



Optimal scheduling of a microgrid with a fuzzy logic controlled storage system



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ABSTRACT

This paper presents an algorithm for reducing the operating cost of microgrids. The proposed algorithm determines the day-ahead microgrid scheduling and builds a fuzzy expert system to control the power output of the storage system. To perform such tasks, two genetic algorithms were employed. One of them generates the microgrid scheduling and determines the fuzzy rules of the expert system, whereas the other is used to tune the membership functions. In this way it is possible to optimize the expert system according to load demand, wind power availability and electricity prices. Simulations were carried out in a microgrid comprising a diesel generator, a microturbine, a fuel cell, a wind turbine and a battery. Both interconnected and island operation modes were considered. Simulation results verify the effectiveness of the proposed algorithm.

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Introduction

Recently the traditional energy network has been undergoing important changes. The penetration of distributed generation has been prompted by several factors such as environmental issues, market deregulation, incentive policies and the growth of global electricity demand. The benefits of distributed generation can include reliability enhancement, power loss reduction, improvement in power quality, the integration of renewable sources and the provision of ancillary services. However, distributed generation can also have negative effects on power stability, network security, system voltage, power system control, etc. [1–3]. It is in this context that microgrids (MGs) arise as a platform where distributed generation technologies can be readily integrated into the distribution network.

A microgrid is a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that act as a single controllable entity with respect to the grid [4]. Depending on the circumstances, it can operate either in parallel with the main grid or in island mode. For the main grid, the microgrid may be seen as a controllable unit that can respond to central control. Micro-sources comprising the MG include technologies such as diesel generators (DGs), fuel cells (FCs), microturbines (MTs), photovoltaic panels and wind turbines.

As for large power systems, the generation scheduling in microgrids is performed by solving the unit commitment and economic dispatch problems. Unit commitment involves determining the schedule of generating units within a power system subject to device and operational constraints. In turn, economic dispatch is a subroutine of the unit commitment aimed at locating optimal outputs of generators so that the entire load may be supplied in the most economic way [5]. However, owing to differences between large power systems and microgrids, special considerations must be taken into account when performing the unit commitment in this case. Some of the most important features of MGs affecting the unit commitment problem are listed below [6–9]:

- MGs usually have a high penetration in renewable sources, which makes it difficult to determine in advance the power available at any instant in the future.
- MGs are usually radial or weakly meshed low voltage networks, which are more prone to problems such as over/under voltage or overloading when the load/generation condition is changed.
- The presence of storage devices, as well as the possibility of exchanging energy with the main grid, adds flexibility to MG operation, but also it increases the solution space of the unit commitment problem.
- The small size of the generators that comprise an MG makes it possible to switch them on and off with a higher frequency than in large power plants.

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Nomenclature

| | | | |
|----------------------------|---|----------------------------|---|
| ΔT | duration of the commitment interval (h) | $P_{d,max}^t, P_{d,min}^t$ | maximum/minimum battery discharge rate during period t (kW) |
| η_d/η_c | discharging/charging battery efficiency | P_{Grid}^{max} | maximum allowed power exchange at the PCC (kW) |
| μ_{ij} | membership function of the j -th fuzzy set of A_i | P_i^{max}, P_i^{min} | maximum/minimum power output of unit i (kW) |
| A_i | input/output variable of the expert system | P_i^t | power output of unit i during period t (kW) |
| a_i, b_i, c_i | coefficients of the fuel cost function of unit i | P_L^t | load demand during period t (kW) |
| a_i^n | linguistic value associated with A_i in the n -th rule | P_{wt}^t | power output of wind turbine during period t (kW) |
| B_{sc} | storage capacity of the battery (kW h) | R^c, R^d | vector holding the charging/discharging rules |
| BSR^t | reserve provided by the battery during period t (kW) | R^t | spinning reserve requirement during period t (kW) |
| c_{ij}, d_{ij}, e_{ij} | geometrical parameters of μ_{ij} | r_c^n, r_d^n | n -th charging/discharging rule |
| E_b^t, E_s^t | electricity buying/selling price during period t (€/kW h) | SC_i | start-up cost of unit i (€/h) |
| F_i | fuel cost function of unit i during period t (€/h) | SOC^0, SOC^T | initial/final state of charge |
| Fit | fitness function | SOC^t | state of charge at the end of period t |
| G | matrix holding the status of the elements of the microgrid | SOC_{max}^t, SOC_{min}^t | maximum/minimum state of charge at the end of period t |
| K | parameter of the fitness function | T_i^{on}, T_i^{off} | continuously on/off time of unit i (h) |
| K_{OMC_i} | incremental operation and maintenance cost of unit i (€/kW h) | $t = 1, 2, \dots, T$ | commitment interval |
| MC | operating cost of the microgrid | U_i^t | status of the unit i during period t (1 for “on” and 0 for “off”) |
| \overline{MC} | mean operating cost of the microgrid | | |
| \underline{MC} | minimum operating cost of the microgrid | | |
| MFA_i | membership functions of A_i | | |
| MUT_i, MDT_i | minimum up/down time of unit i (h) | | |
| m_i | number of fuzzy sets utilized to characterize A_i | | |
| N | number of generating units | | |
| N_r | number of charging/discharging rules | | |
| OMC_b | battery operating and maintenance cost (€/h) | | |
| OMC_i | operating and maintenance cost of unit i (€/h) | | |
| \bar{P} | rated power capacity of the battery (kW) | | |
| P_b^t, P_s^t | power bought/sold from/to the grid during period t | | |
| P_{batt}^t | battery power output during period t (kW) | | |
| $P_{c,max}^t, P_{c,min}^t$ | maximum/minimum battery charge rate during period t (kW) | | |

