A Multi-Agent System-Based Intelligent Heuristic Optimal Control System for A Large-Scale Power Plant

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Abstract—A large-scale power system is required to have a new control system to operate at a higher level of automation, flexibility, robustness, and optimization. In this paper, a Multi-Agent System based Intelligent Heuristic Optimal Control System (MAS-IHOCS) is presented for reference governor and optimal feedforward and feedback controls that improve the performance of the plant in a wide-range of operation. With the proposed architecture of a single agent and an organization of the multi-agent system, the MAS-IHOCS realizes the reference governor for generating optimal set-points and feedback control actions by using Particle Swarm Optimization (PSO). It also realizes feedback control actions which utilize optimal PI control gains obtained by using a Differential Evolutionary (DE) algorithm. The proposed MAS-IHOCS is a functional group in a Multi-Agent System-based Intelligent Control (MAS-IC), which has several functional groups that provide efficient ways to control locally and globally, and to accommodate and overcome the complexity of large-scale distributed systems.

I. INTRODUCTION

The power plants are getting more complex and expansive to run, the optimization problem of power plant operation lies at not only the generation of concurrent optimal control actions but also the design of architecture for control systems. In generating the optimal control actions, standard optimization methods for a large-scale Multiple-Input Multiple-Output (MIMO) nonlinear system result in a heavy computational burden. Moreover, traditional optimization techniques may often become computationally unattractive or even unacceptable [1]. Control system architectures have been considered to reduce the computational complexity and manage the huge amount of distributed data and coupling problems among many subsystems. Recently, there has been a growing interest in heuristic optimization techniques, such as Particle Swarm Optimization (PSO) and Differential Evolution (DE) as variations of Evolutionary Computation (EC). It has been shown that they can provide quality solutions and fast convergences in many applications [13],[14],[22],[23]. The study of Multi-Agent Systems (MASs) has become an important aspect of power system architecture in order to deal successfully with the complexity and distributed problems. Each agent system has special functions to solve the distributed problems. In addition, in the multi-agent system the agents can work together to solve problems, which are beyond the capabilities or knowledge of an individual agent [2].

Many intelligent control techniques have been developed for power plant using basic neural network, diagonal recurrent neural network, evolutionary algorithm, genetic algorithm, fuzzy logic, and neuro-fuzzy logic [3]-[10]. As an optimal set-point generator, the reference governor has been developed by using global programming, genetic algorithm and particle swarm optimizations [11]-[14]. The intelligent identifier for power plant model is utilized to preserve the stability while searching for optimal control actions [4]. In order to overcome the problem associated with large-scale distributed systems, many applications of multi-agent systems or agent-oriented systems have been presented in control and monitoring systems [15]-[21].

The previous application of intelligent optimal controls has been for a small-scale MIMO nonlinear power plant. However, for a large-scale power plant, the intelligent optimal control methods should be re-examined due to the heavy computational complexity and huge amount of distributed data. With a new control framework, the intelligent optimal control problem can be retackled for the large-scale power plant. The optimization tools should be chosen by considering the restrictions and performances in some cases. Moreover, the overall control system should perform in real-time while avoiding the high computational complexity. The intelligent heuristic optimization and multi-agent system paradigms, as the state-of-the-art artificial intelligence software engineering concepts, may provide a comprehensive and unifying framework for building an intelligent heuristic optimal control system for efficient power plant operation.

In this paper, a Multi-Agent System based Intelligent Heuristic Optimal Control System (MAS-IHOCS) is presented for reference governor, optimal feedforward and feedback controls that improve the performance of the plant in a wide-range of operation. With the proposed architecture of a single agent and an organization of the multi-agent system, the MAS-IHOCS realizes the reference governor for generating optimal set-points and feedforward control actions by using Particle Swarm Optimization (PSO). It also realizes optimal feedback control actions which utilize optimal PI control gains obtained by using a Differential Evolutionary (DE) algorithm. The proposed MAS-IHOCS is a functional group in a Multi-Agent System based Intelligent Control (MAS-IC), which has several functional groups that provide efficient ways to control locally and globally, and to accommodate and overcome the complexity of large-scale distributed systems.
Following the introduction, the power plant and Multi-Agent System (MAS) are described in Section II. Section III describes Multi-Agent System based Intelligent Heuristic Optimal Control System (MAS-IHOCS). Section IV shows simulation results to demonstrate the feasibility of the proposed approach and the final section draws some conclusions.

