Optimizing Multi-agent MicroGrid Resource Scheduling by Co-Evolutionary with Preference

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Abstract
This paper presents a multi-agent framework for the control of distributed energy resources organized in Microgrids, which consists of integrated microgrids and lumped loads. Multiple objectives are considered for load balancing among the feeders, minimization of the operating cost, minimizing the emission, minimizing voltage profiles, minimizing active power losses. The agent represents message of microGrid unit and constitutes an autonomic unit. The network is achieved by the evolution of the agent based on the semantic negotiation. Based on the objectives is evaluated by membership functions. We propose a new Immune Co-Evolutionary Algorithm with Preference to solve it. Simulation results demonstrated that the proposed method is effective in improving performance and management of micro-sources.

Keywords: microgrid, multi-agent, optimization model, co-evolutionary with preference.

1. Introduction

As the backbone of the power network, the electricity grid is now at the focal point of technological innovations [1]. The intelligent grid achieves operational efficiency through distributed control, monitoring and energy management. The need for more flexible electric systems, changing regulatory and economic scenarios, energy savings and environmental impact are providing impetus to the development of MicroGrids (MG), which are predicted to play an increasing role of the future power systems. The MG units can meet to the customers load demand at compromise cost and emissions all the time. MG can contain various clean and efficient energy resources, such as solar photovoltaic (PV) modules, small wind turbines, battery storages, controllable loads and other small renewable, and it has an energy management system to regulate power flow in it and provide considerable control over it. It can not only be operated efficiently in its own distribution network, but also be capable to operate in islanding mode when it is required or some faults happen in upstream network [2].

Concurrently, the power system researchers focus on the potential value of multi-agent system (MAS) technology to the power industry [3]. These recent research works have shown that MAS is one of the best technologies for introducing distributed intelligence in power systems. Coordinating behavior of autonomous agents is a key issue in agent-oriented technique, which leads the MAS towards the system goal. MAS is becoming a significant and growing interest in power engineering problems [4-5]. Energy resource scheduling is an important optimization task in the daily operation planning of any power system, which is typically handled by power system managers. Typically, the problem is to minimize the costs associated with energy production, and start-up and shut-down costs. It is a large scale nonlinear optimization problem for which, there is no exact solution technique [6]. Most of the research work on unit commitment has been done in centralized approach [7-9], whereas very little work has been done in distributed approach [10-11]. A rational method of building MGs optimized for cost and subject to reliability constraints have been presented in [12] the problem of management of MG solved as single objective and without considering the balancing with the upper grid. In this paper, the agent approach is presented to handle these challenges. The

formulation of the MG control model and fuzzy preferences co-evolutionary algorithm is proposed to resolve the problem. The simulation results show that the approach can significantly improve performance and adapt well to the changes of dynamic environments.

2. MG Agent Negotiation and Communication Mechanism

As an atomic unit of MG control system, the MG agent includes three modules. Attributes describe the characteristic of an agent itself. Function is designed to evaluate the matching ability of the message to the other MG mobile agents. Behavior contains interface operation, information issue, and energy transmission. MG agent is an atomic unit of MG control platform (MGCP), MGCP is composed of functional modules developed by java. Inspired by systemic network, in the environment, different agents may contribute to different services. MG optimization control result is achieved by service composition of MG agent. It is a novel computing and problem-solving environment where an application service is created out of the interaction of multiple aware agents and the interaction between aware agents and their environment. The ideal model would place the platform on every MG unit as a network node, and functional merits refer to our previous work [13].

In order to collaborate among agents, a set of communication mechanism is needed. The MG agents use RMI-IIOP as transport protocol for communication language (BNCL) messages. RMI-IIOP provides the robustness of CORBA and the simplicity of Java RMI. We present the method of MG agent message discovery based on the message matching. A matching message is exchanged among agents to achieve MG agent message matching for control model. Based on the method of message discovery in workflow, Semantic discovery of atomic processes, delivers a set of MG agent that provide atomic processes which are semantically matching with those of the agent message, the optimization of MG is achieved based on the use of ontology to describe tasks and agent message.

3. Problem Definition for MG Control Optimization Model

The MG consists of a group of radial feeders, which could be part of a distribution system. The feeders also have the micro sources consisting of a photovoltaic, a wind turbine, a fuel cell, a micro turbine, a diesel generator, and battery storage. To serve the load demand and charge the battery, electrical power can be produced either directly by PV, WT, DG, MT, or FC. Each component of the MG system is modeled separately based on its characteristics and constraints. The MG agents interact as to utilize the maximum quantity of available generation possible. This is considered a maximum power utilization strategy.

