LOAD FREQUENCY CONTROL OF AN ISOLATED MICROGRID USING GENETIC ALGORITHM BASED MODEL PREDICTIVE CONTROL

A Thesis Submitted

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ABSTRACT

A load frequency control technique for an isolated microgrid employing a Genetic algorithm-based Model Predictive Controller is provided in this dissertation. In an isolated microgrid, the load frequency deviates from its set value due to an imbalance between electrical power generated and electrical load demand. This power imbalance is caused by the intermittent nature of power generation by renewable energy resources such as wind and solar units, as well as load disruption in an isolated microgrid. Wind and solar power plant power generation is unreliable. Due to the variability in power generation from wind and solar power plants, it is vital to manage the load frequency in such instances. Traditional controllers are unable to give appropriate control action to increase the microgrid's performance. In this case, the load frequency is controlled by controllable power generating units such as a diesel generator and a fuel cell unit, the inputs of which are controlled by a Genetic algorithm-based Model Predictive Controller. In terms of integral square of error (ISE), it has been demonstrated that the performance of a genetic algorithm-based Model Predictive Controller is superior than that of a traditional model predictive controller.

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List of Abbreviations

MPC	Model predictive controller
GA-MPC	Genetic algorithm based MPC
PFC	Primary frequency control
LFC	Load frequency control
GA	Genetic algorithm
PSO	Particle swarm optimization
SISO	Single input single output
MIMO	Multi input multi output
PID	Proportional integral derivative
DMC	Dynamic matrix control
GPC	Generalized predictive control
ISE	Integral square error
MPP	Maximum power point
D	Diode
WT	Wind Turbine
DG	Diesel Generator

List of Symbols

A	State matrix of state space model
B	Input -to-state matrix of state space model
C	State-to-output matrix of state space model
D	Direct feed-through matrix of state space model
(A, B, C, D)	Augmented State space representation of a model
(A1, B1, C1, D1)	Discrete time State space representation
F, ϕ	Pair of matrices used in the prediction equation
$I_{q\,xq}$	Identity matrix with dimensions q x q
O_m	Zero vector with dimensions of m x m
O_1	Zero matrix with dimensions of m x m
N_c	Control horizon
N_p	Prediction horizon
R_w	Control input rate weight
Δ U	Increment in control input sequence vector
Δ u(k+m)	Control input increment at sample time ‘m’
x(k), x_1(k)	State variable matrix
y_{ref}	Reference output
k	Sampling instant
T_i	Initial time instant
n_1	State variable matrix dimensions
m	Number of control inputs
q	Number outputs of the plant
Δ x	Change in state variable matrix from previous sample time to present sample time.
O	Objective function for the MPC design
Y	Output
R_s	Reference
R	Control input rate weight matrix

B_d	Disturbance matrix
$w(k)$	Input disturbance
Δf_{ref}	Frequency deviation reference
Δf	Load frequency deviation
n	Dimension of augmented state matrix

Chapter 1
Microgrid

1.1. Introduction:

The economic and social development of the modern world is greatly dependent on the availability of electrical energy. Fossil fuel consumption share for electrical power generation in India for the year 2014 was 73.58%, which needs to be reduced and replaced by renewable energy resources. In today's world, it is very important to reduce our dependency on fossil fuel resources. The use of fossil fuels contributes to global warming and degrades the environment every year. We must conserve these resources for future generations and to reduce pollution in the environment. Research is going on to increase the consumption of renewable resources. Renewable energy is a source of energy that is both clean and unlimited, as well as becoming increasingly competitive. They differ from fossil fuels primarily in their diversity, abundance, and ability to be used anywhere on the earth. But most importantly, they do not emit greenhouse gases or damaging pollution, which cause climate change. Their costs are also reducing at a steady rate, whereas, despite their current availability, the general cost of fossil fuels is increasing. Some of the renewable energy resources are listed below.

- **Wind energy**: energy obtained by winds.
- **Solar energy**: light (photo voltaic) energy from sun.
- **Hydraulic or hydroelectric energy**: It is the potential energy obtained from stored water.
- **Biomass and biogas**: These are the energy generated from organic wastes.
- **Geothermal energy**: The heat produced Earth’s inner layers.
- **Tidal energy**: The energy produced from the ocean tides.
- **Wave energy**: The energy produced from waves of ocean.
- **Bioethanol**: An organic fuel produced for vehicles by the fermentation of plants.
- **Biodiesel**: organic fuel for vehicles produced by vegetable oils.

The environmental and economic advantages of using renewable energy resources are given below.

1. The generation of electricity from renewable sources does not result in the release of greenhouse gases and reduces levels of air pollution.
2. Energy diversity increases and dependence on imported fuels will reduce.

3. Industries of renewable energy resources are creating economic development and jobs.

1.2. Integration of Renewable energy resources into grid:

The most severe disadvantage of operating a renewable resource plant is that renewable energy sources cannot be used for energy production in the same way as traditional plants. Variations in the solar radiation or the speed of the wind can happen in a matter of seconds or minutes, which results in fluctuating electricity generation. A short-term generation variance in an integrated intermittent resource, such as clouds passing over PV systems, was addressed in [1], [2]. Energy storage will be one of the solutions to the unpredictability of intermittent energy generation. According to the findings of [3,4], intermittent resources paired with energy storage play a unique role in decreasing power fluctuations in microgrids and will have an influence on electric power system reorganisation.

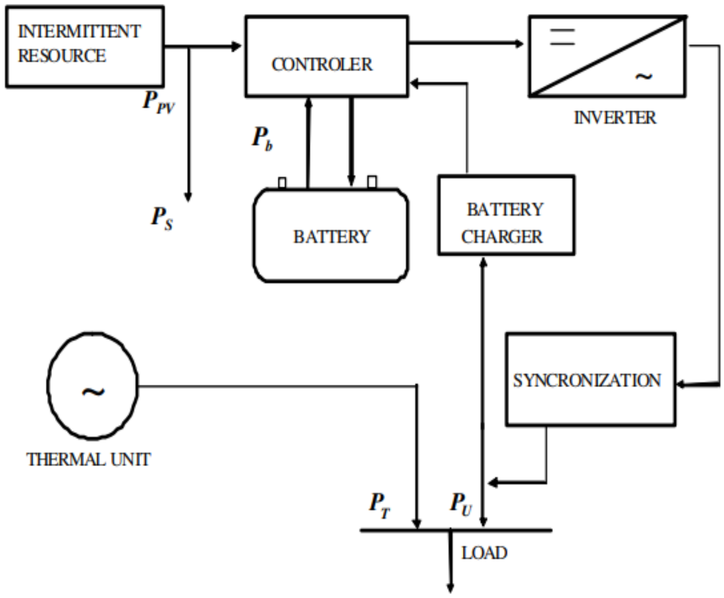

Figure 1.1: Intermittent energy resources with energy storage system integration into grid.

Energy from intermittent resource plants is incorporated into the electrical grid to lower the cost of operating fossil fuel units and the use of fossil fuel in the grid. Figure 1.1 depicts a grid integration of an intermittent renewable energy supply with a centralised storage. The intermittent resources might be dispersed across a vast geographical region [5]. The introduction of renewable energy resources into microgrids enhances power supply dependability while simultaneously generating concerns with stability. Traditional controllers will not offer appropriate performance when renewable energy supplies are integrated into the power system.

1.3. Basic Structure of Microgrid:

The grid concept is complex; it is the interconnection of all large energy generating units over a large geographical area based on a control structure that is centralised. Controlling such a large interconnected network is extremely difficult. A new microgrid concept is introduced to facilitate the regulation and improvement of quality of power system operating parameters such as power, voltage, and frequency. The concept of microgrid is to decentralise the power system's control structure and to improve power supply reliability for local loads.

A micro grid is a collection of small-scale local distributed energy resources, such as solar, wind, small-scale hydro power station, biomass, diesel unit, fuel cell, etc., that are interconnected to form a local grid that is purposely designed to supply power to a small area [6]. Micro grids can be formed by connecting solar, wind, small-scale hydro power station, biomass, diesel unit, and fuel cell systems, among other small-scale local distributed energy resources. A fundamental microgrid network is made up of small-scale micropower generating resources, local loads, energy storage devices, a control mechanism, and common coupling components.

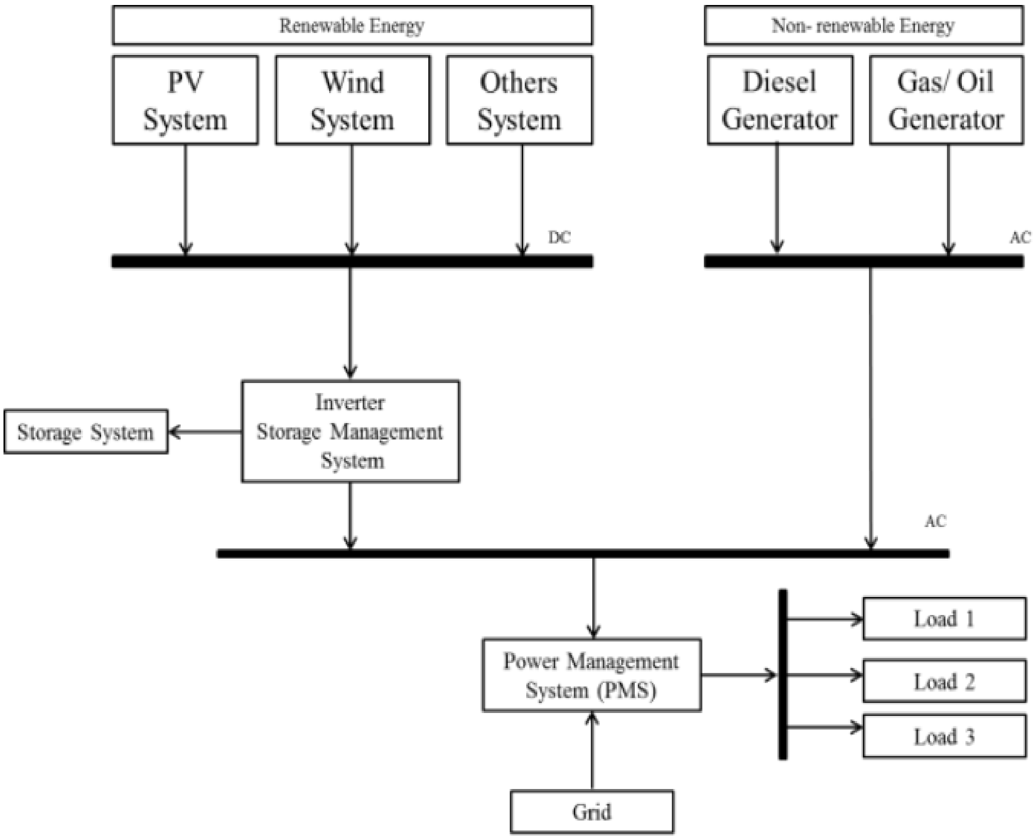

Figure 1.2 Schematic diagram of a microgrid [6]

Renewable energy sources (such as solar units, wind power, and bio mass) and conventional energy sources (such as diesel units, fuel cell units, micro hydro power, and gasoline) can be incorporated into micro-grids. Additionally, micro-grids can receive support from electric and natural gas networks. In general, a microgrid may be connected to the main grid by means of a tie line powerline. However, if it is required for the microgrid to function as an isolated one due to a failure or maintenance schedule in the main grid, the microgrid may be separated from the main grid. The diagram of a fundamental microgrid is displayed in Figure 1.2 above.

1.4. Classification of Microgrids:

When designing a microgrid, consideration is given to the grid connection, support, interactions with different types and quantities of energy sources, and load [6]. Table I shows the most common arrangements. The first classification is listed below.

Criteria	Configurations
Bus	Dc bus Ac bus Hybrid
Interconnection with grid	Remote Grid support Isolated
Back-up energy system	Grid support Batteries support Emergency Plant
Types of energy sources	Conventional energy resources Renewable energy resources Hybrid
Numbers of energy sources	Individual Hybrid Generation
Types of Loads	DC Loads AC Loads

Table I: Configurations of Microgrids

Based on type of bus used in the microgrid, they are classified into three types

1. Dc Bus Microgrid
2. AC Bus Microgrid
3. Hybrid Microgrid (combination of both AC and DC microgrids)

1.4.1.Dc Bus Microgrid:

All types of sources, including those that generate alternating current and direct current, are connected in this microgrid to a single DC bus bar [6]. While dc sources are connected straight to the bus bar, ac sources are connected to the bus bar through the use of an ac to dc converter. The fundamental configuration of a DC Microgrid is shown in Figure 1.3.

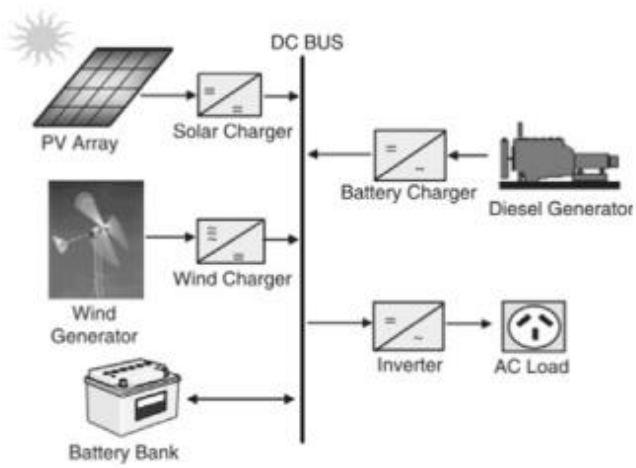

Figure 1.3 : Configuration of a Dc microgrid[29]

In terms of system efficiency, cost, and system size, DC microgrids have more advantage over AC microgrids. Overall efficiency increases as fewer power electronic converters are needed. A DC microgrid's size is also significantly decreased because AC/DC converters do not need transformers. DC microgrid also requires energy storage system like AC microgrid. However, only disadvantage of DC microgrid is, it needs more attention in voltage regulation and over current problems. DC microgrid does not require frequency stabilising support.

1.4.2. Ac Bus Microgrid:

All of the renewable energy sources and loads that make up a microgrid are connected to the same AC bus [6]. The difficulty in controlling and operating AC microgrids is the primary drawback of these types of power systems. Figure 1.4 shows a schematic representation of a conventional AC microgrid's organisational layout. According to the distribution system, microgrid alternating current (AC) can be divided into: single-phase, three-phase without neutral-point lines, and three-phase with neutral-point lines.

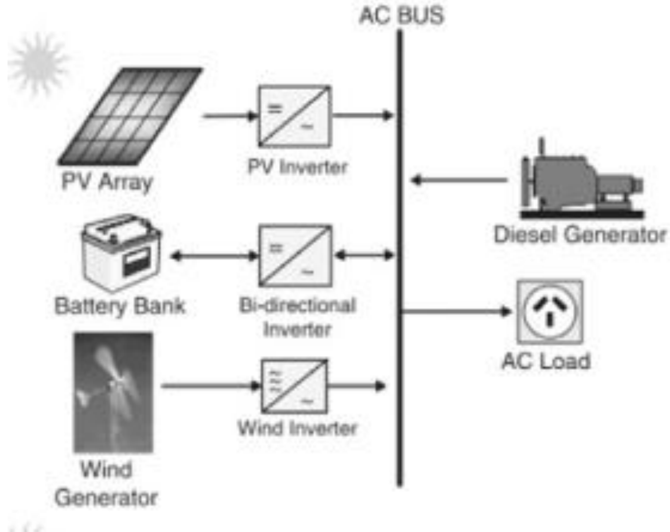

Figure 1.4: Configuration of an Ac microgrid[29]

1.4.3. Hybrid Microgrid:

The hybrid AC-DC microgrid reduces several power conversions in individual AC or DC microgrids and enables simultaneous connection of variable AC and DC sources as well as the loads they are linked with [29],[30]. Figure 1.5 explains the architecture and energy management of hybrid AC-DC microgrid.

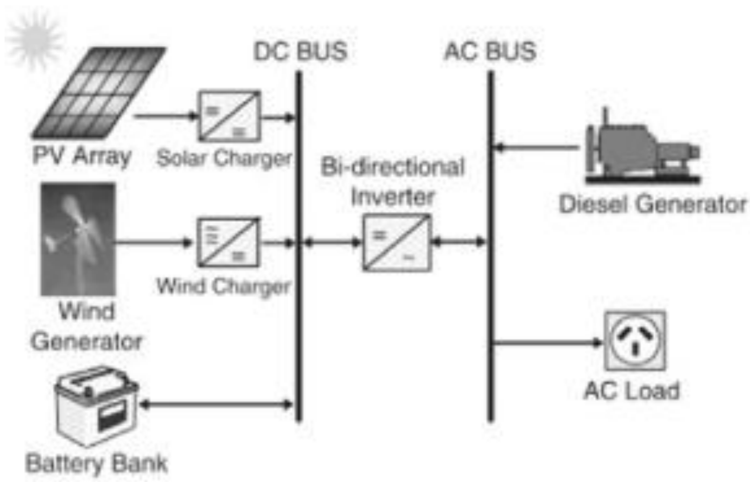

Figure 1.5: Configuration of hybrid microgrid [29]

Due to the imbalance between electrical power generated and electrical load demand, the supply frequency deviates from its specified value. This imbalance between power generated and load in an isolated microgrid is mainly due to the presence of intermittent nature of power generation by renewable energy resources. The load frequency fluctuates with the variation in active power generated by the renewable energy resources and with the load disturbance. The load frequency must be kept within specified limits for the safety and acceptable operation of electrical equipment, as well as the microgrid's stability. When the microgrid is connected to the main grid, it operates at the same frequency as the main grid. When disconnected from the main grid, however, it must regulate both frequency and voltage individually.

