AN OPTIMIZED NEURO-FUZZY CONTROL SYSTEM FOR AFAM VI POWER STATION (IPP)

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Abstract - *This research proposes a methodology to design a Neuro-fuzzy system for the simulated combustion process in utility boilers and optimization control system of Afam VI Power Station (IPP) based on the concept. The control system for a fossil-fuel power unit consists of fossil-fuel power unit agent, reference agent, feedforward control agents, feedback control agents and coordinator agent. Every agent is an intelligent agent making decision according to the operating condition of the power plant. The result shows that Neuro-fuzzy technology is capable of accurately modeling of power system, and therefore able to produce an accurate optimization result when using a Neuro-fuzzy in place of the equations.*

Key Words: **Boilers, Optimization, Neuro-fuzzy, Afam VI, Power Station.**

1. INTRODUCTION

Industrialized civilizations exist today due to the ability of mankind to produce and manufacture products, transport and trade in a large scale. As scientific developments have helped humanity obtain means for a more comfortable life by allowing for manufacturing processes to be more cost-effective and accessible to the common person, there has been an increase in the demand for the energy required to produce and transport such products as well as energy consumed in households.

The weak development and maintenance of the power system has been a crucial topic of discussion in Nigeria, the outages of power affects both individual and industries. The call for a 'Roadmap for Power Sector Reform' by former President Jonathan in August 2010 has been seen as the best approach towards stable electricity outflow [1]. Nigeria a country rich with mineral resources such as solar, wind, hydro, thermal energy and bioenergy but can only produce 4,000 MW of capacity for over 150 million people which is too little and insufficient for the country; in order to develop and manage these available resources, there should be equitable allocation and effective utilization and technical know-how towards the economic development of the country. Moreover, enough supply and distribution of electricity is seen as a central point for development [2].

This research presents an optimized control system for Afam VI Power Station (IPP) based on the concept of neuro-fuzzy system control, which have been applied to other complex problems in the power industry. It applies distributed control methodology to a large-scale power plant optimized control system, improving the overall flexibility, autonomy, and robustness of the control system using Neuro-Fuzzy technology, which in turn increases the efficiency and operation of the power plant.

2. ELECTRICITY GENERATION

A liberalized energy market allows free competition between utility companies pressing them to improve production efficiency in order to reduce costs. At the same time regulations enforce strict laws which demand environment friendly production. These actions stimulate technological changes in the energy sector, which aim to significantly improve this industry.

The number of wind turbines and small combined heat and power (CHP) units, which co-generate electricity and district heating, is constantly increasing. Authors in [3] mentions that in Western Denmark such non-controllable power capacity increased from 20% in 1980 to 70% in 2001.

A sudden decrease in energy production for example from wind parks must be compensated by other (controllable) units, such that the balance between generation and consumption is restored. Such compensation is called load balancing of the grid. We associate a term safety of the grid to a situation where the balancing can be ensured at all times, and there is no risk of brownouts when supplies fall below demands or blackouts when supplies fail completely.

By flexibility of the grid we understand the ability to sustain and handle load variations caused by changes in the generation or demands. Authors in [4] remarks that the load-following capability of controllable plants becomes crucial and it is the most important issue in plant control nowadays.

This means that it is necessary to secure a backup capacity of generation which is used when customer demands increase. Backup capacity relates to the ability of increasing the electricity production quickly, such that the balance is sustained. The necessary capacity can be obtained from hydro power, which in many countries is limited due to the landscape, or thermal power plants. With increasing integration of wind generation on the electricity grid, an important objective for many conventional plants becomes to adjust the power production quickly, that is ensure the flexibility of the grid. Studies by [5] show that at a certain level further increase of wind power leads to fuel saving, but it does not lead to significant reduction in the thermal power plant capacity, which needs to be used when supply from other sources decreases.

