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Optimal Allocation of STATCOMs and Wind-Based Distributed Generators using a Stochastic Mathematical Program

By

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Windsor, Ontario, Canada

Optimal Allocation of STATCOMs and Wind-Based Distributed Generators using a Stochastic Mathematical Program

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DECLARATION OF CO-AUTHORSHIP

I. Co-Authorship

I hereby declare that this thesis incorporates materials that are results of joint research. Dr. Maher Azzouz and Dr. Ahmed Azab contributed with the overall coordination of the research, specifically in terms of optimization and power systems, respectively. In all cases, primary contributions, programming, and data analysis were performed by the author.

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II. Publication

A journal paper has been written using the research findings of this thesis and will be submitted soon.

Thesis chapters	Publication title/full citation	Publication status
3, 4	Mahzan Dalawir, Maher Azzouz, Ahmed Azab, “Optimal Allocation and Sizing of STATCOMs and Wind-Based Distributed Generators using a Stochastic Mathematical Program”	To be submitted to an IEEE journal

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ABSTRACT

In the last two decades, large economies worldwide have been relying increasingly on renewable energy sources to reduce greenhouse emissions and dependence on fossil fuels. This has changed the topology of distribution systems adding complexity to their planning and operation. In this study, a new planning model is proposed to allocate static synchronous compensators (STATCOMs) and wind-based distributed generators (W-DGs), considering the stochastic nature of wind velocities and load demands. The proposed optimization model is a mixed-integer nonlinear program (MINLP), which simultaneously allocates STATCOMs and W-DGs. It minimizes the costs of power losses, investment, operation, and maintenance while maximizing the CO_2 reduction rewards and power generation revenues. The Canadian 41-bus network with loads following the IEEE-RTS generic load model is used to test and validate the proposed planning approach. The achieved results demonstrate the effectiveness of such a planning approach in the allocation of STATCOMs and W-DGs. The installation of wind-based distributed generators (W-DGs) in the form of individual units to supply a few loads or in bulk to supply larger loads have increased. High penetration levels of W-DGs have altered the topology of distribution networks (DNs) from being unidirectional to multi-directional, i.e., active direction networks (ADNs). The government's commitments to clean energy has led to an increase in the investments toward more use of renewable resources to generate clean energy with less environmental impacts. A case study is presented based on actual wind data obtained from Windsor Ontario region. The data is modeled using a Gamma distribution function to model the probabilities of wind speed. Genetic algorithm (GA) is utilized to solve the developed model to allocate and size the W-DGs and the STATCOMs.

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NOMENCLATURE

Sets & Indices

B_{STAT}	Represents the set of candidate buses to connect the STATCOMs
B_{DG}	Represents the set of candidate buses to connect the W-DGs
i, j	Index of Buses
L_{ij}	Set of lines between buses i&j
n_b	Represents number of buses in the power system
S_t	Represents the total number of operating states
S_l	Represents the load probability states
S_w	Represents the wind speed power probability states

Binary Variables

ω_i^+	Binary number to install $\mathrm{Q}_{\mathrm{STATi}}^+$ at candidate bus set $\mathrm{B}_{\mathrm{STAT}}$
ω_i^-	Binary number to install $\mathrm{Q}_{\mathrm{STATi}}^-$ at candidate bus set $\mathrm{B}_{\mathrm{STAT}}$
ω_{DGi}	Binary number to install the W-DGs at candidate bus set B_{DG}
Z_{DG}	Total number of W-DGs connected to the candidate bus set B_{DG}
Z_{STAT}	Total number of STATCOMs connected to the candidate bus set $\mathrm{B}_{\mathrm{STAT}}$

Continuous Variables

$I_{ij,Sl}$	Current flow through branch ij at load state Sl in Ampers
P_{G1}	Active power generated by the generation station
$P_{DGi,st}$	Active power generated by the DG at bus i and state st
P_{D_i}	Active power demand at bus i
P_{busi}^{max}	Maximum Bus power at bus i
$P_{l\ i,sl}$	Active power Loss at bus i and state S_{t}

P_L^{Actual}	Real power loss at bus i and state S_l with no DG or STSCOM
Q_{STATi}^{+}	STATCOM injects reactive power at candidate bus i
Q_{STATi}^{-}	STATCOM absorbs reactive power at candidate bus i
Q_{G1}	Reactive power generated by the generation station
Q_{D_i}	Reactive power demand at bus i
V_i	Voltage at bus i

Parameters

c_1	Cost of Investment
c_2	Cost of Operation
c_3	Cost of total active power system loss
c_4	Cost of generation saving
c_5	Cost of CO_2 reward
c_6	Cost of salvage
CF	Capacity Factor of the Wind Turbine
C_{DG}^{w}	Cost of Wind Turbine per KW
C_{DECOMM}	Cost of Decommissioning
$C_{O\&M}^{W}$	Cost of O&M of the Wind Turbine per KW
C^{STAT}	Cost of STACOM
C_{KVAr}^{STAT}	Cost of KVAr
$C_{O\&M}^{STAT}$	Cost of O&M of the statcom per KVAr
C_{CO2}^{Reward}	Cost of reward from CO_2 reduction
C_{CO2}	Cost of CO_2 emission/KWh in Ontario
C_{loss}	Cost of system active power loss in KWh
C_g	Cost of system active power generation in KWh
E_{em}	CO_2 emission in KG of CO2/KWh
$I_{ij\,max}$	Maximum current allowed at branch ij in Amps

k	Percentage of total allowed DG penetration into the System
M	Big M
P_j	The three penalties $\mathrm{P}_1, \mathrm{P}_2$ and P_3
P_1	Voltage violation penalty above 1.05
P_2	Voltage violation penalty below 0.95
P_3	Current limit violation above allowed limit
P_{DG}	Rated Power of the Wind Turbine
$Prob_C$	Combined load and wind speed probabilities
$Prob_w$	Probability of Wind Speed
$Prob_l$	Probability of Load
P_{av}	Average power generated by the wind turbine
Q_{STAT}^{rated}	STATCOM Rated Reactive Power
$Salv^{STAT}$	STATCOM Salvage Price
$Salv^{wDG}$	W-DG Salvage Price
Y_{ij}	Admittance of Buses $i\&j$
r_{ij}	Resistance of Buses $i\&j$
x_{ij}	Reactance of Buses $i\&j$
V_1	Voltage at bus 1 (Slack bus)
ΔP_{loss}	Active power loss difference before and after adding DGs and statcoms

CHAPTER 1

INTRODUCTION

1.1. Preface

In recent years, the installation of distributed generation (DG) in the form of individual units to supply a few loads or in bulk to supply larger loads have increased. The penetration of a grid close to the loads has changed the topology of the electric power systems from conventional with unidirectional power flow far from the cities to Active Distribution Networks (ADNs) with multi-directional power flow to supply the system close to the load. Government commitments to clean energy has led to an increase in the investments toward more use of renewable resources to generate clean energy with less environmental impacts. The increase in the installation of DG units in power systems comes with economical, environmental and social impacts which led researchers to pay attention towards finding the optimal siting and sizing of DG units at the planning stages to minimize such impacts and to gain the optimal benefits of these new technologies when utilized. The optimal siting and sizing of DGs with or without voltage control devices represented by voltage regulators, capacitor banks, and STATCOMs interested researchers with single or multi objectives to minimize and improve the system losses, improve voltage profile, voltage stability index, minimize cost, maximize profit and to improve power system qualities.

1.2. Static Synchronous Compensator

In any power system network, the electric loads absorb and inject reactive power on an hourly base depending on the load. This can lead to undesirable consequences such as voltage instability, voltage fluctuation, poor power factor, flicker, harmonics, and system loss increase. To overcome these consequences, which will greatly affect the power system, utilities tend to utilize voltage control devices to compensate for the reactive power. These compensators are connected to the grid in shunt or series based on the purpose and application. The interest of this thesis study is in the shunt connected reactive compensators. Shunt compensator solutions can be represented by a range of devices such as capacitor banks, STATCOMs, and static VAR compensators. Most of the distribution network loads are inductive. As a result, the network power factor will be lagging in nature [1]. STATCOMs have been selected as our primary device. STATCOMs provide faster dynamic performance when compared to the static VAR compensators (SVC), particularly because of its time response and its ability to generate or absorb reactive power when the grid voltage drops or increases. Shunt capacitor banks can only inject reactive power when required. STATCOMs improve grid stability through a dynamic supply of the regulating power.

Distribution Static Synchronous Compensators(D-STATCOM) are used to regulate distribution grid voltage. The voltage ratings cover up to 35kv and its reactive power rating up to 10MVAr for distribution networks. The main element of this technology is a three-phase inverter. The cooling system can be water or air. For this study, air-cooled D-STATCOM is selected. The key functions of this device are fast and stable response time of current control, fast active and reactive load current extraction, fast compensation of negative sequence of load current, mitigation of switching transient of capacitor filter, active damping, and mitigation of grid voltage oscillation [use the company presentation].

The cost of a STATCOM is not linear. The reactive power generation cost function is represented by a quadratic polynomial [2]. To determine the cost of a STATCOM within certain ranges, quadratic interpolation is required based on the obtained quotations from the industry. Five to six quotes for required ranges can provide an accurate cost for any level within the selected reactive power ranges. For this thesis study to determine the cost of STATCOMs, a range between 1000KVAr and 6000KVAr is used to determine the cost function. 2000KVAr STATCOM is used to conduct the case study in the later chapter.

1.3. Renewable Distributed Generation

With recent initiatives on renewable energy coupled with the profound public assessment of the environmental impacts of using fossil fuels to generate electricity, penetration of RDG into a power system plays a vital role in the emerging electric power systems [3]. The benefits obtained with DG are not only related to the technical level such as loss reduction, voltage control, current flow reduction in the branches, improved quality of power supply, but also to the environmental sphere since the reduction of costs and technological advances in power electronics, communication systems, control, and automation allow for the use of renewable energy sources which pollute less than conventional generators [4].

DG represents a wide range of technologies and application such as solar photovoltaics, wind turbines, biomass, co-generation, fuel cells, etc. that employs renewable resources to generate power with minimum environmental impacts. Renewable resources are stochastic. For this thesis study, wind distributed generator (W- DG) will be used to generate the active power into the system. The stochastic nature of the wind will be considered using a probability density function for modeling the wind speed probability. The modeling is discussed in detail in later chapters.

1.4. Motivation and Research Objectives

Cost is the main factor in any planning or operation study, where the focus is minimizing the total cost or maximizing the total profit. From the planning point of view, the optimal allocation of the number of equipment installed to perform optimally is key for optimal cost. From an operational perspective, optimal planning will lead to optimal operation and subsequently, optimal system loss. Achieving optimal planning and operation will minimize the cost of investment and operation together. This study will simultaneously allocate STATCOMs and W-DG to achieve optimal investment, operation, and total cost using a stochastic program and genetic algorithms (GAs).

The technical challenges associated with the penetration of RDG have increased the complexity of the planning and operation of the power system. The optimal allocation of STATCOMs and W-DG to achieve minimal cost using a GA, considering the stochastic nature of the wind and load, is modeled. A probabilistic approach for the allocation of the W-DG is used. A stochastic program with a single parametric distribution called Johnson SB distribution is utilized to model the wind probabilities. A pre-defined number of candidate buses are selected to install the STATCOMs and the wind turbines. The probabilistic approach for the wind speed model and the load is combined and used for the selection of the wind turbines. The main objective is to minimize the total cost of the system. This includes investment, operation, maintenance, loss, CO2 rewards, and salvage cost while respecting all constraints and using the total cost as an indication of the optimality of the system.

1.5. Thesis Outline

Chapter 2	Explores the state of the literature and highlights what requires further study to adequately solve the problem at hand.
Chapter 3	Presents the proposed methodology to site and size STATCOMs and W-DGs, including the stochastic program and attractiveness scoring scheme.
Chapter 4	Provides a detailed example that applies the mathematical model and novel scoring scheme to a real area.
Chapter 5	Concludes the thesis with a summary of the contributions and proposes a new topic for future research.

CHAPTER 2

LITERATURE SURVEY

2.1. Penetration of Renewable Distributed Generation

The penetration of RDGs into power networks has increased rapidly over the last two decades. In parallel, the investment into developing renewable energy technologies has gained momentum. Allocating DG units gained significance with more DGs being installed closer to cities. Governments started imposing more aggressive targets to cut on greenhouse gases to meet international commitments by creating a push on cutting the conventional ways of generating electricity, which creates higher pollutions.

Under the Paris Agreement, Canada committed to reducing its GHG emissions by 30% below 2005 levels by 2030, as shown in figure2.1. In 2019, the 2005 level was estimated at 730 Mt CO_2 eq. Under the 2019 Reference Case scenario, it is projected that Canada's emissions in 2030 would be 673 Mt CO_2 eq or 142 Mt CO_2 eq below the projections published in the Second Biennial Report [5]. Internationally, committed governments are cutting on GHG emissions by offering incentives toward greener ways to generate power and expensive rights to pollute policies all combined; this has led to more attention toward renewable energy generation. The focus of this study is on optimizing the allocation of DGs during planning stages.

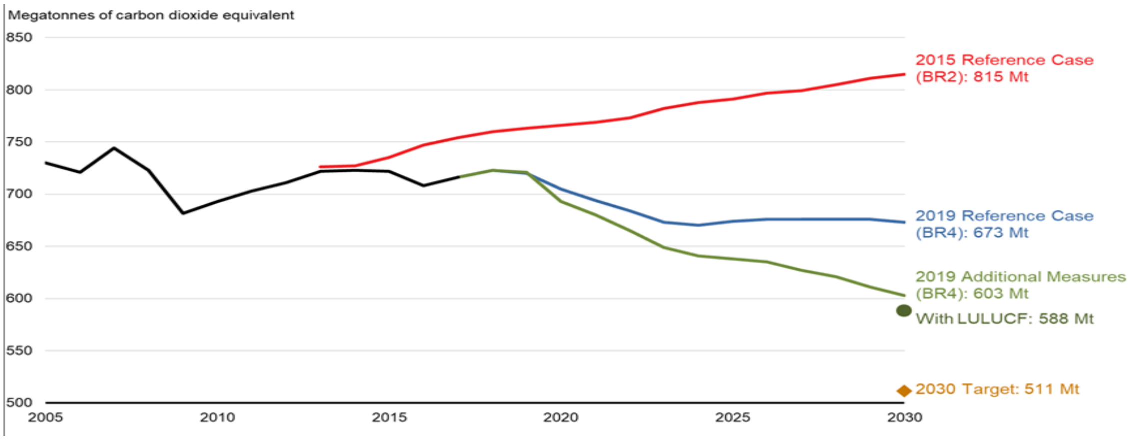

Figure. 2.1: Megatons of Carbon Dioxide equivalent [5].