The major concern in the design of an electrical system that utilizes MG sources is the accurate selection of output power that can economically satisfy the load demand, Minimization of the Cost (the Operating Cost, active power losses) minimizing the emission. Minimizing, hence the system components are found subject to: The network reconfiguration problem in a distribution system is to find a configuration with minimum loss and minimum deviation of the nodes voltage while satisfying the operating constraints under a certain load pattern. The operating constraints are current capacity and radial operating structure of the system. The mathematical formulation reconfiguration problem is presented in the literature in different ways. In this paper, the problem formulation is presented as:

$$F_{loss} = \sum_{i=1}^{L_i} r_i \frac{P_i^{\ 2} + Q_i^{\ 2}}{V_i^{\ 2}} \tag{1}$$

F_{loss} is the membership function for active power losses, r_i represents the resistance of the branch i. P_i , Q_i represent active power and reactive power that flowing the terminal of the branch i. V_i represents the node voltage of the terminal of branch i. L_i represents the number of branches. Voltage variation may be caused by the Distributed Generation output changing.

The objective function is developed according to the above mentioned assumptions to minimize the operating cost in $/h of the MG in the following form:

$$F_{\cos} = (F(P_i) - F(P_{i\_non}))/F(P_{i\_non})$$

$$F(P_i) = F_i C_{ib} + \sum_{i=1}^{N}(C_i F_i + OM_i) \tag{2}$$

Where $F(P_i)$ The operating cost of the generating unit i in \$/h, Ci Fuel costs of the generating unit i in \$/l for the DG, and in \$/kWh for FC and MT, Fi Fuel consumption rate of a generator unit i, OMi Operation and maintenance cost of a generating unit i in \$/h. $F(P_{i\_non})$ is operating cost without DG, $F_i C_{ib}$ is distribution network cost.

The Cost is calculated based on the Operating Cost and active power losses. AF_{co} is define as:

$$AF_{co} = \alpha \cdot F_{\cos} + (1-\alpha) \cdot F_{loss} \tag{3}$$

Where $\alpha \in [0,1]$ is a weight to AF_{co}.

The atmospheric pollutants such as sulphur oxides SO2, carbon oxides CO2, and nitrogen oxides NOx caused by fossilfueled thermal units can be modeled separately. The total emission of these pollutants can be expressed as:

$$E_{po} = E(P_i)/E(P_{i\_non})$$

$$E(P_i) = \sum_{i=1}^{N} 10^{-2}(\alpha_i + \beta_i P_i + \gamma_i P_i^2) + \zeta_i \exp(\lambda_i P_i) \tag{4}$$

Where α, β , γ, ζ, and λ are nonnegative coefficients of the ith generator emission characteristics. In the emission model introduced, we propose to evaluate the parameters α, β, γ, ζ, and λ using the data available. Thus, the emission per day for the DG, FC, and MT is estimated, and the characteristics of each generator will be detached accordingly.

Based on the fuzzy evaluation functions, the multi-objective optimization model is constructed to maximize the satisfactions of different objectives by adjusting transformer tap-changers and shunt capacitors. The multi-objective optimization model is represented as:

$$Min(Mep(AF_{co}), Mep(E_{po}))$$

$$Subject$$

$$\begin{cases} Mep(F_{po}) \leq MepF_0 \\ P_i^{\min} \leq P_i & i \in K \\ P_i \leq P_i^{\max} & i \in K \\ Q \leq Q_j & k \in K \\ \sum_{i=1}^{N} P_i - P_L + (P_{PV} + P_{WT} + P_{batt}) = 0 \\ Q_j \leq Q_j^{\max} & k \in K \end{cases} \tag{5}$$

Where Power balance constraints are that it meets the active power balance, an equality constraint is imposed.

$$\sum_{i=1}^{N} P_i - P_L + (P_{PV} + P_{WT} + P_{batt}) = 0 \tag{6}$$

PL The total power demanded in kW, PPV The output power of the photovoltaic cell in kW, PWT The output power of the wind turbine in kw. Pbatt The output power of the battery storage kw.

