

# Impact Analysis Models of Renewable Energy Uncertainty on Distribution Networks

by

Yousef Elmabruk Saad El-Rayani

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## **AUTHOR'S DECLARATION**

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

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

## Abstract

In the recent years, governments have encouraged the utilization of renewable energy by providing incentives to investors, and enhancing traditional practices in the sector. For example, in Ontario, Canada, local distribution companies can now legally own and operate up to 10 MW generating plant per location as long as it is from a renewable source. Although this trend results in some operational benefits for the host networks, it also creates specific technical challenges and economic problems. New modeling approaches are needed to account for the main features of power produced by these facilities, namely, the uncertainty and uncontrollability.

The uncertainty of power produced by weather-based generating facilities affects the decisions of different activities related to the operation of distribution systems. Examples of these tasks include power procurement decisions, the assessment of voltage magnitude variation, and reactive power management. If not properly included, uncertainty could result in non optimal outcome of operational activities of a distribution system operator. Based on different optimization techniques, the thesis introduces several models that capture the uncertain behavior of renewable resources. Two operational tasks were selected for application using the enhanced models: economical operation of distribution system and impact assessment on voltage magnitude.

The power procurement problem is an operational challenge to acquire the correct economic mix of power purchases to supply the demand of a local distribution company. Three models have been presented to formulate the power procurement problem with a consideration of the stochastic nature of renewable generation. These models select the optimal quantities of bilateral contracts under uncertain renewable generation and give the option to decision makers to recalculate the powers from other sources. In one of these proposed models, the mean-variance theory is utilized to evaluate the risk associated with the variation of renewable power output on the financial efficiency of a local distribution company. Unlike previous studies, in which renewable power production is identified as a decision variable, in this work the generation from these units is represented as a parameter to model their feature of uncontrollability. Comparison of results obtained from using the proposed models showed that the degree of uncertainty plays an important role in selecting the proper mix. In general, stochastic based algorithms are superior to deterministic approaches when increasing contributions from renewable resources are considered.

A major technical problem that may be caused by the uncertain generation of renewable units is the increase of voltage variation. The second part of the thesis introduces a methodology based on a Monte-Carlo technique to assess new installation depending on its impact on the quality of supply voltage. Two different standard measures for supply voltage quality are applied in this approach to provide the decision maker a tool that can be used to authorize new connections of renewable generation. The consistency of results obtained by the two indices applied in the proposed methodology encourages adopting the proposed approach for evaluating the impact of new connections of renewable resources.

The models proposed in the thesis contribute to promote safer integration of renewable resources in distribution systems by modeling two main features: uncertainty and non-controllability.

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## Nomenclature

### Sets:

$N_b$ :	Total number of buses in a system
$N_c$ :	Total number of candidate contracts
$N_{dg}$ :	Number of distributed generation facilities in the system
$N_i$ :	Number of customers experiencing voltage deviations
$N_s$ :	Number of scenarios required to represent a density function
$N_T$ :	Number of customers served from a location where the measurements were taken
$T$ :	Number of hours of a study period

### Parameters:

$B_{ij}$ :	Susceptance of a feeder segment between bus-i and bus-j
$G_{ij}$ :	Conductance of a feeder segment between bus-i and bus-j
FF:	Fill factor; the ratio of power at MPP to the product of $V_{OC}$ and $I_{SC}$
$I_{MPP}$ :	The current at the maximum power point
$I_{SC}$ :	The short-circuit current
$I_\beta$ :	Solar insolation (kW/m <sup>2</sup> )
$K_i$ :	Current temperature coefficient (A/C <sup>o</sup> )
$K_v$ :	Voltage temperature coefficient (V/C <sup>o</sup> )
NOCT:	Cell temperature in a module when ambient is 20C <sup>o</sup> , solar irradiation is 0.8 kW/m <sup>2</sup> , and wind speed is 1 m/s
$P_d$ :	Demanded real power at a bus
$P_{dg}$ :	Real power production of distributed generation
$Q_d$ :	Reactive power demanded at a bus
$S_{max}$ :	Maximum allowable loading of a bus
$T_a$ :	Ambient temperature (C <sup>o</sup> )
$T_{cell}$ :	Cell temperature (C <sup>o</sup> )
$V_{max}$ :	Maximum allowable magnitude of voltage
$V_{MPP}$ :	The voltage at the maximum power point
$V_{OC}$ :	The open circuit voltage
$\lambda_b$ :	Electricity price of real power purchased via a bilateral contract
$\lambda_s$ :	Electricity price of real power purchased on the spot
$\alpha$ :	A factor to penalize the curtailment of renewable generation
$\gamma$ :	A factor to penalize the usage of surplus/deficit of renewable energy in the two-stage stochastic model
$\Theta$ :	Coefficient to weight risk term in objective function
$\omega$ :	Event of a random variable

### Variables:

$P_b$ :	Real power procured from bilateral contracts
$P_c$ :	Real curtailed power from renewable generation
$P_{deficit}$ :	Real power deficit due to uncertainty
$P_o$ :	Real utilized power output from renewable generation
$P_{inj}$ :	Real power injection at a bus
$P_s$ :	Real power purchased from spot market
$P_{surplus}$ :	Real power surplus due to uncertainty
$Q_{inj}$ :	Reactive power injection at a bus

$Q_s$ : Reactive power procured from spot market  
 $V$ : Voltage magnitude at a bus  
 $\delta$ : Phase angle of voltage at a bus

Operators:

$E[.]$ : Expected value of a random variable  
 $P_r(\omega)$ : Probability of occurrence of event  $\omega$   
 $\text{Var}[.]$ : Variance of a random variable

## Acronyms

DG:	Distributed generation
CDF:	Cumulative density function
CHP:	Combined heat and power unit
CV:	Coefficient of variation factor
CVaR:	Conditional- value-at-risk
DM:	Demand management programs
DSO:	Distribution system operator
EA:	Evolutionary algorithms, a category of global optimization
EEV:	Expected outcome of using the expected value
ELD:	Economic load dispatch
EPRI:	Electric power research institute
ESCO:	electricity service company
EV:	Expected value solution
EVPI:	Expected value of perfect information
GAMS:	General algebraic modeling system
GEA:	Green energy act
IEEE:	Institute of electrical and electronic engineers
IESO:	Independent electricity system operator, in Ontario
LDC:	Local distribution company
LFE:	Load flow equations
MINLP:	Mixed integer nonlinear programming
MINOS:	A general purpose nonlinear programming solver.
MPP:	Maximum power point
NOCT:	Nominal operating cell temperature
NREL:	National renewable energy laboratory
NUG:	Non-utility-owned generation
OPF:	Optimal power flow
PDF:	Probability density function
PSO:	Particle swarm optimization
PV:	Photo-voltaic
RMS:	Root mean square
RP:	Solution of a Resource Problem
SARFI:	System average RMS variation frequency index
SBB:	A solver for mixed integer nonlinear programming (MINLP) models.
TOU:	Time of use
UNEP:	United nations environment program
VaR:	Value-at-risk
VSS:	Value of stochastic solution
WSS:	Wait and see solution

# Chapter 1

## Introduction

### 1.1 General

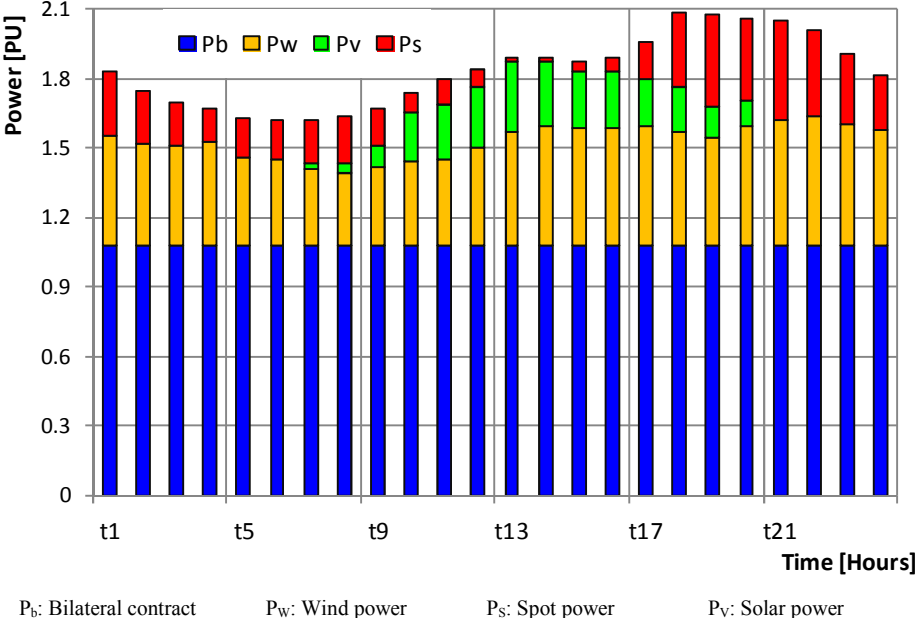
Despite their unpredictable power generation, installations of renewable DG facilities have become significant options to provide electric energy [1]. Recently, regulators of the electric energy sector emphasized the importance of using renewable resources as a clean supply of electric energy [1-3]. According to a report issued by United Nations Environment Program (UNEP) on global trends in renewable energy, worldwide investments in renewable energy reached a record of \$211 billion in 2010 [4]. Small size renewable distributed generation (DG) has a share equal to \$60 billion out of these investments. This share represents a 91% increase compared to that of year 2009 [4]. Most of these DG facilities were based on either wind power or solar irradiance, both of which are unpredictable and intermittent power resources.

A major concern about renewable DG resources are the possible impacts of their outputs' intermittency on the system operation [5]. In distribution systems, the random output of renewable DG units may affect one or more of the following:

- Economic management of power procured for electricity service companies (ESCO's).
- Impact assessment of renewable DG generation on the quality of supply voltage.
- Management of surplus power, generated by intermittent generation.
- Management of control and protection devices: allocation, setting, sizing, and strategy.
- Planning and enhancement of network capabilities: demand is no longer the sole parameter that determines the sizes of distribution assets.

Distribution system operators should take care of the power procurement problem in restructured power systems. They are consistently working to provide electric power to supply a utility's demand at minimum cost. To accomplish this task, the operator may sign bilateral contracts offered by power suppliers, purchase power on the spot and utilize power from renewable generating units connected to the system. A combination of these components obtained from solving the procurement problem for a particular distribution system over a period of time is shown in Figure 1-1. The figure graphically shows the power mix that results in minimum operational cost to balance the demand, illustrated by the solid line in the figure. Traditionally, the problem is formulated as a mathematical programming problem, and consists of binary and continuous variables that are combined in sets of linear and nonlinear constraints to minimize they operational cost. However, this formulation does not consider

the uncertainty of the renewable DG production. The intermittency of renewable generation has an impact on the economic efficiency of local distribution companies (LDC). Any unpredictable changes in the power produced by the solar or wind resources shown in Figure 1-1 result in unbalance and consequently affect the financial efficiency of the distribution company.



**Figure 1-1: A solution of power procurement problem**

Another problem facing the distribution system operator is how to quantify the impact of renewable DG on the voltage magnitude before the actual connection is permitted. The uncontrolled and unpredicted power injections of these units cause changes in current flows leading to variations in voltage drops across the lines and, hence, affect the quality of the supply voltage [6]. The operator of a local distribution company needs a method to assess the potential impacts on the quality of supply voltage before the prospective renewable DG unit is actually connected.

The randomness of small size renewable DG power output necessitates new modeling techniques that incorporate this behavior in formulating distribution system operational studies. This thesis introduces a frame work based on optimization methods to study the effect of intermittency aspect of renewable generation on distribution systems’ operation. The main focus is dedicated towards better inclusion of the random behavior of renewable resources in modeling the operations of distribution systems economically and technically. The objective is to provide models to the decision makers of



distribution systems to address their concerns about the uncertainty of renewable resources and hence resulting in optimal performance.

## **1.2 Motivation and Challenges**

The impacts of renewable resources on distribution systems have been under the consideration by many researchers [5, 7-13]. In the majority of the published reports the power produced by renewable resources was either represented by its average value or treated as a controllable variable. For example, as discussed in Figure 1-1, the deterministic approaches used to solve the procurement problem in the literature will not be optimal if the power from renewable sources deviates from the expected value. Furthermore, if the renewable DG production is represented as a decision variable, like the case in [14], then it is inherently assumed that they are controllable and can be dispatched. Such representations either lack the intermittency aspect of these resources or assume that their output is dispatchable; both do not reflect the characteristics and reality of the generation of renewable resources. The modeling of the output of these facilities should consider the intermittency of these sources and their non dispatchable characteristic in order to create proper tools for the decision maker. This thesis proposes different models based on different optimization techniques to consider the characteristics of uncertainty and controllability of the renewable resources and applies these models in solving the power procurement problem.

Another problem associated with uncertainty is the risk of not achieving the intended objectives. The focus of the reported research on the evaluation of risk was only related to the variation of electricity prices and did not consider the risk due to the uncertainty of the renewable DG production [15-17]. Because the renewable generation can change the optimal mix of power to supply a utility's demand, the power procurement problem should consider the risk associated with this power production. A risk evaluation model is needed to provide the decision makers with a device to consider the economical risk of integrating renewable resources.

The representation of randomness increases the difficulty of the power procurement problem which is already hard to solve. This problem is commonly formulated as a mixed integer nonlinear programming (MINLP) [18-20]. Finding a solution to this problem becomes even more difficult to achieve because of the incorporation of variation in renewable generation. As the number of these facilities increase, the size of the problem becomes larger, leading to a higher degree of complexity and the problem becomes insolvable. Hence, there is a need for a technique that focuses on finding a

solution to the procurement problem without sacrificing its fundamental objectives or its capabilities to represent the uncertainty involved in its formulation.

Another challenge is the evaluation of the voltage variation caused by the stochastic generation of renewable DG facilities. Distribution system operators cannot measure the impact of this generation on the quality of supply voltage before the commissioning of renewable generators takes place. The current practice in assessing the supply voltage variations is to measure the voltages of an existing system and utilize standard indices to evaluate voltage deviations. This procedure is not suitable for evaluating new connections of renewable resources because it depends on the voltage measurements of existing installations. What is needed is a tool that evaluates, before the installation takes place, the impact on the quality of supply voltage. In this thesis, two quality indices are proposed to assess renewable DG contributions to the change in the quality of the supply voltage magnitude.

### **1.3 Research Objectives and Scope**

In this thesis, the main goal is to present suitable models that include the uncertainty of renewable generation to guide the activities of distribution system operators. The purpose of these models is to gain a clear understanding of the influence of renewable DG output on distribution system operations. The following is a list of objectives centered about the consideration of uncertainty of renewable power production:

- 1- Modeling the uncertainties introduced by the power generated from renewable resources. Two methods are utilized to incorporate the uncertainty of renewable power generation: deterministic and statistical. Previously, this kind of generation was represented by a controllable deterministic decision variable which did not reflect the features of this output. The average value of the renewable power production is used in the deterministic method, while several scenarios are applied to represent the uncertain renewable generation in the statistical method.
- 2- Considering risks associated with integrating renewable resources at distribution levels. A mean-variance stochastic model that uses economic load dispatch is suggested to evaluate the risk impact of connecting renewable resources on the financial efficiency of a electricity serving company. The proposed model comprises the minimization of the average operating cost and the risk associated with the deviation from the average by using a risk weighing factor  $\Theta$ , which illustrates the attitude of a decision maker toward risk.

- 3- Modeling the power procurement problem for a local distribution company. Using different approaches that suitably represent the uncertainty of renewable output, three models are proposed to find the optimal mix of power sources that supply the demand of the utility. The three formulations proposed in this thesis are the deterministic model, the two-stage stochastic model and the Markowitz risk evaluation model. The three models are capable of solving the procurement problem.
- 4- Providing a connection assessment tool to evaluate the possible impact of uncertain renewable output on voltage profile. The focus is on developing a measure for the impact of renewable DG output on the variation of the supply voltage. The voltage variation is evaluated using the EN-50160 standard and System Average Root Mean Square Frequency Variation (SARFI) index by utilizing Monte Carlo simulation. The number of deviations and the associated probabilities are computed so the operator of a distribution system can then either permit or suspend a new installation of a renewable DG based on its impact on voltage variation.

#### **1.4 Thesis Outline**

The thesis consists of seven chapters. Following this introductory chapter, Chapter 2 offers a methodical literature review. The definition of power procurement problem and sources of uncertainties related to this problem are defined in Chapter 3 which also contains details of the proposed Two-Step Algorithm. The chapter builds the basic background of the problem and illustrates the need for the stochastic modeling techniques which is discussed next. Chapter 4 covers stochastic programming applications in power procurement problem for distribution systems. It introduces a formulation of power procurement problem as a two-stage stochastic model is presented. The last part of Chapter 4 provides a comparison between deterministic and stochastic solutions of deterministic and stochastic models. In Chapter 5, a risk component is added to the two-stage stochastic model and a simplification methodology is proposed to solve power procurements problem.

In Chapter 6, voltage variation, which is essentially a power quality problem, is assessed. Two major power quality measures were used to evaluate the impact of new connection of renewable DG units on the quality of supply voltage. At the end of this chapter, a comparison between the results obtained from using the two benchmarks is performed. In the last chapter, Chapter 7, conclusions of the thesis are stated. This chapter also summarizes future study directions.

## Chapter 2

### Procurement Problem: Literature Review and Assessment

#### 2.1 Introduction

Recent interest in utilizing distributed generation, especially the generation from renewable resources, has led to increasing difficulties in operating distribution networks [5, 21-23]. The definitions, benefits, disadvantages, construction, applications, and classifications of distributed generation (DG) have been presented in several publications [5, 21-24]. The major concern about the increasing level of penetration of non-utility DG units (NUGs<sup>1</sup>) is the unpredictable energy generation they provide due to random inputs from wind and sun. The need to enable new regulations for higher levels of safe and reliable DG penetration into distribution systems have been noted and discussed [25-28]. This chapter provides a focused review of the energy management problem faced by local distribution companies (LDCs) when renewable DG facilities are involved.

#### 2.2 Literature Review

Although the need for optimal selection of power purchases to be made by a distribution company is significant, the literature contains only a few studies that deal with power procurement as a strategy for an LDC [29, 30]. Using this strategy, a utility can satisfy its demand by selecting from five different sources: spot market, utility owned DG (in-house DG), non-utility DG (NUGs), forward contracts, and/or load curtailment. The distribution company operational problem, then, can be summarized as the determination of the best combination of these power components in order to supply the demand of the company [29, 31, 32]. Based on the techniques applied for solving the power procurement problem, the literature reviewed can be classified into three main streams: deterministic, stochastic, and global optimization approaches. Methods based on a deterministic approach are discussed first.

##### 2.2.1 Deterministic Approaches

Deterministic optimization approaches are characterized by assuming the certainty of information. The assumption that loads, prices, and power injections, as well as other factors, can all be perfectly predicted or completely controlled is the main feature of this technique. Once the parameters

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<sup>1</sup> The terms DG and NUG are used interchangeably in this thesis. Both describe the distributed generation, including small renewable facilities (<10MW), that is connected at the distribution level.

associated with the network operation are assumed, predicted, or scheduled, the rest of the components can be evaluated against the objectives of the company.

Assuming the customer's ability to sell surplus power generated from in-house DG, which is a combined heat and power unit (CHP), and to curtail non-essential demands, a number of models were proposed in [33-36] for a large industrial customer. Reference [33] suggested a unit commitment based model, in which the CHP unit is assigned to produce both the electrical and thermal requirements of the customer. Two improved versions of this model, which include a load curtailment option while utilizing the CHP unit, are used to benefit from participation in demand management (DM) programs during high-price periods [34, 35]. The model was further modified to enable the coordination of plans for long-term yearly profit maximization and short-term cost minimization [36].

Other applications of in-house DG have been proposed, with objectives that include mitigating the impact of electricity prices variations and maximizing the benefits of DG units for large industrial customers [29, 31]. The authors of [29] presented a framework cost minimization plan in a restructured system using in-house DG. The customer schedules its in-house DG and selects adequate volumes of bilateral contracts in its effort to overcome the impact of changes in electricity prices. Reference [31] suggested a model in which the electricity price is set by time-of-use (TOU) rates. The proposed model integrates the operation of in-house DG and the selection of either gas or oil as the fuel supply. The objective is to compute the optimum electrical energy contracts that minimize the customer's operating costs for the whole year.

Both types of DG units, in-house and NUG, have been implemented in short-term solutions to the power procurement problem faced by an LDC [32, 37]. In-house DG was used as the basis for a suggested plan of daily activities for a distribution company within a competitive electricity market [32]. Sensitivity factors were proposed in [37] to reflect the impact of the variations in the electricity spot-market prices and to assess the next-day decisions. Using this plan, the company's operator can choose how much to request, when to start up in-house generation, and/or initiate a call for load curtailment options. As presented in [37], assuming its ability to dispatch investor-owned NUG units, the company incorporated these units into its daily activities plan through two consecutive steps.

### **2.2.2 Stochastic Approaches**

The key aspect of stochastic optimization methods is the use of statistical information about random parameters under consideration [38]. The utilization of stochastic approaches in examining a

distribution company's operational problem is still developing. Reference [39] offers a concise discussion concerning the application of stochastic optimization methods in electrical power systems.

In one of the early reports concerning the procurement problem, an analytical solution based on a stochastic dynamic optimization approach was presented [40]. The method was utilized for solving the energy-purchasing problem of a power provider who participated in energy trading. In this study, the authors obtained optimum purchases while considering electricity price and demand uncertainties.

A multi-stage stochastic model has been applied to optimize the operational cost of a utility capable of selling extra generation [41]. To meet its hourly demand for each week, the utility would evaluate its best operational decisions: which hydro unit should operate, how much power it should generate, and how much water it should utilize, while considering the uncertainties of electrical loads, water inflow volumes, fuel costs, and electricity prices.

Reference [30] presents a model that describes a utility that does not have generating facilities. The aim of the utility is to find the optimal percentage of the power demanded that can be purchased from bilateral contracts while considering variations in spot-market prices. The assumed dependability between long-term and short-term electricity prices is derived based on a linear regression model.

A linear optimization model that represents the operating strategies of a micro-grid network attempting to deal with variations in expected electrical loads, heat demands, fuel costs, and the DG duty cycle was investigated in [42]. The authors proposed a management system for a hypothetical micro-grid that included different types of DG units in order to minimize the operating costs of the micro-grid using a two-stage stochastic model. In another study of a micro-grid system, [43] used gas-fired DG units to reduce power-purchasing costs by applying a Monte Carlo simulation method. Taking into consideration changes in the price of electricity and variations in the cost of fuel, the authors evaluated the optimal operation of the network.

The power-procurement policy of a large industrial customer with considerable aversion to risk was investigated in [20]. The customer could operate an in-house DG unit and purchase power through bilateral contracts to overcome the risks caused by variations in spot-market prices. The proposed model scheduled the amount of power from bilateral contracts, the spot market, and/or the in-house DG by applying a two-stage stochastic model to minimize expected operating costs and limit the risk to tolerable levels.

Despite the small number of technical papers that discuss the power procurement problem of a load-serving entity, researchers have successfully considered the complications in the problem. The uncertainty associated with the operation of local distribution companies is a major factor in the power procurement problem. In the available literature, the impact of several causes of uncertainty has been investigated. However, because the distribution company's power procurement problem is still evolving, one can recognize that the uncertainty associated with renewable generation has been missed in the literature. Another observation about the consideration of DG production in the power procurement problem is the misrepresentation of this production. In the papers reviewed, DG output has been expressed as decision variable rather than as a parameter. The difference is that a variable can be controlled to meet a specific objective while a parameter is a constant that can have any value based on factors beyond the control of the decision maker. A third point that can be noticed in the literature reviewed is that DG was commonly lumped at one location; however, in distribution systems, scattered points with DG connection are more likely than just one spot. This thesis contributes to the literature by adding DG output as an additional source of uncertainty, and by considering DG production as a random parameter at different points of connection. The impact of uncertainty caused by renewable DG on the selection process of an optimal set of power components for supplying the LDC demand was therefore chosen for investigation.

### **2.2.3 Global Optimization Algorithms**

Evolutionary algorithms (EA) are a category of global optimization techniques used to address the random behavior of some parameters while computing the optimal solution of a problem. Only a very few authors have considered the application of EA for solving a distribution company's operational problem. They have reported on the optimization of bilaterally contracted power [44], the management of small DG units at the residential level [45, 46], and the enhancement of the operational and planning performance of a utility [47].

Reference [44] used a fuzzy logic technique to find the optimal amounts of power to be obtained from bilateral contracts so that a retailer's operating costs would be minimized. The relationship between the spot-market price and the demand of small customers is represented using a regression-based analytical model. Targeting residential customers who have installed fuel cells, the authors of [45] presented a model based on particle swarm optimization (PSO), which considers the randomness of the power demanded. They assumed that the surplus power obtained from the fuel cell could be sold to the grid and that switching between the gas and the electrical supply of thermal loads was

fully controlled. In this study, PSO was used first to reduce the number of scenarios and second to solve a multi-stage stochastic optimization model that minimizes the customer's operating costs. An enhanced version of this model was used in [46] to reduce the operational cost of the fuel cells that supply residential customers when their total load and electricity prices are assumed to be uncertain. An adaptive PSO approach was similarly employed to reduce the number of scenarios encountered and then to compute the optimum operating point of the fuel cell units [46].

For distribution systems, both operational and planning aspects have been integrated into a model that reflects the uncertainty in demand, DG generation, and economic information [47]. Fuzzy logic analysis was used to coordinate network operation and planning by targeting network operational costs, expected non-supplied demand, investments in system expansion, the level of system reliability, and the allocation of new feeders [47].

The use of evolutionary algorithms to solve the power procurement problem is in its early stages. In the available research, only [44] discussed the issue of finding the best options for supplying a company's demand. The other few papers discuss other concerns although the problem formulation is the same. Only one paper in this category included DG output as a random variable [47], but the authors were concerned about long-term planning and the impact of DG on network reliability.

### **2.3 General Analysis of the Literature Review**

The reports reviewed agree on the significance of the power procurement problem as one of the main tasks of a distribution system operator. The models presented in the literature all minimize the costs of power delivered from diverse sources, and only a few consider the profit obtained from selling the surplus power. It is observed that different kind of in-house DG units have been included in these models in order to supply an LDC's loads or a large customer's demand, and that operating costs of these units are included directly in the objective function of the models presented. Some of the reports emphasize the consequences of price uncertainty, but none has mentioned the impact of variations in renewable DG output on the economic operation of an LDC.

Detailed analysis of previous work with respect to the power procurement problem reveals drawbacks. A major weakness in the research reviewed is the omission of the production of renewable DG facilities in the formulation of the distribution company's problem. Only one report included the contribution from an investor-owned renewable DG unit in the formulation of the LDC problem [37], but only dispatchable and fully controllable NUG was represented in this single article.



This representation is not suitable for renewable kinds of generation simply because renewable DG production is random. The focus of this thesis is on the proper representation of this randomness and the integration of renewable DG output in the LDC problem formulation.

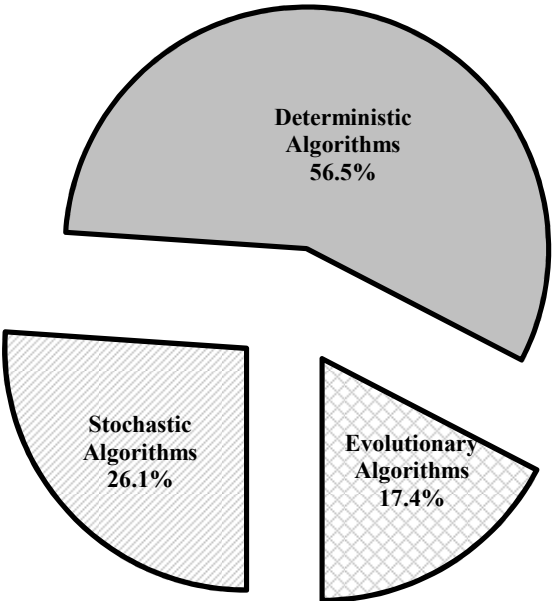
Another important concern with respect to the literature, although beyond the scope of this thesis, is the low number of published reports regarding the distribution power procurement problem. The fundamental reason for such limited interest is the regulation of energy trading at the distribution level. This failure to open the distribution of energy to free trade is a result of the configuration of the distribution system: its close interface with the public and the historical price shield put in place by the government. These reasons contribute to a reduction of interest in exploring research related to distribution systems.

A third point is the lack of inclusion of the technical capabilities of the utility's network in the formulation of the problem with respect to the large customers. Researchers have assumed that any surplus would be accepted by the distribution system irrespective of the need for this injection and its consequences on the operation of the network. Such surplus input into the utility's system would most likely reduce losses by reducing the load current. However, the utility's network may not be able to accommodate input from DG, specifically the renewable kind, and hence may result in unfavorable situation from an operation point of view. Such a scenario may occur because what is considered a low-sized generating unit (e.g., 10 MW) in transmission systems is regarded as relatively large in distribution networks. As an example, the penetration level of a 10 MW wind facility connected to a distribution system that has about 250 MW would be 4.0 %. Connection of another four facilities of a similar kind connected to the utility's network would result in a penetration level that is commonly targeted in future plans for bulk systems.

## **2.4 Technical Assessment of the Literature Review**

The studies presented in the published reports highlight the problem of minimizing operating costs as a fundamental activity of a distribution company, a retailer, or a large industrial customer. Despite the differences in their networks, purposes, and sizes, these entities have a similar problem formulation. A comparison of the techniques applied for solving the distribution company power procurement problem is shown in Figure 2-1. As this figure illustrates, more than 56 % of the studies in the available literature were conducted using deterministic approaches. Even with deterministic models, researchers have noticed the need to represent the randomness in the evaluation of the

distribution system operational problem. Both the expectation of random variables [29] and two-step models [37] have been used in deterministic algorithms to allow the uncertainty to be included in the formulation. Due to its inherent deficiency in tracking randomness, however, the deterministic approach is, in fact, not the best option for solving the power procurement problem for a distribution company operating under uncertainty. Although both stochastic and evolutionary techniques have not been applied as often as they should be, their ability to include a consideration of uncertainty makes them the leading choices. The following present the main points of the models presented in the literature reviewed.



**Figure 2-1: Percentages of the algorithms applied in solving power procurement problem**

### 2.4.1 Deterministic Models

Several observations can be made based on the review of the literature related to deterministic-based models. The evaluation of short-term operation exhibits a trend toward the use of bilateral contracts and in-house DG. This tendency can be noted in several reports [29, 31, 32]. Since these two options can be scheduled in advance, both bilateral contracts and in-house DG are used as mitigating tools to avoid the risk associated with the variations in spot prices. In addition, applications

of in-house DG as an alternative in long-term planning have been observed [47-50]. One reason for the use of these models would be an attempt to find new ways of determining a long-term planning framework for distribution networks in restructured systems [49, 50]. For the problem under consideration, deterministic based strategies still fall short of offering a suitable model that includes the volatilities of the operation of NUG units as an additional element of uncertainty. This deficit is caused mainly by the assumption that renewable DG production is dispatchable and/or predictable. As a consequence of this assumption, a deterministic variable rather than a stochastic parameter is commonly used to represent the output of this source of power. These observations formed part of the motivation for this work.

### **2.4.2 Stochastic and Global Optimization Models**

In contrast to deterministic approaches, models based on stochastic/global optimization have the ability to incorporate variations in random parameters. Table 2-1 summarizes the features of the models reviewed that use either stochastic or global optimization techniques to include uncertainty in the formulation. It also lists the elements of uncertainty that these models have considered. The first column shows the technique used to model the problem, and a list of the sources of uncertainty is provided in the second column. The third and fourth columns point out the components of the objective function and the controlled variables that affect the cost function. This table shows that the randomness caused by renewable DG output is largely missed except in the work shown in the last row presented by Skok et. al., [51]. Despite the inclusion of DG production in this study, the authors were mainly concerned about the reliability of the distribution system [51].

Two main modeling techniques have been applied extensively to the formulation of the power procurement problem. Whereas the two-stage model has been the main formulation applied when stochastic optimization is used, particle swarm optimization has been the major approach that utilizes evolutionary algorithms [45, 46]. Nevertheless, none of the approaches presented in the literature has been applied to investigate the effect of variations in the power generated by renewable units on the evaluation of LDC operational activities. This calls for an extensive investigation and was therefore selected for further study in this research.



for example, risk associated with variation of electricity prices attracted the attention of many researchers [16, 19, 52-60].

A linear model is used in [52] to minimize the risk of loss in profit that may be caused by variations in electricity prices and demand. The risk is measured by the absolute deviation from the expected utility-targeted profit. A model representing power procurement from three markets (bilateral contracts, in-house generating facility and spot market) is utilized in the study to evaluate the robustness of the decisions made by a large customer [52]. In [19], a two-stage stochastic formulation considering risk caused by uncertainty of electricity prices and customers' demand is applied for solving the power procurement problem. Violation of budget constraint was used in [19] to account for the risk impact, and the expected procurement cost was a second term included in the objective function of the model.

A power procurement model has been presented in [54] utilizing the conditional-value-at-risk (CVaR) to calculate the deviation of the energy costs for a distribution company. The power procured by signing bilateral contracts is computed as an allocation ratio where three power resources were considered: spot market, tolling agreements, and forward contracts. A bi-objective optimization model is used in [55] to quantify the risk of the high cost that may occur due to variation in the prices of electricity using Markowitz theory. A factor is introduced to the model such that the risk performance of the decision maker is implemented. High values of this factor means that the decision maker is risk averse, hence less variation is targeted by the model [55].

Value-at-risk (VaR) and Conditional-Value-at-risk (CVaR) were used in [57] to help an electricity trader make decisions given the uncertainty of electricity prices. Both risk measures VaR and CVaR, were included in the constraints of the problem formulation, which was solved by genetic algorithm. The analysis was based on a multi-objective model and allowed the user to simulate the risk aversion attitude of the decision maker by changing the weight of each part of the objective function [57]. An approach utilizing the mean-variance model to optimize procurement cost with limited liquidity is presented in [58]. The work presented in this paper focused on the portfolio optimization for electric utilities that own generation and can sell, and buy, surplus and deficit from the market.

In [16], portfolio optimization theory is implemented for the power procurement problem for local distribution companies. CVaR is adopted and applied to supply the LDC demand and to allocate the electric power resources from three markets. The outcome of solving the presented model is evaluated against a mean-variance Markowitz model. The results showed that the two measures -CVaR and

mean-variance- were consistent. A comparison study of risk measures has been conducted in [59]. The authors investigated the impact of risk on the negotiation of bilateral options between the two parties involved in contracting. Three risk measures were used to investigate the differences in the behavior of suppliers and consumers when negotiating forward contracts.

The research work in the reviewed literature focused mainly on evaluating risk caused by variation of prices in the spot market. Following are other issues that need additional investigations and further analysis.

