WT is connected to the 3rd bus of the MG through an ac/dc dc/ac convertor. WT output uncertainty is simulated by MCS similar to [9]. Wind speed data for each hour of day-ahead within twelve past years (from 2000 to 2011) is considered as input data. It means that there are twelve wind speeds for each hour of the day-ahead which belongs to different years. The Weibull parameters are calculated as follows:

$$r = \left(\frac{\sigma}{w_{mean}}\right)^{-1.086} \qquad c = \frac{w_{mean}}{Gamma(1 + 1/r)} \tag{13}$$

where r, c are Weibull parameters and, σ, w_{mean} are standard deviation and mean values of wind speed in each hour respectively. The Weibull density function ($f(w)$) for each hour is defined as:

$$f(w) = \frac{r}{c}\left(\frac{w}{c}\right)^{r-1} \exp\left[-\left(\frac{w}{c}\right)^{r}\right] \tag{14}$$

A number is generated randomly between 0 and 1 for each hour. This number is found on the Weibull Cumulative Distribution Function (CDF) graph and the corresponding wind speed is considered as wind speed. Twenty-four wind speeds are produced by this way separately. WT output power (P_{wind}) for each scenario based on wind speed (w) is calculated as follows:

$$P_{wind}(w) = \begin{cases} 0 & 0 \leqslant w \leqslant w_1 \\ (a_1 + a_2 w + a_3 w^2) P_{rated} & w_1 \leqslant w \leqslant w_r \\ P_{rated} & w_r \leqslant w \leqslant w_{cut\text{-}out} \\ 0 & w \geqslant w_{cut\text{-}out} \end{cases} \tag{15}$$

Wind cost (C_{wind}) is given by [4]:

$$C_{wind}(t) = (C_{capital\text{-}wind} + Com_{wind}/8760) \tag{16}$$

WT coefficients, a_1, a_2, a_3 are set as 0.1234, −0.0963 and 0.0184, respectively. WT capital cost ($C_{capital\text{-}wind}$) is calculated similar to (11) and (Com_{wind}) is operation and maintenance cost of WT.

Battery cost

MGs need storage devices to control and manage generation variation. Batteries, as one of the most important components of MGs, store power to control and manage generation variation. Battery cost is as follows:

$$C_{bat} = C_{WC,bat} \times |P_{bat}| \times t + C_{O\&M,bat}/8760 \tag{17}$$

$$C_{WC,bat} = \frac{C_{rep,bat}}{N_{bat} \cdot Q_{lifetime}\sqrt{\eta_{bat}}} \tag{18}$$

where P_{bat} represents battery exchange power in each hour.

Network cost

If power flows from upstream network to MG, $p_{buy\text{-}network}$ is equal to P_{grid}, otherwise it is zero. So cost of the power purchased from upstream network is calculated as follows:

$$C_{network} = \rho_{buy\text{-}network} \cdot p_{buy\text{-}network} \cdot t \tag{19}$$

Loss cost

After backward/forward load flow analysis, loss cost (C_{loss}) is calculated using all line losses in each hour.

$$C_{loss}(t) = \sum_{k=1}^{N_{line}} \left(3 \cdot \rho_{loss}(t) \cdot r_k \cdot I_k^2(t,k) \cdot t\right) \tag{20}$$

where ρ_{loss} is loss price and r_k is the real part of k-th branch impedance.

Switching cost

Switching cost ($C_{switching}$), is generated as a result of reconfiguration, includes initial installation and changing topologies cost by opening some lines and closing some others [27].

$$C_{switching} = \rho_{switching} \cdot N_{switching} + C_{Capital\_switching}/8760 \tag{21}$$

$\rho_{switching}, C_{Capital\_switching}$ indicate each switching operation and capital cost of automatic switches respectively.

