A Framework For Microgrid Planning Using Multidisciplinary Design Optimization

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Microgrids are local energy providers that can potentially reduce energy expenses and emissions by utilizing distributed energy resources (DERs) and are alternatives to existing centralized systems. This thesis investigates the optimal design and planning of such microgrids using a multidisciplinary design optimization approach based framework.

Among a variety of DERs it is widely accepted that renewable resources of energy play an important role in providing a sustainable energy supply infrastructure, as they are both inexhaustible and non-polluting. However the intermittent nature and the uncertainties associated with renewable technologies pose sufficient technological and economical challenges for system planners.

Design of complex engineering systems has evolved into a multidisciplinary field of study. We develop a framework for design and planning of complex engineering systems under uncertainty using an approach of multidisciplinary design optimization under uncertainty (MDOUU). The framework has been designed to be general enough to be applicable to a large variety of complex engineering systems while it is simple to apply. MDOUU framework is a three stage planning strategy which allows the system planners to consider all aspects ranging from uncertainty in resources, technological feasibility, economics, and life cycle impacts of the system and choose an optimal design suited to their localized conditions. Motivation behind using MDOUU lies not only in the optimization of the individual systems or disciplines but also their interactions between each other.

Following the modeling of the resources, a deterministic optimization model for planning microgirds is developed and results are evaluated using Monte Carlo simulations. Given the obvious limitations of the deterministic model in not being able to handle uncertainty efficiently and resulting in an expensive design we extended the model to a two stage stochastic programming model which provides a unified approach in determining the sizing of microgrids by considering uncertainty implicitly by means of scenarios. Probabilistic scenarios are developed using C-vine copulas that model nonlinear dependence. We evaluate the significance of the stochastic programming model using standardized metrics evaluating benefits of using the stochastic model.

As any product or service needs to be evaluated for its environmental impacts, MDOUU provisions an LCA module that evaluates the environmental impacts and energy demands of the components of the system based on extensive literature and databases using openLCA as a tool.

The overall system selection involves multiple criteria and interests of different stakeholders. This requires a multi-attribute decision system and a comprehensive ranking approach providing a list of possible configuration based on their relative importance as denoted by the stakeholders. We use Analytical Hierarchical Process (AHP) combined with compromise programming to rank a list of configurations based on economic and environmental attributes such as GHG emissions saved, cost of energy, annual energy production, net present value (NPV) etc. It allows the planners to make decisions considering the interests of a majority of stakeholders.

The MDOUU framework proposed in this thesis with specific application to the microgrid planning problem contributes in helping the planners handle uncertainty of renewable resources of energy and environmental impacts in a systematic way. As such there is no method available in the literature which considers planning of microgrid using such holistic and multidisciplinary framework. The MDOUU framework is a generic tool and is useful for planning problems in a variety of complex systems.

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Dedication

To my mentor, guide, and spiritual guru

Most Revered Prof. Prem Saran Satsangi Sahab

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List of Acronyms

AIC	Akaike Information Criteria
AEP	Annual Energy Production
AMPL	Algebraic Modeling Programming Language
C&I	Capital and Installation Costs
CDF	Cumulative density functions
CED	Cumulative Energy Demand
CI	Consistency Index
CML	Centrum Milieukunde Leiden
CoE	Cost of Energy
CR	Consistency Ration
CRF	Capital Return Factor
CV	Coefficient of Variation
DALY	Disability Adjusted Life Years
DER	Distributed Energy Resources
DOD	Depth of Discharge
DOUU	Design Optimization under Uncertainty
DSM	Design Center Matrix
EPBT	Energy Pay Back Time
EV	Expected Value Solution
EVPI	Expected Value of Perfect Information
GA	Genetic Algorithm
GHG	Green House Gas
GHGI	Green House Gas Intensity/kWh for nonrenewable generation
HPS	Hybrid Power System
IDF	Individual Design Feasible
LCA	Life Cycle Analysis
LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LCOE	Levelized Cost of Energy
LO	Land Occupancy
LOL	Loss of Load
MADM	Multi-Attribute Decision Making
MCDA	Multi-Criteria Decision Analysis
MDO	Multidisciplinary Design Optimization
MDOUU	Multidisciplinary Design Optimization under Uncertainty
MGMRM	Microgrid Modeling Under Risk Model
MPPT	Maximum Power Point Tracking
NOCT	Normal Operating Cell Temperature
NPC	Net Present Cost
NPV	Net Present Value

NR	Number of Renewable Resource Units
NR	Number of Renewable Resource Units
O&M	Operations and Maintenance Cost
PCC	Pair Copula Constructions
PDF	Probability distribution functions
PV	Photovoltaics
RBRDO	reliability based robust design optimization
RES	Renewable Energy Sources
RI	Reliability Index
ROI	Return on Investment
SoC	State of Charge
TNRG	Total Non-Renewable Energy Generated
TRG	Total Renewable Energy Generated
VIKOR	VIseKriterijumska Optimizacija I Kompromisno Resenje
VSS	Value of Stochastic Solution
WSS	Wait and See Solution
WT	Wind Turbine
XDSM	Extended Design Centered Matrix
YLD	Years Lost in Disability
YLL	Years of Life Lost

List of Variables

a	parameter for the Kumaraswamy distribution
AC	annualized cost ($)
A	first stage objective function
Alt_j	Alternative j in MCDA
at_{ij}	the comparative importance of attribute i with respect to attribute j
b	parameter for the Kumaraswamy distribution
B	second stage objective function
C	Copula function
Ce	energy stored in the batteries (kWh)
C_0	fixed installation cost ($)
Chb	charging power for all batteries (kW)
CC	total Cost of PV and wind stand-alone system
C_{Int}	CO_2 intensity in kg/kW
C_{MAX}	maximum allowable charge of a battery (kWh)
C^T	coefficients in the objective function
C_{Tax}	carbon tax in ($/kg)
D	demand (kW)
$DChb$	power supplied by all batteries (kW)
DM	design matrix
DM_{norm}	normalized design matrix
DOD_{MAX}	maximum depth of discharge of the battery (%)
D_{us}	unserved demand (kW)
E_ω	Expectation
f_0	objective function in IDF architecture
FC_{DG}	fuel cost in $/kWh
f_i^-	worst value of all the alternatives for the ith criterion
f_i^*	best value of all the alternatives for the ith criterion
f_{ij}	value of the ith criterion function for jth alternative
F_x	Marginal distribution
F_{xy}	Joint distribution
F_y	Marginal distribution
g	a set of constraints in an optimization problem
G_{ref}	irradiance at reference operating conditions equal to 1000 W/m^2
G_T	hourly irradiance on a tilted surface (W/m^2)
h, h_r	hub height and reference hub height (m)
i	discount rate (%)

I_{DG}, I_{PV}, I_{WT}, IC_{BAT}	levelized Annual Installation Cost of generation sources storage ($) ($/year)
I_{max}	maximum current of PV panel at the reference operating condition (A)
I_{mpp}	maximum power point current for solar panel (A)
I_{SC}	short circuit current for solar panel (A)
J	All possible alternatives for consideration in MCDA
k	Number of parameters in AIC
L	Maximized value of the likelihood function
L_p	metric used as an aggregating function in a compromise programming
m	day of the year
Nd	Number of disciplines
nc	Number of criteria
n	number of years
ns	number of scenarios
N_{BAT}	no. of power generation sources and storage
N_{PV}	no. of power generation sources and storage
$N_{PV,max}$, $N_{WT,max}$, $N_{BAT,max}$, $N_{DG,max}$	maximum number of generation sources and storage
$N_{PV,min}$, $N_{WT,min}$, $N_{BAT,min}$, $N_{DG,min}$	minimum number of generation sources and storage
$O_{DG,}$ O_{PV}, O_{WT}	power output from generation sources (kW)
OM_{DG},OM_{PV},OM_{WT}	levelized Annual Maintenance Cost for generation sources and storage ($) ($/year)
$\boldsymbol{p}$	system constant parameter
PC, F	present cost and future cost at the end of *n* years ($)
P_{mpp}	maximum power point operating power of a solar panel (kW)
P_R	rated power of wind turbine (kW)
P_{WT}	power output of a wind turbine (kW)
$\boldsymbol{R}$	reliability vector specified for each constraint
RC_{DG}, RC_B	rated capacity of diesel generator and battery (kW)
RP	percentage penetration level of renewable energy
s	each scenario in the two-stage stochastic programming
SR	Spinning Reserve
T	technological matrix
t	time in hours
$T_{\boldsymbol{a}}$	ambient temperature of the site under consideration (^oC)
T_b	life of battery in number of cycles
$T_{\boldsymbol{c}}$	PV panel operating temperature (^oC)
$T_{\boldsymbol{ref}}$	PV panel temperature at reference operating conditions is equal to 25^oC

U	Uniform distribution
u_m	Random variable for copulas
v	wind speed in m/s
v_{ci}, v_{co}, v_r	cut in speed, cut off speed and rated speed of a wind turbine (m/s)
vf	weight for the strategy of maximum group utility
v_{hr}	velocity at reference height (m/s)
v_m	Random variable for copulas
V_{max}	maximum voltage of PV panel at the reference operating cond (V)
v_{mean}	mean wind speed for Weibull distribution (m/s)
V_{mpp}	maximum power point voltage for solar panel (V)
V_{oc}	open circuit voltage of PV panel (V)
v_σ	standard deviation of the wind speed
W	recourse matrix in the two-stage stochastic programming framework
w_i	the weights of the criteria
x	a vector of design variables
x^l	lower bound
x^u	upper bound
y	a vector of coupling variables
y^t	a vector of coupling variable target
Z_{max}	parameter for the Kumaraswamy distribution
Z_{min}	parameter for the Kumaraswamy distribution
α, β	cost of a PV panel and battery, respectively
γ_{sd}, γ_d	self discharge efficiency and discharge efficiency of the battery (%)
δ	Level of dependence between the marginals
ϑ	parameter of the t-copula
θr	risk weightage parameter
ρ	parameter of the t-copula
σ_f	standard deviation of the objective function denoted by f
ω	denotes a scenario
Ω	Set of all possible random scenarios
μ_f	mean of the objective function denoted by f
$\mu_{I,SC}$	temperature coefficient for short circuit current (A/^{o}C)
$\mu_{V,OC}$	temperature coefficient for open circuit voltage (V/^{o}C)

Chapter 1
Introduction

1.1 Motivation and Challenges

It is evident that the global demand for energy has been increasing rapidly, which imposes a huge dependence on existing energy resources (fossil fuels/oil); this leads to increasing pollution and global warming **[1]**. It has been analyzed that in the upcoming 25 years the global energy demand is expected to increase by 50 % given the population growth and economic development. In this context renewable energy resources appear to be a promising source of clean energy **[1]**.

In the past, the defining nature of the world's power supply systems has been of centralization and much of which depended on fossil fuels. They have been significant major resources to produce power in large generation facilities to provide low-cost electricity to high population densities. Given the rapidly increasing cost of extension and maintenance of transmission networks from large central grids, many isolated systems have instead adopted distributed generation for local power supply. Renewable energy is also an important alternative for such isolated systems (rural/islands) given the high oil prices, the cost of transmission expansion, and the high cost of transportation of fuel, along with the desire to reduce CO_2 emissions.

Canada is the second leading producer of greenhouse gas (GHG) emissions per capita and one of the fastest growing players contributing to energy demand **[1]**. Although the cost of energy from conventional resources is typically lower than that from the renewable energy resources, an optimal mix of renewable energy with conventional resources can reduce the overall cost of energy in isolated systems, which are often referred to as microgrids. Distributed generation in these systems typically range in capacity from 5kW to 10MW, at or near the end-user to provide the electric power needed **[2]**.

1.2 Research Objectives and Scope

Increasing oil and fossil fuel prices, extreme changes in the climatic conditions have motivated us to direct ourselves to meet our power needs from renewable resources of energy, away from a centralized power system to a more decentralized and hybrid power system. Most of the work done in microgrid design has been done using deterministic methods, but a majority of the referenced work acknowledges the stochastic nature of the renewable generation and demand. It has been really challenging to develop joint stochastic models for the design of small microgrids with high renewable penetration due to multiple disciplines involved and the need to consider both economic and environmental metrics. Developing models which incorporate planning and operation considering inability to dispatch and uncertainty in renewable resources and demands is usually the prime goal. Planning models incorporate a long time horizon with large time intervals while operation models incorporate a short time horizon with smaller time intervals and considering both simultaneously is nearly impossible for most real world systems.

Stochastic models have considerable advantage over deterministic models, one of these advantages is that the overall cost, namely, the sum of investment and operational costs, is lower than the overall cost from its deterministic counterpart and that the stochastic model can meet the requirements for all the foreseeable scenarios, something that a deterministic model cannot do **[3]**.

Developing stochastic models is just not enough in any problem if risk is not considered explicitly. Hence, an optimization model for planning and operation that minimizes risk due to random events is needed. The mean-variance Markowitz theory **[4]** can be applied with an introduction of a single risk factor in the objective function to explicitly account for the trade-offs between the mean and variance in benefits.

Markowitz theory has been used extensively in portfolio optimization and has proven useful. In the context of microgrid planning and design, we have a portfolio of generation and storage resources and costs associated with them. Given various operating, budget and reliability (percent of load unserved) constraints, we wish to minimize our costs and the risk of our investment in long term.

Microgrid planning not only considers the energy needs of the local community but also helps in preventing adverse effects to the environment by reducing the CO_2 and other GHG emissions. They are also helpful in providing local employment. However, it is important to understand that any infrastructural set up will involve investment in the form of money and land usage that may have otherwise been used for agricultural purpose, etc., an issue that came to be understood in recent days from large increase in corn (food/feed crop) prices when used for fuel production **[5]**. In our planning we need to address all these issues together and the framework proposed is expected to help such planning.

Therefore, an important objective of our research is to develop a framework based on the idea of multi-disciplinary design optimization (MDO) and life cycle analysis. The former takes care of the multiple disciplines which we may have to consider for a robust design while the latter one encompasses the cradle to grave analysis of any component involved in the development of the microgrids and their effects on the environment whether positive or negative.

LCA of a microgrid involves a detailed analysis of the individual components of the microgrid ranging from the wind turbines, solar panels, batteries, etc. to the system as a single entity. This allows us to evaluate the microgrid based on a holistic approach and its impact on the environment. There is immense evidence of a broad spectrum of research in the area of LCA useful for renewable energy technologies. Most of the research faces difficulty finding accurate data for local regions but recent advancements in comprehensive databases have reduced this difficulty manifolds.

Microgrids can be autonomous or grid-connected, based on the location and future planning. An analysis towards the feasibility of establishing a microgrid as compared to connecting it to the main grids also plays an important role in the cost and planning analysis **[6]** .

In summary, the list of goals proposed in this research for building the framework:

- Develop statistical models for robust modeling of renewable energy resources and demand given uncertainties inherent in them. It is also important to understand the dependence between renewable energy resources (solar and wind in our case) for optimal planning decisions of systems utilizing such resources. We investigate first order dependence between power generations from renewable resources at various locations in proximity.
- Find an optimal configuration of a microgrid fed by renewable energy resources. This is an optimization problem which considers the minimization of capital and operational costs subject to operational and reliability constraints.
- Develop stochastic optimization model to incorporate the probabilistic uncertainties in supply and demand. Stochastic optimization model is more complete as it encompasses various scenarios of supply and demand. We use the approach of two-stage stochastic programming with recourse for our problem. Markovitz mean-variance model is used to consider risk in investment.
- Microgrids have a diversified impact on the environment and the community. Hence we need to analyze its impacts on the environment in detail and the most obvious approach is to undertake

LCA of the possible microgrid configurations. Since each configuration has multiple varying attributes, we used a Multi-Criteria Decision Analysis (MCDA) method based on compromise programming for selecting a configuration, which is made possible by the proposed multidisciplinary design optimization under uncertainty based framework.

1.3 Thesis Outline

This thesis work is presented in seven chapters. Chapter 2 offers a comprehensive literature review of the research contributions in the area of microgrid planning.

Chapter 3 presents the integration of the models of resource, demand, microgrid planning and LCA. We use Multi-disciplinary design optimization to formulate a general framework for the planning of micro grids using the MCDA approach using compromise programming. The modeling aspects of our work with uncertain resources are explored in Chapter 4. It explains our approach for modeling of wind and solar energy using the Kumaraswamy distribution and the copula based C-Vine approach to model the dependence.

We extend the deterministic optimization model into a two-stage stochastic programming model in Chapter 5. In addition, we used the Markovitz mean-variance model and extended our two-stage stochastic programming model to consider risk explicitly in microgrid planning.

Chapter 6 presents an approach to do life cycle analysis of the possible microgrid configuration (LCA of each resource technology) using the large amount of data available in public data sets. It allows us to choose a microgrid that not only is economically profitable but also suitably addresses any adverse effects on the environment. We used an open source tool called OpenLCA for performing the LCA of our microgrids.

Chapter 7 presents summary and conclusion of the thesis and highlights the major contributions of the thesis. It also lays path for researchers to investigate in newer areas of research.

Chapter 2

Microgrid Planning Problem: Literature Review and Assessment

2.1 Introduction

There has been a thrust by UNFCCC (United Nations Framework Convention on Climate Change), to prevent climate change and global warming by accelerating research and development to enhance the penetration of renewable resources of energy which are capable of replacing fossil fuels. A very precise definition of a microgrid has been stated by **[7]**: A microgrid is a cluster of electricity sources and (possibly controllable) loads in one or more locations that may or may not be connected to traditional wider power systems, or the grid. The most intriguing feature of a microgrid is its ability for local control, allowing it to operate reliably as an island. The success of such distributed microgrids will depend heavily on the availability of renewable resource and the economics of the distributed energy resources.

It is quite clear that the early success of small clusters of such mixed technology generation, possibly grouped with storage, controllable loads and other microgrid elements will empower such systems to succeed. Long term economic, environmental and utility system benefits are evident, policies and strategies are required to propel such microgrids to a more widespread audience. There are still some technical, economical and regulatory issues which restrict the widespread deployment of renewable energy systems (resource is wind and solar, for example) (RES) in any power system. One of the most significant issues with their deployment is their uncontrollability and undispatchability. Most of the recent designs assume the renewable resources to be dispatchable, which is practically not feasible.

Electricity is one commodity that is generally consumed almost instantaneously once generated. Demands are generally fluctuating hence system planners perform complex, multistage planning process that enable the generators to deliver the agreed amount of power and change their output promptly or on a short notice. One way to deal with the problem of uncontrollability of RES is to use them in conjunction with controllable generators and energy storage. It is quite evident from the literature that combinations of RES with controllable generators and storage systems ("Hybrid Power Systems", HPS) are considered as feasible alternatives only in rural areas such as villages, islands and oases, where it is prohibitively expensive to extend power transmission lines from the main grid to serve the loads in these remote areas.

Recently, the outlook towards installation of such HPS has been changing for two major reasons:

- RES and storage units are getting bigger and less expensive.
- Decentralization of the grid is taking place, enabling higher penetration of RES and distributed generation.

The traditional centralized power grid which had a three layered architecture (generation, transmission and distribution) is transforming into a more modular decentralized architecture with poly-microgrids with distributed generation and smart communication protocols to enable high renewable penetration. In this context, development of an optimal strategy for choosing the right mix of renewable resources of energy plays an important role in the planning and operation of the HPS in the microgrid. There has been extensive research performed in this domain but the uncertainty of renewable resources of energy and pricey storage solutions make the process of technology selection a very challenging task.

2.2 Literature Review

Global environmental concerns and the ever increasing need for energy, combined with the steady progress in renewable energy technologies has provided huge thrust in industry and academia to explore solutions for energy which are cheap, environmental friendly, reliable and self-sustaining. Extensive research has been carried out in the past few decades towards design of systems which encompass the above mentioned features. Hence in an attempt to design HPS with mainly solar and wind power as renewable resources of energy we review literature of techniques for designing self-sustaining HPS in isolation and with grid connectivity. Large spectrum of mathematical tools have been employed in an attempt to find an optimal mix of such resources to develop reliable systems.

2.3 Modeling of Random Variables (Renewable Energy Resources)

2.3.1 Wind Energy

Wind energy is the kinetic energy of wind utilized for the production of electricity. There has been a dramatic growth in wind power penetration since the beginning of the 21st century. Total global installed capacity of wind power at the end of 2011 was around 238 GW which was significantly large than 18 GW at the end of year 2000. Almost 41GW was added in 2011 alone. There has been extensive growth in wind power in Asia, overtaking Europe and North America. China, in specific, has become the leader in terms of the total installed capacity in a very short span of time, exceeding United States in 2010. There have also been a number of recent developments in offshore wind projects. A dozen of

European countries have provided their consent for development of an off shore electricity grid in the North Sea **[1]**.

2.3.1.1 Wind Turbine Model

The analysis of power generation using any renewable source is an essential component of the planning studies. In the context of Wind Turbines (WT), it is not possible to achieve a realistic evaluation of the electrical system in question by simply using deterministic analysis. The probability of a given wind speed can be estimated if the probability distribution is known. Once the wind speed is known, the power injected into the grid can be calculated by means of the WT power curve **[8]**.

2.3.1.2 Wind Turbine Characteristics

The output of a wind generator is determined by the average hourly wind speed at the hub height and the output characteristics of the wind generator. For evaluating the output power of the wind generator, the measured data of average hourly wind speed must be converted to the corresponding values at the hub height, using the wind speed at a reference height h_r and wind speed at a specific hub height h for the chosen location as in Equation 2.1, where v is wind speed in m/s, v_{hr} is wind speed at reference height in m/s and γ is the power law exponent **[9]**.

$$v = v_{hr}\left(\frac{h}{h_r}\right)^{\gamma} \qquad \text{2-1}$$

In association with the wind speed evaluated in Equation 2.1, the model **[9]** used to evaluate the wind power $P_{WT}(t)$ W, generated by the wind turbine is as shown in Equation 2.2 where P_R is rated power of wind turbine in kW, v_{ci} is cut in speed of wind turbine in m/s, v_{co} is cutoff speed and v_r is the rated speed of the wind turbine in m/s

$$P_{WT} = \begin{cases} a \cdot v^3 - b \cdot P_R & v_{ci} < v < v_r \\ P_R & v_r < v < v_{co} \\ 0 & otherwise \end{cases} \; where \; a = \frac{P_R}{v_r^3 - v_{ci}^3}, b = \frac{v_{ci}^3}{v_r^3 - v_{ci}^3} \qquad \text{2-2}$$

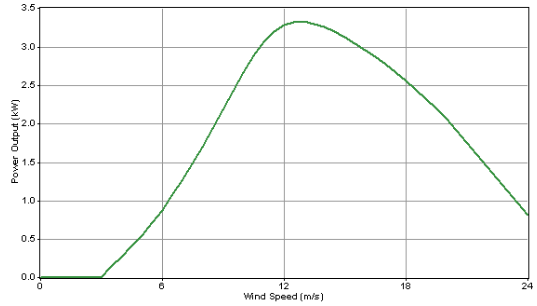


Figure 2-1: Power Curve for Whisper 3kW Wind Turbine

The power curve for the Whisper 3kW (Sothwest Wind Power) **[10]** wind turbine is developed based on the equations above. This is one of the small wind turbines used in a few microgrid projects. The power curve and specification are obtained directly from HOMER. The power curve of most of the wind turbines in the range of 1kW to 30kW follow a similar shape. But the choice of a specific wind turbine is based on the average annual wind speed of the location and economics. Whisper 3kW wind turbine was used in similar a microgrid in South Africa **[11]** and hence we decided to use this wind turbine for our case study.

2.3.1.3 Wind Speed Modeling using Probability Distributions

Hourly wind speed is considered as a random variable and is modeled using the Weibull Probability Distribution (PDF) **[12]**, the mathematical expressions are given by Equation 2-3. This enables planners to predict the wind speed at a given location for any specific time. This information is useful for predicting accurately wind power available at the site.

$$f(v) = \frac{r}{c}\left(\frac{v}{c}\right)^{r-1} exp\left[-\left(\frac{v}{c}\right)^{r}\right] \qquad 2\text{-}3$$

Where *f(v)* is the wind speed PDF and

$$r = \left(\frac{\sigma}{v_{mean}}\right)^{-1.086} \qquad 2\text{-}4$$

$$c = \frac{v_{mean}}{\Gamma\left(1 + \frac{1}{r}\right)} \qquad 2\text{-}5$$

$$\text{Where } \Gamma(n) = (n-1)!$$

where, v_{mean} is the mean speed and σ is the standard deviation of the wind speed for a particular site. The Cumulative Distribution Function (CDF) can be represented mathematically by Equation 2-6.

$$F(v) = 1 - exp\left[\left(-\frac{v}{c}\right)^{r}\right] \quad \text{2-6}$$

2.3.2 Solar Energy

Photovoltaic (PV) systems generate electricity using energy from the sun. They constitute another environmentally friendly alternative way for energy production. They operate quietly without emissions and they can be installed quickly. Their long lifetimes and little maintenance requirements make them an ideal solution for not only urban but rural deployments when used as autonomous systems. PV systems can be located close to the sites where the electricity is to be consumed. Generator systems near the end-user can reduce transmission and distribution costs as well as transmission and distribution losses. At the moment, the major barrier to the widespread adoption of photovoltaic technology is its high cost.

Within Europe there are several countries with extensive experience with grid-connected systems. These include Austria with its 200kW Photovoltaic Rooftop Program **[13]**, Germany with its 1000 Roofs Program (now 100,000 Roofs Program), which led to the installation of more than 2250 systems by 1999, Italy with ENELs 3.3MW PV plant, the Netherlands with an expanding research and demonstration program (several MW of PV have been installed, mainly on roofs) and Switzerland with its Energy 2000 program. There are also, many experimental PV power stations and demonstration projects. Japan with its 70,000 roofs program plans to increase its installed capacity from 10000 systems in 1997 to 4600MWp by 2010. In the UK the potential is seen for building integrated PV systems.

Irradiation or sometimes simply radiation is the radiant energy per unit area on a surface and is measured in J/m^2 or Wh/m^2. Irradiance is the power per unit area on a surface and is measured in W/m^2. Our prediction of solar radiation at a certain location is based on radiation data from the past. The solar radiation data are usually recorded on the horizontal surface.

The solar radiation on a surface of an arbitrary orientation at any time depends on the angle of the solar rays with the surface in question, that is to say, on the relevant position of the surface with respect to the sun. This is determined by the surface orientation and the astronomical parameters. PV system modeling requires the knowledge of radiation on the inclined surface of the PV panel which usually has to be calculated using the radiation on the horizontal surface. The steps in the radiation conversion are as follows: Firstly, the radiation has to be decomposed into the two components; beam and diffuse. The next step is the transposition of each onto the inclined plane. The total (global) radiation contains a sum of the two components as well as the ground reflected radiation. The key procedure is the calculation of diffuse radiation. The key quantity in this calculation is the clearness index which expresses the effect of the atmosphere on the extraterrestrial solar radiation. Since most of the environmental factors are random and we are aware that solar insolation varies from day to day at the same hour we need a technique to model this uncertainty.

2.3.2.1 PV Panel Characteristics

The hourly output power of a PV panel can be calculated by several analytical models which define the current-voltage relationships based on the electrical characteristics of the PV panel.

The model presented by **[14]** is used in all the calculations. It allows for calculating the PV panel current (I_{mpp}) and voltage (V_{mpp}) at the maximum power point using a maximum power point tracker (MPPT). This model includes the effects of irradiation level and panel temperature on the output power as shown in Equations 2.7 – 2.14, where I_{SC} is short circuit current of solar panel in A, V_{max} and V_{oc} are maximum voltage of PV panel at the reference operating condition and open circuit voltage of PV panel in Volts, respectively, $\mu_{V,OC}$ is temperature coefficient for open circuit voltage in V/degC, I_{max} is the maximum current of the PV panel at the reference operating condition, $\mu_{I,SC}$ is temperature coefficient for short circuit current at reference operating conditions, G_T and G_{ref} are hourly irradiance on tilted surface in W/m^2 and irradiance at reference operating conditions equal to 1000 W/m^2, respectively, and $T_{\mathbf{c}}$ and $T_{\mathbf{ref}}$ are PV panel operating temperature and reference temperature in degree Celsius, respectively.

$$I_{mpp} = I_{SC} * \left[1 - C_1 * \left[exp\left(\frac{V_{max}}{C_2 * V_{OC}}\right) - 1\right]\right] + \Delta I \qquad 2\text{-}7$$

$$V_{mpp} = V_{max} + \mu_{V,OC} \cdot \Delta T \qquad 2\text{-}8$$

and the PV panel power at the maximum power point P_{mpp} is expressed as:

$$P_{mpp} = V_{mpp} \cdot I_{mpp} \qquad 2\text{-}9$$

With

$$C_1 = \left(1 - \frac{I_{max}}{I_{SC}}\right) \cdot exp\left(-\frac{V_{max}}{C_2 \cdot V_{OC}}\right) \tag{2-10}$$

$$C_2 = \left(\frac{V_{max}}{V_{OC}} - 1\right) \cdot \left[ln\left(1 - \frac{I_{max}}{I_{SC}}\right)\right]^{-1} \tag{2-11}$$

$$\Delta I = I_{SC} \cdot \left(\frac{G_T}{G_{ref}} - 1\right) + \mu_{I,SC} \cdot \Delta T \tag{2-12}$$

$$\Delta T = T_c - T_{c,ref} \tag{2-13}$$

T_c can be expressed as follows **[14]** where NOCT is Normal Cell Operating Temperature.

$$T_c = T_a + \frac{NOCT - 20}{800} \cdot G_T \tag{2-14}$$

where normal operating cell temperature (NOCT) is defined as the cell temperature when the PV panel operates under 800 W/m^2 of solar irradiation and 20°C of ambient temperature and NOCT is usually between 42°C and 46°C.

Most of the data sources provide only solar irradiation data on a horizontal plane. The power incident on a PV module depends not only on the power contained in the sunlight, but also on the angle between the module and the sun. When the absorbing surface (PV panel) and the sunlight are perpendicular to each other, the power produced is maximum. However, the angle between the sun and a fixed surface is continually changing, the power density on a fixed module is hence always less than that of the incident sunlight.

The tilt angle has a major impact on the solar radiation incident on a surface. For a fixed tilt angle, the maximum power over the course of a year is obtained when the tilt angle is equal to the latitude of the location. However, steeper tilt angles are optimized for large winter loads, while lower title angles use a greater fraction of light in the summer and hence accordingly one needs to change the orientation of the solar panels. For our study we would restrict to the values of horizontal solar irradiation only.

2.3.3 Modeling of Random Variable with non-linear dependence structure

2.3.3.1 Correlation analysis between renewable generation using Copulas

Wind power is one of the world's largest and most accessible resources of renewable energy. Solar power is becoming the second most popular resources of renewable energy. However, intermittency in the availability of the renewable resources of energy presents a barrier to the renewable energy based systems (mostly wind and solar power) to meet the demand entirely. Wind shows sudden changes, and a very high variability. While, solar power is more stable than wind and follows a well-recognized pattern but the power output shows high variability with a slight change in solar insolation. Our analysis is based on locations in Canada and the United States, although our models are general and can be employed to any data set.

Wind speeds in general are non-Gaussian and non-linearly correlated and so are their spatial dependencies. Hence, we utilize the Kumaraswamy distribution to model the wind power. There are two reasons for using Kumaraswamy distribution, firstly, it's a general distribution with similar characteristics as the beta distribution and, secondly, it has a very simple analytical formulation that allows for fast computations and easy integration with copulas, which will be discussed in detail later.

There has been existing literature on the possibility of smoothing wind power based on geographical dispersion or by interconnecting the existing dispersed systems. Most of the literature refers to wind farms. In **[15]**, authors investigate the impact of these arrays of wind turbines of varying sizes. They used data from California and concluded that the reliability of the systems increased with increased in system size. Also recently, it has been found that interconnection has a great impact on reliability and stability of renewable energy generation (mostly wind power) **[16]**.

