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Power plant multiagent control system

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Abstract: To deal with the nonlinear multi-variable and multiple control objective characteristic of power plant, the power plant multiagent control system (PPMACS) is designed. In the PPMACS, the feedforward control agents (FFCAs) make decisions using the neuro-fuzzy systems and the feedback control agents (FBCAs) make decisions using the genetic algorithm-based fuzzy systems. The optimal task decomposition agents (OTDAs) optimally decompose the task of the PPMACS through an optimization agent and a decomposition agent. The coordinator agent (COA) coordinates the agents in the PPMACS according to different operating conditions. Simulation results demonstrate that the PPMACS implement the multiobjective operation and wide range load tracking. Neural netwroks, fuzzy logic and genetic algorithm are effective tools for the agents of the PPMACS in making decisions.

Key words: decision-making; feedback control; feedforward control; fuzzy logic; genetic algorithms; multiagent control system; neural networks

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火电厂多代理控制系统

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摘要: 针对火电厂非线性、多变量和多控制目标的特点,设计了一个火电厂多代理控制系统(PPMACS).在 PPMACS 中,前馈控制代理(FFCAs)采用神经模糊系统进行决策,反馈控制代理(FBCAs)采用基于遗传算法的模糊系统进行决策.优化任务分解代理(OTDAs)通过一个优化代理和一个分解代理来进行多目标优化分解 PPMACS 的任务.协调代理根据运行条件协调 PPMACS 的各个代理.仿真结果显示了火电厂多代理控制系统能够实现火电单元机组的多目标运行和大范围负荷跟踪.神经网络、模糊逻辑和遗传算法是 PPMACS 中的智能代理进行决策的有效工具.

关键词: 决策; 反馈控制; 前馈控制; 模糊逻辑; 遗传算法; 多代理控制系统; 神经网络

1 Introduction

The design of power plant control system is a challenge because it involves designing a real-time controller for nonlinear multi-variable system with multiple control objectives. Conventional PID control and optimal control yield acceptable system performances that are optimal at only a certain operating point. The robust control performs well over a wide range of operation but requires frequency response information to design[1]. Adaptive control improves the reliability and availability of power plant because the operating conditions of the system are tracked and the controller parameters are updated accordingly[2]. However, the robust control and adaptive control that are based on the linearized model of the nonlinear plant will not achieve a desired system performance once the system departs from the nominal operating region. Due to the complexity of nonlinear dynamic characteristics, it is difficult to build an accurate mathematical model of the power plant. Therefore, the intelligent control based on input/output information of the system is acceptable to the power plant control system[3,4].

With the increasing demand in power in the present-day society, the power system is becoming a complicated, enlarged, decentralized and open system. The operation of power plant must meet not only the technical requirements, but also the environmental, political and economical requirements. The minimum prototype of the Intelligent coordinated control system (ICCS-MP) is presented to develop a large-scale intelligent control system for power plant in the form of a multiagent system (MAS)[5]. The ICCS-MP implements a two-level hierarchical intelligent hybrid multiagent coordinated control system for a fossil fuel power plant. The ICCS-MP provided the means to consistently achieve multiobjective optimal control actions and versatility to operate in changing environments characterized by multiple objectives.

A methodology for MAS design was formulated by merging concepts from the fields of software engineering, control engineering, and concepts from intelligent systems theory and intelligent machines in [6]. The resultant control system structure, seen as an open organization of intelligent agents, constitutes a general framework for the

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development of large-scale intelligent control system. A great deal of research can be done based on such framework. A developing multiagent control system is presented in this paper.

2 Power plant multiagent control system

Multiagent systems are the systems in which several intelligent agents cooperate with each other and coordinate their knowledge and activities, and reason about the processes of coordination to accomplish a common goal.

The power plant multiagent control system (PPMACS) consists of fossil-fuel power unit agent (FFPUA), feedforward control agents (FFCAs), feedback control agents (FBCAs), optimal task decomposition agents (OTDAs) and coordinator agent (COA). Given the information they have and their perceptual and effectual capability, intelligent agents in the PPMACS pursue their goals and execute their tasks flexibly and rationally in a variety of environments. The FFCAs make decisions using the neuro-fuzzy systems and the FBCAs make decisions using the genetic algorithm-based fuzzy systems. The OTDAs decompose the task of the PPMACS by multiobjective optimization. The coordinator agent coordinates the agents in the PPMACS according to different operating conditions.

