Advanced Review

Steam power plant configuration, design, and control

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This article provides an overview of fossil-fuel power plant (FFPP) configuration, design and especially, the control technology, both the conventional and the advanced technologies. First, a brief introduction of FFPP fundamentals and configurations are presented, followed by the description of conventional PID-based control system in the FFPPs and its short-comings. As the major part of this writing, different advanced control strategies and applications are reported, with their significant features outlined and discussed. These new technologies are collected from both the academic studies and industrial practices, which can improve the performance of the FFPP control system for more economic and safe plant operation. The final section presents a view of the next generation FFPP control technologies, emphasizing potential business and research opportunities.

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INTRODUCTION

Fossil fuelled power plant (FFPP) refers to a group of power generation devices that convert the chemical energy stored in the fossil fuel such as coal, gas, oil into thermal energy, mechanical energy and finally electrical energy. In the past hundred years, FFPPs are the most widely used facilities in the power industry and play a fundamental role in social production and life. According to the 2013 Key World Energy Statistics published by the International Energy Agency (IEA), in 2011, the annual generation of electricity from all types of sources was 22,126 TWh and FFPPs provided 15,054 TWh, accounted for 68% of the total electricity generation. Although the rapid increase of global energy crisis, combined with the concerns about environment issues has led to an extensive promotion of nuclear and renewable energy, for the most parts of the world, the trend of conventional fossil-fuel-dominated electric power generation will not change in a foreseeable future. For this reason, developing and operating the FFPPs according to the most suitable available technologies are very important and should be the most effective and direct way to save energy and reduce the pollution.

The history of FFPP can be traced back to the late 19th century, the simple D.C. generators were coupled to coal-fired, reciprocating piston steam engines, producing electricity primarily for district lighting. These initial plants typically operated at low temperature and pressure conditions (150°C, 0.9 Mpa) and could only generate 30 kw electricity. Through a century's technological developments, power plants have now been evolved into a highly complex system that can operate at supercritical conditions of 28.5 Mpa and 600°C, generating 1300 MW of electricity with much higher efficiency. Although there are many variations in power plant configuration and design, the basic working principle of the FFPPs keeps the same: fossil fuel is combusted, generating high pressure and temperature steam, which is then expanded to rotate a turbine, and drives the generator to produce electricity.[1]

For the FFPP, the main task of the control system is to regulate the electrical power output to meet the demand of the grid while maintaining the main thermal dynamical variables such as superheater/reheater steam temperature, throttle pressure, furnace pressure, drum water level, within

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given tolerances to keep the power plant operating safely. Generally, such an objective is achieved via the multi-loop proportional-integral-derivative (PID) based controllers. The approach has been proven to be highly reliable and can attain a satisfactory performance under normal operation maintained at base load, where plant characteristics become almost constant.

However, during the past few decades, power industry has undergone some significant changes, and as the primary devices of power production, FFPPs have been endowed with higher operational requirements:

1. The growth of electric power demand increases the magnitude of the cyclic variation of the grid load, and the renewable sources, such as wind, solar and hydro power, are severely influenced by the season and the weather condition; thus, the FFPPs have to participate in the grid power regulation frequently and respond to the load demand variation quickly within a wide operation range.
2. The privatization and deregulation of the electricity industry has changed the power generation business from a cost-plus, monopoly environment with an obligation to serve, to a competitive environment for the sale of its product. For this reason, power plants are increasing in size and becoming more complex in order to achieve high efficiency and the scale of economy. Furthermore, the aforementioned thermal parameters should be more stringently controlled so that the plant can operate in an optimal mode at all times.

Therefore, control problems to deal with issues, such as nonlinearity over a wide operation range, large inertial and time varying behavior, and strong coupling among the multitude of variables, become severe in the FFPPs. Consequently, the conventional PI/PID based controllers are no longer sufficient in meeting performance specifications, even if they are well tuned at a given load level. On the other hand, with the help of modern computer and instrumentation techniques, utilizing Distributed Control System (DCS) is now the routine rather than the exception, which makes the implementation of advanced controllers possible in the FFPPs. The primary purpose of this writing is to present an updated, representative snapshot of various control strategies that are being applied to the FFPPs and describe how they can help in improving the quality and performance of plant operation. The information reported here are collected from both academic researches and engineering practices.

A brief introduction of FFPP fundamentals and configurations are presented first, followed by the description of conventional PID-based control system in the FFPPs and the associated problems. As a major part of this writing, different advanced control strategies and applications are reported, with their significant features outlined and discussed. The final section presents a view of the next generation FFPP control technologies, emphasizing potential business and research opportunities.

PLANT CONFIGURATION AND DESIGN

The essence of power production process in all types of the FFPPs is energy conversion. In the vast majority of the FFPPs worldwide, water/steam is commonly used as the working fluid, which is alternately vaporized and condensed in a closed circuit following a thermal dynamic cycle. Within this cycle, the chemical energy of the fossil fuel is transformed into steam thermal energy by the boiler, then it is transformed into rotational mechanical energy by the turbine, and finally it is transformed into electric energy by the generator. This kind of FFPPs is also called steam power plant, and depending on the operating steam pressure, it can be classified into subcritical plants and supercritical plants.

Subcritical Steam Plant

In subcritical power plants, the steam parameters never exceed the critical point: 22.115 Mpa, 374.12°C. Because under this critical point, liquid water must go through a vaporization stage to become steam; in most of the large-scale subcritical plants, drums are typically utilized to separate the steam out of the boilers.

Figure 1 provides a simplified illustration of a coal-fired subcritical power plant, which is comprised of two basic systems: the fuel/air-flue gas system and the water-steam system.[2–4]

The fuel/air-flue gas system is also called the fire-side of the plant. In this system, the raw coal is transported to the coal hopper by the conveyor and enters the pulverizing mill; where grinding and crushing take place. The qualified (smaller and lighter) coal particles are then separated and entrained in the air flow, and carried into the burner. Finally, the combustion occurs in the furnace, generating high temperature (above 1000°C) flue gases. The air needed for combustion is delivered to the furnace and mill by the forced draught fans and an air preheater is installed in

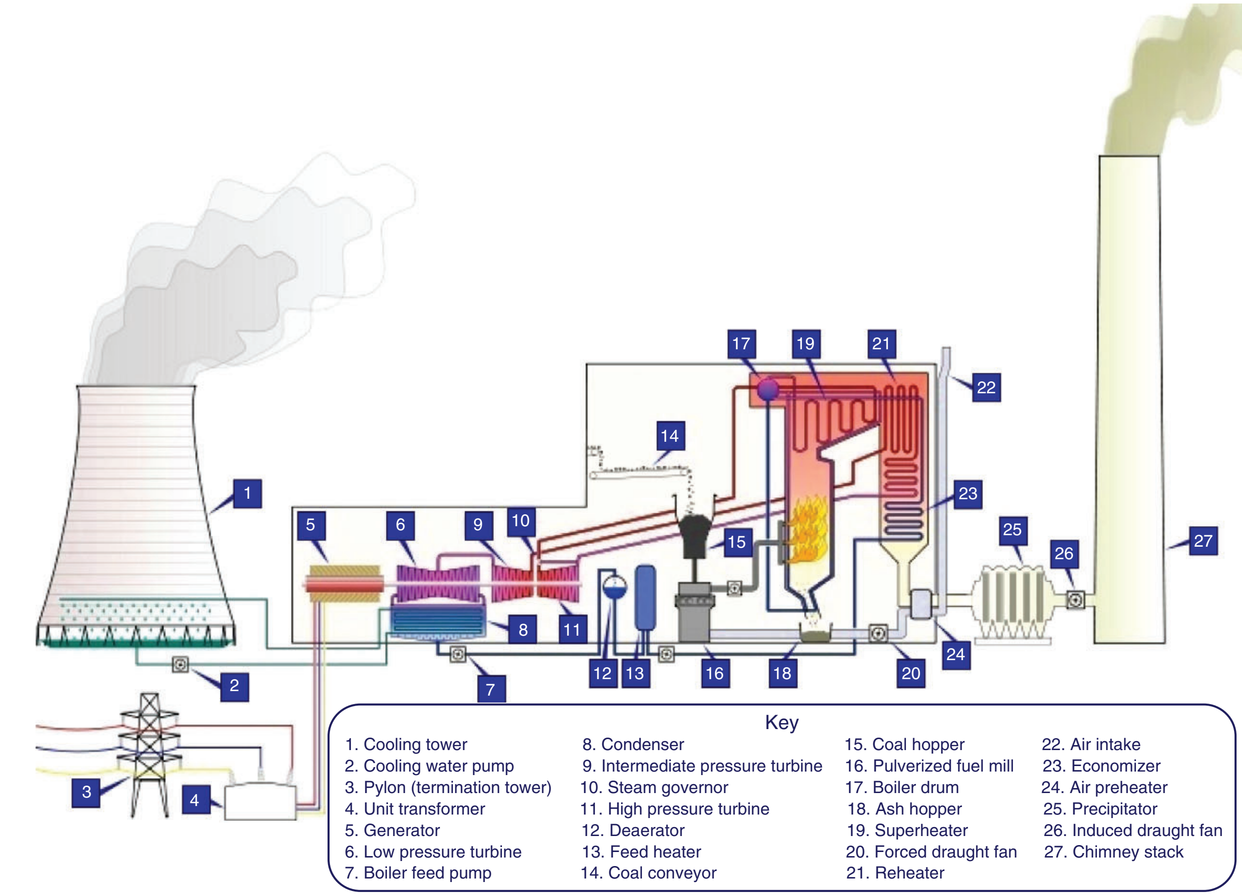

FIGURE 1 | Simplified coal-fired subcritical power plant (Picture from http://en.wikipedia.org/wiki/Thermal_power_station#Boiler_furnace_and_steam_drum).

the path to warm the air being fed utilizing the heat remaining in the exhaust gases leaving the furnace, through which the efficiency of the combustion can be improved. The objective of this process is converting the chemical energy in the fuel into the thermal energy in the flue gases. The flue gases in the furnace transfer the heat to the water wall by radiation and then flow through multiple stages of superheaters, which are suspended on the horizontal passage at the top of the furnace. Depending on the installed positions, some superheaters are radiant type, which absorb heat by radiation; others are convection type, absorbing heat from fluid; some are a combination of the two types. Through either type, the extreme heat in the flue gases is transfered to the superheater piping and the steam within. After leaving the superheater, the flue gases pass over reheater, economizer and air preheater, where almost all of their remaining heat is extracted to reheat the steam or prewarm the feed-water and feed-air. The induced draught fans work in conjunction with the forced draught fans, then pull the flue gases into the precipitator, and finally out of the boiler through the chimney. The falling slags and ashes are collected in the ash hopper and delivered to the ash system of the plant.[2–4]

Water-steam system is also referred to as the waterside of the plant, which operates following the Rankine cycle. The procedure within this system begins with the feedwater being drawn from the condenser and delivered to the boiler by the feed pumps. To improve the plant efficiency, a series of low and high pressure feed heaters and an economizer are utilized to heat the feedwater with the steam bled from the turbine and the remaining heat of the flue gases. The deaerator is also installed in this path to remove the dissolved gases in the feedwater by vigorously boiling and agitating it. The drum supplies the feedwater to the waterwall of the furnace to absorb the radiation heat and separate the resulting saturated steam from the incoming saturated feedwater. The steam is then further heated through multiple stages of superheaters to reach higher temperature and pressure. Finally, the steam expands along the turbines and rotates them to a given high speed (3000/3600 rpm), which then

