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Controlling of Wind Turbine Generator System based on Genetic Fuzzy-PID Controller

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ABSTRACT

In this research, Genetic Algorithm (GA) was used as a feasible solution for optimization/tuning of a simulated Fuzzy Proportional Integral Derivative (FPID) controller for a variable speed wind turbines (WTs). The aim of this research is to tune the membership function (MF) of a FPID controller using genetic programming and investigating the performance of the system. Firstly, Mamdani's Fuzzy Inference System (FIS) is implemented to control the WTs. The MF is encoded to formulate the chromosome by choosing some parameters like centre and left-right base, and then a proper fitness function is designed to minimize mean square error. Finally, the GA is applied and simulated on MATLAB by choosing different number of generation. The GA works by slowly "evolving" a population of chromosomes that represent better and better solutions to the problem. The simulation results show that the proposed method, Genetic FPID (GFPID), has better performance compared to the other controlling techniques discussed in this paper. GFPID system has better transient response and steady state response than the other systems with lower value of overshoot and steady state error.

Key words: Fuzzy Logic, Genetic Algorithm, PID controller, Wind Turbine

1. INTRODUCTION

Wind energy is one of the fastest growing energy resources and it has a significant contribution in the energy sources. In the last thirty years, the wind energy production and the installed wind turbine systems (WTS) worldwide has been increased dramatically. Accordingly, the research work related to the WTS has grown to develop the static and dynamic behavior of the WTs. The main features of the WTs are the steady state, dynamic behavior, and transient responses. Different methods in literature have been achieved to develop the static and dynamic responses of WTs.

The installed capacity of WTs has an enormous growth in recent years. At the end of 2013 the total capacity worldwide has come close to 318.1 Giga-Watts, which is enough to provide 3% of the world's electricity requirement [1].

Controlling complex and non-linear systems is a serious task. Various techniques have been utilized to deal with non-linearity, Proportional Integral Derivative (PID) is a popular controller that is widely used in industrial applications. PID controllers are suitable to control linear systems and have relatively lower cost, more flexibility, and easier to apply to many applications than other methods. However, non-linearity in many applications limits it's using.

The advantages of PID controllers include its simple structure, and robust performance for a wide range of operating environment, moreover, the methods used to tune the PID gains are extensively developed and accurate [2], [40], [41], and [42]. This makes the PID controller one of the most favored control methods. Nevertheless, PID controller design needs exact knowledge about the system which is usually based on some assumptions. These assumptions are generally collected from specific information and factors to develop a certain model to the system. Factors may include friction, backlash, dynamic behavior, and noise or disturbance arising from any of the sources [3].

Recently, research studies have been increasingly interested in the employment of new control techniques such as Neural Networks (NN), Fuzzy Logic (FL), Genetic Algorithm (GA), …, etc. These techniques do not require any mathematical model of the system; Neural Network (NN) needs input-output relations only, while Fuzzy Logic (FL) is based on the expert knowledge and human reasoning to establish the rules (e.g., [4], [5], [6], [7]).

Fuzzy Logic Controller (FLC) has two main parts: the database (Membership Functions (MFs)), and rule-base [4]. Trial and error method is commonly used in optimizing the knowledge base component in order to develop tuned and stable fuzzy controllers [7].

Genetic Algorithms (GAs) offer a powerful method for the optimizing/learning tasks in control systems. GAs are numerical search methods that is based on principles of selection and genetics and evolutionary theory. GAs applied in many fields and has successfully found solutions for such problems. GAs are considered as optimization tools. However, it can be successfully applied in learning tasks [8].

Fuzzy Logic (FL) has been utilized for control systems due to its ability to solve difficult non-linear control problems, low cost-benefit, provided robust characteristic, and high performance system. Fuzzy systems are easy to implement because of using rules that are based on fuzzy linguistic terms, which come from the human reasoning and depend on the expert knowledge [7]. Although it is easy to describe expert knowledge with fuzzy linguistic terms, it is not easy to find its membership functions. Therefore, several methods for automatic fuzzy system design were used such as automatic methods using neural networks, fuzzy clustering, gradient methods, or as in this research GA is used (e.g., [3]- [6]).

The Organization of this paper is as follows: Section 2 presents a literature review related to this paper. Section 3 presents the objectives, the algorithm of the methodology, and the contributions of this research. Section 4 provides the mathematical modeling and explains the wind turbine generator system. Section 5 explains the control system, and illustrates the controllers in details; PID controller, Fuzzy-PD controller, Fuzzy-PID controller, and the integration between the GAs and Fuzzy systems in control system. Section 6 presents the simulation results and analysis for each system, investigates the performance of the system, and identifies the difference between the systems under investigation to choose the best model. Section 7 studies the stability of the controlled model. Finally, Section 8 discusses the findings of the paper and provides a brief conclusion.

2. LITERATURE REVIEW

FC is the application of FL to control systems design [9]. FL was pioneered by Lotfi Zadeh [10] in 1965 to represent imprecision and uncertainty (i.e., "fuzziness"), FL combines human brains and computers to deal with uncertainties, and vagueness. The human brain can deal with uncertainties, and vagueness. Computers can make precise computations.

FL system can be represented by a Boolean logic theory. Uncertainty, vagueness, and imprecision in FL are equivalent to the non-linearity mainly caused by noise and disturbances [4].

GAs are numerical search mechanism especially used to solve search and/or optimization problems and based upon the natural selection mechanism [11] and [12]. Introduced in the 1970's by John Holland at the University of Michigan [8], GAs works by the idea of "survival of the fittest will win", by randomly searching on sequential generations to find the best solution [8], [11] and [12]. GAs has been successfully employed to solve optimizing/learning problems without the need to know prior information about the system [11]. The main operations of a GA are: selection, crossover, and mutation [8]. GA is a stochastic, discrete and nonlinear method, which works without using any mathematical model. Therefore, the parameters can be empirically evaluated [11].

GAs can be used along with FLC as an optimization tool; to optimize the rule-base [13], MFs [14], or knowledge base (For both rule-base and MFs) [15] and [14]. For the rule-base optimization techniques, there are three different approaches for the population: Pittsburgh, Michigan and Iterative Rule.

In GAs, the termination condition is achieved by a number of generations, amount of change in each individual in the population in each generation, predefined time limit, or predefined fitness function (objective value) [8]. A fitness function is usually used to determine the degree of goodness in a GA population for the optimization task [15]. For the PID-FLC, there are many fitness functions that have been successfully used which aim to reduce a certain characteristic of the system response like the mean square error (MSE) [15], integral of absolute error (IAE), integral of time multiplied by square error (ITSE), integral of time multiplied by absolute error (ITAE), or integral square error (ISE) [8], therefore fitness functions determine the performance of the system and the termination condition. Thus, a suitable fitness function must be selected. The GA in each generation evaluates the fitness value using the objective function to determine the performance of each individual in the population [13] and [16]. The best individuals are taken to the next generation while individuals with poor performance are removed. The operation continues until the optimal solution is achieved.

GAs have been strongly used in optimization and non-linear system, but they perform weak in learning and real-time operation. The integration of GA and fuzzy systems, neural networks (ANN), or another Artificial Intelligent (AI) system to create hybrid systems, will enhance the ability of GA system [17].

Many studies in literature have implemented GAs for optimizing/learning FLCs. For example, Lee and Takagi [18] applied GAs to optimize a rule-base of a FLC, while Herrera et al., [19] utilized GAs to determine the number of MFs, and the number of rules. In all these methods, GA is applied using real-valued encodings.

There are many studies on WT control. The most important contributions related to this research effort are discussed now.

Galdi et al. [20], studied the maximum extractable power from a variable speed WT by designing an adaptive controller using Takagi–Sugeno–Kang (TSK) fuzzy controller method, the system has a capability for learning. Clustering methods were used for partitioning the input-output space then combined with GA to form a hybrid system, and recursive least-squares (LS) optimization methods for model parameter adaptation. This method doesn't need an accurate model to be applied, since it had been continuously optimized its internal parameters in order to balance the non-linearity and time variances of the system under control. Fuzzy controller in this paper was found to be more powerful compared to the older methods.

Qi and Meng [21], a Fuzzy-PID controller was used to control the generator speed and the blade pitch angle. Fuzzy controller was used to improve the system's response and minimize the overshoot during the transient period. The PID controller was used during the steady-state period, by adjusting the proportional, differential, integral parameters of the controller to keep the steady-state error at the minimum. Fuzzy and PID controllers were integrated. Since Fuzzy controller has the advantage of fast dynamic response, robustness, etc. and so is suitable to nonlinear multivariable systems. Fuzzy controller is equivalent to a nonlinear PD controller and used to achieve system's rapid response. PID control system has been used for integral portion to reduce the steady-state error ccompared to the system with the classical PI controller, the response and the accuracy of the system are better.

Belghazi and Cherkaoui [22], the genetic algorithm control strategy was used to deal with the strong non-linearity. The main objective of this work is the optimization of power production with simultaneous load reduction of the main WT components and adapts control with respect to real operational conditions. The generator speed has been controlled in order to reach the desired speed and allowing the extraction of the maximum power from the turbine. When the wind speed changes, this designed controller can achieve constant output power and constant rotation speed of WTs.

Donha and Risso [23], this work is concerned with the tuning of a classical PID controller used to optimize the electrical energy production. GA is used to make automatic tuning for a PID controller. This algorithm is used to generate a huge number of possible solutions for the three gains of the controller, which is then evaluated and selected by the optimization of a performance index to find the most suitable solutions.

