Multiagent Control System for a Fossil-Fuel Power Unit

Jiang Chang, Member, IEEE, Kwang Y. Lee, Fellow, IEEE, and Raul Garduno-Ramirez, Member, IEEE

Abstract—This paper proposes a multiagent control system (MACS) for a fossil-fuel power unit (FFPU). The MACS consists of fossil-fuel power unit agent (FFPUA), reference agent (RA), feedforward control agents (FBCAs), feedback control agents (FFCAs) and coordinator agent (COA). The reference agent decomposes the task of the MACS by multiobjective optimization. The FFCAs make decision using the neuro-fuzzy systems and the FBCAs make decision using the genetic algorithm-based fuzzy systems. The coordinator agent coordinates the agents in the MACS according to different operating conditions.

Index Terms—Decision-making, feedback control, feedforward control, fuzzy logic, genetic algorithms, multiagent control system, neural networks

I. 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 accurate mathematical model of the power plant. Therefore, the intelligent control based on input/output information of the system is attractive for power plant control system [3], [4].

With the increasing demand in power in the present-day society, 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 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.

II. 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 multiagent control system (MACS) for a fossil-fuel power unit (FFPU) consists of fossil-fuel power unit agent (FFPUA), reference agent (RA), feedforward control agents (FFCAs), feedback control agents (FBCAs) and coordinator agent (COA). Given the information they have and their perceptual and effectual capability, intelligent agents in the MACS pursue their goals and execute their tasks flexibly and rationally in a variety of environments. The reference agent decomposes the task of the MACS by multiobjective optimization. The FFCAs make decision using the neuro-fuzzy systems and the FBCAs make decision using the genetic algorithm-based fuzzy systems. The coordinator agent coordinates the agents in the MACS according to different operating conditions.
A. Fossil-Fuel Power Unit Agent

The goal of the fossil-fuel power unit agent (FFPUA) is to generate electric power. The FFPUA makes decision based on the dynamics of 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 (uj), steam to the turbine (u2) and feedwater to the drum (u3). The three outputs are the electrical power (E in MW), drum steam pressure (P in kg/cm2) and drum water level deviation (L in m). The state variables are the electric power, drum steam pressure and the fluid (steam-water) density (ρf). The state equations are:

\[
\begin{align*}
\frac{dP}{dt} &= 0.9u_1 - 0.0018u_2P^8 - 0.15u_3 \\
\frac{dE}{dt} &= ((0.73u_2 - 0.16)P^8 - E) / 10 \\
\frac{d\rho_f}{dt} &= (141u_3 - (1.1u_2 - 0.19)P) / 85 
\end{align*}
\]  

(1) (2) (3)

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

\[
\begin{align*}
q_s &= (0.85u_2 - 0.14)P + 45.59u_1 - 2.5u_3 - 2.09 \\
\alpha_s &= (1/\rho_f - 0.0015)/(1/(0.8P - 25.6) - 0.0015) \\
L &= 50(0.13\rho_f + 60\alpha_s + 0.11q_e - 65.5) 
\end{align*}
\]

(4) (5) (6)

where \( q_s \) 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/sec) are limited to:

\[
-0.007 \leq \frac{du_1}{dt} \leq 0.007 \\
-2 \leq \frac{du_2}{dt} \leq 0.02 \\
-0.05 \leq \frac{du_3}{dt} \leq 0.05 
\]

(7) (8) (9)

B. Reference Agent

The goal of the reference agent (RA) is to decompose the unit load demand \( E_{uld} \) into three set-points that are electric power \( E_d \), steam pressure \( P_d \) and water level deviation \( L_d \) optimally under multiple, generally conflicting, operation objectives.

The reasoning process of the RA is known as solving a multiobjective optimization problem defined as following:

\[
\text{minimize } J(u) \quad \text{subject to: } u_i \in \Omega_i(E_{uld}), \quad i = 1, 2, 3 
\]

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

Receiving the commands from the coordinator agent COA such as minimum load-tracking error and improved heat rate, the reference agent RA will make decision to minimize one or more objective functions with the relative preference values \( \beta \). The RA then uses genetic algorithm to minimize the objective functions and calculates the set-points \( E_d, P_d \) and \( L_d \) to send the results to the COA.

C. Feedforward 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 FFCAs include power feedforward control agent, pressure feedforward control agent and level feedforward control agent. All FFCAs have 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 includes shut down and set 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 condition, the FFCAs decide to use different feedforward control policy. Then the FFCAs get the set-points \( E_{ih}, P_{ih}, L_{ih} \) from the coordinator agent COA and provide the feedforward control signals for the fuel valve \( u_{igf} \), steam valve \( u_{igf} \) and feedwater valve \( u_{igf} \) 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) 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 $L_s$ are fixed; their parameters are not modified during 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 a LSE procedure and the changes to the membership function parameters are determined by the backpropagation training algorithm.

D. Feedback Control Agents

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.

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 condition, 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 $\delta e$ to make decision and provide the feedback control signals for the fuel valve $u_f$, steam valve $u_{fb}$ and feedwater valve $u_{fwb}$ 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 $g_o$. The normalized membership functions are shown in Fig. 1.

