A Risk-Averse Energy Management in Micro-grids on Information Gap Decision Theory Using the Genetic Algorithm

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Abstract

In this paper, energy management in a Micro-grid connected to the distribution network has been done with the aim of reducing the cost of operating the Micro-grids and reducing the environmental pollution index. The Genetic Algorithm method is used to optimize the objective function and find Pareto solutions. The Information Gap Decision-making Method has been used to select the appropriate answers from Pareto's set of answers. In the meanwhile, the participation rate of each of the distributed generator sources and the charge and discharge planning of the energy storage system to provide the Micro-grids load has been calculated. In addition, the interaction between the Micro-grids and the distribution network is important. To analyze the proposed method, a planning problem using multi-priced electricity tariffs is presented as an advantage of the energy storage system. To demonstrate the effectiveness of the multivariate optimization method presented in this thesis, modeling and simulation of diesel generators and energy storage in a Micro-grid have been performed. Mathematical models based on probability density functions, renewable energy sources and consumer load have been investigated. Minimizing the cost of fuel to generate power in the Micro-grids, uncertainty related to renewable sources and Micro-grids load consumption has been modeled using the Information Gap Decision-making Method of maximum uncertainty radius for renewable units and load consumption. The results of the Information Gap Decision Method are compared with conventional methods based on probabilistic function analysis such as the scenario tree method. The results presented in this dissertation show the advantages of the proposed method to improve the overall performance of independent and connected Micro-grids to the distribution network.

Keywords: Energy management, Information gap decision theory, Micro-grids, Genetic Algorithm

1. Introduction

Nowadays, due to technological advances and environmental and economic considerations, the use of renewable energy sources and the need for energy management in power systems has attracted much attention. Considering the importance of energy management in power systems and on the other hand the need to reduce pollution of electricity producers, the issue of operation of Micro-grids has been of considerable importance considering these two goals. Environmental management of energy in a Micro-grid is to determine the participation of each of the distributed generation sources, planning the charge and discharge of the energy storage system, as well as the interaction of the Micro-grid with the upstream network to meet local load demand with simultaneous reduction of operating costs and environmental pollution.

Due to the rapid growth of electricity demand, major problems in electricity generation and transmission have arisen in power systems, especially distribution networks. The use of Micro-grids is one of the solutions adopted in different countries, which requires proper energy management in the mentioned networks. The multiplicity of articles on Micro-grids and energy management in recent years shows the importance of the issue.

In reference [1], the Micro-grid energy management system has been considered for designing a combined photovoltaic system with uncertainty of photovoltaic production and load. The model presented in this reference, while minimizing the cost of fuel to generate power in the Micro-grid, also considers the uncertainty related to renewable sources and Micro-grid load consumption, and with the help of Information Gap Decision Theory (IGDT) theory, obtains the maximum uncertainty radius for renewable units and load consumption. Brought, so that the system has the minimum expected performance. The proposed method considers the uncertainty of photovoltaic power generation and load demand simultaneously by solving the problem of two-level multi-objective optimization using decision-making theory based on information gap.

Reference [2] proposes the IGDT for the Micro-grid to obtain the pricing strategy (tendering) of the power purchased from the upstream network. The Micro-grid operator tries to provide local load at the lowest cost from alternative energy sources including upstream grids, micro-turbines, renewable energy sources (photovoltaic systems and wind turbines) and energy storage system. To purchase electricity from the upstream grid, the optimal Micro-grid pricing (bidding) curve must be prepared for bidding to the market operator, which uses IGDT theory to determine the optimal pricing strategy. Includes robustness and opportunity functions to model upstream network price uncertainty. The Micro-grid can consider the decision of resistance (risk-taking) or the decision of opportunity (risk-taking) under conditions of uncertainty. The Micro-grid operator also uses a demand response program that aims to reduce the cost of energy supply. Among these, the proposed stochastic model considers local load uncertainty modeling and output power of renewable energy sources using a stochastic model scenario.