3. OBJECTIVES AND MAIN METHODOLOGY

This paper uses an algorithm to control a WTS by using an Artificial Intelligent (AI) technique which makes with a PID controller an adaptive system. This algorithm is utilized to overcome the nonlinearity in WTSs. The main objectives of this paper are to:

- Find an appropriate model for the research for a variable speed WT with a DFIG.
- Make a model for the aerodynamic, mechanical and electrical components of a variable speed WT with DFIG using MATLAB/SIMULINK software package.
- Develop a controller for the main parameters in WT control system. The primarily two parameters which have a great interest in this research are the generator torque and blade pitch control systems.
- Simulation of the blade pitch angle controller in MATLAB software package.

Different cases are going to be examined and compared such as:

- The classical PID controller.
- The old type Fuzzy-PD controller.
- The Genetic Fuzzy-PD controller.
- The Self-tuning Fuzzy-PID controller.
- The new method which is developed in this paper based on Self-Tuning Genetic Fuzzy-PID controller.

The main approach of this paper can be summarized as in the following steps. Firstly, the model of the WT is chosen. Then the appropriate transfer function (TF) for the system and the PID controller was used. Then, Mamdani's FIS is implemented to control the selected WT, a triangular MFs is used for the inputs and the outputs. These MF's are encoded to formulate the chromosomes by choosing some parameters like center and left-right base. Then, a proper fitness function is designed to minimize the MSE. And finally, the GA is applied and simulated on MATLAB by choosing different number of generations. [24].

This research presents a new method to improve the performance of wind turbine generator systems (WTGSs). FLC is used to adjust the PID parameters by using Self-tuning Fuzzy-PID controller which is an adaptive system compared with the other two types, i.e., classical PID and Fuzzy-PID. A fuzzy auto-tuning-PID controller for the WTGSs is designed, where a simple approach to tune parameters of the Fuzzy-PID controller is developed.

The goal of the Genetic Fuzzy-PID controller is to tune the parameters of PID controller on-line by using an adaptive FLC by utilizing fuzzy control rules. The controller uses the error *(e)* and the rate of change of error *(e')* as its inputs. The PID controller law can be written as [25]:

$$u(t) = K_p\left[e(t) + T_d\frac{de(t)}{dt} + \frac{1}{T_i}\int_0^t e(t)\, d(t)\right] \tag{1}$$

where $u(t)$ is the control variable, $e(t)$ is the system error, K_p is the proportional gain (controller gain), T_d is the derivative time constant, T_i is the integral time constant.

In this design, the main structure of the PID controller is kept without any modification in the control loop, since this method aims to improve the performance and response of the original PID controller. The three parameters of PID are tuned by forming the fuzzy control rule from error *(e)* and the rate of change of error *(e')* and its relation with these parameters.

Unlike the previous techniques, the proposed method does not rely on Ziegler-Nichols method. Instead, it uses Mamdani's Fuzzy systems as the tuning-tool for each of the PID parameters, and a genetic algorithm is used to adjust the parameters of the fuzzy systems, i.e., the shape of membership functions, whereas genetic algorithms are used to optimize the PID parameters in the previous literature.

4. WIND TURBINE SYSTEM

The average size of utility-scale wind turbines has grown extremely in the last 30 years The diameters of wind turbine has become from 15m in 1980 to above 126m nowadays. The new WTs became large, more flexible, operating in several environments like onshore, or offshore, and need to advanced control solutions.

The main purpose of any new controller is to reduce the cost of wind energy by increasing the performance and efficiency of the overall system including the wind turbine and it's generator, and improving the design of the structure to increase the energy extracted or by minimizing structural loading and increasing the lifetime of the parts and turbine structures [26].

4.1 Wind Turbine Basics

WTs come in two types: vertical-axis and horizontal-axis combinations. Horizontal-axis wind turbines (HAWTs) are the most commonly used utility-scale WTs recently. In HAWTs the whole rotor is placed above a tall tower, where it can extract more wind energy than VAWTs because the wind speeds are higher as the height above the ground increased. VAWTs are commonly used for smaller turbines, when these advantages are important in HAWTs is become less important in VAWTs and the advantage of this design to reduce noise appears [26] and [27].

One of the advantages for using VAWTs that the heavy parts such as generators are placed on the ground, so it will spin more freely. Horizontal-axis turbines are usually located on tall towers to extract the largest amount of wind energy as the level above the ground increase [28]. The modern wind turbines can generate from less than 1 kilowatt (kW) to more than 5 MW [29]. The main parts of HAWTs are Tower, Nacelle, and Rotor.

The generator is driven by high speed shaft. The gear box is connected with a high speed shaft which converts the torque from the rotor to a high speed to run the generator. The high speed shaft is connected to the generator. The rotor has the airfoil shaped blades. These blades gather the wind energy and convert it into the rotational kinetic energy of the wind turbine [26], [29] and [30].

WT control has two categories: variable pitch or fixed pitch. The variable pitch-able is able to rotate along its longitudinal axis while the fixed remains fixed about its longitudinal axis. Furthermore, the wind turbines can be classified as a variable speed generator or fixed speed generator [30].

4.2 Wind Turbine Modeling

Modeling is an important part for system analysis and control. The energy conversion in WTGSs is very different from ordinary generators. Modeling the WTGS is achieved by finding the relationships between each subsystem, and then integrating the wind power into the power system.

Conventional WTGSs include the following main parts: wind wheel which is composed of three blades, a high speed asynchronous generator (DFIG), and a transmission system. Asynchronous generators are used for their simplicity, the ability to work at many operation modes, and the final low operating costs. The variable wind speed is provided with a blade pitch angle execution system, where the power generated by the WT can be controlled [31]. A modern wind energy conversion system is presented in Figure 1 [32].

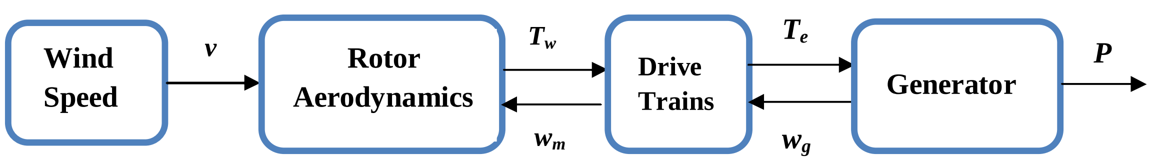


Figure 1: Block diagram of the WT model **[32]**

The WT model consists of four main parts: aerodynamic system, transmission system, generator system, and pitch actuator system. These subsystems will be implemented in MATLAB/SIMULINK programs for the simulation analysis. The blades of WTs can be twisted in or out by changing the pitch angle, when the power output is lower than the desired optimum value or higher than this value. Also, the angle of the rotor blades can be automatically adjusted by the pitching actuator system in order to reach the desired power value. This can be done by regulating the input aerodynamic power flow.

4.2.1 Modelling of the Wind Turbine Aerodynamic

The WT blades convert the wind energy into kinetic energy. The kinetic energy in air [33]:

$$\boldsymbol{K_e} = \frac{1}{2}.\boldsymbol{m}.\boldsymbol{v}^2 \tag{2}$$

Accordingly, the power in the moving air can be computed as:

$$P_w = \frac{dK_e}{dt} = \frac{1}{2}.m.v^2 \tag{3}$$

Where, *m* is the mass flow rate per second.

When the air passes throughout the blades with area (*A*), the wind power can be computed as:

$$\boldsymbol{P_w} = \frac{1}{2}.\boldsymbol{\rho}.\boldsymbol{A}.\boldsymbol{v}^3 \tag{4}$$

and the power extracted from the wind is written as:

$$\boldsymbol{P_{Extracted}} = \frac{1}{2}.\boldsymbol{C_P}(\boldsymbol{\lambda},\boldsymbol{\beta}).\boldsymbol{\rho}.\boldsymbol{A}.\boldsymbol{v}^3 \tag{5}$$

Where, ρ: is the air density; *A*: is the swept area; *v:* is the wind speed; $C_P(\lambda,\beta)$: is the power coefficient (wind energy utilization coefficient) and is given as a function of the tip speed ratio (λ) and the blade pitch angle (β).

The power coefficient is usually given by [33]:

$$\boldsymbol{C_P(\lambda, \beta) = c_1 \cdot \left(c_2 \cdot \frac{1}{\gamma} - c_3 \cdot \beta - c_4 \cdot \beta^x - c_5\right) \cdot e^{-c_6 \frac{1}{\gamma}}}$$
4(6)

γ is defined as:

$$\boldsymbol{\frac{1}{\gamma} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{1+\beta^3}} \quad (7)$$

The coefficients, c_1-c_6 are given as follows: $c_1 = 0.5$, $c_2 = 116$, $c_3 = 0.4$, $c_4 = 0$, $c_5 = 5$, $c_6 = 21$ [33].

Substitute $A = \pi R^2$, the rotor torque can be computed as:

$$\boldsymbol{T_w = \frac{P_{Extracted}}{w_m} = \frac{\frac{1}{2} \pi . C_P(\lambda, \beta) . \rho . R^2 . v^3}{w_m}} \quad (8)$$

The tip speed ratio, λ, depends on the speed of the blades tips and the speed of the wind as shown in:

$$\boldsymbol{\lambda = \frac{w_m . R}{v}} \quad (9)$$

where (R) is the rotor diameter (R). The power coefficient is the main factor that affects the mechanical efficiency in the WT system.