1.5. Distributed Energy Resources used in the Microgrid:

Some of the distributed energy resources which were used in microgrid under study are briefly summarised here.

1.5.1. Photovoltaic Array:

The basic structure of a solar panel is the combination of different photo voltaic cells [20]. A photovoltaic (PV) array operates under uniform illumination and exhibits a current-voltage characteristic with a single maximum power point (MPP), which varies with temperature and irradiance level. The solar panel model incorporates temperature and radiation as inputs to produce voltage and current [19]. At a temperature of 25 degrees Celsius, the value of maximum power is achieved for a radiation of 1000.

Figure 1.6 shows an equivalent circuit for a photovoltaic array, which includes a current source, a light-sensitive diode (D), a series resistor, a shunt resistance. The series resistor is represented by the letter R_s, while the shunt resistance is represented by the letter R_{sh}.

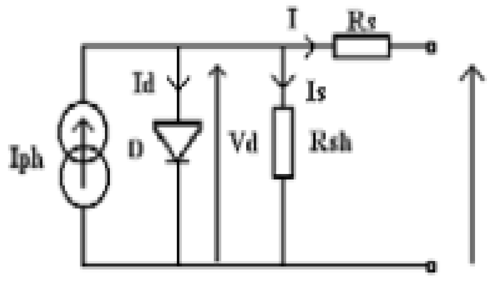

Figure 1.6: A basic structure of a solar cell [20]

The newly built weather station has made it possible to arrive at the conclusion that the PV cell has an average daily solar radiation of 4.27 kWh/m2[6]. It has been shown that the highest value, on average, is equivalent to 678 W/m2. 994 W/m2 is the greatest peak figure that was recorded.

1.5.2. Wind Turbine Generator:

Wind energy is one of the renewable energy sources that is expanding at one of the quickest rates, and its use continues to rise each year in many of nations. Various mechanical and electrical components are used in wind turbine generator (WTG) to convert kinetic energy to electric energy [21],[22]. As shown in Figure 1.7 the main components of a wind turbine are,

Mechanical components: Rotor bearings, rotor hub, rotor blades, main shaft, gearbox, mechanical brake, yaw drives, pitch drives, nacelle, wind measuring unit, foundation, tower, heat exchange system.

Electrical components: Power electronic converter, the wind generator, generator- and grid-side harmonic filters, power cables, wind farm collecting point, step-up transformer, and switch gear.

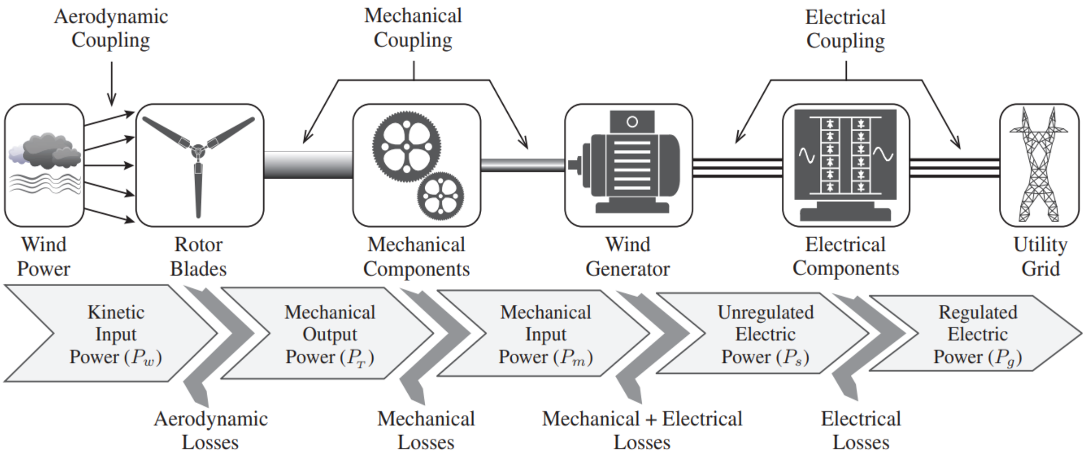

Figure 1.7: The block diagram of wind turbine [22]

1.5.3. Diesel Generator:

A DG is a standard diesel engine that is connected to an electrical generator [23],[24],[25]. Diesel generators are extremely important appliances that generate energy by combusting diesel fuel. These devices generate electricity by combining a diesel engine and an electric generator. Diesel generators burn diesel fuel to convert some of the chemical energy it contains into mechanical energy. Then, a crank that produces electricity is turned using this mechanical energy. Electrical charges are produced in the wire when it is moved through a magnetic field. Usually, two polarised magnets provide the magnetic field in an electric generator. Then, a wire is positioned between the magnets and in the magnetic field, and it is repeatedly wrapped around the crankshaft of the diesel generator. The wires move across the magnetic field when the crankshaft of a diesel engine rotates, creating electric charges in the circuit. A diesel generator will typically use 0.4 litres of diesel for every kilowatt-hour produced. The diesel engine is essentially an internal combustion engine. In contrast to a gasoline engine, a diesel engine burns the injected fuel in the injection chamber by igniting it with the heat of compression. Diesel engines can approximate Carnot efficiency since they have the highest thermal efficiency of any internal combustion engine. Diesel engines can be run on a variety of crude oil derivatives. Natural gas, alcohols, gasoline, wood gas, and diesel are all acceptable combustion fuels for diesel engines.

1.5.4. Fuel cell:

A fuel cell is an energy conversion device that directly turns the chemical energy of a reaction into electricity while producing water and heat as by-products [26],[27],[28]. Figure 1.8 depicts the structure of a simple fuel cell. The fuel cell is made up of an electrolyte layer that comes into contact with two electrodes on either side. The hydrogen fuel is continually delivered to the anode electrode, while the oxidant (or) oxygen from the air is continuously given to the cathode electrode. The hydrogen fuel is decomposed into positive and negative ions at the anode terminal. Only positive ions may move from anode to cathode across the intermediary electrolyte membrane, which also functions as an insulator for electrons. For the system to become stable, these electrons desire to recombine on the other side of the membrane, thus the free electrons are transported to the cathode side through an external electrical connection. At the cathode, positive and negative ions recombine with oxidant to generate depleted oxidant (or) pure water.

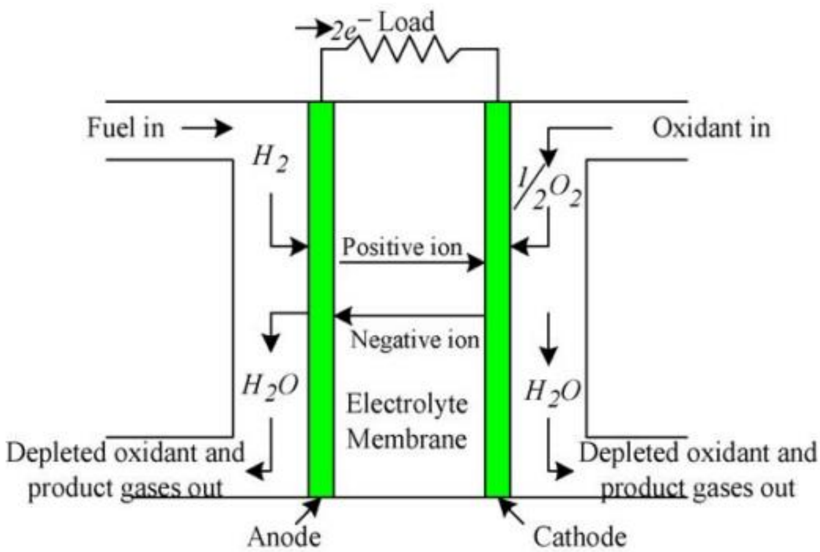

Figure 1.8: Fuel cell structure [26]

The chemical processes that occur in the anode and cathode, as well as the overall reactions, are listed below.

Reaction in Anode: $H_2 \longrightarrow 2H^+ + 2e^-$

Reaction in Cathode: $\frac{1}{2} O_2 + 2\,H + 2e^- \longrightarrow 2H_2O$

Overall: $H_2 + \frac{1}{2} O_2 \longrightarrow 2H_2O$

1.6. Objective of the dissertation:

The renewable energy resources integrated into the microgrid, such as solar and wind generators, are intermittent in nature. They generate variable power due to the variation in photovoltaic irradiation and wind speed. Due to this reason, in an isolated microgrid, there will be an imbalance between the total active power generated and total load demand, which leads to frequency fluctuation [32]. Load demand variation is also the reason for frequency fluctuation in the isolated microgrid. For the electrical equipment in the micro grid to work well, this frequency needs to be carefully stabilized.

The frequency of the power supply can be stabilized at three levels [31], [32].

- First Level: The speed governors of the generating units perform primary control, providing an immediate (automatic) response to sudden changes in load (or frequency) within seconds.

- Second Level: Secondary control adjusts the output of selected generators to restore frequency to its nominal value. Secondary control action takes minutes to control the frequency deviation.

- Third Level: The appropriate power distribution and power exchange between points of common coupling and smart grid are handled by the tertiary control level in order to reduce power losses on the microgrid (MG) lines.

In this dissertation, the secondary frequency control technique, which is also called load frequency control (LFC), is used for the frequency regulation in an isolated microgrid using genetic algorithm-based model predictive control under consideration of load perturbations and power fluctuations in wind and solar power generating units.

1.7. Organization of this dissertation:

This dissertation is organised in six chapters. A complete structure of a microgrid and the renewable energy resources integration into the microgrid is illustrated in Chapter 1. Chapter 2 illustrates various challenges and control methods of frequency regulation in an isolated microgrid which were reported in the previous research. Chapter 3 gives a detailed mathematical formulation of a model predictive control scheme for a control problem. Chapter 4 explains the concept of genetic algorithm technique for the optimal solution of complex problem. In Chapter 5 it is explained how the load frequency is regulated for the given isolated microgrid using a model predictive controller whose tuning parameters are optimized using the genetic algorithm concept and also illustrates the analysis of the results obtained in the frequency regulation problem for an isolated microgrid under various load disruptions and power generation variations in wind and solar units due to the fluctuations in wind speed and solar irradiation. Chapter 6 outlines the conclusion and future scope of the work.

Chapter 2

Frequency Control Techniques

The modern power system network becomes complex due to the increasing use of renewable energy resources in the power system. In such complex network it is very important to control both voltage and frequency. Frequency can be regulated by controlling the active power flow in the network. While the voltage is regulated by controlling reactive power. A survey on various challenges in load frequency control were reported in [7] by Hassan Haes Alhelou, Mohamad-Esmail Hamedani-Golshan, Reza Zamani, Ehsan Heydarian-Forushani and Pierluigi Siano.

Frequency is regulated usually in three categories of control levels. They are

1. Primary control level
2. Secondary control level
3. Tertiary control level

1. Primary frequency control

The Primary Frequency Control (PFC), an important method of maintaining frequency stability, balances the grid's power supply and load consumption. When the Grid frequency limit is not within the predefined dead band restrictions, PFC automatically activates within 30 seconds. Turbine power will be adjusted in the event of any sudden changes in frequency.

2.Secondary frequency control

Secondary frequency control which is also called Load frequency control (LFC) is a type of frequency control for managing frequency in power networks and has two basic objectives: (i) maintaining the frequency to a preferred range; and (ii) managing the interchange power via main tie-lines between the various management zones.

3. Tertiary frequency control

The primary responsibility of the tertiary control level is re-dispatching the power generating units and auxiliary reserve following a severe disruption.

In the domain of frequency regulation in an isolated microgrid, numerous control strategies have been reported. Conventional droop control method for load frequency control in a microgrid [8] is one among them which is reported by Ritwik Majumder, Arindam Ghosh, Gerard Ledwich. Parallel converters are used to get desired active and reactive powers in the microgrid. Droop control is used to control the parallel converters to get desired frequency and voltage by controlling the active and reactive powers in the microgrid.

$$\omega = \omega_s - mP$$

$$\nu = v^* - nQ$$

Where ω is load frequency, ω_s is synchronous frequency, ν is the converter voltage, v^*desired voltage magnitude. P, Q are the active and reactive powers delivered by converter. m, n are the coefficients of droop control.

Mostafa Farrokhabadi, Claudio A Canizares, Kankar Bhattacharya proposed a Voltage - based frequency controller [9]. According them the error between frequency deviation from its set point is given as input to the proposed controller. To ensure that the steady state error is zero, the frequency error is given as input to the controller through Proportional Integral (PI) controller. Then this error signal is passed through a gain block and lead lag compensator to ensure sufficient damping factor and phase difference between voltage regulator input and output.

Proportional Integral control method was proposed for minimizing oscillations of load frequency in an isolated microgrid as given in [10]. The frequency error is given as feedback to PI controller. The controller gain is adjusted automatically to get the desired frequency regulation. Then the performance of this controller was compared with Nicolas-Ziegler PI controller.

It was illustrated by Nicholas T Janssen, Richard W Wies and Rorik A Peterson that how a distributed secondary load with electric thermal storage elements will be used for the secondary load frequency regulation [11]. A diesel generator and distributed secondary loads with thermal storage elements are used. The surplus wind energy is stored as heat energy. In [12] H_∞ and µ-synthesis control techniques were developed for the secondary frequency control loop for an islanded microgrid. They derived linearized state space model of the microgrid to apply the H_∞ and µ-synthesis controllers. This method is based on minimizing an optimization problem. They are designed to reduce the effects of fluctuations in wind and solar plants and load perturbations.

In [13] model predictive control method was designed for individual control area in a two-control area power system with wind turbines. The robustness of model predictive controller is proved in the presence of uncertainties by governor parameter changes in turbine and load perturbations. Kayalvizhi s and D M Vinod Kumar proposes a fuzzy adaptive model predictive control load frequency regulation approach for an isolated microgrid [14]. The tuning parameter of the model predictive controller such as control input rate weight (R_w)

impacts the performance of the controller in the load frequency control of an isolated microgrid. In this research they optimised the design parameter of model predictive controller using adaptive fuzzy logic controller to improve the controller performance in the frequency regulation problem. The output weight and control input rate weights of a model predictive controller for the frequency regulation of an isolated microgrid are optimised using particle swarm optimization and are compared with traditional PI controller based on Nicolas-Ziegler tuning and fuzzy logic as shown in [15].

Chapter 3
Model Predictive Controller

3.1. Introduction:

In a control problem the importance of the controller is to determine the control input to the plant in such a way that the plant output follows the desired reference. Model Predictive Control (MPC) has been in use in chemical process industries and oil refineries since 1980's. Now a days it gains its importance in other departments like automobile engineering, mechanical engineering, electrical engineering, aerospace engineering etc. The objective of MPC is to calculate the sequence of control input to optimize the outputs of a plant or process in future, it calculates the control inputs to the plant while satisfying constraints. It uses the recent plant information by measurement and estimated state information to determine the sequence of control input and future output. By predicting the future outputs, we can apply feedforward control in the plant. MPC is a feedforward as well as feedback control algorithm that uses model of the process/plant to predict the future outputs.

MPC is a multi-input multi-output control technique which uses the explicit model of process or plant, to calculate sequence of control input and predict outputs into the future, it uses an optimizer to calculate these control inputs, such that the plant output follows the desired set point. MPC use the notion of horizon, instead of making the error between setpoint and predicted output zero instantly, it looks the error over a period of time into the future. It calculates the current control action such that the error between set point and predicted output in the future is as minimum as possible.

3.2. Basic Concept of MPC

The basic concept of MPC is explained in the Figure 3.1. The actual plant output y_0, predicted value of the plant output and sequence control input for a single input single output control are shown in the Figure 3.1. The present sampling time is represented by k. At sampling instant k, the MPC calculates sequence of Nc control input {u(k+i-1), i= 1,2,3…Nc}. This sequence of input consists of present input u(k) and Nc-1 control inputs in the future. The input is constant after Nc control inputs. Here sequence of Nc control inputs is calculated such that Np predicted outputs {y(k+1), i = 1, 2, 3…. Np}, at sampling instant k, are as close as possible to desired output. i.e., the control sequence {u(k+i-1), i= 1,2,3…Nc} is calculated such that the sum of squared error between predicted output and desired output over a prediction horizon Np, is as minimum as possible using an optimization technique.