Reference [3] examines the financial risk of demand-response (DR) and renewable energy (RES) collectors in Micro-grids, due to the intermittent and uncertain nature of DR and RES, as well as competition between collectors to maximize their profits. This paper uses two well-known methods of risk assessment, value at risk (VaR) and conditional risk value (CVaR), to predict the power of RES and DR programs at a specific level of risk. VaR and CVaR They are used to estimate the net financial gain from DR and RES in the leading day market. VaR is used to estimate RES power and DR size or load recovery at different levels of reliability. The CVaR is then used to reflect the amount of power against financial risk. This helps the user understand the level of risk associated with the uncertain production of renewables and the size of the DR. The removal and transfer of burden has been considered in this study, which includes indefinite and constant participation of customers to consider the impact of forced and non-forced participation. The results indicate the importance of risk assessment and possible effects on the technical and economic characteristics of the Micro-grid energy market.

In reference [4], the improved PSO algorithm is applied to solve the energy management problem of a sample Micro-grid. The sample Micro-grid includes renewable energy sources, micro turbines, fuel cells and batteries, which are optimally programmed for a time horizon of 24 hours. In this paper, the effect of uncertainty on wind and solar sources is not considered.

In references [5 and 6], research on the issue of Micro-grids in terms of design and the issue of its optimal use has received much attention, among which the issue of energy management is also very important. In some communities, the expansion of transmission lines to supply electricity from power grids may not be possible for reasons such as economic factors and geographical factors. Therefore, the generation of energy for the delivery of electricity to loads, especially in separate systems, must be properly managed. However, the use of a Micro-grid in the main power grid involves many environmental challenges and technical techniques.

In references [7,8], the challenges are uncertainties related to load demand and production of renewable units such as photovoltaic units. There is a case for energy management and system operation for Micro-grid-based diesel production. It focuses on a storage set with an active governor and a load scheduling function to maintain the reliability of the unique unit by considering uncertainty and load forecasting for short-term scheduling.

A fuzzy finite Boltzmann machine: New learning algorithms based on the sharp probability average of fuzzy numbers are referenced in reference [9], modeling the uncertainty of renewable energy sources using stochastic techniques and fuzzy approaches. These techniques also have disadvantages. For example, probabilistic methods such as Monte Carlo in the reference [10], scenario-based modeling in the reference [11] and the probabilistic mean method of fuzzy numbers in the reference [12], cannot achieve uncertainty without access to possible density functions. Reference [10] presents energy system studies including a new standard classification of uncertainty modeling techniques for the decision-making process. These methods have been introduced and compared along with showing their strengths and weaknesses. References [13, 14] present IGDT in industrial applications to deal with uncertainty. In particular, power system engineers seeking to reduce operating costs have become interested in using IGDT. This is because this theory does not require information about the past behavior of the uncertainty parameters.

In the reference [15], the proposed optimal production strategy in the electricity markets is obtained by the IGDT. In references [14,16] IGDT explains the uncertainty regarding the generation of electricity through wind farms. However, in these articles, the daily behavior of uncertainty parameters is not examined. The study presented in [17] illustrates the application of IGDT for unit-based models taking into account the uncertainty of wind farm generation and, of course, without considering the uncertainty of simultaneous load. References [18,19] introduce the Genetic Algorithm (GA), which is one of the multi-objective evolutionary optimization algorithms whose very high efficiency has attracted many researchers.

2. Micro-grid Structure and Modeling

Figure 1 shows a Micro-grid, which includes a photovoltaic generator, wind turbine, energy storage and diesel generator.

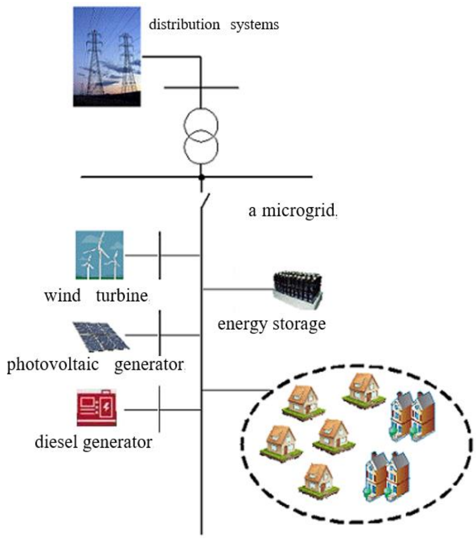

Fig. 1. Micro-network configuration examined in this paper

In this paper, the parameters of uncertainty are load demand and output power of WT and PV. The actual load prediction data of a Micro-grid in Canada and the wind speed of Toronto have been studied. The wind speed forecast of the Meteorological Organization on February 7, 2020 has been used. A Gaussian PDF based error model has also been added for the predicted models compatible with wind, solar and load models. Apart from the initial installation for the WT, the cost of generating electricity is negligible. Equation (1) shows the cost performance of DGs.