The goal of the fossil-fuel power unit agent (FFPUA) is to generate electric power. The FFPUA makes decisions based on the dynamics of the fossil-fuel power unit (FFPU). The essential dynamics of the FFPU have been remarkably captured for a 160-MW oil-fired drum-type boiler-turbine generator unit in a third order multi-input-multi-output (MIMO) nonlinear model for overall wide-range simulations[7]. The inputs are the positions of the valve actuators that control the mass flow rates of fuel (u_1), steam to the turbine (u_2) and feedwater to the drum (u_3). The three outputs are the electrical power (E in MW), drum steam pressure (P in kg/cm^2) and drum water level deviation (L in m). The state variables are the electric power, drum steam pressure and the fluid (steam-water) density (ρ_f). The state equations are

$$\frac{dP}{dt} = 0.9u_1 - 0.0081u_2P^{\frac{9}{8}} - 0.15u_3, \quad (1)$$

$$\frac{dE}{dt} = ((0.73u_2 - 0.16)P^{\frac{9}{8}} - E)/10, \quad (2)$$

$$\frac{d\rho_f}{dt} = (141u_3 - (1.1u_2 - 0.19)P)/85. \quad (3)$$

The drum water level output is calculated using the following equations:

$$q_e = (0.85u_2 - 0.14)P + 45.59u_1 - 2.51u_3 - 2.09, \quad (4)$$

$$\alpha_s = (1/\rho_f - 0.0015)/(1/(0.8P - 25.6) - 0.0015), \quad (5)$$

$$L = 50(0.13\rho_f + 60\alpha_s + 0.11q_e - 65.5), \quad (6)$$

where α_s is the steam quality, and q_e is the evaporation rate (kg/s). Positions of the valve actuators are considered to be in $[0,1]$, and their rates of change (pu/s) are limited to

$$-0.07 \leqslant du_1/dt \leqslant 0.007, \quad (7)$$

$$-2 \leqslant du_2/dt \leqslant 0.02, \quad (8)$$

$$-0.05 \leqslant du_3/dt \leqslant 0.05. \quad (9)$$

3 Feedforward/feedback control agents

The goal of the feedforward control agents (FFCAs) is to facilitate a wide-range set-point driven operation for the FFPUAs, and to provide off-line operator-requested system adaptability to achieve optimal operation. The goal of the feedback control agents (FBCAs) is to provide corrective control actions along the commanded set-point trajectories to overcome the effect of disturbances and uncertainties in the whole operating window of the power unit.

A) Feedforward control agents.

The FFCAs include power feedforward control agent, pressure feedforward control agent and level feedforward control agent. All FFCAs have a similar structure and work in a systematic and automated way. The power, pressure and level feedforward control agents perceive the operating condition to make a decision.

The power plant operation can be divided into two modes: normal and abnormal operation. The normal operation includes continuous and sequence control operation. The sequence control operation involves shutting down and setting up of the power plant. Under the continuous operation, there are 4 cases considered in the power-pressure operating window of the unit: high-pressure limit (HP), constant pressure (CP), sliding pressure (SP), and low-pressure limit (LP).

Under different operating conditions, the FFCAs decide to use different feedforward control policy. Then the FFCAs get the set-points E_d, P_d, L_d from the coordinator agent COA and provide the feedforward control signals for the fuel valve u_{1ff}, steam valve u_{2ff} and feedwater valve u_{3ff} to the COA. The control policy of the FFCAs is based on the fuzzy logic with membership functions tuned by the neural network.

