
Intelligent Fault Recovery Controller for Power Generator at Perdawd CCGS in Kurdistan-Iraq

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ABSTRACT

Different Artificial Intelligent (AI) tools are becoming commonly used to design different intelligent controllers. The objective of this work is to investigate the performance of a suggested intelligent controller of a specific power generation system during and after sudden faults. Two types of AI tools, genetic algorithms and adaptive neuro-fuzzy inference system, have been used in this work to design a control unit for the power station mentioned above as a case study. Simulated models were designed to optimize the control parameters to enhance the performance. A wide range of training data pairs was used to train the controllers and then to test the system performance. A comparison between the performance of the intelligent and conventional controllers has been introduced. The simulation results show a clear prove that the intelligent controller is outperform the classical one especially during the fault recovery time. Damping performance, oscillation, the system stability and the dynamic performance of electrical power system have been studied.

1. INTRODUCTION

Most of the complex control problems cannot be solved by using conventional techniques. Modern intelligent tools are adopted to simplify these complex problems and design more robust controllers using what is known as a Computational Intelligence (CI) [1].

During the last few decades, many researches have studied and applied different Artificial Intelligence (AI) techniques as the most popular methods in Heuristic optimization techniques. There is a growing interest in using AI tools in various fields' electrical power and power generation plants such as using the AI techniques to design a hybrid control systems which integrate the conventional (mathematical approaches) together the intelligent tools in controlling the performance of different electrical power systems. [2, 3]

There are many AI techniques that aimed to compute the optimal or near optimal solutions for different optimization problems such as: Artificial Neural Network (ANN), expert system (ES), Evolutionary Computation (EC), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant colony Optimization, Fuzzy logic and others. Many of these techniques are used to find the optimal working parameters of power control systems, excitation systems and power system stabilizer (PSS) [4-7].

2. ARTIFICIAL INTELLIGENT TECHNIQUES

2.1. GENETIC ALGORITHM

GA is based on the Darwinian principles of inheriting and evolving the best offspring's features which can be used as a search method in finding the optimization and best fit global or parallel solution.

Genetic algorithms operate on a population of potentially huge search spaces that applying the principle of survival of the fittest to look for optimal aggregation of better and better approximations to a solution. [8]

The standard GAs can be implemented through a coding that represents the parameters or variables and select the best criteria for reproduction, recombination (crossover) and mutation. The initial set of chromosomes is representing the initial and each chromosomes is composed of many genes which represent given measures of each single variable. A fitness function (objective function) is normally used to transform the search problem into a minimization problem with which we should find nearest fit (or exact fit in some cases) to the optimal solution or performance [9, 10]:

$$F(x) = g(f(x)) \quad (1)$$

Where:

f , is the objective function;

g , transforms the value of the objective function to a non-negative number;

F , is the resulting relative fitness.

A simple GA can be represented as follows:

- Create a population (string of chromosomes)
- Evaluate a population through fitness factor
- Check the solution if optimum:
 - Reproduction (Selection);
 - Crossover;
 - Mutation;
- Generate a new offspring

The basic elements of a genetic algorithm consist of three types of operators:

Selection: randomly selecting chromosomes from the available the population in order to carry out reproduction operation. Chromosomes are allocated specific priorities proportional to their fitness and thus the fittest individuals are selected as the best chromosomes (solution).

Crossover: the specific or randomly chosen point within the chromosome to exchange between two chromosomes in order to create two offspring (next generation). After that the new string is subjected to a specific probability of mutation operation.

Mutation: is used to avoid a deadlock or falling in a local minimum point which might lead a non-accurate solution. The importance of this operation is extracted to maintain variety in population through performing a gene or bit-wise process.

