A MULTI-STAGE STOCHASTIC MODEL FOR PRODUCTION PLANNING USING ONSITE RENEWABLE GENERATION WITH PROSUMER APPROACH

by

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DEDICATION

This project is dedicated to my family, who with their love and financial support ensured my time in graduate school went as smoothly as possible and to God almighty for wisdom, direction, and protection all through the process.

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LIST OF ABBREVIATIONS

Abbreviation	Description
AMPL	A Mathematical Programming Language
ANOVA	Analysis of Variance
ARIMA	Autoregressive Integrated Moving Average
ASOS	Automated Surface Observing Systems
BSS	Battery Storage Systems
BT	Battery
CHP	Combined Heat and Power
CO_2	Carbon Dioxide
CVaR	Conditional Value at Risk
DER	Distributed Energy Resources
DG	Distributed Generation
DP	Dynamic Programming
DiS	Deterministic into Stochastic
DOE	Design of Experiments
EF	Extensive Form
EPA	Environmental Protection Agency
ESS	Energy Storage System
EV	Electric Vehicle

F&W	Factory and Warehouse
h	Hour
HRES	Hybrid Renewable Energy System
IEEE	The Institute of Electrical and Electronic Engineers
ISO	Independent System Operator
kg	Kilogram
km	Kilometer
kWh	Kilowatt hour
LCOE	Levelized Cost of Electricity
MG	Microgrid
MCP	Market Clearing Price
MPS	Master Production Schedule
MF	Multiplier Factors
M&O	Maintenance and Operation
MW	Megawatt
MWh	Megawatt hour
MSSP	Multi-Stage Stochastic Programming
PEM	Prosumer Energy Micro-infrastructure
PP	Production Planning
PS	Production System

PV	Photovoltaic
Rad	Radian
RE	Renewable Energy
SOC	State of Charge
WPP	Wind Power Producers
WT	Wind Turbine

ABSTRACT

This thesis researches on finding a production plan that minimizes the cost of a manufacturing system facing uncertainties on the demand of its final products over a horizon of multiple periods and considering adoption of renewable power as an energy prosumer (i.e. consumer and seller). Researched energy sources are wind turbines and solar photovoltaics coupled with energy storage systems (i.e. batteries). Renewable generation varies because of daily changes in wind speed and weather conditions. To account for the uncertainty on products demand and power supply, a multi-stage stochastic programing model is proposed. First-stage decision variables are the size of the renewable generation technologies, capacity of the batteries, and amount of production for the first set of periods. Second-stage recourse actions to cope with the uncertainty include: (1) storing final products in inventory or purchasing from vendors, as needed, (2) using battery to discharge or store energy and (3) purchasing/selling energy to/from the grid. In the second-stage, a new production decision for the second set of periods is also determined considering the inventory levels, production and purchasing costs. The third-stage includes deciding again on the best recourse actions to the second-stage decision. The model is implemented using the scenario-tree approach, and it is solved under two operation strategies: (1) factory and warehouse consolidated in Amarillo and (2) factory in Amarillo and warehouse in Phoenix. Numerical experiments show that a prosumer microgrid model is cost-effective (annual cost $7,052,410, levelized cost of electricity (LCOE) $37/MWh) if compared to an island microgrid model (annual cost

$15,150,000, LCOE $70/MWh). Due to high battery costs, the prosumer option reduces amount of battery capacity adopted and purchases some energy to the grid to save cost.

1. INTRODUCTION

The estimated consumption of electricity by the manufacturing industry in the United States is one-third of the total (The National Academy of Sciences, n.d.). According to Carlton (2019), statistics for 2015 global energy consumption by sector showed that industries consumed 54.9% of the energy. The energy consumed in the industrial sector, mainly the manufacturing sector, is used for powering heavy duty machines, lamination, ventilation, and other critical production processes.

Bakir and Byrne (1998) mentioned production planning is a key aspect in manufacturing industries. These industries face multiple uncertainties in product demand, processing times, suppliers' availability, workstation failure and maintenance time. Consequently, proper production planning should consider those uncertainties to minimize costs by reducing the number of resources needed, including energy consumption.

Presently, fossil fuels (natural gas, coals, and liquids) contribute to almost 84 percent of the global energy consumption while nuclear energy provides 4% (Ritchie, 2014). The former emits pollutants at high levels into the atmosphere and the latter produces radioactive waste. Due to the high availability and low cost, fossil fuels, such as coals, gas, and oil, still dominate the market (Sgobba and Meskell, 2019). Unless some action is taken, fuel power stations and their generation will continue increasing as well as the emission of CO_2, which pollutes the air and causes climate change, ozone depletion and emission of radioactive substances. To maintain a clean and green environment fuel use should be diminished gradually, if not eliminated.

An accessible action manufacturing industry can take is the use of renewable energy (RE) sources and technologies such as wind turbines (WT) and solar photovoltaic (PV) systems. Primarily, all types of energy sources on earth are ultimately derived from the sun. The sun provides streams of energy to warm humans and animals, grow crops through photosynthesis and heat land and sea to create winds and waves, respectively. The sun also produces rain used for hydropower generation that comes from water vapor gotten from heat extracted of moisture from the earth (Dincer 2000).

Sinpetru (2014) mentioned quite a few examples of companies that have already adopted RE in their supply chain systems, such as Honda, Apple, and Walmart. Honda has the largest RE purchase in the auto industry; it entered into virtual power purchase agreements for over 60% of its North America electricity coverage with renewable solar and wind power (Honda, 2019). Apple has America's largest onsite generation system consisting of WT and PV to lower carbon footprint of their energy-intensive facilities and offer green quality products to their customers. Since 2011, there has been a 54% greenhouse gas emission decrease from Apple facilities due to the RE projects. Starting on 2014, Apple has all its global data centers powered by 100% renewable energy globally (Apple, 2018). Walmart is considered the largest onsite RE user in the US, currently 28% of its global electricity comes from RE. The aim of Walmart is to reach a state where people do not have to be stuck with the option of choosing between affordable electricity and renewable electricity (Walmart, 2018).

Intel, Kohl's, the National Hockey League, Walmart, and Apple were mentioned as the top five businesses powered by RE (The Climate Reality Project, 2016). Intel has been for eight consecutive years the US largest voluntary corporate purchaser of green power. In 2015, 100% of Intel's US electricity was met with the purchase of 3.4 billion kilowatt-hour (kWh) of RE. Intel leads the US Environmental Protection Agency's (EPA) Green Power National Top 100 list, where the agency's largest green power-using partners are included. (The Climate Reality Project, 2016). Kohl's has 1001 of its 1160 stores energy star-certified with 163 locations featuring on-site solar panels. Kohl's was recently ranked in the top 10 on the EPA Green Power Partnership's Top 30 Retail List (Kohl's, 2018). These successful cases should inspire more manufacturing industries to embrace RE. This initiative will reduce the reliance on fossil fuels, produce green quality products and help to keep a cleaner environment. The motivation of this thesis is to provide mathematical models that can be used by manufacturing industries to optimally plan for the production and the adoption of distributed generation (DG) systems.

A DG system produces RE from dispersed or distributed energy resources (DER), such as WT and PV, installed close to manufacturing, warehouse and commercial facilities, where the energy will be used. A DG system distributes energy, helps to relieve transmission bottlenecks, and reduce carbon emissions. The DG system can also store energy using energy storage systems (ESS). As a type of DG system, a microgrid (MG), typically consists of WT, PV, fuel cells, micro-turbines, and diesel engines (Golari et al. 2017). MG's can operate disconnected from the main grid (i.e. island) or connected to the main grid to mitigate the intermittency on the energy they can generate. Besides power, the heat produced by the DER can be used by the facilities adopting MG's. Seven companies currently serving commercial and industrial needs for MG installation are AlphaStruxure, Bloom Energy, Box Power, Eaton, Gridscape Solutions, Saft, and Siemens (Haggerty, 2019)

The goal of this thesis is to formulate and solve multi-stage stochastic programming (MSSP) models for planning a multi-period, multi-product production facility with net-zero energy performance. The facility has its energy needs co-supplied by the main grid and a MG system that uses WT, PV, and battery DER units. In addition, the facility is an energy prosumer with the ability to purchase energy from the grid and sell renewable energy to the grid. The objective of the models is to simultaneously determine the renewable portfolio, generation capacity and production schedule to minimize the expected total cost of the system, considering uncertainties in product demand, wind speeds, and weather conditions.

This work contributes to the scarce literature on stochastic programming models for production systems that incorporate variable RE. The contributions are: (1) assessing the benefits of the implementation of prosumer energy and battery storage, (2) demonstrating that the scenario tree approach can be tractable for solving a multi-stage version of the production planning problem with multiple random parameters (i.e. product demand and capacity factors of the WT and PV), (3) exemplifying the use of data analytics to portrait the actual day-to-day variability on weather conditions in the cities studied through multiple scenarios and (4) applying the rolling horizon approach over a short-term (i.e. two-months) stochastic model and assessing its accuracy to plan for a longer-term (i.e. twelve months) decision horizon. Thus, this research work extends the one in Golari et al. (2017) by considering prosumer energy, battery storage and two random parameters. This research also extends the work in Yu et al. (2019) by using a multi-stage stochastic programming approach and incorporating detailed aspects of production planning problems and energy prosumers.

The remaining chapters in this thesis are organized as follows. Chapter 2 presents the problem researched on the thesis, the research questions and literature reviews on production planning, production planning incorporating RE use, and multi-stage stochastic models for solving RE integration problems. Chapter 3 discusses the contribution of this thesis in comparison to previous works in the literature. Chapter 4 presents the methodology to solve the proposed problem. The methodology consists of developing MSSP models considering three decision stages. Each stage comprises several pre-defined periods. Chapter 5 elaborates on the scenario tree model used for representing the stochastic demand and on the computations of the capacity factor to model the daily utilization of WT and PV due to changes in the wind speed and weather conditions. Chapter 6 presents numerical experiments for the models developed in Chapter 4. The numerical results are mainly for the following three cases: (1) a stochastic production planning model for a factory that does not consider the use of RE, (2) a stochastic production planning model for a factory that has a warehouse in the same location, uses RE and acts as prosumer (3) a stochastic production planning model for a factory and a warehouse that are located in different places, use RE and act as energy prosumers. Chapter 7 provides the discussions on the numerical results and makes further comparisons and experimentation. Chapter 8 provides conclusions about this study and mentions possible future work.

2. PROBLEM STATEMENT AND LITERATURE REVIEW

This chapter is divided in 3 sections. Section 2.1 defines the problem studied in this thesis. Section 2.2 provides the research questions addressed by this thesis. Section 2.3 provides a literature reviews on relevant topics comprised by the proposed problem.

2.1 Problem Statement

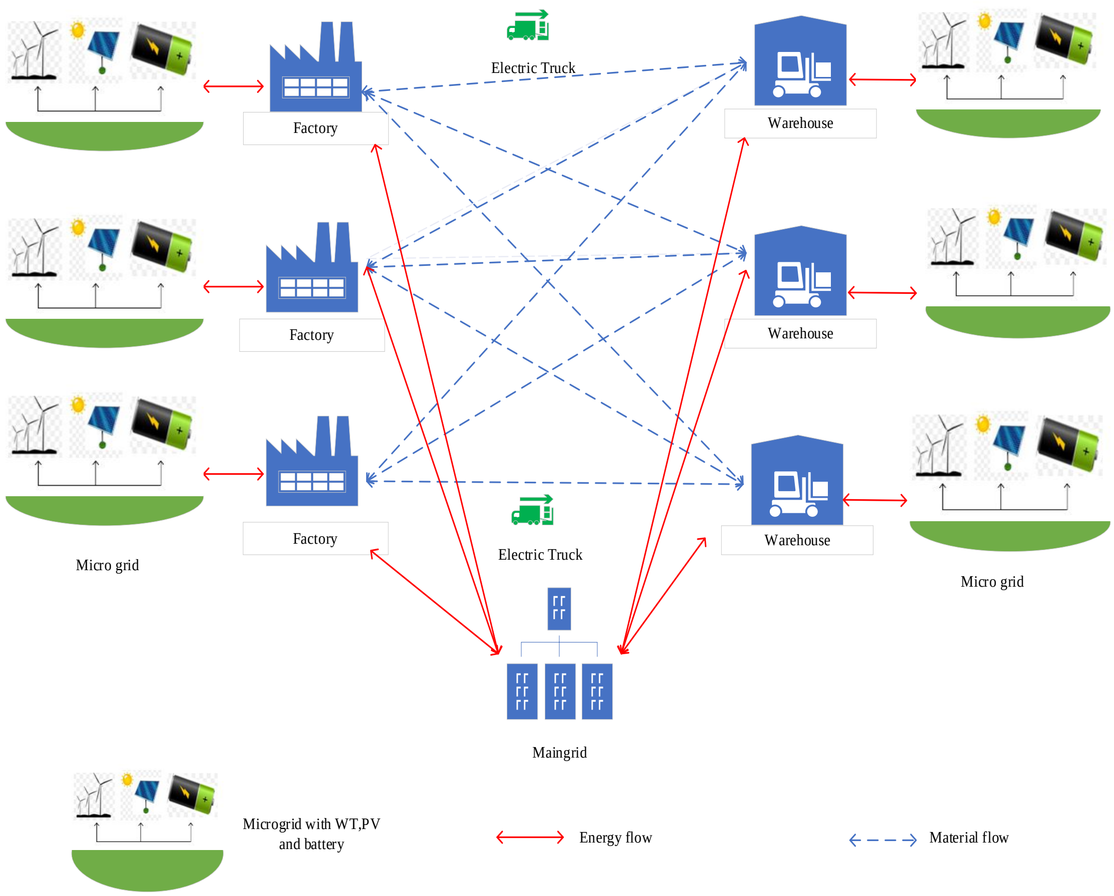


Figure 1. A production system (PS) with onsite renewables

Figure 1 illustrates the production system (PS) under study in this thesis. The PS is comprised of multiple factories using a variety of resources, such as labor hours, machine hours, energy, raw materials, etc. to produce different types of products on multiple time periods. The finished products are shipped to warehouses for storage using a fleet of electric vehicles (EV). The factories and warehouses generate on-site renewable energy (RE) from microgrid (MG) systems they will adopt, which are comprised of wind turbines (WT) and solar photovoltaics (PV), and that can be connected to the main grid. RE is used for production, transportation, storage of products and for being sold to the main grid. The MG system also uses batteries onsite for storing RE in days in which the total energy generated by the WT and PV is greater than the consumption. The energy stored in the battery can then be used on days when the onsite generation is insufficient for meeting the electricity demand. The factories are energy prosumers and thus in days when the available energy (i.e. energy generated and stored in the battery) is unable to meet factory or warehouse demand, energy is purchased from the main grid. Besides, when the MG generates more energy than the actual load (i.e. energy demand) this surplus energy is either stored in the battery and/or sold to the grid.

The goal of the stakeholders of the PS described is to optimally plan for the portfolio of renewables adopted and for the production over multiple time periods to minimize the total expected net annual cost while considering stochastic demands for the finished products, wind intermittency and variable solar output. The net annual cost includes annualized costs of installing the MG, production, logistics and other maintenance and operational energy costs, and revenues from selling extra energy. The stakeholders also aim to ensure net-zero energy operation by requiring that the designed system guarantees that the energy consumed by the facilities over the year be balanced with the renewable energy generated. Besides, the PS has the option of storing finished products in the inventory if product demand is low. Also, the PS can reach external vendors to purchase finished product and satisfy any peaks on the product demands that cannot be satisfied with onsite production.

2.2 Research questions

This thesis answers the following research questions regarding the PS described in Section 2.1:

1. What is the annual cost impact of including energy requirements in a production planning model for the PS described in Section 2.1?
2. What is the difference in levelized cost of energy (LCOE) if running the PS with wind and solar energy and implementing battery instead of purchasing energy to the grid?
3. Is it feasible to run the PS using only the MG onsite renewable energy generated and battery storage and what would be the cost of this option?
4. What is the benefit of modeling the PS using stochastic models instead of deterministic ones?
5. What are tractable modeling approaches to minimize the production and energy costs of the PS over short-term (i.e. two-months) and long-term (i.e. one-year) horizons?
6. What would be the energy costs elements (i.e. renewable energy equipment costs, price from purchasing energy from the grid, revenues from selling energy to the grid) affecting at the greater extent the total cost of the PS?

2.3 Literature review

A variety of studies have been published on the topic of modelling and optimizing production planning (PP) problems. Some of them have focused on assessing the effects of uncertainty in demands or raw materials, while others have engaged on developing and solving models for integrating renewable energy (RE) effectively to maintain an efficient daily operation. The following four subsections of this section present literature reviews on the following topics relevant to the problem studied in this thesis: (1) PP without RE, (2) PP incorporating energy (i.e. mostly RE), (3) stochastic models for solving energy generation planning problems, with emphasis on multi-stage stochastic programming (MSSP) models for RE planning and (4) RE models considering prosumers. Under each sub-section the contributions are listed in chronological order.

Because the literature on PP without RE is extensive, and because the problem researched has stochastic product demands and renewable energy supply, the focus of the literature review on Sub-section 2.3.1 is on presenting contributions that propose exact methodologies that are suitable to tackle these stochastic aspects of the problem. Thus, the survey in sub-section 2.3.1 includes papers using methodologies such as two-stage stochastic programming, MSSP, and dynamic programming (DP). The survey is highly oriented to research works using MSSP. This is because the author of this thesis and her advisor were highly motivated to apply MSSP, a methodology that is known for being appropriate to portrait highly flexible and dynamic production settings in which original production decisions may be reviewed and modified several times in a year. The author of this thesis acknowledges that dynamic programming is another methodology suitable but less used to tackle the problem researched in this thesis; however, she found that her background would permit her to apply MSSP more effectively than DP.

2.3.1 Production planning without renewable energy

PP relates to arranging the acquisition of raw materials and resources and the production activities required to process raw materials into finished goods to satisfy customer demands economically and efficiently (Pochet and Wolsey, 2011). This subsection focuses on PP models dealing with any type of uncertainty.

Federgruen and Zipkin (1984) addressed a production inventory planning problem. In this problem, a central depot faced random demands from different locations. The authors considered inventory and backorders as recourse actions to fulfill the random demands. Their model minimized the total expected inventory holding cost and backorder cost over multiple time periods. The authors formulated the problem using DP and reduced the state space demonstrating that the problem approximates to a single-location inventory problem with multiple products. They validated the approximation by comparing its results to the ones from simulating the system and found that the errors are quite small in most of the cases studied.

Escudero et al. (1993) presented four different scenario-based MSSP models. One of them determines the production amount to minimize the expected cost of holding inventory and lost demand. Such model left the inventory as the only recourse action and is classified as one with simple recourse. Similarly, a model with purchase of product in which such decision and the production amount are fixed over the decision stages is classified as having simple recourse since again inventory is the only recourse action to cope with the uncertainty. In a third model the authors consider all decision variables, production, inventory, and amount of product purchased as possible to alter over the decision stages. Such model is classified as one with full-recourse. The last model aims to determine the amounts of each product to produce, and to purchase from different vendors to minimize inventory, vendor supply and lost demand costs. In the model, production, inventory, and amount of lost demand vary over the stages but the amount purchased does not. Thus, the last model is classified as one with partial recourse. Authors highlighted that even if the scenario modeling formulations made the models large, they still ended with a tractable solution from the computational perspective. Authors also compared the cost of making decisions by using only one scenario in the scenario three, the average demand, and the different types of recourse (simple, partial and full) and demonstrated that the full-recourse model produced the lowest cost.

Escudero et al. (1995) researched on a stochastic PP problem with uncertainty in the demand of products considering different types of recourse actions to meet demands. Like the problem researched in this thesis, the production system considered can store finished goods in inventory or purchase them, if needed. The problem was addressed using a multi-stage stochastic programming (MSSP) model with non-anticipative (or implementable) policies (Wets, 1989), which are defined as those that rely only on the uncertainty realized up to the moment of the decision (Birge and Louveaux, 1997). The demand uncertainty of the model was characterized by scenarios. The paper presented several linear programs corresponding to the extensive formulation (i.e. the deterministic equivalent model) for the stochastic program under two representations: splitting variable and compact. The splitting variable representation was solved with the interior point method while the compact representation was solved with the simplex method. The authors compared these different algorithmic approaches for the prescriptive models and found the compact representation under the simplex solution methodology as the most suitable in their experimentation. Prescriptive models are those that select the most optimal solution for a decision-making problem (Gass and Fu, 2013). Iyoob (2019) defined prescriptive models as those that help to determine what change should be made in the model parameters to improve one or several outcomes.

Mula et al. (2006) discussed the various uncertainties associated with the modeling and optimization of PP problems. The authors reviewed previous works on PP and classified them using two categories for the type of uncertainty: environmental and system. Environmental uncertainty included demand uncertainty and supply uncertainty. System uncertainty included operation, yield, production lead time and quality uncertainty. The literature review concluded saying that stochastic programming was the most used approach for modeling uncertainties in PP problems while the DP approach remained mainly theoretical.

Zanjani et al. (2009) studied the uncertainty in the quality of raw materials, process yields, and product demands and proposed a multi-stage stochastic model to incorporate all these aspects. They addressed the uncertainty in the yield using a random variable with stationary probability distribution. Depending on the availability of the information on the uncertain parameters at the beginning of each stage in the scenario tree, the type of defined recourse varied as explained in the next sentences. Since at the beginning of each stage the decision maker had perfect insight on the demand scenario to be observed, the production plan could be adjusted for demand scenarios (full recourse). However, the yield scenarios revealed only after plan implementation and thus production plan was constant for yield scenarios (simple recourse). A dynamic-stochastic process was used for modeling the uncertain demand and the compact formulation of the stochastic program was solved. The authors' results indicated that the solution from a four-stage stochastic model was significantly better if compared to the solutions from mean-value and two-stage stochastic models. As future research, they proposed to consider seasonal demand and trend differences at the different stages of the stochastic demand tree.

Korpeoglu et al. (2011) researched on generating a master production schedule (MPS) for an auto manufacturer who was starting to produce a new model and thus needed to consider different demand scenarios, limited capacity, and adjustable processing times. The authors modeled the problem using multi-stage stochastic programming and solved the model efficiently. The demand of the first period was assumed known while the demand for the other periods was uncertain but its probability distribution was known. The authors mentioned that very often in the MPS literature uncertainty in demand was ignored and that MSSP models may give better results than two-stage stochastic programming models because they allow more dynamic decision making as future information is revealed. The quality of their stochastic solutions compared favorably to those from solving the problem for a single-scenario. The authors suggested that their model could be implemented under a rolling horizon approach where the problem is solved multiple times assuming a fixed length planning horizon and only the next period's decision is implemented. A simple example of a rolling horizon approach is given by Winston (2004). The rolling horizon approach permits refreshing the product demand estimates and any other values for the parameters every time the model is solved. More references about applications of the rolling horizon approach can be found in Li and Ierapetritou (2010)

2.3.2 Incorporating energy in production planning

Energy demand has increased tremendously over the years and this also means an increase in greenhouse gas emissions. Besides, fossil fuel resources used for energy generation are diminishing and depleting (Vine, 2008). These problems have stimulated the integration and utilization of RE especially in manufacturing and some logistics sectors where there is a high usage of electricity. Another approach is carbon tax and cap-and-trade policies with the aim of reducing greenhouse gas emissions. Evans et al. (2009) assessed and compared the life cycle of different RE technologies, such as wind power, photovoltaic, hydropower and geothermal energy and concluded that wind power has the lowest greenhouse gas emission, consumes the least water and is most favorable in terms of social impact. But on the downside, wind power has a relatively high capital cost, requires more land space, creates noise, and kills wildlife animals, such as birds and bats that fly and collide into the turbine blades. However, Saidur et al. (2011) mentioned that if WT are carefully designed some of these downsides can be minimized.

Recently, Yu et al. (2020) investigated on how a retailer can maximize the profit by managing the inventory of perishable products assuming deterministic demand and considering that the demand of their products originates carbon emissions. In the models, the authors assumed the retailer signed a carbon tax policy or a carbon cap-and-trade policy. The models found the optimal selling price, ordering frequency and preservation technology investment under such policies and demonstrated that the models have unique solutions that help retailers to take more accurate decisions in each case.

2.3.2.1 Deterministic models incorporating renewable energy in production planning

Jin et al. (2015) considered the integration of on-site and off-site renewable wind and solar energy in a production facility. The paper proposed a multi-period production inventory model with production, inventory, backorders, and energy consumption as decision variables. It aimed at minimizing total manufacturing cost to achieve a pre-defined green energy coefficient target. The numerical experiments showed that a desirable green energy coefficient can be achieved if the manufacturer mixes onsite generation with grid renewable energy. For future works, the authors proposed an extension of the current model into a stochastic programming model that considers uncertainty in production demands, power intermittency and other stochastic aspects.

Jin et al. (2017) investigated the feasibility of operating a net-zero-carbon supply chain infrastructure comprised of multiple plants, warehouses, retail stores and electric vehicle logistics. Each facility could install onsite wind and solar generation operating under net metering, a special feed-in-tariff program where the rate the utility company charges for the energy sold is equal to the price the utility company pays to a customer feeding surplus energy. The supply chain system encompassed production, transportation, warehousing, and retailing. The proposed model aimed to minimize the LCOE via determining the optimal generation type and capacity. The authors assumed deterministic demand at the facilities and solved the model using linear programming. The granularity of the energy constraints was kept on a one-year basis. The results showed that wind generation was cost-effective with consistent medium wind speed and that even though PV systems ended less competitive than WT, they can be used if their cost is reduced by 50%.

Pham et al. (2019) studied on designing a joint production net zero microgrid system in a multi-facility system using linear and integer programming. The authors also solved the model using a two-stage solution approach. In the first-stage, they solved a deterministic model to schedule the production to meet a given γ percentile of the product demand. In the second-stage, a deterministic linear programming model found the sitting and sizing of the WT and PV that satisfies the electricity load associated with the optimal production plan found by the first model. Numerical results show that the model under grid connected mode (i.e. no battery installed) is cost effective in certain areas where WT and PV is above 0.25 and 0.45, respectively. The research also found that due to the high cost of the battery, grid-connected microgrid with net metering has lower LCOE in comparison to an island model.

Subramanyam et al. (2020) investigated the use of hourly climate analytics to size a renewable microgrid in a flow shop manufacturing system using a two-stage solution approach. The first-stage solved an integer programming model that minimizes the annual energy required to satisfy the production needs of the flow shop. The second-stage determined the sizing of WT, PV, and battery storage to meet the hourly electricity load over a one-year period using linear programming. The paper addressed the minimization of levelized cost of electricity (LCOE) and stated that wind generation is cost-effective when wind speed at the tower height is above 8m/s. Besides, the paper found that battery storage is not economically attractive to large scale use with its current capacity cost of 0.5M/MWh. However, if the battery capacity cost reduces to 0.25M/MWh, time-of-use tariff can promote the use of battery.

2.3.2.2 Stochastic models incorporating energy in production settings

Ierapetritou et al. (2002) used a two-stage stochastic programming approach to determine an optimal operation schedule for an energy-intensive air separation plant with the aim of minimizing energy cost while considering random product demands and random electricity prices from the utility company fluctuating over time. This fluctuation in prices is common when an industry engages on real time pricing agreement with a utility company. The manufacturing process used electric power to run an air separation unit consuming about 20% total power and a liquefier using the remaining 80%. Every hour and instantly, the plant could switch among three operation modes: regular, shutdown (using just miscellaneous power), and assisted (stopping the liquefier and using stored product for the refrigeration operation). The scenarios for the future power prices (i.e. the ones beyond the next 3 days and running for a lapse between 2-5 days) were generated using an autoregressive integrated moving average (ARIMA) model and chosen at the upper and lower computed confidence intervals to accurately consider price uncertainty. Two solution approaches were developed: generalized benders decomposition and outer approximation. The results showed good accuracy if using the ARIMA model for forecasting. The results also demonstrated the effectiveness of the two-stage stochastic mode on accounting for the future energy price variability in present time.