1. Variation caused by renewable DG units and its impact on cost-risk minimization for distribution companies. This thesis fills this gap by presenting a stochastic model to solve the procurement problem that considers risk of connecting renewable resources to distribution systems.
2. Except the work presented in [20], the rest of the reported studies, to the best of the author's knowledge, did not include detailed activities in a day ahead market in their formulations. Multiple time periods were not studied when risk was included in optimization modeling; instead, only one time period was involved in all of the models reviewed. The models presented in this chapter were designed to overcome this lack of time representation by considering a detailed day-ahead model. This of course brings major computation issues which are solved by using appropriate fan-based scenarios.

## **2.5.2 Quality Assessment of Supply Voltage Magnitude**

The two major concerns about the increasing level of penetration of renewable units into electrical networks are their unpredictable performances and their requests for system enforcement. As noticed and recommended by researchers, new regulations are needed to enhance safe and secure integration of renewable DG plants [25-28]. To improve the integration of DG units' output in distribution systems, the authors of [25] recommended some guidelines, such as changes to distribution system operational practices, and to provide incentives to the LDCs to cope with investment budgets associated with DG connections. Also, compensations for the incremental costs related to energy losses caused by including DG units in utility's network were suggested. The authors of [26] highlighted the regulatory discrimination between large power producers and small DG facilities in Europe and mentioned the non-compensation of distribution system operators for costs associated with DG units' integration.

A need for communication system and bi-directional power management were mentioned in [27] to stimulate the steady growth of installing renewable DG units at distribution levels. Another project funded by National Renewable Energy Laboratory (NREL), technical and analytical barriers that cause less integration of PV systems, renewable DG production, are investigated and studied in [28]. The objective of this report was to explore the impacts of inserting large numbers of PV systems on a distribution system's voltage, and the ability of control equipment to optimally manage the network's operation. The main task investigated in [28] is the voltage regulation considering large penetration of renewable DG resources connected to distribution system at different locations.

Traditionally, load flow analysis is used in these studies to evaluate the benefits and impacts of future installations and designs. In such studies, line flows and voltage magnitudes are computed for a particular scenario of certain demand, generation, and network configuration [61]. When uncertainty is introduced, deterministic load flow will not be as useful as the probabilistic load flow or other algorithm that considers uncertainty [62].

As renewable DG power injections vary according to the changes of the prime source, voltage magnitude will fluctuate along distribution feeders. In order to conduct connection impact assessment for new connections of renewable units, a common practice is to solve the worst case condition. The worst scenario is usually represented by a combination of low demand and high level of power production of renewable DG facilities connected to the network. Even more pessimistic, although unrealistic, zero load and maximum power generation is assumed in some cases [63]. However, the probability for such scenarios to occur in reality is too low to even consider. In addition, relying on these rare conditions causes overestimation of the DG impact and consequently results in lower integration of renewable resources. Hence, a probabilistic approach is required to obtain meaningful results Monte Carlo simulation is a well known method for application in such circumstances [62]. In order to cover the range of uncertain parameters, many load flow model runs are needed with each run representing a probable occurrence of that parameter.

For decades, Monte-Carlo simulation has been used in power system analysis to represent variation of electrical parameters and for validating the results of other methods that include randomness in power system operation [64, 65]. In this method, for electrical power system simulation, deterministic load flow is executed repeatedly after sampling the input parameter(s) each time. Statistical analysis of the results gives insightful probabilistic estimates about the solution of the favorable unknown output [66, 67]. Several models have been proposed in the literature to investigate different aspects of

power systems for both long-term and short-term operations. Reference [62] gives a good overview of recent work based on techniques and applications. One can also refer to [68] for earlier publications on probabilistic analysis of power systems.

## **2.6 Summary**

A literature review of the research on the evaluation of power procurement as a problem for a load-serving entity has been presented. The literature notes the recent trend toward including DG in the formulation of the distribution company operational problem. The literature still lacks effective models capable of handling the uncertainty of renewable power generation, including the risk of integrating their generation, or assessing the impact on the quality of supply the voltage. To the best of the author's knowledge, no model is available in the literature that properly includes the power generated from renewable units in the formulation. The utilization of the expected value may lead to a solution that is suitable for a significant number of cases. Nevertheless, in situations involving increasingly uncertain variations, a robust model that accounts for most of randomness should be introduced. The handling of generation from these small-scale resources is essential to provide useful models for the distribution system operator.



## Chapter 3

### The Procurement Problem Solution: Deterministic Approach

Acquiring economical energy to supply its customers' demand is one of the main targets of a local distribution company (LDC). In restructured power systems, LDCs aim to minimize their operating costs while maintaining a high degree of system reliability. However, in the face of uncertain variations in electricity prices, LDC operators will then look for a dedicated source of power with less price volatility to meet the system's demand. Bilateral contracting is one way for them to achieve this goal. The literature presents several formulations that include cost minimization of power procurement and the assessment of risk of experiencing high variations in electricity prices [15, 29].

An additional source of complexity in the power procurement problem is the uncertainty introduced by the output of renewable DG units [69]. These units are widely encouraged by sector regulators and are used either by the utilities or by investors. The inclusion of random behavior in the power procurement problem thus becomes a significant component in improving the optimization of power acquisition. This chapter presents a two-step algorithm that will provide the operator with a plan for dealing with uncertainty caused by the renewable DG units connected to his/her network. The ultimate objective of this chapter is to show the cost impacts on an LDC for being forced to accept intermittent power produced by renewable energy sources.

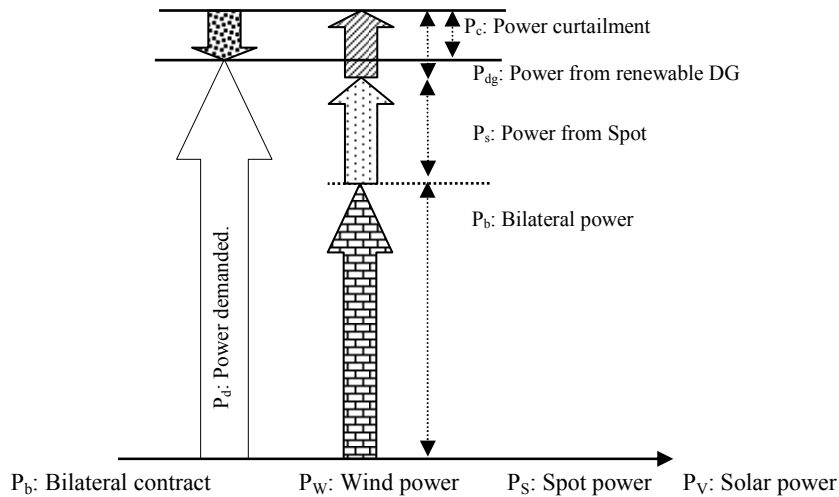
#### 3.1 Definition of the Power Procurement Problem

The distributed renewable generation impacts on the operations of distribution systems have both economic and technical aspects [5, 69]. This chapter discusses concerns about the economic impact on the operating costs of LDC that works in a restructured environment, with a focus on the power procurement problem under the uncertainty of renewable DG production. This problem can be described as finding the optimal amount of power to supply the utility's demand from different suppliers with uncertain contribution from renewable DG facilities. This problem is called power procurement with uncertain renewable generation. The models developed in this research provide details of the quantities and sources of power that will result in optimal operating costs, taking into account the randomness of renewable DG operation.

On a daily basis, the operator of a distribution network in a restructured system submits the projected demand to the transmission system operator. At the same time, the distribution system

operator may select to bilaterally contract with generation companies to manage electricity costs, as these costs are, in general, lower than others, such as spot market costs. In general, with some variations, the literature considers four components of electrical power as a means of fulfilling the power demand: bilateral contracts, spot market, demand curtailments, and power from renewable generation. Figure 3-1 shows schematically the power balance between the demand and a combination of these elements of power for one hour, from an LDC perspective.

The sum of the power procured from the suppliers and that provided by intermittent generation must be at equilibrium with the LDC's forecasted demand. When the electricity prices are high, to avoid expensive purchases, non-essential loads can be curtailed through a demand management (DM) program [32]. These elements are optimized to minimize procurement costs while satisfying the technical constraints of a network. The output of this optimization process gives the amount of power needed, and from which source, in order to efficiently supply the utility's demand.



**Figure 3-1: Power balance between demand and procurements for one hour**

Power procurement is a continuous process; only one hour is shown in Figure 3-1. For each hour of system operation, the equilibrium between the power procured from different suppliers and the power demanded is optimized, as indicated in Figure 3-1. Assuming, for the moment, that the only available sources are bilateral contracts and the spot market, the decision maker will compare the cost of these elements. After estimating spot market prices, the LDC decision maker can then choose the amounts of the bilateral contracts, given that the variations in demand are within a low range. Since bilateral

contracts are fixed for the course of the contract, the power purchased on the spot is used to adjust the power requirement, in order to balance the loads. Errors in specifying the amounts of power required from each component lead to increased operating costs. This problem is formulated as a mixed integer nonlinear mathematical model which is one of the hardest mathematical problem to solve.

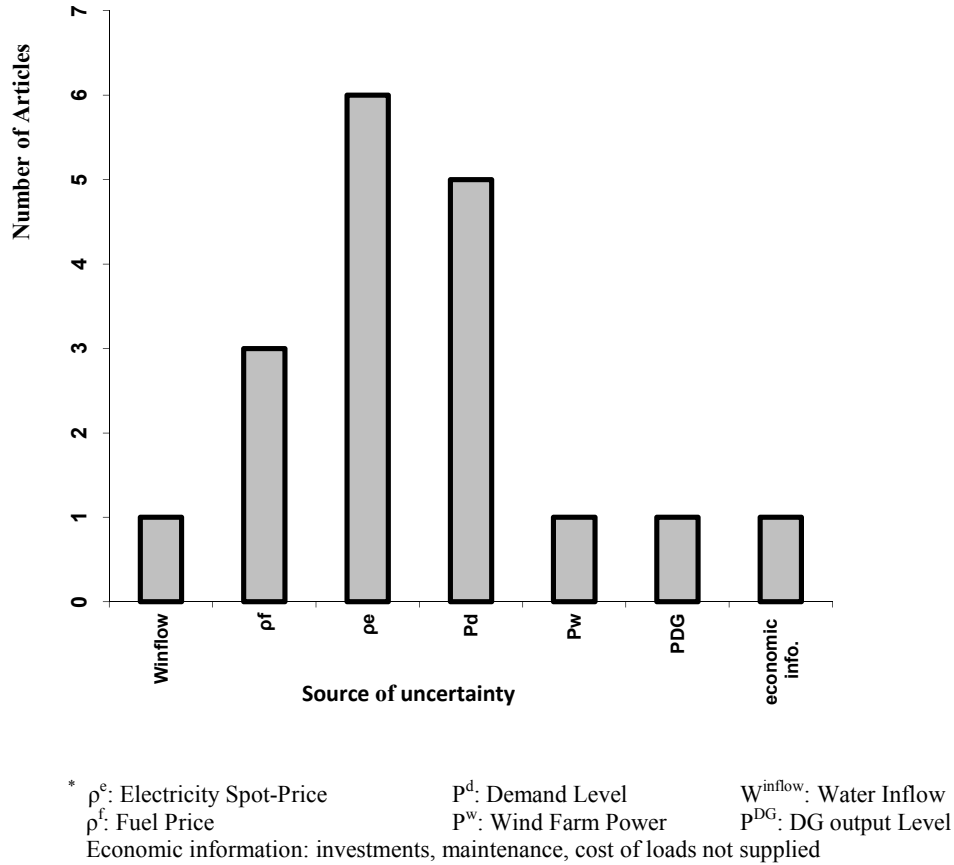
The power procurement problem becomes more complicated when uncertainty is introduced. Several causes of uncertainty related to the operation of power systems have been reported in the literature [39, 69], one of which is power injections from intermittent renewable resources. When such resources are installed at the distribution level, errors in predicting their output result in imbalance between the various powers requested from different markets and the projected demand of the distribution system. In extreme cases, even reverse power flow can occur, causing inefficient system operation [70]. These errors may result in power usage that differs from that specified in the signed contracts or from that called from the spot market. Even with the availability of power on the spot, the discrepancy between actual consumption and that set out in the signed contracts is the cause of economic loss for the LDC. Suitable modeling of this problem must therefore account for the randomness of the parameters that adversely affect the LDC cost minimization process.

### **3.2 Uncertainty Related to the Power Procurement Problem**

The consideration of uncertainties in modeling the procurement problem is essential for representing the real characteristics of renewable production. Reference [39] provides a list of uncertainties that covers almost every type from spot-market price to demand, fuel cost and water inflow, all of which have been investigated in the literature reviewed in Chapter 2. The list provided in [39] can be categorized into three main kinds of random parameters: the first is related to regulatory policies, the second is associated with future information, and the last is correlated with other domains. While the first kind of uncertainty is subjective and hard to predict, the last two categories can be traced and modeled [39]. Instances of the second type are electricity price and demand. Examples of the third type include weather conditions and water inflow, economic information, and fuel costs.

Figure 3-2 shows statistical information obtained from Table 2-1. The number of times that a parameter was considered as a cause of uncertainty in the procurement problem is plotted in this figure. Both Table 2-1 and Figure 3-2 clearly show that researchers mostly focused on variations in demand and electricity prices [30, 41, 42]. However, another two causes of randomness, namely, the power contribution from renewable resources and customer participation in DM programs, have

largely been missed in the literature. Adding these two causes of uncertainty to those provided in [39] creates a more comprehensive list.



**Figure 3-2: Application frequencies of uncertainty causes in LDC problem**

In this thesis, DG production is considered as another source of uncertainty for the hosting network. Previously, the generation from renewable resources has been considered as a deterministic decision variable, which means that the decision maker is assumed to have the ability to dispatch the output of renewable resources. To avoid such a misleading assumption and shed light on potentially fruitful areas of research, the classification of DG units is suggested. This classification and the corresponding techniques that have been applied in the literature to solve power procurement problem are presented in Table 3-1.

Table 3-1 uses three dimensions to categorize the type of DG: controllability, ownership, and capacity. The DG unit can be controlled either cooperatively within the utility’s scope (Utility controlled) or independently outside the operator’s objectives (Non-utility controlled). Utility controlled DG units are owned either by the company itself (Utility) or by investors (Independent) which are operated according to a contractual relationship with the company. As shown in Table 3-1, DG units are divided based on their geographic location into small widespread units (e.g., at the residential level) and large-capacity intense-located generation (e.g., small wind farms). Typical ratings of residential DG units are in the range of kilowatts and those of large renewable generators are less than 10MVA. This organization of the DG-utility relationship is important for a proper study of the consequences of DG operation and for an adequate formulation of their interactions.

**Table 3-1: Mapping of research related to procurement problem including DG generation**

Controllability		Non-utility controlled		Utility controlled	
Ownership		Investor		Utility	Independent
Capacity		Large	Small	Both sizes	Both sizes
Algorithm Applied	Deterministic	Nil	Nil	NLP	NLP
	Stochastic	Nil	Monte-Carlo	NA	NA
	Other	Fuzzy logic and evolutionary algorithms	Evolutionary algorithms	NA	NA

Nil: no research on this topic is found in the literature

NA: The algorithm is not applicable on the problem

Table 3-1 also shows the kind of algorithms that have been applied to investigate the effects of renewable DG output on the decisions for power procurement to supply the distribution system. This table and the literature show a lack of research related to the impact of the randomness of DG

production on distribution systems economic operation, as indicated by the shaded areas in Table 3-1. Work conducted in proper modeling of renewable DG units is expected to produce promising solutions for distribution company decision makers. The research reported in this thesis includes the use of stochastic optimization techniques to advance this promising area of research. A comparison of results of applying the proposed stochastic model with the results of deterministic approaches for solving the power procurement problem is also presented.

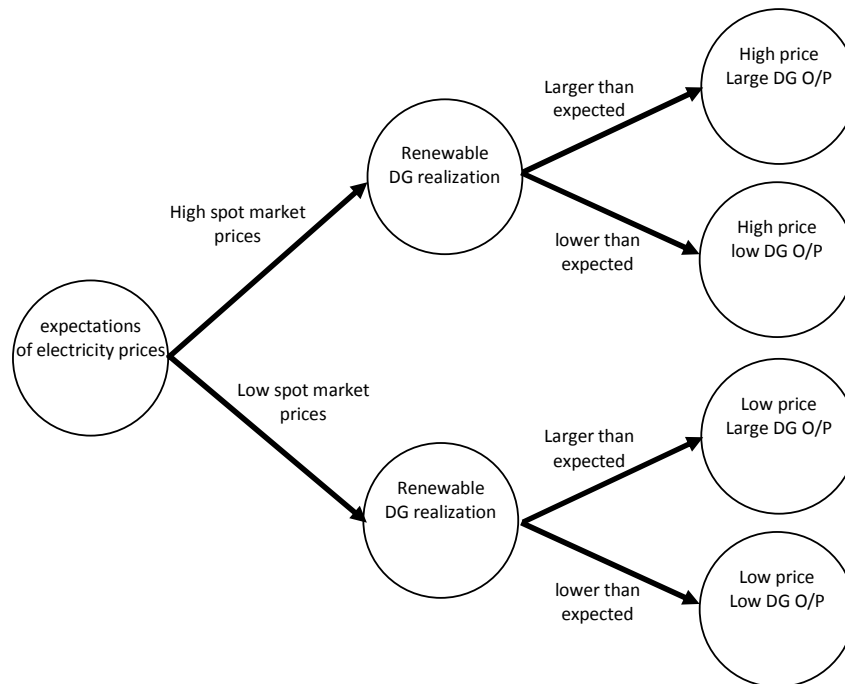
### **3.3 The Environment and Challenges Involved in the Problem**

The power procurement problem is difficult to solve because cheaper bilateral contracts are long-term options and need to be purchased before knowing the random occurrences of some parameters involved in the purchasing of spot market and renewable power. The first means that the time when bilateral contracts are selected is different from the time when spot purchases are evaluated. The former may extend from days to weeks before the delivery time, while the latter can be as short as a few hours. The second factor is the randomness of many elements such as electricity prices and DG production. The following discussion of the effects of these two factors on the power procurement problem highlights their impact on the economic operation of an LDC.

Figure 3-3 shows a decision tree, or scenario tree, which depicts the complete set of operational states based on two-state scenarios. A decision tree is commonly used for analyzing decisions or for stating possible conditions under uncertainty. As shown in Figure 3-3, the decision tree consists of nodes, represented by circles, and branches, represented by arrows. The nodes illustrate the decisions or conditions that exist at any point in time, while the branches illustrate the changes in the value of random parameters. Each node is a result of only one condition or decision, and its outcome can be more than one probable condition or decision. The first node is called the seed, or the root, which corresponds to the assumption, or prediction, about one of the random parameters involved. In Figure 3-3, the expectation of spot market prices has been selected as a root node. Because only two states are considered in this sample figure, either a high or low price state may emerge from evaluating the expected spot market price. If electricity prices are considered to be high, then the decision to procure power from bilateral contracts becomes more economical. Otherwise, when prices are low, lower amounts of power will be secured from bilateral contracts.

For a distribution system to which small renewable resources are connected, the decisions selected are not final because production from these units is not yet included in the discussion. Once again,

two conditions must be used to describe the DG output. As can be expected, bilateral contracts will be low when the DG contribution is high and vice versa. If the contracts selected are chosen based solely on the expected value of the price, then the LDC profit becomes at risk. The level of DG production at the time of consumption has a significant influence on the rest of the power to be procured. At the time when the contracts commence, the actual output of renewable DG units becomes a crucial factor in balancing the demand of the utility and the contracts signed plus the power procured from the spot market at that time.



**Figure 3-3: Decisions tree for an energy management plan for a utility**

Relying on the expected value of renewable resources alone is not the best option. Referring to Figure 3-1, if the renewable DG injection is higher than anticipated, then either the bilateral contracts will not be fulfilled or reverse power might result if renewable production is too high. On the other hand, if the DG output is less than expected, then either costly power must be purchased on the spot or expensive curtailments must be considered. Such possibilities are continuous because the spot price and/or the renewable output vary randomly, and the discrepancies occur simply because the

expectation is a single deterministic value that is used to represent a random parameter. Uncertainty must be effectively accounted for in the problem formulation in order to mitigate its impact on the decision-making process. The impact of variations in the spot market prices on the LDC problem was not formulated because this investigation has already been reported [15, 20]. The focus of this thesis was on the impact of uncertainty caused by renewable DG production because this factor has not been appropriately addressed. The effect of power variations produced from two different renewable units on LDC power procurement decisions is the main topic that was studied.

### **3.4 Two-Step Algorithm**

Applying deterministic approaches to solve the power procurement problem under uncertainty requires precautions because deterministic approaches rely on estimations/predictions and are effective for only one instance of randomness. As discussed in section 3.3, two major elements must be accounted for in the power procurement problem: uncertainty, and the time lag between contracting and consumption. To mitigate their effect, a representation of randomness is required, and the time shift must also be included. A two-step algorithm that incorporates these aspects is thus developed. Each step includes one deterministic optimization model. The two models, solved at different times, interact with each other so that impacts of the two elements mentioned above are reduced.

The strategy for achieving an optimal mix of power components has also been revised so that the newly introduced variations caused by renewable generation can be integrated. Bilateral contracts are usually computed once at the beginning of the contract period and are commonly selected based on considerations of the daily changes in the spot electricity prices and the demand [20, 31]. Any deviation from the selected and signed contracts represents an economic burden on the LDC for that period. Although the prediction of demand is robust, the uncertainty related to renewable generation connected at the distribution level makes errors in load prediction a significant problem. The impact of both the long commitments of bilateral contracts and the power uncertainty can be mitigated by either shortening the bilateral contract period, or allowing the LDC's operator to adjust quantities at fixed times within the contract period. The decision maker may want to divide the period of bilateral contracts into smaller time segments. For example, a month can be divided into four segments, one for each week, as applied in [20]. Such an arrangement provides flexibility that enables decision about bilateral contracts to be corrected when more information about prices and the production levels of renewable generation becomes available.



In this chapter, a two-step deterministic algorithm is developed as a means of handling the difficulties related to power procurement problem. The model will be extended using stochastic programming approach in latter chapters. To overcome the static nature of deterministic optimization methods, the algorithm executes one after another two models that have different formulations. The results of the first-step model are used in order to simplify the solution of the model applied in the second step. The first-step model calculates the amount of bilateral contracts. In the second step, computations of the second model adjust the decisions about spot market purchases according to updated information. The purpose of the second step is to fine tune the decisions and balance the demand.

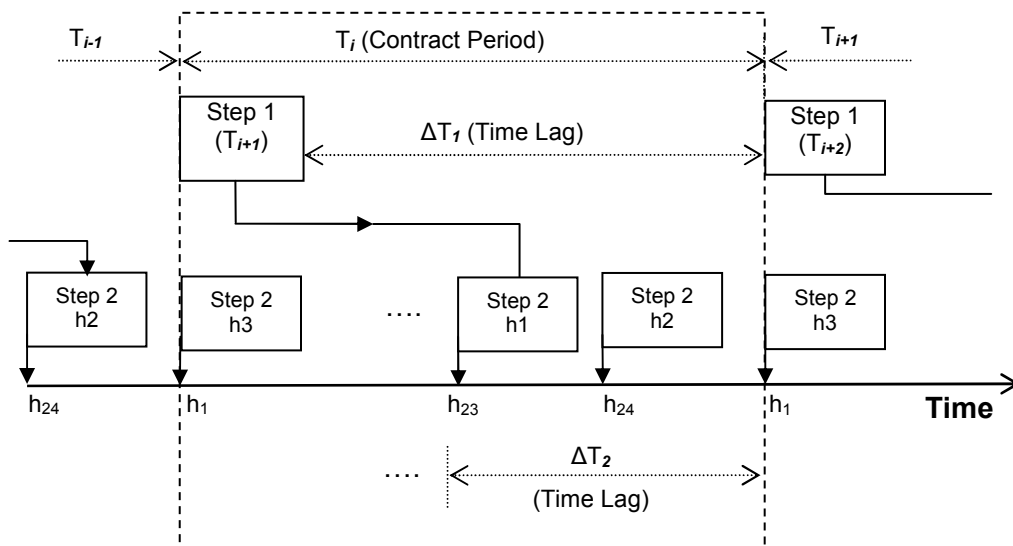
Including uncertainty in deterministic formulations requires consistent use of the average outputs of the different generating units [38]. Because meteorological phenomena are periodic, power generation from wind or sun irradiance is also periodic. Depending on the cyclical aspect of the renewable generation, the hourly mean values for a typical day in a season can be calculated. These values are included to assess the consequences of the behavior of the units' output for the LDC's operational plans during that season. An average value for each hour of the day during a specific time period is calculated and used to represent the renewable generation. This preparation enables the amounts of bilaterally contracted power as close as possible to the demand level and the uncertainties resulting from the connection of intermittent generation to be considered.

### **3.5 Description of the Algorithm**

The developed algorithm has two aspects. First, the level of intermittent generation is represented as a parameter by its average rather than as a dispatched variable. This level becomes an upper limit of two variables introduced to represent the generation of renewable DG. The two variables are then added to the portion of power that is purchased on the spot because it cannot be specified in advance. Secondly, because the power balance constraint is only loosely satisfied in the first step, decisions about spot power are not final. In the second step of the algorithm, which is executed before the actual consumption by the time-lag ( $\Delta T_2$ ), a more accurate decision can be made. The formulation of the first-step problem is a mixed integer nonlinear optimization model. The problem in the second step is a nonlinear optimization model because the integer variables for selecting bilateral contracts were computed in the first step.

The interactions of the two models are shown in Figure 3-4, which indicates the hierarchy of the algorithm. The upper part of the figure illustrates the application-time relationship of the first-step model. This model is executed once for each contract period,  $T_i$ . The lower part of the figure depicts the application of the second-step model. Computations using this model are carried out when needed as long as the market rules permit. The solid arrow that connects the two parts represents the link between the two steps of the algorithm.

The two models are applied sequentially: the first-step model and then, for a multiple number of times, the second-step model. During the contract period,  $T_i$ , the calculations of the first step are executed to calculate the contracts for the next period,  $T_{i+1}$ . These calculations are completed in advance of the commencement of the calculations for the selected contracts with a first-step time-lag ( $\Delta T_1$ ). The shorter this time-lag, the better will be the chances of acquiring more information about the random parameters during the next contract period,  $T_{i+1}$ . As soon as the time for implementing the contracts of period “ $i+1$ ” approaches, the first step model is used, if needed, for computations before the spot market closing time,  $\Delta T_2$ . The minimum time-lag for initiating the second step model,  $\Delta T_2$ , depends solely on the market rules. In Ontario, for example,  $\Delta T_2$  can be as short as two hours before the electricity market closes and the dispatch process begins [71].



**Figure 3-4: Interaction of the models in the two-step algorithm**

While the model of the first step focuses on the evaluation of bilateral contracts, the second-step model works on optimizing costs on the spot. In the first step, the balance between the powers procured from the different suppliers, including renewable production, and the customers' demand, is relaxed. In the second step, the satisfaction of the customers' demand is strictly met. The algorithm aims to achieve minimum overall power procurement costs while considering the effects of variations caused by intermittent generation on the LDC's purchasing costs. The proposed algorithm incorporates the expected values of the uncertain elements as parameters and performs the optimization in two steps in order to retain the features of randomness and differences in time for making critical decisions. Because the formulation of the second step model is direct, it is not discussed. The next section explains the formulation of the first-step model.

### **3.6 The Description of the First-Step Model**

In the literature, the output of DG production is included as a controllable variable in the formulation of the power procurement problem [20, 29, 31, 37]. This approach is misleading because this representation omits two essential characteristics of renewable DG units: uncertainty about their output and non dispatchability. As described in this chapter, the two-step algorithm includes as a parameter the expected value of the power generated by renewable DG. To follow the changes in DG production levels, two consecutive optimization models work in two different time-steps to track the randomness as accurately as possible. The two models are identical except for the representation of the bilateral contracts. In the first-step model, which is more general, binary variables have been introduced as a means of selecting the optimal contracts. These variables are omitted from the formulation of the second-step model because they are no longer needed. Due to this similarity in models, only the first-step model for simulating the LDC problem will be discussed.

The goal of the model is to minimize the expected total cost of the power procurement. The objective function includes the minimization of two costs: the cost of the bilateral contracts and the expected cost of the on-the-spot purchases needed. The selection process is determined based on the accumulated costs of the power purchased from both components over the period of time under investigation. The two factors that dictate the selection process during this time period are the electricity prices and the expected value of the DG output.

The prices of the two power components are set differently although the values are comparable. The prices of bilateral contracts are decided and then fixed between the buyer and the seller. On the

other hand, spot market prices are set by the independent system operator (ISO) according to the system's total demand and the generation available at the transmission level. Since the bilaterally contracted power becomes constant once selected, in the model, this component has been included as a time-invariant variable. The objective function is shown below:

$$\min \sum_{t=1}^{24} \sum_{i=1}^{N_b} \left( \sum_c^{N_c} P_b(i, c) \cdot \lambda_b(i, c) + [P_s(i, t) + (1 - \alpha) * P_o(i, t) + (1 + \alpha) * P_c(i, t)] \cdot \overline{\lambda_s(t)} \right) \quad \text{Eq. (3-1)}$$

In the above equation;  $\mathbf{P}_b$  is an integer variable that represents the bilateral contracts,  $\mathbf{P}_s$  is the power purchasing on the spot,  $\mathbf{P}_o$  represents the portion of renewable production that is consumed by the LDC's demand and  $\mathbf{P}_c$  is the curtailed portion of renewable generation. The search for the optimal solution is limited by several constraints.  $\lambda_b$  and  $\lambda_s$  are, respectively, the cost of bilateral contracts and electricity spot price. The cost of the power produced by renewable resources and consumed by the demand of the LDC is slightly cheaper than the spot price while the cost of curtailing the renewable generated power costs more than the spot price. A parameter,  $\alpha$ , is used in the objective function to illustrate these differences.

To obtain a solution that is acceptable for the standard operation of an electrical network, these constraints, described by equations Eq. (3-2) to Eq. (3-7), are introduced into the formulation. The first two constraints are the power balance equations: one for active power and another for reactive power. They define, at every bus and for every hour, the balance between the powers procured from different resources and the sum of demand of the utility and power injected to the system. The power factor of a renewable DG unit operating at the distribution voltage should be very close to unity [72]. This policy dictates that the renewable DG generating facility works at almost a zero reactive power output. To represent such an operating standard, reactive power terms that denote the contribution of the generating units are dropped from the reactive power balance constraint, as shown in Eq. (3-3). Equation Eq. (3-4) ensures that voltage magnitudes of buses are within acceptable operating ranges. The last two constraints are the power flow equations, which compute the power injected to each bus at particular hour.

$$P_s(i, t) + P_o(i, t) + \sum_{c \in N_c} P_b(i, c) - P_{inj}(i, t) = P_d(i, t) \quad \text{Eq. (3-2)}$$

$$Q_s(i, t) - Q_{inj}(i, t) = Q_d(i, t) \quad \text{Eq. (3-3)}$$

$$V_i^{min} \leq V_i(t) \leq V_i^{max} \quad \text{Eq. (3-4)}$$

$$P_o(i, t) + P_c(i, t) = \overline{P_{DG}(i, t)} \quad \text{Eq. (3-5)}$$

$$P_{inj}(i, t) = V_i(t) * \sum_{j \in N_b} \left[ \begin{array}{c} V_j(t) * G_{ij} \cdot \cos(\delta_{i,t} - \delta_{j,t}) \\ + \\ V_j(t) * B_{ij} \cdot \sin(\delta_{i,t} - \delta_{j,t}) \end{array} \right] \quad \text{Eq. (3-6)}$$

$$Q_{inj}(i, t) = V_i(t) * \sum_{j \in N_b} \left[ \begin{array}{c} V_j(t) * G_{ij} \cdot \sin(\delta_{i,t} - \delta_{j,t}) \\ - \\ V_j(t) * B_{ij} \cdot \cos(\delta_{i,t} - \delta_{j,t}) \end{array} \right] \quad \text{Eq. (3-7)}$$

Generation from renewable DG should be incorporated with caution. Renewable DG production cannot be scheduled in advance, nor can it be predicted with a high degree of accuracy. The production of these units therefore can be included in the model only as a parameter;  $P_{DG}$ . Unless it becomes dispatchable, production from renewable DG units should be dealt with as a participant in the spot market. The constraint described by Equation Eq. (3-5) divides the production of renewable resources into two components, and each of them is a decision variable. The first component is the part accepted by the distribution system, denoted as  $P_o$ . The cost of this component is less than the spot cost by a value  $\alpha$  to represent the priority of using renewable resources set by the regulator. The second component is the curtailed part of renewable resources' production, denoted as  $P_c$ , and costs are set higher than the spot price to avoid the usage of this part as much as possible. The model described by Equations Eq. (3-1) to Eq. (3-7) is a non-linear mixed integer programming model (MINLP). The non-linearity appears in the power flow equations, and the binary variables are required for selecting the bilateral contracts,  $P_b$ , which are constant amounts for chosen periods .

### 3.7 Preparation for the Studies

The algorithm developed in the previous sections was used to investigate the impact of the output of renewable DG units on the LDC decision-making process related to the procurement of power. Two locations were arbitrarily chosen for connecting two small-capacity renewable DG facilities. The first represented a small wind farm. The generation profile of this source was reproduced by using

data from the Independent Electricity System Operator (IESO) [73]. The second renewable source of power was a photovoltaic system. Meteorological data, from a weather station belonging to the University of Waterloo [74], was used in a non-linear model to obtain the corresponding patterns of power production. Figure 3-5, explained in the next section, shows a sample of the data used.