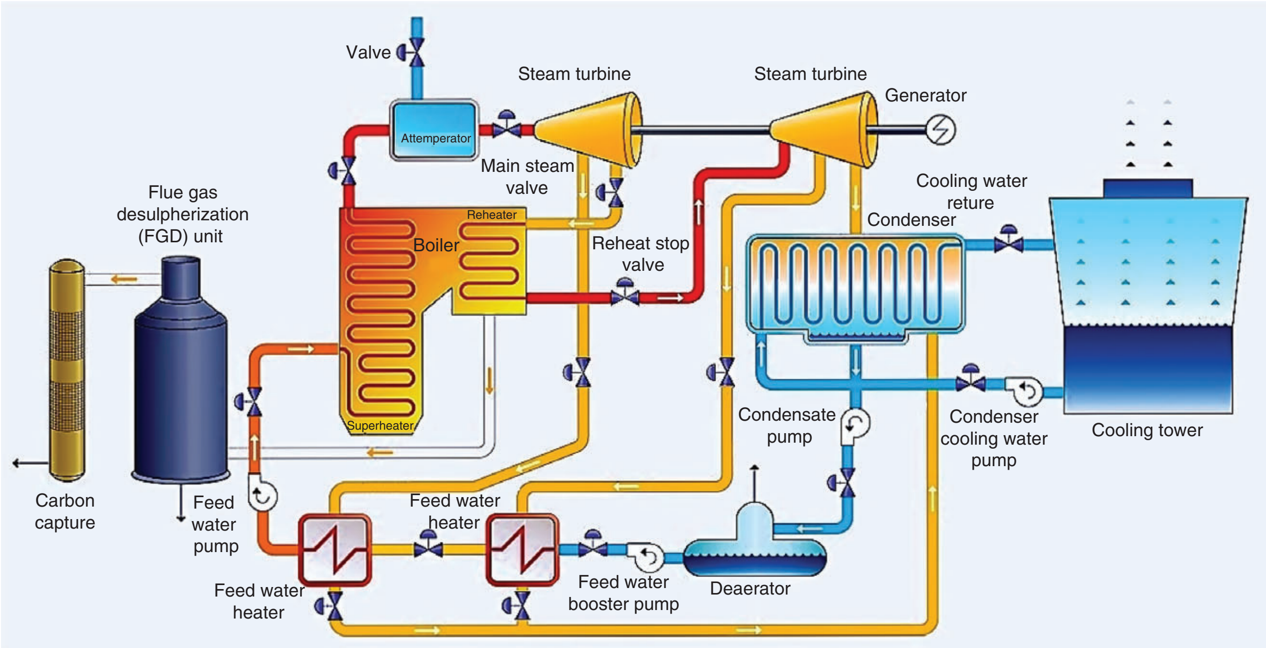

FIGURE 2 | Simplified supercritical power plant (Picture from http://www.flowserve.com/Industries/Power-Generation/Conventional-Steam/Flowserve-Products-Used-in-Supercritical-Units,en_US).

drive a generator to produce electricity. Usually, there are multiple stages of turbines, and for a higher plant efficiency, after the expansion in the high pressure turbine, the steam is extracted and reheated in the boiler, and then delivered to the medium and low pressure turbines. The saturated steam leaving the low pressure turbine is condensed back into liquid in the condenser.[2–4]

Supercritical Steam Plant

In contrast to the subcritical plant, supercritical plant is another type of steam plant, where the steam generator operates at pressure greater than the critical point, 22.115 Mpa. Because above such a pressure, the physical turbulence that characterizes boiling ceases to occur, and instead, the liquid water immediately becomes steam once is heated above the critical temperature (374.12°C). Therefore, the drum used in the subcritical plant, where the evaporation separation process occurs can be completely eliminated, and the feedwater circulates only once in the furnace in each cycle (Figure 2).[2] For this reason, the 'once through steam generator' is designed and employed in all supercritical plant.[4]

Current Status of the Steam Power Plant

The subcritical plant is still expected to remain the main choice in some countries due to its simplicity in operation and control, belief in higher reliability and low technical risk. However, the supercritical/ultra-supercritical plant is now greatly promoted, because operating the plant at higher temperature and pressure can increase its efficiency, potentially lowering the amount of fossil fuel consumed and the emissions generated.

Currently, there are more than 600 supercritical and ultra-supercritical power plants with total capacity above 400 GW in the world (status 2010, Figure 3). These supercritical plants can achieve efficiencies of more than 42%, compared with subcritical plants' 33%–39%. According to the USA DOE power generation initiative: Vision 21, by the year 2020, the steam in the ultra-supercritical power plants is expected to reach 760°C and 38.5 Mpa, which will enhance the plant efficiency to more than 50%.

In spite of the great advantages of the supercritical plants, there are still barriers for building this type of the plant: the high thermal stresses and fatigue cracking in the critical sections of the plants as well as the resulting lower reliability and higher maintenance costs. Thus an identifying, evaluating, and qualifying potential alloy material is the major challenge for the successful implementation of supercritical technology.

CLASSICAL CONTROL OF THE FFPP

As stated previously, the FFPPs, especially the steam power plants, are complex, multivariable, and interactive processes, thus a well-designed control system is

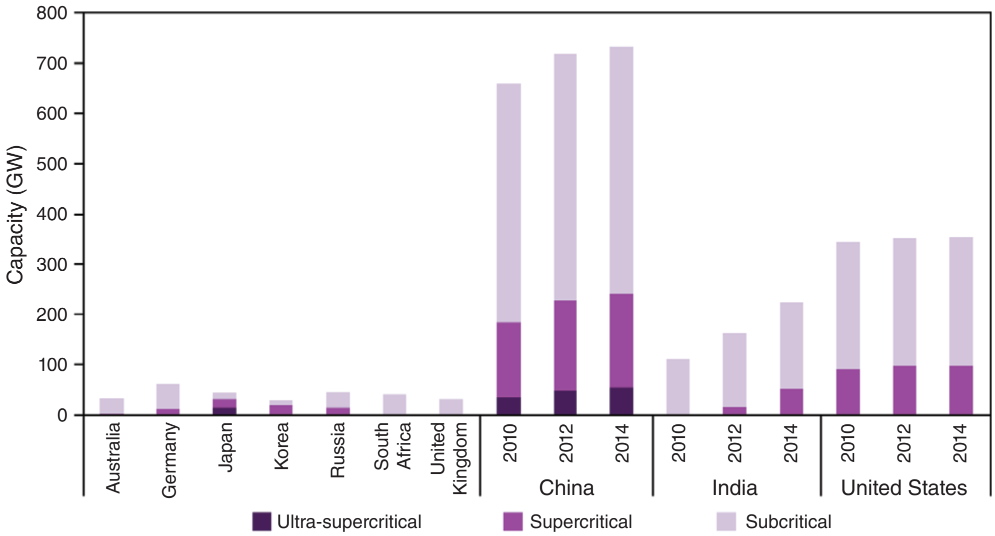

FIGURE 3 | Capacity of supercritical and ultra-supercritical plant in major countries (refers to capacity in 2010 unless specified otherwise, Picture from http://www.iea.org).

required in the plants to ensure the correct operation of the entire process, i.e., rapidly following the grid load demand and controlling relevant process variables such as: throttle pressure, superheater/reheater steam temperature, furnace pressure, drum water level (subcritical plant), etc., so that high efficiency, durability and safety can be attained in the plant.

The boiler-turbine unit control schemes have gone through several decades of evolution and, typically, a cascade of PI/PID controllers based on single-input single-output control loops is designed in the plant to fulfill such tasks.[6,7] The remainder of this section will focus mainly on the conventional boiler-turbine coordinated control system (CCS), steam temperature control system, combustion control system, and feedwater control system, in which the respective thermal dynamic variables are controlled separately.

Boiler-Turbine Coordinated Control System

Current plant or unit control strategies allow generation of the grid load demand while maintaining the balance among the process variables within the unit. Mainly, they match the boiler steam flow energy output to the energy required by the turbine-generator to match the unit load demand at all times.[6] The coordinated control system (CCS) constitutes the uppermost layer of the control system, and it is responsible for driving the boiler-turbine-generator set as a single entity, harmonizing the slow response of the boiler with the faster response of the turbine, to achieve fast and stable unit response during load tracking maneuvers and load disturbances.

For the FFPP, power output and throttle pressure are the two most important variables. Externally, the power output reflects a balance between the plant's power generation and grid's power demand; internally, the throttle pressure naturally represents a balance between the boiler's energy supply and turbine's energy need. The dominant behavior of the unit is governed through the power and pressure control loops. Therefore, the central task of the CCS is to regulate the power output to meet the demand of the grid while maintaining the throttle pressure within a given tolerance. Evolved from multiple single-input single-output control loop (decentralized) configurations based on PID control algorithms, currently, there are two possible modes for coordinated control: coordinated boiler-following (BF) mode and coordinated turbine-following (TF) mode.[1,5,7,8]

Historically, boiler following schemes were the first to be used.[9] In boiler following mode, the boiler awaits the actions of the turbine to match the requested generation. The turbine control valves regulate the steam flow into the turbine in terms of the power demand. Then, the boiler controls respond to the changes in steam flow and pressure. The basic principle of the coordinated BF mode is illustrated in Figure 4. The advantage of this approach is a fast response to load changes, nevertheless, it should be noted that such rapid response is basically achieved by using the stored thermal energy in the plant, thus it is effective only for a small demand change. The disadvantage of the coordinated BF mode is that, in its pure form, this approach shows a less stable throttle pressure control since the boiler has a tendency to

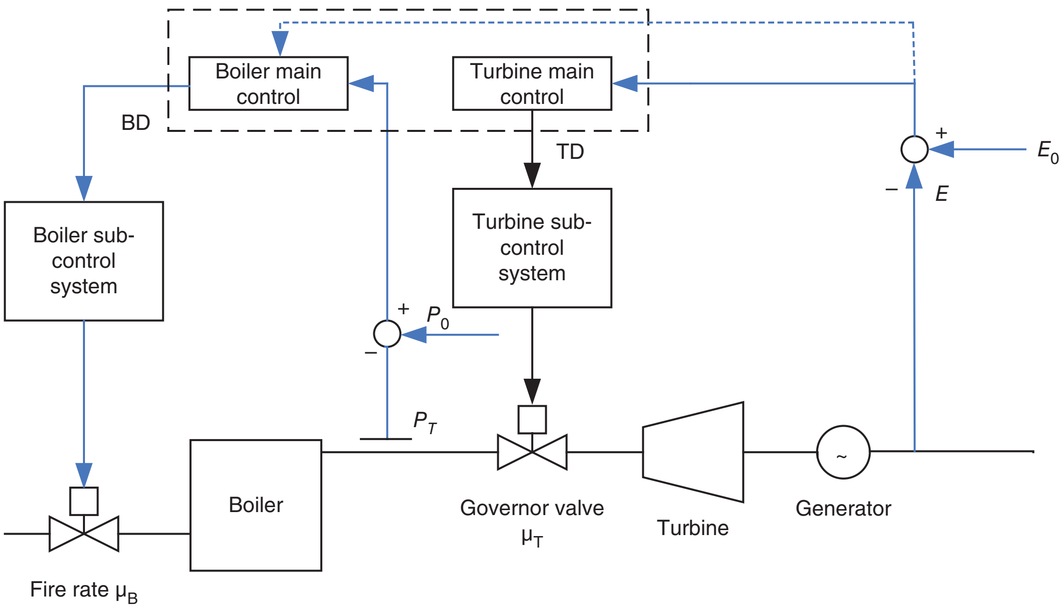

FIGURE 4 | Working Principle of the Coordinated BF mode (E_0: load set-point; P_0: main steam pressure set-point; E: power output; P_T: main steam pressure output; BD: boiler demand; TD: turbine demand).

overshoot because it requires some time to match the turbine.[10]

Turbine following began around the late 1960s and early 1970s.[9] In the coordinated TF mode of control, the turbine follows the actions of the boiler to match the requested generation. The power demand is used by the combustion control at the boiler to adjust the fuel and air into the furnace to modify the steam production. Then the turbine controls respond by adjusting the throttle valve openings to keep the pressure at the setpoint value. The advantage of this approach is its very stable response to load changes with minimal steam pressure fluctuations. The main disadvantage is that this approach does not make use of the energy storage capability of the boiler, thus producing a rather slow response.[10] For this reason, it is mainly used for a large base-load plant or a gas-fired plant, which has a relatively quick response compared to the coal plant.

It is worth mentioning that, to improve the performance of the CCS in both BF and TF modes, the power demand is fed both to the boiler system (BF) and turbine system (TF)[9] (this is shown as dotted-line in Figures 4 and 5), so that the large inertial behavior of boiler can be partly compensated (in BF) and the turbine's ability to respond quickly can be utilized (in TF). This coordinated control scheme is now widely used in practice.