According to [6], the balancing problem can be divided into power balancing and energy balancing problems. Those markets, which are based on forecasts, make sure that a sufficient number of economically sound units are committed to electricity generation. When the wind speed is low, the controllable units and international purchases provide the required production capacity.

A company called EnergiNet.dk3 is responsible for the quality of electricity, which we called the power balance. In order to fulfill this task it contracts ancillary services, that reserves and regulates power, from utility companies. The Manual Regulation Reserve operates with 45 minute horizon ensuring response in 5 – 15 minutes, and they are contracted for long periods of time with utility companies. Additionally Primary Regulation Reserve and Automatic Regulation Reserve supported by Frequency Control are fast response control capabilities that ensure the precise balance.

Recent advances in control of wind parks are driven by the desire to incorporate the renewable energy into power balancing systems. By adjusting the pitch angle of blades in wind turbines at a wind farm, it is possible to control the overall power and the quality of the generated electricity. It is hoped that in the future such parks will be able to balance the production power. Even in the cases where (nominal) installed generation capacity of wind parks exceeds demands, there might be situations where it is not possible to ensure grid balance if the wind speed is very low. In this case low wind speed means simply that the controllable units must be used. If the change of the wind speed is sudden and significant, the intra-day markets need to ensure the balance. Improved flexibility of power generating units lowers the complexity of such a process and ensures higher safety of the grid. This means that more renewable sources can be incorporated safely in the grid.

2.1 Renewable energy in Nigeria

Nigeria is blessed with resources that it can exploit for developing Renewable Energy (RE). The major RE resources that the country has tapped are hydropower, solar energy, wind energy and bioenergy. The potentials of some other resources such as geothermal, nuclear energy, waves, tidal energy, and ocean thermal gradient still remain untapped and unqualified [7]. With vast land resources, moderate wind power and varying heat degrees across the country, every part of the country can efficiently and effectively host renewable power with the right regulatory frameworks in place.

2.2 Afam power PLC

Afam Power Plc is a thermal power plant located in the gas rich Rivers State. The plant has an installed capacity of 977MW. It is an open cycle gas turbine. The plant was built between 1975 and 2001. Afam I-IV has an operating capacity of 836.6MW, while Afam V possesses the capacity to generate 276MW of electric power.

Given its strategic position in the Niger Delta region, Afam Power Plc has the potential of becoming a leading power plant in Nigeria due to its proximity to its source of natural gas and oil, nearness and availability of other raw materials and the increasing demand for power by the multinational companies in the region.

a. Corporate Structure

Before its incorporation as a distinct Public Limited Liability Company on November 8, 2005, Afam Power operated as a semi-autonomous body headed by a Chief Executive Officer (CEO), supported by a management team that reports directly to the CEO, Power Holding Company of Nigeria (PHCN). Full unbundling and transfer of assets and liabilities were completed on 1st July 2006.

b. Privatization

In 1999, the FGN began an aggressive restructuring of the power sector with several aims, including introduction of efficient, private sector standards and management principles, and methodology, leading to reliable power.

In 2001, the FGN approved a National Electric Power Policy (NEPP), followed in 2005 by the Electric Power Sector Reform (EPSR) Act. EPSR Act provides the legal authority for the unbundling of Nigeria's power utility as well as the introduction of a new, regulatory scheme managed by the Nigerian Electricity Regulatory Commission (NERC), an independent regulatory commission, to guarantee open access and ensure efficiency throughout the industry.

In 2005, Shell Petroleum Development Company (SPDC) made attempts to buy Afam I-IV and V but the negotiations fell through instead SPDC initiated the construction of Afam VI. Outright sale option was adopted by the Bureau for Public Enterprises in the sale of Afam I-V which was culminated on the 1st of November 2013. The new owner is Televeras Ltd.