### **3.7.1 Data Preparation**

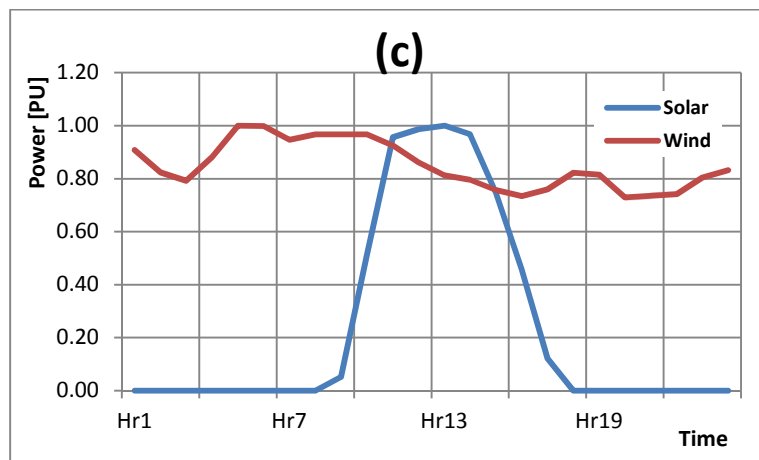
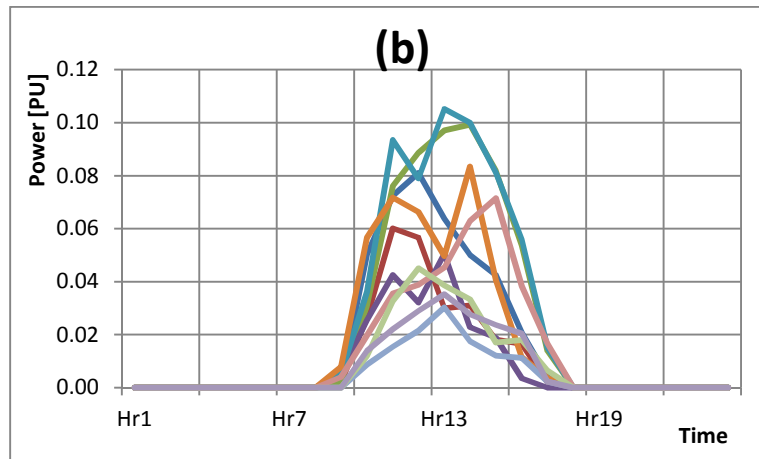
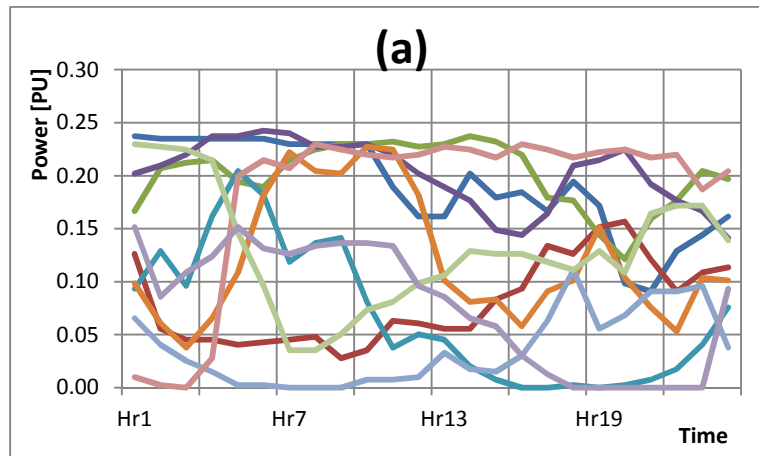
To be applicable in the proposed algorithm, the power generation profile requires some preparation and arrangement. Because the algorithm presented in this chapter depends on a deterministic optimization approach, average values are used for data representation.

Graphs (a) and (b) in Figure 3-5 illustrate random profiles of the generation from two different kinds of renewable facilities for the same month. It shows a number of daily patterns that were extracted from the database. Graph (c) in Figure 3-5 shows two normalized daily-average profiles for wind and solar DG units, computed from the data of the patterns shown in graphs (a) and (b) in the same figure. Both inject electrical power according to changes in the natural resource utilized.

The average DG power output per hour was computed using the monthly data. After the averages for the day were calculated, a typical profile for the first month could be established. The resulting profile was used to represent the DG output for that month. Depending on the availability of raw data, typical weekly profiles could also be used instead. The profiles of the remaining months were similarly developed. The complete set of typical profiles was stored in a database and updated regularly. When computations of power procurement for a specific month are required, the profile of the expected values of DG output associated with that month can be applied. The profiles of the remainder of the random parameters associated with the power procurement problem, such as demand and electricity prices, were similarly estimated.

### **3.7.2 The Network**

The power system used in the investigations, as shown in Figure 3-6, was a modified version of the IEEE 30 bus system [61]. The network shown has three locations that are connected directly to the high voltage network: S/S1, S/S4, and S/S15. These three locations are the only points available for supplying the distribution system. These points are also the only buses available to the LDC for withdrawing power from the selected bilateral contracts. For the purposes of this study, two renewable DG locations were connected at two different buses: a photovoltaic based system (PV) at S/S9 and a wind based unit at S/S16. The rest of the network remained unchanged.



**Figure 3-5: Patterns of wind farm and PV systems and their average profiles**

**(a) wind      (b) PV      (c) Normalized average**

### 3.7.3 Assumptions of the Study

The study involved some initial assumptions. First, because two different renewable units were connected to the system at different locations, independent operation of these units was assumed. The behavior of the spot market prices was also considered to be independent of both the renewable production levels and the demand level. The second assumption was that production from intermittent generating facilities is given priority over the power procured on the spot. This assumption simulates the policies enforced by the regulators' interests in boosting generation from green energy and implemented by setting the parameter  $\alpha$  shown in Equation Eq. (3-1) to 0.1. Clearly, the power from the spot supply will back up any deficiency when bilateral contracts and renewable DG production are insufficient to supply the demand. While the first assumption simplifies the model and makes computations less burdensome, the second makes the representation of renewable units as a parameter more reasonable.

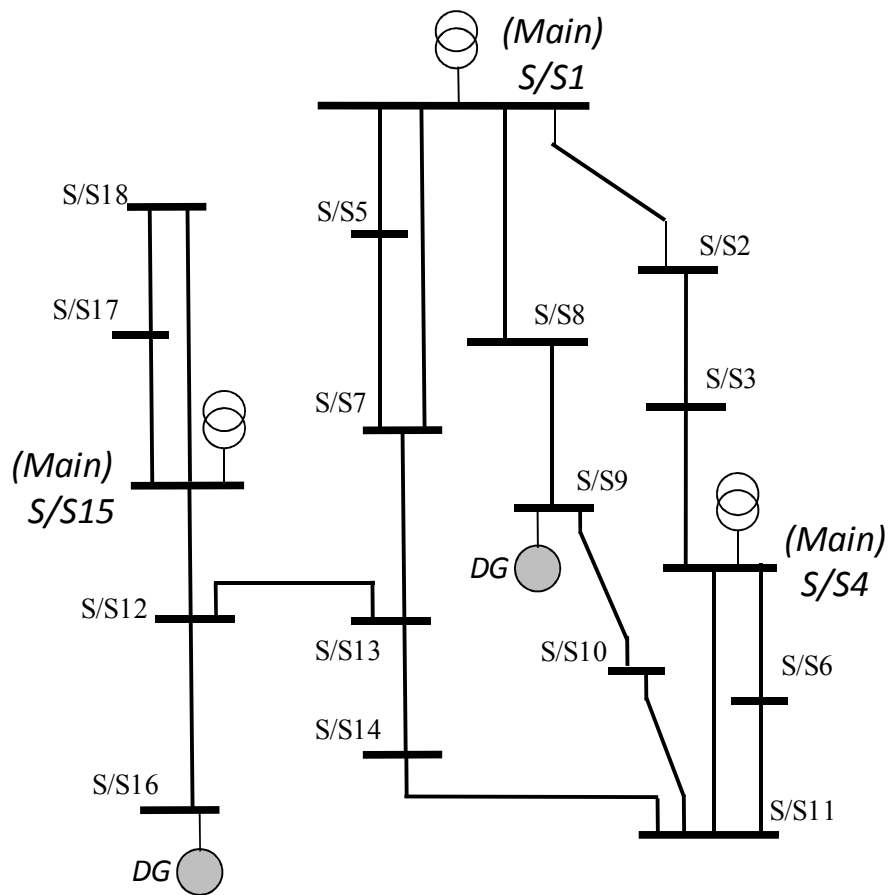


Figure 3-6: Single-line diagram of the modified IEEE 30-bus system



### **3.8 Study objectives**

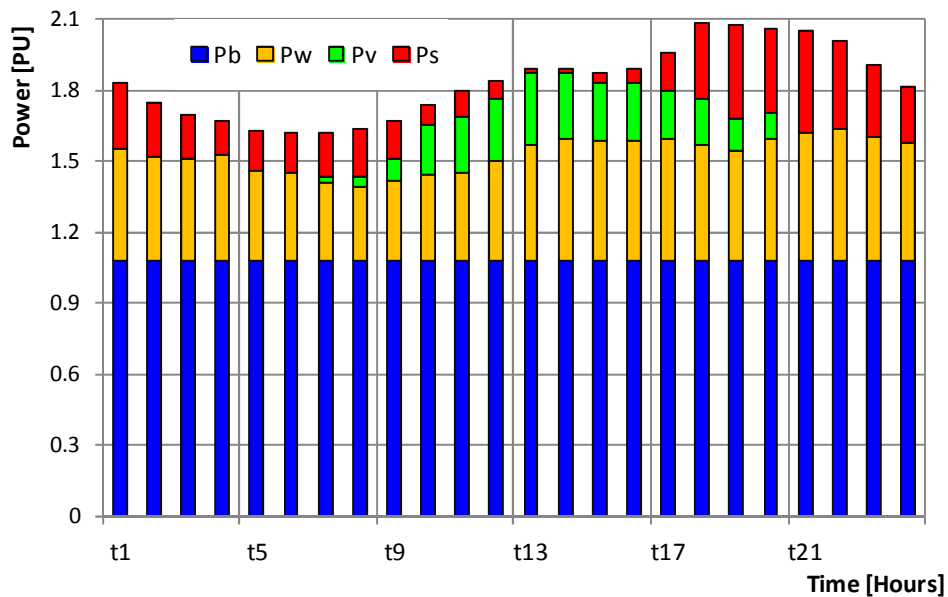
To investigate the performance of the model, several levels of random parameters were studied. Each level indicates an average of the typical profile of a random parameter considered in this study. Four average levels of electricity prices and three levels of output from a wind based generator were examined. One level for PV production was used because both units produce variable power and hence create a similar impact. These choices resulted in twelve case studies that capture a wide range of both power production and electricity prices. These investigations were directed at the following objectives:

1. Checking the performance of the first-step model to understand how the variation of the levels of the random parameters would influence the selection of the power mix.
2. Using the first-step model, the impact of renewable generation and electricity prices on the decisions of the LDC operator regarding the power procurement problem using a deterministic model was studied. This objective was achieved by focusing on an evaluation of optimal bilateral contracts.

### **3.9 Case Studies**

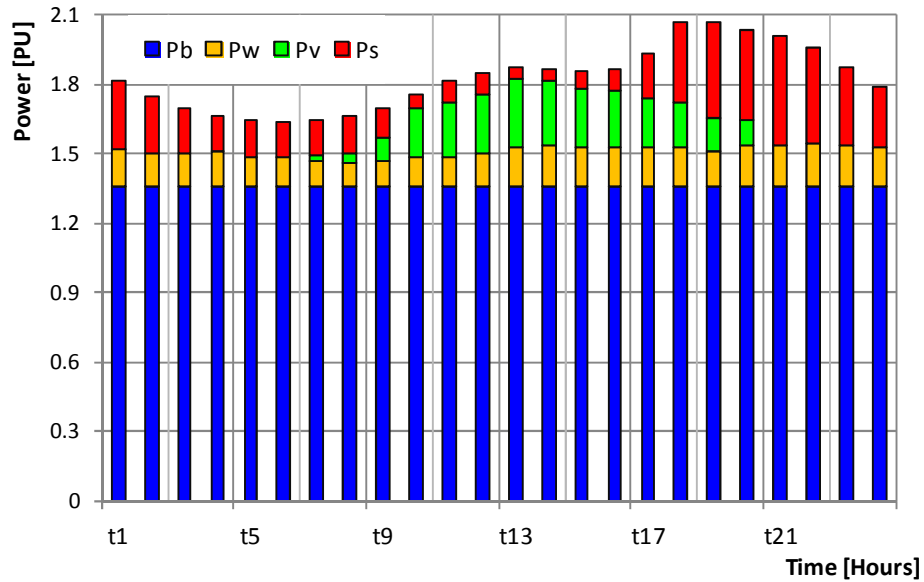
The studies began with a determination of the high-level trends in the random parameters. A large amount of power from renewable generation was combined with high electricity prices in order to observe the effect on the process of selecting bilateral contracts. The results of this case study are shown in Figure 3-7. The model has selected most of the available economical contracts that satisfy the operational constraints of the system (total of 1.08 PU). This result was predictable because the cost of purchasing from the spot market is greater than that of bilateral contracts. This observation confirms the logic presented in Figure 3-3. The only limits to acquiring more bilateral contracts are the expected production of renewable units installed in the system and the capacities of the network components. Clearly, in this case study, as shown in Figure 3-7, the power from the spot market functions as a backup supply. If the production of the renewable units deviated from the expected values, the LDC decision maker can then use the second-step model that focuses on loss minimization at this time. The quantity of power to be purchased on the spot and from which bus the withdrawal of power should occur such that power deficits are avoided and losses are minimized can thus be evaluated. When the spot market prices are high, a higher contribution level of intermittent generation results in a lower selection of bilateral contracts leading to higher operational costs.

To determine the costs incurred by the LDC because of the impact of connected intermittent generation, a second study was conducted with high spot market prices combined with a low contribution from renewable generation. As can be seen in Figure 3-8, the power obtained from the bilateral contracts has become higher, now adding up to 1.36 pu. The difference in costs between these two case studies represents (provided later in this chapter) the expenses that would be saved by the LDC to supply the same demand with a low contribution from intermittent generation. In the second case study, the number of bilateral contracts selected is limited by the power equilibrium constraints during the time between t10 and t16. Throughout this period, although low, the total renewable production limits the selection process and hence no more contracts can be signed during the whole time segment. Under such conditions, as shown by the results of these two case studies, despite their small contribution, sources of intermittent generation cause a loss of opportunity by limiting the ability of the LDC to reduce power procurement costs.



**Figure 3-7: Power procurement solution for the first case (P<sub>w</sub>: high and prices: high)**

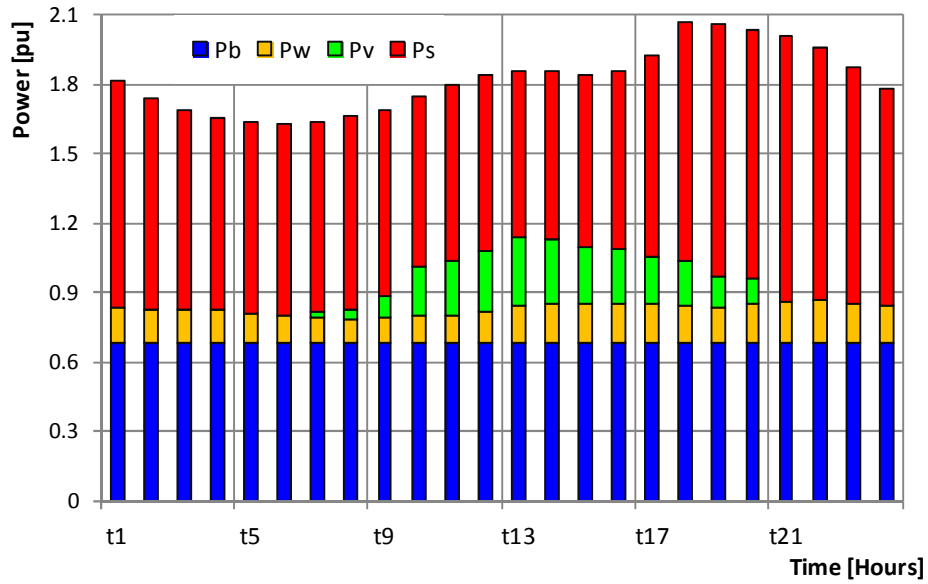
The spot market price is a key factor in the selection of bilateral contracts. When the level of the expected spot market prices is low but within a range comparable to that of the available bilateral contracts, higher purchases from the spot market are chosen. This observation is reflected in Figure 3-9, which shows the results from the model for a low contribution level of the wind facility. In this case, the model has evaluated the costs because economical bilateral contracts are available and can provide up to 0.68 pu for the utilization.



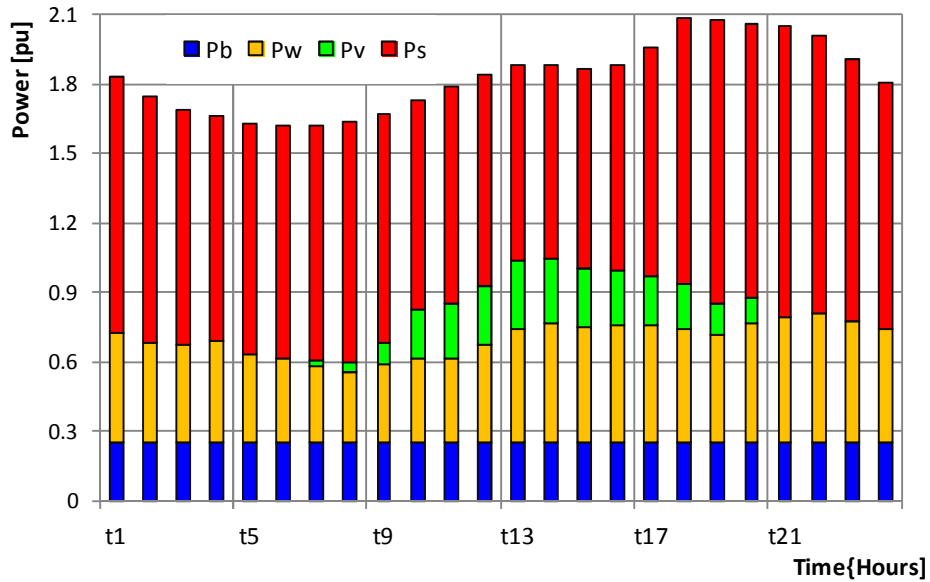
**Figure 3-8: Selected bilateral contracts at a low DG output and high electricity prices**

The effect of high levels of renewable output contribution with low spot market prices is illustrated in Figure 3-10. Clearly, the output of the intermittent resources has adversely affected the distribution company’s ability to minimize procurement costs. A comparison of the results of the last two studies, as shown in Figure 3-9 and Figure 3-10, reveals that the level of bilateral contracts has dropped from 0.68 pu to 0.25 pu. Such a drop causes deviations from the optimal selection of bilateral contracts, such as those that resulted in the cases shown in Figure 3-7 and Figure 3-8.

It can be concluded that intermittent renewable generation limits the economical selection of bilateral contracts and prevents the LDC operator from acquiring an optimal mix of power components. This effect occurs because renewable resources are electrically closer to consumption and also because of the rules imposed by the energy regulator, which give priority over other power components forcing the LDC operator to accommodate their production. Implementation of these policies that lead to an increasing participation of small DG units in distribution systems may need additional measures to compensate for such costs. In summary, while DG producers are encouraged by incentives from the government, the additional costs faced by LDCs for including renewable energy are a factor that needs to be considered in policy decisions. One of the policies considered is curtailment and, of course, its associated costs. The additional costs to an LDC due to the DG inclusion are discussed next.



**Figure 3-9: Power procurements at low electricity prices and low DG output**

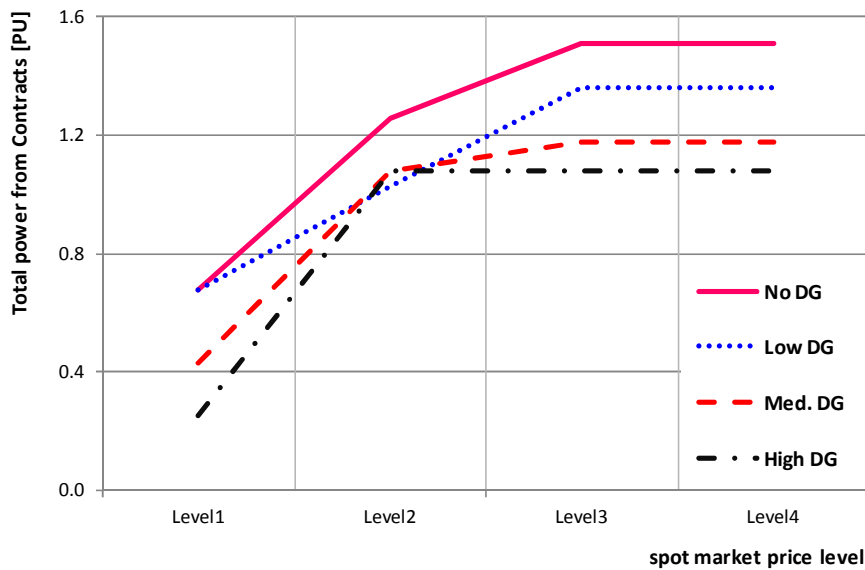


**Figure 3-10: Power procurements at high DG contribution and low electricity prices**

A summary of the results obtained in this work is provided in Figure 3-11 and Figure 3-12. Figure 3-11 shows the relationship between the total amounts of the chosen bilateral contracts and the spot market prices at different contribution levels from renewable DG units. Level-1 on the X-axis of this figure refers to the profile with the lowest average spot market prices, and Level-4 represents the

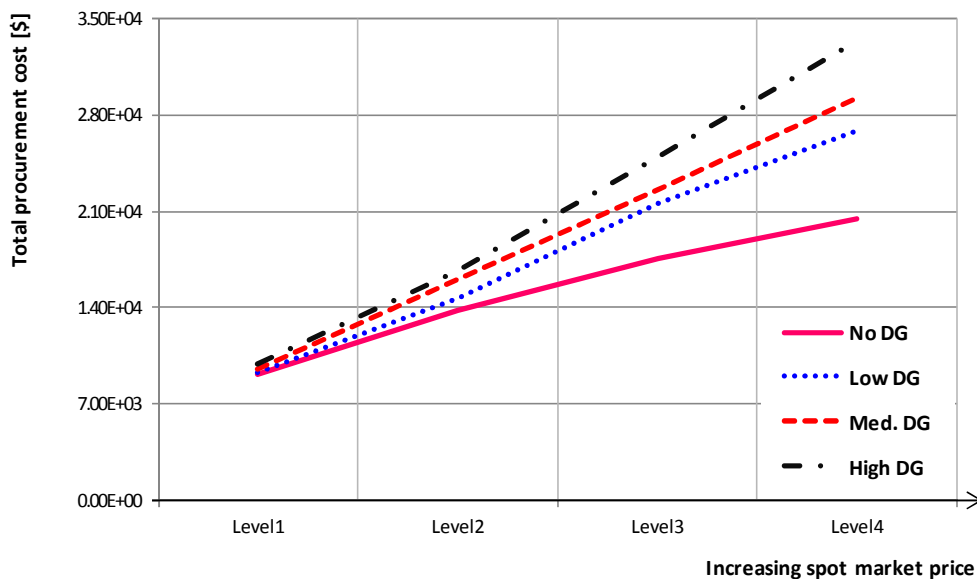
highest of spot market prices. The choices to obtain optimal bilateral contracts when renewable generation is at its minimum level are drawn as a solid line in Figure 3-11. The dotted line and the dashed curve represent, respectively, the optimal solution when medium and high penetrations of DG are modeled. This set of curves illustrates the optimal selections of bilateral contracts as spot market prices change from low to high. As a general observation, a low contribution of renewable DG results in a better position for making decisions about bilateral contracts than a high contribution from these units. Higher levels of production from renewable units reduce the chances of acquiring optimum bilateral contracts from the options available.

The unfavorable impact of intermittent generation on the ability to obtain the most economical mix of power is noticeable, especially at the two extremes of the market prices. At Level-2 of the electricity prices, the difference in the amounts of power procured through bilateral contracts chosen at different DG average injection levels is insignificant. The prices of the spot market at this level are spread around the cost of the available bilateral contracts. The cost of supplying the LDC's demand from either element of power, i.e., bilateral or spot market, would therefore be close. The contracts selected by the model in this case are based on the minimization of system losses.



**Figure 3-11: Contracted power changes with changes in electricity prices and DG input**

The changes in the costs of the energy procured to meet the demand of the network are detailed in Figure 3-12. The tendency of the cost is to increase correspondingly as either the DG injection and/or the spot market price increases. As Figure 3-7 and Figure 3-8 showed, extra uncontrollable injections from intermittent generation reduce the freedom of the LDC to choose economical contracts. The cost of the energy procured in the case illustrated in Figure 3-7 is \$33.3 k, which is higher than in the case of lower DG contribution (\$26.86 k) (Figure 3-12) at price Level 4. The reason for this extra cost is the DG injection, which prevents the decision maker from signing more economical contracts in seasons when electricity prices are high. On the other hand, when the average expected spot market prices are lower than the bilateral cost, lower contracts are selected and the model's search is limited by technical constraints. Contracts that are economically acceptable are rejected due to the higher contribution of intermittent generation. This observation arises from the decline of the total amounts of chosen contracts from 0.68 pu to 0.25 pu at the same market price level (Level 1), as shown in Figure 3-11.



**Figure 3-12: Variation in the procurement costs with electricity prices and DG contributions**

Electricity prices and DG contributions have different rates of impact on the total procurement costs. While DG affects the total costs by forcing the elimination of some economical contracts, increases in the electricity prices directly influence purchasing costs and have more effect. This discrepancy is evident in Figure 3-12. At low electricity prices, the impact of DG injections on the

costs of power purchasing is small: the range is within \$500 at most. However, this range becomes 13 times greater, reaching a difference of \$6500, when the prices of the spot market are at the highest level (Level 4 in Figure 3-12). In the three curves drawn in Figure 3-12, DG causes losses in savings by limiting the operator's ability to choose optimal contracts. As noted in the discussion of Figure 3-11, there is a point along the x-axis at which the impact on the amounts of bilateral contracts is minor. A comparison of the difference in costs in Figure 3-12 at the same point, on the X-axis, shows the increase in cost for all scenarios of DG contribution levels. The impact on the cost of power procurement is only one aspect of the utility-investor relationship. Other factors that should be considered include losses, voltage profile, deferred installations, and influences on the protection systems [5]. An investigative study of these results is required in order to develop a policy that can achieve a compromise between the different effects of DG contribution.

### **3.10 Summary**

The computations conducted in this chapter have demonstrated the complexity of the power procurement problem. A two-step algorithm has been presented as a means to find the economical set of power components to supply LDC demand. It uses the total energy costs to specify the power mix for supplying a distribution company's demand. The total costs of the power acquired from the spot market during the contract period are weighted against the total costs of the power secured from bilateral contracts for the same period to make operational decisions. A mixed integer nonlinear model has been suggested for the first step, in which the bilateral contracts available to supply the LDC demand are evaluated. In the second step of this algorithm, the model can be re-applied and the results related to bilateral contracts of the first step are reused. After acquiring more details about renewable production, the second-step model can be used to compute the amount of power purchased on the spot and where it should be injected so that the operating costs are minimal.

The inability of the deterministic optimization model to follow the uncertainty dictated the need for a two-step plan to deal with the variations in some parameters. As the capacity of intermittent generation becomes larger, more complicated operational circumstances will appear [9]. Stochastic optimization techniques that have the ability to represent uncertainty should be applied to evaluate these issues, as considered in the next chapter.

## Chapter 4

### Stochastic Programming Applications in Procurement Problem

An important category of mathematical programming techniques that can be used to solve the power procurement problem is stochastic programming algorithms, also called stochastic optimization techniques. They are used to find an optimal set of decisions while keeping economic and technical constraints within limits under uncertain information. The uncertainty arises from a lack of perfect information about one or more elements that are involved in the process of making a decision. Several textbooks [38, 75, 76] provide comprehensive theoretic details of these techniques. This chapter introduces an application of stochastic optimization techniques to the power procurement problem. Models that rely on a two-stage algorithm are proposed as a method of formulating the procurement problem, and the results obtained from applying these models are analyzed and compared.

#### 4.1 Basic Deterministic Optimization Problem

Although most of the decision making processes in real life are non-linear, it is common practice to begin with linear models as a starting point. The model  $M_1$ , described by Equations Eq. (4-1) to Eq. (4-3), is a compact form of a linear program. The coefficient  $C$  is a vector that contains elements of the cost factors. The objective of this formulation is to minimize the total costs of selecting decision variables of the column vector  $X$ . The last two equations of this formulation describe the restrictions imposed by the system for determining feasible choices of  $X$ . The coefficient matrix  $A$  illustrates the contributions of the decision variables for fulfilling the demand vector  $b$  shown in the right-hand side of the second equation. Of course, an acceptable solution from an economic point of view must result in positive levels of the decision variables of the vector  $X$ , as illustrated by the third equation. The problem shown could be described as a distribution problem to supply clients' demand  $b$  while keeping the operational costs at a minimal level.

$$\text{Min} \quad C^t \cdot X \quad \text{Eq. (4-1)}$$

$$\text{s.t.} \quad A \cdot X \leq b \quad \text{Eq. (4-2)}$$

$$X \geq 0 \quad \text{Eq. (4-3)}$$



The above model is deterministic, which means that all of the elements of ( $C$ ,  $b$ , and  $A$ ) are well defined and fixed constants. No variation is involved in the parameters; consequently, the solution would also be deterministic. The calculation of these decisions is straightforward once this formulation is set up and the required data is available with certainty.

## **4.2 Two-Stage Stochastic Optimization Model**

In practice, many parameters are random. For example, it can be assumed that the information about the demand vector,  $b$ , is not completely known but rather it is described probabilistically. In this case, a deterministic solution that is suitable for all possible variations of the demand cannot be obtained by using the model  $\mathbf{M}_1$ . To effectively acquire better solutions, the randomness of the demand  $b$  must be included in the formulation, and the problem represented by  $\mathbf{M}_1$  must be reformulated.

### **4.2.1 Expected-Value-Based Model**

A common practice is to substitute for the random demand by its average value. The resultant model is then the same as the one represented by  $\mathbf{M}_1$ . The only difference is that the vector  $b$  is replaced by an average value. Following this strategy means that the size of the model would not change, this is the main advantage of applying the average value. The two-step algorithm described in Chapter 3 is an example of this category. Although non-linear and mixed integer, it is essentially deterministic because it uses one value, i.e., the average renewable production, in order to consider the randomness.

However, the decision obtained in this manner may not be the optimum solution to a problem of this nature. Although this approach is commonly used, it is not the only effective one. A solution based on the expected value alone should not be relied upon. The reason is that using the average value does not reflect the variation associated with the randomness. Based on the average, obtained results may lead to unwanted situations, especially when the range of the variation is wide, as in the case of renewable DG production. The deterministic model developed in Chapter 3, which depends on the expected value, will be upgraded in this chapter to include details about randomness in renewable generation.

### 4.2.2 Two-Stage Stochastic Model

The two-stage stochastic program with recourse is the model most commonly utilized for solving optimization problems under uncertainty. Details about other modeling approaches can be found in general textbooks on stochastic programming [38, 75, 76]. The following formulation represents the problem originally shown in  $\mathbf{M}_1$ , assuming that the random demand has three possible scenarios:

$$\min \quad C^t \cdot X + E[H(\omega, Y)] \quad \text{Eq. (4-4)}$$

$$\text{s.t.} \quad A \cdot X \leq b \quad \text{Eq. (4-5)}$$

$$T_1 \cdot X + W_1 \cdot Y = d_1 \quad \text{Eq. (4-6)}$$

$$T_2 \cdot X + W_2 \cdot Y = d_2 \quad \text{Eq. (4-7)}$$

$$T_3 \cdot X + W_3 \cdot Y = d_3 \quad \text{Eq. (4-8)}$$

$$X \geq 0, \quad Y \geq 0 \quad \text{Eq. (4-9)}$$

The above model,  $\mathbf{M}_2$ , defined by the set of the equations Eq. (4-4) to Eq. (4-9) represents a linear two-stage stochastic formulation with recourse under uncertainty of the demand.  $H(\omega, Y)$  is a cost function in terms of the deficits (D) and surpluses (S) that might result from the difference between the selected decisions  $\mathbf{X}$  and the random demand, and  $\omega$  presents the random realization. These variables are contained in the vector  $Y$  as one surplus and one deficit variable per each scenario. The expected value of the cost to be incurred due to the application of these variables is designated by the term  $E[H(\omega, Y)]$ .  $T_i$  and  $W_i$  are matrices represent the relationship between the change in the demand and the first and second stage variables. Although this is a general form allowing for randomness in  $T$  and  $W$  matrices, in our problem,  $T_i$  is constant for all  $i$ , and  $W$ 's are unit matrices.

Since only three scenarios are considered as a representation of the randomness of the demand, the corresponding constraint has been repeated three times: once for each scenario. The two new variables  $D$  and  $S$  are introduced, represented by  $Y$  and  $\omega$  in the objective function, in order to facilitate a feasible solution to this problem. The cost of adding these variables is represented by the expectation term in the cost function. These additions have been inserted to help solve the problem under the newly introduced condition of uncertain demand.

The introduction of possible variations in the demand requires a construction of two sets of decision variables in addition to the expectation term in the objective function. The decision maker must first choose the levels of  $X$  that satisfies the demand without having complete information about its quantity. This step represents the first stage in solving the problem, and hence these variables are the first-stage variables, i.e., the first variables to be known in advance of the other variables. Another name for these variables is *here-and-now* they are computed before clear information about the uncertain parameters is known. Their values should not be affected by the randomness of the demand. In other words, the levels of these variables will not change but rather are fixed over the course of both the first stage and successive stages. The second set of variables varies as the random demand changes in order to satisfy the constraints of the program; they are described next.

Although the main goal is to compute the first-stage decisions, the second-stage variables must be included in the formulation. The computations in the second stage target the impact on the objective function and the evaluation of the variables that vary with the random elements. This set of decision variables is crucial to balancing the demand either by supplying the deficit or by managing the surplus caused by the selection of the first-stage variables. It must be noted that the two sets of variables, the first-stage and the second-stage, are distinguishable only according to the time the decision is made. The decision about second stage levels is delayed until more information becomes available to the decision maker. These decisions are made as a corrective action for the inability to anticipate the randomness. Another name for the second stage variables is *recourse variables*. In the program shown in the above example,  $D$  and  $S$  (represented in  $Y$ ) illustrate this kind of variable. The variable  $D$ , which stands for deficit, will have a positive value if the selected first-stage variables are not enough to match the demand and a value of zero if the demand is met or exceeded. The other variable,  $S$ , which stands for surplus, will provide a means of handling the extra levels that are greater than the demand; however, both variables when they are nonnegative also introduce additional costs.

Therefore, due to uncertainty in the demand, not only new variables are introduced but additional cost terms are also needed. These added terms account for the newly included variables. Because the demand is statistically described, the decision maker may use the expected value as one of the existing options for minimization. The expected value of the stochastic model thus represents the will of the decision maker to incur an additional cost to meet the demand. This cost term is the recourse action that the decision maker should apply to consider the impact of the uncertainty.