However, the PI/ PID control systems, which are based on a cascade of separate SISO loops, cannot fully account for the interactions among the different process variables in the nonlinear multi-input multi-output (MIMO) power plant. Therefore, it is still very difficult for the classical CCS to achieve a satisfactory control performance in both power output and throttle pressure.

For this reason, various advanced modeling and multivariable control technologies are studied, aiming to realize a real coordinated control of boiler-turbine. This will be introduced in the next section.

Combustion Control System

Under the CCS, the mission of the combustion system is to provide enough thermal energy while guaranteeing the efficient and safe operation of the boiler. Such requirements are fulfilled by controlling relevant variables in the plant, namely:

(a) Fuel flow rate to maintain throttle pressure (in BF mode) or electrical power output (in TF mode);
(b) Excess air coefficient or optimal oxygen content in the flue gases to ensure appropriate air flow rate;
(c) Furnace pressure to guarantee the safety of the boiler.

The regulation of the above three variable can be achieved through the manipulation of fuel feeders, forced draught (FD) dampers and induced draught

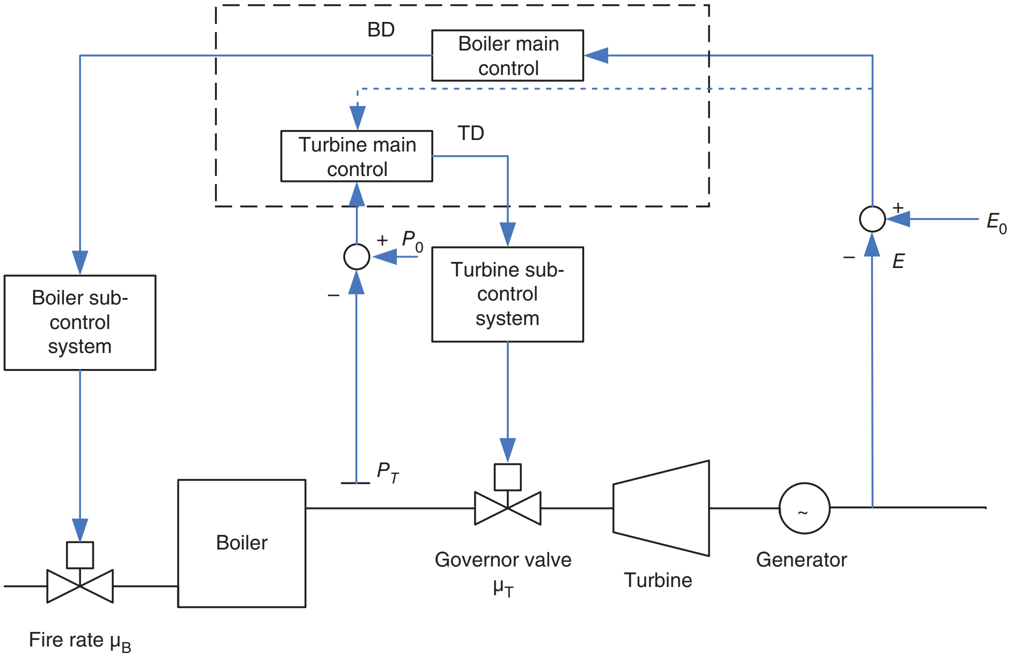

FIGURE 5 | Working Principle of the Coordinated TF mode (E_0: load set-point; P_0: main steam pressure set-point; E: power output; P_T: main steam pressure output; BD: boiler demand; TD: turbine demand).

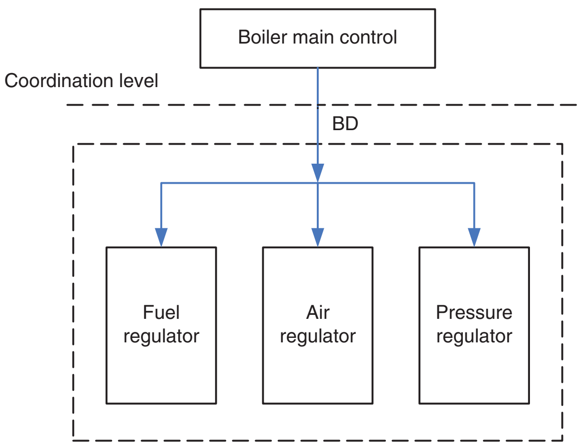

FIGURE 6 | Combustion control system (BD: boiler demand).

(ID) dampers, respectively, resulting in three indivisible sub-regulators, i.e., the fuel regulator, air regulator and pressure regulator as shown in Figure 6, which form the combustion control system.[3,5]

The task of the *fuel regulator* is to provide enough fuel to the boiler so that the generated thermal energy can exactly match the load demand. A cascade control strategy is usually employed in this system, which is shown in the left part of Figure 7 for a BF mode plant. Because the fuel flow rate, especially for the coal flow, is difficult to measure, and the feeder speed signal cannot reflect the variation of the heating value of the fuel, in most of the FFPPs, the heat quantity signal M is used in the inner loop to rapidly deal with any disturbances due to the variation of the fuel in heating values. The heat quantity signal can be estimated through the equation

$$\mathrm{M} = D + C_b dp_b/dt, \tag{1}$$

where, D is the steam flow rate representing the heat absorbed by the working substance, and P_b is the drum pressure representing the heat stored in the boiler, C_b is the heat storing coefficient of the boiler.

The *air regulator* is used to guarantee the efficiency of the combustion; to be specific, guarantee a suitable ratio between the amounts of fuel and air being supplied to the furnace. An undersupply of the air will prevent the fuel from complete burning; in contrast an oversupply of the air will absorb heat and thus increase the heat waste in the exhaust gas. In practice, a certain amount of excess air is needed rather than keeping the fuel/air ratio at the stoichiometric value.

Since the fuel flow rate has already been determined by the fuel regulator, it is direct to design a ratio controller to keep the air flow rate matching the fuel flow rate. However, considering that the heating value of the fuel can vary from time to time, it is a challenge to set the ratio co-efficient in operation; therefore, the oxygen content in the flue gas is measured which can reflect the combustion condition directly, regardless of the fuel variation.

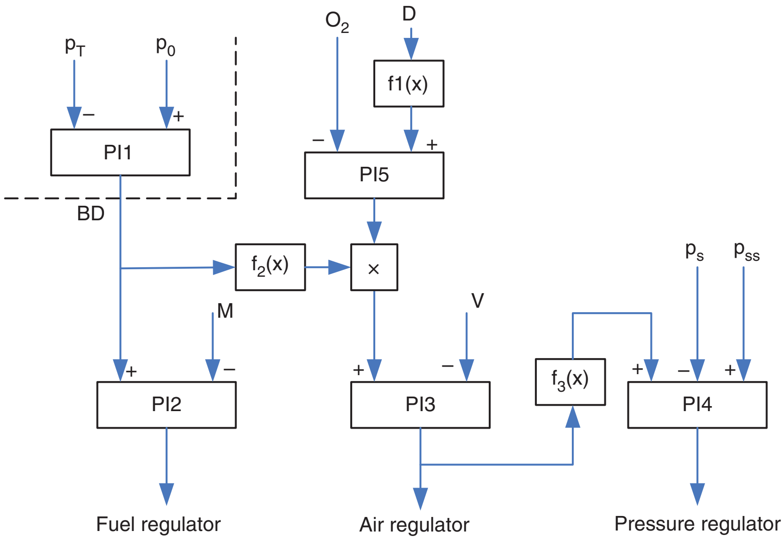

FIGURE 7 | Three sub regulators of boiler combustion control system (P_0: main steam pressure set-point; P_T: main steam pressure output; D: main steam flow rate; O_2: oxygen content in the flue gas; V: air flow rate; P_{ss}: furnace pressure set-point; P_s: furnace pressure output; BD: boiler demand).

A classic air regulator using the oxygen content signal is illustrated in the middle part of Figure 7. It is a cascade control system. The inner loop receives the fuel signal and air signal to attain a basic fuel/air ratio and the outer loop receives the oxygen content signal and compare it with the optimal oxygen content value (which is calculated offline for a given load) to achieve a tight control of the air input.

The task of the pressure regulator is to maintain the furnace pressure close to the atmospheric pressure; so that the hazardous gases escaping and cool air entering the boiler can be prevented. Usually, furnace pressure is required to be maintained at 20–50 Pa below the atmospheric pressure. Such a task is achieved by the use of feedforward-feedback control system as shown in the right part of Figure 7.

Feedwater Control System

The objective of the *feedwater control* is to supply enough water to the boiler to match the evaporation rate. For the subcritical plant, because the separation of steam from water always happens at the drum, maintaining the drum level naturally represents the balance between the feedwater supply and steam generation.

Controlling the drum water level within a given tolerance is important for the safe operation of the plant: a high level will increase the risk of water being carried over into the steam circle, which may not only lead to a fluctuation of steam temperature, but also cause fouling and damage of the superheaters; conversely, a low level will cause the waterwall piping to be damaged from insufficient cooling. Both can result in catastrophic failures.

The drum water level is determined by both the volume of the water in the drum and the volume of the steam bubbles under the water level. Thus, the drum water level can be influenced by feedwater flow rate, steam flow rate, heat quantity generated from combustion and many other variables, and its control presents a complex problem due to the large inertia behavior of these disturbances and a ‘swell and shrink’ effect.[3]

For these reasons, a *three-element* cascade controller is typically used in the plant, which is illustrated in Figure 8. The steam flow rate signal D is used as the feedforward signal; such a design can make the feedwater flow rate respond quickly to the variation of the steam flow rate, thus avoid the effect of ‘swell and shrink’. The feedwater flow rate signal is used to form the inner-loop of the control system and a secondary controller is designed for a quick rejection of the disturbance inside the feedwater system. The drum water level H is finally fed back to the primary controller for an accurate regulation.[3,5]

The main difference between a supercritical plant and subcritical plant is at the water-steam system. For the supercritical plant, feedwater circulates only once in the furnace in each cycle and there is no clear disengagement surface between steam and water. However, both the fuel flow rate and feedwater flow rate can greatly influence the position of the surface, if such a surface deviates far away from a designed level, the steam temperature in the superheater would also have a deviation far away from the set-point. Therefore, generally, a ratio controller is designed for the supercritical plant to regulate the feedwater flow rate, keeping it matching the fuel flow rate, so that the steam temperature/enthalpy out of the separator can be controlled within the given range.

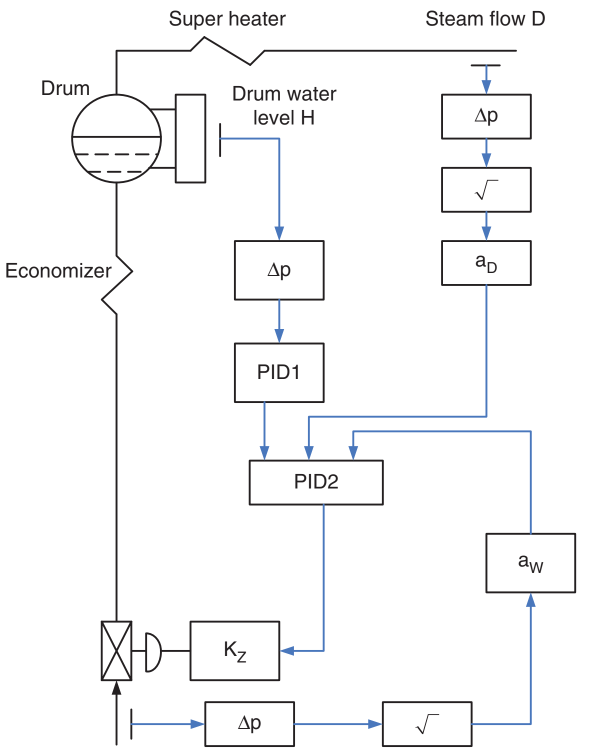

FIGURE 8 | Three elements cascade feedwater control system for a drum type boiler (Δp is the differential pressure transmitter; √ is the square root extractor; a_W, a_D are the sensitive coefficients of feedwater flow rate and steam flow rate signals; K_z is the actuator of the feedwater flow control valve).