The Energy Sector contributes to the bulk of Canada’s greenhouse gas emissions (about 80%) and includes greenhouse gas emissions (CO_2, CH_4, and N_2O) from stationery and transport fuel combustion activities as well as fugitive emissions from the fossil fuel industry[6]. The Pricing

Act to apply pricing on pollution will push towards more incentive to reduce emissions and to explore greener ways to generate energy. Renewable planning for generation stations and utilities will receive more attention when the pricing system itself is designed to provide incentives for innovation and maintain economic competitiveness.

2.2. Allocation of Voltage Control Device in Distribution Power Systems

Voltage control devices such as capacitor banks, STATCOMs, static VAR compensators, voltage regulators, on-load tap changes, etc. are devices used to maintain the system voltages. During load increase, system voltage decreases, and during load decrease, system voltage increases. Ideal loads are resistive with a unity power factor, but this is not the case in the real world. The nature of the load on the system is mostly inductive, and others, especially at the transmission section, can be capacitive, making voltage control devices required.

Depending on the time and location, the power system load can change, causing the power factor to change at the same time. Injecting and absorbing reactive power into the power system will maintain and improve the power factor, voltage stability, voltage profile, minimize system losses, and improve the power system capacity. Reactive power is required for steady-state and dynamic conditions. The steady-state requirement can be supplied by static and/or dynamic compensating devices, but dynamic conditions can only be supplied by dynamic compensating devices [7].

Dynamic sources are typically generators capable of producing variable levels of reactive power by automatically controlling the generator to regulate voltage[8]. Extensive studies have been conducted to sit and size reactive shunt compensators to maintain the system voltage by injecting reactive power.[2] presented an optimal allocation of flexible AC transmission system (FACTS) devices using a GA to minimize the overall cost function. The paper presented four types of FACTS devices. This thesis study will be utilizing STATCOMs, which will inject and absorb reactive power dynamically.

2.3. Allocation of DGs in Distribution Systems

Greener ways of generating electricity have increased the dependency on technologies used to capture renewable energy resources, which are considered inextensible, inexpensive, and clean.

Optimal siting and sizing of DGs in power systems have been a hot topic by many researchers due to the environmental benefits associated with it. Since the input power into the DGs is stochastic, the output power will be unpredictable. Proper allocation of DG units into an existing distribution system plays a crucial role in the improvement of the system's performance; therefore, optimal allocation of DG is one of the most important aspects of DG planning [9].

2.4. Allocation of DGs and VCDs in Distribution Systems

The shift from conventional power network systems, with one mainstream generation station far from the cities, to ADNs with multi renewable distributed generators closer to loads has changed the topology of power system networks. The ADNs system added more resiliency to the supply side, making it more available. Noticing wind turbines or solar panels as individual units of in bulks as farms are possible while driving within the cities. The benefits of green energy come with some environmental, political, and social impacts.

To minimize such impacts, optimal allocation of the DGs combined with the voltage control devices gain importance to maximize benefits and minimize any drawbacks during the planning stages. Researchers conducted studies to optimally sit and size DGs with voltage control devices with a variety of objectives mainly being the system loss. Authors of [9],[10] used a hybrid harmony search algorithm and analytical approach respectively to optimal sit and size DGs and shunt capacitor banks to achieve a single objective of minimizing the total system loss. Authors of [11],[12] used water cycle algorithm, GA, cuckoo search algorithm, particle swarm optimization respectively to optimal sit and size DG and shunt capacitor banks to achieve a combination of multi objectives such as system total loss, system costs, voltage profile, voltage stability index and environmental objectives related to emission reduction.

Authors in [13],[14],[10] simultaneously located and sized DG and shunt capacitor banks using intersect differential evolution, particle swarm optimization, and improved metaheuristic techniques respectively to achieve minimization of the system total loss as a single objective. Simultaneous siting and sizing DG and shunt capacitor banks using multi-objective particle swarm optimization and hybrid ICA and GA are presented in [15],[16], respectively, to achieve the multi objectives such as total system loss, voltage profile, stability index, and cost. Other researchers worked solely on optimal siting and sizing of distributed generation such as wind turbines or photovoltaic to achieve single or multi objectives mentioned above. Siting and sizing of DGs only are presented in [17],[19]. Ant lion optimization algorithm, artificial bee colony, and multi-objective GA are used respectively to achieve optimal siting and sizing of the DG unit and considering the output power of the DG units as deterministic.

A probabilistic approach for the optimal allocation of DGs is presented in [20],[9]. Wind only and renewable resource mix of wind, PV, and biomass are used. Mixed-integer nonlinear programming is formulated with the objective of minimizing system loss with the assumption of DG units generating active power only. The author of [21] presented a stochastic investment model by formulating a stochastic two-stage multiperiod model to minimize multi cost objectives. This two-stage multi-period mixed-integer linear programming model provides investment decisions in the first stage and scenario dependent operation variables in the second stage. [22] minimized investment and operational cost by considering the stochastic power output of the W- DGs. The model simultaneously allocates distributed generation with fixed and switched shunt capacitor banks using hybrid tabu search and GA. The objective was to minimize the investment and operational costs.

A multi-objective joint planning model for active distribution systems using a multi-objective natural aggregation algorithm is presented in [24]. A scenario-based stochastic modeling approach based on Wasserstein distance metric and K-medoids scenario analysis is developed to model the stochastic nature of renewable generation. [23] Presented a multi-objective simultaneously DG and STATCOM allocation using a cuckoo searching algorithm. The objective function is to minimize the power loss and the cumulative voltage deviation. The proposed DG output power is deterministic. Based on the presented literature review above, it can be noted that many papers presented different approaches and mythology to allocate voltage control devices, mainly shunt capacitor banks, to solve the power system under voltage problem and steady-state load conditions. The authors of [24],[25] used a hybrid harmony search algorithm and analytical approach respectively to optimal locate and size DG and shunt capacitor banks to achieve a single objective of minimizing the system total loss.

Other papers presented different approaches to allocate DGs into the power system with the assumption of the deterministic power output of the DGs and assuming DGs as active power generators. Installation of DGs at non-optimal places can result in an increase in system losses, reconfiguration of the protection scheme, voltage rise, and fluctuations, increase in costs, etc. [26].

Other papers proposed algorithms to sit and size mixed DGs technologies [27],[28], such as wind turbines, photovoltaic(PV), and energy storage. On the other hand, [29] added a different approach by considering an ADN with near-zero power generation from a power plant using dispatchable DGs utilizing biomass along with shunt capacitors. The dispatchable DGs amid the blitz of renewables and added the option for biomass powered DGs to operate at unity or lagging power factor. The sensitivity index value is utilized to select the candidate nodes for DG installation.

The disadvantage of renewable resources lies in its stochastic nature. Predicting nature's behavior is not possible; however, estimating the probabilities is possible. This can be done by modeling historical data, such as wind speed or solar radiation, then extracting the probabilities can provide a good estimation on what to expect, but the challenge is to create a good model that can capture more accurate probabilities to optimize the DG power output when utilized in the power system. Table 2.1 presents a summary of the literature survey conducted and will be used to present the contributions of the current thesis.

2.5. Gap Analysis and Synthesis Matrix

From the literature survey, it can be noted that most papers treated the RDGs as deterministic. Few papers took into consideration the stochastic nature of the renewable DG output power; meanwhile, other papers considered the output power as the rated power. Many papers considered siting and sizing static reactive compensators such as shunt capacitor banks, which can only inject reactive power. Shunt capacitors are low in cost and can take care of the undervoltage in the system, but it can not act fast when there are sudden changes in the loads. For dynamic compensations of reactive power, which involves injecting and absorbing reactive power, STATCOMs are used. STATCOMs can take care of undervoltage and overvoltage issues of the system.

Other papers combined STATCOM and DGs allocation but considered the DG output power as deterministic. A probability approach to allocate W-DG was presented by one of the authors. The wind speed data was modeled using Weibull PDFs to determine the probabilities with the assumption of W-DG only injects active power. This thesis study will model the wind speed data obtained from the Windsor-Ontario region. The goodness of fit is used to process the wind data to obtain a resolution to relate the wind data to a specific statistical model. Easy fit is used to find the proper distribution following the obligatory steps explained in the later chapter.

The W-DGs and STATCOMs are simultaneously allocated to determine the optimal total cost using a stochastic program. Very few papers approached the reduction of CO_2 footprint when associating the optima allocation of W-DGs and voltage control devices with emission reduction. In this study, a comprehensive cost reduction is researched by considering economic and environmental, operation, and maintenance aspects.

Table 2.1: Literature Survey Summary.

Ref.	**DG & SCB**	**DG types**	**Voltage control Device**				**Non Dispatchable DG Modelling**		**Obj Function**		**minimize**	**Solution Method**	**Published**
			SCB	**FCB**	**CSTAT**	**UNSTAT**	**Stochastic**	**Deterministic**	**Multi**	**Single**			
[1]	Simultaneous	Not specified	×	×	✓	×	×	✓	✓	×	Loss, cost, v profile	BFOA	2015
[4]	Separate	Wind	✓	✓	×	×	✓	×	✓	×	cost	TB & CBGA	2016
[6]	SCB	No DG	×	✓	✓	×	×	✓	✓	×	Cost	GA	2016
[7]	No SCB	Wind, PV and Biomass	×	×	×	×	✓	×	×	✓	loss	MINLP	2011
[8]	Simultaneous	Not specified	×	✓	×	×	×	✓	✓	×	Loss Voltage	GA, PSO, CSO	2015
[9]	Separate	Not specified	×	✓	×	×	×	✓	✓	×	Loss V profile V stability Cost	WCA	2018
[10]	No SCBs	Not specified	×	×	×	×	×	✓	✓	×	Loss V-Deviation	GA	2015
[11]	SCH	No DG	✓	×	×	×	×	×	✓	×	Loss, cost, Voltage	cuckoo	2013
[12]	Separate	Wind	×	×	×	×	×	✓	✓	×	Cost & V profile	PSO	2014
[13]	Simultaneous	Not specified	×	✓	×	×	×	✓	×	✓	Loss	IMDE	2016
[14]	Simultaneous	Not specified	×	✓	×	×	×	✓	×	✓	loss	PSO	2013
[15]	Simultaneous	Not specified	×	✓	×	×	×	✓	✓	✓	Loss, VS, I	MOPSO	2014
[16]	Simultaneous	Not specified	×	✓	×	×	×	✓	✓	×	Loss V-Profile V-Deviation Load balance	ICA & GA	2013
[17]	Separate	PV and Wind	×	×	×	×	×	✓	✓	×	Loss V-Profile V-Deviation	ALOC	2016
[18]	DG and Capacitor	Not specified	×	×	×	×	×	✓	×	✓	loss	ABCA	2011
[19]	No SCBs	Wind			×	×	✓	×	✓	×	Cost loss	MOGA	2015
[20]	No SCB	Wind	×	×	×	×	✓	×	×	✓	loss	MINLP	2010
[21]	No SCBs	Wind & PV only	×	×	×	×	✓	×	×	✓	System Cost	MILP	2015

[22]	NO SCBs	EVCSs, RESs,BESSs	×	×	×	×	✓	×	✓	×	Cost and reliability	MONAA	2019
[23]	Simultaneous	DG and SATCOM	×	×	✓	×	×	✓	✓	×	Loss and Voltage deviation	Cuckoo Searching Algorithm	2018
[24]	Separate	PV & Micro Turbines	×	✓	×	×	×	✓	×	✓	Loss	PABC	2015
[25]	Separate	Not Specified	×	✓	×	×	×	✓	✓	✓	Loss	Analytical Approach	2013

Table 2.2. Abbreviation of the Algorithms.

Algorithm	Abbreviation
Ant Lion Optimization Algorithm	ALOA
Imperialist Competitive Algorithm	ICA
Genetic Algorithm	GA
Multi Objective particle swarm optimization	MOPSO
Intersect Mutation Differential Evolution	IMDE
Artificial Bee Colony Algorithm	ABCA
Particle Swarms Optimization	PSO
Cat Swarm Algorithm	CSA
Mixed Integer Linear Programing	MILP
Artificial Bee Colony Algorithm	ABCA
Water Cycle Algorithm	WCA
Tabu Search Algorithm	TBA
Chu–Beasley Genetic Algorithm	CBGA
combined Genetic Algorithm with Linear Programming solver	GALP
Multi-Objective Natural Aggregation Algorithm	MONAA

CHAPTER 3

DISTRIBUTION NETWORK PLANNING USING A STOCHASTIC PROGRAM

3.1. Uncertainty Modelling

3.1.1. Stochastic Modeling of Wind Speed

Wind speed is stochastic in nature. Allocating W-DGs at planning stages requires good estimation of the output power of the W-DGs. To obtain a good idea of the output power generated by W-DGs, a good modelling of the behavior of the wind speed is required. Hourly wind speed data for years 2016 and 2017 is obtained from [30] and [31] for Windsor, Ontario, Canada. The data used is hourly wind speed in m/s. The details of the data used is shown in Table 3.1. The data sample is picked as 2 days (48hours) for each month. Each month provides 48 data of wind speed. The total data set for the two years is given as 1152 winds speed data.

The collected wind speed data is processed using Goodness-of-Fit (Go
F). The GoF is used to determine how well our set of data fits a distribution which implies a comparison of the observed data with the data expected under the model using some fit statistic, or discrepancy measure, such as residuals, Chi-square or deviance[32]. There are many available distributions that can be used based on how well they fit a certain distribution. The three most common goodness-of-fit tests are the chi-squared, the kolmogorov–smirnov (K–S) and the Anderson-Darling tests[33].

To assess the feasibility of each distribution, the given data is tested using the three tests. Once the tests are complete each distribution will be given a rank that represents the order of suitability of each distribution. Using the GoF tool called Easyfit [34], the top three probability distribution function (PDF) that represent wind data are Gamma, Rayleigh and Weibull respectively. The rank was based on the collective score of all three tests in terms of the P-value. This is explained below. Most papers use Weibull PDF but for this study thesis, Gamma PDF is used. A comparison between the three mentioned PDFs are presented in the alter pages.

Table 3.1: Wind speed sample statistics for Windsor-Ontario Region.