The fuzzy systems considered in FFCAs are of the Takagi-Sugeno-Kang (TSK) type[8] with the adaptive neuro-fuzzy inference system (ANFIS)[9] technique using steady-state input-output process data. With the ANFIS technique, the TSK fuzzy system is represented as a 3-input 1-output 5-layer feedforward neural network. The network has 3 distribution units in layer L_0, 9 neurons in L_1, 27 neurons in L_2, L_3, and L_4, 1 neuron in L_5. Layer L_0 is not considered as a neural processing layer. In gross terms, L_1 constitutes an input fuzzification stage, then each row across in L_2, L_3, and L_4 evaluates a knowledge rule, and finally L_5 computes the final output value. Neural units in L_1 and L_4 are adaptive; their parameters are learned during training. Neural units in L_2, L_3, and L_5 are fixed; their parameters are not modified in the training. Each input signal spans its whole operating range with three overlapping fuzzy regions. The consequent parameters of the neuro-fuzzy system are to be estimated using an LSE procedure and the changes to the membership function parameters are determined by the backpropagation training algorithm.

B) Feedback control agents.

The FBCAs include power feedback control agent, pressure feedback control agent and level feedback control agent. The power, pressure and level feedback control agents also perceive the operating condition to make a decision.

Under different operating conditions, the FBCAs decide to use different feedback control policy. Then the FBCAs perceive the error e between the set-points and the behaviors of the FFPUAs and the change in error $\dot{e}$ to make decision and provide the feedback control signals for the fuel valve $u_{1\mathrm{fb}}$, steam valve $u_{2\mathrm{fb}}$ and feedwater valve $u_{3\mathrm{fb}}$ to the COA. The control policy of the FBCAs is based on the fuzzy logic whose membership functions are tuned by genetic algorithm.

Every feedback control agent has two inputs with scaling gain g_1, g_2 and one output with scaling gain g_0. The normalized membership functions are shown in Fig. 1.

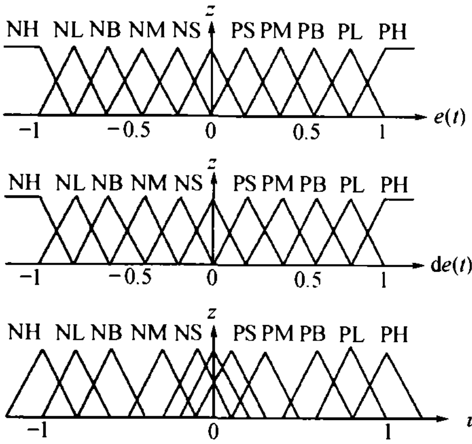


Fig. 1 Membership functions of the feedback control agents.

The scaling gains g_0, g_1 and g_2 are tuned by genetic algorithm[10]. Firstly, the scaling gains are encoded to the chromosome represented by decimal-strings. Within the bounds of the decision variables g_0, g_1 and g_2, the initial population consisting of 20 chromosomes is created randomly. The fitness values of strings can be evaluated using the following equation:

$$F = \int_0^t |e(t)| \, \mathrm{d}t. \qquad (10)$$

Normalized geometric ranking selection is used. It assigns the probability P_i based on the rank of the i-th individual. Hybrid crossover[11] is used for the crossover of the individuals representing steady-state control signals. Hybrid crossover increases the solution space of the offsprings. Uniform mutation is used for the real-valued representation mutation operation.

4 Optimal task decomposition agents

The optimal task decomposition agents (OTDAs) decompose the task of PPMACS through an optimization agent and a decomposition agent. The goal of the optimization agent is to find the optimal steady-state control signals within their feasibility regions. As a result, the optimal steady-state control signals will be sent from the optimization agent to the decomposition agent. The decomposition agent aims to decompose the main task E_{uld} into three sub-tasks E_{d}, P_{d} and L_{d} according to the message receiving from the optimization agent.

A) Decision-making of OTDAs.

Central to the decision-making of the optimization agent is the solution of a multiobjective optimization problem formulated based on genetic algorithm (GA). Since GA works with many points in the search space simultaneously, it provides a rapid convergence to sub-optimal solutions. GA is especially suitable for multiobjective optimization.

The decision-making of the decomposition agent is simply calculating the optimal set-points based on the knowledge of the steady-state power unit model. The steady-state model is obtained by setting the derivatives of the dynamic state equations of the fossil fuel power unit (FFPU) to zero.

