Group Selection Clone Immune Model of Microgrid Optimization

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Abstract. In this paper, we have proposed a Group Selection Clone Immune Model for energy resource scheduling of microgrid, 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 active power losses. The agent represents message of unit and constitutes an autonomic unit. By understanding properties of messages, the agent use projection-join closure to capture such message situations. The network is achieved by the evolution of the agent based on the semantic negotiation. Based on the objectives evaluated by membership functions respectively, we propose a Group Selection Clone Immune algorithm to solve it. Simulation results demonstrated that the proposed method is effective in improving performance and management of micro-sources.

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 power system researchers focus on the potential value of multi-agent system (MAS) technology to the power industry [2,3], 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. The ideal model would place the platform on every MG unit as a network node, and functional merits refer to our previous work [4]. The MG agent represents message and constitutes an autonomic unit. 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. *MG1 (Pr1,SI_{ES1}*)represented the request of matching with an output message, MG*2 (Pr2,SI_{ES2}*) represented message with input message of agent, The matching strength of message $SS^{ws}_{Agent}(MG1,MG2)$ is defined as the matching ability . the matching strength of interface message MS^{ws}_{Agent}.

$$MS^{ws}_{Agent}(SI_{ES1},SI_{ES2})=\frac{1}{n}\left[\sum_{j=1}^{n}\max_{i=1}^{m}(SM(C_i,C_j'))\right]$$

(1)

$MS^{ws}_{Agent}(SI_{ES1},SI_{ES2})\in[0,\quad 1]$

$SI^{ws}_{Agent}(\mathrm{Pr}1,\mathrm{Pr}2)$ is defined as the matching ability to e-service property's similarity. Pr1 and Pr2 are property.

$$SI^{ws}_{Agent}(\mathrm{Pr}1,\mathrm{Pr}2)=\frac{Max\sum_{i=1}^{m}\sum_{j=1}^{n}SM_{con}(C_i^{\mathrm{Pr}1},C_j^{\mathrm{Pr}2})+Max\sum_{i=1}^{p}\sum_{j=1}^{q}SIM_{pro}(P_i^{pr1},P_j^{pr2})}{Min(mn)+Min(p,q)} \tag{2}$$

Where $SM_{con}(C_i^{\mathrm{Pr}1},C_j^{\mathrm{Pr}2})=\dfrac{b\times(L_i+L_j)}{(Dis(C_i^{\mathrm{Pr}1},C_j^{\mathrm{Pr}2})+b)\times Max(|L_i-L_j|,\ 1)}$ $\quad SIM_{pro}(P_i,P_j)=\begin{cases}1 & P_i=P_j\\ \dfrac{1}{Dis(P_i,P_j)} & P_i<P_j,P_i>P_j\\ SM_{con}(P_i,P_j) & P_i\neq P_j\end{cases}$

Concept $C_i^{\Pr 1}$ is in level L_i, concept $C_j^{\Pr 2}$ is in level L_j. b is a constant and can be set to the distance when the similarity of two words is equal to 0.5. Let $SIM_{pro}(P_i, P_j)$ be the similarity of two properties and $Dis(P_i, P_j)$ is the node distance of two parameters on the hierarchical structure.

Problem definition for MG control optimization model

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. In this paper, the problem formulation is presented as

$$F_{loss} = \sum_{i=1}^{L_i} r_i \frac{P_i^2 + Q_i^2}{V_i^2} \tag{3}$$

$$F_{\cos} = (F(P_i) - F(P_{i\_non})) / F(P_{i\_non}) \tag{4}$$

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

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

(5)

The atmospheric pollutants such as sulphur oxides SO_2, carbon oxides CO_2, and nitrogen oxides NOx caused by fossilfueled thermal units can be modeled separately. The total emission of these pollutants can be expressed as [5]:

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

$$E(P_i) = \sum_{i=1}^{N} 10^{-2} (a_i + b_i P_i + g_i P_i^2) + z_i \exp(l_i P_i)$$

(6)

Where α, β , γ, ζ, and λ are nonnegative coefficients of the ith generator emission characteristics. In the emission model introduced in [6], 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. The multi-objective optimization model is represented as:

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

$$Subject$$

$$\begin{cases} Mep(F_{po}) \le MepF_0 \\ P_i^{\min} \le P_i \qquad i \in K \\ P_i \le P_i^{\max} \qquad i \in K \\ Q \le Q_j \qquad k \in K \\ \sum_{i=1}^{N} P_i - P_L + (P_{PV} + P_{WT} + P_{batt}) = 0 \\ Q_j \le Q_j^{\max} \qquad k \in K \end{cases} \tag{7}$$

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

$$\sum_{i=1}^{N} P_i - P_L + (P_{PV} + P_{WT} + P_{batt}) = 0 \tag{8}$$

$$P_i^{\min} \le P_i \le P_i^{\max} . i = 1, ...N \tag{9}$$

$$F_{po} = \sum_{i=1}^{n_b} [\frac{P_i}{P_{i,\max}} (1 + a_i^{K_i (P_{i,\max} - P_i)})] \tag{10}$$

We proposed a group selection clone immune algorithm (GSCIA), Algorithm can create a group of antibody by asexual propagation:

Algorithm: ***ImmuneClone***
Input: Antibody group **icg**;
Output: Immune clone result **icc**;
Begin
Step 1: Calculate each immune cells crowding degree in **icg**, and define the border objects or non-border objects by this degree.
Step 2: Find non-border cells and separate all antibodies to construct an antibody group **ag**; and each antibody a**i** in **ag** has a colon size:

$$Q_i = N \frac{d(a_i, icg)}{\sum_{j=1}^{N} d(a_i, icg)} \quad (11)$$

Step 3: clone **ai** as **qi** size and add them in to **icc**;
END
The **GroupSelection** algorithm can select elite objects from groups:

Algorithm: ***GroupSelection***
Input: Object group **g**
Output: Elite groups **eg**
Begin
Step 1: Use EM algorithm unsupervised split **g** into catalogs (g_1, g_2, …, g_3) by antibody's characters ;
Step 2: For each catalog **gi** , select 50% objects which have adaptive value into **ei** .
Step 3: **eg=**(e1,e2, … en).
END
With the help of **ImmuneClone** and **GroupSelection** algorithm our multi-objective optimized model can be describe as follows:

Simulation and results

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 400 kVA, 20 kV/0.4 kV, and its leakage impedance is 0.01+j0.04 *pu*. The locations and capacities of the DGs interconnected to the network are as follows: A 10 kW photovoltaic generation systems and a 10 kW wind turbine generator are connected. A 10 kW fuel cell generation system is connected to system with three-phase inverter. A 30 kW micro turbine generator is connected to system with three-phase inverter.

Table 1 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). It shows that Low-carbon power scheduling strategy can also reduce the line loss, reducing emissions from four indicators in table. 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.

Table 1. 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%

Conclusions and further work

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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References

[1] M.E.Khodayar, M.Barati, M.Shahidehpour, Integration of High Reliability Distribution System in Microgrid Operation, IEEE Transactions on Smart Grid, 2012 ,3(4): 1997 - 2006

[2] E.Sortomme,S.S.Venkata,J.Mitra.Microgrid Protection Using Communication-Assisted Digital Relays., IEEE Transactions on Power Delivery, 2010, 25(4).pp. 2789 – 2796

[3] I.Maity, S.Rao, Simulation and Pricing Mechanism Analysis of a Solar-Powered Electrical Microgrid. IEEE Systems Journal, 2010 , 4 (3),pp. 275 - 284

[4 H.B. Sun, Y.S. Ding. The Evolutionary Stability Affected by Flow of Energy in the Bio-Network Architecture, Neurocomputing. 2008. 72 pp.162:169

[5] S.Eppe, M.Lopez-Ibanez, T.Stutzle, Y.De Smet. An experimental study of preference model integration into multi-objective optimization heuristics. IEEE Conference on Evolutionary Computation, 2011, pp. 2751 – 2758

[6] X.N.Shen, Y.Guo, Q.W.Chen. A multi-objective optimization evolutionary algorithm incorporating preference information based on fuzzy logic. Computational Optimization and Applications. 2008, 40, pp. 55-64