Locations	Minimum	Maximum	Sample Size	Mean	St. Dev.
Windsor	0.5	39.5	1152	16.379	7.6045

A single distribution of statistical distribution has been taken into consideration. The parameters of the model used have been estimated using the maximum likelihood estimation (MLE) method, which represents the probability of obtaining a specific set of data [35]. As explained, wind speed data obtained from Windsor, Canada has been evaluated using the Kolmogorov–Smirnov (K–S) goodness-of-fit test, and two statistical error measurements: Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Gamma distribution is used, and its capacity for use as a wind speed distribution is presented. The data collected is ready to be used to determine the best distribution function based on the following steps detailed in the next section.

3.1.2 Probability Density Function

Fitting a distribution includes locating a mathematical function that represents a statistical variable in an appropriate course of action. For fitting a distribution, five obligatory steps have been considered: Hypothesis family of distribution, estimation of the measure of parameters, quality of fit assessment, the goodness of fit tests, and monitoring the level of error measurements [36]. For this study Gamma distribution is considered. The distribution of Normalized Wind Speed data (NWS) is evaluated by the Gamma distribution PDF for the years 2016 and 2017. In the tables below, the results will be compared to the Rayleigh and Weibull PDFs.

Equation (3.1) is the probability distribution function, and (3.2) is the Gamma distribution function.

$$f(x) = \frac{(\frac{x-\mu}{\beta})^{\gamma-1} exp(-\frac{x-\mu}{\beta})}{\beta\Gamma(\gamma)} \tag{3.1}$$

$$\Gamma(a) = \int_0^\infty x^{a-1} e^{-x} dx \tag{3.2}$$

where f(x) is distribution function; Γ is the gamma function; a is a real number; x ≤ μ; γ is the shape parameter; is location parameter and β is a scale parameter.

The Kolmogorov–Smirnov (K–S) Goodness-of-fit test presented a resolution that collected data comes from a specific statistical model. To conclude strong evidence, results are picked based on P-value ($p > 0.05$) analogous in strong proof that the null hypothesis is true. Consequently, the data does not return remarkable results if a false null hypothesis is obtained at the end of the goodness-of-fit test. The p-values obtained from the K–S test for each distribution are given in table 3.2 for the mentioned locations. The selected Gamma model resulted in having a more significant P-value and lower two type error measurements compared to the Rayleigh and Weibull PDFs. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) results are presented in tables 3.3 and 3.4. The standard mathematical error measure formulas are given in (3.3) and (3.4)

Mean Absolute Error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |x_i - \hat{x}_i| \tag{3.3}$$

Root Mean Square Error:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (x_i - \hat{x}_i)^2} \tag{3.4}$$

where n is the number of bins of wind speed data, x_i represents the number of observations, and $\hat{x}_i$ shows the probability of the wind speed and i is the calculated bin from the data set ($i = 1, \dots, n$).

P-value results are presented in Table 3.2. For the selected distribution, its P-values must be highest.

For verification purposes, we have included two more location to verify our results regarding the P-Value, MAE and RMSE. To prove the selected distribution provides better results at any location, Newfoundland and Hamilton locations are selected for comparisons. Wind data for 2016 and 2017 are selected as well.

Table 3.2: P-values based on K-S Goodness-of fit test.

Site	Gamma	Rayleigh	Weibull
Windsor	0.02800	0.00000	0.00033
Newfoundland	0.01200	0.00000	0.00005
Hamilton	0.00300	0.00000	0.00053

Tables 3.3 and 3.4, list the estimated MAE and RMSE, including improvement percentage in connection with Gamma distribution. Based on the analysis of the Windsor wind site, the lowest errors in terms of MAE and RMSE have been represented by the Gamma model.

Table 3.3: Mean Absolute Error.

Site	Gamma	Rayleigh	Weibull
Windsor	0.00409	0.00000	0.00446
Newfoundland	0.00404	0.00000	0.00450
Hamilton	0.00542	0.00000	0.00505

Table 3.4: Root Mean Square Error.

Site	Gamma	Rayleigh	Weibull
Windsor	0.00652	0.00783	0.00716
Newfoundland	0.00535	0.00722	0.00600
Hamilton	0.00697	0.00800	0.00750

Figures 3.1 and 3.2 show how well the wind data obtained fits the Gamma probability density function when compared to Rayleigh and Weibull PDFs.

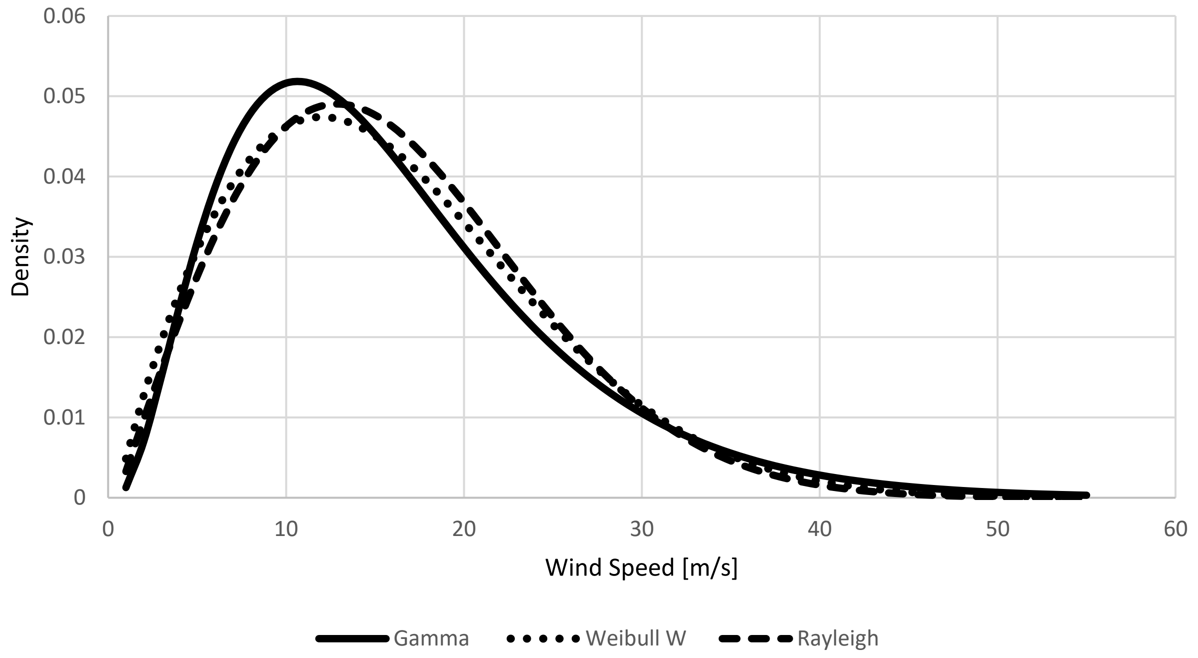

Figure. 3.1: Gamma PDF vs. Rayleigh and Weibull PDFs for Windsor Location.

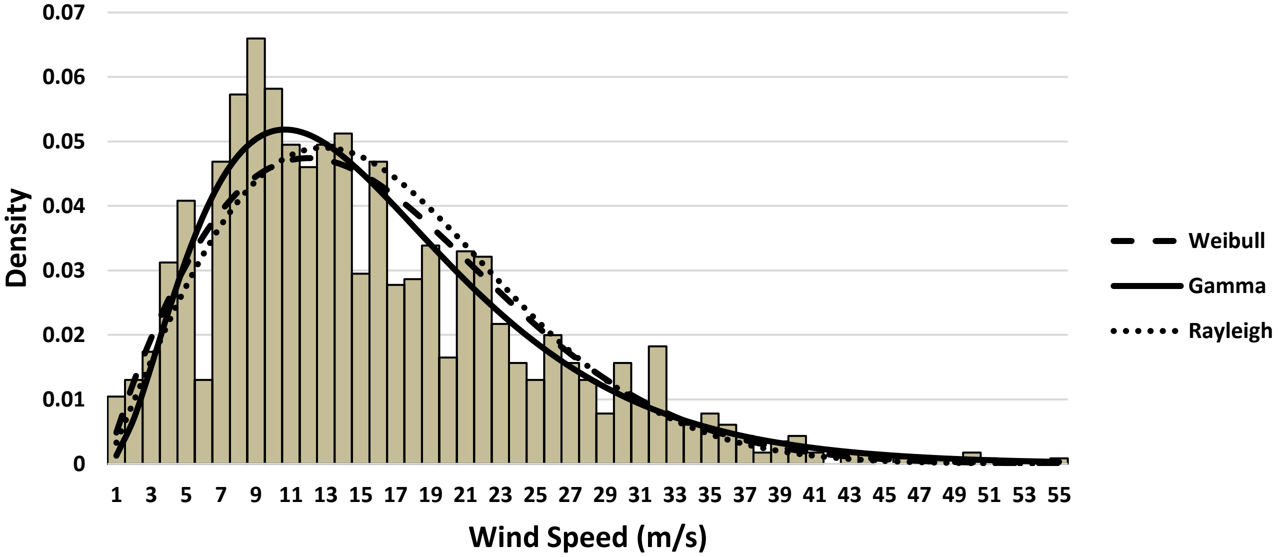

Figure 3.2: Histograms Considering Gamma PDF vs. Rayleigh and Weibull PDFs.

3.1.3. Wind Probability Model Development

By taking into consideration the Goodness-of-fit test and finalizing the results regarding P-value and the two type error measurements for the distributions, we can obtain the PDF, which represents an accurate fit to our data. After determining the candidate model, the following step is to consider the observed values of the best PDF. In this analysis, the Windsor location in Canada has been considered to compare the accuracy of the different distributions. So, the location has a column consisting of 12 rows, which represent the probability of a specific bin. By merging observed values according to the location, a single column of probabilities will be obtained, as presented in Table 3.5, based on Figure 3.3 for wind speed vs. power output. Each wind speed is specified within a specific limit. This is applied directly to the wind turbine used in this thesis rated at 1100kW. The cut-in speed of wind turbines is approximately 4 m/s, and the cut-out speed is set at 25 m/s. Any wind outside of this range will result in zero power output. The power generated between the cut-in speed and 14 m/s increases linearly from zero to the maximum rating of the wind turbine. The generated power output is steady at the rated power of 1100kW between 14 m/s and the cut-out speed. The combined states can be formed , by multiplying the wind states and percentages of the load states of the system's peak load, as shown in Table 3.7 that is assumed to follow the hourly load shape of the IEEE-RTS [30].

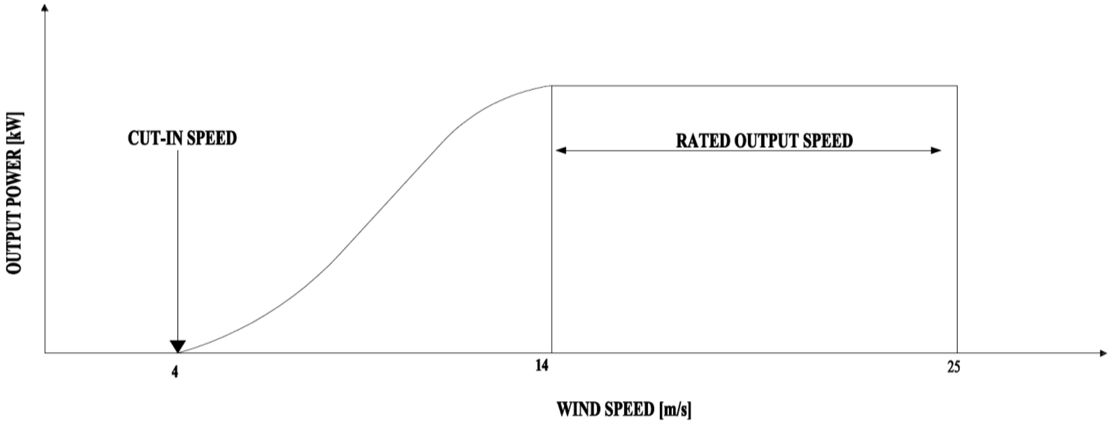

Figure 3.3: Turbine output in kW vs. wind speed in m/s.

From Figure 3.3, it can be noted that the cut-in-speed of the wind turbine is at 4m/s and the cut-out-speed is at 25m/s. No power is generated below 4m/s wind speed or above 25m/s wind speed.

Table 3.5: Wind Speed Probabilities

State no.	Probability States %	Generated Output Power in kW
1	0.04715	0
2	0.03176	54.9824
3	0.03858	164.9472
4	0.04397	219.9296
5	0.04787	384.8768
6	0.05038	494.8416
7	0.05163	604.8064
8	0.05179	714.7712
9	0.05107	824.736
10	0.04963	934.7008
11	0.04764	1044.6656
12	0.34725	1100

3.1.4. Load Probability Model Development

The system peak load demand is assumed to follow the hourly load shape of the IEEE-RTS [37]. Based on this assumption, the load will be divided into ten levels, which was utilized when developing the ten states' probability for the load by [20], which verifies that choosing ten equivalent load levels (states). Table 3.6 presents the ten load states to their probabilities.

Table 3.6: Load Probability States

State no.	% of peak load	Probability of each state
1	1	0.01
2	0.853	0.056
3	0.774	0.1057
4	0.713	0.1654
5	0.65	0.1654
6	0.585	0.163
7	0.51	0.163
8	0.451	0.0912
9	0.406	0.0473
10	0.351	0.033

3.1.5. Convolution of the Independent Stochastic Elements

Convolution is a mathematical operation between two matrices. The purpose of utilizing convolution is to sort and multiply two independent stochastic sets when two sets of states are combined to produce one set that presents all the probabilities. In this case, ten states of load demand probabilities are combined with 12 states of wind generation output probabilities to produce a unique set of combined probability states with considering the existence of all the probability states. In other words, every probability state in the load demand set must be multiplied by every probability state in the wind generation output set. In performing the convolution, the combination of the wind and load states probabilities will be fulfilled. A MATLAB script is created to perform the convolution, as shown in Algorithm 3.1. Two sets of probability states are used, generic load demand (Sd1) and wind generation output (Sw1). It contains ten values for load demand probability and 12 values for the wind generation probability, respectively. Steps 2 to 4, for example, show how the first set is convolved. Each set must be sorted differently to ensure that every possible combination is considered. The final output of Algorithm 3.1 is a single set of 120 values.