The purpose of variable-speed WTs is to hold the system at the maximum efficiency by keeping a constant λ corresponding to the maximum C_p and by changing the blades velocity depending on the wind speed profile. Therefore, variable-speed WTs are defined to run the system at optimum energy efficiency, with neglecting the wind speed changes [31].

4.2.2 Modelling of the Transmission System

The gear box model presented in this paper is based on the assumption of two masses: the gear box along with generator as a mass and the blades connected with hubs as another mass. The components of the transmission model are presented in Figure 2 [34].

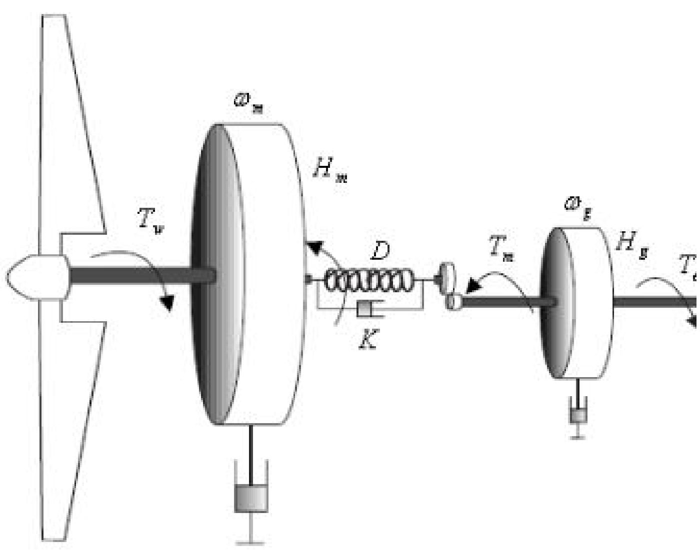


Figure 2: WT transmission model [34]

The equation of motion of the WT transmission model is given by:

$$H_g \cdot \frac{dw_g}{dt} = T_e + \frac{T_m}{n} \quad (10)$$

The equation of motion of the windmill shaft is given by:

$$H_m \cdot \frac{dw_m}{dt} = T_w + T_m \quad (11)$$

The mechanical torque can be described by the following relation:

$$\boldsymbol{T_m = K . \frac{\theta}{n} + D . \frac{w_g - w_m}{n}} \qquad 4 \qquad (12)$$

$$\boldsymbol{\frac{d\theta}{dt} = w_g - w_m} \quad (13)$$

Where, n: is the gear ratio, θ: is the angle between the generator rotor and the turbine rotor, w_m: is the turbine rotor speed, w_g: is the generator rotor speed, H_m: is the turbine moment of inertia, H_g: is the generator moment of inertia, K: is the stiffness, D: is the damping constants, Tw: is the wind torque, and Te: is the electromagnetic torque.

4.2.3 Modelling of the Generator

The asynchronous generator model is used in this paper, which is represented by the following equations [33]:

Magnetic flux:

$$\boldsymbol{\varphi_{ds} = X_s . I_{ds} + X_m . I_{dr}} \quad (14)$$
$$\boldsymbol{\varphi_{qs} = X_s . I_{qs} + X_m . I_{qr}} \quad (15)$$
$$\boldsymbol{\varphi_{dr} = X_r . I_{dr} + X_m . I_{ds}} \quad (16)$$
$$\boldsymbol{\varphi_{qr} = X_r . I_{qr} + X_m . I_{qs}} \quad (17)$$

Voltage:

$$\boldsymbol{V_{ds} = -R_s . I_{ds} + w_s . \varphi_{qs}} \quad (18)$$
$$\boldsymbol{V_{qs} = -R_s . I_{qs} - w_s . \varphi_{ds}} \quad (19)$$
$$\boldsymbol{0 = -R_r . I_{dr} + s . w_s . \varphi_{qr} - \frac{d\varphi_{dr}}{dt}} \quad (20)$$
$$\boldsymbol{0 = -R_r . I_{qr} - s . w_s . \varphi_{dr} - \frac{d\varphi_{qr}}{dt}} \quad (21)$$

The slip of the rotor, s, is expressed by:

$$\boldsymbol{s = \frac{w_s - w_g}{w_s}} \quad (22)$$

The electrical torque is defined as:

$$\boldsymbol{T_e = \varphi_{qr} . I_{dr} - \varphi_{dr} . I_{qr}} \quad (23)$$

Finally, the active, reactive, and apparent power outputs are defined by the following equations:

$$\boldsymbol{P_{active} = V_{ds} . I_{ds} + V_{qs} . I_{qs}} \quad (24)$$
$$\boldsymbol{P_{reactive} = V_{qs} . I_{ds} - V_{ds} . I_{qs}} \quad (25)$$
$$\boldsymbol{P = V_{ds} . I_{ds} + V_{qs} . I_{qs} + V_{qs} . I_{ds} - V_{ds} . I_{qs}} \quad (26)$$

4.2.4 Simulation Parameters

The WTG parameters used for the simulation are given in Table 1 [33].

Table 1: Wind turbine parameters **[33]**

Parameter	Value
Rotor radius, R	25 m
Air density, ρ	1.225 $kg.m^{-3}$
Aerodynamic coefficients, c_1-c_6	c_1=0.5,c_2=116,c_3=0.4, c_4=0,c_5=5,c_6=21
Gear ratio, n	65.27
Stator resistance, R_s	0.0121 Ohm
Stator reactance, X_s	0.0742 H
Mutual reactance, X_m	2.7626 H
Rotor resistance, R_r	0.008 Ohm
Rotor reactance, X_r	0.1761 H
Number of pole pairs, n_p	2

5. THE CONTROL SYSTEM

Control techniques such as classical PID, fuzzy-PD, fuzzy-PID, genetic fuzzy-PD, and as in this paper self-tuning genetic fuzzy-PID controllers are typically used to regulate the pitch angle of a wind turbine.

This research aims to design a controller for the power output of a WT, by controlling the pitch angle of the blades. The WT system model is built using MATLAB/SIMULINK software package. The main objective of using these controllers is to improve the power resulted from the generator to be more smooth and non-fluctuating. The power fluctuates because of the varying wind energy and speed over time.

5.1 Classical PID Controller

PID controllers have been considered to be linear controllers. Ziegler and Nichols developed a method to tune the PID parameters in 1942 [35]. Nowadays, PID controllers have been used in many industrial applications because of its simplicity and flexibility.

Anaya-Lara et al. [36] showed that the classical PID controller is done in a closed-loop control system. A closed-loop control is different from an open-loop control system because it has the ability to control the output of the system by using a feedback loop. Feedback loop is used as a negative loop to transfer output from the system to the summing junction point with the desired output or reference input, the difference between the desired output and the actual output of the system produces the error signal. Error signal is used to guide the controller to obtain the desired output, and then to instruct the system to the required behaviour. A schematic illustration of the closed-loop PID control system is shown in Figure 3.

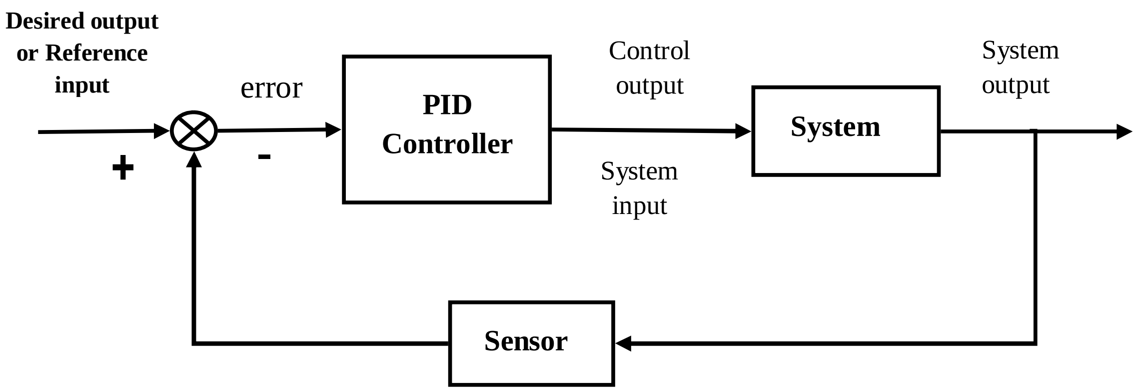


Figure 3: Feedback loop with PID controller

The PID controller algorithm involves three main parameters, which is called the three-term control: the proportional, the integral and derivative values, denoted by P, I, and D. The proportional value depends on the reaction to the current error, the integral value determines the reaction based on the sum of present errors (the accumulation of past errors), and the derivative value determines the reaction based on the rate at which the error has been changing (which is a prediction of future errors). The accumulated sum of these three parameters is used to adjust the process via a control component such as the speed of a WT.

The response of the controller can be clarified through the degree of the controller response to an error, the amount of overshoot from the desired output, and the degree of the system oscillation. The common formula for a PID controller is shown in the following equation, where; *u(t)*: is the output signal used to control the system; *y(t)*: is the measured output; *r(t)*: is the desired output [36].

$$u(t) = K_P\, e(t) + K_I \int e(t)d(t) + K_D \frac{d}{d(t)}\, e(t) \quad (27)$$

The following equation provides the error signal:

$$e(t) = r(t) - y(t) \quad (28)$$

The effect of PID tuning parameters are shown in Table (2) below [25]:

Table 2: Effects of PID parameters change

Parameters	Rise Time	Overshoot	Settling Time	Steady State error
Proportional (P)	Decrease	Increase	No change	Decrease
Integral (I)	Decrease	Increase	Increase	removed
Derivative (D)	No change	Decrease	Decrease	No change

5.2 Fuzzy-PD or Fuzzy-PID Controller Design Procedure

The FL-based controller design includes the following steps:

1. Determining the input and output variables.
2. Constructing the control rules.
3. Determining the mechanism of representing system state in terms of fuzzy sets, i.e., selecting fuzzification method and fuzzy membership types.