Dependence is quantified usually using measures of association, such as linear correlation coefficient **[17]**. It has been shown in the literature that the linear correlation coefficient of the power from wind power plants tends to decrease with increase in the separation and has opposite behavior for longer averaging periods **[18]**.

The linear correlation coefficients provide general information about dependence; it does not uniquely describes the structure of dependence. Unfortunately, it doesn't translate well into specific, actionable information that can be used by system operators or planners. Let us for example assume a system planner wishes to know the number of hours in a year the aggregate wind power in the system will be above or below some threshold value. It has been demonstrated that the information on linear correlation coefficient, even coupled with knowledge of marginal distributions of wind power is not sufficient to determine the actions or specific information. The only possible way to describe the dependency structure fully is by using joint distribution functions. On the other hand, no multivariate distribution models are available for wind power and moreover no common joint distributions fit wind power data accurately.

There are always options for modeling such scenarios, one possible way studied in the literature is by decomposing the assumed correlation matrix using Cholesky decomposition **[19]**. This approach is only suitable if one has linear correlation, and it allows the planner to have no control in utilizing the possible nonlinear dependence structure. Hence a more appropriate approach to model non-linear, non-normal, and more complex dependency structure is by using *Copulas* [18, 20-23].

Copulas are very widely used in the field of finance [17, 24], and authors possess some unique characteristics which make them attractive and appropriate for wind power modeling **[23]**. The most important feature of copulas is their ability to model the dependence structure independently of the marginal distributions of the participating variables. This is quite important as output of wind power at different locations is often not trivial and therefore finding this dependence independently of their behavior is of great advantage for the system planners. The correlation between the locations can be estimated from characteristics such as separation distance, averaging period etc [25-27]. Therefore, if only basic information is available about the location of the wind turbines, quite accurate model of the dependency structure can be produced. The selection of an appropriate copula function is very important at this point. Inappropriate selection of the copula can result in unacceptable errors.

In literature it is most commonly found that the default choice for copula is the Gaussian copula, but it has not been rigorously investigated that if this is an appropriate choice for wind power. In **[22]** wind power was modeled using the standard Gaussian copula and their decision to use the Gaussian copula was based on the qualitative assessment of the Q-Q plots. While a more comprehensive approach was adopted in **[27]** where they tested a number of standard copulas on wind speed rather than wind power and only tested the Archimedean copulas **[17]**.

The most important usage of modeling wind power using copulas is in the generation of scenarios **[28]**. As it will be demonstrated in this thesis, wind power production scenarios are necessary for stochastic programming which is a common decision making tool in power system analysis and planning research. For example, **[29]** utilized Gaussian copulas to generate these scenarios, while Empirical copulas were used in **[30]** where authors modeled the dependency structure between the wind speed and the wind power output. In **[31]** copulas are used for wind speed forecasting, where they utilized a quantile-copula kernel density estimator to improve the probabilistic wind power forecasts.

It has been shown in the literature for a quite a long time that wind speed are non-normally distributed and recent studies on the evaluation of the dependence structure of the wind speed has confirmed that they are non-linearly dependant [18, 22] and many more.

Hence when the multivariate data is not normally distributed the quantiles of sums of margins may not be calculated from sums of variances and covariances. In **[18]**, authors have modeled the univariate time series of wind speed using a seasonal ARMA model which was proposed by Benth and Benth **[32]** for each location individually. To model the correlation between the various locations, they analyze the correlation between the residuals of the various univariate time series and fit copulas to the residuals developing copulas-GARCH models. They have addressed this issue based on daily mean wind speed and we feel that a stronger correlation structure underlies the wind power on an hourly basis as wind has finite velocity and change in wind velocity at one location is time-lagged correlated to the other and the correlation is significant and cannot be neglected.

2.3.4 Microgrid Planning - Deterministic Approaches

In **[33]**, Ofry et. al. developed a graphical method based on the loss of power supply probability to design a stand-alone solar electrical system. The idea adopted by **[33]** was to minimize a linear cost function comprising the cost of battery and solar arrays. The minimum is obtained by finding the derivative of the cost function. The linear cost function is shown below, where CC is the total cost of the system, α is the cost of a single PV panel, β is the cost of a single battery and C_O is the fixed installation cost. All costs are in dollars ($):

$$CC = \alpha N_{PV} + \beta N_{BAT} + C_O \tag{2-15}$$

In **[33]**, the authors expressed the feasibility of their model using a real world example of a low power communication box, which means that extending the idea of such stand-alone systems to large power applications was a challenge.

A very similar approach to **[33]** was carried out a few years later **[34]**. An analytical approach was adopted with which extensive simulations were performed on meteorological data obtained from various places in Italy. The system under study in **[34]** also consisted of a photovoltaic array, power tracker, battery storage, inverter and a controllable load. Given the extensive research being carried out in the domain of design of stand-alone systems, a sizing hand-book was published, which summarized all the techniques developed till then based on the sizing curves and loss of power supply probability. The report **[35]** extended the work to include seasonal variations in the meteorological data.

In **[36]**, the author has presented an analytical technique for the design of standalone solar and battery systems. He presents an analogy between the battery storage and reservoir, queues and stocks and approached the problem by formulating the energy deficit as *Markov process*. He discretized the probability distribution for the energy deficit and solar power generated and converted them into finite states. States were then evaluated using the transition probability matrices.

Design of HPS for a house was carried out initially by **[37]**. Authors fixed the number of wind turbines and developed a methodology for calculation of an optimal size of a battery bank and the PV array for a wind-PV system. Long term hourly meteorological data was used to evaluate average wind power and PV power for every hour of a typical day of a month. The load was considered as a typical household in the city of Massachusetts. Given the load and desired loss of load probability an optimal number of batteries and PV modules were calculated based on minimum cost criteria.

In **[38]**, design of a HPS without considering the daily variation in the meteorological parameters is presented. Instead they consider the monthly variation which prevents over sizing of the system design. In their work they do consider the impact of battery storage but do not discuss about the size of the battery. It becomes an important parameter in design of HPS to obtain an optimal number of batteries or any other storage since it governs an important and significant portion of the systems cost. The work in **[38]** considers the problem of optimal design by a graphical technique by building graphs of PV vs Wind and identifying the feasible region. These graphs are usually referred to as *sizing curves*. Seasonal variations in the meteorological information have also been considered as a part of the analysis. Interesting conclusion of **[38]** was that the principal reason for HPS being the cheaper solution than PV or wind alone is the fact that the energy generated by the hybrid can be matched more closely to the load and prevents over sizing of systems which may be too expensive.

The work in **[39]** addresses the design and integration of an isolated HPS. A goal of this work was to design a stationary electric power system for Necker Island near California, which allows full operation and future expansion of the facility and drastically reducing the environmental impact of the current fossil fuel generation. In **[39]**, the power system of Necker Island was redesigned which integrated the Island's hot water, electrical and water desalination systems. They formulate the combined optimization problem based on the performance and by constraining carbon emissions. Issue of voltage stability is also addressed in the context of low voltage grid. They employ the idea of distributed control to enable each unit float their frequency to ensure system stability with changing demand and supply profiles.

2.3.5 Microgrid Planning - Stochastic Approaches

Stochastic design approach has been recently adopted by Chandy et. al. **[40]**, where authors discretized the battery state and modeled it as a Markov process. They considered the state of energy deficit as an absorbing state and hence at any instant, to evaluate the probability of loss of power supply, it was obvious to find the probability of the storage to be in the absorbing state. Very similar stochastic models have already been used in hydrology to understand and model the reservoir, which have a direct analogy to a battery in our case. In **[41]**, Ponnambalam et. al. presented an analysis of a multireservoir system based on the development of first and second moment expressions for the stochastic storage state variables. The expressions in **[41]** give explicit consideration to the maximum and minimum storage bounds in the reservoir system. Their formulation provided analytical results for various parameters such as variance of storage, reliability levels and failure probabilities, which are of significant importance to a power system under consideration as well. The ideas of using indicator functions from **[41]** was extended in **[42]** to analyze the F-P Method from **[41]** in capacity design of a battery bank in renewable energy systems with constant demand and uncertain supply.

Analytical expressions similar to **[34]** were obtained for the probability of deficit of the storage system. An important inference from **[43]** and others is that there exists a threshold on array size below which no amount of storage capacity will suffice to ensure prescribed system reliability.

The techniques discussed above reveal one important aspect. The numerical models are accurate in estimating the loss of load probability, however they are time consuming and complex. On the other hand, all analytical models allow sizing of PV systems in a very simple way by means of straightforward calculations. However they lack significant amount of accuracy. In **[44]**, authors developed an accurate analytical method for sizing of PV systems based on location specific coefficients obtained from the site topography.

Interest in the community has been developing to increase the penetration of RES and hence methods to design HPS have increased. In **[45]**, authors develop a linear programming technique to solve the design problem of an integrated electrical distribution system considering variety of loads, electricity resources (conventional and renewable) and energy storage. The model developed by **[45]** determines the optimal size and site of all the types of power supply units and connection lines. Their model has flexibility to be extended towards considering the expansion of power distribution systems by converting it into a multi-stage model.

In **[37]**, authors develop probability density functions for the wind power (Weibull distribution) and the PV power (bimodal distribution). Once the model is set up with the power output from the renewable resources, simulations are performed given the system operational constraints and the charging and discharging of the battery bank. Iteratively, optimal number of battery bank and PV modules are obtained by minimizing the systems cost. They also used the Equation 2.1 for finding the optimal minimal cost combination.

Demand and supply both have an uncertainties which need to be considered carefully while designing any system. The stochastic behavior of both the entities injects substantial degree of complexity into the systems design framework. Posadillo et. al. **[46]** developed a statistical technique for the design of stand-alone HPS for an uncertain demand. Sizing methods for HPS depend solely on the distribution function of the daily global irradiance. As a standard approach **[46]** also used the loss of load probability as a parameter to characterize the system design and includes information on the standard deviation of loss of load probability, annual number of system failures and standard deviation of annual number of system failures. The use of a detailed statistical characterization of daily solar radiation is a significant contribution of **[46]**.

Thermal generation is required for reliable HPS operation with high renewable penetration **[47]** . The authors present the operational aspect of such HPS where a fuzzy logic controller is used for solving the thermal unit commitment problem with integrated wind power. Inclusion of battery with wind power is essential to compensate the frequency and voltage fluctuations. They try to model the uncertainty and imprecision in the wind energy by fuzzification. The traditional unit commitment problem is then solved using a modified differential evolution approach. A trivial differential evolution approach is modified to embed the mixed-integer nature of the unit commitment problem which needs discrete optimization.

In another approach to handle the uncertainty and unpredictability in renewable resources, **[48]** applied stochastic optimization to identify the size of the storage in wind-diesel isolated grids. Energy storage is important in wind-diesel hybrid systems as it is a means for optimizing the energy use and for reducing the consumption of the diesel fuel. An important inference of the work is that the storage size and cost of delivered energy is dependent on wind penetration levels, storage efficiency and diesel operating strategy. Various scenarios for wind and demand profiles are considered. They also employ the two-stage stochastic programming technique where the first stage variables being power rating and energy rating of the energy storage along with the initial energy storage, whereas the second stage variables constitute diesel generator power, dump load, binary variables associated with the diesel generator dispatch and energy discharged from the storage at any given instant of time.

There have been numerous attempts for the design of microgrids using various open source applications, HOMER developed by University of California, Berkeley is one of the most commonly used one. It performs techno-economic analysis and prioritizes the solutions based on cost. One of the very successful attempts towards microgrid design using HOMER is **[6]**. Unfortunately, the software has many approximations and assumptions which need to be addressed using a detailed mathematical formulation to handle the uncertainty and unpredictability in the renewable energy resources and demand.

Inclusion of market impact with the planning of RES and storage is of vital importance given the increasing penetration of RES. Muela et. al **[49]** considers the stochastic nature of the wind power in terms of inherent variability and unpredictability even in short term. Including storage of any sort in the system has always been an intuitive approach towards complementing wind energy and handling positive and negative energy imbalances. The approach adopted by **[49]** is that of using standard two-stage stochastic optimization framework including two random variables; wind generation and market prices. Joint configuration is modeled and compared with an uncoordinated operation. An economic analysis of the inclusion of pumped storage in an islanded system which has abundant renewable energy available is performed in **[50]**. Their model addresses the capacity sizing for the pumped storage using a linear programming problem framework. The stochastic nature of load and renewable resources is handled using scenarios generated using fuzzy clustering. The model optimizes the unit capacity, storage size and operating strategy.

If more than one microgrids are connected to the main grid then they would start energy exchange at the bus. Sarkar et. al **[51]** addresses this issue of energy exchange by multiple microgrids using the concepts from *game theory* and explicitly compute the condition of *Nash Equilibrium* and show that it is unique.

2.3.6 Microgrid Planning - Global Optimization Approaches

Optimization has always been a challenging task, and global optimization techniques, such as Genetic Algorithms or Evolutionary Algorithms have been employed extensively in the design of HPS. In **[52]**, the authors use the genetic algorithmic framework for optimal sizing and operation of a HPS. Given the non-linearity in the system model and the system components, it becomes a very difficult and challenging optimization problem. In **[52]**, the authors divided the algorithm into two parts: one for the optimal sizing and the other for the optimal operation of the HPS. This results in an optimal selection of a HPS configuration and an operating strategy for the given site. Genetic Algorithms have also been used in **[53]** for distributed energy resource selection, sizing and effective coordination. The problem was formulated as a mixed integer non-linear problem which minimizes the total capital cost, operational and maintenance cost subject to constraints as energy limits, emission limits and loss of power supply probability. Simulated Annealing based approach for optimal sizing and siting is used in **[54]**.

A very similar approach as in **[38]** and **[52]** was adopted by **[55]** towards optimal sizing of the generation units for stand-alone and hybrid systems. Authors in **[55]** consider a location specific scenario in a remote area in Montana with a typical residential load. They designed the system using a simple numerical approach, later on they compared three major scenarios for economic feasibility: setting a new HPS; extending the connection to the main grid; and supplying load with the conventional generating units.

In **[56]**, a more recent algorithm, DIRECT (Dividing Rectangles), was used to solve the horizon planning optimization problem for sizing of a wind/PV system. DIRECT was developed by **[57]**, as a global optimization method. It is an effective deterministic algorithm **[56]**. It finds the minimum of a Lipschitz continuous function without knowing the Lipschitz constant. In DIRECT an assumption is made that the rate-of-change of the objective function and constraints are bounded. In brief, the entire search space is divided into a set of rectangles and optimal direction is determined by evaluating the objective function at the center points of the subdivided boxes. In this case, they used a few varieties of renewable energy resources types and capacities to choose from but it made the search space high dimensional.

A recent work by **[58]**, recommends an optimal design model for designing of an HPS including battery banks. The model evaluates optimal system configuration and ensures that the annualized cost of the system is minimized while satisfying the custom required loss of load probability. The decision variables of their model include the number of PV modules, the PV module slope angle, the number of wind turbines, the wind turbine installation height and the battery capacity. The method has been applied to a low power telecommunication relay station along the south east coast of China. They utilized Genetic Algorithms (GA) for determining the optimal configurations.

In **[59]**, the authors address more operational issues in a microgrid operating in autonomous or grid-connected mode. Concept of Particle Swarm Optimization is utilized for finding the optimal parameters for the control system. Whereas **[60]** uses Computational Intelligence technique such as neural networks and fuzzy system for microgrid control and operation.

2.3.7 Microgrid Planning - Multidisciplinary Design Optimization based Approaches

Microgirds, as mentioned earlier find extensive application in remote and rural communities. In **[61]**, the work is towards the design of a village microgrid with RES and performs evaluation of its economic feasibility. They follow a four stage process: initializing based on the natural environment and demand analysis, the selection of appropriate distributed renewable energy resources and the electrical network design and, power network analysis, and its economic evaluation. A case study of Changwon Dongjeun village in Kyoungnam province in China is taken as a case study where the load diversity ranges from single family houses, commercial buildings, apartment buildings and a public park.

An integrated approach is used in **[62]** to solve the problem of PV-Wind-Diesel-Battery HPS. They address the problem as a multi-objective optimization problem with two objectives: minimizing the total cost and minimizing the total CO_2 emissions, while capping the Expected Unserved Energy. Direct and indirect assessments of emissions of all the components are obtained using Life Cycle Assessment (LCA) techniques. The approach was applied to a city with 50,000 thousand residents. The results obtained from the linear programming model were used to construct the Pareto front, which represented the best trade-off between cost and emissions under different reliability conditions. Even in **[63]**, authors considered the two objectives but approached the problem using the Mesh Adaptive Direct Search (MADS) method.

Khaparde et. al **[64]** presents a very sophisticated approach towards solving the complexities involved in selection of various distributed generation technologies based on a set of attributes. An approach referred to as Multi-Attribute Decision Making (MADM) has been proposed. Important attributes in reference to a microgrid are incremental losses, capital costs and percentage time for which demand is not served for all users.

2.4 Literature Analysis

A detailed review paper on the distributed generation and its realization using the microgrids was done recently **[65]** and **[66]**. It touches upon various aspects of distributed generation and microgrid design. Various distributed energy resources as diesel engines, micro-turbines, fuel cells, photovoltaic, small wind turbines etc. and their coordinated operation and control with controllable loads and storage devices such as capacitors, flywheels, batteries etc. are main focus of the microgrid design. Operational strategies for microgrids, grid-connected or in an islanded mode. In **[66]**, various case studies of microgrids around the world have been discussed.

It can be seen quite evidently that a lot of research has been done in the past in the area of microgrid planning. A large majority of work falls under the category of deterministic algorithms. While in the recent past, in the last 5-8 years there has been an increasing trend in the number of papers using a variety of stochastic approaches towards planning of microgrids. We can clearly see that there is still a need for a more comprehensive research in the development of stochastic approaches which consider the inherent uncertainties in supply and demand.

Lastly, the planning of microgrids or any power system (either micro or large) is seen as a multidisciplinary problem, considering not only economics of the system but also the social and environmental impacts of the system as a whole. We do see a few papers working in the area of multi-criteria design analysis in planning of power systems but not a single paper is found using the approach of multidisciplinary design optimization and multi-criteria decision analysis (MCDA) together. Our work is an attempt to fill the gaps in this area of research.

2.5 Summary

A detailed and a comprehensive literature review of the research being carried out on the planning and operation of microgrids suggests that the problem although seems quite simple but is challenging. With the advancements in the renewable energy technology and thrust from various government agencies and worldwide consortiums has led to an increase investments in the research and implementation of robust techniques and approaches in power system planning based on renewable resources of energy and more towards decentralized power systems. The entire literature survey reveals that the methods available currently lack in considering uncertainties in the system design inherently. Also, it is quite clear that power system planning at any scale, in this case even a micro-level planning is a complex project affecting many domains together ranging from economics, social, and environmental. We have proposed methods which fill this gap in the research for planning of microgrids. We not only propose a more complete methodology for planning of microgrids based on stochastic programming but also incorporate other aspects on environment using a more complete LCA and MCDA based approaches.

Chapter 3

Multidisciplinary Design Optimization (MDO) – A systems Approach

3.1 Introduction

Engineering problems are complex and often multidisciplinary. It is usually desirable to break the complex problem into smaller sub-problems defined by disciplines as each discipline may have different requirements.. Each sub-problem may involve a discipline dependent system. Multi-disciplinary design optimization offers us a structured platform to analyze and solve complex engineering problems using various optimization and analysis techniques already used by the discipline-specific researchers, while considering the overall objective simultaneously.

3.2 Multidisciplinary Design Optimization

Multidisciplinary design optimization (MDO) is a new upcoming domain in engineering that focuses on the use of the numerical optimization techniques in association with various statistical tools for design of systems involving multiple disciplines or systems.

The motivation behind using MDO based techniques lies not only in the optimization of the individual systems or disciplines but also their interactions between each other. Considering these interactions in a single optimization problem requires extensive mathematical foundation and is often challenging. Therefore MDO based architectures are designed to suit various problem structures and simplify the mathematical complexity for the system under consideration. It is still an evolving field but early results have been promising enough in reducing the time and cost of the design cycle by making appropriate use of computational analysis tools **[67]**.

An important challenge one faces in using MDO architectures is to decide how to organize the discipline-specific analysis models, approximation models and optimization models, and their various interactions.

There are as many MDO architectures to solve a given problem, as many as there are optimization algorithms to solve a given design problem. However, the choice of the architecture has a significant impact on the solution time and the final design.

It involves choosing from the right algorithm to the types of interconnections of disciplines. A simple example of such a scenario could be using a global optimization algorithm versus a gradient based algorithm. The former leads to a global optimal solution but may consume a lot of time while on the other hand gradient based algorithms are faster but may get stuck in local maxima/minima. Therefore, it is a choice a system designer needs to make by understanding the problem and suitable methods in detail so as to find the best fit.

It is important to consider if the calculations in a given architecture can be computed in parallel then, then one can use it to efficiently perform calculations. In most cases, a distributed architecture with support for parallel processing is preferred over monolithic architectures. In general, careful consideration of the human and computing environments, the available algorithms, and the design problem at hand is important in deciding an appropriate MDO architecture **[68]**.

In our work, we primarily focus on methods for solving MDO problems with a single objective function and continuous design variables. We assume that the optimality of a design corresponds to the satisfaction of the Karush-Kuhn-Tucker (KKT) optimality conditions **[69]** . These conditions are necessary for local optimality; hence it is necessary for functions to be differentiable and continuous to be able to obtain optimal points. Although there has been a wide variety of work done in the context of MDO using global optimization approaches, such techniques are not the focus of this thesis and hence shall not be discussed.

In a recent review on various architectures for multidisciplinary design optimization techniques two main categories of MDO architectures have been listed as monolithic and distributed architectures **[70]**. Our work uses the monolithic architecture given the structure and nature of our problem.

3.2.1 MDO Problem Formulation

Like traditional optimization problems, MDO problems can be represented by a fundamental problem formulation which describes the goals of the optimization. This fundamental formulation is comprised of a set of six things:

1. Local design variables
2. Global design variables
3. Objective(s)
4. Constraints
5. Coupling variable pairs
6. Analysis components

We shall introduce the various terms and nomenclature used commonly in the MDO literature. A design variable is a quantity in the MDO problem that is always under the explicit control of the optimizer. The design variables may be local or they may be shared by multiple disciplines. Another important aspect in MDO is discipline analysis; it refers to the analysis of simulation that models the behavior of one aspect of a multidisciplinary system resulting in the state variables as responses of the disciplines.

In MDO, most disciplines exchange coupling variables to model the interactions of the entire system. In many MDO based design, multiple copies of coupling variables is made to allow independent discipline analysis and concurrently. As mentioned in **[70]** these copies of variables function as design variables in the problem formulation and are often referred to as the *target variables.*

3.2.2 Architecture Diagram

It is important to understand that reformulation of a given problem into the MDO framework allows us to analyze and solve the problem in a comprehensive manner with a more in depth understanding. The idea behind the MDO architecture is to reformulate the problem using the standardized notation. Unfortunately, describing the entire chain of operations required in implementing the model poses significant challenge for the system planners **[70]**.

In an attempt to coherently describe our exposition we adapted the approach referred as the extended design structure matrix (XDSM) **[71]**. As the name suggests, XDSM is based on the DSM (Design Structure Matrix), a commonly used approach in systems engineering **[72]**. It is used in systems engineering to visualize the interconnections among components of complex systems. The traditional DSM shows the components and the connections between the components but the meaning of the connections is left ambiguous. This problem was addressed in the XDSM architecture. For most of the MDO problems, one needs to represent two types of connections: data dependency and process flow. XDSM amalgamates the two dependencies very neatly in a single diagram. More details on XDSM can be found in the work by **[71]**.

Monolithic IDF (Individual Discipline Feasible) Architecture

This is one of the simplest architectures. It uses a single optimizer to drive the whole process. The XDSM for IDF is shown in Figure 3-1. The main reason for the choice of IDF architecture was primarily due to its computational efficiency **[73]** and ease of managing the coupling variable along with individual discipline feasibility. The problem formulation based on the IDF architecture used in this thesis is described by Equations 3-1 to 3-4 in their most general forms. The IDF formulation provides a way to avoid a complete multidisciplinary design analysis at optimization **[74]**. It maintains the individual discipline feasibility, while allowing the optimizer to drive the individual disciplines to multidisciplinary feasibility and optimality by controlling the interdisciplinary coupling variables. In IDF, the specific analysis variables that represent communication, or coupling, between disciplines are treated as a part of the optimization design variables and are in fact indistinguishable from the design variables from the point of view of single discipline analysis.

In the above formulation the equality constraints also contain the interdisciplinary constraints. The XDSM framework for the IDF formulation is shown in the Figure 3-1. Here the x is a vector of design variables, y is a vector of coupling variables or outputs from other disciplines or analysis, y^t is a vector of coupling variable target or in some sense input to the discipline based analysis, f_0 is the objective function and g are the constraints, Nd denotes the number of disciplines, $(\,)_0$ indicates variables shared by the more than one disciplines, $(\,)_i$ is for individual discipline constraints and $(\,)^c$ relates to the constraints consisting of coupling variables.

$$\min_{x,y} f_0(x, y(x)) \qquad 3\text{-}1$$

s.t.

$$g_0(x, y(x)) \leq 0 \qquad 3\text{-}2$$

$$g_i(x, y(x)) \leq 0, \text{ for } i \in 1 \ldots Nd \qquad 3\text{-}3$$

$$g_i^c(x, y(x)) = \mathrm{y}_i^t - y_i(x) = 0, for\ i \in 1 \ldots Nd \qquad 3\text{-}4$$

XDSM for Individual Discipline Feasible **(**IDF) architecture is shown in Figure 3-1. XDSM diagrams describe both data flow and process flow, so they provide a complete description of the algorithm. The thin-black lines in the diagram describe process flow, indicating what order the blocks get executed in. The thick-grey lines describe the movement of data, with vertical lines indicating inputs to a given block and horizontal lines indicating outputs. All of the parallelogram blocks are data-blocks, representing variables. All other blocks represent components or drivers in the analysis. When any given block is shown stacked up, and has an i in the title (e.g. Analysis i), that indicates that n such blocks could exist and could be run in parallel if desired. Each step in the process is given a numeric label (the first step in the process is always 0), which applies to both process flows and data flows. For a process flow, the labels are used to indicate loops (e.g. solver loops, optimizations). For example in Figure 3-1 the optimization loop is given the label “0, 3 →1”. This indicates that starting at 0, you follow the path through from 1 to 2 to 3 and then step 3 loops back through step 1 until an optimum is reached. The numeric labels in data-blocks indicate during which step the data is either input to or output from the block.

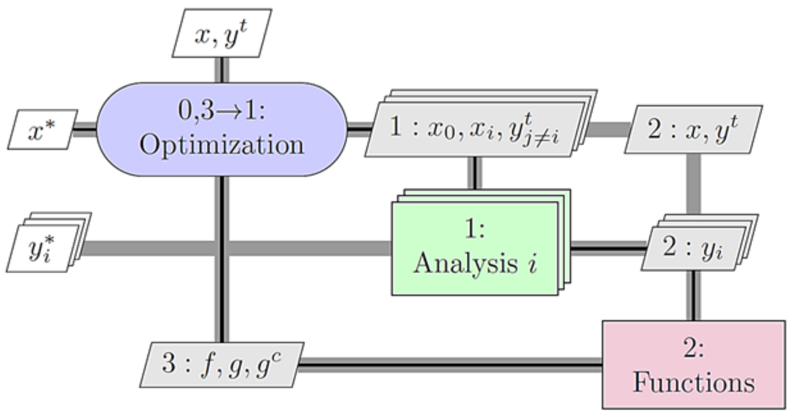


Figure 3-1: XDSM for IDF Framework

3.2.3 Multidisciplinary Design Optimization under Uncertainty (MDOUU)

In traditional deterministic designs, to account for uncertainties, the constraints were generally reformulated based on some predefined factors instead of the ideal ones. This ideology was based on the philosophy of marginal design, which was used to maintain redundancy of the system in face of uncertainties **[75]**. It is obvious that with this approach the designs and optimization are prone to reach solutions which are too conservative and over redundant, resulting in excessive cost and size penalty. This is quite revealing and convincing that these traditional methods of implicitly and roughly dealing with uncertainty are far from enough to economically improve systems performance, robustness and reliability.

This challenges us to develop more advanced and accurate analytical approaches based on a deeper mathematical foundation for uncertainty analysis and modeling. It would enable us to tackle uncertainties systematically and rationally.

Design optimization under uncertainty (DOUU) has been a research field for quite some time **[76]**. The major application of the methodologies developed in DOUU have been observed in aerospace engineering and civil engineering which have stringent regulation towards system reliability and robustness [77, 78].

DOUU has recently penetrated more formally in the domain of MDO **[79]**. It has been observed that DOUU can greatly improve design of systems by making use of the coupling between the disciplines and enabling collaborative optimization, and meanwhile enhancing the reliability and robustness.

As part of this work our intention is to introduce the concepts of DOUU in MDO framework in the context of microgrid planning, although these concepts are general enough and can be applied for other more complex design problems. As we refer to uncertainty throughout this thesis we would like to clarify that we refer to uncertainty in the probabilistic sense. We shall define a few terminologies for understanding design optimization under Uncertainty.

- **Uncertainty:** The incompleteness in knowledge and the inherent probabilistic or statistical variability of the system and its environment (also referred to as 'aleatoric uncertainty').
- **Robustness:** The degree of tolerance of the system to be insensitive to variations in both the system itself and the environment.
- **Reliability:** The likelihood that a component (or system) will perform its intended function without failure for a specified period of time under stated operating conditions.

In design optimization theory, the process for obtaining a design under certain constraints is referred to as design optimization more specifically deterministic design optimization, the mathematical problem can be formulated as:

$$\min f(x,p) \tag{3-8}$$

$$\text{s.t.}$$

$$g(x,p) \leq 0 \tag{3-9}$$

$$x^l \leq x \leq x^u$$

where **x**, is the design variable, **p** is system constant parameter vector, x^l and x^u are lower bound and upper bounds of **x** which defines the boundaries of the search space, $f(\cdot)$ is the optimization objective function and $g(\cdot)$ is the constraints.

There are a variety of mathematical models for DOUU such as *robust design optimization*, *Reliability-based design optimization*, *Two-Stage Stochastic optimization* etc. Depending upon one's problem and data we may choose one paradigm over the others.

- Robust Design Optimization: It is the methodology to optimize the design which is insensitive to various variations. The mathematical formulation is stated below

$$\min \tilde{f}(x,p) = F(\mu_f(x,p), \sigma_f(x,p)) \tag{3-10}$$

$$\text{s.t.}$$

$$g(x,p) \leq 0 \tag{3-11}$$

$$x^l \leq x \leq x^u \tag{3-12}$$

It is considered here that both **x** and **p** could be uncertain and μ_f and σ_f are the mean and standard deviation of the original optimization objective function $f(\cdot)$. It is interesting to observe here that by incorporating σ_f into the objective function, minimization of system sensitivity to uncertainties can be achieved.

- Reliability-based design optimization: This kind of optimization deals with obtaining optimal design and meeting reliability constraints. Hence it is a methodology to optimize the design which is reliable with small chance of failure under predefined acceptable level. The mathematical formulation of reliability based design optimization is given below

$$\min \tilde{f}(x,p) = \mu_f(x,p) \tag{3-13}$$

$$\text{s.t.}$$

$$P\{g(x,p) \leq 0\} \leq R \tag{3-14}$$

$$x^l \leq x \leq x^u \tag{3-15}$$

Where $P(\cdot)$is the probability of the condition in the curly brackets to be true and $\boldsymbol{R}$ is the reliability vector specified for each constraint.