Once the optimal steady-state control signals u^* are found by the optimization agent, they are used to calculate the optimal set-points through the steady-state model obtained from the dynamic state equations (1) ~ (3). The results of the decision-making of the decomposition agent are set-points given by

$$E_{\mathrm{d}} = \frac{0.73u_2^* - 0.16}{0.0018u_2^*}(0.9u_1^* - 0.15u_3^*), \qquad (11)$$

$$P_{\mathrm{d}} = \frac{141u_3^*}{1.1u_2^* - 0.19}, \qquad (12)$$

$$L_{\mathrm{d}} = 0. \qquad (13)$$

B) Operation of OTDAs.

Intelligent agents continuously operate in an iterative perceive-reason-act (PRA) cycle[12]. The OTDAS perceive within the ICCS-MP environment and perceive the model of FFPU as their internal knowledge, reason based on their knowledge and act in the environment. The reasoning process of the OTDAS is known as solving a multiobjective optimization problem defined as follows:

$$\min J(u)$$
$$\text{subject to } u_i \in \Omega_i(E_{\mathrm{uld}}),\ i = 1,2,3, \qquad (14)$$

where $J(u) = [J(u)_1, J(u)_2, \cdots, J(u)_k]^{\mathrm{T}}$ is a k-dimensional vector of objective functions, and $u = [u_1, u_2, u_3]^{\mathrm{T}}$ is the three-dimensional vector of control signals, whose optimal values are to be determined. Ω_i is the feasibility regions of control signals. E_{uld} is the unit load-demand or desired power generation in MW.

With the aim of implementing an operating policy to attain minimum load-tracking error and improved heat rate, the following objective functions can be considered

$$J_1(u) = |E_{uld} - E_{ss}|, \quad (15)$$

$$J_2(u) = u_1, \quad (16)$$

$$J_3(u) = -u_2, \quad (17)$$

$$J_4(u) = -u_3, \quad (18)$$

where E_{ss} is the corresponding steady-state power generation as provided by the static model.

Three cases are considered in the operation of OTDAS. First, the load-tracking error $J_1(u)$ is considered in the one objective case, which should always be included in other cases. Second, in addition to the load tracking error, the fuel usage $J_2(u)$ is added in the two objective cases. Finally, the throttling losses in the steam value $J_3(u)$ and in the feedwater value $J_4(u)$ are added in the four objective case.

In the first case, $J_1(u)$ is mininized with a relative preference value $\beta_1 = 1$ for top priority. The second case also minimizes $J_2(u)$ with preference value $\beta_2 = 0.5$. The third case minimizes $J_3(u)$ and $J_4(u)$ with preference values $\beta_3 = 1$ and $\beta_4 = 0$, respectively.

We use genetic algorithm to resolve such multiobjective optimization problem. Perceiving the steady-state model of the FFPU, the optimization agent of OTDAS can obtain the information of the upper and lower limits of the feasibility regions along the whole unit load operating range. Consequently, the optimization agent reasons and acts in GA to achieve the multiobjective optimization.

5 Coordinator agent

The goal of the coordinator agent is to coordinate the agents in the PPMACS according to different operating conditions.

A) Decision-making of COA.

The coordinator agent COA is an important agent in the PPMACS. It perceives the environment of the PPMACS to make system level decision. It gets different information from every agent in the PPMACS and even from the operator. It analyzes and decides what kind of message should be sent to which agent.

Firstly, the COA checks the unit load demand and the operation command from the operator. Then the COA checks the state of the PPMACS according to the output of the FFPUA. If the unit load demand changes large and rapidly, the COA will decide to ask the OTDAs to generate optimal set-points and asks the FFCAs to generate feedforward control signals. At the same time, if the error between the set-points and the output of the FFPUA is found to be a big one, the COA will ask the FBCAs to eliminate it as soon as possible. Otherwise, if the unit load demand does not change, the COA will decide not to ask the OTDAs and the FFCAs to act.

