Size Optimization of Hybrid Renewable Energy System using Meta-Heuristic Algorithm

by:

Md. Arif Hossain

MASTER OF SCIENCE

IN

ELECTRICAL AND ELECTRONIC ENGINEERING

Department of Electrical and Electronic Engineering

Islamic University of Technology (IUT)

Board Bazar, Gazipur-1704, Bangladesh

December, 2019

CERTIFICATE OF APPROVAL

The thesis titled 'Size Optimization of Hybrid Renewable Energy System using Meta-Heuristic Algorithm' submitted by Md. Arif Hossain, St. No. 161021010 of Academic year 2016-17 has been found as satisfactory and accepted as partial fulfilment of the requirement for the Degree MASTER OF SCIENCE IN ELECTRICAL AND ELECTRONIC ENGINEERING on December 12, 2019.

Board of examiners:

Chairman

Dr. Ashik Ahmed (Supervisor)
Associate Professor,
Department of Electrical and Electronic Engineering,
Islamic University of Technology (IUT), Gazipur.

Ex-Officio

Dr. Md. Ruhul Amin
Professor and Head,
Department of Electrical and Electronic Engineering,
Islamic University of Technology (IUT), Gazipur.

Member

Dr. Mohammad Rakibul Islam
Professor,
Department of Electrical and Electronic Engineering,
Islamic University of Technology (IUT), Gazipur.

Member (External)

Dr. Md. Monirul Kabir
Professor,
Department of Electrical and Electronic Engineering,
Dhaka University of Engineering and Technology (DUET), Gazipur.

Declaration of Candidate

It is hereby declared that this thesis report or any part of it has not been submitted elsewhere for the award of any Degree or Diploma.

Dr. Ashik Ahmed
Associate Professor,
Department of Electrical and Electronic Engineering,
Islamic University of Technology (IUT), Gazipur.
Date: 12th December, 2019

Md. Arif Hossain
Student No.:161021010
Academic Year: 2016-17
Date: 12th December, 2019

Dedicated to my parents.

Table of Contents

List of Figures

List of Tables

List of symbols and abbreviations

a	Constant
b	Constant
α	Power law exponent
β	Tilt angle expressed in degree
δ	Declination
η_{bat}	Efficiency of a battery
ω	Solar hour angle
ϕ	Latitude of a site
ρ_g	Ground reflectance
σ	Self-discharge rate of a battery
η_{bat}	Battery charging efficiency
η_{PV}	Efficiency of PV modules and corresponding converters
η_{WG}	Efficiency of WG and corresponding converters
A_{WG}	Total swept area of a WG
C_n	Total capacity of batteries
C_{bat}	Capital cost of a battery
C_{bat}	Nominal capacity of a battery
C_h	Capital cost per unit height of WG tower
C_{PV}	Capital cost of a photovoltaic module
C_{WG}	Capital cost of a WG
D	Diffuse component of hourly global radiation
$FF(t)$	Fill factor

$G(t,\beta)$	Global solar irradiance on a PV module at a tilt angle of β°
h	WG installation height
I_{SC-STC}	Short circuit current under STC
$I_{SC}(t,\beta)$	Short circuit current of a PV module
k_T	Sky clearness index
K_I	Short circuit current temperature coefficient
K_V	Open circuit voltage temperature coefficient
M_{bat}	Annual maintenance cost of a battery
M_h	Annual maintenance cost per unit height of a WG tower
M_{PV}	Annual maintenance cost of a PV module
M_{WG}	Annual maintenance cost of a WG
N_P	Number of photovoltaic modules connected in parallel
N_S	Number of photovoltaic modules connected in series
N_{bat}	Total number of batteries in a system
N_{Pbat}	Number of batteries connected in parallel
N_{PV}	Number of photovoltaic modules
N_{Sbat}	Number of batteries connected in series
$NCOT$	Nominal Cell Operating Temperature
$P_{available}$	Power available from the system
P_r	Rated power
P_{LOAD}	Demand
P_{PV}	Power produced by PV modules
P_{WG}	Power produced by WGs
P_W	Specific power output of a WG

T_A	Ambient temperature
v	Wind speed at hub height
V_{bat}	Nominal voltage of each individual battery
V_{BUS}	DC bus voltage
v_{ci}	Cut in speed of WG
v_{co}	Cut out speed of WG
V_{OC-STC}	Open circuit voltage under STC
$V_{OC}(t,\beta)$	Open circuit voltage at a particular hour and tilt angle
v_{ref}	Wind speed at reference height
v_r	Rated speed of WG
y_{bat}	Expected number of battery replacements during the life of HRES
DOD	Depth Of Discharge
BG	Biogas
BM	Biomass
BS	Battery System
DG	Diesel Generator
FC	Fuel Cell
HG	Hydro Generator
GA	Genetic algorithm
PV	Photovoltaic
WG	Wind turbine Generator
WT	Wind Turbine
ACS	Annual Cost System
GWO	Grey Wolf Optimizer

HES	Hybrid Energy System
LCE	Levelized Cost of Energy
MBA	Mine Blast Algorithm
MOO	Multi-Objective Optimization
PSO	Particle Swarm Optimization
RES	Renewable Energy Systems
SOC	State of charge
SOO	Single Objective Optimization
STC	Standard Test Condition
TMY	Typical Meteorological Year
GAMS	The General Algebraic Modeling System
HOMER	Hybrid Optimization Model for Electric Renewables
HRES	Hybrid Renewable Energy System
LOLE	Loss Of Load Expected
LPSP	Loss of Power Supply Probability
NREL	National Renewable Energy Laboratory
NSGA	Non-dominated Sorting Genetic Algorithm
DOIRES	Determining Optimum Integration of RES
GRHYSO	Grid-connected Renewable Hybrid Systems Optimization
ORIENTE	Optimization of Renewable Intermittent Energies with Hydrogen for Autonomous Electrification

Acknowledgements

First and foremost, I would like to express my heartiest gratitude to the almighty Allah (SWT), for giving me the patience to accomplish this research work.

I would like to express my sincere gratitude to my thesis supervisor, Dr. Ashik Ahmed for his continuous guidance and support throughout the course of this work. I am thankful to my supervisor for introducing me to the topics focused in this research and encouraged me whenever I was overburdened with this work. His constant suggestions helped me to have a better understanding on the related topics.

I would also like to thank all the faculty members of the department of EEE, IUT for their motivation and inspiration during this research work.

Finally, I am extremely grateful and express my deepest gratitude to my parents and my wife for their continuous moral support throughout this research work. Without their support and sacrifice it would never have been possible for me to make it this far. Special thanks to my friends for their motivation and support.

Md. Arif Hossain

December, 2019.

Abstract

Rapid decline of fossil fuel reserves and rise of average global temperature has compelled energy scientists to look for non-conventional energy sources, preferably environment friendly and renewable in nature. Among the renewable sources, wind and photovoltaic based energy conversion processes are capturing recent interests. As the input to these two kinds of energy conversion processes are highly unpredictable, incorporation of energy storage device becomes imperative for uninterruptible power supply. However, considering hybrid renewable power generation for fulfilling load demand, arbitrary mixing among participating generating units could result in non-profitable outcome for power supplying entities. Hence, in this work, an optimal sizing of a Wind-Photovoltaic-Battery system has been suggested using a hybrid single objective optimization (SOO) method integrating a genetic algorithm (GA) and grey wolf optimizer (GWO) in phase one and in phase two a multi-objective optimization (MOO) method integrating a non-dominant sorting Genetic Algorithm (NSGA) II and the Grey wolf optimizer (GWO) is proposed. In the SOO phase the population undergoes cross-over and mutation and then the population is updated according to GWO. In the MOO phase the population of each generation of NSGA II is passed through the GWO before they are allowed to crossover and mutate in order to increase the probability of avoiding local minima. A comparative analysis of the performance of the applied hybrid algorithm with NSGA II and multi-objective Particle Swarm Optimization (MOPSO) has been carried out in phase two and the hybrid SOO algorithm in phase one is compared with GA. The analysis shows that the applied hybrid algorithms show better performance compared to the other existing algorithms in terms of convergence speed, obtaining global minima, lower mean (for minimization objective) and a higher standard deviation.

Chapter 1: Introduction

1.1 The need of alternative sources of energy

The world has seen a rapid development in the field of technologies in the last decade. The population is also on the rise as usual. It is reported by [1] that the world energy demand will see a rise of about 53% by the year 2035. The increased population and advanced technologies have drastically increased the energy consumption. Energy consumption have specially escalated in buildings due to the following reasons [2]

- Population growth
- More times spent indoors
- Increased demand for building functions
- Indoor environment quality
- Global climate change

And in order to meet these increased energy demands, we are heavily dependent on the non-renewable energy sources like coal, fuels, generators, oil, etc. But these sources of energy not only harm our environment but are also diminishing rapidly. The popular non-renewable sources like oil, gas and coal will roughly last for another 40, 60 and 200 years respectively [3]. Authors in [4] claim that the present situation is most likely unsustainable and is further aggravated due to resource scarcity. The declination in oil is substantially worsening the water problems, and this gradually increases energy problems. Authors in [5] claim that renewable energies are one of the main reasons of global warming and solar energy has the greatest potential to solve energy and water problems. Generation of electricity from fossil fuels, transportation and industrial processes are increasing CO_2 . Studies [6] show that non-renewable energy consumption increases the emission of CO_2 and on the other hand the consumption of renewable energy decreases the CO_2 emission. Due to the increased demand of electricity, nuclear sources of energy are being considered now-a-days to act as a source of energy. But this will cause huge emission of CO_2. So definitely nuclear sources can’t be considered as ideal sources of energy. Photovoltaics, on the other hand is green in nature and have the full potential to replace nuclear power [7]. So in order to meet the demand in energy it is needed to have [8]

- Reliable

- Cost-effective
- Everlasting

source of energy, which is, without a doubt renewable in nature and it is claimed that solar energy is the best in this aspect.

1.2 Literature Review

1.2.1 Hybrid Renewable Energy System

So it is high time researchers focused on renewable sources of energy rather than non-renewable sources. Some of the popular renewable sources of energy are:

- Biomass
- Hydropower
- Geothermal
- Wind
- Solar

It is reported by [9] that the average annual direct normal solar radiation from the sun on the horizontal surface of the earth varies from 800 W/m^2 to higher than 1000 W/m^2. Wind energy is another popular form of energy and it is less expensive, sustainable, safe and pollution free [3]. However, the unpredictable nature of these renewable sources in their output makes them expensive which necessitates the use of more than one sources of energy in order to complement each other. Such a system is known as Hybrid Renewable Energy System (HRES). A stand-alone HRES provides much reliable outcome in comparison to a single source based system in terms of cost and efficiency [10]. HRES is gaining popularity specially in the remote areas due to rise in prices of petroleum products [11].

1.2.2 HRES Combinations

There can be a number of combinations of a HRES. In 2006, authors in [12] used wind, photovoltaic and fuel cell (FC) generation system for satisfying load of a typical home in the Pacific Northwest. In this system hydrogen storage tank was used as the energy storage system. Other studies where a similar combination was used were in [13-16]. But because of the high initial cost of the hydrogen tank and the need of FC makes the system expensive [17]. Another popular combination is the use of PV, wind and diesel generator (DG). Different authors in [18-21] opted for this combination and in most of the cases battery system was used as the energy storage device. Some other combinations like Photovoltaic (PV), Wind Turbine (WT) and Biomass (BM) was applied in [22] and PV, WT, Hydro Generator (HG), BM and Biogas (BG) was applied by the authors in [23]. However, various studies [24, 25] prove that, photovoltaic (PV), wind turbine (WT) and battery system (BS) is the most economical and environment friendly combination. Authors in [26] have proven using seven different optimization techniques that hybrid PV-WT-BS is the most cost effective combination for outlying areas compared to PV-BS, WT-BS and PV-WT configurations.

1.2.3 Sizing of HRES

Sizing of HRES is a very complicated issue. While an oversized HRES can easily satisfy the load demand, it is unnecessarily expensive, on the other side; an undersized HRES is economical but very often fails to satisfy the load demand. Thus an optimum sizing of HRES is expected and it depends on the mathematical model of the system components [27]. There are a lot of sizing techniques available in the literature. Some of the sizing methodologies are described below [28]:

- Software tools
- Evolutionary algorithms
- Nature inspired algorithms
- Linear programming
- Dynamic programming
- Iterative and probabilistic approach
- Matrix approach
- Design space based approach

A lot of software tools are available for this sizing methodology of HRES. However, the most popular software in this field is Hybrid Optimization Model for Electric Renewables (HOMER) which was developed by National Renewable Energy Laboratory (NREL), United States [29]. A lot of researchers used HOMER as the sizing tool in their design of HRES. The use of HOMER can be found in [30-34]. But besides HOMER there are other similar software tools like

- The General Algebraic Modeling System (GAMS) [35]
- Optimization of Renewable Intermittent Energies with Hydrogen for Autonomous Electrification (ORIENTE) [36]
- Determining Optimum Integration of RES (DOIRES) [37]
- Grid-connected Renewable Hybrid Systems Optimization (GRHYSO) [38]

Evolutionary and nature inspired algorithms are probably the most used approach in the field of any kind of optimization. These algorithms are originated either from some evolutionary processes or from some nature inspired approaches. These processes are then carefully mathematically modelled to generate an optimization algorithm which can be applied in almost any optimization problem by making the necessary modifications. Among the evolutionary algorithms, probably the most popular is the Genetic Algorithm (GA) [39]. The application of GA can be found in a lot of research papers and articles like [40-44]. Among the nature inspired algorithms, Particle Swarm Optimization (PSO) is found very popular in the literature. The application of PSO has been made by the authors in [45-48]. Another recent nature inspired algorithm, which made some promising results, is Grey Wolf Optimizer (GWO). GWO was developed by Mirjalili et al in [49]. The use of GWO in the field of HRES is not so prominent due to the fact that the algorithm is very new. However, very recently, in 2019 GWO has been used by the authors in [50] for the sizing approach of their design.

The use of other sizing algorithms is also available in literature, but they are not so popular in comparison to the discussed approaches. In the field of HRES, researchers in the recent years opt for various optimization algorithms. It is due to the fact that artificial and hybrid methods can often identify the global optimum system and they also have a better convergence probability [51]. So in this study GA and GWO will be hybridized to create a hybrid Single Objective Optimization (SOO) and Non-dominated Sorting Genetic Algorithm (NSGA) and GWO will be hybridized to create a hybrid Multi Objective Optimization (MOO).

1.2.4 Single Objective Optimization (SOO)

An optimization problem is termed as SOO when the problem needs only one objective function to be satisfied. The objective function will contain a number of optimizing parameters which will be linked with each other with the help of the objective function. It is a common phenomenon that each optimizing parameter will/may have its own constraints.

Surveying the literature, a lot of works in this field can be found. GA is one of the most popular approaches with the researchers in this particular aspect. In 2006 Koutroulis et al. applied GA in [40] in order to size the parameters of a HRES keeping the load satisfied at all time. Later in 2008 a similar work was presented in [41] where the authors incorporated the variation of weather in the load demand while keeping the Loss of Power Supply Probability (LPSP) zero. In 2014 another work was presented by the authors in [52] where a methodology for optimal sizing design and strategy control based on differential flatness approach was applied to a stand-alone wind-PV system. The algorithm applied in this study was also GA. Nature inspired algorithms like PSO has also been used by authors in [53] for reducing the Levelized Cost of Energy (LCE). PSO was also applied in [19] where the HRES consisted of diesel, PV, wind and battery storage cell. Other algorithms like Mine Blast Algorithm (MBA) was used in [13] to solve the optimal sizing of a hybrid system consisting of photovoltaic modules, wind turbines and fuel cells (PV/WT/FC) to meet a certain load of remote area in Egypt. Ant Colony Optimization (ACO) is another popular nature inspired algorithm that was employed in [54] for sizing and performance analysis of a standalone HES.

1.2.5 Multi Objective Optimization (MOO)

An optimization problem is termed as MOO when it is required to simultaneously satisfy more than one objective function. In this approach it is needed that the objective functions have an inverse relation with each other. So the optimizing algorithm tries to find the point where both the objective functions are simultaneously minimum (for minimizing problem) or simultaneously maximum (for maximizing problem). It may also happen that it is needed to maximize some objective functions and minimize the rest. The optimizing parameters are also interlinked with each other by these objective functions. Studies in [55] shows that MOO provides a better flexibility to the designers in selecting the most optimal solution. In this aspect MOO has been carried out by authors in [56] where both Annual Cost System (ACS) and LPSP were minimized applying multi objective genetic algorithm. In 2015, Azadeh et al. in [24] employed Non Dominated Sorting Algorithm-II (NSGA-II) in order to achieve minimum system cost and maximum reliability. Recently Authors in [57] applied hybrid GA-PSO for SOO and multi objective PSO (MOPSO) for MOO in order to minimize the total present cost and Loss of Load Expected (LOLE). However, none of the previous studies had performed a comparative analysis of the results obtained with other multi-objective algorithms.

