

Multiple Objective Optimizations for Energy Management System under Uncertainties

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Abstract

Recently, micro-grid gains more and more concerns, because it is flexible and environmentally friendly. Optimization of the distributed generators operation in micro-grid is a complicated and challenging task, a multi objective optimal model was designed to cut off the operation cost, improve the economic benefits and reduce the emission. However, the randomness of the renewable energy generation and load demand makes the decision process much more complicated. Chance constrained programming (CCP) was employed to deal with these uncertainties. Besides, the satisfaction degree of the decision was taken into consideration to coordinate the conflicts among different targets. Through the weighted satisfaction degree and coordinate degree, the multi-objective programming can be transformed into single-objective programming. To gain the solution of the optimization problem, genetic algorithm was utilized to search for the optimal strategy. To verify the validity of the proposed model, an energy management system of micro-grid with five types distributed generators was taken as the case study. The results indicate the effectiveness of the proposed method.

Keywords: micro-grid, energy management, uncertainty, chance constrained programming, multiple objective

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1. Introduction

Due to the lack of the traditional energy resource, the up-trend of energy price and the public concerning on social environment, the electric power system faces significant transformation from the conventional hierarchical structure to the innovative flat structure. In the former, concentrated large power stations (like thermal power, hydroelectric and nuclear power) are the main forms. And the total number of these large power stations is small, therefore, electricity power is eventually transported to the end user though long-distance transmission network and large-area distribution network. While micro-grid is the typical form of the latter, which mainly consist of distributed generators, including wind turbine (WT), photo voltaic (PV), diesel engine (DE), micro turbines (MT) and fuel cell (FC) [1]. The future development of distribution energy gains more and more concern, including the relative technology of micro-grid, the forecasting of the renewable energy, the problems of distributed generation connecting electric grid, the evaluation of the micro-grid operation and so on. The operator and manager would utilize proper energy management tools to coordinate the distributed energy, transformer substations and energy storage system for the both purposes of economy and environmental friendly.

Scholars home and abroad have done abundant research on the energy management of micro grid from several different points of view, which can be divided into mid-long term programming and short term programming according to planning horizon. From the former perspective, the determination of location and capacity and the expand programming of distributed generation in the micro grid. In [2], a modified teaching-learning based optimization algorithm is proposed to determine the optimal placement and size of DG units. As to the later, history literature studied the power optimization of each type of distributed generation in micro-

grid to the aim of cutting the cost, improving the reliability and minimum the emissions. Paper [3] proposes Signaled Partical Swarm Optimization to address the energy resources management problem considering storage devices. Most of these researches have taken the energy management of micro-grid as a determinacy issue. Study dealing with the uncertainties in the energy management system is not that much. Paper [4] presents a robust optimization method to determine the optimum capacity of DG in the face of uncertain energy demand. However, in fact due to the intrinsic intermittency and uncertainty of wind power and photovoltaic power and the randomness in the demand side, the strategy got from determinate model may be not optimum, even out of the operation limits. These uncertainties have a great impact on the decision making progress and make it more complicated, thus it is necessary to consider them in the model.

To deal with the uncertainties of wind power, photovoltaic power and demand side, this paper tries to find the optimal strategy to coordinate the storage and transform of electricity power with the power demand for the combined benefits of operation cost, economic benefits and environment pollution. The chance constrained programming is employed to deal with the uncertainties and find the optimal solution. Besides, the satisfaction of decision makers is also taken into consideration for the multiple objective problems.

2. Proposed Dynamic Overmodulation Method

Most uncertainties can be simulated by probabilistic method like probability density function, whose parameters can estimated though history data and the analysis of system's future development. Stochastic programming, fuzzy programming, dynamic programming and robust optimization are the main methods to handle the uncertainties [5-10]. So far, chance constraints programming has been applied in several aspects in electricity system successfully. The mathematical model of chance constraints programming via probabilistic method is described as following:

$$\begin{cases} \min \bar{f} \\ s.t. \quad \Pr\{f(x, \xi) \leq \bar{f}\} \geq \beta \\ \quad \quad \Pr\{g_i(x, \xi) \leq 0\} \geq \alpha \end{cases} \quad (1)$$

Where, x and ξ are the decision vector and random vector respectively; $f(x, \xi)$ is the object function; $g_i(x, \xi)$ is the random constraint function; $\Pr\{\cdot\}$ is the probability of events; α and β are the confidence level of constraint condition and the object function, which are set in advance; \bar{f} is the minimum value of object function under the confidence level at β .