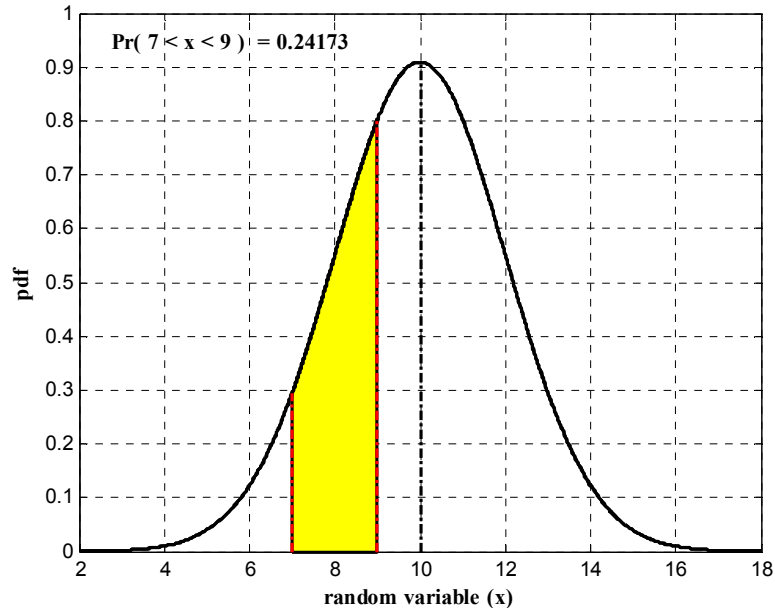
### 4.3 The Cost Function of the Recourse Problem

The additional elements, i.e., the second-stage variables and the associated cost terms, constitute the recourse problem. The purposes of incorporating these variables are to maintain the feasibility of the solution and to account for their impacts. In other words, due to uncertainty, the constraints of the recourse problem can be fulfilled only by adding the second stage variables. However, the extra cost associated with the surplus and deficit variables must also be included as a result of the uncertainty. This cost, called the recourse cost, is evaluated based on the expected value of the upcoming expenses. Since statistical information about the random elements is assumed to be accessible, it makes sense to apply the expectation as a measure to quantify the expected costs related to the randomness and to add it to the objective function of the model.

A fundamental assumption on which stochastic programming is based is the availability of the probability density function (pdf) of the random variable. Knowing the pdf enables one to weigh the associated scenario by its probability of occurrence. When the density function  $f(x)$  is known, these weighting factors can be evaluated according to the following formula:

$$Prob(\omega) = \int_{x_1}^{x_2} f(x)dx \quad \text{Eq. (4-10)}$$

Equation described by Eq. (4-10) gives the probability that the variable  $X$  has a value between  $x_1$  and  $x_2$ , where  $\omega$  is the event that  $x_1 \leq X \leq x_2$ . For example, Figure 4-1 shows the pdf of a random variable that follows a normal distribution with a mean of 10 and a deviation of 4. The probability of the event that this random variable is between 7 and 9 is equal to (0.242), which is represented by the highlighted area under the curve  $f(x)$ . When the function  $f(x)$  is multiplied by the level of the random variable and integrated over its range, the result is the expected value of the random variable. If the expected value of the cost term and its derivative can be computed, the program described by  $\mathbf{M}_2$  can be treated as a standard nonlinear optimization problem [38]. However, this is not the case because of the difficulty of evaluating the integral form used in the term of the expected value. Hence, it is more practical to use approximation by dividing the range of the random parameter into small segments and replace the integration by an equivalent summation.



**Figure 4-1: Density function of a random variable**

This division of the pdf is called discretization. The pdf is sliced into small subdivisions, and the probability of realizing the random variable between the boundaries of each slice is computed. This discrete version is described by equation Eq. (4-11), shown below, which makes the problem easier to solve by overcoming the obstacles mentioned.

$$E[x] = \sum_{i=1}^{i=N} P_r(\omega_i) \cdot x(\omega_i) \quad \text{Eq. (4-11)}$$

Approximation is a twofold aspect technique that leads to a limited number of scenarios, but it must be well designed. Too many scenarios result in a better approximation of the pdf, but at the same time, the problem size becomes very large. On the other hand, too few scenarios jeopardize the accuracy of the modeling of the randomness, but simultaneously, the size of the problem decreases to a small model and makes the problem more tractable. Between the two extremes, one must judge how many scenarios to use to get the most tractable and accurate result.

#### 4.4 Structure of the Two-Stage Stochastic Model

Because of the required approximation, stochastic programming models have very large sizes with a variety of structures. To demonstrate how large the problem size can become, an extensive format of the constraints, described by Eq. (4-5) to Eq. (4-8), is written in matrix format below:

$$\begin{bmatrix} [A] \\ [T_1] \\ [T_2] \\ [T_3] \end{bmatrix} \begin{bmatrix} [W_1] \\ [W_2] \\ [W_3] \end{bmatrix} \begin{bmatrix} X \\ Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} b \\ d_1 \\ d_2 \\ d_3 \end{bmatrix} \quad \text{Eq. (4-12)}$$

The first row represents the constraints of the first-stage section of the equivalent deterministic model. The remaining rows indicate the constraints of the individual scenarios that are chosen in order to model the recourse problem. Many methods have been used for considering the structure of this type of problem [38]. The basic structure that is commonly applied, as used in Eq. (4-12), is the L-shaped method. Other variants of the L-shaped method are explained in [38].

#### 4.5 Non-Linear Stochastic Optimization

The theory of linear stochastic optimization can be generalized to non-linear programming under uncertainty. The steps for dealing with uncertainty in non-linear programming are very similar to those used in linear models. As in the previous section, the process begins with a deterministic model.

A general formulation of a non-linear optimization problem is described by the following equations [77]. The following formulation, model M<sub>3</sub>, is expressed by equations Eq. (4-13) to Eq. (4-16). It is a deterministic version where all of the parameters assumed in defining the relationships between the variables are known perfectly:

$$\min \quad Z(X) \quad \text{Eq. (4-13)}$$

$$\text{s.t.} \quad g_i(X) \leq 0 \quad \forall i \quad \text{Eq. (4-14)}$$

$$h_i(X) = 0 \quad \forall i \quad \text{Eq. (4-15)}$$

$$X \geq 0 \quad \text{Eq. (4-16)}$$

This model is a general non-linear optimization program. The components of the model contain an objective function and two sets of constraints. The terms of these components are Z(x), the objective function given by Eq. (4-13); g<sub>i</sub>(x), a set of inequality constraints illustrated by Eq. (4-14); and h<sub>i</sub>(x), a set of equality constraints defined by Eq. (4-15). All of the above equations are functions of X, which is a vector of continuous variables. If the above problem is convex, a global optimal solution is

guaranteed [77]. Even for non-convex problems, some algorithms for finding the best set of decisions that minimize the objective function can be found (without guaranteed global optimality, however). Other kinds of challenges arise when the randomness occurs in at least one parameter.

A strategy similar to that applied to consider uncertain parameters in a linear programming is followed for including the randomness in non-linear models. A penalty element is added to the original objective function. This added term includes the expected cost that might be incurred as a result of lacking precise information about the future. The size of the problem also explodes because the decision maker would like to include as many probable scenarios as possible. The outcome of these two adjustments can be seen in the following formulation  $M_4$ :

$$\min \quad Z^{(1)}(X) + Z^{(2)}(X, Y(\omega), \omega) \quad \text{Eq. (4-17)}$$

$$\text{s.t.} \quad g_i^{(1)}(X) \leq 0 \quad \forall i \quad \text{Eq. (4-18)}$$

$$h_i^{(1)}(X) = 0 \quad \forall i \quad \text{Eq. (4-19)}$$

$$f_i^{(2)}(X, \omega) + g_i^{(2)}(X, Y(\omega), \omega) = 0 \quad \forall i \text{ and } \omega \quad \text{Eq. (4-20)}$$

$$f_i^{(2)}(X, \omega) + h_i^{(2)}(X, Y(\omega), \omega) = 0 \quad \forall i \text{ and } \omega \quad \text{Eq. (4-21)}$$

$$X \geq 0, \quad Y(\omega) \geq 0 \quad \text{Eq. (4-22)}$$

Comparing the last three models, one can easily observe the terms. In this model, the objective function, the term  $Z^{(1)}(X)$  shown in Eq. (4-17), accounts for the costs of the first stage, which is identified by the superscript 1. This term represents the cost paid to start the task; it means that it is feasible and profitable to select some of the here-and-now variables ( $X$ ) and to begin the activity. The second stage costs are defined, statistically, by the second term of the objective function:  $Z^{(2)}(X, Y(\omega), \omega)$ . Because no certain and complete knowledge about the future is possible, the expected cost associated with the random variables is included. Other terms, such as variance, can be added to account for the risk as another measure of an unfavorable outcome of the variations. The remaining equations stand for the constraints incorporated into the program.

The first two constraints of  $M_4$ , appearing in Eq. (4-18) and Eq. (4-19), belong to the first stage. They remain untouched except for the addition of a superscript in order to distinguish them from the second stage. Equations Eq. (4-20) and Eq. (4-21), with the superscript 2, are added to account for the selected scenarios that represent the stochastic behavior. It must be noted that, to represent the randomness, these sets of constraints should be repeated for every scenario involved. As with the linear cases, a set of new variables should be incorporated so that feasibility is maintained.

#### **4.6 Stochastic Optimization: General Aspects**

Linear and nonlinear, stochastic optimizations work by a mechanism which can be expressed as follows. Because fewer data are available when decisions are made about a specific operational plan, the decisions can be divided into two groups of variables.

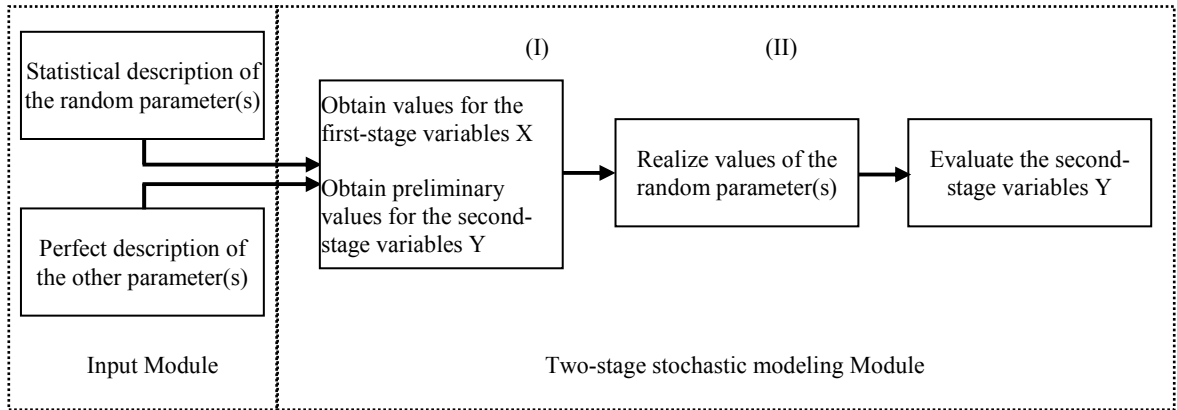
- The first group must be decided before accurate information is available for all elements involved in the decision process. These decisions must be computed in order to initiate the operational plan itself. They must be calculated without the acquisition of perfect and complete data about some or all of the parameters involved in the planning process.
- The second-step variables are not fixed. They vary as a function of both the first-stage variables and the randomness. Because of their nature, decisions about the values of these variables are left to the next stage. As time passes, more information about the unknown parameters becomes available, and hence when the first-stage variables are computed, better decisions about the variables can be made. This second round may be needed in order to revise the actions taken with respect to the variables of the first stage.

In both models, linear or nonlinear, the first-stage variables are given the symbol  $X$ . The second-stage decisions are represented by  $Y(\omega)$  or  $Y(X,\omega)$ , since they are influenced by the first-stage variables and randomness  $\omega$ . Figure 4-2 shows the procedure followed to find the optimal decisions and hence describes the way in which the two-stage stochastic modeling technique works.

The procedure shown in Figure 4-2 includes the basic steps in solving an optimization problem under uncertainty. First, a statistical description of the cause of uncertainty is provided along with the information about the rest of the well-defined parameters. This step represents the Input Module shown in Figure 4-2, but the optimization process does not start until the two-stage stochastic module begins. Given the output of the Input Module, the decision maker must decide on the levels of the first-stage variables before the actual values of the random parameters can be known. The Greek



letter I in the parenthesis above the left textbox shown in this module indicates the first-stage period. In time, more information becomes available to the decision maker and it becomes feasible to make concrete decisions about the rest of the variables, i.e., the second-stage variables. However, such decisions are dictated by the levels chosen for the first-stage variables during the first period. The process of obtaining-realization-evaluation is repeated sequentially as required by the model.



**Figure 4-2: Steps in the stochastic optimization modeling technique**

#### 4.7 Application to the Power Procurement Problem

The selection of appropriate amounts of power to be procured from multiple options available to the decision maker of an LDC is a challenge due to uncertainty. Bilateral contracts are commonly evaluated as a part of the power procurement process in order to achieve economic goals. The selection process of optimal procurements includes some uncertainty due to variations in demand and changes in spot market prices. These variations result in deviations from optimal power procurement decisions. The challenge of solving the power procurement problem increases as a result of the additional uncertainty caused by the power production of renewable energy sources. In this section, the power procurement problem is formulated as a two-stage stochastic model that incorporates the variations in the power production from renewable DG units. Several studies were conducted in order to show the effectiveness of the developed model in selecting bilateral contracts under such situations.

An LDC operator buys the power that meets the system's demand. A cost function that accounts for the different components should therefore be determined. Building such a function required the

elements illustrated in Figure 3-1. The sources of power that were considered in this research are the bilateral contracts, the spot market, and the renewable DG units. An operator of an LDC would minimize the costs associated with procuring power from these sources.

Before formulating the cost function, the distinctions between the variables were needed in order to know the variables for each stage. As discussed in section 4.5 above, two sets of variables are needed for the formulation of a two-stage stochastic model. In the power procurement problem, evidently the power from the bilateral contracts should be represented as first-stage variables. After these contracts are signed, their quantities should be constant over the period of power consumption. This aspect matches the characteristic of the first-stage variables of a two-stage stochastic model. Moreover, these quantities must be evaluated some time before the commencement of the contract, which is a second characteristic of the first-stage variables. Accordingly, the bilateral contracts were chosen to become the first-stage variables, which must be decided a month, a week, or even a day before the consumption time [78]. The rest of the power procured then become the second-stage variables.

#### 4.7.1 Two-Stage Stochastic Formulation

The goal of the power procurement problem is to acquire integrated purchasing and scheduling of power from a variety of sources that will minimize the total operating cost.

$$\min \left[ \text{Cost}(P_b) + \text{Cost}(P_s) + \text{Cost}(P_o) + \text{Cost}(P_c) + \text{Cost}(P_{\text{defict}}) + \text{Cost}(P_{\text{surplus}}) \right] \quad \text{Eq. (4-23)}$$

Where

$$\text{Cost}(P_b) = \sum_{t=1}^T \sum_{i=1}^{N_b} \left( \sum_{c=1}^{N_c} P_b(i, c) * \lambda_b(i, c) \right)$$

$$\text{Cost}(P_s) = \sum_{s=1}^{N_s} \left[ \sum_{t=1}^T \sum_{i=1}^{N_b} P_o(i, t, \omega_s) * 1.0 * \overline{\lambda_s(t)} \right] . \text{Pr}(\omega_s)$$

$$\text{Cost}(P_o) = \sum_{s=1}^{N_s} \left[ \sum_{t=1}^T \sum_{i=1}^{N_{dg}} P_o(i, t, \omega_s) * (1 - \alpha) * \overline{\lambda_s(t)} \right] . \text{Pr}(\omega_s)$$

$$\text{Cost}(P_c) = \sum_{s=1}^{N_s} \left[ \sum_{t=1}^T \sum_{i=1}^{N_{dg}} P_c(i, t, \omega_s) * (1 + \alpha) * \overline{\lambda_s(t)} \right] . \text{Pr}(\omega_s)$$

$$\text{Cost}(P_{surplus}) = \sum_{s=1}^{N_s} \left[ \sum_{t=1}^T \sum_{i=1}^{N_{dg}} P_{surplus}(i, t, \omega_s) * (1 + \beta) * \overline{\lambda_s(t)} \right] \cdot \text{Pr}(\omega_s)$$

$$\text{Cost}(P_{deficit}) = \sum_{s=1}^{N_s} \left[ \sum_{t=1}^T \sum_{k=1}^{N_{dg}} P_{deficit}(k, t, \omega_s) * (1 + \beta) * \overline{\lambda_s(t)} \right] \cdot \text{Pr}(\omega_s)$$

The main decision variables are bilateral transactions ( $P_b$ ) and spot market purchasing ( $P_s$ ) at the market interfacing buses. The power generated by renewable DG units ( $P_{dg}$ ) is represented as a parameter to stand for the priority to utilize this production set by regulators. The costs associated with the utilizing/curtailing renewable production are the same as those applied in Chapter 3. A prohibitive penalty coefficient,  $\beta$ , is introduced in the calculations of the costs related to the surplus and deficit variables in order to make the solver avoid using them unless required. The cost associated with providing power from all of these power elements would be minimized. This minimization is subject to the system-wide demand and technical requirements explained in the following paragraph.

The most important task of the LDC is its duty to supply demand. This responsibility is represented by the equality constraints of the load flow equations. Due to the random nature of both the wind and the irradiance that reaches PV cells, it is hard to provide information about the power output from each unit. Therefore, the production of renewable DG units has been included as a random parameter, denoted as  $P_{dg}$ . These constraints are implemented in the following equations:

$$\sum_{c \in N_c} P_b(i, c) + P_s(i, t, \omega_s) + P_o(i, t, \omega_s) + P_{deficit}(i, t, \omega_s) - P_{inj}(i, t, \omega_s) - P_{surplus}(i, t, \omega_s) = P_d(i, t, \omega_s) \quad \text{Eq. (4-24)}$$

$$Q_s(i, t, \omega_s) - Q_{inj}(i, t, \omega_s) = Q_d(i, t, \omega_s) \quad \text{Eq. (4-25)}$$

$$P_o(i, t, \omega_s) + P_c(i, t, \omega_s) = P_{dg}(i, t, \omega_s) \quad \text{Eq. (4-26)}$$

The minimum and maximum requirements with respect to voltage magnitude and substation capacities were also included in the model in order to keep the search for an optimal solution within standard operational technical limits.

$$V^{Min} \leq V(i, t, \omega_s) \leq V^{Max} \quad \text{Eq. (4-27)}$$

$$P_{inj}(i, t, \omega_s) = V(i, t, \omega_s) * \sum_{j \in N_b} \left[ \begin{array}{c} V(j, t, \omega_s) * G_{ij} \cdot \cos(\delta_{i,t,\omega_s} - \delta_{j,t,\omega_s}) \\ + \\ V(j, t, \omega_s) * B_{ij} \cdot \sin(\delta_{i,t,\omega_s} - \delta_{j,t,\omega_s}) \end{array} \right] \quad \text{Eq. (4-28)}$$

$$Q_{inj}(i, t, \omega_s) = V(i, t, \omega_s) * \sum_{j \in N_b} \left[ \begin{array}{c} V(j, t, \omega_s) * G_{ij} \cdot \sin(\delta_{i,t,\omega_s} - \delta_{j,t,\omega_s}) \\ - \\ V(j, t, \omega_s) * B_{ij} \cdot \cos(\delta_{i,t,\omega_s} - \delta_{j,t,\omega_s}) \end{array} \right] \quad \text{Eq. (4-29)}$$

$$P_s(i, t, \omega_s) + P_o(i, t, \omega_s) + \sum_c^{N_c} P_b(i, c) \leq S_i^{\max} \quad , i \in N_b \quad \text{Eq. (4-30)}$$

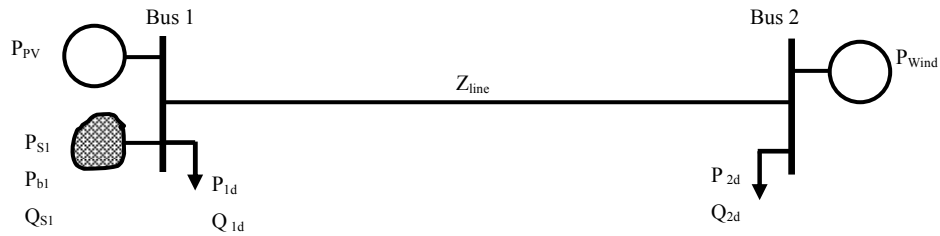
## 4.8 Two-Bus System Exploration Study

To investigate the performance of the model proposed in the previous section, a small system composed of two buses was designed. The purpose of conducting these investigative studies on a small system was to explore the capabilities of the formulation. Another reason for using this example was to obtain a good picture of the limitations of the proposed model in order to present a plan of the studies to be conducted for a larger network. Once these targets were achieved and the model's capabilities become known, similar steps could be followed for applying this model for solving the power procurement problem for an LDC represented by a modified version of the IEEE-30 bus system.

### 4.8.1 System Description

The studies were conducted on the two-bus system shown in Figure 4-3. Two renewable DG units were connected to this system: one to each bus. The two buses were connected via a line which had an impedance of  $(0.02 + j0.08)$  pu. The supply from the electricity markets was injected into this system at Bus-1 to feed the shown two load centers.

There are two renewable DG units connected to this system. Without accurate details about their production, the system operator has to take decisions and calculate the economic bilateral contracts to provide power to its customers. However, statistical information, which may be obtained from historical data of meteorological phenomena or from other similar installations, can be used for these calculations. Five scenarios of power production per each generator and for two time periods were assumed in these studies. The incidents of these scenarios were equally likely, i.e., all realizations had the same probability of occurrence.



**Figure 4-3: Single line diagram of the small two-bus system**

The second step in preparing the input data was to create the most probable scenarios of the random elements and the associated probabilities. Table 4-1 contains the five realizations of power generated by the two DG units. There are many ways to find the output of renewable facilities; the scenario information used in the thesis was obtained from actual locations, as described in Section (3.7). As shown in Table 4-1, each row illustrates the five scenarios of power production at a particular location and time. Each column of the table describes a scenario of power produced by the two resources at the two locations for the two time periods. The last two columns show respectively the average value of renewable DG output and the spot price of the electricity at the associated times.

Details of the candidate bilateral contracts are the last part of the input data; they are given in Table 4-2. The first row of this table illustrates the power quantities (in discrete values) of the contracts offered by the different producers in the forward market, while the corresponding costs are listed in the second row. The LDC operator can select any of these contracts to satisfy his/her cost minimization criteria. To easily monitor the selection mechanism of the model, the quantities of all contracts except one are made identical. The input data provided by the two tables describe the ability of the utility's operator to purchase power from two different sources in addition to the power provided by the renewable DG facilities. The following section describes the results obtained by using the two proposed formulations: deterministic and two-stage stochastic models.

**Table 4-1: Scenarios of renewable DG power production**

Node	Time	W1 [pu]	W2 [pu]	W3 [pu]	W4 [pu]	W5 [pu]	Average P <sub>DG</sub> [pu]	Price <sub>spot</sub> [\$/pu]
bus-1	t01	1.069	0.315	0.000	0.188	1.069	0.528	48.80
	t02	0.006	1.027	0.008	0.033	0.176	0.250	47.70
bus-2	t01	0.137	0.209	0.232	0.017	0.288	0.177	48.80
	t02	0.102	0.100	0.289	0.010	0.163	0.133	47.70

**Table 4-2: Offered discrete bilateral contracts for the small example**

	Con-1	Con-2	Con-3	Con-4	Con-5	Con-6	Con-7	Con-8
Power [pu]	0.100	0.100	0.100	0.100	1.700	0.100	0.100	0.100
Price \$/pu	46.000	48.100	49.000	47.990	35.000	45.250	46.250	50.990

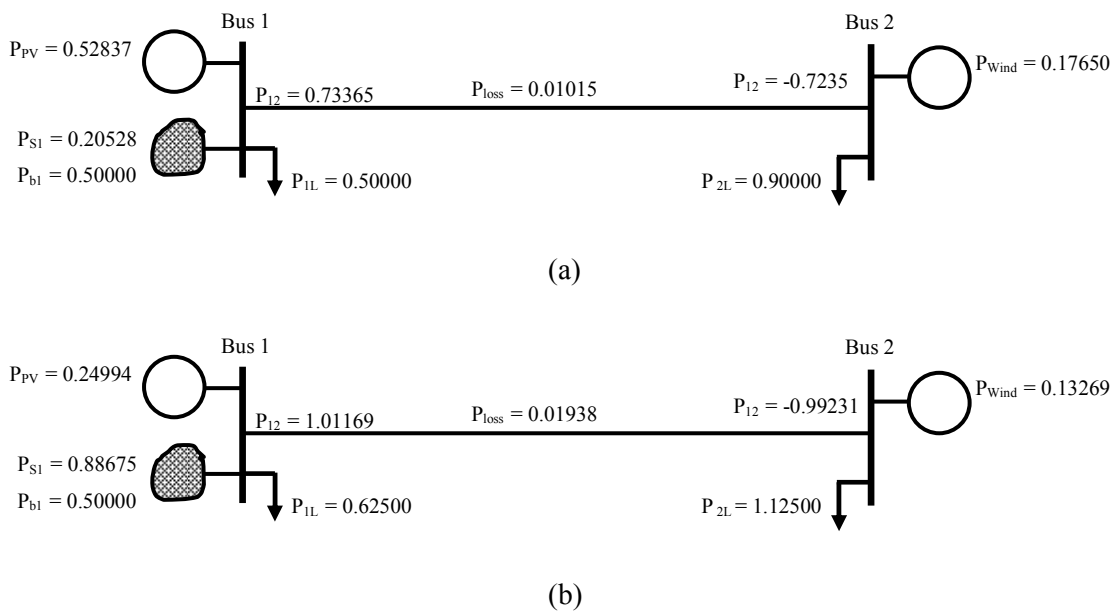
#### 4.8.2 Results of Deterministic Model

The proposed deterministic model described in Section 3.6 was used to evaluate the impact of uncertainty on computation of bilateral contracts for LDC for this case study; in this chapter it had another use. It was needed to gauge the performance of the deterministic model with respect to that of the stochastic model, i.e., to compare the benefits of using a stochastic model from a deterministic model. The first advantage of the deterministic formulation is the small size of the problem because the random elements are represented by their expected values. This feature has a very significant factor when the problem size is an issue. For example, although the system consisted of only two buses, it required 41 equations that related 49 single variables to set up the deterministic problem. When the formulation was converted to a stochastic model, the size increased. The power procurement problem with the deterministic formulation was solved using SBB<sup>2</sup> using the GAMS programming system [79].

The expected cost to procure power from all resources to supply the demand for the two time periods was \$14641.79. The deterministic optimal solution associated with this production level is shown schematically in Figure 4-4. The upper part of this figure describes the solution for the first

<sup>2</sup> SBB is a new GAMS solver for Mixed Integer Nonlinear Programming (MINLP) models. It is based on a combination of the standard Branch and Bound (B&B) method known from Mixed Integer Linear Programming and some of the standard NLP solvers already supported by GAMS. SBB is produced by ARKI Consulting and Development A/S.

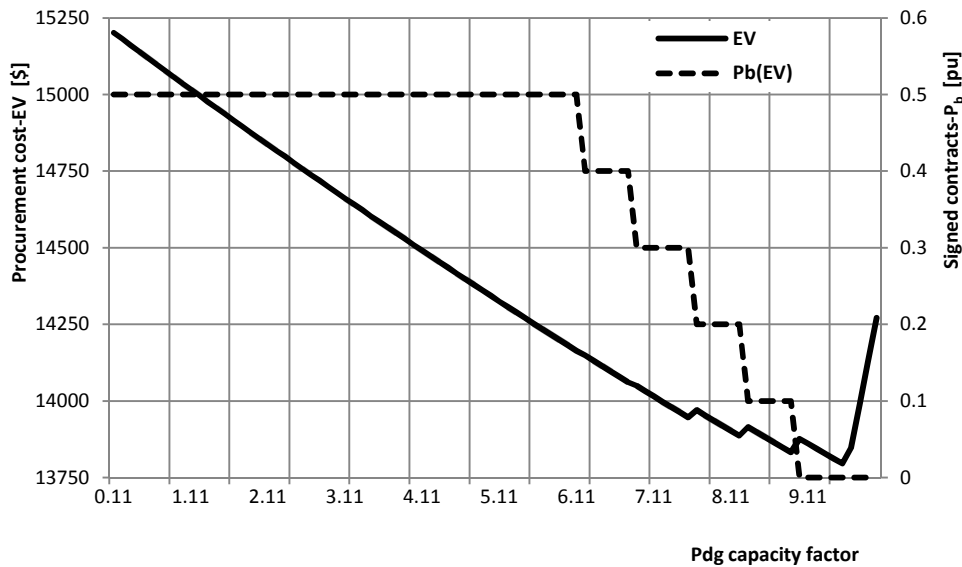
time period ( $t_{01}$ ), while the lower shows the results for the second period. Five bilateral contracts guaranteeing a total of 0.5 pu of power were chosen to supply a share of the system demand for both periods. The rest of power supply was procured from the spot market given the contribution of renewable DG output were at their average values. Because in actual operations there is no guarantee that the DG output will be at its average, the power procured on the spot was not final. Instead, the power purchased on the spot depended on the actual output of the renewable facilities and changed as the output of the renewable units varied.



**Figure 4-4: Power procurement deterministic solution for the two-bus system: (a) solution for first period, (b) solution for second period**

The above results were obtained for the given circumstances and for a particular capacity of DG facilities. A scaling factor was utilized in the code to implement several studies for many capacity levels of the renewable units. It changed both the means and the variances of their production, resulting in different contributions from these units. By changing the scaling factor, several cases were conducted. Hence, the impact on procurement costs and optimal amounts of power to be contracted can be analyzed as seen in the previous discussions. Figure 4-5 summarizes the results of solving the power procurement problem for a wide range of DG production contribution. The dashed

line represents the total amount of power that comes from contracts ( $P_b$ ) in order to minimize the overall operating costs while the solid line shows the total cost of the power procured from all resources. Recall here the x-axis is the scaling factor which represents the increase in using renewable generation. As observed from this figure and discussed in Chapter 3, the contribution from DG units does not affect the choices of bilateral contracts up to the scaling factor of about 6 after which contracts start to be rejected one after another. With a scaling factor between 7.5 and 9.5, the graph that represents the cost jumps a small step at a time because the contribution of the DG units results in additional overall cost by rejecting economic contract. This observation confirms what has been discussed in the previous chapter: connecting DG units to distribution systems increases the opportunity operating cost because the unpredicted renewable output does not allow the operator to acquire cheaper bilateral contracts.

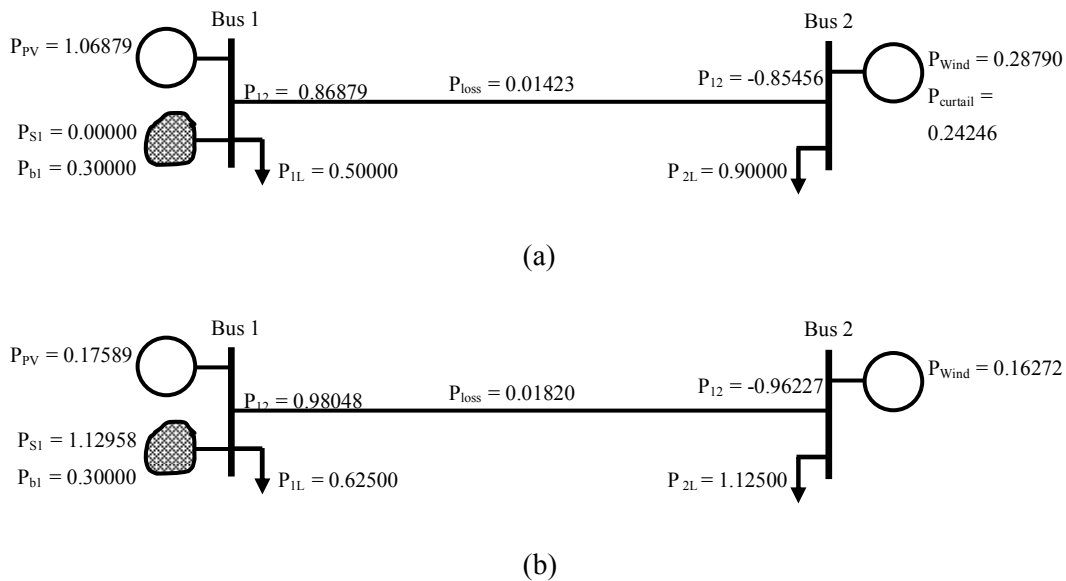


**Figure 4-5: variation of procurement cost and number of signed contracts**



### 4.8.3 Results of the Stochastic Model

In contrast to the deterministic approach which represents random elements by their expected values, stochastic modeling technique explicitly considers the uncertainty. By following this approach to solve the power procurement problem, the decision maker becomes capable of choosing the best options that suit the different scenarios considered without the complete information. Hence, when applying this technique, it is important to include as many scenarios as possible in order to gain a better solution. The here-end-now and recourse variables associated with the two stages are tied in one formulation which, when solved, will result in properly related decisions. As opposed to the deterministic approach which gives a solution, that is not suitable for all scenarios; solving the procurement problem using two-stage stochastic model produces a solution that fits all of the scenarios involved.



**Figure 4-6: Solution of fifth scenario provided by two-stage stochastic model for power procurement problem (a) solution for first period, (b) solution for second period**

Figure 4-6 shows a solution of the problem using the stochastic model for a single scenario. The values provided in this figure illustrate the case when the productions of the renewable DG facilities are given by the fifth scenario. Although the other four solutions can be similarly constructed it was preferable to tabulate them. As shown in Figure 4-6, the output of the two DG units connected to buses 1 and 2 equal are, respectively, 1.069 pu and 0.288 pu for the first period and, 0.176 pu and 0.163 pu for the second period. In the fifth scenario and for the first period, a curtailment of 0.242 pu is chosen because it is more profitable to the LDC to incur the cost associated with this reduction rather than rejecting a more economic decision. The rest of the power components required to supply the demand under the fifth scenario are also illustrated in the two parts of the figure, as well as the line flows and losses. The information needed to obtain similar diagrams for the first four scenarios are found in Table 4-3. The expected cost of this solution is \$ 15052.81. Although this expected cost is higher than the cost given by the deterministic solution to supply the same amount of load and under the same circumstances, the stochastic solution fits all of the scenarios included in the study; further comparisons are presented in the next section.