Fig 1: Afam VI Power Station (IPP)

2.3 Adaptive Neuro-Fuzzy Control System

Neuro-Fuzzy Control (NFC) has been widely used in many control system applications (Barton, 2004). It represents a control approach where fuzzy logic and artificial neural networks are combined. The basic idea of a neuro-fuzzy system is to model a fuzzy logic system by a neural network and apply the learning algorithms developed in the field of neural networks to adapt the parameters of the fuzzy system. An NFC can be defined as a multi-layer network that has the elements and functions of typical fuzzy logic control systems, with additional capability to adjust its parameters via learning techniques [8]. The motive of combining fuzzy logic with neural networks is to take advantage of their strengths and overcome shortcomings. In fact, fuzzy logic systems and neural networks can be considered complementary technologies. In a neuro-fuzzy system, the fuzzy system can be provided by an automatic tuning mechanism without altering its functionality.

2.4 Adaptive Neuro-Identifier

Control systems have played an important role in the advance of modern life and technology. They are found in various applications such as space-vehicle systems, power systems, manufacturing, industrial process, robotic systems and others. The basic concept of a control system is to maintain the conditions of a system at determined values and counteract random disturbances caused by external forces. This can be achieved via a feedback system where a controller senses the operation of a system, compares it against a desired behaviour, computes corrective actions and actuates the system to obtain the desired response. Nonetheless, if the parameters of the controlled system vary over a wide range of operating conditions and are subject to disturbances, the performance of the conventional controller, with constant parameters, cannot provide effective control and its performance will deteriorate. Therefore, it is desirable to develop a controller that has the capability to adjust its parameters according to the environment in which it works to provide satisfactory control performance.

An adaptive control system provides an effective solution for designing controllers applied to systems whose parameters change continuously during operation and no prior knowledge can be obtained of when these changes will take place. By using this type of control scheme, the controller can constantly adapt itself to the current behavior of the system. The adaptive control techniques can be classified as [9]:

i. Direct Adaptive Technique
ii. Indirect Adaptive Technique.

In the direct adaptive approach, known as Model Reference Adaptive Control (MRAC), the difference between the output of the plant and the output of the model, known as plant model error, is used to directly adjust the parameters of the controller in real-time. The adjusting mechanism continues until the plant model error reaches zero. The performance of this technique relies on the determination of a suitable reference model and the derivation of an appropriate learning mechanism. This type of adaptation scheme is described in Fig.2.

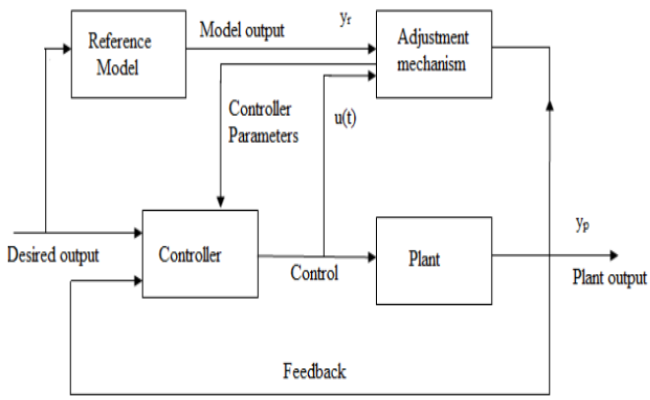

Figure2: Direct adaptive control scheme

3.0 METHODOLOGY

For the 600 MW FFEPU Afam VI Power Station (IPP) considered in this research, a coordinated boiler-turbine control framework was applied. This framework was chosen because of its combined advantages of the boiler-following control framework and turbine-following control framework, making the FFEPU control system faster, more stable, and more responsive to load changes [9]. Shown in Fig. 2, the FFEPU control structure utilizes three basic control modules to implement a coordinated-control structure. These control modules are the following: reference governor, feed-forward controller, and feedback controller. An additional control module called a gain optimizer is included in the overall FFEPU control structure to make system operation more optimal, but the gain optimizer is not necessary to achieve the objectives of coordinated-control. In a coordinated-control framework, set-points are simultaneously provided for the boiler and turbine modules of the FFEPU for a corresponding common unit load demand signal E_{uld}. For the 600 MW FFEPU, the set-points are power demand E_d, pressure demand P_d, re-heater temperature demand RT_d, and super-heater temperature demand ST_d.