1.3 Thesis objectives

i. To propose a hybrid optimization algorithm for wind-photovoltaic-battery hybrid renewable energy system which ensures a zero loss of power supply probability (LPSP) and makes the system cost effective.
ii. To conduct a comparative study among several proposed hybrid optimization algorithms for wind-photovoltaic-battery based hybrid renewable energy system.

1.4 Organization of this thesis

Chapter two introduces the mathematical of the HRES consisting of PV, WT and batteries. Each component of the hybrid model is explained along with its mathematical model. In the later part of this chapter the objective function is formulated which is based on LPSP.

Chapter three discusses the SOO namely GA and GWO. The detailed explanation of these algorithms is presented along with the associated mathematical formulae. The two SOO are then hybridized to generate a single algorithm. The hybrid algorithm is presented in a flowchart and discussed in details.

In chapter four MOO algorithms are discussed. NSGA and NSGA-II are introduced with detailed mathematical formulae with the help of flowcharts and equations. The NSGA-II is then hybridized with GWO to create a hybrid MOO algorithm. This algorithm is explained with the help of a flowchart.

The algorithms introduced in chapter three and four are put to test and the results and in depth analysis is presented in chapter five. The results are analysed with the help of various graphs and tables and the chapter concludes by discussing various aspects of these algorithms.

Chapter six basically contains the summary of all the previous chapters and provides future direction for further exploration in this field.

Chapter 2: Mathematical Model of HRES and Objective Function Formulation

The studied HRES consists of WT, PV and batteries are used as storage component. The chapter begins by showing how these components are interconnected to each other. Further these components are introduced along with their mathematical formulae. The specifications of these components for this study are also presented. At the end of this chapter the objective function is presented which is based on LPSP.

Whenever multiple sources of energy are deployed to generate electric power, the system is termed as hybrid renewable energy system (HRES). Both renewable and non-renewable sources of energy can be used to create a HRES. However, HRES mainly focuses on the use of renewable sources of energy since this concept came with the view to replacing the non-renewable sources of energy. Unlike the non-renewable sources of energy, renewable sources are unpredictable and thus this necessitates the use of multiple sources in order to bring stability in the system. Undoubtedly a system consisting of multiple energy sources provides much more reliability in terms of cost and efficiency in comparison to a system consisting of a single source of energy [10, 58]. Besides, HRES employing renewable sources of energy are gaining popularity especially in the remote areas due to the inflation in prices of petroleum products [11]. Different sources of energy like HG, geothermal, BM, BG, WT, solar energy utilized in PV cells, hydrogen, nuclear and fossil fuels along with an energy storage system are used by researchers in various parts of the world. The literature review suggests that PV-WT-BS is the most cost effective combination among all of them.

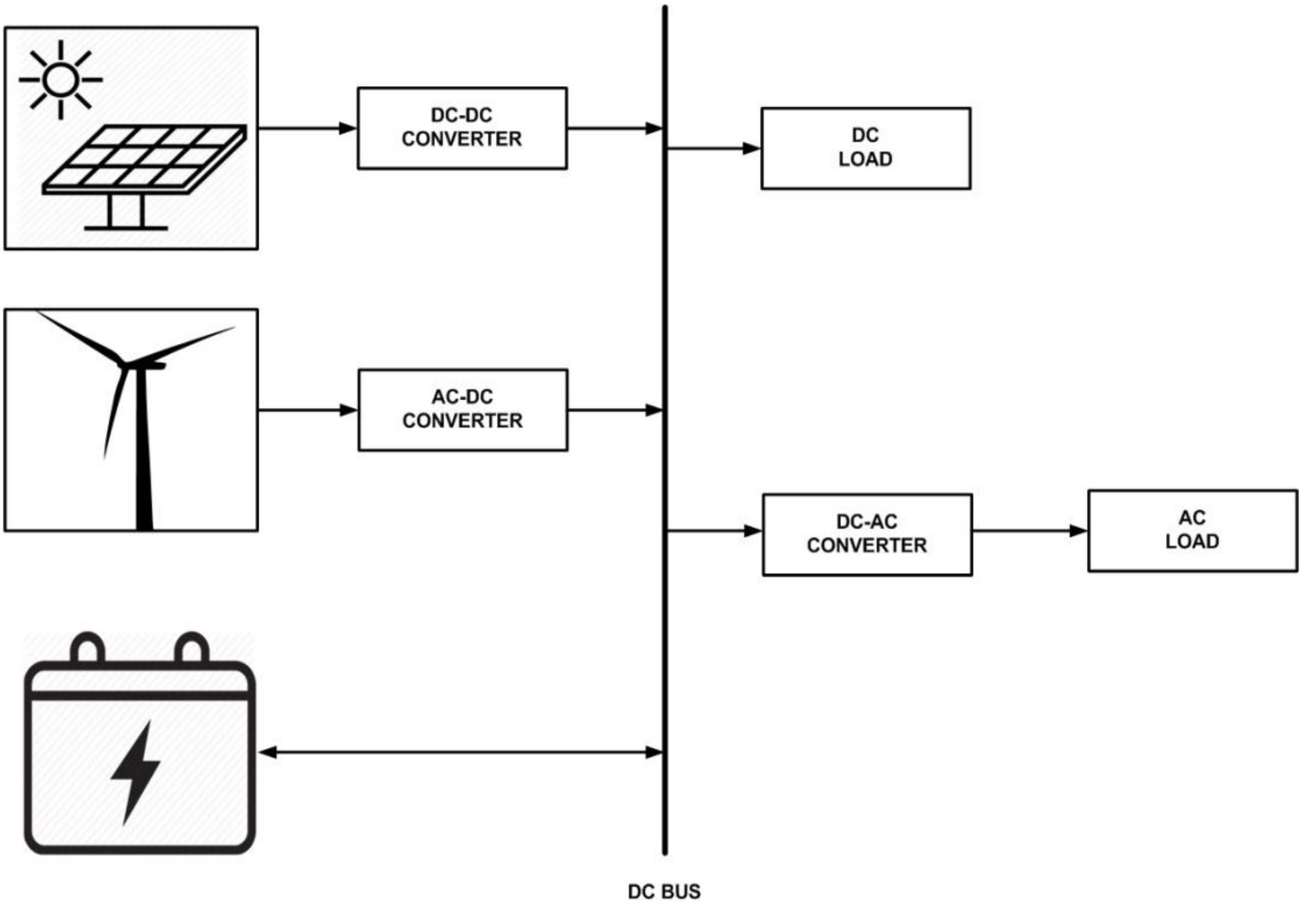

Fig. 2.1: A PV-WT-BS hybrid renewable energy system.

In this study, the HRES consists of two sources of energy which are wind generator and photovoltaic cells and as an energy storage system, a battery is employed. Each of the components is discussed below:

2.1 Wind turbine model

Any wind turbine may be selected for the HRES. However, the type of chosen wind turbine should be analysed based on the non-linear power characteristics curve provided by the manufacturer of the specific wind turbine. A typical power characteristic curve is presented to provide some insight in understanding the behaviour of a wind turbine.

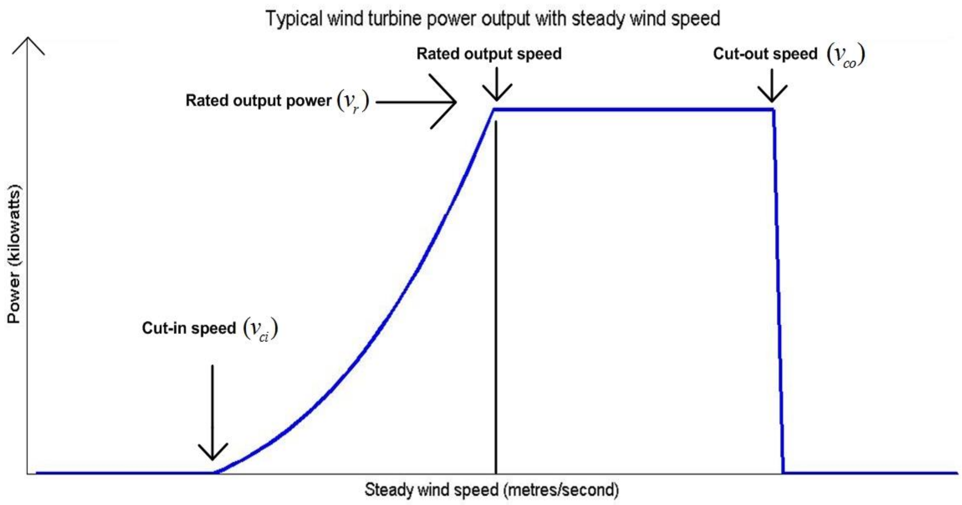

Fig. 2.2: Wind turbine power output characteristics

From Fig. 2.2 it is obvious that wind speed of a particular site plays a vital role for generating power. The wind speed at a reference height (approximately 33m) of the site under study, can be obtained from the Typical Meteorological Year (TMY) data. Based on the study by [59], the specific power output, P_w (W/m^2), depends on the wind speed of that particular site and is expressed by

$$\begin{aligned} &P_w(t) = 0 && v(t) < v_{ci} \\ &P_w(t) = av^3(t) - bP_r && v_{ci} \le v(t) < v_r \\ &P_w(t) = P_r && v_r \le v(t) < v_{co} \\ &P_w(t) = 0 && v(t) \ge v_{co} \end{aligned} \tag{2.1}$$

where $a = \dfrac{P_r}{v_r^3 - v_{ci}^3}$, $b = \dfrac{v_{ci}^3}{v_r^3 - v_{ci}^3}$. v_{ci}, v_r and v_{co} represent the cut in, rated and cut out speed of the WG respectively. P_r denotes the rated power. Cut in, rated and cut out speed of the wind turbine can be found from the manufacturer of the selected turbine [60]. In order to implement the above equation, the velocity of wind at hub height is needed. In order to find the velocity we use the following equation[61]

$$v_h = v_r \left(\frac{h}{h_r} \right)^{\alpha} \tag{2.2}$$

In equation 2.2, v_r and v are the wind speed at the reference height and hub height respectively, α is the power law coefficient, h is the WG installation height and h_r is the reference height.

From [41] it can be concluded that the value of α is less than 0.10 for very flat land, water and ice and is more than 0.25 for a heavily forested landscape. For this study α is taken to be 0.14, because the site considered is almost like an open terrain of grasslands and [62] suggests that it is a good approximation for such an area. So incorporating all the above facts, it can be finally concluded that the actual electric power output as obtained from a wind turbine is represented by

$$P_{WG} = P_w A_{WG} \eta_{wG} \tag{2.3}$$

where P_{WG} is the power produced by the WGs, A_{WG} is the total swept area of a WG and η_{wG} is the efficiency of WG and the corresponding converters. The details of the considered WT are given in the Table 2.1.[63]

Table 2.1: Specification of the WG

Power (W)	h_{low} (m)	h_{high} (m)	WG capital cost ($)	Tower capital cost ($/unit length)
1000	11	40	2400	55

2.2 Photovoltaic (PV) module model

This is the second source of renewable energy which is employed in this study. It is to be noted here that electricity generation of PV modules are dependent on solar radiation and thus are not capable of producing any power at night. Besides solar radiation, other factors like ambient temperature and irradiation conditions influence the power generation of PV modules and these conditions differ from modules to modules. The manufacturer of the PV modules provide these data for the Standard Test Conditions (STC) (cell temperature at 25 $^{\circ}C$ and solar irradiance of 1 kW/m^2). Incorporating these data from the manufacturer, the output power of a PV module at a given time is found out from the following equation [40]

$$
\begin{aligned}
&P_{PV}(t,\beta) = N_S.N_P.V_{OC}(t,\beta).I_{SC}(t,\beta).FF(t) \\
&V_{OC}(t,\beta) = \left\{V_{OC-STC} - K_V T_C(t)\right\} \\
&I_{SC}(t,B) = \left\{I_{SC-STC} + K_I\left[T_C(t) - 25^\circ C\right]\right\}\frac{G(t,\beta)}{1000} \\
&T_C(t) = T_A + \left(NCOT - 20^\circ C\right)\frac{G(t,\beta)}{800}
\end{aligned}
\tag{2.4}
$$

In equation 2.4, P_{PV} is the power produced by PV modules, t is a particular time (hour in this study), β is the tilt angle of the PV modules, N_S and N_P are the number of PV modules connected in series and parallel respectively, V_{OC} and I_{SC} represent the open circuit voltage and short circuit current of a PV module respectively, FF is the fill factor which is the ratio of the actual maximum obtainable power to the product of the open circuit voltage and short circuit current, K_V and K_I are the open circuit voltage temperature coefficient and short circuit current temperature coefficient respectively, G represents the global solar irradiance on a PV module, T_A is the ambient temperature and $NCOT$ is the nominal cell operating temperature.

From equation 2.4 it is evident that we need the value of global solar irradiance which is incident on the PV module. Though hourly global irradiation on a horizontal plane can be found from the data seta of meteorological year (TMY), it is not sufficient for this study since the PV modules are not placed horizontally. For a tilted PV module, the solar irradiance is decomposed into beam and diffuse components. So we need both of these components in order to get our resultant global solar irradiance. k_T is the hourly clearness index and it gives the ratio of beam (G) and diffuse (D) components. The correlation between $\frac{G}{D}$ and k_T is given by the following expression [64-67]

$$
\frac{G}{D} = \begin{cases}
1.0 - 0.09k_T & 0 < k_T < 0.22 \\
0.9511 - 0.1604k_T + 4.388{k_T}^2 - 16.638{k_T}^3 + 12.336{k_T}^4 & 0.22 < k_T \le 0.80 \\
0.065 & k_T > 0.8
\end{cases}
\tag{2.5}
$$

The site under study is in New Zealand which is located in the southern hemisphere and thus it is obvious that the PV modules will be facing true north at some fixed angle. R_b is a geometric factor which is the ratio of beam radiation on a tilted surface to that on a horizontal surface at any time. R_b is given by the following equation [64]

$$R_b = \frac{\cos(\phi+\beta)\cos\delta\cos\omega + \sin(\phi+\beta)\sin\delta}{\cos\phi\cos\delta\cos\omega + \sin\phi\sin\delta} \tag{2.6}$$