The below diagram illustrates the whole cycle of the GA operation:

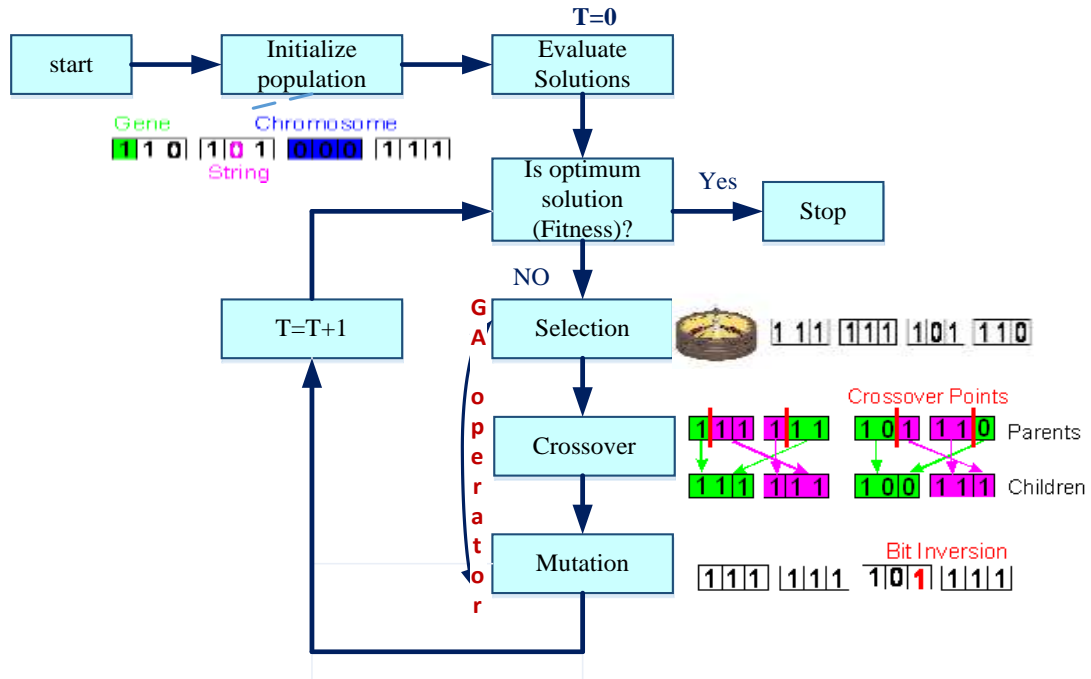


FIGURE 1. A simple cycle of Genetic Algorithm

In this work, an initial population of randomly selected chromosomes have been represented to simulate the variables of the power plant control unit. The chromosome's representation is used to describe the structures and value of each of the addressed variables. Each individual or chromosome that mapped the variables of control unit is made up from a binary strings (0's, 1's). A suitable fitness function was designed to measure the outcome fitness after each iteration or new generation. A good objective function is a core issue in determining the best solution for the addressed control problem. The optimization solution here can be defined as following:

$$F(x)_{Max} : x_{min} \leq x \leq x_{max}; \tag{2}$$

Where x is a parameter of genetic algorithm which must be design.

2.2. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

Adaptive Neural network based fuzzy inference system is a type of artificial neural network which is based on Takagi-Sugeno fuzzy inference system. ANFIS was presented in the early 1990 from Wang, since, it's combined both neural networks and fuzzy logic principle and convened the benefits of both in a one framework [11].

ANFIS is a hybrid learning techniques which uses back propagation training algorithm during the initial training section to optimize the parameters of fuzzy system. Three types of membership functions are usually used to implement ANFIS, these three types are: membership function, Gaussian, generalized bell and sigmoid. Each input variable of fuzzy inference system can have an arbitrary number and mix of these membership functions.

In this work, the first order Sugeno system with two fuzzy IF-THEN rule has been implemented as follows: [12, 13].

Rule 1: if x is A₁ and y is B₁ then f₁= p₁x+q₁y+r₁

Rule 2: if x is A₂ and y is B₂ then f₂= p₂x+q₂y+r₂ (3)

Where: A_1, A_2, B_1, B_2 , are membership functions for inputs (x, y) , and $(p_1, q_1, r_1), (p_2, q_2, r_2)$ are the parameters of output functions. The architecture of ANFIS can be represented as shown in figure (2).