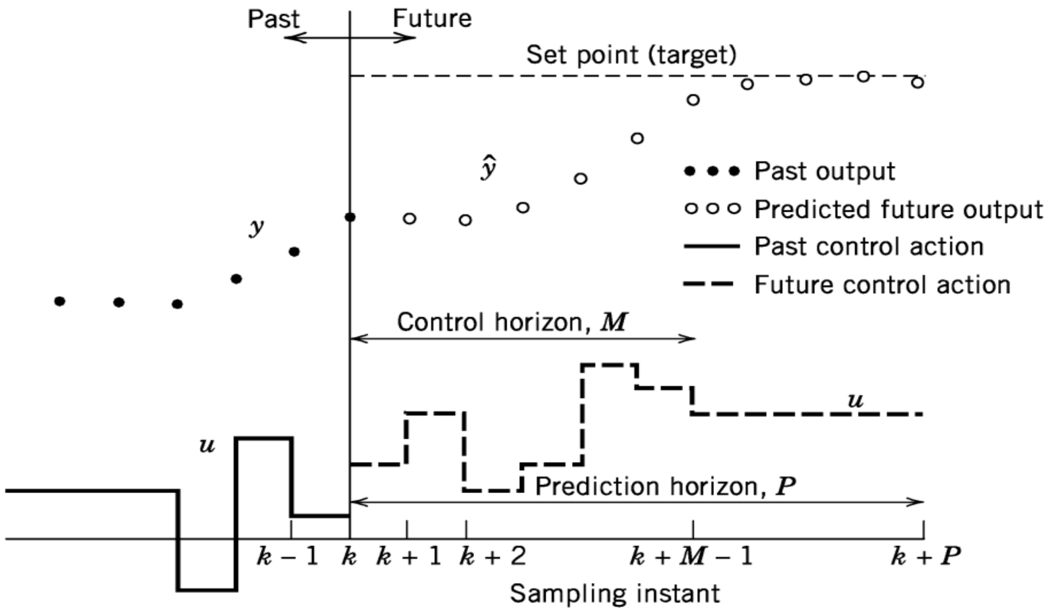

Figure 3.1*: Concept of Model Predictive Controller.*

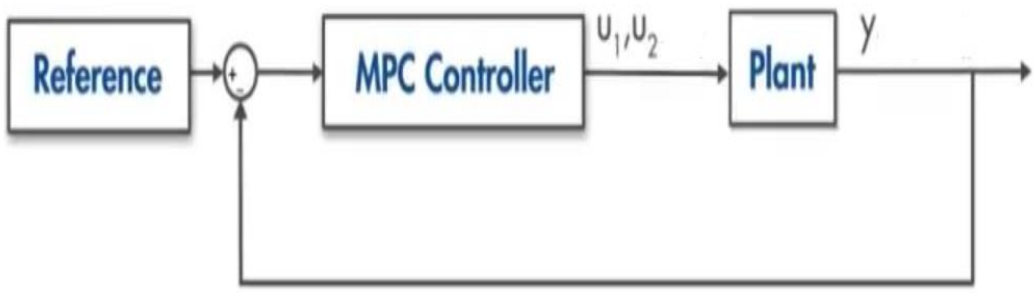

Figure 3.2: *Basic structure of a Model predictive controller*

The cost function used in the optimization technique is,

$$O = \sum_{k=1}^{Np} (y(k+1) - y_{ref})^2 \tag{3.1}$$

Here,

$y(k+1)$ = N_p number of predicted outputs calculated at sampling instant k

y_{ref} = Desired output or reference output

If we want include the weightage or constraints to control input or control input rate, the cost function modified as follows,

$$O = \sum_{k=0}^{Np} (y(k+1) - y_{ref})^2 + \sum_{k=0}^{Nc-1} \Delta u(k)^2 \tag{3.2}$$

Here,

Δu = Vector of Control input rate

An important characteristic of an MPC is the receding horizon control that it possesses. Although we calculate Nc number of control inputs at sampling instant k, we only apply the first control input to the plant or process and ignore the remaining (Nc-1) control inputs. This is because we only implement one control input at a time. We continue on to the next sampling time, k+1, using the new data that was measured at k. Once again, we calculate the new sequence of control inputs (Nc), but once again, at the sampling instant k+1, we only apply the first control input. The same technique is carried out at each and every sample time.

3.3. Important terms used in MPC

In general, in an MPC, the terms used are Control horizon, Prediction horizon, moving horizon window, receding horizon control, sampling time etc.

Control horizon (Nc): Instead of determining only the present control input to a plant, in an MPC, we will look into determining sequence of control inputs such that the output in future is optimized to achieve desired setpoint. The no of such control inputs that we wish to determine is called Control horizon. It is represented with ‘Nc’. The use of determining sequence of control inputs is to avoid aggressive control action.

Prediction horizon (Np): It gives us an idea of how far in the future we wish to predict the plant's outputs. Specifically, how many future outputs do we want to predict in the current sampling time.

Moving horizon Control: It is a time-dependent horizon. In this method, the parameters are measured or estimated at regular time intervals over a period of time. Here the window is from an arbitrary time T_i to T_i+ (Np)* Ts. Here, T_i is the initial time at which the control action is to be started, Np is the prediction horizon, and Ts is the sampling time or time interval over which the parameters are estimated or calculated.

Receding horizon control: Though we calculate the sequence of control inputs over a period of time to avoid aggressive control action, only the first control input is implemented at each sampling time while neglecting the rest of the control inputs.

3.4. Models used in design of Predictive controller:

There are two general approaches to predictive control action.

1.Dynamic Matrix control (DMC), which uses the finite impulse response model of the plant or finite step response model of the plant. This method was in use in the early years of formulation of model predictive control. This concept is used for both stable and unstable systems, but it requires a greater number of step response coefficients or impulse response coefficients for the formulation of control action.

2.Generalised predictive control (GPC), which uses the transfer function model or state space model of the plant or process whose output is to be controlled. This concept of control action is used for stable systems only.

3.5. Solution of model predictive controller with output feedback:

Different MPC formulations exist, but the outcomes are generally similar, and the state space formulation is the most recent development. The MPC uses state space model of the plant. Here we are using the discrete time state space model of the plant to determine the control inputs. State variable x(k) represents the current information needed to predict the future

3.5.1. For SISO systems:

For easy understanding MPC is applied for SISO system initially, later the same concept is extended to MIMO systems, which is straight forward. Assume a single input single out put discrete time state space model of a plant given below.

$$x_1(k+1) \quad = A_1 x_1(k) + B_1 u(k) \qquad (3.3)$$

$$y(k) \ = C_1 x(k) + D_1 u(k) \qquad (3.4)$$

Where, u is control input, y is plant output, x_1 is state variable vector with dimensions of (n1) x (n1). We have to modify the model to include an integrator in the state space model, which is called augmented model.

We make the assumption that the current control input u(k) does not have an effect on the output y(k) at the same sampling time while working with a moving horizon control. The present control input u(k) at the moment k can have an effect directly on the output y(k+1) at the k+1 sampling instant. Therefore, in equation (3.4), we can make the direct assumption that D_1 equals zero.

$$x_1(k+1) \quad = A_1 x_1(k) + B_1 u(k) \qquad (3.5)$$

$$y(k) \ = C_1 x(k) \qquad (3.6)$$

Taking difference equation of (3.5),

$$x_1(k+1) - x_1(k) = A_1(x_1(k) - x_1(k-1)) + B_1(u(k) - u(k-1)) \qquad (3.7)$$

The difference of state variable is given by,

$$x_1(k+1) - x_1(k) \quad = \Delta x_1(k+1)$$
$$x_1(k) - x_1(k-1) = \Delta x_1(k)$$

The difference of control input is given by,

$$u(k) - u(k-1) = \Delta u(k)$$

Now the difference equation (3.7) will be,

$$\Delta x_1(k+1) = A_1 \Delta x_1(k) + B_1 \Delta u(k) \qquad (3.8)$$

Taking difference equation of (3.6),

$$y(k+1) - y(k) = C_1(x(k+1) - x(k)$$
$$= C_1 \Delta x_1(k+1)$$
$$= C_1(A_1 \Delta x_1(k) + B_1 \Delta u(k))$$
$$y(k+1) \quad = C_1 A_1 \Delta x_1(k) + C_1 B_1 \Delta u(k) + y(k) \qquad (3.9)$$

By combining the equations (3.8) & (3.9), the state space model of a plant will be,

$$\begin{bmatrix} \Delta x_1(k+1) \\ \Delta y(k+1) \end{bmatrix} = \begin{bmatrix} A_1 & O_1^T \\ C_1 A_1 & 1 \end{bmatrix} \begin{bmatrix} \Delta x_1(k) \\ y(k) \end{bmatrix} + \begin{bmatrix} B_1 \\ C_1 B_1 \end{bmatrix} \Delta u(k) \qquad (3.10)$$

$$y(k) \quad = [O_1 \;\; 1] \begin{bmatrix} \Delta x_1(k) \\ y(k) \end{bmatrix} \qquad (3.11)$$

Here,

$O_1 = |0\ 0 \ldots.|$, with 1 x n1 dimensions.

Compare equations (3.1) & (3.2) with standard discrete time state space model given below.

$$\mathrm{x(k+1)} \quad = \mathrm{Ax(k) + Bu(k)} \qquad (3.12)$$

$$\mathrm{y(k)} \quad = \mathrm{Cx(k) + Du(k)} \qquad (3.13)$$

Here,

$$A = \begin{bmatrix} A_1 & O_1^T \\ C_1 A_1 & 1 \end{bmatrix}$$

$$B = \begin{bmatrix} B_1 \\ C_1 B_1 \end{bmatrix}$$

$$C = [O_1 \;\; 1]$$

Here the state space model given in equation (3.10) & (3.11) is called the Augmented model of the given system, which is used in MPC.

Now assume that we are at time instant k, k>0, now our aim is to calculate the sequence control input to the plant which are assumed to be applied to the plant at k, k+1, k+2……etc such that the corresponding output of the plant at each time instant k+1, k+2, k+3…...k+Np are as minimum as possible.

Assume that at time instant k, k>0, the state variable vector $x(k)$ is available. The state variable vector at k gives the plant information at k. The sequence of control input to the plant is denoted by,

$$\Delta u(k), \Delta u(k+1), \Delta u(k+2), \Delta u(k+3) \ldots\ldots\ldots\ldots\ldots. \Delta u(k+\mathrm{Nc}-1)$$

Where, Nc is the control horizon, gives the information that how many future control inputs that we wish to calculate. With the use of current state vector $x(k)$ at k we will determine the future state variable vectors for Np number of time instants, where, Np is prediction horizon. The future state variable vectors are denoted by,

$$x(\mathrm{k}+1|\mathrm{k}), x(\mathrm{k}+2|\mathrm{k}), x(\mathrm{k}+3|\mathrm{k}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots x(\mathrm{k}+\mathrm{Np}|\mathrm{k})$$

The no of control horizon Nc, is selected such that it is less than or equal to prediction horizon, Np.

With the use of augmented state space model of the plant given in equation (3.12), (3.13) we will find the future state variable vectors,

$$x(\mathrm{k}+1|\mathrm{k}) = \mathrm{A}\, x(\mathrm{k}) + \mathrm{B}\, \Delta u(\mathrm{k})$$

$$x(\mathrm{k}+2|\mathrm{k}) = \mathrm{A}\, x(\mathrm{k}+1) + \mathrm{B}\, \Delta u(\mathrm{k}+1)$$

$$= \mathrm{A}\, (\mathrm{A}\, x(\mathrm{k}) + \mathrm{B}\, \Delta u(\mathrm{k})) + \mathrm{B}\, \Delta u(\mathrm{k}+1)$$

$$= \mathrm{A}^2\, x(\mathrm{k}) + \mathrm{AB}\, \Delta u(\mathrm{k}) + \mathrm{B}\, \Delta u(\mathrm{k}+1)$$

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$$x(\mathrm{k}+\mathrm{Np}|\mathrm{k}) = \mathrm{A}^{\mathrm{Np}} x(\mathrm{k}) + \mathrm{A}^{\mathrm{Np-1}}\mathrm{B}\Delta u(\mathrm{k}) + \mathrm{A}^{\mathrm{Np-2}}\mathrm{B}\Delta u(\mathrm{k}+1) + \mathrm{A}^{\mathrm{Np-3}}\mathrm{B}\, \Delta u(\mathrm{k}+2) \ldots\ldots\ldots\ldots$$

$$+ \ldots\ldots\ldots\ldots + \mathrm{A}^{\mathrm{Np-Nc}}\,\mathrm{B}\, \Delta u(\mathrm{k}+\mathrm{Nc}-1).$$

With the use of these predicted state variables, we will predict the future output variables using the following equations,

$$\mathrm{y}(\mathrm{k}+1|\mathrm{k}) = \mathrm{C}x(\mathrm{k}+1)$$

$$= \mathrm{C}\, (\mathrm{A}\, x(\mathrm{k}) + \mathrm{B}\Delta u(\mathrm{k}))$$

$$= \mathrm{CA}x(\mathrm{k}) + \mathrm{CB}\Delta u(\mathrm{k})$$

$$\mathrm{y}(\mathrm{k}+2|\mathrm{k}) = \mathrm{C}x(\mathrm{k}+2)$$

$$= \mathrm{C}\, (\mathrm{A}^2\, x(\mathrm{k}) + \mathrm{AB}\, \Delta u(\mathrm{k}) + \mathrm{B}\, \Delta u(\mathrm{k}+1))$$

$$= \mathrm{C}\, \mathrm{A}^2\, x(\mathrm{k}) + C\mathrm{AB}\, \Delta u(\mathrm{k}) + \mathrm{C}\, \mathrm{B}\, \Delta u(\mathrm{k}+1))$$

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$$y(k+Np|k) = Cx(k+Np)$$
$$= C\,(A^{Np}x(k)+A^{Np-1}B\Delta u(k)+A^{Np-2}B\Delta u(k+1)+A^{Np-3}B\Delta u(k+2)\ldots\ldots + \ldots\ldots\ldots + A^{Np-Nc}B\,\Delta u(k+Nc-1))$$
$$= C\,A^{Np}x(k)+C\,A^{Np-1}B\Delta u(k)+C\,A^{Np-2}B\Delta u(k+1)+\ldots\ldots\ldots\ldots + C\,A^{Np-Nc}B\,\Delta u(k+Nc-1)$$

Here all the predicted output variables are defined in terms of current state variable $x(k)$ and sequence of future input control variable $\Delta u(k+i)$, i= 0,1,2…... Nc-1.

The predicted output variables and control variables in vector form,

$$Y=[\,y(k+1|k)\quad y(k+2|k)\quad y(k+3|k)\ldots\ldots\ldots\ldots\ldots y(k+Np|k)]^T$$

$$\Delta U=[\Delta u(k|k)\ \Delta u(k+1|k)\ \Delta u(k+2|k)\ldots\ldots\ldots\ldots\ldots\Delta u(k+Nc-1|k)]^T$$

In compact form, all of the predicted outputs can be written as,

$$Y = F\,x(k)+\phi\,\Delta U \qquad (3.14)$$

Here,

$$F=\begin{bmatrix} CA \\ CA^2 \\ CA^3 \\ . \\ . \\ . \\ . \\ CA^{N_P} \end{bmatrix};\ \Phi=\begin{bmatrix} CB & . & . & . & . & . \\ CAB & CB & . & . & . & . \\ CA^2B & CAB & CB & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ CA^{N_P-1}B & CA^{N_P-2}B & . & . & . & CA^{N_P-N_C}B \end{bmatrix}$$

The objective function to determine sequence of control input ΔU,

$$O = (Y-R_s)^T\bar{Q}(Y-R_s) + \Delta U^T\bar{R}\,\Delta U \qquad (3.14)$$

Where, Y set of predicted output, R_s set point or reference vector, Q is output weight matrix, ΔU is sequence of control input rate vector, $\bar{R}$ is control input rate weight matrix.

$\bar{R}_s=\begin{bmatrix} 1 \\ 1 \\ 1 \\ . \\ . \\ . \\ 1 \end{bmatrix}$*r(k), size of R_s is Np, r is reference value.

$\bar{R} = R_w I_{Nc\ x\ Nc}$, R_w is any real positive number, ($R_w \geq 0$), I is a unit identity matrix of the dimensions Nc x Nc, r(k) is reference value.

In the objective function shown in equation (3.14), the first term is related to minimise the error between the predicted output and reference, the second term is related to minimising the size of control input ΔU, when the objective function O is optimized. The term R_w is tuned to get desired closed loop performance of the plant. R_w=0, means that we do not care the size of control input, how large it would be or how minimum it would be. A high value of R_w indicates that we are concerned about the size of the control input and that we want it to be as small as feasible while still minimising the amount of difference that exists between the output and the reference. It is assumed that Q equals 1 in this study.