II. POWER PLANT AND MULTI-AGENT SYSTEM

A. Description of Power System [25], [26]

The power plant under consideration is a 600MW oil-filed drum-type boiler-turbine-generator unit. It is a balanced draft, controlled recirculation drum boiler capable of delivering $4.2 \times 10^6$ lb/hr of steam at a pressure of 2600 psig and at 1005ºF. Six recirculation pumps supply the required recirculation flow to provide sufficient flow for full load operation. Two forced draft fans supply the primary air, and two induced draft fans are controlled to maintain a furnace pressure at a desired pre-set value. Two condensate pumps and a combined booster and main boiler feedpumps handle the feedwater flow.

The turbine is a tandem compound triple pressure steam turbine. It consists of three parts: a high-pressure turbine, an intermediate pressure turbine, and low twin pressure turbines rotating on a common shaft at a rated speed of 3600 rpm and exhausting pressure at a 2 inch Hg absolute. The generator is coupled with the turbine and has a 685,600 kVA, 3 phase, 60 Hz, 22 kV, with a power factor of 0.90.

The developed model represents an extension of some existing models [27]-[29] in two primary areas. First, the condensate and feedwater side dynamics have been modeled and second, the electrical prime movers which run fans and pumps and their dependence upon driving voltage and frequency have been modeled. The overwhelming majority of electric power generation is by conventional, drum-type, steam power plants. In this paper, the model has twenty-three state variables associated with physical processes. The model is reorganized into four main modules; which are boiler system, turbine-generator system, condenser system, and feedwater system. The proposed MAS-IHOCS is one of the functional systems based on multi-agent system which is interconnected with the subdivided and distributed subsystems that are components of the four main modules. Fig. 1 shows the large-scale distributed thermal power plant model and MAS. Most blocks are subsystems, represented by model. The proposed scheme will be applicable to other types of plants, including nuclear and fuel cell plants.

B. Multi-Agent System [30]

An agent is a computer software program that is autonomous and situated in some distributed environments in order to meet its design objectives. Since the agents are faced with different environments, they are designed differently and properly for the given environment. Moreover, the agent is intelligent because it is reactive, proactive, social, flexible, and robust. In a large-scale distributed complex system, the agent's autonomous and intelligent properties can reduce the complexity by reducing the coupling problems between the subsystems. Furthermore, the proactive, reactive, and robust properties can be well suited for applications in a dynamic and unreliable situation [31],[32].

In order to design the control systems, design of architecture for single agent and an organization for multi-agent system are required in advance. First, the architecture of single agent system is shown in Fig. 2. Since the agent is situated in an environment that is the power plant,
it needs a perceptor and effecter to act and react. First, the sensed raw data are processed and mapped into a scenario, and then an objective, which is a sub-goal, is initialized under the situation to achieve the main goal that is the optimal operation. The initial objective is sent to other agents through the communicator for eliminating redundancy and conveying the mission of the agent to others. After confirming the objective, the best plan is chosen for the objective (sub-goal) in the decision-making. Depending on the plan, an algorithm module is selected to launch the plan. Finally, the action made by the algorithm module effects through the effecter into the environment. Most decisions are made in the decision-making process, which is like in a human brain [15],[16].

A Multi-Agent System (MAS) can be defined as a loosely coupled network (organization) of problem solvers (agents), which interact to solve problems that are beyond the individual capabilities or knowledge of each problem solver (agent). In order to perform the cooperative works, it is presented to build multiple hierarchical structures for the multi-agent system organization as shown in Fig. 3. The organization has low level, middle level, and high level, and agent in each level has a specific role in the society so that there is a conceptual idea of supervision for processing the tasks. In this paper, the high level agents are the task delegation and interface agents, the middle level agents are the mediate and monitoring agents, and the low level agents are intelligent agents. The hierarchical structure that has three levels gives advantages for dynamic organization and autonomous systems. Moreover, the idea of multiple hierarchical structures is well suited for the large-scale distributed system [17],[31]. Although there are multiple hierarchical structures, each hierarchical structure has a different formation from others because the structures are constructed to fit for controlling each real physical subsystem so that the organization is better optimized for a given power plant system [33]-[36]. Fig. 4 shows the composition of MAS-IC for power plant.

III. MULTI-AGENT SYSTEM BASED INTELLIGENT HEURISTIC OPTIMAL CONTROL SYSTEM

The MAS-IHOCS consists of three control components, which are reference governor, feedforward, and feedback controls. The optimal feedforward control actions are obtained through the reference governor while generating the optimal set-points. In order to get optimal feedback control actions, a heuristic optimization algorithm is applied in searching for the optimal PI control gains. Each control component is built upon the MAS to realize both in the on-line operation and in the asynchronous computation. Moreover, agents communicate each other to provide the optimal power plant operation. Fig. 5 shows the structure of MAS-IHOCS.