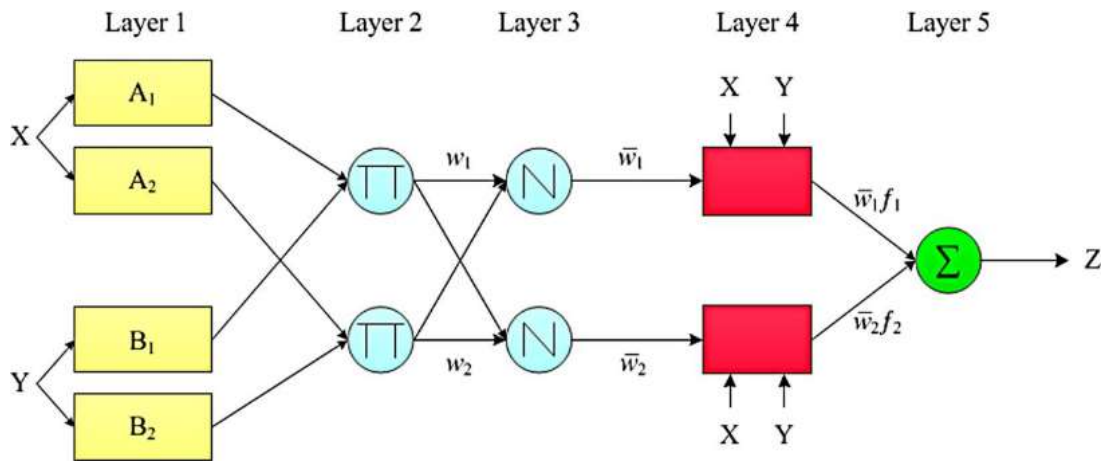


FIGURE 1. A simple cycle of Genetic Algorithm

A set of numerical data consisting of an input–output space is usually used to construct a neuro-fuzzy system. The construction of the system involves two essential phases:

- (I) Optimization of the structure or structure learning phase and
- (II) The parameter learning phase.

The partitioning of input–output space is a technique used to form and visualize the mapping relation of fuzzy rules and explain how the fuzzy rules are related to the input space. The structure and the number of fuzzy rules are influenced by the partitioning techniques. The most common partitioning method is grid-type partitioning and clustering. Figures 3 and 4 illustrate the input-output space partitioning[14].

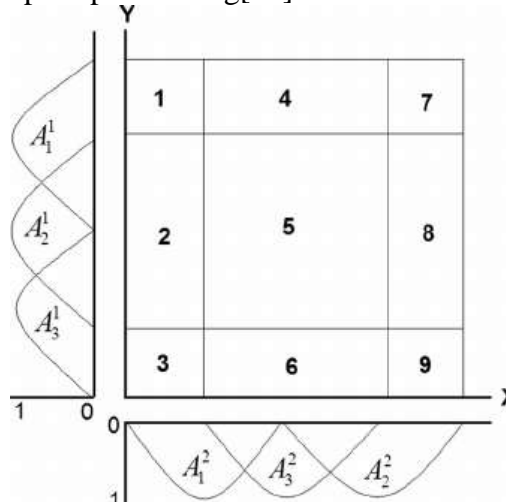
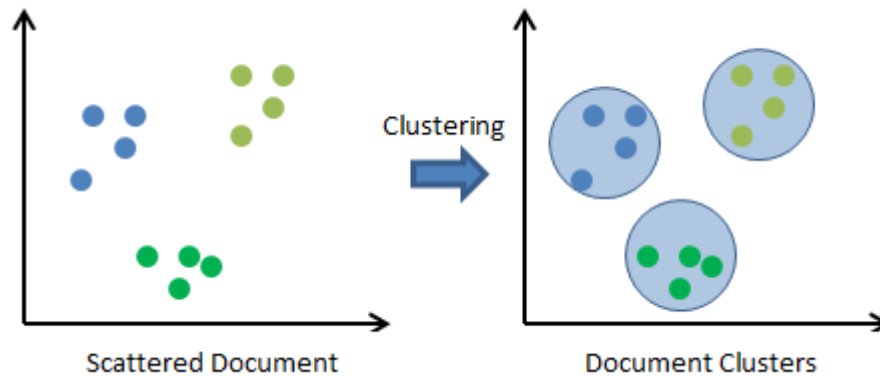