The reference governor generates the optimal set-points by solving a multi-objective optimization problem with conflicting requirements such as, load following, fuel conservation, life extension of equipment, reducing pollution, etc. [10]. Through the multi-objective optimization, a set of control actions, which correspond to the different modules of the FFEPU, are also generated.

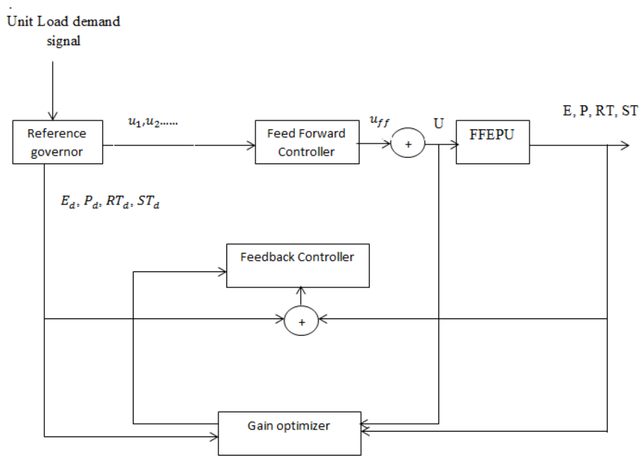

Fig. 3: FFEPU Control Structure.

The full mathematical model extended in [8], and initially developed in [11], is characterized by the following features:

• The model was developed based on actual physical processes with parameters coming from plant manufacturer data on material properties used in the plant.

• System nonlinearities were included to keep the model from being too conservative, thus making the model valid over a greater operating range.

• In order to provide physically realistic thermodynamic properties, steam table property fits were utilized.

• In most existing boiler-turbine models, modeling of the dependence of principal plant components on voltage and frequency is not typically done. This model incorporates such features and explicitly models principal plant auxiliaries, such as fans and pumps along with their induction motors.

• Another incorporation in this model that is not typical of other models is the modeling of feed-water and condensate side dynamics. In normal operations, these dynamics do not significantly affect the system; however, in emergency situations with real power plants, these dynamics can significantly limit the response and operation of the power plant.

• This model was developed from a prototype of an actual current operating power plant so that the model could be verified against actual plant data.

The power plant model used to develop and test the optimized multiobjective control system discussed in this research is a mathematical model of a 160 MW oil-fired drum-type boiler-turbine-generator unit, a detailed formulation of which can be found in [12]. It is modeled as a third-order three-input three-output nonlinear model. The inputs to the system are positions of valve actuators that control the mass flow of fuel (represented as $u1$ in per unit), steam to the turbine ($u2$ in per unit), and feedwater to the drum ($u3$ in per unit). The outputs are electric power generated by the plant (E in MW), drum steam pressure (P in kg/cm2), and drum water-level deviation (L in meters). The resulting state variables are electric power (E), drum steam pressure (P), and steam-water density (ρf). The dynamic equations for the third-order model were developed by Bell and Åström in [12] and are as follows:

$$\frac{dE}{dt} = ((0.73u_2 - 0.16)P^{\frac{9}{8}} - E)\,/10 \qquad (1a)$$

$$\frac{dP}{dt} = 0.9u_1 - 0.018u_2P^{\frac{9}{8}} - 0.15u_3 \qquad (1b)$$

$$\frac{d_{p_f}}{dt} = (141u_3 - (1.1u_2 - 0.19u_1)P)/85 \qquad (1c)$$

The drum water level deviation from a fixed, drum-specific setpoint is calculated from the solution for ρf in equation (1c) in conjunction with the algebraic equations below:

$$q_e = 45.59166u_1 + (0.8537u_2 - 0.14746)\text{p} - 2.51431u_3 - 2.0958 \quad (2a)$$

$$\alpha_s = \frac{(1/p_f - 0.00154)}{(1/(0.8P - 25.6) - 0.00154)} \quad (2b)$$

$$L = 6.3565u_1 + 3000\alpha_s + 5.5556q_e - 3275 \quad (2c)$$

where qe is the evaporation rate (kg/s) of water in the boiler and αs is the steam quality.