To find the solution of this chance constraint programming, genetic algorithm is introduced here. In genetic algorithm, the fitness rules of biological evolution and information exchange mechanism of chromosomes in population are combined together to search for the best solution in complicated space. Its specific steps are described as following:

- 1) Initialization. The number of chromosomes, crossover probability and mutation probability are the input parameters in genetic algorithm. Initial individual are generated randomly.
- 2) Carry out the simulation for each chromosome in the population, and test if it meets the chance constraint condition. If satisfied, enter into the next step, otherwise, new generation will be generated though mutation operation, and this step will be repeated.
- 3) Select the chromosomes met with the chance constraint condition, and calculate its object function value.
- 4) Choose the elites from the population.
- 5) Conduct the mutation operation and crossover operation among these elites, as a result, we obtain a new generation.
- 6) Continue above operation until the maximum number of iterations, otherwise, we should repeat the steps from 2 to 4.
- 7) The best chromosomes found in the whole process are the optimal strategies.

2.1. The description of object function

The operation management of micro-grid should meet both economy and environmental protection targets [11-13], in other words, we should minimize the operation cost as well as the gas emissions. It is obviously that the micro grid energy management optimization is a multi-objective problem, including the fuel cost of distributed generators, the start and stop cost of units and the purchasing cost from main grid. CO₂, SO₂ and NO₂ are the main emission, while the cost of wind turbine and photovoltaic power is relative low, and their emission is nearly zero. So in this paper, we only consider the generation cost and emission cost of MT, FC and DE.

1. The object of minimum operation cost

Considering the fuel cost, the start and stop cost of units and the purchasing cost from main grid, the objective function tries to optimize the output power of each distributed generator and the storage batteries, aiming at the minimizing the total operation cost.

$$\min f_1 = \sum_{t=1}^T \left(\sum_{i=1}^{m_{DE}} C_{DEi,t} + \sum_{i=1}^{m_{FC}} C_{FCi,t} + \sum_{i=1}^{m_{MT}} C_{MTi,t} \right) + \sum_{t=1}^T \sum_{i=1}^I (Cost_{shut,i,t} + Cost_{start,i,t}) + \sum_{t=1}^T P_{u,t} \cdot Price_t \quad (2)$$

(1) Diesel generator

The fuel cost of diesel generator at time t is usually expressed as:

$$C_{DE}(P_{Gi}^t) = a(P_{Gi}^t)^2 + b(P_{Gi}^t) + c \quad (3)$$

Where, P_{Gi}^t is the output power of the G_i^{th} diesel generator at time t ; a , b and c are constants determined by the type of diesel generator, here $a=0.0547$, $b=1.7362$, $c=3.2456$.

(2) Fuel cell

During the normal operation of fuel cell, the relationship between fuel consumption and the output power can be described as:

$$C_{FC}(P_{FCi}^t) = c_{fuel} \sum_{i=1}^I \frac{P_{FCi}^t}{L \cdot \eta_{FCi}} \quad (4)$$

Where, C_{FC} is the fuel operation cost; P_{FCi}^t is the output power of fuel cell; c_{fuel} is the price of the gas fuel, set as 3.58 ¥/m³; L is the low heating value of gas, η_{FCi} is the utilization efficient of fuel, here $L \cdot \eta_{FCi} = 8.1$.

(3) Micro gas turbine

$$C_{MT}(P_{MTi}^t) = c_{gas} \sum_{i=1}^I \frac{P_{MTi}^t}{\eta_{MTi} \times LHV_f} \quad (5)$$

Where, C_{MT} is the natural gas operation cost; P_{MTi}^t is the output power of the MT_i^{th} micro gas turbine at time t ; c_{gas} is the price of natural gas, 2.05 ¥/m³; η_{MTi} is the efficiency of the MT_i^{th} micro gas turbine, LHV_f is the lower calorific value, $\eta_{MTi} \times LHV_f = 7.6$.

