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A Self-Learning Network Reconfiguration Using Fuzzy Preferences Multi-Objective Approach

Hongbin Sun*[1], Chunjun Zhou[2]
[1]School of Electrical Engineering and Information, Jilin university
[2]School of Electrical Engineering and Information, Changchun Institute of Technology, Changchun, 130012,China
*Corresponding author, e-mail: hbsun@mail.dhu.edu.cn

Abstract

The paper proposes a self-learning evolutionary multi-agent system for distribution network reconfiguration. The network reconfiguration is modeled as a multi-objective combinational optimization. An autonomous agent-entity cognizes the physical aspects as operational states of the local substation, the agent-entities establish relationship network based on the interactions to provide service. Multiple objectives are considered for load balancing among the feeders, minimum deviation of the nodes voltage, minimize the power loss and branch current constraint violation. These objectives are modeled with fuzzy sets to evaluate their imprecise nature and one can provide the anticipated value of each objective. The method completes the network reconfiguration based on the negotiation of autonomous agent-entities. Simulation results demonstrated that the proposed method is effective in improving performance

Keywords*: network reconfiguration, fuzzy preferences, multi-objective, optimization*

1. Introduction

The distribution network reconfiguration problem is to find a radial operating structure that minimizes the system power loss and minimum deviation of the nodes voltage while satisfying operating constraints. In recent years, many of the distributed generations are set up in the vicinity of the customer, with the advantage that this decreases transmission losses. Two objectives considered are real-power loss reduction, maximum nodes voltage deviation is kept within a range, and the absolute value of branch currents is not allowed to exceed their rated capacities. The radial constraint and discrete nature of the switches prevent the use of classical techniques to solve the reconfiguration problem.

Most of the algorithms in the literature are based on heuristic search techniques. Considerable research has been conducted for loss minimization in the area of network reconfiguration of distribution systems. Distribution system reconfiguration for loss reduction was first proposed by Merlin and Back [14]. They have used a branch-and-bound-type optimization technique to determine the minimum loss configuration. In this method, all network switches are first closed to form a meshed network. The switches are then opened successively to restore radial configuration. The solution procedure starts by closing all of the network switches which are then opened one after another so as to establish the optimum flow pattern in the network [1]. A heuristic method [2] have been proposed to determine a distribution system configuration which would reduce line losses by using a simplified formula to calculate the loss reduction as a result of load transfer between two feeders. Two approximation formulas for power flow in the transfer of system loads were made to improve the method of heuristic [3]. Artificial-intelligence-based applications in a minimum loss configuration have been proposed [4-7]. Das [8] has presented an algorithm for network reconfiguration based on heuristic rule and fuzzy multi-objective approach.

Agent-oriented computing provides a big possibility of implementation for this problem. The agent communities are actually groups of software cooperatives and communicative but independent agents, which are expected to join decisions and actions to achieve a common goal. The purpose of the common goal is to provide a glue to bind individuals' actions into a cohesive whole. The proposed architecture implements similar groups of collaborating software agents. In our previous work, we have implemented the prototype of agent-network service

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simulation platform [9]. The software development framework aimed at developing multi-agent systems and applications conforming to FIPA [10] standards for intelligent agents. Developed the design of the system resulted in agent communities, each consisting of three software agents. The main contribution of this paper is to present the autonomous system of network configuration based on the agent-network. We propose a Fuzzy Preferences Multi-Objective Approach to solve it. Simulation results demonstrated that the proposed method is effective in improving performance.

2. A Self-Learning Evolutionary Multi-Agent System for Distribution Network Reconfiguration

2.1. The Agent-Entity Design

As an atomic unit of Distribution Network Reconfiguration, the Agent-Entity (mobile agent) includes three modules, as shown in Figure 1. Attributes describe the characteristic of an agent itself. Function is designed to evaluate the matching ability of the message to the other mobile agents. Behavior contains interface operation, information issue, and energy transmission.

The Agent-Entity is a unit developed by java. Different Agent-Entity may contribute to different inforamtion services. Network Reconfiguration is achieved by service composition of Agent-entity. 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 [9]. The ideal model would place the platform on every device as a network node, and functional merits refer to our previous work [11,12].