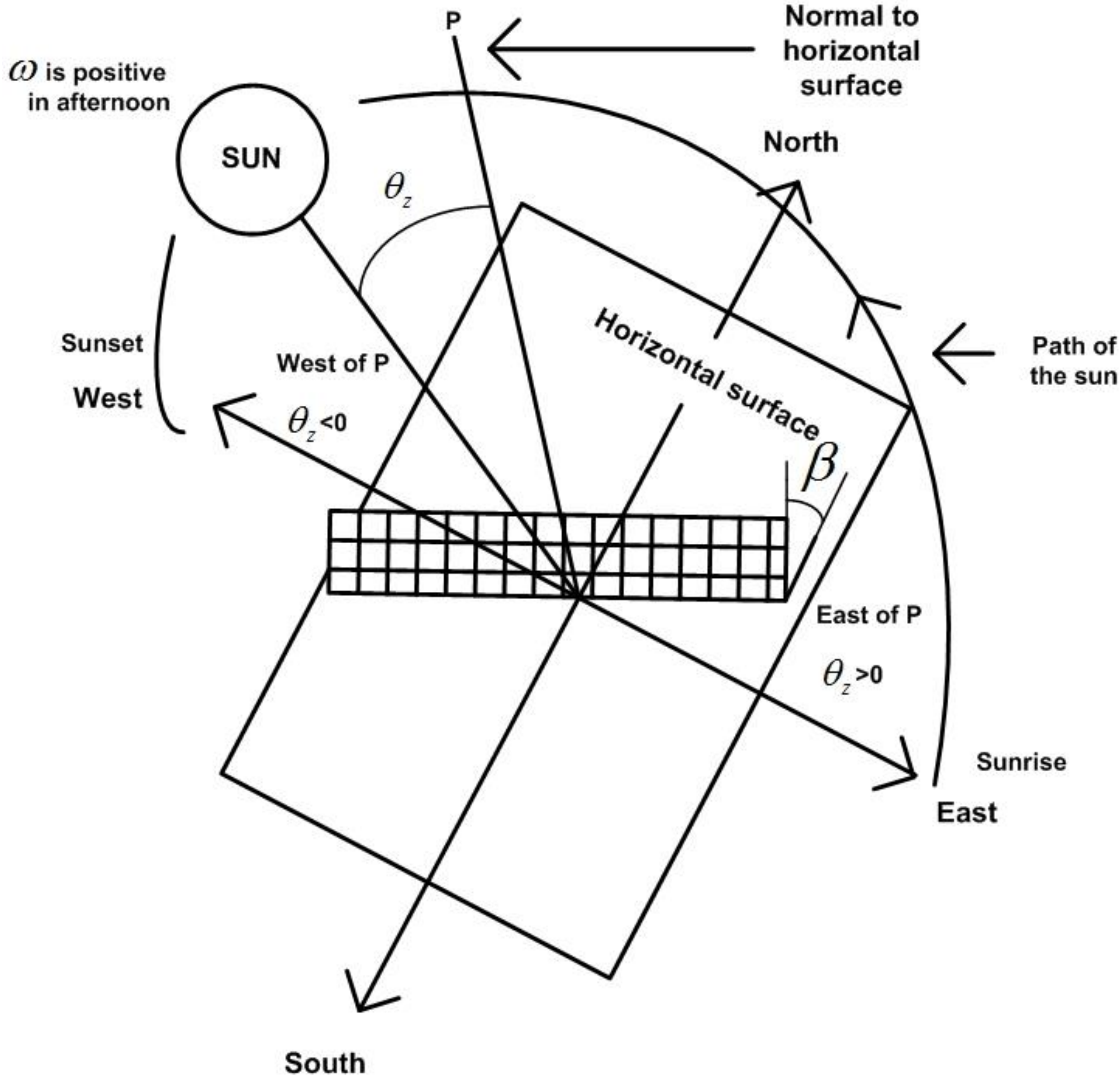

Fig. 2.3: Angles related to the sun

To understand the angles associated in equation 2.6 let us take a look at Fig. 2.3. ϕ is the latitude of the site, β is the tilt angle of the PV module. From Fig. 2.3 it can be seen that the PV module is tilted at β degree from the horizontal surface. ω is the hour angle, which is the angular displacement of the sun east or west of the local meridian due to rotation of the earth on its axis at 15^o per hour. The hour angle is positive in the afternoon and vice versa. The angle between the vertical and the line to the sun is represented by θ_z and is known as the zenith angle. δ is the declination of the sun i.e the angular position of the sun at solar noon with respect to the plane of the equator. The angle of declination is considered to be positive in the northern hemisphere and negative in the southern hemisphere and it varies from -23.45^o to 23.45^o. The declination angle is represented by equation 2.7.

$$\delta = 23.45 \sin\left(360 \frac{284+n}{365}\right) \tag{2.7}$$

In equation 2.7, n is the day of the year. For example, for a random date of 17th January, the value of n is 17 and for 16th March, the value is 75.

Now incorporating the tilt angle of the PV module, the total hourly global radiation can be found by [64]

$$G(t,\beta) = (G-D)R_b + D\left(\frac{1+\cos\beta}{2}\right) + G\rho_g\left(\frac{1-\cos\beta}{2}\right) \tag{2.8}$$

In equation 2.8 ρ_g is the ground reflectance and R_b is obtained from equation 2.6.

Finally incorporating efficiency the total output power follows the following expression

$$P_{array}(t,\beta) = \eta_{PV} N_S N_P P_{PV}(t,\beta) \tag{2.9}$$

where η_{PV} is the PV-module's and related converter's efficiency [60]. It is to be noted that in the present study the numbers of PV modules in series is determined by the magnitude of the DC bus voltage whereas the numbers of parallel PV modules is obtained from the optimization algorithm.

The details of the considered PV module are given in Table 2.2.[63]

Table 2.2: Specification of the PV module

V_{OC} (V)	I_{SC} (A)	$V_{\max}$ (V)	$I_{\max}$ (A)	$P_{\max}$ (W)	Capital cost ($)
64.8	6.24	54.7	5.86	320	640

2.3 Battery Model

As mentioned earlier, the chosen sources of energy are inconsistent with nature. So it is very obvious that sometimes the generated electricity is more than the current demand and sometimes it is less than the required load. In order to maintain a steady state of operation, it is therefore needed to have an energy storage system which will store the surplus energy and provide energy when the production is below the required load. Signifying that the battery will charge and discharge based on the situation. For this phenomenon, state of charge (SOC) plays a very important role. For knowing the current SOC of a battery, knowledge on three things are needed: initial SOC, the charge/discharge time and the current flowing. From [41] the SOC at a particular instance can be represented by equation 2.10.

$$SOC(t) = SOC\left(t-1\right).\left(1-\frac{\sigma.\Delta t}{24}\right)+\frac{I_{bat}(t).\Delta t.\eta_{bat}}{C_{bat}} \tag{2.10}$$

where σ is the self-discharge rate of a battery, I_{bat} is the battery current, C_{bat} is the nominal capacity of a battery and η_{bat} is the battery charging efficiency.

According to [41] σ depends on the accumulated charge and in this study the value is assumed to be 0.2% per day [68], charging efficiency is set to 0.8 and discharging efficiency is assumed to be 1 in accordance to the study in [41].

While discharging, the battery cannot be allowed to be completely empty as this drastically reduces the battery longevity. Authors in [69] suggest that life of a battery can be extended by avoiding overcharge and critical discharge. So the minimum permissible limit of the battery is given by

$$C_{\min} = DOD \times C_n \tag{2.11}$$

where C_n is the total capacity of the connected batteries and the maximum depth of discharge (DOD) is to be given by the system engineer and typically it is expressed in percentage. In order to calculate the capacity of the battery bank in equation 2.11, we need to know the number of batteries connected in parallel since the batteries connected in series depend on the DC bus voltage and is given by

$$N_{Sbat} = \frac{V_{BUS}}{V_{bat}} \tag{2.12}$$

In equation 2.12, N_{Sbat} gives the number of batteries connected in series, V_{BUS} is the DC bus voltage and V_{bat} is the nominal voltage of each individual battery.

Thus capacity of the battery bank is now given by

$$C_n = N_{Pbat} \times C_{bat} \tag{2.13}$$

where N_{Pbat} is the number of batteries connected in parallel. To visualize the connection of the batteries in series and parallel, let us take a look at Fig. 2.4.

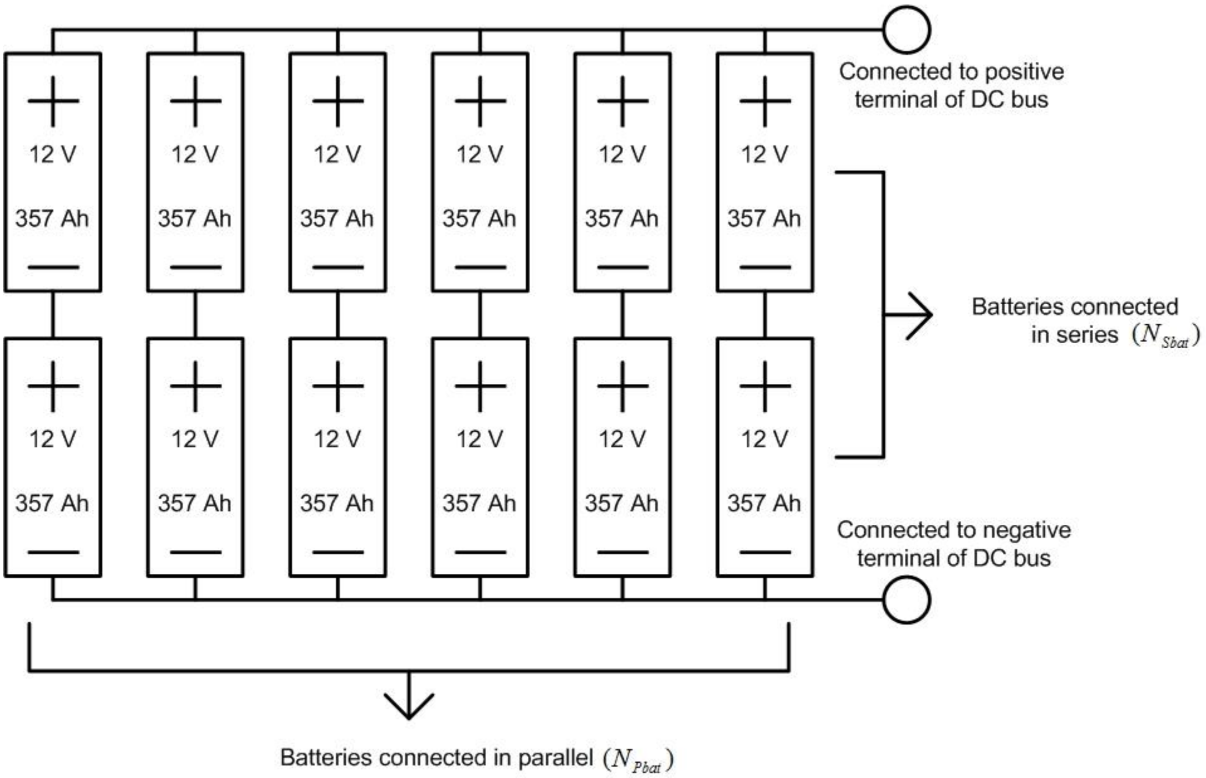

Fig. 2.4 Batteries connected in series and parallel

It is to be noted that number of batteries in parallel is one of the optimizing parameters since the number of batteries in series can be readily obtained from the bus voltage. The total number of batteries of course depends on both the series and parallel connected batteries and is given by equation 2.14.

$$N_{bat} = N_{Sbat} \times N_{Pbat} \tag{2.14}$$

where N_{bat} represents the total number of batteries in the system.

So finally, the current obtained from the battery due to its incorporation with PV and WG, as can be seen from Fig.2.1, is given by the equation 2.15

$$I_{bat}(t) = \frac{P_{PV}(t) + P_{WG}(t) - P_{Load}(t)}{V_{bat}(t)} \tag{2.15}$$

The details of the considered battery model are given in the following table [63].

Table 2.3: Specification of the battery model

Price ($)	Voltage (V)	Capacity (A h)
1239	12	357

2.4 Objective function formulation based on Loss of Power Supply Probability (LPSP)

There is a probability that the Hybrid model under study may sometimes be unable to satisfy the load demand in order to be economically viable, such probability is defined as loss of power supply probability (LPSP) [70]. The value of LPSP can vary from zero to one. An LPSP of zero signifies the utmost reliability of a model meaning that the load will always be satisfied and on the contrary, an LPSP of zero means that the load will never be satisfied. LPSP is governed by the following equation [41]

$$LPSP = \frac{\sum_{t=0}^{T} Loss\,of\ Power\ Supply\,Time}{T} = \frac{\sum_{t=0}^{T} Time\left(P_{available}(t) < P_{Load}(t)\right)}{T} \tag{2.16}$$

For calculating LPSP from equation 2.16 two more factors are needed to be considered. One is the load demand $P_{Load}(t)$ at a particular time period which can readily be obtained from the load demand file of the site under study, and the other factor is the available power $P_{available}(t)$ from the hybrid model at that particular time period. In equation 2.16, T is the total number of hours in a given year and $\sum_{t=0}^{T} Loss\,of\ Power\ Supply\,Time$ represents the summation of all the hours during which the available power was less than the demand. The available power at a particular instant from an HRES consisting of PV, WG and battery is given by equation 2.17 [41]

$$P_{available} = P_{pv}(t) + P_{WG}(t) + C.V_{bat}.Min\left[I_{bat,\max} = \frac{0.2C_{bat}}{\Delta t}, \frac{C_{bat}.\left(SOC(t) - SOC_{\min}\right)}{\Delta t} \right] \tag{2.17}$$

In the equation 2.17 C is a constant and $SOC_{\min} = 1 - DOD$ [41].When the battery is charging the value of C is zero and one for the discharging process. It is to be noted that the analysis is done on hourly basis and so the numerical values of power is equal to energy.

The main aim of this study is to reduce the cost of the HRES. This objective is carried out in two phases. In the first phase LPSP is kept at zero, which ensures maximum reliability and then calculating the cost, resulting in an SOO. Since the LPSP is kept at zero, so there is only one objective function which is equation 2.18 and thus it becomes an SOO. In the second phase both LPSP and cost are allowed to vary so as to provide a designer a greater flexibility in terms of financial aspect, resulting in an MOO. In this phase, the objective is to minimize both equation 2.16 and 2.18, thus there is more than one objective to satisfy and so is termed as MOO.

In this study, the lifetime of the HRES under study is assumed to be 20 years and the associated costs not only include the initial set up cost of the PV, WG and batteries, but also the maintenance cost throughout its life span. According to [40], the objective function is given by

$$\begin{aligned} Minimize\ f\left(N_{PV}, N_{WG}, N_{bat}, \beta, h\right) = [& N_{PV}\left(C_{PV} + 20M_{PV}\right) + \\ & N_{WG}\left(C_{WG} + 20M_{WG} + h.C_h + 20hM_h\right) + \\ & N_{bat}\left(C_{bat} + y_{bat}C_{bat}\right) + \left(20 - y_{bat} - 1\right)M_{bat}] \end{aligned} \tag{2.18}$$

Subject to the constraints

$$\begin{aligned} & N_{WG} \geq 0, \\ & N_{PV} \geq 0, \\ & N_{bat} \geq 0, \\ & 90^\circ \geq \beta \geq 0, \\ & 11 \geq h \geq 40. \end{aligned} \tag{2.19}$$

In equation 2.18, N_{PV}, N_{WG} and N_{bat} are the number of PV modules, WGs and batteries respectively, C_{PV}, C_{WG} and C_{bat} are the capital cost of a PV module, WG and battery respectively, M_{PV}, M_{WG} and M_{bat} are the annual maintenance cost of a PV module, WG and battery respectively, C_h is the capital cost per unit height of WG tower, M_h is the yearly maintenance cost per unit height of a WG tower and y_{bat} is the expected number of battery replacements during the life of HRES.

Thus in phase one, the focus is only on equation no. 2.18, keeping LPSP equal to zero and in phase two, the target is to minimize both LPSP and total cost of the HRES. In order to decrease the value of LPSP it is needed to increase the value of $P_{available}$ in equation 2.16. From equation 2.17 it is understood that increasing the values of P_{pv} and P_{WG} will increase the value of $P_{available}$, but on the contrary this will result in an increase in the total cost of the HRES (from equation 2.18). So it is obvious that equation no. 2.18 and 2.16 are inversely proportional to each other and thus it is needed to translate the problem into an MOO.

2.5 Summary

Thus the HRES is now explained along with the objective functions associated with this thesis. It can be well understood that the HRES relies a lot on the climate of the particular site where it is implemented. So the incorporation of an energy storage device becomes mandatory and this inclusion of battery makes the system expensive. That is why it is very important to try and utilize the generated energy in the most economical way possible.

Chapter 3: Hybrid GWO-GA SOO

In this chapter two single objective optimization algorithms namely GA and GWO are elaborated. The mathematical equations which are applied in each algorithm along with the working principle of these algorithms are also discussed. Finally both the algorithms are merged to create a hybrid algorithm. The hybrid algorithm is explained with the help of a flowchart at the end of this chapter.

3.1 Genetic Algorithm (GA)

Genetic Algorithm (GA) is an evolutionary optimization algorithm which can be applied in any domain using computer simulations. This approach mimics the Darwinian principle of reproduction and survival of the fittest. And thus the process includes cross-over and mutation which is analogous to the naturally occurring genetic operations [71] . This is an SOO which initially starts with a number of randomly generated populations from a population set. Each population set is termed as chromosome and the variable in a population set are known as genes of that chromosome.

