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An Improved Multi-Agent System Based on GA and Its Application on Power System

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Abstract: *This paper proposes an improved multi-agent system based on genetic algorithm (GA). In order to apply the algorithm to power system state estimation, the special technical problems are proposed. According to the algorithm, the paper develops a real-time state inspection system. In the measured system, the calculation signals are induced from the consensus filter which the signal affected by the noise can be dealt with. The system was applied to the power system on account of the real data. Simulation results demonstrate that this design of the improved multi-agent system is successful, and the state inspection problem may be given a new method to be solved.*

Keywords: *power system, improved multi-agent system, state estimation*

1. Introduction

Over the last decades, efforts have been made to improve the stability of the nonlinear system. This paper presents an artificial intelligence control method for the performance of complex nonlinear systems. In the last decades, the study of nonlinear system has become one of the popular research fields, many research have been conducted and several solutions were given. Due to its complicated system, it is difficult to give a most suitable solution. [1]. Especially the condition detection has not been an ideal way. In this paper, a new way is presented and has been used in the power system.

Considering the high accuracy and wide applicability, the multi-agent is optimized based on the genetic algorithm relatively perfect for big complicated system such as power system state inspection.

The complicated system has its particular characteristic as below: (1) its intension and extension is quite complex; (2) individual has relative independence; (3) the different individuals has intelligence character; (4) individuals have the concurrency. Since the power system is a nonlinear system, it is not easy to describe or to analyze the operating characteristics by the linear controlling methods. Artificial intelligence techniques are becoming useful as alternative approaches to conventional techniques or as components of integrated systems**.** They have been used to solve complicated practical problems in various areas and are becoming more popular nowadays especially in the power systems. The analysis tells how to establish a tool to be used to know the future generation potential areas in any utility by achieving the following.[2] This paper is organized as follows: the main results of the approach and the design of the inspection system in section 2 and 3. In section 4, the testing system is to be used and the result of the simulation result is given. Finally, in section 5, the comments and conclusions are given.

2. Optimization of Multi-Agent

In the section, a new method is presented, the difference between the multi-agent genetic algorithm and the simple genetic algorithm is that the former characterize the problem by the agent instead of the encoding string. The agent is a compute body, which has the characters of the sociality, initiative, which can play its role in a certain circumstance.

2.1. Genetic Algorithm

A GA is a stochastic algorithm that mimics the natural process of biological evolution. Inspired by the living way of organisms, GA is adapted to the harsh realities of life in a hostile world, i.e., by evolution and inheritance. The algorithm imitates in the process, the evolution of population by selecting only appropriate individuals for reproduction. Therefore, a GA is an optimum search technique based on the concepts of natural selection and survival of the fittest.

2.2. Multi-agent Method

Multi-agent system can help application designers to conceptualize solutions better: this paradigm may be more naturally suitable for certain types of applications; they can help improve code modularity and reusability; they can help hide network, system and protocol heterogeneity.[3][4] The features – autonomy, sociality, and communication possessed by agents make it easy to decompose a complex task into some simple ones and then to assign them to individual agents that collaborate, negotiate and eventually achieve the common goal.

2.3. The Algorithm Design

In the genetic algorithm, the individual is substituted by the agent and each has the cooperation ability. And all the agent are put in a N*N network. Each in the algorithm has certain energy and some actions in a specific neighborhood [5]. Each individual has the information exchange with the neighborhoods and the ones with lower energy will be cleared away from network, and the stronger will survival. After several gaps, the excellent gene will spread throughout the network. All the actions of the networks, such as evolution, variation, genetic, mutation, can affect and reform the whole circumstance. Each agent in the network should apply with the following rules: (1) the life cycle and self-learning ability; (2) perception ability only to the neighborhood; (3) according to the survival of the fittest. It is optimizing and combining the agent and the genetic algorithm. Also, it has the ability of the agent coding in the power system as the multi-agent society.