Generation capacity constraints is restricted by lower and upper limits for stable operation,real power output of each generator, as follows:

$$P_i^{\min} \le P_i \le P_i^{\max} .i = 1,.......N \tag{7}$$

$P_i^{\min}$ Minimum operating power of unit i, $P_i^{\max}$ Maximum operating power of unit i, P_i , $P_{i,\max}$ represent the real running power and the maximum permitted power of the transformer. a_i is penalty function parameter. F_{po} is the membership function for power.

$$F_{po} = \sum_{i=1}^{n_b} [\frac{P_i}{P_{i,\max}} (1 + a_i^{K_i(P_{i,\max} - P_i)})] \tag{8}$$

4. Fuzzy Preferences Co-Evolutionary Algorithm

There are many MO solution algorithms allowing the attainment of these results, like PESA-II [14], NSGA-II [15]. An important issue in multiple objective optimizations is the handling of human preferences. Finding all Pareto-optimal solutions is not the final goal. Such preferences can usually be represented with the help of fuzzy logic. Based on preference relations [16-17] and induced orders, these linguistic categories were transformed into real weights and a weighted Pareto dominance relation was introduced.

In this paper, the novel fuzzy preferences evolutionary algorithm (FP-EA) is proposed. Suppose that the size of evolutionary population P is n, and Pt is t-th generation of the population. Qt is a new evolutionary population from Pt that is updated by the selection, crossover and mutation operators, and the size of Q, is also n. Let Rt=Pt∪Qt, and the size of Rt is 2n. The non-dominated set P1 is generated from Rt, with the quick sort procedure. If|P1|>n, the clustering procedure is used to reduce the size of P1, and to keep the diversity of P1 at the same time. The size of P1 will be n after the clustering process. $\approx$ is equally important, $<$ is less important, $<<$ is much less important, $\neg$ is not important, $!$ is important.

Definition1:(Weighted dominance relation) For a given weights–vector $w = (w_1....w_k)$ summing to 1 and a real number $0 < \tau \le 1$, a real vector $x = (x_1....x_k)(w, \tau)-$ dominates a real vector $y = (y_1....y_k)$ written as $x \ge_w^\tau y$ if and only if:

$$\text{x} \ge_w^\tau \text{y} \Leftrightarrow \sum_{i=1}^{k} w_i \cdot I \ge (\text{x}_i, \text{y}_i) \ge \tau \tag{9}$$

Where $I \ge (x, y) = \begin{cases} 1 & x \ge y \\ 0 & x < y \end{cases}$

The standard definition of dominance could be obtained by setting $\tau = 1$ and $w_1 = ...w_n = 1/k$. Note that in the standard definition of dominance it is required that at least one of the $x_i \ge y_i$ inequalities is strict. However this is not a problem since these two orders are definable in terms of each other.

Definition 2: (Weighted score). The number nine is used here for the grades of relative importance between objectives because we take the well-known technique of analytic hierarchy process (AHP) for reference. For each $x_i \in X$ compute weight as normalized leaving score.

$$w(x_i) = \frac{SL(x_i, R)}{\sum_{x_j \in X} SL(x_j, R)} \tag{10}$$

Definition 3: (Fitness evaluation). Suppose there are N individuals in the current population pop. The positive strength $S^+(x_k)$ of each individual $x_k \in pop$.

$(k = 1,2, N)$ is calculated. Suppose $S_{\min} = \min_{k=1,2,,N}(S^+(x_k))$, $d_{\max} = \max_{k=1,2,,N}(d_k)$. The fitness of each individual $x_k \in pop(k=1,2,,N)$ is calculated according to the following formulation:

$$fit(x_k) = (S^+(x_k) - S_{\min} + 1) \times (d_k / d_{\max})^2 \tag{11}$$

Algorithm : FP-EA Algorithm

Pt , t = 0 ;// Set t = 0. Generate an initial population P[t], for each $x_i \in X$ compute weight as normalized leaving score:

$$w(x_i) = \frac{SL(x_i, R)}{\sum_{x_j \in X} SL(x_j, R)}$$

While (t ≤T) do //T is maximum number of generations

$\{fit(x_k) = (S^+(x_k) - S_{\min} + 1) \times (d_k / d_{\max})^2$ //Calculate the fitness value of each individual in Pt, $x_k \in P_t$ $(k=1,2,,N)$