FIGURE 3. Grid type partition.**FIGURE 4. Clustering based partitioning.**

3. APPLY AI FOR ENHANCING THE DYNAMIC STABILITY OF ELECTRICAL POWER SYSTEM

Case study of this work is the Perdawd Combined Cycle Gas Station (PCCGS). The Kurdistan Regional Power System of Iraq (KRPS) comprises two hydro power stations, Dokan (400 MVA) and Darbandikhan (249 MVA) in addition to two gas stations cited at Perdawood (500 MVA) and Chamchamal (750 MVA). Another two more gas stations are under construction in Duhok (200 MVA) and TaqTaq(200 MVA). The four gas stations are private sector investments. Currently, KRPS uses 35 load nodes at 132 kV substation ends totaling 2202 MW. The system serves five million population in an area of 80,000 square km[15].

3.1. THE MODEL OF PCCGS

A two axis nonlinear machine model is representing the generator of the suggested case study (Perdawd CCGS). The control unit of power station is implemented through excitation system, type IEEE ST1A, and power system stabilizer, type conventional Lead/Lag (CPSS). The electrical part of Perdawd CCGS is modeled by Simulink tools of using MatLab software program as shown in figure (5).

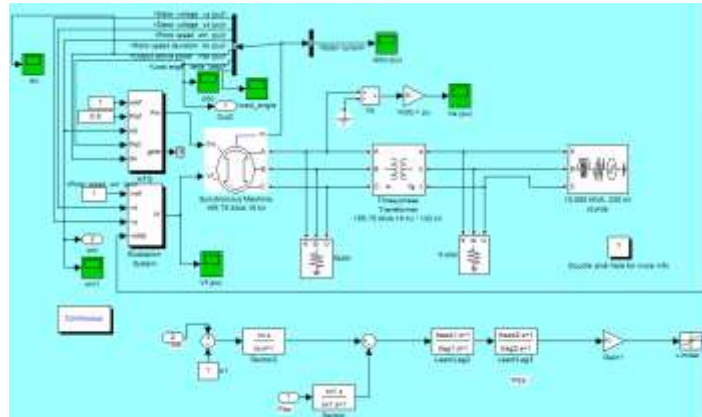


Figure.5. model of Perdawd CCGS at Simulink\Matlab

3.2. TUNING PARAMETERS OF THE CONTROL UNIT USING GA

The objective is to optimize the key parameters of control unit (exciter and CPSS) using the genetic algorithms in order to reduce the angular speed oscillation (ω) and the load angle (δ) at minimum values with best settling time for transient state for the suggested case study under any possible sudden disturbance.

3.2.1. Fitness function

It's used to provide an index of how the best solution is achieved in the problem search space, can be seen as a minimization problem. The multi –objective function of our case study is characterized such as:

$$\text{Minimum } J \text{ for CPSS and exciter parameters} = \sum (WJ);$$

Where J is defined as a sum of square error which is represented the disparity between desired and real value of variables (terminal voltage of exciter (vt), rotor speed (ωm) and settling time (ts)).

$$J_1 = (vt_{desired} - vt_{real})^2 \tag{4}$$

$$J_2 = (\omega m_{desired} - \omega m_{real})^2 \tag{5}$$

$$J_3 = (ts_{desired} - ts_{real})^2 \tag{6}$$

The weight coefficients (W) are employed to include the effective weight or the importance of each individual parameter in the objective functions.

Based on the evaluation of fitness function at nominal operating of power station and randomly initialization generation of individuals, the genetic algorithm will produce a new version of population in a process which should continue until convergence is accomplished.

TABLE 1.

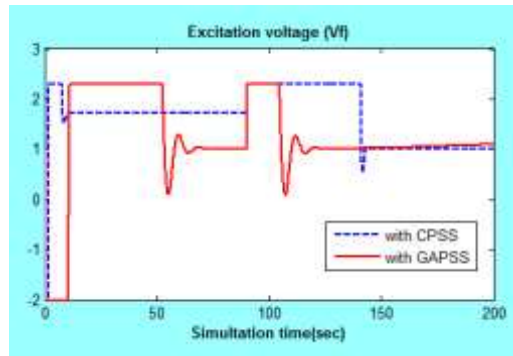
Genetic algorithm variables for case study