![Fig. 2. Single agent architecture.](image)

![Fig. 3. Organization of MAS.](image)

![Fig. 4. Composition of MAS-IC for power plant.](image)

![Fig. 5. Structure of MAS-IHOCS.](image)
Multi-Agent System-Based Reference Governor [36]

Multi-Agent System based Reference Governor (MAS-RG) realizes the optimal mapping between set-points and varying unit load demand by searching for the best solution to the multiobjective optimization problem. The set-points are considered for the main steam pressure and reheater/superheater steam temperatures in a 600 MW oil-fired drum-type boiler power unit. The optimal set-points are determined by solving the multiobjective optimization problem with conflicting requirements such as load following, fuel conservation, heat loss rate, life extension of equipments, reducing pollution, etc. The composition of MAS for the power plant is shown in Fig. 4. Although all agents are connected with network, the reference governor cluster, which is made of set-point generation agent and inverse steady-state model agent, performs mainly for the MAS-RG. However, the reference governor cluster will cooperate with the monitoring system, knowledge processing system, and reinforcement system clusters to obtain better performances. An operator will command and monitor the preference and status through the interface agent to/from the reference governor delegation agent who has all access for the MAS-RG.

In order to realize the MAS-RG, first, all feasible operating points, which satisfy all imposed constraints, need to be found using the on-line performance monitoring agent and virtual simulation agent. The virtual simulation agent simulates the power output responses with various set-point conditions. Since system response is in steady-state, the constant control inputs and static power, pressure, and temperature outputs form pairs of operating points, where the admissible power outputs can be obtained within an appropriate steam pressure and reheater/superheater temperature ranges. Fig. 6 shows the power output responses with different steam pressure values for 450MW set-points. The figure shows that the same power output can be obtained with different steam pressure. During the simulation by the virtual simulation agent, the on-line performance agent evaluates the operating points in order to find the admissible power, steam pressure, and reheater/superheater temperature operating points. The power-pressure operating window is obtained in Fig. 7. The reheater/superheater temperature operating range is $1359.67^\circ R \sim 1459.67^\circ R$ ($900^\circ F \sim 1000^\circ F$) for all power ranges. Since the design and operation of reheater are essentially the same as the superheater, the reheater and superheater temperature set-points will be equal in this paper. Fig. 8 shows the power-control input operating windows.

Next step is the development of approximators for steady-state models using the inverse steady-state model agent. The main algorithm module of the inverse steady-state agent is Neural Network (NN), which is the best approximator for nonlinear systems. The steady-state models are called Multi-Agent System based Intelligent Steady-State Models (MAS-ISSMs) [35] and expressed as follows:

\[
Power: E_d = \phi_i (u_1, u_2, \ldots, u_z)
\]  

(1a)
Steam pressure: \(P_d = \Phi_2(u_1,u_2,\ldots,u_{12})\)  
(1b)

Reheater / Superheater temperatures:
\[RT_d = ST_d = \Phi_1(u_1,u_2,\ldots,u_{12}),\]
(1c)

where, \(u_1\): fuel flow, \(u_2\): gas recirculation, \(u_3\): induced draft fan, \(u_4\): forced draft fan, \(u_5\): combustor gun tilt, \(u_6\): superheater spray flow, \(u_7\): reheater spray flow, \(u_8\): governor control valve, \(u_9\): intercept valve, \(u_{10}\): deareator valve, \(u_{11}\): feedwater valve, \(u_{12}\): feedpump turbine flow.

The MAS-ISSMs are adaptively changed by learning using the updated operating windows which are adjusted to the conditions of power plant. With the operating windows and MAS-ISSMs, the multiobjective optimization problem can be tackled by the set-point generation agent and the cooperation of other agents. In this paper, the objective functions are accounting for the minimization of load-tracking error, fuel consumption, heat loss rate, pollutant emission, and extension of duty life on the equipment. Thus, the objective functions are

\[J_f(u) = |E_{sd} - E_d|, \quad J_1 = u_1, \quad J_2 = -u_2, \quad J_3 = u_3, \quad J_4 = -u_4, \quad J_5 = -u_5, \quad J_6 = u_6, \quad J_7 = u_7, \quad J_8 = -u_8, \quad J_9 = -u_9, \quad J_{10} = -u_{10}, \quad J_{11} = -u_{11}, \quad J_{12} = -u_{12},\]
(2)

where, \(E_{sd}\): unit load demand.