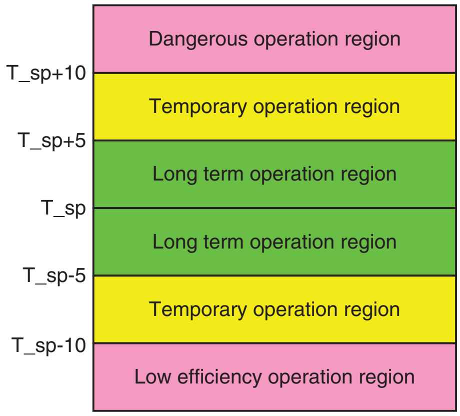

FIGURE 9 | Operation regions of superheater steam temperature (T_sp is the temperature set-point and the numbers represent temperature deviations in Celsius degree).

Steam Temperature Control System

Superheater steam temperature (SST) and Reheater steam temperature (RST) are two of the most critical variables to be controlled in a steam power plant. They must be tightly controlled within a small range, as shown in Figure 9, for the following safety and economy reasons:

1. Excessively high temperature will lead to material damage on the superheater/reheater steam pipes at the inlet of the turbine;
2. Lower temperature will reduce the efficiency of the plant, moreover, it will build up the steam humidity in the rear of the low pressure turbine that would erode the turbine blades; and
3. Large temperature variation will increase the thermal stress of the piping material and magnify the variations of the air gap between rotor and stator of the turbine, thus threatening the safety of the plant.

For the subcritical plant, there are many factors that will influence the SST: mostly the rate of the steam flow, heat transfer from flue gas and the rate of spray water flow. The first two have a relatively quick influence on the SST while the spray water's influence is quite slow. However, during the operation, the steam flow rate has to match the load demand; the regulation of heat transfers (for example, the burner tilt or the gas recirculation) will influence the efficiency and security of combustion. Therefore, the spray water flow becomes the only variable to control the SST and the cascade control system is generally employed, which uses an inner loop to handle the large inertia property.

A classical SST control system is illustrated in Figure 10. The inner loop receives the steam temperature signal T_2 immediately after the attemperation, which is required to reject the temperature disturbances originating upstream as well as the self disturbance in the spray water. The inner loop is, of course, much faster than the outer loop, which receives the final steam temperature signal T_1 to achieve an accurate control performance.[2,5]

For the supercritical plant, as analyzed in section 3.3, the regulation capability for the spray water is very limited, and the superheater steam temperature is mainly controlled by regulating the fuel/feedwater ratio. The steam temperature/enthalpy out of the separator is first controlled by keeping the feedwater flow rate matching the fuel flow rate; spray water is then used for a tighter control of the superheater steam temperature.

The control of the reheater steam temperature is mainly attained by regulating the dampers that control the flow of the flue gases across the reheater tube banks. The spray water is only used in emergency case, because it will reduce the amount of steam which expands in the high pressure turbine and will reduce the efficiency of the whole plant.

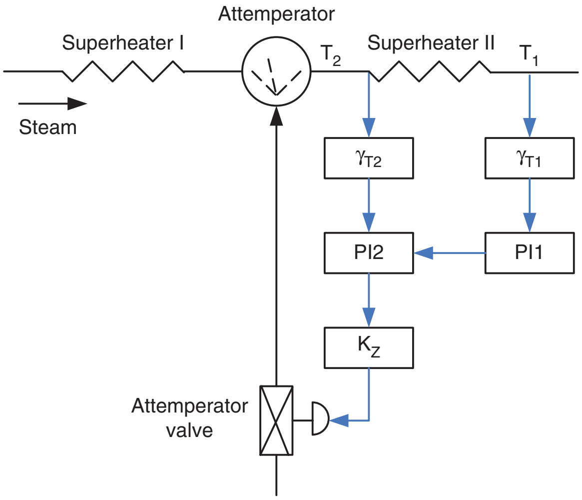

FIGURE 10 | Classical cascade SST control in the FFPP (T_1 is final steam temperature; T_2 is the steam temperature signal immediately after the attemperation; γ_{T1} and γ_{T2} are the temperature transmitters; K_z is the actuator of the attemperator valve).

The Drawbacks of the Conventional Control

The conventional PI/PID based control system has been successful in FFPPs and are very reliable. Such a design has also been proved for its value for regulation and disturbance rejection during normal operation maintained at/around a base load. However, as the FFPPs increase in size and participate in grid load regulation more frequently, control of FFPP unit has been shown to be a challenge, due to severe nonlinearity in the multitude of variables over a wide operation range, tight operating constraints and large inertia behavior. Moreover, the equipment wear, environmental changes, fuel variation, etc., will result in significant disturbances and plant behavior variations. Consequently, the conventional PI/PID strategies are no longer sufficient in meeting performance specifications because of the following drawbacks:

(a) The main drawback of the PI/PID control systems, based on separate single-input, single-output (SISO) loops, is that they do not account for the interactions of the different thermal properties in the plant.

(b) In general, the PI/PID controller parameters are optimized at a given operating point and then fixed. Therefore, when wide-range load following is required for the FFPPs, the performance of the plant operation is decreased because the nonlinearity becomes significant.

(c) The PI/PID controllers are not possible to handle the constraints of manipulated variables in the controller calculation stage, thus even when the controller parameters are well tuned, the performance is still decreased when physical limitations (both magnitude and rate) of the valves are involved. This may also cause the integral windup when a sharp change of the power demand occurs.

Therefore, various advanced control strategies have been proposed in both academic studies and industrial practices, aiming at improving the performance of the FFPP control system for economic and safe plant operation. A migration from classical PI/PID based control system to new concepts based on advanced control techniques in FFPPs will take place in a foreseeable future. The next section introduces four types of different control strategies with diverse applications in the FFPPs.

ADVANCED CONTROL OF THE FFPP

Advanced PI/PID Control

The advanced PI/PID control refers a class of methods which implement the state-of-the-art design or tuning technologies on the basis of conventional PI/PID control loops. Because the PI/PID based control system has already been widely accepted and employed throughout the FFPPs, such a method can directly and effectively improve the operation performance without altering the original simple structure, operation procedures and concepts which are well understood by plant engineers and operators. Recently, auto-tuning and gain scheduling PI/PID controls are two extensively studied methods in power plants.

Auto-Tuning PI/PID Control

As stated before, the power plant control system consists of many SISO PI/PID loops which are strongly interacting to each other. The most common method of tuning these controllers in the FFPPs is the so called ‘trial and error’ method.[11] It generally tunes the control loops sequentially, beginning from the one with least interaction. For complex MIMO system like FFPP, such a method requires considerable expertise and experience and may still be difficult to attain a satisfactory overall performance. An alternative method is to design an analytical compensation of control-loop interactions for wide-range plant operation.[12]

Auto-tuning PI/PID control can potentially handle the interactions among process variables and loops, where an objective function reflecting an overall dynamic control performance is utilized and through minimization of this objective function, all controller

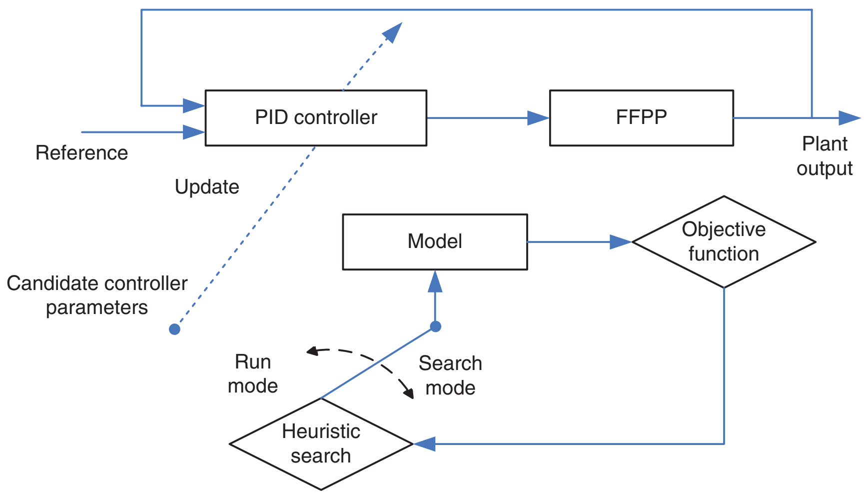

FIGURE 11 | Block diagram of a typical tuning method for PI/PID parameters.

parameters can be determined simultaneously and optimally.

Figure 11 shows the block diagram of a typical tuning method in Refs 13–15, in which a dynamic model of the plant is used to test different groups of controller parameters. Model plays a fundamental role in this method, where the tuning result and computational requirement depend greatly on the structure, accuracy and complexity of the model. If an operation around a given loading condition is considered, linear model may be enough to achieve a good performance; otherwise, nonlinear analytical or identified model must be employed due to the nonlinear behavior of the plant.

Besides the model, another feature that is considered essential to this method is the objective function. Any output or input variables of interest in the controller tuning can be included in the objective function, and various types of functions can be designed. The following quadratic output performance objective function over a finite horizon N is commonly used:

$$J_k = \sum_{t=1}^{t=N} \left(\hat{y}_{k+t} - r\right)^T Q \left(\hat{y}_{k+t} - r\right) \tag{2}$$

where k is the current instant, $\hat{y}_{k+t}$ is the expected model output vector at instant $k+t$ based on the candidate controller parameters, which could include the interested variables, such as power output, throttle pressure, and so on, r represents the corresponding references to these output variables, and Q is the weighting matrix.

If linear model is employed in the method, the minimization of the objective function can be formulated into a quadratic programming (QP) problem, which is computationally efficient. However, in most of the cases, nonlinear models are utilized to better model the plant behavior; thus the optimization procedure becomes a non-convex problem with heavy computational load, and may get stuck in a local minimum far from the optimal value. Consequently, various heuristic search algorithms, such as Genetic Algorithm (GA),[14] Evolutionary Programming (EP),[13] Particle Swarm Optimization (PSO),[15] are proposed to find the optimal controller parameters. A basic working principle for these heuristic search techniques is:

1. *Initialization*: generate initial controller parameter candidates randomly in the given solution space.
2. *Evaluation*: simulate the power plant model with these parameters and evaluate the corresponding objective function;
3. *Modification*: modify the parameters and continue to evaluate the performance until finding the satisfactory parameters.

The results in works[13–15] show that, quality solutions and fast convergences can be provided in many applications. However, the nonlinear optimization is still time consuming, which brings difficulties in making frequent online updates. Fortunately, the PI/PID controller gains do not have to be updated for each time increment, thus a large window size can be chosen to tune the gains.[15]

Another drawback for this auto-tuning method is the model-dependence character. An accurate model which can capture the dynamics of the power plants over wide operation range is difficult to develop. Therefore, it is worth mentioning here that recently, model-free direct tuning methods using the closed-loop experimental data are employed in the power plant to achieve an optimal tuning of the

PI/PID controller parameters. In Ref 11, iterative feedback tuning (IFT) technique is employed for a simultaneously tuning of six main control loops in the power plant. In Ref 16, extremum seeking (ES) technique is utilized to find the optimal PID gains of the superheater steam temperature control system in the FFPP.

Similar to the ordinary model based methods, different overall control objective functions can also be designed in these approaches, but the gradient search based minimization of these objective functions is time consuming and lacks robustness. One attractive feature for these model-free based approaches is that they potentially eliminate or reduce the modeling effort, but instead, a number of experiments are required for gradient computation, which have to be designed carefully to make sure the operation of the plant is not under too much stress.

The last technique introduced in this part is the expert knowledge-based PI/PID auto-tuning approach, where the expert knowledge is utilized to determine and coordinate the controller gains. For example, to obtain a desired step response, a large control signal is needed in the beginning to achieve a fast rise time, which requires a big proportional gain and a small derivative gain. Also, because processes have large time-delay, a small integral gain is desired to reduce the overshoot. When the output response is near the set-point, the proportional gain and integral gain should be changed from large to small and from small to large, respectively, to make the controlled output converge to the set-point quickly.