Mutation Rate, % μ	0.8
Population Size, N _{pop}	20
Number Of Variables	13
Maxi. Gen.	250
Gen. Gap	0.75
Precision	20

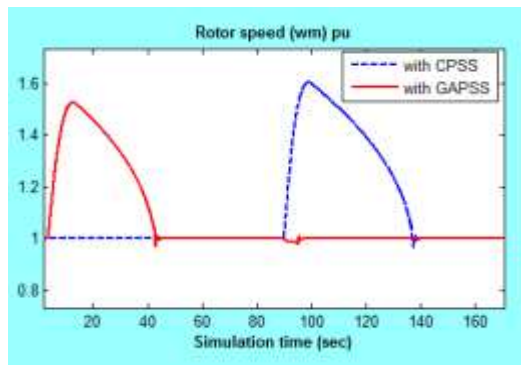
3.2.2. Simulation Analysis

High value of crossover and mutation rates were used in the proposed simulation method in this simulation to help find the best choice of PSS and Exciter parameters which can guarantee speedy converges of GA. Matlab software program is used to simulate the power station model under disturbance (three phase fault) at nominal operation of station. The performance of the control unit (under different parameter values) has been evaluated for both situation (Conventional and GA based controllers) and it is clearly proving how the GA based control system is outperforming the conventional one especially when recovering a faulty operation. The CG based controller is also better than the classical control unit in reducing oscillation and increasing the cleaning of critical time.

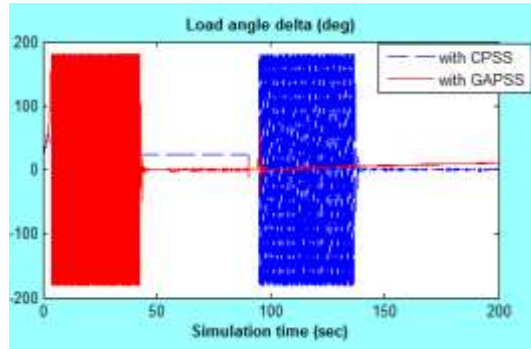
Figure 6 illustrates the dynamic response of station studied at classical control, and with genetic control.



a



b



c

FIGURE. 6. Simulation of power station with GA for three situations: (a) exciter voltage v_f , (b) speed of rotor, ω_m , (c) the load angle delta ($\Delta \delta$)

3.3. ENHANCING THE CONTROLLER DYNAMIC STABILITY USING ANFIS-GRID

The core of the proposed ANFIS based controller is designed using fuzzy linear model type Sugeno which converts a fuzzy inference engine into an adaptive network which is used to train the pairs of inputs, dedicated by both factors, the operating conditions and parameters of excitation system (T_{lead} , T_{lag} , $K=f(k_1, k_2)$, T_i , K_F , T_F), consequently with outputs, implemented by the parameters of PSS (K_{pss} , T_w , T_{w1} , $T_{Lead1,2,3}$, $T_{Lag1,2,3}$). 1600 samples of training input–output data pairs are used to train the ANFIS based power station control unit. It's worth noted that, these pairs of data are partitioned in two sets, one for training set which is used as a training data and the other is to system testing to evaluate performance of ANFIS during a validation state [16].

In this study, three membership functions (MFs) are assigned to each variable, and the desired network has 751 fuzzy rules as shown in figure 7. The training algorithm is implemented on the PSS parameters of studied station. The raining process of ANFISGRID network has consumed (50200 sec) of CPU time for each parameter of PSS