Tang et al. (2012) researched on a multi-product multi-period PP problem in the iron and steel industry considering not only production and inventory costs but also energy costs because the manufacturing processes in this type of industry are highly energy consuming. They modeled the costs of energy consumption as a non-linear function of the production quantity and assumed stochastic product demands. The authors took a scenario-based approach and approximated the mixed integer nonlinear programming model with piecewise linear functions. A stepwise Lagrangean relaxation method is proposed to solve the problem. The conclusion of the research was that the proposed solution approach could be used to solve other stochastic PP problems with non-linear costs.

Emec et al. (2013) presented a mixed integer programming formulation embedded in a simulation framework to schedule the next-day production of a set of machines on a manufacturing line in an automotive industry. The model jointly considered stochastic orders, energy loads of each machine and the actual price of the energy needed. It was assumed that the company could buy energy from a European electricity market. Two machine stages with different associated energy consumptions were considered: waiting and processing. The paper demonstrated large cost savings could be achieved if comparing to the case in which the price of the electricity is constant. Authors suggested as future work considering multi-criteria optimization: the joint minimization of the CO_2 emissions and the energy costs.

Golari et al. (2017) researched on adopting onsite intermittent renewable power and grid renewable for operating a multi-period, multi-plant, production-inventory system. The problem was first modeled as a deterministic planning model before being extended to a multistage stochastic optimization model that considers the uncertainty of the renewable energy supply. The authors used a modified Benders decomposition algorithm to create an optimal production schedule using the scenario tree approach. This paper addressed the power intermittency issue and proposed the use of a green energy coefficient for the assessment of sustainable manufacturing. The results showed that it is affordable for manufacturing companies to achieve a high level of green energy coefficient with onsite and grid renewable energy integration.

Recently, Gao et al. (2020) compared the effect of two production strategies on the optimal order policy of raw materials for a multi-period, multi-raw material inventory management problem under carbon emission constraint in make-to-order foundry enterprises. The authors assumed that the carbon cost was incurred only in transportation and the raw material consumption was random. A probabilistic DP model was used to solve the problem under the two different strategies.

2.3.3 Stochastic models for solving energy generation planning problems

Yu et al. (2019) investigated on the design of a hybrid renewable energy system (HRES) which consist of renewable energy sources, loads, a fuel base generator and an energy storage system (ESS) operating under uncertainty in energy supply and demand. They developed a two-stage stochastic programming model to minimize the daily expected cost of operating the HRES and investigated on effective scenario-generation methods. The authors transformed the model into a mixed integer linear program with multiple scenarios. In their results, the stochastic model was compared to a deterministic one. As expected, the deterministic model resulted costlier than the stochastic model. The authors stated that in future works, a better ESS design and operation can reduce the overall cost of the HRES.

Subsection 2.3.3.1 focuses on reviewing work related to multi-stage stochastic models for solving energy generation planning problems. All works except the one in Ding et al. (2018) relate to RE.

2.3.3.1 Multi-stage stochastic models for solving energy generation planning problems

Meibom et al. (2007) worked on a multi-stage stochastic linear model to optimize the wind power capacity commitment considering four electricity markets and one thermal market in five European countries. The aim of the model was to minimize the cost of unit commitment. Due to the large number of time periods in the model, the use of a single-scenario tree on hourly basis turned out to be intractable. Consequently, the authors adopted a multi-stage recursion with rolling-horizon planning solution approach. Each planning period is modeled using a three-stage scenario tree. The first-stage has 3-hours length and occurs 12 hours before the delivery period (i.e. one day ahead). In this stage, the power generators must decide on the amount of electricity bidding without knowing the effective wind power production. The second-stage also has 3-hours length and 5 scenarios and the third-stage covers the reminder number of hours in the planning period and 10 scenarios. In the rolling horizon approach, the amount of power sold to or bought from the day-ahead market is determined in the first planning period. In the subsequent planning periods, the variables that represent the amounts of power traded on the day- ahead market are fixed to the values found in the previous planning period, and the optimization concerning other decisions for the intra-day market is done. The research showed that the total operation cost of the model decreases if there is higher wind power penetration. Also, this high penetration increases the saved water in hydro storages.

Shafie-khah et al. (2014) proposed a model for optimal self-scheduling of wind power producers (WPP) using MSSP and considering the establishment of forward markets. Self-scheduling refers to the commitment of WPP to supply an energy production level, which must be delivered for an agreed period. The research focused on the participation of multiple producers in the electricity service market for profit maximization. Uncertain parameters, such as wind power, market prices and independent system operator (ISO) quantity of activated reserve is modeled using a scenario-based approach and the Monte Carlo method. The hourly market prices are fitted to a log-normal distribution. The authors proposed a three-stage stochastic model that incorporated the Conditional Value-at-Risk (CVaR) technique for risk management to achieve a desirable tradeoff between the risk and the expected profit for WPP. Experimentation was done in a 50MW wind farm operating on the Spanish electricity market. It allowed to study the effect of participation in forward and ancillary service markets on the optimal trading of WPP. In conclusion, the increase in expected profit of WPP is led by an establishment of an optimal amount of participation in the forward market.

A MSSP model for planning the expansion of combined power and natural gas systems considering non-anticipativity constraints was presented by Ding et al. (2018). The research had as objective to minimize total investment and operation cost of the combined system over its several planning periods. The authors mentioned that the deterministic formulation of the problem solves as a mixed integer linear program that couples discrete investment variables of successive periods and uses continuous operational variables. The authors proposed two-stage and a multi-stage stochastic programming models for addressing the problem of considering stochastic net load demand during the planning periods. They experimented with the stochastic models using three different IEEE networks (6-bus, 24-bus, and 118-bus). In conclusion, the experiments showed that the multi-stage stochastic programming model will yield a smaller total investment cost than the two-stage stochastic model because in the multi-stage model the decisions are more flexible and adaptable as they are taken in a sequential or wait and see manner. The authors found as a disadvantage of multi-stage stochastic programming that the computational complexity of the problem grows as the number of scenarios increases.

Yin et al. (2019) presented a research on wind generation that included decision-dependent uncertainty in the WT power curve. The authors called this type of uncertainty as endogenous. The study aimed at minimizing the total expected cost of the system throughout its planning period including operation cost of the thermal generators and investment cost of the wind generation. The authors presented a multi-stage stochastic programming model that also considered the external uncertainties of load and wind speed. The model used non-anticipativity constraints for the scenarios of power that at a point in time have the same realizations of uncertainty in the scenario tree. Yin et al. (2019) opted to model and approximately solve the Y-stages problem by decomposing it into a set of Y mixed-integer linear programming models and updating the non-anticipativity constraints according to the uncertainty that has been realized up to a particular stage. The research concluded that planning with a multi-stage model reduces the total cost if compared to using a single-stage model because the corrective actions can be based on more accurate predictions. The authors also discovered that increases in wind turbine power curve prediction error escalates the total expected cost.

Ioannou et al. (2019) used MSSP to determine the optimal generation mix for the Indonesian power system considering randomness in energy demand, fuel prices and capital cost of the RE. The uncertainty in the fuel prices was modeled through Monte Carlo simulation. It permitted a representation using continuous probability distributions. The uncertainty in the other factors was modeled through a scenario tree that considered a finite number of possible of combined scenarios. The paper showed that coupling Monte Carlo simulation with scenario tree approach better portraits the randomness in the model parameters. From the practical point of view, the model permitted the country to foresee the need for more investment on RE to meet the future CO_2 target levels.

2.3.4 Renewable energy (RE) models considering prosumers

RE models have started to incorporate the idea of energy prosumers, where the energy consumer can act as both, a consumer, and a provider of energy to power distributors or other consumers. The literature found on a single energy prosumer is scarce. The works of Perkovic et al (2017) and Wongwut and Nuchprayoon (2017) fall in the single prosumer category. The work of Choi and Min (2017) considers a prosumer aggregator of a grid industrial complex comprised by multiple customers. The works of Rathnayaka et al. (2011), Fice and Debousky (2016) and Liu et al. (2017) and consider the operations of multiple prosumers.

Rathnayaka et al. (2011) presented a literature review on smart grid energy sharing with attention to prosumer management and participation. The paper studied the shortcomings of other published research works, such as lack of: (a) approach in discussing energy sharing between prosumers and consumers, (b) methods for identifying the risk associated with prosumer negative behaviors and (c) reward schemes that consider the financial and non-financial incentives for prosumers. The paper also proposed the implementation of goal-oriented virtual prosumer communities and the development of smart techniques or approaches to manage the prosumer communities.

Fice and Debowski (2016) studied the optimal management of an electric grid prosumer system using solar PV generator and ESS. It was assumed that the grid is embedded in a prosumer energy micro-infrastructure (PEM) that integrates electronic energy counters, power grid, meter, control, and management systems. The PEM is modeled as a control system working in a feedback loop and using a controlling algorithm to schedule the switching on and off for several electrical devices, depending on the weather forecast. The model objective is to minimize the flow of energy through the connection points with the power grid system and balancing instantaneous power of the PEM. The analysis of numerical experiments showed positive economic effects with the increased usage of RE sources. Also, battery usage let to improve energy efficiency and increased the energy usage rate defined as the ratio between energy send to the power grid and energy generated by RE. For future works, the authors propose the use of production forecast to automatically schedule electric devices in the PEM and introduce multi-zone tariffs for managing the battery SOC.

Perković et al. (2017) discussed and analyzed a hypothetical prosumer factory using fuel (natural gas) as input to run a combined heat and power (CHP) system, electric power purchased from the day-ahead electricity market and PV to run its operations. The problem had multiple objectives which aimed at minimizing operation costs along with investment costs related to equipment for minimizing energy generation cost, such as the size of the thermal storage, capacity of the warehouse for storing the products, and installed capacity of PV. The thermal storage keeps thermal energy directly from combined heat and power (CHP) and from the power to heat coming from the electricity bus. Electric energy comes from the electricity market, from the CHP unit and from the PV. Thermal and electric demands per product were assumed known and linear. Thus, the total thermal and energy loads were determined through the multiplication of number of products supplied per year and the unit demands. The price of the fuel, demand for products and solar irradiance were assumed known in advance and thus the approach to model the problem was through a deterministic linear programming model with weighted objective function. Pareto frontiers were derived and the sensitivity of them ended higher for the objective related to operating costs. The research concluded that, assuming that the prices of electricity and fuel keep at the values used in this study, the increased potential for saving in energy supply can be caused by a larger fluctuation in the electricity market clearing price (MCP)..

Wongwut and Nuchprayoon (2017) optimized the daily costs of operation of a single prosumer which can generate, consume, and store energy on an hourly basis. It was assumed that the prosumer operated under the time-of-use pricing scheme. The model found the prosumers daily generation schedule and determined if a battery should be installed, its size and its charging and discharging condition. The problem was first formulated as a linear programming problem but new binary variables for the battery operation and on-site generation transformed the problem into a mixed integer programming problem.

Choi and Min (2017) presented a model for a prosumer aggregator of a grid-connected industrial complex with contracted customers and prosumers loads. The microgrid implemented WT, solar PV, electric load and ESS. The aim was maximizing the prosumer aggregator profits by controlling the ESS in different operating conditions and minimizing its operation cost while still fulfilling the contract of providing certain amount of energy to its consumers. The paper studied the coordination between day-ahead optimization and real- time operations. Two cases with a prosumer test-bed coming from actual field data of a grid connected industrial complex were studied. Day-ahead optimization was modeled as a quadratic program to determine the optimal charging and discharging schedules of the ESS and minimize the operational cost of the system, given by the electricity price paid to the utility company, and the rate of change of state of charge (SOC). The real-time operation was modeled as a re-optimization that occurs if at some point during the day, the real-time monitoring system detects large differences between the forecasted RE produced and the actual throughput. If this happens, the quadratic model is run again with adjusted values for the power produced by the RE system during the remaining interval of the day. In conclusion, the study showed that operating cost can be effectively saved by taking corrective actions based on the information coming from real-time monitoring systems.

Liu et al. (2017) developed an energy sharing model among prosumers with price-based demand response. Such paradigm seemed cost effective for prosumers in comparison to purchasing energy from a distribution center. The model considered prosumers adopting PV systems and it assumed that the PV used the maximum power point tracking control to maximize the output. The authors configured a basic model of the power consumption of the PV and an internal price model to fulfil supply and demand. The authors also developed, a cost model of the PV prosumer that considers changes in the profiles of power consumption of the prosumers, and an income model of the Energy Sharing Provider (ESP) related to the service fee charge. A distributed iterative algorithm was proposed for solving model and the benefits of the energy sharing among prosumers model were demonstrated. Including the power loss during the energy sharing is mentioned as one of possible extensions of the research work.

3. CONTRIBUTIONS OF THE PROPOSED THESIS

The literature reviews presented in Chapter 2 show that some authors have focused on models to implement efficient production planning (PP) in manufacturing industries and recognized the need for considering stochastic aspects of the problem, such as product demands. More recently, there is evidence of a few works to minimize the total cost of production and consider renewable energy (RE) implementation. However, at the best of our knowledge no previous work have solved a PP problem considering stochastic product demand and RE supply, battery storage, and energy prosumers. In the RE aspect, efforts have been made to implement mostly wind turbine (WT) technology and solar photovoltaic (PV) systems. Few studies have incorporated batteries and some other RE technology to reduce the use of energy from the main-grid system.

This thesis, unlike the works presented in the literature review in the previous chapter, proposes to use a multi-stage stochastic programming model to assess the cost advantages of adopting on-site RE (WT and PV) and battery system in manufacturing settings experiencing uncertainty in the product demands, wind speeds and climate conditions, and operating as energy prosumers over a multi-period planning horizon. Table 1 contrasts the contributions of the most closely related works discussed in the literature review in the previous chapter and the contribution of this proposed thesis.

Table 1. Contribution of this thesis vs. previous contributions in the topic

Author	*PP	RE	Battery storage	P	Uncertainty in the Model	Model Type	Solution Approach
This thesis	Yes	Yes	Yes	Yes	Product demand, wind intermittency and weather conditions	Multi-stage stochastic program (MSSP)	MSSP with multiple scenarios and compared to a deterministic model
Escudero et al. (1993) and Escudero et al. (1995)	Yes	No	No	No	Demand of products and inventory holding cost	Multi-stage stochastic program	Deterministic equivalent under a splitting variable and a compact representation
Zanjani et al. (2009)	Yes	No	No	No	Raw materials quality, process yields and product demands	Multi-stage stochastic program (MSSP)	Solved compact formulation of the MSSP
Golari et al. (2017)	Yes	Yes	No	No	Renewable energy supply	Multi-stage stochastic program Multi-period Multi-plant	Modified Benders decomposition
Pham et al. (2019)	Yes	Yes	Yes	No	Single percentile for demand, single set of capacity factors for WT and PV	Deterministic Multi-period Multi-plant	Integer and linear programming
Subramanayan et al. (2020)	No	Yes	Yes	No		Deterministic Multi-period	Integer and linear programming
Yu et al. (2019)	No	Yes	Yes	No	Energy supply and demand	Two-stage stochastic program	Mixed integer programming
Choi and Min. (2017)	No	Yes	Yes	Yes	State of charge (SOC)	Deterministic Quadratic	Day ahead optimization and real time optimization
Perković et al. (2017)	No	Yes	No	Yes	No considered	Deterministic with two objectives	Linear program
Wongwut and Nuchprayoon. (2017)	No	Yes	Yes	Yes	No considered	Linear mixed integer programming	Mixed integer programming

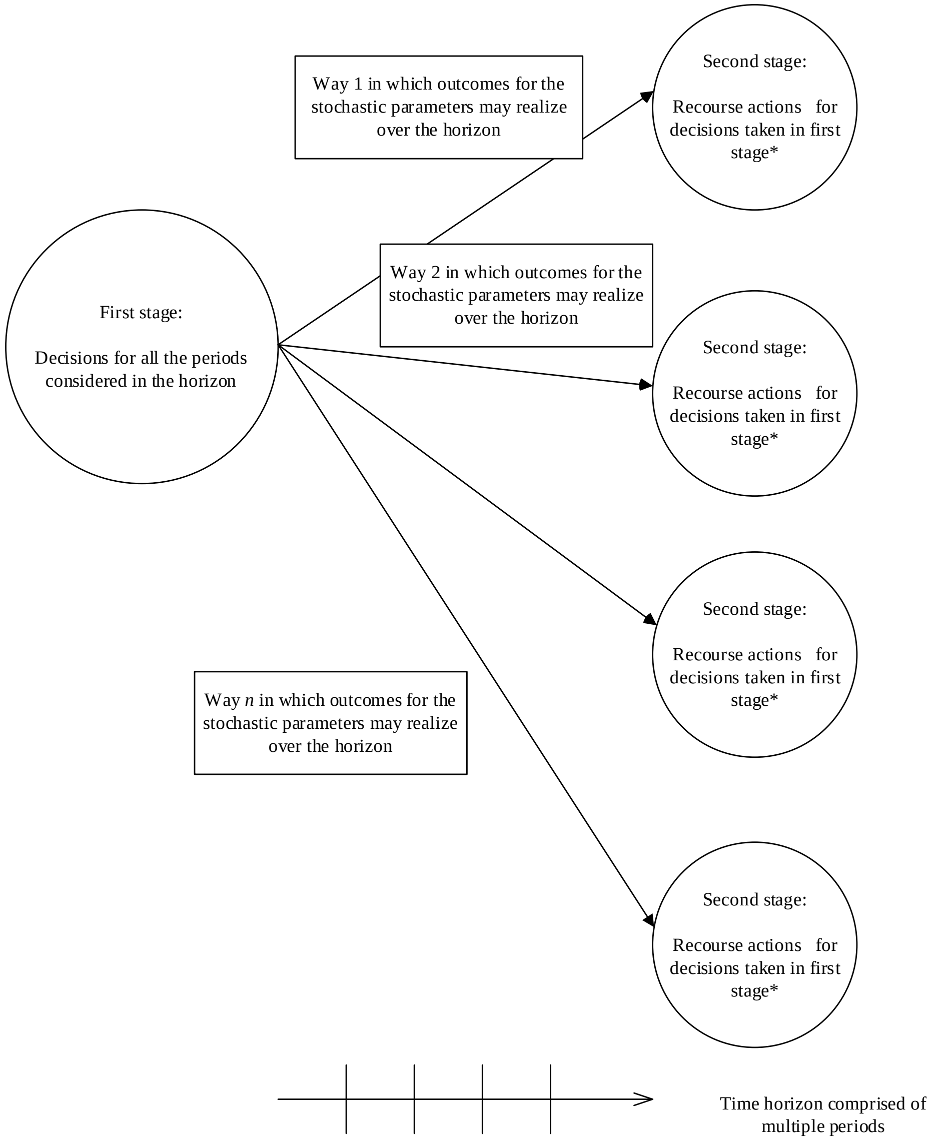
PP = Production planning, P = Prosumer

* If problem was not a multi-period production-inventory second column answer is No.

4. MODELING AND METHODOLOGY

The production planning (PP) with renewable energy (RE) problem described in Chapter 2 is modeled as a multi-stage stochastic program (MSSP) with recourse. A stochastic program is a mathematical program in which some of the parameters or input data are random and this uncertainty is explicitly included in the program (Birge and Louveaux, 1997; Gupta and Grossmann, 2011; Rardin, 2017). Thus, the exact values for some of the input data are unknown, but their probability distributions are known. The inclusion of the probability distributions helps to choose the best values for the decision variables in the mathematical program. Stochastic programs with recourse are those in which a corrective action can be taken after the uncertainty of the parameters is realized. Stochastic programs with recourse are very well suited to model situations where there are uncertain parameters, and it is the case in the PP problem proposed in Chapter 2. In practice, most problems do have some form of uncertainty in the parameters at the time of decision making.

Figure 2 provides a graphical representation of a two-stage stochastic program with recourse. In problems modeled as two-stage stochastic programs with recourse, a decision is made in the first-stage before the uncertainty about the random input data is realized. It is assumed that once the realization of the random data occurs the decision maker can take further decisions (i.e. recourse actions) that depend on the observed realizations of the uncertain data (i.e. scenarios). The recourse actions look for recovering feasibility at an associated cost. To seek feasibility for all possible scenarios of the uncertainty, a two-stage stochastic program with recourse finds values for the first-stage decision variables and the second-stage recourse actions that are feasible for all scenarios



* The way the outcomes for the stochastic parameters reveal may be sequential over the periods and also the way the recourse actions are taken. However, the critical part is that in two-stage stochastic programs the initial decisions taken are not revisited or modified over the periods in the time horizon

Figure 2. A two-stage stochastic program

by optimizing simultaneously, the cost of the first-stage decisions and the expected cost of second-stage decisions or actions (Beasley et al., n.d.; Shapiro and Philpot, 2007). Since two-stage stochastic programs include the possible second-stage recourse actions they are larger than deterministic programs. To keep stochastic programs tractable, the stochastic elements are usually assumed to follow discrete probability distributions and the two-stage stochastic program is formulated on its extensive form (EF) (Birge and Louveaux, 1997; Rardin, 2017; Novoa et al., 2018). The EF of a two-stage stochastic program is often called the deterministic equivalent (NEOS, 2019).

A three-stage stochastic program with recourse is an extension of a two-stage stochastic program. As in the two-stage stochastic program, the first-stage decisions occur before all the uncertainty about the input data is realized. It is assumed that on a second-stage, once some of the uncertainty is realized, recourse actions for the first-stage decisions can be taken. The recourse actions depend only on the realizations of the uncertain data for that stage and thus they assume no knowledge about the realizations of the uncertain data for the next stages. Furthermore, in contrast to two-stage stochastic programs, in the second-stage new decisions are taken before any uncertainty about the input data for the next stage is realized. On the third-stage, recourse actions that depend on and all the realization of the uncertainty (i.e. scenario) are taken. As in the two-stage stochastic program, the cost of all the decisions and the expected cost of the recourse actions are optimized with a single objective function.

A general extension of a three-stage stochastic program with recourse is known as a MSSP. In a MSSP, the following events repeat in a sequential manner: (1) decisions for a stage, (2) realizations or outcomes for some of the stochastic parameters occur, (3) decisions about the values of the recourse variables to implement in each scenario and if the stage is not the last one, new stage decisions that are also scenario dependent. Repetition of events (2) and (3) occur until the last stage is reached. If the uncertain parameters follow discrete probability distributions and the planning horizon has a fixed number of decision stages, the mathematical model for a MSSP can also written in its EF and the randomness of the problem can represented graphically on a scenario tree that will be discussed more in detail in Section 5.4. The EF of a MSSP is a large mathematical program that explicitly includes all scenarios and their associated recourse actions.

The reminder of this chapter presents the EF for the two MSSP models (Model 1 and Model 2) proposed to solve the PP problem with RE depicted in Figure 1 in Chapter 2. The main difference between the models is the length of the time horizon and the frequency of change in the random demands. For both models, the notation used is general since it assumes that the production system may consist of multiple factories and multiple warehouses. However, in this thesis, the numerical experimentation with the models considers: (1) one factory and one warehouse in the same geographic location and (2) one factory and one warehouse in different geographic locations.

4.1 Model 1

In the Model 1, the program is implemented as a three-stage stochastic one, as presented and depicted in Beasley et al. (n.d.). The first-stage decisions correspond to the size of the RE technologies (WT and PV) and battery capacity installed at the beginning of the time horizon and the production decisions for the first period, which is assumed to be of a length equal to one month. The second-stage decisions are the recourse actions to the production decisions taken in the first-stage and the production decisions for the second period. The third-stage decisions are only recourse actions to the production decisions taken in the second-stage.

The reason for selecting the length of the periods elapsed between stages equal to one month in Model 1 is to portrait production systems where the product demands are unknown and change often. It would be desirable to portrait such highly variable production setting over a horizon of one year with decision stages occurring every month. However, the scenario tree (see more explanations about a scenario tree in Section 5.4) would grow significantly. It would make the problem difficult to solve with a commercial solver without implementing any solution method to tackle the resulting large-scale program, such as Bender's decomposition.

Even if the planning horizon of Model 1 is two periods (i.e. months), the author in this thesis uses the rolling horizon approach mentioned in Chapter 2 as a method to optimize the production and energy decisions over an entire year. It is common in some industry settings to have planning horizons of one year and this is the reason because the author of this thesis chose one year as the planning horizon to perform the rolling horizon method. A brief but more detailed description for how the rolling horizon approach was implemented and its results are presented in Section 7.8. More details about a rolling horizon approach can be found in Winston (2004) and Meibom (2007). The rolling horizon method is also used by Li and Ierapetritou. (2010) to address a production planning and scheduling optimization problem. The authors mentioned as advantages of the method the usually small-scale size of the model and its fast solutions. Li and Ierapetritou also proposed a parametric programming method for incorporating accurate production capacity information and a heuristic network decomposition strategy to reduce the computational complexity and showed that these strategies improved the solution quality of the rolling-horizon method.

Notation used in Model 1 and Model 2 is given in Tables 2-7. Model 1 is presented and explained immediately below Table 7. Then, Model 2 is introduced, and the additional notation used in Model 2 is given in Tables 8-10. Model 2 is presented and explained below Table 10.