$$C_{DG;i} = \sum_{i=1}^{N} (a_i + b_i P_{DG;i} + c_i P_{DG;i}^2) \quad (1)$$

The coefficients a_i, b_i, and c_i are the coefficients of the DG cost functions. N is the number of DGs. PDG, i and CDG, i are the output power of i'th DG and their costs.

The energy storage system is intended to store the surplus energy of the network's renewable generators.

Information Gap Decision Theory

Information gap decision making theory is a practical strategy without the need for probability distribution function, which does not need to consider probabilistic approaches such as stochastic programming methods. Information gap decision making theory is an evaluated decision-making process, which uses two modes of robustness and opportunism to make some cost-effective and strong decisions against uncertain parameters. In the optimization process, parameters with uncertainty are undesirable and can cause more costs and less profit or, conversely, cause less costs and more profit.

Information gap theory models uncertainty as a subset of u(a, ũ) around an estimated point ũ. The estimation point is considered with high accuracy and uncertainty and generally without limitations. Uncertainty measures the distance between an estimate and its acceptability. Uncertainty is the average size between a point (point estimate) and the maximum probability of error, and as a result, it expresses the sensitivity. In other words, the margin of error is determined.

$$u(a;\tilde{u}) = \left\{ u(x): |u(x) - \tilde{u}(x)| \begin{matrix} \le a\tilde{u}(x); \\ for\ all\ x \in X \end{matrix} \right\} \quad ;\ a \ge 0$$

If a u(a,y) is a family of information gap theory models. A function model of information gap theory is defined as follows.

$$u(a;\tilde{u}) = \{u(x): u(x) \in U(a;\tilde{u}(x))\ for\ all\ x \in X\}\ a \ge 0 \qquad (2)$$

Information gap theory follows two obvious hypotheses. nested model, and summary model.

3.1 Nesting model

If a<a′, the information gap model u(a,ũ) will be nested.

$$u(a;\tilde{u}) \subseteq u(\acute{a};\tilde{u}) \qquad (3)$$

3.2 Contraction model

If u(0,ũ) is a monomial set containing its center point.

$$u(0,\tilde{u}) = \{\tilde{u}\} \qquad (4)$$

The nested model uses the feature of *clustering* to apply the feature of uncertainty in problem analysis. In addition, the mentioned model expresses the set of uncertainty u(a, ũ). As a increases, the uncertainty increases. Uncertainty can be harmful or beneficial. In other words, uncertainty changes may be unfavorable or favorable. Negative uncertainties mean that the error is less than the estimated limit and brings the possibility of failure, while positive uncertainties mean that the error is more than the estimated limit and increases the probability of success and profit. The theory of information gap decision-making is based on the quantification of these two aspects of uncertainty and the choice of action that considers one or both uncertainties at the same time. The destructive and constructive aspects of uncertainty are modeled by two "safety functions" the robustness function expresses immunity against loss and failure, while the opportunistic function expresses immunity against increasing profit and victory. The robustness function represents the highest level of uncertainty in which failure cannot occur. Opportunistic function is the lowest level of uncertainty, which leads to the possibility of wide success. Robustness and opportunism functions, respectively, eliminate the destructive and beneficial aspects of uncertainty.

$$\hat{\alpha}(q) = \max\{\alpha: \text{min requirements are always satisfied}\} \qquad (5)$$

$$\hat{\alpha}(q) = \min\{\alpha: \text{sweeping success is possible}\} \qquad (6)$$

The equation 5 is the strength relationship and α in this relationship is the minimum requirement that is always met. The equation 6 is the relationship of opportunism and α is the degree of possible success in this relationship.

q is a decision vector of parameters such as design variables, start time, model parameters or operational options. Robustness and opportunity functions can be expressed as a maximum or minimum set of values of the uncertainty parameter a of an information gap model. The robustness function includes the maximum adverse state and can generally be the maximum possible bad error and shows the maximum level of uncertainty required for failure. On the contrary, the opportunistic function includes the maximum favorable situation and in general can be the maximum possible positive error and shows the maximum level of uncertainty necessary for victory. Now the uncertainty functions of strength and opportunism can be expressed more clearly with the help of the following relations.