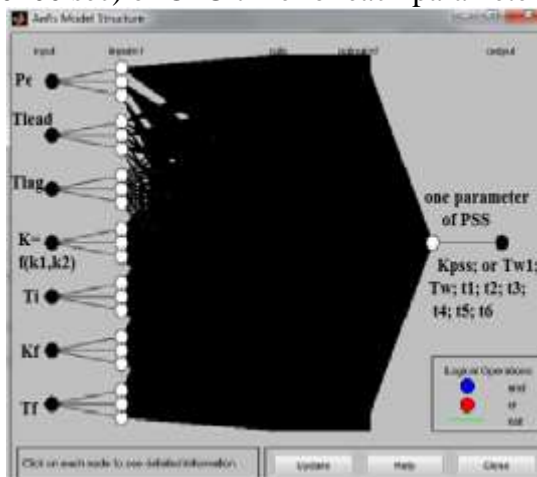


FIGURE.7. The ANFISGRID structure for station studied

3.3.1. SIMULATION ANALYSIS

Time domain simulations with ANFIS-PSS has been simulated for Perdawd CCGS under three-phase fault (5-cycle of simulation time) at nominal loading conditions. MATLAB\Simulink has been used to run the analysis and evaluate the performance. Figure 8 illustrates the dynamic response of station studied with CPSS, and with adaptive PSS (ANFIS-PSS).

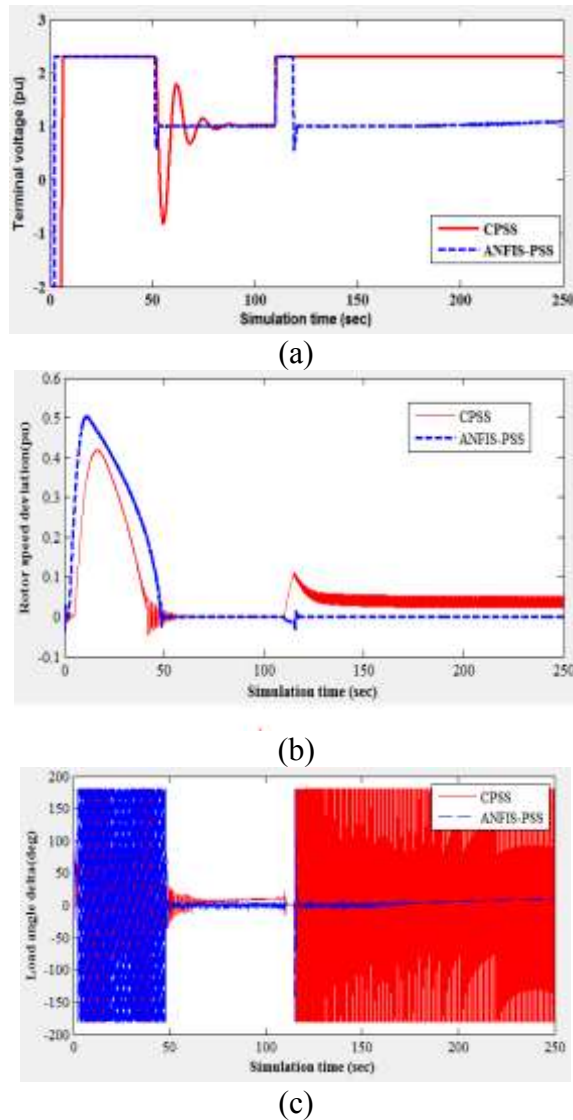


FIGURE. 8. Simulation of power station with ANFIS for three situations : (a) Exciter voltage v_f , (b) speed of rotor, ω_m , (c) the load angle delta ($\Delta \delta$)

4. DISCUSSION AND CONCLUSION

A case study analysis has been carried out on Perdawd CCGS power generator controller when it was at transient state. The simulation result shows that a high oscillation and instability of voltage is detected in response to a faulty situation as shown in the above figures. Conversely, the efficiency of the GA based controller is verified and the evolved values of the optimal control unit parameters have led to reduce the oscillation and increase

the ability to produce better damping over a wide operating range and enhances the performance of the power station. It has been noticed that the response of the system studied with CPSS is unstable at external voltage ($V_f = 1$ pu) during the disturbance, could cause to melting. While, the dynamic stability of system studied enhances and stability by using adaptive power system ANFIS-PSS. Also, the critical clearing time (CCT) of the control system at CPSS is very high compared with other situation (ANFIS-PSS) that is equal (35 sec).

As a general conclusion, it is confirmed that the outcome of the intelligent controller is much better than the classical (conventional) controller from different point of views. Adding intelligent component to the controller has contributed to reduce the oscillation of power signal when fault occurs, increase capability to recover on critical time of instability and return the situation of the power signal to stability extremely when exposing fault tolerance to the power station

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