Qt = make-new-pop (Pt) // Use selection, crossover and mutation to create a new
    population Qt
Rt = Pt ∪Qt // Combine parent and children population
If (| Pt + 1 | < = N) Then { Pt + 1 = Pt + 1 ∪ select - by - random (Rt - Pt + 1, N - | Pt +
    1 |) } // randomly selected N - | Pt + 1 | elements and joined into Pt + 1
Else if (| Pt + 1 | > N)
    Then {crowding - distance - assignment (Pt + 1)
    // Calculate crowding distance.
  Sort (Pt + 1 , ≥n) // Sort in descending order using ≥n
  Pt + 1 = Pt + 1 [1: N]} // Choose the first N elements
  t = t + 1}
It can be proved that the time complexity of Algorithm (FP-EA) is less than O (nlogn). It is better than O (n2) in the NSGA II.

5. Results and Analysis

This sample system is used to simulate the transformer loadings, line flow profiles, and system losses of the microgrid. Besides, the parameters of the distribution transformer, conductor, generation, and load are described in the following subsections. The related parameters for simulation of the MV/LV distribution transformer are listed in Table 1. This transformer is 400kVA, 20kV/0.4kV, and its leakage impedance is 0.01+j0.04pu. The locations and capacities of the DGs interconnected to the network are as follows: A 10kW photovoltaic generation systems and a 10kW wind turbine generator are connected. A 10kW fuel cell generation system is connected to system with three-phase inverter. A 30 kW microturbine generator is connected to system with three-phase inverter.
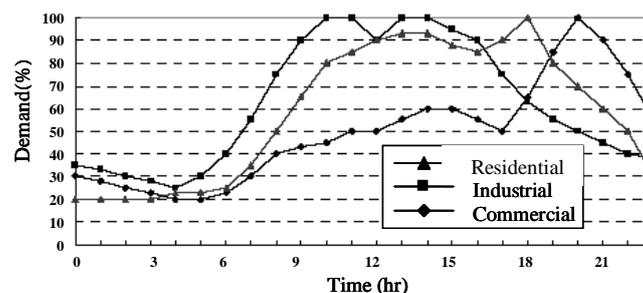

Figure 1. Daily Load Curves for the Three Load Types of the Microgrid

Table 1 .The MV/LV Distribution Transformer

Capacity (kVA)	Primary Side (kV)	Secondary Side (kV)	R(pu)	X(pu)
400	20	0.4	0.01	0.04

Table 2. The Real Power Output Curves for Four Types

Output curves (Time)	0	2	4	6	8	10	12	14	16	18	20	22	24
PWT	0	2	3	0	1	1	2	4	8	6	4	0	0
PPV	0	0	0	0	0	5	6	5	4	3	0	0	0
PFC	10	10	10	10	10	10	10	10	10	10	10	10	10
PMT	30	30	25	28	30	30	30	30	30	30	30	30	30

The power generations of the PV and WT are calculated by the proposed formulas with insulation, temperature, and wind speed-related parameters. Additionally, the power generated by the fuel-cell generation system and microturbine generator is calculated under the minimization of total fuel cost in the microgrid by direct search method. These curves are used as the power generation data for a full day's analysis.

Based on the evaluation functions, the multi-objective optimization model is constructed to maximize the satisfactions of different objectives by adjusting transformer tap-changers and shunt capacitors. The coordination control strategies were discussed above, it can be used to reach the target of maximizing the efficiency of Microgrid. In this paper, the novel fuzzy preferences evolutionary algorithm (FP-EA) is proposed.

Figure 3 and 4 shows the relationship of the cost and emission objectives of non-dominated solutions obtained by multi-objective optimization. The cost of the non-dominated solutions thus appears to be inversely proportional to their emissions. It can see that the Pareto optimal set has a number of non-dominated solutions. It can be concluded that the proposed approach is capable of exploring more efficient and non-inferior solutions of optimization problems.