There has been some work on combining the two methods above and developing methods called as reliability based robust design optimization (RBRDO).

- Two-stage stochastic programming:

$$\min_{x} f(x,p) + E_{\omega} Q(x,\omega) \tag{3-16}$$

$$\text{s.t.}$$

$$g(x,p) \leq 0 \tag{3-17}$$

$$x^{l} \leq x \leq x^{u} \tag{3-18}$$

Where

$$Q(x,\omega) = \min_{y} d_{\omega}^{T} y \tag{3-19}$$

$$\text{s.t.}$$

$$T_{\omega} x + W_{\omega} y = h_{\omega} \ \forall \omega \tag{3-20}$$

$$y \geq 0 \tag{3-21}$$

Here $E_{\omega}$is the expectation, ω denotes a scenario or a possible outcome with respect to the probability space (Ω, P) . The variables **x** are called the first stage variables, as they have to be decided upon before the outcome of the stochastic variable ω is observed. The variables **y** are the second stage variables: they can be calculated after the outcome of ω is known. The second stage problem depends on the data $\{q, h, T, W\}$ where any or all elements can be random. Matrices T and W are called the technological and recourse matrices. The second stage problem can be considered as penalty for the violation of the constraint $=\ h$. $Ax =\ b$, are the equality constraints which are not affected by the random variables are a first stage decisions. We shall consider only discrete distributions of P for the scenarios, so we can write:

$$E_{\omega}Q(x,\omega)=\sum_{\omega\in\Omega}p(\omega)Q(x,\omega) \tag{3-22}$$

Therefore now we can formulate this as a deterministic optimization problem where $f(x,p)=C^{T}X$ is a linear objective function.

$$\min_{X,Y} C^{T}X+\sum_{\omega}p(\omega)d_{\omega}^{T}y_{\omega} \tag{3-23}$$

$$\text{s.t.}$$

$$Ax=B \tag{3-24}$$

$$T_{\omega}+W_{\omega}y_{\omega}=h_{\omega},\ \forall\omega, x\geq 0, y_{\omega}\geq 0 \tag{3-25}$$

The chain of events in this model is as follows: first the decision maker implements the first stage decisions **x.** Then the system will be subjected to the random process described by (Ω, P), which results in an outcome $\omega \in \Omega$. Finally the decision maker will execute the second stage decisions **y** accordingly.

MDOUU is an approach towards systematic organization of the components involved in the multidisciplinary design optimization under uncertainty. It is important to understand that uncertainty has to be modeled at the system level and at the component level to ensure a reliable and robust system design. However, arranging these components in a sequence which leads to optimal decision is challenging given the complex cross coupling between the disciplines.

An intuitive approach to solve the MDOUU is to follow an iterative process. One needs to analyze and model the uncertainty in the underlying system under consideration (uncertainty may be in the parameters or design variables in the optimization problem). A systematic and simplistic approach towards solving MDOUU has been proposed **[75]** but it lacks the evaluation of alternatives based on the stake holder weightage. All of the currently available MDOUU models do not consider the cradle to cradle or cradle to grave based approach when considering the design of any engineering system. We integrate the MDOUU approach with Life Cycle Analysis using MCDA (Compromise Programming/VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method) as a tool.

This ensures that the engineering system design is not only robust and reliable but also economical and environmental friendly.

3.3 Multidisciplinary Design Optimization under Uncertainty for Microgrid Planning

3.3.1 Framework for Microgrid Planning

We provide the microgrid planners and policy makers a tool which is general enough and allows for an algorithmic approach towards planning of microgrids. It enables the planners to model and analyze the inputs that are significant locally and have an impact at a global scale. The inputs in real world are uncertain and we allow for probabilistic modeling of the uncertainties for robust system design. The framework allows for inputs to be used by design module that can use the information to produce results that are optimal and consider risk explicitly. Subsequently the planners and policy makers have the flexibility to modify parameters to suit the local needs and preferences. The framework not only takes into account economical issue but also environmental impact of the systems using life cycle analysis. Eventually, the planner is presented with various options given each has its own pros and cons, for the criteria most important to the local population. Thus we provide statistical tools that are useful for such a planning framework and present a detailed procedure for using them in the most optimal way. The framework is flexible enough to adapt to varying geographical and social environments. A broad overview of the framework is shown in Figure 3-2.

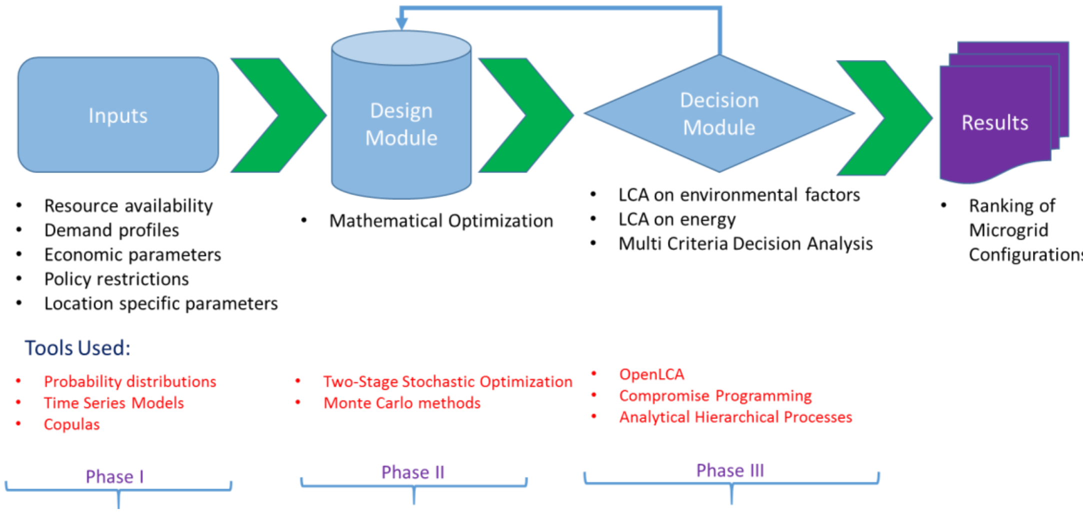


Figure 3-2: Framework for Microgrid Planning using Multidisciplinary Design Optimization: An Overview

In Figure 3-2, the statistical tools used in each module are listed below. These allow for a robust modeling of microgrids resulting in ranking of microgrid configurations given preferences and local regulatory and policy constraints.

In multidisciplinary design optimization under uncertainty, we shall model the uncertainties in each discipline, followed by simultaneous optimization using stochastic programming approaches, following which we need to evaluate the solution of the optimization based on certain criteria using approaches such as sensitivity analysis and multi-criteria decision analysis. Subsequently we shall either accept the solution or reiterate the optimization problem undergoing a parametric modification. Our framework for MDOUU is as shown in Figure 3-3.

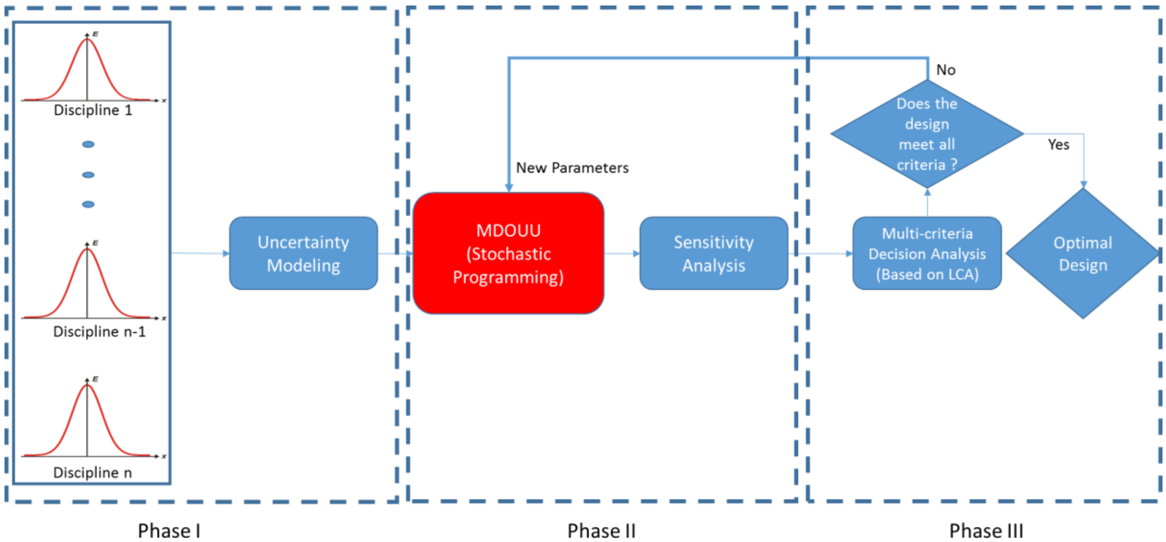


Figure 3-3: MDOUU Framework

As shown in the Figure 3-2 and Figure 3-2, the framework formulates a generalized model for most design problems where uncertainty in the design variables and parameters cannot be avoided. This framework ensures a reliable and a robust design and a complete economical and environmental analysis ranging from modeling of uncertainties in probabilistic sense to performing a stochastic optimization and analyzing the results by undergoing a Life Cycle Analysis of the proposed design and then choosing the most appropriate one based on a specified set of criteria. In an attempt to simplify the architecture for planners to execute their design we divided the framework into three phases, which can be briefly described as below:

Phase I: It refers to modeling the uncertainty in the system parameters or design variables in a probabilistic sense. This ensures a more robust modeling approach for producing scenarios for the purpose of reliable design. We use Kumaraswamy distribution **[80]** as a standard tool for modeling all of our parameters as it is a general distribution equivalent to the beta distribution**[81]** but with a simple analytical form.

Phase II: This acts as an engine of the entire framework which brings together the modeled parameters of phase I and for finding an optimal design keeping the design constrained within the technological, economic and environmental limits (MDO). It is flexible enough and allows the choice of the stochastic optimization paradigm that suits the problem at hand. The problem can be modeled as a mathematical optimization problem where we try to minimize/maximize a quantity (such as cost/benefits, environmental emissions/life time) subject to various technological/economical/environmental constraints. Followed by the optimization, we perform a detailed sensitivity analysis of the outcome to find out the response of the system to variations in parameters. We can use any of the monolithic or distributed MDO architectures here to obtain an optimal design. In our work for microgrid planning, we will use the IDF architecture as discussed previously.

Phase III: This phase involves comparing various feasible designs obtained from Phase II based on certain criteria as set by the system planners. This completes the framework for system design that not only ensures technical and economic feasibility but also considers the effect of environmental and social impacts into the design. To evaluate the impacts on environment and social life from the system we use Life Cycle Analysis (LCA) as a tool to measure and evaluate these more subjective parameters. It has been known that there is no fixed set of parameters to measure the social benefits or costs and hence it is left to the system planner and experts to choose the set of criteria they want the design to meet. We use Multi-criteria decision analysis (MCDA) approach to finalize the most appropriate. If chosen criteria are met, we accept it or else we need to modify the parameters in phase II and reiterate till we achieve a feasible result.

In our work for planning for microgrids we use the two-stage stochastic programming algorithm as a tool to solve a part of the complex MDO problem. We also extend this model to more generalized model by incorporating risk, and probabilistic constraints, which shall be shown in the later chapters of this thesis. We use the monolithic architecture given that multiple disciplines can be modeled using a single optimization problem, however, as the problem size increases a distributed MDO should be used. If we segregate the disciplines involved in microgrid planning, they can be categories into three broad categories:

- Economic Analysis (cost analysis, net present value, LCOE (Life Cost of Energy), ROI (Return on Investment) etc.)
- Environmental and Social Analysis (CO_2 emissions, GHG emissions, land usage, employment, LCA etc.)
- Technical Analysis and Feasibility (power demand, renewable resources available, spinning reserves, storage efficiency, LOL etc.)

Limiting the scope of our research for the purpose of proof of concept we shall consider specific parameters in each domain. Planners may wish to add additional parameters as per their need and the framework is expected to perform equally well. We consider some specific parameters from each discipline for Phase II where we perform MDOUU. LCA requires a more in depth understanding and expert knowledge as it helps us to analyze not only the technological feasibility but also the social and environmental impacts following a cradle to grave idea.

Therefore, possible configurations of the microgrids obtained from the MDOUU optimizer in Phase II undergo a detailed LCA and the results of LCA analysis are fed into an MCDA (Multi-criteria decision analysis) to choose a final configuration based on a set of criteria. If none of the configuration meets the criteria, we re-iterate and go to Phase II. The parameters are tuned and the process continues until a feasible configuration is obtained.

3.4 Multi Criteria Decision Analysis (MCDA): The Compromise Programming Approach

Planning of microgrids is a laborious task as it involves huge investments and multiple factors affect the success of a renewable energy in a microgrid. Multiple factors need to be evaluated and analyzed in decision making but also conflicting objectives need to be considered because of the increasingly complex social, economics, technological, and environmental factors that are present in such problems. Different groups of decision makers become involved in the process, each group bringing along different criteria and points of view, which must be resolved within a framework of understanding with mutual compromises **[82]**.

It is quite clear that the traditional single criteria decision making is not able to handle these complex problems. Therefore, the policy for substitution of fossil fuels by renewable energy needs to be addressed in a multi-criteria context. The complexity of the energy planning and energy projects make the multi-criteria analysis a valuable tool in decision making process. We use in our work Compromise Ranking Method, also known as VIKOR method as an effective tool for multi-criteria decision making **[83]**.

This method introduces the multi-criteria ranking index based on a particular measure of closeness to the ideal solution. The application of this method in the selection of a renewable energy investment project is demonstrated in Chapter 6.

In this thesis we use the Compromise Ranking Method, also known as the VIKOR method, in the selection of the renewable energy project. The method is enhanced by introducing the Analytical Hierarchy Process for assigning the weights of relative importance of attributes. There has been similar works **[84]** where the method is applied for material selection in an engineering process and in **[85]** where the method is applied in the selection of coal suppliers for thermal power enterprises in China.

The microgrid configuration obtained from the Phase II of the MDOUU and a detailed LCA is performed on it enables us to evaluate each configuration based on a few criteria explained later. We evaluate each configuration according to a criteria function, the compromise ranking is done by comparing the closeness to the ideal solution. The compromise solution is a feasible solution that is the closest to the ideal solution and a compromise means an agreement established by mutual consensus **[86]**. The multi-criteria measure for compromise ranking is developed from the L_p −metric used as an aggregating function in a compromise programming method [87, 88] and shown in Equation 3-26.

$$L_{p,j} = \left\{\sum_{i=1}^{n}\left[\frac{w_i(f_i^* - f_{ij})}{(f_i^* - f_i^-)}\right]^p\right\}^{1/p},\ 1 \le p \le \infty, j = 1,2, \dots, J \qquad 3\text{-}26$$

Here L_{1j} or $L_{\infty j}$ are used to formulate the ranking measure. Within the VIKOR method, the various J alternatives are denoted as $Alt_1, Alt_2, \dots, Alt_j$. For the configuration Alt_j the rating of the ith aspect is denoted byf_{ij}, i.e. f_{ij} is the value of the ith criterion function for the alternative Alt_j, and nc is the number of criteria. The compromise ranking algorithm VIKOR has the following four steps:

Step 1: Determine the best f_i^* and the worst f_i^- values of all criteria functions, $i = 1..nc$. If the ith function represents a benefit then $f_i^* = \max f_{ij}$ and $f_i^- = \min f_{ij}$, while if the ith function represents a cost $f_i^* = \min f_{ij}$ and$f_i^- = \max f_{ij}$.

Step 2: Compute the values of S_j and R_j for $j = 1..J$ by the relations

$$S_j = \sum_{i=1}^{n} \frac{w_i(f_i^* - f_{ij})}{(f_i^* - f_i^-)} \qquad 3\text{-}27$$

$$R_j = \max_i \frac{w_i(f_i^* - f_{ij})}{(f_i^* - f_i^-)} \qquad 3\text{-}28$$

where w_i are the weights of the criteria, expressing the decision-maker's preference as the relative importance of the criterion. In any renewable energy based project involving multiple stakeholders they act as the decision makers and play a significant role in determining their preferences for weighing the importance of different criteria. The weights of relative importance of the attributes are assigned using the AHP [84, 89], the steps are stated below:

1. Find out the relative importance of different attributes with respect to the objective. To achieve that, one has to construct a pairwise comparison matrix using a scale of relative importance. The judgments are entered using the fundamental scale of AHP. An attribute compared with itself is always assigned the value 1 so the main diagonal entries of the pair-wise comparison matrix are all 1. The numbers 3, 5, 7, and 9 correspond to the verbal judgments "moderate importance", "strong importance", "very strong importance", and "absolute importance" (with 2, 4, 6, and 8 for compromise between the previous values). Assuming n attributes, the pair-wise comparison of attribute i with attribute j yields a square matrix $DM_{n\times n}$where at_{ij} denotes the comparative importance of attribute i with respect to attribute j. In the matrix, $at_{ij} = 1$, when $i = j$ and $at_{ij} = 1/at_{ij}$.

2. We need to know the vector $WA = [WA_1, WA_2, WA_3 \dots, WA_{NC}]$which indicates the weight that each criteria is given in pair-wise comparison matrix DM. To recover the vector W from DM the process is mentioned below:

   - Divide each entry of column i in A by the sum of entries in column i. We get a new matrix called DM_{norm}(for normalized) in which the sum of all the entries in each column is 1.
   - Estimate of W_i is the average of the entries in the row i of DM_{norm}.

   Once we have obtained the pair-wise comparison matrix it is necessary to check it for consistency. We used the following four step procedure to check for consistency in the decision maker's comparisons. From now on, W denotes our estimate of the decision maker's weight.

   - Compute $(DM)W^T$
   - Find the maximum Eigen value of weight matrix

$$\lambda_{max} = \frac{1}{n}\sum_{i=1}^{nc}\frac{i^{th}\ entry\ in\ AW^T}{i^{th}\ entry\ in\ W^T} \quad 3\text{-}29$$

   - Compute the Consistency Index (CI) as follows:

$$CI = (\lambda_{max}) - \frac{nc}{nc-1} \qquad 3\text{-}30$$

The smaller the CI, the smaller the deviation from the consistency. If CI is sufficiently small, the decision maker's comparisons are probably consistent enough to give useful estimates for the weights for their objective. For a perfectly consistent decision maker, the ith entry in $(DM)W^T = nc \times$ (ith entry of W^T). This implies that a perfectly consistent decision maker has CI = 0.

- Compare the Consistency Index to the Random Index (RI) for the appropriate value of nc, used in decision making **[89]**. If CI/RI < 0.10, the degree of consistency is satisfactory, but if CI/RI > 0.10, serious inconsistencies may exist, and the AHP may not give useful results.

Step 3: Compute the values of Q_j using the relation below:

$$Q_j = vf\ (S_j - S^*)/(S^- - S^*) + (1 - vf)\left(R_j - R^*\right)/(R^- - R^*) \qquad 3\text{-}31$$

Where $S^* = \min_j S_j$; $S^- = \max_j S_j$; $R^* = \min_j R_j$; $R^- = \max_j R_j$ and vf is introduced as a weight for the strategy of maximum group utility, whereas $(1 - vf)$ is the weight of the individual regret where normally the value of vf is taken as 0.5. However vf can take any value from 0 to 1.

Step 4: The solution obtained by $\min_j S_j$ is with maximum group utility ("majority rule"), and the solution obtained by $\min_j R_j$ is with a minimum individual regret of the "opponent". Rank the alternatives, by sorting the values of S, R and Q in decreasing order. The results are three ranking lists. Proposed is a compromise solution, the alternative $Alt^{(1)}$, which is the best ranked by the measure Q(minimum), if the following two conditions are satisfied:

a. Acceptable advantage, $Q(Alt^{(2)}) - Q(Alt^{(1)}) \geq DQ$, where $DQ = 1/(J-1)$ and $Alt^{(2)}$is the alternative with second position on the ranking list by Q.

b. Acceptable stability in decision-making. The alternative $Alt^{(1)}$must also be ranked by S and/or R. This compromise solution is stable within a decision making process, which could be the strategy of maximum group utility (when $vf > 0.5$ is needed), or "by consensus" ($vf = 0.5$), or with veto ($vf < 0.5$).

If one of the above conditions is not satisfied, then a set of compromise solutions is proposed, which consists of:

c. Alternatives $Alt^{(1)}$ and $Alt^{(2)}$ if only condition above is not satisfied, or

d. Alternatives $Alt^{(1)}, Alt^{(2)}, Alt^{(3)}, \dots, Alt^{(M)}$if the first condition is not satisfied. $Alt^{(M)}$is determined by the relation $Q(Alt^{(M)}) - Q(Alt^{(1)}) < DQ$ for maximum n (the positions of these alternatives are in closeness.

Ranking of alternatives by VIKOR method/Compromise Programing gives us, as a compromise solution for all the values of v considered, which acts as an aid to the planners and decision makers.

3.5 Summary

This chapter introduces improvements to current MDO models by introducing MCDA and LCA as a part of the architecture. Multidisciplinary Design Optimization is a new field of research only about a decade old. This has been mostly used in the field of aerospace engineering given the complex nature of the problem. It has been observed that using the MDOUU framework leads to a systematic design of systems in clear steps. It uses the foundations from various domains such as statistics and optimization theory for developing robust mathematical model for solving the problem. We observed that these frameworks could be very useful in systematic planning of any engineering system, therefore we developed these systems further to develop a generalized framework which considers not only uncertainty in the design process but also the opinion of stake holders as they are the ones who shall be using the system.

Environmental concerns are tremendous given the extreme weather conditions and effects of global warming. It becomes our prime duty as system planners to ensure our systems are environmentally friendly, which drives us to bring in the idea of LCA in the framework. We use MCDA tools of compromise programming to conclude to a final design choice based on the constraints and the restrictions of various stake holders. Next chapter shall focus mainly on Phase I of our MDOUU framework towards modeling of uncertainty in the parameters.

Chapter 4

Microgrid Planning: Wind and Solar Resource Modeling

4.1 Introduction

In this chapter we will introduce mathematical models for wind and solar based renewable resources of energy which are utilized in the production of electrical energy. We will investigate the mathematical models for understanding and analyzing the characteristics of these renewable resources of energy to enables us plan and design microgrids more reliably. Novel approaches using copulas have been investigated to understand the dependence (correlation) between renewable energy resources in the spatial domain. Since these correlations are deterministic and hence not considering them lead us to over or under designed systems. Whereas, considering this correlation allows us to design appropriate systems with higher reliability.

4.2 PV/Solar Energy and Wind Energy modeling using Probability Distributions

It has been observed in the literature that solar irradiation is quite precisely modeled using the Hollands and Huggets distribution which can be closely approximated using a Gamma Distribution **[90]**. Wind speed is considered as a random variable and is modeled using the Weibull Probability Distribution (PDF) **[12]**. However, we used the Kumaraswamy distribution as mentioned earlier as a general tool to model all our parameters for the reasons described next. We obtain the parameters for each hour of the day and for three seasons in the year (Fall, Winter and Spring). This ensures that both hourly and seasonal variations are embodied into the distribution.

4.2.1 Kumaraswamy Distribution: A generalized tool to model parameters

The Kumaraswamy distribution is given by the Equations 4-1 and 4-2, where *f(x)* is the PDF and *F(x)* is the CDF.

$$f(x) = abx^{a-1}(1 - x^a)^{b-1} \qquad \text{4-1}$$

where $a \geq 0$, $b > 0$ and $x \in [0,1]$

$$F(x) = [1 - (1 - x^a)^b] \qquad \text{4-2}$$

Kumaraswamy distribution is used as a general tool to model renewable resource for two main reasons, firstly we are interested in energy/power which is a non-linear transformation of the resource and ease to integrate with copulas and hence a more general tool is required. Secondly, Kumaraswamy distribution is equivalent to the Beta distribution **[81]**, a most general distribution, but has a much simpler analytical form than the Beta distribution making it also computationally fast. It is important to note here that we used Kumaraswamy distribution not only for our resource modeling but also the demand. Utilizing the knowledge about the geographical location we will use Vine Copulas to model the dependency structure [91, 92]. It is important to note here that the copulas are used here to model the dependency structure of the wind power and not wind speed which is a unique approach. Non-linearity and non-monotonicity of the power curve inhibit this approach to be directly applied to wind speed in general. Wind power is what system planners are more interested rather than just the wind speed. We chose three sets of locations, Pittsburgh area in the USA, Toronto area in Ontario Canada and one of the remote sites in Canada in northern Alberta. We took data from RETScreen **[93]** for the available sites.

In our model we try to find the parametric best fit for the wind power generated at each location based on standard benchmark wind turbine (3kW Turbine based on HOMER **[94]**). Given the general nature and simplistic analytical form of the double bounded Kumaraswamy distribution **[80]** we fit the wind power to the distribution. Once we obtain the marginal for each location, then we establish the dependence structure using the pair copula construction (PCC) also known as Vine Copulas [91, 92].

Since the dependence of wind power at different locations is highly non-gaussian, it's not captured completely by correlation measures. Although an exact multivariate dependence model is possible using copula functions, unfortunately the non-Gaussian nature and the high dimensionality of our data complicates the finding of an adequate copula function. The only solution to this problem is PCC. We used rank correlation because it is robust to non-Gaussian data **[95]**.

4.2.2 A brief theory of Copulas

Copulas have become popular for modeling dependencies in random variables. The word *copula* is a Latin noun which mean 'a link' and was used first by a mathematician Abe Sklar [17, 96, 97].

Mathematically, copulas are functions which allow us to combine univariate distributions to obtain a joint distribution with a particular dependence structure.

Most simplistic demonstration of a copula is derived from how distributions are used. To demonstrate how copulas are used, one needs to recall how a cumulative density function (CDF) of a distribution is used to generate a random sample: most commonly to draw a value from a distribution one would start by sampling from a uniform distribution $U(0,1)$. Subsequently, this observation is treated as an observation of your variable`s CDF, one can obtain a sample from a PDF as explained in **[24]** and shown in Figure 4-1.

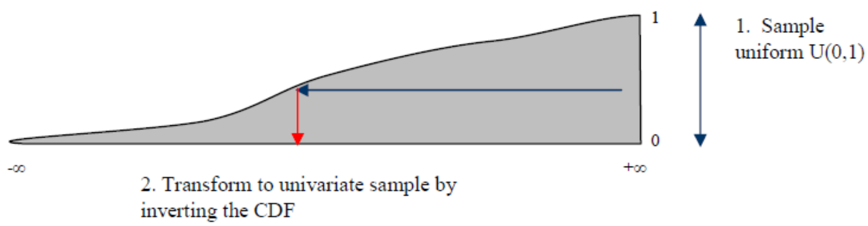


Figure 4-1: Obtaining a random sample from a CDF

Copulas extend this method to two or more distributions. Sklar's theorem is the foundation [17, 97] of copulas which states that, for a given joint multivariate distribution function and relevant marginal distributions, there exists a copula function that relates them.

4.2.3 Sklar's theorem

Let F_{xy} be a joint distribution with margins F_x and F_y. Then there exists a function $C: [0,1]^2 \rightarrow [0,1]$ such that

$$F_{XY}(x,y) = C(F_x(x), F_y(y)) \qquad 4\text{-}3$$

If X and Y are continuous, then C is unique; otherwise, C is uniquely determined on the (range of X) X *(range of Y).*

Conversely if C is a copula and F_x and F_y are distribution functions then the function F_{xy} defined by Eqn.4.3 is a joint distribution with margins F_x and F_y.

The proof of the above theorem can be found in **[17]** and **[96]**.

C must be a function of particular type with certain properties as described by **[97]** and explained well in **[17]**.

C is a copula if $C: [0,1]^2 \rightarrow [0,1]$ *and*

a. $C(0, u_m) = C(v_m, 0) = 0$
b. $C(1, u_m) = C(u_m, 1) = u_m$
c. $C(u_{m2}, v_{m2}) - C(u_{m1}, v_{m2}) - C(u_{m2}, v_{m1}) + C(u_{m1}, v_{m1}) \geq 0$ *for all* $v_{m1} < v_{m2}$, $u_{m1} < u_{m2}$
d. If *C* is differentiable once in its first argument and once in its second then, c. is equivalent to $\int_{v_{m1}}^{v_{m2}} \int_{u_{m1}}^{u_{m2}} \frac{\partial^2 C}{\partial u_m \partial v_m} du_m dv_m \geq 0$ for all $v_{m1} < v_{m2}$, $u_{m1} < u_{m2}$

.

This definition simply states that a copula is itself a distribution function, defined on *[0,1]*^{2} with uniform marginal. Each of the marginal distributions produces a probability of the one dimensional events. The copula function takes these probabilities and maps them to a joint probability, enforcing a relationship on the probabilities.

Therefore, using copulas to build multivariate distributions is a very flexible and powerful technique as it separates choice of dependence from the choice of marginal [17, 20, 96].

Sklar's theorem establishes one of the easiest ways of constructing a copulas. In this case, if F_x *and* F_y.are the marginal distributions, then copula is given by the formulation as shown in Equation 4-.

$$C(u_m, v_m) = F_{XY}(F_X^{-1}(u_m), F_Y^{-1}(v_m)) \qquad 4\text{-}4$$

4.2.4 Choosing the right Copula

The most important aspect in modeling any data using distributions is making the right choice for the selection of the distribution. As we have a large variety of distributions available we also have a large range of copulas to choose from. Quite often the choice of the copulas is based on the familiarity and analytical tractability. It is quite evident from the literature that Gumbel copula is used for extreme distributions, the Gaussian copula for linear correlations and the Archimedean copula and the t-copula for the dependence in tails, and so on [17, 96].

As the name suggests, the Gaussian copula is obtained from the normal distribution, various other geometrical and definition based methods are used to generate a wide range of copulas.

If we want to generate a copula given the marginal distributions for the two variables, let's say one with a Kumaraswamy distribution **[80]** with parameters *a* and *b* and other with lognormal distribution with parameters μ and σ, then we can use a copula from a member of the Frank family which is given by the following Equation 4.5 by substituting the relevant distribution functions and hence we generate a new joint distribution. The Kumaraswamy distribution for statistical design centering of integrated systems was done using copulas to formulate the dependence between the parameters [98, 99].

$$C(u_m, v_m) = -\frac{1}{\delta} ln\left(1 + \frac{(e^{-\delta u_m} + 1)(e^{-\delta v_m} - 1)}{(e^{-\delta} - 1)}\right) \quad 4\text{-}5$$

Here the parameter δ determines the level of dependence between the marginals.

There has been a lot of work already done in obtaining the marginal distributions **[100]**. Various approaches have proven to be good in various situations, such as either using the empirical distribution or using the parametric best fit. Usually the approach adopted is to start with an empirical distribution but due to discrete nature one may apply cubic splines or kernel smoothing technique to obtain a smooth curve.

Similarly another copula used for modeling tails is t-copula, also known as the *student t-copula*, as presented in Equation 4-6.

$$C_{\rho,\vartheta}(u_m, v_m) = \int_{-\infty}^{t_v^{-1}(u_m)} \int_{-\infty}^{t_v^{-1}(v_m)} \frac{1}{2\pi(1-\rho^2)^{1/2}} \left\{1 + \frac{x^2 - 2\rho xy + y^2}{\vartheta(1-\rho^2)}\right\}^{-(\vartheta+2)/2} dsdt \quad 4\text{-}6$$

The t-copula allows for joint fat tails and an increased probability of joint extreme events compared with Gaussian Copula, where ρ and ϑ are the parameters of the copula, and t_ϑ^{-1} is the inverse of the standard univariate t-copula with ϑ degrees of freedom, expectation 0 and variance $\frac{\vartheta}{\vartheta-2}$ **[96]**.