Algorithm 3.1: Sorting of two arrays of probabilities for convolution.

```
for j=1 to length (Sd1) do
    for i=1 to length (Sw1) do
        Sd (i+j*length (Sw1)-length (Sw1))→Sd1(j)
    end
end
for k=1 to length ($S_l$) do
    for j=1 to length ($S_w$) do
        $S_w$ (j+12*k-12) → $S_w$ (j)
    end
end
$Prob_l$ → [load probabilities]
$Prob_w$ → [wind probabilities]
for j=1 to length ($Prob_l$) do
    for $i$=1 to length ($Prob_w$) do
        $Prob_l$ ($i$+j*length ($Prob_w$)-length ($Prob_w$)) → $Prob_l$ (j)
    end
end
for k=1 to length ($Prob_l$) do
    for j=1 to length ($Prob_w$) do
        $Prob_w$ (j+12*k-12) → $Prob_w$ (j);
    end
end
for $i$=1 to 120 do
    $S_t$ ($i$) → $Prob_l$($i$)* $Prob_w$ ($i$);
end
```

Table 3.7 illustrates the combined probabilities of the wind generation output states and the first load demand state at the value of 0.01, which produces the first 12 combined states out of the total 120 combined states. By convolution, a matrix of 120 states, representing all the combined wind generation output and load demand state probabilities are achieved.

Table 3.7: Combined probabilities of the Wind and the Load States.

Wind states	Wind Prob	% of Load states	Load Probabilities	Combined probabilities
1100	0.33718	1	0.01	0.0033718
1044.6656	0.04493	1	0.01	0.0004493
934.7008	0.04693	1	0.01	0.0004693
824.736	0.04856	1	0.01	0.0004856
714.7712	0.04968	1	0.01	0.0004968
604.8064	0.05011	1	0.01	0.0005011
494.8416	0.04964	1	0.01	0.0004964
384.8768	0.04803	1	0.01	0.0004803
219.9296	0.04505	1	0.01	0.0004505
164.9472	0.04045	1	0.01	0.0004045
54.9824	0.03411	1	0.01	0.0003411
0	0.05357	1	0.01	0.0005357

In this sub-section, the convolution of the two stochastic sets is presented. A methodology to run it, producing the 120 states that include all the probabilities combined in one set, is given. The resulting set of the 120 states of probabilities is very crucial when it is used in the mathematical model. It allows it to consider the variability of the parameters. In the next section, the purpose of this mathematical model is presented.

3.2. Mathematical Model

3.2.1. Purpose and Parameters

The planning problem is proposed as a mathematical model which is formulated in a Mixed Integer Non-Linear Programming (MINLP) optimization problem which in turn will consider the stochastic nature of load and wind. Due to the inherent combinatorial nature of the problem, mathematical programming will solve exact small to mid-range problems; approximate algorithms will be attempted for larger instances of the problem.

The objective function is to minimize the total cost, which is explained in the next section in detail. The developed model optimally and simultaneously allocates the STATCOMs and the W-DGs in the active distribution system. The model involves distribution network considerations, load demand, wind speed data, and associated costs.

The parameters in this model are, as follows:

1) Cost of W-DG installation is $1500/KW [38]
2) The yearly operation and maintenance cost of a WPDG is $40/kW [38]
3) The Hourly Ontario Energy Price (HOEP) for 2019 is 5cents/kWh plus global adjustment cost which is 10 cents: Total = 15 cents/kWh [39]
4) The utility sets a limit for renewable DG penetration in the entire system [12].
5) The utility sets a limit for the renewable DG penetration in each bus modeled using the symbol ($Pbus$) [12].
6) The utility sets a limit for installed STACOM/bus to one STATCOM
7) The cost of STACOM reactive power is based on the cost equation (3.33)
8) Cost of yearly operation and maintenance of the STATCOM is 1% of the STATCOM cost.
9) Cost of one ton of coal is as per [40]–[42]
10) Cost of one ton of CO2 emission is as per [43],[41]
11) W-DGs generate active power only, i.e., operating at a unity power factor

3.2.2. Decision Variables

The decision variables in this thesis serve to allocate the STSCOMs and W-DGs in the ADN. $\boldsymbol{\omega}_{\mathbf{i}}^{+}$ is a binary number to install, $\mathbf{Q}_{\mathbf{STATi}}^{+}$ at candidate buses $\mathrm{B}_{\mathrm{STAT}}$, $\boldsymbol{\omega}_{\mathbf{i}}^{-}$ is a binary number to install, $\mathbf{Q}_{\mathbf{STATi}}^{-}$ at candidate buses candidate $\mathrm{B}_{\mathrm{STAT}}$, $\boldsymbol{\omega}_{\mathbf{DGi}}$ is a binary number to install W-DGs at candidate buses B_{DG}, $\mathbf{Z}_{\mathbf{DG}}$ is the total number of DG connected to the candidate buses, and $\mathbf{Z}_{\mathbf{STAT}}$ is the total number of STATCOMs connected to the candidate buses.

3.3. Objective function

The objective function is formulated as a profit maximization problem. The profit is maximized by minimizing the system investment, O&M, and total system losses. The objective function consists of six terms. The first three terms to be minimized and the last three terms to be maximized are represented by generation savings, CO2 reduction rewards, and salvage costs. The objective function calculates the optimal allocation of the W-DGs and STATCOMs installation. By achieving the optimal allocation, O&M, and system total loss minimizations are achieved, which in turn will maximize the generation saving and CO2 rewards. For budgeting and investment planning purposes, and to analyze the profitability of a projected investment, the present value (PV) of a single receipt and the present value of an annuity receipt must be considered due to the time value of money. To create a realistic model, (3.5) and (3.6) are utilized to achieve all the costs at a one-time value that is the present time value.

The present value of a single future receipt or disbursement is expressed as (P/F, i, n)[44] and calculated using (5)

$$PF(i,n) = \frac{1}{(1+i)^n} \tag{3.5}$$

The present value of an annually recurring receipt or disbursement is expressed as (P/A, i, n) [44] and calculated using (6)

$$PA(i,n) = \frac{(1+i)^n - 1}{i(1+i)^n} \tag{3.6}$$

$w$here,i is the interest rate; n is the number of periods in years. The interest rate is considered as 7%. Based on the author's discussions with some financial institutions and [45], the rates are ranging between 5-10%. Many models in energy economics assess the cost of alternative power generation technologies. As an input, the models require well-calibrated assumptions for the cost of capital or discount rates to be used, especially for renewable energy for which the cost of capital differs widely across countries and technologies[45]. The number of periods in which payments are made is considered annually for 20 years.

The objective function is given in equation (3.7). The objective is to minimize the overall cost.

$$min\ (C_1 + C_2 + C_3 - C_4 - C_5 - C_6) \tag{3.7}$$

Each term of the objective function above is as follow:

$$C_1 = [((\textstyle\sum_{i\in B_{DG}} \omega_{DGi}) \times P_{DG}^{W} \times C_{DG}^{w})+(\textstyle\sum_{i\in B_{STAT}} (\omega_i^{+} + \omega_i^{-}) \times C^{STAT})] \tag{3.8}$$

In (3.8) the aim is to minimize the investment cost by allocating the W-DGs and the STATCOMs. During the planning stage, achieving optimal planning will reduce investment costs and will run the system in optimal condition by minimizing the total system loss. This cost is considered in the present value. The first term of equation (3.8) multiplies the summation of the installed number of W-DGs by the power of the W-DG in kW and the cost of the W-DG per kW. The second term of the of equation (3.8) multiplies the summation of the installed number of STATCOMs by the cost of one STATCOM. This cost is in present value.

$$C_2 =(\sum_{i\in B_{DG}} \omega_{DGi})*P_{DG}^{W} \times C_{O\&M}^{W})+((\sum_{i\in B_{STAT}}\times (\omega_i^{+} + \omega_i^{-})\, Q_{STATrated} \times C_{O\&M}^{STAT})]\times PA(int,n) \tag{3.9}$$

Equation (3.9) the aim is to minimize the O&M cost of the installed W-DGs and the STATCOMs. The first term of the equation is the summation of the number of the installed W-DG multiplied by the power of the W-DG in kW and the cost of the O&M per each kW. The second term of the equation is the summation of the installed STATCOMs multiplied by the rated reactive power of the STSTCOM and the cost of O&M per each STATCOM. The equation for the present worth of an annually recurring receipt or disbursement for the time horizon n with interest int is included in every equation where there are annual receivables or expenses.

$$C_3 = [\left(\sum_{i=1}^{nb}\sum_{t=1}^{st} Pl_{i,t}\right)\times 8760 * C_{loss}]\times PA(int,n) \tag{3.10}$$

In (3.10) the costs of the active power loss in the system is calculated in each state st. $\mathrm{Pl}_{\mathrm{i,St}}$ represents the power losses (kWh) in all distribution lines in the system for each probability state and this is multiplied by the cost of loss $\mathrm{C}_{\mathrm{loss}}$ in dollars of generating and supplying one kWh. The equation for the present worth of an annually recurring receipt or disbursement for the time horizon n with interest i is included in every equation where there are annual receivables or expenses.

$$\mathrm{C}_4 = [(\sum_{\mathrm{i}\in \mathrm{B}_{\mathrm{DG}}} \sum_{\mathrm{t}=1}^{\mathrm{st}}(\omega_{\mathrm{DGi}}\times \mathrm{P}_{\mathrm{DGi,t}}^{\mathrm{W}})) \times 8760\times \mathrm{C}_{\mathrm{g}} +\Delta \mathrm{P}_{\mathrm{loss}} \times 8760 \times \mathrm{C}_{\mathrm{g}}]\times PA(int,n) \tag{3.11}$$

In (3.11) the summation of the generated annual output power from the installed W-DGs added with the active power loss saved due to the installation of the W-DGs and STATCOMs. This amount is considered again. The equation for the present worth of an annually recurring receipt or disbursement for the time horizon n with interest i is included in every equation where there are annual receivables or expenses.

$$C_5 = [(\sum_{i\in B_{DG}} \sum_{t=1}^{st}(\omega_{DGi} \times P_{DGi,t}^{W})) \times 8760 \times E_{emi} \times C_{CO2} + \Delta P_{loss} \times 8760 \times E_{emi} \times C_{CO2}] \times PA(int, n) \tag{3.12}$$

In (3.12) the reward from clean energy production is calculated. The power generated from the W-DGs is obtained. The saving reward from the CO$_2$ emission is calculated by multiplying the cost of CO$_2$ emission by the annual power generated from the W-DGs. The same assumption is made for the system active power losses. The reduction in the total annual active power loss due to the installation of the W-DGs and STATCOMs is calculated. This amount is subtracted from the total annual active power loss before adding the W-DGs and STATCOMs. The difference is multiplied by the cost of CO$_2$ emission. Both values are added and considered as a reward cost saved. The equation for the present worth of an annually recurring receipt or disbursement for the time horizon n with interest i is included in every equation where there are annual receivables or expenses.

$$C_6 = \left[\sum_{i\in B_{DG}} \omega_{DGi} \times Salv^{\omega DG} + \sum_{i\in B_{STAT}} (\omega_i^{+} + \omega_i^{-}) \times Salv^{STAT} - \sum_{i\in B_{DG}} \omega_{DGi} \times C_{DECOMM}\right] \times PF(int, n) \tag{3.13}$$

In (3.13) the salvage cost is calculated. The return from recycling the W-DGs and STATCOMs after their end of life is calculated. The end-of-life of the utilized equipment is assumed to last on average of 20 years. A good example of the component materials and weights is presented in [46]. This amount is considered as a cost that will be returned to the revenue. This cost is considered in the present value. However, what is not considered from a practical point of view is that the salvage cost of the wind turbine at end-of-life can be nulled by considering the decommissioning cost. Based on inputs and discussions with Siemens Gamesa Renewable Energy the author has conducted, the proper model to practically represent the salvage cost is zeroed when the cost of decommissioning is added to it. The decommissioning cost will mainly include manpower, environmental fees, mobile cranes, excavating machines, heavy-duty equipment, cutting material on site to simplify transport, removing paints, sorting materials, and transport. Based on that the salvage cost will be minimal if any.

3.3.1. Distribution Network Constraints

The distribution system active power loss calculated using (14)

$$Pl_{\boldsymbol{t}} = 0.5 \times \sum_{i=1}^{nb}\sum_{j=1}^{nb} G_{ij} \times \left[\left(V_{i,t}\right)^2 + \left(V_{j,t}\right)^2 - 2 \times V_{i,t} \times V_{j,t} \times cos\left(\delta_{j,t} - \delta_{i,t}\right) \right] \forall i,j \in nb \qquad (3.14)$$

where, $\mathrm{Pl_t}$ represents the power losses in the distribution system at state t ; $V_{i,t}$ and $\theta_{i,t}$ are the voltage magnitude and angle of bus i at state st, respectively; nb is the total buses in the system and G_{ij} and B_{ij} are the conductance and susceptance of line *ij*, respectively.

The power flow constraints for the distribution network are calculated using (3.15) and (3.16) per each bus i and load states l.

$$\mathrm{P_{G1,t}} - \sum_{i=1}^{nb}\sum_{l=1}^{st} \mathrm{P_{Di,t}} + \sum_{i=1}^{B_{DG}}\sum_{t=1}^{st} \mathrm{P_{DGi,t}} = \sum_{j=1}^{n_b} \mathrm{V_i} \times \mathrm{V_j} \times \mathrm{Y_{ij}} \times \cos\left(\theta_{ij}+\delta_j - \delta_i\right) \quad \forall \mathrm{i},\mathrm{j} \in \mathrm{n_b}, \forall\, \mathrm{S_t} \qquad (3.15)$$

$$\mathrm{Q_{G1,t}} - \sum_{i=1}^{nb}\sum_{l=1}^{st} \mathrm{Q_{Di,t}} + \sum_{i=1}^{B_{STAT}}\sum_{t=1}^{st} \mathrm{Q_{STATi,t}} = - \sum_{j=1}^{n_b} \mathrm{V_i} \times \mathrm{Y_{ij}} \times \sin\left(\theta_{ij}+\delta_j - \delta_i\right) \quad \forall \mathrm{i},\mathrm{j} \in \mathrm{n_b}, \forall\, \mathrm{S_t} \qquad (3.16)$$

The power flow constraints take care of the power flow balance. Generation always equals demand. This is represented by the real and reactive power flow at each bus are shown in equations (3.15) and (3.16). Notations PG1l and QG1l represent the active and reactive power generated by the substation at bus 1. $\mathrm{P_{Di,Sl}}$ represents the set of generic demand at each bus and each load state. $P_{DGi,St}$ and $\mathrm{Q_{Di,Sl}}$ represent the peak real and reactive power demand at bus i and load state l . Notation $P_{DGi,St}$ is the set of wind turbine power generation states at each W-DG candidate bus set B_{DGi} and total combined load and wind state probabilities St.The notation $Q_{STATi,Sl}$ represent the injected and absorbed reactive power at candidate bus set of B_{STATi} and load state l . On the right-hand side of the equations (3.15) and (3.16), the variables V and δ represent the voltage and voltage angle while the parameters Y and θ represent the Y-bus magnitudes and phase angles. The generation bus constraints are given in (3.17) -(3.19)

$$\mathrm{P_{Gi,l}} = 0 \qquad \forall i \neq 1 \tag{3.17}$$

$$\mathrm{Q_{Gi,l}} = 0 \qquad \forall i \neq 1 \tag{3.18}$$

$$V_1 = 1.0 \qquad \& \qquad \delta_1 = 0 \text{ (Slack bus voltage and angle)} \tag{3.19}$$

The distribution system voltage constraint is given in (3.20).

$$V_{min} \leq V_i \leq V_{max} \qquad \forall i \notin generation\ bus \tag{3.20}$$

(3.20) ensures the voltage at any bus i in the system except bus 1, must remain within the predefined limits of V_{min} and V_{max} at all time. The feeder capacity constraint is given in (3.21)

$$I_{ij} \leq I_{ij\,max} \qquad \forall i\,, j\ \in n_b \tag{3.21}$$

(3.21) ensures the current limit at any branch connecting two buses not to exceed the maximum capacity of the branch.