**Table 4-3: Power procurement solution for two-bus system using stochastic model**

Scenario	Period	P <sub>bilateral</sub>	Bus N1				Line terminals			Bus N2				
			P <sub>Spot</sub>	P <sub>DG</sub>	P <sub>DG</sub> (Supplied)	P <sub>demand</sub>	P <sub>injected</sub>	Losses	P <sub>injected</sub>	P <sub>DG</sub>	P <sub>curtailed</sub>	P <sub>DG</sub> (Supplied)	P <sub>demand</sub>	P <sub>balance</sub>
1	t01	0.300	0.000	1.069	1.069	0.500	0.869	0.014	-0.855	0.137	0.092	0.045	0.900	0.092
	t02	0.300	1.363	0.006	0.006	0.625	1.044	0.021	-1.023	0.102	0.000	0.102	1.125	0.000
2	t01	0.300	0.585	0.315	0.315	0.500	0.700	0.009	-0.691	0.209	0.000	0.209	0.900	0.000
	t02	0.300	0.344	1.027	1.027	0.625	1.046	0.021	-1.025	0.100	0.000	0.100	1.125	0.000
3	t01	0.300	0.876	0.000	0.000	0.500	0.676	0.009	-0.668	0.232	0.000	0.232	0.900	0.000
	t02	0.300	1.167	0.008	0.008	0.625	0.850	0.014	-0.836	0.289	0.000	0.289	1.125	0.000
4	t01	0.300	0.910	0.188	0.188	0.500	0.899	0.015	-0.883	0.017	0.000	0.017	0.900	0.000
	t02	0.300	1.431	0.033	0.033	0.625	1.139	0.025	-1.115	0.010	0.000	0.010	1.125	0.000
5	t01	0.300	0.000	1.069	1.069	0.500	0.869	0.014	-0.855	0.288	0.242	0.045	0.900	0.242
	t02	0.300	1.130	0.176	0.176	0.625	0.980	0.018	-0.962	0.163	0.000	0.163	1.125	0.000

Table 4-3 depicts the complete list of variables provided in the solution for the procurement problem using the stochastic model. The table is divided into four main sections with each containing a particular set of variables: common variables, variables related to bus 1, transmission line variables, and variables associated with bus 2. The common variables are those found constant for all scenarios and time periods, i.e. first-stage variables. They show the amount of power that is procured by signing the contracts chosen by the solver. The second, and similarly the fourth, contain values of power used to supply the demand at a particular time for each scenario and procured from the other resources connected either to bus 1 or bus 2. The last section shows the power injections and the losses of the feeder connecting the two buses. As observed from Table 4-3, the values of variables listed in the table fluctuate as the scenario and time vary. These variables represent the second-stage variables, and they adapt to the variations of the random elements involved in the problem formulation. After achieving this solution, provided by the stochastic approach, the operator of the LDC has a very clear view about the decisions that should be taken to minimize the procurement costs while considering the uncertain production of the renewable DG facilities. The solution shown in Table 4-3, provided by the stochastic model, outweighs that offered by the deterministic formulation in three ways: it considers more scenarios, fits most of the possible DG productions, and results in a lower expected cost of system operation.

## **4.9 Discussion**

The above example shows how different are the outcome of the two optimization techniques to solve the power procurements problem. Although the stochastic model gives comprehensive detailed results, offers more economic decisions, and involves the features of the random parameters, the deterministic approach still provides a simpler formulation and results in a smaller problem size. But these aspects of comparing the results, obtained by the two approaches, do not consider the quality of the decisions taken based on the solutions provided by the two models. Table 4-4 is constructed to give insight of the worth of selecting either of these approaches.

Table 4-4 includes three solutions for the example described above with the same input data, and each approach treated the randomness differently. The first column of the table gives the deterministic solution in which the random parameters are represented by their expected values; hence it is called the expected value (EV) solution. The power mix of this solution comprises of three power components with different cost elements: bilateral contracts, power from the spot market, and power supplied by the DG units. The name of the second solution is the recourse problem (RP), another

name for the stochastic solution, which is listed in the second column of Table 4-4. As described above, this solution is achieved by explicitly describing the randomness by means of a number of scenarios. The last column contains a solution that presents the expected outcome of using the expected value (EEV). It is achieved by fixing the decisions about the first stage variables that resulted from the deterministic solution as an input to the stochastic solution, i.e., this presents the true cost of the deterministic solution. In addition, computations of a Monte Carlo based model are carried out, named the wait-and-see solution (WSS). This is the cost if perfect information is available. The WSS value for the two-bus system equals to \$14683.83. The results shown in Table 4-4 are utilized to compare the quality of model outcome by using the measures described next.

Two measures have been utilized to select the right formulation that suits the problem’s situation: *value of stochastic solution (VSS)* and *expected value of perfect information (EVPI)* [38], a method applied for power system problems in [60]. The first is computed by subtracting the solution of the recourse problem (RP) from the objective of solving the same problem after fixing the first-stage variables to the levels obtained for the EV problem, i.e. EEV. It is used to justify the application of the stochastic model especially when it becomes fairly high [38]. Mathematically, VSS can be computed according to the following formula.

**Table 4-4: Cost details of procurement solution with different consideration of uncertainty**

	EV	RP	EEV
Total Expected Cost	14641.79	15052.81	15512.48
Cost of selected $P_{\text{bilateral}}$	4671.80	2750.00	4671.80
Expected cost of $P_{\text{spot}}$	5231.55	7499.14	5959.54
Expected cost of $P_{\text{curtailed}}$	0.00	358.77	784.83
Expected cost of $P_{\text{DG-Supplied}}$	4738.439	4444.90	4096.31
Number of contracts signed	5	3	5

$$VSS = EEV - RP \quad \text{Eq. (4-31)}$$

The second measure is the EVPI which gives the cost that the decision maker is willing to pay for getting perfect information about the random parameters. This payment will assure the usage of the deterministic model since the randomness becomes, theoretically, known. For example, EVPI can be

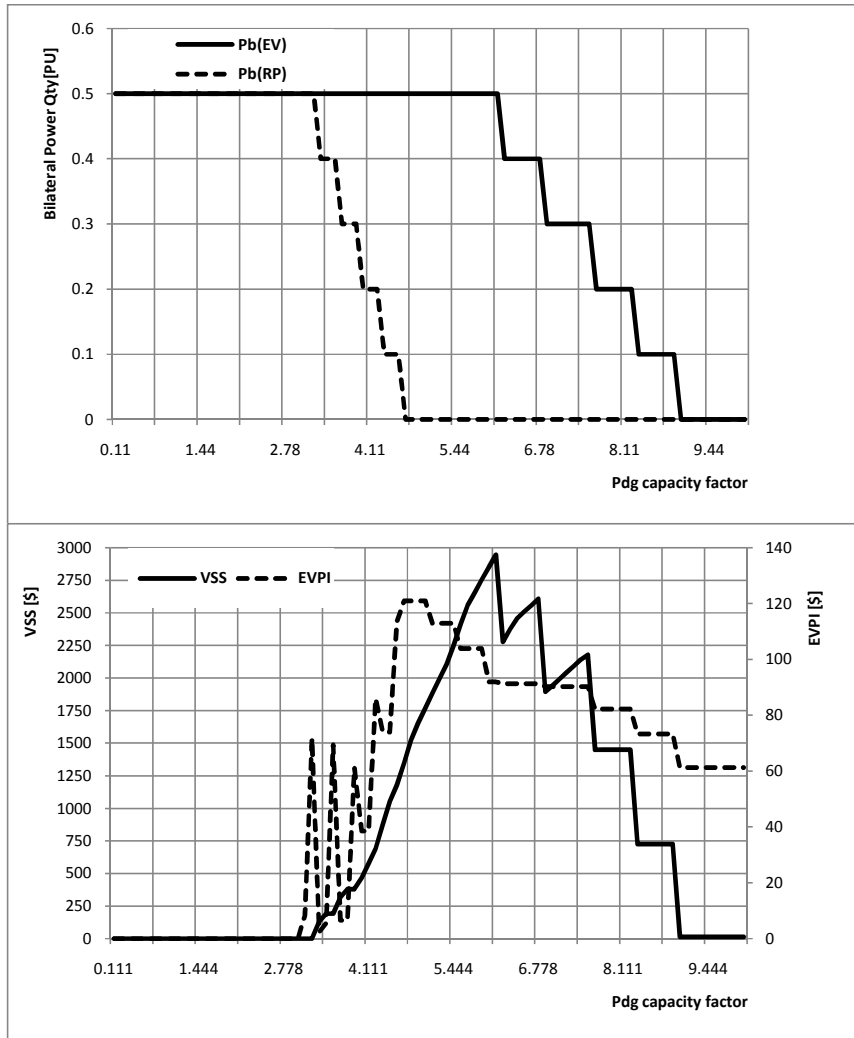
considered as the cost of using prediction techniques so a decision maker gains more information about the stochastic parameters. EVPI can be calculated using the equation below:

$$EVPI = RP - WSS \quad \text{Eq. (4-32)}$$

For the two-bus example, at the same contribution level of renewable DG units the values of the VSS and EVPI are given by \$ 459.67 and \$ 368.98 respectively. The first number quantifies the expected savings if the stochastic model is chosen to formulate the problem. Or, in other words, it tells how much the extra cost would be if the deterministic model is applied. This saving, or cost, is earned, or incurred, only because either the consideration or ignorance of randomness in modeling the procurement problem. These values are functions of the power contributed by renewable resources. In order to explore this relationship, Figure 4-7 is created.

Figure 4-7 shows the variation in the values of both VSS and EVPI and total amounts of the signed bilateral contracts for a wide range of renewable DG capacity scaling factor defined earlier. The upper part of the figure demonstrates the change in the number of signed contracts; the dashed line is for the results obtained by using the stochastic solution; and, the solid line is for the contracts selected by the deterministic formulation which used the expected value.

In the lower part of Figure 4-7, the dashed line shown describes the impact of the change in DG capacity on the EVPI value. And in the same part, the solid line illustrates the behavior of the VSS for the same range of DG capacity represented by the multiplication factor. As shown in this part, when the scaling factor is below 3.0, VSS and EVPI are equal to zero, which can be interpreted as that the randomness is low. With this low contribution, the impact was minor such that the RP, EEV, and WSS are all equal and hence zero for the two measures was the result. At this low capacity of renewable DG power production, it is recommended to use a simpler formulation, i.e., the deterministic model. When the  $P_{dg}$  capacity factor varies between 3.0 and 4.5, the EVPI increases in spikes corresponding to whenever a bilateral contract is rejected, according to the RP solution. Referring to the upper part of Figure 4-7, losing a cheaper contract, see  $P_b(RP)$ , rises the cost calculated by RP model. This increase in the computed cost in conjunction with constant levels of WSS for the same contribution factors causes an increasing trend of EVPI. After all available contracts are rejected, the gap between the two solutions provided by RP and WSS start to become closer and the EVPI start to diminish step wise until it approaches about \$60.



**Figure 4-7: Change of VSS and EVPI with a range of renewable DG contribution**

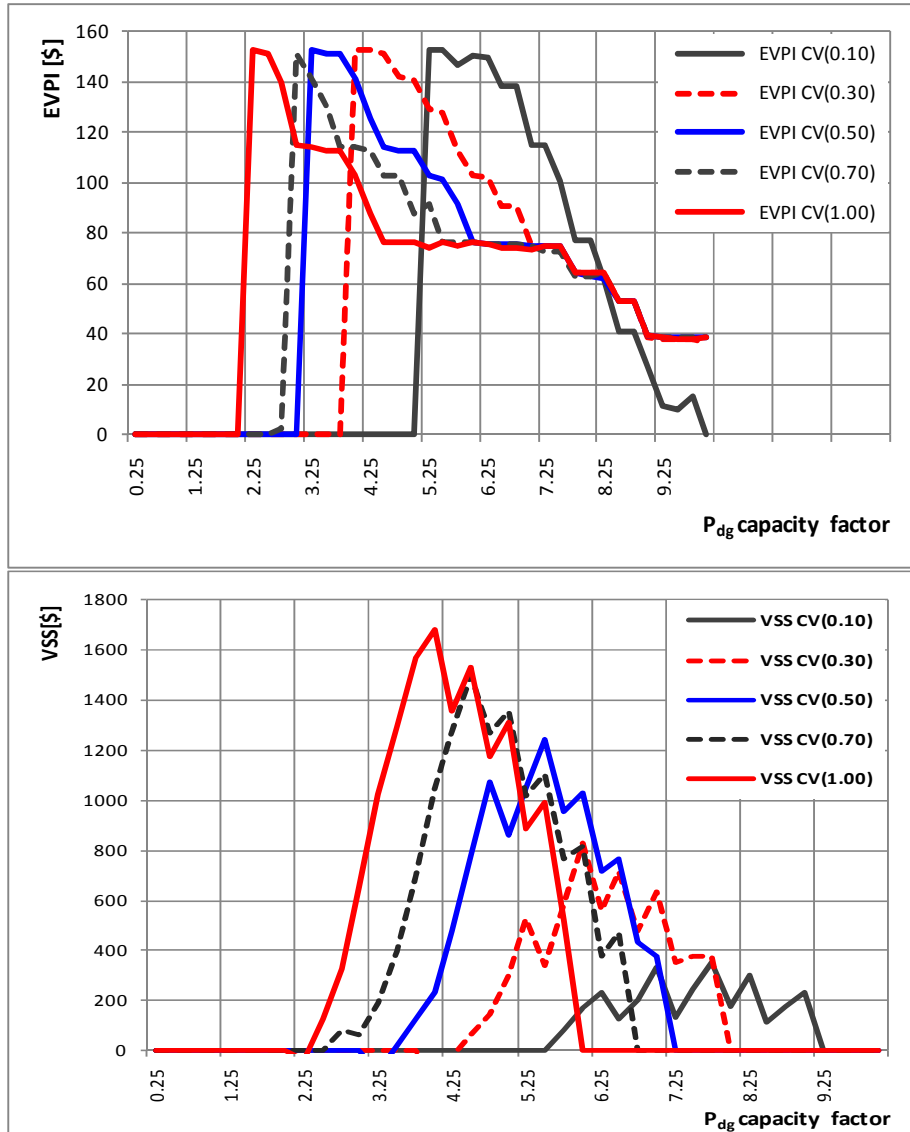
The VSS curve in the lower part of Figure 4-7 is described by the solid line. The VSS curve increases steadily with the scaling factor from 3 to about 6, after which the curve starts to decrease step wise. The reason for this increase is because the gap between the EEV solution and RP solution starts to increase as can be inferred from the upper part of the figure. Following the value of 6.0 for the scaling factor, the trend of VSS curve starts to decline. When a contract is turned down based on a decision taken according to EV, the VSS starts to decrease because EEV becomes closer to RP, see the number of chosen contracts in the upper part of the figure. The curve reaches zero again because the renewable DG production become large enough to reject the entire candidate bilateral contracts

resulting in no difference between RP and EEV solutions. That is, both had to choose the same bilateral contracts, which are now zero, and any left over demand being satisfied by the spot market. At this contribution level, the ability of the LDC operator to select an additional economic contract is limited because the power produced by the DG facilities is large, and consequently opportunities to choose the cheaper economic options are lost. These types of results are unknown until now.

In addition, not only the capacity of the renewable DG facilities has a significant impact on the operation of distribution systems, the degree of the uncertainty has considerable effect in integrating the renewable resources in these systems besides the above features of the decision making process. Figure 4-8 provides graphs of VSS and EVPI, which are similar to those shown in Figure 4-7, computed for the two-bus system. The results shown in this figure were obtained for the small system by changing the coefficient of variation factor, CV. This factor measures the dispersion of the random variables, i.e., the severity of the uncertainty. By changing its value, the randomness of the uncertain element varies, resulting in different behaviours of the random elements. For example, if a random variable follows a normal distribution, the higher the CV, the more spread would be the pdf curve leading to a large variation in its random values. These studies were introduced to investigate the impact of connecting different types of DG units and their collective impact by changing their randomness severity. The following is a discussion of the results obtained for the two-bus system where the CV is changed in discrete steps within the range [ 0.1 – 1.0]. To accommodate the results of these studies, the curves that represent the EVPIs and those correspond to VSSs are drawn separately in Figure 4-8.

In the two parts of Figure 4-8, the change in the capacity of the renewable DG units is depicted on the X-axis, and the Y-axis gives the values of the EVPI and VSS corresponding to the change in the DG output and CV level. Each curve of the VSS in the lower part of the figure, on its own, complies with the above discussion regarding the results obtained for the VSS and shown in Figure 4-7. Referring to the lower part of Figure 4-8, which shows VSS variations, the main observation that can be made is that applying the stochastic solution becomes more significant than the deterministic approach as the degree of randomness is increased. This observation is illustrated by two shifts: one is toward the positive direction of the Y-axis and the second is to the left direction of the X-axis. The shift on the X-axis shows that the stochastic solution should be used at lower capacity factors as the severity of uncertainty increases. Similarly, the shift on the Y-axis shows the importance of using the stochastic solution as the CV becomes higher. This result should be expected because, as measured by

the VSS, the need for including the uncertainty in the formulation becomes more valuable as the degree of randomness increases.



**Figure 4-8: VSS and EVPI variation with  $P_{dg}$  contribution and coefficient of variation**

Similar observations are noticed for EVPI, as shown in the upper part of Figure 4-8. For each value of CV, the EVPI curve jumps abruptly to a particular level of renewable DG contribution then corresponds to the behaviour of EVPI curve shown in Figure 4-7. Analysis of the EVPI curves also



shows that the EVPI curves shift to the negative direction of the X-axis, as happened with the VSS curves when more varying renewable production is involved. This shift causes an increase in the values of EVPI at lower capacities of renewable generation. This indicates that acquiring information about intermittent generation is needed at earlier stages when CV levels increase. It is also important to notice the bigger spread of these curves along the X-axis as CV increases, which is also a new result.

#### **4.10 Summary**

In this chapter, a two-stage stochastic model was presented and used to solve the power procurement problem for a small system. The impact of the variation of renewable resources on the ability of a utility's operator to choose optimal procurements to supply the demand was studied using the proposed model. Furthermore, the model was used to explore the impact of uncertainty degree, which was represented by the coefficient of variation, on the optimal decisions to procure power to an LDC. Results show that applying stochastic approaches become more valuable when the uncertainty of renewable resources, or its degree, reaches specific levels. These particular levels depend on system demand profiles and on the prices of electricity purchased on the spot. The next chapter discusses the application of a stochastic approach to solve the procurement problem for large systems.

## Chapter 5

### The Power Procurement Problem: A Large System Case Study

When uncertainty is involved in a process, the risk of experiencing higher costs becomes a factor that should be considered. Stakeholders in the electricity sector face many kinds of risk such as regulatory, financial, and natural. To cope with risk, they either share its consequences or transfer it to a third entity to create a better working environment. In this chapter, the risk initiated by the uncertain production of renewable DG units is discussed and its impact on the solution of the power procurement problem is investigated for a realistic large problem.

This chapter is dedicated to investigating the impacts of risk associated with the inclusion of the energy produced from renewable DG units in the mix of power supplies. It introduces a formulation based on economic load dispatch (ELD) to solve the procurement problem for large networks with risk consideration. The last part of this chapter discusses the results of the studies conducted for different risk averse factors using the proposed risk model.

#### 5.1 Steps of Risk Evaluation:

There are four steps sequentially applied to quantify the risk associated with randomness, and to mitigate its impact. Four steps are commonly followed to evaluate risk related to the power procurement problem, they are

- 1- Building a business model
- 2- Identification of variables
- 3- Simulation
- 4- Interpretation of results and mitigation of risk.

The following is a description of these steps.

##### 5.1.1 Building a Business Model:

To compute the outcome of a procurement operation, a mathematical model is needed. Any of the power procurement models presented in the previous chapters can be used. They compute the optimum mix of the power components to supply the utility's demand at minimum cost. The model described in Chapter 3 is a deterministic formulation that requires a simulation technique such as the

Monte Carlo method to draw a probability distribution graph of the outcome. The two-stage stochastic model presented in Chapter 4 can be altered to include a risk measure and then it becomes capable of considering risk directly during optimization to find a solution to the power procurement problem. This model is chosen for applications in this chapter.

### **5.1.2 Identification of Variables:**

The purpose of this step is to limit the focus of the investigation to particular variables. Some of these variables are under full control of the decision maker, for example, position of switches to configure the network, setting of tap changer to control voltage, or transformation of demand to share the load equally among transformers. Other variables are not under the control of the decision maker; they are the main cause of uncertainty. In power procurement problems, electricity prices, renewable generation, customers' demand, and generation behind the meter are examples of this type. These uncertain variables need to be identified in this step and then a statistical model that represents the uncertainty is required to generate scenarios in order to run simulations.

Not all of the uncertain variables are significant. Some cause large variations in the objective of cost minimization and others have less impact on the cost function of the problem. A judgment based on sensitivity analysis using the business model is needed to select the most significant variables that affect the cost function. For the problem at hand, the most important causes of uncertainty are production of renewable DG facilities, prices of the electricity in the spot market, and variation of customers' demand. The reviewed literature considered the risk that resulted from the last two causes of uncertainty. Risk caused by renewable DG production has been overlooked so far. In this chapter, the focus is directed towards studying its impact on power procurement decisions.

### **5.1.3 Simulation:**

Depending on the selection of the business model, the simulation procedure will differ. If the model proposed in Chapter 3 is used, then repetitive computations are needed to observe the variations in the cost function and hence identify the risk. A commonly applied method is the Monte Carlo method in which the values of uncertain variables are generated from a statistical model. These values are then fed to the business model to calculate the outcome. After computing the objective, its value is graphed to show its variations as a function of the uncertain variables.

The simulation is used to build a relationship between the objective and the variables involved. The results are used to find the probabilities of exceeding particular limits set by the decision maker. A

common practice is to create a cumulative distribution function and its associated curve. These graphs are then interpreted to find the best risk mitigating strategy.

#### **5.1.4 Interpretation of Results and Mitigation of Risk:**

After completing the simulation, the results are assessed to infer conclusions and make decisions. A decision maker who looks for safer investments - known as risk-averse - will accept low risk choices. In contrast to the risk-averse investor is the risk-taker, who targets solutions with high expected gains, or lower costs, regardless the associated high risk caused by the wide variation of such choices. In general, the decision maker is looking at two main objectives: minimize the risk and maximize the benefits which might be interpreted in some cases as the cost minimization.

The last step in evaluating the risk is to mitigate its impact. Based on the strategy followed by the decision maker towards risk, several options can be followed. In this chapter, the mean variance approach is used to achieve an optimization model that presents a quantitative evaluation of risk in the daily activities of an LDC operator. The model provides the operator of local distribution company with a tool that helps solving the power procurement problem, i.e., finding the optimal mix of power that meets the demand and, at the same time, minimizes the risk of not fulfilling its duties.

## **5.2 Strategies for Dealing with Risk**

The strategies for mitigating the impact of risk could be divided into three main categories: applications of robust design, utilizing flexible options. When the uncertainty is too low, risk can be ignored. The following is a short description of these items [80, 81].

### **5.2.1 Robust Design**

Robustness in this context means choosing a solution that satisfies a significant number of values the uncertain variable may reach. Such a strategy might lead to acquiring a solution with higher cost due to the need to reduce the impact of uncertainty. It can be described as risk avoidance which is achieved by averting from or reducing the utilization of the uncertain variable even if it is more expensive to use. This goal can be satisfied by identifying the optimal alternatives that satisfy the decision maker's attitude towards risk with the existing information.

Another way for robust design to mitigate risk is by hedging risk by pooling a group of options with different characteristic of variation. In other words, combining diverse options with different risk

levels is the strategy followed in this tactic. It permits the decision maker to choose the options that minimize the overall risk of the selected alternatives.

When risk is beyond the financial capability of the decision maker, it can either be limited or shifted to a third party. In Ontario, for example, the risk of variation in prices of spot market is passed to customers where deferral and variance accounts are created for all electricity LDCs and used to reflect the electricity cost in its rates [82]. If the actual cost of the electricity is less than that paid by the customers, a credit will be given to the customers, or else a charge will be imposed on the customers' account. This amount of credit or charge, which is reflected in the electricity costs of the next period, represents the share of variance that is passed to the customers.

### **5.2.2 Utilizing Flexible Options**

Flexible options are adjustable or can be deferred and characterized by small, easy and economical commitments. Several small options can replace one large investment that contains a considerable risk to implement, or alternatives with short life time can replace a choice with long life span. To match uncertain futuristic changes, selecting solutions that can adapt to new technologies or circumstances become more attractive as compared to non-adaptable decisions. Sometimes waiting is the best option to avoid risk. For example, if a decision depends on the approval of a specific policy then acquiring more knowledge and waiting until the policy is passed is all that it needs to make a firm decision. Utilizing these strategies is better than robust design options because of the flexibility and adaptability characteristics associated with these solutions [80].

### **5.2.3 Ignoring Uncertainty**

If the risk is irrelevant or insignificant, it becomes better to ignore it. Sometimes the impact of uncertainty is negligible, the project itself is small, or when the cause of risk is well predicted then saving the time and cost to consider such risks is worth more than dealing with it. In summary, risk is investigated only when its impact becomes pronounced; otherwise, it can be ignored.

## **5.3 The Mean-Variance Approach**

The above mentioned strategies are common ways to manage risk for general applications; the selection of the method that fits a particular problem is important. For power procurement problem, the risk of experiencing high electricity prices is mitigated by signing bilateral contracts. Preferred results of following this strategy may not be achieved due to the unpredictable production of DG units

connected to the system. Yet this problem is still a hot research topic; some researchers have proposed the curtailment of DG production and others have suggested the utilization of storage systems [8, 83, 84]. Presenting a strategy to mitigate such risk is avoided in this thesis because it diverges from focusing on the bilateral contracts that is the main objective for solving power procurement problems. Instead, a model that solves for the optimum mix of power components that also provides a mechanism to consider risk of uncertain DG production is presented. The Mean-Variance approach is used to evaluate this kind of risk and the decision makers can use the results, from this model, and their own risk preferences to choose an appropriate decision.

The Mean-Variance optimization model developed by Markowitz offers a direct way to include two contradictory objectives; the mean of the benefits (or costs) and their variances (which is a measure of risk) [85]. The collective target of this model, described by the below equation, is to minimize the total risk while at the same time to maximize the expected return, or to minimize the expected cost, of the available options. The term that represents the mean shows the willingness of the decision maker to maximize expected returns, or minimize the cost. The second term, which includes the variance of the expected return, or cost, minimizes the probability of not achieving a favourable outcome. A balance, or compromise solution, between these two contradictory objectives depends on the decision maker's preference to deal with risk. The decision maker's ability to accept risk can be implemented by incorporating weighting factors in the combined objective function. The objective of the Mean-Variance optimization model can be formulated as follows:

$$Z = E(f(x)) + \theta \sqrt{Var(f(x))}$$

In the above equation,  $E()$  is the expected value of the utility function  $f(x)$  which is random due to the involved uncertainty. The standard deviation of the above function is shown in the second term, where  $\theta$  is the weighting factor that indicates the risk aversion characteristic of the decision maker. The goal is to minimize the expected cost while minimizing the deviation of the cost from its mean value. The weighting factor,  $\theta$ , scales the significance of minimizing the variance in the objective function  $Z$  as compared to the expected return which has unity scaling factor.

#### **5.4 Simplified Formulation of the Power Procurement Problem**

The application of the stochastic model, proposed in Chapter 4, to find a solution to the procurement problem of a large system creates some difficulties: the curse of dimensionality, integrality and nonlinearity.

The first obstacle is a consequence of discretizing the probability density function which is needed to use stochastic optimization techniques. For example, the number of equations and variables needed to formulate the procurement problem for the two-bus system are 41 and 49, respectively, when using the deterministic model while they become 123 and 203 when the stochastic formulation is used. The size of the problem increases exponentially as the number of scenarios representing the random parameters increase, sometimes to the point that the problem becomes intractable.

The need for including binary variables is a second source of complexity that must be included in the formulation of the power procurement problem. With the nonlinearity, this aspect categorizes the formulation of the procurement problem among the operation research problems that are hard to solve [86-88]. As a mixed integer nonlinear program, it is an NP-complete problem which is not solvable in polynomial time, i.e., not solvable in rational time [89]. Because it is so difficult to solve NP-complete problems in a reasonable time, it is common to use approximations to find near optimal solutions [89, 90].

The last obstacle is the need to use the highly nonlinear power flow (PF) equations. These equations can lead to difficulties in achieving an optimal solution or even infeasibility may result, because they contain a quadratic components resulting from the multiplication of the voltage magnitudes and a cyclic component created by the sine and cosine terms as shown in Eq. (5-1). The feasible region for a large distribution system consists of the intersection between as many planes, described by similar equation, as the number of buses in the system. This means that the feasible region of this set of equations is complex, and, when binary variables are included, it becomes a nonconvex problem. If a linearization of LF equations can be achieved for distribution systems, solutions of optimization models that employ these linearized equations become much easier to obtain.

$$P_{1_{inj}} = V_1 \cdot V_1 \cdot G_{1,1} + V_1 \cdot V_2 \left[ G_{1,2} \cdot \cos(\delta_1 - \delta_2) + B_{1,2} \cdot \sin(\delta_1 - \delta_2) \right] \quad \text{Eq. (5-1)}$$

Several methods are available to linearize power flow equations. These methods rely on several assumptions that depend on the aspects of the system. The first characteristic is the fact that the values of both the voltage magnitudes and phase angles are contained in a narrow range of operations. Another reason for making this linearization valid is the relative values of resistances of the transmission lines are much less than the values of the reactances. Although the voltage magnitudes

and phase angles are in a small range, distribution systems' parameters make the second reason for linearization not applicable. Hence, applying these methods to simplifying power flow equations for distribution networks becomes incorrect. Therefore, the approach that should be followed needs to be based on other strategies and aspects of the problem.

The three barriers to solve optimally the procurement problem, mentioned above, should be deeply analyzed to reach the best possible approximation. Firstly, solving the procurement problem using stochastic techniques requires a number of scenarios to represent the uncertainty. In this regard, the larger the number of scenarios, the more accurate the representation of uncertainty will be. Therefore, it is beneficial from the formulation perspective to include as many scenarios as possible. Secondly, the aspect of selecting the bilateral contracts is achieved by introducing binary numbers. This property cannot be avoided because it is required to select/deselect a candidate contract. Hence, thirdly, the attention should be refocused on the nonlinearity as a reason that complicates the process of finding a feasible solution for a large system.

The core goal of solving the power procurement problem is to find the optimal amounts of power and to select the sources of these amounts to supply the network. Therefore, the need for a detailed model to represent the electrical network can be revisited, especially if all what the detailed model provides is computations of losses which represent, at most, 5% of the system's demand. Because voltage magnitudes are mainly controlled by transmission system operator and are well managed, in most of the time they fall in a tight range, and calculating their levels can be ignored. Phase angles of bus voltages are not as significant in distribution systems as they are in transmission/generation levels. Depending on these reasons, the load flow equations can be eliminated from the model's formulation without perturbing the essence of the objectives of the solving power procurement problem. A detailed power flow model can be applied on the spot after computing the values of the bilateral contracts and then losses can be minimized as an objective. Following is the proposed simplified model.

#### **5.4.1 Economic Load Dispatch-Based Model for Power Procurement Problem**

Traditionally, Economic Load Dispatch (ELD) is used to dispatch available generators to supply a system's load such that the operating cost of these generators is a minimum. Although the ELD concept is typically utilized in sharing the demand between generating units at the transmission level, its implementation in distribution systems for solving the procurement problem and associating its formulation with the evaluating of bilateral contracting has not yet been reported.



Essentially, the two-stage stochastic model suggested in Chapter 4 to solve the procurement problem is the most suitable one if the obstacles mentioned above are solved. Hence, this model is the core of the simplified ELD model, with the only exception being the omission of the power flow equations. This deletion of power flow equations is because of their significant contribution to the difficulty of finding a solution. Therefore, the resulting formulation becomes a mixed integer non-linear problem which considers randomness and risk associated with integrating renewable power production.

This elimination has led to two-fold benefits although the losses have been ignored. The first benefit of this elimination is a reduction of the execution time. Because the constraints of the proposed model are linear, a huge reduction in the computation time was observed. This outcome allowed for utilizing a larger numbers of scenarios, improving the representation of the uncertainty, which is the focus of the proposed model. The second is a considerable simplification of the model resulting in a significant reduction of the variables required to formulate the procurement problem. Because of this elimination, the need to include the voltage magnitude, phase angle, and injected power was avoided. The power balance constraint, which should be maintained at all times and for all scenarios, is now changed into a linear function as a consequence of deleting the terms of injected power. This constraint is still an equality constraint that describes the equilibrium between the demand on one side and the power to be procured from the different resources plus the power injected into the system on the other side. The objective function and the rest of the constraints remain unchanged from the original model shown in the previous chapter. This step changes the model into a mixed integer nonlinear (quadratic) program (MINLP) that is tractable and solvable. The nonlinearity now resulted from the second order term added to the objective function to account for the risks imposed by the uncertainty. The following is a mathematical formulation of the proposed simplification.

$$\text{Min } [E(\text{Cost}) + \theta \cdot \sqrt{\text{Var}(\text{Cost})}] \quad \text{Eq. (5-2)}$$

Where,

$$\text{Cost}(P_b) = \sum_{i=1}^{N_b} \sum_{c=1}^{N_c} \sum_{t=1}^T P_b(i, c) * \lambda_b(i, c)$$

$$\begin{aligned}
\text{Cost}(P_s) &= \sum_{s=1}^{N_s} \left[ \sum_{t=1}^T P_s(t, \omega_s) * 1.0 * \overline{\lambda_s(t)} \right] \cdot P_r(\omega_s) \\
\text{Cost}(P_o) &= \sum_{s=1}^{N_s} \left[ \sum_{t=1}^T \sum_{k=1}^{N_{dg}} P_o(k, t, \omega_s) * (1 - \alpha) * \overline{\lambda_s(t)} \right] \cdot P_r(\omega_s) \\
\text{Cost}(P_c) &= \sum_{s=1}^{N_s} \left[ \sum_{t=1}^T \sum_{k=1}^{N_{dg}} P_c(k, t, \omega_s) * (1 + \alpha) * \overline{\lambda_s(t)} \right] \cdot P_r(\omega_s) \\
\text{Cost}(P_{surplus}) &= \sum_{s=1}^{N_s} \left[ \sum_{t=1}^T \sum_{k=1}^{N_{dg}} P_{surplus}(k, t, \omega_s) * (1 + \beta) * \overline{\lambda_s(t)} \right] \cdot P_r(\omega_s) \\
\text{Cost}(P_{deficit}) &= \sum_{s=1}^{N_s} \left[ \sum_{t=1}^T \sum_{k=1}^{N_{dg}} P_{deficit}(k, t, \omega_s) * (1 + \beta) * \overline{\lambda_s(t)} \right] \cdot P_r(\omega_s)
\end{aligned}$$

Subject to

$$\begin{aligned}
\sum_{c=1}^{N_c} \sum_{i=1}^{N_b} P_b(i, c) + P_s(t, \omega_s) + \sum_{k=1}^{N_{dg}} P_o(k, t, \omega_s) + \sum_{k=1}^{N_{dg}} P_{deficit}(k, t, \omega_s) \\
- \sum_{k=1}^{N_{dg}} P_{surplus}(k, t, \omega_s) = P_{demand}(t, \omega)
\end{aligned} \tag{5-3}$$

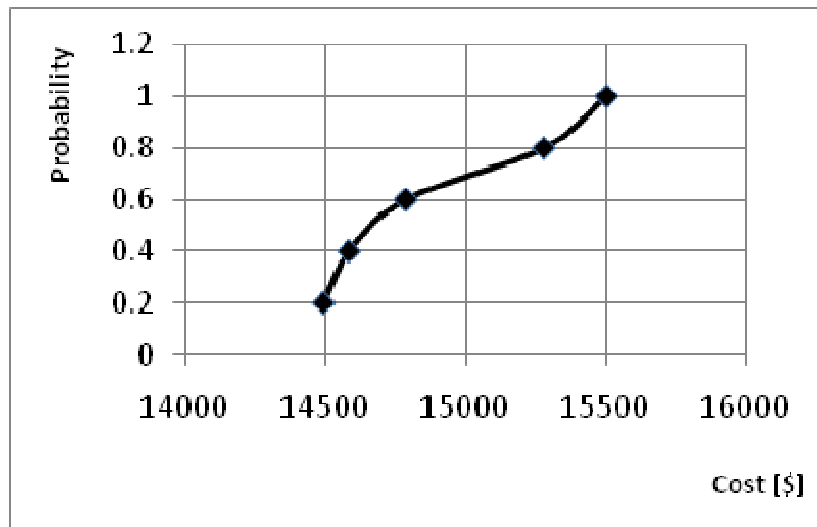
$$P_o(k, t, \omega_s) + P_c(k, t, \omega_s) = P_{dg}(k, t, \omega_s) \quad , \text{ for all DG units} \tag{5-4}$$

In summary, in the above model, the voltage magnitudes, the angles, and the reactive power are eliminated from the formulation. This elimination resulted in an easier to solve optimization problem, and allowed for more scenarios to be included, reduced the execution time, and provided an ability for further options to be included in the objective function discussed next.