The Student's t-dependence structure introduces an additional parameter compared with the Gaussian copula, namely the degrees of freedom v. Increasing the value of v decreases the tendency to exhibit extreme co-movements.

The other copula utilized in our work is the *Gumbel copula.* The Gumbel copula is also an asymmetric copula, but it exhibits greater dependence in the positive tail than in the negative. This copula is given by Equation 4.7 where δ is the parameter controlling the dependence **[96]**.

$$C_\delta(u_m, v_m) = \exp(-[(-\log u_m)^\delta + (-\log v_m)^\delta]^{1/\delta}) \quad 4\text{-}7$$

The last copula explored in this work is the BB8 copula which is Joe-Frank Copula. This is a two parameter family of Archimedean copula. The copula CDF is given by Equation 4-8.

$$C_{\vartheta,\delta}(u_m, v_m) = \delta^{-1}(1 - \{1 - \eta^{-1}[1 - (1 - \delta u_m)^{\vartheta}][1 - (1 - \delta v_m)^{\vartheta}]\}^{1/\vartheta}),$$
$$\vartheta \geq 1, 0 \leq \delta \leq 1 \qquad 4\text{-}8$$

Where

$$\eta = 1 - (1 - \delta)^{\vartheta} \text{ and } 0 \leq (u_m, v_m) \leq 1 \qquad 4\text{-}9$$

We simulate data based on the model above and use it for simulating the optimization model discussed below.

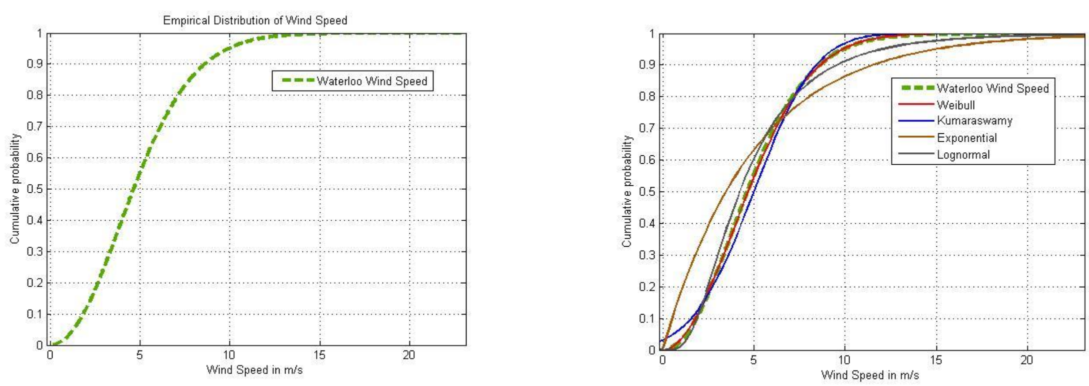
4.3 Results and discussions

This section presents detailed results of each of the model presented in this chapter.

4.3.1 Renewable Energy Source: Wind and Solar

As mentioned in Section 4.2, we modeled Wind and Solar power using Kumaraswamy distribution as described by Equations 4-1and 4-2 (the pdf and cdf of the distribution function are shown).

We tried fitting various distributions to sample data for the city of Waterloo, Ontario, Canada and found that the Weibull Distribution fits the best. In Figure 4-2 (b) empirical CDF for wind speed is compared with others.



(a) (b)

Figure 4-2: In the figure it is evident that Weibull Distribution and Kumaraswamy distribution fits the empirical wind speed distribution well

The Table 4-1 also shows the comparison of the Akaike's Information Criteria (AIC) for various distributions which confirm our visual notion. AIC is defined as shown below in Equation 4-

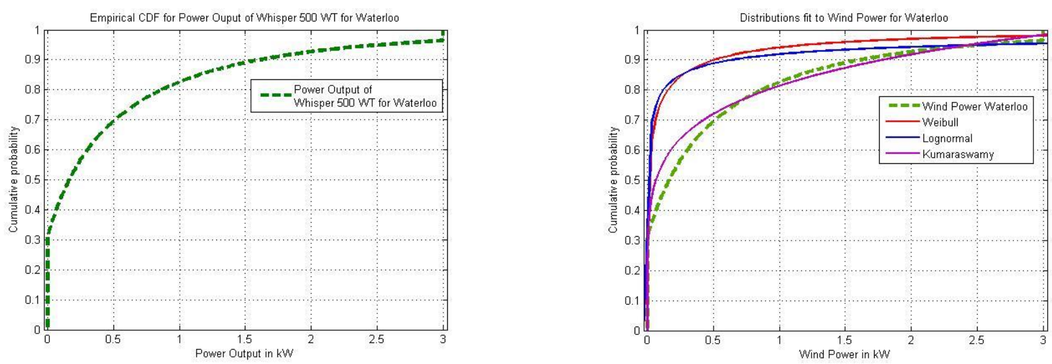
$$AIC = 2k - 2\ln(L) \tag{4-10}$$

Where k is the number of parameters in the distribution and L the maximized value of the likelihood function. The minimum value of AIC is chosen to be the best fit **[101]**.

Distribution	AIC
Weibull	40914.8
Kumaraswamy	41079.8
Exponential	45722.4
Lognormal	42156.2

Table 4-1: AIC for various distributions fit to Wind Speed

As a system planner, considering the efficiency of the wind turbine we are interested in the wind power generated and hence to analyze the wind power generated using the Whisper 500 wind turbine. We tried to fit the power generated to various distributions as shown in Figure 4-3.

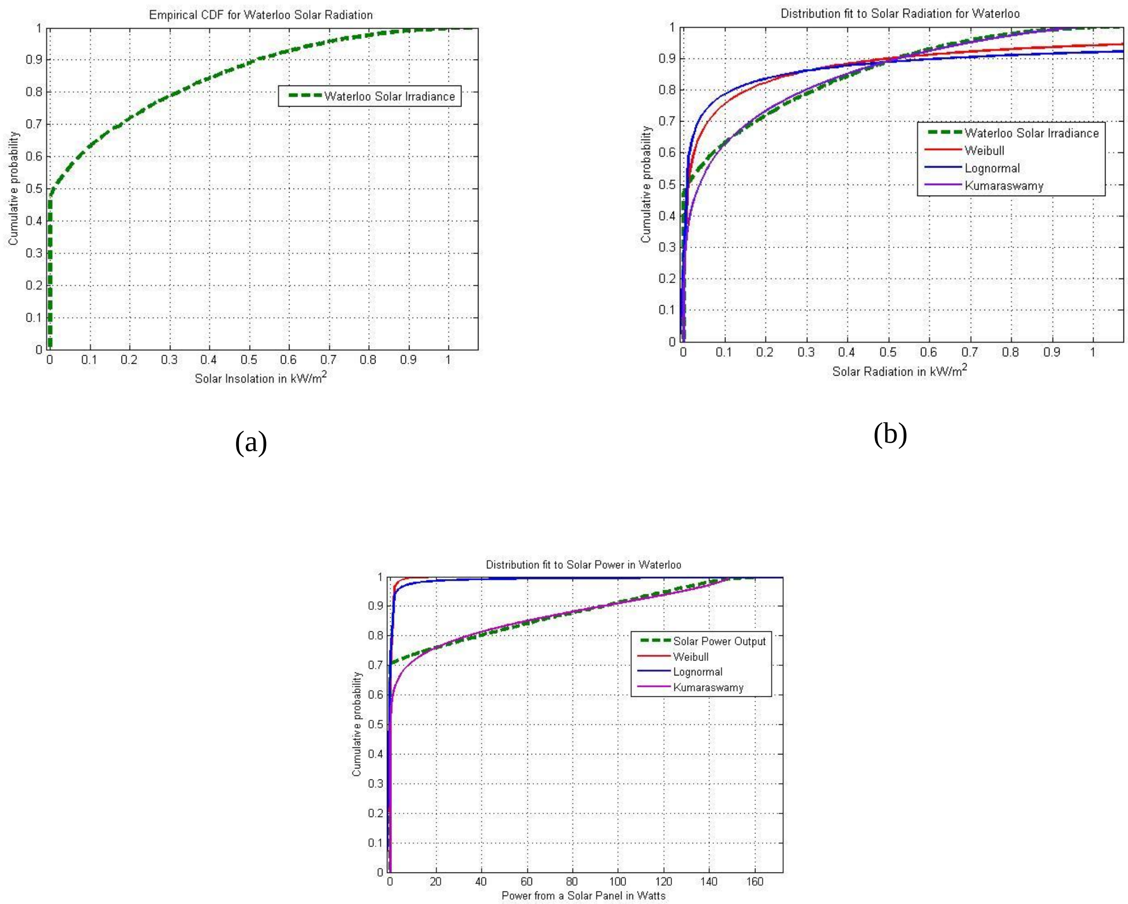


(a) (b)

Figure 4-3: Empirical distribution and distribution fitting to Wind Power generated from Whisper 500 3kW wind turbine

It is quite evident that no specific distribution fits the power generated quite well. We chose the Kumaraswamy Distribution (given by Equation 4.1 and 4.2) which seems to fit the wind power the best. It is one of the 4 parameter distribution and hence it is not surprising that it represents the data better than the others but its form is simple.

We tried fitting a few probability distribution functions for solar radiation but concluded that a good fit is not really obtained using the Gamma distribution **[90]** which has been used so in the literature; again, Kumaraswamy distribution has a good statistical fit as can be seen in Figure 4-4.



(a) (b)

(c)

Figure 4-4: Distributions fit to solar radiation and solar power data of Waterloo, ON

From the above analysis Kumaraswamy distribution was chosen as the most appropriate choice for modeling solar and wind power. We modeled for each hour and three seasons independently resulting in overall 24 hours, 3 seasons and 4 parameters for each distribution to a total of 288 parameters for wind power. Whereas for solar power which is available for 12 hours in a day we have approximately 144 parameters for the Kumaraswamy distribution.

4.3.2 Spatial dependence between renewable resources of energy

In Section 4.2.3, we discussed about the correlation and dependence between the renewable resources of energy. It is found that modeling wind power just using marginal distributions is good but adding the spatial domain to it increases the accuracy substantially. Also, this tool (copulas) is general and gives us flexibility to model wind power in places with highly non-linear dependence data. We chose 12 locations with 3 sites, each having 4 locations. Two sites are in Canada and one in the United States. It was important to analyze the 3 sites independently given they were spatially very far off and their impact on each other would be negligible. The idea of choosing these three locations was to investigate the nature and typical correlation structure present among nearby location which may possibly be part of the same microgrid or the grid. Figure 4-5 shows the histogram for wind energy generation of each location using a 3kW wind turbine. Figure 4-6 shown the geographical locations of the sites chosen for study.

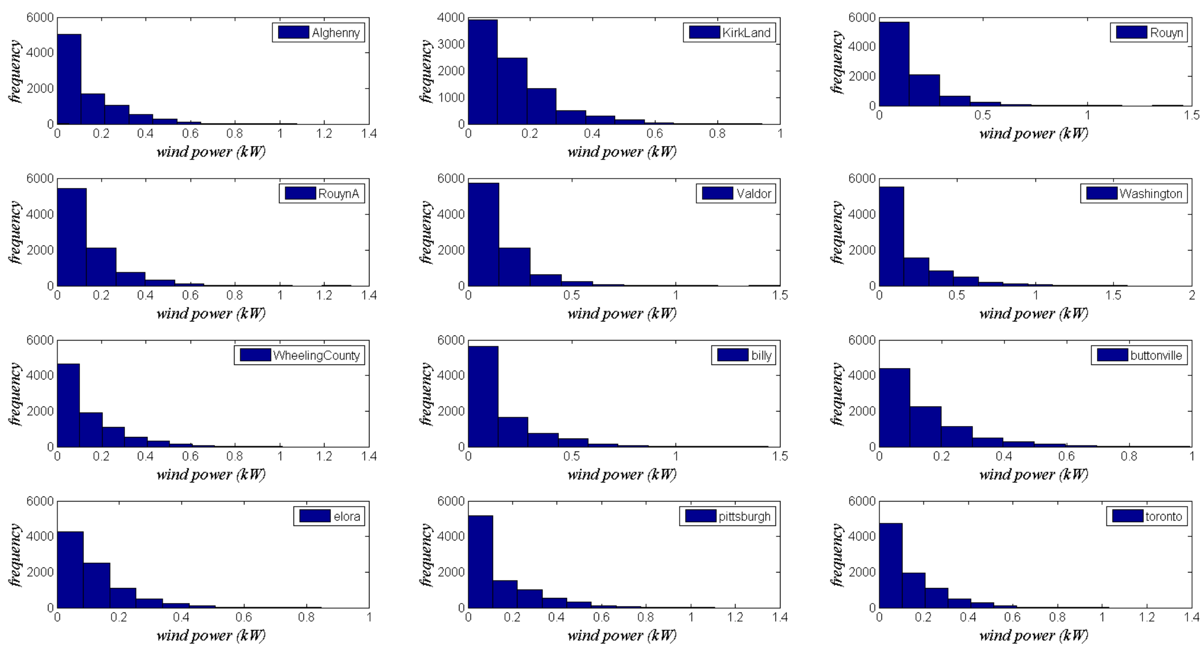


Figure 4-5: Histogram for the 12 Locations, the data represented in the histograms is the wind power generated by a standard wind turbine with 3kW rating

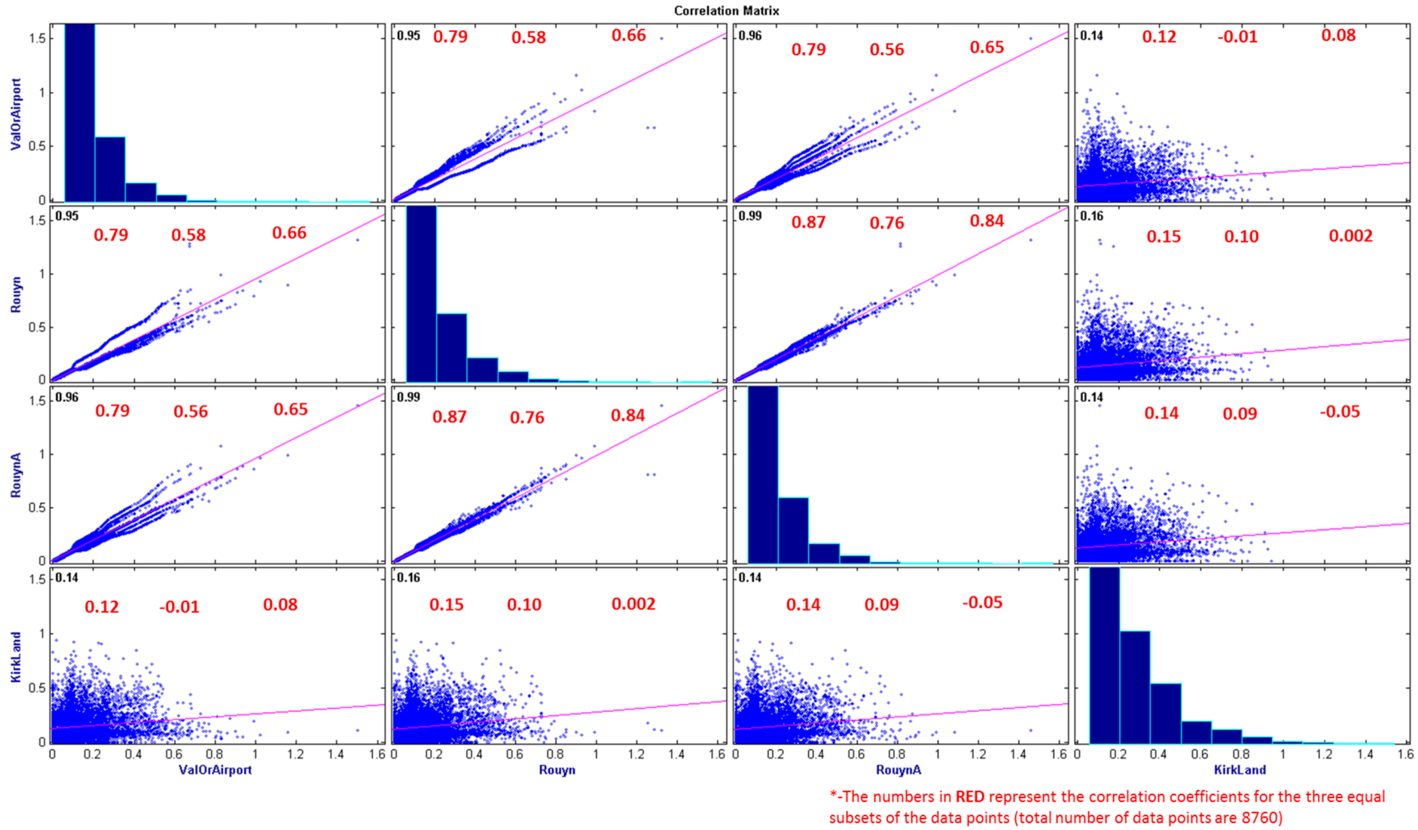
(a) (b) (c)

Figure 4-6: Spatial distribution of the four sites in each location is shown (a) in the northern communities starting from the left (KirkLand Lake, Rouyn, RouynA and ValdOr Airport) (b) in Greater Toronto Area (Buttonville, Toronto, Billybishop Airport and Pearson) (c) in the United States of America in the Pittsburgh area (Algheny, WheelingCounty, Pittsburgh and Washington)

In Figure 4-6 (a) this location was chosen more specifically because the objective is to allocate the power in remote communities which are stand alone and we wish to have a stable power profile from the renewable energy based systems. Figure 4-6 (b) site was chosen in the middle of the province of Ontario, Canada. The area nearby city of Toronto, it has a very unique location given the proximity to a large water body, the lake Ontario, and also its association with the main grid. The electricity demand in this location is very high and critical. Therefore achieving stable power is of great importance. Increase in penetration of the renewable energy based systems, more specifically wind power, may lead to instability in the power on the grid. Figure 4-6 (c) Lastly we chose the area in and around Pittsburgh in USA given its central location. It is not close to a large water body and also is connected to the grid.

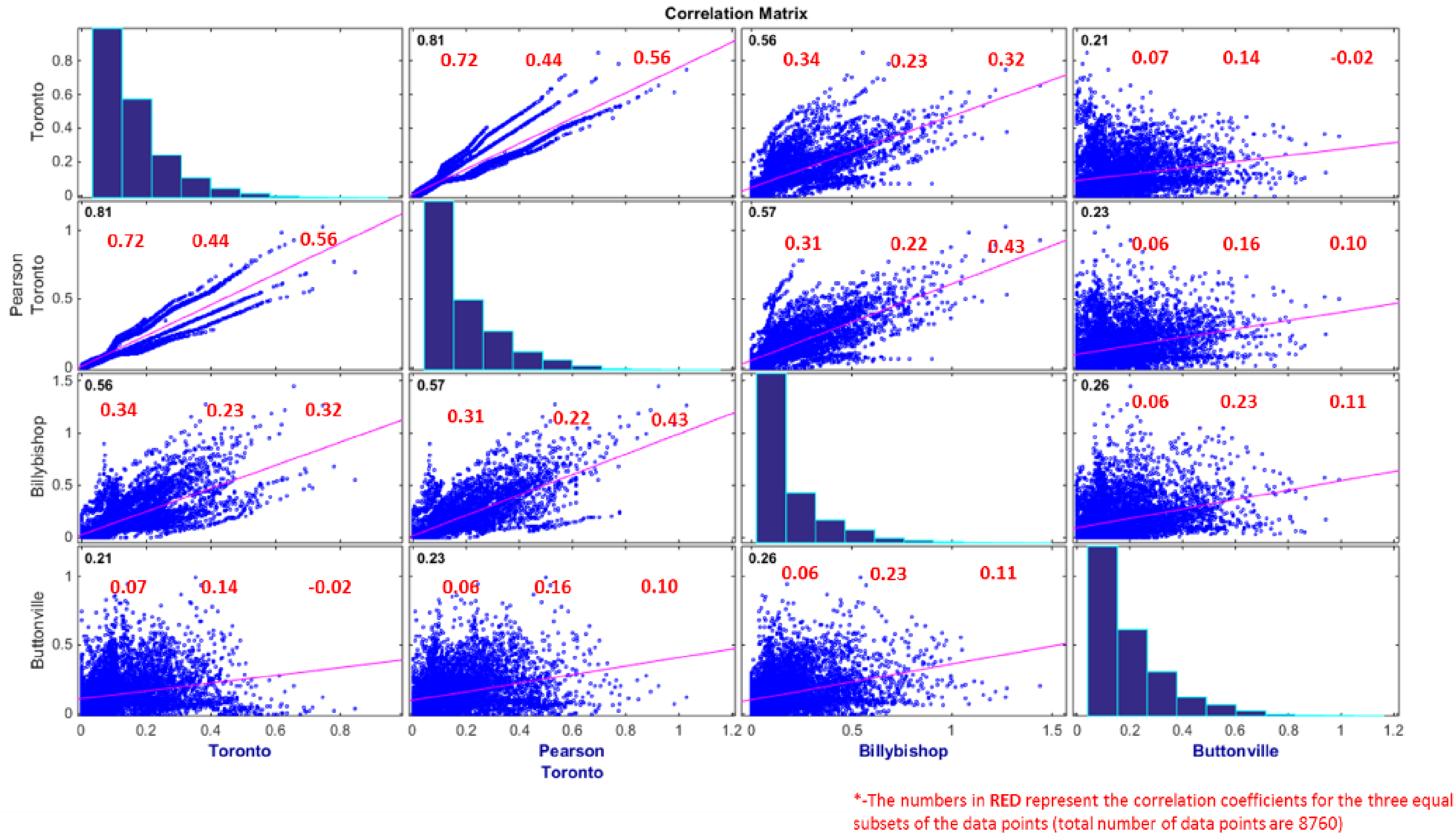
We analyzed the correlation between the wind energy at each of these sites. Based on the varying correlation coefficients in the three zones of the dataset it is confirmed that the correlation is non-linear and data being non-Gaussian we chose Kendall rank correlation as the choice of correlation parameter.

In Figure 4-7 (a), it can be seen that in Site 1 that correlation between Kirkland and other locations is highly non-linear while others it appears linear but in fact it is non-linear as we performed some more detailed analysis by segregating the dataset into three halves and evaluating the correlation in them. It reveals that although the overall exploratory analysis of data may show linear correlation but it is actually non-linear (the numbers in red in the Figure 4-7 are the correlation coefficients of the three sub-segments of the data). Figure 4-7 (b) if we observe similar data at a site close to a water body it is observed that the dependence structure between the locations is more non-linear and non-Gaussian, which shows the Greater Toronto Area. This cannot be generalized and geography of the location plays a very important role we can see in Figure 4-7 (c) that the dependence is not the same as others. Therefore, as there is no standard way of defining the correlation structure and the correlation is non-linear we need more generalized tools and hence *Copulae* seem to be a perfect choice for this purpose.



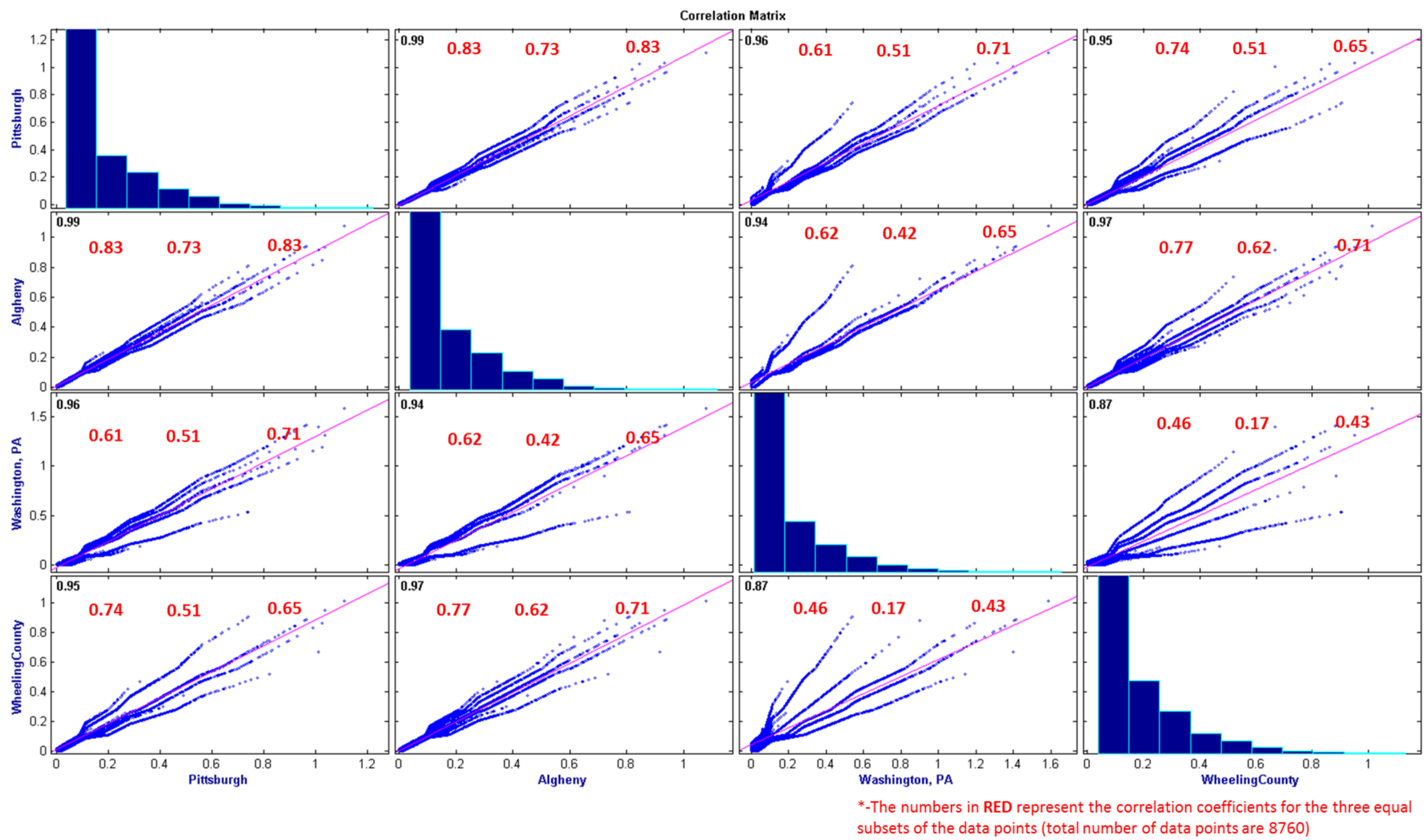
(a)

Cross-Correlation between various sites (KirkLand Lake, Rouyn, RouynA and ValdOr Airport)



(b)

Cross-Correlation between various sites (Buttonville, Toronto, Billybishop Airport and Pearson)



(c)

Cross-Correlation between various sites (Algheny, WheelingCounty, Pittsburgh and Washington)

Figure 4-7: Cross-Correlation between various sites is shown (a) (KirkLand Lake, Rouyn, RouynA and ValdOr Airport) (b) (Buttonville, Toronto, Billybishop Airport and Pearson) (c) (Algheny, WheelingCounty, Pittsburgh and Washington)

From the observations above we propose that marginal distribution of wind power at each location can be modeled using the Kumaraswamy distribution as it provides an excellent fit and also has the simple analytical form for the distribution function. While the dependence structure between the locations within a site we utilized the approach of Vine Copulas, the choice was driven upon analyzing the following main factors:

- The wind power in each location was non-normally distributed
- The dependence was highly non-linear as evident from the Figure 4-7 (a) and Figure 4-7 (b)

Using Vine Copulas made much sense given the ease of modeling of the dependence between a pair of locations and connecting them with each other. The marginal for each locations are modeled using the Kumaraswamy distribution and the estimates are shown in Table 4-2.

	Kumaraswamy Distribution Parameters			
Location - Site	a	b	Z_{min}	Z_{max}
KirkLand Lake - 1	0.412	1.582	0	0.975
Rouyn - 1	0.358	1.783	0	1.475
RouynA - 1	0.460	2.033	0	1.329
ValdOr Airport - 1	0.298	1.353	0	1.510
Buttonville - 2	0.432	1.995	0	0.994
Toronto - 2	0.310	1.786	0	0.931
Billybishop Airport - 2	0.449	2.298	0	1.548
Pearson - 2	0.434	1.976	0	1.080
Algheny - 3	0.511	2.455	0	1.085
WheelingCounty - 3	0.511	2.306	0	1.060
Pittsburgh - 3	0.360	2.024	0	1.135
Washington - 3	0.260	1.377	0	2.447
Site 1 - (KirkLand Lake, Rouyn, RouynA and ValdOr Airport), Site 2 – (Buttonville, Toronto, Billybishop Airport and Pearson), Site 3 – (Algheny, WheelingCounty, Pittsburgh and Washington)				

Table 4-2: A set of Kumaraswamy Distribution parameters for the wind power for hour 12 at each location

In Table 4-2, we show only a set of the parameters for the Kumaraswamy distribution fitted to the hourly data for the 12 locations in 3 sites for one hour.

Now more importantly, we need to model the dependence between the locations within a given site. Let us start with Site-2 in which the dependence structure seems to be highly non-linear (both from exploratory plots and sub-segmented data correlation analysis) for all cases as a benchmark case.

The data had to be converted from the real domain to the copula data which lies inside the [0,1] hypercube. We converted the data by taking the Kumaraswamy cdf of the individual data series.

	Toronto	**Pearson**	**BillyBishop Airport**	**ButtonVille**	**Sum**
Toronto	1.000	0.811	0.561	0.213	2.585
Pearson	0.811	1.000	0.566	0.233	**2.610**
BillyBishop Airport	0.561	0.566	1.000	0.255	2.382
ButtonVille	0.213	0.233	0.255	1.000	1.701

Table 4-3:The Kendall Correlation Matrix

We need to make a choice to define our copula structure using the C-Vine. Therefore in deciding upon the root node we use the approach of the node with highest sum of Kendall correlation coefficients. Therefore Pearson site is chosen as the root node for our C-Vine Copula. In this case we do not require the second order dependence as first order dependence models the structure very efficiently.

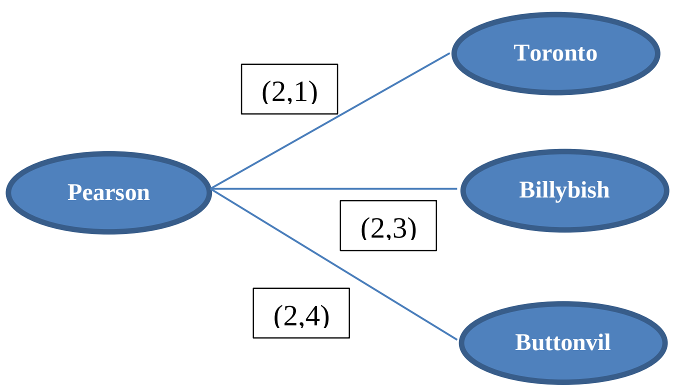
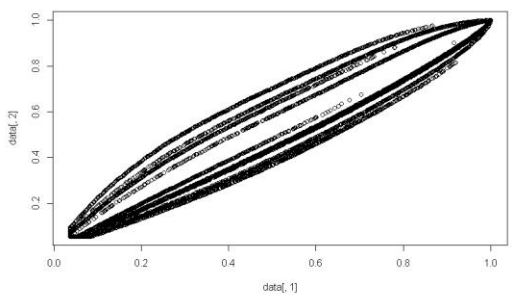


Figure 4-8: C-Vine, primary tree for dependence based on Kendall Correlation

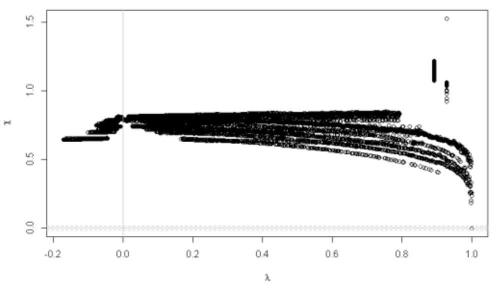
Before we can finalize on a specific copula for the data, we need to perform exploratory analysis which gives us better understanding of the dependence structure and ability to choose the right copula. The three plots used for analyzing the dependence structure for our studies are:

- Scatter Plot: They are plots displaying the set of data points on X-Y plane. They are helpful in understanding the underlying relationship between the data points.
- Chi-plots **[102]**: They are used in conjunction with a scatterplot, to investigate possible association of two variates as manifested in a sample of bivariate measurements. The method is designed so that the plot is approximately horizontal under independence, and under various forms of association it produces corresponding characteristic patterns.