On the above classical tuning knowledge, fuzzy rules are generated in Ref 17 to adjust the PID parameters according to the current output error $e(k)$ and its first difference value $\Delta e(k)$, and a fuzzy auto-tuning PID controller is designed for the main steam pressure loop in the FFPP, which can enhance the robustness and control performance of the PID controller with fixed parameters.

The expert knowledge rule-table could be produced off-line, and once finished; the PID parameters can be determined directly and efficiently by the look-up table. However, no optimality can be achieved since no optimization is performed in this approach.

Gain Scheduling PI/PID Control

The computational complexity of the online-tuning of the PI/PID parameters leads to the development of gain-scheduling PI/PID control methodology, which is more practical to deal with the limitation of fixed parameter PI/PID controller and attain a better wide-range operation performance in the power plant.

The essential idea of the gain scheduling control is to change the controller parameters according to the variations of process dynamics. A measurable process variable, which is descriptive of the operating condition, is known as a scheduling variable and used to adjust the controller parameters.

For the FFPPs, the power load is usually selected as the scheduling variable since its variation naturally represents various operating points of the plant, especially when the plant is operating under a 'constant-pressure' mode. Then several typical loading points are selected and at each point, the PID controller parameters are tuned offline. In online operation, according to the value of the scheduling variable, the PID parameters can be determined through some interpolations between the parameters predesigned at typical loading points.[17–19] The block diagram of a typical gain scheduling PID control is shown in Figure 12.

Robust Control

One major issue in the control of FFPPs is the uncertainty. First, modeling mismatches are difficult to avoid due to the complex dynamics of the plant and the desire to use simplified model; and secondly, the unknown disturbances commonly exist all over the plant due to the equipment wear, environmental changes, fuel variation, and so on.

In contrast to the adaptive approach which attempts to learn the uncertainties of the plant and eventually adjusts the controller to be best suited for the plant, the robust control has a fixed structure which yields acceptable performance for a given plant uncertainty set. Because the robust controllers are simpler to implement without online-tuning to the plant variations, they have been extensively studied for FFPPs over the past few decades.

The H_∞ control is the subject of the largest share of the robust control researches in the FFPPs. The basic idea of the H_∞ control comes from the theory in the frequency domain. The H_∞ norm of the transfer function (the maximum singular value of the function over the H_∞ space) can be interpreted as a maximum gain between bounded input energy and output energy; thus, developing a controller which could minimize the H_∞ norm as an objective function will naturally reduce the closed-loop impact of a perturbation, and enhance the stabilization or performance.[20,21]

To guarantee robust performance of the controllers under unexpected uncertainties, in Refs 22–25 the H_∞ control approaches are proposed to the boiler-turbine coordinated system, gas and oil-fired heating/cogeneration industrial boilers and gas turbine. In these works, an H_∞ approach with mixed sensitivity has been utilized in the controller design,

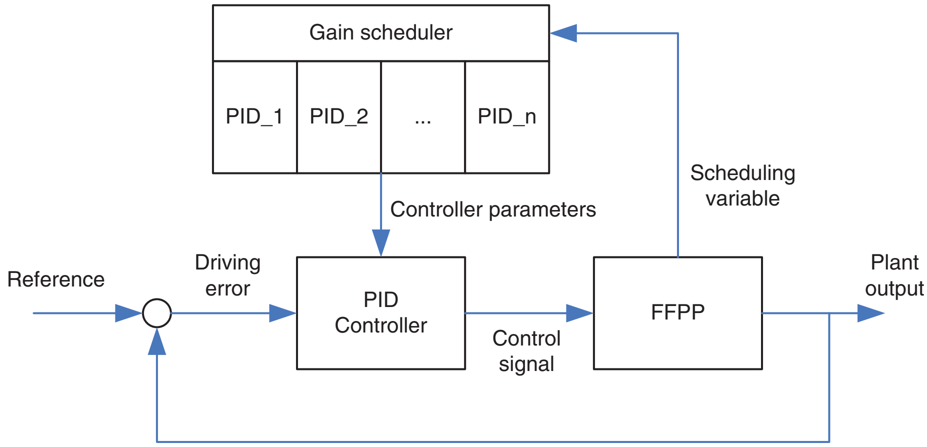

FIGURE 12 | Gain Scheduling PID control.

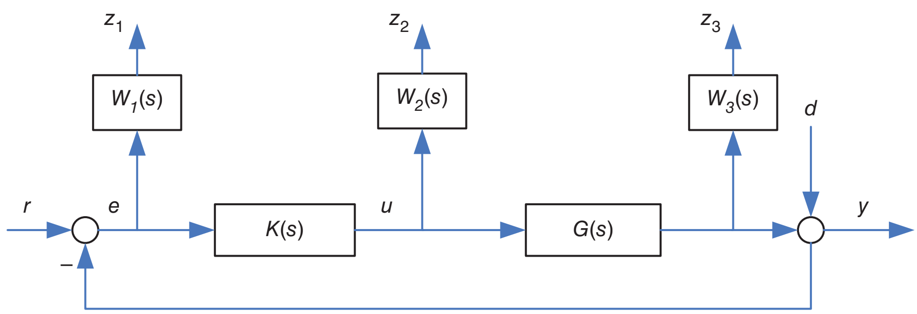

FIGURE 13 | Block diagram of a typical H_∞ mixed sensitivity problem.

which can achieve a trade-off between the robustness and performance.

Figure 13 shows the block diagram of a typical H_∞ mixed sensitivity problem, where $G(s)$ is the transfer function of the plant, $K(s)$ is the controller; the variables r, e, u, d, and y are the reference, control error, control input, disturbance input and system output, respectively; $W_1(s)$, $W_2(s)$, and $W_3(s)$ are weighting matrices, and z_1, z_2, z_3 are corresponding weighted control system outputs.

Performance and robustness are characterized by various well-known closed-loop functions, in particular the sensitivity function $S(s)$, the input sensitivity function $R(s)$ and the complementary sensitivity function $T(s)$:

$$S(s) = (I + G(s)K(s))^{-1}, \tag{3}$$

$$R(s) = K(s)(I + G(s)K(s))^{-1} = K(s)S(s), \tag{4}$$

$$T(s) = G(s)K(s)(I + G(s)K(s))^{-1} = I - S(s), \tag{5}$$

Here, $\|S(s)\|_\infty$ reflects the disturbance rejection and reference following ability of the system, $\|R(s)\|_\infty$ reflects the allowed amplitude of additive uncertainties $G(s) + \Delta(s)$, $\|T(s)\|_\infty$ reflects the allowed amplitude of multiplicative uncertainties $(I + \Delta(s))G(s)$.

A generalized plant $\overline{G}(s)$ can be built as follows:

$$\begin{bmatrix} z_1 \\ z_2 \\ z_3 \\ e \end{bmatrix} = \overline{G}(s)\begin{bmatrix} r \\ u \end{bmatrix} = \begin{bmatrix} W_1(s) & -W_1(s)G(s) \\ 0 & W_2(s) \\ 0 & W_3(s)G(s) \\ I & -G(s) \end{bmatrix}\begin{bmatrix} r \\ u \end{bmatrix}, \tag{6}$$

$$u = K(s)e, \tag{7}$$

and a transfer matrix from the disturbance input d to the control system outputs $\mathbf{z} = [z_1, z_2, z_3]^T$ can be constructed as:

$$\Phi(s) = \begin{bmatrix} W_1(s)S(s) \\ W_2(s)K(s)S(s) \\ W_3(s)T(s) \end{bmatrix}. \tag{8}$$

Then, shaping the closed loop transfer functions $S(s)$, $R(s)$, and $T(s)$ for the control system design is converted to find the controller $K(s)$ which can minimize $\|\Phi(s)\|_\infty$.

In Ref 22, H_∞ controller is compared with other modern control design methods, such as μ-synthesis and H_2 approaches through the simulation on a boiler-turbine coordinated system model. Their test results show that under the presence of complicating factors such as coupling between multi-variables, time delay, modeling uncertainty, output disturbances and sensor noise in the FFPPs, the H_∞ controller can provide performance and robustness superior to that attainable by other designs.

In Refs 26–28, the H_∞ loop shaping technique is utilized to design multi-variable robust PI/PID controllers for the FFPPs. The results show that, owning to the advantages of the H_∞ design approach such as: yielding MIMO control laws, providing strong robustness of the system, the proposed controllers can achieve better performances than the conventional PI/PIDs.

However, there are some drawbacks which may limit the application of H_∞ design approach in practice:

1. Relying on the linear model of the plant;
2. The weighting matrices $W_1(s)$, $W_2(s)$, and $W_3(s)$ are important to attain a balance among various control performance objectives, however, the setting and tuning of them is indirect and inconvenient;
3. In general, the resulting controller has high order, thus order reduction has to be carried out without degradation in performance and robustness;
4. Cannot deal with the input constraints effectively (although tuning $W_2(s)$ can impose limitations on the inputs to some extent);

As the FFPPs are required to operate in a wide loading range, the liner model based H_∞ approach is becoming insufficient, even if the robustness can be guaranteed within a certain range around the typical operating point. Therefore, multi-model based H_∞ approaches are proposed recently.

In Ref 29, two transfer function models are developed at different operating point of the boiler-turbine unit of a coal-fired power plant, and two H_∞ controllers are built based on these models to guarantee the robustness in each local-region. A bumpless switchover mechanism is designed to achieve a smooth transition between the two operating regions, thus a wide range load following is attained. In Refs 30 and 31, robust H_∞ tracking controllers are designed for the boiler-turbine unit via Takagi-Sugeno (T-S) fuzzy model. Based on the state-space type of local models, Lyapunov theory and Linear Matrix Inequality (LMI) technique are employed in these methods, and a robust tracking control of the boiler-turbine is achieved in a wide operation range with the stability of the closed-loop system being guaranteed.

Although H_∞ approach is the most popular one in the area of FFPP robust control, it is by no means the only approach. Other robust control approaches such as linear quadratic Gaussian with loop transfer recovery[32] (LQG/LTR) and μ-synthesis[33] are also applied to the FFPPs to enhance the system robustness and performance.

Model Predictive Control

Although better control performance can be attained by the use of advanced PI/PID controller or robust controller, none of them can effectively deal with the input constraints during the controller design stage. Therefore in practice, when physical limitations of valves in the FFPPs are involved, the performance of the controllers will be degraded. In this context, the model predictive control (MPC) has been widely employed in recent years.

MPC refers to a class of control approaches which utilize an explicit process model to predict the future response of a plant and calculate the control inputs through the minimization of a dynamic objective function within the predictive horizon.[34] Originally applied mainly in the petrochemical industry, the predictive control has progressed steadily and gradually made a significant impact on the FFPPs control. The main reasons for its success in FFPP studies and applications are:

1. It can effectively handle the actuator limitations and allow the operation closer to constraints, which frequently leads to more rapid response and more profitable operation.
2. It handles multivariable control problems naturally.
3. It can effectively deal with the large inertial and time-delay behavior of the plant.
4. The tuning of the parameters is easy and intuitive; no special attention needs to be placed on constraints and optimization.

The basic idea and principle of the MPC is shown in Figure 14, and can be briefly explained in three steps:

1. At current time k, based on the available information and predictive model, predict the future response of the plant within the predictive

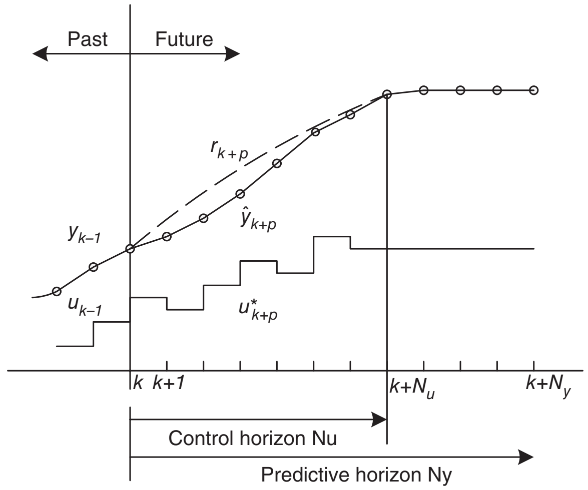

FIGURE 14 | Basic working principle of the MPC.

horizon N_y, and express the future predictive outputs $\left\{\hat{y}_{k+1}, \hat{y}_{k+2}, \dots, \hat{y}_{k+N_y}\right\}$ in terms of future inputs $\left\{u_{k+1}, u_{k+2}, \dots, u_{k+N_u}\right\}$.