Table 2. Sets and indices in the models

Notation	Description
I	Set of products
T	Set of production periods
R	Set of resources needed to produce the products (i.e. labor hours, machine hours)
S	Set of scenarios
G	Set of renewable generation technologies
N	Set of warehouses
K	Set of factories
J	Sets of days in all the production periods
η_t	Set defining the scenarios that need to be equal up to period t to preserve the non-anticipativity or implementability constraints
i	Index for product type
t	Index for production period
s, s'	Indexes for scenarios
r	Index for resources (i.e. labor hours, machine hours)
k	Index for factory
n	Index for warehouse
g	Index for generation technology
j	Index for the days of a month
J_t	Set of days in the production period *t*

Table 3. Decision variables in the models

Notation	Description	Units
x_{ikt}	Amount of product *i* produced at factory *k* in period *t*	Items
x_{ikts}	Amount of product *i* produced at factory *k* in period *t* under scenario *s*	Items
y_{ints}	Amount of inventory of product *i* to store at warehouse *n* at the end of period *t* under scenario *s*	Items
z_{ikts}	Amount of product *i* purchased to satisfy the product demand at factory *k* in period *t* under scenario *s*	Items
P_{kg}^{c}	Capacity of generation technology *g* in factory *k*	MW
P_{ng}^{c}	Capacity of generation technology *g* in warehouse *n*	MW
B_{k}^{c}	Battery storage capacity adopted in factory *k*	MWh/day
B_{n}^{c}	Battery storage capacity adopted in warehouse *n*	MWh/day

Table 4. Continuation of decision variables in the models

B_{kj}^{f}	Daily energy stored in battery at factory *k* at day *j* (here and in the next three entries of the table the superscript *f* is used to represent storage)	MWh/day
B_{nj}^{f}	Daily energy stored in the battery at warehouse *n* at day *j*	MWh/day
B_{kjs}^{f}	Daily energy stored in the battery at factory *k* at day *j* under scenario *s*	MWh/day
B_{njs}^{f}	Daily energy stored in the battery at warehouse *n* at day j under scenario *s*	MWh/day
Q_{kjs}^{-}	Daily energy sold from factory *k* at day *j* under scenario *s*	MWh/day
Q_{njs}^{-}	Daily energy sold from warehouse *n* at day *j* under scenario *s*	MWh/day
Q_{kjs}^{+}	Daily energy purchased from factory *k* at day *j* under scenario *s*	MWh/day
Q_{njs}^{+}	Daily energy purchased from warehouse *n* at day *j* under scenario *s*	MWh/day

Table 5. Parameters in the models

Notation	Description	Units
θ_{it}	Production cost of product *i* in period *t*	\$/item
μ_{it}	Transportation cost of product *i* in period *t*	\$/item
p_s	Probability of scenario *s*	N/A
h_{it}	Holding cost of product *i* in period *t*	\$/item/period
o_{it}	Purchasing cost of product *i* produced in period *t*	\$/item
φ_g	Capital recovery factor of generation technology *g*	N/A
a_g	Capacity cost for generation technology *g*	\$/MW
φ_b	Capital recovery factor of battery	N/A
a_b	Capacity cost for battery	\$/MWh
b_g	O&M cost of generation technology *g*	\$/MWh
c_g	Penalty cost or tax incentive of generation technology *g*	\$/MWh

Table 6. Continuation of parameters in the models (1)

Notation	Description	Units
τ_{gj}	Number of generation hours in day *j* for generation technology *g*	h/day
τ_g^*	Total number of generation hours for generation technology *g* over the entire production periods	h
e_i^p	Energy consumed for producing one unit of product *i*	MWh/item
e_i^f	Energy consumed for storing one unit of product *i*	MWh/item
q_v	Electric vehicle (EV) energy intensity rate (see detailed explanation for this parameter in the glossary immediately after the Appendix section)	MWh/kg/km
d_{kn}	Distance between facility *k* and warehouse *n* and d_{nk} being the distance in between warehouse *n* and facility *k*	km
β	Number of daily trips	trip/day
m_v	Vehicle self-weight	kg
δ	Daily operating hours of a facility (warehouse or factory)	h/day
L_{ks}	Base electricity load of factory *k* (assumed the same under each scenario *s*)	MW
L_{ns}	Base electricity load of warehouse *n* (assumed the same under each scenario s)	MW
m_i	Unit weight of product *i*	kg/item
$\|J\|$	Size of the set of days over the entire production period considered	days
J_t	Number of days in period *t*	days
D_{ikts}	Demand for product *i* in factory k in period *t* under scenario *s*	item/period
w_{krt}	Amount or resource *r* available in period *t* at factory *k*	h/period
v_{ikr}	Amount or resource *r* needed to produce product *i* at factory *k*	h/item
B_k^m	Maximum battery capacity to adopt at factory *k*	MWh/day
B_n^m	Maximum battery capacity to adopt at warehouse *n*	MWh/day
$P_{kg}^{\max}$	Maximum capacity of generation technology *g* at factory *k*	MW
$P_{ng}^{\max}$	Maximum capacity of generation technology *g* at warehouse *n*	MW
λ_{gjs}	Capacity factor of generation technology *g* in day *j* under scenario *s*	N/A

Table 7. Continuation of parameters in the models (2)

Notation	Description	Units
Q_{kjs}^{Max}	Maximum allowed energy sold daily from factory *k* at day *j* under scenario *s*	MWh/day
Q_{kjs}^{Max}	Maximum allowed energy sold daily from factory *k* at day *j* under scenario *s*	MWh/day
Q_{kjs}^{Max}	Maximum allowed energy sold daily from factory *k* at day *j* under scenario *s*	MWh/day
Q_{njs}^{Max}	Maximum allowed energy sold daily from warehouse *n* at day *j* under scenario *s*	MWh/day
u	Selling price of extra RE generated	$/MWh
u^*	Cost of purchasing energy	$/MWh

Mathematical Model 1:

Minimize total expected cost:

$$
\begin{aligned}
z = {} & \sum_{i\in I}\sum_{k\in K}(\theta_{i1}+\mu_{i1})x_{ik1} + \sum_{i\in I}\sum_{s\in S}\sum_{k\in K} p_s o_{i1} z_{ik1s} + \sum_{i\in I}\sum_{s\in S}\sum_{n\in N} p_s h_{i1} y_{in1s} \\
& + \sum_{t\in T\setminus\{1\}}\sum_{i\in I}\sum_{s\in S} p_s \left[\sum_{k\in K}((\theta_{it}+\mu_{it})x_{ikts} + o_{it} z_{ikts}) + \sum_{n\in N} h_{it} y_{ints}\right] \\
& + \sum_{g\in G}\sum_{k\in K}\varphi_g a_g P_{kg}^c + \sum_{k\in K}\frac{\varphi_b a_b B_k^c}{\vartheta} + \sum_{g\in G}\sum_{n\in N}\varphi_g a_g P_{ng}^c + \sum_{n\in N}\frac{\varphi_b a_b B_n^c}{\vartheta} \\
& + \sum_{k\in K}\sum_{g\in G}\sum_{s\in S} p_s (b_g - c_g)\tau_g^*(\sum_{j\in J}\frac{\lambda_{g\,js}}{|J|})P_{kg}^c - \sum_{k\in K}\sum_{j\in J}\sum_{s\in S} p_s u \frac{Q_{kjs}^-}{\vartheta} + \sum_{k\in K}\sum_{j\in J}\sum_{s\in S} p_s u^* \frac{Q_{kjs}^+}{\vartheta} \\
& + \sum_{n\in N}\sum_{g\in G}\sum_{s\in S} p_s (b_g - c_g)\tau_g^*(\sum_{j\in J}\frac{\lambda_{g\,js}}{|J|})P_{ng}^c - \sum_{n\in N}\sum_{j\in J}\sum_{s\in S} p_s u \frac{Q_{njs}^-}{\vartheta} + \sum_{n\in N}\sum_{j\in J}\sum_{s\in S} p_s u^* \frac{Q_{njs}^+}{\vartheta}
\end{aligned}
\tag{4.1}
$$

Subject to:

$$x_{ikt} + y_{\mathrm{int}-1} - y_{ints} + z_{ikts} = D_{ikts} \qquad \forall i \in I, t = 1, \forall s \in S, \forall k \in K, \forall n \in N \tag{4.2}$$

$$x_{ikts} + y_{\mathrm{int}-1s} - y_{ints} + z_{ikts} = D_{ikts} \qquad \forall i \in I, t \in T\setminus\{1\}, \forall s \in S, \forall k \in K, \forall n \in N \tag{4.3}$$

$$\sum_{i\in I} v_{ikr} x_{ikt} \le w_{krt} \qquad \forall r \in R, t = 1, \forall k \in K \tag{4.4}$$

$$\sum_{i\in I} v_{ikr} x_{ikts} \le w_{krt} \qquad \forall r \in R, t \in T\setminus\{1\}, \forall s \in S, \forall k \in K \tag{4.5}$$

$$x_{ikts} = x_{ikts'},\ y_{ints} = y_{ints'}, z_{ikts} = z_{ikts'} \quad \forall (s,s') \in \eta_t, \forall i \in I, \forall k \in K, \forall n \in N, \forall t \in T \tag{4.6}$$

$$x_{ik1}, y_{\text{in}1s}, z_{ik1s} \geq 0 \quad \forall i \in I, \forall s \in S, \forall n \in N, \forall k \in K \tag{4.7}$$

$$x_{ikts}, y_{\text{int}\,s}, z_{ikts} \geq 0 \quad \forall i \in I, t \in T \setminus \{1\}, \forall s \in S, \forall n \in N, \forall k \in K \tag{4.8}$$

$$\begin{aligned} &\sum_{i \in I} (e_i^p + q_v d_{kn} m_i) \frac{x_{ikt}}{J_t} + \delta L_{ks} + \\ &q_v \beta d_{kn} m_v + B_{kjs}^f - B_{kj-1}^f + Q_{kjs}^- \\ &= \sum_{g \in G} \tau_{gj} \lambda_{gjs} P_{kg}^c + Q_{kjs}^+ \end{aligned} \quad j = 1, t = 1, \forall k \in K, \forall n \in N, \forall s \in S \tag{4.9}$$

$$\begin{aligned} &\sum_{i \in I} (e_i^p + q_v d_{kn} m_i) \frac{x_{ikts}}{J_t} + \delta L_{ks} + \\ &q_v \beta d_{kn} m_v + B_{kjs}^f - B_{kj-1s}^f + Q_{kjs}^- \\ &= \sum_{g \in G} \tau_{gj} \lambda_{gjs} P_{kg}^c + Q_{kjs}^+ \end{aligned} \quad \begin{aligned} &j \in J_t \setminus \{1\}, t = 1, \forall k \in K, \forall n \in N, \forall s \in S \\ &or\ j \in J_t, t \in T \setminus \{1\}, \forall k \in K, \forall n \in N, \forall s \in S \end{aligned} \tag{4.10}$$

$$\begin{aligned} &\sum_{i \in I} (\frac{y_{\text{ints}}}{\omega_t}) e_i^f + \delta L_{ns} + \\ &q_v \beta d_{nk} m_v + B_{njs}^f - B_{nj-1}^f + Q_{njs}^- \\ &= \sum_{g \in G} \tau_{gj} \lambda_{gjs} P_{ng}^c + Q_{njs}^+ \end{aligned} \quad j = 1, t = 1, \forall k \in K, \forall n \in N, \forall s \in S \tag{4.11}$$

$$\begin{aligned} &\sum_{i \in I} (\frac{y_{\text{ints}}}{\omega_t}) e_i^f + \delta L_{ns} + \\ &q_v \beta d_{nk} m_v + B_{njs}^f - B_{nj-1s}^f + Q_{njs}^- \\ &= \sum_{g \in G} \tau_{gj} \lambda_{gjs} P_{ng}^c + Q_{njs}^+ \end{aligned} \quad \begin{aligned} &j \in J_t \setminus \{1\}, t = 1, \forall k \in K, \forall n \in N, \forall s \in S \\ &or\ j \in J_t, t \in T \setminus \{1\}, \forall k \in K, \forall n \in N, \\ &\forall s \in S \end{aligned} \tag{4.12}$$

$$B_{kjs}^f = B_{kjs'}^f,\ Q_{kjs}^- = Q_{kjs'}^-, Q_{kjs}^+ = Q_{kjs'}^+ \quad \forall (s,s') \in \eta_t, \forall j \in J_t, \forall k \in K, \forall t \in T \tag{4.13}$$

$$B_{njs}^f = B_{njs'}^f,\ Q_{njs}^- = Q_{njs'}^-, Q_{njs}^+ = Q_{njs'}^+ \quad \forall (s,s') \in \eta_t, \forall j \in J_t, \forall n \in N, \forall t \in T \tag{4.14}$$

$$0 \leq B_{kj}^f \leq B_k^c \quad j = 1, \forall k \in K \tag{4.15}$$

$$0 \leq B_{nj}^f \leq B_n^c \quad j = 1, \forall n \in N \tag{4.16}$$

$$0 \le B_{kjs}^{f} \le B_{k}^{c} \qquad t=1, j \in J_t \setminus \{1\}, \forall k \in K, \forall s \in S \quad or\ t \in T \setminus \{1\}, j \in J_t, \forall k \in K, \forall s \in S \tag{4.17}$$

$$0 \le B_{njs}^{f} \le B_{n}^{c} \qquad t=\{1\}, j \in J_t \setminus 1, \forall n \in N, \forall s \in S \quad or\ t \in T \setminus \{1\}, j \in J_t, \forall n \in N, \forall s \in S \tag{4.18}$$

$$0 \le P_{kg}^{c} \le P_{kg}^{\max} \qquad \forall g \in G, \forall k \in K \tag{4.19}$$

$$0 \le P_{ng}^{c} \le P_{ng}^{\max} \qquad \forall g \in G, \forall n \in N \tag{4.20}$$

$$B_{k0}^{f} = B_{k}^{c} \qquad j=0, \forall k \in K \tag{4.21}$$

$$B_{n0}^{f} = B_{n}^{c} \qquad j=0, \forall n \in N \tag{4.22}$$

$$B_{k}^{c} \le B_{k}^{m} \qquad \forall k \in K \tag{4.23}$$

$$B_{n}^{c} \le B_{n}^{m} \qquad \forall n \in N \tag{4.24}$$

$$Q_{kjs}^{-} \le Q_{kjs}^{\max} \qquad \forall k \in K, j \in J, s \in S \tag{4.25}$$

$$Q_{njs}^{-} \le Q_{njs}^{\max} \qquad \forall n \in N, j \in J, s \in S \tag{4.26}$$

In the multi-stage stochastic Model 1 presented above, the first-stage has the following strategic decisions: (a) the size of the generation technologies at the factories and warehouse, P_{kg}^{c} and P_{ng}^{c}, respectively, and (b) the battery size to install at each factory and warehouse, B_{k}^{c} and B_{n}^{c}, respectively. The first-stage also performs (c) the operational decision of selecting the amount of finished product to produce in the first period, x_{ik1}. In the experimentation with Model 1, a production period is considered equal to a month which is comprised of a set of days and the production is assumed to be spread evenly over the days.

The decisions on the remaining stages of Model 1 are operational. Recourse actions assumed to occur in each scenario are purchases, z_{ikts}, or storages, y_{ints}, of final product, daily energy stored in the battery in the factory and warehouse, B^{f}_{kjs} and B^{f}_{njs}, respectively, daily energy sold in the factory and warehouse, Q^{-}_{kjs} and Q^{-}_{njs}, respectively, and daily energy purchased from main grid in the factory and warehouse, Q^{+}_{kjs} and Q^{+}_{njs}, respectively .The amount to produce of each product under each scenario, x_{ikts}, as well as the recourse decisions z_{ikts}, y_{ints}, B^{f}_{kjs}, B^{f}_{njs}, Q^{-}_{kjs}, Q^{-}_{njs}, Q^{+}_{kjs} and Q^{+}_{njs} are decisions that must be taken in all stages (except the first one) based only on the information known or realized.

The stochastic parameters in the model are the product demand, D_{ikts}, and the RE capacity factors, λ_{gjs}, that describe the daily utilization of the generation technologies given the changes in the hourly wind speed and weather conditions experienced at the geographical place the system will be installed. The capacity factors are defined as the ratio of the average power generated divided by the rated peak power and they directly affect the power output of the wind turbine (WT) and solar photovoltaic (PV) generation technologies at factories and warehouses, P^{c}_{kg} and P^{c}_{ng}, respectively.

In a nutshell, the objective function in equation (4.1) is to minimize the total expected cost incurred to produce the product, transport finished goods between the factory and warehouse, purchase finished products, if needed, hold inventory in the warehouse and acquire and maintain generation technologies and batteries required to produce and store renewable energy. The objective function also includes the expected profit of selling any extra energy generated in the factory and warehouses that ends not being stored in the batteries and the expected cost of any purchases of energy to the grid. Constraints (4.2) and (4.3) are the production-demand balance equations for the first and the remaining periods, respectively. They ensure that on-hand product availability plus any purchased product equal demands plus any leftover inventory. Constraints (4.4) and (4.5) are the resource constraints which guarantee that for each particular resource *r*, the sum of resource used to produce all the products does not exceed the total amount available of such resource in a period *t*. Constraints (4.6) are the non-anticipativity constraints which ensure that the production, inventory and purchasing decisions made in a particular period *t* under a particular scenario *s* are influenced only by previous decisions and outcomes. They ensure that in period *t*, all scenarios in the scenario tree (see a detailed discussion of the scenario three in Section 5.4) branching out from the same decision node will have the same decisions; this means they have stored the same amount of product and will decide to produce and purchase the same number of products. In the model presented above, the non-anticipativity constraints are written as presented in Beasley et al. (n.d.) and Escudero et al. (1993) but they were implemented as proposed in the Section 1.2 in Birge and Louveaux (1997). Constraints (4.7) and (4.8) are the sign constraints for number of products to produce, amount of inventory and product purchased.

Constraints (4.9) and (4.10) are the daily energy balance equations for the factory in the first day of the first production period and on the remaining days, respectively. They show that in each day and under a particular scenario, the sum of energy: (a) consumed by the factory in production and electric vehicle transportation, (b) needed to satisfy a base load, (c) stored in the battery and (d) sold , must be equal to the RE generated in conjunction with the energy stored in the battery from the previous day and any energy purchased from the grid. Constraints (4.11) and (4.12) are the daily energy balance equations for the warehouse in the first production day and the remaining ones, respectively. They resemble to constraints (4.9) and (4.10) by showing that in each day and scenario, energy needed to store the product, drive empty vehicles back to the factories and satisfy the base load, plus energy to be stored in the battery and to be sold must be equal to the RE generated in conjunction with the energy stored in the battery from the previous day and any energy purchased from the grid.

Constraints (4.13) and (4.14) are also non-anticipativity constraints related to the daily energy decisions. They ensure that for those scenarios that look the same up to a particular point in time *t*, the decisions about energy stored in the battery, to be sold or purchased to the grid are influenced only by previous decisions and outcomes. Thus, these constraints ensure that if any two scenarios, s and s', are identical up to a point in time then all the decisions made for all the previous stages and the current one must be identical.

Constraints (4.15) to (4.18) ensure that the daily energy stored in (or discharged from) the battery should not exceed the battery capacity. The constraints are given for day 1 and for the remaining ones at the factory and the warehouse, respectively. Constraints (4.19) and (4.20) require that the generation capacity at the factory and warehouse be non-negative. However, it is capped by a maximum power capacity. Constraints (4.21) and (4.22) state that the initial state of the battery at the warehouse and factory is fully charged. Constraints (4.23) and (4.24) require that the battery capacity to be adopted by the factory and warehouse does not exceed a certain pre-defined maximum capacity. Similarly, constraints (4.25) and (4.26) require that the energy sold at the factory and warehouse be capped by a pre-defined maximum value. Constraints (4.23) - (4.26) were added mainly to avoid any unboundedness in the numerical experiments performed in this research.

4.2. Model 2

Model 2 is also a three-stage stochastic program in the way presented and depicted in Beasley et al. (n.d.) but the length of the planning horizon is a year. The first-stage decisions correspond to the size of the RE technologies (WT and PV) and battery installed at the beginning of the time horizon and a single production decision for the first six months. The second-stage decisions are the monthly recourse actions to the production decisions, the daily recourse actions to the energy decisions taken in the first-stage, and the new production decision for the remaining of six months. The third-stage decisions are the daily recourse actions to the energy decisions and the monthly recourse actions to the production decision taken for the last six months.

Birge and Louveaux (1997) mention that the definition of stage relates to before and after a random experiment and thus the stages may contain a series of decisions and events that do not necessarily have to occur at the same point in time. In Model 2, those decisions not occurring at a single time are of two types. Monthly recourse actions related to production belong to the first type. and daily recourse actions related to energy decisions belong to the second type. Recourse actions related to production include small monthly adjustments (i.e. increases or decreases) to the first and second stage production decisions, and monthly inventory and purchases of final product that occur in response to the realization of the product demands over the lapses of 6 months. Recourse actions related to energy include daily storage or discharge of energy from the batteries, and purchases of energy or sales of extra RE.

The reason for selecting the length of the periods elapsed between decision stages equal to six months in Model 2 is to portrait production systems where the product demands are unknown and but do not change monthly. It is the case of some thermo-electric manufacturing industries in Texas and for industries manufacturing products for two seasons (i.e. winter and summer). As mentioned in Model 1, it is typical for many industries to consider a time horizon of one year for planning the production of their products and thus this one of the reasons because the author of this thesis selected one year for the planning horizon. A second reason for choosing the one-year horizon is because it is typical to annualize the energy installation and maintenance costs and then managing production, logistics and energy costs over annual periods is convenient. Note that in Model 2 the terms production period and decision stage are not the same. It is assumed that there are 12 production periods (i.e. months) in a year and two-stages (i.e. two-times) for the production decisions to occur or being revisited, the first occurring in month 1 and the second one in month 7.

Tables 8 – 10 introduce a few new notations used in Model 2 and the changes in the meaning of the subscripts for some variables and parameters already used in Model 1. Model 2 is presented below the tables.

Table 8. New definition for some sets and indices used in Model 2

Notation	Description
T	Set of production periods (i.e. months) in which a new production decision is taken. *T* = {1, 7}
M	Set of production periods (i.e. months) in the planning horizon. *M* = {1, 2, …,12}
T	Index running over decision stages or periods in set *T* When *t* =1 the model refers to the first production decision done in period 1 and when *t*=7 the model refers to the second production decision done in period 7
M	Index running over production periods in set *M*

Table 9. New definition for some decision variables used in Model 2

Notation	Description	Units
x_{ikts}	Amount of product *i* decided to be produced for the next 6 periods (i.e. months) at factory *k* in decision period *t* under scenario *s*	Items
x_{ikms}	Amount of adjustment (increase or decrease) on the production of product *i* at factory k to be implemented in period *m* to correct the production decision taken in period *t* under scenario *s*	Items
y_{inms}	Amount of inventory of product *i* to store at warehouse *n* at the end of period *m* under scenario *s*	Items
z_{ikms}	Amount of product *i* purchased in period *m* under scenario *s* to satisfy the product demand at factory *k*	Items

Table 10. New meaning for some parameters used in Model 2

Notation	Description	Units
θ_{it}	Production cost of product *i* decided to produce in stage *t*	\$/item
μ_{it}	Transportation cost of product *i* decided to produce in stage *t*	\$/item
θ_{im}	Adjustment to production cost of product *i* in period *m*	\$/item
μ_{im}	Adjustment to transportation cost of product *i* in period *m*	\$/item
h_{im}	Holding cost of product *i* in period *m*	\$/item/period
o_{im}	Purchasing cost of product *i* produced in period *m*	\$/item
w_{krm}	Amount or resource *r* available in period *m* at factory *k*	h/period
D_{ikms}	Demand for product *i* in factory k in period *m* under scenario *s*	item/period
ψ	Number of production periods in each decision stage t. Because one year is divided into two decision stages this parameter has the value of 6 months	months
κ	Limit to the adjustments (i.e. increases or decreases) to the production	Items

Mathematical Model 2:

Minimize total expected cost:

$$
\begin{aligned}
z = & \sum_{i\in I}\sum_{k\in K}(\theta_{i1}+\mu_{i1})x_{ik1} + \sum_{m=1}^{6}\sum_{i\in I}\sum_{k\in K} p_s(\theta_{im}+\mu_{im})x_{ikms} + \sum_{m=1}^{6}\sum_{i\in I}\sum_{s\in S}\sum_{k\in K} p_s o_{im} z_{ikms} \\
& + \sum_{m=1}^{6}\sum_{i\in I}\sum_{s\in S}\sum_{n\in N} p_s h_{im} y_{inms} + \sum_{i\in I}\sum_{s\in S}\sum_{k\in K} p_s \left[\sum_{t\in T/\{1\}} (\theta_{it}+\mu_{it})x_{ikts} + \sum_{m=7}^{12}(\theta_{im}+\mu_{im})x_{ikms} + \sum_{m=7}^{12} o_{im} z_{ikms} \right] \\
& + \sum_{i\in I}\sum_{s\in S}\sum_{m=7}^{12}\sum_{n\in N} p_s h_{im} y_{inms} + \sum_{g\in G}\sum_{k\in K} \varphi_g a_g P_{kg}^c + \sum_{k\in K} \frac{\varphi_b a_b B_k^c}{\vartheta} + \sum_{g\in G}\sum_{n\in N} \varphi_g a_g P_{ng}^c + \sum_{n\in N} \frac{\varphi_b a_b B_n^c}{\vartheta} \\
& + \sum_{k\in K}\sum_{g\in G}\sum_{s\in S} p_s (b_g - c_g)\tau_g^* (\sum_{j\in J} \frac{\lambda_{g\,js}}{|J|}) P_{kg}^c - \sum_{k\in K}\sum_{j\in J}\sum_{s\in S} p_s u \frac{Q_{kjs}^-}{\vartheta} + \sum_{k\in K}\sum_{j\in J}\sum_{s\in S} p_s u^* \frac{Q_{kjs}^+}{\vartheta} \\
& + \sum_{n\in N}\sum_{g\in G}\sum_{s\in S} p_s (b_g - c_g)\tau_g^* (\sum_{j\in J} \frac{\lambda_{g\,js}}{|J|}) P_{ng}^c - \sum_{n\in N}\sum_{j\in J}\sum_{s\in S} p_s u \frac{Q_{njs}^-}{\vartheta} + \sum_{n\in N}\sum_{j\in J}\sum_{s\in S} p_s u^* \frac{Q_{njs}^+}{\vartheta}
\end{aligned}
\tag{4.27}
$$

Subject to:

$$(x_{ikt}/\psi) + x_{ikms} + y_{\text{in}\,m-1} - y_{inms} + z_{ikms} = D_{ikms} \qquad \forall i \in I, t = 1, m = 1...6, \forall s \in S, \forall k \in K, \forall n \in N \tag{4.28}$$

$$(x_{ikts}/\psi) + x_{ikms} + y_{\text{in}\,m-1s} - y_{inms} + z_{ikms} = D_{ikms} \qquad \forall i \in I, t \in T \setminus \{1\}, m = 7...12, \forall s \in S, \forall k \in K, \forall n \in N \tag{4.29}$$

$$\sum_{i\in I} v_{ikr} (\frac{x_{ikt}}{\psi} + x_{ikms}) \le w_{krm} \qquad \forall r \in R, t = 1, m = 1...6, \forall k \in K \tag{4.30}$$

$$\sum_{i\in I} v_{ikr} (\frac{x_{ikts}}{\psi} + x_{ikms}) \le w_{krm} \qquad \forall r \in R, t \in T \setminus \{1\}, m = 7...12, \forall s \in S, \forall k \in K \tag{4.31}$$

$$x_{ikts} = x_{ikts'} \qquad \forall (s,s') \in \eta_t, \forall i \in I, \forall k \in K, \forall t \in T \tag{4.32}$$

$$x_{ikms} = x_{ikms'}, y_{inms} = y_{inms'}, z_{ikms} = z_{ikms'} \qquad \forall (s,s') \in \eta_t, \forall i \in I, \forall k \in K, \forall n \in N, \forall m \in M \tag{4.33}$$

$$x_{ik1}, y_{\text{in}\,ms}, z_{ikms} \ge 0 \qquad \forall i \in I, \forall s \in S, \forall n \in N, \forall k \in K, m = 1..6 \tag{4.34}$$

$$x_{ikts}, y_{\text{in}\,ms}, z_{ikms} \ge 0 \qquad \forall i \in I, t \in T \setminus \{1\}, m = 7...12, \forall s \in S, \forall n \in N, \forall k \in K \tag{4.35}$$

$$\sum_{i\in I}(e_i^p + q_v d_{kn} m_i)(\frac{x_{ikt}}{\psi} + x_{ikms}) / J_t + \delta L_{ks} + q_v \beta d_{kn} m_v + B_{kjs}^f - B_{kj-1}^f + Q_{kjs}^- = \sum_{g\in G}\tau_{gj}\lambda_{gjs}P_{kg}^c + Q_{kjs}^+ \qquad j=1, t=1, m=1, \forall k\in K, \forall n\in N, \forall s\in S \tag{4.36}$$

$$\sum_{i\in I}(e_i^p + q_v d_{kn} m_i)(\frac{x_{ikts}}{\psi} + x_{ikms}) / J_t + \delta L_{ks} + q_v \beta d_{kn} m_v + B_{kjs}^f - B_{kj-1s}^f + Q_{kjs}^- = \sum_{g\in G}\tau_{gj}\lambda_{gjs}P_{kg}^c + Q_{kjs}^+ \qquad j\in J_t\setminus\{1\}, t=1, m=1\ldots 6, \forall k\in K, \forall n\in N, \forall s\in S \quad or \quad j\in J_t, t\in T\setminus\{1\}, m=7\ldots M, \forall k\in K, \forall n\in N, \forall s\in S \tag{4.37}$$

$$\sum_{i\in I}(\frac{y_{\mathrm{inms}}}{\omega_j})e_i^f + \delta L_{ns} + q_v\beta d_{nk} m_v + B_{njs}^f - B_{nj-1}^f + Q_{njs}^- = \sum_{g\in G}\tau_{gj}\lambda_{gjs}P_{ng}^c + Q_{njs}^+ \qquad j=1, t=1, m=1, \forall k\in K, \forall n\in N, \forall s\in S \tag{4.38}$$

$$\sum_{i\in I}(\frac{y_{inms}}{\omega_j})e_i^f + \delta L_{ns} + q_v\beta d_{nk} m_v + B_{njs}^f - B_{nj-1s}^f + Q_{njs}^- = \sum_{g\in G}\tau_{gj}\lambda_{gjs}P_{ng}^c + Q_{njs}^+ \qquad j\in J_t\setminus\{1\}, t=1, m=1\ldots 6, \forall k\in K, \forall n\in N, \forall s\in S \quad or \quad j\in J_t, t\in T\setminus\{1\}, m=7\ldots M \quad \forall k\in K, \forall n\in N, \forall s\in S \tag{4.39}$$

$$B_{kjs}^f = B_{kjs'}^f, Q_{kjs}^- = Q_{kjs'}^-, Q_{kjs}^+ = Q_{kjs'}^+ \qquad \forall(s,s')\in\eta_t, \forall j\in J_t, \forall k\in K, \forall t\in T \tag{4.40}$$

$$B_{njs}^f = B_{njs'}^f, Q_{njs}^- = Q_{njs'}^-, Q_{njs}^+ = Q_{njs'}^+ \qquad \forall(s,s')\in\eta_t, \forall j\in J_t, \forall n\in N, \forall t\in T \tag{4.41}$$

$$0\le B_{kj}^f \le B_k^c \qquad j=1, \forall k\in K \tag{4.42}$$

$$0\le B_{nj}^f \le B_n^c \qquad j=1, \forall n\in N \tag{4.43}$$

$$0\le B_{kjs}^f \le B_k^c \qquad t=1, j\in J_t\setminus\{1\}, \forall k\in K, \forall s\in S \quad or\ t\in T\setminus\{1\}, j\in J_t, \forall k\in K, \forall s\in S \tag{4.44}$$

$$0\le B_{njs}^f \le B_n^c \qquad t=1, j\in J_t\setminus\{1\}, \forall n\in N, \forall s\in S \quad or\ t\in T\setminus\{1\}, j\in J_t, \forall n\in N, \forall s\in S \tag{4.45}$$

$$0 \le P_{kg}^{c} \le P_{kg}^{\max} \qquad \forall g \in G, \forall k \in K \qquad (4.46)$$

$$0 \le P_{ng}^{c} \le P_{ng}^{\max} \qquad \forall g \in G, \forall n \in N \qquad (4.47)$$

$$B_{k0}^{f} = B_{k}^{c} \qquad j = 0, \forall k \in K \qquad (4.48)$$

$$B_{n0}^{f} = B_{n}^{c} \qquad j = 0, \forall n \in N \qquad (4.49)$$

$$B_{k}^{c} \le B_{k}^{m} \qquad \forall k \in K \qquad (4.50)$$

$$B_{n}^{c} \le B_{n}^{m} \qquad \forall n \in N \qquad (4.51)$$

$$Q_{kjs}^{-} \le Q_{kjs}^{\max} \qquad \forall k \in K, j \in J, s \in S \qquad (4.52)$$

$$Q_{njs}^{-} \le Q_{njs}^{\max} \qquad \forall n \in N, j \in J, s \in S \qquad (4.53)$$

$$-\kappa \le x_{ikms} \le \kappa \text{ and } URS \qquad \forall i \in I, \forall s \in S, \forall k \in K, m \in M \qquad (4.54)$$

In the multi-stage stochastic Model 2, the first-stage has the same strategic decisions as Model 1: finding the size of the generation technologies at the factories and warehouses, P_{kg}^{c} and P_{ng}^{c}, respectively, and the battery capacity to install at each factory and warehouse, B_{k}^{c} and B_{n}^{c} , respectively. The first-stage also has the operational decision of selecting the amount of finished product to produce in the first decision period, x_{ik1}. After such first decision period there is a lapse of six months and it is assumed that the production spreads evenly over the days.