4. Selecting the compositional rule method of inference engine.
5. Selecting defuzzification approach, i.e., transformation of the fuzzy control system into a crisp value to make a particular control action.

5.3 Fuzzy-PD Controller

The first method is the fuzzy-PD controller. The fuzzy inference is used in this type of controller to tune the output from the PD controller, then the output from fuzzy entered to integrator to complete the PID controller loop. The proportional gain improving overall response proportional to the error signal, the integrator gain reduces the steady state error through the low frequency compensation by an integrator, and the derivative term improves the transient response of the system.

5.3.1 Selection of Input and Output Variables

The main parts of the fuzzy-PD controller are shown in Figure (4). The input variables for the fuzzy controller are two: the error (*e*) and the rate of the change of error (*e'*). The controller has one output variable (CU) [35].

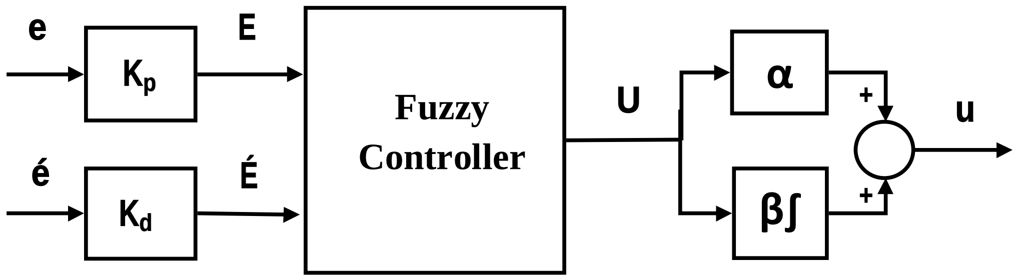


Figure 4: Fuzzy-PD controller parts

5.3.2 Selection of the Membership Function (MF)

The triangular MFs are used to determine the degree of membership. Seven linguistic variables are used for input and output fuzzy variables. Table 3 shows the change from negative big (NB) to positive big (PB) in the linguistic variables. The linguistic variables are connected with each other by using a triangular MF to make a set of seven MFs for the input and output fuzzy variables. The MFs of input and output variables are shown in Figure 5.

Table 3: MFs for fuzzy-PD variables

NB	Negative Big
NM	Negative Medium
NS	Negative Small
ZE	Zero Error
PS	Positive Small
PM	Positive Medium
PB	Positive Big

5.3.3 Developing Fuzzy Rule Base

A set of rules to identify the relationship between the input error (*E*), input change error (*CE*), and the output (*CU*) of the fuzzy-PD controller can be constructed using the expert knowledge in the field of the concerned system. These rules are written using the linguistic variables in Table (4). The two inputs, error (*E*) and change of error (*CE*), result in 49 rules. All the 49 rules are shown in Table (4).

5.4 Self-tuning Fuzzy-PID Controller

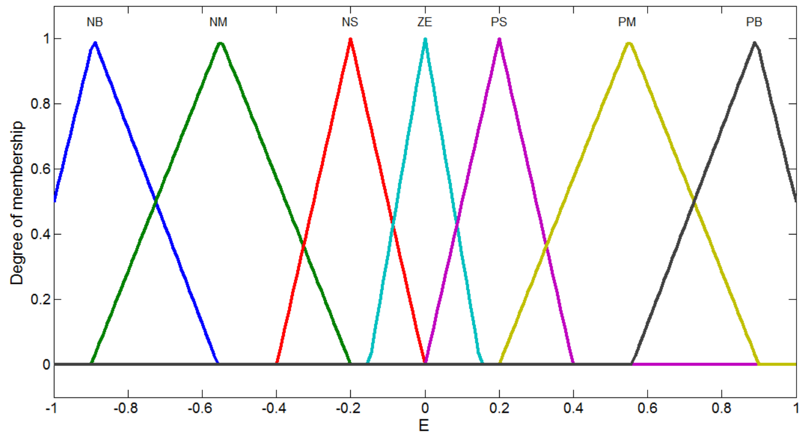
The second method is shown in reference [37]. The fuzzy inference is used to tune the PID parameters to provide a nonlinear mapping between the error and derivative of error to the PID parameters. The parameters are tuned between the initial parameter boundaries. FL consists of three steps: fuzzification, rule evaluation, and deffuzzification.

Fuzzy-PID is a controller that consists of: the classical PID controller and FL controller. The fuzzy controller, as shown in Figure (6), is used to adjust the gain of the PID controller, which makes the PID adaptive.

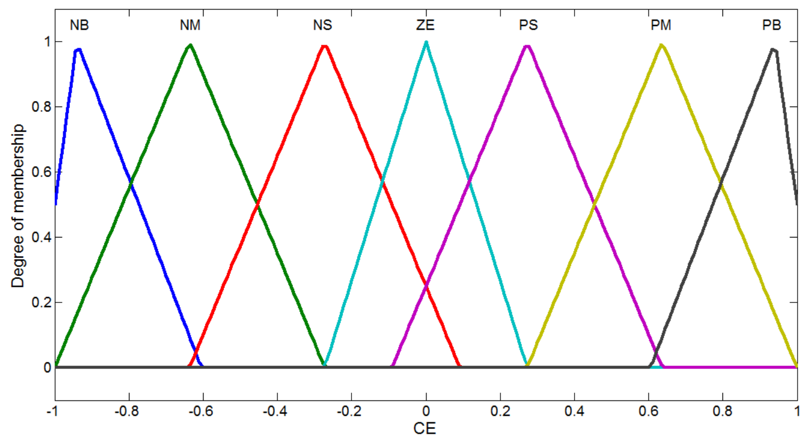
The error and the derivative of the error are the input to the FL control. The rules are based on the designer's experience and knowledge of the dynamic system. The outputs of the FL controller are the tuned gain values of the classical PID controller. The common procedure for designing a classical PID controller is followed to determine the parameters (K_p, K_d, and K_i). The rules of the FL are provided using these principles [37]:

- The proportional gain K_P at the beginning of the control operation must be kept as large as possible to minimize the rise time, increase the transient response, and increase the speed of the control operation.
- K_P must be decreased gradually to a smaller value to minimize steady state error.
- Derivative gain K_d must be large at the beginning and then must be decreased gradually as the change of error gets smaller.
- The overshoot of the control system and change of error can be controlled and terminated by the derivative gain *Kd*.

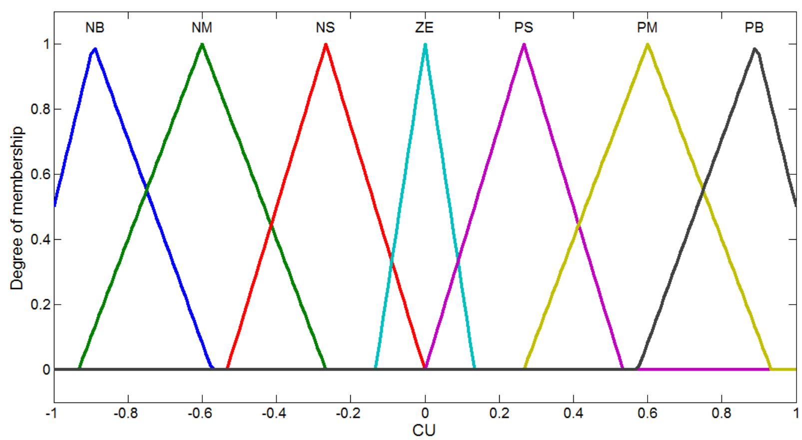
- Steady state error is adjusted by the integral gain K_i, thus, K_i must be small at the beginning of the control operation to improve the response of the system, and then K_i must be increased gradually over the time of controlling process to decrease the steady state error and provide the smallest steady state error.