The COA harmonizes the slow response of the boiler and the fast response of the turbine through the OTDAs, FFCAs and the FBCAs. In the OTDAs, the set-points E_d, P_d and L_d are obtained from the load demand E_{uld}. In the FFCAs, the power feedforward control agent generates the feedforward control signals for the fuel value u_{1ff} from the set-points E_d, P_d and L_d. In the FBCAs, the power feedback control agent generates the feedback control signals for the fuel value u_{1fb} from the power set-point E_d and the measured generated power. The u_{1ff} and the u_{1fb} are added to the power control signal u_1. In the FFCAs, the pressure feedforward control agent generates the feedforward control signals for the throttle value u_{2ff} from the set-points E_d, P_d and L_d. In the FBCAs, the pressure feedback control agent generates the feedback control signals for the throttle value u_{2fb} from the pressure set-point P_d and the measured throttle steam pressure. The u_{2ff} and the u_{2fb} are added to the pressure control signal u_2. In fact, the above control scheme is a kind of boiler following coordinated control. It allows the generation of the necessary power to satisfy the load demand, and simultaneously maintain the balance among the transformation process within the FFPUA.

B) Communication between agents.

Every agent is an intelligent and flexible entity with goals, actions, and domain knowledge. They collaborate each other through communication to achieve a global goal that is beyond the ability of each individual agent.

In the PPMACS, one agent gets the useful information from other agents in order to make effective decision and provides the required information for other agents through message passing. The communication between agents in the PPMACS is flexible. It can be an inquiring-answering communication or a sending-responding communication. The communication between the agents in the PPMACS is shown in Fig. 2.

As shown in Fig. 2, the COA communicates with every agent by passing messages. There are two kinds of messages: data and text in the PPMACS. For the text message, the COA sends "run" or "stop" command to the OTDAs, FBCAs and FFCAs, and they in turn reply "yes" or "no" to the COA. As for the data message, the OTDAs send the set-points E_d, P_d, L_d to the COA, the FBCAs send the feedback control signals u_{1fb}, u_{2fb}, u_{3fb} to the COA, the FFCAs send the feedforward control signals u_{1ff}, u_{2ffb}, u_{3ff} to the COA. The COA sends the control signal u_1, u_2, u_3 to the FFPUA. The FFPUA will send output E, P, L to the COA when asked.

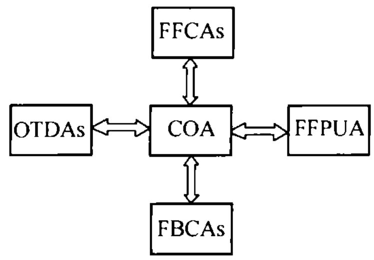


Fig. 2 Communication between agents of the PPMACS

6 Simulation results

The simulation of the power plant multiagent control system is implemented in SIMULINK of MATLAB.

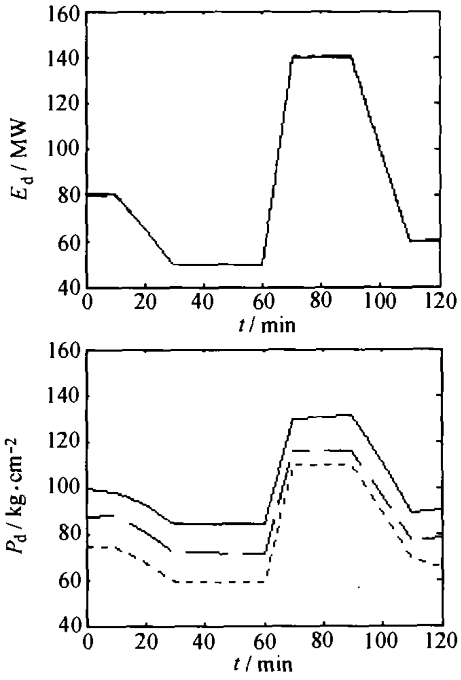
A) Behavior of OTDAs.

We use the Normalized geometric selection whose parameter q is 0.08, the Uniform mutation and Hybrid crossover for the simulation of the optimization agent. The different behaviors of the optimization agent for the three cases are obtained when the load demand changes following a typical load cycle.

Receiving the message from the optimization agent, the decomposition agent reasons and acts based on the knowledge of the steady-state model of the FFPU to decompose the task of PPMACS.