2. Through minimizing a given dynamic control objective function, calculate the optimal future control sequence $\left\{u^*_{k+1}, u^*_{k+2}, \dots, u^*_{k+N_u}\right\}$, which can drive the predictive output $\hat{y}$ to follow the reference r in an optimal way.
3. Send only the first input in the optimal sequence to the plant, and repeat the entire calculation at subsequent time.

Linear MPC

The first generation of MPCs applied to the FFPPs is the linear MPCs, in which linear model for the plant is utilized and the optimal control inputs are determined through minimizing a finite horizon quadratic performance objective:

$$
\begin{aligned}
J(k) = & \sum_{j=1}^{N_y} \left[\hat{y}(k+j|k) - r(k+j)\right]^T \\
& \times Q\left[\hat{y}(k+j|k) - r(k+j)\right] \\
& + \sum_{j=1}^{N_u} \Delta u(k+j-1|k)^T R \Delta u(k+j-1|k).
\end{aligned}
\tag{9}
$$

The future projected output $\hat{y}$ can be related directly back to the input vector Δu through the linear model and the objective function can be re-written in the form of a standard quadratic programming (QP) problem with all input output constraints collected into a matrix inequality involving the input vector. As QP is one of the simplest possible optimization problems, the optimal inputs can be found efficiently.[34]

Because the linear step response model of the plant can be easily obtained, dynamic matrix control (DMC) has been extensively studied. In Ref 35, DMC is applied to a drum-type boiler-turbine system to achieve a simultaneous control of electrical power, drum pressure and water level. It shows that the step-response model based on the test data is better suited than the linearized model. In Refs 36 and 37, DMC techniques have been applied to control the superheater/reheater steam temperature of the FFPPs, the results demonstrate that better control performance can be achieved as compared to the conventional PID control.

Another linear MPC that has been widely used in the FFPPs is the generalized predictive control (GPC), where auto regressive moving-average model is employed.[38–41] In Refs 38 and 39, multi-variable GPCs are developed for a coordinated control of the boiler-turbine; their simulation results indicate that, compared with PID, the GPCs can not only track the target value smoothly and rapidly with smaller overshoot and shorter adjusting time, but also has stronger robustness. In Ref 40, GPC is designed to regulate the superheater and reheater steam temperatures of a 200 MW power plant. To further enhance the robustness of the system and attain a wide range operation of the plant, recursive least square based adaptive algorithm is added to the GPC, which can tune the controller parameters online using the real-time input/output data. In Ref 41, the adaptive GPC is tested in a real power plant and evident improvements were observed in the results.

Nonlinear MPC

Although the linear MPC can effectively improve the control performance of FFPPs, due to the fact that the linear model works only for linear system, its application is limited to a small operating region of a plant. For this reason, nonlinear plant model has been used instead of the linear model in the MPC design to achieve a wide range plant operation.

To overcome the issues associated with nonlinear modeling and computational requirement, artificial intelligence techniques have been applied. In Ref 42, the nonlinear analytical model of the plant is employed as the predictive model, and GA is utilized to calculate the optimal control sequence under the input constraints. In Ref 43, neural network-auto regressive exogenous (NN-ARX) model is identified for a 200 MW oil-fired drum-boiler plant, and an MPC is designed based on the model. Simulation results show that a satisfactory control of main steam pressure and temperature and reheat steam temperature can be attained during load-cycling and other severe plant operating conditions. To improve the computational performance of the nonlinear optimization, the particle swarm optimization (PSO) and its modifications have been used in Refs 44–46 to search for the optimal control sequence in the NN based nonlinear MPC; the advantages and effectiveness of these approaches have been clearly shown through simulations of the superheater and reheater steam temperature control of the FFPPs. In Refs 15 and 47 online-update diagonal recurrent neural network (DRNN) models have been developed for 500 and 1000 MW FFPPs, and PSO based nonlinear MPCs are then designed to achieve a plant-wide control.

Besides the intelligence-based nonlinear MPC, in Ref 48, a load-dependent exponential ARX (Exp-ARX) model that can effectively describe the plant nonlinear properties is identified off-line, and then used to establish a constrained multivariate multistep predictive controller. Simulation studies on a 600 MW FFPP indicate that owing to the ability of the nonlinear model capturing the plant dynamics, much better control performance can be attained without using the online-update method. Based on the technique of input-output feedback linearization, GPC is combined with the nonlinear state feedback controller in Ref 49 to solve the control problem of a 160 MW boiler-turbine unit.

The nonlinear MPC is naturally suited for control of the nonlinear FFPPs; however, there are two main issues, which greatly limit its application: (1) the satisfactory nonlinear dynamic model is difficult to build; and (2) the nonlinear optimization lacks in robustness and suffers from computational requirement. To overcome these issues, the multi-model based predictive controllers are developed recently.

Multi-Model MPC

The essential idea of the multi-model technique is ‘divide and conquer’, which uses a combination of several linear models to approximate the nonlinear behavior of the plant.[50] Because the advances in linear modeling and control theory can be directly taken into account, the multi-model techniques bring an alternative way to handle the nonlinearity, and its integration with the MPC approach has been shown to be effective to control the power plants.[49,51–66]

The earliest multi-model MPC used in power plant control is presented in Ref 51, where networks of dynamic local linear models are created after dividing the whole operating region into a number of zones and the global model is built by using the interpolation among these local models. GPC is then designed on the basis of the global model to achieve a wide range control of the power plant, as shown in Figure 15. Based on the Radial Basis Function (RBF) neural network and Adaptive Neuro-Fuzzy Inference System (ANFIS) approaches, local linear MPCs developed at different loading points are combined for the coordinated control of a 500 MW plant.[52,53] Although the multi-model strategy seems more complicated than the direct nonlinear approaches, in fact, it is easier and more efficient to implement. To improve the wide-range operation of a boiler-turbine system, a fuzzy interpolated DMC is proposed in Ref 54, which can be viewed as an extension of the linear DMC in Ref 35.

In Refs 49, 55, 56, GPCs are developed on the basis of neuro-fuzzy networks (NFNs), both the local linear model weighted and controller weighted approaches are given in these works. Through the simulation studies on the boiler-turbine coordinated system and superheater steam temperature system, better control performance is shown compared to the linear GPC.

In Refs 57–66, multi-model MPCs are proposed on the piecewise linear (PWL) models, piecewise affine (PWA) models or Takagi-Sugeno (T-S) fuzzy model using various kinds of objective functions and computational tools, such as QP,[57,58,60] LMIs,[63–66] multi-parameter programming (MPT),[59] GA[61] and iterative learning control (ILC).[62] Besides Ref 62, it is interesting to note that, a state-space type of local linear model is adopted in most of the multi-model MPCs because of the advances in multi-variable systems and the-state-of-the-art control techniques for linear systems.

In Refs 59 and 61, the stability of the closed-loop control system is achieved and the overall control performance is improved by including a terminal inequality constraint, which forces the states at the end of the finite prediction horizon to lie within a prescribed terminal region, and by adding a quadratic terminal state penalty cost in the objective function. In Refs 63–66, an infinite-horizon objective function is adopted and a Lyapunov function is constructed to find the upper-bound of the objective function and ensure the stability. The control input can be solved by minimizing this upper-bound while subjecting to the stability and input constraints in the form of linear matrix inequalities (LMIs). In Refs 61, 65, 66, a disturbance observer and steady-state target calculator (SSTC) are added to the MPC structure to achieve a tracking control of the boiler-turbine unit even in the case of significant unknown disturbances or plant parameter variations.

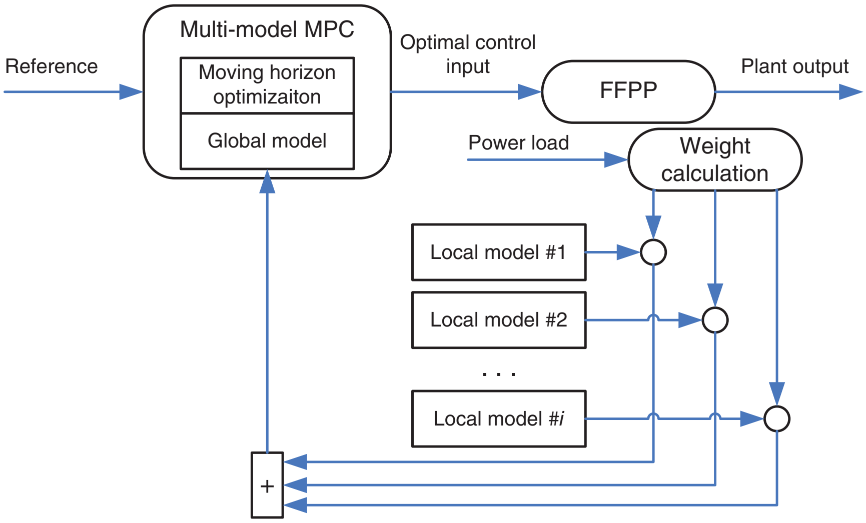

FIGURE 15 | Control diagram of model-weighted multi-model MPC.

Intelligent Control

The development of intelligent techniques in power plant control are increasing steadily in recent years owing to its advantages, such as overcoming the significant nonlinear and uncertain dynamics, computational complexity and other problems associated with large-scale distributed complex power plants.

Intelligent control is a class of control techniques that use various computational intelligence techniques to develop the computer-based control systems. Because, the intelligent control system behaves as humans or species in nature, with the ability to learn and discover knowledge, emulate human expertise and decision making, and accomplish the tasks, it can autonomously achieve a high level goal even in the complicated or unexpected case.[67]

As was already introduced in the *advanced PI/PID control* and *MPC* sections, many different intelligent techniques have been applied to power plant control, and their structures are modified in general depending on the purpose of application. The most popular intelligent techniques are neural network, fuzzy logic, evolutionary programming, genetic algorithm, particle swarm optimization, multi-agent systems, as well as their combinations.

The first intelligent technique investigated in the section is the neural network (NN). Since the NN has outstanding abilities in knowledge discovery, or discovering underlying, hidden patterns in data sets, it provides an effective way to develop the model for the nonlinear power plant using only the input-output data, which is generally the first and foremost important step in the advanced controller design.

To provide dynamic information about the plant for controller design, the usual NN modeling is combining the conventional feedforward networks (such as BP or RBF neural networks) with tapped delays.[68] Beside this, in Refs 44–46, Elman neural networks (ENN) and their modifications are utilized to approximate the behavior of the steam temperature systems of FFPPs. The ENN differs from the conventional feedforward networks in that it includes recurrent or feedback connections. The delay in these connections store values in the previous time-step and use them as inputs in the current step, which makes the network sensitive to the history of input and output data, suitable for dynamic system modeling.

The basic structure of an ENN with M inputs and N outputs is shown in Figure 16, where the recurrent neurons are in the *context layer*. The outputs in each layer of an ENN are given by:

$$x_j(k) = f\left(\sum_{i=1}^{M} W_{i,j}^1 u_i(k) + \sum_{i=1}^{R} W_{i,j}^3 c_i(k)\right), \tag{10}$$

$$c_i(k) = x_i(k-1), \tag{11}$$

$$y_j(k) = g\left(\sum_{i=1}^{R} W_{i,j}^2 x_i(k)\right), \tag{12}$$

where, $W_{i,j}^1$ is the weight that connects node i in the input layer to node j in the hidden layer; $W_{i,j}^2$ is the weight that connects node i in the hidden layer to node j in the output layer; $W_{i,j}^3$ is the weight that connects node i in the context layer to node j in the hidden layer; and $f(\cdot)$ and $g(\cdot)$ are the transfer functions of the hidden layer and the output layer neurons, respectively, where $f(\cdot)$ mostly takes *logsig* or *tansig* function and $g(\cdot)$ often takes *purelin* function.