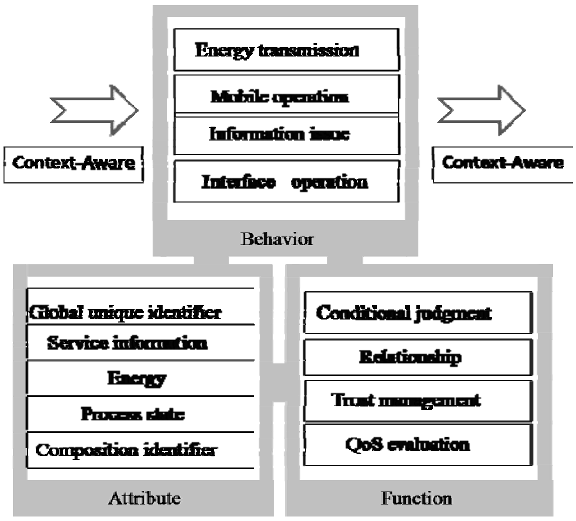

Figure 1. The Structure of Agent-Entity Includes Three Modules: Attribute, Function and Behavior

2.2 The model of Reconfiguration Network in Distribution System

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.

V_N is voltage rating; V_i is real voltage of the system; F_{vol} is the membership function for voltage profiles.

$$F_{vol} = \sum_{i=1}^{n} \frac{(V_i - V_N)^2}{V_N^2} \tag{2}$$

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.

$$F_{po} = \sum_{i=1}^{n_b} [\frac{P_i}{P_{i,\max}} (1 + a_i^{K_i(P_{i,\max} - P_i)})] \tag{3}$$

Based on the fuzzy evaluation functions, the multio-bjective optimization model is constructed to maximize the satisfactions of different objectives by adjusting transformer tap-changers and shunt capacitors. The objectives include voltage profiles, active power losses. The multio-bjective optimization model is represented as:

$$\begin{aligned} & Min\ (Mep\ (F_{vol}), Mep\ (F_{loss})) \\ & Subject \\ & \begin{cases} Mep\ (F_{po}) \le MepF_0 \\ T_k^{\min} \le T_k & k \in K \\ T_k \le T_k^{\max} & k \in K \\ Q \le Q_j & k \in K \\ Q_j \le Q_j^{\max} & k \in K \end{cases} \end{aligned} \tag{4}$$

Which Tk is the ratio of transformer k; Qj is the capacity of capacitors at node j, $Mep(F)$ is the value to evaluate F , $T_k^{\max}$, $Q_j^{\max}$ represents the threshold of criterion.

3. The Fuzzy Preferences Evolutionary Algorithm

There are many MO solution algorithms allowing the attainment of these results, like SPEA2 [16], PESA-II [17], NSGA-II [13]. 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 [12, 13] 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$\cup$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, $\prec$ is less important, $<<$ is much less important, $\neg$ is not important, !is important.

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

$$x \geq_w^\tau y \Leftrightarrow \sum_{i=1}^{k} w_i \cdot I \geq (x_i, y_i) \geq \tau \tag{5}$$

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

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 $x_i \geq y_i$ 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

$$w(x_i) = \frac{SL(x_i, R)}{\sum_{x_j \in X} SL(x_j, R)} \tag{6}$$

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:

$$fit(x_k) = (S^+(x_k) - S_{\min} + 1) \times (d_k / d_{\max})^2 \tag{7}$$

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□.

4. Simulation and Discussion

In our previous work, we have implemented the prototype of Agent-network service simulation platform [11,12], including software, general objects and simulators in java. It supports pluggable functions and provides a generic easy-to-use programming API. It contributes to implement our approach in real deployment with minimal modifications. The Self-Learning Evolutionary Multi-Agent System has been designed as a simple prototype. The simulation experiment is constructed on Windows 2000 operation system with Intel Pentium 4 processor (2.4 GHz) and 1G RAM. The proposed method is tested in a 69-bus distribution system [2] (Figure 1). The parameters of on-load tap-changer, the test system is a hypothetical 12.66kV system, 69 busses, 5 looping branches (tie lines). System data is given together with the voltage profile of the base configuration. Real power loss reduction is 10.49% and minimum voltage of the system has improved. In fact, the voltage profile of the base system configuration is lower than the usual lower. It is assumed that every branch in the system is available for branch-exchange.

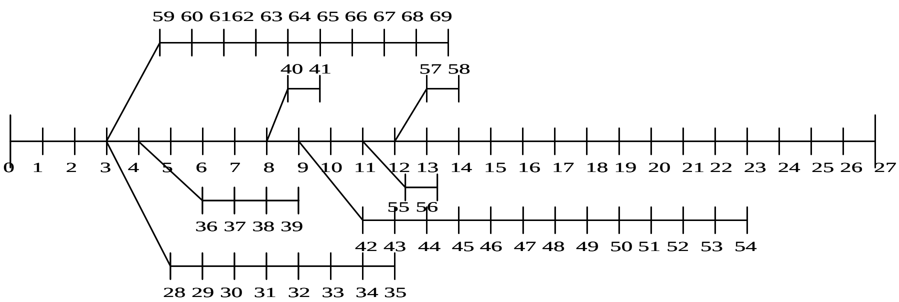

Figure 2. A 69-node Distribution System Before Reconfiguration.