The decisions on the remaining decision stages of the model (i.e. from second to last stage) are operational. The second production decision is to select the amount of finished product to produce in the second decision period is notated as x_{ikts}. After the second decision period there is also a lapse of six months.

Recourse actions assumed to occur during the lapses of six-months in each scenario are: a) alterations (i.e. slight increases or decreases) in the planned production notated as x_{ikms}, b) purchases, z_{ikms}, or storages, y_{inms}, of final product, c) daily storages of energy in the battery in the factory and warehouse, B^{f}_{kjs} and B^{f}_{njs}, respectivey, d) daily sales of energy in the factory and warehouse, Q^{-}_{kjs} and Q^{-}_{njs}, respectively, and e) daily purchases of energy from main grid in the factory and warehouse, Q^{+}_{kjs} and Q^{+}_{njs}, respectively .The decisions, x_{ikms}, z_{ikms}, y_{inms}, B^{f}_{kjs}, B^{f}_{njs}, Q^{-}_{kjs}, Q^{-}_{njs}, Q^{+}_{kjs} and Q^{+}_{njs} are based only on the information known or realized up to the moment.

The stochastic parameters in Model 2 are also the product demand, D_{ikms}, and the capacity factors, λ_{gjs}, that describe the daily utilization of the generation technologies given the changes in wind speed and weather conditions at the geographical place the system will be installed. These capacity factors directly affect the power output of the WT and PV generation technologies at factories and warehouses, P^{c}_{kg} and P^{c}_{ng}, respectively.

The objective function in equation (4.27) is like equation (4.1). It minimizes the total expected cost incurred to produce in the factory, transport finished goods between the factory and warehouse, purchase finished product, if needed, hold inventory in the warehouse, and acquire and maintain RE generation technologies and batteries. However, this objective function also includes the expected cost of doing slight alterations to the production decisions taken at the two-predetermined decision times *t*, the expected profit of selling any extra energy generated in the factory and warehouses that ends not being stored in the batteries and the expected cost of any purchases of energy to the grid.

Constraints (4.28) and (4.29) are the production-demand balance equations for the production periods comprised in the first decision stage and the ones comprised in the second decision stage, respectively. They ensure that on-hand product availability plus any purchased product equal demands plus any leftover inventory. Because a production decision is done for the lapse of 6 months, it needs to be divided by the number of production months in the decision stage. Constraints (4.30) and (4.31) are the resource constraints in the months comprised in each decision stage, respectively. They guarantee that for a particular resource type, the sum of resources used to produce all the products does not exceed the total amount of available resource in production period *m*.

Constraints (4.32) and (4.33) are the non-anticipativity constraints which ensure that the production (the one originally decided and its alterations), inventory and purchasing decisions made in a particular decision period *t*, under a scenario *s* are influenced only by previous decisions and outcomes. These constraints guarantee that in decision period *t*, all scenarios in the scenario tree (see details about scenario tree in Section 5.4) branching out from the same decision node will have the same decisions. Constraints (4.34) and (4.35) are the sign constraints for number of products to produce in each six-months lapse, amount of inventory and product purchased.

Constraints (4.36) and (4.37) are the energy balance equations for the factory for the first day in the first decision period and for the remaining days, respectively. They show that in each day and under a particular scenario, the sum of energy: (a) consumed by the factory in production and electric vehicle transportation, (b) needed to satisfy a base load, (c) stored in the battery and (d) sold , must be equal to the RE generated in conjunction with the energy stored in the battery from the previous day and any energy purchased from the grid. Constraints (4.38) and (4.39) are the energy balance equations for the warehouse for the first day in the first decision time and for the remaining ones, respectively. They resemble to constraints (4.36) and (4.37) by showing that in each day and scenario, energy needed to store product in the warehouse, drive empty vehicles back to the factories and satisfy the warehouse base load, plus energy to be stored in the battery and to be possibly sold must be equal to the RE generated in conjunction with the energy stored in the battery from the previous day and any energy purchased from the grid.

Constraints (4.40) and (4.41) are also non-anticipativity constraints related to daily energy decisions. They ensure that for those scenarios that look the same up to a particular decision time *t*, the daily decisions about energy stored in the battery, to be sold or purchased to the grid are influenced only by previous decisions and outcomes. Thus, these constraints ensure that if any two scenarios, *s* and *s'*, are identical up to a decision stage then all the decisions made for all the previous stages and the current one must be identical.

Constraints (4.42) to (4.45) ensure that the daily energy stored in (or discharged from) the battery in the factory and the warehouse should not exceed the battery capacities. The constraints are given for the first day in the first decision stage and for the remaining days. Constraints (4.46) and (4.47) require that the generation capacity at the factory and warehouse be non-negative. However, such generation is capped by parameters representing the maximum power capacity of each generation type.

Constraints (4.48) and (4.49) state that the initial state of the battery at the warehouse and factory is fully charged. Constraints (4.50) and (4.51) require that the battery capacity to be adopted by the factory and warehouse does not exceed a certain pre-defined maximum capacity. Similarly, constraints (4.52) and (4.53) require that the energy sold at the factory and warehouse be capped by a pre-defined value. Constraints (4.50) - (4.53) were added mainly to avoid any unboundedness in the numerical experiments performed. Constraint 5.54 says that variables representing slight production alterations (i.e. increases or decreases to the monthly production amount decided in each stage, which can be done in each production period) have lower and upper limits and are unrestricted in sign.

5. ESTIMATION AND REPRESENTATION OF THE UNCERTAIN PARAMETERS OF THE MODELS

This Chapter is divided into four sections. The first one presents the estimation of the product demand used in the models. The second describes the procedure used for the estimation of WT capacity factors. The third one presents the estimation of the PV capacity factors and the fourth provides further details about the scenario tree used to represent the uncertainty in the models.

5.1 Estimation of product demands

For the implementation of Model 1 presented in Chapter 4, the size of the set of different products to produce, I, is assumed equal to 2, the size of the set of production periods, T, is also assumed equal to 2 and each period, t, corresponds to a month. For Model 2, I, is assumed equal to 2, the size of the set of production periods, M, is assumed equal to 12, and each production period, m, corresponds to a month.

Monthly product demands (in number of items) in Model 1 and Model 2 are assumed to follow discrete uniform distributions with low (L) and high (H) parameters, usually notated as a and b in probability books. The values for the low and high parameters of the uniformly distributed monthly product demands used in Model 1 are listed in Table 11. These values are synthetic but resemble to the ones found in industry.

The author of this thesis found that it is practical to assume that the monthly product demand follows a uniformly distribution in settings manufacturing new products since minimum and maximum parameters of the products are easy to estimate (Wanke, 2008). In these settings, the uniform distribution is appealing to use because managers in absence of historical data for the demand of the product can subjectively assume with not too much difficulty the minimum and maximum values for the demand without having to wrongly compromise with strong assumptions about a more elaborated probability distribution and the values for its parameters. Such case relates very well to the ones portrayed by Model 1 and Model 2 in this thesis since the models represent practical situations where stakeholders are opening production systems and considering to start by the first time both the production of their products and the integration of renewable energy. Besides, in small manufacturing settings with a single or very few customers, like in some thermo-electrical companies in the Texas area, is also applicable to assume that the monthly demand is not exactly known but the probability of each outcome occurring over a given interval is equally likely.

Table 11. Discrete uniform distributions used for the generation of product demands

Product	Period 1	Period 2
1	U [800, 1600]	U [800, 2000]
2	U [800, 1800]	U [1500, 2100]

In Model 2 the same distributions presented in Table 10 were used. For months 1-6 the distribution used is the one under the column Period 1 and for months 7-12 the distribution used is the one under the column Period 2.

5.2 Estimation of WT capacity factors

Standard wind speed measurements are typically recorded at heigh h_g=10m above the ground by automated surface observing systems (ASOS) (Weather underground, n.d.). Since modern WT is typically installed at a height h=80m or above, equation (5.1) below is used to extrapolate the wind speed at height h, notated as v_h, based on the near the ground measured wind speed (v_g). In equation (5.1), the Hellman exponent (k)

considers seaside location, air stability and terrain shape. The range for this exponent is between 0.14 (i.e. 1/7) and 0.37-0.203log v_g as presented by Spera and Richards, (1979).

$$v_h = v_g (\frac{h}{h_g})^k; \quad for \quad h \geq h_g \tag{5.1}$$

The power output of a wind turbine (WT) can be determined from its power curve (Novoa and Jin, 2011). Figure 3 depicts a typical cubic WT power curve. It shows the relation between the wind speed, v (generally notated as *x* in the figure) and the WT power output.

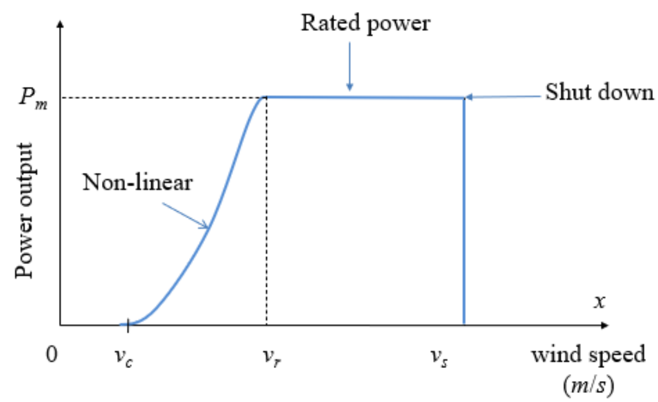


Figure 3. A WT power curve

The WT power curve is developed based on the kinetic theory of the air flow dynamics (Thiringer and Linders, 1993). The WT power curve has four phases. The first one is the standby phase. In this phase, power is not generated because the wind speed, v is below the minimum needed to operate the turbine ($v < v_c$). The next phase is the non-linear production phase ($v_c \leq v \leq v_r$). In this phase, power is proportional to the cube of the wind speed. In the rated power phase, ($v_r \leq v \leq v_s$), the power output is equal to the rated power, P_m. In the cut-off phase, ($v > v_s$), no power is generated since the turbine needs to be shut down for protection purposes.

The theoretical power captured by the blades of a WT can be computed using equation (5.2). This equation permits to convert any wind speed v into electrical power $P_w(v)$. In equation (5.2), $\eta_{\max}$ is used to describe the conversion rate from wind power to electrical power, ρ is the air density, and A is the area covered by the WT blades. The theoretical value for $\eta_{\max}$ is 0.5926, but the actual value could be lower between 0.3 and 0.5.

$$P_w(v) = \begin{cases} 0 & v < v_c, v > v_s \\ 0.5\eta_{\max}\rho A v^3 & v_c \le v \le v_r \\ P_m & v_r \le v \le v_s \end{cases} \tag{5.2}$$

In this research, the power is computed by the author of this thesis using: (1) wind speed data collected from ASOS and reported by Weather Underground (n.d.) for a couple of cities selected and (2) the cubic model given by equation 5.3 . The values for v_h are computed as in equation (5.1) at heights *h* = 80 and *h* = 90m , which are typical heights of a WT of 1.5-3 MW. The assumed values for the Hellman exponent or *k*-value are 0.27 and 0.37, respectively. Once v_h is computed, its value is plugged in the quadratic model given by equation (5.3) to estimate $P_w(v_h)$ in terms of the parameters, v_c , v_r, and P_m. The assumed values for v_r and P_m are 12 m/s and 1MW, respectively.

$$P_w(v_h) = \begin{cases} 0 & v < v_c, v > v_s \\ P_m(v/v_r)^3 & v_c \le v \le v_r \\ P_m & v_r \le v \le v_s \end{cases} \tag{5.3}$$

The capacity factor (λ) of a WT is the ratio of the actual power generated by the WT over a period of time and the rated peak power P_{m} over the same period. Thus λ is a fraction between zero and one. Assuming the wind speed over a period of time is in the non-linear production phase, $v_c \leq v_h \leq v_r$, λ can be estimated using equation (5.4). If the wind speed is in the standby phase the capacity factor will be zero and if it is in the rated production phase the capacity factor will be 1.

$$\lambda = \frac{\text{Power in non-linear production phase}}{\text{Maximum generation capacity}} = \frac{P_m\left(\frac{v}{v_r}\right)^3}{P_m} \tag{5.4}$$

Hourly wind speed data available from Weather Underground (n.d.) in years 2013, 2014 and 2015 for the cities of Amarillo and Phoenix, USA was collected by the author of this thesis and some other students at Texas State University and used to compute three different sets of daily WT capacity factors. The 3 sets of daily capacity factors used in Model 1 were for a lapse of 59 days (i.e. first two months of the year) while the 3 sets used for Model 2 were for a lapse of 365 days. The sets used in each model are labeled with the consecutive numbers 1, 2, and 3. Appendix A, Tables A1.7 to A1.12 present the sets of 365 daily WT capacity factors after averaging the hourly capacity factors computed for the cities of Amarillo using equation (5.4). The factors computed in the city used 26,280 observations (365 daysx24 hours/dayx3 sets) for the wind speed profile.

Based on the study in Lantz et al. (2019), there are some opportunities to increase the power output of WT installed in windy cities centrally located in the US if increasing the turbine tower height from the current 80m to values in the range >80-160m. Because Amarillo is a windy city centrally located in the U.S., in this study, the values for, v_h are computed assuming an updated but still conservative turbine tower height, *h*, of 90m and a Hellman exponent of 0.37 since the airflow is more dynamic if the turbine is installed at a higher height. For the city of Phoenix, the assumed values for the turbine tower height, *h,* and the Hellman exponent, *k*-value, were kept as 80m and 0.27, respectively.

5.3 Estimation of PV capacity factors

The photovoltaic effect permits a solar PV to convert the solar radiation into electricity. Tables 12-13 provide the notation for the relevant solar PV generation parameters and variables used to estimate the PV capacity factors (i.e. utilizations). The tables also provide a brief description of the meaning of each parameter or variable. Note that one radian (rad) equals $180/\pi$ or 57°.

Table 12. Parameter and variables used to compute the solar PV generation

Parameter or variable	Notation	Description
Date	d	Input parameter representing the day of the year, $d \in \{1, 2, \ldots, 365\}$
Local time (hour)	t	Input parameter. $t \in \{1, 2, \ldots, 24\}$
Declination angle (rad)	δ	Variable depending on the date. It can be computed as follows: $\delta = 0.40928 \sin(2\pi(d+284)/365)$
Latitude (rad)	ϕ	Variable that depends on the geographic location considered
Solar hour angle (rad)	ω	Variable related to local clock hour. Starting from $\omega = -\pi/2$ at 6am, it increases 15° every hour until reaching $\omega = \pi/2$ at 6pm. Knowing t (in hours) ω can be computed by setting aside for ω in the expression: $t = 12 + \frac{\omega^{\circ}}{15}$ and then converting degrees to rad
Sun zenith angle (rad)	γ	Angle between sun ray and the normal to the ground. This variable is computed as: $\cos\gamma = \cos\delta\cos\phi\cos\omega + \sin\delta\sin\phi$
Direct solar beam incident on the ground at time *t* on day *d* *(W/m²)*	$I_d(t)$	Variable that under clear sky condition it is computed as in equation (6.5)
Surface azimuth angle (rad)	α	Input parameter. If the panel is facing south, α=0

Table 13. Continuation of parameter and variables used to compute the solar PV generation

Parameter or variable	Notation	Description
PV tilt angle (rad)	β	Input parameter describing the angle between PV and ground surface
PV incident angle (rad)	θ	Angle between sun ray and the normal to PV surface. This variable depends on δ, ϕ, β, α and ω and is computed as in equation (6.6)
Sunrise hour angle (rad)	ω_{rise}	Variable computed as function of δ, ϕ, and β using the following relation: $\cos(-\omega_{rise}) = \cos(-\omega_{set}) = -\tan(\phi - \beta)\tan\delta$ It is as perceived by the PV. Thus, a PV system has no power output when the solar hour $\omega<\omega_{rise}$ or $\omega>\omega_{set}$
Sunset hour angle (rad)	ω_{set}	See comment in previous entry
Irradiance incident on the PV surface at time *t* on day *d* *(W/m²)*	$I_{PV}(t)$	Variable that depends on the PV tilt and incident angles computed as in equation (6.7). Its value is computed only when the solar hour $\omega>\omega_{rise}$ or $\omega<\omega_{set}$
Weather condition at local time (hour) *t*	W_t	Random variable ranging from 0 (Snow) to 1 (Clear) as shown in Table 13
PV size (m^2)	A	PV module area
PV efficiency	η	Typically, it is between 15-25%
PV temperature (°C)	T_o	Solar PV operating temperature
PV output (W)	$P_{PV}(t)$	PV power depending on the weather condition at time *t* computed as in equation (6.8) and only if the solar hour falls in $\omega>\omega_{rise}$ or $\omega<\omega_{set}$
Rated capacity of a PV system (W)	P_{PV}^{Max}	Maximum output power of the PV panel considered
PV Capacity factor	λ_{PV}	Depends on the actual output of the PV system in comparison to the maximum PV rated capacity
Total number of generation hours	T	Depends on the sunrise and sunset hour. In the equator, it is 8760/2=4380 h

The steps shown in the flowchart in below, the equations above the flowchart, and hourly data collected from Weather Underground (n.d.) by the author of this thesis and other students at Texas State University for the weather conditions (i.e. clear sky, …, snow) in the US cities of Amarillo and Phoenix for years 2013, 2014 and 2015 were used to compute the hourly power and three sets of daily PV capacity factors. The decision of using three different years was to agree with the procedure performed for the estimation of the WT capacity factors in the previous sub-section. Table 14 shows W_t, the numerical value to assign to each of the nine most frequent weather conditions that a geographical location can be at time t. This value is one of the final inputs (i.e. parameters) needed for computing the PV output $P_{PV}(t)$ as shown in equation (5.8).

Table 14. Numerical values of different weather conditions

Condition No.	1	2	3	4	5	6	7	8	9
Description	Clear Sky	SC	PC	MC	Overcast	Rain	Fog	Storm	Snow
W_t	1	0.7	0.5	0.3	0.2	0.1	0.1	0.1	0

$$I_d(t) = 1370 \times \left(0.7^{(\cos\gamma)^{-0.678}}\right)\left(1 + 0.034\cos\left(\frac{2\pi(d-4)}{365}\right)\right) \quad (5.5)$$

$$\cos\theta = \sin\delta\sin(\phi - \beta) + \cos\delta\cos(\phi - \beta)\cos\omega \quad (5.6)$$

$$I_{pv}(t) = I_d(t)\left(\cos\theta + 0.1\left(1 - \frac{\beta}{\pi}\right)\right) \quad (5.7)$$

$$P_{pv}(t) = W_t \eta A I_{pv}(t)\left[1 - 0.005(T_o - 25)\right] \quad (5.8)$$

$$\lambda_{PV} = \frac{1}{P_{PV}^{\max} T}\sum_{t=1}^{T} P_{PV}(t) \quad (5.9)$$

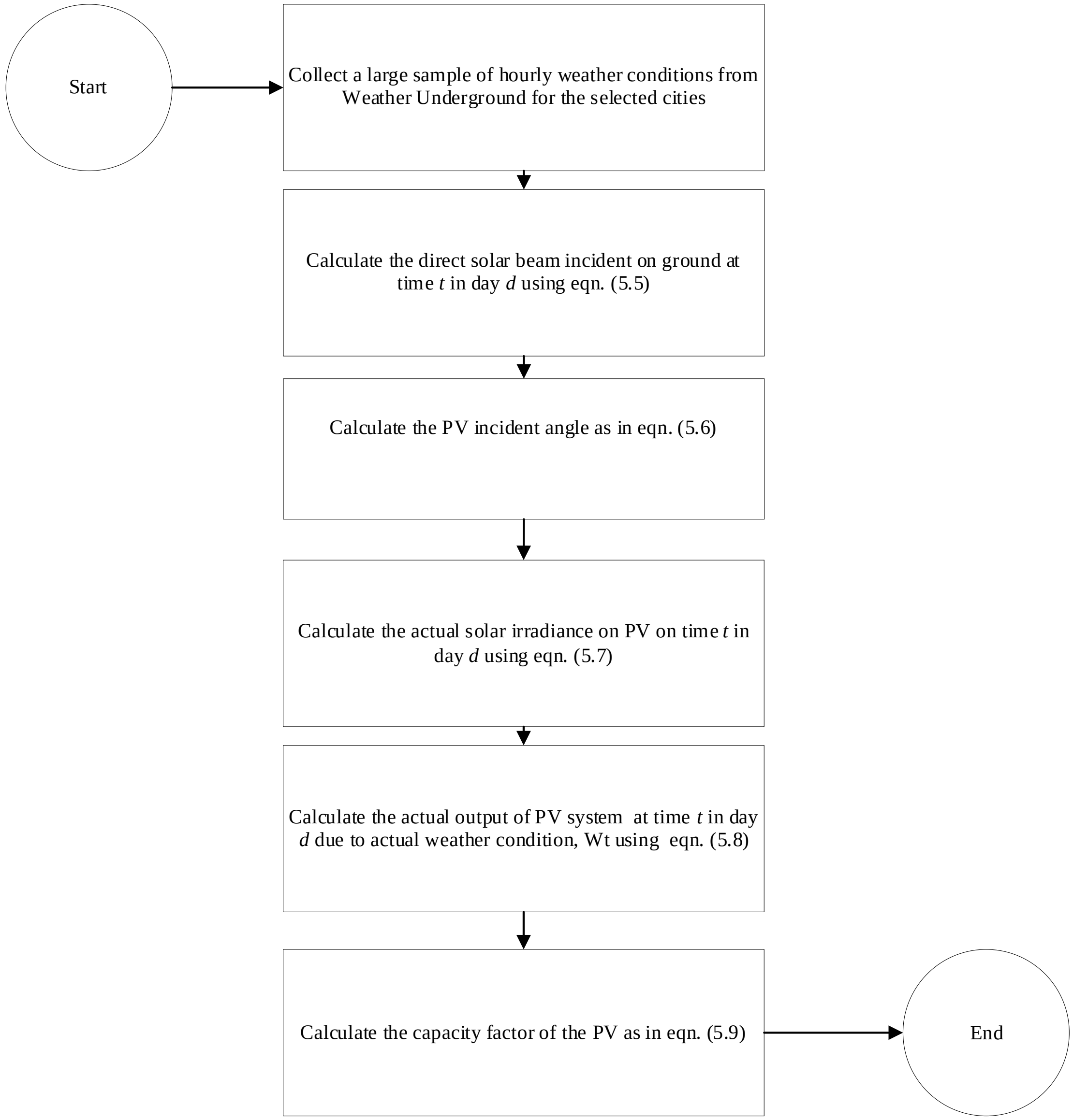


Figure 4. PV capacity factor calculation flowchart

The steps in the flowchart in Figure 4 resemble the ones in Tao et al. (2010) and in the 3-step PV generation model reported in the Appendix A of the research paper by Pham et al. (2019). In the computations of the capacity factors for the cities of Amarillo and Phoenix, P_{PV}^{Max} was assumed 160 W, the efficiency, η, as 0.2, the PV size A equal to $1m^2$ and the solar PV operating temperature, T_o, as 45°C. In Appendix A, Tables A1.1 to

A1.6 present the three sets of 365 daily PV capacity factors resulting after using equation (5.9) and averaging the hourly PV capacity factors for each day for the city of Amarillo.

5.4 Scenario tree representation used in the MSSP Models

The scenario tree methodology presented in Birge and Louveaux (1997) is used to build up a particular scenario three for the Model 1 considering 2 products, 2 demand levels and 3 vectors or sets of daily capacity factors (i.e. averaged over the 24-hours observed in each day) for 2 different production periods (i.e. months). Thus, there are $(2*2*3)^2 = 144$ scenarios assuming that the demands for the products are independent. The scenario tree is presented in Figure 5. The first node provides details about the first-stage decisions. These decisions are the amount of product *i* to produce in the first period, the size of the WT and the battery to install. The 12 arrows that emanate from the first node represent the different scenarios for the first-month demand of each of the two products and for the daily capacity factors realized. For instance, the label LL1 corresponds to a scenario where both products to be produced have a low monthly demand and the daily WT and PV capacity factors are those estimated with the first year (i.e. year 2013) of hourly wind speed and weather conditions collected from Weather Underground (n.d.) considering only two particular months of the year (i.e. July and August).

The 12 nodes near the middle of the scenario tree in Figure 5 coincide with: (1) second-stage recourse actions to take (i.e. amount of each product to store in inventory, amount of each product to purchase, amount of energy to store daily in the battery, amount of energy to sell or amount of energy to purchase from the grid) if the given scenario is realized and (2) the second-stage production decision for how much of each product to produce in the second period given the realization of the demand in period 1 and the second-stage recourse actions taken. In the same way explained for the first node, now 12 arrows emanate from each of the nodes near the middle of the figure. They represent different scenarios for the second-month demand of each of the two products and for the daily capacity factors.