(a)



(b)



(c)

Figure 5: MF for (a) input error (*E*), (b) input change of error (*CE*), (c) output (*CU*)

Table 4: Rules for *CU*

Error (E)	Derivative of error (CE)						
	NB	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
NB	NB	NB	NB	NB	NB	NM	NM
NM	NB	NB	NB	NB	NM	NM	NS
NS	NB	NB	NB	NM	NM	NS	NS
ZE	NB	NB	ZE	ZE	ZE	NB	NB
PS	PS	PS	PM	PM	PB	PB	PB
PM	PS	PM	PM	PB	PB	PB	PB
PB	PM	PM	PB	PB	PB	PB	PB

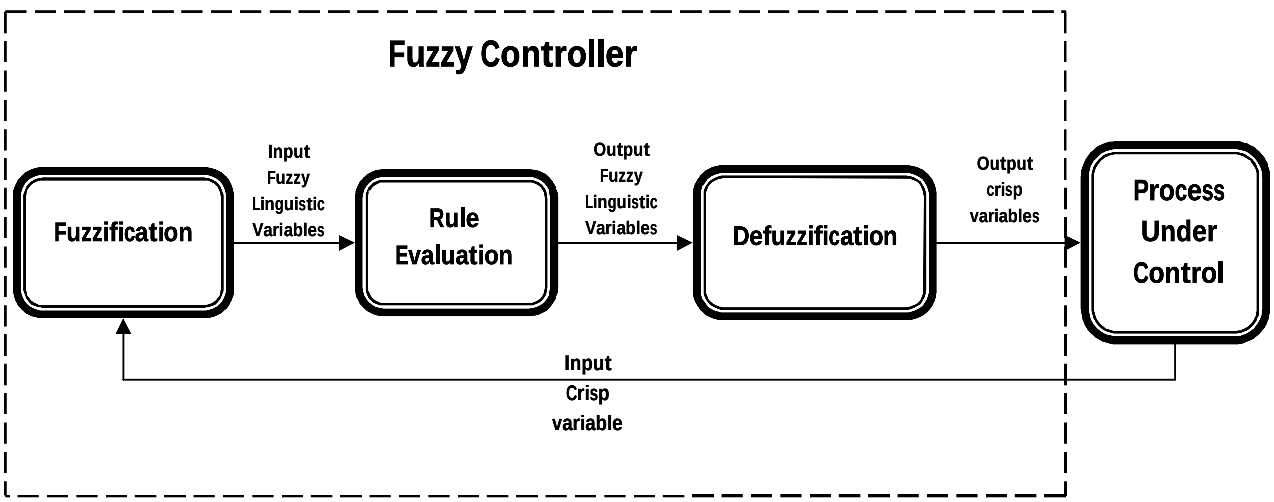


Figure 6: FL structure

5.4.1 Selection of Input and Output variables

As shown in Figure 7. The inputs for the self-tuning Fuzzy-PID Controller are two input: the error (e) and the rate of the change of error (ec) and has three outputs which represent the gain of the PID controllers; the proportional gain (K_p), integrator gain (K_i), and derivative gain (K_d).

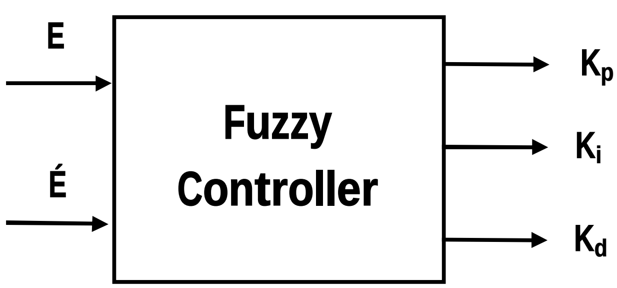


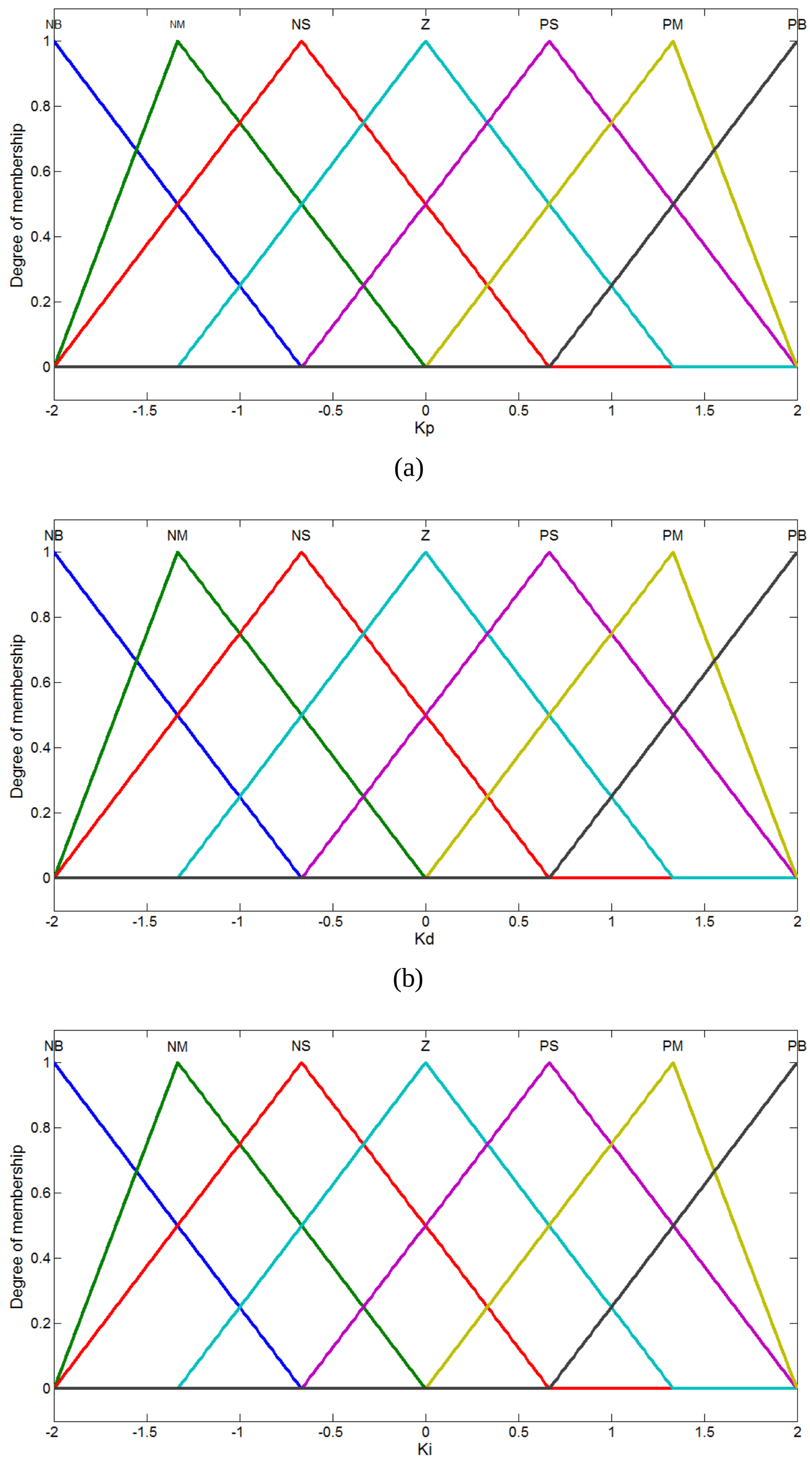
Figure 7: Inputs and outputs for fuzzy-PID controller

5.4.2 Selection of Membership Function

The same MF that used in the previous system and shown in section 5.3.2 is employed here, but there are three output MFs constructed, as shown in Figure 8 (a, b, and c).

5.4.3 Making Fuzzy Rule Base

A set of rules that represents the relationships between the inputs (E and CE), and the outputs (K_p, K_i, and K_d) of fuzzy controller can be constructed using the expert knowledge based on the principles mentioned earlier in section 5.3.3. The typical rules using the linguistic are shown in Table (5), Table (6), and Table 7.



(a)

(b)

(c)

Figure 8: MF for a) output (K_p), b) output (K_d), c) output (K_i)

Table 5: Rules for K_p

Error (E)	Derivative of error (CE)						
	NB	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
NB	PB	PB	PM	PM	PS	Z	Z
NM	PB	PB	PM	PS	PS	Z	NS
NS	PM	PM	PM	PS	Z	NS	NS
ZE	PM	PM	PS	Z	NS	NM	NM
PS	PS	PS	Z	NS	NS	NM	NM
PM	PS	Z	NS	NM	NM	NM	NB
PB	Z	Z	NM	NM	NM	NB	NB

Table 6: Rules for K_i

Error (E)	Derivative of error (CE)						
	NB	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
NB	NB	NB	NM	NM	NS	Z	Z
NM	NB	NB	NM	NS	NS	Z	Z
NS	NB	NM	NS	NS	Z	PS	PS
ZE	NM	NM	NS	Z	PS	PM	PM
PS	NM	NS	Z	PS	PS	PM	PB
PM	Z	Z	PS	PS	PM	PB	PB
PB	Z	Z	PS	PM	PM	PB	PB

Table 7: Rules for K_d

Error (E)	Derivative of error (CE)						
	NB	**NM**	**NS**	**ZE**	**PS**	**PM**	**PB**
NB	PS	NS	NB	NB	NB	NM	PS
NM	PS	NS	NB	NM	NM	NS	Z
NS	Z	NS	NM	NM	NS	NS	Z
ZE	Z	NS	NS	NS	NS	NS	Z
PS	Z	Z	Z	Z	Z	Z	Z
PM	PB	PS	PS	PS	PS	PS	PB
PB	PB	PM	PM	PM	PS	PS	PB

5.5 Incorporating Genetic Algorithms (GAs) into Fuzzy System Design

Genetic Algorithm (GA), shown in Figure (9), is a search mechanism based on the principle of natural selection and population genetics that are transformed by three genetic operators: selection, crossover and mutation. Each string is the solution for the system being optimized and each bit (or group of bits) gives some value or some variable of the system.

The degrees of the solutions are determined by an evaluation function (fitness function). The aim is to get better values (fitness), to get better solutions [5]. To integrate GAs into fuzzy controller system, the appropriate genetic coding must be determined for the desired parameter and the correct method to evaluate its fitness must be chosen.

The MF is expressed by the left base, right base, and distance from the previous centre point (see Figure 10 (a)), and then by encoding the centres as a distance from the previous centre (the first centre was given as an absolute position) and the base values as the distance from the corresponding centre point (see Figure 10 (a)). These parameters are used to generate different possibilities for interference between MF as shown in Figure 10 (b).