System constraints

It is supposed that the MG is connected to the upstream network in one bus and according to its benefit can decide when to exchange power with the upstream network. For observing stability criterion, voltage stability, power balance and other constraints should be in the allowable limitations. Whereas the load demand may be more than the MG installed capacity in some hours especially in peak load (it can also be because of the probabilistic nature of WT generation, load demand, the amount of energy stored in the battery and the rate of battery discharge in one hour), the MG has to exchange power (buy power) with the upstream network and load shedding is neglected in this paper. The system constraints are as below:

1. Topology: MG topology should be radial with no loop.
2. Node voltages must be in an acceptable range.

$$V_K;\ V^{min} < V_K < V^{max} \tag{22}$$

where V_K is the voltage of k-th bus and V^{min} and V^{max} are minimum and maximum acceptable voltages.

3. Branch currents should be less than the maximum allowed current.

$$I_K;\ I_K < I_K^{max} \tag{23}$$

where I_K is the current of k-th branch and I_K^{max} is the maximum acceptable current.

4. All loads should be supplied, and power balance constraint should be provided.

$$\sum_{k=1}^{N_{mt}} P_{mt,k}(t) + P_{wind}(t) \pm P_{bat}(t) \pm P_{grid}(t) - \sum_{i=1}^{N_{load}} P_{load,i}(t) - P_{loss}(t) = 0 \tag{24}$$

where P_{grid} and P_{loss} are MG's power exchange with the upstream network and power loss respectively.

Unit constraints

The constraints of the MG's units are formulated as follows:

$$P^{min} \leqslant P_{mt} \leqslant P^{max} \tag{25}$$

$$(T_{j-1}^{on} - MUT)(u_{j-1} - u_j) \geqslant 0 \tag{26}$$

$$(T_{j-1}^{off} - MDT)(u_j - u_{j-1}) \geqslant 0 \tag{27}$$

$$p_{bat\text{-}min} \leqslant P_{bat} \leqslant p_{bat\text{-}max} \tag{28}$$

$$SOC_{min} \leqslant SOC(t) \leqslant SOC_{max} \tag{29}$$

$$P_{grid};\ |P_{grid}| < P_{grid}^{max} \tag{30}$$

where P^{min}, P^{max} are MT's minimum and maximum output active power in (25). MT's on/off constraints are formulated in (26) and (27). $p_{bat\text{-}min}$, $p_{bat\text{-}max}$ are battery's minimum and maximum output active power in (28). SOC_{min}, SOC_{max} are battery's minimum and maximum state of charge in (29). P_{grid}^{max} is maximum MG's power exchange with upstream network in (30).

System topology

For modeling different MG topologies in the optimization algorithm, one number is attributed to each topology. When a topology number is chosen by the optimization program for each hour, the related MG configuration is used for power flow calculations and checking constraints at that hour. According to Fig. 1, the MG has eleven topologies. So each hour topology number is a discrete variable for PSO algorithm, which is denoted with ($n\_topology$) in the decision variables.