To determine optimised ΔU, that will minimise the objective function O, from equation (3.14),

$$O = \left(\bar{R}s - Fx(\mathrm{k})\right)^T(\bar{R}s - Fx(\mathrm{k})) - 2\,\Delta U^T \phi^T(\bar{R}s - Fx(\mathrm{k})) + \Delta U^T(\phi^T \phi + \bar{R})\,\Delta U \quad (3.15)$$

Now,

$$\frac{\partial O}{\partial \Delta U} = -2\phi^T\left(\bar{R}s - Fx(\mathrm{k})\right) + 2(\phi^T \phi + \bar{R})\,\Delta U \quad (3.16)$$

For the objective function to be minimum, $\frac{\partial O}{\partial \Delta U} = 0$

$$-2\phi^T\left(\bar{R}s - Fx(\mathrm{k})\right) + 2(\phi^T \phi + \bar{R})\,\Delta U = 0 \quad (3.17)$$

The optimized control input to the plant is,

$$\Delta U = (\phi^T \phi + \bar{R})^{-1}\, \phi^T\left(\bar{R}s - Fx(\mathrm{k})\right) \quad (3.18)$$

In this section, we calculated the sequence of control input ΔU, which is comprised of the control input at the present sampling time instant k, as well as future control inputs at time instants k+1, k+2, ...k+ Nc-1.

Though we calculated Nc number of control inputs at k, we will implement only the first control input at k, ignoring the rest of control inputs. Now moving to next sampling time and with the latest state variable information, we will determine the sequence of control inputs again at k+1 using the same procedure explained above. Again, we will implement only the first control input to the plant at k+1 time instant. Again, moving to the next sampling time, this procedure is repeated until the output reaches the desired setpoint. This is called the receding horizon control method.

3.5.2. MIMO systems:

The operation of MPC for a MIMO system is straightforward and may be thought of as an extension of SISO systems. Consider for a moment that the plant possesses m inputs, q outputs, and n1 states. We suppose that m is greater than q for improved control action. If the number of outputs is more than the number of inputs, it is impossible for us to hope to control each of the measured outputs separately with zero steady-state errors. In the general formulation of the problem with the predictive control, we also take into consideration the disturbance and noise caused by the plant. The discrete time model of the plant considering the plant noise and disturbance is given in (3.19).

$$x_1(k+1) \quad = A_1 x_1(k) + B_1 u(k) + \; B_d w(k) \tag{3.19}$$

$$y(k) \quad = C_1 x(k) \tag{3.20}$$

Where $B_d w(k)$ is input disturbance.

Taking difference on both sides of equation of (3.17),

$$x_1(k+1) - x_1(k) = A_1(x_1(k) - x_1(k-1)) + B_1(u(k) - u(k-1)) + B_d(w(k) - w(k-1)) \tag{3.21}$$

The difference of state variable is given by,

$$x_1(k+1) - x_1(k) \quad = \Delta x_1(k+1)$$

$$x_1(k) - x_1(k-1) = \; \Delta x_1(k)$$

The difference of control input is given by,

$$u(k) - u(k-1) = \Delta u(k)$$

$$B_d\big(w(k) - w(k-1)\big) = \mathcal{E}(k)$$

Now the difference equation (3.19) will be,

$$\Delta x_1(k+1) = A_1 \Delta x_1(k) + B_1 \Delta u(k) + B_d \mathcal{E}(k) \tag{3.22}$$

Taking difference equation of (3.20),

$$\begin{aligned} y(k+1) - y(k) \quad &= C_1(x(k+1) - x(k) \\ &= C_1 \Delta x_1(k+1) \\ &= C_1(A_1 \Delta x_1(k) + B_1 \Delta u(k)) \\ y(k+1) \quad &= C_1 A_1 \Delta x_1(k) + C_1 B_1 \Delta u(k) + y(k) \end{aligned}$$

$$\begin{bmatrix} \Delta x_1(k+1) \\ \Delta y(k+1) \end{bmatrix} = \begin{bmatrix} A_1 & O_1^T \\ C_1 A_1 & I_{q\mathrm{x}q} \end{bmatrix} \begin{bmatrix} \Delta x_1(k) \\ y(k) \end{bmatrix} + \begin{bmatrix} B_1 \\ C_1 B_1 \end{bmatrix} \Delta u(k) + \begin{bmatrix} B_d \\ C_1 B_d \end{bmatrix} \mathcal{E}(k) \tag{3.23}$$

$$y(k) \;\; = \begin{bmatrix} O_1 & I_{q\mathrm{x}q} \end{bmatrix} \begin{bmatrix} \Delta x_1(k) \\ y(k) \end{bmatrix} \tag{3.24}$$

Here, in this case, the identity matrix $I_{q\mathrm{x}q}$ has dimensions q x q while the zero matrix O_1 has dimensions q x n1. The dimensions of A_1, B_1, and C_1 are n1 x n1, n1 x m, and q x n1 respectively. For the sake of clarity in the notation, we will refer (3.23) & (3.24) by

$$x(k+1) = Ax(k) + B\Delta u(k) + B_d \mathcal{E}(k) \tag{3.25}$$

$$y(k) = C\,x(k) \tag{3.26}$$

The dimensions of the augmented state-space equation (3.25) are assumed to be n (= n1 + q).

The extension of solution for MIMO systems is straight forward and we need to pay attention in taking dimensions of the state, control vectors and output vectors in Multi Input Multi Output systems. The output and input control rate vectors are defined as below.

$$\mathrm{Y}=[\,\mathrm{y}(\mathrm{k}+1|\mathrm{k})^T \quad \mathrm{y}(\mathrm{k}+2|\mathrm{k})^T \quad \mathrm{y}(\mathrm{k}+3|\mathrm{k})^T \quad \ldots\ldots\ldots\ldots\ldots.\mathrm{y}(\mathrm{k}+\mathrm{Np}|\mathrm{k})^T]^{\mathrm{T}} \tag{3.27}$$

$$\Delta U = [\Delta u(k|k)^T \Delta u(k+1|k)^T \Delta u(k+2|k)^T \ldots\ldots\ldots\ldots\ldots..\Delta u(k+\mathrm{Nc}-1|k)^T]^T \tag{3.28}$$

The future state variables are generated sequentially using the set of future control parameters based on the state-space model (A, B, C).

$$x(\mathrm{k}+1|\mathrm{k}) = \mathrm{A}\,x(\mathrm{k})+\mathrm{B}\,\Delta u(\mathrm{k})+\mathrm{B_d}\mathcal{E}(\mathrm{k})$$

$$x(\mathrm{k}+2|\mathrm{k}) = \mathrm{A}\,x(\mathrm{k}+1|\mathrm{k})+\mathrm{B}\,\Delta u(\mathrm{k}+1|\mathrm{k})+B_d\mathcal{E}(k+1)$$

$$= \mathrm{A}\,(\mathrm{A}\,x(\mathrm{k})+\mathrm{B}\,\Delta u(\mathrm{k}))+\mathrm{B}\,\Delta u(\mathrm{k}+1)$$

$$= \mathrm{A}^2\,x(\mathrm{k})+\mathrm{AB}\,\Delta u(\mathrm{k})+\mathrm{B}\,\Delta u(\mathrm{k}+1)+\mathrm{AB_d}\mathcal{E}(\mathrm{k})+\mathrm{B_d}\mathcal{E}(\mathrm{k}+1|\mathrm{k})$$

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$$x(\mathrm{k}+\mathrm{Np}|\mathrm{k})= \mathrm{A}^{\mathrm{Np}}x(\mathrm{k})+\mathrm{A}^{\mathrm{Np-1}}\mathrm{B}\Delta u(\mathrm{k})+\mathrm{A}^{\mathrm{Np-2}}\mathrm{B}\Delta u(\mathrm{k}+1)+\mathrm{A}^{\mathrm{Np-3}}\mathrm{B}\,\Delta u(\mathrm{k}+2)\ldots\ldots\ldots\ldots$$
$$+\,\mathrm{A}^{\mathrm{Np-Nc}}\mathrm{B}\,\Delta u(\mathrm{k}+\mathrm{Nc}-1)+\mathrm{A}^{\mathrm{Np-1}}\mathrm{B_d}\mathcal{E}(\mathrm{k})+\mathrm{A}^{\mathrm{Np-2}}\mathrm{B_d}\mathcal{E}(\mathrm{k}+1||\mathrm{k})\ldots\ldots\ldots.$$
$$+\mathrm{B_d}\mathcal{E}(\mathrm{k}+\mathrm{Nc}-1|\mathrm{k}).$$

The future disturbance at the future sample time is not predictable by us. We can assume $\mathcal{E}(\mathrm{k}+\mathrm{i}||\mathrm{k}) = 0$.

In compact form, all of the predicted outputs can be written as,

$$\mathrm{Y}= \mathrm{F}\,x(\mathrm{k})+\phi\,\Delta U \tag{3.29}$$

Here,

$$\mathbf{F}=\begin{bmatrix} CA \\ CA^2 \\ CA^3 \\ CA^4 \\ . \\ . \\ . \\ CA^{N_P} \end{bmatrix} ; \quad \Phi = \begin{bmatrix} CB & . & . & . & . & . \\ CAB & CB & . & . & . & . \\ CA^2B & CAB & CB & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ CA^{N_P-1}B & CA^{N_P-2}B & . & . & . & CA^{N_P-N_C}B \end{bmatrix}$$

Within one optimization window, the incremental optimal control is given by

$$\Delta U = (\phi^T \phi + \bar{R})^{-1} \phi^T(\bar{R}s - Fx(k)) \tag{3.30}$$

Here the dimension of the matrix $\phi^T\phi$ is $mN_c \times mN_c$ and dimension $\phi^T F$ is $mNc\times$ n, and $\phi^T\bar{R}_s$ is same as the last q columns of ϕ^T F. The weight matrix R is matrix with m-blocks and with the same dimension as that of $\phi^T\phi$.

The set-point signal is $r(k)=\begin{bmatrix} r1(k) \\ r2(k) \\ . \\ . \\ . \\ . \\ rq(k) \end{bmatrix}$, as the q set-point signals to the multi-output system.

The first m elements in ΔU are taken as the incremental optimal control to the plant using the receding horizon control approach.

$$\Delta u(k) = [I_m \; o_m \; o_m \; \ldots o_m](\phi^T \phi + \bar{R})^{-1} \phi^T(\bar{R}s - Fx(k)) \tag{3.31}$$

Here I_m is identity matrix with m x m dimension, o_m is zero matrix with dimension m x m.

3.6. Advantages of MPC

1. Model predictive controllers are simple to apply to linear and nonlinear systems directly.
2. MPC implementation for univariable or multivariable plants is simple.
3. While minimising the difference between predicted output and reference, MPC might include constraints in input, input rate, or output variables.
4. For improved performance, model predictive controller parameters such as control input rate weight, output weight, prediction horizon, control horizon, and sampling time can be optimised.

3.7. Disvantages of MPC

1. MPC suffers from a severe disadvantage in terms of computational complexity because it has to compute the future control inputs and outputs repeatedly at each sample period.
2. It need a strong, quick CPU with enough of memory.

3.8. Differences between PID controller and MPC

Though there exist several control techniques in the literature, the standard basic control loops in many industries such as chemical process industries, automobile industries, electrical engineering field are still PID controllers, because they are very effective, easy to understand and simple to design and work with.

PID:

1. The PID control method is prescriptive in nature and is the same for all process with the exception of PID parameter selection.
2. PID makes sure that the current output is close to the set point at a certain time.
3. Control law is a solution to analytical expression.
4. When computing the control law, constraints are not allowed to be incorporated in the analytic expression.
5. Typically employed in single-input, single-output systems. Designing for multi-input-multi-output systems is difficult. More controllers for multi-input multi-output plants are required.

MPC:

1. MPC employs an explicit plant or process model.
2. MPC incorporates the impact of present actions on future outputs into its formulation by specifying a future horizon.
3. Control law is an optimization problem solution.
4. The Control law may incorporate the use of constraints in its computations.
5. It may be utilized for both the SISO systems and the MIMO systems simultaneously.

Chapter 4
Genetic Algorithm

4.1: Introduction to genetic algorithm:

The term "genetic algorithm" refers to a method of optimization that is based on the natural process of evolution that biological organs go through [16],[17]. John Holland invented Genetic Algorithms (GA) in 1975 (Holland, 1975), based on the notion of natural evolution of biological organs provided by Charles Darwin. According to Darwin (1859), "a species evolves and adapts to its environment by methods of variety and natural selection." It may be used to solve difficult problems with constraints or without constraints, and it always produces the optimum answer.

It's a good idea to introduce some of the biological terms that will be used throughout genetic algorithm. These biological terminologies are employed in the context of genetic algorithms in the spirit of similarity with actual biology.

All living species are made up of cells, and each cell has the identical set of chromosomes—DNA strings that serve as the organism's "blueprint." A chromosome can be split into genes, each of which codes for a different protein. A gene can be thought of as encoding a characteristic, such as eye color.

In many species, each cell contains several chromosomes. The genome is the collection of genetic material (all chromosomes together) that makes up an organism. The term genotype refers to the group of genes that make up a genome. The same genotype refers to two individuals that have identical genomes. The genotype determines the organism's phenotype—its physical and mental features, such as eye color, height, brain size, and intelligence—during prenatal and later development. Diploid species have their chromosomes arranged in pairs, while haploid organisms have their chromosomes unpaired. Most sexually reproducing organisms, including humans, are diploid in nature, with 23 pairs of chromosomes in each somatic (nongerm) cell in the body. Recombination (or crossover) happens during sexual reproduction: genes are transferred between each pair of chromosomes in each parent to make a gamete (a single chromosome), and then gametes from the two parents combine to form a full set of diploid chromosomes. Genes are transferred between the single strand chromosomes of the two parents in haploid sexual reproduction. Single nucleotides (elementary pieces of DNA) are modified from parent to child in a process known as mutation. These alterations are commonly caused by copying mistakes. An organism's fitness is often described as the likelihood that it will live long enough to reproduce (viability) or as a function of the number of offspring it has (fertility).

The term chromosome is used in genetic algorithms to refer to a proposed solution to a problem, which is commonly stored as a bit string. The "genes" are single bits or small blocks of adjacent bits that encode a specific aspect of the candidate solution (for example, in multiparameter function optimization, the bits representing a specific parameter might be regarded a gene). In a bit string, an allele is either 0 or 1; wider alphabets allow for more alleles at each locus. Crossover is the process of genetic material being exchanged between two single chromosome haploid parents. Mutation involves flipping a bit at a random locus (or, in bigger alphabets, replacing a symbol at a random locus with a randomly determined new symbol).

Haplotype individuals, particularly single chromosome people, are used in the majority of genetic algorithm applications. In a GA employing bit strings, an individual's genotype is just the arrangement of bits in that individual's chromosome. Although many researchers have lately experimented with GAs that have both a genotypic and phenotypic level (e.g., the bitstring encoding of a neural network and the neural network itself), there is often no concept of "phenotype" in the context of GAs.

4.2: Genetic algorithm operators:

Genetic algorithm yields optimal solution to a complex problem through a process of selection, crossover, mutation. The steps involved in a genetic algorithm are illustrated below.

Step1: Initial population

The first step in using a genetic algorithm is to randomly choose the initial population of chromosomes. In this context, chromosomes refer to a numerical value represented in bits (zeros and ones). The population to be chosen is determined by the difficulty of the optimization issue to be solved. Based on the challenge, several hundreds or thousands of initial chromosomal populations will be chosen.

Step 2: Fitness Function

At this stage, a fitness criterion is chosen, such as highest quality, best color, etc., so that the best chromosomal population from the original population is separated out for the next step. The genetic algorithm uses this fitness function for evaluating the best possible optimal solution for the given problem.

Step 3: Selection

In this step the individuals with fittest chromosomes are paired, which are used in the reproduction for the next generation new offspring. The fittest individual among the initial assumption of chromosomes will be filtered and paired for the reproduction in next step.

Step 4: Crossover

In this step a new generation with new best features is generated by exchanging the genetic information of individual in a pair of parents selected in step 3. Compared to original parent population the new generation will have best qualities. The crossover is done using single point crossover, two points cross over or by using uniform crossover methods. For instance, the strings 10000100 and 11111111 may be crossed across to generate the two children 10011111 and 11100100. The crossover operator approximates the process of biological recombination that occurs between two haploid organisms with a single chromosome each. An example of cross over is illustrated in Figure 4.1.

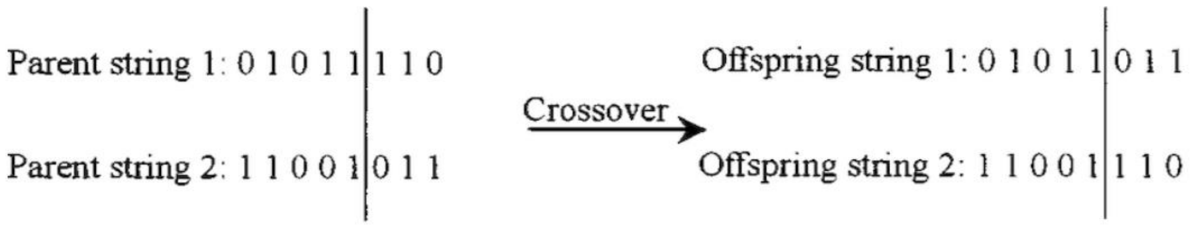

Figure 4.1: Crossover process

Step 5: Mutation

In this step some of the bits of the individual chromosome are switched to get new genetic information in the offspring. If we take an example 000100010 may be mutated to get 010100011 in its second position. Figure 4.2 depicts example of mutation.