The last circles in the scenario tree represent the third-stage recourse actions to take once the scenarios for product demands and capacity factors for the second period are realized. The last column in in Figure 5 labels all the 144 scenarios and exemplifies how each scenario is defined as an ordered pair of the realizations for the random parameters in first-and second period. Thus, the last scenario labeled as (HH3,HH3) corresponds to the case in which the demand for both products was high in both production periods and the daily capacity factors realized correspond to the ones computed with the hourly wind speed collected in the last year (2015 or data set 3).

The scenario tree for Model 2 also has 144 scenarios and it is very similar to the one in Figure 5. The major difference is that the number of production periods (i.e. months) between decision stages is equal to 6 (instead of 1 month). Thus, the presentation of such tree is omitted for brevity purposes.

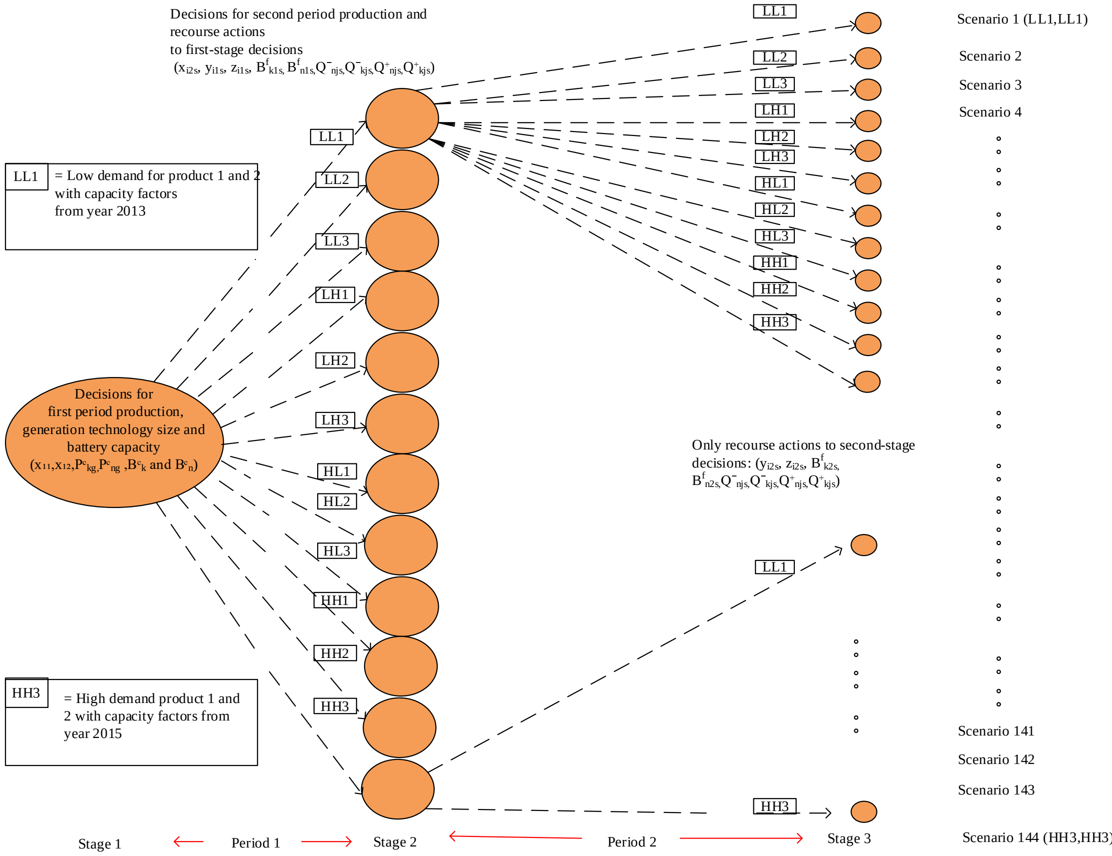


Figure 5. Scenario tree for the multi-stage stochastic model researched

6. NUMERICAL EXPERIMENTS

This chapter is divided in two main sections. The first one presents the numerical values used for the input parameters in the model experimentation. The second one presents and discusses numerical results from experimenting with the models presented in Chapter 4.

6.1 Values for the input parameters

Tables 15 -17 present the values for the parameters used for solving instances of the multi-stage stochastic programming (MSSP) models in Chapter 4 and their units. The numerical experiments assume wind turbines (WT) and solar photovoltaics (PV) as the renewable energy (RE) generators to adopt. The experiments also assume the industry adopting the microgrid system has only one factory located in the city of Amarillo, Texas and one warehouse located in the city of Phoenix, Arizona and thus those parameters using the subscripts *k* and *n* have those subscripts equal to 1.

Values assumed for costs of production, transportation, purchasing, holding and for the amount of resources (i.e. labor and machine hours) required per product, total amount of resources available per period, and energy consumed per product are synthetic for both models but they resemble the ones for industries where production costs are not too high but energy costs are high such as the air separation or the sea water desalination industries. These industries are very energy intensive; an example is cryogenic air separation which is one of the most effective and efficient ways of separating air components such as oxygen, nitrogen and more (Misra et al. 2018). For the seawater desalination sector, which is also energy intensive, unit production cost has significantly decreased due to technological progress (Gao et al. 2017). Anderson et al. (2017), Pham et al. (2019), and data available on-line about renewable energy costs disseminated by renewable energy research laboratories gave insights for the assumed values for the capital cost of the battery and its capital recovery factor and for the capital cost, recovery factor, and maintenance and operational (M&O) costs of WT and PV. Similarly, the values assumed for the weight of the product and the base energy loads in factory and warehouse are also a result of consultation on the web.

Table 15. Values for the parameters of the MSSP models

<table>
<tr><th>Notation</th><th>Value</th><th>Units</th></tr>
<tr><td>θ_{it}</td><td><table><tr><th></th><th colspan="2">Period</th></tr><tr><td>Product</td><td>1</td><td>2</td></tr><tr><td>1</td><td>5</td><td>5</td></tr><tr><td>2</td><td>5</td><td>5</td></tr></table></td><td>$/item</td></tr>
<tr><td>μ_{it}</td><td><table><tr><th></th><th colspan="2">Period</th></tr><tr><td>Product</td><td>1</td><td>2</td></tr><tr><td>1</td><td>26</td><td>26</td></tr><tr><td>2</td><td>26</td><td>26</td></tr></table></td><td>$/item</td></tr>
<tr><td>p_s</td><td>All the 144 scenarios in the scenario tree in Figure 5 are assumed equally probable for Model 1 and then $p_s = 1/144 = 6.94\text{x}10^{-3}$. Similarly, the 144 scenarios in Model 2 are also equally probable.</td><td>N/A</td></tr>
<tr><td>h_{it}</td><td><table><tr><th></th><th colspan="2">Period</th></tr><tr><td>Product</td><td>1</td><td>2</td></tr><tr><td>1</td><td>5</td><td>5</td></tr><tr><td>2</td><td>5</td><td>5</td></tr></table></td><td>$/item/period</td></tr>
<tr><td>o_{it}</td><td><table><tr><th></th><th colspan="2">Period</th></tr><tr><td>Product</td><td>1</td><td>2</td></tr><tr><td>1</td><td>1000</td><td>1000</td></tr><tr><td>2</td><td>1000</td><td>1000</td></tr></table></td><td>$/item</td></tr>
<tr><td>φ_g</td><td>0.08581
The factor listed above converts a present sum of money to annuity and is computed as: $\frac{r}{1-(1+r)^{-h}}$, where r is the annual interest rate and h is the number of years during which a present cost is paid off. The assumed values for r and h are 7% and 25, respectively.</td><td>N/A</td></tr>
<tr><td>a_g</td><td><table><tr><th colspan="2">Generation technology (g)</th></tr><tr><td>WT</td><td>PV</td></tr><tr><td>1.5 M</td><td>1M</td></tr></table></td><td>$/MW</td></tr>
<tr><td>φ_b</td><td>0.1424
Formula to compute the factor above is the same used to compute φ_g
However, here the assumed annual interest rate r is 7% and the number of years h is 10.</td><td>N/A</td></tr>
</table>

Table 16. Continuation of values for the parameters of the MSSP models (1)

<table>
<tr><th>Notation</th><th>Value</th><th>Units</th></tr>
<tr><td>a_b</td><td>520,000</td><td>$/MWh</td></tr>
<tr><td>b_g</td><td><table><tr><td>WT</td><td>PV</td></tr><tr><td>12</td><td>12</td></tr></table></td><td>$/MWh</td></tr>
<tr><td>c_g</td><td><table><tr><td>WT</td><td>PV</td></tr><tr><td>0</td><td>0</td></tr></table></td><td>$/MWh</td></tr>
<tr><td>τ_g^*</td><td>Values vary in each model as shown below:<table><tr><td></td><td>Model 1</td><td>Model 2</td></tr><tr><td>WT</td><td>1,488
(i.e. 62 days x 24h/day)</td><td>744
(i.e. 62 x 12h/day)</td></tr><tr><td>PV</td><td>8,760
(i.e. 365 days x 24h/day)</td><td>4,380
(i.e. 365 x 12h/day)</td></tr></table></td><td>h/year</td></tr>
<tr><td>τ_{gj}</td><td><table><tr><td colspan="2">Generation technology</td></tr><tr><td>WT</td><td>PV</td></tr><tr><td>24</td><td>12</td></tr></table></td><td>h/day</td></tr>
<tr><td>e_i^p</td><td><table><tr><td colspan="2">Product</td></tr><tr><td>1</td><td>2</td></tr><tr><td>0.9</td><td>1.2</td></tr></table></td><td>MWh/item</td></tr>
<tr><td>e_i^f</td><td><table><tr><td colspan="2">Product</td></tr><tr><td>1</td><td>2</td></tr><tr><td>0.01</td><td>0.01</td></tr></table></td><td>MWh/item</td></tr>
<tr><td>q_v</td><td>1.19×10^{-7}
See detailed explanation for the computation of the parameter above in the glossary after the appendix section</td><td>MWh/kg/km</td></tr>
<tr><td>d_{kn}</td><td>1210
A similar value as the one above is assumed for d_{nk}</td><td>km</td></tr>
<tr><td>β</td><td>1</td><td>trip/day</td></tr>
<tr><td>m_v</td><td>2630</td><td>kg</td></tr>
<tr><td>δ</td><td>24</td><td>h/day</td></tr>
<tr><td>L_{ks}</td><td>2</td><td>MW</td></tr>
<tr><td>L_{ns}</td><td>7</td><td>MW</td></tr>
<tr><td>m_i</td><td><table><tr><td colspan="2">Product</td></tr><tr><td>1</td><td>2</td></tr><tr><td>10</td><td>15</td></tr></table></td><td>kg/item</td></tr>
<tr><td>$\lvert J \rvert$</td><td>Model 1 = 62
Model 2 = 365</td><td>days</td></tr>
<tr><td>J_t</td><td><table><tr><td colspan="2">Month</td></tr><tr><td>July (1)</td><td>August (2)</td></tr><tr><td>31</td><td>31</td></tr></table>The above information is with respect to Model 1. Model 2 has the remaining 12 months of the year.</td><td>days</td></tr>
</table>

Table 17. Continuation of values for the parameters of the MSSP models (2)

<table>
<tr><th>Notation</th><th>Value</th><th>Units</th></tr>
<tr><td>D_{ikts}</td><td><table><tr><th rowspan="2">Product</th><th colspan="2">Period 1</th><th colspan="2">Period 2</th></tr><tr><th>Low (L)</th><th>High (H)</th><th>Low (L)</th><th>High (H)</th></tr><tr><td>1</td><td>870</td><td>1560</td><td>870</td><td>1990</td></tr><tr><td>2</td><td>860</td><td>1790</td><td>1530</td><td>2060</td></tr></table>Explanatory paragraph is on first paragraph below Table 18.</td><td>Items/period</td></tr>
<tr><td>w_{krt}</td><td><table><tr><th></th><th colspan="2">Period</th></tr><tr><th>Resource</th><th>1</th><th>2</th></tr><tr><td>1</td><td>119,040</td><td>119,040</td></tr><tr><td>2</td><td>617,520</td><td>617,520</td></tr></table>Same amounts for the 12 production periods in Model 2</td><td>h/period</td></tr>
<tr><td>v_{ikr}</td><td><table><tr><th></th><th colspan="2">Resource</th></tr><tr><th>Product</th><th>1</th><th>2</th></tr><tr><td>1</td><td>16</td><td>100</td></tr><tr><td>2</td><td>24</td><td>200</td></tr></table></td><td>h/item</td></tr>
<tr><td>B_k^m</td><td>300</td><td>MWh/day</td></tr>
<tr><td>B_n^m</td><td>300</td><td>MWh/day</td></tr>
<tr><td>$P_{kg}^{\max}$</td><td>150</td><td>MW</td></tr>
<tr><td>$P_{ng}^{\max}$</td><td>150</td><td>MW</td></tr>
<tr><td>λ_{gjs}</td><td>See the values tabulated for the capacity factors in Appendix A.</td><td>N/A</td></tr>
<tr><td>ϑ</td><td>24</td><td>h</td></tr>
<tr><td>ω_t</td><td>Factor to compute the amount of product in inventory up to day j in period t requiring energy in the warehouse</td><td>day</td></tr>
<tr><td>Q_{kjs}^{Max}</td><td>2400</td><td>MWh/day</td></tr>
<tr><td>Q_{kns}^{Max}</td><td>2400</td><td>MWh/day</td></tr>
<tr><td>u^*</td><td>130</td><td>$/MWh</td></tr>
<tr><td>u</td><td>35</td><td>$/MWh</td></tr>
</table>

As mentioned in Chapter 5, the scenario trees for the implemented models (i.e. Model 1 and Model 2) have 144 scenarios (i.e. $|S| = 144$) to realize the uncertain parameters. These scenarios result from considering 2 products with 2 demand levels, low (L) and high (H), and 3 sets of daily WT capacity factors over 2 production periods. Thus, 144= $(2x2x3)^2$. If ignoring the capacity factors, there are 16= $(2x2)^2$, different demand scenarios that result from realizing demand values for the two products in the two periods for Model 1 and in the two decision periods for Model 2 even if they are of length 6 months each. For instance, in Model 1 the scenario (HL, LH) means that for the first period the demand for product 1 is high and the demand for product 2 is low while for the second period these demands are low and high, respectively. Similarly, in Model 2 the scenario (HL, LH) means that for the first 6 production periods the demand for product 1 is high and the demand for product 2 is low while for the next 6 production periods these demands are low and high, respectively. The entries for D_{ikts} in Table 16 correspond to 4 values chosen to represent the low demand (L) and 4 values selected for the high demand (H) of the two products in the two periods. These 8 realized values serve as the input to construct the 16 demand scenarios. The particular (L) and (H) values presented in Table 16 resulted from generating large random samples for the discrete uniform distributions in Table 11 using Python 3.7 and choosing the lowest and highest generated values. Following the same procedure, the values for D_{ikms} were obtained.

To simplify the numerical experiments, the values for θ_{it}, μ_{it}, h_{it} and o_{it} in the models are assumed not to vary by product or by period. The numerical values for θ_{it} and θ_{im} in Model 2 are assumed equal and they are the same as the one for θ_{it} in Model 1. Similarly, the values for μ_{it} and μ_{im} in Model 2 are assumed equal and the same as the one for μ_{it} in Model 1. However, the demand D_{ikts} and the energy consumed per product in the factory, e_i^p, vary by product. To avoid any arbitrage, the cost of purchasing product to other vendor o_{it} is assumed very high in comparison to the cost of manufacturing, transporting and holding the product. The selling price of the products, which is not part of the model, need to be higher than those costs to make the business competitive. Given that the production system is not in place, it seemed reasonable to assume a scarce knowledge about the future and to keep assuming equal probabilities for the scenarios, p_s. The incentives of the PV were assumed as zero to take a conservative approach. As in practice, the current incentives for WT are considered nonexistent.

The mass of the electric vehicles and the distances between factory and warehouse and warehouse to factory were collected on the Internet. It is assumed that the company has large trucks to transport the products in such a way that only one trip per day is necessary between the factory and the warehouse.

Note that the value for the cost of purchasing energy, u^*, is necessarily assumed greater than the energy selling price, u. One hypothesis is that if the actual cost of the battery per MWh of energy generated ends not too high, this would incentive prosumers to store energy to avoid purchasing it and to get some revenue from selling any extra energy. However, if the actual cost of the battery per MWh of energy generated is too high, the option of purchasing energy to the grid would be preferred even if keeping $u^* > u$. Another hypothesis is that to balance the cost of the battery per MWh of energy generated the prosumer may need to significantly increase the installed WT and PV capacity, sell the extra energy generated and avoid any purchasing. These hypotheses will be validated in the experiments in the remaining of this chapter and in Chapter 7.

6.2 Computational results

The MSSP models presented in Chapter 4 correspond to the extensive forms (EF) of multi-stage stochastic programs and are linear as it can be appreciated from observing that the objective function and all the constraints are linear on the decision variables.

Besides, the number of decision variables and constraints were counted by the author of this thesis. Model 1 has 52,424 decision variables and 86,816 constraints. Model 2 has 326,024 decision variables and 653,206 constraints. Both Models were coded using the AMPL mathematical programming language (Fourer et al., 2003) and solved through AMPL 3.6.1 using the Cplex 12.10 solver. The input data file for Model 1 was generated in two ways: by inputting the values directly in a text file and by writing code in Python 3.7 to generate such data file. The first way was used to solve the problem in AMPL and the second one was fun and useful, even if it is not entirely necessary, to solve the problem using the AMPL Python API, the AMPL Application Programming Interface to Python. Model 2 was solved only in AMPL.

The numerical experiments were conducted using a Dell Optiplex 990 desktop (3.4 GHz intel i7 2600 processor, 16GB RAM, 500GB hard drive with a 64-bit windows 10 operating system) and a HP pavilion x360 convertible (2.20GHZ Intel® Core™ i3-8130U processor, 8GB RAM with a 64-bit windows 10 operating system). Following some statistics regarding computational times of the models which were collected using AMPL build-in functions.

Experiment in Model 1 had an average AMPL user time of 0.203 CPU seconds and a total solve time (solve system time plus solve user time) of 1.6092 CPU seconds on the HP pavilion x360. Experiments in Model 1 had**,** an average AMPL user time of 0.203 CPU seconds and a total solve time of 4.438 CPU seconds on the Dell Optiplex. Experiments in Model 2 had an average AMPL user time of 1.406 seconds and a total solve time of 27.6562 CPU seconds on the HP pavilion x360 while they had an average user time of 1.391 CPU seconds and a total solve time of 55.031 CPU seconds on the

Dell Optiplex. All these times seem very appealing for the current and future users of the models. The AMPL user time is defined as the user CPU seconds used by the AMPL process itself (Fourer et al., 2003). The solve system time is defined as the operating system CPU seconds used by the latest solve command, including reading and writing files. The solve user is the time spend by the latest process outside the operating system. The total solve time (solve system time plus solve user time) seems a comprehensive way to appraise the models computational time as seen from the definitions. However, it seemed interesting to also access the GAP between the AMPL user time and the total solve time. This is the reason for collecting these two types of built-in timing functions.

Even if the objective function of both models is to minimize the total expected annual cost (denoted as expected annual cost in the reminder of this document), the results in this chapter also show the levelized cost of electricity (LCOE). It is defined as the needed constant price of electricity that permits the project to reach a break-even point over the lifetime of the power plant (i.e. or the power generation technology) (Walraven et al. 2015). LCOE can be seen also as the cost of producing one MWh of energy and its units are $/MWh. LCOE is used in industry as a main indicator to decide if a renewable energy project is attractive because it permits to compare the electricity costs for a system vs. the one from using traditional sources of energy. The goal is to obtain LCOE values in the range of $50-$200 per MWh because the actual cost of traditional sources of energy falls in such range.

The remainder of this section is divided into 7 subsections. Subsection 6.2.1 presents a formula to compute the LCOE for the case in which the system behaves as a non-prosumer of energy and an updated LCOE formula for the case in which the system behaves as prosumer. Subsections 6.2.2 – 6.2.7 present the results from solving several cases for the two MSSP models. For all the cases solved, the recourse action of purchasing product (i.e. vendor supply) in cases of product shortage was dropped from the Models. Table 18 describes the cases solved with Model 1 and Table 19 the cases solved with Model 2

Table 18. Cases solved for Model 1 (two-months planning horizon)

Subsection	Case
6.2.2	Production planning (PP) system allowing production and storage in the factory without considering any energy aspects
6.2.3	PP system allowing production and storage in the factory considering energy is purchased from the grid
6.2.4	PP system allowing production and inventory storage in the factory, considering power is generated from WT and PV, battery can be installed, extra renewable energy is sold, and energy needed can be purchased (energy prosumer)
6.2.5	PP system having production in the factory and inventory storage in a separate warehouse, considering power is generated from WT and PV, battery can be installed, extra renewable energy is sold and energy needed can be purchased (energy prosumer)

Table 19. Cases solved for Model 2 (one-year planning horizon)

Section	Case
6.2.6	PP system allowing production in the factory and inventory storage in a separate warehouse, considering power is generated from WT and PV, and battery can be installed but any extra energy is spilled (island system).
6.2.7	PP system having production in the factory and inventory storage in a separate warehouse, considering power is generated from WT and PV, battery can be installed, and extra renewable energy is sold and energy needed can be purchased (energy prosumer)

6.2.1 Levelized cost of electricity (LCOE) Computation

The levelized cost of electricity (LCOE) for the island systems can be calculated using equation 6.1, which resembles the one given by Shea and Ramgolam. (2019)

$$\text{LCOE} = \frac{\text{Total cost of energy production (\$)}}{\text{Total energy produced (MWh)}} \tag{6.1}$$

In (6.1), the total cost of energy production is the sum of RE equipment and battery installation costs, RE operation and maintenance costs, and RE carbon credits over the entire production period considered. The total energy production is the total energy generated in the same period by the RE technologies.

The LCOE for the prosumer cases can be computed as shown in equation (6.2) below. In (6.2), the numerator is the sum of the cost of RE production and the cost of energy purchased. The denominator of (6.2) is the sum of the total energy produced and energy purchased. In equation (6.2), the total energy sold is already part of the total energy produced, hence no extra term in the denominator of this equation needs to be considered.

$$\text{LCOE} = \frac{\text{Total cost of energy production (\$) + Total cost of energy purchased (\$)}}{\text{Total energy produced (MWh) + Total energy purchased (MWh)}} \quad (6.2)$$

6.2.2 Production planning model without energy aspects and no product purchase

The first numerical experiment was performed on a very simplified instance of the MSSP Model 1 presented in Chapter 4 in which: (1) production and inventory storage happen in the factory (i.e. there is no warehouse), (2) final product cannot be purchased from vendors and (3) energy aspects are not considered. Note that this model is still a stochastic one since final product demands and weather conditions remain random. Table 19 summarizes the results from running this instance, which served as a benchmark to check the production results generated by the other cases researched for Model 1.

Table 20. Results production planning Model 1 with no energy adopted

Expected annual cost ($)	41,109	
	Period 1	Period 2
Production (items):	3,350	3,240
Product 1	1,560	1,645
Product 2	1,790	1,595
Inventory (items):	810	825
Product 1	345	560
Product 2	465	265

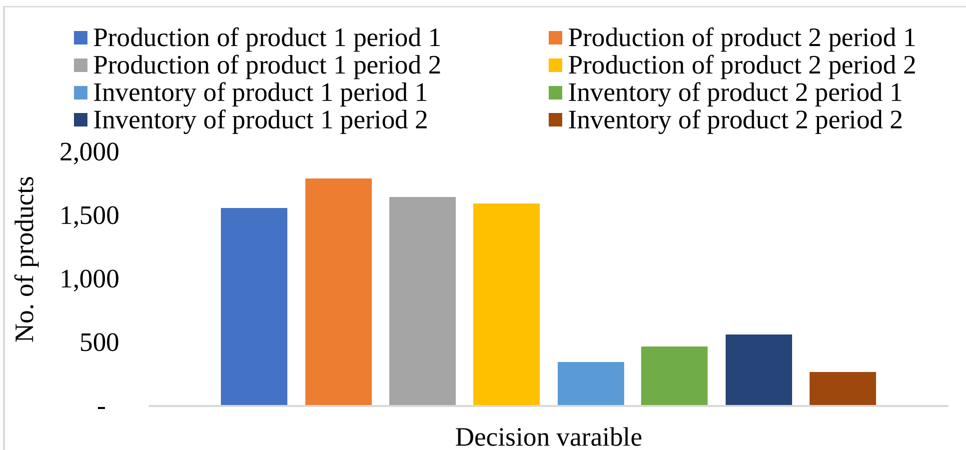


Figure 6. Production and inventory levels for the model without energy

From the input parameters for the product demand given in Table 17, it can be assumed that the large variation in the demand for product 2 in period 1 explains why in Figure 6 the amount of product 2 produced in period 1 (orange bar) is larger than the amount for product 1 for the same period (first blue bar). The large demand variation for product 2 in period 1 also led to a greater amount of inventory for product 2 (green bar) if compared to the inventory for product 1 in period 1 (light blue bar). Besides, for both products the inventory levels in the second period (dark blue and marron bars) do not equal zero as it is the case for a deterministic model. It occurs because for each product, the MSSP model must consider all the variation on the demands for the different scenarios when planning for the optimal production amount to satisfy the expected demands and such optimal amount will lead to inventory accumulation after demands are realized. Table 20 also reports that the minimum expected annual cost of the system without considering energy aspects is $41,109.

6.2.3 Model with main-grid energy purchase without product purchase

Table 21 presents the expected annual cost and LCOE results from running a simplified case of the MSSP Model 1 which considers: (1) production and inventory storage happen in the factory, (2) final product cannot be purchased from vendors and (3) energy is purchased from a main grid source.

The expected annual cost of this case is $2,385,238 as shown in the first row. This cost is significantly larger than the one in Table 20 because it considers the cost of purchasing the energy from a main grid source at a cost of $130/MWh for production, storage of products in inventory and satisfaction of a base load. Thus, for this model the production and inventory costs are $41,109 and the cost of purchasing energy to the main grid is $2,344,130.

Table 21. LCOE of Model 1 with main grid energy purchase in single factory

Expected annual cost		$2,385,238					
		Period 1			Period 2		
Product demand (items):		Low	High	Average	Low	High	Average
Product 1		870	1,560	1,215	870	1,990	1,430
Product 2		860	1,790	1,325	1,530	2,060	1,795
Production (items):	Total:	3,350			3,240		
Product 1	3,205	1,560			1,645		
Product 2	3,385	1,790			1,595		
Inventory (items):		810			825		
Product 1	905	345			560		
Product 2	730	465			265		
Total energy consumed by factory (MWh/period)		18,032					
Total energy cost ($ over a 59-days period)		2,344,130					
Total energy purchased from the grid (MWh)		18,032					
LCOE ($/MWh)		$ 130 (i.e. 2,344,130/18,032)					

6.2.4 Model 1 without product purchase and with renewables in single factory (energy prosumer)

Table 22 presents the objective function costs coefficients used in the models for the energy related decision variables. The values for these parameters were given previously in Tables 15-17. Since they apply for all the cases presented in the remainder of this chapter, they are displayed in a succinct way again in Table 22.

Table 22. Costs coefficients for energy related decision variables

Item	Notation in Tables 14-16	Value
Selling price ($/MWh)	u	35
Buying cost ($/MWh)	u^*	130
WT cost ($/MW)	a_g (g=1)	1.5M
PV cost ($/MW)	a_g (g=2)	1M
Battery cost ($/MWh)	a_b	0.52M

Table 23 presents the expected annual cost and LCOE results from running a simplified case of the MSSP Model 1 which considers: (1) production and storage happen in the factory, (2) final product cannot be purchased, (3) renewable power from WT and PV, and energy storage system (i.e. battery) can be adopted and (4) energy can be sold and purchased from the main grid and thus the industry performs as an energy prosumer.