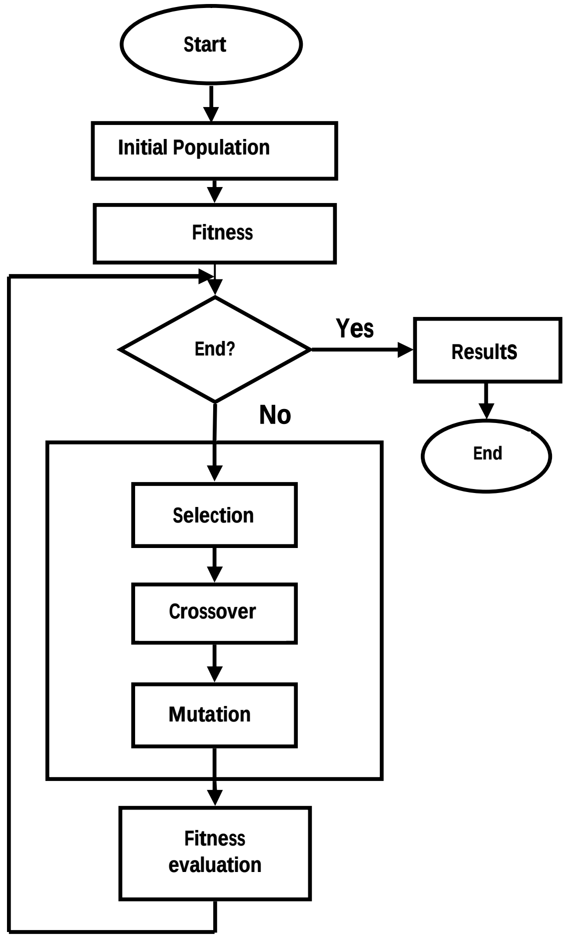


Figure 9: General flow chart for GA

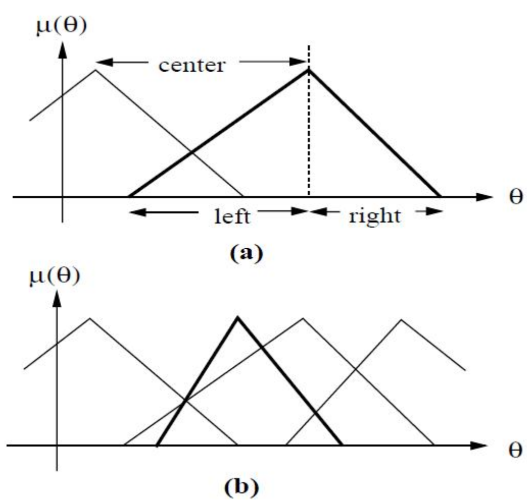


Figure 10: a) MF representation, b) possible MFs **[5]**

5.5.1 Membership Functions Encoding

As shown in references [4] and [5], there are different types of coding methods for triangular MFs that depend on the parameter used to represent the triangle. The following method is used in this paper.

5.5.2 Evaluating Fuzzy System Performance (Fitness Function)

In any GA system, fitness function plays an important rule of guiding the direction of the search. There is no standard method to determine a fitness function for a problem; however, it's always designed such that the best solution has to get the higher fitness value [8]. The fitness of genes are determined by decoding the gene's binary representation and then inserting its value into the fitness function.

5.6 Control Architecture

The control architecture used here is shown in Figure 11. It represents a block diagram of the closed-loop control system. There are many chromosomes for the MFs each one consists of a specific number of genes. The MFs are updated at the end of each generation until a stop criteria is reached.

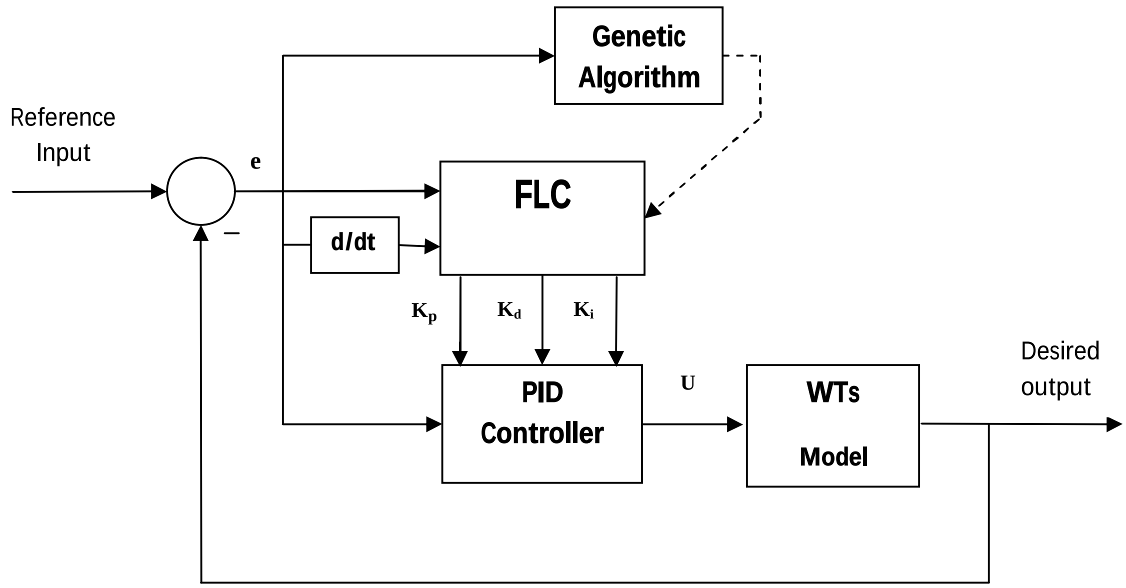


Figure 11: GA-optimized FLC architecture

5.7 Wind Turbine Control

Modern WTs have different region of control, which can be classified as: '**supervisory control**,' '**operational control**,' and '**subsystem control**' [38]. The supervisory control, which is "top-level" of the control operation, depends on the wind speed for starting at the operation region, and turning off at the cut-off region, as well as shows the health of the turbine. The operational control in regions 2 and 3 shows whether the turbine reached its control purpose or not [30].

The subsystem controllers regulate the operation of the generator, power electronics, pitch drive, and other subsystem actuators. Figure (12) shows the operational control loops, the pitch controller. The rotor speed *(ω_T)* measurements are usually the only measurements used in the feedback loops for the blade pitch control [38]. The model that is used in this paper is based on a variable speed WT with a DFIG.

6. RESULTS AND DISCUSSION

The main objective is to design a controller for the WTGS, by changing the pitch angle of the blades with wind speed. The controller was constructed in MATLAB and the wind turbine model was built using MATLAB/SIMULINK software package.

Performance indices are used to measure the performance of a closed-loop control system. Three types of performance indices are used in this paper and shown below [36]:

1. Integral of the square error
$$ISE = \int_0^T e^2(t)dt \qquad (29)$$
2. Integral of the absolute magnitude of the error
$$IAE = \int_0^T |e(t)|dt \qquad (30)$$
3. Integral of time multiplied by absolute error
$$ITAE = \int_0^T t|e(t)|(t)dt \qquad (31)$$

These indices are computed over a specified interval of time $0 \le t \le T$. The time interval T is selected to cover the transient response of the system as possible, which is usually determined until the system approaches the steady state value, i.e., when it reaches the settling time (T_s). The first two indices indicate the weight of the error at an interval T, and this describes the transient performance (overshoot and rise time) of the system. While the last one gives greater weight to the error at the end of interval (steady state error).

Table (8) shows the performance indices for all the controllers under investigation. The GF-PID has the best performance. The IAE and ISE values confirm that this system has the better transient response and also ITAE confirms that the system has the minimum steady state error and minimum oscillation compared to the other systems. Table (8) shows improvement in the system performance of the F-PID over PID and F-PD controller, especially in the steady state response. The ITAE value decreased from 15.64

to 9.16 compared to the fuzzy-PD system. Thus, this system is more stable and smoother. In regards of GF-PD system, Table 8 shows improvement in the transient response, since the effect of this controller is done on the proportional gain *(K_p)* and the differentiator gain *(K_d)*. The ITAE almost remains constant, because there is no effect on the integrator gain. For the GF-PID controller, Table 8 shows improvement for the transient and steady state responses.