3.3.2. W-DG constraints

Maximum penetration constraint of all DG into the distribution network is given in (3.22)

$$\sum_{i=1}^{B_{DG}} CF * P_{DGi} \leq k * \sum_{i=1}^{n_b} P_{Di} \qquad \forall i\ \in n_{b,} \forall i \in B_{DG} \tag{3.22}$$

It ensures that the total W-DG generation will not exceed the total penetration allowed by Ontario power regulations. The allowed penetration k is set at 30% of the total system demand. As per the equations above, to maintain the allowed penetration, only 13 wind DGs can penetrate the system at any time. The capacity factor of the W-DG is given in (3.23).

$$CF = \frac{p_{ave}}{p_{rated}} \tag{3.23}$$

where p_{av} is the average power of W-DG; p_{av} is the rated power of W-DG.

The maximum number of allowed DG to be installed in the system is given in the equation (3.24) and (3.25)

$$\text{Maximum DG Generation} = \text{CF}^* \ \text{K}^*\text{P}_{\text{Di}} \tag{3.24}$$

$$\text{Z}_{\text{DG}} = \frac{\text{Maximum DG Generation}/\text{CF}}{\text{p}_{\text{rated}}} \tag{3.25}$$

The total allowed installation of W-DG constraint is given in (3.26)

$$\textstyle\sum_{i=1}^{B_{DG}} \omega_{DGi} \ \leq Z_{DG} \qquad \forall i \in B_{DG} \tag{3.26}$$

(3.26) ensures that the maximum installed W-DG in the distribution network not to exceed the total allowed number at any time.

The discrete size of W-DGs is given in (27)

$$\alpha_{\text{DGi}} * \text{P}_{\text{DG (rated)}} \leq \text{P}_{\text{busi}}^{\text{max}} \qquad \forall i \in B_{DG} \tag{3.27}$$

Equation (3.27) ensures the maximum number of W-DGs installed at each candidate bus in the B_{DG} set not to exceed the maximum capacity of the bus. This is represented by P_{busi}^{max} which is also a value set by the utility [IESO]. $\text{P}_{DG\ (rated)}$ is the rated power of a wind turbine. This limits the total allowed number of the W-DGs that can be connected to one bus.

3.3.3. STATCOMs Constraints

The STATCOMs added to the candidate buses will be predefined. This will be up to the utility based on its availability. The constraints below ensure that the installed STATCOMs will be installed at the voltage sensitive buses. The set of candidate buses is noted as B_{STAT} The constraints for the installed STSACOMs are given in (3.28) and (3.29).

$$Q_{STATi}^{+} \leq M * \omega_i^{+} \quad \text{for } \ i \in B_{SASTi}\ , \omega_i^{+} \ \in [0,1]\ , Q_{STATi}^{+} \ \geq 0 \tag{3.28}$$

$$-Q_{STATi}^{-} \leq M * \omega_i^{-} \quad \text{for } i \in B_{SASTi}\,, \omega_i^{-} \in [0,1]\,, Q_{STATi}^{-} \leq 0 \tag{3.29}$$

Equations (3.28) and (3.29) ensure that only one STATCOM can be installed at a candidate bus. ω_i^{+} and ω_i^{-} are decision variables that can be either 0 or 1. If the installed STATCOM injects reactive power then the decision variable ω_i^{+} =1, making the constraint true and installing a STATCOM at that bus; otherwise, the constraint is untrue, and no STATCOM is installed. The same condition applies for the decision variable ω_i^{-}. If the bus absorbs reactive power, then ω_i^{-}=1, making the constraint true and installing a STATCOM at the bus; otherwise, the constraint is untrue, and no STATCOM is installed. The installed STATCOM can either inject or absorb reactive power. This constraint is met using (3.30)

$$\omega_i^{+} + \omega_i^{-} \leq 1 \qquad \text{for } i \in B_{SAST} \tag{3.30}$$

(30) ensures that at any candidate bus belonging to the B_{STSTi} set, if a STATCOM is installed, then the STATCOM can only inject or absorb reactive power. The summation of the decision variable ω_i^{+} and ω_i^{-} must be less or equal to one.

The maximum allowed STSTCOMs to be installed in the power system is met using (31)

$$\sum_{i=1}^{B_{STAT}} (\omega_i^{+} + \omega_i^{-}) \leq Z_{STAT} \qquad \text{for } i \in B_{STAT} \tag{3.31}$$

(3.31) ensures that the total number of the installed STATCOMs in the system not to exceed the total predefined number by the utility. As an example, if the number of the candidate buses equals ten, then the utility can allocate any number of STATCOM less than ten to be installed at the most sensitive and support requiring candidate buses.

$$\omega_i^{+}, \omega_i^{-} \quad \forall i \in [0,1] \tag{3.32}$$

Equation (3.32) declares the decision variables ω_i^{+} and ω_i^{-} binary variables [0,1].

3.3.4. STATCOM Cost Function

The cost fuction of STATCOMs is represented by a quadratic polynomial equation. Based on data obtained in the industry from one of the STATCOM manufacturing companies, the cost function is developed. The range of the STATCOM rating included in the cost function is between 1000kVAr and 6000kVar. These ratings are more to be used in the distribution applications. Based on the obtained date the cost function is developed in (3.33):

$$\mathrm{C}_{\mathrm{KVAr}}^{\mathrm{STAT}} = 0.0028*(Q_{STAT}^{rated})^2+30*Q_{STAT}^{rated}+2.4*10^5 \tag{3.33}$$

where $\mathrm{C}_{\mathrm{KVAr}}^{\mathrm{STAT}}$ is the cost in $\frac{\$}{kVAr}$ and Q_{STAT}^{rated} is the rated power of the selected STATCOM. The cost function for the distribution ranges for STATCOMs are shown in Figure3.4.

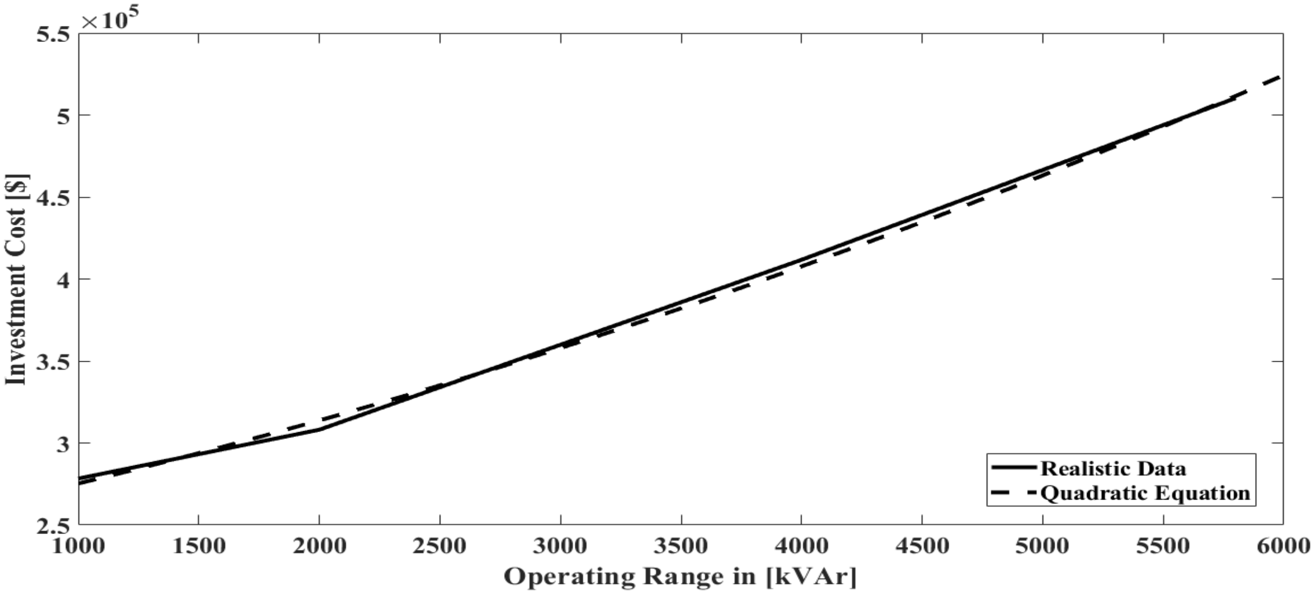

Figure 3.4: The cost function of the STATCOMs.

From the curve above the cost of $\frac{\$}{kVAr}$ is determined for any rated power within the given range.

3.3.5. Candidate Buses

- Candidate Buses to Install STATCOMs

Selecting the correct candidate buses to install the STATCOMs will help the system stay healthy. Installing the reactive power control device at a healthy bus will lead to increase in the voltage above or below the allowed limit making that bus unhealthy. Researchers utilized different techniques to select the right buses or the buses that require reactive power support. Usually, the selected buses are buses that are voltage or loss sensitive. L Index, Power Stability Index (PSI), Voltage Deviation Index (VDI), Stability Index (SI), Voltage Stability Index (VSI), Fast Voltage

Stability Index (FVSI), Jacobian Matrix are among the techniques used to identify the sensitive buses to be considered as candidate buses for the installation of reactive power control devices.

For this thesis study, the selection of the candidate buses is performed by using the inverse of the Jacobean matrix. This is a simple and quick method to determine the candidate buses with the highest sensitivities. The Jacobean matrix in power systems is a part of the Newton Raphson Load Flow Analysis. The load flow analysis determines the voltage magnitude and phase at each bus in a power system for any given Load. The Jacobian matrix is a square matrix that consists of four sub-matrices as presented in (3.34).

$$J=\begin{bmatrix} \frac{\partial P}{\partial \delta} & \frac{\partial P}{\partial V} \\ \frac{\partial Q}{\partial \delta} & \frac{\partial Q}{\partial V} \end{bmatrix} \tag{3.34}$$

where J is the Jacobian matrix; J1= $\frac{\partial P}{\partial \delta}$; J2= $\frac{\partial P}{\partial V}$; J3= $\frac{\partial Q}{\partial \delta}$; J4= $\frac{\partial Q}{\partial V}$.

To determine the sensitive buses in the system, the inverse of J4 of the Jacobean matrix is used. This is expressed as $\frac{\partial V}{\partial Q}$. The buses with a higher number of changes are considered candidate buses. For this study, the ten highest buses are selected as candidate buses. A MATLAB code is developed to determine the inverse of the J4 sub-matrix. Then bus numbers are arranged in a descending arrangement with the first ten buses with the highest $\frac{\partial V}{\partial Q}$ being selected as the candidate buses.

- Candidate Buses to Install the W-DGs

To determine candidate buses for installing W-DGs a different approach is considered. The factors will be depending on the availability of land, the wind, the geography of the area and the loads available. For this study, the candidate buses set selected by [20] is utilized.

CHAPTER 4

PROPOSED METHOD PERFORMANCE EVALUATION METHODOLOGY

4.1. System Information

The distribution system used in this case study is a radial 41-bus distribution system. The system represents a typical rural distribution system. The total load demand of the system at the peak is 17,009.7 kW and the details of the real and reactive loads in each bus are shown in Table (A.3) in Appendix A. The system network feeder data is given in Appendix A in Table A.4. The candidate buses for the W-DGs, represented by the candidate bus set B_{DG} and selected following [21]. The candidate buses for the STATCOMs are represented by the candidate bus set B_{STAT} and are selected using the inverse of the J4 of the Jacobean matrix. Figure 4.1 shows the single line diagram for the 41-bus system.

The generation station is at the westernmost point at bus#1, which is the slack bus. The slack bus provides the power demand for all the remaining 40 buses in the system. The objective is to allocate the STATCOMs and the W-DGs optimally to achieve the total cost reduction.

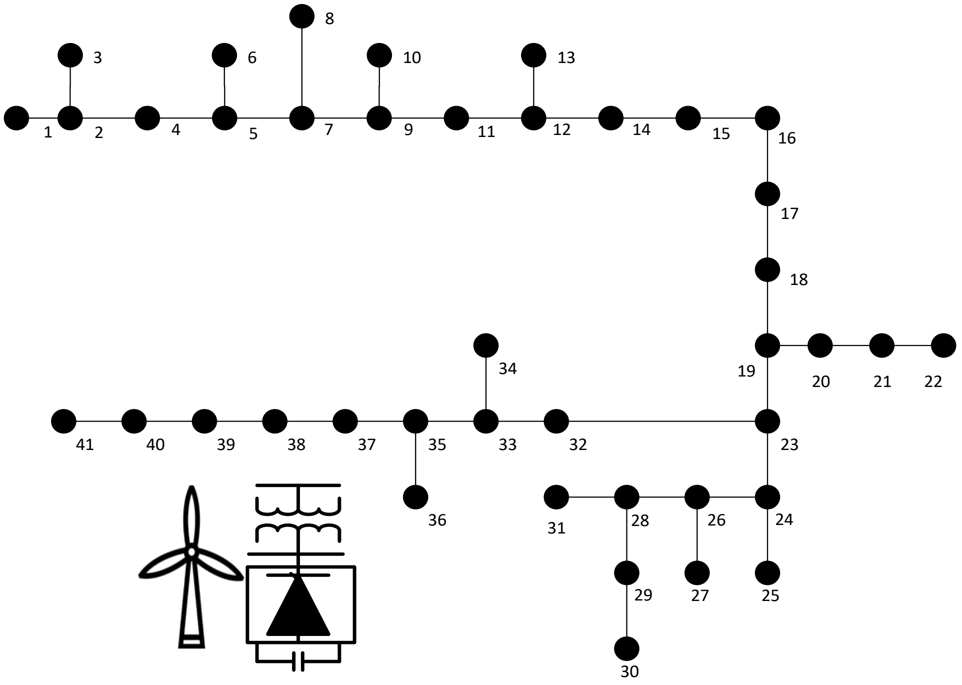

Figure. 4.1: The 41-Bus Distribution System Network.