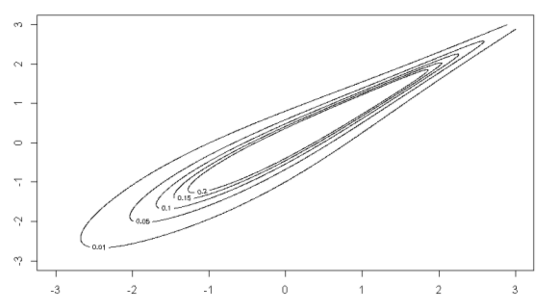
Scatter Plot of Data

(a)



Chi-Plot

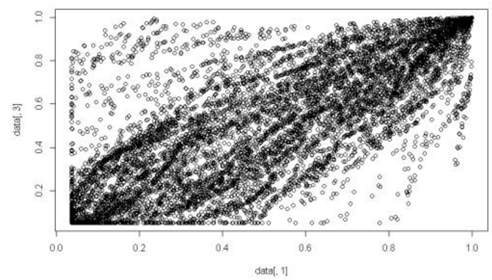
(b)



Contour Plot of fitted gumbel copula

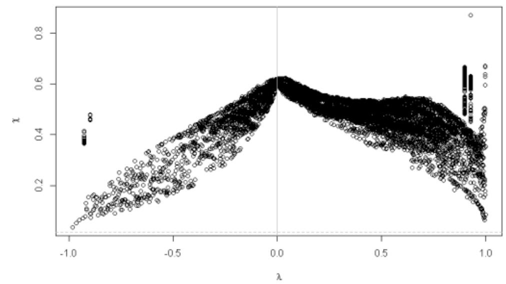
(c)

Figure 4-9: Shows the scatter plot, chi-plot and simulated data from copula for Class 4 – Gumbel Copula, alpha = 5.301, for two locations – Pearson Airport and Toronto downtown



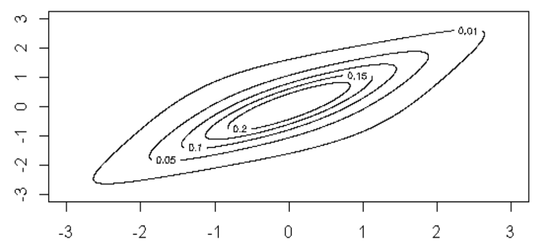
Scatter Plot of the data

(a)



Chi-Plot

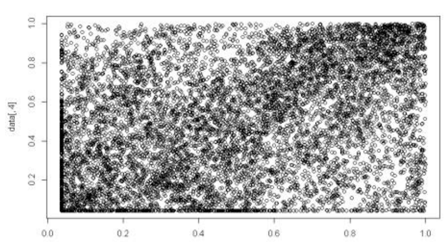
(b)



Contour Plot of the t-Copula

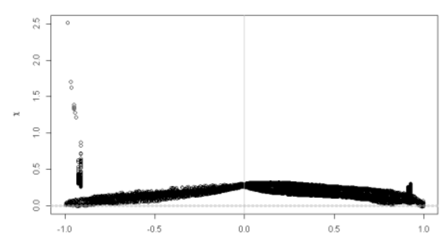
(c)

Figure 4-10: Shows the scatter plot, chi-plot and simulated data from copula for Class 2 - t-copula, par1 = 0.77, par2 = 4.8, for two locations - Pearson vs Billybishop



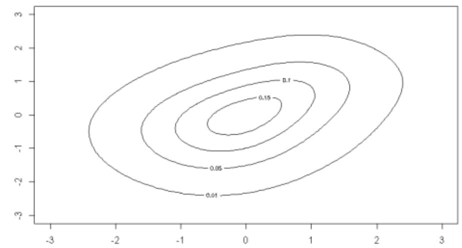
Scatter Plot

(a)



Chi-Plot

(b)



Contour Plot of BB8 Copula

(c)

Figure 4-11**:** Shows the scatter plot, chi-plot plot and simulated data from Class 10 – BB8 Copula, par1 = 2.69 par2 = 0.68, for two locations – Pearson vs Buttonville airport

Examining the above plots, in Figure 4-9 and Figure 4-10 we can see that Chi-plots and the scatter plot indicate a non-linear dependence where as in Figure 4-11 the scatter plot looks random but Chi-plot does indicate slight non-linear dependence.

Hence based on the above observation and estimation of the best fit, maximum likelihood estimates for the copula parameters we finalize the C-Vine structure as shown in Figure 4-12. The choice of copula is made by comparing the fit of various copulae using AIC as goodness of fit test. The respective copula for each pair is shown in Figure 4-9(c), Figure 4-10 (c) and Figure 4-11 (c).

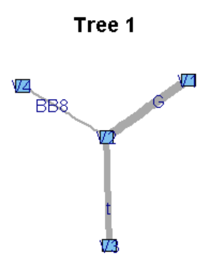


Figure 4-12: Tree 1 estimated using Maximum Likelihood Estimates for Site-2 (Toronto Area)

Once the underlying the C-Vine copula structure is found we can simulate the data. Figure 4-12 shows the structure of the C-Vine for our example where vertices V1, V2 , V3 and V4 show the four locations in the site while the edges show the type of copula used for modeling the dependence between the two nodes (BB8, G – Gumble, t-Copula). For simulation using C-Vine we need the Vine matrix which defines the connections and parameter matrices stating the parameters of each of the copulas represented by each link. We simulate data based on the C-Vine whose structure, copulae and parameters are defined based on the approach adopted in **[92]**

4.4 .Summary

This chapter introduces three main aspects of this thesis and more specifically parts of the MDOUU framework in Phase I. We modeled the uncertainty in the resources using probabilistic approach, mainly using the Kumaraswamy distribution. We also used the idea of dependence to model correlation between uncertain parameters by introducing the idea of copulas. Copulas are mostly used in the domain of financial engineering to model dependence in portfolios. Here we used to model dependence in wind power in spatial domain.

We utilized the data models from this chapter in the future models for generating data and using then in the optimization problems presented in Chapter 5.

Chapter 5
Microgrid System Planning Optimization Models

5.1 Introduction

In an isolated microgrid system planning with small carbon footprint, the penetration of renewable energy is usually high. In such power grids energy storage is important to guarantee an uninterrupted power supply. Renewable sources of energy are highly uncertain and have relatively high capital investment but have a positive impact on the environment. We introduce the basic optimization framework using a deterministic optimization model. In planning and design of renewable energy based microgrid systems, we introduce the approach of two-stage stochastic programming to incorporate the various possible scenarios for renewable energy generation and costs in the planning of microgrid. Most planning problems are similar to an investment decision and hence we wish to minimize the risk in our investment. Therefore we introduce the idea of *Markovitz* objective function to consider the uncertainties in the second stage variables. Hence we develop an overall minimal risk based stochastic programming approach for planning of such systems. The model is generic to be used for any location to suit their geographical topography and demand/supply needs.

5.2 Deterministic Optimization Model

HPS capacity optimization problem has been extensively studied in the literature from different perspectives. In most cases, the design strategy was to select system configuration following a heuristic approach **[103]** conduct system simulations using static rules and pick an operating policy that minimizes cost. Several simulation tools such as HOMER and HYBRIDS have been used to compare capacity decisions and operating strategies in different scenarios.

In this work, an approach to simultaneously find the optimal configurations and operating plan of a HPS is presented. We formulate the problem as a non-linear programming optimization problem.

Mathematical Model

Equations 5.1 – 5.12 constitute the mathematical formulation of the deterministic optimization problem for the planning and operation of the micro grid. In the model below N_{DG} is the total number of non-renewable generators, I_{DG} (diesel generation), I_{PV} (PV panels), I_{WT} (wind turbine), IC_{BAT} (batteries) are the levelized annual installation cost of generation resources and storage ($). Levelized annual operation and management cost for generation resources are given by OM_{DG}, OM_{PV}, OM_{WT} in ($/year) and FC_{DG} is the fuel cost in $/kWh. The charging power Chb and power supplied by all the batteries DChb is given in kW and kWh respectively. The maximum allowable charge of a battery is C_{MAX} (kWh). The power output from generation sources O_{DG}, O_{PV} and O_{WT} (kW). The demand D is in kW while D_{us} is the unserved demand in kW. The rated capacity of diesel generator and battery are given by RC_{DG} and RC_B (kW). The energy stored in the battery is Ce (kWh). The self-discharge and discharge efficiencies of a battery are γ_{sd}, γ_d in %. The maximum allowable depth of discharge of a battery in % is DOD_{MAX}. T_b is the lifetime throughput in kWh of one battery. The hour of the day is *t* and *m* is day.

Objective Function

In Equation 5-1, the objective function of the optimization problem is shown, it constitutes the various installation and operation costs for a micro grid **[62]**.

$$\begin{gathered} minimize\ N_{DG}[I_{DG} + OM_{DG}] + N_{PV}[I_{PV} + OM_{PV}] + N_{WT}[I_{WT} + OM_{WT}] \\ +IC_{BAT}\left[\frac{\sum_{m=1}^{365}\sum_{t=1}^{24} C\,b(t,m)}{T_b * C_{MAX}}\right] + FC_{DG}\left[\sum_{m=1}^{365}\sum_{t=1}^{24} O_{DG}(t,m)\right] \end{gathered} \qquad 5\text{-}1$$

Constraints

The optimal solution must satisfy the following set of constraints:

1) Supply-Demand balance at any time interval is given as: power demand is equal to the power supply from RES, diesel and battery plus the unserved load.

$$\begin{gathered} D(t,m) + Chb(t,m) \le O_{DG}(t,m) + N_{PV} \cdot O_{PV}(t,m) + N_{WT} \cdot O_{WT}(t,m) \\ +DChb(t,m) + D_{us}(t,m) \\ \forall t,m \end{gathered} \qquad 5\text{-}2$$

2) Diesel Generator output limit: Power output of the diesel generators cannot exceed their gross rated capacity

$$O_{DG}(t,m) + SR(t,m) \le N_{DG} \cdot RC_{DG}\ \ \forall t,m \qquad 5\text{-}3$$

3) Battery State of Charge (SoC): An energy conservation constraint which links the energy stored in the battery at any time with the charging and discharging processes.

$$Ce(t,m) = Ce(t-1,m) \cdot (1-\gamma_{sd}) + Cb(t-1,m) - \frac{Db(t-1,m)}{\gamma_d} \ \forall t,m \qquad 5\text{-}4$$

4) Battery capacity limits: The battery has an upper limit with respect to its SoC, there is a maximum depth of discharge (DOD) that can be reached in a cycle

$$(1-DOD_{MAX}) \cdot C_{MAX} \cdot N_B \le Ce(t,m) \le C_{MAX} \cdot N_B \qquad 5\text{-}5$$

5) The electric power charged to or discharged from the battery cannot exceed its rated capacity

$$Chb(t,m) \le N_B \cdot RC_B \qquad 5\text{-}6$$

$$DChb(t,m) \le N_B \cdot RC_B \qquad 5\text{-}7$$

6) Reliability Constraint: It is to ensure that a desired loss of load is achieved

$$\frac{\sum_{m=1}^{365}\sum_{t=1}^{24} D_{us}}{\sum_{m=1}^{365}\sum_{t=1}^{24} D} \le EUE_{MAX} \qquad 5\text{-}8$$

7) Budget/Resource Constraints: To make sure the number of RES and storage units used in the system do not go beyond budget and the solution is practical. This constraint may be also be modeled using the monetary value of the components too.

$$N_{(PV,min)} \le N_{PV} \le N_{(PV,max)} \qquad 5\text{-}9$$

$$N_{(WT,min)} \le N_{WT} \le N_{(WT,max)} \qquad 5\text{-}10$$

$$N_{(B,min)} \le N_B \le N_{(B,max)} \qquad 5\text{-}11$$

8) Preventing simultaneous charging and discharging of batteries: This constraint eliminates the possibility of the simultaneous charging and discharging of the batteries

$$Chb(t,m) \times DChb(t,m) = 0 \ \forall t,m \qquad 5\text{-}12$$

9) Energy to Power Ratio (E/P): The energy capacity of any battery for a certain power rating is determined based on its E/P ratio, which is a relationship between the power and energy size for a certain energy storage technology. The energy size represents the maximum amount of energy that can be stored for a certain time. Whereas the power size is the rate at which the energy storage is capable of discharging/charging power continually.

$$EPR\ or\ \frac{E}{P} = \frac{Energy\ Capacity, kWh}{Power\ Rating, kW} \tag{5-13}$$

$$\underline{EPR} \cdot N_B \cdot RC_B \leq Ce(t,m) \leq \overline{EPR} \cdot N_B \cdot RC_B\ \ \forall t,m \tag{5-14}$$

5.2.1 Economic Analysis

When the time value of money is to be taken into consideration, one must bring all the cash flow in the different time frames to the same time frame, i.e., a payment in the future at the end of the year n and the set of yearly installments for n years can be brought to the present in order to compare them.

The annual equivalent method converts all the cost during the lifetime of a plant (or the duration of the planning period) into an annual cost and then compares all the options. The future cost *F* at the end of for year *n* can be brought to the present cost PC using

$$PC = F\frac{1}{(1+i)^n} \tag{5-15}$$

where *i* is the discount rate. Once this is done the annuities can be evaluated using

$$AC = PC\frac{i(1+i)^n}{(1+i)^n - 1} \tag{5-16}$$

$$CRF(i,n) = \frac{i(1+i)^n}{(1+i)^n - 1} \tag{5-17}$$

where AC is the annual value, *CRF* is the capital return factor for a given interest rate *i* and period *n* years. In this system, we consider the annual rate of interest as 6%. The real interest rate is equal to the nominal interest rate minus the inflation rate. The project life time is considered as 25 years. We evaluate the annualized cost of the entire system and the operational cost of the diesel generator to ensure reliable operation of the system for a desired loss of load.. We also included in our model a constraint for the maximum annual capacity shortage, varying from 0% to 30%

A wide variety of criteria play a part in the economics of DER based planning. The two principal economics elements in any such design are the total net present cost (NPC) and the levelized cost of energy (LCOE), which depends on the annualized cost of the system. In order to determine the cost effectiveness of RES technologies, the estimated cost of electricity from a RES may be compared with cost of electricity from other technologies. The cost of electricity (COE) is comprised of three components: capital and installation (C&I), operation and maintenance (O&M), and fuel (F) and is given by the Equation 5-18. The total cost of electricity from a RES device is the sum of these three components, expressed in dollars (or cents) per kilowatt-hour.

The capital cost component varies based on the capital and installation costs, as well as on the fixed charge rate and capacity factor of the RES system. The cost of electricity decreases as the amortization period of the RES device increases (e.g., as the fixed charge rate decreases). RES systems with high capacity factors also have a lower cost of electricity.

The operation and maintenance cost component takes into account both the fixed and variable O&M costs of the RES technology.

The fuel cost component is simply the cost of the fuel required to generate electricity with the device. The fuel cost component varies with the efficiency (or heat rate) of the equipment and with the cost of fuel. Therefore, a specific generation technology may have a lower cost of electricity in some geographic locations than in others due to fluctuations in the cost of natural gas, propane, or diesel. Some generation equipment, such as photovoltaic systems and wind turbines, will not have a fuel cost as no fuel is required.

$$Total\ COE\left(\frac{\$}{kWh}\right) = C\&I + O\&M + F \qquad \text{5-18}$$

5.3 Stochastic Optimization: An Introduction

There have been numerous attempts for the design of microgrid using various open source applications, HOMER developed by National Renewable Energy Laboratory (NREL) , Boulder, CO is one of the most commonly used one. It performs techno-economic analysis and prioritizes the solutions based on cost. One of the very successful attempts towards microgrid design using HOMER is **[6]**. Unfortunately, the software has many approximations and assumptions which need to be addressed using a detailed mathematical formulation to handle the uncertainty and unpredictability in the renewable energy resources and demand.

One of the latest approaches **[104]** have developed a two-stage stochastic programming model for planning and operation of the distributed energy systems, unfortunately their model doesn't consider risk in their planning design. Also, their title is misleading as they do not use stochastic programming to solve their model, while utilize a two-stage decomposition to utilize the power of the genetic algorithms to solve the model. They employ the standard approach of Monte Carlo simulations to deal with the uncertainty in the second stage. Although, a detailed comparison of the results are done to compare the benefits of the model as compared to the deterministic one.

Unfortunately, none of the models shown above consider risk explicitly in their model nor do they consider the uncertainty in the renewable generation explicitly. We therefore address these two important issues in our MGMRM (MicroGrid Modeling under Risk Model).

5.4 Two-Stage Stochastic Programming based Model

A standard two stage stochastic programming model for solving MDOUU has been shown in Chapter 3, using Equations 3-16 to 3-25. We use the same model to extend the deterministic microgrid planning model shown by Equation 5-1 to 5-14.

The deterministic model lack the ability to handle uncertainty in demand and supply (renewable energy). Therefore we use the two-stage stochastic programming with recourse for planning of microgrid under uncertainty. The stochastic nature is captured in the model in the form of scenarios of the random variables. Our first stage design variables are for determining the capacity of installation for solar power, wind power, diesel generation and storage one needs to install for a given microgrid installation given a range of possible scenarios. The recourse or the second stage decisions are the operating variables which decide upon the amount of power which needs to be generated from the diesel generators and/or supplied from the batteries. It is important to note that there is variability in the second stage variables as they will need to be decided upon when the uncertainty occurs. Therefore minimizing the capital investment cost along with the operating costs seems to be a feasible approach. We not only incorporate the economic costs but also take in to consideration the environmental costs in terms of CO_2 emissions resulting from diesel generation. We do also consider the CO_2 and the GHG emissions resulting from the manufacturing of the technology used for power generation, but it is not a part of the optimization model but used in the Phase III of the MDOUU is using the LCA . It has been presented in detail in Chapter 6.

The two-stage stochastic programming model for planning of microgrids is presented below. Equation 5-18 to 5-35 constitute the mathematical formulation of the two-stage stochastic optimization problem for the planning and operation of the micro grid. In the model below N_{DG} is the total number of non-renewable generators, N_{WT} is the number of wind turbines, N_{PV} is the number of PV panels, IC_{DG} (diesel generation), IC_{PV} (PV panels), IC_{WT} (wind turbine), IC_{BAT} (batteries) are the levelized annual installation cost of generation sources and storage ($). Levelized annual operation and management cost for generation sources are given by OM_{DG}, OM_{PV}, $OM_{WT,}$, OM_{BAT} in ($/year) and FC_{DG} is the fuel cost in $/kWh. The charging power Chb and power supplied by all the batteries DChb is given in kW and kW respectively. The maximum allowable charge of a battery is C_{MAX} (kWh). The power output from generation sources O_{DG}, O_{PV} and O_{WT} (kW). The demand D is in kW while D_{us} is the unserved demand in kW, C_{US} is the cost of unserved power in $/kW. C_{Tax} and C_{Int} are the carbon tax in ($/kg) and CO_2 intensity in kg/kW. The rated capacity of diesel generator and battery are given by RC_{DG} and RC_B (kW). The energy stored in the battery is Ce (kWh). The self discharge and discharge efficiencies of a battery are γ_{sd}, γ_d in %. the maximum allowable depth of discharge of a battery in % is DOD_{MAX}. T_b is the life in cycles of one battery.

Objective Function

$$\begin{aligned}\min \quad & \bar{N}_{PV}\big(IC_{PV} + OM_{PV}(N_{PV})\big) + \bar{N}_{WT}\big(IC_{WT} + OM_{WT}(N_{WT})\big) \\ & + N_{DG}\big(IC_{DG} + OM_{DG}(O_{DG})\big) + \bar{N}_{BAT}(IC_{BAT} + OM_{BAT}) \\ & + \frac{1}{ns}\left(\sum_t \sum_s \left(C_{us} D_{us_t}^s\right) + FC_{DG}\left(\sum_s \sum_t O_{DG}{}_t^s\right)\right. \\ & \left. + \left(\sum_s \sum_t O_{DG}{}_t^s \cdot CTax \cdot CInt\right)\right)\end{aligned} \tag{5-18}$$

Where *ns* is the total number of scenarios and $s \in ns$ and $t \in 1..8760$, t is in hours.

Any two stage stochastic programming model has two sets of variables, the here and now variable and the recourse variables. The former means the decisions which one has to take during the planning phase while the recourse variables or the second stage variable are the decisions which one has to execute when the uncertainty has happened in the operational phase. In this case the installation of the wind turbines (N_{WT}), solar panels (N_{PV}), diesel generator (N_{DG}) and the batteries (N_{BAT})are the initial installations which one has to do before the systems comes into operation. The second stage variables or the recourse variables are the ones and in this case it is the real time production of energy from diesel generation (O_{DG}), energy supplied from battery (DChb) or the unserved load (D_{US}).

Constraints

1) Supply-Demand balance at any time interval is given as: power demand is equal to the sum of power supply from RES (O_{PV} and O_{WT} (kW)), diesel (O_{DG}) and battery (DChb). Certain amount of energy may go unserved (D_{US}) or extra energy beyond the storage capacity may need to be dumped.

$$\begin{gathered} D(t,s) = O_{DG}(t,s) + N_{PV} \cdot O_{PV}(t,s) + N_{WT} \cdot O_{WT}(t,s) \\ +DChb(t,s) + D_{us}(t,s) - Chb(t,s) \\ \forall\, t \in 1..time, s \in 1..ns \end{gathered} \tag{5-19}$$

2) Diesel Generator output limit: Power output of the diesel generators O_{DG} cannot exceed their gross rated capacity (RC_{DG}) where $SR(t,s)$ is the spinning reserve. Here spinning reserve is also a function of the *s* as we need to make sure the desired quantity of power is available at each scenario.

$$O_{DG}(t,s) + SR(t,s) \leq N_{DG} \cdot RC_{DG} \;\forall t \in 1..time, s \in 1..ns \tag{5-20}$$

3) Battery State of Charge (SoC): An energy conservation constraint which links the energy stored in the battery at any time with the charging and discharging processes.

$$Ce(t,s) = Ce(t-1,s) \cdot (1-\gamma_{sd}) + Cb(t,s) - \frac{Db(t,s)}{\gamma_d} \;\forall t \in 1..time, s \in 1..ns \tag{5-21}$$

4) Battery capacity limits: The battery has an upper limit with respect to its SoC, there is a maximum depth of discharge (DOD) that can be reached in a cycle

$$(1 - DOD_{MAX}) \cdot C_{MAX} \cdot N_B \leq Ce(t,s) \leq C_{MAX} \cdot N_B, \;\forall\, s \in 1..ns \tag{5-22}$$

5) The electric power charged to or discharged from the battery cannot exceed its rated capacity

$$Chb(t,s) \le N_B \cdot RC_B,\ \forall t,s \qquad 5\text{-}23$$

$$DChb(t,s) \le N_B \cdot RC_B,\ \forall t,s \qquad 5\text{-}24$$

6) Reliability Constraint: It is to ensure that a desired loss of load doesn't exceed the maximum allowed expected unserved energy limit (EUE_{MAX})

$$\frac{\sum_{t=1}^{8760} D_{us}{}_t^s}{\sum_{t=1}^{8760} D_t^s} \le EUE_{MAX},\ \forall\, s \in 1..ns \qquad 5\text{-}25$$

7) Budget/Resource Constraints: To make sure the number of RES and storage units used in the system do not go beyond budget and the solution is practical. This constraint may be also be modeled using the monetary value of the components.

$$N_{(DG,min)} \le N_{DG} \le N_{(DG,max)} \qquad 5\text{-}26$$

$$N_{(PV,min)} \le N_{PV} \le N_{(PV,max)} \qquad 5\text{-}27$$

$$N_{(WT,min)} \le N_{WT} \le N_{(WT,max)} \qquad 5\text{-}28$$

$$N_{(BAT,min)} \le N_{BAT} \le N_{(BAT,max)} \qquad 5\text{-}29$$

8) Initial State of Battery in each scenario

$$Ce_t^s = \frac{C_{MAX} \times N_{BAT}}{2}\ \forall\, s \in 1..ns, t = 1 \qquad 5\text{-}30$$

Another major component considered as a part of the modeling of such a system was the renewable energy penetration. As the capital cost of diesel generation is quite low as compared to the renewable resources of energy the optimizer would tend to provide most of the energy from it. Hence we explicitly need to specify and optimize the percentage contribution of renewable source along maintaining the specified reliability measure as presented next.

9) Minimum penetration levels of RES

$$\sum_{t=1}^{time} N_{wt} * O_{wt}(t,s) + \sum_{t=1}^{time} N_{PV} * O_{PV}(t,s) \geq RP * \sum_{t=1}^{time} (D(t,s) - D_{us}(t,s)) \ \forall\, s \in 1..ns \qquad 5\text{-}31$$

Where RP is the percentage penetration level of renewable energy

These above constraints force the optimizer to ensure a required penetration level of renewable generation in the microgrid.

10) Spinning Reserve

$$SR(t,s) \geq SRmin * D(t,s) \forall\, t \ \in 1..8760, s \ \in 1..ns \qquad 5\text{-}32$$

11) Preventing simultaneous charging and discharging of batteries: This constraint eliminates the possibility of the simultaneous charging and discharging of the batteries

$$Chb(t,s) \times DChb(t,s) = 0 \ \forall t, s \qquad 5\text{-}33$$

12) Energy to Power Ratio (E/P): The energy capacity of any battery for a certain power rating is determined based on its E/P ratio which is a relationship between the power and energy size for a certain energy storage technology. The energy size represents the maximum amount of energy that can be stored for a certain time. Whereas the power size is the rate at which the energy storage is capable of discharging/charging power continually.

$$EPR \ or \frac{E}{P} = \frac{Energy\ Capacity, kWh}{Power\ Rating, kW} \qquad 5\text{-}34$$

$$\underline{EPR} \cdot N_B \cdot RC_B \leq Ce(t,s) \leq \overline{EPR} \cdot N_B \cdot RC_B \ \forall t, m \qquad 5\text{-}35$$

5.5 Risk Averse Two-Stage Stochastic Programming Model: NLP Problem

Modeling a microgrid with uncertainty involves risk. In planning power transmission systems, distribution systems and currently microgrids with renewable energy source exposure to economic and environmental risks cannot be avoided.

We extend the proposed stochastic two-stage model to consider risk by incorporating ideas from portfolio optimization. We modify the objective function of Equation 5-16 to a new objective function as per Markovitz which considers risk explicitly **[105]**. This has not been found in any literature in microgrid power system planning studies including storage. We utilized the theory of **[105]** in our objective function as below:

Given our variance is in the second stage variables hence we need to evaluate the variance of the second stage variables. Let us assume the second stage objective function is denoted by B hence our new second stage objective function would become like Equation 5.35– 5.36

$$\min \ A + \theta_r \sqrt{Var(B)} \qquad 5\text{-}35$$

Where $Var(B)$ is given by the following Equation

$$Var(B) = E[B^2] - (E[B])^2 \qquad 5\text{-}36$$

Where the second term is a simple square of the earlier objective function while the first term may be evaluated as following:

$$E[B^2]_s = \sum_{s=1}^{n} B_s^2 \times \Pr(s) \qquad 5\text{-}37$$

Where Pr(s) is the probability of occurrence of scenario s, and B_s^2 is the cost function squared for each scenario.

Based on the Equation 5-16, our new objective function with risk transforms into a non-linear objective function with risk as shown in Equation 5-38

$$\boldsymbol{A} = \bar{N}_{PV}\big(IC_{PV} + OM_{PV}(N_{PV})\big) + \bar{N}_{WT}\big(IC_{WT} + OM_{WT}(N_{WT})\big) + N_{DG}\big(IC_{DG} + OM_{DG}(O_{DG})\big) + \bar{N}_{BAT}(IC_{BAT} + OM_{BAT})$$

$$\boldsymbol{B} = \frac{1}{ns}\left(\sum_{t}\sum_{s}\left(C_{us}D^{s}_{us_t}\right) + FC_{DG}\left(\sum_{s}\sum_{t} O_{DG}{}^{s}_{t}\right) + \left(\sum_{s}\sum_{t} O_{DG}{}^{s}_{t} * CTax * CInt\right)\right) \quad \text{5-38}$$

$$\mathbf{min\ E[A + B] + \theta_{\mathit{r}}\sqrt{Var(B)}}$$

The constraints all remain the same as in Equation 5-17 to 5-34. The new objective function considers the variance of the uncertainties explicitly in the objective function.

Two-stage stochastic programming approach has been applied to a variety of problems in various domains, such as supply chain planning **[106]**, process design and operations **[107]** and infrastructure planning **[108]**. In this paper we try to solve the two-stage stochastic programming problem with the objective function as mentioned in Equation 5-38 using MINOS solver. We utilized the AMPL programming environment to model the mathematical model.

5.6 Results and Discussions

5.6.1 Deterministic optimization model based design results

Based on the model described in Section 5.3, the ratings and cost of the various components used in the study are specified in Table 5-1 and has been adopted from **[6]**.

Options	Capital Cost	Replacement Cost	O&M Cost	Life
Wind	$7800/turbine	$9000/turbine	$30/year	15 years
Solar	$7.5/W	$7.5/W	0	20 years
Battery	$75/battery	$75/battery	$2/battery/year	845kWh
Grid Extension	$2000/km	$2000/km	$100/km/year	
Diesel	For a 4.25kW – 12.5kW $2550 - $7000	$2550	$0.15/h	5000h

Table 5-1: Input data for the cost of options available

Table 5-1 lists costs and life of various components used in the optimization model for microgrid planning. Life of a battery is given in kWh which is the lifetime throughput of energy from one battery. It is used as a standard in battery modeling using HOMER .

We evaluate the levelized annual cost of the each component as shown in Table 5-2: Levelized Equivalent Annual Cost, Life and Sizes of various components

, to evaluate the optimal mix of RES using the linear programming optimization model described in Section 5-3,

Options	Capital Cost	Annualized Cost	Life	Size
Wind	$7800/turbine	$678.5/turbine	20 years	3kW/Turbine
Solar	$1350/panel	$117.31 /panel	25 years	180 Wp
Battery	$75/battery	$6.51 /battery	845 kWh	225 Ah, 12V
Diesel	For 8kW, $5500	$477.95	5000h	8kW

Table 5-2: Levelized Equivalent Annual Cost, Life and Sizes of various components

We used the data for battery from **[109]** as shown below in Table 5-3:

Battery Type	Li-ion
Charging Efficiency	95%
Discharging Efficiency	95%
Maximum DOD	100%
E/P Ratio Range	1-6
Battery Rating	225 Ah, 12V

Table 5-3: Battery data for optimization

Fuel cost per kWh is considered as \$0.264 as per **[62]** in the optimization problem. We evaluated N_{PV}, N_{WT}, N_{BAT}, N_{DG} and the total installation cost and operational cost including the fuel cost */kWh* for the diesel generators. We introduced the constraints and a penalty on the unserved demand. Budget constraints were introduced in terms of the maximum number of solar panels, wind turbines and batteries. We considered 4 distinct cases based on **[6]** in order to determine the most favorable option for microgrid planning as shown in Table 5-4.