In Table 23, the expected annual cost of the model (first line) results from adding the following costs: production and transportation, inventory, equipment installation, maintenance and operation, carbon credits, and cost from purchasing energy. The revenue from selling energy is also subtracted from the sum. The total annualized energy cost (fourth line from bottom to top) only includes equipment installation, maintenance and operation, and carbon credits. The third line of the table from bottom to top, named total energy cost for the factory over a horizon of two months, computes the energy cost prorated for two months as follows:

Energy cost over two months = Total annual energy cost*(h in two months)/(h/year)

The energy cost is prorated for two months to compute the LCOE as fair as possible by considering only the energy cost of two months vs. the energy production of two months (i.e. it is the same as considering the energy cost for 12 months and assuming the energy produced will be 6 times the one for two months). However, notice that if the factory opens for production for only two months of the year, as it was really the situation represented by Model 1, the fair computation of LCOE would be a ratio of the annual energy cost divided by the energy production of two months.

Since the wind speed in Amarillo is high, the model opted to install WT capacity of only 12MW. An explanation for this result is that the higher the wind speed in a particular geographical location the less WT technology required. Besides, there was no PV installation in Amarillo, due to the low PV capacity factor in comparison to the WT capacity factor. Also, due to the option of selling the excess renewable energy generated and the high cost of battery the model did not install a battery storage system. To optimize the expected annual cost, the model chose to sell the excess energy generated at any point in time and buy energy from the grid when the energy from the WT was not able to satisfy the load. This model has an expected total annual cost of $2,015,120 and an LCOE of $32/MWh.

Table 23. LCOE of Model 1 with WT, PV, and battery in factory (energy prosumer)

Expected annual cost ($)	2,015,120					
Revenue from selling renewable energy ($)	4,222					
Cost of purchasing energy to the grid in ($)	264,182					
Total energy purchased from grid over time horizon (MWh)	2,032					
Total energy sold to grid over time horizon (MWh)	121					
WT capacity (MW)	12					
PV capacity (MW)	0					
Battery capacity (MWh)	0					
	Period 1			Period 2		
Product demand (items)	Low	High	Average	Low	High	Average
Product 1	870	1,560	1,215	870	1,990	1,430
Product 2	860	1,790	1,325	1,530	2,060	1,795
Production (items):						
Product 1	1,560			1,645		
Product 2	1,790			1595		
Inventory:						
Product 1	345			560		
Product 2	465			265		
Total annualized energy cost factory ($)	1,714,050					
Total energy cost for the factory over a horizon of two months ($)	291,154					
Total energy produced by the factory over a horizon of two months (MWh)	15,506					
LCOE ($/MWh)	32 (i.e. (291,154+264,182)/(15,506+2,032))					

6.2.5 Model 1 without product purchase with renewables in factory and warehouse (energy prosumer)

Table 24 presents the results from running a simplified version of the MSSP Model 1 which considers: (1) production occurs in the factory and inventory storage happen in the warehouse, (2) final product cannot be purchased , (3) renewable power from WT and PV, and energy from energy storage system (i.e. battery) can be adopted in both factory and warehouse and (4) energy can be sold and purchased from the main grid and therefore the system performs as an energy prosumer. Demands, production and inventory are not reported in Table 24 because they are the same as in Table 23.

Because the wind speed in Amarillo (factory location) is higher than the one in Phoenix (warehouse location), the model installed a WT at the Amarillo factory which has a capacity of 7 MW. No WT was installed in Phoenix. For the warehouse, it ended cheaper to purchase energy at a cost of $130/MWh than installing a WT at a capital cost of $1.5M/MW. There was no solar PV system installed at any of the two locations. It is because solar power at Amarillo was low and in Phoenix the PV system at a cost of 1M/MW ended being not cost efficient either. Besides, no battery was installed in the factory or the warehouse because it resulted more cost efficient to buy energy from the grid and sell the excess energy generated than installing a battery with a cost of 0.52M/MWh. This model has an expected annual cost of $2,712,550 and an LCOE of $82/MWh, which is higher than the one computed in the previous subsection (i.e. $32/MWh). The increase in total expected costs vs. the one in the case in the previous subsection is explained by the amount of energy purchased and the additional energy required due to the factory and warehouse being in different locations.

Table 24. LCOE of Model 1 with renewables and battery in factory and warehouse (energy prosumer)

Expected annual cost ($)	2,712,550	
	Factory	Warehouse
Revenue from selling energy ($)	5,306	0
Cost of purchasing energy ($)	159,059	1,364,820
Total energy purchased from over time horizon (MWh)	1,224	10,499
Total energy sold over time horizon (MWh)	152	0
WT capacity (MW)	7	0
PV capacity (MW)	0	0
Battery capacity (MWh)	0	0
Total annual energy cost ($)	981,584	0
Energy cost incurred over a horizon of two months ($)	166,735	
Total energy produced over a horizon of two months (MWh)	8,880	0
LCOE ($/MWh)	82 (i.e.(166,735+159,059+1,364,820)/(8,880+1,224+10,499))	

6.2.6 One-year model (Model 2) without product purchase with renewables in factory and warehouse (island)

Table 25 presents the results from running the MSSP Model 2 considering: (1) production occurs in the factory and inventory storage happen in the warehouse, (2) final product cannot be purchased, (3) renewable power from WT and PV, and energy from energy storage system (i.e. battery) can be adopted in both factory and warehouse and (4) energy cannot be sold and purchased from the main grid, in other words, extra energy generated is either stored in the battery or spilled.

Table 25. LCOE of one-year island model with renewables and battery in factory and warehouse

Expected annual cost ($)	15,150,000	
	Factory	Warehouse
Total energy spilled over time horizon (MWh)	34,083	42,909
WT capacity (MW)	8	0
PV capacity (MW)	32	59
Battery capacity (MWh)	16	17
Total energy cost ($)	6,105,030	7,657,260
Energy cost incurred over a horizon of one year ($)	13,762,290	
Total energy produced over a horizon of one year (MWh)	91,780	104,483
LCOE ($/MWh)	70 (i.e. 13,762,290/(91,780+104,483))	

In this case, because the wind speed in Phoenix (warehouse location) is lower than the one in Amarillo (factory location) the model installs a WT at the Amarillo factory, which has a capacity of 8MW, and no WT at the Phoenix warehouse. For the Amarillo factory, the model also ends needing to install PV of 32MW to meet the production and the base load. For the Phoenix warehouse, the model prefers to install a PV of 59MW and no WT. It is because in Phoenix it is more profitable to install a PV over WT due to the stronger sunlight in comparison to wind speed. Since there is no option of purchasing or selling energy, the model installed a battery size of 16MWh and 17MWh in the factory and the warehouse, respectively. These batteries permit to store energy when the factory and warehouse generate more energy than required and to use that stored energy when energy is in short supply from the generation technologies (WT and PV). This model has an expected annual cost of $15,150,000 and an LCOE of $70/MWh, which is cheaper than purchasing energy at a cost of $130.

6.2.7 One-year (Model 2) without product purchase with renewables in factory and warehouse (energy prosumer)

Table 26 presents the results from running the MSSP Model 2 after considering: (1) production occurs in the factory and inventory storage happen in the warehouse, (2) final product cannot be purchased , (3) renewable power from WT and PV and energy from energy storage system (i.e. battery) can be adopted in both factory and warehouse and (4) energy can be sold and purchased from an electricity company and therefore the system performs as an energy prosumer.

Table 26. LCOE of one-year prosumer model with renewables and battery in factory and warehouse

Expected annual cost ($)	7,052,410	
	Factory	Warehouse
Revenue from selling energy ($)	21,350,700	466,571
Cost of purchasing energy ($)	17,210	807,942
Total energy purchased over time horizon (MWh)	132	6,215
Total energy sold over time horizon (MWh)	610,020	13,331
WT capacity (MW)	105	0
PV capacity (MW)	0	39
Battery capacity (MWh)	0	2
Total annual energy cost ($)	22,276,940	4,383,692
Energy cost incurred over a horizon of one year ($)	26,660,632	
Total energy produced over the horizon period (MWh)	667,934	68,875
LCOE ($/MWh)	37 (i.e. (17,210+807,942+26,660,632)/(132+6215+667,934+68,875)	

In this case, because the wind speed in Phoenix (warehouse location) is lower than the one in Amarillo (factory location) and Phoenix generates more sunlight than wind speed , the model installed only WT at the Amarillo factory and only PV in the warehouse at Phoenix. The model adopted a very large WT in Amarillo because it ended very profitable to generate energy and sell to an electricity company while keeping the energy purchased from the company low over the one-year period. In the warehouse in Phoenix, some profit was also generated from selling energy to the electricity company to absorb near 10% of the PV annualized purchasing and maintenance cost. Such percentage is the ratio of $466,571 revenue from selling energy in the warehouse and $4,383,692 annualized cost of PV and battery. Battery capacity in both locations was close to zero because with a battery cost of $0.52M/MWh, it ended better to sell energy at a price of $35 when the factory or warehouse generated excesses instead of storing them in a battery. Also, it ended more advantageous to purchase energy at a cost of $130 when the factory or warehouse could not meet the load with their onsite generation. This model has an expected annual cost of $ 7,052,410 and an LCOE of $37 which is cheaper than considering only purchasing energy at a cost of $130.

In conclusion, from comparing the results for the annual models presented in subsection 6.2.6 and 6.2.7, the prosumer model is more cost-efficient (LCOE $37) than the island one (LCOE $70) because even if the prosumer model installs a lot more WT capacity, it can sell most of the generated energy and it earns revenue to compensate especially for the large WT installation costs at the factory. The island model is forced to satisfy its energy load without an option of generating revenue with energy sales.

7. RESULTS DISCUSSION AND COMPARISONS

Sections 7.1, 7.3 and 7.5.1 compare the results from solving instances of the multi-stage stochastic programming (MSSP) Model 1 (two-month model presented in Section 4.1) assuming no final product purchase option to the ones resulting from doing other relevant modifications, such as dropping from the system the energy prosumers behavior (Section 7.1), decreasing the capacity factors of the generation technologies (Section 7.3) and removing the assumption of stochastic parameters when solving the model (Section 7.5.1).

Sections 7.2, 7.5.2 and 7.6 present also relevant results arising from further experimenting with Model 2 (one-year model presented in Section 4.2) assuming no product purchase option. Section 7.2 compares the results of considering the system as an energy prosumer vs considering it as an island one. Section 7.5.2 presents the results from dropping the assumption of stochastic parameters for the model. Section 7.6 presents a design of experiments (DOE) to identify about the most critical factors affecting the model expected total cost. The cost of purchasing energy from the main grid is assumed to be \$130/MWh and the price of selling energy to the grid is assumed to be \$35/MWh as in Chapter 6. The columns of Tables 27 and 28 below describe the model instances studied in each section of this chapter.

Table 27. Description of model instances studied

	Model instance				
Section	1	2	3	4	5
Section 7.1	Model 1 factory with main grid energy purchase and no product purchase (presented in Subsection 6.2.3)	Model 1 factory with renewable energy and no product purchase (energy prosumer; presented in Subsection 6.2.4)	Model 1 factory with renewable energy and no product purchase (island)	Model 1 factory and warehouse (F&W) with renewable energy and no product purchase (energy prosumer; presented in Subsection 6.2.5)	Model 1 factory and warehouse (F&W) with renewable energy and no product purchase (island)
Section 7.2	Model 2 factory and warehouse (F&W) with main grid energy purchase and no product purchase	Model 2 factory with renewable energy and no product purchase (energy prosumer)	Model 2 factory with renewable energy and no product purchase (island)	Model 2 factory and warehouse (F&W) with renewable energy and no product purchase (energy prosumer)	Model 2 factory and warehouse (F&W) with renewable energy and no product purchase (island)
Section 7.3		Model 1 Sensitivity analysis to changes on capacity factors for factory with renewable energy and no product purchase (energy prosumer)		Model 1 Sensitivity analysis to changes on capacity factors for factory and warehouse with renewable energy and no product purchase (energy prosumer)	
Section 7.4		Model 1 Factory with renewable energy and no product purchase (Energy prosumer; presented in Subsection 6.2.4)		Model 1 Factory and warehouse (F&W) with renewable energy and no product purchase (Energy prosumer; presented in Subsection 6.2.5)	

Table 28. Continuation of description of model instances studied

Section	Description
Section 7.5	7.5.1 MSSP Model 1 (i.e. two-months) factory and warehouse with renewable energy and no product purchase and energy prosumer (presented in section 6.2.4) vs. its deterministic counterpart 7.5.2 MSSP Model 2 (i.e. one-year) factory and warehouse with renewable energy, no product purchase and energy prosumer (presented in section 6.2.6) vs. its deterministic counterpart
Section 7.6	Design of experiments (DOE) for MSSP Model 2 (i.e. one year) with battery, PV, energy selling price and energy purchasing costs as factors and expected total annual cost as response variable

7.1 Comparison of production planning model instances without considering product purchase

Table 29 describes again the instances of Model 1 (two-months model) contrasted in this section. Tables 30 compares the production and inventory results among the instances. Table 31 presents the relevant renewable energy (RE) related results.

Table 29. Description of the Model 1 instances compared without product purchase

Model Instance				
1	2	3	4	5
Model 1factory with main grid energy purchase and no product purchase (presented in subsection 6.2.3)	Model 1 factory with renewable energy and no product purchase (Energy prosumer; presented in Sub-section 6.2.4)	Model 1 factory with renewable energy and no product purchase (Island)	Model 1 factory and warehouse (F&W) with renewable energy and no product purchase (Energy prosumer; presented in Subsection 6.2.5)	Model 1 factory and warehouse (F&W) with renewable energy and no product purchase (Island)

Table 30 shows the total production and inventory of the different instances analyzed. As presented in Section 6.1, Tables 15-17 with values for the parameters of the MSSP models, the demands for product 2 are higher than for product 1 in both periods.

Besides, the assumed value for the energy required to manufacture the product 2 is higher than the energy requirements for product 1 while the value for the energy required to store both products is the same. The values for e_i^p and e_i^f for product 2 are 1.2 and 0.01 MWh/item, respectively while these values are 0.9 and 0.01 for product 1. The results in Table 30 show that the higher product demands and energy requirements for product 2, caused that the island instances (3 and 5) took different production decisions than the prosumer instances and purchasing from the main grid instances (1, 2 and 4). The island instances produce more of product 2 in the first period and less of product 2 in second period if compared to the other instances. This result can be explained because the island models must prepare better (i.e. take more conservative decisions) to satisfy high final product demands and high energy requirements since energy cannot be purchased from the grid. The island models carried more inventory in period 1 but produced less in period 2 and ended with the same inventory level than the prosumer models at the end of period 2. They took advantage of the low energy load requirements for the product in the warehouse, the battery installed and the favorable wind and weather conditions to produce some of the period 2 demand for product 2 in period 1 and storing it inventory.

Table 30. Production and inventory comparison among Model 1 instances without production purchase option

Model instance	1 Factory Main Grid	2 Factory Prosumer	3 Factory Island	4 F&W Prosumer	5 F&W Island
Production (items):	6,590	6,589	6,588	6,588	6,585
Period 1	3,350	3,350	3,832	3,350	3,759
Product 1	1,560	1,560	1,560	1,560	1,560
Product 2	1,790	1,790	2,272	1,790	2,200
Period 2	3,240	3,239	2,757	3,238	2,826
Product 1	1,644	1,644	1644	1,644	1,644
Product 2	1,595	1,595	1,113	1,594	1,182
Inventory (items):	1,635	1,635	2,116	1,635	2,046
Period 1	810	810	1,291	810	1,222
Product 1	345	345	345	345	345
Product 2	465	465	946	465	877
Period 2	825	825	825	825	824
Product 1	560	560	560	560	560
Product 2	265	265	265	265	265

The expected annual cost entry in Table 31 (i.e. first line) shows that Instance 2 in which the production and inventory storage operations are consolidated in the factory, and the system is an energy prosumer is the one with the lowest cost ($2,015,120). It is because Instance 2 has the options of selling energy and purchasing energy from the main grid installing a WT capacity of 12MW in the factory at Amarillo. Due to the size of the WT installed and the consolidated operations without incurring in energy expenses due to transportation, Instance 2 purchases the lowest amount of energy from the main grid and it also gains a good revenue from selling the excess energy generated.

Table 31. Costs and energy comparisons among Model 1 instances without product purchase option

Model instance	1 Factory Main Grid	2 Factory Prosumer	3 Factory Island	4 F&W Prosumer	5 F&W Island
Expected annual cost ($)	2,385,238	2,015,120	2,762,250	2,712,550	6,722,650
Revenue from selling energy ($)	0	4,222	-	5,306	-
Cost of purchasing to the grid ($)	2,344,130	264,182	-	1,523,879	-
Total energy purchased from the grid over the time horizon (MWh)	18,032	2,032	-	11,723	-
Total energy spilled over the time horizon (MWh)	-	-	3,884	-	3,807
Total energy sold to grid over the time horizon (MWh)	0	121	-	152	-
WT capacity (MW)	0	12	16	7	22
PV capacity (MW)	0	0	0	0	31
Battery capacity (MWh)	0	0	5	0	10
Total energy cost ($)	-	1,714,050	2,718,730	981,584	6,508,180
Energy cost incurred over a horizon of two months ($)	2,344,130	291,154	461,812	166,735	1,105,499
Total energy produced over a horizon of two months (MWh)	-	15,506	21,281	8,880	24,507
LCOE ($/MWh)	130	32 (i.e. (291,154+ 264,182)/ (15,506+ 2,032))	22 (i.e. (461,812/ 21,281))	82 (i.e. (166,735+ 1,523,879)/ (8,880+ 11,723))	45 (i.e. (1,105,499/ 24,507))

In Instance 4, the factory and warehouse are in different places. Because of variations in wind speed and solar power in the locations, the relatively high cost of the PV, along with differences in the base load requirements (i.e. factory has a lower base load than the warehouse), the model opts for installing only 7 MW of WT in Amarillo. Thus, this model instance needs to purchase more energy, especially in the warehouse where no renewables are adopted, and hence its cost goes up to $2,712,250 (i.e. 34.60%

higher than instance 2). The comparison of the costs for Instances 2 and 4 vs. the cost of Instance 1, which is a single factory with purchased energy from the main grid shows that Instance 1 is more expensive than Instance 2 because it only purchases energy at a flat rate of $130/MWh without any other option leading to a cost of $2,385,238 (i.e. an increase in cost of 18.36% vs. Instance 2).

Instances 3 and 5 correspond to island cases, where all the energy used in the company is generated on-site. These instances are the most expensive ones when compared to the rest because they are forced to install a larger capacity of RE and to adopt some battery capacity to satisfy their energy loads. The expected annual costs of Instances 3 and 5 are $2,762,250 and $6,722,650, respectively. Those costs are 37.08% and 233.61% higher than Instance 2.

The expected annual cost comparison presented in Table 31 shows that it is more cost efficient to install a model with RE, energy sales and purchase option (Instance 2) than a model with just conventional energy purchase option (Instance 1).

On a closer look, the analysis of the levelized cost of energy (LCOE) for these 5 instances shows that at a purchasing cost of energy of $130/MWh the single factory instances, (Instances 2 and 3), have the cheapest LCOE's , $32/MWh and $22/MWh, respectively. The factory and warehouse, (Instances 4 and 5), have LCOE's of $82/MWh and $45/MWh, respectively.

An explanation for the higher LCOE results for Instance 2 (factory prosumers, $32/MWh) vs Instance 3 (factory island, $22.MWh) is that even if the island instances adopted RE incurring in higher installation costs, they did not incur in the high extra costs of purchasing energy. For example, Instance 3 (island) had a cost of producing energy of

$461,812 because installed a WT of 20 MW while Instance 2 (prosumer) had a cost of $291,154 because it installed a WT of 12 MW. However, Instance 2 incurred in an additional cost of purchasing energy from the grid at a cost of $264,182 and then had a total energy related cost of $555,336. Besides, the total energy generated by Instance 3, even if some was spilled, was 21,281 MWh while Instance 2 generated only 15,506 MWh and purchased 2,032 MWh. Thus, the LCOE computation for Instance 3 has a smaller total cost value in the numerator and a larger total energy value in the denominator and both facts contribute to get a lower LCOE for Instance 3.

Due to the short-term horizon of Model 1, it would be more reliable to compute the LCOE's for Model 2 which considers a one-year horizon. Those results are in the next subsection.

7.2 Comparison of Model 2 instances without product purchase option

Table 32 describes the 5 instances of Model 2 (i.e. one-year model) contrasted in this section. Table 33 provides the results of running these three cases.

Table 32. Description of the Model 2 instances compared without product purchase

Model instance				
1	2	3	4	5
Model 2 factory and warehouse (F&W) with main grid energy purchase and no product purchase	Model 2 factory with renewable energy and no product purchase (energy prosumer)	Model 2 factory with renewable energy and no product purchase (island)	Model 2 factory and warehouse (F&W) with renewable energy and no product purchase (energy prosumer)	Model 2 factory and warehouse (F&W) with renewable energy and no product purchase (island)

Table 33. Costs and energy comparisons among Model 2 instances without product purchase

Model instance	1 F&W Main Grid	2 Factory Prosumer	3 Factory Island	4 F&W Prosumer	5 F&W Island
Expected annual cost ($)	27,212,347	2,091,033	10,782,100	7,052,410	15,150,000
Revenue from selling energy ($)	0	21,052,500	-	21,817.271	-
Cost of purchasing from the grid ($)	25,810,930	93,305		825,152	-
Total energy purchased from the grid over the time horizon (MWh)	198,546	718	-	6,347	-
Total energy spilled over the time horizon (MWh)	-	-	57,239	-	6,992
Total energy sold to grid over the time horizon (MWh)	0	601,500	-	623,351	-
WT capacity (MW)	0	111	14	105	8
PV capacity (MW)	0	0	55	39	91
Battery capacity (MWh)	0	0	27	2	33
Energy cost incurred over a horizon of one year ($)	-	22,662,620	10,396,630	26,660,632	13,762,290
Total energy produced over a horizon of two months (MWh)	-	702,976	158,959	736,809	196,263
LCOE ($/MWh)	130	32 (i.e. (22,662,620 +93,305)/ (702,976 + 718))	65 (i.e. (10,396,630 /158,959))	37 (i.e. (26,660,632 +825,152)/ (86,347 + 736,809))	70 (i.e. (13,762,29/ 196,263))

The expected annual cost entry in Table 33 (i.e. first line) shows that again Instance 2 in which the production and inventory storage operations are consolidated in the factory, and the system is an energy prosumer is the one with the lowest cost ($2,091,033). It is because Instance 2 has the options of selling energy and purchasing energy from the main grid installing a WT capacity of 111 MW in the factory at

Amarillo. Due to the size of the WT installed and the consolidated operations without incurring in energy expenses due to transportation, Instance 2 purchases the lowest amount of energy from the main grid and it also gains a good revenue from selling the excess energy generated.

In Instance 4, the factory and warehouse are in different places. Because of variations in wind speed and solar power in the locations, the relatively high cost of the PV, along with differences in the base load requirements (i.e. factory has a lower base load than the warehouse), the model opted for installing 105 MW of WT in Amarillo and PV of 39 MW in Phoenix. Thus, this model instance sold majority of the energy produced for revenue generation. It in turn reduced the total cost of the system when the revenue generated is subtracted from the installation cost, production cost, energy generation cost, energy purchase cost, and hence bringing its cost to $7,052,410 (i.e. 237% higher than model instance 2). The comparison of the costs for Instances 2 and 4 vs. the cost of Instance 1, which is a single factory and single warehouse with purchased energy from the main grid shows that Instance 1 is more expensive than Instance 4 because it only purchases energy at a flat rate of $130/MWh without any other option leading to a cost of $27,212,347 (i.e. an increase in cost of 285% vs. Instance 4).

Instances 3 and 5 correspond to island cases, where all the energy used in the company is generated on-site. These instances are the most expensive ones when compared to prosumers because they are forced to install a larger capacity of RE and to adopt some battery capacity to satisfy their energy loads. The expected annual costs of Instances 3 and 5 are $10,782,100 and $15,150,000, respectively. Those costs are 415% and 625% higher than Instance 2.

The expected annual cost comparison presented in Table 33 shows that it is more cost efficient to install a model with RE, energy sales and purchase option (Instance 4) than a model with just conventional energy purchase option (Instance 1).

On a closer look, the analysis of the levelized cost of energy (LCOE) for these 5 instances shows that at a purchasing cost of energy of $130/MWh the prosumer instances, (Instances 2 and 4), have the cheapest LCOE's, $32/MWh and $37MWh, respectively. The islanded instances, (Instances 3 and 5), have LCOE's of $65/MWh and $70/MWh, respectively.

There are two encouraging results to highlight from the experiments with the one-year model, Model 2, in this subsection. First, even if the island instances adopted an assortment of RE technologies and battery incurring in high installation costs, they ended with LCOE's lower than $130/MWh and thus being more cost efficient than the option of just purchasing energy from the grid. Second, both prosumer instances got lower LCOE's than the island counterparts, a result that may motivate manufacturing companies to adopt RE under the prosumer approach.

7.3 Sensitivity analysis on capacity factors input to the models

This section performs sensitivity analysis to the capacity factors in model Instances 2 and 4, compared in Section 7.1 (i.e. factory and factory and warehouse under energy prosumer option). To perform this sensitivity analysis, the 3 sets of daily capacity factors are multiplied by the following set of fixed and increasing multiplier factors (MF): 0.2, 0.4, 0.6, 0.8, and 1.0 (base) and Model 1 is solved in each case. As it has been mentioned in Chapter 5, the reason for including several vectors or sets of daily capacity factors simultaneously in the MSSP model is to account for the yearly variations (i.e. variations among years) that occur on the daily wind speeds and climate conditions.

Figure 7. presents the sets of daily WT capacity factors computed for Phoenix. Figure 8. presents the sets of daily WT capacity factors computed for Amarillo, Figure 9 presents the sets of daily PV capacity factors computed for Phoenix. Figure 10 presents the sets of daily PV capacity factors computed for Amarillo.