4.2. Case Study

In this section, the system under study is put under two scenarios. The first scenario is the pre-planning scenario where the system has no STATCOMs or DGs installed. The power flow program is executed, and the system's total active power loss is determined. In scenario two, the candidate buses are determined; the load probability is modeled; the wind speed probability is modeled. Load and wind speed probabilities are then combined using convolution. All the previous steps will be used with the proposed solution algorithm in the coming sections.

4.2.1. STATCOMs and W-DGs Candidate Locations

The candidate buses for the STATCOMs, represented by the candidate bus set B_{STAT} and selected by taking the inverse of the fourth quarter J4 of the Jacobean matrix. Based on the inverse of J4 for the proposed distribution system the 10 candidate buses selected in the set B_{STAT}={8,28,29,30,31,36,37,38,39,41}

The candidate buses for the W-DGs, represented by the candidate bus set B_{DG} and selected following [21]. This selection is based on wind regime and the land availability, the candidate buses to connect the DG units are included in the set B_{DG}= {19, 23, 32, 33, 35, 37, 38, 39
40}.

As shown in Figure.4.2, the red-colored nodes are STATCOM candidate bus locations, and the blue colored nodes are the W-DG candidate bus locations, and the rectangle grey colored buses are the common candidate buses for installing STATCOMs or WTs. The three candidate buses with the red & blue color can have either both STATCOM and W-DGs or one of them installed or non.

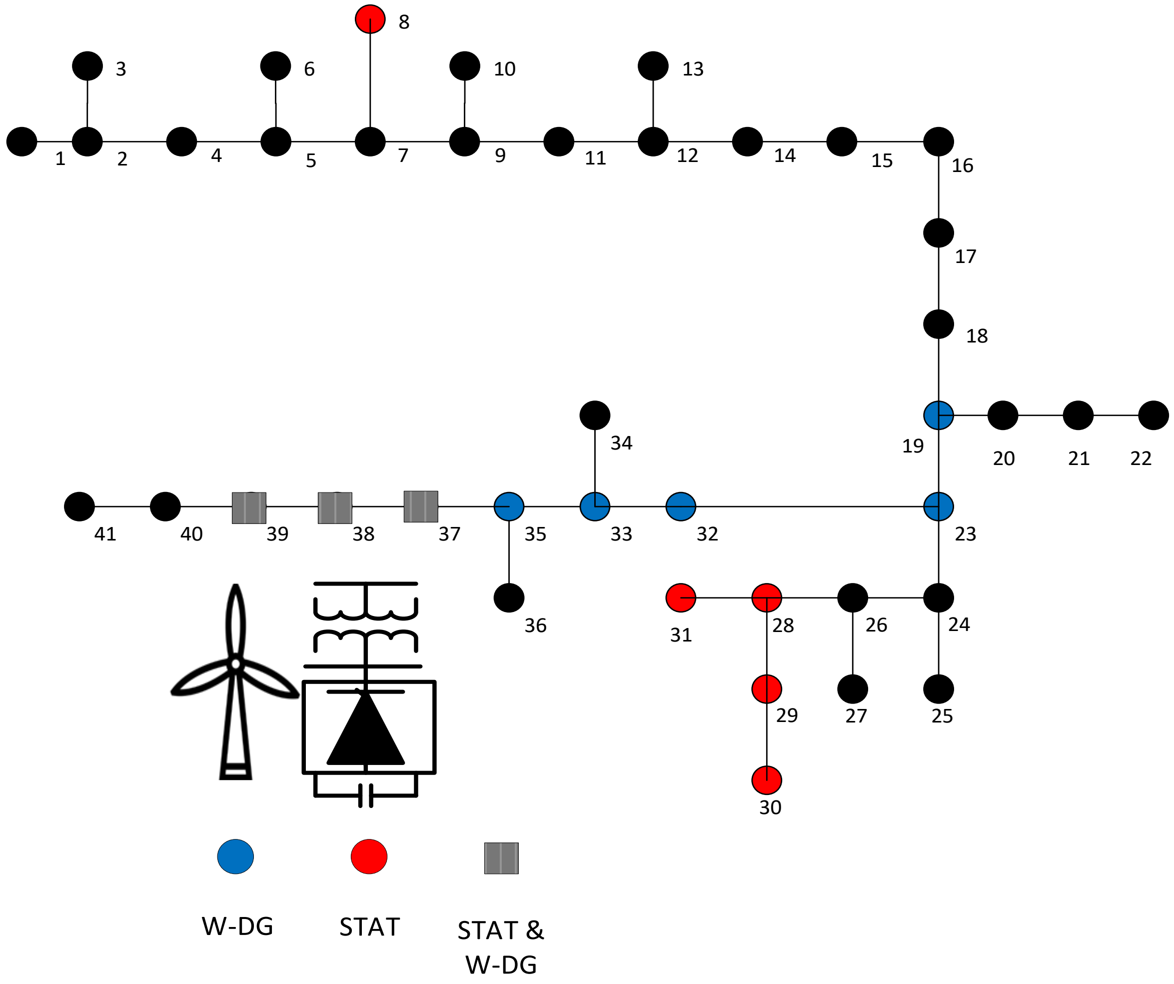

Figure 4.2: The 41-Bus Distribution System Network with Candidate Buses Assigned.

The allowed penetration of renewable energy in Ontario, Canada, is determined by the Independent Electricity System Operator (IESO)[47], which is set at 30% of the maximum total load demand of the system. Local distribution companies (LDCs) and decided that the maximum MW allowed at each bus is limited to 10 MW i.e. P_{busi}^{max} =10 MW. This will make the maximum penetration limit at each bus at 30% of the peak load (K= 0.3).

4.2.2. W-DG Technical Specification

The proposed wind turbine is a 1100kW wind turbine. The characteristics of the wind turbines available are listed in table 4.1.

Table 4.1: Available wind Turbine Characteristics.

Wind Turbine Characteristics	Turbine 1	Turbine 2	Turbine 3	Turbine 4
Rated Power (kW)	850	1.1	2	3
Cut-in Speed(m/s)	4	4	4	4
Rated Speed (m/s)	16	14	15	15
Cut-out Speed (m/s)	25	24	25	25

Figure 4.3 demonstrates the capacity factor of the available wind turbines. From the columns, it can be noticed that wind turbine 2 comes with the highest capacity factor among the other presented turbine, which means its power output based on average power to rated power ratio is higher than the other presented turbines.

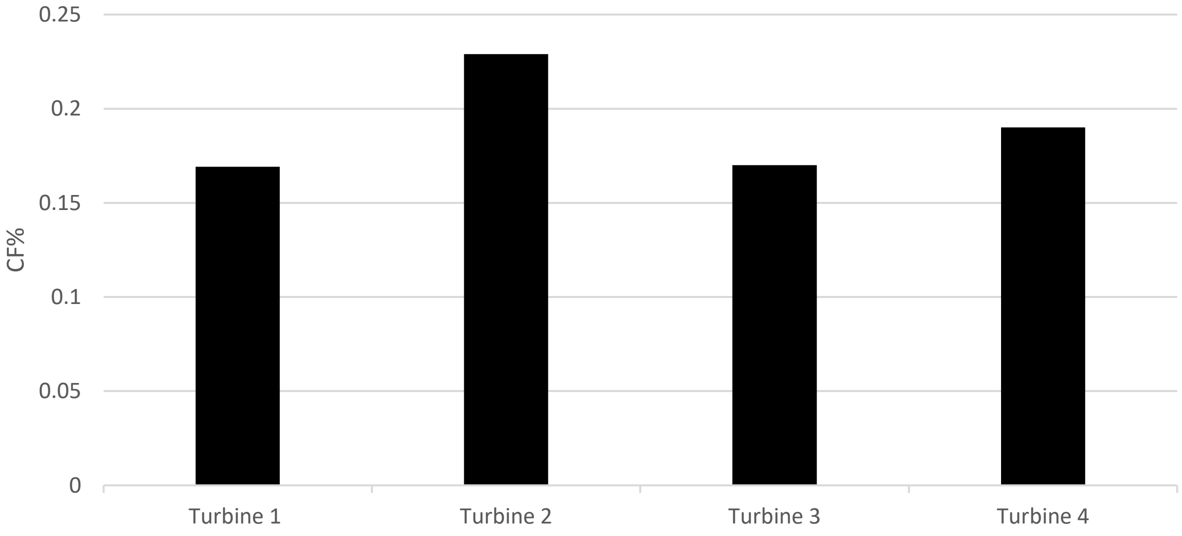

Figure 4.3: Capacity factor CF of the wind turbines available.

For the wind data the max wind speed =39.5 m/s; mean wind speed = 0.5 m/s. For the W-DG, the rated power (P_r) is 1100kW; cut-in speed = 4 m/s; nominal speed =14 m/s; cut-off speed = 25 m/s Based on the characteristics of Wind Turbine 1, the probabilistic wind output power model generated, and the capacity factor is determined. The capacity factor is calculated to be 22.09%, where the wind speed and wind power probabilities are shown in Table 3.6.

4.2.3. STATCOM Technical Specifications

The STATCOM in this simulation has a rated reactive power capacity of 2000kVAr, with a air-cooled cooling system, and is rated voltage at 12.6KV±10%. The obtained information included ranges from 1000 KVAr to 6000kVAr. The design of this industrial STATCOM is based on low voltage inverters, specially developed for power quality issues on the distribution system. All the STATCOM proposed in this study comes with a dry-type transformer solution to provide the secondary voltage up to 33KV.

Selecting the proper STATCOM requires some attention to the requisitions. These requisitions must specify the STATCOMs application, secondary rated voltage, the cooling type, vector group, the overall dimensions, the need of a step-up transformer if standard units come with a lower voltage, rated current, vector group, features tap changer and communications. Specifying the characteristics plays a big role in obtaining accurate cost function when accruing the quotation of four to five units of similar characteristics bus with different rated power to determine a more accurate cost function. For the cost function in this thesis, five separate quotes where obtained. Each quote represented a rated power. The five quotes represented a reactive power range starting from 1000kVAr and ending with the fifth quote of 5800kVAr. Due to the complexity of the STATCOMs and the features and characteristics involved a good understanding of the applications, functions, and technologies used are required to specify the required STATCOM.

Different designs of STATCOMs are available based on the application. Different designs for different applications are available. Designs are based on low voltage invertors or cascaded-H bridge topology or thyristor-controlled reactor switch designs are available.

4.2.4. Proposed Solution Algorithm

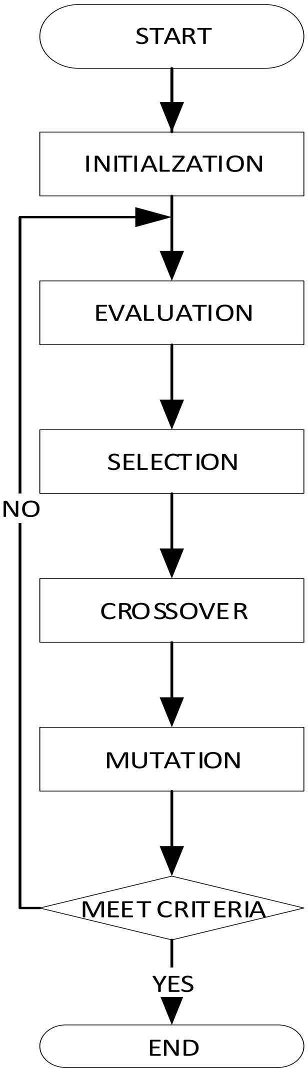

Figure 4.4: A Typical GA Flow Chart

GA is utilized to solve the model. GA is a population-based searching algorithm. The flow chart of a typical GA is presented in Figure 4.4. Each population consists of chromosomes. Each chromosome consists of several genes. For this model, each chromosome consists of 48 variables or genes. Figure 4.5. presents the configuration of a chromosome and its 48 decision variables. The flow chart in Figure 4.6 depicts the logical flow of the code developed on MATLAB using the GA solver. This highlights how the mathematical model was implemented and how it was integrated with the solution algorithm to provide the results needed.

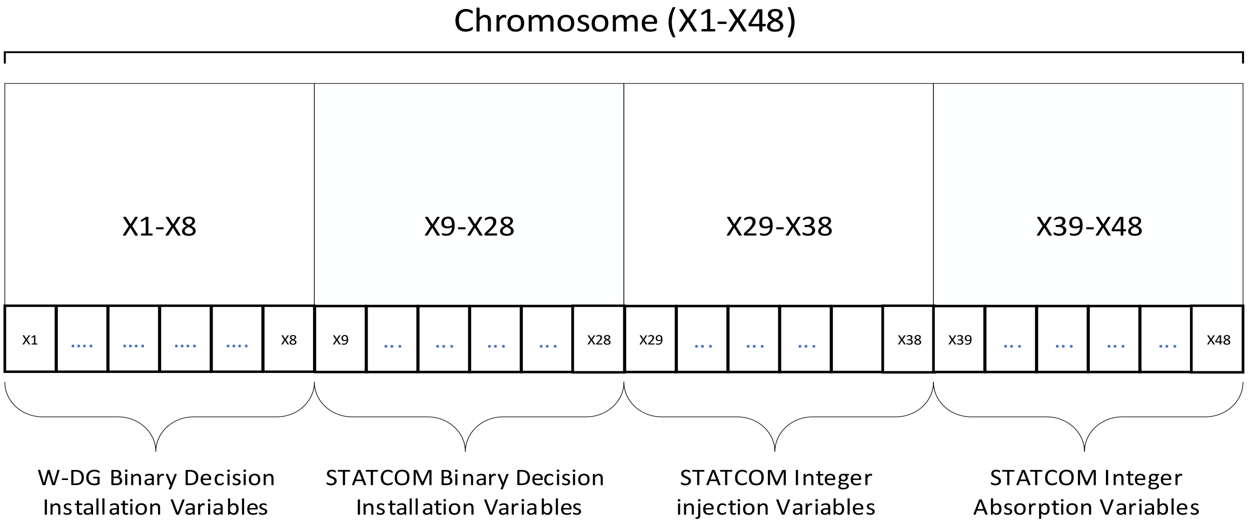

Figure 4.5: The Chromosome of the 48 Decision Variables.