These graphs show very clear separation of Pareto fronts obtained using different preferences, 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 network reconfiguration are inadequate and inconvenient to use.

In valley load condition, reverse power flow raises the voltage and power losses. After optimization, the over voltage is alleviated, and the voltage profiles are improved. The power losses comparison shows that, the optimal control scheme decrease the power losses by reducing reactive power transferred. Although the maximum voltage variation increases very slightly, the integral satisfaction improved evidently.

Table 1. Optimal Sets of The Reconfiguration Result

	Power loss	Deviation of the nodes voltage
1	90.67	0.0215
2	91.69	0.0221
3	95.4	0.0223
4	96.7	0.0228

Response time in self-learning evolutionary multi-Agent system represents the efficiency ofnegotiation, In all 100 minutes (Figure 3), response time decrease slowly. At the beginning, response time reaches 700ms. When the request is changed, the agent-entities start evolutionary learning, Each agent-entity should negotiate with others based on the capabilities that can be executed. With the time passing by, the high effective are presented . Finally, the response time decreases dramatically, until it reaches the minimum value to be about 150ms.

we can see that the excessive migration behaviors decrease for the agent-entities, it also exhibits the less cost.

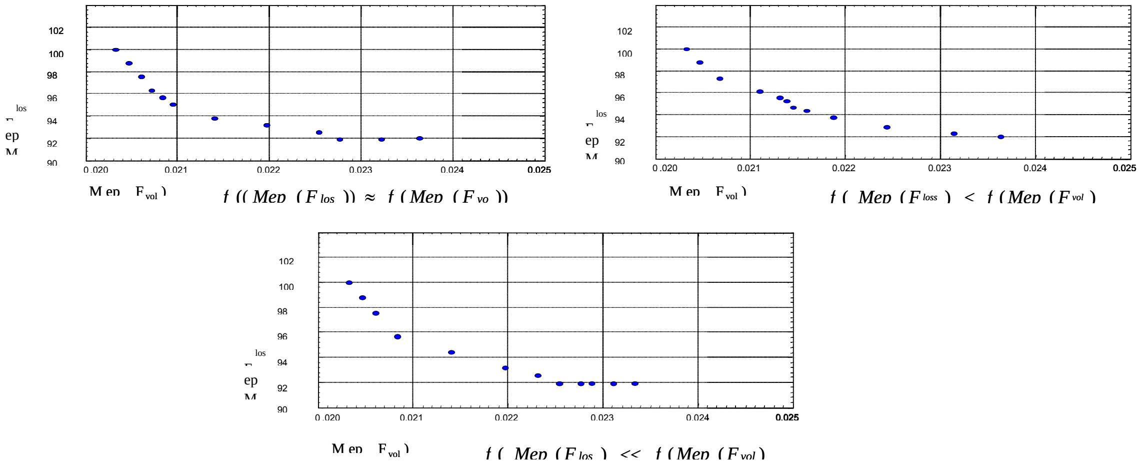

Figure 3. The Pareto Optimal Front in Reconfiguration

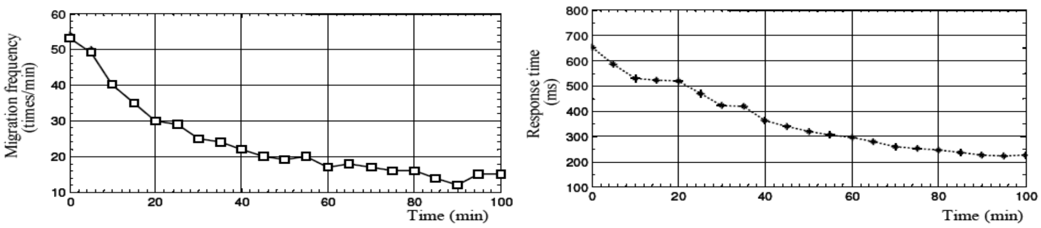

Figure 4. Response Time and Migration Frequency

5. Conclusion

The network reconfiguration is modeled as a multi-objective combinational optimization, a self-learning evolutionary multi-agent system based on Fuzzy Preferences multi-objective approach has been proposed to solve the network reconfiguration problem in a radial distribution system. The method completes the network reconfiguration based on the negotiation of autonomous agent-entities. The objectives considered attempt to maximize the fuzzy satisfaction of the load balancing among the feeders, minimization of power loss, deviation of nodes voltage and branch current constraint violation subject to radial network structure. Simulation results demonstrated that the proposed method is effective in improving performance.

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