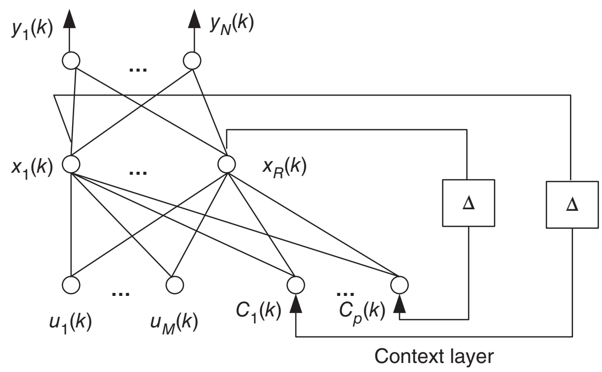

FIGURE 16 | Basic structure of the ENN.

As a special case of the ENN, the diagonal recurrent neural network (DRNN) is also popular in the area of FFPP dynamic modeling.[13,15,47,69] Compared with the ENN, the context layer of DRNN is collapsed to the hidden layer, which eliminates the cross talks and reduces the number of weights between the context layer and the hidden layer. Therefore, fewer training iterations are needed and the DRNN is better suited for real-time application.[69]

In order to capture the complex dynamic of the whole power plant, the DRNN based combined model is proposed in Refs 15 and 69, where each primary component of the plant is approximated by a DRNN model. Then these DRNNs are connected by using the outputs of a DRNN as the inputs of another DRNN. The composed hierarchical structure can achieve a satisfactory accuracy, thus can be used as the plant simulator.

With the dynamic process model being successfully developed, various advanced controller can be designed, for example, the aforementioned *Auto-tuning PI/PID Control* and *nonlinear MPC*. To generate solutions to the highly complex nonlinear optimization problem, heuristic optimization techniques, such as evolutionary programming (EP),[13,70] genetic algorithm (GA)[14,42] or particle swarm optimization (PSO)[15,44–47] have been employed extensively, providing quality solutions and fast convergence compared with the conventional nonlinear programming.

The basic principle for all these heuristic optimization algorithms can be concluded as: *initialization*, *evaluation* and *modification* as we introduced in the *Auto-tuning PI/PID Control* section. In Ref 71, basic GA and PSO algorithms are compared and the results show that PSO can attain a better performance. However, because the search procedure by the PSO strongly depends on the agent best value so far (*pbest*) and the global best value (*gbest*), the search area can be limited by them, which may lead to the local minima.

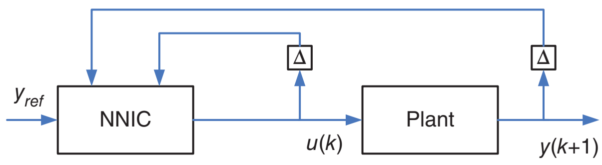

FIGURE 17 | Control system of the NNIC.

Therefore, by introducing a natural selection mechanism, which is usually performed by the EP and GA, the effect of *pbest* and *gbest* is gradually curtailed and a broader search area can be realized. The resulting hybrid PSO can have a higher performance.

Besides the traditional model based controller, the neural network technique can also be used to design the model-free controllers directly, which is called the neural network inverse control (NNIC).

The essential idea of the NNIC is to identify an input/output mapping:

$$u(k) = g\left(y(k+1), y(k), y(k-1), \dots, y(k-n), u(k-1), u(k-2), \dots, u(k-m)\right), \quad (13)$$

which can be viewed as a nonlinear inverse mapping of the conventional dynamic model:

$$y(k+1) = g\left(y(k), y(k-1), \dots, y(k-n), u(k), u(k-1), \dots, u(k-m)\right). \quad (14)$$

The inverse mapping function $g(\cdot)$ can be identified by using the ENN or DRNN, and it is capable to find the control input $u(k)$ to drive the system to an expected point $y(k+1)$. Therefore, it can be used as a controller by replacing the future expected output $y(k+1)$ in Equation (13) with the desired output, y_{ref}. If the network represents the exact inverse, the control input produced by the network will drive the system output $y(k+1)$ to y_{ref}. Figure 17 illustrates how the NNIC is applied as a controller in the system.

As the NNIC is a feedforward controller, in order to deal with the unavoidable modeling mismatches and the unknown plant variations and disturbances, a PID compensator is usually augmented to the system, and the resulting control structure is shown in Figure 18. The NNIC is used as a feedforward controller, which provides the main contribution to the control signal to make the plant respond quickly to the set-point changes, thus shorten the stabilization time and reduce the overshot of the control process, and the PID compensator is serving as the feedback controller to eliminate the steady-state control error induced by the NNIC.

The feedforward-feedback control system is utilized in Refs 72 and 73 to regulate the superheater

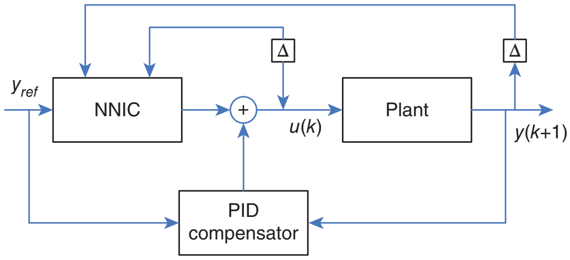

FIGURE 18 | NNIC augmented by a PID compensator.

steam temperature in the FFPPs. The results in these works show that owing to the advantages of both NNIC and the PID compensator, better control performance can be realized than the original cascade PID control.

Another intelligent technique being widely used in the area of FFPP modeling and control is the fuzzy logic control (FLC), which has advantage in capturing the tacit knowledge of the system. The Takagi-Sugeno (T-S) fuzzy modeling technique is now the most popular FFPP modeling strategy.[74] Its basic idea is using the fuzzy set to divide the whole operation region of the system into several overlapping local regions; in each local region, a simple linear model is developed to represent the local dynamics of the system, and then the global model is finally derived from the weighted summation of all the local models. Because the T-S fuzzy model can approximate the nonlinear behavior of the plant using the combination of several linear models, the advanced linear control theory can be used to overcome the nonlinear control problem. Moreover, since the overlaps between different regions can guarantee smooth transitions between local models, the T-S fuzzy model naturally provides a bumpless switchover.

Take the discrete-time, state-space form of local model, for instance, the T-S fuzzy model can be described as follows:

$$R^i : IF\ z_1(k)\ \ is\ \ \mathrm{M}_1^i,\ z_2(k)\ is\ \mathrm{M}_2^i,\ \dots,\ z_N(k)\ is\ \mathrm{M}_N^i,\ THEN:$$
$$\begin{cases} x(k+1) = A_i x(k) + B_i u(k) \\ y(k) = C_i x(k) + D_i u(k) \qquad i = 1, 2, \dots L \end{cases} \tag{15}$$

where R^i denotes the ith fuzzy rule, L the number of fuzzy rules, $\mathrm{M}_j^i (j = 1, 2, \dots, N)$ the fuzzy sets; $x(k) \in \mathfrak{R}^n$ the state vector, $u(k) \in \mathfrak{R}^m$ the control input vector, and $y(k) \in \mathfrak{R}^l$ the output vector. The matrices (A_i, B_i, C_i, D_i) are local system matrices, and $Z(k) = (z_1(k), z_2(k), \dots, z_N(k))$ is the antecedent vector of the fuzzy model, which is composed by current and past measurable variables of the plant.

By using fuzzy blending, the dynamic fuzzy model (15) can be expressed by the following global model:

$$\begin{cases} x(k+1) = A_Z x(k) + B_Z u(k) \\ y(k) = C_Z x(k) + D_Z u(k) \end{cases} \tag{16}$$

where $A_Z = \sum_{i=1}^{L} w_i(Z(k)) A_i$, $w_i(Z(k)) = \mathrm{M}^i(Z(k)) / \sum_{i=1}^{L} \mathrm{M}^i(Z(k))$, $\mathrm{M}^i(Z(k)) = \prod_{j=1}^{N} \mathrm{M}_j^i(z_j(k))$, and all other matrices B_z, C_z, and D_z are defined in the same way.

In Refs 30, 60–62, 64–66 an approximation or transformation of the nonlinear system has been used to obtain the linear state-space model at different loading conditions, then according to the expert knowledge or the nonlinear investigation of the plant, the fuzzy rules are developed to connect the local models and form the integrated T-S fuzzy model of the FFPP. In Ref 75, a data-driven fuzzy modeling strategy is proposed, where Gaustafson-Kessel (G-K) clustering is used to provide an appropriate division of the operation region and develop the structure of the T-S fuzzy model. Then by combining the input data with the corresponding fuzzy membership functions, the subspace identification (SID) method is extended to extract the local state-space model parameters. Owing to the advantages of the both methods, the resulting fuzzy model can represent the boiler-turbine unit of an FFPP very closely for advanced controller design.

The fuzzy technique also provides an effective way to design the controller. In Refs 76 and 77, control rules are first given based on the expert knowledge to determine the linguistic value of the control signal corresponding to the current output error $e(k)$ and its first difference value $\Delta e(k)$. Fuzzy logic controllers are then developed based on Gaussian and Triangular-shaped membership functions to control the nonlinear boiler system and boiler-turbine system in the FFPP, respectively.

In Ref 78, a Fuzzy Auto-Regressive Moving Average (FARMA) controller is applied to the boiler–turbine system, the controller is an inverse mapping of the FARMA model, which finds the control input according to the reference value and historic input–output data. Unlike a conventional FLC, where an expert gives the linguistic values of the antecedent and consequent variables and makes rules; in the FARMA controller, these linguistic values are determined from the crisp values of the input–output history at each sampling time. It has been shown in the simulation that by using the self-organizing procedure to update the rule base, better controls can be applied as time progresses.

Meeting the power demand of the grid has been the primary FFPP operation task. However, due to the energy shortage and environmental concern worldwide as well as competition among utilities and other society driven forces, more stringent requirements, such as minimization of fuel consumption, maximization of duty life and minimization of pollution, etc., have to be fulfilled by the power plant to achieve an optimal operation. Therefore, not only the conventional dynamic control performance, but also the set-point optimization considering the aforementioned multiple objectives is important to realize an integrated optimal control of the FFPP, where various computational intelligence techniques are utilized to overcome the nonlinear modeling and calculation issues of the FFPP.

In Refs 79–81, multi-objective optimization is performed to adjust the power-pressure mapping to optimally accommodate different operating scenarios, where more economic, environmental and safety concerns are taken into account. Steady-state ANN models are first developed in these works to capture the steady-state nonlinear behavior between multi-variables in the boiler-turbine system, and then PSO algorithm is employed to calculate the optimal set-points. In Refs 13, 15, 71, the similar methods are used in large-scale FFPP simulators to achieve a plant wide optimization of the set-points.

To reduce the nitrogen oxides (NO_x) emission during coal combustion in the FFPPs, combustion optimization is studied in Refs 82–85 to find the optimal openings for the primary, secondary and over-fire air valves at different layers of the boiler. Since the development of an accurate analytical model for a coal-fired boiler is difficult owing to the complexity of the system, data-driven modeling methods such as ANN, support vector machine (SVM), fuzzy c-means clustering as well as their mixtures are proposed to build the steady-state relationships between these air valves and NO_x emission.

The electric utility industry is charged to deliver power as inexpensively and as reliably as possible. Meeting these dual obligations has become increasingly difficult over the past 30 years. Environmental and economic concerns pressed the utility industry to develop clean and efficient ways of burning coal and oil. This has required major improvements in not only the optimization and control, but also the monitoring of electric power plant components such as boilers. It has become a challenge to measure high temperature distributions of high-pressure liquids, steam, combustion gases, and heat transfer components in extremely adverse power plant environments. Traditional sensors have not exhibited sufficient stability and long-term accuracy without requiring expensive maintenance and recalibration. However, intelligent distributed parameter estimation coupled with the fiber-optic sensor system promises better estimate of the temperature distribution of a boiler furnace and for improved combustion.[85,86] The basic approach in developing the intelligent monitoring system is in two folds: (1) development of distributed parameter system (DPS) models to map the three-dimensional (3D) temperature distribution for the furnace; and (2) development of an intelligent monitoring system for real-time monitoring of the 3D boiler temperature distribution based on the 1D fiber-optic sensors.