Several data sets are required before the solver can begin as in step one. It includes information about the distribution network under study, the stochastic elements of wind and load are convolved. The data sets include all the parameters that will be a part of the cost function. Constraints included the power flow constraints, the WPDG related constraints, the STATCOM related constraints in the distribution network, and equations. Step two utilizes a function that convolves the three independent stochastic elements and outputs 120 states with the associated combined probabilities of those states. Step three sets the initial values of the decision variables, such as the location and number of WPDGs and the STATCOMs in the system.

Step four is where the power flow simulation is run with the initial values set in the previous step, to calculate the impact of the current set up. In step five, a series of calculations take place based on the resulting values of the simulation. Voltages of buses and currents through lines are saved in matrices. Transmission losses are recorded. The reactive power injection and absorption are calculated per each candidate bus, placed in the candidate locations, and this sum is also recorded. Finally, the total power generated from the WPDGs is also calculated. Steps four and five are repeated 120 times for each scenario.

Step seven is where the six terms of the objective function are calculated using all the collected data from the 120 states and considering the probability of each scenario. A final value is given, representing the profit over the entire planning horizon. The termination criteria consider the incremental change in the profit from each iteration to the next as well as a set number of stall generations. This allows the solver to reach a good solution in a limited amount of time. If the termination criteria are not met, the decision variables are amended by selecting the best parents and following the crossover and mutation rules before step 4 begins again.

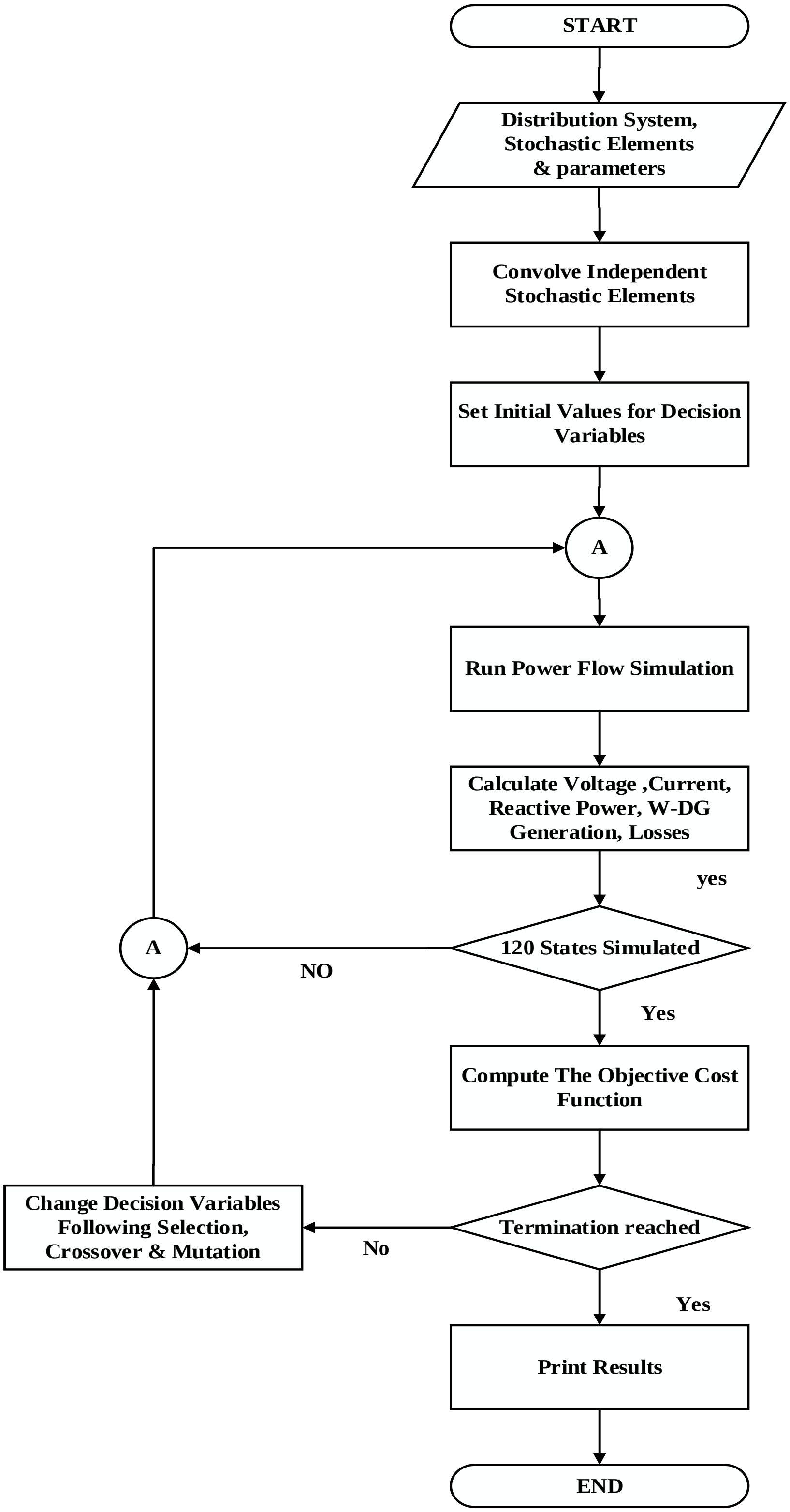

Figure 4.6: High-level code of model and solution algorithm.

The MINLP model is NP-hard and so a metaheuristic is required to solve it. Two hours is required to acquire the results on a laptop with an 8th generation i-7 intel octa-core processor and 32GB of RAM. The model considers all 120 possible combinations of independent stochastic elements for every GA iteration, so it is reasonable that such a long time is needed for this strategic decision. Moreover, the consideration of all the distribution network elements in addition to the traffic network elements and their relationships makes this model highly complex.

4.2.5. Results

A list of the parameters used in the case study are shown in tables A.1 and A.2 in Appendix A. The 41-bus system load data is shown in table A.3 and the feeder data in table A.4, also in Appendix A. Each load state represents a percentage of the peak power except for the wind states, which directly represent the kWh generated by the turbine. See table A.5 in Appendix A for the states of each stochastic variable.

A dedicated MATLAB script was developed to convolve the two independent stochastic elements as explained earlier in Algorithms 1. This provides 120 combined stochastic states. Table A.6, in appendix A, shows the probabilities of the states before they were convolved. The developed mathematical model using MATLAB and GA solver is used to execute the model. A list of results is returned.

By conducting detailed analysis of these results, author of this thesis started with the allocated STATCOMs and W-DGs in the 41-bus system. Figure 4.6 presents the flow chart of the problem execution. Figure 4.7 presents the allocation of STATCOMs and WPDGs in the distribution system. Prior to installing and STATCOMs or W-DGs the system total active loss is at 1,135.8MWh

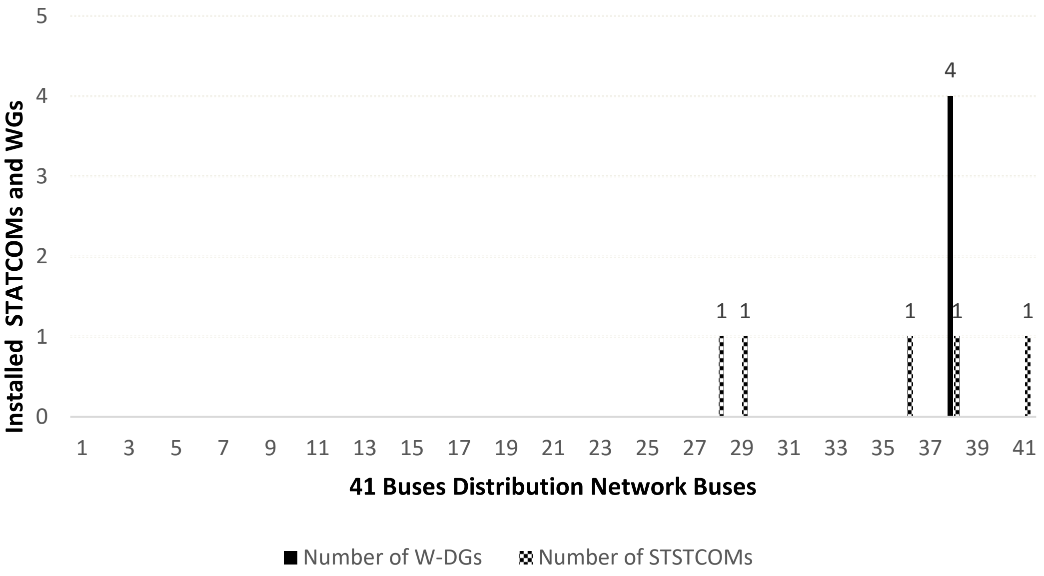

Figure 4.7: Number of STSTCOMs and W-DGs Installed in the system.

The mathematical model implemented with the condition of installing up to five STATCOMs on the ten candidate buses and for the W-DGs up to 13 wind turbines to be installed on eight candidate buses in total without exceeding nine wind turbines per each candidate bus. It shows five STATCOMs have been installed on buses 28, 29, 36, 38, and 41; meanwhile, for the W-DGs, four wind turbines have been installed at bus 38. Most of the locations where the installations occurred are in buses far from the substation. The loads would cause large transmission losses, measured in (10), the fourth term of the objective function for both pre and post of installations. These losses were converted into their dollar values and considered as part of the cost function.

The investment cost for the installed STATCOMs in the present value is \$1,600,000 in total for the 5 installed STATCOMS. Meanwhile, the cost of installing the W-DGs in the present value is \$5,000,000 in total. The installation locations selected by the mathematical model better support the loads in different areas and reduces transmission losses when comparing the total active loss before and after the installation equipment.

The operation and maintenance cost for the STATCOMs and W-DGs in the present value of annually recurring receipt over 20 years with dollar amount totaling \$1,865,600. This cost is mainly representing the O&M cost of the W-DGs as the O&M cost for the STATCOMs is neglected.

The System Active power loss is 594kWh. The saving in power losses is 532. 8kWh. The dollar amount saved in the present value of annually recurring receipt over 20 years is $943,569.

The total active power generated from the installed wind turbines is 20,197,000KWh. The generated power is converted to cost using the feed-in tariff for the 4 wind turbines. This, in turn, will save the generation station from generating this amount using coal as a fuel. The dollar amount savings in the present value of annually recurring receipt is $32,082,934.5 over 20 years.

From the active power loss saving and clean energy generated by the W-DGs, the CO_2 emission saved equals to 5,398 tons of CO_2. This cost is the CO_2 reward cost savings. Subsequently, the saving rewards are in the present value of the annually recurring receipt and the dollar amount over 20 years is $2,858,311.953.

The salvage cost is estimated at 1% of the investment due to the decommissioning cost. A minimal return of an insignificant amount is allocated. The estimated return equals $66000. This amount is calculated as a single future receipt or disbursement.

Figure 4.8. presents the expenses breakdown for the installed four wind turbines and the five STATCOMs. The total investment cost is $6,600,000, as represented by the black slice. The next cost is the O&M cost of $1,865,600. This is represented by the dotted slice. The last expense is represented by the dashed slice at a total cost of $943,569. All the expenses are added to present the total expense cost, which is used with the revenue to determine the profit. The large drop in the system losses indicates the importance of considering the losses in the model.

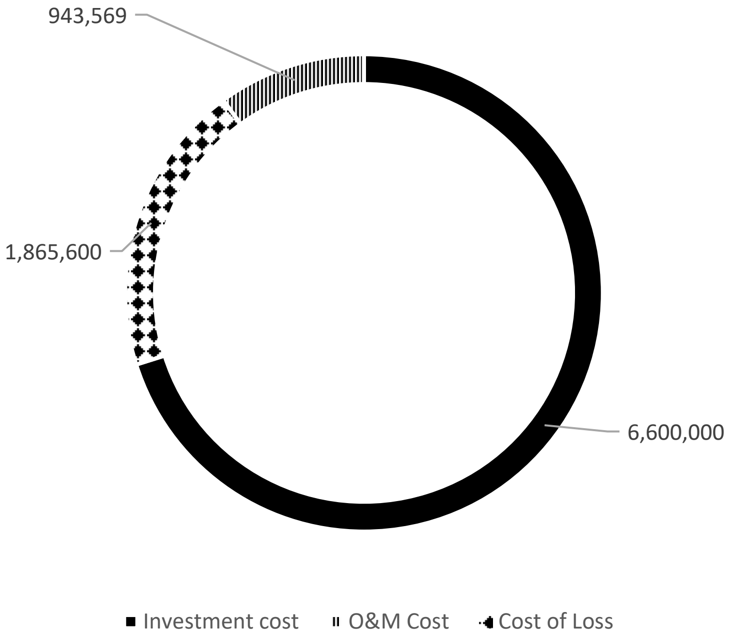

Figure 4.8: The Expense Breakdown for investment, loss, and O&M.

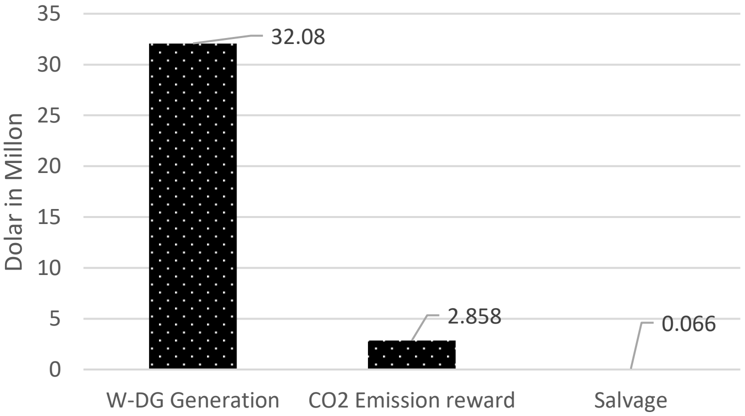

Figure 4.9: Revenue and saved cost rewards.

In Figure 4.9. the revenue resources are presented. The revenue from the W-DGs generation represents most of the revenue. This clearly presents the importance of the investment when it comes to decision-making. The clean generation will provide a revenue of $32,082,934.50. The revenue from the CO2 saving due to the loss reduction and the clean energy generated by the wind turbines. This will contribute an income of $2,858,311.95. From the figure, it can be concluded that 92% of the revenue comes from wind turbine power sales to the grid and 8% from the CO_2 reward and less than 1% from the salvage return.

From the above two charts, we can determine the net present value of profit over the planning horizon of 20 years.