(4) Start and stop cost

$$Cost_{shut,i} = \max(0, U_{i,t-1} - U_{i,t}) \quad (6)$$

$$Cost_{start,i} = \max(0, U_{i,t-1} - U_{i,t}) \quad (7)$$

Where, $U_{i,t}$ is the state variable of the i^{th} unit at time t , 0 means the unit has been shut down, and 1 means the unit is at running status.

2. The object of minimum emission

$$\min f_2 = \sum_t \left[\sum_{i=1}^I (p_1 CO_{2,i,t} + p_2 SO_{2,i,t} + p_3 NO_{2,i,t}) + p_1 CO_{2,U,t} + p_2 SO_{2,U,t} + p_3 NO_{2,U,t} \right] \quad (8)$$

Where, $CO_{2,i,t}$, $SO_{2,i,t}$ and $NO_{2,i,t}$ are the various emission of unit i at time t . $CO_{2,U,t}$, $SO_{2,U,t}$, $NO_{2,U,t}$ are the emission of main grid at time t . $p_1=0.023$, $p_2=7$, $p_3=9$.

3. Multiple target transformation

To deal with the multi objective optimization problem, it is usually transformed into single objective optimization problem. The maximum value f_k^{\max} and minimum value f_k^{\min} of each individual goal can be optimal calculated. However, there are some conflicts among them, and here we employ weighting technique combining with distance function. By combining the weighted sum of satisfaction degree (WSSD) with coordination degree (CD), the optimal function can be transformed into:

$$WSSD = \sum_{k=1}^K s_k AD_k SD_k \quad (9)$$

Where, SD_k indicates the satisfaction degree to the k^{th} goal.

$$SD_k = \begin{cases} 1 & f_k \leq f_k^{\min} \\ \frac{f_k^{\max} - f_k}{f_k^{\max} - f_k^{\min}} & f_k^{\min} \leq f_k \leq f_k^{\max} \\ 0 & f_k^{\max} \leq f_k \end{cases} \quad (10)$$

Table 1. The Satisfaction Degree

Satisfaction Degree	Not Satisfying	Little Satisfying	Satisfying	Very Satisfying
SD_k	[0, 0.5)	[0.5, 0.75)	[0.75, 1)	1

Considering SD_k should arrive at its minimum value SD_k^* at least, there will be an additional constraint condition:

$$SD_k \geq SD_k^* \quad (11)$$

$$AD_k = SD_k^* / \sum_{k=1}^K SD_k^* \quad (12)$$

$$s_k = \begin{cases} 0 & \text{if } SD_k < SD_k^* \\ 1 & \text{if } SD_k \geq SD_k^* \end{cases} \quad (13)$$

K-dimension Euclidean distance will be utilized to coordinate the relationship among each single goal, the coordination degree (CD) will be calculated as follows:

$$CD = d_1 / d_2 \quad (14)$$

$$\text{Where, } d_1 = \begin{cases} \sqrt{\sum_{k=1}^K (f_k^{\max} - f_k)^2} & \text{for MIN object function} \\ \sqrt{\sum_{k=1}^K (f_k - f_k^{\min})^2} & \text{for MAX object function} \end{cases}, d_2 = \sqrt{\sum_{k=1}^K (f_k^{\max} - f_k^{\min})^2}.$$

2.2. The Description of Constraint Condition

The main constraint conditions are described and analyzed as following:

1. Load balance

$$\sum_i^T P_{i,t} U_{i,t} + \sum_j^S P_{j,t} U_{j,t} + P_{u,t} = P_{D,t} \quad (15)$$

Where, $P_{D,t}$ is the total actual load demand under the micro grid at time t ; $P_{u,t}$ is the load purchased from main grid, if $P_{u,t} > 0$, that means power load is purchased from main grid, while, if $P_{u,t} < 0$, that indicates micro grid sell the electricity to the main grid.

2. The limits of distributed generators

$$P_i^{\min} \leq P_{i,t} \leq P_i^{\max} \quad (16)$$

Where, P_i^{\min} and P_i^{\max} are the lower and upper limits of the i th unit respectively.