As can be seen in Figure 3 and 4, the distribution characteristics of the approximate weighted Pareto optimal layer are different in different preferences circumstances. Figure 3 is $Mep(AF_{co}) \approx Mep(E_{po})$ Pareto curve, the curve reflects the features of left sparse and right dense based on $Mep(E_{po})$ preference. Figure 5(c) is $Mep(AF_{co}) \prec\prec Mep(E_{po})$ Pareto curve, it showed more obvious feature of left sparse and right dense, when it is more preferred objective function $Mep(E_{po})$. Weighted Pareto method can obtain approximate Pareto optimal solution in different preferences to meet the needs of decision maker.
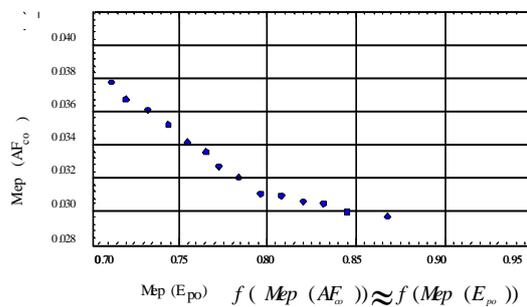

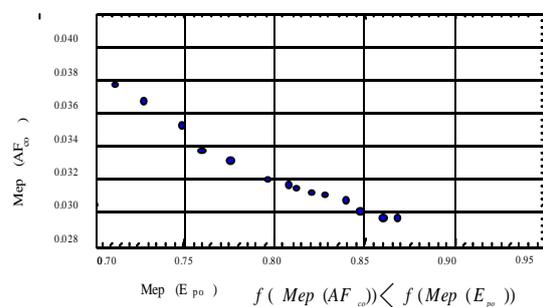Figure 2. The Pareto Optimal Front in Multi-objective Optimization(A)

Figure 3. The Pareto Optimal Front in Multi-objective Optimization(B)

These graphs show very clear separation of Pareto fronts obtained using different preferences. It performs well on the convergence and the diversity. The traditional methods

solve the multi-objective a problem is to translate the vector of objectives into one objective by averaging the objectives with a weight vector. The most profound drawback of traditional algorithms is their sensitivity towards weights or demand levels. This discussion suggests that the classical methods to the problems of MG control optimization model are inadequate and inconvenient to use.
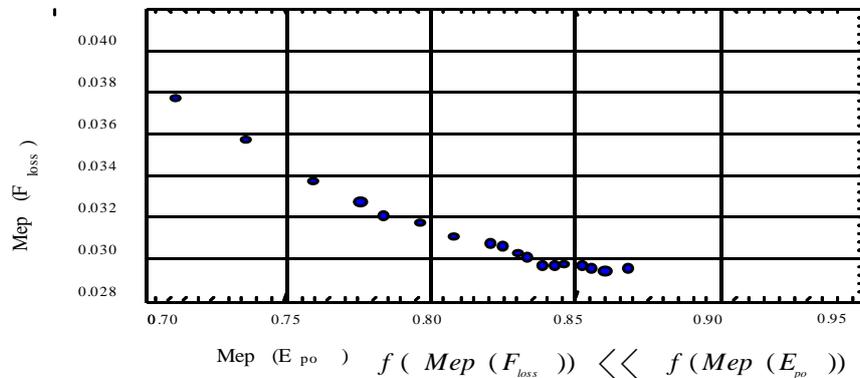

$f\ (\ Mep\ (F_{loss}\ ))\ \ll\ f\ (Mep\ (E_{po}\ ))$

Figure 4. The Pareto Optimal Front in Multi-objective Optimization(C)

Table 3 Compare and analysis of different preferences approximate weighted Pareto optimal layer. The programs of low carbon dispatch are designed as LCDP1 (40%, 60%), LCDP2 (25%, 75%), LCDP3 (0, 100%), EWD (equal weights dispatch).

Table 3. The Three Programs Of Low Carbon Dispatch

	EWD	LCDP1	LCDP2	LCDP3
Mep (AFCo)	5.7%	5.6%	5.8%	5.7%
Mep(Epo)	85%	81%	79%	73%

It shows that Low-carbon power scheduling strategy can also reduce the line loss, reducing emissions from four indicators in Table 3. Compared with equal weight strategy, carbon power scheduling policy reduces greater extent to reduce emissions, but the cost of power generation increases slightly. The results obtained using our proposed technique to minimize the total cost and total emissions were compared with some conventional strategies of settings.

6. Conclusion
This paper presents a general framework for the control of distributed energy resources organized in Microgrids. A agent is in communication with other agents by passing a message. Message received are handled by the message interpreter of an agent, the agents have the ability to dynamically model community based on negotiation in the organizational model of computation with observe its environment and exchange message among the agents. The formulation of the MG control model and fuzzy preferences evolutionary algorithm is proposed to resolve the problem. The simulation results show that the approach can significantly improve performance and adapt well to the changes of dynamic environments.

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