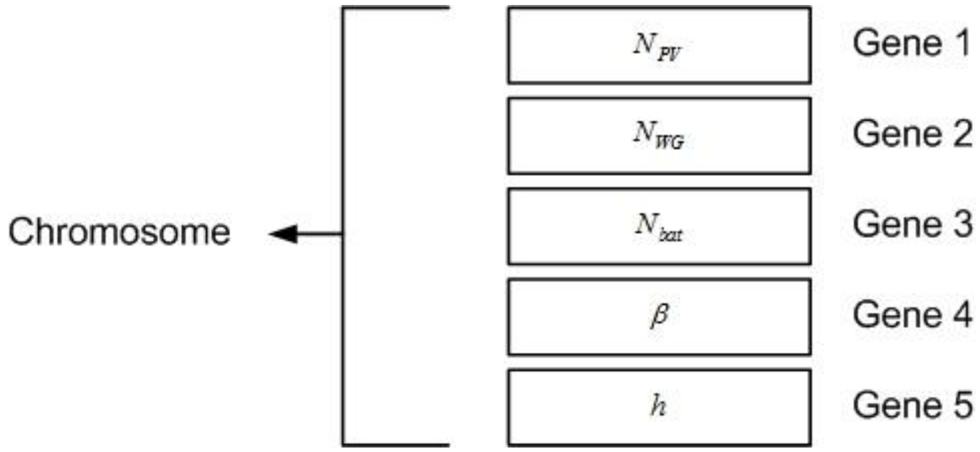

Fig. 3.1: Representation of the optimizing parameters as genes in a chromosome

Then for each chromosome, the algorithm checks if the provided objective function is satisfied or not. Before checking the objective functions, the genes of a chromosome are required to fulfil any given constraints. Upon satisfaction of the objective function (equation 2.18 in this study), the probable solutions enter the process of cross-over and mutation.

3.1.1 Cross-over

In cross-over operation, any two accepted solutions/chromosomes are chosen randomly to generate two new off-springs which are termed as the next generation of solution. In this study we follow the line cross-over and it is expressed by equation 3.1 [72]

$$z_i = \lambda x_i + (1-\lambda) y_i \text{ for } i = 1:n \tag{3.1}$$

where z_i is the offspring chromosome, x_i and y_i are the parent chromosomes and λ is a random number between 0 and 1.

Cross-over plays a significant role in GA. If the cross-over rate is high, newer chromosomes are generated more quickly but at the same time newer chromosomes with high performance are also discarded quickly in comparison to the improvements provided by the selection rate. On the other hand if the cross-over rate is lower, the algorithm will have a much lower exploration capability [39].

After cross-over, again a randomly accepted solution/chromosome is chosen to undergo the mutation process.

3.1.2 Mutation

Mutation is directly related with the variability of the population, a higher mutation rate increases the variability and vice-versa. A lower mutation rate prevents a gene from remaining converged to a single value in the entire population set [39]. In this study the Gaussian mutation is applied which is governed by equation 3.2 [72]

$$z_i = z_i + N(0, \sigma_i) \tag{3.2}$$

where $N(0, \sigma_i)$ is an independent random Gaussian number with a zero mean value and σ_i is the associated standard deviation. Both z_i and $N(0, \sigma_i)$ depend on mutation rate. Mutation rate determines how many genes in a chromosome will undergo mutation.

It is to be noted that not all the chromosomes undergo cross-over and mutation, but only some randomly selected chromosomes enter this process. This approach prevents the algorithm from being stuck at some local minima (for minimization problems). The off-springs are then again re-evaluated and thus the process continues. Finally the chromosome with the minimum (for minimizing objective functions) value is chosen as the optimum solution.

3.2 Grey Wolf Optimizer (GWO)

Grey wolf optimizer is rather a new nature inspired optimization algorithm which was proposed by the authors in [49] in 2013. This is also an SOO in nature. This algorithm mimics the hierarchy and hunting mechanism of grey wolves (*Canis lupus*).

Grey wolves are divided into four classes known as alpha ($g\alpha$), beta ($g\beta$), delta ($g\delta$) and omega ($g\omega$). The alphas are the leaders of the pack and essentially all the decisions of the pack are taken by the alphas. The second in hierarchy are the betas. They basically carry out and implement the orders given by the alphas and at the same time advise them in making of various decisions. The deltas are the third in hierarchy; they basically follow the orders given by the alphas and betas and at the same time dominate the omegas. And finally, the lowest in the hierarchy are the omegas who submit to all other wolves. Social hunting is one of the main activities of the grey wolves which basically constitute of three phases [73]

- Tracking, chasing and approaching the prey
- Pursuing, harassing and encircling the prey until it stops moving
- Attack toward the prey.

These phenomenon which takes place in the pack of grey wolves, are mathematically modelled by the authors in [49]. The encircling phase of the pack is given by:

$$
\begin{aligned}
\vec{D} &= \left|\vec{C}\vec{X}_p(t) - \vec{X}(t)\right| \\
\vec{X}(t+1) &= \vec{X}_p(t) - \vec{A}\left(\vec{D}\right)
\end{aligned}
\tag{3.3}
$$

where t is the value of the current iteration, $\vec{A}$ and $\vec{C}$ are the coefficient vectors which are calculated from equation 3.4, $\vec{X}$ is the position vector of a grey wolf and $\vec{X}_p$ is the position vector of the prey.

In equation 3.3 $\vec{A}$ and $\vec{C}$ are calculated as follows

$$
\begin{aligned}
\vec{A} &= 2\vec{a}\vec{r}_1 - \vec{a} \\
\vec{C} &= 2\vec{r}_2
\end{aligned}
\tag{3.4}
$$

In equation 3.4, $\vec{r}_1$ and $\vec{r}_2$ are two random vectors which are in the range of [0, 1] and the value of $\vec{a}$ is linearly decreased from 2 to 0 over the course of iterations.

In the hunting phase of the grey wolves, it is assumed that the alpha, beta and delta wolves have the better knowledge about the location of the prey and all other wolves update their positions based on the positions of the best search agents (preferably assumed to be the alphas). This is again mathematically modelled as follows [49]

$$\begin{aligned}
&\vec{D}_{g\alpha} = \left|\vec{C}_1 \vec{X}_{g\alpha} - \vec{X}\right| \\
&\vec{D}_{g\beta} = \left|\vec{C}_2 \vec{X}_{g\beta} - \vec{X}\right| \\
&\vec{D}_{g\delta} = \left|\vec{C}_3 \vec{X}_{g\delta} - \vec{X}\right| \\
&\vec{X}_1 = \vec{X}_{g\alpha} - \vec{A}_1\left(\vec{D}_{g\alpha}\right) \\
&\vec{X}_2 = \vec{X}_{g\beta} - \vec{A}_2\left(\vec{D}_{g\beta}\right) \\
&\vec{X}_3 = \vec{X}_{g\delta} - \vec{A}_3\left(\vec{D}_{g\delta}\right) \\
&\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}
\end{aligned} \tag{3.5}$$

In equation 3.5, $\vec{D}_{g\alpha}$, $\vec{D}_{g\beta}$ and $\vec{D}_{g\delta}$ are the distances travelled by the $g\alpha$, $g\beta$ and $g\delta$ wolves respectively over the course of time. To visualize all these parameters let us a take a look at Fig. 3.1

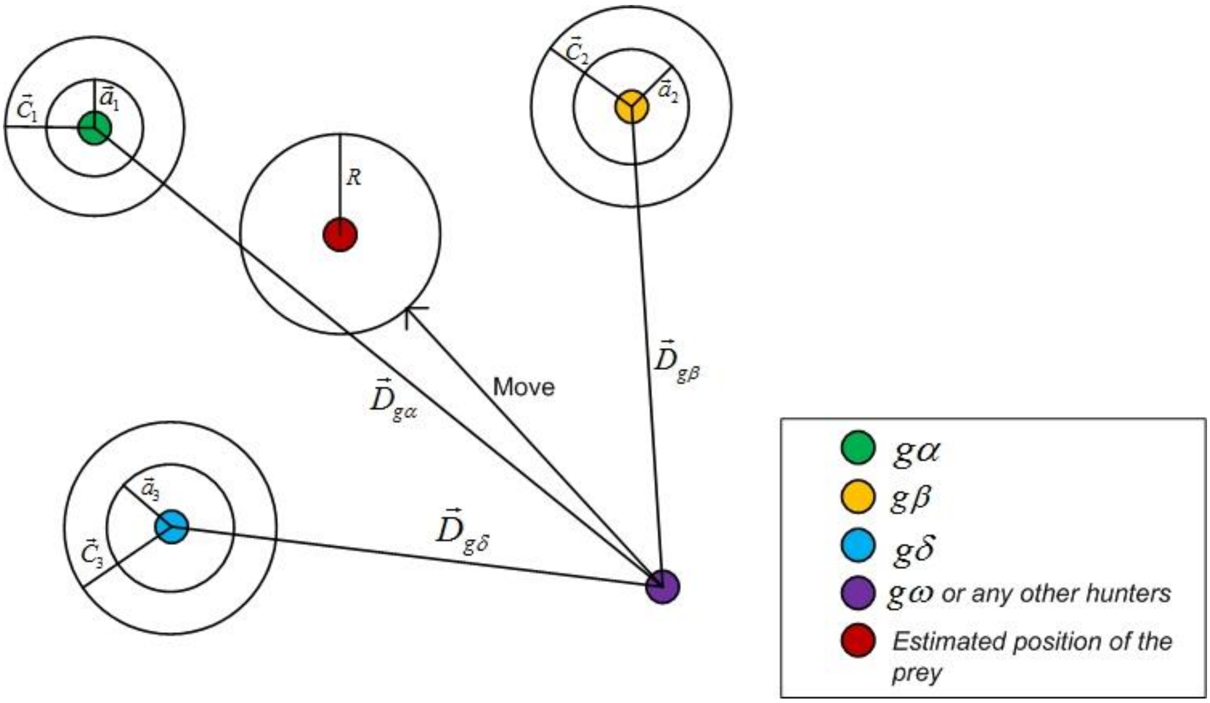

Fig. 3.2: Position updating in GWO [49]

From Fig. 3.1 it can be visualized that with the increase in iteration the value of $\vec{\alpha}$ decreases. Here $\vec{a}_3 > \vec{a}_2 > \vec{\alpha}_1$. As the number of iterations increases, the wolves gradually approach the prey and encircle it. The wolves finally attack the prey once the prey stops moving. It is to be mentioned that the $\vec{C}$ parameter is a random vector whose value ranges from two to zero [49]. This parameter defines a random radius and provides a random weight for a prey. If the value of $\vec{C}$ is greater than 1 then the wolves emphasize on that particular prey and vice versa. In equation 3.5, $\vec{C}$ parameters play a significant role in avoiding local optima stagnation.

3.3 Hybrid GWO-GA Optimization

In this study GWO and GA algorithm are merged together to generate a hybrid algorithm in order to achieve a better result. This study merges two optimization algorithms of different nature. GWO is a nature inspired algorithm whereas GA is an evolutionary algorithm. The studied flowchart of the algorithm is given in Fig. 3.2.

In this study, the objective is to attain the minimum cost over the life cycle of the hybrid HRES. The objective function is already formulated in Chapter 2 and now the optimization algorithm is applied. The algorithm starts by randomly generating the initial parameters, setting iteration equal to one and defining certain variables which will be needed throughout the algorithm. Provided the maximum number of iteration is not reached, now the algorithm enters the phase where each solution set is checked to find the associated cost. According to the cost, the position of alpha, beta and delta wolves are updated. This is done in the following manner: if the fitness value (associated cost) of a particular set of solution is smaller than the cost saved in alpha (alpha score), then the position of alpha is updated with that particular set of solution. The condition for updating the beta position is that, the associated cost of the set of solution has to be greater than the alpha score but smaller than the stored beta score. And similarly for delta, the fitness value has to be greater than the beta score and smaller than the stored delta score. The algorithm comes out of this block of code once this system is carried out for all the initially declared solutions in the population set. Of course before evaluating the cost function, it is checked whether the variables in the population set satisfy the given constraints or not. After this, the population is sorted according to the fitness value and the first best population of size P_G enters the next phase, which is basically GA portion of the algorithm. In this phase of the hybrid algorithm, crossover and mutation takes place. Before cross-over and mutation, the whole population set

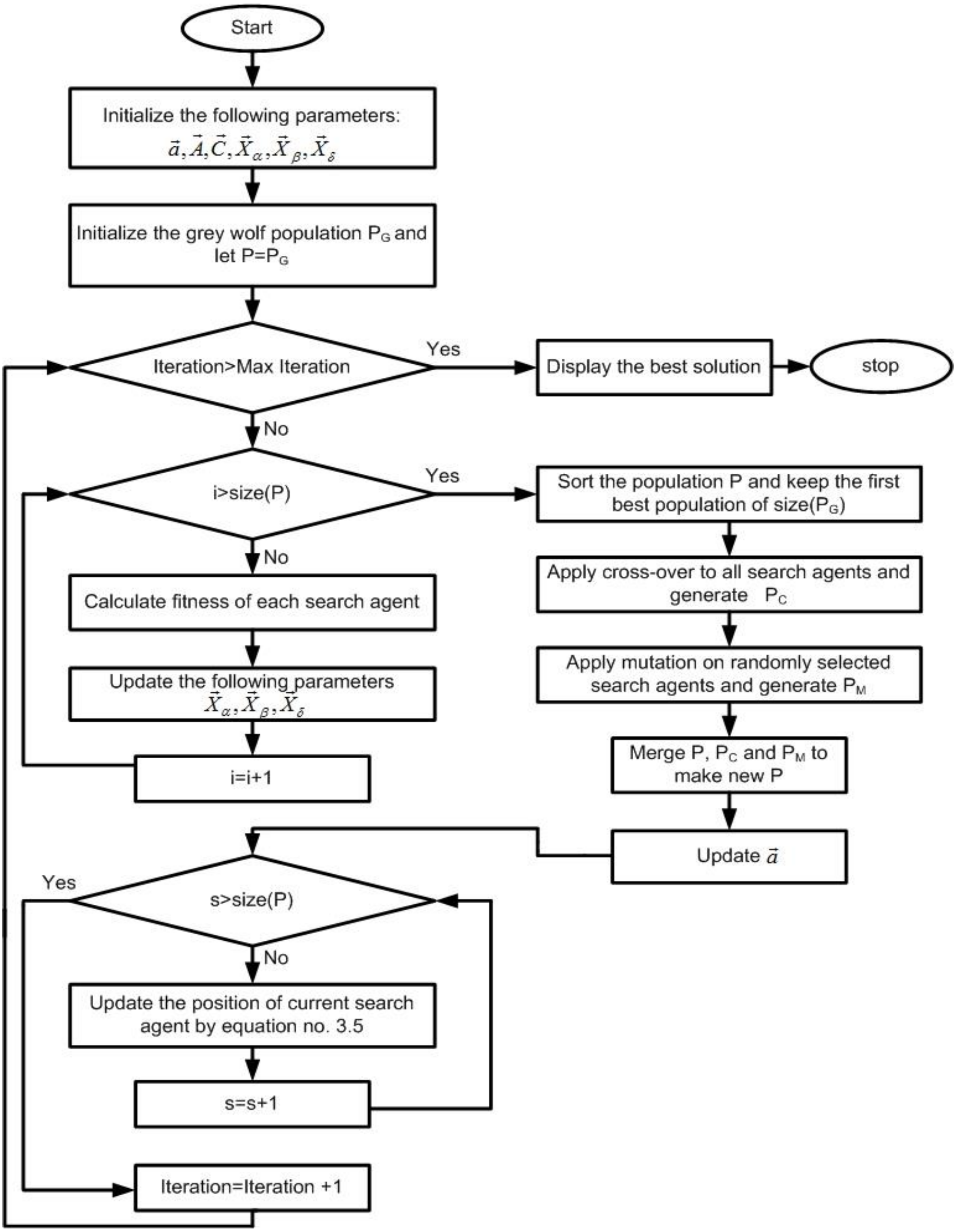

Fig. 3.3: Flowchart of hybrid GA-GWO algorithm

is sorted based on equation 2.18 and the best population of size P_G produces off-springs namely P_C and P_M after cross-over and mutation. All these population sets are now merged to generate a bigger set of population which now enters the core portion of the GWO. In this phase, the position of each search agent is updated following equation no. 3.5 and thus the whole set of updated population enter the next iteration.

This process continues until maximum number of iterations is reached and consequently displays the best population set with the associated cost. The whole algorithm is depicted in Fig. 3.2.

3.4 Summary

In this chapter LPSP was kept constant at zero and the main focus was on equation 2.18. Two single objective algorithms GA and GWO were merged to create a hybrid algorithm with the expectation of obtaining a better result. Each algorithm was also explained in detail so as to make the hybrid algorithm easily understandable. These algorithms are tested for a load profile of Auckland, New Zealand in Chapter 5.

Chapter 4: Hybrid NSGA-GWO MOO Optimization

This phase aims at transforming the problem into a multi-objective optimization (MOO) problem. In general, a MOO has more than one objective functions and often the objective functions are conflicting in nature. It is already mentioned in Section 1.6 that NSGA is one of the MOO algorithms which attracted a lot of researchers because it is comparatively easy to implement and attains a set of pareto optimal solutions. None of the solutions in pareto-optimal set can be termed as *dominating* the others in respect to the given objective functions. This decision solely lies on the designer's perspective and provides a lot of flexibility in determining the best solution from the pareto-optimal set based on the specific requirements/conditions.