The aforementioned intelligent techniques have been applied extensively in the area of power plant modeling, control, optimization and monitoring, and their effectiveness in dealing with the nonlinearity and uncertainty of the plants has been demonstrated through simulations. However, both the FFPP and its operation system are large-scale complex system consisting of many subsystems and functions, and it is difficult and dangerous to manage the system using only the centralized control schemes or loosely decentralized control schemes because a single failure can bring down the entire system. Therefore, recently, there has been growing interest in multi-agent systems (MASs) in order to deal successfully with the complexity and distributed problems in power plants and make the control system operate at a higher level of automation, flexibility and robustness.

The basic unit in the MAS is the agent which has intelligent and autonomous properties because it is reactive, proactive, social, flexible and robust, and has multiple algorithms for solving problems. After receiving and confirming the objective through the communication with other agents, the agent will choose a plan for the objective and select an algorithm to launch the plan.

The agents are arranged into a hierarchical structure and form the MAS. In the highest level of the MAS, the task delegation agent allocates tasks to different agents and investigates the performance and problems of the lower level. In the middle level, the mediate agent coordinates the cooperation of the lower agents such as, asks a certain agent to share the information directly with the information requesters. A monitoring agent is also placed in this layer to select, store and analyze the sensing data of the power plant. In the lowest level, intelligent agents that have multiple algorithm modules are cooperating together to identify the system, perform the multi-objective optimization and determine the set-points and control law. Design of single agents and the integrated MAS as well as its implementation in the FFPPs are well introduced in Refs 13, 67, 79, 80.

ADVANCED CONTROL TECHNOLOGY PRODUCTS FOR THE FFPP

Although the power plant industry may still be reluctant to accept changes that would revolutionize well assessed procedures due to the reasons such as: reliability, complex design, tuning parameters and training of plant personnel, the environment of growing energy and pollution issues, increased FFPP control challenges as well as the significant improvements reported by the academic studies has already led to the technology development in the industry. Moreover, over the course of the last two decades, the widespread use of distributed control system (DCS) in power plant and the development of computer technologies have facilitated the employment of advanced control approaches. The new control software could be installed in the programmable logic controllers (PLCs) or industrial computers and communicates with the DCS through the object linking and embedding for process control (OPC) or Modbus protocols, which will then collect the required data and send the commands to regulate the actuators. For these reasons, several companies have presented their own commercial FFPP control solution products, aiming at improving the operation performance of the FFPPs. The purpose of this section is to introduce several examples of commercial products provided by different companies to demonstrate the effectiveness of the advance technologies in the FFPP practice.

The first product introduced is the BCOS-ZOLO offered by ZOLOBOSS,[87] which is an FFPP operation optimizer on the basis of direct monitoring of the combustion zone in the furnace and combustion optimization. As is well known, the combustion in the furnace is the energy source of the FFPP, however, the high temperature (beyond 1500°C) in the combustion zone of the furnace makes it impossible to measure the combustion condition (temperature, and the contents of O_2, CO, etc., in the flue gas) using the traditional instrumentations such as the thermocouple, Zirconium oxide detector, CO detector, and so on. Therefore, so far, the plant personnel can only estimate the parameters in the combustion zone according to the experience; based on the measurement data around the rear flue gas channel, which is inaccurate and thus brings great challenges in the combustion control and the resulting difficulties in steam temperature and pressure control.

For this reason, a novel laser based measurement product is developed by the ZOLOBOSS based on the technology of tunable diode laser absorption spectroscopy (TDLAS). The TDLAS instruments rely on well-known spectroscopic principles and sensitive detection techniques, coupled with advanced diode lasers and optical fibers developed by the telecommunications industry. The principles are straightforward: Gas molecules absorb energy at specific wavelengths in the electromagnetic spectrum. At wavelengths slightly different from these absorption lines, there is essentially no absorption. Thus, by (1) transmitting a light beam through the gas mixture in the boiler furnace where the target gas is contained, and (2) tuning the wavelength of the beam to one of the absorption lines of the target gas, and (3) accurately measuring the absorption of that beam, one can deduce the concentration of target gas molecules as well as the flue gas temperatures distributed over the beam's path. In general, multiple light paths are assigned in the grid form on the certain layer of the furnace, so that through the computer aided calculation and tomography, the temperature and gas concentration distribution can be obtained and viewed.

Knowing the combustion condition in the furnace will provide a direct guidance for the FFPP operators to achieve a safe and efficient operation of the boiler; for example, prevent the dust deposition and slagging in the furnace, reduce the deviation of the flue gas temperature at the exit of the furnace to prevent the explosion of the heating surface, etc. Moreover, by using the data in the combustion zone of the furnace, more accurate combustion model can be developed or updated. The BCOS-ZOLO proposes the use of the ANN to capture the dynamics between the boiler operation condition (load, fuel variations, environmental temperature, etc.), distributions of fuel and air, and the performance of the combustion (boiler efficiency, NO_x emission, etc.). On the basis of the model, the best distributions of the fuel and air can be calculated for different loading condition and fuel variation through multiple computational intelligence algorithms to realize an optimal operation of the boiler.

Furthermore, the flue gas temperature in the furnace can be used to calculate the equivalent radiation energy in the boiler, which can represent a balance between the boiler and turbine. Thus, by using the radiation energy signal as a feedforward signal, the issues of large inertia behavior of the steam pressure and temperature control system can be overcome to a large extent, and a better load following operation can directly be achieved.

A similar TDLAS based FFPP optimization is also offered by the SIEMENS SPPA-P3000 Process optimizer.[88] Both the two products have now been applied in more than 20 FFPPs in the world, mostly in the United States, Germany and Korea. The main features of them can be concluded as:

1. Direct measuring of the parameters in the combustion zone of the boiler through the TDLAS;
2. Developing the combustion model using the ANN technique;
3. Using the computational intelligence technologies to optimize the combustion;
4. Improving the control performance of the steam pressure and temperature.

To improve the control performance of the large-scale power plant, many companies such as SIEMENS,[89] EMERSON,[90] ABB[91] and HONEYWELL,[92] have launched their own FFPP coordinated control optimizers. The common features of these commercial products are: (1) identifying the process model to approximate the dynamics of the plant; and (2) utilizing advanced control strategies such as multi-variable control methods, MPCs or intelligent control algorithms to improve the performance of the plant.

Among these commercial products, the PROFI UCC offered by SIEMENS[89] is the most widely used one. The essential idea of the PROFI UCC is developing/updating a nonlinear model of the boiler and using the technology of MPC to estimate the 'thermal energy' produced by the boiler, through which, a pre-action command can be given to the fuel feeder to compensate for the inertia and delay behavior of the boiler so that a quick load following performance and a smooth response of the main steam pressure and temperature can be achieved.

On the basis of model prediction, a multi-input multi-output rate-optimal controller (MIMOROC) is proposed by the HONEYWELL's UES[92] for the optimization of the combustion, steam pressure and temperature control. By using the MPC's ability of dealing with the input–output constraints, the MIMOROC allows operation closer to the constraints compared with conventional control, which leads to quicker load following and more efficient and profitable operation. Remarkable plant efficiency and profit improvement have been reported on the FFPPs, where these advanced plant operation optimizers are implemented.

DISCUSSIONS AND CONCLUSIONS

Over the past hundred years, FFPPs have been the primary power generation plants in the world, and made a solid foundation for the people's lives, and social and industrial developments. Design of FFPP has evolved dramatically in the area of scale, working parameters, configurations and techniques to meet the growing power demand.

In recent 20 years, in order to solve the control issues of FFPPs such as wide range load following, fuel and plant behavior variations, and achieve a more safe and efficient operation, various advanced FFPP control techniques have progressed swiftly in both the academic researches and industrial applications, challenging the classical PI/PID based control system. The major FFPP control developments include:

1. Advanced PI/PID controllers using auto tuning or gain scheduling techniques to improve the operation of the FFPPs in a wide load range;
2. Robust controllers in order to deal with the fuel and plant behavior variations, uncertainties and disturbances;
3. Linear, nonlinear or multi-model based MPCs to handle the large-inertia behavior and the strict input–output constraints of the plants;
4. Computational intelligence techniques in modeling, optimization and control, solving the nonlinear issues of the plants.

These advanced control methods as well as their mixtures have all been implemented in the FFPP control practices and we cannot answer which one is the best and will be the future trends of the FFPP control. But, considering the benefits brought by these advanced technologies and the facilities provided by the wide use of DCS and fast development of computer technologies, it is safe to say that much more development in nonlinear, intelligent and model-based MIMO control of FFPPs is ahead of us, and the advanced control techniques will replace the classical PI/PID controllers in a foreseeable future.

However, through the investigation of many advanced FFPP control works, there are several issues that may need to be studied further in the future:

1. Measurement of key parameters during the plant operation. For example, novel measurement technologies can be developed to monitor the pulverized coal concentration and primary air flow rate from pulverizing mills to the burners (Some products have already been

developed recently, for example, the PfMaster by ABB/Greenbank). These parameters are unknown in the FFPPs, but have been found to be the main factors causing the uneven distribution of the temperature field in the furnace and the explosions of the waterwalls and superheaters. Therefore, through the measurement of them, additional regulators can be installed in the outlets of the pulverizing mills to guarantee even and balanced combustion in the furnace.

Another example is the coal properties. Currently the variation of the fuel is one of the key problems in the coal-fired power plants, the uncertainty greatly influences the safety, stability and efficiency of the combustion and plant operation. Therefore, soft measurement technologies of the coal properties are expected to be developed using the combination of thermodynamic knowledge and plant operation data, so that more optimal and robust control can be attained through its estimation.

2. Optimal control. As mentioned before, in the context of global energy and environmental issues, the control objective of the FFPP should be broadened from a simple objective of dynamic control optimality to simultaneous and multiple objectives of plant economic operation, emission and dynamic control performance. Thus, on the one hand, advanced multi-objective optimization with Pareto optimality can be developed based on the plant models and dynamics and environmental changes to provide optimal set-points for the control layer, replacing current fixed and non-optimal set-points given at specific loading condition; on the other hand, more simple and efficient method such as novel economic MPC can be investigated, where both the dynamic control objective and other non-quadratic economic objectives are integrated together in the controller.
3. Closed-loop data-driven modeling. Modeling is the first and foremost important step in advanced controller design. In most of the studies, the researchers focused on the control algorithm, but failed to consider the model development. In many of their works, the results are relying on the availability of the nonlinear analytical model. However, considering the complexity of real FFPP, it is difficult to develop an accurate analytical model without the knowledge of thermodynamics and design specifications of many components, which becomes the major limitation for the application of advanced control methods. For this reason, system identification methods using the closed-loop plant operation data provide an efficient way to develop a control oriented model in practice. In that case, how to design an optimal input signal for identification, examine and polish the data, select the model structure, and test the model sufficiently for healthy interaction with the identification theory, are all important issues in the FFPP practices.
4. Better combination of the analytical model and modern control theory. Although difficult to develop, an analytical model is after all the best one to accurately portray the dynamics of nonlinear FFPPs; it can also provide much information which will guide the controller design. Therefore, how to better integrate the knowledge of analytical model and advanced control technology to develop a controller better suited for the FFPP is a possible future research topic, for example, leading to an analytical model based nonlinear predictive controller.
5. Reliability. Although the advance controllers will effectively deal with the control issues of the FFPP and greatly improve the operational performance, we have to admit that, compared to the single-input, single-output PI/PID control loops currently used in FFPPs, these advanced controllers are complicated in structure, parameter tuning and computation; therefore, it has limitations in reliability. Furthermore, because the multi-variable controller would work in a centralized control unit in most of the applications, a failure of the control algorithm would induce a failure of the entire plant. These are also the main reasons that the plant personnel are reluctant to employ the modern control techniques.

Besides careful design and testing of the controller and training of the plant personnel, a possible way to directly ensure the reliability of the system is keeping the well-assessed SISO PID loops present in the control structure. Thus, the new control system could be disconnected at anytime, without compromising the plant safety. In this case, study of bumpless switchover mechanism between advanced controller and PID controller could be made.

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