## 5.5 The Mean-Variance Model for the Power Procurement Problem

When ignoring risk, such as in the formulation proposed in Chapter 4 by the equations Eq. (4-23) to Eq. (4-30), a variation of the targeted objective occurred. By reviewing these equations, it can be observed that this formulation includes only the expected value of the cost function without

considering any form of risk evaluation. Such modeling of the procurement problem results in an optimal mix of power components without an assurance of realizing the targeted objective. The reason for not guaranteeing the outcome is the variation of the solution's outcome as a function of the randomness. For example, the procurement cost for the two-bus system from before can be as low as \$14500 and may reach up to \$15500. This range is shown in Figure 5-1, where the cumulative density function (cdf) was traced for the small system when five scenarios were considered to represent renewable DG power production. Despite the small range of variation, its value increased with the increase of deviation of power generated from renewable resources. The cdf shown in Figure 5-1 was obtained with consideration of DG production alone. Another important source of variation is the electricity prices which were not considered here but it would have been trivial to include. In practical systems, the chance of not realizing the targeted costs becomes larger, which leads to risk in a utility's short and long term plans. The following describes the additions needed to overcome this deficiency in the two-stage stochastic model proposed in Chapter 4 but adapted here with the mean-variance function to consider risk.



**Figure 5-1: Cumulative density function of the power procurement cost for the two-bus**

Application of this model to the power procurement problem is straight forward with little changes needed to create a bi-objective two-stage stochastic model similar to the formulation presented by Eq. (4-23) - Eq. (4-30). The first term of the objective function of the proposed model is the same as that described by Eq. (4-23):  $E(\text{cost})$ . This part of the objective function represents the decision maker's

goal to minimize the expected procurement cost. To include risk, a second term should be added. There are several ways to include risk, the standard deviation, the square root of variance, is chosen in this thesis for this task [91]. The following equation describes this term.

$$Var(Cost) = E(Cost^2) - [E(Cost)]^2 \quad \text{Eq. (5-5)}$$

where

$$E[(Cost(\omega_s))^2] = \sum_{s=1}^{Ns} (Cost(\omega_s))^2 * Pr(\omega_s)$$

In equation Eq. (5-5), the first term stands for the expected value of the square of the cost function and the second term is the square of the expected cost mentioned in Eq. (4-23). The outcome of equation Eq. (5-5) is the variance of the cost function; the square root of this equation is the standard deviation of the cost function and illustrates the variation of the procurement costs.

This new bi-objective function differs from Eq. (4-23) in two ways: it considers risk, and it contains a multiplying factor  $\Theta$  to weight risk aversion behavior. Higher value of this factor means more averse behavior of the decision maker. The constraints listed in Section 4.7 remain untouched except for the omission of load flow equations. The resulting model is an MINLP formulation that solves for the optimal mix of power components to supply a utility's demand and assures the deviation from the obtained expected cost is also minimal.

## 5.6 Case Study: Solving the Procurement Problem with Risk Consideration

In this section, an optimal electricity procurement mix and risk associated with power injections of renewable DG facilities to the network were evaluated for an electricity serving company. After adding the risk term, the two-stage stochastic model discussed in section 5.4 is employed in these studies. In this model, the demand was supplied mainly from the two markets: bilateral and spot, and the only source of uncertainty was the variation in the renewable DG power output. Under these circumstances, the goal was to minimize the operating costs, and at the same time, to minimize the risk. With a risk level, acceptable to the decision maker, the model can assure a minimum expected operating cost. The model provides an effective tool to manage the networks' short-term operating costs in a restructured power systems environment.

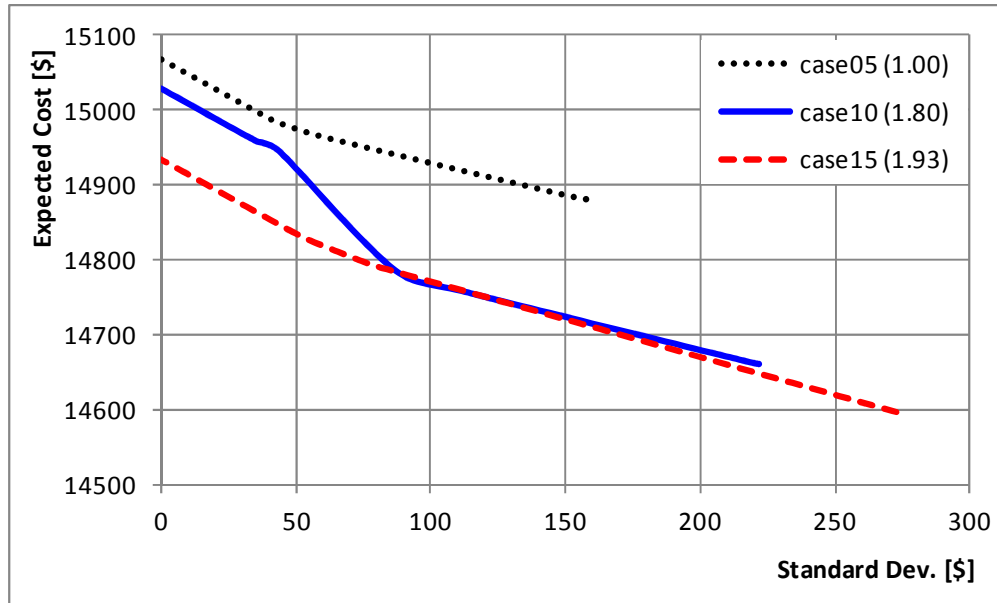
In order to illustrate how risk affects the optimal solution for power procurement problem, the same example system studied in Chapter 3 is used. As in Chapter 3, the impact of variable power from renewable DG on the optimal power procurement mix to supply the LDC's demand was investigated in two dimensions: Risk attitude of the decision maker and DG penetration level. The factor  $\Theta$  introduced to weigh the risk term in the objective function was varied from high to low values. Varying  $\Theta$  resulted in different optimal pair of values: mean and variance from which the standard deviation was computed. These pairs were then plotted on an x-y plane for the decision maker to decide the level of power mix to be procured and the associated risk.

The other direction that affects the solution of the power procurement-risk model and included in the study is the capacity of renewable generation connected to the system. The renewable DG power contribution was scaled by a capacity factor to alter the penetration of renewable DG power production in the system. Hence, the power procurement solution was studied with two dimensions to investigate: the attitude of the decision maker towards risk, and the installed capacity of the renewable DG as shown in the following set of graphs.

Five figures, Figure 5-2 to Figure 5-6, illustrate the mean-variance frontiers were calculated, when solving power procurement problem, for the system under consideration. Each graph illustrates a relationship between the expected cost depicted on the Y-axis and the risk, which is represented by the standard deviation of costs on the X-axis. As can be seen in these figures, the curves follow the same trend: downward sloping. This interprets the real live behavior; if risk minimization is the prime objective, then higher expected costs are likely to happen. If the objective is switched to reduce the expected cost, then more risky choices would be accepted. Based on renewable DG capacity, this group of graphs was divided into three categories: low, high and medium.

The results obtained for low contribution levels of DG are shown in Figure 5-2. As observed from these curves, low risk decisions shown at the left side of the graph involve high cost to procure power. The mean-standard deviation pairs used to produce these parts of the graphs were calculated when the renewable DG capacity factor was below 2.0 and combined with low values for the factor  $\Theta$ . As it can be seen from Figure 5-2, increasing the capacity of the installed renewable DG units leads to a decrease in the curve level. This confirms the results obtained in Chapter 4, the increase in the penetration of the renewable DG production reduces the procurement cost for a certain range. At these capacities of DG penetration, the negative impact of selecting the optimal mix and associated cost was still minor, as measured by the differences between the curves. For the same cases shown in

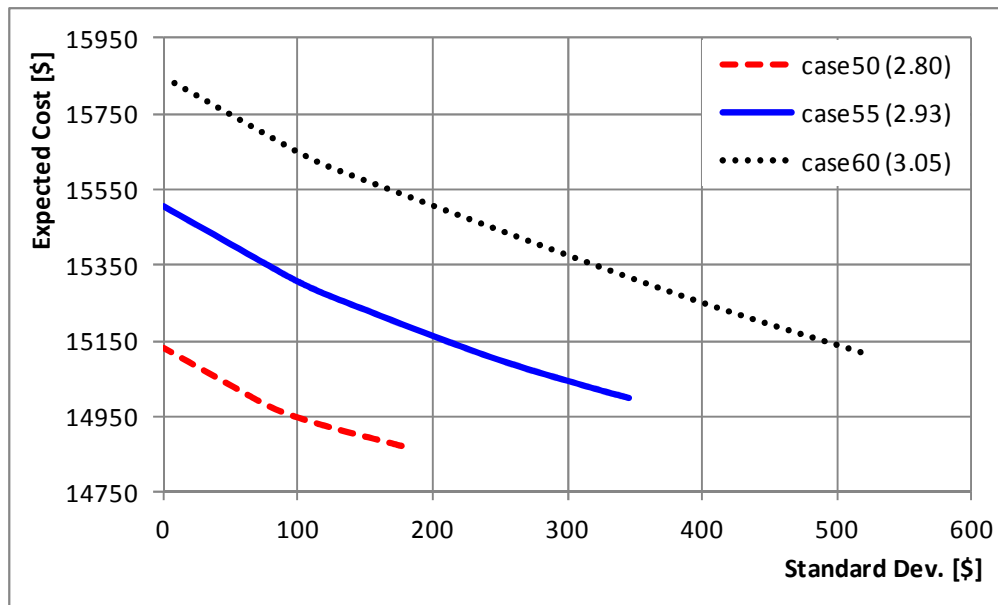
Figure 5-2, however, an early sign of inversion of this observation can be seen if the decision maker becomes more risk averse. After a particular level of  $\Theta$ , the two lower curves become identical. This observation becomes clearer at high levels of DG contributions as shown in the next set of figures.



**Figure 5-2: Mean-standard dev. frontiers as function of DG capacity**

At high capacity levels of renewable units, where the capacity factor is equal to or greater than 2.8 ( $\geq 2.8$ ), the curves are smooth and well predicted. The risk-expected cost behavior is consistent with Markowitz theory, but opposite to the previous observation of Figure 5-2. The curves in these case studies move toward higher values as the DG contribution increased see Figure 5-3 and Figure 5-4. These results show that any addition of power from renewable DG units increases the expected cost of power procurement for the electricity service company. As noticed in the figures shown in Section 3.9, the additional cost is incurred because optimal bilateral contracts were rejected due to contributions from renewable DG facilities. At the same time, if risk is not considered or made a second priority, higher costs could result due to higher deviations. These observations need to be considered when the distribution system operator computes the amounts of power procured to meet

the demand of the network. Also, the risk level (scale of x-axis) increases when there is a higher DG contribution.



**Figure 5-3: Optimal risk frontiers for a large system at high contributions from DG units**

The outcome related to the third category, medium DG capacity levels, is illustrated in Figure 5-5 and Figure 5-6. Despite the coherent trend of these curves with the other two categories, they do not follow a particular tendency. In Figure 5-5, for example, the frontier labeled case-20 with 2.05 capacity factor, the expected cost is about \$15200 at very low degree of risk. For the same system the cost sunk to less than \$15000 for just a little increase of DG capacity, as much as 0.13 (case 25). When the DG capacity is increased another 0.12 to reach 2.3 (case 30) the cost at zero risk (or very low) remain unchanged. For the three capacity levels shown in Figure 5-5, the frontiers become almost identical if the decision maker becomes more of a risk taker, as seen in left part of this figure. Similar conclusions can be extracted from Figure 5-6.

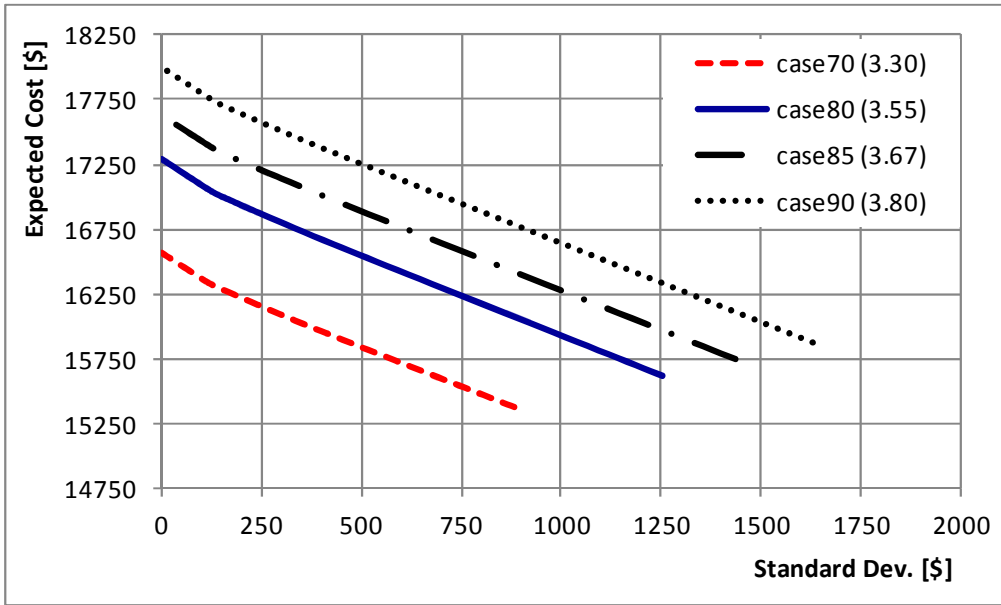


Figure 5-4: Efficient frontiers at high capacities of connected renewable resources

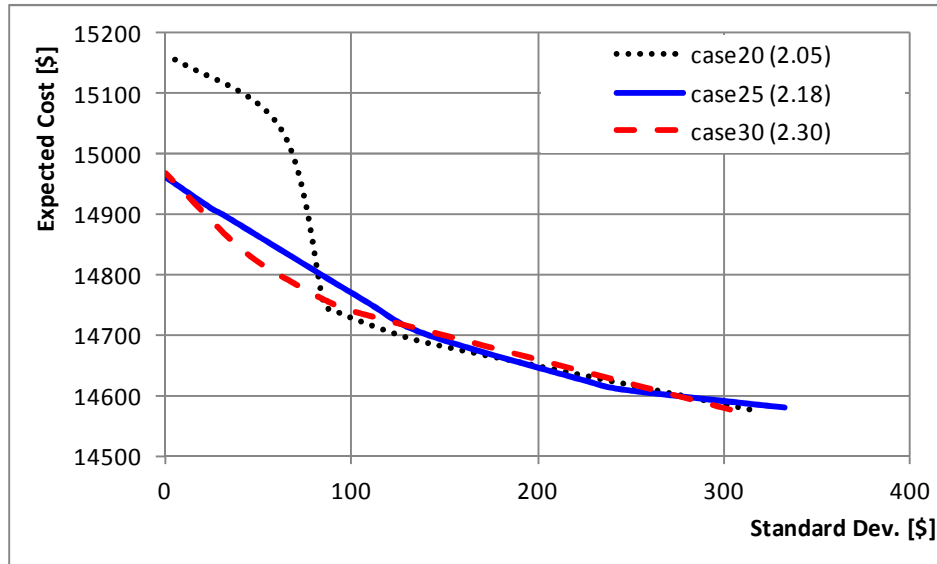
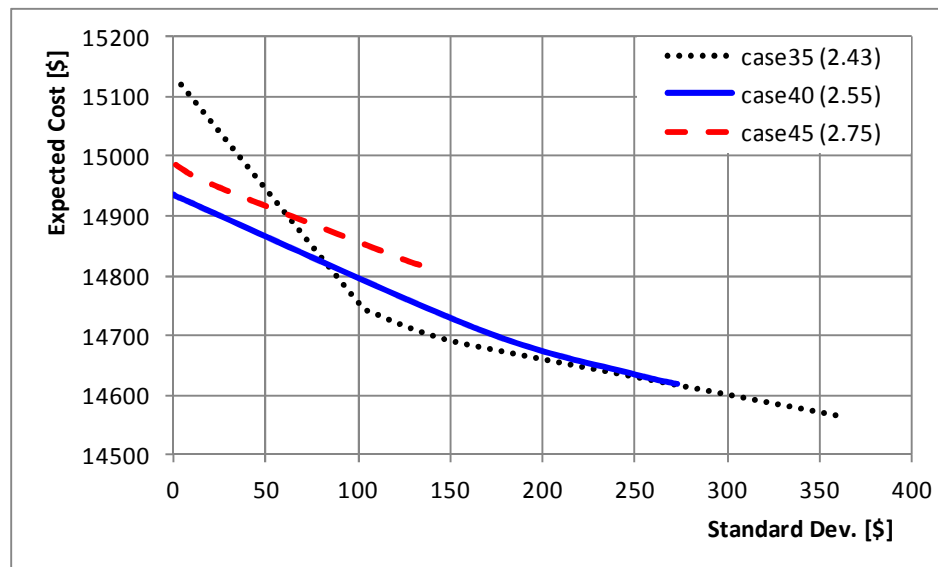


Figure 5-5: changes in Mean-Standard dev. with different DG capacities



The curves shown in Figure 5-6 have some similarities of those illustrated in Figure 5-5. In both figures, the curves intersect with each other, showing a change in the frontier's behavior. This change can be referred to the impact of the production from renewable units and also due to the nonsmooth properties introduced to the model by integer variables of the bilateral contracts. It is known that power injection to the electrical system will be beneficial to the network's operation up to a particular level, after which such injection will be disadvantageous to the system. This has been noticed in the studies discussed in Chapter 3, and what is illustrated by the figures in this chapter is another observation of the same conclusion. Another factor contributed to this change in the behavior of the frontiers was the risk factor,  $\Theta$ , introduced to consider the significance of the risk in the objective function.



**Figure 5-6: Risk versus expected cost for small distribution system**

## 5.7 Summary

A simplified Markowitz model was presented in this chapter to compute optimal procurement decisions for an electricity service company. Although the model ignores the losses of the system by omitting the power flow equations, the results obtained in the chapter were similar to those obtained in Chapter 3 and Chapter 4. By utilizing the simplified model, 35 scenarios for each renewable DG

unit were included, with the ability to add more scenarios. Consideration of such a number of scenarios was not possible to incorporate in the formulation if detailed power flow model was used.

Another benefit of the simplified formulation is that the problem became solvable and tractable. The reason for this was that the non-linearity found in the simplified model is only one quadratic term in the objective function while a larger number of complex nonlinear constraints were included in the full formulation. It can be concluded that the accuracy sacrificed due to ignoring losses has been outweighed by the resulting benefits to solve a complex problem like the power procurement model. This conclusion can be relied on to justify the utilization of the simplified model to make an economical evaluation of alternatives available to operator to supply the network's demand.

## **Chapter 6**

# **Assessment of Renewable DG Production Impacts on the Supply Voltage Magnitudes**

This chapter is dedicated to studying technical issues caused by the variation of the output of the renewable DG facilities connected to a local distribution network. It investigates the impacts of installing different renewable DG units on voltage profiles of an existing distribution network. A Monte Carlo technique is applied focusing on the voltage profile by solving the steady state load flow model. The chapter presents a new application for two known power quality measures, namely: System average rms variation frequency index (SARFI) and the probability of voltage magnitude violation. This method can provide a quantitative indicator of power quality to the decision maker that describes the expected effects on the voltage of a feeder. Since the issue investigated in this chapter is technical, it complements the work presented in this thesis regarding the economical concerns about the introduction of renewable energy into local distribution networks.

After an introductory section which focuses, as an example, on procedures followed in Ontario to encourage new installations of renewable resources, a description of the applied algorithm to judge these new applications is provided. Thereafter, a description of the probabilistic load flow and the fundamentals of the proposed evaluation process are discussed. The last two sections present results of the case studies.

### **6.1 Introduction**

The present installed capacity of wind power generation in Ontario is more than 1600 MW as compared to 15 MW in 2003 [73]. For example, in just three continuous days, Ontario's renewable power generation, wind and solar, produced over 1000 MW and such a generation pattern is frequently observed during the last two years [73]. The Green Energy Act (GEA), passed on 2009, is targeting to harness 10 GW of renewable power by the year 2015 and to reach 25 GW by 2025.

Recall that only after the GEA, gives local distribution companies (LDCs) in Ontario the right to possess and operate a generating facility with capacity up to 10 MW per location [92]. Previously, LDCs transferred energy from the transmission level to low voltages and charge the consumers for the service.

The benefits from the GEA may not be easy to achieve unless a well-designed system addressing the unique nature of renewable resources is implemented. Due to the uncertain characteristics of these generating units, the power produced by wind turbines or photovoltaic systems may affect the operational aspects of the electrical network. It is expected that most of the investor-owned DG units, rated at 10 MW or less, will be connected at the distribution level. Hence, LDCs need to investigate the technical impacts of injecting production from these units into their electrical systems.

## **6.2 Algorithm description**

Monte-Carlo methods have been applied in distribution systems' studies to investigate variations of demand, DG, either wind farm or PV system production, voltage control actions, and system re-configuration [65, 93-95]. These studies were aimed at operational objectives that included coordinated operation of voltage control devices, or targeted planning goals such as sizing of DG capacity. In the application presented in this chapter the Monte Carlo method is used to represent the variations of power production from renewable DG units installed at the distribution level. The aim of this simulation focuses on the voltage profile along a distribution feeder.

The input information to the algorithm is divided into two parts: measured and calculated. Historical demand data, wind power, temperature, and irradiance were used. From the meteorological measured data, PV system output was calculated. The first two elements of data were collected from a local distribution company and a wind farm close to the Region of Waterloo. The PV power output was computed from the last two elements of historical data available at the University of Waterloo. The correlation between the parameters used in the studies and the data elements utilized in the simulation was considered by collecting this information from geographically close locations in Southern Ontario and within same time frame. Because the focus was on presenting a methodology, not to investigate the impact on voltage variation of a particular feeder, a scaling process was needed to match the exemplary feeder's electrical parameters.

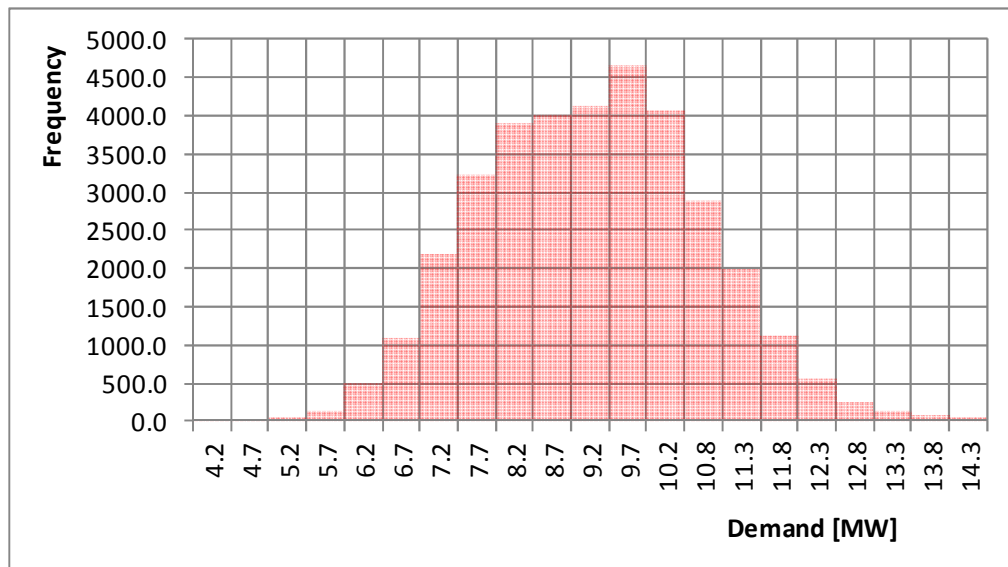
The following series of steps are applied to determine whether a new DG unit is acceptable for connection or not based on its output ability to affect the quality of supply voltage. First the procedure is stated without detailing the computations of the power quality measure and later the equations needed to complete the calculations are described.

### 6.3 Data Preparation and Post Analysis Criteria

Before simulation, input data need reformation and calculations of post-simulation require identification. The next subsections describe the steps required to prepare the input data to perform the computations for simulating the quality of supply voltage.

#### 6.3.1 Feeder Description

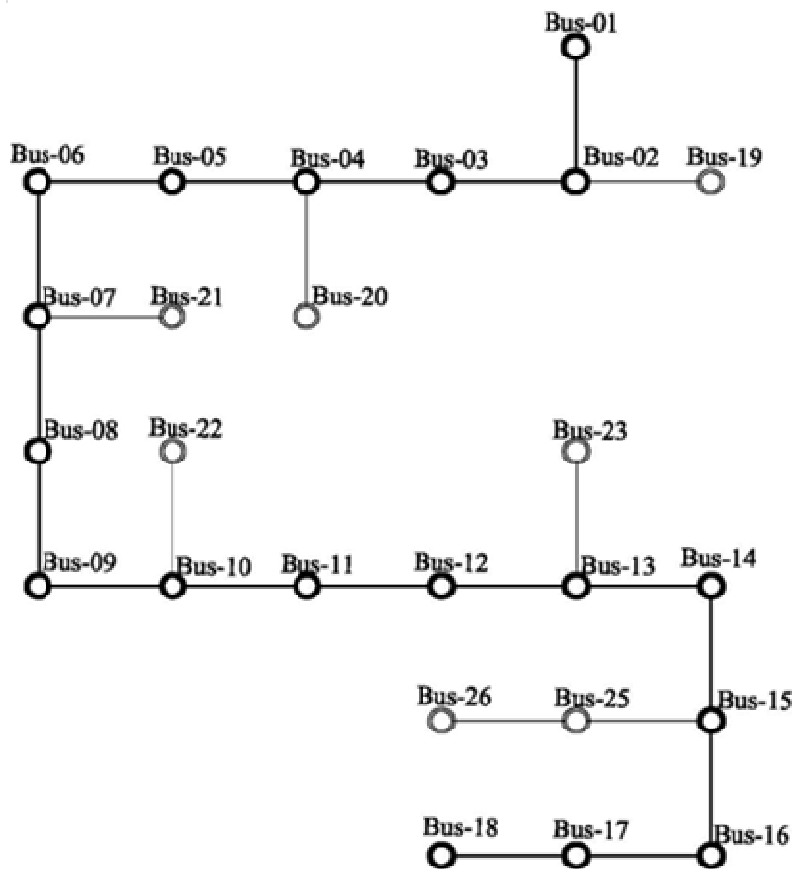
A representative distribution feeder was selected from a network that belongs to a local distribution system. The distribution feeder was chosen based on an application submitted by an investor for installing a new photovoltaic system at the feeder's remote end. The voltage level of this sub-system was 27.0 KV, and the maximum connected active and reactive power demands were 14.3 MW and 7.6 MVAR respectively. A histogram of real power demand is presented in Figure 6-1. This demand varies during the year between peak and off-peak seasons. At low demand season, the consumption of real power becomes as low as 4.3 MW, while the average power is approximately 9.0 MW. Later, in this chapter, a wind based resource is added to the system to obtain a comprehensive investigation of the presented application. Also, different capacities of renewable resources were included in the studies conducted in this chapter on this representative distribution feeder.



**Figure 6-1: Histogram of system real power demand**

The single line diagram of the feeder as modeled in this study is depicted in Figure 6-2. The feeder includes 26 buses and 6 laterals connected in a radial configuration. The total length of the wires is

approximately to 35 Km of overhead lines, mostly of three different types of conductors. The interconnections with the other supplying substations through adjacent feeders of the distribution network are not included in this study. Most of the time, the power is supplied from Bus-01, and occasionally from two other main substations due to short-term supply interruptions or maneuvering requirements for operational reasons. The locations of renewable DG units are assumed to be connected at two locations along this distribution feeder.



**Figure 6-2: Single line diagram of the exemplary distribution feeder**

### 6.3.2 Description of Case Studies and Applied Assumptions

The studies conducted in this chapter focused on two scenarios. The first case study was conducted to observe the impact of connecting a new PV system to an existing distribution feeder. The second

case study was executed on the same feeder with two renewable DG units in service: a PV system producing power during the day, and a wind power generator that injects power as long as wind blows. The capacities of the two resources were varied to observe their output randomness on the voltage profile and illustrate the change in the quality when additional renewable resources are added to the network.

To evaluate the consequences of the DG production on the operational voltage level, some assumptions were introduced. The first assumption is related to the existence of voltage regulating devices. It was assumed that the voltages of buses along the feeder were not controlled at any bus; hence, no voltage regulators exist in the feeder under study. Also, at the main substation, Bus-01, the reactive power injection can vary corresponding to the feeder's demand (i.e., slack bus). In section 6.3.4, this assumption is modeled and described mathematically. The second assumption was related to the location of renewable DG units. At the beginning, only one DG was connected at bus-18, as requested by an investor. Another wind based DG unit was connected to Bus-23, injecting power into the system through Bus-13.

A third assumption was related to the busbar modeling for formulating the power flow model. All buses, except Bus-01, are considered load buses. This assumption was made to comply with the IEEE-standard 1547, where, it is recommended that DG units not participate in voltage control by providing or consuming reactive power [96]. This was also in favor of the investor, whose main interest was to produce and sell active power. Although the renewable resources produce active power because they cannot exchange reactive power this representation is the most suitable way to follow.

The fourth assumption was related to the protection of the feeder at the main substation Bus-01. Reverse power protection allows back feed of both active and reactive power, if a surplus of power is available during off peak periods, to the transmission system via power transformers located in this substation. Finally, neither abnormal operation nor the impact of DG locations was introduced for investigation since the purpose of this chapter was only to study the outcome of accepting new connections of renewable DG facilities to distribution systems.

Given the above assumptions, three case studies using various DG capacities were conducted. The capacities were chosen as follows: DG with a capacity of 1MW is connected to bus-18, and then the capacity was upgraded to 4MW and 7.25 MW, respectively. Additionally, a base case study, that is, the original system with no renewable resource, was simulated. This sequence was arbitrarily

designed to investigate the system status before the connection of the DG, and after the installation of the renewable DG resources with different contribution levels. When a second resource was connected, the same capacities were used.

### 6.3.3 Calculation of PV Farm Generation

The computation of the power generated from a PV system is carried out by direct usage of historical weather information. Another way is by estimating the irradiance, based on a probability density function, and then calculate the PV output [93]. Applying the following set of equations, Eq. (6-1) to Eq. (6-5) [97], the PV production was computed using weather parameters measured at a weather station that belongs to the University of Waterloo.

$$T_{cell} = T_a + I_{\beta} \left( \frac{NOCT - 20}{0.8} \right) \quad \text{Eq. (6-1)}$$

$$I = I_{\beta} [I_{sc} + K_i (T_{cell} - 25)] \quad \text{Eq. (6-2)}$$

$$V = V_{oc} - K_v * T_{cell} \quad \text{Eq. (6-3)}$$

$$P = N * FF * V * I \quad \text{Eq. (6-4)}$$

$$FF = \frac{V_{MPP} * I_{MPP}}{V_{oc} * I_{sc}} \quad \text{Eq. (6-5)}$$

Where,

- $T_{cell}$ : Cell temperature  $C^{\circ}$
- $T_a$ : Ambient temperature  $C^{\circ}$
- $I_{\beta}$ : Solar insolation ( $kW/m^2$ )
- NOCT: Cell temperature in a module when ambient is  $20C^{\circ}$ , solar irradiation is  $0.8 kW/m^2$ , and wind speed is  $1 m/s$
- $I_{sc}$ : The short-circuit current
- $K_i$ : Current temperature coefficient  $A/C^{\circ}$
- $V_{oc}$ : The open circuit voltage
- $K_v$ : Voltage temperature coefficient  $V/C^{\circ}$
- FF: Fill factor; the ratio of power at MPP to the product of  $V_{oc}$  and  $I_{sc}$
- $V_{MPP}$ : The voltage at the MPP
- $I_{MPP}$ : The current at the MPP



The load current and terminal voltage of a PV cell can be calculated as functions of ambient temperature, sun irradiance, and specifications of the cell itself. The first two elements of data are available at many locations, and the cell information can be found at websites of the PV cells' manufacturers. These equations give good estimate of PV production that considers the effect of temperature on cell current and voltage. Such a computation procedure provides more realistic values for the PV farm than then using a density function to estimate irradiance and then calculate the generation of the PV farm.

The calculations are conducted to compute the PV output power by the hour for four years. The outcome is a matrix of 8760 by 4, which is matched with data for: the wind power generation. Available historical loading data for the same time period has been synchronized with the time frame of the weather information. Generation patterns from a wind farm located in a geographically close location to the region, and for the same time frame, are used in the problem modeling. The unified time frame and geographical locations of the measured historical data eliminated the concern about the correlation between the demand, output of renewable units and about the joint probability distribution. The accuracy of the input data depends mainly on the precision of the set of equations given above and on the measurement of historical data. After setting the input data, an initial solution is provided for solving the load flow of the first iteration.

#### **6.3.4 Optimal Power Flow Model**

This section describes a mathematical formulation based on the optimal power flow (OPF) to solve the load flow problem for a distribution feeder. The motivation to apply OPF is the physical structure of the electrical distribution network, i.e., its radial configuration. OPF is a powerful tool to compute minimum operational cost and to calculate voltages and line flows associated with a specified objective. In this section, the power flow problem for a distribution feeder is simulated as an OPF problem to avoid complications caused by the system's configuration.