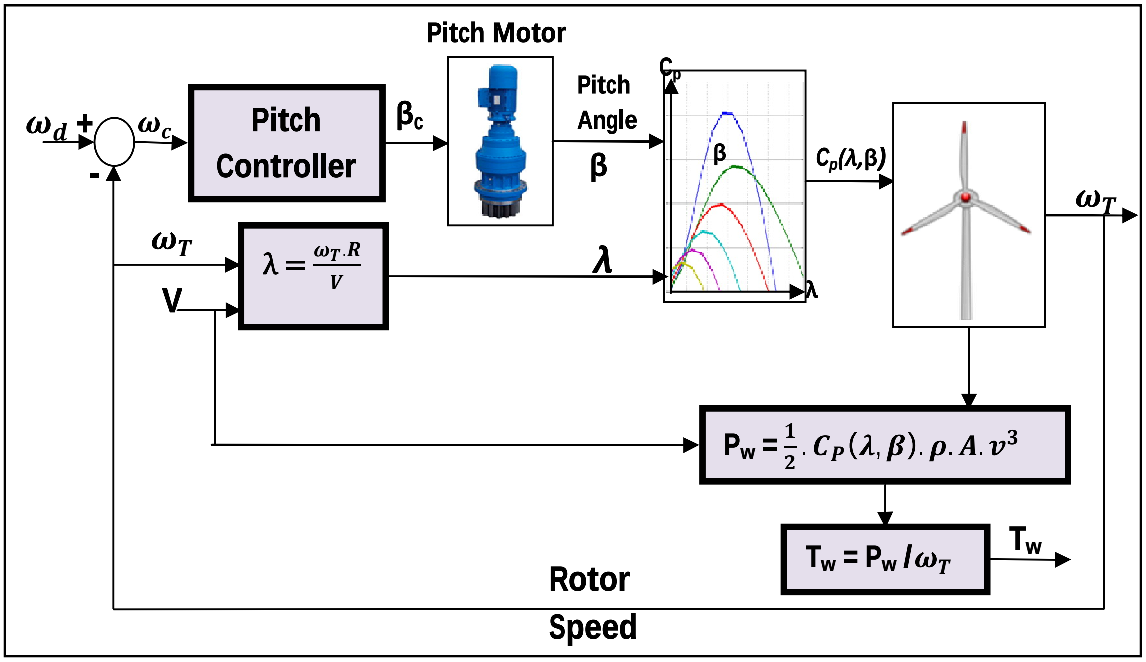


Figure 12: WT control block diagram [38]

Table 8: Performance indices for different controllers

Controller type / Error Criteria	PID	F-PD	F-PID	GF-PD	GF-PID
IAE	0.4386	0.423	0.406	0.421	0.354
ISE	0.00399	0.003303	0.005828	0.003285	0.003013
ITAE	16.33	15.64	9.16	15.55	7.16

The time response parameters of all the implemented controllers for the electrical power are shown in Table 9 and Figure 13. The results show improvement of GF-PID controller over the other controllers. Figure 13 shows the electrical power outputs with time response for the PID, genetic fuzzy-PID (GF-PID), fuzzy-PD (F-PD), fuzzy-PD (F-PD), fuzzy-PID (F-PID), and genetic fuzzy-PD (GF-PD) controllers. It can be observed that the performance of GF-PID is the best among all the systems. GF-PID model controller has fast rise time, the smallest overshoot, the smallest oscillation, and has reached to the steady state value faster than the other systems.

Table 9: Time response results for electrical power

Controller type / Parameter	PID	F-PD	F-PID	GF-PD	GF-PID
Rise time (t_r) (s)	5.577	7.915	8.232	8.01	7.639
Peak time (t_p) (s)	10.84	14.62	14.37	14.94	13.26
Maximum overshoot (M_p) (kW)	5.13	61.98	62.04	60.52	49.78

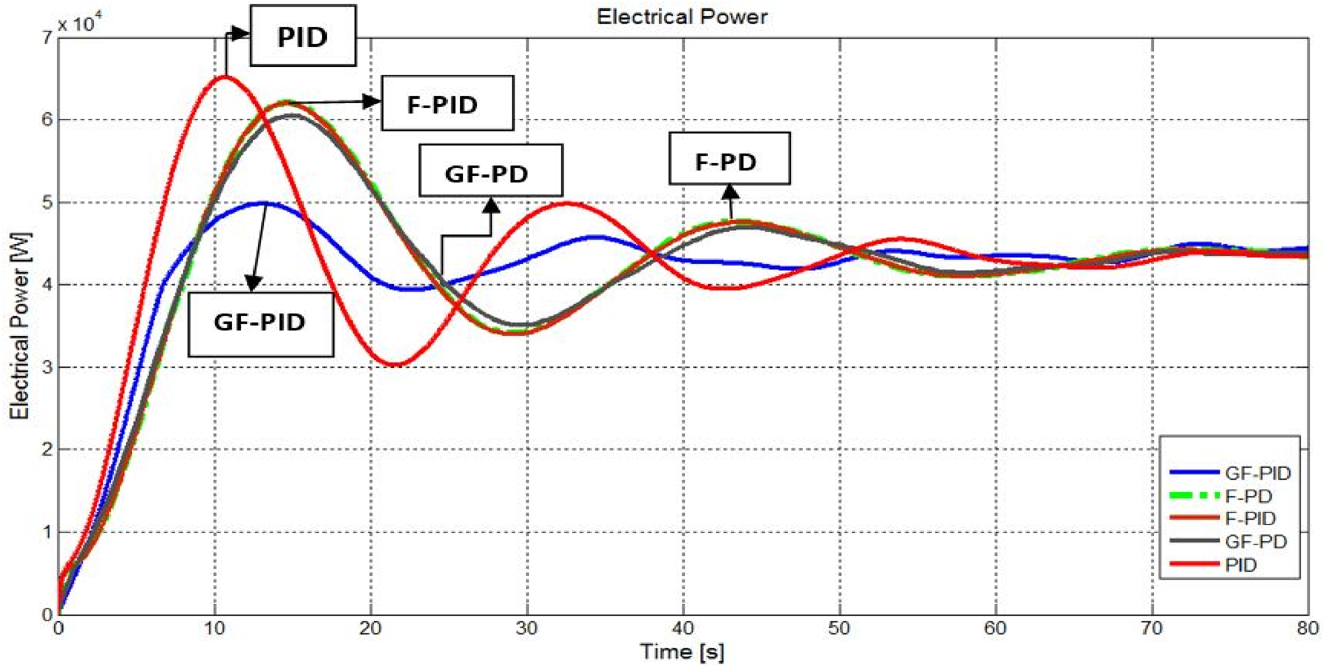


Figure 13: Time response for electrical power output (for the five systems)

PID controller has a good response and performance. The system has the fastest rise time compared with the other systems, but has the biggest overshoot value, and oscillates more than the other systems. Both, the fuzzy-PD controller and genetic fuzzy-PD controller have good performance values; they have the slowest rise time, but have lower overshoot value and oscillation than PID controller.

7. STABILITY ANALYSIS

The PID controller has a significant influence on the stability of the controlled system. The system becomes unstable when the proportional gain, integral gain, and derivative gain are tuned incorrectly. In general, the stability of the system response is desired and the response must not oscillate for any process input and operation situations. However, bounded oscillations (marginally stable system) in some controlled systems are acceptable and required for the system to work correctly.

In this section, the stability of the system is investigated. A step input is applied to the model and built in a MATLAB/SIMULINK application. The results are compared for each controlled mechanisms.

The study of the transient response is called the time performance. The first step to study the time performance is done by utilizing a standard input signal (unit step) and then by determining whether the system is stable or unstable. The performance of the system is measured by some standard parameters like: rise time, peak time, overshoot, settling time, and steady state error.

The transfer function of the mechanical and electrical system from the turbine to the generator can be represented as following [39]:

$$T(s) = \frac{W_G(s)}{T_G(s)} = \frac{K_G\, .S^2 + K_T\, .K_{Shaft}}{S^3 + (K_T . K_{Shaft} + K_G\, .K_{Shaft})\, .\, S} \qquad (32)$$

Constants K_T and K_G are $1/J_T$ and $1/J_G$ respectively, where J_T: is turbine moment of inertia, J_G: is the generator moment of inertia, K_{shaf}: shaft torsional spring constant (stiffness). Substitute the values of constants: K_T=6.25*10^5; KG=35.184; Kshaft=0.35 in equation 32 [33], then T(s) is:

$$T(s) = \frac{35.184\, S^2 + 2.1875 * 10^5}{S^3 + 2.19 * 10^5 S} \qquad (33)$$

Table 10 shows the performance parameters for the five controllers used in this thesis. When the input signal is a unit step input, the parameters verify the performance and the stability for the system.

The PID controller shows a good performance for the step response especially, in the rise time, peak time, and settling time, but has a poor response for the overshoot value. The response for a unit step input using fuzzy-PD controller is better especially in the transient portion. As a comparison with the fuzzy-PD, it can be noticed there is no improvement in the performance of F-PID parameters except the overshoot percent is smaller. For GF-PID, a comparison with the previous system (genetic fuzzy-PD), it can be seen there is a big improvement in the performance in terms of the overshoot percent and the settling time. In all cases, the system shows stable behavior; since the real part of its poles is located at the left half of the pole-zero map.

Table 10: Performance parameters for different controllers

Controller type / Performance Parameter	PID	F-PD	F-PID	GF-PD	GF-PID
Rise time (T_r) [second]	0.00146	0.00134	2.84	0.000846	0.239
Peak time (T_p) [second]	0.06	0.44	14.1	0.31	2.12
Percent of overshoot (P.O)	17%	9.72%	1.28%	12.2%	0.00634%
Settling time (T_s) [second]	0.212	1.54	5.11	1.61	0.402

8. CONCLUSION

It can be conclude that GF-PID has the best performance without adding any complex analytical and mathematical model to get these improved results. The inclusion of GA to the fuzzy-PID controller presents a new hybrid system that gives exceptional results as shown in Table (8) and Table (10); the genetic fuzzy-PID controller has the minimum overshoot, and an average values for the rest parameters. Therefore, the system has a better quality and Performance.

In summary, wind energy is a fast growing field, and this growth has led to a large interest in the modeling and control of WTs and wind farms. The uncertainties and obstacles in computing the wind inflow of WTs increase the interest to develop control techniques. Therefore, more advanced control process should be investigated to minimize the cost of wind energy.

FL is a trial and error system based. For that reason, GA was used in this paper for automatic fuzzy system. GA works as an optimization tool by slowly “evolving” a population of chromosomes that represent better and better solutions to the MFs shape.

The wind energy resource available in Jordan is large, and much of the future demands of electrical energy can be provided by wind energy alone if the technologies in modeling and control are significantly improve the efficiency, operation and lifetimes of WTG system.