When the unit load demand, \(E_{sd}\) is given from a central dispatch center, the set-point generation agent creates the solution space, \(\Omega_1, \Omega_2, \ldots, \Omega_{12}\), using the power-control input operating windows, Fig. 8. An operator provides the objective functions and their preferences for the multiobjective optimization problem through the interface agent. The reference governor delegation agent adjusts the preference values by investigating the condition of power plant with historical data. After confirming the preference values, the multiobjective optimization problem is solved by PSO [22]. The PSO is one of the algorithm modules in the set-point generation agent. During the search for the solution, one of the MAS-ISSMs, \(E_{sd} = \phi_1(u_1,u_2,\ldots,u_{12})\), is utilized to evaluate the load-tracking error. The PSO algorithm is well suited for the reference governor and the performances are shown in other references [13],[14].

After finding the optimal solution, \(u_1^*, u_2^*,\ldots,u_{12}^*\) using the PSO, the MAS-ISSMs are applied to map the optimal solution into demand power \(E_d\), steam pressure \(P_d\), reheater temperature \(RT_d\) and superheater temperatures \(ST_d\) using (1). The set-point scheduler block processes the task under the observation of set-point generation agent. Fig. 9 shows the configuration of MAS-RG. Since the feedforward control is the inverse function of (1), the optimal solution of the steady-state control inputs, \(u_1^*, u_2^*,\ldots,u_{12}^*\), can be used for the optimal feedforward control actions. Once, the feedforward control system receives the optimal solution of the steady-state control inputs, they need to be scaled up using the minimum and maximum values which were utilized in scaling down for NN in the MAS-ISSM. With the efficiency of PSO techniques, the multiobjective optimization problem can be solved well for on-line operation [13],[14]. The steam pressure and reheater/superheater temperature set-points need to be updated only when the unit load demand is changed during the load cycle. Because of the fast convergence of PSO techniques, it is possible to search for the optimal feedforward control actions at every different unit load demand. When the unit load demand is changing continuously the optimization should be performed very fast if the unit is to be in the load-following mode. For some units, where the unit load demand is given in advance, the multiobjective optimization can be performed in advance and the steam pressure and reheater/superheater temperature set-points and the optimal control actions can be made available in the form of a look-up table.

### B. Multi-Agent System-Based Gain Optimizer for Feedback Control

There are 33 distributed subsystems in the four main modules: boiler, turbine-generator, condenser and feedwater systems. For instance, the boiler subsystems are shown in Table I. There are seven boiler feedback control loops, i.e., for fuel flow, air flow, throttle pressure, furnace pressure, superheater temperature, reheater temperature, and gas recirculation. The control inputs corresponding to the control loops are \(u_{a1}\): fuel flow, \(u_{a2}\): gas recirculation, \(u_{a3}\): induced draft fan, \(u_{a4}\): forced draft fan, \(u_{a5}\): combustor gun tilt, \(u_{a6}\): superheater spray flow, \(u_{a7}\): reheater spray flow.

### TABLE I

<table>
<thead>
<tr>
<th>Subsystem #1</th>
<th>Forced Draft Fan</th>
<th>Subsystem #7</th>
<th>Drum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subsystem #2</td>
<td>Air Preheater</td>
<td>Subsystem #8</td>
<td>Primary super gas</td>
</tr>
<tr>
<td>Subsystem #3</td>
<td>Induced Draft Fan</td>
<td>Subsystem #9</td>
<td>Primary Superheater</td>
</tr>
<tr>
<td>Subsystem #4</td>
<td>Downcomers</td>
<td>Subsystem #10</td>
<td>Spray Heater</td>
</tr>
<tr>
<td>Subsystem #5</td>
<td>Furnace Gas</td>
<td>Subsystem #11</td>
<td>Secondary super gas</td>
</tr>
<tr>
<td>Subsystem #6</td>
<td>Waterwall</td>
<td>Subsystem #12</td>
<td>Secondary Superheater</td>
</tr>
</tbody>
</table>
The boiler feedback control system consists of a boiler master demand process and seven PI control loops. When the boiler feedback control system receives the set-points of main steam pressure \( (P_d) \), reheater temperature \( (RT_d) \), and superheater temperatures \( (ST_d) \) from the reference governor, the boiler master demand process generates set-points for the boiler feedback control loops with given fixed reference values such as turbine speed and furnace pressure values. For example the fuel flow control, \( u_{bf,1} \) applies a PI action on the error between the total fuel flow and fuel demand made by the boiler master demand process. Then, the control signal goes to an actuator simulator, which represents the delay due to the action of the fuel actuators. Although PI controllers are used in the feedback control, their effectiveness is often limited due to poor gain tuning. The manual gain tuning of PI controllers is a time-consuming task and it requires frequent changes of the environment of the plant. Thus, the problem of optimal feedback control actions can be addressed by obtaining optimal PI control gains [37].