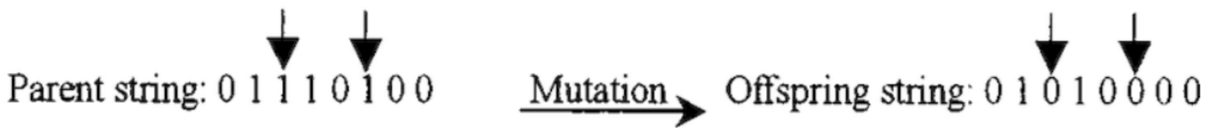

Figure 4.2: Mutation process

The flow chart of a genetic algorithm showing how it works is given below in Figure 4.3.

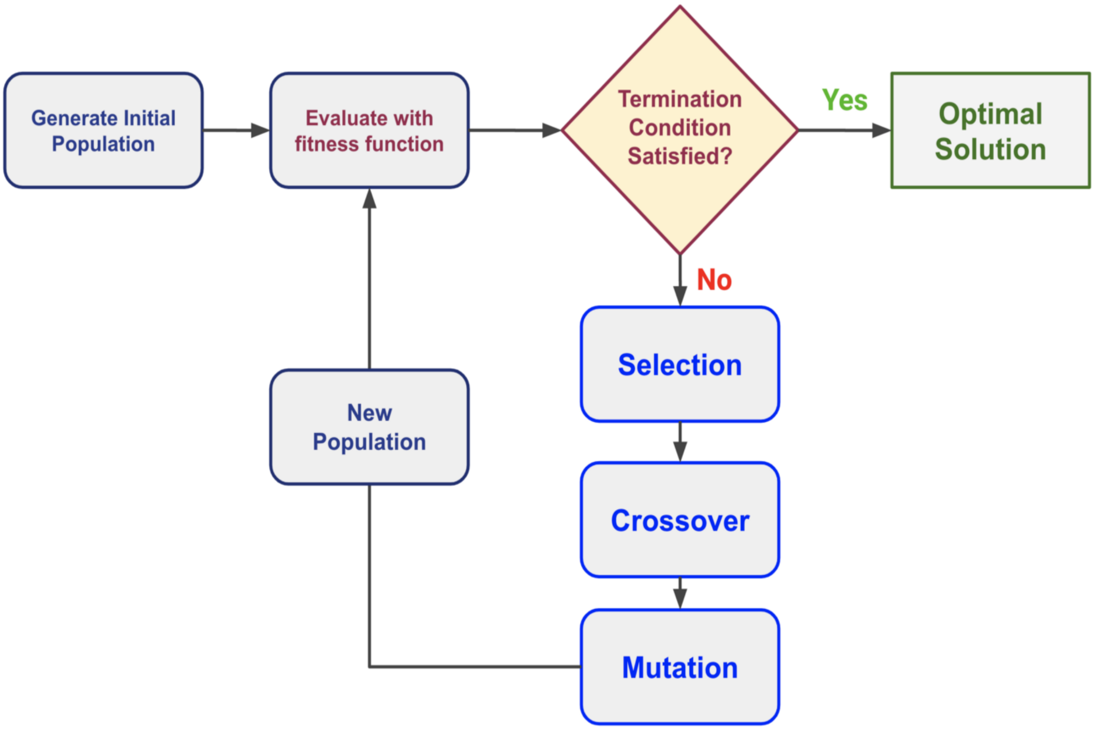

Figure 4.3: Flow chart showing the genetic algorithm

Chapter 5

Application of GA-MPC for the LFC of an Isolated Microgrid

5.1: Microgrid configuration used in the study:

An ac microgrid that is disconnected from the main grid is taken into consideration here for the purpose of load frequency stabilization in the presence of load disturbance and taking into account the variation in power generation from renewable energy resources like wind turbine generators and solar power units. Figure 5.1 shows a schematic diagram of an isolated microgrid that is separated from the main grid and consists of intermittent uncontrollable renewable energy resources like solar and wind power generation units in addition to a battery storage system. In addition to that, it consists of sources of controllable power generation such as a diesel generator and fuel cell units, the ratings of which are taken from [14].

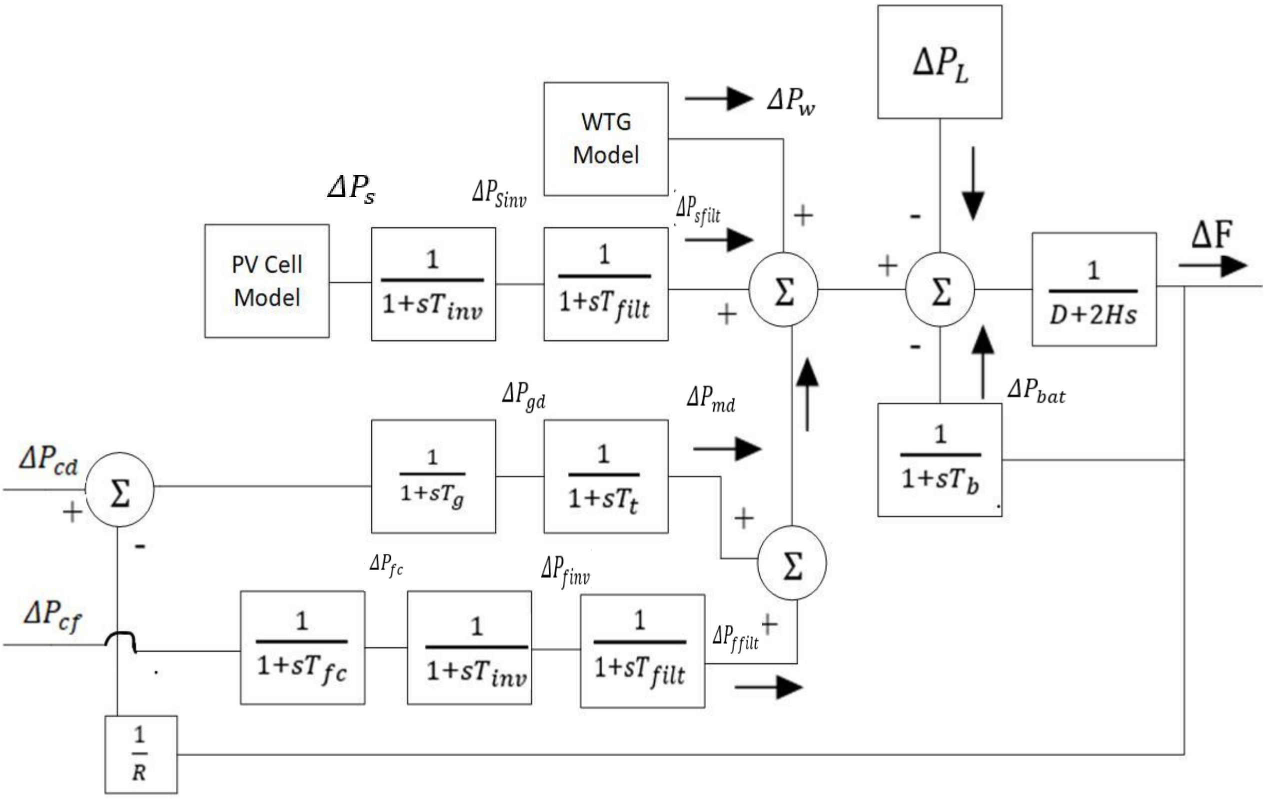

Figure 5.1: Configuration of load frequency model of isolated microgrid.

When the microgrid is connected to the main grid through tie line, it follows the frequency of the main grid. In that case we need to take care of magnitude and quality of voltage, power only. We need not bother about the frequency. However, when the microgrid is separated from the main grid in the event of failure in main grid or when there is maintenance schedule in the main grid, the microgrid become autonomous and it needs to take care of magnitude and quality of voltage, frequency and power. If it fails to regulate the power supply characteristics, it loses stability and consumers will have to suffer from power supply discontinuity.

In this dissertation the load frequency issues and its regulation in the isolated microgrid given in Figure 5.1 is studied using genetic algorithm-based model predictive controller. The renewable energy resources connected in the microgrid generate unreliable power due to which there is imbalance between power generated and the load demand. Variable power generation in solar power unit and wind turbine generator are due to changes in the irradiance of the sun and the speed of the wind which happens in a matter of a few seconds to minutes. Load demand variation from time to time is also one of the reasons for this power imbalance in the isolated microgrid. Whenever there is change in sun irradiance or wind speed the active power generated by solar and wind units' changes which leads to the fluctuation in frequency of power supply. This fluctuation in frequency needs to be stabilised immediately for the acceptable performance of electrical equipment in the microgrid system and also for the stability purpose.

5.2: Implementation of GA-MPC for the LFC of Isolated Microgrid:

The frequency is stabilised by predicting the future plant frequency response and determining the sequence of control inputs to the microgrid's diesel and fuel cell generators using the Model Predictive Control concept [18] explained in chapter 3. First the dynamic state space model of the microgrid is estimated. This state space model is then converted into discrete time state space model. An augmented state space model is derived from the discrete state space model [18]. This augmented state space model is used to determine the control input to diesel unit and fuel cell unit for stabilising the load frequency in the event of fluctuation in power generation or fluctuation in load demand. Whenever the difference between active power generated in the microgrid and load demand is positive, it means that the frequency increases beyond the specified limit. Then immediately control input is generated with the help of MPC to decrease the power generation by controllable power generating units (diesel and fuel cell unit) in the microgrid. If the difference between net active power generated in the microgrid and load demand is negative, it means that the frequency decreases below the specified limit. Immediately a control input is generated with the help of MPC to increase the power generation by controllable power generating units (diesel and fuel cell unit) in the microgrid.

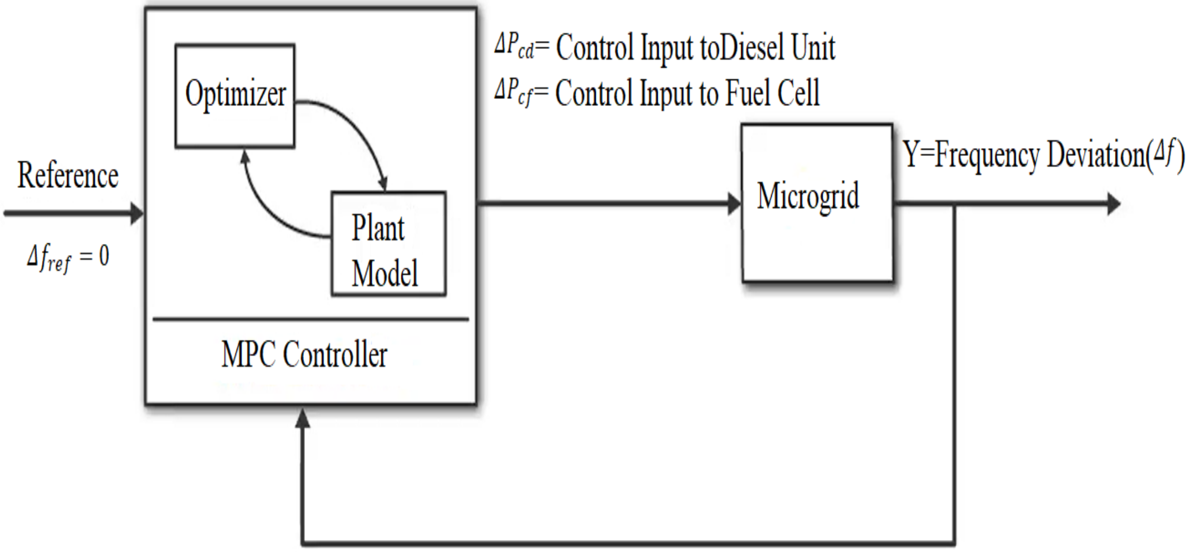

Figure 5.2: Basic structure of MPC implemented for the LFC of an isolated microgrid.

A model predictive controller structure is shown in Figure 5.2 which is used to generate control inputs to diesel and fuel cells for the load frequency regulation of microgrid under the study.

$$\Delta \dot{f} = \frac{1}{(2H)}\left(\Delta P_{sfilt} + \Delta P_{md} + \Delta P_{w} - \Delta P_{L} + \Delta P_{ffilt} - \Delta P_{bat} - D \times \Delta f\right)$$

$$\Delta \dot{P}_{sinv} = \frac{1}{(T_{inv})}(\Delta P_{s} - \Delta P_{sinv})$$

$$\Delta \dot{P}_{sfilt} = \frac{1}{(T_{filt})}(\Delta P_{sinv} - \Delta P_{sfilt})$$

$$\Delta \dot{P}_{gd} = \frac{1}{(T_{g})}\left(\Delta P_{cd} - \frac{\Delta f}{(R)} - \Delta P_{gd}\right)$$

$$\Delta \dot{P}_{md} = \frac{1}{(T_{t})}(\Delta P_{gd} - \Delta P_{md})$$

$$\Delta \dot{P}_{fc} = \frac{1}{(T_{fc})}\left(\Delta P_{cf} - \frac{\Delta f}{(R)} - \Delta P_{fc}\right)$$

$$\Delta \dot{P}_{finv} = \frac{1}{(T_{inv})}(\Delta P_{fc} - \Delta P_{finv})$$

$$\Delta \dot{P}_{sfilt} = \frac{1}{(T_{filt})}(\Delta P_{finv} - \Delta P_{ffilt})$$

$$\Delta\dot{P}_{bat} = \frac{1}{(T_b)}(\Delta f - \Delta P_{bat}) \quad (5.1)$$

Here,

Δf	Frequency fluctuation in the load
R	Droop in load frequency
D	Damping coefficient of the microgrid,
H	Inertia constant of rotating parts in microgrid
ΔP_L	Load disturbance, ΔP_L= Disturbance in solar power
ΔP_{md}	Power fluctuation in mechanical power output of turbine in Diesel unit
ΔP_{gd}	Power fluctuation in governor of Diesel unit
ΔP_{ffilt}	Power fluctuation in filter unit of Fuel cell
ΔP_{finv}	Power fluctuation in invertor unit of Fuel cell
ΔP_{fc}	Fuel cell unit power output fluctuation
ΔP_{bat}	Battery unit power output fluctuation
ΔP_{cd}	Input to the diesel unit from MPC
ΔP_{cf}	Input to the Fuel cell unit from MPC
T_t	Time constant of turbine,
T_g	Time constant of governor
T_{filt}	Time constant of filter unit
T_{inv}	Time constant of invertor unit
T_{fc}	Time constant of fuel unit
T_b	Time constant of battery energy storage system

Equation (5.1) depicts the dynamic state space model of the microgrid used for the study of frequency regulation.

The nine dynamic equations described above are utilised to create the state space model of the microgrid depicted in Figure 5.1. The derived state space model of the microgrid is given in (5.2) & (5.3).

$$\frac{dx(t)}{dt} = Ax(t) + Bu(t) + B_d u(t) \quad (5.2)$$

$$y = Cx(t) \quad (5.3)$$

Here,

x=$[\Delta f \ \Delta P_{sinv} \ \Delta P_{sfilt} \ \Delta P_{gd} \ \Delta P_{md} \ \Delta P_{fc} \ \Delta P_{finv} \ \Delta P_{ffilt} \ \Delta P_{bat}]^T$

$$A=\begin{bmatrix}
\frac{-D}{2H} & 0 & \frac{1}{2H} & 0 & \frac{1}{2H} & 0 & 0 & \frac{1}{2H} & \frac{-1}{2H} \\
0 & \frac{-1}{T_{inv}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & \frac{1}{T_{filt}} & \frac{-1}{T_{filt}} & 0 & 0 & 0 & 0 & 0 & 0 \\
\frac{-1}{RT_g} & 0 & 0 & \frac{-1}{T_g} & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & \frac{1}{T_t} & \frac{-1}{T_t} & 0 & 0 & 0 & 0 \\
\frac{-1}{RT_{fc}} & 0 & 0 & 0 & 0 & \frac{-1}{T_{fc}} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & \frac{1}{T_{inv}} & \frac{-1}{T_{inv}} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{T_{filt}} & \frac{-1}{T_{filt}} & 0 \\
\frac{1}{T_b} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{-1}{T_b}
\end{bmatrix}$$

$$B=\begin{bmatrix}
0 & 0 \\
0 & 0 \\
0 & 0 \\
\frac{1}{T_g} & 0 \\
0 & 0 \\
0 & \frac{1}{T_{fc}} \\
0 & 0 \\
0 & 0 \\
0 & 0
\end{bmatrix};\; C=\begin{bmatrix}1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0\end{bmatrix};\; D=\begin{bmatrix}0\end{bmatrix}$$

$$E = \begin{bmatrix} \frac{-1}{2H} & \frac{1}{2H} & 0 \\ 0 & 0 & \frac{1}{T_{inv}} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}; \; U = \begin{bmatrix} \Delta P_{cd} & \Delta P_{cf} \end{bmatrix}^T; W = \begin{bmatrix} \Delta P_L & \Delta P_W & \Delta P_S \end{bmatrix}^T$$

The continuous time state space model of the microgrid given in equations (5.2) and (5.3) are converted into discrete model. An augmented state space model is derived using this discrete model using the concept of MPC as shown in equation (3.23) and (3.24). A compact form of predicted output is calculated using the equation (3.29),

$$\Delta f_o = F\, x(k) + \phi\, \Delta U \qquad (5.4)$$

The sequence of optimal control input $\Delta U(k)$, here two control inputs i.e., ΔP_{cd} to diesel input and ΔP_{cf} to fuel cell, is determined using the model predictive controller such that the objective function given in (5.5) is minimized. This objective function is sum of weighted square sum of predicted errors between load frequency deviation (Δf_o) and reference ($\Delta f_{ref} = 0$) and weighted square sum of control input increment.

$$O = (\Delta f_{ref} - \Delta f_o)^T \bar{Q} (\Delta f_{ref} - \Delta f_o) + \Delta U^T \bar{R}\, \Delta U \qquad (5.5)$$

The first component in the objective function given above is connected to minimising the error between predicted output and reference, while the second term is related to optimal predicted control input, which optimises the cost function.