Key techniques to solve the problems by using genetic algorithm and agent are to seek the coding expression of gene space suitable to the problem itself. Crossover and the mutations operator correspond to chromosome encoding method as well as fitness function form with the chromosome encoding method [6]. Therefore, this can introduce the problem-related domain knowledge and the constraint conditions into the genetic algorithm, which will enable the algorithm to be more stable and effective, as well as speed up the convergence rate of the algorithm and improve the quality of the solutions.

2.4. Calculation Flow

In the algorithm, each agent has the original energy and the perception ability to the neighborhood. According to the genetic algorithm, the agent act as the cross operator rules, so the lower energy agent will be cleared away from the network and the stronger ones has the position [7].

In the next chat flow, Best' is the most excellent agent until now after t generations and CBest is the most excellent agent at the t generation, $Best^0$ is the original agent. The calculating process is presented as follow:

(1) Initializing the agent network L^0, renew $Best^0$, $0 \rightarrow t$

(2) Acting the rules on each agent

If U (0,1)<Pc, then act the neighborhood competitive operator

If U (0,1)<Pc, then act the neighborhood variation (3)get the $CBest^0$ in L^t

(4) Acting the agent self-learning operators on the $CBest^0$

(5) Judging the inequality Eng $(CBest^t) > Eng(CBest^{t-1})$,

If it is yes, then $CBest^t \rightarrow Best^t$ then (7)

If it is not, then $Best^{t-1} \rightarrow Best^t$ and $Best^{t-1} \rightarrow CBest^t$ then (7)

(6) Judging if the calculation satisfy the stopping rules?

(7) If yes, then give the best result.

(8) If not, then $t+1 \rightarrow t$, then (2)

As introduced above, the several operators act on the agent, and each of them can get the

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information or the energy in the neighborhood by the evolution, and then improve the energy of the whole network, which make the search space close faster to the optimal solution, as the flow chat presented above.

3. Application on state inspection

3.1. State estimation of the power system

The stability of the power system is reflected by several factors, among which the load flow is mostly consider as an important index. The load-flow problem is one of the most important tasks performed by operation engineers of power system. In fact, the steady state operating conditions of the power systems are determined by performing a load-flow analysis on the underlying systems. Continuous growth and complexity of the power have originated the adoption of calculating methods for efficient planning, operation and control of their systems.[3] Artificial neural networks for solving the power flow problem is used in electric power systems. Usually, these methods perform the load-flow analysis on the systems. The load-flow analysis is intrinsically a time-consuming task, because the set of non-linear algebraic equations of load-flow are, in general, solved by employing iterative numerical methods. Therefore, these numerical methods are not fully suitable for on-line applications.

For the power system, on the line, the load flow varies all the time, during normal operation of the system, the load flow is in normal range. When the system is at the edge of power grid blackout, the load flow is beyond the limit, if it lasts a long time, the system is blackout. The state estimation of the system is the first step of the calculation[9]

The parameters in the calculation process are all got from different parts of power system such as lines, generators, reactive power compensation and so on.

According to one parameter, the equation as follows based on the Kirchhoff Law:

$$z = h(x, p, s) + v_z + v_p + b \tag{1}$$

Where z is an n-dimensional measuring amount, including active power , reactive power, voltage magnitude and current magnitude. h(x, p, s) is the dependent variable parameter according to the grid parameter; v_z is the data error; v_p is the error connection of the grid.

Given the measured value Z,

Where the $\Delta \hat{x}^{(l)}$ is the error of the $\hat{x}_i$ after the lth iterative; ε_x is the iterative cutoff constant, the value is $10^{-6} – 10^{-4}$ times of the current reference.

For the complicated system, h(x) is the nonlinear function, from the introduction above , the state estimation of the operation can be summarized as follows:

(1) Calculating the nonlinear function h(x) and the Jacobian matrices $H(x^{(0)})$ if the parameters of initial condition $x^{(0)}$ is given.

(2) Calculating the residual error($z-h(x^{(l)})$) and the objective function $J(x^{(l)})$ if given the remote measure data z .

(3) Calculating the information matrix $[H^T – R^{-1}H]$ and vector $H^T – R^{-1}H[z-h(x^{(l)})$ when given the Jacobian matrices $H(x^{(1)})$

(4) Calculating the condition $\Delta \hat{x}^{(l)}$ from the inequality (1), then get the maximum $\max\limits_i \left|\Delta \hat{x}^{(l)}\right|$.