4.1 NSGA

Non-dominated Sorting Algorithm (NSGA) was proposed by the authors in [74] in 1995. Since then a few versions of NSGA has already evolved. However, the core algorithm still remains the same. NSGA is basically a modified version of GA. It is already mentioned that GA is an SOO, so NSGA transforms this SOO into an MOO. The cross-over (Section 3.1.1) and the mutation (Section 3.1.2) are same in both the algorithms, but the difference is created in the selection process. Before the selection process, the whole population is divided into different non-dominated fronts based on each individual's non-domination [74]. Further, each front is assigned some dummy fitness value and the process continues until all the population are divided into various fronts. Finally, at the end of the algorithm, a single front is presented as the solution set, which contains a lot of solutions, and all the solutions are termed as pareto-optimal solutions.

Though NSGA is capable in solving multi-objective problems, this algorithm is criticised by a lot of researchers due to the following reasons [75]

- Computational complexity
- Non-elitism approach
- The need for specifying a sharing parameter.

In order to overcome these problems, a new and improved algorithm known as NSGA-II is proposed by the authors in [75]. The main difference is created in this algorithm by the introduction of crowding distance operator and introduction of diversity among the non-dominated solutions [75].

4.1.1 Non-Dominated sorting

In NSGA-II, the initialized population is sorted based on non-domination. The algorithm is depicted in Fig. 4.1.

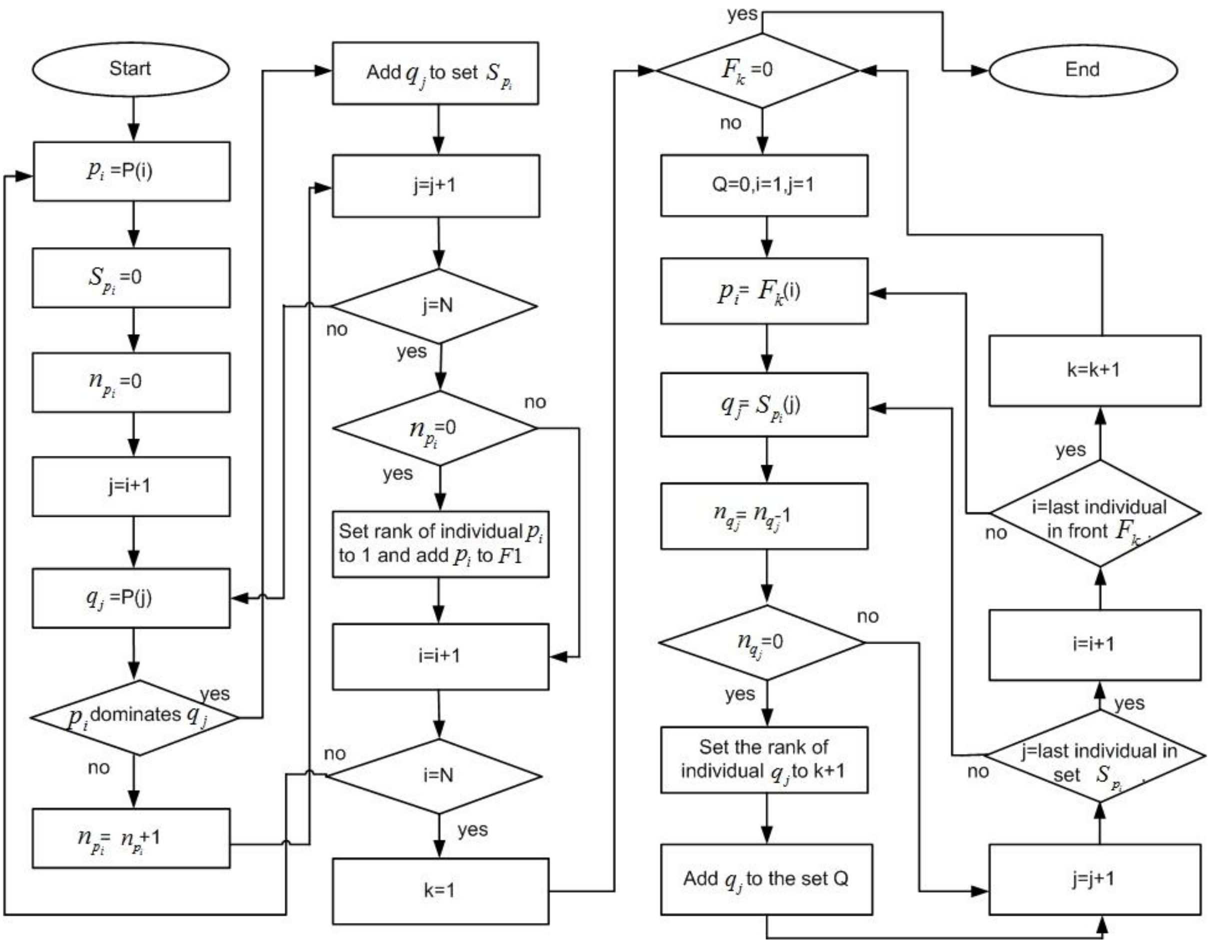

Fig. 4.1: Non-dominated sorting algorithm flowchart

The steps are elaborated below:

- p_i is considered as an individual in the main population P which contains N individuals.
- S_{p_i} contains the set of all individuals which are dominated by p_i and is set to zero.

- n_{p_i} is the number of individuals that dominate p_i and is set to zero.
- q_j is considered as the following individual of p_i in the main population P.
- If p_i dominates q_j, q_j is added to the set S_p .i.e. $S_{p_i} = S_{p_i} \bigcup \{q_j\}$
- Else the domination counter of p_i is incremented by one, i.e. $n_{p_i} = n_{p_i}$ +1
- If n_{p_i} =0 then the rank of individual p_i is set to one and p_i is added to $F1$. F is the set of fronts and $F1$ signifies the first front in the system. $F1 = F1 \bigcup \{p_i\}$
- The above steps are carried out for all the individuals in the main population P.
- k is the front counter which is initialized to one.
- The following steps are carried out as long as $F_k \neq 0$.
- Q is the set for storing the individuals for (k+1)th front and is initialized to zero.
- p_i is an individual in the front F_k.
- q_j is an individual in the set S_{p_i}.
- The domination count for individual q_j is decremented by one i.e. $n_{q_j} = n_{q_j}$ -1.
- If n_{q_j} =0 then $q_{j(rank)}$ =k+1 and the set Q is updated with q i.e. Q=Q$\bigcup\{q_j\}$. This means that none of the individuals in the subsequent fronts would dominate q_j.
- Else if $n_{q_j} \neq 0$ then the algorithm moves to the next individual in the set S_{p_i}.
- The above steps are carried out for all the individuals in the front F_k.
- The front counter is incremented by one and the algorithm continues as long as $F_k \neq$ 0.

This algorithm sorts the initial population. According to [76] this algorithm makes the NSGA-II [75] better and more efficient than the original NSGA [74] since it takes into consideration about the set that an individual dominate (S_{p_i}).

4.1.2 Crowding distance operator

After non-domination sorting, the population is again sorted based on the crowding distance operator. The equation involving the distance update equation is given by [75]

$$I(d_k) = I(d_k) + \frac{I(k+1)m - I(k-1)m}{f_m^{\max} - f_m^{\min}} \tag{4.1}$$

where, d_k corresponds to the distance of k^{th} individual in a particular front, I is the set consisting the distances of all the individuals in a front, $I(k)m$ is the value of the m^{th} objective function of the k^{th} individual in I and $f_m^{\max}$ and $f_m^{\min}$ are respectively the maximum and minimum values obtained for the m^{th} objective function.

The algorithm on how a crowding distance operator operates is presented in Fig. 4.2

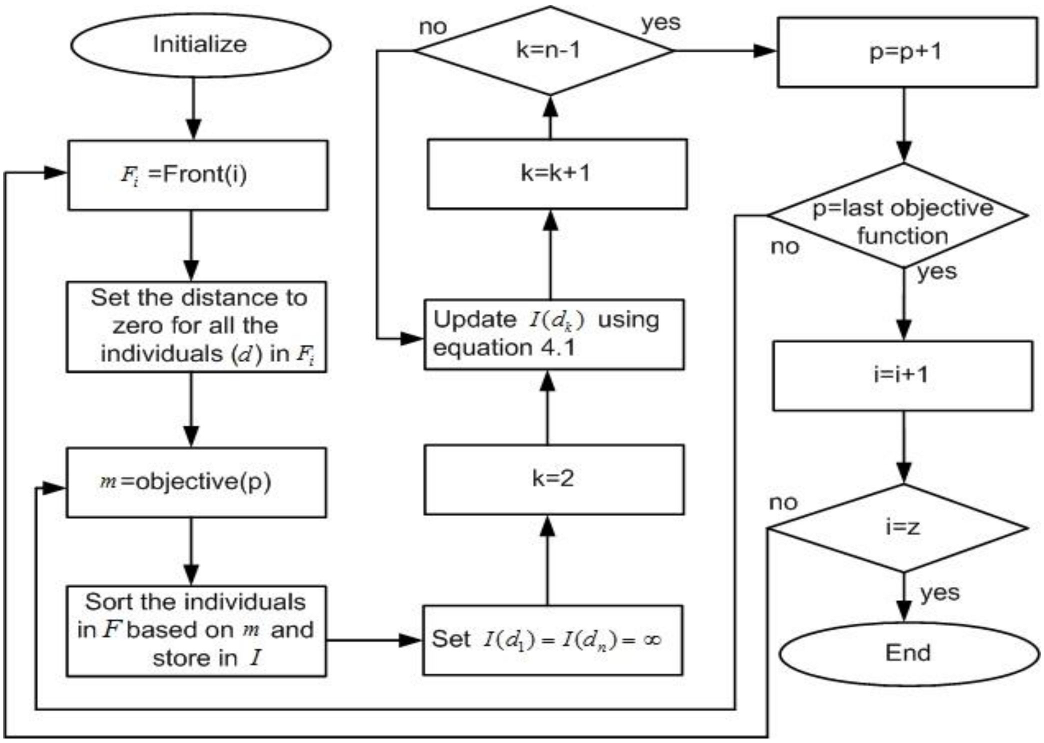

Fig. 4.2 Crowding distance calculation algorithm

The steps involving the crowding distance algorithm are described below:

- The algorithm is initialized by setting i=0 and p=0.
- Let there be z number of fronts where F_i is a front consisting of n individuals.
- Initialize the distance to be zero for all the individuals in a front where each individual is represented by d. So d_j signifies the distance of j^{th} individual in a front.

- Let there are a number of objective functions where each objective function is represented by m.
- All the individuals in the front are now sorted based on the selected objective function and stored in I.
- The individuals in the boundary are assigned infinite distance.
- The variable k is initialized to two (Since the individual in the boundary is already assigned one, and k is allowed to increase up-to n-1 as the individual in the other boundary is assigned n).
- The distance for the k^{th} individual is updated following equation 4.1
- k is incremented by one and then checked if it is equal to n-1
- If k=n-1, p is incremented by one, else the value of the next individual is updated.
- If p is the last objective function, i is incremented by one else the algorithm continues for the next objective function.
- If i=last front, the algorithm stops, else the algorithm moves to the next front and all the previous steps are carried out.

Crowding distance basically finds the Euclidian distance between each individual in a front based on the objective functions and the individuals in the boundary are always selected since infinite distance is assigned to them. It is to be noted that, in this study, the algorithm used to generate the hybrid algorithm is NSGA-II and not NSGA.

4.2 Hybrid NSGA-GWO Optimization

GWO is already discussed in Section 3.2. It is to be noted that, though GWO is an SOO, it is used in an MOO to generate pareto-optimal solutions. While merging the two algorithms, only the "search-agent update" portion of the GWO was utilised and care was taken that none of the aspects of NSGA-II were hampered. In this way, both the algorithms preserved their individual ingenuity and combinedly generated the result. The proposed flowchart of the hybrid algorithm is given in Fig. 4.3.

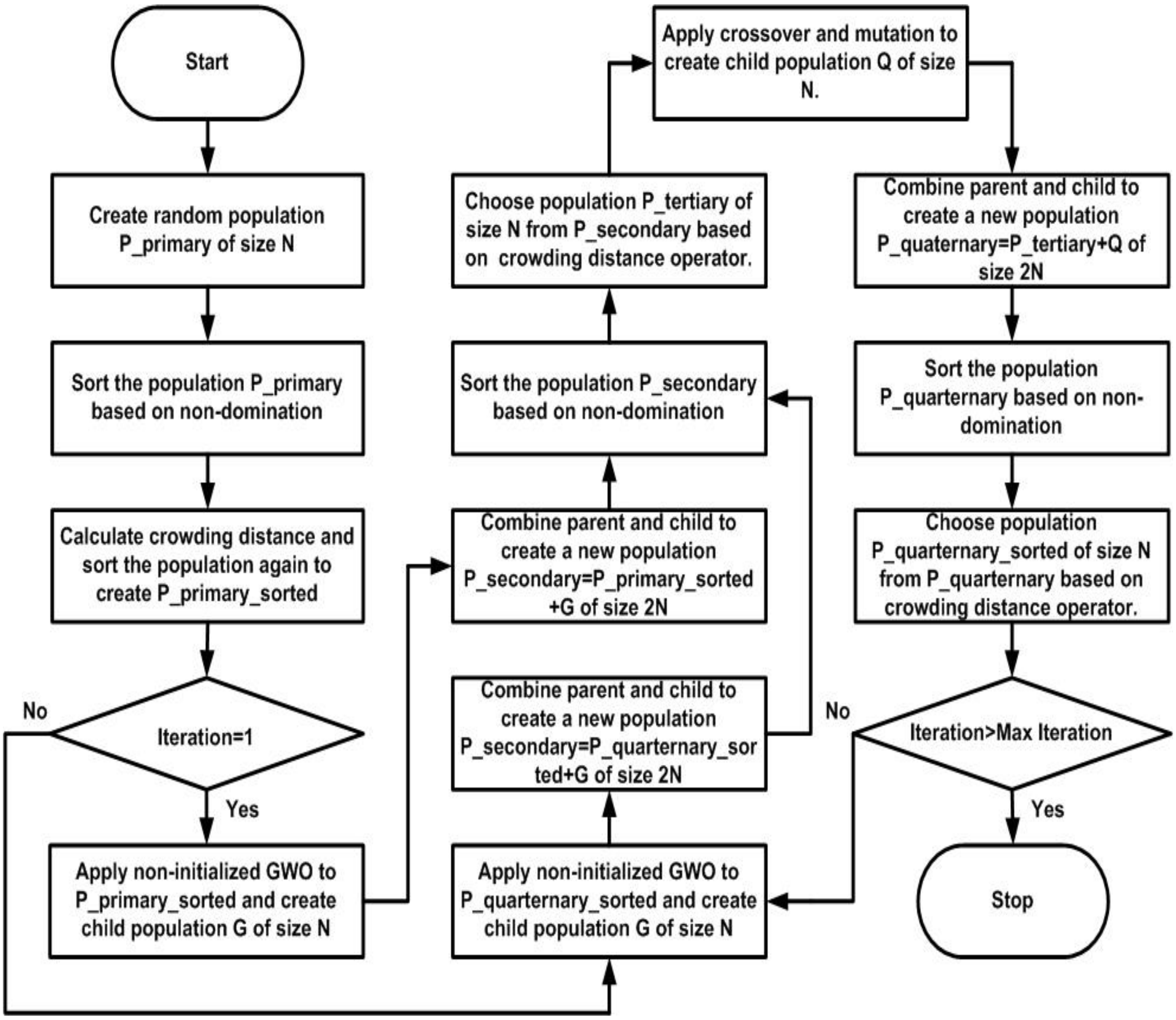

Fig. 4.3: Flowchart of hybrid multi-objective NSGA-GWO algorithm

The hybrid algorithm commences with the normal initialization of NSGA II [75]. It is to be noted here that NSGA II is well known for being able to generate the pareto-optimal solution [77]. From Fig. 4.3 it is seen that a random population of *P_primary* is created and it is a set of population consisting of $N_{PV}, N_{WG}, N_{bat}, \beta$ and h. This population is now sorted based on non-domination (Section 4.1.1) and crowding distance operator (Section 4.1.2), and the new population is termed as *P_primary_sorted*. However, before accessing the core part of NSGA algorithm which is cross-over and mutation, the population termed as *P_primary_sorted* is fed to another algorithm known as grey wolf optimizer [49]. GWO promises to have a high local optima avoidance probability and better exploration ability. It is to be noted that the GWO is declared to be non-initialized because instead of generating a random population in GWO, the *P_primary_sorted* population obtained from the initial population set of NSGA II is taken to be the initial population of GWO. Though GWO is an

SOO, it produces child population *G* of the same size as that of the parent population. It is due to the fact that, GWO updates the positions of all the search agents and sorts them based on the fitness value in each iteration. So the first member in the sorted search agents is declared to be the best search agent in each iteration and the process is continued for the defined number of iterations. In the hybrid algorithm, instead of taking the best search agent, the whole pack of search agents is considered to be the child population and obviously the first member remains as the best search agent. Thus the size of child population *G* remains equal to that of the parent population. This child population *G*, as obtained from GWO is added with *P_primary_sorted* (when iteration=1) or *P_quarternary sorted* (when iteration>1) to create a new population named as *P_secondary*. *P_secondary* is now sorted again based on non-domination and crowding distance operator to obtain *P_tertiary* population on which the crossover and mutation take place, producing a child population *Q*. Finally *P_quarternary* is generated which again goes through a similar sorting operation, to produce the population *P_quarternary_sorted*. Provided the algorithm reaches the maximum number of iterations, it stops, otherwise the algorithm continues as depicted in Fig. 4.3. So the hybrid algorithm preserves the ingenuity of both the algorithms and combines them in order to generate a much reliable outcome.