Here

Δf_{ref}= Load Frequency deviation

Δf_o= Reference of Load frequency deviation

$\bar{Q}$ = Output (Load frequency deviation) weight matrix.

$\Delta U = \begin{bmatrix} \Delta P_{cd} \\ \Delta P_{cf} \end{bmatrix}$

$\bar{R}$ = Input control rate matrix

$\bar{R} = R_w I_{Nc \times Nc}$

R_w = Real positive number, ($R_w \geq 0$)

I = A unit identity matrix of the dimensions Nc × Nc

The sequence of control input rate values, i.e., the diesel unit input rate (ΔP_{cd}) and fuel cell unit input rate (ΔP_{cf}) values, are calculated in the first time instant irrespective of frequency fluctuation in the microgrid by using the method of model predictive control based on the available state variable values. But only the first control input in the sequence is implemented on the diesel unit fuel cell unit. Then, moving to the next sampling time instant again, a new sequence of control input is determined using the latest measurement of the state variable and previous data. Again, here, only the first control input in the new sequence is implemented. This process is repeated until the frequency deviation equals zero. This is how the receding horizon control is implemented.

The optimal performance of a model predictive controller is improved by proper selection of the MPC controller design parameters such as control input rate weight, prediction horizon, control horizon. With the use of MPC whose control parameters are optimally tuned by using genetic algorithm, we can have better control on load frequency when compared with other traditional frequency control methods.

Here the genetic algorithm finds the optimal tuning parameters of MPC such that the integral square error between load frequency deviation of the microgrid and the reference value (Δf_{ref}) is as minimum as possible. Here our intention is to make the frequency deviation zero. i.e., the reference is taken zero. Table II provides the parameter values that were utilized in the microgrid [14].

Parameter	Value	Parameter	Value
D (p. u. MW/Hz)	0.015	T_g(s)	0.08
2H(s)	0.1667	T_t(s)	0.4
T_{fc}(s)	0.26	T_b(s)	0.1
T_{inv}(s)	0.04	R (Hz/p. u MW)	3
T_{filt}(s)	0.004		

Table II: Microgrid parameter values

5.3. Result Analysis:

The load frequency model of the isolated microgrid assumed in Figure 5.1 is simulated using MATLAB software. A model predictive controller is designed to produce the sequence of control inputs to the diesel generator and fuel cell units at each sampling time instants. For each sample period, the first input in the series of control inputs is used to adjust the load frequency. The load frequency management of an isolated microgrid was investigated using a genetic algorithm-based model predictive controller under various load disturbances and power generation variations in solar and wind power plants owing to changes in solar irradiance and wind speed. The effective performance of the proposed genetic algorithm based MPC is evaluated by determining Integral square error (ISE) and compared to a traditional MPC with constant design parameters.

A genetic algorithm is utilized in order to optimize the MPC control parameters in order to achieve the smallest load frequency deviation feasible. Some of these parameters include the control input rate (Rw), the prediction horizon (Np), and the control horizon (Nc). It has been demonstrated that the performance of an MPC that is based on a genetic algorithm performs better than the performance of a traditional MPC whose control parameters, control input rate weight (Rw), prediction horizon (Np), and control horizon (Nc) values are 8,10, & 2, respectively, which are chosen arbitrarily for the load frequency problem. This has been demonstrated in each and every scenario. The numerous case studies that were examined here are listed below. In this particular investigation, a sample period of 0.01 seconds is assumed.

In every case study the genetic algorithm is used to find optimal control parameters of MPC such as Rw, Np and Nc such that the integral square error between output of frequency response model (Frequency deviation, Δf) and a reference($\Delta f_{ref} = 0$) is as least as possible.

Objective function used by genetic algorithm is,

$$J = (Y_0 - Y_{ref})^2$$

$$= (\Delta f - \Delta f_{ref})^2 \qquad (5.6)$$

In each case study the integral squared error (ISE) is computed. The integral square error computed with the use of traditional MPC for the load frequency regulation in microgrid is compared with the integral square error computed with the use of genetic algorithm based MPC. It is proved that the integral square error is less in case of GA-MPC when compared with traditional MPC for the load frequency regulation in microgrid. Table III provide the integral squared error being calculated in each case.

Case	ISE With Traditional MPC (Rw=8, Np=10 and Nc=2)	ISE With proposed Genetic algorithm based MPC
Case I	0.5369	0.0359
Case II	7.9586	0.4264
Case III	4.5519	0.9478
Case IV	7.9586	0.8431

Table III: Performance index comparison

Case I:

In Case I, the performance of genetic algorithm-based MPC was evaluated in the absence of wind turbines and solar panels. The microgrid is assumed to have load disruption, as shown in Figure 5.3. The programming results show that the frequency deviation is minimum in terms of magnitude of oscillation and also, settling time is reduced by the use of the model predictive control method with its tuning parameters, control input rate (R_w), prediction horizon (Np), and control horizon (N_c) are optimised cautiously using genetic algorithms when compared with a traditional MPC. Figure 5.4 shows the frequency response comparison of the microgrid for both traditional MPC and GA-MPC.

The cost function minimisation for the internal MPC calculations is clearly depicted in Figure 5.5. Also, the control inputs generated by genetic algorithm-based model predictive controller for the diesel unit and fuel cell unit are illustrated in Figure 5.6. It is observed that the optimised tuning parameters by proposed genetic algorithm are control input rate weight (Rw) = 0.1, prediction horizon (Np) = 39, and control horizon (Nc) = 7.

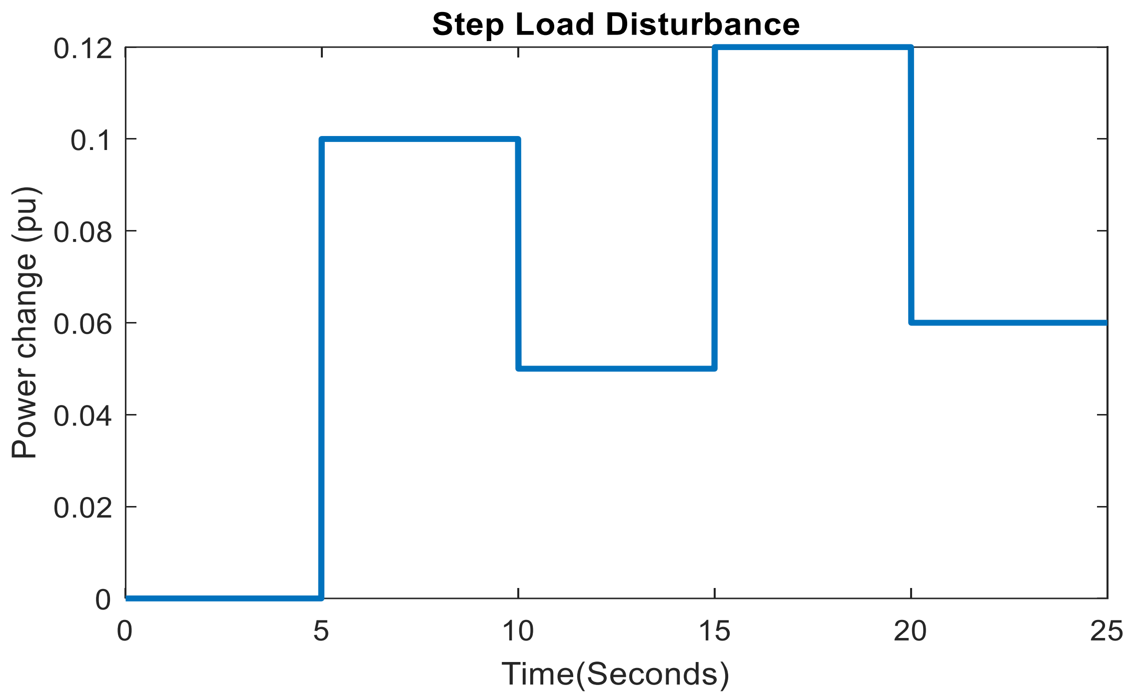

Figure 5.3: Load disruption for case I

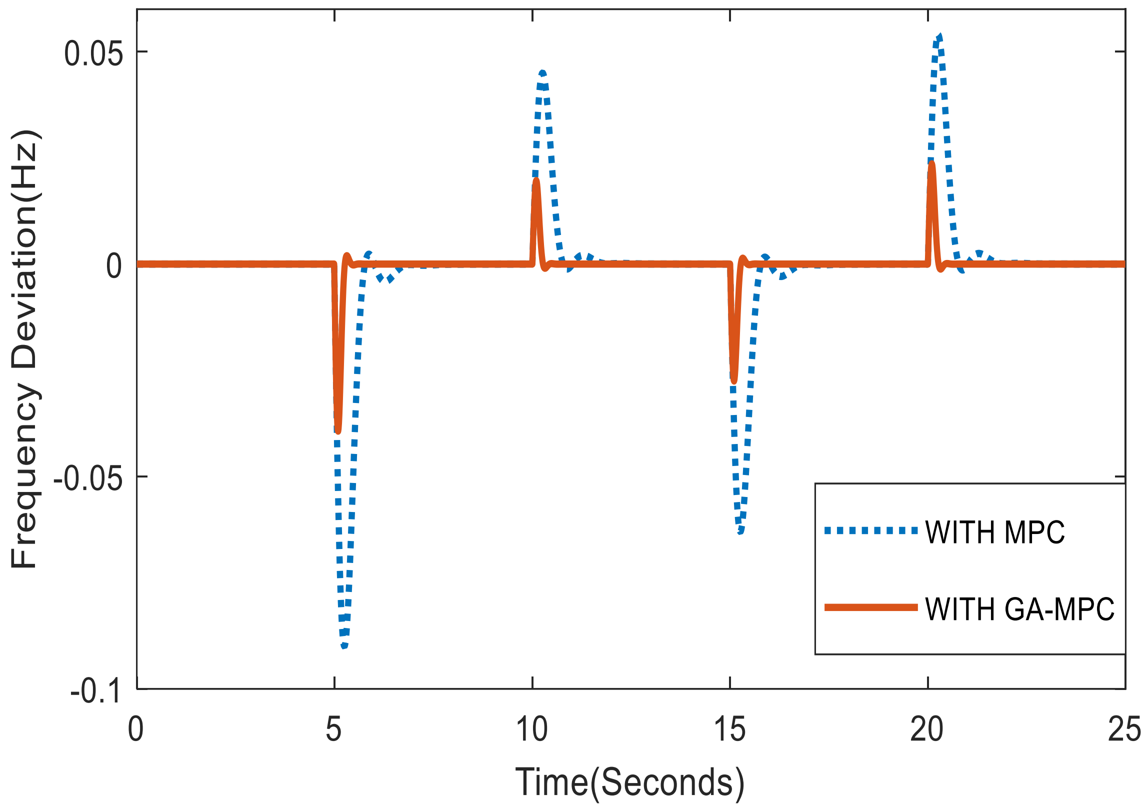

Figure 5.4: Frequency deviation response of the microgrid for case I

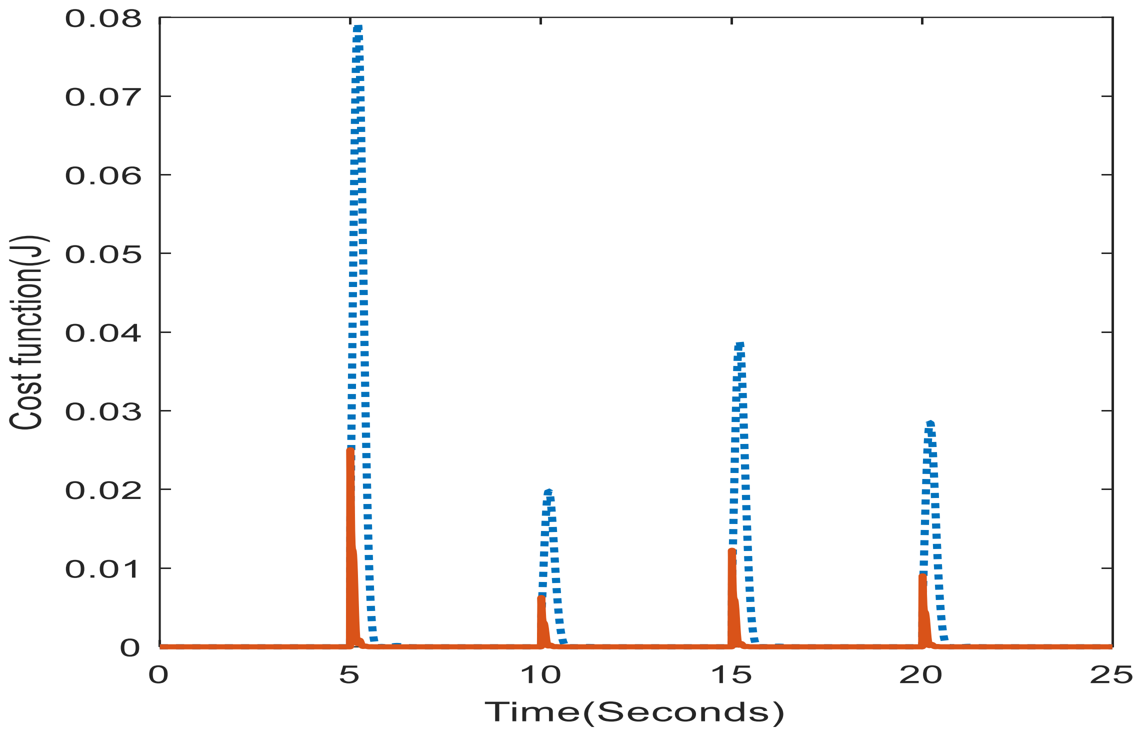

Figure 5.5: Cost function response of MPC for case I

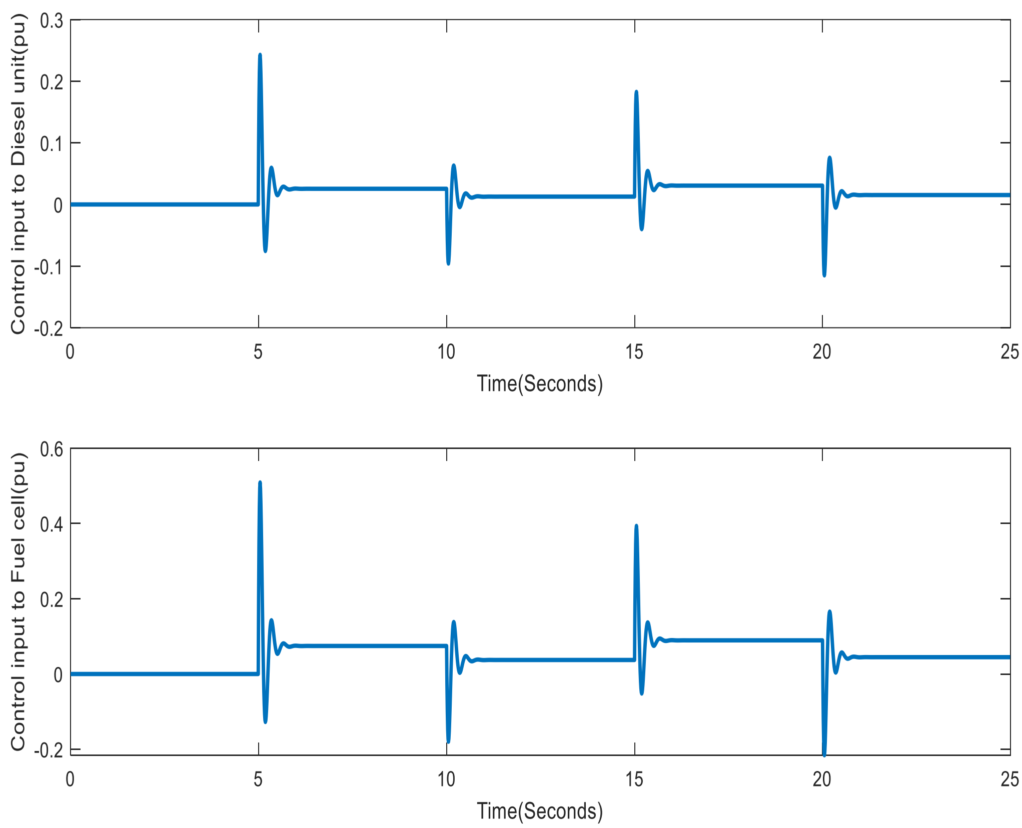

Figure 5.6: Control inputs generated by GA-MPC for frequency regulation for case I

Case II:

In this case, it is assumed that renewable energy resources such as wind generators and solar panels are operating in the microgrid. The performance of the genetic algorithm-based model predictive controller is tested under the inclusion of load disturbance and power variation in wind generator and solar unit due to fluctuations in wind speed and solar irradiance depicted in Figure 5.7. When compared to a traditional MPC, the MATLAB results show that the frequency deviation is minimum in terms of magnitude of oscillation and settling time is also reduced by using the model predictive control method with its tuning parameters control input rate (Rw), prediction horizon (Np), and control horizon (Nc) optimally tuned by a genetic algorithm, which is illustrated in Figure 5.8.