$$\hat{\alpha}(q; r_c) = \max\{\alpha: r_c \leq \min R(q;u)\ ;\ u \in U(\alpha;\tilde{u})\ \} \quad (7)$$

$$\hat{\beta}(q; r_w) = min\{\alpha: r_c \leq \max R(q;u)\ ;\ u \in U(\alpha;\tilde{u})\} \quad (8)$$

$\hat{\alpha}(q; r_c)$ is the maximum level of uncertainty corresponding to the guaranteed reward not less than the critical reward r_c. while $\hat{\beta}(q; r_w)$ is the lowest level of uncertainty that must be accepted in order to reach the default size of r_w. The complementary but asymmetric structure of safety functions is evident from equations 7 and 8. These definitions can be modified to arrive at multi-criteria reward functions. Likewise, similar definitions apply when R(q,u) is a loss rather than a reward. The relationships shown show the flexibility and ability to change this method according to the user's wishes.

The following equations are used to calculate the fuel cost of diesel generators.

$$F_{cost}^{DG1} = 0.0225P_1^2 + 15P_1 + 12.5 \quad (9)$$
$$F_{cost}^{DG1} = 0.0345P_1^2 + 14.5P_1 + 26.5 \quad (10)$$

The triple price tariff used for distribution network electricity is used with the help of Toronto Canada tariff [20]. Table 1 shows the electricity tariff used in this article.

Table 1. of the triple electricity price tariff used in this article.

On peak	Mid peak	Off peak	time
14	11.4	7.7	Cost (₵)

The wind turbine installed in the system is 500 kW. The standard deviation of the predicted errors of wind speed and load demand are 5% and 18%, respectively [21]. A battery with an efficiency of 86% in energy storage and an efficiency of 86% in the discharge phase is considered. Therefore, the total efficiency of the batteries in two stages of charging and discharging is 73.9%.

Table 2 shows the results of economic distribution of Micro-grid load. In this table, the load and power values of all energy sources are shown in kilowatts during the day and night. A negative sign in the power column of the distribution network indicates that the Micro-grid injects power into the distribution network. Diesel generators inject power into the power distribution network during peak hours and do not work during other hours. The last columns of the tables show the power and energy of the battery in the studied modes.

Simulation Results

In simulation result, the Micro-grid is examined in the state connected to the national network. The objective function under consideration is the cost function of energy produced in the network. There is an exchange of energy between the network and the Micro-grid. The flow is two-way, therefore, the excess power of the hybrid network can be injected into the network.
The battery bank delivers power to the grid during peak hours, similar to an electric energy generator, and acts as a consumer

during low-load hours, drawing power from the grid and storing it. Figure 2 is the load power curve of the consumers and the production power of all the generator components of the Micro-grid and shows the result of the economic distribution of the load in the form of a curve. Another result of the problem of economic distribution of the peak shift load, which can be seen in Figure 2. Batteries and wind and solar generators play an important role in changing the peak during peak times.

According to table 2, diesel generators work only in the hours of 8 to 11, 18 and 19, and the cost of electricity production in other hours considering that the cost of electricity production by wind turbine, solar generator and battery is zero. It is only the cost of electricity purchased from the distribution network, which is known according to the tariff in table 1.

Table 2. Economic dispatch results

Hour	Load	P_{DG1}	P_{DG2}	P_{WT}	P_{PV}	P_{Grid}	P_{Bat}	E_{Bat}
1	32	0	0	124	0	3.24	-95	420
2	28	0	0	117	0	89	0	500
3	28	0	0	118	0.5	90.5	0	500
4	26	0	0	118	3	95	0	500
5	192	0	0	116	8.5	67.5	0	500
6	442	0	0	143	16	283	0	500
7	488	0	0	143	25.5	319	0	500
8	512	67	51	142	37.5	115	100	500
9	520	67	51	141	49	112.61	100	381
10	540	67	51	145	54.5	123.11	100	261
11	564	67	51	150	55.5	141.14	100	142
12	568	0	0	149	55.5	363.5	0	23
13	570	0	0	143	52.5	363.5	0	23
14	570	0	0	142	46.5	381.5	0	23
15	572	0	0	140	37.5	394.5	0	23
16	574	0	0	140	36.5	407.5	0	23
17	570	0	0	145	15.5	409.5	0	23
18	560	67	51	142	6	274.61	20	23
19	552	67	51	140	1	293.61	0	0
20	550	0	0	144	0	506	-100	0
21	532	0	0	142	0	490	-100	84
22	508	0	0	148	0	460	-100	168
23	64	0	0	144	0	20	-100	252
24	32	0	0	132	0	0	-100	336