![Normalized membership functions of the feedback control agents.](image)

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:

$$F = \int_0^t |e(t)| dt$$

(12)

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.

E. Coordinator Agent

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

The coordinator agent COA is an important agent in the MACS. It perceives the environment of the MACS to make system level decision. It gets different information from every agent in the MACS 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 MACS according to the output of the FFPUA. If the unit load demand changes large and rapidly, the COA will decide to ask the reference agent RA 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 big, the COA will ask the FBCAs to work to eliminate the error as soon as possible. Otherwise, if the unit load demand does not change, the COA will decide not to ask the RA and the FFCAs to work.

F. 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 MACS, one agent gets a 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 MACS is flexible. It can be inquiry and answer or send and response. The communication between the agents in the MACS is shown in Fig. 2.

![The communication in the MACS.](image)
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 MACS. For the text message, the COA sends run or stop command to the RA, FBCAs and FFCAs, and they in turn reply yes or no to the COA. As for the data message, the RA sends the set-points $E_d$, $P_d$, $L_d$ to the COA, the FBCAs send the feedback control signals $u_{1f}$, $u_{2f}$, $u_{3f}$ to the COA, the FFCAs send the feedforward control signals $u_{1g}$, $u_{2g}$, $u_{3g}$ 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.

III. SIMULATION RESULTS

The simulation of the multiagent control system for a fossil-fuel power unit is implemented in SIMULINK of MATA LAB. Two cases under the sliding pressure operating condition are considered in the MACS. In the first case, power is required to increase from 80 MW (half load) to 90 MW in 150 seconds, that is a 6.25% power set-point change with a rate of 2.5%/min, which would be normally considered an easy test. In the second case, a large unit load demand change from 80 MW (50% base load) to 160 MW (100% base load) in 600 seconds (10 min), that is a 50% change in unit load demand at a rate of 5%/min, which corresponds to the fastest rate allowable in practice. The power, pressure and water level responses to unit load demand ramp in the two cases are shown in Figs. 3 and 4. During the period from 20 seconds to 170 seconds in Fig. 3, the COA realizes that the unit load demand change continually and decides to ask the RA, FFCAs and FBCAs to work. The RA receives the command from the COA and decides to optimize one objective function. Then the RA will calculate and send the ramp references $E_d$, $P_d$ to the COA. The water level set-point $L_d$ is zero.

During the period from 170 seconds to 300 seconds in Fig. 3, the COA knows that the unit load demand is not changing and decides to stop the RA and the FFCAs. The set-points and the feedforward control signals saved in the memory of the COA still can be used. It is easier for the FBCAs to eliminate the error with the help of the existing feedforward control signals.

IV. CONCLUSION

The multiagent control system (MACS) for a fossil-fuel power unit consists of fossil-fuel power unit agent, reference agent, feedforward control agents, feedback control agents and coordinator agent. Every agent in the MACS is an intelligent agent making 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 MACS 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 can be added in the future research.
Fig. 4. Response to unit load demand ramp over large range.

V. REFERENCES


VI. BIOGRAPHIES

Jiang Chang received her B.S., M.S., and Ph.D. degrees from the Dynamic Engineering Department of Wuhan University of Hydraulic and Electric Engineering, China, in 1991, 1994, and 1997, respectively. She has been teaching in the Industry Center of Shenzhen Polytechnic, China. She worked in the Electric Engineering Department of Pennsylvania State University, USA as a visiting scholar from 2002 to 2003. Her interests include Neural Networks, Fuzzy Logic, Genetic Algorithm, Multiagent Systems and Intelligent system application to power system. She is a Member of IEEE.

Kwang Y. Lee received his B.S. degree in Electrical Engineering from Seoul National University, Korea, in 1964. M.S. degree in Electrical Engineering from North Dakota State University, Fargo, in 1968, and Ph.D. degree in System Science from Michigan State University, East Lansing, in 1971. He has been with Michigan State, Oregon State, Univ. of Houston, and the Pennsylvania State University, where he is now a Professor of Electrical Engineering and Director of Power Systems Control Laboratory. His interests include power system control, operation, planning, and intelligent system applications to power systems. Dr. Lee is a Fellow of IEEE, Associate Editor of IEEE Transactions on Neural Networks, and Editor of IEEE Transactions on Energy Conversion. He is also a registered Professional Engineer.

Raul Garduno-Ramirez received his B.S. degree in Electrical Engineering from the National Polytechnic Institute (IPN), Mexico, in 1985, his M.S. degree in Electrical Engineering from Advanced Research Centre of the IPN, Mexico, in 1987, and his Ph.D. degree in Electrical Engineering at the Pennsylvania State University in 2000. He was a Fulbright Fellow during his Ph.D. program at Penn State. During 1986 he stayed at the National Mechanical Laboratory, Tsukuba, Japan, and during 1987–1995 at the Electric Research Institute, Mexico, where he was involved in the development of control systems for power plants. His current interest is in control software development and intelligent control.