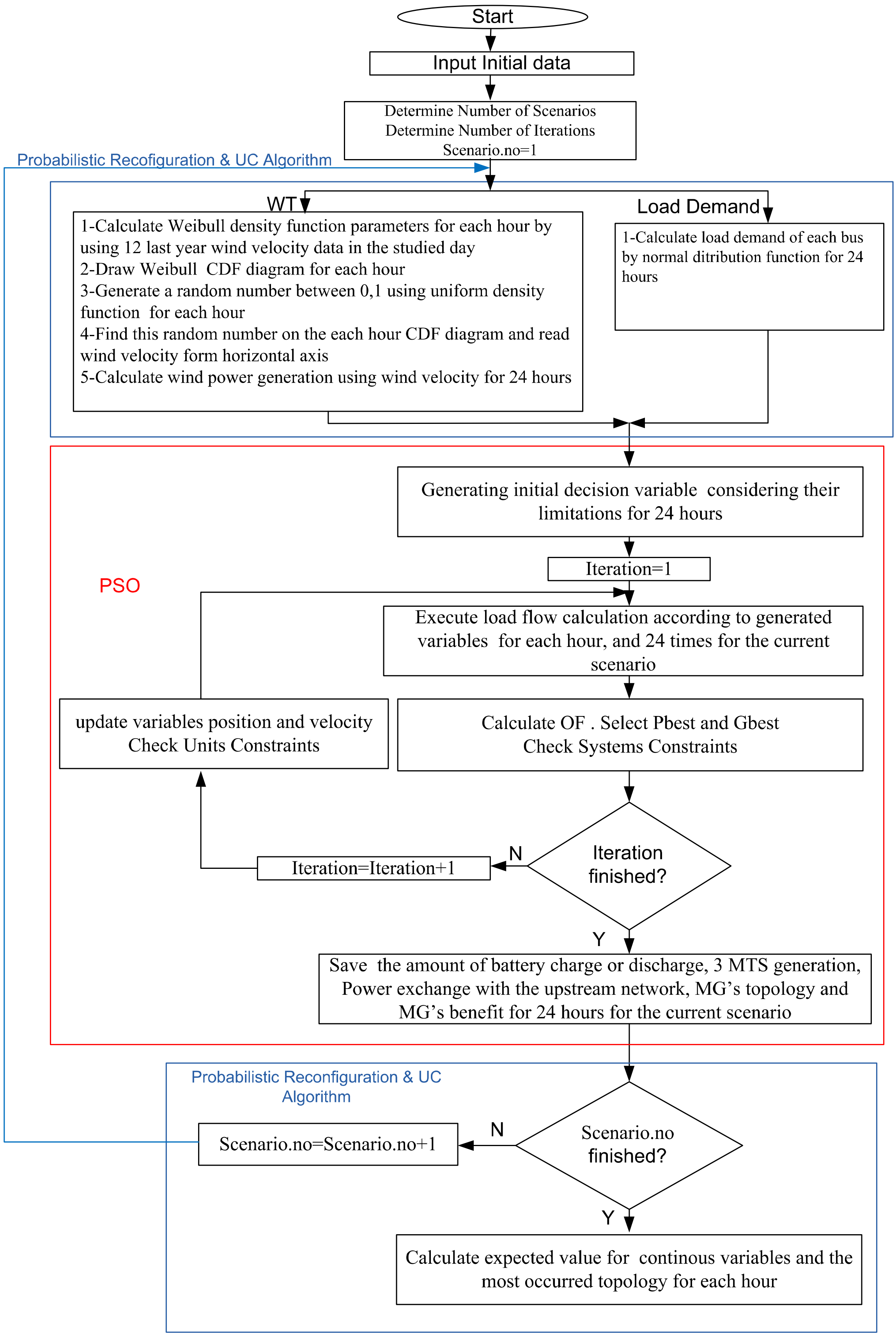

Fig. 2. Proposed algorithm.

Table 1
Line impedance of MG.

From bus	To bus	Line number	R (pu)	X (pu)	Imax (A)
1	2	1	0.0025	0.01	400
2	3	4	0.0125	0.00375	250
2	6	5	0.0125	0.00375	250
2	8	7	0.0125	0.00375	250
3	4	2	0.021875	0.004375	250
4	5	3	0.02125	0.005625	250
6	7	6	0.023125	0.00625	250
6	4	10	0.0125	0.00375	250
8	6	11	0.0125	0.00375	250
8	9	8	0.021875	0.004375	250
8	10	9	0.0125	0.00375	250

Uncertainty model

Uncertainty is modeled by MCS. Some scenarios are generated for uncertain inputs, i.e. wind speed and load demand. The system is analyzed under these scenarios as deterministic inputs. So there are different states which are studied by using different scenarios. The expected value (f) is used for scenario aggregation.

$$f = \sum_{i=1}^{Ns} p_s \cdot f_s \tag{31}$$

p_s is the probability of each scenario, and f_s is the amount of variables in each scenario.cv_x which is defined in (32) is called the coefficient of variance.

$$cv_x = \frac{\sigma_x}{\mu_x \cdot N_s^{1/2}} \tag{32}$$

If cv_x is less than a specific tolerance, the result will be relatively good [28].