Fig. 3 shows the power and pressure set-points behavior of the decomposition agent in the three cases.

The feedwater level set-point is always zero. It should be noted that while the power set-point remains the same in the three cases, the pressure set-point changes as additional objectives are added. In other word, it is possible to follow the load while operating at different pressure in order to satisfy additional requirements such as reducing the fuel usage and extending the life cycle of control valves.



——1 obj; - - - 2 obj; ·····3 obj

Fig. 3 Set-point behaviors of the decomposition agent

The multiobjective optimization problem is solved by genetic algorithm. The convergence of the best fitness function of generations in the GA operation process of OTDAS is shown in Fig. 4. From this, GA is shown to be an effective tool for making an optimal decision for an agent.

B) System response

With the set-points behavior from the OTDAs, the behavior of the control signal demand in three cases is shown in Fig. 5.

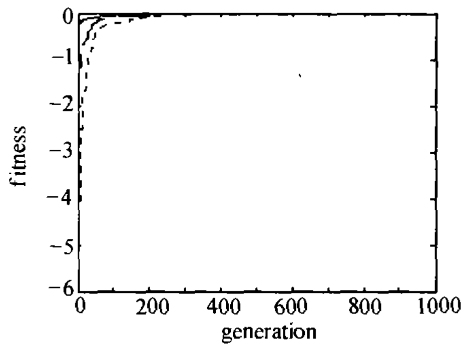


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Fig. 4 Convergence of the fitness function

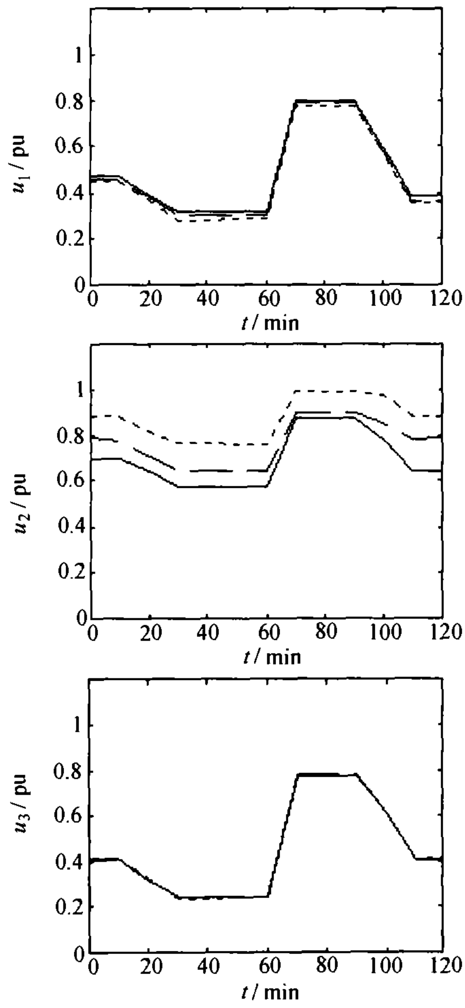

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Fig. 5 Behavior of the control signal demand

It can be observed that when additional objectives are added to the load tracking error, the fuel valve position decreases slightly, but the steam valve position increases significantly. On the other hand, feedwater valve position remains the same in all the cases.

Receiving the control signal demand in Fig. 5, the behavior of the FFPUA is shown in Fig. 6. The results demonstrate that the tracking of the power and pressure is satisfying.