3. The transmission power limit between main grid and micro grid

$$P_t^{\min} \leq P_t \leq P_t^{\max} \quad (17)$$

4. Energy storage devices

As advanced energy storage device emerge, the energy storage device is playing an increasingly important role in power system. It can be used to store the electricity power, when the electricity price is low, instead, it can discharge the power when the price is high, to gain more economic benefits. At current, storage battery, Flywheel energy storage (FES), superconducting energy storage and super capacitor are the popular late-model energy storage technologies. In this paper, we discuss the most commonly applied battery energy storage, and the rules of charge-discharge are expressed as following:

$$\begin{aligned} \varphi_{j,t} = & \varphi_{j,t-1} + \eta_{charge,j} P_{charge,j,t} \Delta t \\ & - \frac{1}{\eta_{discharge,j}} P_{discharge,j,t} \Delta t \end{aligned} \quad (18)$$

$$\varphi_j^{\min} \leq \varphi_{j,t} \leq \varphi_j^{\max} \quad (19)$$

$$P_{charge,j,t} \leq P_{charge,j}^{\max} \quad (20)$$

$$P_{discharge,j,t} \leq P_{discharge,j}^{\max} \quad (21)$$

Where, $\varphi_{j,t}$ is the storage capacity of the j th battery at time t ; $P_{charge,j,t}$ and $P_{discharge,j,t}$ are the charge rate and discharge rate of the j th battery after Δt ; $\eta_{charge,j}$ and $\eta_{discharge,j}$ are the charge efficiency and discharge efficiency of the j th battery; φ_j^{\min} and φ_j^{\max} are the lower limit and upper limit of the j th battery; $P_{charge,j}^{\max}$ and $P_{discharge,j}^{\max}$ are the maximum charge rate and discharge rate of the j th battery during Δt . These parameters are set as: $\eta_{charge,j} = 80\%$; $\eta_{discharge,j} = 85\%$; $\varphi_j^{\min} = 240\text{kWh}$; $\varphi_j^{\max} = 1200\text{kWh}$; $P_{charge,j}^{\max} = 350$; $P_{discharge,j}^{\max} = 450$.

2.3. The Uncertainties in the Target Power System

1. Wind power

Suppose $P_w(v)$ as the output power of wind turbine generation, its relationship with wind speed can be expressed as:

$$P_w(v) = \begin{cases} 0 & v < v_C \text{ or } v > v_F \\ P_R \frac{v^k - v_C^k}{v_R^k - v_C^k} & v_C \leq v \leq v_R \\ P_R & v_R < v \leq v_F \end{cases} \quad (22)$$

Where, P_R is the nominal power of wind turbine generator, here set as 30kW; v_C , v_F and v_R is the cut-in wind speed, cut-out wind speed and rated wind speed, and set as 3m/s, 25m/s and 11m/s respectively. According to past studies, the probability density function of wind speed

follows Weibull distribution $\phi(v) = \frac{k}{c} \left(\frac{v}{c}\right)^{k-1} e^{-(v/c)^k}$, where, the k is Weibull shape parameter [14],

usually falls in [1.8,2.8], and c is the scale parameter, in this paper we set them as 2 and 6.5 respectively.

2. Photovoltaic power

Solar cell is the foundation and kernel of photovoltaic power generation system, whose output power is closely related to light intensity. Suffering the strong randomness of light intensity, the output power is also uncertain. According to statistics, during a certain period (one or several hours) the sun's ray can be regarded as Beta distribution approximatively, and its probability density function is described as:

$$P_{PV} = P_{STC} \frac{G_{AC}}{G_{STC}} (1 + k(T_c - T_t)) \quad (23)$$

Where, P_{STC} is the maximum test power under standard test condition (sunlight incident intensity as 1000W/m², the environmental temperature as 25°C); G_{AC} is the illumination intensity; G_{STC} is the illumination intensity under STC, as 1000W/m², k is the temperature power coefficient, here set as -0.0047; T_c is the panel's working temperature; T_t is the reference temperature, 25°C.

3. Case Study

In this paper, we simulate a micro grid including five types distributed generators, wind turbine, photovoltaic power, fuel cell, diesel power and micro gas machine. The upper limit of physical transmission capacity between micro grid and main grid is 30kW. The time interval is set at 1 hour, which means 24 periods a day. The power load is subjected to the uniform distribution with the forecasting value as mean value and 0.1 as the variance. The output of wind power and photovoltaic power is obeyed to the uniform distribution with ±10% deviation. The emission cost of different generator units is listed in Table 2.