4.3 Summary

This chapter presented a detailed explanation of the two main features of NSGA-II which are non-domination sorting and crowding distance operator. NSGA-II was then merged with single objective GWO to create a hybrid multi objective algorithm.

Chapter 5: Results and Analysis

This chapter discusses the application of the algorithms discussed in Chapter 5 and Chapter 6. The obtained results are analysed in order to find the credibility of the algorithms and a comparative analysis is also carried out among the different algorithms.

5.1 Load profile

In order to apply the algorithms, demand is necessary. In this study a site located in Auckland, New Zealand is chosen because of ease of accessibility of the required load data. It is to be noted that the associated values of solar radiation, global solar irradiation and value of power law exponent for this location has already been verified by the authors in [63]. Hourly house hold load demands were recorded for a complete year and is used as the load demand profile for this study in order to analyse the HRES. Hourly household demand was obtained from the available typical hourly summer domestic demand of Auckland, New Zealand from [78] and from the number of houses [79]. Fig. 5.1 shows the hourly summer household load of a typical day

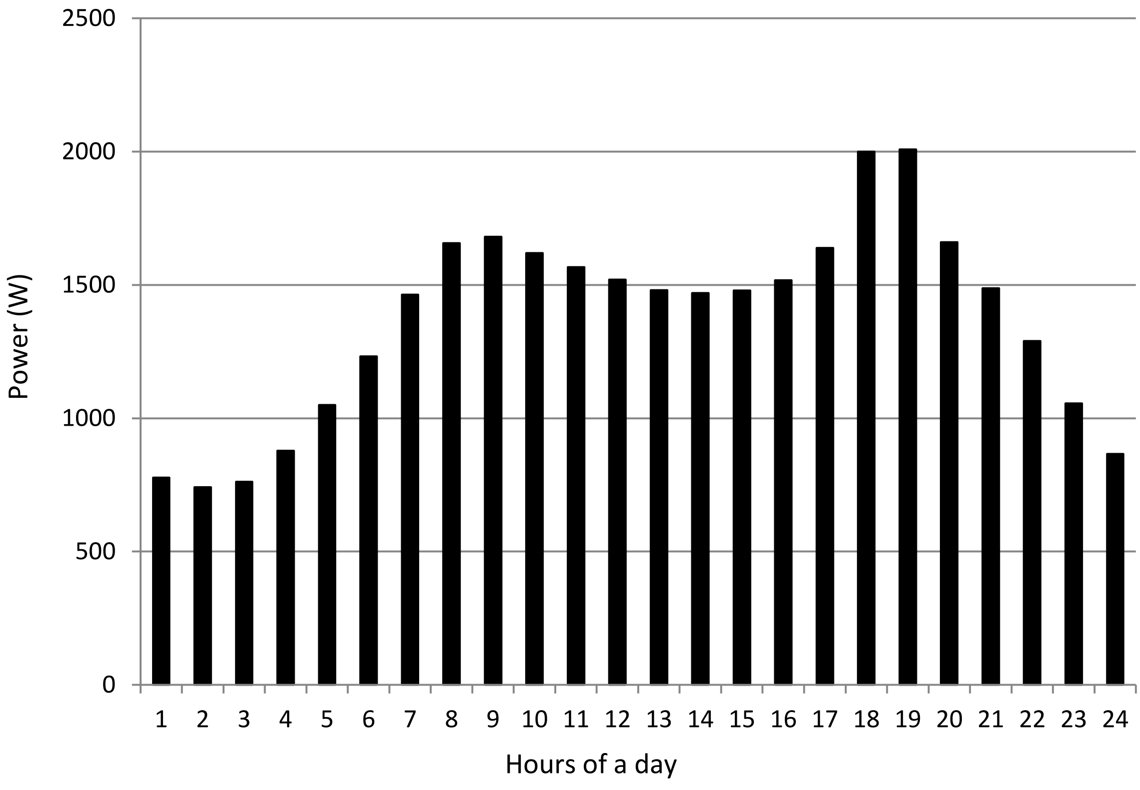

Fig. 5.1: Hourly load for a typical day

5.2 Hybrid GWO-GA for SOO

The developed algorithm in section 3.3 was put to test for the load profile presented in section 5.1. GA was also applied for the same load profile to generate a comparative analysis. The obtained results were then investigated using SPSS [80].

5.2.1 Simulation environment

The load consisted of 8760 hours, which is for a complete year. A total of 30 independent runs of the algorithm were carried out. In these 30 independent runs, each run constituted of 300 iterations so as to ensure a very thorough implementation of the algorithm. That means each independent run started with a random set of population and constituted of 300 iterations. All the adopted algorithms in this work stop once the maximum number of iterations is reached. Based on the studies in section 3.1.1 and 3.1.2, the number of chromosomes was taken to be 32, natural selection was 0.5, cross-over rate was 0.8 and mutation rate was 0.4.

5.2.2 Obtained results

The obtained data for both the hybrid GWO-GA and GA are presented in Table 5.1.

Table 5.1: Descriptives of the cost in $ (Equation 2.18) of the adopted HRES applying GA-GWO algorithm and GA

	GA-GWO Algorithm		GA	
	Statistic	Std. error	Statistic	Std. Error
Mean	38019.06	20.65665	39424.70	22.83751
Median	37997.40		39479.70	
Variance	12800.920		15646.552	
Std. Deviation	113.1411		125.0861	
Minimum	37943.70		39149.70	
Maximum	38429.70		39479.70	

From Table 5.1 it can be seen that the mean of the hybrid algorithm is far less than that of the GA (38019.06 to 39424.70). In fact it is about 3.103% better than the value obtained from GA. But, then again, only mean cannot justify the superiority of an algorithm. The prime objective of the hybrid algorithm in this study is to minimize the cost. So the most important fact is what minimum value the algorithm could achieve. From Table 5.1 it is observed that the minimum value obtained by the hybrid algorithm is 37943.70 $ and by the GA is 39149.70 $. This again is 3.08% better than GA. Variance measures how far a data set is spread out. GA has a higher variance than the GA-GWO algorithm, signifying that the data obtained from GA is more spread out than GA-GWO algorithm. Both standard deviation and mean also support this conclusion since standard deviation measures how far the data is spread out from the mean value and median gives the middle value of the data set. From Table 5.1, both median and standard deviation is higher for the GA. All these conclusions signify that GA needs more number of independent runs in order to obtain a reliable result, since there is significant difference between the results obtained in each independent run.

The normality test was also carried out for both the algorithms in order to understand the distribution nature of the data in the data set using SPSS and is portrayed in Table 5.2.

Table 5.2: Normality test of the cost (Equation 2.18) of the adopted HRES employing GA and GA-GWO algorithm using KS and SW methods

	Kolmogorov-Smirnov (KS)			Shapiro-Wilk (SW)		
	Statistic	df	Sig.	Statistic	df	Sig.
GA-GWO Algorithm	0.509	30	0.00	0.376	30	0.00
GA	0.503	30	0.00	0.452	30	0.00

There are two types of test of normality. One is the Kolmogorov-Smirnov or more popularly KS test and the other is the Shapiro-Wilk test. In both the cases, the importance lies on the value of Sig. which is the significance. The null hypothesis states that the data is not statistically significantly different from the normal distribution. For both the algorithms, the value of significance is less than 0.05 which concludes that the null hypothesis is rejected and the data is statistically significantly different from normal distribution. The result is as expected, because the data which are recorded and analysed, are the final costs obtained after 300 iterations in each independent run. So the costs, all cluster at the lowest possible value and there is not much difference between the values in the 30 independent runs. Thus, the data is not normally distributed.

A further analysis of the algorithms were carried out where the best five and the worst five values of each algorithm were recorded and is presented in Table 5.3 so as to ensure a better credibility of the hybrid algorithm.

Table 5.3: Best and worst five data of the cost (Equation 2.18) of the adopted HRES applying GA and GA-GWO algorithm

			Independent run number	Value ($)
GA-GWO Algorithm	Highest	1	5	38429.70
		2	17	38429.70
		3	1	37997.40
		4	2	37997.40
		5	3	37997.40
	Lowest	1	30	37943.70
		2	22	37943.70
		3	16	37943.70
		4	15	37943.70
		5	29	37997.40
GA	Highest	1	1	39479.70
		2	3	39479.70
		3	4	39479.70
		4	5	39479.70
		5	6	39479.70
	Lowest	1	28	39149.70
		2	21	39149.70
		3	20	39149.70
		4	12	39149.70
		5	2	39149.70

It is noticed that the cost obtained by the GA does not differ in different independent runs. This suggests that GA often tends to get stuck at some local minima rather than going for the global minima. But introducing the core part of the GA which is cross-over and mutation, into GWO, greatly increases the probability of reaching the global minima.

From the above analysis, it can now be safely assumed that the hybrid algorithm has a very high probability of reaching the global minima and it clearly outperforms the GA in the field of HRES.

Table 5.4: Optimized parameters of the components of the adopted HRES

Independent run	30	29	5
N_{PV}	24	8	22
N_{WG}	3	5	4
N_{bat}	2×1	2×2	2×1
β	13	16	1
h	35	29	23
Cost ($)	37943.7	37997.40	38429.7

Table 5.4 shows the number of different optimizing parameters that are needed for the implementation of the HRES. It is observed that most of the times the number of battery is kept at minimum since it is the most expensive component of the system. However, increasing the number of battery just by one can significantly reduce the required number of WGs. So if it is possible to design more cost effective batteries, the overall cost can be reduced further.

5.3 Hybrid NSGA-GWO for MOO

The mentioned hybrid algorithm incorporating non-initialized GWO and NSGA II is applied for a load profile of Auckland, New Zealand. In the present study, *optimum result* of the total system cost is obtained while maintaining an LPSP of zero. It is due to the fact that modern research should focus on assuring the best quality and thrive to find the minimal cost for ensuring that quality. However, there can still be cost constraints and as such this study also focuses on the cost obtained by increasing LPSP from zero to one. In order to ensure the viability of the hybrid algorithm, NSGA and MOPSO are also applied to the same load profile and a comparative study is carried out. The *optimum values* obtained for each independent run from the three algorithms are recorded and analysed using SPSS [80].

5.3.1 Simulation environment

The load consisted of 8760 hours, which is for a complete year. 30 independent runs of the hybrid algorithm was recorded where each run constituted of 100 iterations. Population size was set to 50, cross-over and mutation rate were 0.7 and 0.02 respectively and cross-over and mutation percentage were respectively 0.7 and 0.4.

5.3.2 Obtained results

The descriptives of the results are displayed in Table 5.5. From the table we can see that a minimum value of $32797.48 was recorded from the hybrid algorithm where NSGA II obtained a slightly higher cost of $33139.64 and MOPSO obtained a higher cost of $36512.70. These results confirm that the *optimum value* achieved by the hybrid algorithm is indeed a global minima and is not stuck at some local minima, because the other two algorithms also reached a similar (though slightly higher) value. Moreover the normality tests of all the three algorithms are carried out using SPSS and the results are demonstrated in Table 5.6.

From Table 5.6 it is observed that the significance value of the hybrid algorithm in both the tests is greater than 0.05 and for the other algorithms it is less than 0.05. This confirms the fact that the data (*optimum costs*) obtained from hybrid algorithm is not statistically significantly different from normal distribution whereas the data recorded from the other two algorithms are not normally distributed. Since the data is normally distributed and the standard deviation of the hybrid algorithm is also higher than NSGA II (Table 5.5), the hybrid algorithm explores more extensive area and gives the designer a wider range of options. It is to be noted that the standard deviation is not compared with MOPSO because the results obtained from MOPSO are not at all competitive with the other algorithms for this specific case. The highest (worst) five costs as well as the lowest (best) five costs are also documented and are displayed in Table 5.7

Table 5.5: Descriptives of the cost in $ (Equation 2.18) of the adopted HRES employing NSGA-GWO algorithm along with NSGA-II and MOPSO

	NSGA-GWO Algorithm		NSGA II		MOPSO	
	Statistic	Std. Error	Statistic	Std. Error	Statistic	Std. Error
Mean	33871.11	116.4525	33948.51	102.2213	69637.78	5071.5462
Median	33812.78		33785.08		67215.25	
Variance	406835.86		313475.80		771617454.3	
Std. Deviation	637.8368		559.8891		27778.00	
Minimum	32797.48		33139.64		36512.70	
Maximum	35261.47		34929.67		127670.09	

Table 5.6: Normality test of the cost (Equation 2.18) of the adopted HRES using NSGA-GWO algorithm, NSGA-II and MOPSO using KS and SW methods

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
NSGA-GWO Algorithm	0.116	30	0.200	0.960	30	0.315
NSGA II	0.170	30	0.026	0.907	30	0.012
MOPSO	0.174	30	0.021	0.892	30	0.005

Table 5.7: Best and worst five data of NSGA-GWO algorithm along with NSGA-II and MOPSO

			Independent run number	Value ($)
NSGA-GWO Algorithm	Highest	1	3	35261.47
		2	16	35131.18
		3	28	35019.92
		4	23	34546.88
		5	21	34483.75
	Lowest	1	30	32797.48
		2	2	32820.37
		3	1	32820.37
		4	7	33003.05
		5	27	33205.67
NSGA II	Highest	1	20	34929.67
		2	21	34879.74
		3	3	34810.39
		4	12	34810.39
		5	27	34743.39
	Lowest	1	11	33139.64
		2	23	33212.46
		3	26	33359.79
		4	6	33366.01
		5	5	33375.19
MOPSO	Highest	1	17	127670.09
		2	18	127670.09
		3	20	127670.09
		4	4	116709.74
		5	19	99690.79
	Lowest	1	26	36512.70
		2	24	36645.21
		3	15	36915.85
		4	14	37914.61
		5	2	38471.77

From these above results it can be clearly stated that the hybrid algorithm outperforms the other two algorithms in all aspects. Besides, it also reaches the pareto optimal front in a much lower number of iterations than NSGA II. Every optimization algorithm ultimately reaches a pareto front where the number of solutions in the set is equal to the initial population. Both the hybrid algorithm and NSGA II reached the pareto optimal front where the number of solutions were equal to the initial population, but MOPSO, even in 100 iterations could not reach a pareto front where the number of solutions were equal to the initial population. The number of iterations required to reach the pareto optimal front for both NSGA II and the hybrid algorithm is portrayed in Fig. 5.2

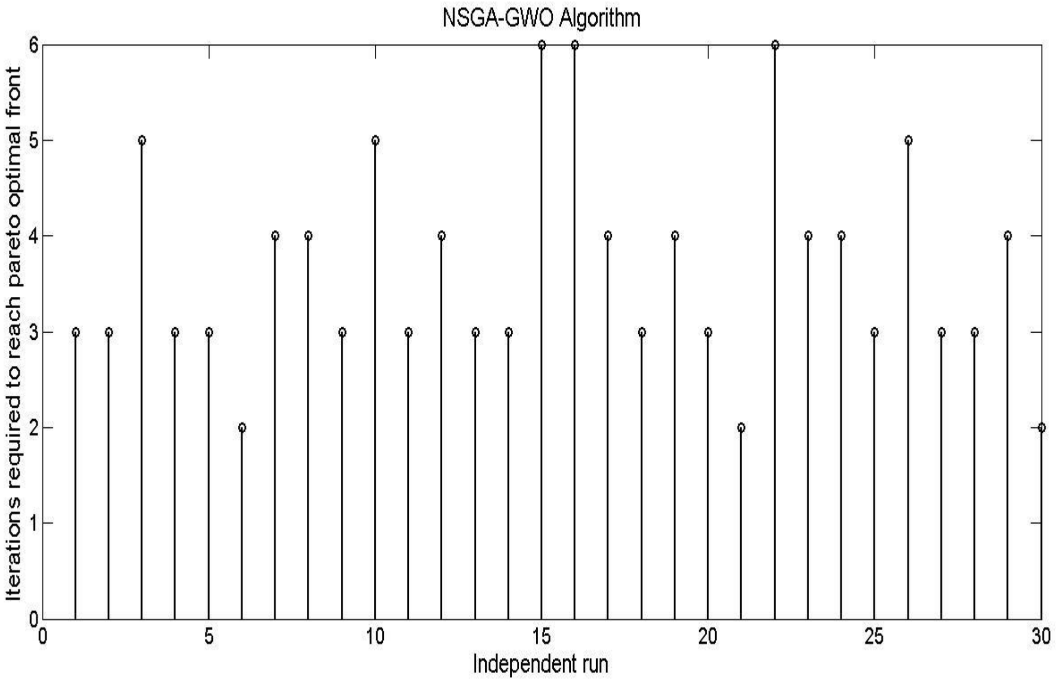

Fig. 5.2 (a): Number of iterations required in each independent run to reach the pareto optimal front employing NSGA-GWO Algorithm.