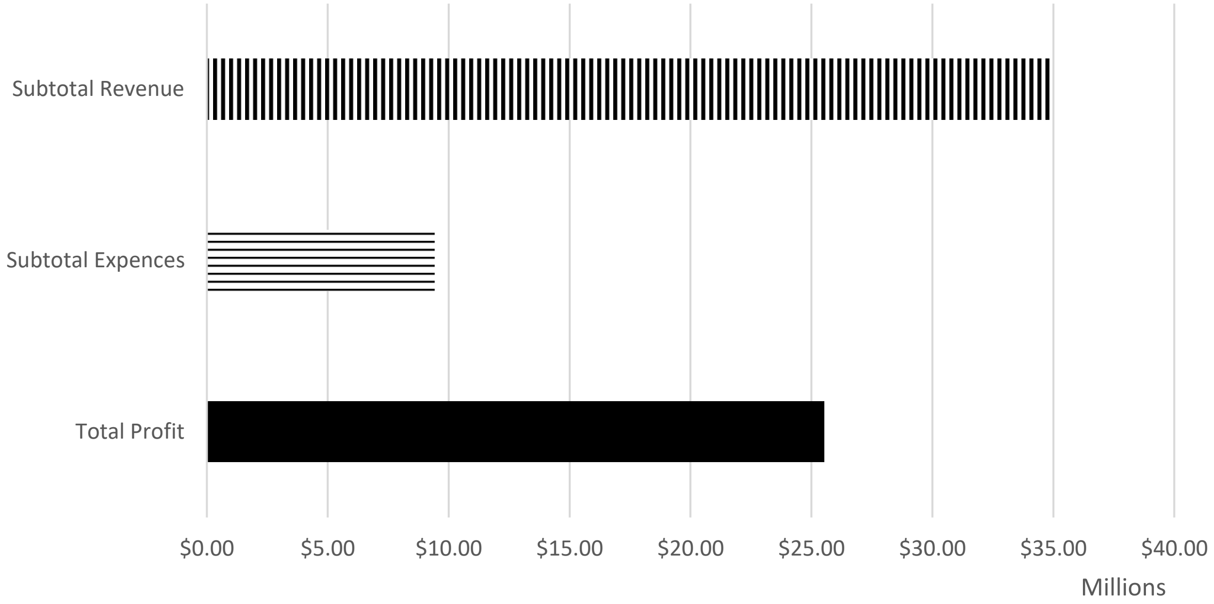

Figure 4.10. The Total Profits over 20 Years.

Figure 4.10. represents the total profit throughout the planning horizon. All values are expressed in net present value. From the financial point of view, the return on investment over the 20 years appears promising, and from the environmental point of view, the saving in the CO_2 emission due to loss reduction and all the active power generated from the wind turbines which could have been active power generated using conventional ways of generations.

In addition, the important role the STATCOMs played in reducing the system loss by improving the grid stability through the dynamic supply of the regulating power. The combination of the W-DGs and STATCOM generated the needed active and reactive power, respectively, to support the grid as per the load changed. Power system operators apply requirements on wind turbines at the grid connection point, like what is applied to conventional power plants. This involves, including other things, inductive or capacitive reactive power must be available, and the static voltage must be controlled. Depending on the type of system used and the electrical grid topology of the wind, the wind turbines alone are often unable to meet all these requirements.

In this chapter, the mathematical model has been implemented. Each step has been explained in detail. The data collected from the Windsor region has also been recorded and presented in tables providing a useful starting point for other researchers to apply their models and calculations to the same data to compare results. The next chapter concludes the thesis and lists the contributions herein. Moreover, a topic for future work is proposed and discussed.

CHAPTER 5

CONCLUSION AND FUTURE WORK

5.1. Conclusion

The presented planning framework simultaneously allocates STATCOMs and W-DGs, considering the dynamic reactive nature of the load and the stochastic nature of the wind. A stochastic MINLP is formulated to minimize the total cost and maximize profits. This will effectively defer the need for DN system upgrades. The results obtained from the model demonstrates its effectiveness in simultaneously allocating optimal STATCOMS and W-DGs based on real data used in the load and wind model probabilities. The model can be used as an effective tool in planning stages and avoids unnecessary investments. As a conclusion, the presented model is a very useful tool addressing long term budgets and power planning objectives on behalf of investors, namely the electric utility and local power distributors

The importance of the STATCOMs comes from its ability to respond to the dynamic of reactive power in the distribution system in conjunction with its influence over reducing the overall system power loss through improving the grid stability is presented. The reduction of the CO2 emissions consequently due to the reduction of the active power loss in the system and the utilization of environmentally clean power generation represented by installing W-DGs, which play a significant role in minimizing the carbon level emitted during the typical bulk power generation. The hybrid uses of the STATCOMs and W-DGs render the grid with lower losses as well as the loads are served with active power closer to its location. This will save on conventional means of generation and long transmission lines that will be added to the losses. The case study presented effectively addresses the interests of the investors, namely the electric utility and local power distributors as well as providing guidelines for urban planning.

A novel allocation scheme has been developed to simultaneously allocate the STATCOMs and the W-DGs to their candidate buses by considering the stochastic nature of the wind speed and the load demand. The solved program is mixed-integer non-linear. Different objectives were examined, such as minimization of investment cost, O&M cost, and power loss cost meanwhile maximizing the wind turbine generation, the CO2 reduction rewards, and the salvage cost. The wind data collection, process, and utilization were explained.

The mathematical model developed, tested, and solved, offers a new perspective implemented in a systematic and reliable approach. The mathematical model provides a cost function that consists of multi objectives. The objective function consists of six terms of the problem and allocates simultaneously the STSTCOMs and WPDGs in the 41-bus distribution network system to provide an optimal cost, maximize profit, minimize loss, and CO2 emissions. The GA was used to solve this very complex planning problem on MATLAB, and results were shown and discussed, such as the return on investment for both STATCOMs and W-DGs as well the reduction in transmission losses and CO2 emission.

Multiple stochastic elements for wind speed and load demand were developed, based on real wind data obtained in Windsor Ontario, and then implemented into the model, A long-term power planning approach was followed.

5.2. Contributions

In synopsis, the contributions of this thesis study are listed below:

1. A set of cost equations were established based on the simultaneous allocation of the STATCOMs and W-DGs at the preassigned candidate bus locations.

2. Allocation of the STATCOMs and the W-DGs were based on the stochastic base. The stochastic nature of the load demand and wind speed probabilities were accounted for throughout the allocation process.

3. Stochastic modeling of the wind speed states based on real wind speed data obtained for the years 2016 and 2017 for the Windsor Ontario region is utilized to simulate a realistic scenario.

4. Formulation of an MINLP model to simultaneously allocate STATCOMs and W-DGs in a distribution network considering its electrical constraints for the distribution network system STATCOM and W-DGs. The model is designed for stochastic planning of the elements in the distribution network system to ensure the distribution network’s constraints and not violated. Additionally, the combination of the allocation of STATCOMs and W-DGs resulted in the installation of optimal W-DGs to serve the loads closer and saving the substation overload or generating extra power to deliver to long distances with excess losses.

5. Estimating the required investment in STATCOMs and W-DGs based on recently surveyed market costs and real data, taking into consideration the stochastic nature of wind speed and load demand.

6. A stochastic model of the load demand probability of the system combined with the wind power probability is presented using convolution to present accurate scenarios that will include all the proposed probabilities.

7. Minimizing the total cost that includes the cost of investment, O&M, losses, and maximize revenue generated by W-DGs, CO2 reward reduction, and salvage costs

5.3. Future Work

Future work requires further attention to the economic, environmental, social, and technical impacts that the increased installation of renewable energy technologies might have when installed close to urban areas or when used in bulk. Government commitments to clean energy have led to an increase in the investments toward more use of renewable resources to generate clean energy with less environmental impacts and pollution. The economy of renewable energy is one of the subjects that need more studies using actual rates and terms put in place by financial institutes. There is a big area of research when it comes to the actual financial conditions in the deployment of the renewable energy market for realistic and accurate outputs. Experience rates can be added as an affecting factor. Where high costs of capital are considered, major obstacles to renewable energy technologies deployment. By the same logic, low costs of capital can contribute to the observed cost reductions for solar PV and wind energy [48].

Another area of future work may include the reactive power aspect of the installed renewable energy technologies. Most studies consider the wind turbines are operating at unity power factor, generating active power only. The dynamic of the reactive power injected or absorbed by the wind turbines changes due to the power changes at different wind speeds. In the meantime, the increase in the installation of renewable energy technologies such as wind farms contributes to the energy production is growing and consequently increasing the reactive power dynamics in large scale renewable energy farms that must be taken into considerations.

In terms of renewable technologies, a mix of renewable technologies and STATCOMs can be added for simultaneous allocation. Energy storage system (ESS) can be the next technology added to the model to study the effect of such combination that can capture the wind power at times not needed. This will improve system reliability through the allocation of distributed storage units [49]. In addition, it will optimize the wind turbine usage to include any time of the day whenever there is a wind that generates power.

From the operational point of view, a mobile aspect can be added to the problem where mobile STATCOMs are utilized to service the buses requiring reactive power at any time buy routing the STATCOMs among the buses.

Overall, determining the optimal investment cost model and optimal allocation model of RET in the power system will provide feasible investment opportunities in the renewable energy infrastructure, which can be used as an important tool at planning, installing, and operating stages. With the consideration of what has been presented, we can be steps closer to a more carbon-free electric grid when dependencies on conventional ways of power generation are replaced with green and clean ways of electric power generation.

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APPENDIX.A

Table A.1: Parameters-A.

Parameter Name	Description	Value	Reference
C_{DG}^{W}	Cost of Wind Turbine per KW	\$1500/kW	[41]
$C_{O\&M}^{W}$	Cost of O&M of the Wind Turbine per KW	\$40/kW	[41]
C_{KVAr}^{STAT}	Cost of KVAr	\$155/kVAr	N/A
C_{KVAr}^{STAT}	Cost of STATCOM Unit	\$310,000	N/A
$C_{O\&M}^{STAT}$	Cost of O&M of the statcom per KVAr	\$0.015/kVAr	[50]
C_g	Cost of system active power generation in KWh	\$0.15/kWh	[42]
C_{loss}	Cost of system active power loss in KWh	\$0.15/kWh	[42]
C_{CO2}^{Reward}	Cost of reward from CO2 reduction	\$50/ton	[4] & [6]
E_{em}	CO2 emission in KG of CO2/KWh	0.343KG CO2/KWh	[3],[4] ,[42]

Table A.2: Parameters-B.

Parameter Name	Description	Value	Reference
K	Max DG penetration in the System as a percentage of the total peak power system demand	30%	[51]
P_{busi}^{max}	Max allowed DG penetration in a single bus	10MW	[47]
n	Number of years for the planning horizon	20	
Int	Annual Interest Rate	7%	[45]
P_{ave}	The weighted average power generated from WPDG rated at 1100 kW	545	
P_{DG}	Rated power of W-DG in kW	1100	[20]
Q_{STAT}^{rated}	Statcom Rated Reactive Power	2000	

Table A.3: 41 Bus system load data.

Bus No.	Pd	Qd	Bus No.	Pd	Qd
1	0	0	22	47.5	15.61
2	0	0	23	9.5	3.12
3	0	0	24	0	0
4	6413.46	2108	25	289.75	95.24
5	0	0	26	0	0
6	903.06	511.79	27	152	49.96
7	0	0	28	0	0
8	3187.25	1047.6	29	0	0
9	576	507.98	30	194.75	64.01
10	0	0	31	517.75	170.18
11	0	0	32	0	0
12	0	0	33	931.25	295.68
13	288.18	93.41	34	204.25	67.13
14	346.75	113.97	35	0	0
15	0	0	36	80.75	26.54
16	0	0	37	104.5	34.34
17	0	0	38	950	340
18	0	0	39	813	280
19	0	0	40	0	0
20	0	0	41	1000	320
21	0	0			

Table A.4: Line (feeder) data for the 41-bus system.

From	T	R (pu)	X (pu)	B(pu)	From	T	R (pu)	X (pu)	B(pu)
1	2	0.025308	0.062586	0.000858	23	2	0.017732	0.023862	0.000278
2	3	0.004484	0.01109	0.000152	24	2	0.022393	0.030135	0.000351
2	4	0.001776	0.004392	6.02E-05	24	2	0.014898	0.020049	0.000233
4	5	0.001687	0.004172	5.72E-05	26	2	0.0174	0.015288	0.000165
5	6	0.000577	0.001427	1.96E-05	26	2	0.019377	0.026076	0.000303
5	7	0.000755	0.001867	2.56E-05	28	2	0.010585	0.0093	0.0001
7	9	0.001154	0.002855	3.92E-05	29	3	0.010875	0.009555	0.000103
9	1	0.000622	0.001537	2.11E-05	28	3	0.023216	0.031242	0.000363
9	1	0.001687	0.004172	5.72E-05	23	3	0.002614	0.004334	5.25E-05
11	1	0.002486	0.006149	8.43E-05	32	3	0.001888	0.00313	3.79E-05
12	1	0.001332	0.003294	4.52E-05	33	3	0.05191	0.045609	0.000491
12	1	0.014785	0.036563	0.000501	33	3	0.00559	0.009271	0.000112
14	1	0.004573	0.011309	0.000155	35	3	0.019011	0.025584	0.000298
15	1	0.004662	0.011529	0.000158	35	3	0.032743	0.0543	0.000658
16	1	0.004795	0.011858	0.000163	37	3	0.014386	0.035575	0.000488
17	1	0.007282	0.018007	0.000247	38	3	0.001332	0.003294	4.52E-05
18	1	0.002087	0.005161	7.08E-05	39	4	0.00222	0.00549	7.53E-05
19	2	0.004296	0.005781	6.73E-05	7	8	0	0.333333	0
21	2	0.035083	0.012068	0.000132	20	2	0	0.	0
19	2	0.001737	0.002337	2.72E-05	40	4	0	0.333333	0

Table A.5: Stochastic load states probabilities.

State number	% of Peak load	Probability of load state
1	1	0.01
2	0.853	0.056
3	0.774	0.1057
4	0.713	0.1654
5	0.65	0.1654
6	0.585	0.163
7	0.51	0.163
8	0.451	0.0912
9	0.406	0.0473
10	0.351	0.033

Table A.5: Stochastic wind states probabilities.

From bin	To bin	Wind Probabilities	% of peak power generated
0	4	0.04715	0
4	5	0.03176	54.9824
5	6	0.03858	164.9472
6	7	0.04397	219.9296
7	8	0.04787	384.8768
8	9	0.05038	494.8416
9	10	0.05163	604.8064
10	11	0.05179	714.7712
11	12	0.05107	824.736
12	13	0.04963	934.7008
13	14	0.04764	1044.6656
14	25	0.34725	1100
25	INF	0.14128	0

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