Values for the control valve positions are represented by values on [0,1], 0 representing a completely closed valve and 1 representing a completely open valve, and have rates of change limited as shown below, as determined in [13]:

$$-0.007 \le d_{u_1}/dt \le 0.007 \quad (3a)$$

$$-2.0 \le d_{u_2}/dt \le 0.02 \quad (3b)$$

$$-0.05 \le d_{u_3}/dt \le 0.05 \quad (3c)$$

Steady-state equations for this power plant model are obtained by setting the dynamic equations in (2) to zero and solving for $u1$, $u2$, and $u3$. This result gives an inverse steady-state model of the dynamic equations, shown below, consisting of only algebraic equations:

$$u_1 = \frac{0.018u_2P^{9/8} - 0.15u_3}{0.9} \quad (4a)$$

$$u_2 = \frac{0.16P^{9/8} + E}{0.73P^{9/8}} \quad (4b)$$

$$u_3 = \frac{(1.1u_2 - 0.19)P}{141} \quad (4c)$$

Similarly, the steady-state electric power and drum steam pressure can be calculated from the control valve positions by solving (4) for E and P, whose result is shown below:

$$E = \frac{0.73u_2 - 0.16}{0.0018u_2}(0.9u_1 - 0.15u_3) \quad (5a)$$

$$P = \frac{141u_3}{(1.1u_2 - 0.19)} \quad (5b)$$

The above equations are used to model the power plant in software by calculating initial conditions for E, P, L and ρf, and continually solving the equations in (1) and (2) for a specified time-step. The equations in (1) are solved using an ordinary differential equation solver, followed by the straightforward calculation of the equations in (2).

Control of the power plant is simulated by calculating the input values, $u1$, $u2$, and $u3$ using the described control system implemented in software.

The multi objective optimization problem of the FFPU is to find an optimal solution in the solution space that minimizes the load tracking error, fuel usage, and throttling losses in the main steam and feed water control valves [13]. Therefore, the following objective functions can be described for minimization:

$$J_1(u) = |E_{uld} - E_{ss}| \quad (6a)$$

$$J_2(u) = u_1 \quad (6b)$$

$$J_3(u) = -u_2 \quad (6c)$$

$$J_4(u) = -u_3 \quad (6d)$$

where E_{uld} is the unit load demand (MW), and E_{ss} is the corresponding generation (MW) as provided by the steady-state equation:

$$E_{ss} = ((0.73u_2 - 0.16)/0.0018u_2)(0.9u_1 - 0.15u_3) \quad (7)$$

The objective functions are described as following:

$J_1(u)$ accounts for the power generation error, $J_2(u)$accounts for fuel consumption through the fuel valve position, and $J_3(u)$ accounts for energy loss due to pressure drop across the steam valve. Since the pressure drop increases as the valve closes, it is desired to keep it open as wide as possible, thus it is desired to maximize u_2 , or equivalently minimize $-u_2$. Similarly, $J_4(u)$ accounts for energy loss due to the pressure drop in the feedwater control valve. Thus, the multi objective optimization is to be performed to minimize all objective functions defined above under a given set of preference.

4.0 RESULTS AND DISCUSSION

To test whether or not the ANFIS is capable of accurately modeling the equations in (4), and therefore able to produce an accurate optimization result when using a ANFIS in place of the equations, both the equation model and the ANFIS model were implemented in set point optimizations performed for power demand levels from 10 MW to 180 MW in increments of 5 MW. Each test performed used the optimization parameters. To give a quantifiable result, the mean-squared and maximum error of the difference in setpoints generated by the two methods, shown in Fig. 4, are given for each control variable in Table 1.