The traditional power flow model cannot be successful in solving distribution system's load flow. The radial configuration of such networks results in an ill-conditioned Jacobian matrix and hence the load flow solution diverges. In contrast to economic studies, in which system losses may not be significant, linearization of load flow for a distribution system to solve a technical issue is not practical. A linear model such as decoupled load flow is based on assumptions that are not valid for distribution networks. Also, such linear models cannot be used to calculate voltage magnitudes which are the main goal of the study needed in this chapter. Algorithms provided for solvers of nonlinear

optimization problems can because overcome such obstacle and a solution can be achieved. OPF, as a nonlinear model, is applied of the availability of special algorithms that can handle ill-conditioned Jacobian matrices.

OPF model, as an optimization problem, consists of two main parts: the objective function and constraints. For the distribution feeder where there is only one input to the system and no other generator, the objective function could be any dummy variable or a constant, because there is no option to supply the network's demand but from that single source. To neutralize the effect of the objective function in the OPF model applied in this chapter, power produced from DG facilities is defined as a parameter, for two reasons: the first is to avoid interference that comes from the objective function, and the second is because of the lack of controllability over the output of renewable DG units.

In the formulation used in this chapter, described below by equations Eq. (6-6) - Eq. (6-11), constraints define the operating point of the distribution feeder and the optimized objective function was a fixed number. Basically, two main sets of equations were needed: real and reactive power flow equations. However, an additional set was required to comply with the current standards of DG operation. The reactive power injected by the DG at the point of common coupling was eliminated in Equation Eq. (6-8), so no reactive power could be contributed by the renewable DG unit. Also, voltage magnitudes were allowed to change within a wider range than the normal operation in order to observe their variations. The optimization solver MINOS has been used to find the solution for the load flow model described by the equations Eq. (6-6) to Eq. (6-11) [98]. These computations were repeated for every hour, and the total time period for study was four years. After completing the iterations, post analysis was conducted to investigate the effect of the renewable production on voltage profile of the hosting distribution system.

$$\min(100) \tag{Eq. (6-6)}$$

$$\text{s.t.} \quad P_s(i) + P_{DG}(i) - P_{inj}(i) = P_d(i) \tag{Eq. (6-7)}$$

$$Q_s(i) - Q_{inj}(i) = Q_d(i) \tag{Eq. (6-8)}$$

$$V_i^{min} \leq V_i \leq V_i^{max} \tag{Eq. (6-9)}$$

$$P_{inj}(i) = V_i * \sum_{j \in N_b} [V_j * G_{ij} \cdot \cos(\delta_i - \delta_j) + V_j * B_{ij} \cdot \sin(\delta_i - \delta_j)] \quad \text{Eq. (6-10)}$$

$$Q_{inj}(i, t) = V_i(t) * \sum_{j \in N_b} [V_j * G_{ij} \cdot \sin(\delta_i - \delta_j) - V_j * B_{ij} \cdot \cos(\delta_i - \delta_j)] \quad \text{Eq. (6-11)}$$

The aim of the above mathematical program is to solve the power flow equations hence a scalar is used in the objective function. Constraints Eq. (6-7) and Eq. (6-8) are, respectively, the active and reactive power balance equations, which guarantee the equilibrium between the input and output power of the bus. Equation Eq. (6-9) represents the voltage limits constraint while the last two equations describe the active and reactive power flow equations which were discussed in Chapter 5.

### 6.3.5 Post simulation analysis

Statistical representation of the results is the final step in Monte Carlo simulation. Both the mean and variance are computed from the solutions obtained from the simulation. Based on these values, probabilities of violations are computed to help evaluate decisions and designs of new candidates of renewable DG. In this way, the impact of renewable DG production on the power quality of the distribution network can be assessed.

Because of the random nature of energy supplied by DG units, LDC operators are hesitant to accept such new connections. EN-50160, IEEE- P1564, and IEEE-P1159 have included several voltage variation measuring indices that are easy to realize. These standards specify operational voltage limits acceptable to general customers and fair to the utilities [99-101].

Originally, the use of the RMS voltage variation indices was to gauge the voltage quality of a distribution bus, feeder, or the whole distribution network [99-102]. The voltage variation is either initiated by an abrupt change in the loading condition or due to a temporary fault. However, in this application, these indices are used to benchmark the impact on the quality of supply voltage due to the connection of a renewable DG facility with a capacity comparable to the demand of distribution feeder. The objective of this chapter is to provide a tool to the distribution systems operators to evaluate any new application for connecting a renewable DG unit to a distribution system. This tool addresses the concern about assessing the stochastic behavior of the electrical power, supplied by the renewable DG units.

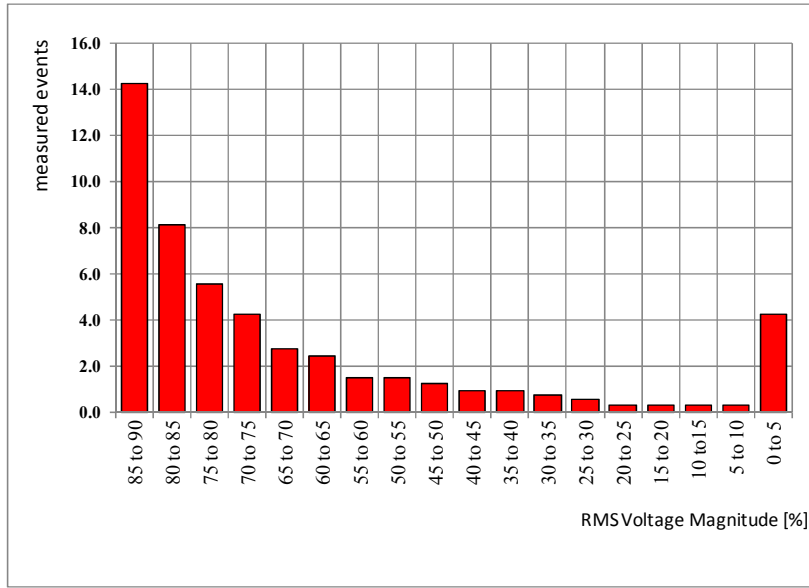
### 6.3.5.1 System Average RMS Variation Frequency Index (SARFI)

The system average rms variation frequency index (SARFI) is a power quality index that gives the sum of voltage changes as caused by faults or large demand switching. It can be applied for the whole of a distribution system or to just a segment of the system like a substation, a feeder or even a customer. In this section, introductory details about SARFI will be discussed.

The first introduction of the term SARFI was in 1996. The index counts the number of violations that the rms values of voltage magnitude either exceeds or drops below a particular limit. For example, SARFI-110 is a measure of the times when the RMS value becomes equal to or above 110% of the nominal value. When the voltage magnitude drops below a certain limit such as 90%, for example, then the index is called SARFI-90. This index was the outcome of an investigative study funded by Electric Power Research Institute (EPRI) to classify the voltage variation at distribution levels [103]. In this investigative study, events that captured voltage magnitude changes such as sags and interruptions that lasted for one-minute or less were detected and measured for two years at 300 sites on 95 distribution feeders [99, 103]. Figure 6-3, which is a reproduction from [104], describes some results for RMS measurements obtained and documented by the EPRI. The figure illustrates the number of times that the voltage magnitude violated the standard level of operation.

This figure is produced for measurements of voltage variations that lasted for maximum of one-minute time duration, interruptions for times longer than one-minute is not included in this figure. As seen in Figure 6-3, about 14 incidents of the recorded events the RMS levels were between 90 and 85 percent of the standard magnitude. In order to quantify such a variation, SARFI was proposed in 1996 by EPRI for measuring the changes of RMS values of distribution systems.

SARFI is used to identify the quality of supply voltage for a location in the distribution system. To calculate SARFI at a particular location, the number of customers who realized an RMS value other than the standard and the total number of customers who were connected to that location must be known. The following equation is a general mathematical description of SARFI that can be applied for different possible levels of interest [102]. SARFI-x represents the average number of events that a specified RMS value x occurs over the assessment period per customer served. The specified disturbances are those with a magnitude less than x for sags or a magnitude greater than x for swells.



**Figure 6-3: RMS Voltage Magnitude Histogram, 1-Minute Aggregation.**

$$SARFI_x = \frac{\sum N_i}{N_T} \quad \text{Eq. (6-12)}$$

where

- x : RMS voltage limit; possible values: 140, 120, 110, 90, 80, 70, 50, and 10.
- N<sub>i</sub> : Number of customers who experienced voltage magnitude deviations above x% for x >100 or below x% for x <100.
- N<sub>T</sub> : Number of customers served from the location where the measurements were taken.

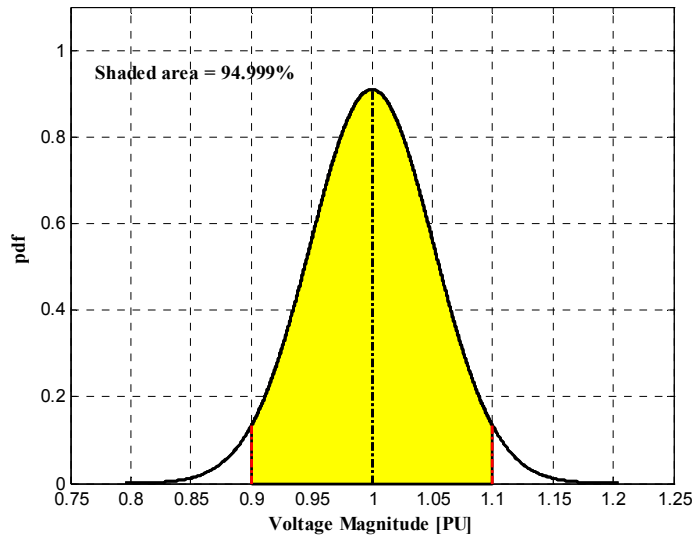
For example, if a group of customers were subjected to voltage sags less than 70% of nominal voltage, then SARFI-70 is used to assess this issue. Measurements of RMS values for specific time periods are conducted and then analysis of the measured values are used for the computations of SARFI-70. It is worth to note that SARFI can be used for variations of short-duration as defined by IEEE 1159 [105]. This concept is adopted in this thesis to benchmark the variations that might occur to customers' supply voltage if renewable DG units are connected to an existing feeder at distribution level. This new application of the index can be used to make decisions from a technical point of view about new connections of renewable DG units at the distribution level.

### 6.3.5.2 Statistical Power Quality Measure of Supply voltage EN-50160

Another way to evaluate the quality of supply voltage is detailed in EN-50160, which is European standard concerned with the parameters of the supply voltage as managed by operators of distribution systems [106]. The supply voltage is defined by the EN-50160 standard as the RMS value of the line-to-line or line-to-neutral voltage measured at the connection point to the customer, i.e. at the meter, installation point, or point of common coupling over a specific time period [100]. The voltage variation defined by this standard is the deviation from the nominal voltage caused by changes in the total load of either the whole distribution system or a part of it. Similar to the practice in North America, temporary voltage variations are initiated primarily by switching operations or temporary faults [100]. Similarly, requirements stated by EN-50160 are proposed to be used for investigating the variations of supply voltage when renewable DG facilities are connected to an existing distribution feeder. A comparison between the results of applying SARFI and EN-50160 requirements will be discussed.

The permissible deviation range for RMS voltage magnitude is characterized for medium voltage systems by EN-50160 to be within  $\pm 10\%$  for 95% of time measurement, commonly a period of a week [106]. In other words, the voltage magnitude is allowed to vary within a range of 90% to 110% of the nominal level 95% of the time or longer. The other 5% of the time is given for voltage deviation outside the prescribed range to cover unusual conditions. If the range of voltage magnitude becomes out of the 90%-110% range, then the utility should provide a voltage supporting device to keep it within these limits. This is not difficult to fulfill by power distributors since, in extreme cases, voltage is acceptable by EN-50160 to be at 90% of nominal level for all times. Because EN-5016 requires the distributors to provide electrical energy with minimum requirements of voltage characteristics, sector regulators in the European Union rely on more strict rules to supplement the standard.

Essentially, with different degrees, voltage varies as demand and many other system parameters, such as system impedance or configuration, and power injections change. Hence, a statistical analysis of voltage variation becomes more important, especially when randomness is introduced to the network by DG units. Therefore, a statistical method to evaluate the voltage variation and the associated probability is needed to evaluate such variations, such as that illustrated by the shaded area shown in Figure 6-4.



**Figure 6-4: Probability density function of voltage variation, EN-50160**

According to EN50160, for a medium voltage level, [1 kV - 35 kV], the voltage variation must fall at least 95% of the time between 0.9 and 1.1 per unit voltage. For the remaining 5% time, the voltage may be outside this range. This requirement can be described by a normal distribution that has a mean of 1.0 pu and standard deviation of 0.05, as shown in Figure 6-4. The pdf shown in this figure represents the standard variation of voltage at any location contained in a distribution network. The shaded area, which is equal to 0.95, demonstrates the probability that the voltage magnitude will be within limits [0.9 – 1.1] as required by EN-50160.

The other two regions shown not shaded in the figure are where the voltage can be above 1.1 and below 0.9, with a probability of occurrence equal to 0.025 for each. Although it is not acceptable from an operational point of view to operate electrical system at such levels, voltage magnitudes out of the operating range were allowed in this research. It is worth mentioning that, in practice, these limits are calculated from RMS measurements every ten minutes for a minimum time period of a week. In the application proposed in this thesis, the same criterion was applied to judge the impact of renewable resources on voltage profile of the hosting distribution system. The focus is to investigate, by simulation, how often the voltage magnitude would be violated, or how much would be the increase or decrease in the probability of satisfying the EN-50160. This requirement is suggested to be used as a tool, along with SARFI, for the decision maker of a distribution system to assess the impact of renewable DG output on voltage profile of the network.

## 6.4 Results and discussions

Two main streams are considered in this chapter. The first examines the behavior of the quality measures when renewable resources are installed. The second investigates the consistency of the two applied measures when units with different characteristics are involved. To see the impact of power injected by renewable units, several case studies were compared with each other and with a base case where no DG was connected to the network.

This section presents the results obtained for the case studies considered in this chapter. Scenarios for several penetration levels of DG units' have been considered in these studies to scrutinize the difference in voltage magnitude variation. The data of the original system configuration without including power production from small scale renewable units is first executed. The outcome of this base case is then compared with the results when power from renewable DG units is involved. The voltage magnitude at all buses, the real and reactive power injections from main substation, as well as the system losses have been recorded.

Bus-26 is located at the remote end of the feeder and this is the reason why its voltage magnitude was vulnerable to more deviations than the rest of buses. The average magnitude of voltage at this bus is 0.914 PU, the lowest among all averages of the other buses. Also, as measured by the standard deviation, it has the highest level of variation at 0.0158 pu. For the base case, the histogram of the voltage magnitude at Bus-26 is shown in Figure 6-5. The range of variation is from 0.96 to 0.85 as shown in this figure, which shows that customers may sometimes experience voltage magnitude less than 0.9 pu. After connecting a PV system to Bus-18, these values change in response to the injected power from the renewable DG facility.

For voltage, Bus-26 is selected for assessment because it is closely connected to the installed PV system, and also it happens to have the greatest voltage variation as calculated in the base case, refer to Figure 6-5 and as it is expected, installation of a PV system at the end of a feeder will improve the voltage profile of the feeder. The probability of not violating EN-50160 requirements at Bus-26 increases to 90.8% when the PV facility with 1MW rating is installed at Bus-18. The probability that the voltage magnitude becomes above 0.9 pu reached 83.9%, 89.0%, and 90.8% when the PV system rating becomes 1.0 MW, 4.0 MW, and 7.25 MW, respectively. These results are shown graphically in Figure 6-7.



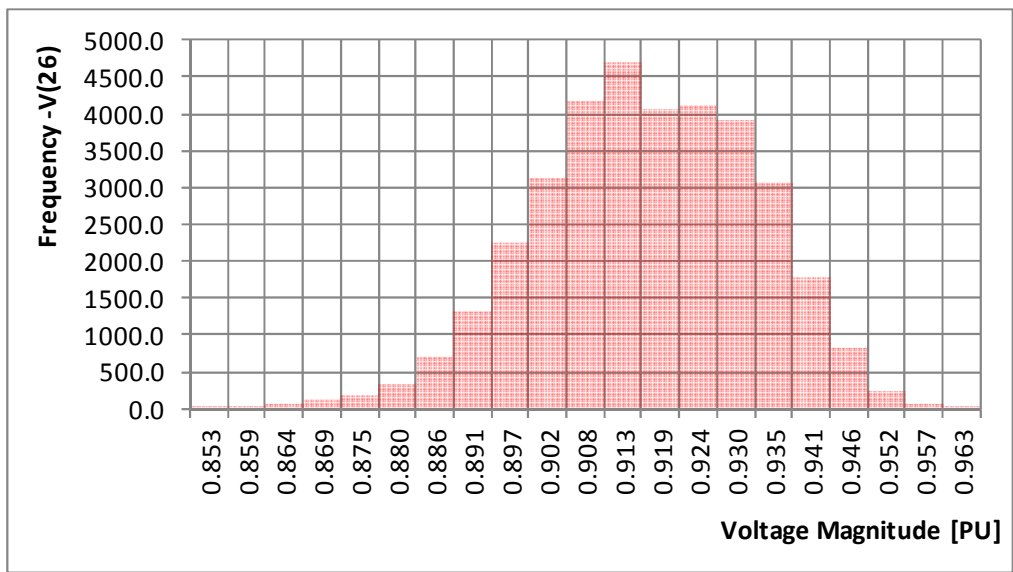


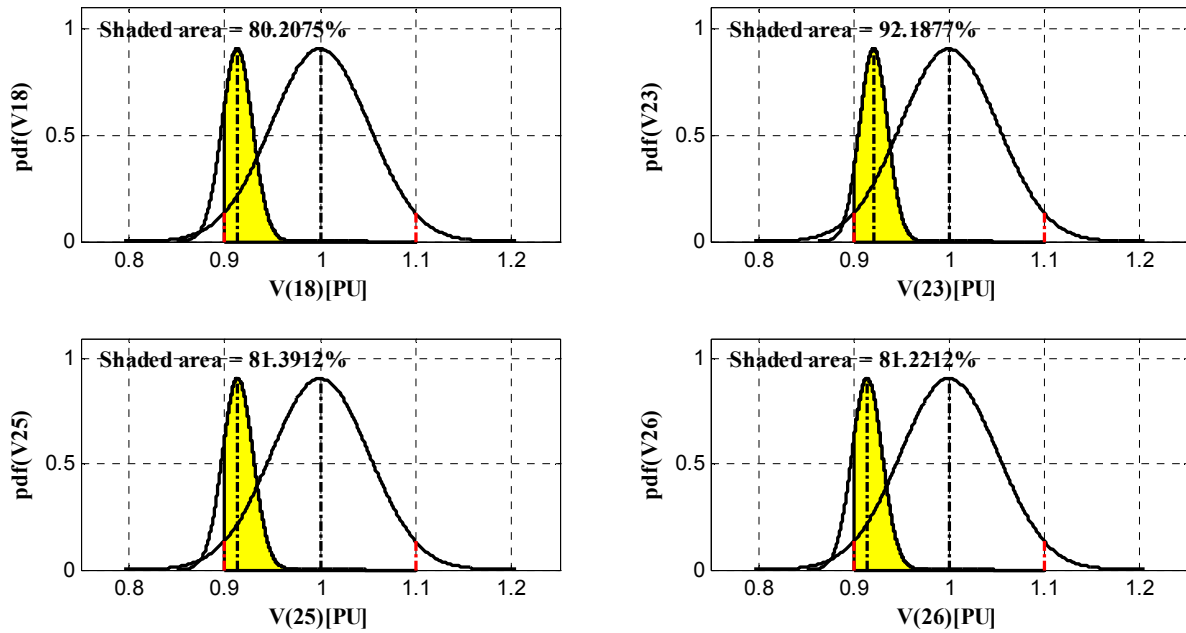
Figure 6-5: Bus-26 voltage histogram, base case

**6.4.1 First Case Study: One Renewable DG unit**

A photovoltaic system was installed at Bus-18. In order to study the impact of renewable facility on the voltage profile, three capacity levels of the PV system were assumed: 1MW, 4MW, and 7.25MW. Due to the size of the study, only results for Bus-26 will be shown and discussed. Figures that show results of other buses can be found in Appendix A.

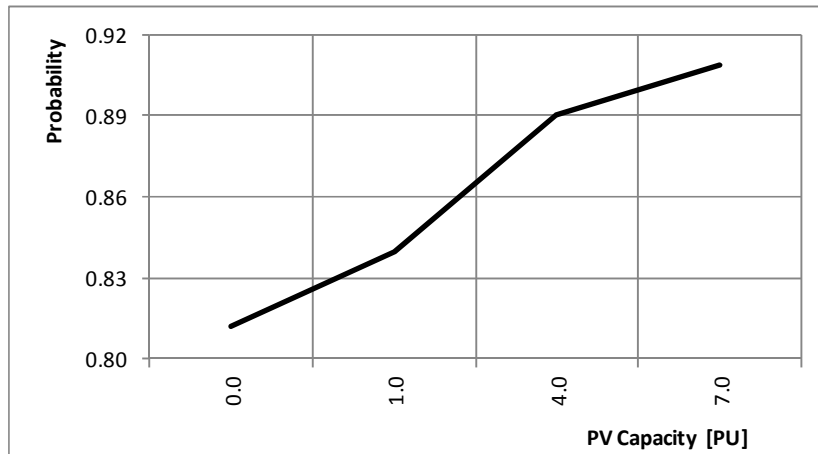
To examine the voltage supply quality along the feeder, the probability density functions of the calculated voltage magnitudes for several sample buses, including Bus-26, are plotted in Figure 6-6 for base case. Nine buses were chosen to observe the statistical characteristics of voltage magnitude, and, more significantly, the probability of deviation from the mean value of each bus of the sample is shown. Each graph in the figure depicts two density functions: the standard pdf of voltage variation and the calculated pdf that belongs to a particular bus along the feeder. According to the required EN 50160 characteristic, a shaded area is shown for each calculated pdf to highlight when the voltage magnitude is within limits. In each part of Figure 6-6, the shaded area represents the probability that the voltage magnitude at the particular bus is within the limits set by EN-50160; it is drawn over the standard pdf to highlight the change from the standard. The buses with the lowest probability of

compliance with EN-50160 are shown in this figure. For example, the chance that the voltage at Bus-26 becomes higher than 0.9 pu is 81.2% as described by the shaded area given in the bottom-right corner of Figure 6-6. There is a very low chance to experience voltage magnitude above 1.1 pu at Bus-26, hence violating this threshold is not a concern at this moment. The probability illustrated by the shaded area for some of the buses, see the top left sub-plot, is higher than the limits set by EN-50160, i.e.  $\Pr(0.9 \leq V \leq 1.1) \geq 95.0\%$ . The voltage magnitudes at the rest of the network are even safer.



**Figure 6-6: Density functions of voltage magnitude for sample buses: base case (No DG)**

Tracking the change in the probability of the voltage magnitude to comply with EN-50160 requirements at Bus-26 is shown in Figure 6-7. The figure shows the relationship between the probabilities of the voltage magnitude being within the EN-50160 limits and the rating of renewable unit connected to the feeder. Despite being lower than the threshold, the magnitude of supply voltage improves with the contribution of the photovoltaic system. This improvement is observed in levels of the calculated average of voltage and by the increase of probability of complying with EN50160.



**Figure 6-7: Probability of compliance with EN-50160 for Bus-26 voltage-magnitude**

Figure 6-7 shows a monotonic increase in the enhancement of quality of supply voltage at Bus-26 as the power produced by the renewable DG unit increases. This improvement in quality of voltage magnitude is expected because of the location of the DG facility. Also, another reason is that Bus-26 is located at the remote end of the feeder, (see Figure 6-2) close to the PV system which is installed at Bus-18. In such configurations, where a source is connected at the end of the feeder, the voltage drop becomes less due to the supply current from the renewable resource and hence the level of the supply voltage becomes better. However, the focus of this chapter is to provide a measure by which the improvement or deterioration of voltage magnitude can be assessed to make a decision regarding new applications for connecting renewable facilities in a distribution feeder.

The other benchmark considered in this study is the SARFI index. Table 6-1 contains results of calculating SARFI-90 for the above mentioned buses by using the same outcome of the conducted simulations. The first row of the table includes levels of SARFI-90 calculated for selected buses along the feeder when no renewable DG is connected to the distribution feeder. The second to fourth row show the calculated SARFI-90 for the same buses, but for the other three capacity levels of the PV system connected to Bus-18. The numbers listed in each column represent the SARFI<sub>90</sub> index computed for the corresponding bus with the associated change in capacity factor listed in the first column. The last column of the table illustrates the feeder's SARFI-90 level. The values listed in Table 6-1 were obtained by applying Eq. (6-12) to the results of the simulation to evaluate the degree of variation in the quality of supply voltage caused by variations in DG power output.

**Table 6-1: Simulated system and individual SARFI-90 index**

Capacity Factor	Bus-09	Bus-11	Bus-13	Bus-15	Bus-17	Bus-18	Bus-22	Bus-24	Bus-26	Feeder
(0PV , 0Wind)	347	1198	2686	6373	6900	6900	648	3999	6622	2225.31
(1PV , 0Wind)	274	1010	2288	5457	5936	5937	527	3393	5745	1905.15
(4PV , 0Wind)	142	700	1690	3900	4208	4180	331	2455	4114	1357.46
(7PV , 0Wind)	96	588	1409	3261	3535	3517	263	2067	3460	1138.42

Similar conclusions to those observed in the previous analysis are extracted when SARFI index is applied. Only SARFI-90 was computed to be able to compare the results obtained by the other benchmark considered in this section using EN50160. As seen in the table, the SARFI's level of Bus-26 decreases as the DG output increases showing an enhanced quality of supply voltage. This statement is correct for the other buses and for the system indices as depicted last column of Table 6-1.

The results shown in Table 6-1 reveal a significant result: opposite to was stated in [5], the quality of supply voltage is improved regardless of the level of penetration. The extensive simulation conducted in this chapter and the evaluation show a decrease in the number of violations measured by SARFI-90 for each bus with the introduction of renewable resource. This improvement is also noticed when this phenomenon was examined by EN-50160. Although stochastic, the injected power from the DG unit, connected to Bus-18 at the end of the feeder, is the reason behind this improvement. At the end of the feeder, part of the demand is supplied by the DG which is closer to the loads than it is to the main station, and consequently less voltage drop and variations result. This was reflected on lower values of the indices. The rest of buses on the feeder have better quality of supply as they are closely located to the main substation, which is modeled as slack bus in the load flow model, i.e. constant voltage.

#### **6.4.2 Second Case Study: Two Renewable DG Facilities**

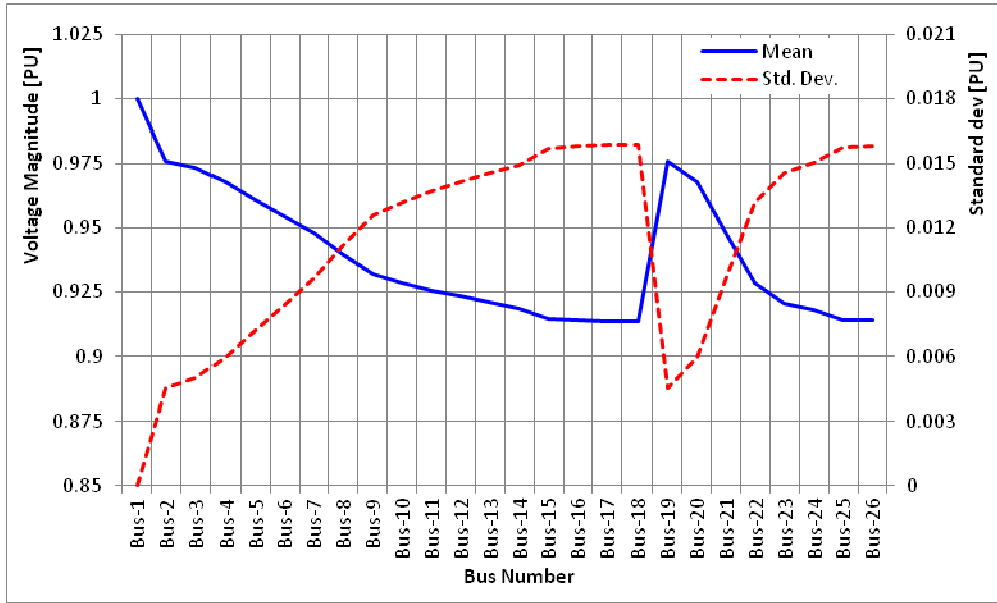
In the previous section one renewable DG unit installation was studied. In this section, a case study of two renewable units is examined. The case study was designed to investigate the effect if another G unit with a different behavior was connected to the feeder that already had a renewable resource connection. Two objectives were set in this case study. The first was to see how the magnitude of the

customers' supply voltage would change with two different random sources added to the system. The second, which is more important, was to observe the consistency of the two indices selected to judge the impact of the randomness under such circumstances. It is worth mentioning that surplus power is allowed to flow as a reverse power to the rest of the distribution system through the slack bus. The same capacity factors were applied in this case for the two DG units resulting in 12 simulations. Similar to the above section, discussion of the results is based on the results obtained for Bus-26, and a sample of results belonging to this case study is found in Appendix B.

Before discussing the results, an analysis based on traditional approach is presented. Figure 6-8 shows the mean and standard deviation of magnitudes for each bus in the distribution feeder under investigation. The left Y-axis in the figure illustrates the average value of voltage magnitude. The right Y-axis presents the level of standard deviation with zero as minimum.

The solid line represents the profile of the mean value. It is decreasing with an increasing distance from Bus-1, as a natural consequence of the voltage drop caused by the load current. Another peak starts at Bus-19 because this bus is connected to Bus-2 through a lateral, hence their mean voltage magnitudes and their deviations are close. The dashed line shown in Figure 6-8 stands for the change in the deviation for each bus in the feeder. The trend of this curve illustrates that the voltage magnitude shows more variation at the end of the feeder than that at its origin. Because bus-1 is modeled as a slack bus, at fixed voltage magnitude and zero phase angle, it has a deviation of zero and a voltage magnitude of 1.0 pu.

The first impression from observing Figure 6-8 is that the voltage profile is acceptable: the minimum average value of voltage magnitude is above 0.9 pu and the maximum deviation is less than 1.6%. In this traditional observation, the average values were utilized to make decisions regarding operational plans, as was done in previous chapters. However, as shown in the previous chapters, such a strategy might be misleading. Deeper analysis of these profiles reveals significant issues that require corrective actions, without the need to reproduce figures like those shown in Figure 6-6.



**Figure 6-8: Mean and variance profiles for the buses of the feeder under study**

The two indices used to measure the impact of renewable DG units on the variation of supply expose important observations that show how the traditional analysis which relies on average values may lead to false decisions. Beside this observation, Figure 6-9 and Figure 6-10 present an important aspect of the two indices. The consistency between the two indices is significant enough to allow for them being used as tools for making fair decisions about new connections of renewable DG units. Figure 6-9 shows the values of SARFI-90 for all buses of the feeder. As in Figure 6-8, the profile of SARFI index changes with distance from the main station Bus-1. Referring to Figure 6-9, SARFI-90 index is zero at buses where no violations are experienced and larger at buses that experienced some violations. For buses at the end of the feeder - such as buses Bus-15 to Bus-18 - the level of the index reaches its maximum level. Buses Bus-22 to Bus-26 are demand nodes connected at the end of laterals attached to the main feeder. For example, Bus-23 is connected to Bus-13 and hence the levels of SARFI-90 at these two buses are close to each other. The figure also illustrates that the profile of SARFI-90 becomes lower as the contribution of the DG units increases.

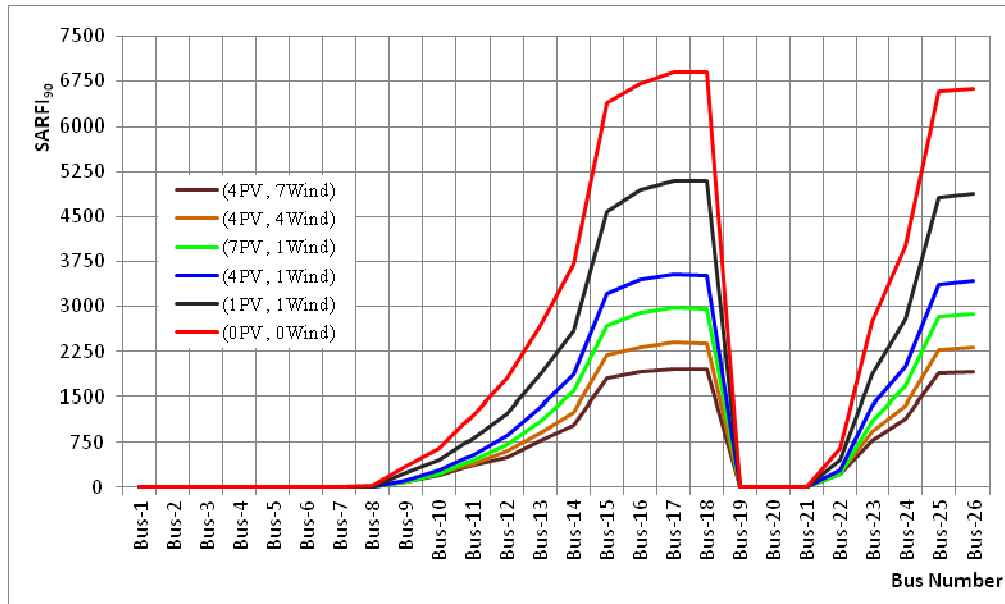


Figure 6-9: Profiles of SARFI-90 index for all buses of the distribution feeder

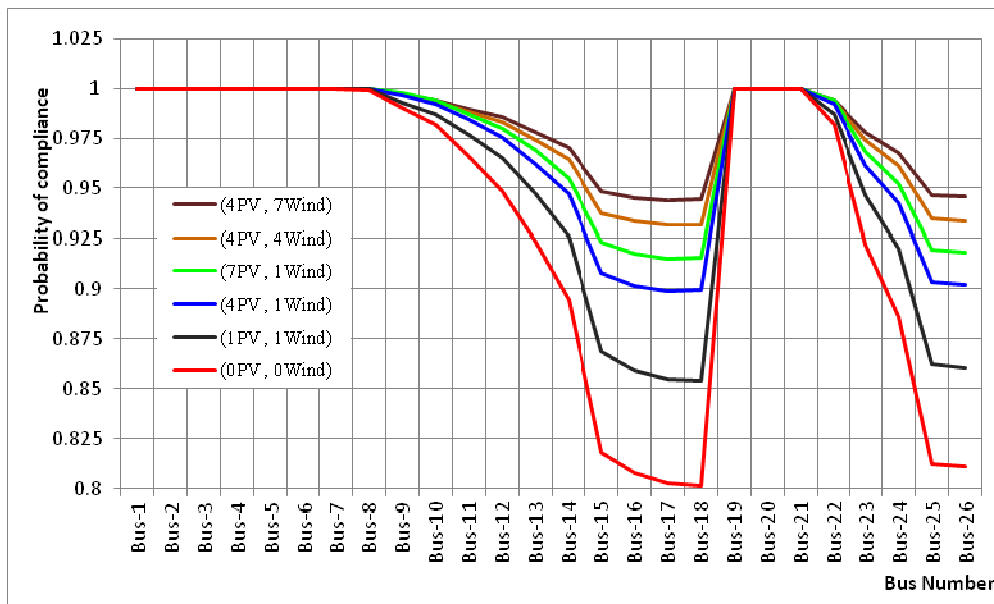


Figure 6-10: Probability of compliance with Standard EN-50160 for all buses in the feeder

Another outcome that can be extracted from Figure 6-10 is the change of the profiles of the index with change in the degree of DG capacity ratings. As remarked in the previous section, increasing the contribution from renewable DG units positively enhances the quality of supply voltage. The decrease in the profiles of SARFI90 shown in the figure reveals a lower number of times in which voltage magnitudes became less than 90%. This decrease in number of violations translates into an improvement in the quality of supply voltage as a consequence of injecting power from renewable generating units to the feeder.