Case	Description of the case
1	Diesel dependent microgrid (base case)
2	Renewable based microgrid (wind, solar PV, battery, converter)
3	Diesel-renewable mixed microgrid (Diesel, wind, solar PV, battery, converter)
4	Microgrid-connected to external grid

Table 5-4:Summary of cases studied

The optimal microgrid designs for the various cases considered above are obtained using the optimization model as described in Section 5-3 and the results are shown in Table 5-5 where the parameters of sizes are presented in Table 5-2 and Table 5-3.

Components	Case – 1	Case – 2	Case – 3	Case – 4
Diesel (8 kW each)	6	0	1	0
Solar PV, (panels)	0	40	33	0
Wind, (turbines)	0	37	31	0
Battery, numbers	0	22	17	0
External Grid (kW)	0	0	0	50

Table 5-5: Optimal Configuration for various cases

We compare the cost of components for various cases in Table 5-5. In Case – 4 we assume that the distance of the hypothetical rural community from the main grid is 100 km and the cost of electricity from grid is 0.15$/kWh [38] and cost of grid connection is $2000/km **[110]**.

Items	Case – 1	Case – 2	Case – 3	Case – 4
Total Cost ($)	2,79,558.5	1,00,625.5	86,548.16	2,00,000
Levelized Cost of Energy (COE) $/kWh	3.5	1.25	1.08	0.15

Table 5-6: Comparison of cost components for various cases

Comparison of electrical energy production and consumption of various microgrid configurations are conducted and presented in Table 5-7. It can be observed that in Case – 1 and Case – 4 the total energy produced is equivalent to the demand but they are not the best alternatives as they impact the environment by producing CO_2 emissions, which is considered later, and also are expensive. On the other hand in Case – 2, which is totally based on renewable energy generates, excess energy is produced over and above the demand which is dumped. This is due to the fluctuations in renewable energy resources and their undispatchability nature on the other hand in Case – 3 which is a mixture of diesel generation with penetration of renewable resources is a better option with less waste of energy.

Component Production kWh/year	Case – 1	Case – 2	Case – 3	Case – 4
Diesel Generator	79999.9	0	11249.2	0
Solar PV	0	15268	12323.8	0
Wind	0	148460	122117	0
External Grid	0	0	0	79999
Renewable Energy Contribution	0	100%	85%	0
Total	79999.9	163728	145690	79999

Table 5-7: Case wise comparison of Energy Production and Consumption with 100 % demand fullfillment

The effect of capacity shortage on the microgrid is examined by allowing a small fraction of the annual load remains unmet and determining the corresponding optimal microgrid configuration for Case – 3. We formulate four cases with varying percentage of maximum allowable energy unmet from 10%, 20%, 30% and 40%. We present the comparison of Case – 3 with various percentages of maximum allowable unserved energy in Table 5-8.

Component	**Maximum Allowable Unmet energy = 10%**	**Maximum Allowable Unmet energy = 20%**	**Maximum Allowable Unmet energy = 30%**	**Maximum Allowable Unmet energy = 40%**
Demand (kWh/year)	79999.00	79999.00	79999.00	79999.00
Objective Function Cost ($/year)	83322.45	53993.76	41173.91	37196.06
Diesel, (kWh/year)	7804.72	0	0	0
Solar, (kWh/year)	14601.00	11444.68	0	0
Wind , (kWh/year)	160322.90	143441.60	103867.70	68744.95
Unserved Power (kWh/year)	7999.90	15999.80	23999.70	31999.60
Renewable Energy Contribution to Supply	174923.90	154886.30	103867.70	68744.95

Table 5-8: Comparison of Case - 3 optimal plan with variation in maximum allowable unmet energy

It may be inferred from tables above, for the data considered here, that the most optimal decision for stand-alone systems is usually a combination of RES and traditional generators. An important aspect of this optimization problem is that the cost of not being able to supply the electricity to the customers. This is often accounted for as penalty costs and can be analyzed from a producer as well as a consumer perspective.

Overall we developed deterministic approaches towards the optimal sizing of microgrids with renewable generation. These models still do not take into the consideration the uncertainty in the renewable resources of energy in the model, which shall be considered with stochastic models developed in future. Another important factor is the impact of carbon emissions need to be incorporated in these decision models [61] which is considered later.

5.6.2 Stochastic Optimization Model Results and Analysis

5.6.2.1 Metrics for Evaluation of Stochastic Solutions

We have embarked on formulating a stochastic programming model for microgrid planning, without stating specific methods for evaluating about whether or not is a worthwhile thing to do. Most decision problems are certainly affected by randomness, but that is not the same as saying that the randomness should be introduced into a model. We all know that the art of modelling amounts to describing the important aspects of a problem, and dropping the unimportant ones. We must remember that randomness, although present in the situation, may turn out to be one of the unimportant issues.

We shall now, briefly, outline a few approaches for evaluating the importance of randomness

5.6.2.2 .Comparing the Deterministic and Stochastic Objective Values

The most straightforward way to check if randomness is unimportant is to compare the optimal objective value of the stochastic model with the corresponding optimal value of the deterministic model (probably produced by replacing all random variables by their means). When we compare the optimal objective values (and also the solutions) in these two cases, we must be aware that what we are observing is composed of several elements. The major point here is that the deterministic model has lost all elements of dynamics (it has several time periods, but all decisions are made here and now). Therefore decisions that have elements of options in them will never be of any use. In a deterministic world there is never a need to do something just in case.

Therefore, even if these two models come out with about the same optimal objective value, one does not really know much about whether or not it is wise to work with a stochastic model.

It is clear from the above discussion that there are two main points one needs to consider when comparing the two models. One is the optimal objective value, the other the optimal solution. The choice depends on the situation that is important. Sometimes one’s major concern is if one should do something or not; in other cases the question is not if one should do something, but what should one do.

The deterministic solution in which the random parameters are represented by their expected values; hence it is called the expected value (EV) solution. Another probelm is the recourse problem (RP), another name for the stochastic solution. This solution is achieved by explicitly describing the randomness by means of a number of scenarios. Then the last problem is that which uses the expected values (EEV) and presents the expected outcome of using the EV. EEV is obtained by first solving the expected (or mean) value problem, which is the problem obtained by setting the random variables to their expected values. From the solution to this deterministic optimization problem, we fix the values of the first stage variables and solve the second-stage problem over all possible scenarios. In addition, computations of a Monte Carlo based model are carried out, named the wait-and-see solution (WSS). This is the cost if perfect information is available. Two measures have been utilized to select the right formulation that suits the problem's situation: *value of stochastic solution (VSS)* and *expected value of perfect information (EVPI)***[3]**.

Expected Value of Perfect Information

For simplicity, assume that we have a two-stage model. Now compare the optimal objective value of the stochastic model with the expected value of the wait-and-see solutions. The latter is calculated by finding the optimal solution for each possible realization of the random variables. Clearly, it is better to know the value of the random variable before making a decision than having to make the decision before knowing. The difference between these two expected objective values is called the expected value of perfect information (EVPI), since it shows how much one could expect to win if one were told what would happen before making one's decisions. Another interpretation is that this difference is what one would be willing to pay for that information. This payment will assure the usage of the deterministic model since the randomness becomes, theoretically, certainly known. In other words, EVPI can be considered as the cost of using prediction techniques so a decision maker gains more information about the future outcome of the stochastic parameters. EVPI can be calculated using the Equation 5-35.

$$EVPI = RP - WSS \tag{5-35}$$

Larger value of EVPI indicates that randomness plays an important role in the problems while a small value of EVPI indicates that randomness doesn't play a significant role in the problem and one could do with the deterministic solution as well.

Value of Stochastic Solution

Value of Stochastic Solution or VSS is computed by subtracting the solution of the recourse problem (RP) from the objective of solving the same problem after fixing the first-stage variables to the levels obtained for the EV problem, i.e. EEV. It is used to justify the application of the stochastic model especially when it becomes fairly high **[3]**. Mathematically, VSS can be computed according to the Equation 5-36.

$$VSS = EEV - RP \tag{5-36}$$

5.6.3 Scenario Generation for Stochastic Programming

Any two-stage stochastic programming problem needs to deal with the issue of scenario generation. In our problem the first stage variables are the capital investment decisions for installation capacity of wind, solar and diesel generation with storage. While the second stage variables are the operating variables. The uncertain parameters are the demand of electricity and the renewable energy available at any location. We already modeled the uncertain parameters in Chapter 4. We use the same models for generation of scenario of supply for the microgrid under consideration. We used copula based dependence model for generation of solar and wind energy with Kumaraswamy distribution modeling the marginals.

5.6.4 Deterministic Vs Two-Stage Stochastic Solutions

In this section we present the results of our primary two-stage stochastic model vs the standard deterministic mode. The best approach to compare these results is by using the metrics defined in Section 5.6.2. We shall find the solution of the RP, EEV and WSS to find the values of EVPI and VSS which shall be useful for analyzing the advantages of our stochastic solution for planners.

The table below shows the comparisons of the objective values of the deterministic and the two-stage stochastic solution for 200 scenarios of random variables. Each scenario comprises of hourly annual data representing 8760 hours. The data is generated carefully to keep into consideration the day/night variations and the seasonal variation in both the supply and the demand. The second stage decisions enable us to compare the impacts of storage and diesel generation in terms of cost as well as environmental impacts.

It is important to note here that problem size is very large given the number of scenarios, the problem size increases exponentially. In our case for 200 scenarios with hourly data the total number of variables spanned to a minimum of $200 \times 8760 = 1{,}752{,}000$. The problem is computationally expensive and takes approximately 54 min on a computer with 16GB RAM, Intel Core i7 processor run using AMPL programming environment.

	EV	RP	EEV
Demand (kWh/year)	79999.4	79999.4	79999.4
Objective Function Cost ($/year)	**61135.94**	**78567.89**	**82141.17**
Diesel, (kWh/year)	2815.73	5830.88	8729.96
Solar, (kWh/year)	12519.2	18664.8	12520.1
Wind , (kWh/year)	125314	197320	125314

Table 5-9: Optimization results for main decision variables in varying problem formulations

Based on the solution in Table 5-9: Optimization results for main decision variables in varying problem formulations

, we can calculate VSS = EEV – RP = $3573.28. It is important to see that VSS indicates a 5 % benefit in solving the stochastic problem rather than the deterministic equivalent. The value of EVPI for the above model is EVPI = RP – WSS, where WSS was obtained using the monte-carlo simulations to be $34607.20. Hence EVPI = $**78567.89** – $**34607.20** = $43961.

The above result indicates the advantage of using a stochastic approach over a deterministic or simulation based approach. It not only indicates the advantage of using one approach over the other but also indicates one can save approximately 5 % in costs. This is just an example, for large variance and uncertainty with large costs, this saving can be even higher.

We will analyze important results here where we do not provide the constraint for renewable energy penetration but we let the optimizer evaluate the penetration with specified loss of load tolerance.

Component	Method	EUEmax= 0%	EUEmax = 10%	EUEmax = 20%	EUEmax = 30%	EUEmax=40%
Demand (kWh/year)	Stochastic	79999.40	79999.40	79999.40	79999.40	79999.40
	Deterministic	79999.40	79999.40	79999.40	79999.40	79999.40
Objective Function Cost ($/year)	Stochastic	104100.00	78568.00	58382.00	49503.00	42566.14
	Deterministic	114832.10	83322.45	53993.76	41173.91	37196.06
Diesel, (kWh/year)	Stochastic	14137.38	5830.88	1523.98	677.67	0
	Deterministic	17890.09	7804.72	0	0	0
Solar, (kWh/year)	Stochastic	18520.12	18664.78	16297.70	15174.03	13031.59
	Deterministic	14344.70	14601.00	11444.68	0	0
Wind , (kWh/year)	Stochastic	122019.90	123948.50	104361.20	83800.92	68287.73
	Deterministic	160039.40	160322.90	143441.60	103867.70	68744.95
Unserved Power (kWh/year)	Stochastic	0	7871.14	13789.35	18802.02	24310.21
	Deterministic	0	7999.90	15999.80	23999.70	31999.60
Renewable Energy Contribution	Stochastic	140540.00	142613.30	120658.90	98974.95	81319.32
	Deterministic	174384.10	174923.90	154886.30	103867.70	68744.95

Table 5-10:Comparison on penetration levels using deterministic and stochastic programming approach

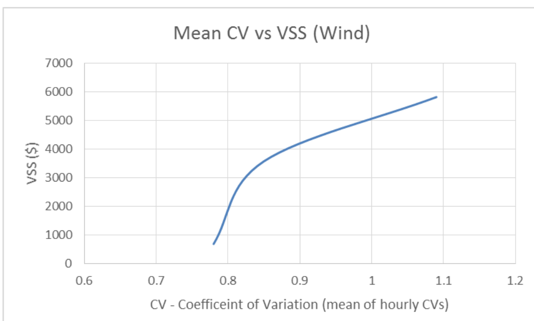
Table 5-10 presents the results of a comparison between the results of the deterministic model and the stochastic model. Overall stochastic solutions performs better than the deterministic solution in the cases of high reliability where allowance for demand going unserved is limited to 0 % and 10 % whereas deterministic solution performs better at low reliability levels. This indicates the importance of using stochastic solution as indicated by the values of the overall objective function.

It is also interesting to note as we move towards low reliability levels with higher degree of load unserved the diesel generation is reduced to zero and the entire demand is supplied by the renewable resource (wind/solar) with support from energy storage. For higher percentages of EUEmax (Expected Energy Unrserved) we see that stochastic solution provides some energy using diesel generation while reducing the capital investment in renewable technologies.

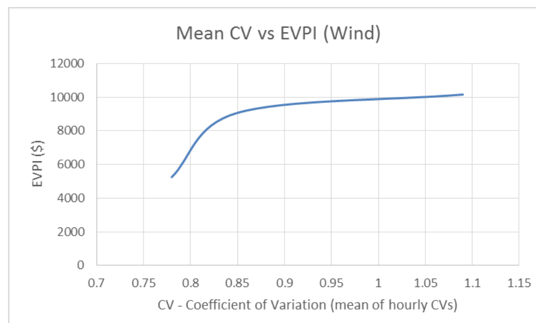
In addition to the above analysis, one important thing to observe is the variation of VSS and EVPI with increasing variability in our random variables as that gives us a clear indication of the impact of stochastic programming based solutions over deterministic solutions.

We can see in Figure 5-1 and Figure 5-2, as we increase the coefficient of variation (CV) for the random parameters (in our case solar and wind energy) we see that the VSS and EVPI both increase hence elucidating the importance of using a stochastic programming approach. Here in Equation 5-37, σ is standard deviation and μ is mean.

$$CV = \frac{\sigma}{\mu} \quad (5\text{-}37)$$



(a)



(b)

Figure 5-1: Variation of (a) VSS and (b) EVPI vs varying coefficient of variation (CV) for Wind

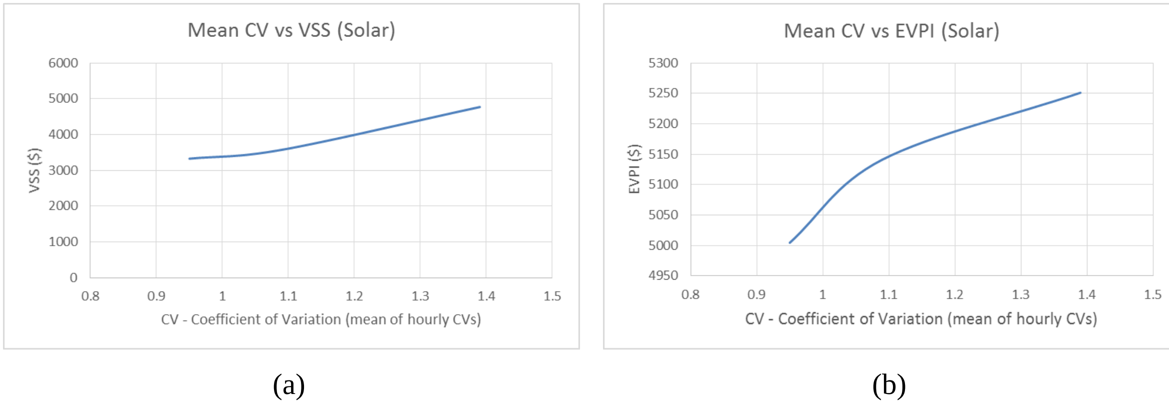


Figure 5-2: Variation of (a) VSS and (b) EVPI vs varying coefficient of variation (CV) for Solar

In Figure 5-1and Figure 5-2 we mention mean of hourly CVs because the CV varies with the hour of the day. We used mean of the CVs for the 24-hour duration and used it as a single point on the X-axis and Y-axis presents the VSS/EVPI value obtained at that specific mean CV. We used mean hourly CV because there was high variation of CV at each hour and varying each hourly CV equally was not possible whereas the notion behind varying CVs to evaluate the added value in using the stochastic solution can be easily seen using just the mean CV. Both these indices are indicators of importance of stochastic methods in solving problems with higher degree of uncertainty in the random variables. An increase in the value indicates the benefit one can obtain from using the stochastic method.

5.6.5 Risk-Averse Two-Stage Stochastic Solution

In this section we shall see the results of the model using our approach for risk-averse two-stage stochastic programming technique.

Risk is an important factor to consider when investing in projects involving large capital investment. Given the information about the uncertainties in demand and supply we are able to generate mean-variance frontier using the Markovitz objective function. The data used in our problem was obtained from recent literature [6, 111].

We shall vary the parameter θ, between 0.01 – 0.9 and obtain a mean-variance frontier and unspecified penetration levels for solar and wind energy systems. The parameter θ does not have any physical significance, it is used for analyzing the tradeoff between the expected cost and the variance/risk This enables us/planners to decide an appropriate configuration for a system based on the risk one is willing to take. In general we shall consider a complete system with Wind, Solar, Diesel and Batteries. We assumed the expected percentage of unserved energy can be left at 10% annually as infrequent brownout spread across the year are not troublesome in remote places where electricity is not even available and no critical tasks are dependent on it. In Figure 5-3, we see the variation of the standard deviation vs the risk parameter θ and observe that larger the risk weighting parameters lesser is the standard deviation indicating that with if one wants to minimize the effect of uncertainty and compensate with diesel generation or storage larger value of risk parameters is desirable.

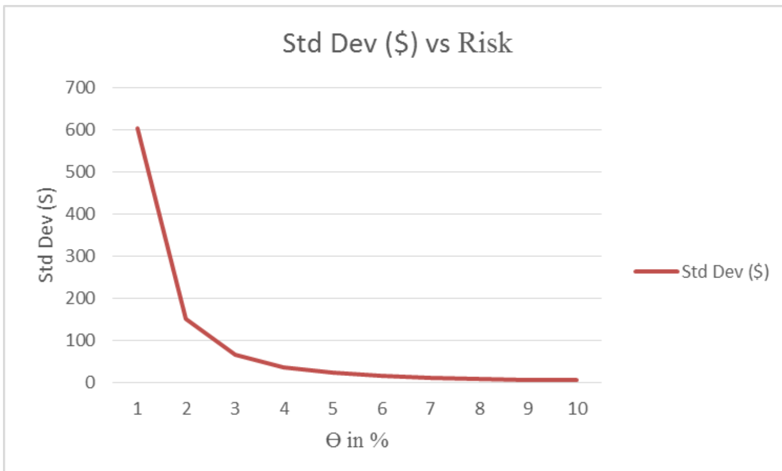


Figure 5-3: Standard Deviation vs Risk parameter

It may also be observed that by varying the risk parameter we can obtain efficient frontiers which are an indication of the optimal strategy for storage utilization, diesel generation or electricity from grid if available. Efficient frontiers are plots between standard deviation and expected cost for the second stage variables i.e. the diesel generation and carbon taxes etc. The efficient frontiers are shown for two specific cases with 10% and 20% expected unserved energy in Figure 5-4 and Figure 5-5 *where the risk decreases along the x-axis towards the right.* It is seen that the expected cost increases as we try to minimize the risk or the standard deviation because in an attempt to minimize the variation one needs to compensate the variations by either diesel generation, which adds to the cost.

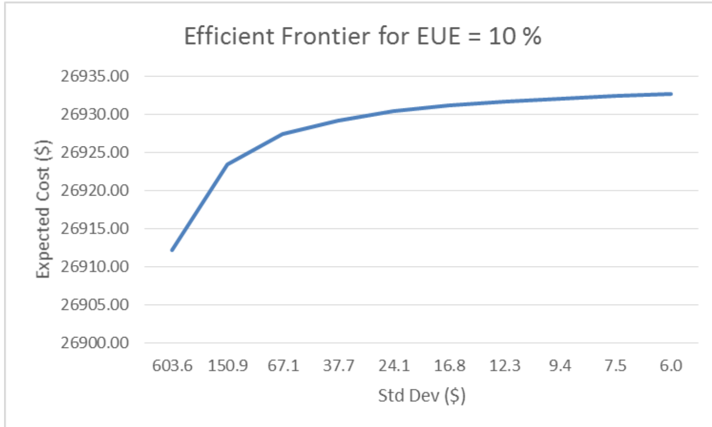


Figure 5-4: Efficient frontier for 10 % load unserved

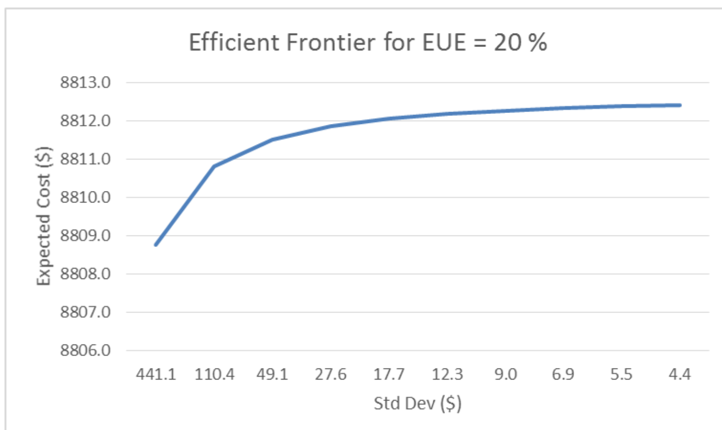


Figure 5-5: Efficient frontier for 20 % load unserved

If we analyze the **Figure 5-4** and **Figure 5-5** it is clear that by investing in a few extra dollars one is able to obtain a large reduction in standard deviation which provides us with motivation to use the risk-averse model.

5.7 Summary

In this chapter we introduced a deterministic optimization model for the planning of microgrid, we extend the model to a stochastic programming framework which forms an integral part of the Phase II of the MDOUU framework. We use the two-stage programming model for the design of microgrids under uncertainty. This model enables us to handle uncertainty in both demand and supply. We enhance the model by using the Markovitz objective function to minimize risk. This is useful for planning of systems under variable demand and supply as one need to minimize the effect of uncertainty on the overall system.

With the MDOUU framework one is free to use any optimization model/algorithm that is suitable for the problem at hand. The modeling of the resources as shown in Chapter 4 is used as input to the model here. This allows us to model our input data based on expert knowledge using various models which allows us to approximate the underlying phenomenon accurately. In the next Chapter we shall provide a detailed explanation of the LCA approach as used in Phase III of the MDOUU framework.

Chapter 6
Life Cycle Anaysis (LCA) based Microgrid Planning

6.1 Introduction

6.2 Introduction

This study is concerned mainly with the high level design stage where the planner's goal is to determine a reasonable estimation of the overall facility deployment costs and associated economic risks of a configuration servicing a projected load demand. We have used a risk averse two-stage stochastic programming framework for estimating a preliminary configuration. In this chapter, we deploy a detailed life-cycle analysis (LCA) as a major component of the Phase III of the MDOUU to estimate the most appropriate configuration that considers both economic and environmental objectives. LCA is used to assess the environmental impacts of the power system. The methodology presented in this Chapter uses an opensource software package OpenLCA to do a detailed LCA of the individual components of the microgrid, to analyze their environmental impacts. Using the multi-criteria decision making approach as outlined in Chapter 3 that uses compromise programming is used to evaluate an appropriate configurations. Overall, this Chapter introduces a methodology for planning of microgrids/micropower systems where the environmental criteria is addressed in the design by integrating a LCA in the framework.

The methodology presented in this work is based on the life cycle analysis methodology **[112]**. LCA is a methodology through which environmental impacts related to human consumption can be evaluated. It is a comparative approach in which alternative products and processes are assessed to find their relative fit and performance. The LCA methodology consists of 4 stages, namely, goal and scope determination, life cycle inventory, impact assessment and system improvement. In this work we show how LCA is integrated into the MDOUU framework for any planning problem.

All the studies are conducted on a hypothetical microgrid, where the historical data for the renewable energy is taken for the city of Waterloo and based on model in Chapter 4. The power demand is taken for a hypothetical set of 30 houses based on **[111]**.

6.3 Life Cycle Analysis

Environmental problems are problematic to analyze given their inherent complexity. LCA attempts to unravel some of the analytic complexity of environmental systems through a systematic approach which breaks down the problem into a number of stages in an attempt to achieve two main goals:

- Characterizing the system by a "cradle to grave" approach
- Ensuring simplicity and transparency in the methodology

The *cradle-to-grave* approach attempts to define the system boundaries for the system under consideration. The system is referred to as a process system, and it begins with the raw material extraction from the earth and terminates at the point(s) at which the materials are returned back to the earth as either emissions or disposal at the end of the useful life of the product or they are recycled to be used again for manufacturing. In LCA, this approach of considering the upstream and downstream processes in the product life cycle is sometimes referred to as *internalizing externalities.* This is a highly complex view of a production systems because it must account for not only the upstream processing of raw materials and sub-components of the product, but also the downstream consumer use, confluence of sub-products into primary products, transportation and the eventual product disposal. To add to this, much of the time multiple product streams must be evaluated even in the simple products. For instance, a cradle-to-grave view of an electric lamp would need to assess the cradle-to-grave systems for light bulbs, electric cords manufacture, and possible glass or textile manufacture or the cosmetic aspects of the lamp. This approach can be onerous and seem over-complicated, but it allows for reasonably unbiased and standardized framework where highly disparate products can be reviewed and compared.

The LCA uses the cradle to grave approach by first accounting for energy and material inputs and outputs at each stage of the product's life and then conducting analyses on these results. Simplicity and transparency is maintained through a rigorous and systematic accounting procedure, which allows for straightforward auditing of the study and ascertainment of particular figures were calculated. For environmental problems, complex systems must be clearly delineated for external review (e.g. legal and environmental auditing). In addition, the communication of the results must be understandable when there are often multi-disciplinary decision makers. Figure 6-1 shows the generic life cycle of a product/process from cradle to grave. According to ISO 14040: "*LCA addresses the environmental aspects and potential environmental impacts throughout a product's life cycle from raw material acquisition through production, use, end-of-life treatment, recycling and final disposal (i.e. cradle-to-grave)".*

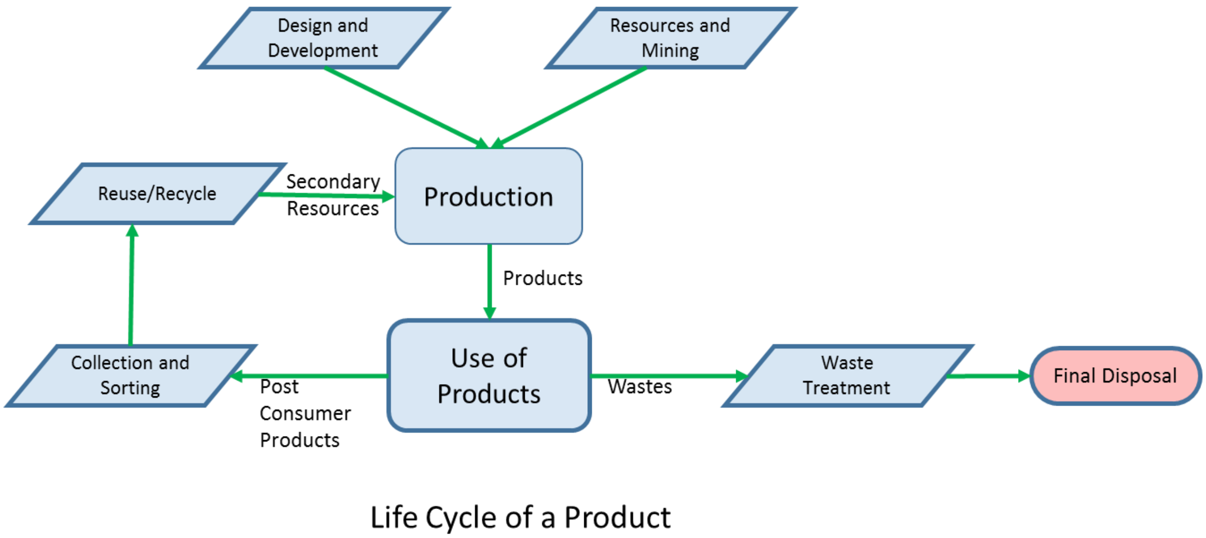


Figure 6-1: Life Cycle of a product where most block input has resource and output emissions/wastes

The LCA consists of four main stages **[112]**:

- Goal and scope definition
- Inventory
- Impact assessment
- Improvement

The LCA procedure is highly interactive and requires often refinements on each phase. The LCA phases and some of the applications are shown in Figure 6-2. In the next few paragraphs each of these phases will be further elaborated following the ISO 14044.

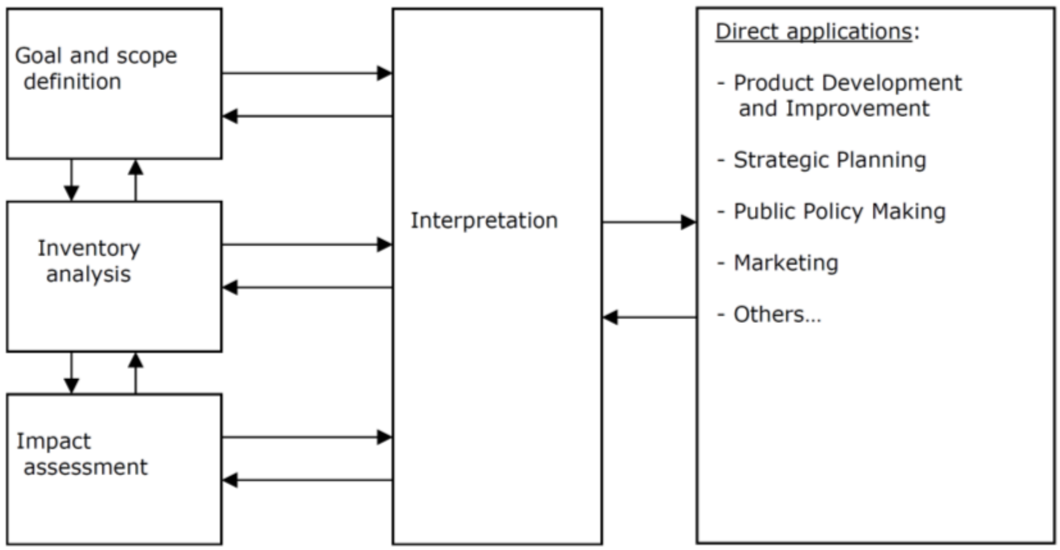


Figure 6-2: Stages of an LCA Study

Goal and Scope definition: It pertains to focusing the study around the measurable goals and deliverables of the overall study, whereas scoping looks at developing the process model and deciding which stages of the system are included in the study and which stages are beyond the scope of the overall study.

Life Cycle Inventory (LCI): It is the accounting of materials, energy and other metrics (such as natural resources like land) within the process model. The results of the LCI show where relative consumption of resources are concentrated and rates at which consumption occurs. From these results, impact assessments are made.

Impact assessments: They are typical measures or simulations, which help to define the environmental burden or societal effect of the system in terms relative to the overall goals of the study.