Load

Load uncertainty is modeled with a normal distribution function [4].

$$diff(P_k(t)) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(P_k(t)-\mu)^2}{2\sigma^2}} \tag{33}$$

where μ, σ are mean and standard deviation of each load. The standard deviation of loads is considered 4% in each hour. The vital load must have a more reliable supply and so the price is more expensive. This fact is more sensible when a line is out of order but in this paper line outage is ignored.

Proposed algorithm

The proposed algorithm, as shown in Fig. 2, starts by determining the WT output power and each load point demand in a probabilistic manner for each hour of the current scenario. The load demand using mean value, standard deviation and normal distribution function are also obtained like Ref. [4]. Therefore, the current scenario consists of a 1×24 vector for WT output power and a 10×24 matrix (10 bus load demand in each hour) for day-ahead load demand. In the next step, decision variables based on PSO algorithm are generated for a 24-h period considering their limitations. It is important to notice that all decision variables of day-ahead are optimized simultaneously and the MG topology is determined in addition to the UC. Then power loss is determined by backward/forward load flow analysis and system constraints are checked for each hour. If each system constraint is not observed, OF is penalized. As the PSO algorithm iterations are finished, the optimal set points of dispatchable units, power exchange and the best topology of MG are determined for the current scenario. After enough scenario generation, the amount of MG's benefit, optimal set points of units and MG's topology for each hour are determined by scenario aggregation. Finally expected value for each variable is calculated. The average of continuous variables and the most repeated topology for each hour are determined for scenarios as a suggestion for the next day. The average of MG's benefit is also determined for scenarios.

Simulation results

The proposed algorithm has been implemented on a MG, including WT, battery, MTs, vital and non-vital loads. The MG is connected to the upstream network in one bus. The value of *Sbase* and *Vbase* are equal to 100 KVA and 400 V. Table 1 represents the MG's structure data. The characteristic of MG's units is shown in Tables 2–6. Load data are presented in Tables 7–9. Power market price in each hour is shown in Table 10. There are eleven acceptable topologies in the MG. Therefore, MG topology can have a code from 1 to 11 for each hour. This code show which lines are under operation, and which ones are unused. The code which is attributed to each topology is shown in Table 11. Wind speed data calculated for each hour by using 12-last-year data is shown in Table 12.

As it is seen in Table 13, after scenario aggregation in the first hours, MTs do not operate with nominal output power, and batteries start to be charged because of low power price. In the hours that power price is high (15–21) battery mean power shows a discharge and MTs operate near nominal output power with minimum variance. 1st and 11th topologies have the most repetitions. These values are proposed as the unit output set point. Power exchange with the upstream network in most hours is sold because of less internal unit output power price but during the hours (19–22) power is purchased while the power price is high in these hours. This is because of high load demand low power generation of WT in the most scenarios.

Considering real data of the same day date at year 2012 as a deterministic criterion, two modes of operation are analyzed: 1 – stochastic UC and 2 – stochastic UC and reconfiguration

Table 3
The cost characteristics of MTs (capital, maintenance and emission cost coefficients).

	I (\$)	n (year)	i (%)	CF_{mt}	Kom (\$/kW h)	β_{em} (¢/kW)
MT1	4000	20	5	0.4	0.00587	0.1
MT2	4000	20	5	0.4	0.00587	0.1
MT3	4500	20	5	0.4	0.00587	0.1

Table 2
The cost characteristics of MTs (fuel and startup cost coefficients).

	P_{min} (kW)	P_{max} (kW)	α_{mt} (¢)	β_{mt} (¢/kW)	γ_{mt} (¢/kW^2)	$\alpha_{st,mt}$ (¢)	$\beta_{st,mt}$ (¢)	MUT (h)	MDT (h)	τ (h)
MT1	0	60	4	1.6	$3 * 10^{-4}$	5	10	1	1	2
MT2	0	60	4	1.6	$3 * 10^{-4}$	5	10	1	1	2
MT3	0	120	6	1.8	$3 * 10^{-4}$	5	10	1	1	2

Table 4
The WT unit characteristic.