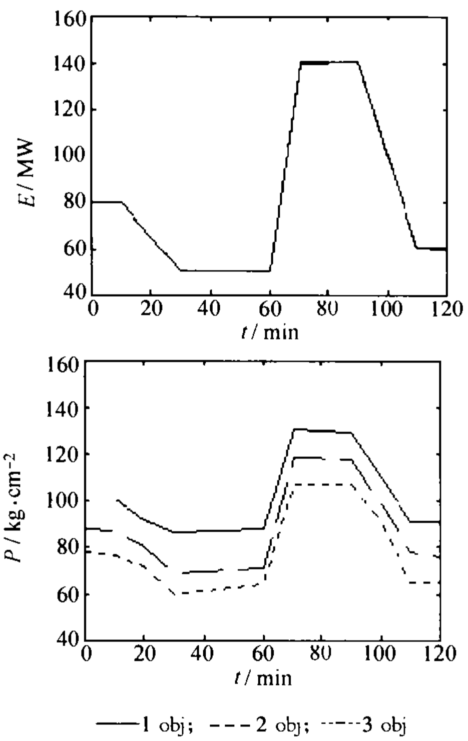

Fig. 6. Behaviors of the FFPUA

7 Conclusion

Every agent in the power plant multiagent control system PPMACS is an intelligent agent who is able to make decision according to the operating condition of the power plant. The feedforward control agents have the learning capabilities provided by ANFIS. The feedback control agents do not require a model of process and its tuning procedure can be automated by genetic algorithm. The two controller agents collaborate to attain wide-range operation of the FFPU. Neural networks, fuzzy logic and genetic algorithm are effective tools for the agents in making decisions.

The PPMACS is an open and flexible multiagent control system. The coordinator agent coordinates the agents to make the system work efficiently and optimally. The agents get the information through communication. New agents such as fault diagnosis agent and fault accommodate agent will be added in our future research.

References:

[1] BENTSMAN J, TSE J, MANAYATHARA T, et al. State space and frequency domain predictive controller design with application to power plant control [C]// IEEE. *Proc of the 3rd IEEE Conf on Control Applications*. Piscataway, NJ: IEEE Press, 1994, 1:729 - 734.

[2] ODA K, TOYODA Y, NAKAMURA H. Model reference control for steam temperature of power plant at start-up stage [C]// IEEE. *Proc of the 34th SICE Annual Conf on Int Session Papers*. Piscataway, NJ: IEEE Press, 1995:1609 - 1614.

[3] HARNOLD Chi-Lima, LEE K Y. A free-model based model reference adaptive inverse controller design for a boiler-turbine plant by using functional mapping [C]// IEEE. *Proc of IEEE Power Engineering Society Summer Meeting*. Piscataway, NJ: IEEE, Press, 2000, 1:212 - 216.

[4] BEN-ABDENNOUR A, LEE K Y. An autonomous control system for boiler-turbine units [J]. *IEEE Trans on Energy Conversion*, 1996, 11(2):401 - 406.

[5] GARDUNO-RAMIREZ R, LEE K Y. Multiobjective optimal power plant operation through coordinate control with pressure set point scheduling [J]. *IEEE Trans on Energy Conversion*, 2001, 16(2):115 - 122.

[6] GARDUNO-RAMIREZ R, LEE K Y. Intelligent multiagent control for power plants [M]// LEONDES C T. *Intelligent Systems: Technology and Applications*. New York: CRC Press, 2002, 1:181 - 209.

[7] BELL R D, ASTROM K J. A fourth order non-linear model for drum-boiler dynamics [C]// IEEE. *Proc of IFAC 13th Triennial World Congress*. Piscataway, NJ: IEEE. Press, 1996:31 - 36.

[8] TAKAGI T, SUGENO M. Fuzzy identification of systems and its applications to modeling and control [J]. *IEEE Trans on System, Man, and Cybernetics*, 1985, 15(1):116 - 132.

[9] JANG ANFIS J S R. Adaptive-network-based fuzzy inference system [J]. *IEEE Trans on System, Man, and Cybernetics*, 1993, 23(3):665 - 685.

[10] DUMITRESCU D, LAZZERINI B, JIAN L C, et al. *Evolutionary Computation* [M]. New York: CRC Press, 2000:21 - 37.

[11] LEE K Y, MOHAMED P S. A real-coded genetic algorithm involving a hybrid crossover method for power plant control system design [C]// IEEE. *Proc of IEEE World Congress on Computational Intelligence*: 2002 Congress on Evolutionary Computation. Piscataway, NJ: IEEE. Press, 2002: 1069 - 1074.

[12] MIAO C Y, GOH A, MIAO Y. A multi-agent framework for collaborative reasoning [M]// LEONDES C T. *Intelligent Systems: Technology and Applications*. New York: CRC Press, 2002, 1:151 - 167.

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