Table 2. Emission of Different Generator Unit

Gas	CO ₂	SO ₂	NO _x
External cost discount (¥/kg)	0.023	7	9
Fuel cell (kg/MWh)	489	0.0027	0.014
Micro gas turbine (kg/MWh)	724	0.0036	0.2
Diesel generator (kg/MWh)	649	0.206	9.89
Main Grid (kg/MWh)	1230	0.42	2.35

Figure 1 illustrates the 24 hour daily load demand of micro-grid. The output power of wind turbine and photovoltaic power is described in Figure 2. The confidence interval value is set at 0.9, and the single objective programming and multi objective programming are discussed respectively.

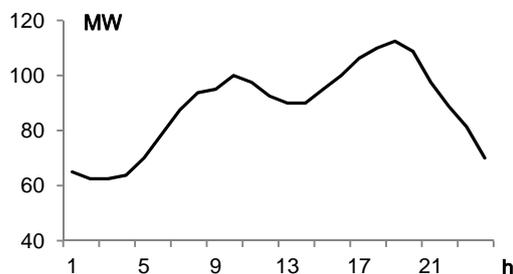


Figure1. 24 hour daily load curve of micro-grid

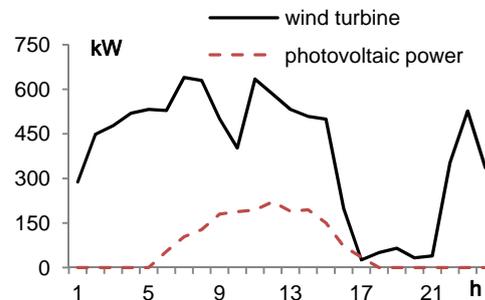


Figure2. The output power of wind turbine and photovoltaic power

4. Results Analysis

The results from single-objective and multi-objective optimization are illustrated in Table 3 respectively. It's obviously that the results got from the multi-objective optimization lie between the corresponding minimum and maximum value from the single-objective optimization. Only considering the generation cost, the minimum value is 6348.12 ¥; as to only considering emission, the minimum value is 130.58 ¥. The optimal generation cost obtained from multi-objective is 6854.28 ¥, which is 7.97% higher than the minimum value under single-objective programming. While, the optimal emission value got from multi-objective is 142.63 ¥, which is 9.24% higher than the minimum value under single-objective programming. The optimization and coordination of the three objectives simultaneously make all the SD_s well satisfied, which means that all the objectives exceed their setting values of SD_s .

Table 3. Comparison between Single and Multi-objective Optimization Results

Objectives	Single-objective		Multi-objective	
	Min	Max	Optimum	SD_s
Generation Cost(¥)	6348.12	7105.62	6854.28	0.6987
Emission(¥)	130.58	151.24	142.65	0.5214
WSSD.CD	-	-	0.4356	-

Table 4. Comparison among Different Confidence Interval

Confidence interval value	Generation cost(¥)	Emission(¥)	WSSD.CD
0.80	6671.35	140.21	0.4251
0.85	6725.20	143.56	0.4298
0.90	6854.28	142.65	0.4356
0.95	6935.12	144.25	0.4510

Besides, the impacts of different confidence interval values are also analyzed here. According to Table 4. The confidence value is set to be 0.80, 0.85, 0.90 and 0.95 respectively, and the generated solutions can be used for various decision options that are associated with different levels of risks. It can be found that the generation cost, the emission and the WSSD.CD value change a little under different confidence interval values. The higher the confidence interval value is, both the generation cost and emission cost will be greater.

5. Conclusion

In this paper, a multi-objective optimization model has been developed to coordinate the economic and environmental problems in micro grid energy management. The uncertainties brought by the renewable energy generation and power demand are handled by chance constraint programming. The satisfaction degree and coordination degree is introduced with the consideration of decision makers' requirement. The simulation results indicate the model is efficient and viable. This model proposed in this paper can provide the decision makers the optimal strategy within feasible solutions. However, the combined heat and power generation is not considered here. The genetic algorithm may be not the best and fastest method to search for the best solution, and it can be improved in the future.

Acknowledgment

This work was supported in part by NSFC under Grant Nos. 71071052 and Grant Nos. 71201057, as well as "the Fundamental Research Funds for the Central Universities" under Grant Nos. 12QX23.

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