	Pmin (kW)	Pmax (kW)	w_1 (m/s)	w_r (m/s)	$w_{cut\text{-}out}$ (m/s)	I ($)	n (year)	i (%)	CFwt	Com, wt ($/year)
WT (100 kW)	0	100	3	10	25	90,000	20	5	0.35	1000

Table 5
Battery parameters.

$C_{O\&M,bat}$ ($/year)	$C_{rep,bat}$ ($)	$Q_{lifetime}$ (kW h)	N_{bat}	SOC_{min} (kW)	SOC_{max} (kW)	P_{min} (kW)	P_{max} (kW)	SOC_{in} (kW)
10	900	10,569	40	80	300	−40	40	200

Table 6
Switching parameters.

$\rho_{switching}$ (¢)	$C_{Capital_{switching}}$ ($)
1	9071

Table 7
Loads priority.

Load bus number	Priority
Load3	Vital
Load4	Not vital
Load5	Vital
Load6	Not vital
Load7	Not vital
Load8	Vital
Load9	Vital
Load10	Not vital

simultaneously (the proposed algorithm). As Table 14 shows the mean value and standard deviation of MG's benefits are 49,891 and 3270 cents respectively, when using simultaneous probabilistic reconfiguration and UC. However, if only probabilistic UC is used, the mean value and standard deviation are 53,068 and 13,863 cents respectively. Comparing these results with deterministic combined reconfiguration and UC management using real data of the same date on year 2012 show that absolute relative error is 1.58% for the proposed algorithm (probabilistic reconfiguration and UC), however absolute relative error is 4.69% for probabilistic UC. This fact show that the proposed algorithm directs the MG manager to achieve to a better approximation of the day-ahead benefit and optimal units set points. This combined reconfiguration and UC algorithm determines the optimal MG's topology in addition to the units' set points for day-ahead under uncertainty environment. Besides, comparing with deterministic UC management using real data of the same date on year 2012, the absolute relative error is 0.75% for the proposed algorithm and 5.57% for probabilistic UC. This is another result that proves the proposed algorithm effectiveness. The probability distribution function of MG's benefit is shown in Fig. 3. The analysis shows an estimation of MG's benefit with different possible input states. The conver-

Table 10
Hourly power price.

Hour	$\rho_{sell\text{-}network}$ (¢/kW h)	$\rho_{buy\text{-}network}$ (¢/kW h)	ρ_{load} (not vital) (¢/kW h)	ρ_{load} (vital) (¢/kW h)
1	7	11	6	11
2	7	11	6	11
3	7	11	6	11
4	7	11	6	11
5	7	11	6	11
6	7	11	6	11
7	10	13	9	13
8	10	13	9	13
9	10	13	9	13
10	10	13	9	13
11	10	13	9	13
12	12	15	11	15
13	12	15	11	15
14	12	15	11	15
15	14	18	13	18
16	14	18	13	18
17	14	18	13	18
18	16	24	9	24
19	16	24	9	24
20	16	24	9	24
21	14	18	5	18
22	12	15	5	15
23	12	15	5	15
24	8	11	3	11

Table 8
Mean value of loads in each hour.

	Load3	Load4	Load5	Load6	Load7	Load8	Load9	Load10
Pmean (kW)	18	15	40	20	20	18	40	12

Table 9
Normalized load coefficient (to calculate the hourly mean value) for each hour.

Hour	1	2	3	4	5	6	7	8
Pload (pu)	0.63	0.57	0.51	0.47	0.37	0.36	0.57	0.71
Hour	9	10	11	12	13	14	15	16
Pload (pu)	1	0.98	0.96	1.08	1.1	1.02	1	0.96
Hour	17	18	19	20	21	22	23	24
Pload (pu)	0.96	1.28	1.63	1.8	1.84	1.77	1.39	1.24

Table 11
Code for each configuration topology.