(5) Comparing the result and checking if satisfying the inequality (1) and the function convergence .

(6) if not satisfy, modify the status expression, let the

$$\Delta\hat{x}^{(l)} = [H^T - (\hat{x}^{(l)})R^{-1}H(\hat{x}^{(l)})^{-1}H^T - (\hat{x}^{(l)})R^{-1}[z - h(\hat{x}^{(l)})] \tag{2}$$

And

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$$\hat{x}^{(l+1)} = \hat{x}^{(l)} + \Delta \hat{x}^{(l)} \tag{3}$$

going on the iterative step until the convergence.

(7) Calculating the result and enter the entrance of the bad data detection.

3.2. Dealing with the signal of the nonlinear system

Generally the characteristics of power system development are as follows: the increasing of overall capacity of power station and capacity of a single generator, the prolonging distance of transmitting electricity, and loads far away from power source with intense fluctuation. It is difficult to deal with the signal because the signal in the DC lines on account of the effect of the random noise.[8]

The consensus filter is usually used in the signal processing, the signal got from the DC lines are classified and extracted the faults features effectively. From the Distributed Kalman filtering, the dynamic consensus algorithm can be presented as follow:

$$\dot{x}_i(t) = \sum_{j \in N_i} a_{ij}[x_j(t) - x_i(t)] + \sum_{j \in j_i} a_{ij}[u_j(t) - x_i(t)] \tag{4}$$

Where x is the state of the matrix, u is the input, a_{ij} is the node in a network. In this paper, the network is matrix consisted of the consensus filter-processed signals from power system.[9] Also the distributed algorithm defined as above gives a strict proof, which can deal with the signal on the lines, that is, in the calculation processing the signal got from many testing instruments along the DC lines are transferred into the controlling center, then the signal processing instruments begin working by the consensus filters.[10]

4. Verification and comparison

Simulation Model

A single-machine infinite-bus system connecting at the high voltage side in a boost substation is given as Fig.1.

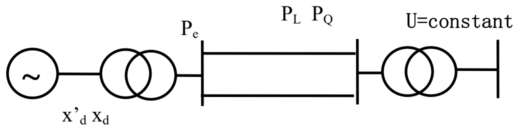

Fig.1. A single-machine infinite-bus system.

From the simulation result, the model can simulate almost the transient state. The simulation parameters of the power system model are as follow: the system parameters is x_d=x_q=2.12, x_d'=0.257, x_e=2.2404, x_T=0.0804, D=2, T'_{d0}=5.8, T_J=4.06, x_L=0.32. Based on the optimum multi-agent algorithm, the verification of the system is done by the MATLAB simulation[11][12].

The training data, noise-processed, is obtained from the power system. In the simulation processing, the parameters should be changed several times and the different model function get the different result.

Table 1: Result of the comparison.

data	Parameter comparison (accuracy 1-6)					
	1	2	3	4	5	6
A	56.29	67.03	72.39	79.22	83.99	90.89
B	50.45	61.12	67.13	70.76	76.01	88.43
C	60.30	69.28	72.93	78.38	80.37	87.43

A: rectifier output line to ground fault

B: commutation failure

C: single line to ground fault

Where the parameter 1-6 refer to the parameters of the genetic algorithm and the multi-agent, and

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these data are the basis of the calculation. And the appropriate parameter is critical to the simulation result.

The results demonstrate that the accuracy of the algorithm for the data from the power system depends on the parameters given to the algorithm model, which tell the applicability of the multi-agent genetic algorithm.

5. Conclusions

This paper puts emphasis on condition detection by the improved multi-agent based on genetic algorithm. The proposed method is used to computing the power system state estimation.

From the analysis of optimized multi-agent, the paper has the powerful ability to deal with the nonlinear problem. In the algorithm, the agents replace the operators of the genetic algorithm. Simulation results show that this control method is effective, which is superior to those by a single method.

To sum up, the algorithm has a good application prospect, and will be further developed in the future.

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