REFERENCES

[1] WWE. Association, "World wind energy installed capacity," [Online]. Available: http://www.wwindea.org/home/index.php. [Accessed 2014].

[2] P. Rocco, "Stability of PID Control for Industrial Robot Arms," *IEEE Transactions on Robotics and Automation,* vol. 12, no. 4, pp. 606-614, 1996. https://doi.org/10.1109/70.508444

[3] S. K. Mallick and M. A. Khan, "Study of The Design and Tuning Methods of PID Controller Based on Fuzzy Logic and Genetic Algorithm," Electronics and Instrumentation Engineering. Thesis, National Institute of Technology, Rourkela, India, 2011.

[4] E. El-kholy, A. Dabroom and A. E. El-kholy, "Adaptive Fuzzy Logic Controllers for DC Drives: A Survey of the State of the art," vol. 2, pp. 116-145, 2006.

[5] F. Herrera, "Genetic Fuzzy Systems: Status, Critical Considerations and Future Directions," *International Journal of Computational Intelligence Research,*, vol. 1, pp. 59-67, 2005. https://doi.org/10.5019/j.ijcir.2005.23

[6] J. Casillas, O. Cordón, M. José del Jesus and F. Herrera, "Genetic Tuning of Fuzzy Rule Deep Structures Preserving Interpretability and Its Interaction With Fuzzy Rule Set Reduction," *IEEE Transactions on Fuzzy Systems,* vol. 13, no. 1, pp. 13-29, 2005.

[7] C. C. Lee, "Fuzzy Logic in Control Systems: Fuzzy Logic Controller, Part I," *IEEE Transactions on Systems, Man, and Cybernetics,* vol. 20, no. 2, pp. 404-418, 1990. https://doi.org/10.1109/21.52551

[8] K. F. Man, K. S. Tang and S. Kwong, "Genetic Algorithms: Concepts and Applications," *EE Transactions on Industrial Electronics,*, vol. 43, no. 5, pp. 519-534, 1996.

[9] D. Nauck, F. Klawonn and R. Kruse, "Fuzzy Sets, Fuzzy Controllers, and Neural Networks," *Scientific Journal of the Humboldt-University of Berlin, Series Medicine,* vol. 41, pp. 99-120, 1992.

[10] L. A. Zadeh, "Fuzzy Sets," *Information and Contro,* vol. 8, pp. 338-353, 1965.

[11] T. M. Mitchell, Machine Learning, McGraw-Hill Science, 1997.

[12] W. Darrell, "A Genetic Algorithm Tutorial," *Statistics and Computing,* vol. 4, pp. 65-85, 1994. https://doi.org/10.1007/BF00175354

[13] O. Cordon, F. Gomide, F. Herrera and F. Hoffmann, "Ten Years of Genetic Fuzzy Systems: Current Framework and Trends," *Fuzzy Sets and Systems,* vol. 141, pp. 5-31, 2004.

[14] F. Herrera and L. Magdalena, "Genetic Fuzzy Systems: A Tutorial," Spanish Comision Interministerial de Ciencia y Technologia.

[15] Y. Shi, R. Eberhar and Y. Chen, "Implementation of Evolutionary Fuzzy Systems," *IEEE Transactions on Fuzzy Systems,* vol. 7, pp. 109-119, 1999.

[16] P. Thrift, "Fuzzy Logic Synthesis with Genetic Algorithms," Texas Instruments, Dallas, Texas.

[17] K. Tomsovic, M. Y. Chow and e. al., "Tutorial on Fuzzy Logic Applications in Power Systems," in *Prepared for the IEEE-PES Winter Meeting in Singapore*, Singapore, 2000.

[18] M. A. Lee and H. Takagi, "Integrating Design Stages of Fuzzy Systems using Genetic Algorithms," *In Proc. 2nd IEEE Int. Conf. on Fuzzy Systems*, pp. 612-617, 1993.

[19] F. Herrera, M. Lozano and J. L. Verdegay, "Tuning Fuzzy Logic Controllers by Genetic Algorithms," *International Journal of Approximate Reasoning*, vol. 12, pp. 299-315, 1995. https://doi.org/10.1016/0888-613X(94)00033-Y

[20] V. Galdi, A. Piccolo and P. Siano, "Exploiting maximum Energy from variable speed Wind Power Generation Systems by using an Adaptive Takagi-Sugeno-Kang Fuzzy Model," *Energy Conversion and Management*, vol. 50, pp. 413-421, 2009.

[21] Y. Qi and Q. Meng, "The application of Fuzzy PID Control in Pitch Wind Turbine," *Energy Procedia*, vol. 16, pp. 1635-1641, 2012. https://doi.org/10.1016/j.egypro.2012.01.254

[22] O. Belghazi and M. Cherkaoui, "Pitch Angle Control for Variable Speed Wind Turbine using GA's Algorithms Controller," *Journal of Theoretical and Applied Information Technology*, vol. 39, pp. 6-10, 2012.

[23] D. C. Donha and G. Risso, "Wind Turbine Controller Tuning by Genetic Algorithm," *ABCM Symposium Series in Mechatronics*, vol. 1, pp. 346-354.

[24] Ahmad Ashour, *Design of Genetic Fuzzy-PID Controller: Controlling of Wind Turbine Generator System*, Irbid: Yarmouk University, 2014.

[25] J. Smuts, "PID Controllers Explained," *Canadian Process Equipment and Control News*, 2002.

[26] J. F. Manwell, J. G. McGowan and A. L. Rogers, Wind Energy Explained: Theory, Design and Application, West Sussex, England: John Wiley and Sons Ltd, 2002. https://doi.org/10.1002/0470846127

[27] "800 Foot Tall Wind Turbines are Feasible and doubling power of a wind turbine reduces emissions by 14% per kwh," 4 2014. [Online]. Available: http://nextbigfuture.com/2012/06/800-foot-tall-wind-turbines-are.html.

[28] T. Burton, D. Sharpe, N. Jenkins and E. Bossanyi, Wind Energy Handbook, West Sussex, England: 2001, 2001. https://doi.org/10.1002/0470846062

[29] F. D. Bianchi, H. De Battista and R. J. Mantz, Wind Turbine Control Systems: Principles, Modeling and Gain Scheduling Design. Advanced in Industrial Control, Springer, 2006.

[30] Symscape, "Computer-Aided Engineering for All. Darrieus Verticalaxis Wind Turbine.," 2014. [Online]. Available: http://www.symscape.com/node/406.

[31] A. PERDANA, "Dynamic Models of Wind Turbines: A Contribution towards the Establishment of Standardized," Ph.D. dissertation, Chalmers University of Technology, Dept. of Energy and Environment, GÄoteborg, Sweden, 2008.

[32] T. Petru, "Modeling of Wind Turbines for Power System Studies,"Thesis for The Degree of PhD, Chalmers University of Technology, Dept. of Electric Power Engineering, Goteborg, Sweden, 2003.

[33] J. Martinez, "Modelling and Control of Wind Turbines,"Thesis for The Degree of M.Sc. in Process Systems Engineering, Department of Chemical Engineering and Chemical Technology, Imperial College London, London SW7 2AZ, UK, 2007.

[34] O. Anaya-Lara, N. Jenkins, J. Ekanayke, P. Cartwright and M. Hughes, Wind Energy Generation: Modelling and Control, West Sussex, United Kingdom: John Wiley & Sons Ltd., 2009.

[35] I. Erenoglu, I. Eksin, E. Yesil M. Guzelkaya, "An Intelligent Hybrid Fuzzy PID Controller," *Istanbul Technical University, Faculity of Electrical and Electronics Engineering Department, Turkey*, 2006.

[36] R. C. Dorf and R. H. Bishop, Modern Control System, New Jersey: Prentice-Hall Inc., 2011.

[37] S. Soyguder, M. Karakose and H. Alli, "Design and Simulation of Self-tuning PID-type Fuzzy adaptive control for an Expert HVAC System," *Expert System with Application*, vol. 36, pp. 4566-4573, 2009.

[38] L. Y. Pao and K. E. Johnson, "A Tutorial on the Dynamics and Control of Wind Turbines and Wind Farms," in *American Control Conference*, St. Louis, Mo, USA, 2009.

[39] R. H. Overseth, T. M. Undeland and T. Gjengedal, "Doubly fed induction generator in a wind turbine," Norwegian University of Science and Technology.

[40] L. Mezher, "Position Control for Dynamic DC MOTOR with Robust PID Controller using MATLAB," International Journal of Advanced Trends in Computer Science and Engineering, Vol. 8, No.3, pp. 963-942, 2019. https://doi.org/10.30534/ijatcse/2019/92832019

[41] A. Zahir, S. Alhady, W. Othman, Z. Low, A. Wahab, "Genetic Algorithm Optimization and Implementation of Velocity Control PI Controller for Cart Follower Application," International Journal of Advanced Trends in Computer Science and Engineering, Vol. 8, No.5, pp.1886 1892, 2019. https://doi.org/10.30534/ijatcse/2019/12852019

[42] B. Ganthia, S. Sahu, S. Biswal, A. Abhisekh, S. Kumar Barik, "Genetic Algorithm based Direct Torque Control of VSI fed Induction Motor Drive using MATLAB Simulation," International Journal of Advanced Trends in Computer Science and Engineering, Vol. 8, No.5, pp. 2359 2369, 2019.

https://doi.org/10.30534/ijatcse/2019/76852019