Code	1	2	3	4	5	6	7	8	9	10	11
Open lines	L4 L5	L4 L7	L4 L11	L5 L7	L5 L11	L2 L5	L2 L7	L2 L11	L5 L10	L7 L10	L10 L11

Table 12
Wind speed data calculated for each hour using the 12-last-year data.

Hour	1	2	3	4	5	6	7	8
w_{mean}	4.05	4.65	4.67	3.84	4.53	3.75	3.78	3.23
σ	2.14	2.94	3.3	2.53	2.8	2.2	2.58	2.16
Hour	9	10	11	12	13	14	15	16
w_{mean}	4.62	6.2	6.06	5.57	5.69	6.68	6.89	7.77
σ	2.4	4.43	2.38	2.7	2.62	3.88	3.91	4.12
Hour	17	18	19	20	21	22	23	24
w_{mean}	7.82	6.93	5.56	5.12	4.78	6.37	5.02	4.46
σ	4.37	4.37	3.91	2.49	3.45	4.4	3.16	3

Table 13
Simultaneous optimal configuration and UC result for the mean value of WT and load demand.

Hour	Battery (kW)		MT1 (kW)		MT2 (kW)		MT3 (kW)		Power exchange (kW)		Code
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ	
1	4.49	16.45	42.4	24.1	47.27	20.09	94.55	36.41	−69.64	60.97	11
2	4.57	17.47	40.43	24.05	39.57	23.11	80.2	46.23	−66.77	62.52	1
3	3.27	15.57	34.97	25.43	39.33	24.74	68.92	49.19	−59.87	75.22	11
4	1.6	17.14	34.25	25.51	39.12	24.13	79.12	44.26	−68.99	60.64	11
5	3.16	17.16	28.09	25.47	30.86	26.17	68.31	45.18	−67.01	61.55	11
6	−0.47	15.28	28.79	25.49	33.93	25.01	62.82	45.94	−62.65	60.68	1
7	0.12	16.82	45.61	22.05	46.12	20.27	97.15	39.73	−87.11	63.07	11
8	−2.88	16.09	52.13	15.96	51.8	16.15	102.48	33.72	−82.8	54.91	11
9	−2.76	18.28	50.69	17.49	55.53	10.04	108.34	27.72	−44.68	47.18	11
10	0.83	18.19	54.07	18.32	51.68	17.28	108.72	27.81	−57.55	55.16	11
11	−3.04	15.89	56.27	15.71	49.09	18.52	110.75	23.79	−65.96	44.54	11
12	−1.4	17.08	54.79	10.99	55.56	12.19	114.51	18.05	−47.31	32.7	1
13	−3.8	17.22	51.29	14.21	55.29	12.66	113.51	19.96	−45.3	45.67	11
14	−2.52	17.93	54.33	18.21	53.08	16.05	106.36	30.02	−64.89	54.05	11
15	−4.99	19.43	55.76	13.13	52.3	16.11	112.48	20.85	−77.06	48.49	11
16	−3.1	19.93	55.77	12.09	54.46	14.25	109.44	27.07	−90.27	48.6	11
17	−2.95	17.7	59.22	13.67	55.43	12.46	109.78	21.55	−89.3	46.01	11
18	−9.56	16.6	59.99	4.44	57.93	6.44	118.64	6.03	−44.49	36.29	11
19	−19.06	15.28	59.95	0.43	59.72	2.85	119.59	1.8	21.1	33.79	11
20	−21.48	15.77	59.98	0.15	59.95	0.51	119.53	2.23	52.06	26.66	11
21	−12.5	19.92	59.45	3	59.76	1.44	118.77	6.61	69.72	35.03	11
22	−9.71	17.87	59.18	5.58	59.72	1.6	117.16	12.89	50.95	41.68	11
23	−7.24	16.5	58.83	4.67	58.89	4.86	117.58	8.64	−0.62	35.32	1
24	0.58	17.64	49.8	20	48.53	19.83	105.84	31.53	−26.6	55.74	11

Table 14
Simulation results.