Improvements: The impact assessments and the LCI are used to determine the possible improvements in the system. This could take the form of comparing different processes or finding the component(s) in a system that are most likely to provide the greatest benefits through revision of the components. The next section presents the LCA of a microgrid with renewable energy technologies.

6.4 LCA of Renewable Energy based Microgrid

6.4.1 Goal Determination

The product of the goal determination stage should make clear the scope and purpose of the study. This requires the definition of both the study deliverables and the constraints under which the study is conducted. The purpose of the study is usually a combination of issues pertaining to:

- Product Design
- Setting up industrial/governmental policy
- Environmental system assessment

The product design study may be summarized under two main area of concentration. The first is to use the LCA to identify stages within the life cycle of a product or process where a reduction in resource use and emission might be achieved. The second is to compare the system inputs and outputs in order to compare the performance between alternative products, processes or activities. The policy is focused on determining general guidelines and procedures to foster desired environmental performance within the system(s). Environmental system assessment studies attempt to establish a baseline of information on a system's overall resource use, energy consumption, and environmental loading. The constraints that should be stated at this stage of the study are the time for conduction of the study, operating budget and the informational availability/requirements of the project. The goals of the study are to help focus the exercise by giving direction on how information and data are processed, to determine methods for producing the final deliverables and to communicate the overall results.

6.4.2 System Scope

Based on **[112]** a general "cradle-to-grave" system has four stages; namely raw material acquisition, manufacturing, use/re-use/maintenance, and recycling/waste management. The relationship between the four stages is shown in the Figure 6-3.

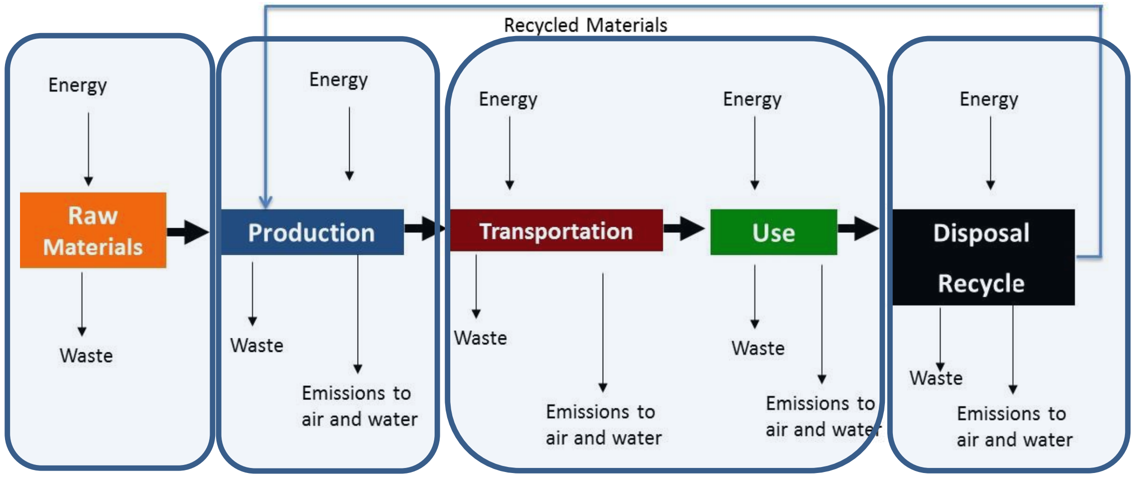


Figure 6-3: Defining system boundaries, Source: Modified from **[112]**

realities that exist in these particular systems. In particular the energy consumed and wasted as a part of the manufacturing of the systems. LCA of microgrids means the LCA of the components of the microgrid which are power generating technologies (renewable/non-renewable). Power generation systems have many irregularities in their manufacture, use and disposition. One of the other difficulties with these systems more specifically in microgrids is that the employ a wide variety of power generating technologies. In addition these projects are constructed, operated and disposed of is highly dependent to the technology. Another way to look at the LCA of microgrids is by giving a third dimension of time which is the deciding factor of each of the technologies. We have shown a complete system boundary using time and technologies as two dimensions for system scope of LCA of microgrids in **[113]**. It shows that the overall system is made up of a number of full life-cycle sub systems. It is shown that they all share the same streams while have different manufacture, construction, operation and disposition.

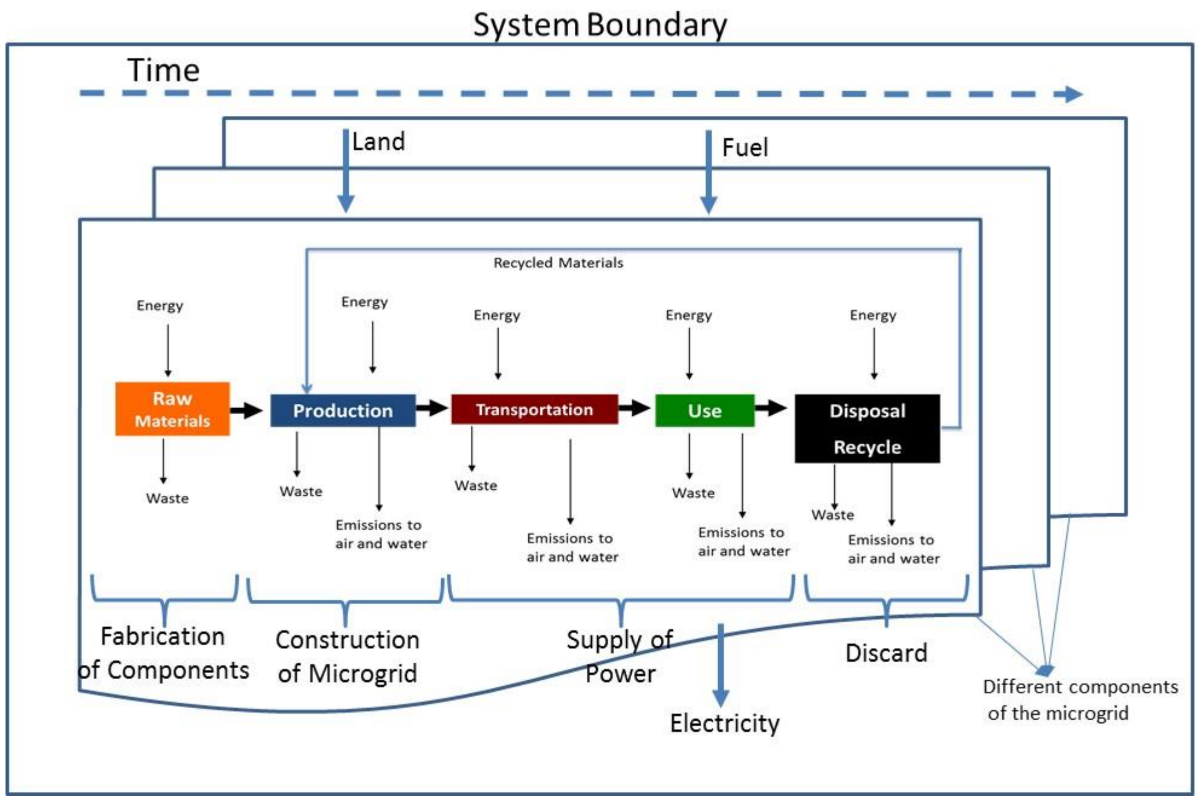


Figure 6-4: System Boundary for microgrid LCA Scope

In the system shown in Figure 6-4, there are three system boundaries that must be addressed in order to define the system. These are the process stage, temporal and spatial boundaries of the system.

Process Boundary

The general process of generating electricity includes all the upstream activities such as the raw material acquisition, in both the fabrication of the components and the construction of the plant and the required infrastructure. The supply of power constitutes the operating phase of the life cycle which accounts for attributes such as transportation costs, storage and procurement of fuels. At the end is the disposal of the generating facilities. Process boundary mainly focuses on the material and the energy requirement of haulage, landfills and recycling.

Temporal Boundary

Time frames of each generating technology is different. For example, the solar panels have a life of 25 years while wind turbines have a life of 30 years, batteries if used for storage have a very short span (e.g. Three years) as compared to the generating technologies. It is important for one to consider the lifetimes and stage time frames of the different technologies. These issues highly affect the performance because the power per unit material is strongly related to the equipment lifetime, and the useful operating lifetimes.

Spatial Boundary

This is one of the most important points of discussion for installation of distributed generation and in the contexts of microgrids. As the technologies used in our work for generation of energy use a variety of resources such as wind and sun, these technologies not only require land but also properly situated land. Hence the location of these facilities is very important in achieving the desired performance. The location of this land affects not only the local population but is also important for analyzing the transmission losses and availability of resources. In the next section we shall introduce the OpenLCA as a tool for performing the LCA of the microgrids.

6.5 LCI and Impact Assessment using OpenLCA for LCA of Microgrid

6.5.1 Introduction to OpenLCA

OpenLCA is the open source software for Life Cycle Assessment (LCA) and Sustainability Assessment, developed since 2007 by GreenDelta, www.greendelta.com. As an open source software, it is freely available, e.g. from the project website, www.openlca.org, without license costs. Version 1.4 was released in June, 2014. Core of any LCA modelling is the modelling of the life cycle of the product under study. In OpenLCA (as in ISO 14040), the life cycle model of a product is called product system, and there are different ways for creating and completing product systems, depending on the database and user preferences. We use OpenLCA v1.4 for our LCA analysis in this thesis as it has access to extensive data base of products we are interested in analysing.

6.5.2 Life Cycle Inventory: Solar, Wind and Li-ion Battery

The inventory analysis is the most labor intensive stage in performing an LCA. The processes related to the product system must be determined. Data is collected regarding these processes, which may include extraction of raw materials, disposal processes and transportation. The material and energy inputs and outputs of the emissions produced by these processes must be tabulated. Some processes with multiple outputs may require allocation, or distribution of impact amongst the multiple outputs. This data collection process is continued down the process chain as far as is practical.

We use the OpenLCA interface to perform the LCI of wind and solar using the ecoinvent database v3.1 **[114]** for LCI of solar and wind energy.

6.5.3 Impact Assessment

ReCiPe is a life cycle impact method released in 2008 **[115]**. The goal of ReCiPe is to harmonize midpoint and endpoint impact categories in a single framework. This method builds on the previously existing Centrum Milieukunde Leiden (CML 2002) and Eco-indicator 99 methods, the former of which uses the midpoint approach, and the latter, uses the midpoint approach, which are explained next **[115]**..

Midpoint and Endpoint Indicators

The advantage of using the ReCiPe framework for this work is because the results can be presented using either or both midpoint or endpoint indicators. These indicators have been developed using a system consistent in the methods and level of detail included in the models used to develop the indicators **[115]**.

There are eighteen midpoint impact categories and three endpoint impact categories in the ReCiPe method. Characterization factors are used to convert emissions to the units of the midpoint impact categories, and from midpoint to endpoint. Note that the midpoint impact category of climate change contributes to both the damage to human health and damage to ecosystems' endpoint categories. The relationship between the midpoint and endpoint impact categories is shown in Figure 6-5 **[115]** for the sake of completeness and understanding the categorization.

There are both advantages and disadvantages to using midpoints and endpoints. Midpoints are generally fairly accurate, but the units, usually in terms of a reference compound, such as CO_2 for climate change, can render it difficult for the analyst or a policy maker to understand the overall impact. In contrast, endpoints are much easier to conceptualize. Endpoints are expressed in terms of tangible effects using a point system, dollar amounts, number of species affected, or number of human life years lost (DALY), to which it is easier to relate. However, the method of translating the midpoint impacts to endpoint units incorporates much uncertainty.

This uncertainty stems from poor understanding of the mechanisms through which pollutants affect ecosystems and human life and the dependence these mechanisms may have on geographical factors. Thus, the tradeoff between result accuracy and result interpretation becomes quite evident.

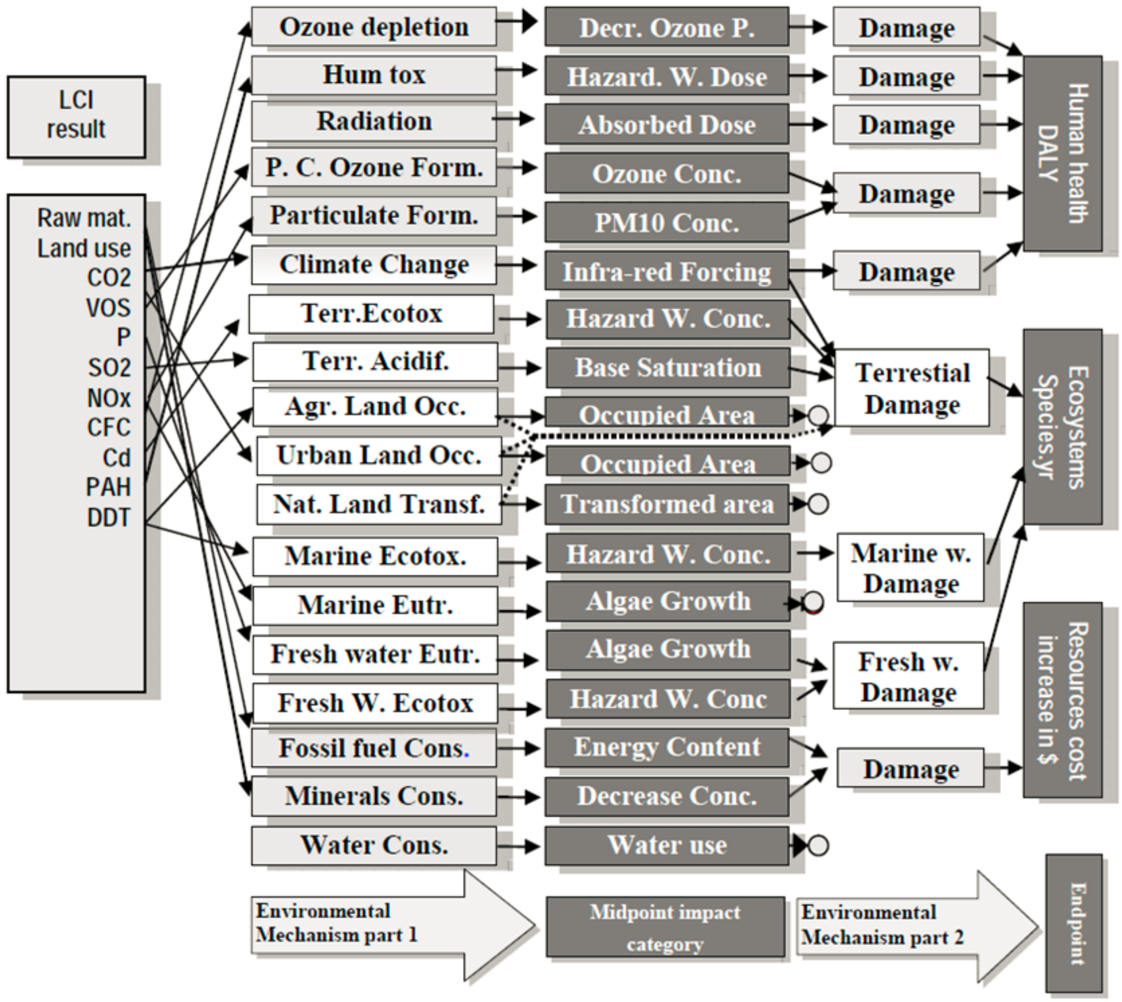


Figure 6-5: Relationship between life cycle inventory results, midpoint and endpoint indicators (Taken from **[115]**)

6.6 LCA of Renewable Energy based systems

We performed a detailed LCA of each component of the microgrid using OpenLCA and the results are presented below:

Numerous databases were investigated which referred to most recent literature for LCA data. ecoinvent database was used for all the studies as it provided most reliable and recent data for LCI. We used ecoinvent v3.1 database **[114]** for all our LCI and impact assessment.

6.6.1 Wind Power

Early development of wind energy in Canada was located primarily in Ontario, Quebec, and Alberta. Throughout the late 1990s and early years of the 21st Century every Canadian province has pursued wind power to supplement their provincial energy grids. Alberta built the first commercial wind farm in Canada in 1993. British Columbia was the recent province to add wind power to its grid with the completion of the Bear Mountain Wind Park in November 2009[4]. With increasing population growth, Canada has seen wind power as a way to diversify energy supplies away from traditional reliance on fossil fuel burning thermal plants and heavy reliance on hydroelectricity in some provinces. In provinces like Nova Scotia, where only 12% of electricity comes from renewable resources [5], the development of wind energy projects will provide a measure of electricity security that some jurisdictions are lacking. In the case of British Columbia, wind energy will help close the electricity deficit that the province is facing into the 2010s and help reduce the reliance on importing power from other jurisdictions that may not use renewable energy sources. An additional 2,004 megawatts of wind power is to come on stream in Quebec between 2011 and 2015. The new energy will cost 10.5 cents per kilowatt-hour, a price described as "highly competitive".

The installed capacity of wind power plants in other countries has been rapidly increasing, especially in China, Denmark, Germany and Spain. Up to now, mainly onshore turbines have been installed, but offshore wind parks are expected to have important growth rates because of the higher yields compared to onshore sites.

Since wind power is expected to play a major role in a majority of microgrid design, an assessment of its environmental performance is necessary to serve as a basis for a fair comparison of different options. There have been numerous studies for LCA of the wind energy [116, 117, 117, 118, 118, 119, 119] with varying scope but most of them indicate a clear dominance of the material used in production and the large amounts of indirectly produced waste.

The product chain for the wind turbines is not very complicated. The important components are the materials and the energy consumption for construction as well as the life time and the capacity factor for the operating microgrid. The capacity factor is an indicator of the fraction of year, during which the turbines would continuously produce electricity at rated power to generate the actual average annual amount during their lifetime.

Goal and Scope of the study

The datasets used for the study have been taken from a wind turbine installation as listed in the Table 6-1**,** the basic information comes from the manufacturers of the wind turbines and the electricity production data over the past years for that location we choose.

Type	Description (ecoinvent database process markers)
Wind	Electricity generation, at wind power at plant, average – CA- ON (includes construction, operation & maintenance, and disposal processes for a single wind turbine considering life of 20 years on a per kWh basis)

Table 6-1: Dataset from ecoinvent databased used for LCA of wind turbine

Due to lack of availability of data for small turbines, we used a 30kW wind turbine as benchmark **[120]**.

The production chain for wind power can be represented by the following schematic as shown in Figure 6-6.

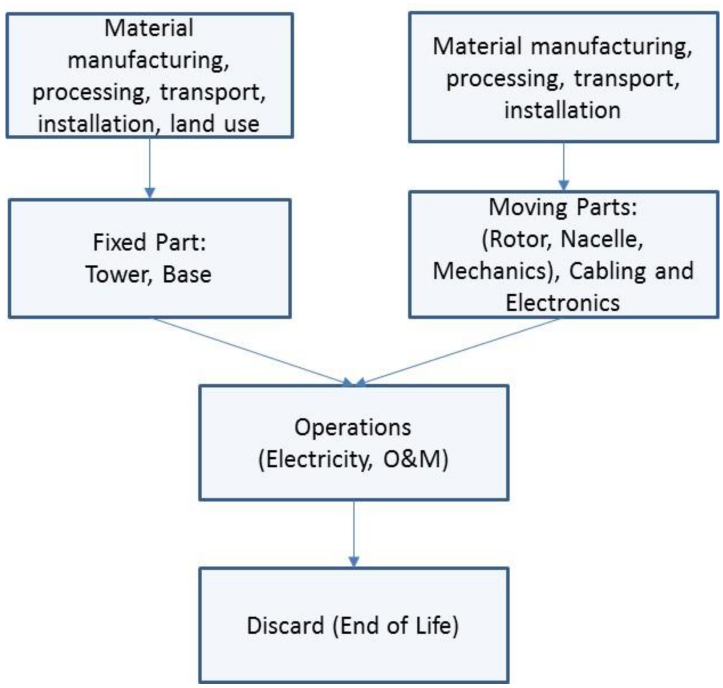


Figure 6-6: Production chain for wind energy

Life Cycle Inventory

The Table 6-2 shows key parameters for life cycle inventory in the ecoinvent database v2.2 for the 30kW turbine. The full life cycle inventory with their processes for all production stages can be found in the ecoinvent database **[121]**. A detailed process analysis of all relevant upstream and downstream processes, for example, that the construction of the tower includes not only energy and material requirements as well as emissions of the steel production, but also the relevant extraction of the ore, its processing and transport with the same level of detail has been considered **[122]**.

Wind Turbine	Units	30kW
Type		Hummer 30
Capcity Factor		9 %
Lifetime tower, basement	years	40
Lifetime nacelle	years	20
Length of cable to distribution	m	500
Rotor diameter	m	10
Turbine weight	kg	1350

Table 6-2: Wind Turbine key parameters for LCI

In addition to the material consumption, the inventory includes: material processing; its transport to the manufacturer of components and to the site; energy requirements; particle emission during preparation of the sea bottom with excavation and concrete pouring; disposal of plastics; and land use. However, manufacturers only provide total masses of the parts of the turbines and the breakdowns for individual materials have to be assumed, which can be difficult. All metals in the tower and nacelle as well as the rotor blades are assumed to be recycled. Also, the preparation of the sea bottom for the offshore turbines, e.g. digging of navigation channels and trenches for the cables, is taken into account. No replacement of main components during the lifetime is considered. Material consumption for the connection of the turbines to the electricity grid are based on our own estimations, since available information is limited.

Results

All the calculations are based on for a 1 kWh of energy. One can easily scale it in terms of capacity using the graphical interface in OpenLCA.

Using selected endpoint indicators for the ReCiPe impact assessment method as shown in the Table 6-3 we obtain the results for a wind turbine for its entire life cycle for producing electricity with 10% capacity factor.

LCIA Endpoint Impact category	Reference unit	Value
Ecosystems - Agricultural land occupation	species.yr	3.0042E-11
Ecosystems - Climate Change	species.yr	4.50463E-10
Ecosystems - Freshwater ecotoxicity	species.yr	1.22347E-11
Ecosystems - Freshwater eutrophication	species.yr	7.43166E-13
Ecosystems - Marine ecotoxicity	species.yr	8.36434E-10
Ecosystems - Natural land transformation	species.yr	4.71603E-10
Ecosystems - Terrestrial acidification	species.yr	1.85958E-12
Ecosystems - Terrestrial ecotoxicity	species.yr	8.41846E-12
Ecosystems - Urban land occupation	species.yr	4.44566E-11
Ecosystems-total	species.yr	1.85623E-09
Human Health - Climate Change	DALY	8.45557E-08
Human Health - Human toxicity	DALY	7.9787E-07
Human Health - Ionising radiation	DALY	2.92284E-11
Human Health - Ozone depletion	DALY	5.10163E-12
Human Health - Particulate matter formation	DALY	2.21073E-08
Human Health - Photochemical oxidant formation	DALY	4.93056E-12
Human Health-total	DALY	9.04569E-07
Resources - Fossil depletion	$	0.001185641
Resources - Metal depletion	$	0.0016452
Resources-total	$	0.002830842

Table 6-3: LCIA based on endpoint indicators for wind turbine per kWh

In Table 6-3 the reference units enable the policy makers and planners to be able to compare the alternatives. The explanation for the units is stated below:

- species.yr: Loss of species during a year
- DALY: ‘disability-adjusted life years’, The DALY of a disease is derived from human health statistics on life years both lost and disabled. Values for disability-adjusted life years have been reported for a wide range of diseases, including various cancer types, vector-borne diseases and non-communicable diseases. When equal weightings are applied to the importance of 1 year of life lost for all ages and any discount for future damages is disregarded, DALY is the sum of years of life lost (YLL) and years of life disabled (YLD): DALY = YLL + YLD where $YLD = w \times D$, where w is a severity factor between 0 (complete health) and 1 (dead), and D is the duration of the disease.
- $ (Dollar): Additional cost incurred because of resource utilization such as damage to resource availability, cost related to activities associated with mining of resources etc.

6.6.2 Solar Power

Goal and Scope

LCA studies for photovoltaic power plants have a long tradition of more than 15 years [123-128]. The published literature shows a high variation in the results and conclusion. The major issues during the modelling of an LCI for photovoltaic power are: modeling of the silicon inputs, and use off-grade or solar grade silicon, allocation between different silicon qualities, power mixes assumed for the production processes and process specific emissions. The production technology for the photovoltaic power plants has been constantly improved over the last decades, e.g. for the efficiency of cells, the amount of silicon required, and the actual capacity of production processes. The data availability is a significant problem for establishing a high quality inventory, because not many producers do provide reliable and verifiable data. Although with progress in time more reliable and accurate data is getting available.

We investigated a small scale plant with 3kWp capacity based on the availability of reliable data. We used the data for poly crystalline cell type, pc-Si.

Type	Description (ecoinvent database process markers)
Solar	Electricity production,photovoltaic, 3kWp, mult-Si, panel, mounted average – CA- ON (includes construction, operation & maintenance, and disposal processes for a single wind turbine considering life of 25 years on a per kWh basis)

Table 6-4: Dataset from ecoinvent databased used for LCA of PV panel

Life Cycle Inventory

In principle, all the components shown in the Figure 6-7 are a part of the system boundary. The process data is taken from ecoinvent database v 3.1, it includes quartz reduction, silicon purification, wafer, panel and laminate production, manufacturing of converter and supporting structure assuming a life time of 30 years. Furthermore, transports of materials, energy carriers, semi-finished products and the complete power plant, and waste treatment processes for production wastes and end of life wastes are considered. Air- and waterborne process-specific pollutants are included as well. The photovoltaic system in particular is divided into unit processes for each of the process steps shown.

In several photovoltaic LCAs, all inputs and outputs for the purification process of MG-silicon have been allocated to the EG-silicon (required for wafer production) and none to the silicon tetrachloride. However, in an LCA study of vacuum insulation (based on silicic acid), inputs and outputs of the purification process have been allocated on the basis of the revenues of EG silicon and $SiCl_4$ **[129]**. Hence, more than 100% of total inputs and outputs of the MG-Si purification process have been allocated to the two coproducts, when adding up the LCI results of the photovoltaic and the vacuum insulation study. This is not according to ISO 14041, which states that "the sum of the allocated inputs and outputs of a unit process shall equal the unallocated inputs and outputs of the unit process" (International Organization for Standardization (ISO) 1998). Large background LCI databases like ecoinvent require a consistent modelling of such processes. Where possible, processes have been split up in order to avoid allocation.

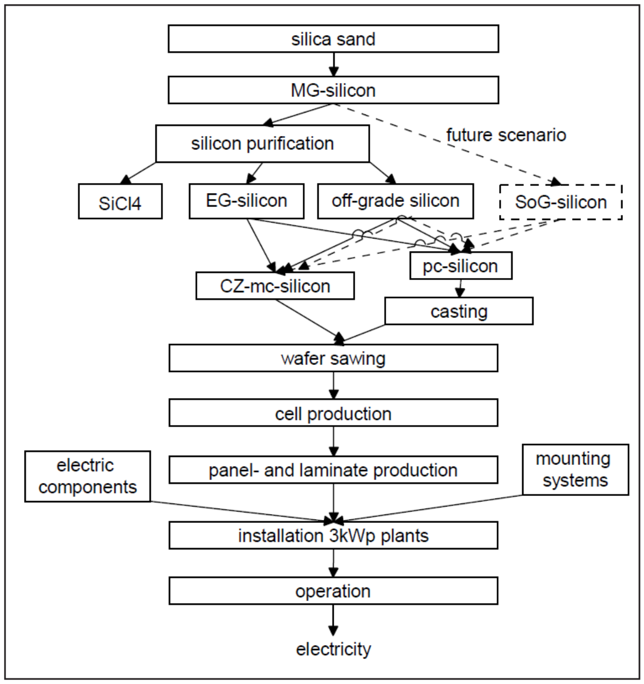


Figure 6-7: Different subsystems in photovoltaic energy production, future possible processes ar shown in dotted line

Key components of the pc-Si photovoltaic life cycle processes and subsystems for different photovoltaic technologies is presented in **Figure 6-7**.

LCIA Endpoint Indicators	Reference Unit	Value
Ecosystems - Agricultural land occupation	species.yr	9.72718E-11
Ecosystems - Climate Change	species.yr	1.61578E-09
Ecosystems - Freshwater ecotoxicity	species.yr	1.20383E-11
Ecosystems - Freshwater eutrophication	species.yr	3.77587E-12
Ecosystems - Marine ecotoxicity	species.yr	1.14926E-09
Ecosystems - Natural land transformation	species.yr	1.43454E-09
Ecosystems - Terrestrial acidification	species.yr	1.35576E-12
Ecosystems - Terrestrial ecotoxicity	species.yr	1.23483E-10
Ecosystems - Urban land occupation	species.yr	2.68367E-11

Ecosystems-total	species.yr	4.4641E-09
Human Health - Climate Change	DALY	3.03275E-07
Human Health - Human toxicity	DALY	3.64142E-06
Human Health - Ionising radiation	DALY	1.52591E-10
Human Health - Ozone depletion	DALY	3.67096E-11
Human Health - Particulate matter formation	DALY	3.83045E-08
Human Health - Photochemical oxidant formation	DALY	1.47697E-11
Human Health-total	DALY	3.9832E-06
Resources - Fossil depletion	$	0.003824705
Resources - Metal depletion	$	0.003404501
Resources-total	$	0.007229206

Table 6-5: LCIA based on Endpoint indicators for PV panel per kWh

The LCIA of a PV panel using the ReCiPe Endpoint indicators is shown in Table 6-5. The definitions of the reference units remain the same as that in the LCIA of wind turbine.

6.6.3 Battery – Li-ion Battery

Goal and Scope

The functional unit was chosen as the production of one Li-ion battery. Impacts were reported for functional units based on mass measured in kilograms (kg) and in terms of nominal energy capacity measured in kilowatt-hours (kWh) using the midpoint and endpoint categories.

Life Cycle Inventory

Data in this section are taken from ecoinvent v3.1 life cycle inventory database. The battery is an NCM Li-ion battery. Each battery cell is made with a cathode based on Li(NixCoyMnz)O2 and an anode based on graphite. One battery vehicle pack is made up of two battery subpacks connected in parallel. The weight of the battery is 253 kg, of which the battery cells makes up 60% of its total weight. The battery's energy capacity is 26.6 kWh, and under normal use the battery efficiency is 95% to 96%. The number of cycles the battery can perform before its nominal capacity falls below 80% of its initial rated capacity is often referred to as the battery's cycle life (Kalhammer et al. 2007). With 100% depth of discharge (DOD), the battery is expected to reach a nominal cycle life of 1,000 cycles, whereas 50% DOD extends the expected number to 5,000 cycles.

The battery components were grouped into four main components: battery cell; packaging; battery management system (BMS); and cooling system. All of these components consisted of subcomponents Figure 6-8. The battery has 12 battery modules, each made up of 30 battery cells, for a total of 360 battery cells.

Given the restrictions on the availability of the data we used this data for evaluating LCIA on per kg basis of the battery. Since we were evaluating other technologies on a per kWh basis we converted the results to per kWh given the life and weight of the battery. In our case the life of the battery was given in terms of total energy throughput of 845kWh and the weight was 160 kg.