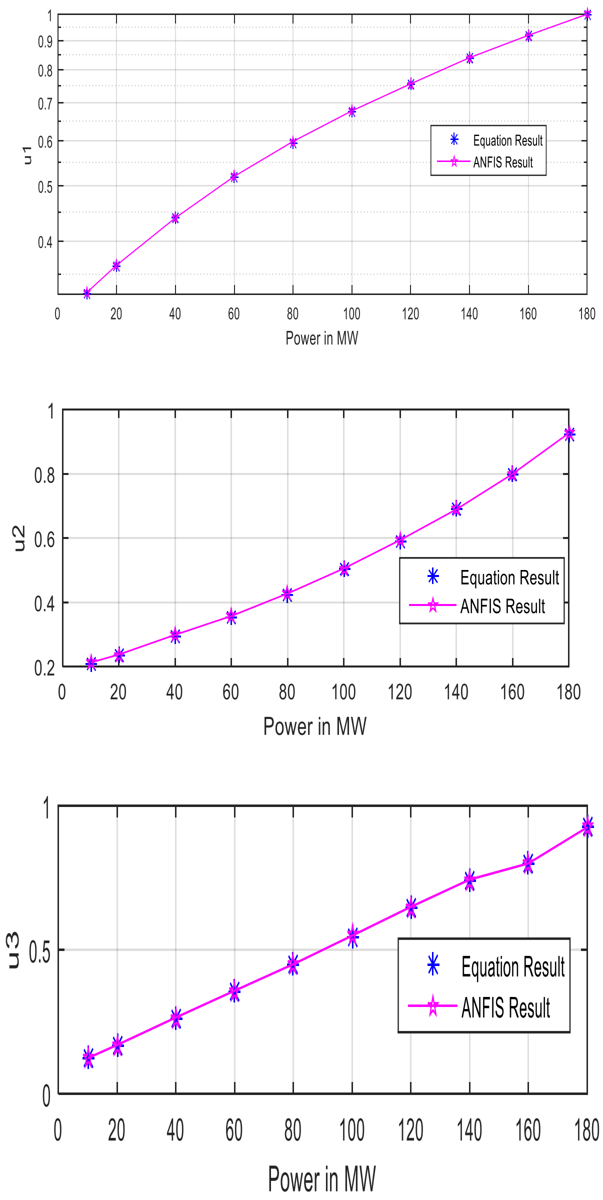

Fig. 4: The result of setpoint optimization performed comparing the equation model with the ANFIS

Table 1: The mean-squared and maximum error of the difference in setpoints generated by the setpoint optimization using the equation and ANFIS models.

	$u1$	$u2$	$u3$
MSE($u$eq-$u$nn)	2.6013e-16	1.0594e-12	2.3694e-14
max(|$u$eq-$u$nn |)	1.1315e-11	4.3260e-6	1.1159e-7

5.0 CONCLUSION

The agents developed to implement the control system are the Feed forward agent, Feedback agent, Gain Optimizer agent, Neural Network agent, Interface agent, Monitoring agent and Free agent. These agents were developed and individually tested by performing various experiments, the results of which were analyzed for agent performance. The agents were also implemented in coordination and tested by using the Neuro-fuzzy Network to control a 160 MW FFPU model and analyzed the results.

The Feed forward agent was developed to implement an optimal reference governor that provides customizable coordinated control (CC) by optimizing control set points according to prioritized operating objectives that can be changed online. This agent uses a feed forward artificial neural network (ANN) model to evaluate the performance of the optimal set points to determine the optimal references. Each of the operating objective functions was tested to confirm that they had the desired effect on the set point optimization results. Because these tests were successful, it was shown that the set point optimization can be successfully used to optimize control set points according to programmed operating objectives. Also, the Neuro-Fuzzy model is shown to accurately represent the steady-state equations by producing the same result when used in the optimization.

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