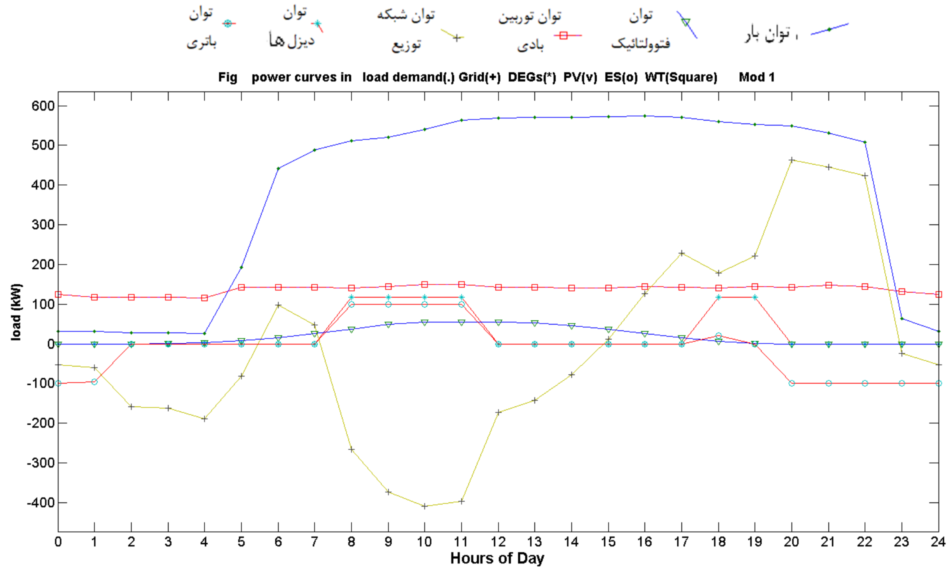

Figure 2. Load demand and production power curves of all Micro-grid generator components

In additton, during the mentioned hours that the diesel generators work, the cost of electricity includes the electricity purchased from the distribution network and the production power of the diesel generators. The cost of diesel generator power generation using equations 9 and 10 is 1118 and 856 cents, respectively. The total cost of Micro-grid power supply is presented in Table 3. The negative sign in Table 3 in the cost column indicates that the power sold to the distribution network and the resulting profit is more than the total production costs, and the main reason for this is the purchase of power from the network during off-peak hours and the sale of power to The distribution network is at peak hours. Even during some busy hours of the day and night, the micro-grid is generating excess power, the profit of which has financial benefits and in some hours environmental benefits for the user. Table 3 shows the total electricity cost of operating the Micro-grid during the day and night with $\varsigma_c = 0$.

Table 3. total cost of electricity during the day and night with $\varsigma_c = 0$

Total cost (₵)	Load (KW)	Hour	Total cost (₵)	Load (KW)	Hour
4943	570	13	28	32	1
5038	570	14	-774	28	2
5207	572	15	-787	28	3
5379	574	16	-826	26	4
5405	570	17	587	192	5
4942	560	18	2462	442	6
5284	552	19	2780	488	7
4402	550	20	2072	512	8
4263	532	21	2026	520	9
4002	508	22	2016	540	10
174	64	23	22539	564	11
0	32	24	4798	568	12

Conclusion

In this article, energy management in a Micro-grid connected to the distribution network has been carried out with the goals of reducing the cost of Micro-grid operation and reducing the environmental pollution index. The GA method was used to optimize the objective function of reducing the cost of economic distribution in the Micro-grid. Information gap decision making method was used to determine the uncertainties of wind and solar energy production sources and demand power. The contribution rate of each source of distributed generators and the charging and discharging planning of the energy storage system to supply the Micro-grid load was calculated.

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