The proposed Multi-Agent System based Gain Optimizer (MAS-GO) can provide optimal PI control gains using a heuristic optimization technique. The configuration of MAS-GO is shown in Fig. 10. With candidate optimal gains, \( K_1, K_2, ..., K_n \), PI controllers as the feedback control system generate control actions on the error between references and outputs from an identifier. The identifier is called Multi-Agent System based Intelligent Identification System (MAS-IIS) [38]. The MAS-IIS is constructed by using off-line modeling agent and on-line modeling agent (Fig. 4). The MAS-IIS consists of NN based models which represent all subsystems corresponding to the main module: boiler, turbine-generator, condenser and feedwater systems. MAS-IIS is adaptively updated with the changing of the environments. During a given simulation time, \( (t_{final}) \), the heuristic optimization technique utilizes the cost value, which is the integrated value of the control inputs and the error between set-points and outputs of MAS-IIS. The heuristic optimization technique keeps on trying to find optimal PI control gains by minimizing the cost value.

In this paper, Differential Evolutionary (DE) algorithm for MAS-GO is chosen as the heuristic optimization technique. The main reason to use DE instead of PSO is the reduced elapsed time in the search procedure. In PSO algorithm, it is required to evaluate two times per candidate per iteration for \( P_{best} \) and \( G_{best} \) [22]. However, the DE needs only one evaluation per candidate per iteration [23]. Although the performances of PSO and DE depend on applications [24], the elapsed time for calculation of cost values for PSO is quite long, which can not be ignored in this case. Therefore, we use the DE as a heuristic optimization technique for MAS-GO.

IV. SIMULATION RESULTS

In the following simulation, the results by the MAS-IHOCS will be shown. When the MAS-RG receives a unit load demand from a central dispatch center, the MAS-RG realizes the optimal mapping by searching for the best solution to the multiobjective optimization problem. The multiobjective optimization problem is minimization of all objective functions (2) with respective preference values given: \([1,0.25,0.25,0,0,0,0.25,0.25,0.25,0.25,0.25,0.25]\). This means the objective functions (2) are weighted with the preference values, where 1 is the highest and 0 is the lowest priorities for the corresponding objectives. The results of MAS-RG are optimal set-points for power \( (E_d) \), steam pressure \( (P_d) \), and reheater/superheater temperatures \( (RT_d, ST_d) \). Fig. 11 shows the given unit load demand \( (E_{ud}) \) and optimal set-points generated by MAS-RG.

During the generation of optimal set-points, the MAS-RG also provides optimal control inputs, \( u^*, u^*_2, ..., u^*_n \). The feedforward control system rescales the optimal control inputs to produce optimal feedforward control actions \( Uff \), as shown in Fig. 12. Due to the limitation of space, only the results of boiler feedforward control actions are shown. Fig. 13 shows the feedback control actions, \( Ubf \), which are produced by using the updated optimal PI control gains. The MAS-GO continuously tries to find the best PI control gains. Fig. 14 shows the cost values of MAS-GO through the iteration. The optimal PI control gains will be compared at the every end of iteration. If the cost value is better than previous one, the MAS-GO sends the new PI optimal gains to the feedback control system. In Fig. 13, the control values are pre-actuator values. Note that the \( u_i \) is control action of gun tilt position. It will be converted via transducer (-0.5-0.5). Fig. 15 shows the outputs of the plant and the given set-points. In power industry, the most interesting part is optimization. However, the classical optimization methods have many restriction and they are unattractive in a real situation. The proposed PSO and DE are applicable for on-line mode and they provide quality solutions as shown in the results. Moreover, the MAS-based control system reduces the computational complexities by cooperative and negotiate works of agents.
V. CONCLUSION

A new concept of the intelligent heuristic optimal control system based on multi-agent system is presented for a large-scale power plant. In order to deal with the difficulty of handling a large-scale system, architecture of single-agent and an organization of Multi-Agent System (MAS) are designed as basis for MAS-IHOCS. The MAS-IHOCS provides optimal set-points, optimal feedforward and feedback control actions. The reference governor, feedforward and feedback control systems are built upon the MAS which can reduce the computation complexity and manage the distributed data. The PSO and DE are utilized for the optimal power plant operation and they can accommodate
well to realize the optimal control actions on-line. The proposed MAS-IHOCS is one of the functional groups in the MAS-IC, in which each agent can accomplish the given tasks. Therefore, the heuristic optimization, PSO/DE, and MAS are efficient methodologies to design the intelligent control system for a complex large-scale power plant.

REFERENCES