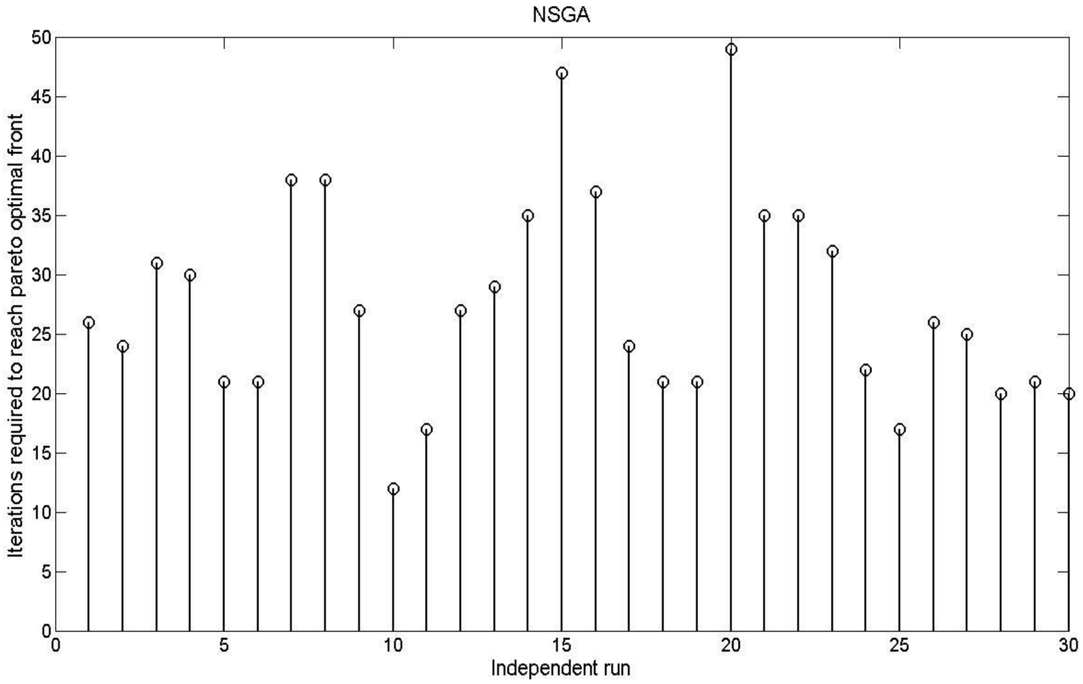

Fig. 5.2 (b): Number of iterations required in each independent run to reach the pareto optimal front employing NSGA II.

It can be seen from Fig. 5.2 that the minimum number of iterations required by NSGA II to reach the optimal front is 12 and that for the hybrid algorithm is 2. It can be explained by the fact that a random population is fed to NSGA II for cross-over and mutation but in the hybrid algorithm, the updated and sorted population attained from the GWO is fed for cross-over and mutation. For this reason the number of iterations required to reach the optimal front reduces significantly. It is evident from the above analysis that the hybrid algorithm not only ensures global optimum result but also provides a better outcome in comparison to both NSGA and MOPSO in the field of HRES. Finally the graph generated by varying both LPSP and cost employing the hybrid algorithm as well as NSGA II is given in Fig. 5.3 for a better comparative study. From the graph it can be clearly observed that the cost reduces significantly once the LPSP is allowed to escalate. Thus the decision now solely rests with the designer/company to choose the optimum result based on the requirements and ability of the designer/company.

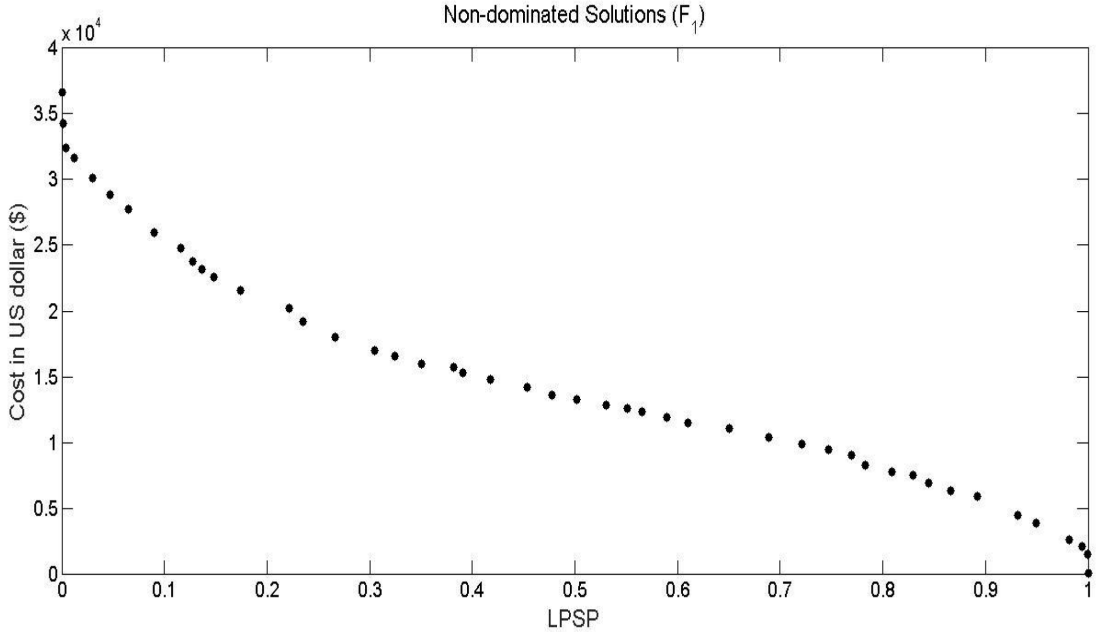

Fig. 5.3 (a): Cost versus LPSP graph employing NSGA-GWO Algorithm.

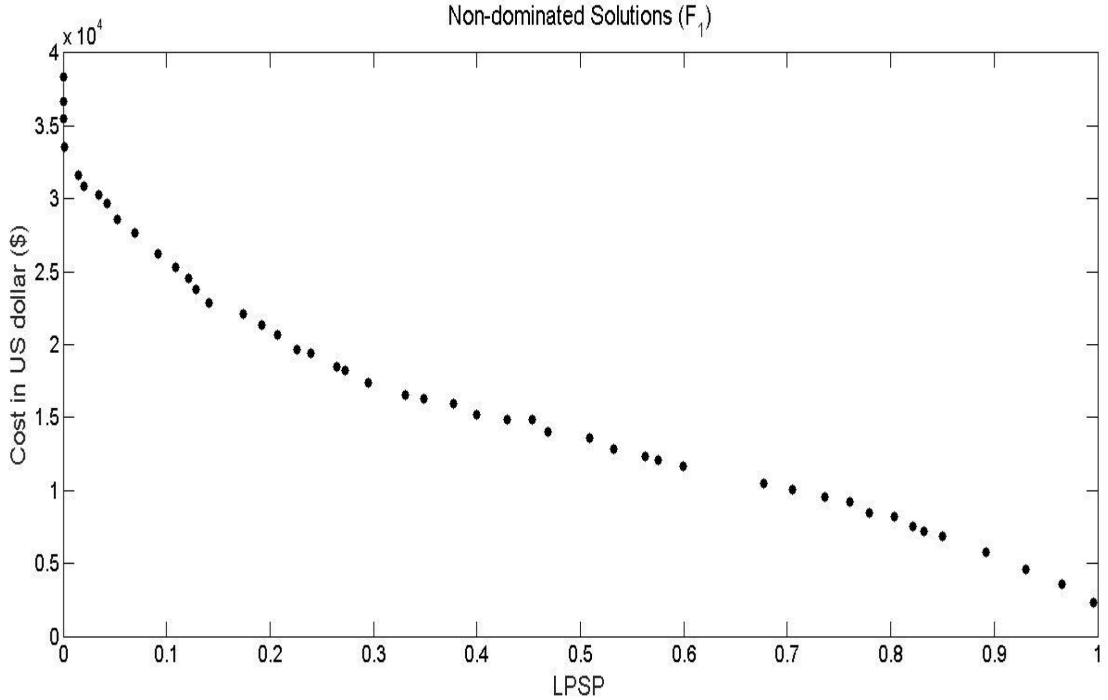

Fig. 5.3 (b): Cost versus LPSP graph employing NSGA II.

The results obtained so far are, of course, theoretical and the algorithm even considers fraction as a result. But for practical implementation, we can't have fractional number of WTs, PV panels or batteries. So we need to round up the values to the next integer and find the corresponding cost. So for practical implementation, the number of WTs, PV panels and batteries are rounded up to the next integer for the three best obtained results from the hybrid algorithm. The data obtained are displayed in Table 5.8. Though only integers are acceptable in this specific optimization problem, the algorithm was allowed to take fractions as well. This was done intentionally in order to have an in depth analysis of the studied algorithm. Unlike the current problem in hand, a lot of optimizing problems often require/accept fractions as solutions. So in order to verify the credibility of the studied hybrid algorithm, it was allowed to take even fractions as solutions.

Table 5.8: Modifications needed for practical implementation

Independent run number	30		2		7	
	Theoretical	Practical	Theoretical	Practical	Theoretical	Practical
N_{PV}	5.4244	6	4.5705	5	5.3778	6
N_{WG}	4.5978	5	4.9533	5	4.9795	5
N_{bat}	2×0.9312	2×1	2×0.8929	2×1	2×0.8996	2×1
β	19.5281	19.5281	1	1	3.0993	3.0993
h	38.6184	38.6184	35.2532	35.2532	33.4254	33.4254
Cost ($)	32797.48	35693.77	32820.37	33815.25	33003.05	33980.08

Independent run number 30, 2 and 7 were among the 5 best independent runs in NSGA-GWO algorithm (In Table 5.7). The number of WTs, PV panels and batteries as obtained from the algorithm are shown in Table 5.8. But since these numbers cannot be kept as fractions, these are rounded up to the next integer and the associated increase in cost is also shown in the table. However, the tilt angle β and the height h are still kept as fractions as these can be accepted and implemented in fractional values as well.

5.4 Summary

In this chapter all the algorithms were put to test and a detailed analysis of all the algorithms has been presented. The studied hybrid algorithms were also compared with the existing popular algorithms. It is seen that the hybrid algorithm performed better in all the aspects in comparison to the other algorithms. Thus it is expected that these hybrid algorithms, both in SOO and MOO will leave a significant impact in the field of optimization of HRES.

Chapter 6: Conclusion and Future Research Directions

6.1 Conclusion

In chapter 1 the present scenario of energy crisis was presented and the need of alternative sources of energy was emphasized. A detailed literature review in the field of HRES, various aspects of HRES, SOO and MOO was also elaborated. The chapter concluded by mentioning the thesis objectives along with the organization of this thesis.

After the introduction, the mathematical model of the proposed HRES was discussed in chapter 2. In this chapter there were separate sections explaining the PV module, Wind turbine model and batteries. Each section contained the associated equations necessary to implement this system. The related costs of each component along with the specifications were also provided. At the end of this chapter the objective functions were presented which are to minimize the cost of HRES for a time period of 20 years and the expression of LPSP which is in fact the criterion for determining the reliability of a system.

Chapter 3 was the first phase of this thesis which focused on SOO. In this chapter the most popular evolutionary algorithm GA was discussed with its two most important aspects namely cross-over and mutation. A much recent nature inspired algorithm, GWO was then discussed with all the associated equations and figures so as to give the reader a clear concept of the algorithm. These two algorithms were then merged, which is one of the main objectives of this thesis, and the hybrid algorithm was discussed with the help of a flowchart.

Chapter 4 was the second phase of this thesis where unlike chapter three, LPSP (equation 2.16) was also allowed to vary along with the cost function (equation 2.18). NSGA-II was discussed in details along with the explanation of cross-over and mutation. It is to be mentioned that NSGA is a non-elite approach whereas NSGA-II preserves elitism. GWO which was already introduced in chapter three was then merged with NSGA-II to create a hybrid MOO algorithm.

Chapter 5 contains the detailed result and analysis of the previously mentioned algorithms along with another popular nature inspired algorithm MOPSO. This chapter started by giving a small idea of the studied load profile. SPSS was used to analyse all the obtained data and

MATLAB was used to plot the graphs. This chapter also explained the superiority of the hybrid algorithm over the other algorithms.

In this study an evolutionary algorithm GA and a nature inspired algorithm GWO is hybridized for SOO and NSGA-II and GWO is hybridized for MOO to optimize N_{PV}, N_{WG}, N_{bat}, β and h keeping cost as variable in case of SOO and both LPSP and cost as variables in case of MOO. A practical load of Auckland, New Zealand was taken to evaluate the hybrid algorithms. The main objective is to find the minimum costs by varying the LPSP and provide the designer/company all the potential solutions. At the same time, a comparison with other renowned algorithms are shown, which signifies that the proposed hybrid algorithms have a higher probability to reach the global optimum solution and provide a much quicker convergence, a lower minimum cost, a lower mean, a normally distributed data set (for MOO) and a higher standard deviation in comparison to the other algorithms. Though the cost increased slightly for practical implementation due to rounding up the values, this is equally applicable for other algorithms as well. Thus it can be safely said that for optimal sizing of an HRES, hybrid algorithms can often outperform other algorithms and provide much more options to choose from ensuring the best solution for the objective function in hand.

6.2 Future research directions

The work presented in this thesis was an offline work. The load that was used was previously recorded load, so there is a lot of scope to work with real time loads. Also the data taken for PV modules and WT models did not incorporate any weather uncertainties. Incorporation of these weather uncertainties will make the work much more reliable. Besides the work is solely based on software simulations, so transforming the work into hardware model will increase the reliability of the model. So it is expected that in the future real time load demands along with weather uncertainties will be studied and if circumstances permit hardware implementation in a miniature form will also be carried out.

References:

[1] M. Z. Jacobson and M. A. Delucchi, "Providing all global energy with wind, water, and solar power, Part I: Technologies, energy resources, quantities and areas of infrastructure, and materials," *Energy policy,* vol. 39, pp. 1154-1169, 2011.

[2] X. Cao, X. Dai, and J. Liu, "Building energy-consumption status worldwide and the state-of-the-art technologies for zero-energy buildings during the past decade," *Energy and buildings,* vol. 128, pp. 198-213, 2016.

[3] W. Zhou, *Simulation and optimum design of hybrid solar-wind and solar-wind-diesel power generation systems*, 2008.

[4] J.-M. Chevalier, "The new energy crisis," in *The New Energy Crisis*, ed: Springer, 2009, pp. 6-59.

[5] J. Blanco, S. Malato, P. Fernández-Ibañez, D. Alarcón, W. Gernjak, and M. Maldonado, "Review of feasible solar energy applications to water processes," *Renewable and Sustainable Energy Reviews,* vol. 13, pp. 1437-1445, 2009.

[6] S. Shafiei and R. A. Salim, "Non-renewable and renewable energy consumption and CO2 emissions in OECD countries: A comparative analysis," *Energy Policy,* vol. 66, pp. 547-556, 2014.