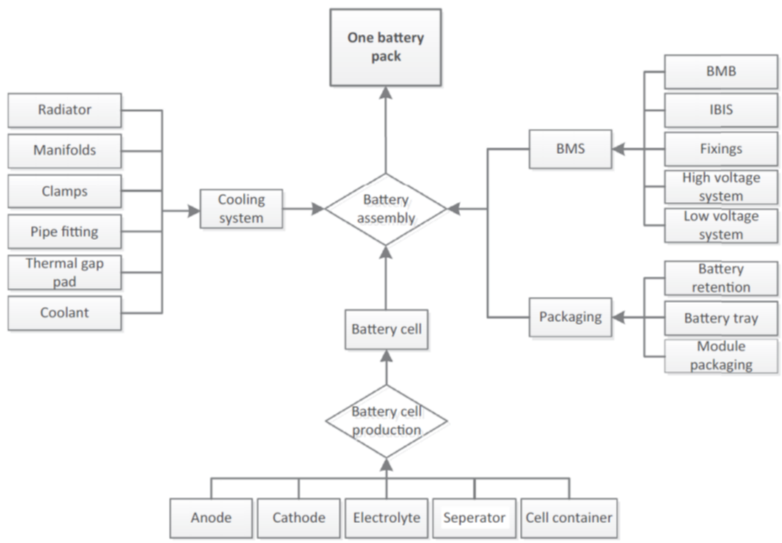


Figure 6-8: Simplified flow diagram for Battery pack. BMS: Battery Management System, BMB: Battery Management Board and IBIS: Integrated Battery Interface System

Impact category	**Reference unit**	
Ecosystems - Agricultural land occupation	species.yr	6.9507E-09
Ecosystems - Climate Change	species.yr	8.18937E-08
Ecosystems - Freshwater ecotoxicity	species.yr	8.62192E-10
Ecosystems - Freshwater eutrophication	species.yr	1.14948E-09
Ecosystems - Marine ecotoxicity	species.yr	1.97713E-07
Ecosystems - Natural land transformation	species.yr	-3.37644E-08
Ecosystems - Terrestrial acidification	species.yr	1.23864E-09
Ecosystems - Terrestrial ecotoxicity	species.yr	9.52106E-09
Ecosystems - Urban land occupation	species.yr	-9.94235E-10
Ecosystems-total	species.yr	2.64497E-07
Human Health - Climate Change	DALY	1.53713E-05

Human Health - Human toxicity	DALY	0.001435406
Human Health - Ionising radiation	DALY	7.20435E-09
Human Health - Ozone depletion	DALY	7.73373E-10
Human Health - Particulate matter formation	DALY	6.20758E-06
Human Health - Photochemical oxidant formation	DALY	5.11116E-10
Human Health-total	DALY	0.001456993
Resources - Fossil depletion	$	0.237561345
Resources - Metal depletion	$	1.836369061
Resources-total	$	2.073930405

Table 6-6: LCIA based on Endpoint indicators for Li-ion Battery per kWh

The LCIA of a Li-ion battery pack using the ReCiPe Endpoint indicators is shown in **Table 6-6**. The definitions of the reference units remain the same as that in the LCIA of wind turbine and the PV panel.

Analysis

Analyzing the data obtained from LCI of wind in Table 6-3 ,solar in Table 6-5 and battery in **Table 6-6**, we can say that wind power is comparatively better than solar in almost seventeen of the twenty endpoint indicators. A few indicators have negligible numerical values but that can be ignored for the sake of comparison. In Table 6-7 we compare both solar and wind using the midpoint indicators using standardization for unit kWh of energy. Out of 18 midpoint indicators solar exceeds the wind on 15 indicators while diesel generation exceeds solar on 12 indicators. The most critical of those being climate change where diesel power exceeds solar impacts by atleast 14 times and wind impacts by 51 times.

Numbers indicate that diesel is not a good performer on climate change, terrestrial acidification and fossil depletion which are very important for climate and adoption of renewable technologies. On the other hand looking at indicators of marine toxicity and fresh water ecotoxicity diesel generation is better than the two renewable technologies. Therefore in conclusion it is important to consider the location specific regulations, policies, habitat in order to finalize the technology selection.

Midpoint Indicators	Units	All results are for 1kWh of energy produced				
		Solar	**Wind**	**Diesel**	**Hyrdo**	**Battery**
Agricultural land occupation	m^2	0.008097	0.002505	0.0009509	0.00059	0.021989946
Climate Change	**kg CO_2 eq**	**0.086401**	**0.024089**	**0.3941612**	**0.004511**	**0.165838637**
Fossil depletion	**kg oil eq**	**0.023116**	**0.007166**	**0.1554949**	**0.000995**	**0.054371936**
Freshwater ecotoxicity	kg 1,4-DB eq	0.014061	0.01426	0.001859	0.000529	0.038127668
Freshwater eutrophication	kg P eq	8.48E-05	1.67E-05	4.780E-06	1.24E-06	0.000977221
Human toxicity	**kg 1,4-DB eq**	**5.202051**	**1.139822**	**3.8544595**	**0.055085**	**2.862427617**
Ionising radiation	kg U235 eq	0.00932	0.001785	0.0014469	0.000278	0.016664356
Marine ecotoxicity	**kg 1,4-DB eq**	**6.522401**	**4.745454**	**1.0736880**	**0.214305**	**4.633114106**
Marine eutrophication	kg N eq	4.44E-05	9.13E-06	1.229E-05	8.96E-07	0.00015842
Metal depletion	kg Fe eq	0.047615	0.02301	0.0034701	0.002688	0.972628956
Natural land transformation	m^2	1.1E-05	3E-06	4.329E-05	3.35E-07	1.51E-06
Ozone depletion	kg CFC-11 eq	1.27E-08	2E-09	1.169E-08	3.42E-10	1.28091E-08
Particulate matter formation	kg PM10 eq	0.000147	8.5E-05	0.000319	2.49E-05	0.000904153
Photochemical oxidant formation	kg NMVOC	0.000379	0.000126	0.0005358	2.38E-05	0.000496443
Terrestrial acidification	**kg SO_2 eq**	**9.51E-05**	**0.000131**	**0.001411**	**2.19E-05**	**0.003303421**
Terrestrial ecotoxicity	kg 1,4-DB eq	0.00082	5.59E-05	3.466E-05	4.57E-06	0.002391817
Urban land occupation	m^2	0.001296	0.002148	0.0001586	7.18E-05	0.001818914
Water depletion	**m^3**	**1.478758**	**0.133154**	**0.0904764**	**45.01798**	**2.084487822**

Table 6-7: LCIA based on midpoint indicators for PV, Wind, Diesel,Hydro and Li-ion Battery per kWh

We present hydro power also for the sake of clarity and comparison although we did not consider it as a part of the microgrid. Over all these numbers are small and may not be clear indicators of the system under consideration and hence we need to undertake a cumulative LCA of the microgrid which is presented in the next section.

6.6.4 Microgrid – Cumulative LCA

Modeling the LCA for a microgrid is an aggregation of the LCA of its individual components for the quantities required for the respective microgrid. It is important that LCA for each component required for the microgrid is done in totality before the aggregation as LCA varies with component capacities and quantities. Here we analyze the microgrid and its components independently not only for their environmental impact but also in terms of the cumulative energy demand and then analyzing the energy payback time for the system. As we are all aware the non-renewable energy based power will have a negative impact on the environment hence we compare the GHG emissions of a renewable microgrid with a traditional diesel generation.

We shall evaluate any microgrid configuration on two main aspects of LCA:

- Environmental Assessment
- Energy Payback time

6.6.4.1 Environmental Assessment

The most important factor for environmental assessment of a microgrid is the GHG emissions produced by the system attributing to climate change. It is quite obvious that GHG from diesel generation are far more and increasing over time whereas they are only during the cradle to gate period of the renewable generation technologies. We compare the five important indicators for the renewable energy technologies including the hydro power (just for the purpose of comparison) and diesel generation. We evaluated the technologies on a per kWh of energy. These indicators allow us to decide on the degree of penetration of the candidate technologies as shown in Figure 6-6 and comparative charts are shown in Figure 6-9 for any given location.

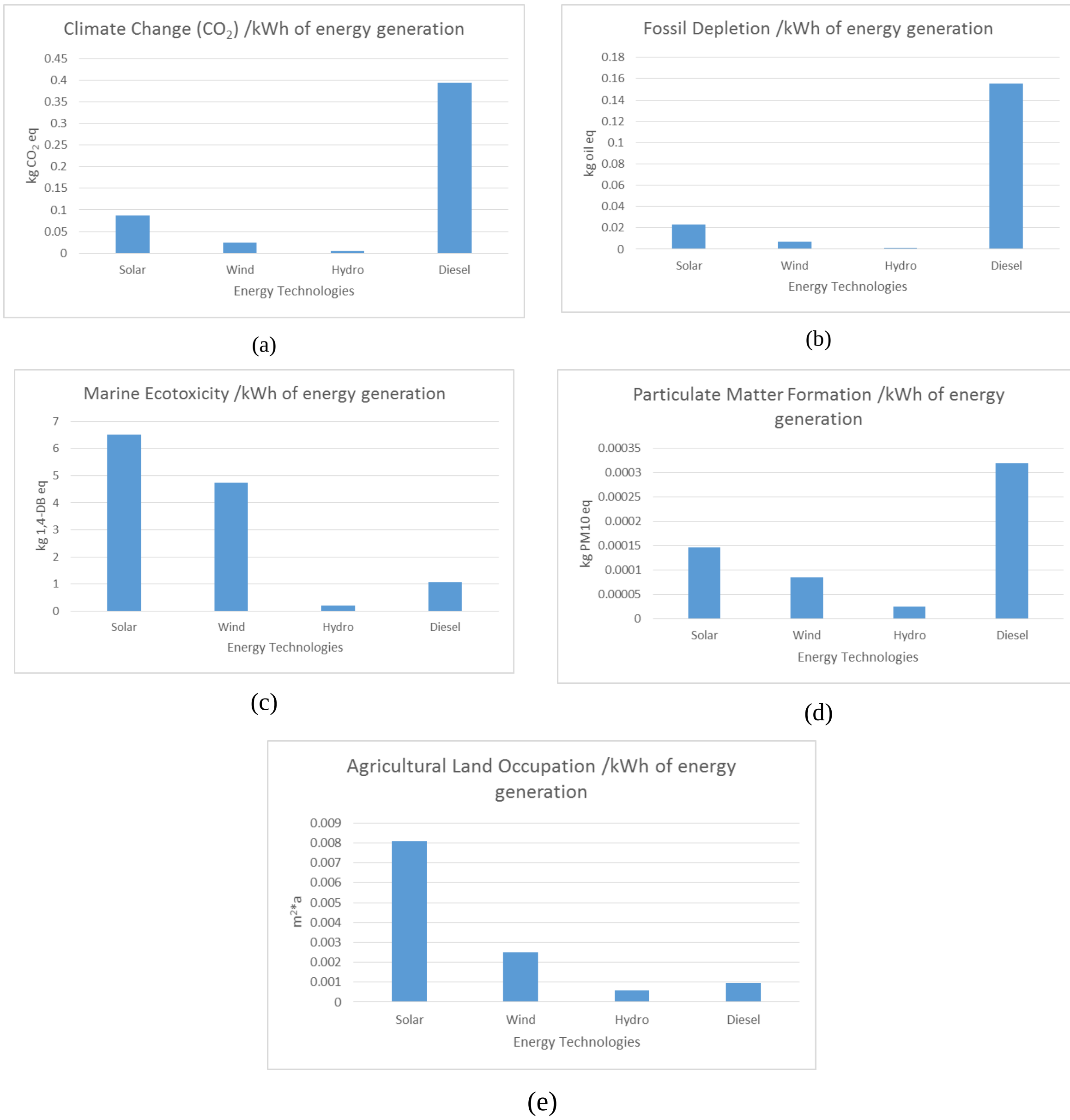
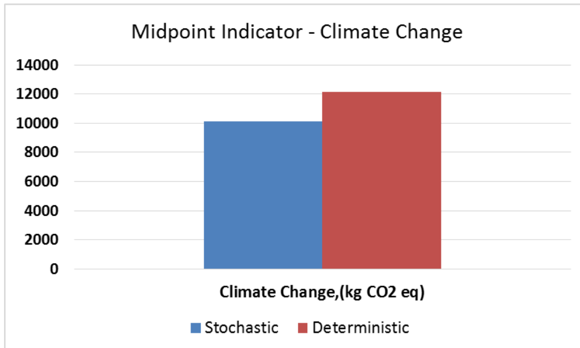


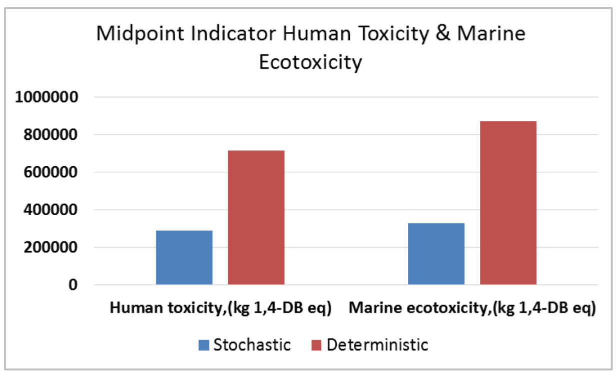
Figure 6-9: Comparison of impact of individual technologies on the five midpoint indicators

In Figure 6-9 (e) the variations among the four technologies is presented where non-renewable technology is very space economical whereas solar occupies much larger space. Similarly, on other criteria such as particulate matter formation (Figure 6-9 (d)), marine ecotoxicity (Figure 6-9 (c)), climate change (Figure 6-9 (a)) and fossil depletion (Figure 6-9 (b)) has been presented to allow planners to choose from a range of technologies to suit the local needs and regulations.

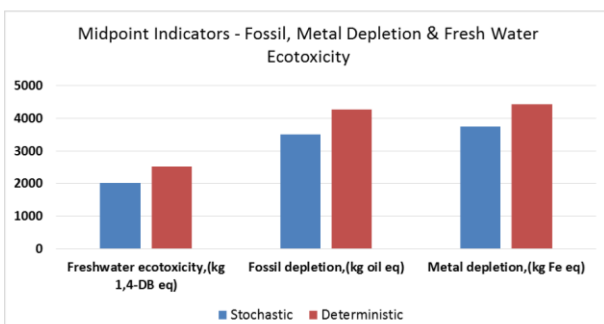
Overall to evaluate the benefits of cumulative LCA and our stochastic optimization technique it is important to compare the environmental impacts of the microgrid configuration obtained in **Table 5-10**. We used the case of stochastic solution with EUEmax = 0 % and the results are presented below using the midpoint indicators. Figure 6-10(a), (b) and (c) indicate that our stochastic solution performs better on all the midpoint indicators over deterministic solution.



(a)



(b)



(c)

Figure 6-10:Midpoint Indicators for the Microgrid (Solar+Diesel+Wind+Battery)

6.6.4.2 Cumulative Energy Demand – Energy payback time analysis

In order to quantify the life cycle energy demand of a product, the indicator Cumulative Energy Demand (CED) is defined as the sum of energy of all resources required to provide a process or product. The energy requirement of one unit of process output was then obtained by dividing the total energy requirement by the number of unit outputs during the time period. The emergence of large life cycle databases such as ecoinvent enables and facilitates a product-specific approach, since such databases provide the resource demand for each unit process. Hence, improved CED scores can be calculated that indicate the energy demand of a single product directly. CED is specified in MJ equivalents to highlight that it is an impact assessment indicator and not an inventory elementary flow.

We shall evaluate the microgrid (renewable technologies) using CED.

CED for renewable resources of energy

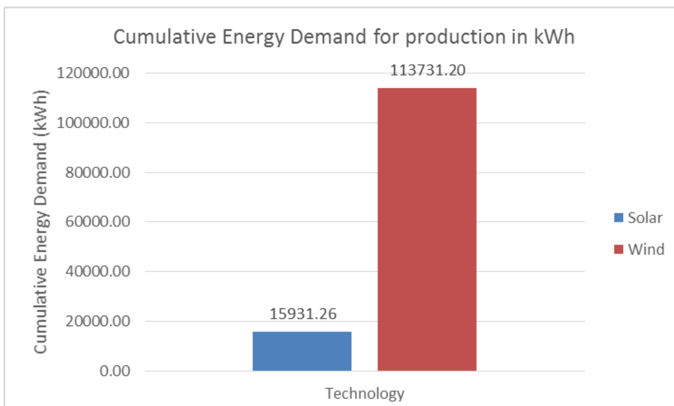


Figure **6-11:** Cumulative energy demand for the manufacture of Wind and Solar technologies

We show the in how much time the renewable energy technology shall be able to return this energy back into the system in a cleaner and greener way in Figure 6-12. Wind uses far more energy than solar given the large amount given the need for a large amount of accessories. Solar/PV technology on the other hand uses far less energy for its manufacture. We find that the energy payback time for wind is far less as compared to wind based on the data we used for our microgrid design. Figure 6-10 shows comparison between the energy pay back times of solar and wind given the resources availability for the location under consideration. It is seen that EPBT for both the technologies is less than half times the total life of each of the technologies which is an indicator of a profitable option as the technology is beyond the breakeven where it may not be generating any net positive energy during its life time.

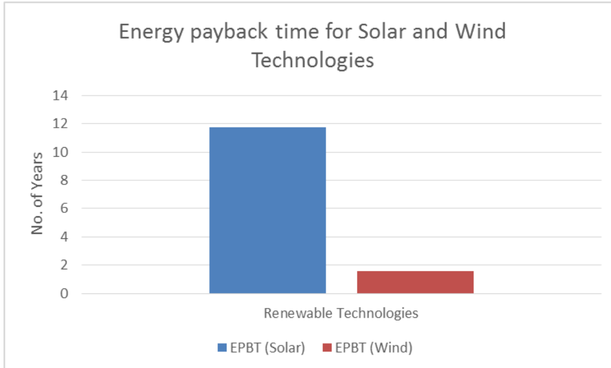


Figure 6-12: Energy Pay Back time for the manufacture of Wind and Solar technologies for microgrid

6.6.5 MCDA for Microgrid Configuration Selection

In planning of microgrids an important step after MDOUU is to select the most appropriate configuration which satisfies the needs and requirements of all the stake holders. We described a detailed procedure for finding an appropriate solution using VIKOR method which is the most suitable for the problem at hand, given the complex nature of the microgrid planning problem.

We firstly decide upon the attributes which will be used in the computation of the best alternative and subsequently compromised solutions. The list of attributes which are most significant and affect the decision maker in his choice are listed below:

	Attribute	**Unit**
	Environmental Attributes	
at_1	Green House Gas (GHG) Emissions Avoided	kg/kWh
a_{t2}	Land Occupancy (LO)	m^2
at_3	Annual Energy Production (AEP)	kWh
	Economic Attributes	
at_4	Cost of Energy (CoE)	$/kW
at_5	Net Present Value (NPV)	$
at_6	Energy Payback Period (Renewable Technology) - EPBT	Years

Table 6-8: Criteria for evaluating the microgrid configurations

The choice of the attributes in Table 6-8 is based on various papers published in the past for evaluating renewable energy systems [86, 131, 132]]. We evaluate each of the attributes based on simple formulation using the results obtained in Section 5.6.4.

The formulas to obtain the attributes are shown by

GHG: Green House Gas

TRG: Total Renewable Energy Generated

GHGI: Green House Gas Intensity/kWh for nonrenewable generation

NR: Number of Renewable Resource Units

LOP: Land Area Occupied per unit of equipment

TNRG: Total Non-Renewable Energy Generated

CoE: Cost of Energy

CED: Cumulative Energy Demand

AEPR: Annual Energy Produced by a Renewable Technology

EPBT: Energy Pay Back Time

$$GHG\ Avoided\ \left(\frac{kg}{year}\right) = TRG\left(\frac{kWh}{year}\right) * GHGI\left(\frac{kg}{kWh}\right) \tag{6-1}$$

$$LO(m^2) = NR * LOP(m^2) \tag{6-2}$$

$$AEP(kWh) = TRG(kWh) + TNRG(kWh) \tag{6-3}$$

$$CoE\left(\frac{\$}{kWh}\right) = \frac{Total\ Cost}{TRG + TNRG} \tag{6-4}$$

$$NPV\ (\$) = Total\ Net\ Present\ Value \tag{6-5}$$

$$EPBT(years) = \frac{CED\ (kWh)}{AEPR\left(\frac{kWh}{year}\right)} \tag{6-6}$$

Hence all our designed systems will be evaluated on the attributes and then use VIKOR method to conclude upon the choice of configuration.

The various possible configurations or alternative which we have are listed below:

	Alternatives/Possible Configurations
Alt_1	Wind (30kW/turbine, Qty - 2) + Diesel (Qty - 2, 8kW each) + Storage (Qty – 23, 225Ah-12V)
Alt_2	Diesel (Qty-5, 8kW each)
Alt_3	Solar (Qty:56, 180Wp) + Diesel (Qty-3, 8kW each) + Storage (Qty – 44, 225Ah-12V)
Alt_4	Wind (30kW/turbine, Qty - 2) + Solar (Qty-21, 180Wp) + Diesel (Qty-2, 8kW each) + Storage (Qty – 20, 225Ah-12V)
Alt_5	Wind (10kW/turbine, Qty - 6) + Solar (Qty-25, 180Wp) + Diesel (Qty-2, 8kW each) + Storage (Qty – 21, 225Ah-12V)
Alt_6	Wind (3kW/turbine, Qty - 25) + Solar (Qty-29, 180Wp) + Diesel (Qty-2, 8kW each) + Storage (Qty – 24, 225Ah-12V)

Table 6-9: Few possibilities of alternatives for microgrid configurations

We can also have possible combinations of the alternative Alt_5 by varying the number of each of the components in the configuration (as in no. of wind turbines, no. of solar panels, no. of diesel generators and batteries). This technique may be helpful in finalizing the configuration when a large number of alternatives based on design of experiment are obtained.

The attribute values for the MCDA are obtained from the optimizer of Phase II and LCA of Phase III.

6.7 Results and discussions

We shall demonstrate applicability to the MCDM for microgrid planning given the six attributes in Table 6-8. We rank 6 possible configuration which were obtained from Phase II given various restrictions on land availability, cost, eco-friendly zone etc which forced the planners to compromise from having the most optimal configuration given the restrictions on any of the possible attributes.

Alternatives	Attributes					
	GHG AVOIDED $(\frac{kg}{year})$ at_1	**LO** (m^2) at_2	**AEP** (kWh) at_3	**CoE** $(\$/kWh)$ at_4	**NPV** (\$) at_5	**EPBT** $(Years)$ at_6
Alt_1	463130	61636	199180.53	1.18	94210.25	2
Alt_2	0	760	90287.16	3.99	318936.39	NA
Alt_3	125852	1449	119649.83	2.99	239352.67	12
Alt_4	308984	43400	161116.94	1.07	85206.02	6
Alt_5	156330	13900	104331.59	1.64	131364.34	8
Alt_6	133010	7896	107904.98	2.28	182247.62	9

Table 6-10: Attributes and alternatives for microgrid selection

	GHG AVOIDED $(\frac{kg}{year})$ at_1	**LO** (m^2) at_2	**AEP** (kWh) at_3	**CoE** $(\$/kWh)$ at_4	**NPV** (\$) at_5	**EPBT** $(Years)$ at_6
	MAX	MIN	MAX	MIN	MIN	MIN
f_i^*	463130	760	199180.53	1.07	85206	2
f_i^-	0	61636	90287.16	3.99	318936	12

Table 6-11: Best and Worst values of each attribute

Now we need to construct the A matrix of relative importance of each attribute as mentioned in Section 6.6.5. The DM matrix for our set of attributes is given by the following formulation

$$DM = \begin{bmatrix} 1 & 3 & 3 & 5 & 1/3 & 5 \\ 1/3 & 1 & 3 & 1/7 & 1/5 & 3 \\ 1/3 & 1/3 & 1 & 1/7 & 1/9 & 1/3 \\ 1/5 & 7 & 7 & 1 & 3 & 5 \\ 3 & 5 & 9 & 1/3 & 1 & 9 \\ 1/5 & 1/3 & 3 & 1/9 & 1/9 & 1 \end{bmatrix}$$

We use the A matrix to obtain $A_{norm}$and the mean of the elements of the rows give us the weights as

wa_1	wa_2	wa_3	wa_4	wa_5	wa_6
0.2533	0.0722	0.0305	0.2871	0.3140	0.0429

Table 6-12: Weights of all the attributes based on AHP

Once we have evaluated the weights we find the maximum eigen value, $\lambda_{max} = 7.4055$ and consistency index (CI) $CI = 0.2811$, to assess the consistency of our comparison we generate another Random index for n = 6 it is 1.24 and estimate the Consistency ratio $CR = CI/RI$= 0.2811/1.24 = 0.22 i.e. 22% inconsistency in the decision matrix. This probably indicates a reassignment of weightage is required.

Having obtained the values of the weights we shall now obtain the values of S_j and R_j as shown in Table 6-13 .

	$\boldsymbol{Alt_1}$	$\boldsymbol{Alt_2}$	$\boldsymbol{Alt_3}$	$\boldsymbol{Alt_4}$	$\boldsymbol{Alt_5}$	$\boldsymbol{Alt_6}$
S_j	0.1262	0.9278	0.6087	0.1689	0.3375	0.4708
R_j	0.1031	0.3140	0.2071	0.0843	0.1678	0.1806

Table 6-13: Values for $\boldsymbol{S_j}$ and$\boldsymbol{R_j}$ for all alternatives

Once we have obtained the attribute values for each of the possible alternatives under consideration we need to find the ideal values for each of the attribute's maximum if it's a benefit and minimum if it's a cost. We need to evaluate the S_j and R_j for all the possible alternatives. In Table 6-14 we show the value of each alternative for the corresponding weight for the strategy of maximum group utility.

vf	Alt_1	Alt_2	Alt_3	Alt_4	Alt_5	Alt_6
0	0.0817	1.0000	0.5345	0.0000	0.3635	0.4190
0.2	0.0654	1.0000	0.5480	0.0107	0.3435	0.4212
0.4	0.0490	1.0000	0.5615	0.0213	0.3235	0.4234
0.5	0.0327	1.0000	0.5750	0.0320	0.3035	0.4256
0.6	0.0163	1.0000	0.5884	0.0426	0.2836	0.4277
0.8	0.0000	1.0000	0.6019	0.0533	0.2636	0.4299
1.0	0.0817	1.0000	0.5345	0.0000	0.3635	0.4190

Table 6-14: Values of $\boldsymbol{Q_j}$ for different values of $\boldsymbol{vf}$

Using the values obtained in the Table 6-14, we sort the alternatives using the Q, S and R. The best alternatives is ranked by Q_{min} is Alt_4 which is also ranked the best by R. Hence Alt_4 (Wind (30kW/turbine) + Solar + Diesel + Storage) taken as the best choice of microgrid based on the preferences listed where as Alt_1 (Wind (30kW/turbine) + Diesel + Storage) is ranked as the compromise solution. Overall we see that wind along with solar, diesel and storage is the best combination for the location but otherwise if land is a constraint a solar panels can be possibly replaced by wind turbines as indicated by the by the Alt_1 at an extra cost. We therefore address multiple objectives and preferences and try to achieve an optimal solution suited to local conditions.

6.8 Summary

Overall this Chapter introduces the LCA for renewable technologies using ecoinvent database in the openLCA tool. LCA for renewable technologies, wind and solar elucidates their contribution towards the GHG emissions. Using various LCIA methods one is able to assess each technology on a variety of attributes. In any system which produces energy it is important that it produces energy more than that was required to produce it. We used the indicator of CED or Cumulative Energy Demand to estimate the total energy requirement of a technology with given specifications. This helps us to evaluate the energy payback time of the technology. Based on the capacity factor and the location one can estimate an approximate energy payback time for the technology. This would not only assist the planners in making an appropriate choice of technologies but a more rational decision can be made for a greener environment.

LCA is the major component of the Phase III of the MDOUU framework, the output of the LCA analysis are attributes of the MCDA which is another component in Phase III enabling in choosing appropriate configuration based on a scientific methodology.

Chapter 7
Summary, Conclusions, Contributions and Future Work

7.1 Thesis Summary

The thesis focuses on developing a multidisciplinary design optimization framework for design of engineering systems under uncertainty. We try to solve the problem considering a holistic approach and provide a full package which is general enough to be applied to any engineering design problem. In this thesis we focus mainly on the planning of microgrids considering the solar insolation and wind as uncertain parameters. Our main objective is to provide a complete package which can be used for design of almost any system that has significant impacts on earth over a long time and involves multiple disciplines.

Traditionally, deterministic approaches have been used in planning of systems, in reference to microgrid planning, there has been much research in planning of microgrids where most of the work does mention about the uncertainty in the resources but no models have incorporated the uncertainty explicitly into the model. We address the issue of uncertainty in the resources in terms of modeling the parameters as well as considering them explicitly into the model.

As a part of the planning of any engineering system we need to consider the environmental impact of the system given the rising rate of global warming. No planning models/frameworks have considered the environmental impacts in detail. Hence we incorporated the Life Cycle Analysis (LCA) as a part of the planning framework which is a novel idea in the area of planning of engineering systems. Lastly, methods that can be considered for multi objective and multi criteria optimization have not been explored, as we have presented here.

7.2 Contributions

The work completed in this thesis provided considerable contributions. Different mathematical formulations were proposed for an improved representation of uncertain renewable power production and with dependence modeling. In addition to these formulations, the thesis provided a systematic review of the literature and highlighted new areas of research that still need more investigative work from an economic as well as technical points of view. The ideas and the models discussed and presented in this work can form foundation of frameworks for more complex systems design that incorporate multidisciplinary design optimization under uncertainty.

The first major contribution of this thesis was to modeling uncertainty in renewable resources. We used the Kumaraswamy distribution as a standard approach to model the resources given the general form of the Kumaraswamy distribution and its simple analytical form. Another major contribution of the work was in modeling of dependence structure in the resources using Copulas. They provide a useful tool for modeling non-linear dependence between entities.

We further develop a deterministic optimization model for planning of microgrids using wind and solar as the main source of renewable generation. The objective function incorporated not only the life of batteries but also a term on carbon taxes on the diesel generation which increased the penetration of the renewable generation.

As it has been mentioned several times earlier in the thesis about the uncertainty in the parameters leading to infeasible or economically expensive designs for microgrid. In order to mitigate such possibility we used the approach of stochastic programming using the two stage stochastic programming paradigm for microgrid planning which gave not only reliable but also economically and environmentally cheap designs.

Another contribution of the thesis for was extending the two-stage stochastic programming model to risk-averse model using the Markovitz objective function. We considered the microgrid planning problem as an investment problem where the risk is due to uncertainty in the resources. Hence, as an investor needs to minimize the risk of this investment so does the planner of the microgrid.

Any manufactured systems along with its components has impact on the environment locally as well as globally. To analyze and infer useful indices we used the approach of LCA to incorporate all the impacts of an engineering design from its manufacture to end-of-life. The idea of LCA was incorporated along with MCDA to give the planners a flexibility to choose from a range of possible scenario depending upon ones circumstances.

Hence overall, combining all of the above mentioned techniques combines into a single framework led us to develop our MDOUU framework for planning of complex and large-scale engineering systems.

7.3 Future Work

All of the models presented in the thesis are proposed with uncertainty in mind to solve economic, technical and environmental issues related to planning of microgrids. However, there are several concerns that need more investigative studies. The following are extensions for future research work that could be incorporated in the planning of microgrids:

- One of the first extensions to above presented MDOUU framework may be to provide all the entities as one package for the ease of use by either providing a web based system or a software package
- Improvements can be done in the optimization model for microgrid planning by considering variety of renewable resources and storage with varying capacities which would give the planners a more diverse range of possibilities in the system design, this is possible while the optimization model may need to be modified.
- The risk-averse stochastic model deals with the problem of large number of variables and scenarios for solving the problem and hence the need for large computation power. We can modify the optimization model using the chance constrained programming. The challenge one may face is in evaluating those constraints for variety of distribution function and in case of multivariate dependence in evaluation of inverse copula functions.
- Another important improvement may be performed in the LCA framework whereby incorporating the concept of Social LCA which is still under development and not much literature is available for reference. Some preliminary work has been done [132-134] but we need to generate specific impact assessment methods to be able to characterize one's design. This can be possibly done using the specific indicators such as employment generation, cost of living, stress level of individuals etc.

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