Figure 6-10 summarizes the results of evaluating the quality of supply voltage for the same cases used to produce Figure 6-9. Figure 6-10 illustrates the change in the probability of complying with the requirements set by EN-50160. The probability of compliance depicted on the Y-axis is calculated from the mean value and variances resulted from the Monte-Carlo simulation. For each bus in the distribution feeder, the probability of supply voltage magnitude to remain between 1.1 pu and 0.9 pu is computed. The maximum value of each probability profile is one, which means that for all iterations executed in the Monte-Carlo simulation the magnitude of voltage at this bus is complying with EN-50160 limits, i.e. within the range. As recommended by EN-50160, the magnitude of supply voltage should be within the limits for 95% of the time in order to consider the variation of voltage magnitude acceptable. Any probability less than 95% requires a corrective action and should provide a voltage regulating device in order to boost the voltage magnitude. This well defined decisive threshold is an advantage for EN-50160 over SARFI index which still does not have such a decisive limit. The reader is referred to the investigative study conducted by Electric Power Research Institute (EPRI) reported in [103] regarding characteristics of SARFI. Based on this decisive limit, Figure 6-10 declares that a voltage supporting device should be installed at Bus-11 or Bus-12 to boost the probability profile above the 95% threshold while enhancing the voltage profile.

It is noticeable that the shape of the graphs shown in both figures: Figure 6-9 and Figure 6-10 are symmetrical around the X-axis. While the profiles of SARFI index increases, in the first figure, the curves of probability compliance decrease in the second. The reason behind this symmetry is that both families of curves track the behavior of the same phenomenon, i.e., voltage magnitude violation of the same threshold 0.9 pu. The only difference between the two sets of curves shown in the two figures is the mathematical approach used to evaluate the quality of supply voltage. Because the two indices evaluate the results obtained from the same Monte-Carlo simulations, the outcome of this evaluation will not be identical unless they consistently and correctly indicated the same



phenomenon: the quality of supply voltage. This observation is very important to adopt the method for assessing the impact of renewable resources on voltage profile.

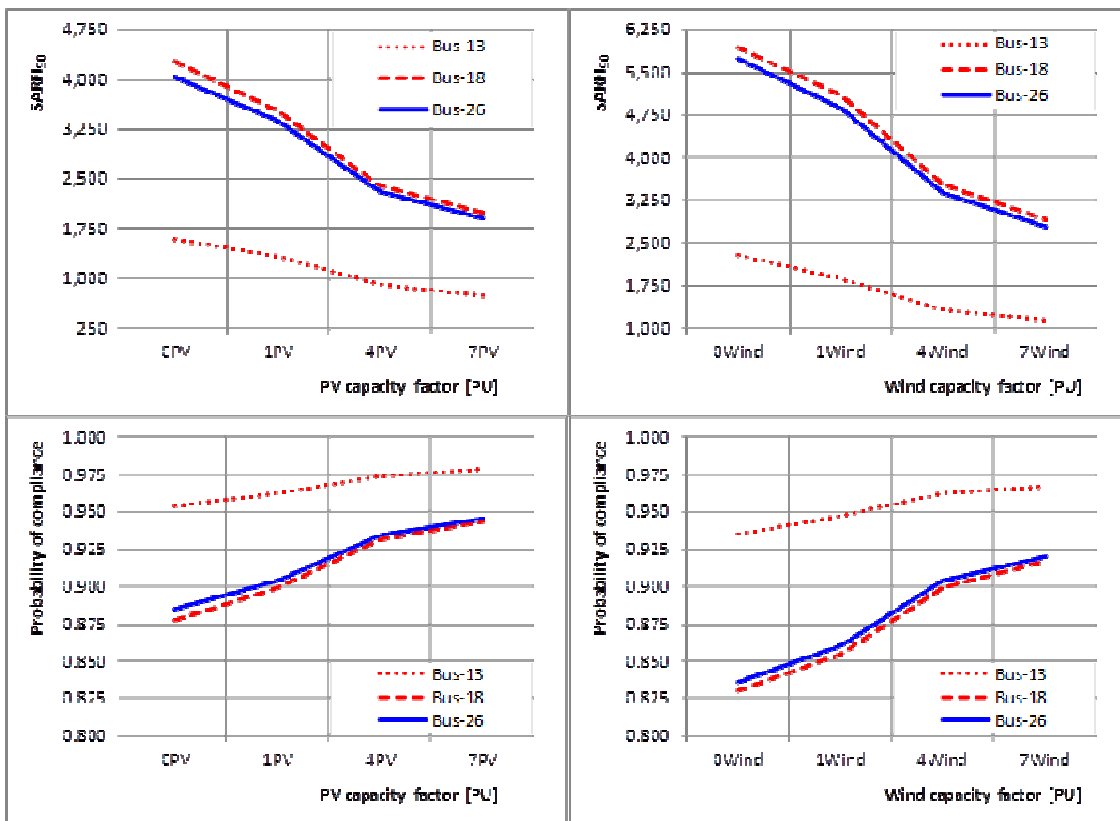
Another set of curves is shown in Figure 6-11. The upper-right sub-graphs show the change in SARFI-90 for three buses in the system: Bus-13, Bus-18, and Bus-26, with changes in contribution from the wind generator while the capacity rating for the photovoltaic facility was 1MW. In the lower-right sub-plot, the probabilities of compliance to EN-50160 are plotted for the same buses and at the same circumstances. The other two sub-figures on the left side of Figure 6-11 are similar to those on the right but for different capacities of photovoltaic combined but when the wind generator was rated at 4.0MW. As can be seen, the curves are symmetric around the X-axis, and also behave identically over the range of variation along the X-axis. This is a second view, in addition to Figure 6-9 and Figure 6-10, illustrating the outcome of simulation results.

The observations obtained from analyzing the above figures can be summarized in one word: stability. It could be concluded that the outcome of applying either index will lead to the same result. Both indices have shown identical and consistent improvement in the quality of supply voltage magnitude. Although not accomplished, it can be assumed that the two indices would be stable and consistently to show the deterioration of quality of supply voltage caused by injections from renewable DG units if such impact occurs. This conclusion is restricted, however, by the distribution of demand throughout the electric network as observed in [107].

The significance of considering deviation rather than average alone should be highlighted. Previously, when Monte-Carlo simulation is used, both the average value and standard deviation are usually calculated and plotted. Figure 6-8 illustrates the profiles of average and standard deviation of voltage magnitudes for the studied system. The minimum average value is about 0.92 pu which is acceptable for normal operation. Furthermore, the maximum standard deviation is 0.016 pu, which is less than 5% and a common threshold for voltage variation in distribution systems. However, these average magnitudes and deviations do not satisfy the requirements of EN-50160 standard as observed from the profile shown in Figure 6-10. The probabilities of compliance with the standard are less than the requirement, despite the average voltage magnitudes being above 0.9 pu. This indicates again that relying on average values alone or even combined with the deviation like those of the graphs shown in Figure 6-8 without further analysis might not alert the decision maker to take corrective actions as results of Figure 6-10 do. This observation in turn highlights the importance of considering the stochastic characteristics in the analysis of distribution systems and to explore non-deterministic

approaches in studying the dynamics of these systems. The exploration of new techniques that allow the inclusion of stochastic nature of renewable resources will benefit decision makers by offering new options and will improve safer integration of renewable resources.

The basic question about the applicability of the two proposed indices that should be asked is about the threshold of each index. What is the level that can be used to indicate acceptable quality level of supply voltage? The answer to this question is provided by the probability compliance with EN50160. In the case of SARFI, this question needs more investigations. As recognized in the right side of Figure 6-11, all buses do not comply with EN50160, except for Bus-13 and only after connecting 1MW wind generator, see the dotted line in the bottom right subplot of the figure.



Wind = 4 MW

PV = 1 MW

Figure 6-11: Coherency between SARFI and EN-50160 requirements

Referring to the right-top sub-plot, the value of SARFI-90 for Bus-13, corresponding to the threshold of 0.95 provided by EN-50160, is 1750. Nevertheless, this does not mean that this level of SARFI-90, is absolute as is the case of the probability given by EN50160. The reason is that SARFI is computed as a function of the number of customers. To illustrate, assume the quality of voltage supply of two identical networks but with different numbers of customers to be studied using SARFI. Two different levels of SARFI result will be observed because of the mathematical formulation of the index; refer to Eq. (6-12). This point needs more research work to make SARFI index an absolute quality measure.

## **6.5 Summary**

The work provided in this chapter complements the research conducted in the previous chapter. It proposed a method and suggested a new application of two power quality measures to assess the impact of renewable power production on voltage magnitudes. The two measures proposed for assessment are consistent, although their mathematical formulas are different. The presented method can be used to assess the contribution of new connection of renewable resources to change the quality of supply voltage before they are actually installed. Another application of these indices is to identify the buses of an existing network that may need voltage support action due to probable degradation of the supply voltage.

## **Chapter 7**

### **Summary, Conclusions, Contributions and Future Work**

The thesis is centered on the inclusion of the inherited characteristic of randomness associated with the intermittent and random renewable generation connected to distribution systems. More research was needed to investigate the consequences of connecting renewable units by considering this behavior in the modeling techniques. This thesis focused on this objective.

This feature of renewable generation causes decision makers in utilities to become reluctant to connect renewable resources. The reason for this reluctance might be referred to the lack of understanding of the system behavior and operating conditions. A mathematical tool that improves understanding of this behavior would be a valuable addition to decision analysis. Traditionally, deterministic approaches were used on a daily basis to analyze the distribution systems. These approaches cannot model this behavior because they are not able to track randomness. Studying the operation of distribution systems under uncertain operation of renewable resources should include use of stochastic techniques. The outcome of these studies will provide suitable models to solve issues associated with production of renewable facilities. Such models and solutions may assist the practitioners in implementing the renewable generation into distribution systems. This thesis provided models and investigative studies to pave the road for more integration of renewable DG facilities in distribution networks given their uncertain generation.

#### **7.1 Thesis Summary and Conclusions**

The concerns about connecting renewable DG units were highlighted and investigated in this thesis. The decision making process to optimally procure a power mix to supply a utility's demand under uncertain power injections from DG facilities was first studied. It was found that installing renewable DG units at the distribution level reduces the ability to choose from other available energy sources in restructured power systems. At the same time, introduction of renewable generation close to load centers at distribution level brings technical and economical benefits to the utility. Examples of these benefits are lower losses and voltage drop reduction. The results obtained in the first part of the thesis highlight the need to weight the financial impact of renewable resources and to provide incentives to distribution utilities to encourage higher penetration of renewable resources.

Chapter 1 introduced the power procurement problem and what would be the expected outcome from the models presented in this thesis. The chapter also introduced the second concern investigated in this thesis which is related to technical issues. In Chapter 2, a comprehensive literature review highlighted previous research work conducted on finding an optimal power mix. The chapter contributed by demonstrating statistics to draw the researchers' attention to a significant gap in the previously applied method to solve the power procurement problem. The literature review unveiled new areas of research that needed more investigative studies.

Chapter 3 presented a deterministic algorithm to solve the power procurement problem under uncertain production of renewable units. Although it is not the best approach, the proposed deterministic model served two objectives: to provide a simple formulation, and to find fast estimates of the optimal power mix. As illustrated in Chapter 3, uncertainty caused by renewable resources has considerable impact on the economic efficiency of local distribution systems. Since renewable sources can offer good alternatives in long-term planning and, as presented in Chapter 3, can impact the short-term operation of distribution systems, both the benefits and drawbacks should be weighted. To obtain an optimal decision that weighs those pros and cons, incentives should be included to compensate for the restrictions resulting from this production. In addition, this chapter emphasized the need for a comprehensive representation of randomness.

A two-stage stochastic model was suggested in Chapter 4 to solve the power procurement problem for a distribution utility in a restructured environment. The model considered four elements of power components in order to supply the demand. Opposite to the formulations presented in the literature where renewable generation was represented as a controllable decision variable, in this thesis it was included in the formulation as random parameter. Following this method allowed for imitation of real life practices that gave priorities to use power from DG facilities over the rest of the available resources. To give freedom of preference to the decision maker, who operates the system in fully restructured network, the random parameters were divided into two components, each of which is a decision variable: utilized DG output and curtailed DG production. This distinction of renewable power will provide more options to the distribution system operator to manage the resources based on economic factors, i.e., procurement cost reduction. The model included the stochastic behavior of DG power production in the constraints section and weighs the impact of DG output in the objective function.

In order to quantify the performance of the proposed models, two measures were used: VSS (value of stochastic solution) and EVPI (expected value of perfect information). The first computed the extra cost that would be incurred if the representation of randomness was ignored. The second gave the cost estimate of obtaining perfect information so a deterministic model could be utilized. In Chapter 4, the impact of different capacities of renewable DG units and different randomness severities were investigated using a small network as an example. The obtained results showed the superiority of stochastic techniques proposed in Chapter 4 over the deterministic model presented in Chapter 3.

The studies conducted in Chapter 4 using the stochastic model have also shown two new topics to be covered in this work. First, the studies have shown that, when applied, the two-stage stochastic formulation to large system the problem became insolvable. The second was how to evaluate the risk of connecting renewable DG units and its impact on financial performance. These two questions were answered in Chapter 5. In this chapter, a risk evaluation process was summarized and causes of problem solution complexities were discussed. The Markowitz economic load dispatch (ELD) risk model was formulated for solving the power procurement problem under uncertain DG production. The introduction of the ELD formulation in solving the power procurement problem under uncertainty for distribution systems improved the speed of finding optimal solution. The ELD-risk formulation also allowed for a larger number of scenarios to be added, which meant better representation of the uncertainty. This unique model, proposed in Chapter 5, is capable of the following tasks:

- 1) calculating the optimal mix of power components to supply a utility's demand under uncertain production of renewable DG production;
- 2) computing when and from where the power component should be purchased and injected in order to supply the demand at reduced operating costs; and,
- 3) evaluating the risk level associated with the introduction of renewable DG power production. The model has the ability to balance cost and risk in the objective function based on the decision maker's risk aversion.

Several cost studies were considered to investigate and realize these capabilities. The results obtained from conducting these studies confirmed the observations obtained in Chapter 3 and Chapter 4: increasing renewable output has significant impact on the financial efficiency of an LDC. In addition, variations of average cost versus risk were illustrated by group of figures for different levels

of risk aversion. Using the proposed model, the simulation results showed that the LDC operator can guarantee to purchase the system's demand requirements with acceptable degree of risk. The model provides an effective tool for the operator to manage risk and reduce operating costs in electricity-purchase decisions under uncertain generation from small-scale renewable resources. Chapter 5 ends the research work on the impact of renewable DG production on economical decisions of a distribution operator.

The quality of supply voltage is a key factor that dominates decisions to accept new connections of renewable DG units at distribution levels. A method that uses Monte Carlo simulation was presented in Chapter 6 to help decision makers decide whether to permit or modify a new installation of renewable DG. Probabilistic voltage variation and System Average Root Mean Square Frequency Variation index (SARFI) were utilized to give insightful decisions regarding new installations of renewable DG units at the distribution levels. Even though the two measures are well known and have been applied in measuring the quality of supply voltage in established distribution systems, their application to evaluate the impact of future installations of renewable resources on voltage profiles is new to the literature.

The studies conducted in this chapter showed that connecting renewable resources enhances a feeder's voltage profile. This improvement is an expected consequence of the location of DG resource in the system studied. However, what is more significant to the decision maker in this chapter is to study the consistency of the selected benchmarks and whether if they correctly and consistently reflect the impact on voltage profiles of distribution feeders. The comparison of the results obtained from calculating the two measures of quality of voltage supply demonstrated an encouraging consistency. The investigative simulations and calculations showed that the two measures are consistent, even though their fundamental mathematical formulations are different. This observation strengthens the conclusion to recommend applying either of these two measures to assess the impact of renewable resources on voltage profile.

Another application of this method is to help designers of distribution systems to recognize the areas in the network that have the potential to negatively influence the supply voltage. This second application came from the utilizing standard deviation to compute the probability of violating the EN50160 standard operational voltage magnitude at specific locations rather than relying on the profiles of average values and variance without further analysis.

## 7.2 Contributions

The work completed in this thesis provided considerable contributions. Different mathematical formulations were proposed in the thesis with improved representation of uncertain renewable power production. In addition to these formulations, the thesis provided a systematic review of the literature and highlighted new areas of research that still need more investigative work from an economic as well as technical points of view. The ideas and the models discussed and presented in this work can become a starting point for further enhancement and exploration of other applications not covered in this thesis. The main contributions follow:

The first contribution is a deterministic optimization algorithm to include uncertainty of renewable generation in the power procurement problem. Before this work, the production of renewable DG units was represented as a controlled deterministic variable, which contradicts with the stochastic and intermittent characteristic of this production. The uncertainty is partially included in the steps of this algorithm and the uncontrollability is introduced by modeling the renewable power output as random parameter. In contrast with the work reported in the literature, in which only one location that contains an aggregated DG output is considered, the proposed model can represent multiple renewable DG connections at several locations.

The second contribution is the two-stage stochastic model which evaluates the available options for the decision maker, taking into account the randomness of renewable DG generation. The model selects the most economic options that minimize operating costs including curtailments of DG output for some time if such curtailments will allow choosing more economical bilateral contracts. The objective of this optimization process is to meet the demand of the electric service provider at minimum cost. This formulation overcomes the low efficiency of the above deterministic approach by explicitly including the uncertainty.

The third contribution is the combined Markowitz and economic load dispatch (ELD) formulation. Previous to this work, stochastic risk models were used to assess issues related to variation of electricity prices without integrating the different power components available to the decision maker and not including uncertainty of renewable resources. The main advantage of using the ELD representation is to avoid the complexities when the two-stage stochastic model is used to solve the power procurement problem for practical systems. A second accomplished task targeted by this new formulation (the Markowitz-ELD model) is to fill the gap of not considering the risk associated with the uncertain generation of renewable facilities. The only drawback of this model is it does not



account for system losses, which, in the worst case, would not exceed 5% of system demand. However, the presented model considerably simplified the formulation, largely reduced the size of the problem but allowing for a larger number of scenarios to represent uncertainty and significantly reducing the execution time.

The fourth contribution is an assessment method based on a Monte-Carlo technique to evaluate the impact of new connections of renewable resources on the quality of supply voltage. This method is one of early research work that presents a tangible approach in considering the impact of prospective connections of renewable resources. For the studied feeder, the renewable facilities were arbitrarily located at the end of the feeder. This has resulted in an improved voltage profile of the feeder, a reduced losses and minimized loading patterns. Despite these benefits, the goal of the proposed method was intended to investigate the ability to evaluate the impact of the random generation of these resources on voltage variation instead of the significance of renewable allocation.

### **7.3 Future Work**

All of the models presented in the thesis are proposed with uncertainty in mind to solve economic and technical issues related to distribution system operation. However, there are several concerns that need more investigative studies. The following are extensions for future research work that incorporate renewable power production in distribution systems operations:

- The presented two-stage stochastic model computes the power mix for distribution networks with all main substations interconnected. However, distribution systems are operated in radial configuration. Hence developing an algorithm that integrates the outcome of the proposed model with an algorithm to reconfigure the electrical network would be of great interest to distribution companies. This could be solved by incorporating an iterative algorithm where at the beginning the procurement model is solved using the two-stage stochastic model and then to reconfigure the network to provide a the radial topology.
- Another enhancement of the presented two-stage stochastic model would be to include storage system per each renewable resource location. This enhancement deals with the uncertainty by reusing the power generated rather than adapting to it as followed in this thesis. This new approach should compare the cost of storing electricity to the cost of curtailing it.
- In the second section of the thesis, the two measures used were suggested to either accept or reject a new application of renewable resources based on tangible calculations. However, these

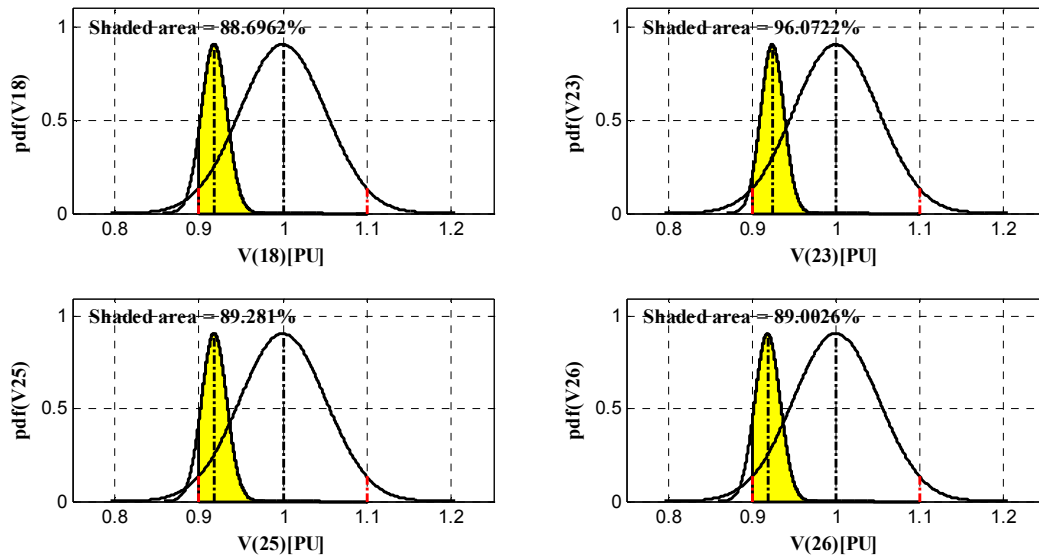
measures do not determine the contribution of the individual DG unit to the enhancement, or deterioration, of the quality of supply voltage. For illustration consider the following scenario. If a network already contains a number of DG units and a new facility need to be connected, but with an added voltage regulating device, then who is going to pay the cost of this regulating device. Is it the owner of the new application, the utility or all of the owners of the existing generators because each one of them has a contribution to the unfavorable impact?

- As discussed, the System Average RMS Variation Frequency Index (SARFI) does not have a threshold that can be used to define the boundaries of acceptable and unacceptable levels of the index. More investigative research is needed to understand this issue to add this important feature to SARFI.
- It was noticed during research conducted in this thesis that some infeasible solutions arose because there was only one reactive power resource in the system: the slack bus. Hence, some rethinking about the reactive power capabilities of DG units is needed. Renewable DG units should exchange reactive power with the system and provide limited voltage control functions. When contributions from renewable DG units become high enough to offset the demand of a distribution feeder, the feeder can be considered as an electrical island, and the ability of DG units to supply reactive power would be beneficial in this case.

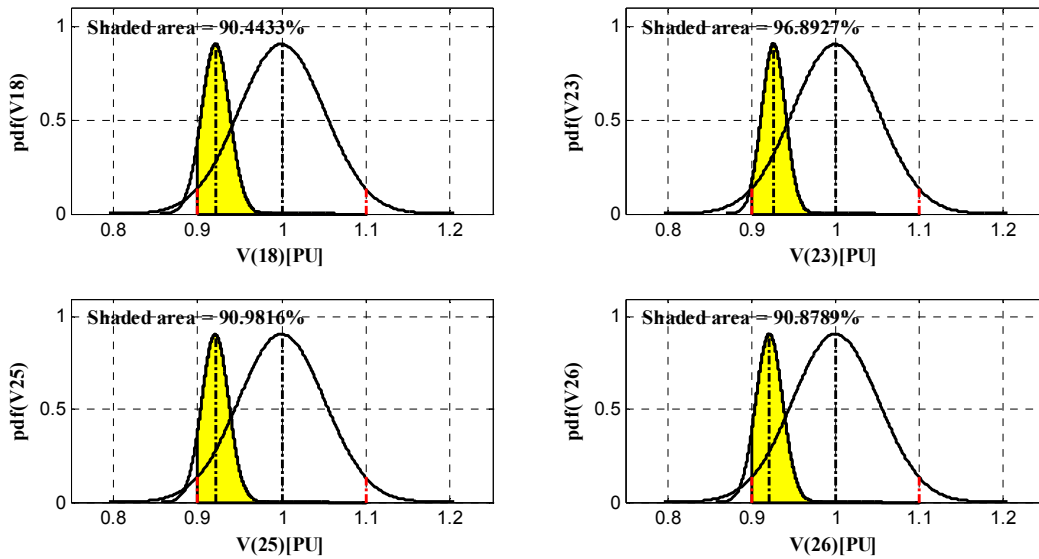
## Appendix A

### Sample Results of Simulation

The following is a collection of figures show the change in the probabilities of compliance with EN-50160 standard as the contribution of the renewable resources change.



**Figure A-I: Probabilities of compliance at  $P_{PV} = 4.0$ ,  $P_{wind} = 0.0$**



**Figure A-II: Compliance probabilities for  $P_{PV} = 7.0$ ,  $P_{wind} = 0.0$**

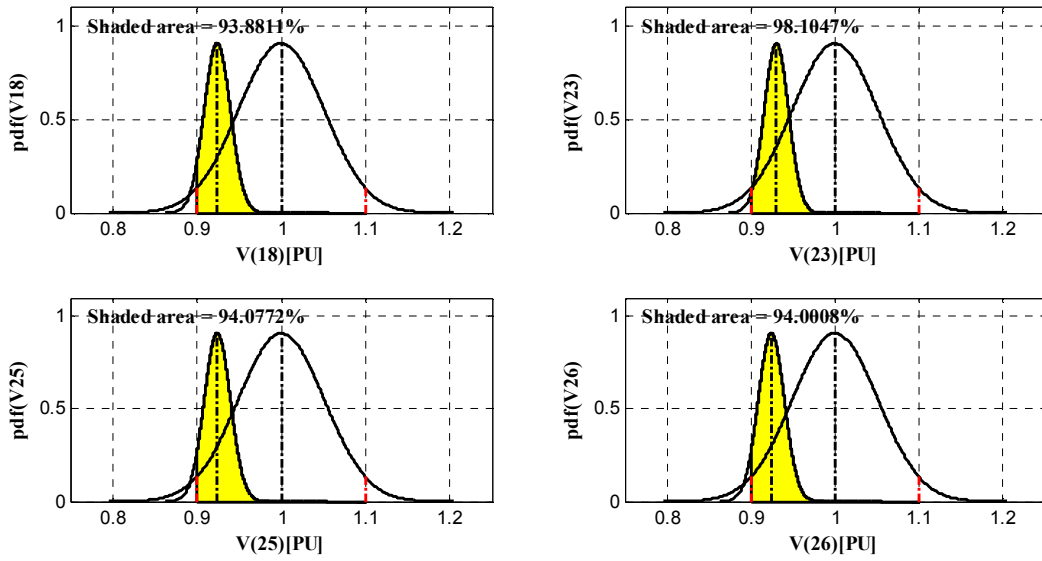


Figure A-III: Change in compliance probabilities at  $P_{PV} = 4.0$ ,  $P_{wind} = 4.0$

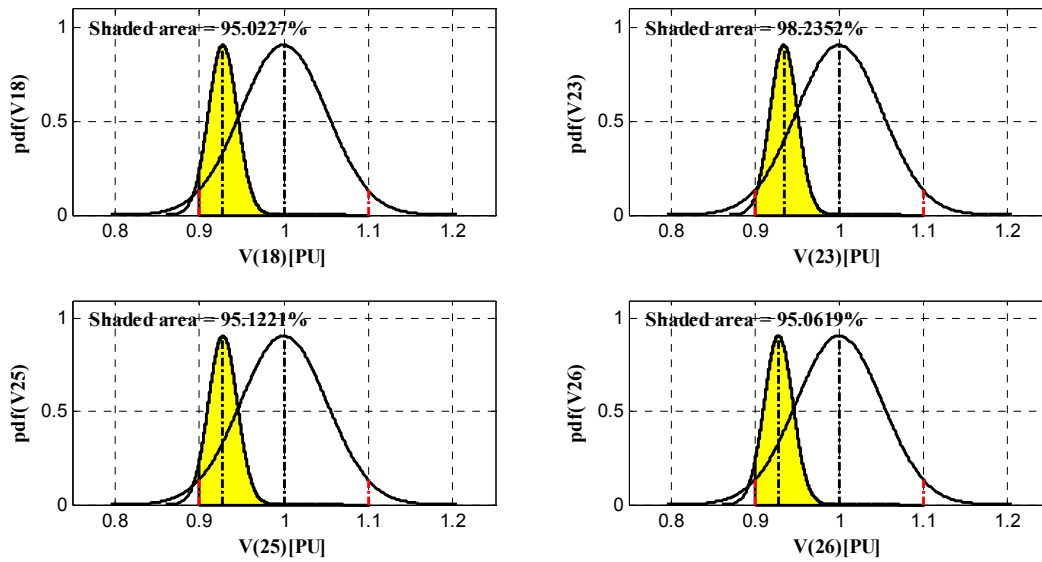


Figure A-IV: Probability of compliance with EN-50160 at  $P_{PV} = 4.0$ ,  $P_{wind} = 7.0$

## Appendix B The PV characteristics

The following table contains the PV characteristics used to calculate the power production from the solar resource.

Characteristic	Value
Watt peak (W)	60.00
Open circuit voltage (V)	21.10
Short circuit current (A)	3.80
Voltage at maximum power (V)	17.10
Current at maximum power (A)	3.50
Voltage temperature coefficient (mV/°C)	75.00
Current temperature coefficient (mA/°C)	3.10
Nominal cell operating temperature (°C)	43.00

## Appendix C

### Network Data

Two systems were used in the studies conducted in the thesis. The following is a data description of the utilized networks, the single line diagrams can be found in the associated chapters.

#### B-1: IEEE 30-Bus system

The line and bus data of the modified IEEE 30-bus test system are given in Tables B-1 and B-2, respectively. The data is on 100 MVA base.

Table B-1: Line data of the modified IEEE 30-Bus system

From	To	R (pu)	X (pu)	From	To	R (pu)	X (pu)
S/S1	S/S2	0.0324	0.0845	S/S8	S/S9	0.0340	0.0680
S/S1	S/S5	0.0348	0.0749	S/S9	S/S10	0.0639	0.1292
S/S1	S/S7	0.0727	0.1499	S/S10	S/S11	0.1073	0.2185
S/S1	S/S8	0.0936	0.2090	S/S11	S/S14	0.1000	0.2020
S/S2	S/S3	0.0824	0.1923	S/S12	S/S13	0.1885	0.3292
S/S3	S/S4	0.0945	0.1987	S/S12	S/S15	0.1093	0.2087
S/S4	S/S6	0.1231	0.2559	S/S12	S/S16	0.2544	0.3800
S/S4	S/S11	0.0662	0.1304	S/S13	S/S14	0.1320	0.2700
S/S5	S/S7	0.0116	0.0236	S/S15	S/S17	0.2198	0.4153
S/S6	S/S11	0.2210	0.1997	S/S15	S/S18	0.3202	0.6027
S/S7	S/S13	0.1150	0.1790	S/S17	S/S18	0.2399	0.4533

Table B-2: Bus data of the modified IEEE 30-Bus system

Bus	P[pu]	Q[pu]	Bus	P[pu]	Q[pu]
S/S1	0.358	0.020	S/S10	0.032	0.009
S/S2	0.090	0.058	S/S11	0.282	0.025
S/S3	0.035	0.018	S/S12	0.000	0.000
S/S4	0.112	0.075	S/S13	0.087	0.067
S/S5	0.175	0.112	S/S14	0.032	0.016
S/S6	0.062	0.016	S/S15	0.000	0.000
S/S7	0.000	0.000	S/S16	0.035	0.023
S/S8	0.022	0.007	S/S17	0.024	0.009
S/S9	0.495	0.034	S/S18	0.106	0.019

## B-2: Distribution Feeder

A distribution feeder belongs to a local distribution company in the Region of Waterloo is used in the studies of Chapter 6. The following table includes the line and loads data of the feeder. The base values are 10 MVA and 27.6KV.

Table B-3: Bus data of the modified IEEE 30-Bus system

From	To	R [pu]	X [pu]	P_Load	Q_Load
Bus_01	Bus_02	0.000731	0.003040	0.000000	0.000000
Bus_02	Bus_03	0.000101	0.000307	0.013150	0.016000
Bus_03	Bus_04	0.000340	0.000413	0.265700	0.019200
Bus_04	Bus_05	0.000298	0.000901	0.156000	0.090500
Bus_05	Bus_06	0.000309	0.000935	0.022250	0.015050
Bus_06	Bus_07	0.000336	0.001018	0.174050	0.111900
Bus_07	Bus_08	0.000426	0.001476	0.234700	0.116350
Bus_08	Bus_09	0.000420	0.001455	0.151950	0.069850
Bus_09	Bus_10	0.000182	0.000631	0.066700	0.028100
Bus_10	Bus_11	0.000209	0.000723	0.122150	0.236900
Bus_11	Bus_12	0.000265	0.000325	0.234050	0.071900
Bus_12	Bus_13	0.000261	0.000556	0.363500	0.087550
Bus_13	Bus_14	0.000362	0.000560	0.608000	0.306600
Bus_14	Bus_15	0.001074	0.002577	0.058150	0.027300
Bus_15	Bus_16	0.000322	0.000772	0.253400	0.065650
Bus_16	Bus_17	0.000311	0.000646	0.180500	0.070500
Bus_17	Bus_18	0.000201	0.000361	0.157000	0.054000
Bus_02	Bus_19	0.000289	0.000320	0.092500	0.041450
Bus_04	Bus_20	0.000331	0.000546	0.166000	0.090500
Bus_07	Bus_21	0.000350	0.001598	0.206150	0.093200
Bus_10	Bus_22	0.000146	0.000159	0.197600	0.095750
Bus_13	Bus_23	0.000233	0.000473	0.185000	0.080300
Bus_14	Bus_24	0.000955	0.001408	0.260500	0.155600
Bus_15	Bus_25	0.000431	0.000291	0.106000	0.062020
Bus_25	Bus_26	0.000250	0.000351	0.228500	0.095500

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