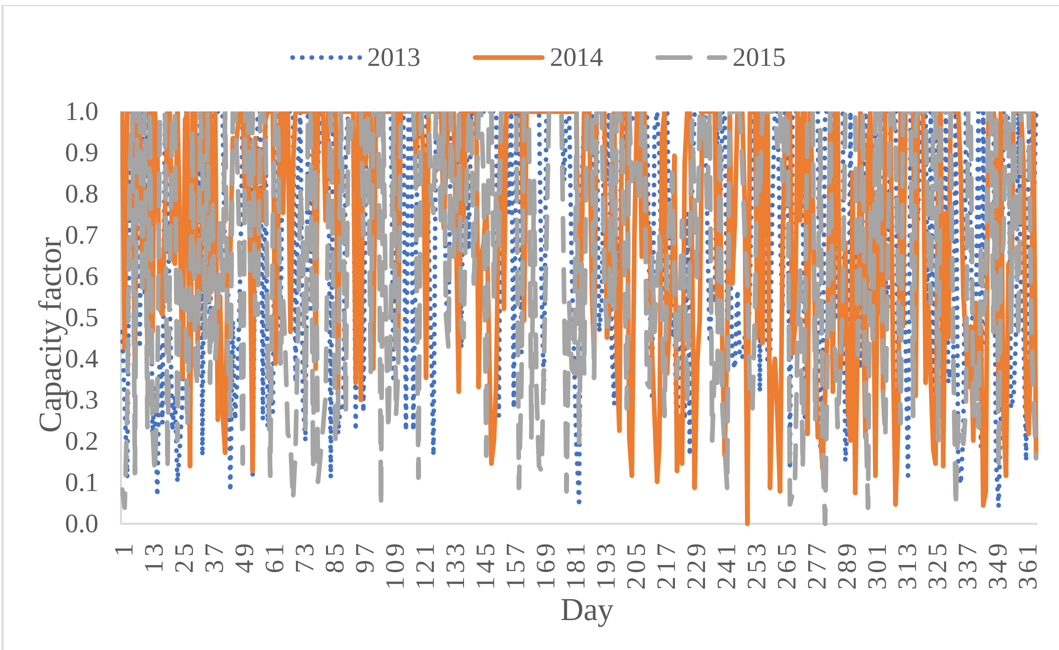


Figure 7. WT capacity factor computed for Amarillo

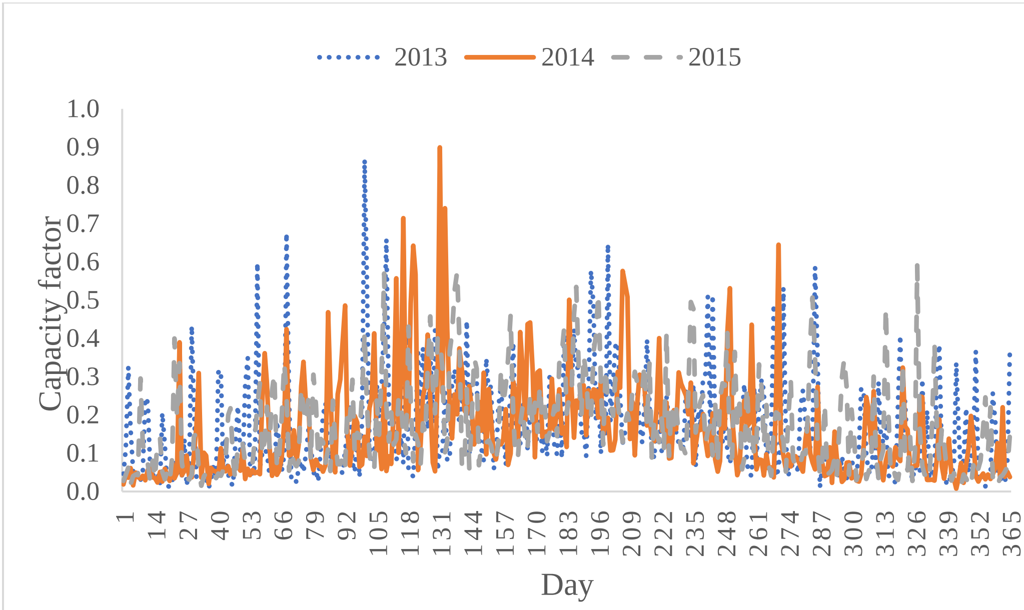


Figure 8. WT capacity factor computed for Phoenix

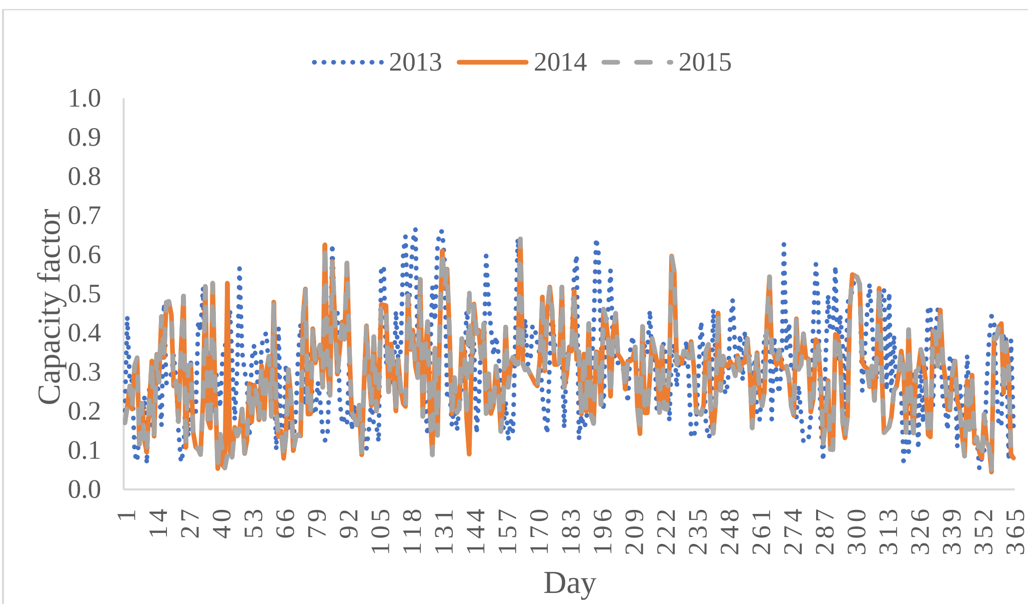


Figure 9. PV capacity factor computed for Amarillo

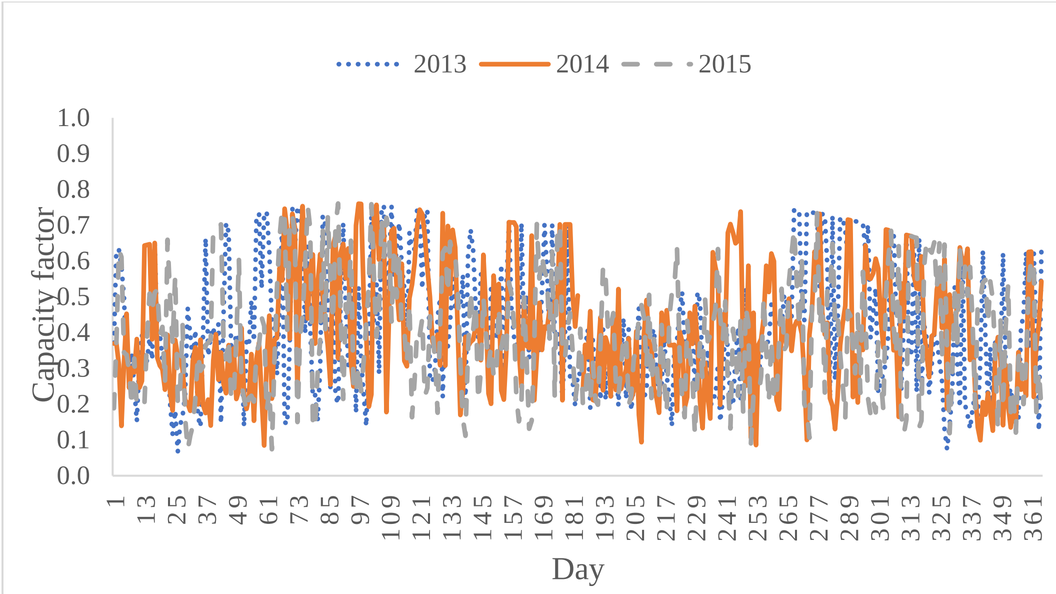


Figure 10. PV capacity factor computed for Phoenix

Table 34 presents statistics for the daily capacity factors computed for WT and PV, respectively. The values in the tables indicate that the average WT capacity factors in Amarillo are about four times higher than the ones in Phoenix. The table also shows that the average PV capacity factors in Phoenix are 34.9%, 41.2% and 32.9% higher than the ones in Amarillo for the years 2013, 2014, and 2015, respectively. Tables 35 and 36 abbreviate battery as (BT). The tables show similar behaviors. They show that if the capacity factors are reduced by a multiplier factor (MF) of 20%, the warehouse and factory will prefer to purchase energy from a main grid because the energy that will be generated by the WT and PV will be too little to satisfy the demand of the factory and warehouse.

Also the results show that if such reduction in renewable power generated occurs, it will be cheaper to purchase energy at a cost of \$130/MWh than installing a WT and PV at a cost of 1.5M/MW and \$1M/MW, respectively. In Case 5, where the capacity factors are in the highest (i.e. real) values, WT is installed in the factory due to the high wind speed generation in Amarillo but WT is not installed in the warehouse at Phoenix due to lower wind speed generation. Also, comparing the cost of WT and the cost of purchasing energy, it is preferable to install a WT.

Table 34. Statistical analysis of Amarillo and Phoenix daily capacity factors

		Amarillo			Phoenix			
Year		Mean	St. dev	Median	Mean	St. dev	Median	Sample
2013	WT	0.737	0.312	0.957	0.162	0.134	0.122	365
	PV	0.309	0.134	0.309	0.417	0.178	0.386	365
2014	WT	0.745	0.310	0.979	0.159	0.135	0.114	365
	PV	0.291	0.122	0.302	0.411	0.173	0.386	365
2015	WT	0.685	0.324	0.755	0.169	0.122	0.137	365
	PV	0.298	0.125	0.307	0.396	0.169	0.388	365

Table 35. Comparison of WT, PV, and battery size adopted in Model 1 instance with single factory if increasing the capacity factor multiplier

Case number	1	2	3	4	5
Capacity factor multiplier	0.2	0.4	0.6	0.8	Base
Expected annual cost ($)	2,385,238	2,385,238	2,385,238	2,385,238	2,015,120
WT in factory (MW)	0	0	0	0	12
PV in factory (MW)	0	0	0	0	0
Battery in factory (MWh)	0	0	0	0	0
Revenue from selling energy ($)	0	0	0	0	4,222
Cost of purchasing to the grid ($)	2,344,130	2,344,130	2,344,130	2,344,130	264,182
Total energy purchased from grid over the time horizon (MWh)	18,032	18,032	18,032	18,032	2,032
Total energy sold to grid over the time horizon (MWh)	0	0	0	0	121
Total energy cost ($)	2,344,130	2,344,130	2,344,130	2,344,130	1,714,050
Energy cost incurred over a horizon of two months ($)	2,344,130	2,344,130	2,344,130	2,344,130	291,154
Total energy produced over a horizon of two months (MWh)	0	0	0	0	15,506
LCOE ($/MWh)	130	130	130	130	32

Table 36. Comparison of size of WT, PV and battery adopted in Model 1 instance with single factory and warehouse if increasing the capacity factor multiplier

Case number	1	2	3	4	5
Capacity factor multiplier	0.2	0.4	0.6	0.8	Base
Expected annual cost ($)	2,870,913	2,870,913	2,870,913	2,870,913	2,712,550
WT in factory (MW)	0	0	0	0	7
WT in warehouse (MW)	0	0	0	0	0
PV in factory (MW)	0	0	0	0	0
PV in warehouse (MW)	0	0	0	0	0
BT in factory (MWh)	0	0	0	0	0
BT in warehouse (MWh)	0	0	0	0	0
Revenue from selling energy ($)	0	0	0	0	5,306
Cost of purchasing to the grid ($)	2,658,520	2,658,520	2,658,520	2,658,520	1,523,879
Total energy purchased from grid over time horizon (MWh)	20,451	20,451	20,451	20,451	11,723
Total energy sold to grid over time horizon (MWh)	0	0	0	0	152
Total energy cost ($)	0	0	0	0	981,584
Energy cost incurred over a horizon of two months ($)	0	0	0	0	166,735
Total energy produced over a horizon of two months (MWh)	0	0	0	0	8,880
LCOE ($/MWh)	130	130	130	130	82

The option for adopting battery in these cases studied is not selected due to the high cost of battery at $0.52M/MWh and the option of selling extra energy at a cost of $35/MWh. Thus, this study concludes that installed WT capacity is highly sensitive to changes in capacity factors and that increases in battery capacity are not cost-effective options to respond to those changes. It may be explained due to the relatively lower cost of the WT vs battery. The results also suggest that if the system needs to add more generation due to winds lower than usual, it is cheaper and more impactful first to increase WT capacity.

7.4 Effect of consolidating vs splitting the factory and the warehouse

This subsection further compares Model 1 Instances 2 and 4 presented in Section 7.1. Table 37 describes again the model instances.

Table 37 provides the extra WT capacity installed for Instance 2, where the factory does both production and inventory storage, compared to Instance 4 which does production and storage in two different locations. In the warehouse, the capacity factor of WT (Phoenix) is almost four times less than in the factory (Amarillo) hence Phoenix would have required more WT technology to satisfy its energy load. However, it would be costlier than purchasing energy from the grid. Also, because the PV capacity factors for both the factory and warehouse locations are not very high, Instance 4 did not install PV system and opted for energy purchase from the main grid. Also, in both instances there was no battery installed due to high cost of the battery ($0.52M/MWh) but the instances sold the excess energy at a price of $35/MWh. In this comparison, Instance 2 was the cheapest due to the power generation from wind considered for only the city of Amarillo. Instance 2 also had to satisfy only the factory base load while Instance 4 had to satisfy both factory and warehouse base load with less wind speed in the city of Phoenix.

Table 37. Description of the model instances compared without product purchase

Model instance	
2	4
Model 1. Factory with renewable energy no product purchase (energy prosumer; presented in Subsection 6.2.4)	Model 1. Factory and warehouse (F&W) with renewable energy and no product purchase (energy prosumer; presented in Subsection 6.2.5)

Table 38. Comparison of the size of WT and battery for model single factory vs. model with factory and warehouse without product purchase

Model instance	2 Factory Prosumer	4 F&W Prosumer
Expected annual cost ($)	2,015,120	2,712,550
WT in factory (MW)	12	7
WT in warehouse (MW)	-	0
PV in factory (MW)	0	0
PV in warehouse (MW)	-	0
BT in factory (MWh)	0	0
BT in warehouse (MWh)	-	0
Revenue from selling energy ($)	4,222	5,306
Cost of purchasing to the grid ($)	264,182	1,523,879
Total energy purchased from grid over the time horizon (MWh)	2,032	11,723
Total energy sold to grid over the time horizon (MWh)	121	152
Total energy cost ($)	1,714,050	981,584
Energy cost incurred over a horizon of two months ($)	291,154	166,735
Total energy produced over a horizon of two months (MWh)	15,506	8,880
LCOE ($/MWh)	32	82

7.5 Comparison of stochastic and deterministic approaches factory and warehouse model without product purchase (energy prosumer)

This section compares the expected annual costs and energy results from solving the two MSSP models presented in Chapter 4 (Model 1 and Model 2) to the ones from solving their deterministic counterparts in which product demands are fixed to the mean values and only one set or vector of daily capacity factors is input to the model. The compared models consider that: (1) production happens in the factory, (2) inventory storage happens in the warehouse, (3) final product cannot be purchased , (4) energy is sold to a main grid with its locations in Amarillo and Phoenix, and (5) energy is purchased from a main grid source with its locations in Amarillo and Phoenix.

The inputted cost of the deterministic model results from completing the following 3 steps:

Step 1. Solve the deterministic model with product demands fixed to the mean values and only one set or vector of daily capacity factors and find the optimal amount of PV, WT, and battery to adopt,

Step 2. Plug only the PV and WT generation and battery capacity solution from Step 1 into the stochastic model,

Step 3. Solve the modified version of the stochastic model in which PV, WT generation and battery capacity are input parameters coming from the solution gotten in Step 1 to find the optimal value for the other decision variables (i.e. production, inventory, product purchasing, energy sold and energy purchased) and collect the expected total cost of such model instance.

The model instance solved with the 3-step procedure above will be called Deterministic into Stochastic (DiS) in the reminder of this document. Table 39 shows again the cost coefficients used for the energy related terms in the objective functions of the models. Note that they are the same provided in Table 17 and Table 22. Subsection 8.5.1 provides the comparisons between the MSSP Model 1 (two-months model) and the DiS version. Subsection 8.5.2 provides the comparison for the MSSP Model 2 (i.e. one-year model) and the DiS version.

Table 39. Cost coefficients for the energy related terms in the objective function of the stochastic and deterministic models

Item	Notation in Table 11	Value
Selling price ($/MWh)	u	35
Buying cost ($/MWh)	u^*	130
WT cost ($/MW)	a_g (g=1)	1.5M
PV cost ($/MW)	a_g (g=2)	1M
Battery cost ($/MWh)	a_b	0.52M

7.5.1 Model 1

Table 40 presents the production and inventory results from running the two-months MSSP, Model 1, and the DiS model generated and assessed with the 3-steps procedure given in Sub-section 7.5. Both models have a production, inventory, and transportation cost of $212,395. Table 41 presents the expected annual costs, and the energy cost differences between the models.

Table 41 below shows that for the two-months model case, both the total cost and the LCOE of the stochastic model are lower than the ones for the deterministic into stochastic (DiS) model. The LCOE's are $82/MWh and $86/MWh for the stochastic and DiS models, respectively. The table also allows to calculate the expected total cost saving from solving the stochastic version instead of the deterministic one by subtracting the costs in the first row of the table. Such cost saving is $4,910 which is still relevant considering that the time horizon of the model is only two months and that the economy is currently tight.

Table 41 explains the $4,910 cost saving by showing that to satisfy the energy loads, the stochastic model incurred in a higher energy cost in the factory (about 10%

higher) by installing a 1MW more WT capacity than the deterministic model. Hence, the stochastic model reduced the energy purchasing cost by acquiring less energy from the main grid than the deterministic model and counterbalanced the extra cost incurred in RE technology. Also, because of a higher installed WT in the factory, the stochastic model got a little more revenue from selling energy to the grid than the deterministic model. All these decisions brought the total cost of the stochastic programming model below the one for the stochastic programming model.

Table 40. Production and inventory results for the two-months stochastic and deterministic models

		Month	
		1	2
Production:	Total	3,350	3,240
Product 1	3,205	1,560	1,645
Product 2	3,385	1,790	1,595
Inventory:	1,635	810	825
Product 1	905	345	560
Product 2	730	465	265

Table 41. Comparison of stochastic and deterministic into stochastic (DiS) models without product purchase (Model 1 - Two-months model)

	Stochastic		Deterministic into Stochastic (DiS)	
Expected annual cost ($)	$2,712,550		$2,717,460	
	Factory	Warehouse	Factory	Warehouse
Revenue from selling energy ($)	$5,306	$0	$2,144	$0
Cost of purchasing to the grid ($)	$159,059	$1,364,820	$237,466	$1,364,820
Total energy purchased from grid over time horizon (MWh)	1,224	10,499	1,827	10,499
Total energy sold to grid over time horizon (MWh)	152	0	61	0
WT capacity (MW)	7	0	6	0
PV capacity	0	0	0	0
Battery capacity (MW)	0	0	0	0
Total energy cost factory ($)	$981,584	$0	$904,925	$0
Energy cost incurred over a horizon of two months ($)	$166,735		$153,713	
Total energy produced over a horizon of two months (MWh)	8,880	0	8,186	0
LCOE ($/MWh)	$82		$86	

7.5.2 Model 2

Tables 42 and 43 present the resulting expected optimal production and inventories from solving the one-year model (Model 2) under the stochastic and the DiS approaches, respectively.

Table 43 presents the expected annual cost and the energy cost differences from solving the one-year MSSP, Model 2, and the DiS model obtained with the 3-steps procedure given in Subsection 7.5.

Table 44 above shows that the expected annual cost of the stochastic model ends lower than the deterministic model. The one-year stochastic model has a favorable cost saving of $10,990 when compared to the deterministic model. It is the subtraction of the costs reported in the first row of the table. Table 44 shows that the stochastic model ends purchasing a little more energy in the factory but a little less energy in the warehouse because of slightly reducing the WT in the factory and increasing the PV capacity in the warehouse if compared to the deterministic model. When compared to the deterministic model, the stochastic model has a cost saving from less energy cost and less energy purchased from the grid which is $3,922 higher than the decrease in revenue from selling energy. The remaining $6,967 cost saving in the stochastic model is explained because of the lower production, inventory and transportation cost this model gets. This last result indicates that the stochastic one-year model ended with a better production plan for all the months by incorporating the scenarios and deciding on the optimal RE capacity simultaneously. On the other hand, the deterministic model had to respond with an optimal production plan to a less than optimal RE capacity portfolio gotten from using the mean demands and a single set of capacity factors. Because the deterministic model did not consider scenarios for product demand, wind, and weather conditions, it found appropriate to produced less of both products in period 1 that the stochastic model. But then the deterministic model had to react with higher production of both products in period 2 than the stochastic model.

Table 42. Expected production and inventory results for the one-year stochastic model

	Production decisions for each stage	Production including the recourse production adjustment		Inventory		
		*P1	*P2	Total	*P1	*P2
Month		18,600	19,695	39,611	20,715	18,896
1	$\sum_{i \in I} x_{ik1} = 19{,}260$ (*P1=8,940 for six months or 1,490 per month, *P2= 10,320 for six months or 1,720 per month)	1,525	1,755	740	310	430
2		1,525	1,755	1,480	620	860
3		1,525	1,755	2,220	930	1,290
4		1,525	1,755	2,960	1,240	1,720
5		1,525	1,755	3,700	1,550	2,150
6		1,525	1,755	4,440	1,860	2,580
7	$\sum_{i \in I} \sum_{s \in S} p_s x_{ik2s} = 18{,}600$ (*P1=9,450 for six months or 1,575 per month, *P2=9,150 for six months or 1,525 per month)	1,575	1,529	4,319	2,005	2,314
8		1,575	1,529	4,198	2,150	2,048
9		1,575	1,525	4,073	2,295	1,778
10		1,575	1,529	3,952	2,440	1,512
11		1,575	1,529	3,827	2,585	1,242
12		1,575	1,525	3,703	2,730	973

*P1= Product 1, *P2 = Product 2

Table 43. Expected production and inventory results for the one-year DiS model

	Production decisions for each stage	Production including recourse production adjustment		Inventory		
		*P1	*P2	Total	*P1	*P2
Month	Total	18,710	19,845	39,254	20,460	18,794
1	$\sum_{i \in I} x_{ik1} = 19{,}260$ (*P1=8,940 for six months or 1,490 per month, *P2=10,320 for six months or 1,720 per month)	1,508	1,738	705	293	413
2		1,508	1,738	1,410	585	825
3		1,508	1,738	2,115	878	1,238
4		1,508	1,738	2,820	1,170	1,650
5		1,508	1,738	3,525	1,463	2,063
6		1,508	1,738	4,230	1,755	2,475
7	$\sum_{i \in I} \sum_{s \in S} p_s x_{ik2s} = 19{,}064$ (*P1=9,667 for six months or 1,611 per month, *P2=9,397 for six months or 1,566 per month)	1,609	1,572	4,186	1,934	2,252
8		1,611	1,573	4,146	2,116	2,030
9		1,609	1,560	4,090	2,295	1,795
10		1,611	1,577	4,053	2,476	1,577
11		1,611	1,568	4,008	2,657	1,351
12		1,611	1,570	3,964	2,838	1,125

*P1= Product 1, *P2 = Product 2

Table 44. Comparison of stochastic and deterministic into stochastic (DiS) models without product purchase (Model 2 – One-Year Model)

	Stochastic		Deterministic	
Expected annual cost ($)	$7,052,410		$7,063,400	
	Factory	Warehouse	Factory	Warehouse
Total production, inventory and transportation cost ($)	1,383,951		1,390,918	
Revenue from selling energy ($)	21,350,700	466,571	21,488,700	465,357
Cost of purchasing to the grid ($)	17,210	807,942	16,599	860,919
Total energy purchased from grid over time horizon (MWh)	132	6,215	128	6,622
Total energy sold to grid over time horizon (MWh)	610,020	13,331	613,963	13,296
WT capacity (MW)	105	0	106	0
PV capacity	0	39	0	38
Battery capacity (MW)	0	2	0	2
Total energy cost ($)	22,276,940	4,383,692	22,418,380	4,330,594
Total energy produced	667,934	68,875	672,177	68,438
LCOE ($/MWh)	37		37	

However, The LCOE's are $37/MWh for both the stochastic and deterministic models. Since the LCOE does not consider the advantages in production, transportation and inventory costs the stochastic model gets, this result basically indicates that the renewable energy portfolio selected by both models ended very similar in $/MWh. This result is explained is because the numerator of the LCOE formula, which is the sum of the costs of energy produced and purchased ended larger for the deterministic than for the stochastic model ($27,626,492 vs $27,485,784, respectively), However, the deterministic model compensated it with a higher sum of the energy produced and purchased than the stochastic model (747,365 vs 743,156, respectively). In other words, the option of selling energy that both models had helped the deterministic model to counterbalance the non-optimal decision taken regarding the RE portfolio.

7.6 Experimentation with one-year model (Model 2) factory and warehouse in different locations

This section presents the results of performing a Design of Experiments (DOE) with the one-year MSSP model, Model 2, presented in Chapter 4, Modeling and Methodology for the case in which the single factory and the single warehouse are in different locations. The aim of the DOE is learning which parameters in the MSSP model, which will be named as factors in the DOE, significantly affect its objective function value using a significance level of 5% (confidence level 95%).

A four factors and two experimental levels (2^4) DOE was carried to find out which one of four pre-selected factors are more significantly affecting the total expected cost of the MSSP model and what would be the optimal levels of those factors to reduce the cost of the model. Thus, in this DOE the total expected annual cost is the response variable and in this section of the document it will be denoted as total cost. The four factors selected of interest are: battery cost, PV cost, energy selling energy price and energy purchasing cost. All these factors are continuous in practice. The two levels (i.e. low and high) selected for the factors are displayed in Table 45. Also, 2 replications of this experiment were carried out for a total number of 16 experimental conditions and 32 experimental runs. The replications result from running the MSSP Model 1 with perturbed values for the demands of the products in the scenarios.

Montgomery (2017) suggests that if the purpose of the DOE is screening which factors are significant it is usually best to keep the number of factor levels low. Following this suggestion, the number of factor levels in this DOE was set to 2. Also, Montgomery (2017) mentions that because resources are usually limited, the number of replications that the experimenter can perform may be small and, in some cases, restricted to a sample size equal to one. The risk of conducting an experiment with only one replication or run at each test combination (i.e. experimental condition) is that misleading conclusions can be taken if the variability in the response variable is high because it will be ignored. Montgomery (2017) suggests that increasing the distance between the low and high level of a factor makes the probability of incorrect conclusions smaller. In this research, the values for the low and high levels of the factors were selected according to this recommendation and relevant practical considerations.

Table 45. Levels of the factors in the DOE for the one-year model

Level	Battery cost ($)	PV cost ($)	Energy selling price ($)	Energy purchasing cost ($)
Low	250,000	500,000	7	130
High	520,000	1,500,000	35	250

Minitab statistical software (Minitab, n.d.) version 18 was used to generate and analyze the DOE. The 2^4 experiment with 2 replications runs in random order generated by Minitab is listed is in Table 46. The table provides information concerning the levels of the factors in each experimental run using a coded format, and the value of the experimental response is listed in the last column, such value was collected after running MSSP Model 2 using the experimental settings prescribed by each run. A value of -1 in a cell in Table 46 indicates that the factor in the column is at low level and value of 1 indicates that the factor is at high level.

Table 46. Minitab DOE

Run	Run Order	Battery cost	PV cost	Selling price	Buying cost	Total cost
19	1	-1	1	-1	-1	10,264,500
21	2	-1	-1	1	-1	4,352,060
20	3	1	1	-1	-1	10,461,900
26	4	1	-1	-1	1	8,309,080
12	5	1	1	-1	1	1,1951,800
23	6	-1	1	1	-1	7,978,150
14	7	1	-1	1	1	4,408,630
15	8	-1	1	1	1	8,588,990
7	9	-1	1	1	-1	7,859,000
6	10	1	-1	1	-1	4,352,060
30	11	1	-1	1	1	4,289,710
25	12	-1	-1	-1	1	7,935,860
13	13	-1	-1	1	1	4,407,300
22	14	1	-1	1	-1	4,235,110
24	15	1	1	1	-1	8,090,440
28	16	1	1	-1	1	11,793,900
8	17	1	1	1	-1	7,971,230
4	18	1	1	-1	-1	10,318,100
27	19	-1	1	-1	1	11,487,600
32	20	1	1	1	1	8,843,930
9	21	-1	-1	-1	1	7,781,920
2	22	1	-1	-1	-1	7,563,950
16	23	1	1	1	1	8,722,400
11	24	-1	1	-1	1	11,332,400
10	25	1	-1	-1	1	8,152,650
17	26	-1	-1	-1	-1	7,318,350
1	27	-1	-1	-1	-1	7,178,840
3	28	-1	1	-1	-1	10,123,200
18	29	1	-1	-1	-1	7,421,830
29	30	-1	-1	1	1	4,288,390
31	31	-1	1	1	1	8,467,610
5	32	-1	-1	1	-1	4,235,110

Minitab has two statistical methodologies useful to analyze an experiment with quantitative or continuous factors. They are known as Analysis of Variance (ANOVA) and regression analysis (Montgomery, 2017). The observations for the response variable of a four-factor ANOVA model can be written in an effects model and using general notation as in equation (8.1).

$$\begin{aligned}
&y_{ijklm} = \mu + \tau_i + \beta_j + \gamma_k + \delta_l + (\tau\beta)_{ij} + (\tau\gamma)_{ik} \\
&+(\tau\delta)_{il} + (\beta\gamma)_{jk} + (\beta\delta)_{jk} + (\gamma\delta)_{kl} \\
&+(\tau\beta\gamma)_{ijk} + (\tau\beta\delta)_{ijl} + (\beta\gamma\delta)_{jkl} + (\tau\gamma\delta)_{ikl} + (\tau\beta\gamma\delta)_{ijkl} + \varepsilon_{ijklm} \\
&i = 1, 2, ..., a;\ j = 1, 2, ..., b; k = 1, 2, ..., c; \\
&l = 1, 2, ..., d; m = 1, 2, ..., n
\end{aligned} \tag{7.1}$$

In equation (8.1), y_{ijklm} is the observed response variable, μ is the overall mean, τ_i is the effect of the i-th level of the first factor, β_j is the effect of the j-th level of the second factor, γ_k is the effect of the k-th level of the third factor, δ_l is the effect of the l-th level of the fourth factor, *a, b, c*, and *d* are the number of levels of the first, second, third and fourth factor, respectively, and ε_{ijklm} is a random error with *m* representing the index running over the *n* replicates of each experimental condition.