The cost function variation of the MPC and GA-MPC are clearly illustrated in Figure 5.9. Also, it is verified from the figure that cost function variation is minimum with the use of genetic algorithm for tuning of MPC control parameters.

The control inputs to the diesel unit and fuel cell unit generated by GA-MPC for the load frequency regulation is depicted in Figure 5.10. It is observed that the optimised tuning parameters by genetic algorithm are control input rate weight (Rw) = 0.1, prediction horizon (Np) = 39, and control horizon (Nc) = 7.

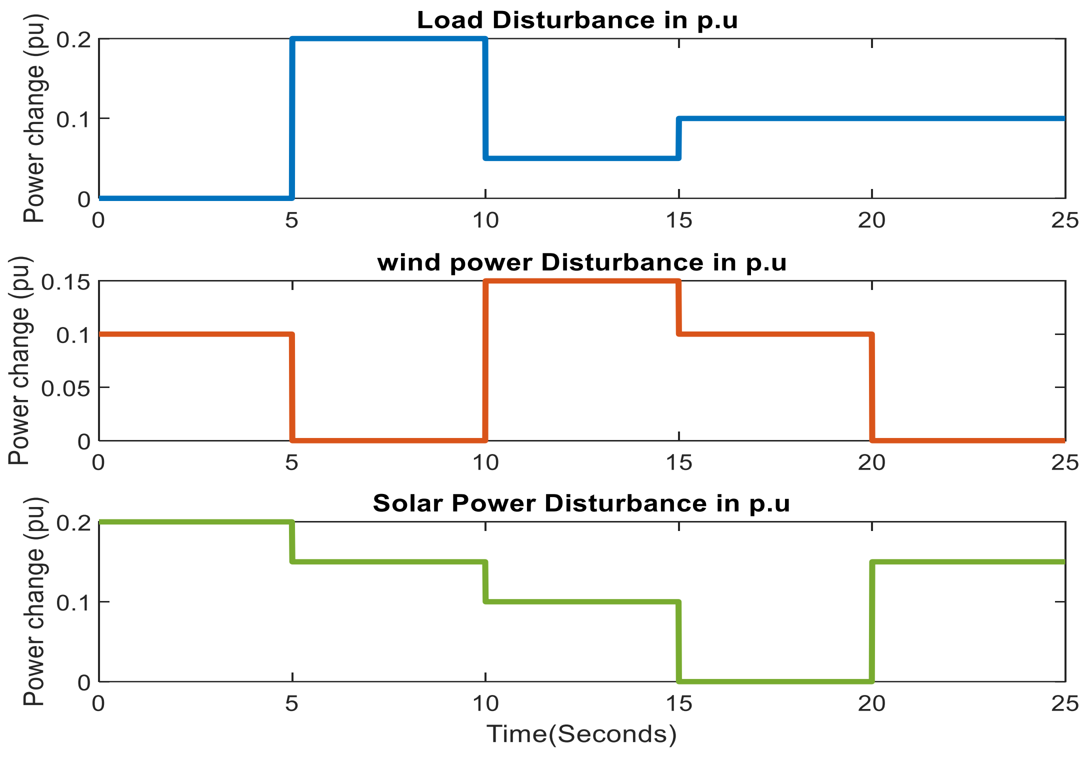

Figure 5.7: Load disruption, power fluctuation in wind and solar units for case II

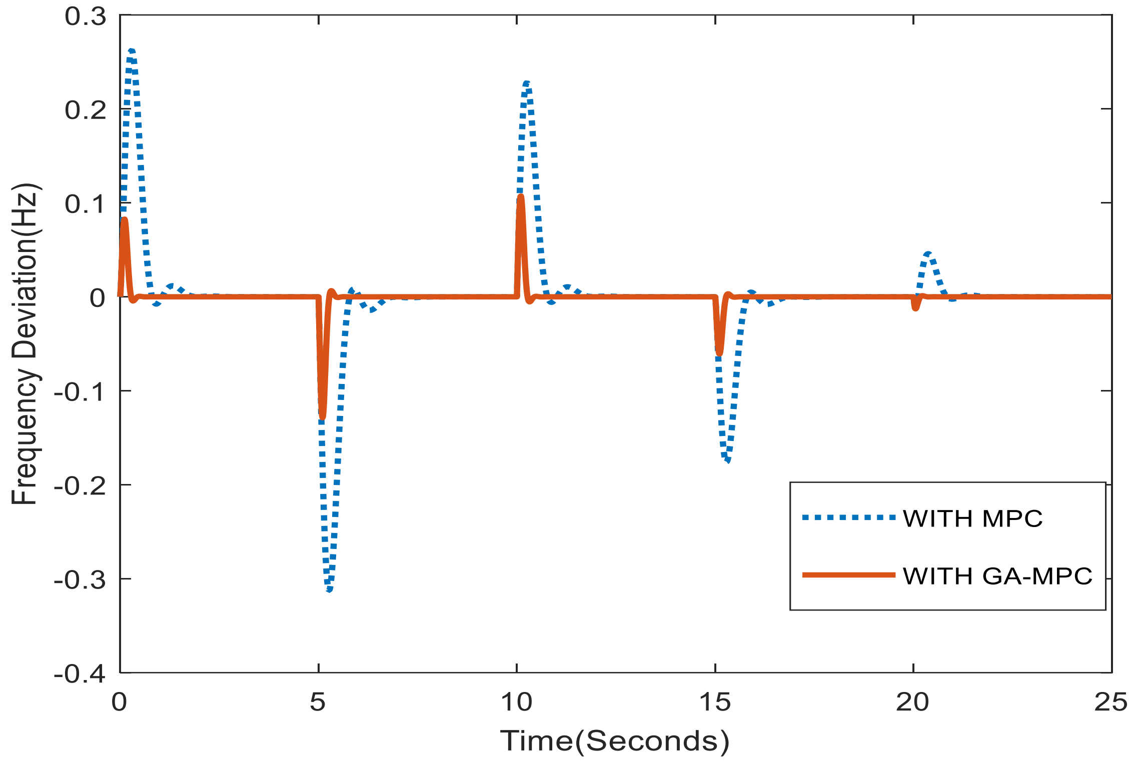

Figure 5.8: Frequency deviation response of the microgrid for case II

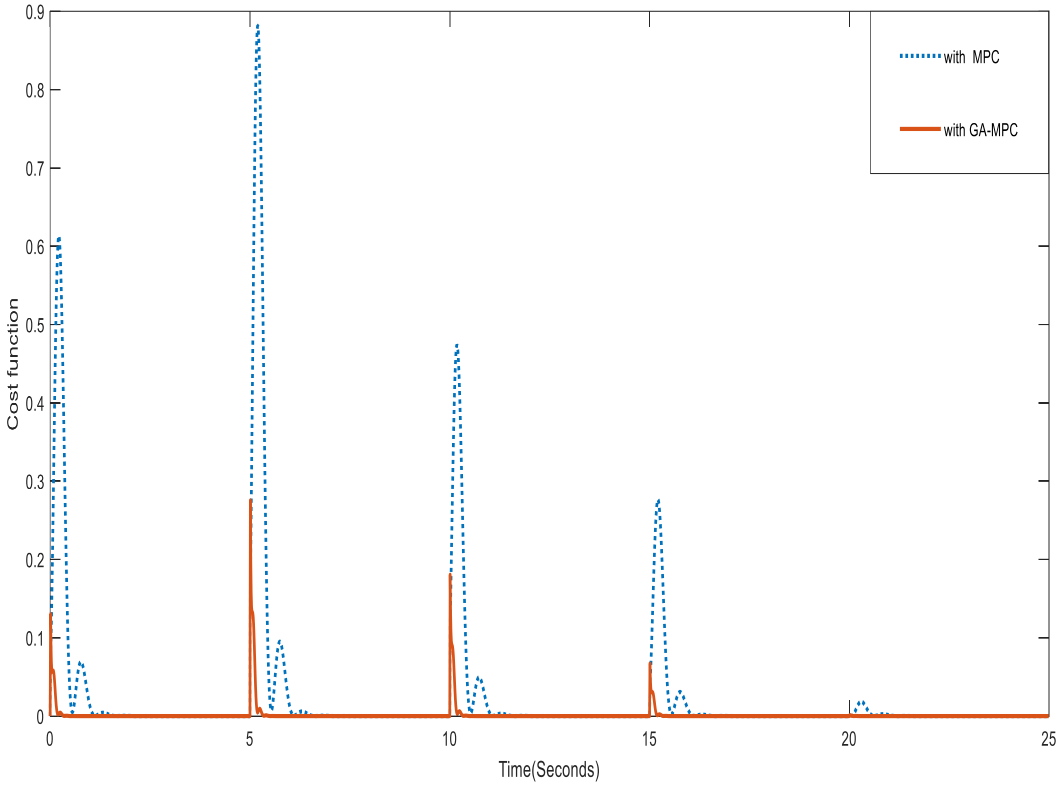

Figure 5.9: Cost function response of MPC for case II

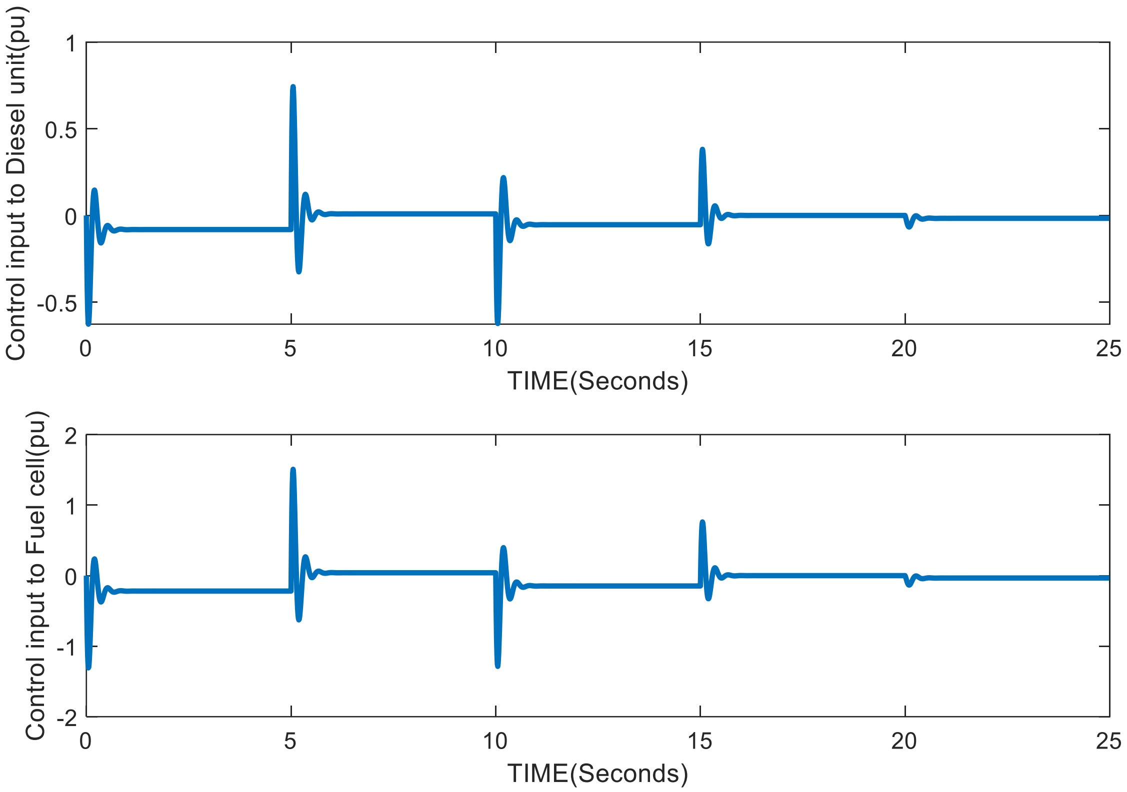

Figure 5.10: Control inputs generated by GA-MPC for frequency regulation of case II

Case III:

This case illustrates the frequency response of the microgrid with a disruption of step change in load, step change in output power of wind and solar power generating units. A step load disruption of 0.02 pu, A step change of 0.2 pu in solar power and a step disturbance of 0.25 pu in wind power generation are assumed to be present in the microgrid operation. The GA-MPC minimizes the frequency deviation effectively when compared to a traditional MPC which is seen clearly from the frequency variation response of the microgrid depicted in Figure 5.11. The cost function comparison which needs to be minimized with in the model predictive control procedure is shown in Figure 5.12. the control input rate generated by the genetic algorithm-based model predictive controller to diesel unit and fuel cell for the frequency deviation minimization is illustrated in Figure 5.13.

The sampling period for MPC design is assumed as 0.01 seconds. The optimum tuning parameters obtained using the proposed genetic algorithm are control input rate weight (Rw) = 1.0628, prediction horizon (Np) = 41, and control horizon (Nc) = 4.