List of abbreviations

| | |
|--------|--|
| DG | diesel generator |
| FC | fuel cell |
| FES | fuzzy expert system |
| GA | genetic algorithm |
| GA-MFT | genetic algorithm for membership function tuning |
| GA-SRD | genetic algorithm for scheduling and rules determination |
| MG | microgrid |
| MT | microturbine |
| PCC | point of common coupling |

- Due to the distance between producers and consumers, congestion in transmission lines in large power systems is probable. However, in microgrids local load is satisfied mostly by local generation, and therefore the possibility of dealing with such a problem is significantly lower than in the previous case.

During the last decade many papers related to energy management in microgrids have been published. Some of the techniques employed to deal with the unit commitment problem in large power systems are utilized in MGs as well. In [7], a genetic algorithm (GA) based method was proposed to solve the unit commitment problem. To accelerate the solution search a simulated annealing based operator was devised. In [10], Lagrange relaxation was used to determine the scheduling of a microgrid under island operation mode. The proposed method incorporates a GA to update the Lagrange multipliers. In [11], an energy management system which considers the forecast errors of renewable power generators was suggested. The proposed system employs a dynamic programming based algorithm to optimize the battery schedule. In [12], the day ahead unit commitment problem was solved using mixed linear integer programming. In order to handle uncertainty a multi-scenario stochastic model was adopted. Since many different objectives may be pursued simultaneously, multi-objective optimization approaches are widely used. In [13], an ant colony algorithm was proposed to optimize the microgrid operation from the economic and environmental point of view. A multi-objective energy management system for cost and emission minimization

has been designed in [14]. The suggested system includes a forecasting module and a fuzzy logic controlled battery.

Energy storage systems can be used to cope with some of the technical and economic challenges of microgrid operation. In order to deal with the uncertainties of non-dispatchable sources, storage systems can store energy during high availability periods and redispatch it when there is a power shortage. These devices can also take advantage of time of use tariffs by purchasing power from the upstream grid during the off-peak hours and selling it back to the upstream grid during the peak demand hours. Other benefits of using storage systems in microgrids are detailed in [15].

Expert systems based on fuzzy logic are usually employed in microgrids [14,16,17] in order to control the power output of the storage devices. Fuzzy logic is a powerful tool for dealing with imprecision and nonlinearity. In addition, it enables the translation of qualitative knowledge to quantitative knowledge suitable for microprocessor implementation and automation [18]. When building a fuzzy system, one of the most important things is to generate appropriate fuzzy rules and membership functions. To perform such a task the aforementioned papers make use of human expertise. However, the construction of a rule base and membership function set based exclusively on expert knowledge may be a challenging task that requires time and experience [19–21]. Even so, good results are not always guaranteed. As an alternative several authors propose the use of evolutionary algorithms to generate the rules and membership functions [22–25].

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