Mode of operation	Mean value (cent)	Standard deviation (cent)	Absolute relative error (%)	
			Compare with row 3	Compare with row 4
1 – Probabilistic reconfiguration and UC	49,891	3270	1.58	0.75
2 – Probabilistic UC	53,068	13,863	4.69	5.57
3 – Deterministic reconfiguration and UC with real data of the same date at year 2012	50,691	–	–	
4 – Deterministic UC with real data of the same date at year 2012	50,266	–	–	

gence of benefit coefficient of variation is shown in Fig. 4. In order to verify the results, the optimization algorithm is changed from PSO to teacher-learning algorithm. The MG's benefit resulted by the teacher-learning algorithm is equal to 49,529 cents for the deterministic UC with real data of the same date on year 2012 and proved the accuracy of the method.

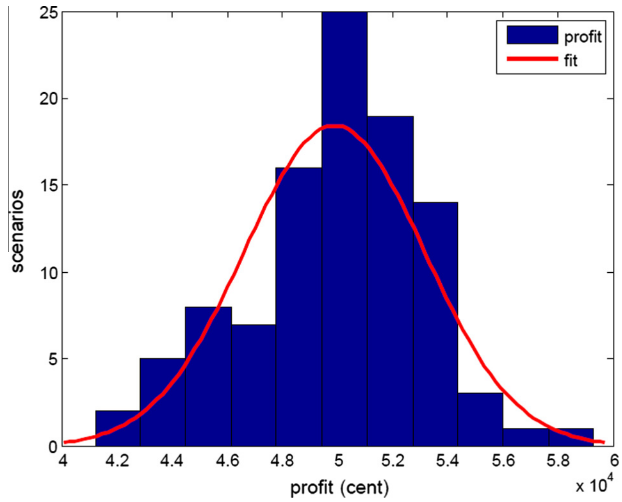

Fig. 3. Probability distribution function of MG's benefit.

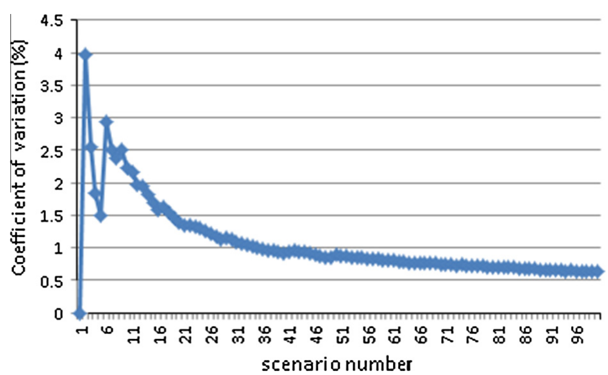

Fig. 4. Benefit coefficient of variation converges versus scenarios.

Conclusion

A stochastic method for simultaneous MG reconfiguration and UC is proposed for each hour of the day-ahead. MG operation and performance are analyzed with different input scenarios. The results show more benefit of this algorithm than only economic dispatch. The proposed algorithm is able to approach to the optimal MG benefit, the units' set points and MG's topology for each hour of day-head. WT generation and load demand are considered as uncertain inputs. Considering enough scenarios, optimal three MTs generation, battery charge or discharge power exchange with upstream network and the most repeated topology are determined for each hour of the next day. The average of continuous variables and the most repeated topology for each hour are assessed by scenarios as a suggestion for the next day. This method was applied to a typical MG. The benefit coefficient of variation becomes converges after approximately 50 iterations.

The future work in the field of this paper should take substantial problems which MG manager faces into consideration. Some of the examples include demand response, photovoltaic generation, plug-in hybrid electric vehicles, and uncertainty of prices.

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