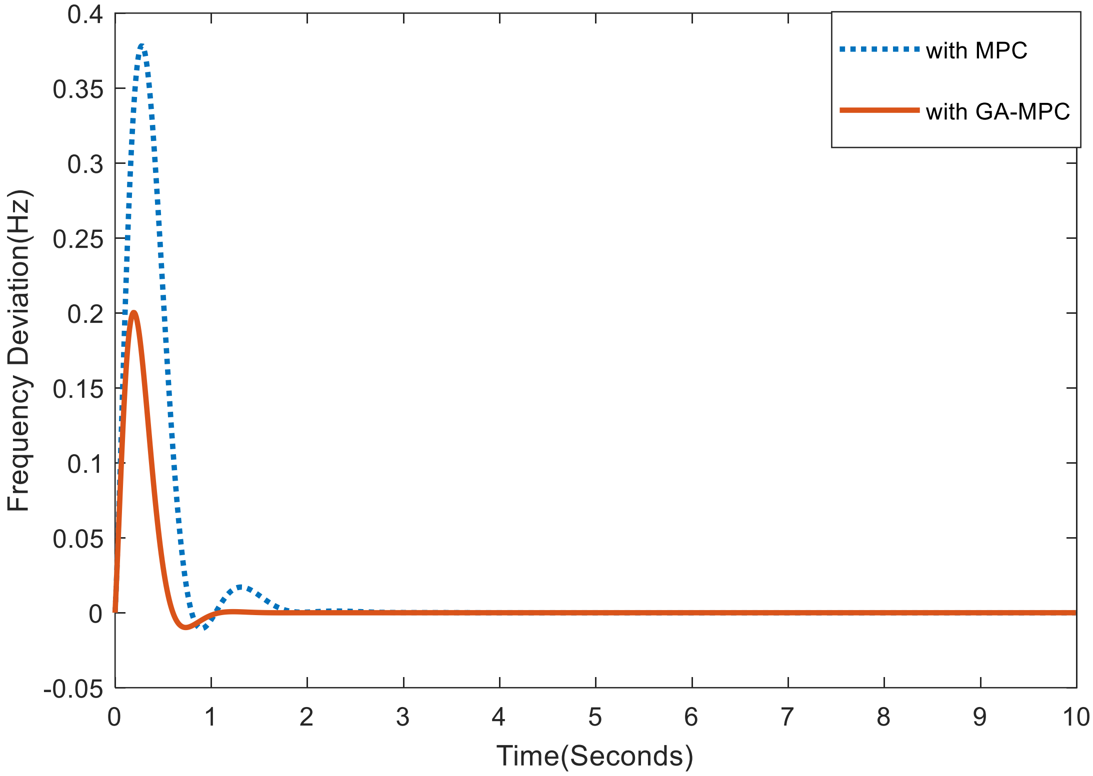

Figure 5.11: Frequency deviation response of the microgrid for case III

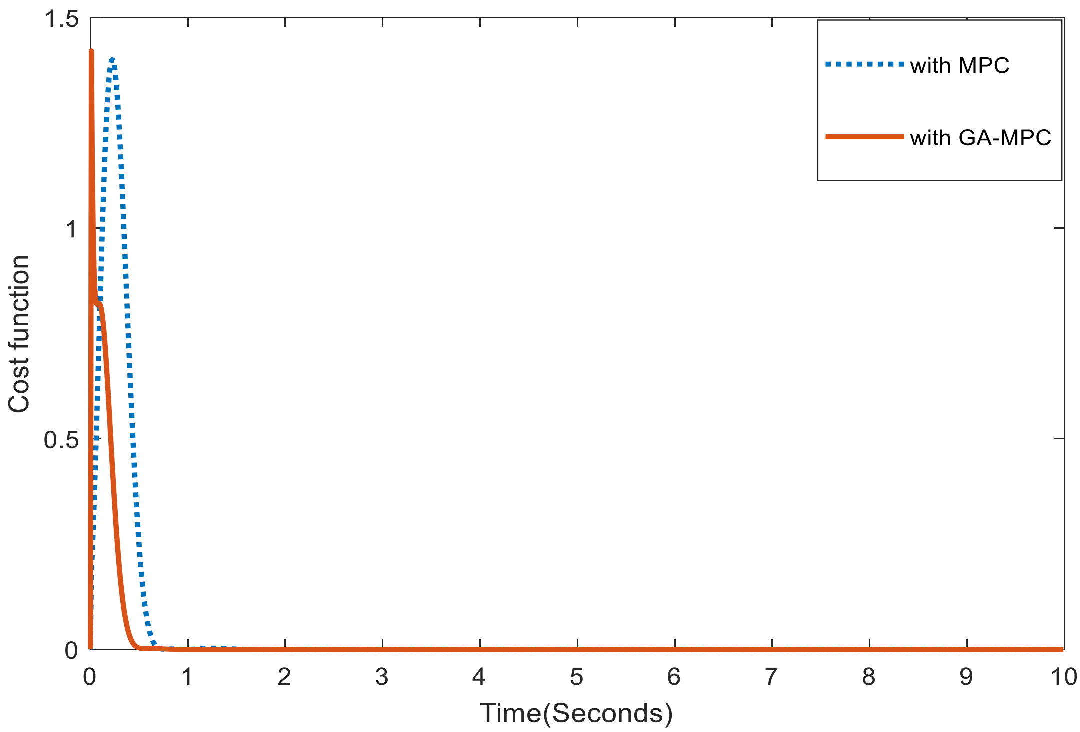

Figure 5.12: Cost function response of MPC for case III

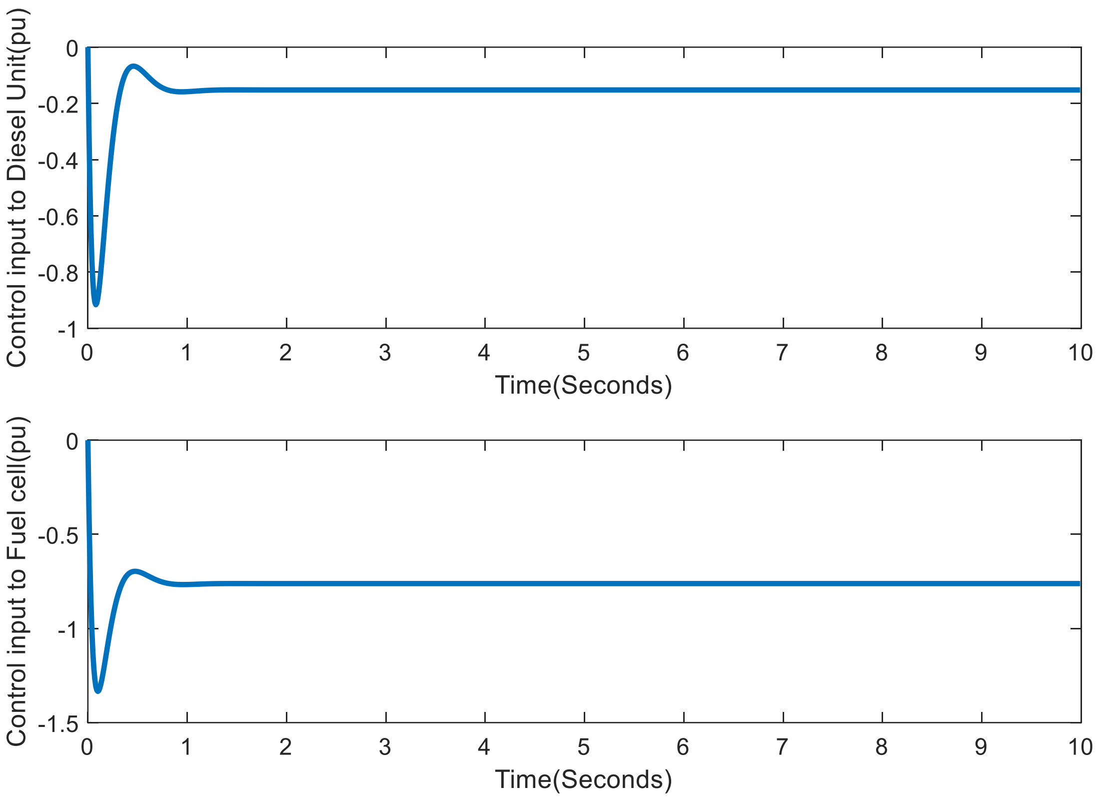

Figure 5.13: Control inputs generated by GA-MPC for frequency regulation of case III

Case IV:

In this particular instance, a genetic algorithm-based MPC is applied in order to explore the load frequency response of the microgrid system in response to changes in the parametric variables of the microgrid. R=+30 percent, D= -40 percent, H= + 50 percent, Tt= - 50 percent, Tg= +50 percent, Tb= -45 percent. In this scenario, the load disturbance and fluctuation in electrical generation from wind and solar power that were discussed in Case II are also put into play. The response of the microgrid to a frequency variation is shown in Figure 5.14. A sampling period of 0.01 seconds is assumed for the implementation of MPC. The cost function variation comparison in the MPC design calculations for control input rate is depicted in Figure 5.15.

The generated control input rate applied to diesel generator and fuel cell unit by GA-MPC are shown in Figure 5.16. The best values for the MPC tuning parameters that were derived in this case study using the proposed genetic algorithm are control input rate weight (Rw) = 0.1, Prediction horizon (Np) = 50, and Control horizon (Nc) = 10.

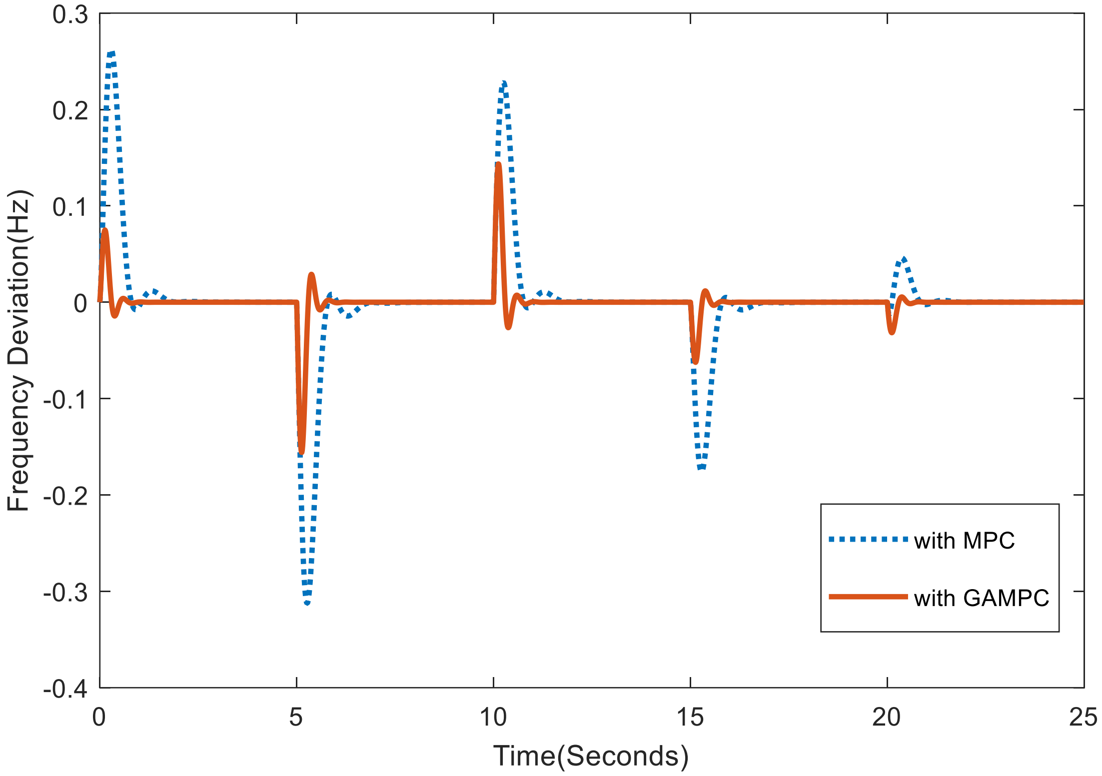

Figure 5.14: Frequency deviation response of the microgrid for case IV

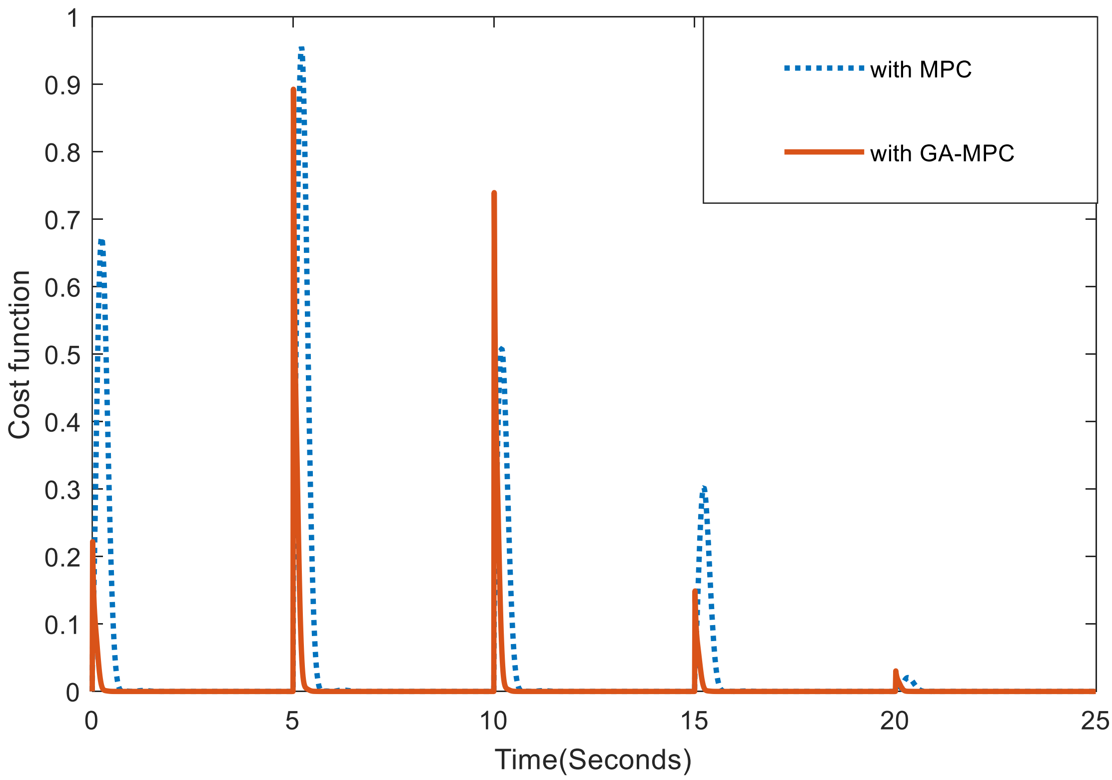

Figure 5.15: Cost function response of MPC for case IV

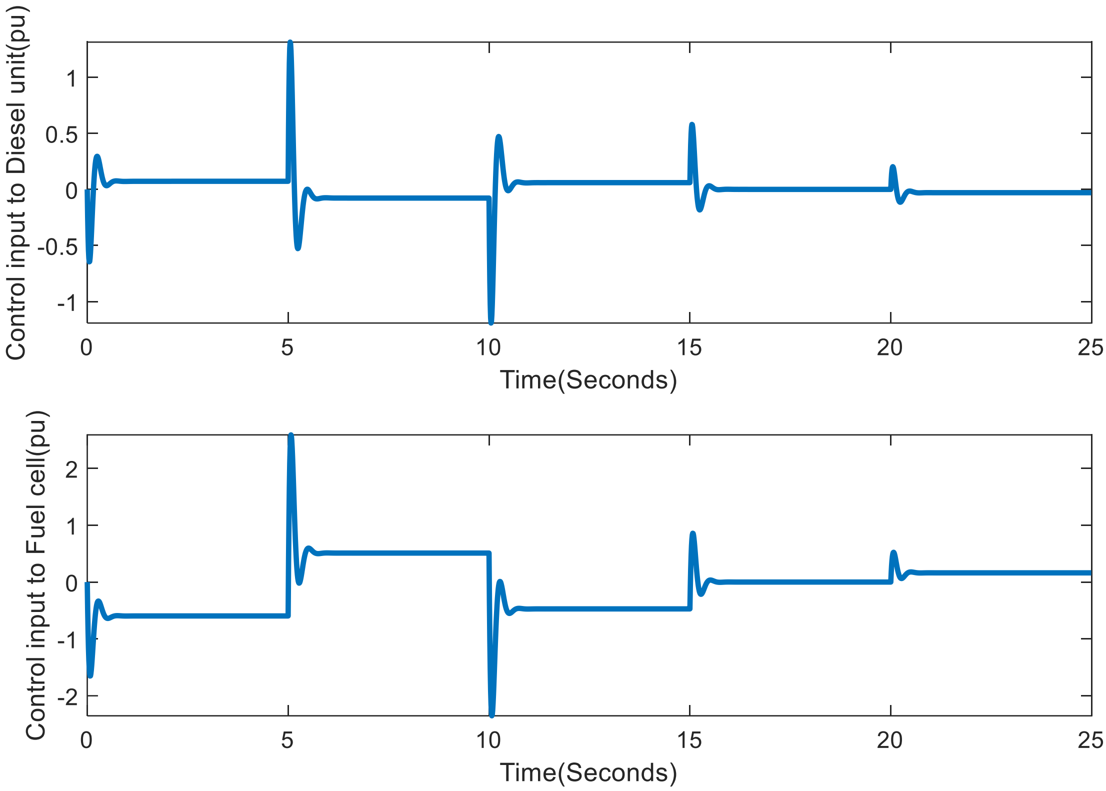

Figure 5.16: Control inputs generated by GA-MPC for frequency regulation of case IV

Chapter 6
CONCLUSION AND FUTURE SCOPE

6.1: Conclusions:

The microgrid under study is simulated using a MATLAB script. First, the traditional model predictive controller is implemented for regulating the load frequency in microgrid under various load disruptions and power fluctuations in wind and solar units. Then the controller tuning parameters such as control input rate weight, control horizon, and prediction horizon of MPC are tuned optimally using a genetic algorithm such that the sum of squared error between frequency deviation and set point is optimum. Then the model predictive controller with the use of these optimised tuning parameters is implemented for load frequency regulation of the microgrid under study. It is verified that the proposed genetic algorithm based MPC gives better results for optimizing the frequency fluctuation in the microgrid under various disruptions in load and power generation of wind and solar units when compared with the load frequency deviation response of the microgrid with traditional MPC.

The magnitude of frequency deviation oscillations both in positive and negative directions are reduced to minimum possible value in all the cases with the use of proposed genetic algorithm-based model predictive controller. The settling time is reduced drastically in all the case studies. The integral square error between output (load frequency deviation) and reference (zero deviation) is observed least with the use of proposed genetic algorithm-based model predictive controller when compared with traditional MPC.

The effectiveness of the genetic algorithm-based model predictive controller is proven to be the best for secondary load frequency regulation in terms of integral square error (ISE) when compared to the efficiency of the traditional MPC with fixed design parameter values. In terms of the amplitude of the oscillations and the time it takes for the oscillations to settle the genetic algorithm-based model predictive controller has been found to be better than the traditional MPC.

6.2: Future scope:

In this work the performance of a model predictive controller for load frequency control of an isolated microgrid is improved by optimizing design parameters such as control input rate weight, prediction horizon, and control horizon. This improves the microgrid's load frequency control. The following considerations have been proposed in order to achieve significantly improved load frequency performance via MPC: -

1. Include constraints on the output (frequency deviation), control inputs, and control input rate in the MPC design.
2. Optimize the MPC's design parameters, such as sampling time and output weight, as well as the other design parameters discussed in this dissertation like control input rate weight, prediction horizon and control horizon.
3. Soft computing techniques such as Artificial intelligence, fuzzy logic control and neural network techniques may be implemented for the optimal tuning of MPC design parameters Rw, Np, Nc for quick diminishing of load frequency oscillations.
4. Other optimization techniques such as PSO, P&O, pattern search etc., may be used for the optimization of MPC’s design parameters.

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