[7] K. Barnham, M. Mazzer, and B. Clive, "Resolving the energy crisis: nuclear or photovoltaics?," *Nature materials,* vol. 5, p. 161, 2006.

[8] N. Kannan and D. Vakeesan, "Solar energy for future world:-A review," *Renewable and Sustainable Energy Reviews,* vol. 62, pp. 1092-1105, 2016.

[9] F. Trieb, C. Schillings, M. O'sullivan, T. Pregger, and C. Hoyer-Klick, "Global potential of concentrating solar power," in *SolarPACES Conference,* 2009, pp. 15-18.

[10] Y. Sawle, S. Gupta, and A. K. Bohre, "Review of hybrid renewable energy systems with comparative analysis of off-grid hybrid system," *Renewable and Sustainable Energy Reviews,* vol. 81, pp. 2217-2235, 2018.

[11] M. Deshmukh and S. Deshmukh, "Modeling of hybrid renewable energy systems," *Renewable and Sustainable Energy Reviews,* vol. 12, pp. 235-249, 2008.

[12] D. Nelson, M. Nehrir, and C. Wang, "Unit sizing and cost analysis of stand-alone hybrid wind/PV/fuel cell power generation systems," *Renewable energy,* vol. 31, pp. 1641-1656, 2006.

[13] A. Fathy, "A reliable methodology based on mine blast optimization algorithm for optimal sizing of hybrid PV-wind-FC system for remote area in Egypt," *Renewable energy,* vol. 95, pp. 367-380, 2016.

[14] V. M. Sanchez, A. Chavez-Ramirez, S. M. Duron-Torres, J. Hernandez, L. Arriaga, and J. M. Ramirez, "Techno-economical optimization based on swarm intelligence algorithm for a stand-alone wind-photovoltaic-hydrogen power system at south-east region of Mexico," *International journal of hydrogen energy,* vol. 39, pp. 16646-16655, 2014.

[15] H. Baghaee, M. Mirsalim, G. Gharehpetian, and H. Talebi, "Reliability/cost-based multi-objective Pareto optimal design of stand-alone wind/PV/FC generation microgrid system," *Energy,* vol. 115, pp. 1022-1041, 2016.

[16] A. Maleki and A. Askarzadeh, "Artificial bee swarm optimization for optimum sizing of a stand-alone PV/WT/FC hybrid system considering LPSP concept," *Solar Energy,* vol. 107, pp. 227-235, 2014.

[17] R. Hosseinalizadeh, H. Shakouri, M. S. Amalnick, and P. Taghipour, "Economic sizing of a hybrid (PV–WT–FC) renewable energy system (HRES) for stand-alone usages by an optimization-simulation model: case study of Iran," *Renewable and Sustainable Energy Reviews,* vol. 54, pp. 139-150, 2016.

[18] A. Ogunjuyigbe, T. Ayodele, and O. Akinola, "Optimal allocation and sizing of PV/Wind/Split-diesel/Battery hybrid energy system for minimizing life cycle cost, carbon emission and dump energy of remote residential building," *Applied Energy,* vol. 171, pp. 153-171, 2016.

[19] P. Paliwal, N. Patidar, and R. Nema, "Determination of reliability constrained optimal resource mix for an autonomous hybrid power system using particle swarm optimization," *Renewable energy,* vol. 63, pp. 194-204, 2014.

[20] B. Shi, W. Wu, and L. Yan, "Size optimization of stand-alone PV/wind/diesel hybrid power generation systems," *Journal of the Taiwan Institute of Chemical Engineers,* vol. 73, pp. 93-101, 2017.

[21] J. Zhao and X. Yuan, "Multi-objective optimization of stand-alone hybrid PV-wind-diesel-battery system using improved fruit fly optimization algorithm," *Soft Computing,* vol. 20, pp. 2841-2853, 2016.

[22] S. Singh, M. Singh, and S. C. Kaushik, "Feasibility study of an islanded microgrid in rural area consisting of PV, wind, biomass and battery energy storage system," *Energy Conversion and Management,* vol. 128, pp. 178-190, 2016.

[23] S. Rajanna and R. Saini, "Development of optimal integrated renewable energy model with battery storage for a remote Indian area," *Energy,* vol. 111, pp. 803-817, 2016.

[24] A. Kamjoo, A. Maheri, A. M. Dizqah, and G. A. Putrus, "Multi-objective design under uncertainties of hybrid renewable energy system using NSGA-II and chance constrained programming," *International Journal of Electrical Power & Energy Systems,* vol. 74, pp. 187-194, 2016.

[25] S. Sanajaoba and E. Fernandez, "Maiden application of Cuckoo Search algorithm for optimal sizing of a remote hybrid renewable energy System," *Renewable energy,* vol. 96, pp. 1-10, 2016.

[26] A. Maleki and F. Pourfayaz, "Optimal sizing of autonomous hybrid photovoltaic/wind/battery power system with LPSP technology by using evolutionary algorithms," *Solar Energy,* vol. 115, pp. 471-483, 2015.

[27] B. Bhandari, S. R. Poudel, K.-T. Lee, and S.-H. Ahn, "Mathematical modeling of hybrid renewable energy system: A review on small hydro-solar-wind power generation," *international journal of precision engineering and manufacturing-green technology,* vol. 1, pp. 157-173, 2014.

[28] O. Erdinc and M. Uzunoglu, "Optimum design of hybrid renewable energy systems: Overview of different approaches," *Renewable and Sustainable Energy Reviews,* vol. 16, pp. 1412-1425, 2012.

[29] N. M. Razali and A. Hashim, "Backward reduction application for minimizing wind power scenarios in stochastic programming," in *2010 4th International Power Engineering and Optimization Conference (PEOCO)*, 2010, pp. 430-434.

[30] S. K. Nandi and H. R. Ghosh, "Techno-economical analysis of off-grid hybrid systems at Kutubdia Island, Bangladesh," *Energy Policy,* vol. 38, pp. 976-980, 2010.

[31] A. M. Haidar, P. N. John, and M. Shawal, "Optimal configuration assessment of renewable energy in Malaysia," *Renewable Energy,* vol. 36, pp. 881-888, 2011.

[32] P. Bajpai, N. Prakshan, and N. Kishore, "Renewable hybrid stand-alone telecom power system modeling and analysis," in *TENCON 2009-2009 IEEE Region 10 Conference*, 2009, pp. 1-6.

[33] T. M. Weis and A. Ilinca, "The utility of energy storage to improve the economics of wind–diesel power plants in Canada," *Renewable energy,* vol. 33, pp. 1544-1557, 2008.

[34] M. T. Chaichan, H. A. Kazem, A. M. Mahdy, and A. A. Al-Waeely, "Optimal sizing of a hybrid system of renewable energy for lighting street in Salalah-Oman using

Homer software," *International Journal of Scientific Engineering and Applied Science (IJSEAS),* vol. 2, pp. 157-164, 2016.

[35] K. Mousa, H. AlZu'bi, and A. Diabat, "Design of a hybrid solar-wind power plant using optimization," in *2010 Second International Conference on Engineering System Management and Applications*, 2010, pp. 1-6.

[36] C. Darras, S. Sailler, C. Thibault, M. Muselli, P. Poggi, J. Hoguet*, et al.*, "Sizing of photovoltaic system coupled with hydrogen/oxygen storage based on the ORIENTE model," *International Journal of Hydrogen Energy,* vol. 35, pp. 3322-3332, 2010.

[37] P. Berberi, S. Thodhorjani, and R. Aleti, "Integration and optimization of alternative sources of energy in a remote region," in *2009 8th International Symposium on Advanced Electromechanical Motion Systems & Electric Drives Joint Symposium*, 2009, pp. 1-4.

[38] R. Dufo-López, J. L. Bernal-Agustín, and F. Mendoza, "Design and economical analysis of hybrid PV–wind systems connected to the grid for the intermittent production of hydrogen," *Energy Policy,* vol. 37, pp. 3082-3095, 2009.

[39] J. J. Grefenstette, "Optimization of control parameters for genetic algorithms," *IEEE Transactions on systems, man, and cybernetics,* vol. 16, pp. 122-128, 1986.

[40] E. Koutroulis, D. Kolokotsa, A. Potirakis, and K. Kalaitzakis, "Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms," *Solar energy,* vol. 80, pp. 1072-1088, 2006.

[41] H. Yang, W. Zhou, L. Lu, and Z. Fang, "Optimal sizing method for stand-alone hybrid solar–wind system with LPSP technology by using genetic algorithm," *Solar energy,* vol. 82, pp. 354-367, 2008.

[42] B. O. Bilal, V. Sambou, P. Ndiaye, C. Kébé, and M. Ndongo, "Optimal design of a hybrid solar–wind-battery system using the minimization of the annualized cost system and the minimization of the loss of power supply probability (LPSP)," *Renewable Energy,* vol. 35, pp. 2388-2390, 2010.

[43] J. Lagorse, D. Paire, and A. Miraoui, "Hybrid stand-alone power supply using PEMFC, PV and battery-Modelling and optimization," in *2009 International Conference on Clean Electrical Power*, 2009, pp. 135-140.

[44] M. Kalantar, "Dynamic behavior of a stand-alone hybrid power generation system of wind turbine, microturbine, solar array and battery storage," *Applied energy,* vol. 87, pp. 3051-3064, 2010.

[45] V. Sánchez, J. M. Ramirez, and G. Arriaga, "Optimal sizing of a hybrid renewable system," in *2010 IEEE International Conference on Industrial Technology*, 2010, pp. 949-954.

[46] S. Dehghan, H. Saboori, A. Parizad, and B. Kiani, "Optimal sizing of a hydrogen-based wind/PV plant considering reliability indices," in *2009 International Conference on Electric Power and Energy Conversion Systems,(EPECS)*, 2009, pp. 1-9.

[47] A. K. Kaviani, G. Riahy, and S. M. Kouhsari, "Optimal design of a reliable hydrogen-based stand-alone wind/PV generating system, considering component outages," *Renewable energy,* vol. 34, pp. 2380-2390, 2009.

[48] L. Wang and C. Singh, "PSO-based multidisciplinary design of a hybrid power generation system with statistical models of wind speed and solar insolation," in *2006 International Conference on Power Electronic, Drives and Energy Systems*, 2006, pp. 1-6.

[49] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey wolf optimizer," *Advances in engineering software*, vol. 69, pp. 46-61, 2014.

[50] P. Anand, M. Rizwan, and S. K. Bath, "Sizing of renewable energy based hybrid system for rural electrification using grey wolf optimisation approach," *IET Energy Systems Integration,* 2019.

[51] S. Sinha and S. Chandel, "Review of recent trends in optimization techniques for solar photovoltaic–wind based hybrid energy systems," *Renewable and Sustainable Energy Reviews,* vol. 50, pp. 755-769, 2015.

[52] I. Tégani, A. Aboubou, M. Ayad, M. Becherif, R. Saadi, and O. Kraa, "Optimal sizing design and energy management of stand-alone photovoltaic/wind generator systems," *Energy Procedia,* vol. 50, pp. 163-170, 2014.

[53] M. Amer, A. Namaane, and N. M'sirdi, "Optimization of hybrid renewable energy systems (HRES) using PSO for cost reduction," *Energy Procedia,* vol. 42, pp. 318-327, 2013.

[54] P. Suhane, S. Rangnekar, A. Mittal, and A. Khare, "Sizing and performance analysis of standalone wind-photovoltaic based hybrid energy system using ant colony optimisation," *IET Renewable Power Generation,* vol. 10, pp. 964-972, 2016.

[55] M. Fadaee and M. Radzi, "Multi-objective optimization of a stand-alone hybrid renewable energy system by using evolutionary algorithms: A review," *Renewable and sustainable energy reviews,* vol. 16, pp. 3364-3369, 2012.

[56] B. O. Bilal, V. Sambou, P. Ndiaye, C. Kébé, and M. Ndongo, "Multi-objective design of PV-wind-batteries hybrid systems by minimizing the annualized cost system and the loss of power supply probability (LPSP)," in *2013 IEEE International Conference on Industrial Technology (ICIT)*, 2013, pp. 861-868.

[57] N. Ghorbani, A. Kasaeian, A. Toopshekan, L. Bahrami, and A. Maghami, "Optimizing a hybrid wind-PV-battery system using GA-PSO and MOPSO for reducing cost and increasing reliability," *Energy*, vol. 154, pp. 581-591, 2018.

[58] M. D. Al-Falahi, S. Jayasinghe, and H. Enshaei, "A review on recent size optimization methodologies for standalone solar and wind hybrid renewable energy system," *Energy Conversion and Management*, vol. 143, pp. 252-274, 2017.

[59] R. Chedid, H. Akiki, and S. Rahman, "A decision support technique for the design of hybrid solar-wind power systems," *IEEE transactions on Energy conversion*, vol. 13, pp. 76-83, 1998.

[60] M. R. Tito, T. T. Lie, and T. Anderson, "Sizing Optimization of Wind-Photovoltaic Hybrid Energy Systems Under Transient Load," *International Journal of Power and Energy Systems*, vol. 33, pp. 168-174, 2013.

[61] R. P. Mukund, "Wind and solar power systems," ed: CRC press, 1999.

[62] P. Gipe, *Wind energy comes of age* vol. 4: John Wiley & Sons, 1995.

[63] S. Tito, T. Lie, and T. Anderson, "Optimal sizing of a wind-photovoltaic-battery hybrid renewable energy system considering socio-demographic factors," *Solar Energy*, vol. 136, pp. 525-532, 2016.

[64] J. A. Duffie and W. A. Beckman, "Solar Thermal Power Systems," *Solar Engineering of Thermal Processes, Fourth Edition, John Wiley & Sons, Inc., Hoboken, NJ, USA. doi,* vol. 10, p. 9781118671603, 2013.

[65] D. Erbs, S. Klein, and J. Duffie, "Estimation of the diffuse radiation fraction for hourly, daily and monthly-average global radiation," *Solar energy*, vol. 28, pp. 293-302, 1982.

[66] J. Orgill and K. Hollands, "Correlation equation for hourly diffuse radiation on a horizontal surface," *Solar energy*, vol. 19, pp. 357-359, 1977.

[67] D. T. Reindl, W. A. Beckman, and J. A. Duffie, "Diffuse fraction correlations," *Solar energy*, vol. 45, pp. 1-7, 1990.

[68] D. Guasch and S. Silvestre, "Dynamic battery model for photovoltaic applications," *Progress in Photovoltaics: Research and applications*, vol. 11, pp. 193-206, 2003.

[69] S. Duryea, S. Islam, and W. Lawrance, "A battery management system for stand alone photovoltaic energy systems," in *Conference Record of the 1999 IEEE Industry Applications Conference. Thirty-Forth IAS Annual Meeting (Cat. No. 99CH36370)*, 1999, pp. 2649-2654.

[70] H. Yang and L. Lu, "Study of typical meteorological years and their effect on building energy and renewable energy simulations," *ASHRAE transactions*, vol. 110, p. 424, 2004.

[71] J. R. Koza, "Genetic programming," 1997.

[72] Y. Yoon and Y.-H. Kim, "The roles of crossover and mutation in real-coded genetic algorithms," in *Bio-inspired computational algorithms and their applications*, ed: IntechOpen, 2012.

[73] C. Muro, R. Escobedo, L. Spector, and R. Coppinger, "Wolf-pack (Canis lupus) hunting strategies emerge from simple rules in computational simulations," *Behavioural processes*, vol. 88, pp. 192-197, 2011.

[74] N. Srinivas and K. Deb, "Muiltiobjective optimization using nondominated sorting in genetic algorithms," *Evolutionary computation*, vol. 2, pp. 221-248, 1994.

[75] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE transactions on evolutionary computation*, vol. 6, pp. 182-197, 2002.

[76] C. Senthilkumar, G. Ganesan, and R. Karthikeyan, "Optimization of ECM process parameters using NSGA-II," *Journal of Minerals and Materials Characterization and Engineering*, vol. 11, p. 931, 2012.

[77] W. Peng, Q. Zhang, and H. Li, "Comparison between MOEA/D and NSGA-II on the multi-objective travelling salesman problem," in *Multi-objective memetic algorithms*, ed: Springer, 2009, pp. 309-324.

[78] T. E. Authority. [Online]. Available: https://www.ea.govt.nz/dmsdocument/4755

[79] T. K. Auckland. [Online]. Available: http://www.knowledgeauckland.org.nz/home/publications/publications_home.cfm?oID=3E2663E0-BC92-A83D-9AE6-B7368DFCD7E0

[80] S. Inc, *SPSS-X user's guide*: SPSS Incorporated, 1988.