For a four-factorial experiment with quantitative continuous factors, a regression model representation can be given by equation 8.2.

$$\begin{aligned}
&y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_1 x_2 + \beta_6 x_1 x_3 + \beta_7 x_1 x_4 + \\
&\beta_8 x_2 x_3 + \beta_9 x_2 x_4 + \beta_{10} x_3 x_4 + \beta_5 x_1 x_2 x_3 + ... + \varepsilon
\end{aligned} \tag{7.2}$$

In equation (8.2) *y* is the response, β ’s are coefficients to be determined, x_1 represents the value on the coded scale (+1, -1) of the first factor, x_2 the value of the second factor, etc. The term ε is the random error and $x_1 x_2$ represents the interaction between the first and second factor and so on. Since equation 8.2 is linear on the unknown coefficients, β, the model is linear and the coefficients $\hat{\beta}$ are estimated through the least squares method. The adequacy of the model is checked by analyzing the residuals of the model $e_{ijklm} = y_{ijklm} - \hat{y}_{ijkl}$ which are assumed to be normally distributed and with constant variance.

The equation for the regression model fitted to the data collected in the DOE performed in this thesis, information concerning the statistical significance of the regression coefficients at a 5% significance level (Table 47), the summary of the regression model reporting about the significance of the regression (Table 48), and a brief report regarding the only observation that was classified as unusual because its standardized residual was out of the plus or minus two standard deviations range (Table 49) are shown below.

$$
\begin{aligned}
&\textit{Regression Equation}: \textit{Total cost} = 7,827,688 + 102,733 \textit{ Battery Cost} \\
&+ 1,813,259 \textit{ PV Cost} - 1,509,555 \textit{ Selling Price} + 344,948 \textit{ Buying Cost} \\
&+ 25,533 \textit{ Battery Cost} * \textit{PV Cost} - 56,676 \textit{ Battery Cost} * \textit{Selling Price} \\
&+ 33,644 \textit{ Battery Cost} * \textit{Buying Cost} + 183,827 \textit{ PV Cost} * \textit{Selling Price} \\
&+ 162,684 \textit{ PV Cost} * \textit{Buying Cost} - 160,961 \textit{ Selling Price} * \textit{Buying Cost} \\
&+ 20,192 \textit{ Battery Cost} * \textit{PV Cost} * \textit{Selling Price} \\
&+ 17,519 \textit{ Battery Cost} * \textit{PV Cost} * \textit{Buying Cost} \\
&- 15,653 \textit{ Battery Cost} * \textit{Selling Price} * \textit{Buying Cost}
\end{aligned}
\tag{7.3}
$$

Table 47. Coefficients of the regression model

Term	*MN	Effect	Coef	SE Coef	T-value	P-value	*S
Constant			7,827,688	16,859	464.31	0.000	
Battery Cost	A	205,465	102,733	16,859	6.09	0.000	Y
PV Cost	B	3,626,519	1,813,259	16,859	107.56	0.000	Y
Selling Price	C	-3,019,110	-1,509,555	16,859	-89.54	0.000	Y
Buying_ Cost	D	689,896	344,948	16,859	20.46	0.000	Y
Battery Cost*PV Cost	AB	51,066	25,533	16,859	1.51	0.149	N
Battery Cost*Selling Price	AC	-113,352	-56,676	16,859	-3.36	0.004	Y
Battery Cost*Buying Cost	AD	67,289	33,644	16,859	2.00	0.063	N
PV Cost*Selling Price	BC	367,654	183,827	16,859	10.90	0.000	Y
PV Cost*Buying Cost	BD	325,367	162,684	16,859	9.65	0.000	Y
Selling Price*Buying Cost	CD	-321,921	-160,961	16,859	-9.55	0.000	Y
Battery Cost*PV Cost*Selling Price	ABC	40,384	20,192	16,859	1.20	0.248	N
Battery Cost*PV Cost*Buying Cost	ABD	35,038	17,519	16,859	1.04	0.314	N
Battery Cost*Selling Price*Buying Cost	ACD	-31,306	-15,653	16,859	-0.93	0.367	N
PV Cost*Selling Price*Buying Cost	BCD	-12,315	-6,157	16,859	-0.37	0.720	N
Battery Cost*PV Cost*Selling Price*Buying Cost	ABCD	283	141	16,859	0.01	0.933	N

* MN = Minitab abbreviated notation for the term, S = Significant, Y = Yes, N = No

Table 48. Regression model summary

S	R-sq	R-sq(adj)	R-sq(pred)
338,551	98.33%	98.08%	97.66%

Table 49. Fits and diagnostics for unusual observations in the regression model

Observation	Total cost	Fit	Residuals	Std Residuals
11	4,289,710	4,952,554	-662,844	-2.13R

Table 47 shows that the *p*-values of all the four factors studied, (i.e. Battery Cost, PV Cost, Selling Price, Buying Price) and of the following two-factors interactions: Battery Cost*Selling Price, PV Cost*Selling Price, PV Cost*Buying Cost and Selling Price*Buying Cost are less than 0.05. Hence, these factors and interactions are the only ones significantly affecting the expected total cost of the model (i.e. MSSP Model 2 presented in Chapter 4). All these regression terms contribute to the explanation of the system cost. Additionally, Table 48 shows that 98.08% of the variance in the response variable (i.e. expected total cost) is explained by the regression model.

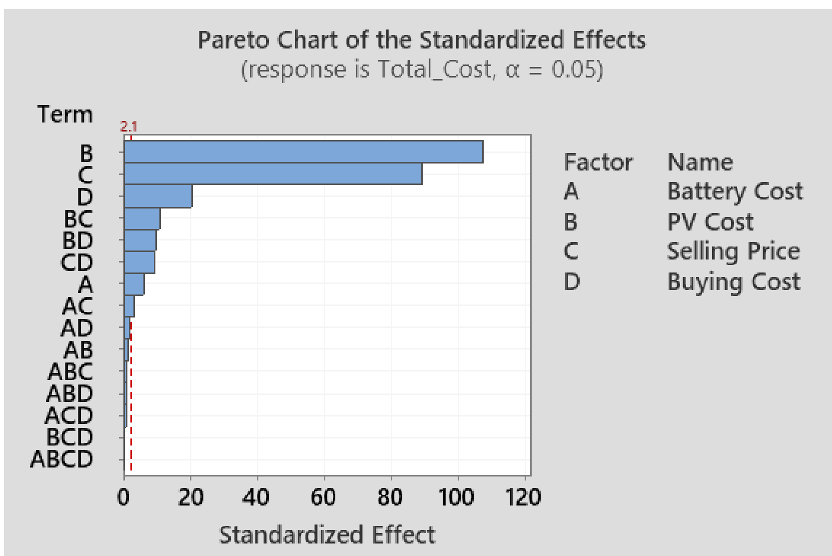


Figure 11. Pareto chart of standardized effects

Minitab also notates the four factors in an experimental design as A, B, C, and D. The Pareto chart of standardized effects provided by the ANOVA method in Minitab is shown in Figure 11 above. It is useful to corroborate in a visual way that the absolute values of the standardized effects of PV cost (B), energy selling price (C), energy buying cost (D) , PV cost*Selling price (BC), PV cost*Buying cost (BD) , Selling price*Buying cost (CD), battery cost (A), and Battery cost *Selling price (AC) lie above the critical t-value, t=2.1 (i.e. have p-values less than 0.05), and thus these factors and interactions are statistically significant, but the effect of their significance is based on their level above the red line. Then, Factor B, PV cost, has the highest impact on the expected annual cost followed by Factor C, Selling Price.

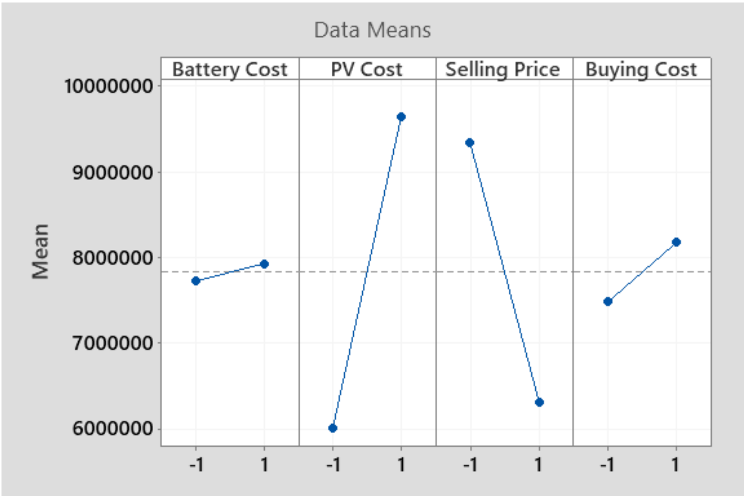


Figure 12. Main effects for total cost

The ANOVA methodology provides a way to visualize the effect of each of the experimental factors known as the Main Effects Plot. The plot is useful to identify the differences on the average response due to changes in the level for one or more factors (Minitab, n.d.). Figure 12 is the Main Effects plot for the DOE performed. Since the resulting lines are not horizontal, the figure indicates that the battery cost, PV cost and buying energy price factors have a positive slope and from these slopes the larger is the one for PV cost. Energy selling price has a negative slope, which is also of a large magnitude. It means that if battery cost, PV cost or buying energy cost increases the cost of the model increases. On the other hand, if the energy selling price decreases, the cost of the model increases. However, it could be concluded that the model is more sensitive to changes in the levels of PV cost (B) and energy selling price (C) but it is needed also to check the effect of the interaction between these factors (see next paragraph). If it is possible to negotiate the PV cost to the low level and the energy selling price to the high level, it will produce the most cost-effective model. This result seems very intuitive; however, the magnitude of the effect of these changes was not known. Thus, the DOE is very useful to learn about the magnitude of the effects in an experiment that is changing several factors at a time.

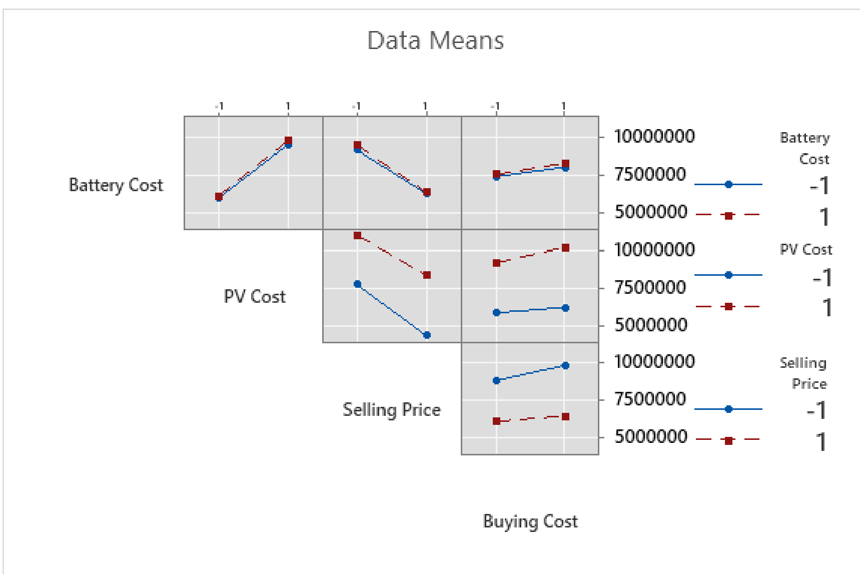


Figure 13. Interaction plot for total cost

The interaction plots in Figure 13 above serve to visualize the effects on the total cost of the MSSP Model 2 to two-factors interactions in the ANOVA model. Note that the y-axis scale given towards the right of the plot represents the MSSP Model 2 cost. Those interaction plots in which the two lines displayed for the behavior of the response variable (y-axis) at two different levels of one of the factors (i.e. blue and red lines) are obviously non-parallel show that the total cost of the model changes in a different magnitude when there are modifications to the levels of the other factor (i.e. the one changing over the x-axis) and thus the interaction is significant. Consequently, in the DOE performed, significant interactions are PV Cost vs Selling Price (BC), PV cost vs. buying cost (BD), and selling price vs. buying cost (CD), which is a negative two factor interaction (notice red line is below blue line in this case). For the other 3 interactions in which the lines are almost parallel, the interaction plot is more difficult to use since it could be that: (1) there is no significant interaction, such as in the case of battery cost and PV cost (AB) and battery cost and buying price (AD) or (2) if the interaction ends significant, its magnitude is very small, such as in the case of battery cost and selling price (AC), which ended statistically significant in Table 47 and Figure 10.

Joining the information provided by Figures 12 and 13 regarding the positive effect of PV cost, negative effect of selling price, and positive effect on the interaction between PV cost and selling price in the total cost of the MSSP model, if it is possible to negotiate the PV cost to the low level and the energy selling price to the high level, the net effect in total cost is a reduction but not as drastic as if the interaction of the factors was inexistent.

The four graphs shown in Figure 14 below are the residual plots of the regression model. The graphs are provided by Minitab and useful to validate the assumptions of normality and constant variance of the residuals of the fitted regression model. The normal probability plot (top left) in Figure 14 implies that the distribution of the residuals is not entirely normally distributed because some points do not fall closely to or along the straight line. The histogram (bottom left) shows that the mode of the residuals is not zero as in a normal distribution. The mode is $150,000 and the residuals are more skewed towards the left than the ones coming from a normal distribution. In the same Figure 14, the residuals versus fits plot (top right) shows that the variance of the residuals is relatively constant without showing any obvious trends as the magnitude of the fitted value increases. The residuals versus order chart (bottom right) shows that the residuals are randomly distributed because they fall unsystematically above and below zero and they do not show any trend or pattern. Thus, from this chart it can be concluded that the residuals are independent of each other.

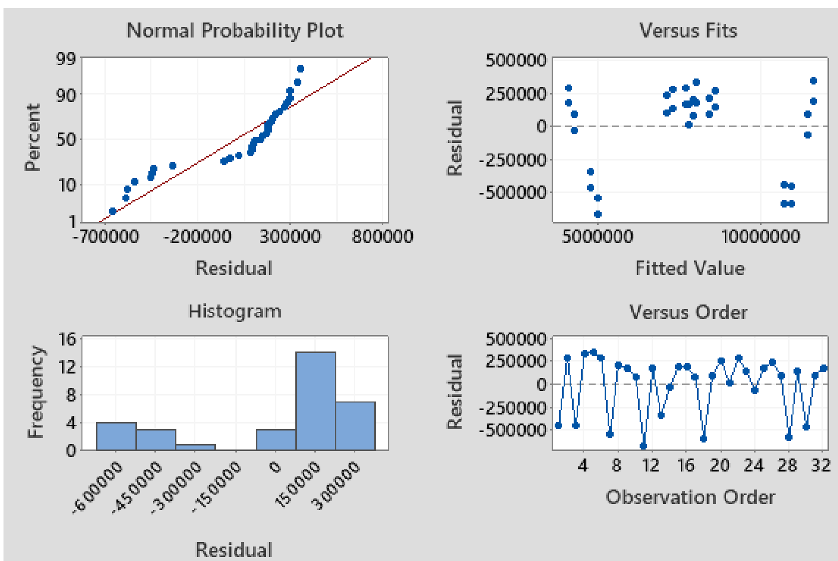


Figure 14. Residual plots for the regression model

The total expected cost of the MSSP Model 2 can be finally predicted by the new regression model given below this paragraph. It considers only factor and interactions that ended significant in the DOE performed. The Pareto chart of standardized effects and the residual plots for this new regression model are in Figures 15 and 16. The Pareto chart, as expected, shows that all factors are significant. The residual plots for this new regression model permit to conclude that the assumptions of normality and constant variance of the residuals are not violated.

$$\begin{aligned} &\textit{Final Regression Equation}: \ \textit{Total cost} \ = \ 7,827,688 + 102,733 \ \textit{Battery Cost} \\ &+ 1,813,259 \ \textit{PV Cost} \ - \ 1,509,555 \ \textit{Selling Price} \ + \ 344,948 \ \textit{Buying Cost} \\ &- 56,676 \ \textit{Battery Cost} * \textit{Selling Price} \ + \ 183,827 \ \textit{PV Cost} * \textit{Selling Price} \\ &+ 162,684 \ \textit{PV Cost} * \textit{Buying Cost} \ - \ 160,961 \ \textit{Selling Price} * \textit{Buying Cost} \end{aligned} \tag{7.4}$$

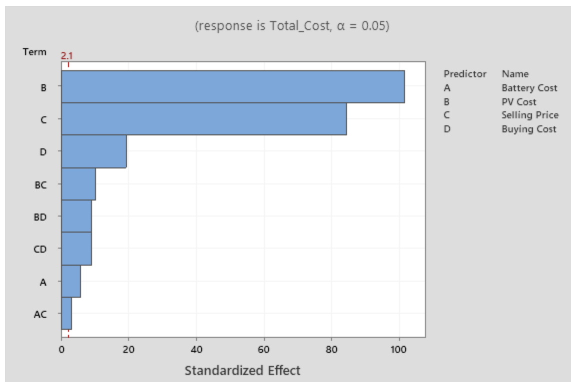


Figure 15. Pareto chart of standardized effects from final regression for one-year MSSP

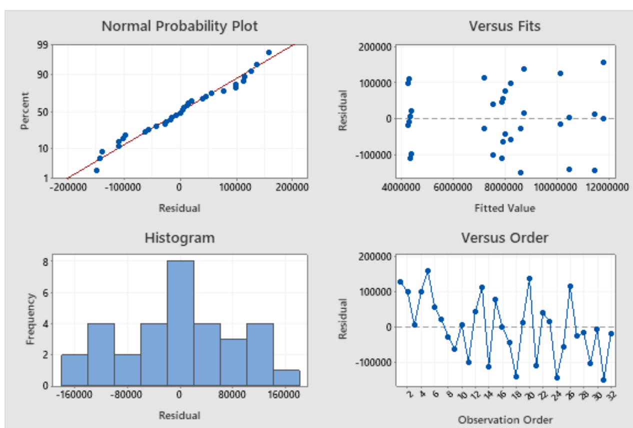


Figure 16. Residual plots from final regression model for one-year MSSP model

7.7 Comparison of energy load (i.e. energy demand) and power generation at the factory for the case with factory and warehouse in different locations

This section highlights the importance of adopting battery, purchasing energy and selling energy in the MSSP Model 1 (instance 4) whose results have been presented in Sections 6.2.5, 7.1 and 7.4. In the mathematical model, the first three terms in the left hand sides of the energy constraints (4.9) and (4.10) are useful to calculate the factory daily energy load while the first term in the right hand side is useful to calculate the energy generation based on the adopted WT and PV capacity and the daily capacity factors. Figure 17 provides a comparison of the daily load and the total energy generated in the factory considering the model optimal solution and a single scenario for the capacity factors and consequently, for the power generation.

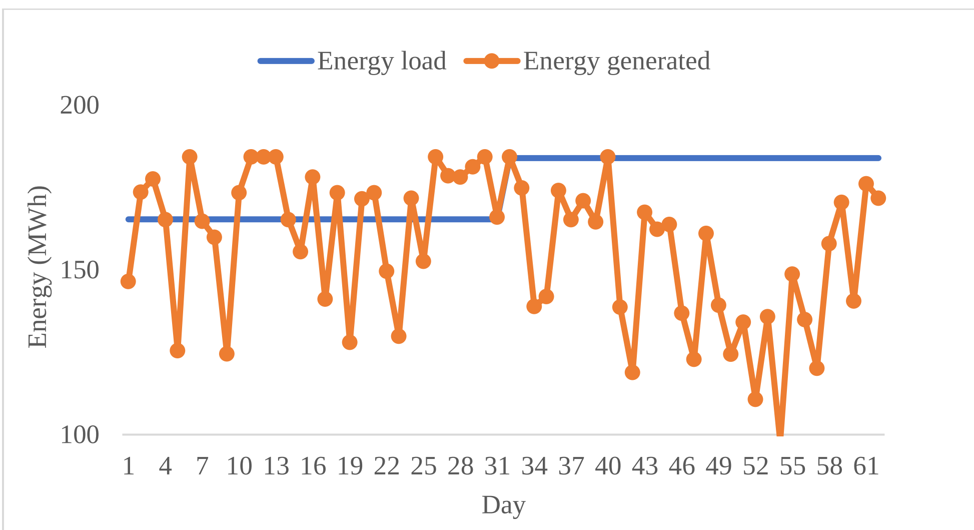


Figure 17. Daily energy load and generation at the factory for scenario 144

In Figure 17, the variability of the total daily energy generated, and the total daily energy load (i.e. demand) is shown for the scenario 144 which has high demand of Product 1 and high demand of Product 2 (HH). This scenario is one of the most challenging ones in terms of meeting load with just RE produced. On some days, such as day 5, the energy generated is insufficient to carry the factory's load for that day. On day 13, the energy generated is sufficient to fulfil the energy load of the factory. The figure above shows that there are more days when the energy load is greater than the energy generated. Hence the figure let to visualize the reasons for implementing the options of buying a battery storage system (BSS) or purchasing energy. For this instance, the model opted to not adopt battery and bypass these cases by purchasing energy from the grid. The figure shows also that in this high product demand scenario there are still some days were the energy load (blue line) is low and the system can store extra energy in the BSS or sell it to generate revenue. For this instance, since the model did not adopt battery the option was to sell all extra energy generated in each of those days.

7.8 Limitations of the Models

MSSP Model 1 has some limitations which can be further improved upon. For example, the assumption that the production and inventory related activities are done for only two production periods spanning two months. Model 1 can be extended using a rolling horizon approach like the ones practiced by several previous authors such as Meibom, (2007).

The rolling horizon procedure the author of this thesis implemented is described as the following list of steps.

- Step 1. A variable named *month_solved* is set to the value of 1
- Step 2. The first-stage optimal decisions for RE capacity and production of the first month are determined by solving the MSSP Model 1 considering

the product demands and capacity factors of the first two months of the year.

- Step 2. The cost of implementing the optimal decisions found for the first of the two months considered in the model is computed. Such cost is a portion of the expected annual cost of the model solved.
- Step 3 The RE related decisions are turned into parameters in the model and removed from the list of decision variables if it has not done in a previous iteration. This new model is named as *MSSP model with RE as parameters,*
- Step 4. The variable *month_solved* is increased by 1
- Step 5. The *MSSP model with RE as parameters* is solved now with the set of product demands and capacity factors for the month numbers represented by the values of the variables *month_solved* and *month_solved* plus one.
- Step 5. Steps 2, 3, 4 and 5 are repeated until the operational decisions (monthly production, monthly inventory, daily energy stored in battery, daily energy purchased from the grid, and daily energy sold to the grid) are found for the all the months of the year.

The rolling horizon method described in the previous paragraph provides the optimal decisions and the annual cost for one year by repeatedly solving the MSSP Model 1 and carrying out the decision(s) of a single month in the year (i.e. *month_solved*) in each iteration. Table 49 provides the results of performing such rolling horizon procedure on Instances 2 and 4. These instances are the ones that consider factory and warehouse in the same location and factory and warehouse in different locations, respectively. Also, the instances consider that there is no final product purchase, and that the company is an energy prosumer.

Table 50 shows that the cost of the one-year model found with the rolling horizon approach is about 2.5 times that of the two-months model. This result is explained because the largest costs, which are the installation costs for PV, WT and battery occur only at the beginning of the first month. Also, note that the LCOE's provided by the rolling horizon approach seem more real since both energy produced and energy cost were computed considering the product demands and capacity factors of the entire year since the factory is producing in all months.

Table 50. Comparison of two- month model (Model 1) and a one-year model found with the rolling horizon

Model instances	Two-month Factory	Two-month F&W	One-Year Factory model from rolling horizon approach	One-Year F&W model from rolling horizon approach
Expected annual cost ($)	2,015,120	2,712,550	5,856,695	11,542,682
Revenue from selling energy ($)	4,222	5,306	85,652	988
Cost of purchasing to the grid ($)	264,182	1,523,879	4,112,480	9,158,148
Total energy purchased from grid over time horizon (MWh)	2,032	11,723	31,634	70,447
Total energy sold to grid over time horizon (MWh)	121	152	2,447	28
WT capacity (MW)	12	7	12	7
PV capacity	0	0	0	0
Battery capacity (MW)	0	0	0	0
Total annualized energy cost ($)	1,714,050	981,584	1,642,690	960,108
Total energy cost over a horizon of two months ($)	291,154	166,735	279,032	163,087
Total energy produced over the time horizon of each model (MWh)	15,506	8,880	69,968	46,040
LCOE ($/MWh)	32	82	57	87

Another limitation of the stochastic models presented is not considering that the decision maker may confront practical space or budget restrictions. Finally, the models presented in this thesis have implemented WT, PV, and battery as DER units in the microgrid. Other sources of energy, such as small hydro energy can be considered.

8. CONCLUSIONS AND FUTURE WORK

The main contribution of this thesis is to solve two multi-stage stochastic programming models to determine cost effective production plans considering on-site renewable energy generation and battery system while the industry is also acting as an energy prosumer. The goal of the models is to determine the optimal production quantities and the sizes of WT, PV, and battery. As in Escudero (1993), inventory storage and purchase of final product (i.e. vendor supply) are considered in the models as full-recourse actions to cope with the uncertainty in product demand. In addition, novel recourses, such as sales and purchase of energy and use of energy storage systems (i.e. battery), let to hedge from the uncertainty in the wind and solar power.

The models are fed with large realistic sets of climate data collected from different cities in the word. The data sets are statistically analyzed and used to calculate WT and PV capacity factors that reflect the variability of climate conditions over the hours, days, and years. The numerical experiments show the feasibility of implementing WT and PV renewable energy technologies in a factory and a warehouse in the cities of Phoenix and Amarillo, respectively. WT is being preferred over PV in the city of Amarillo due to its higher windspeed profile all year. Purchasing from the grid is preferred over PV in Phoenix because even if Phoenix is sunny almost all year the PV cost used for solving the model is high and the efficiency of the PV generation is not as high as the one for a WT installed in a windy place.

In the experiments performed to learn about the benefits of using a stochastic model vs. a deterministic one, the stochastic models perform best when compared to the deterministic models. For the model considering a planning horizon of twelve months (i.e. one-year), the total expected cost of the stochastic model is $7,052,410 and its LCOE is $37/MWh while the deterministic model had a cost $7,063,400 and an LCOE of $37/MWh This result is because the stochastic model considers the variability in the product demands and on the windspeed and sunlight generated, as opposed to the deterministic model which only considers average product demands and a single set of WT and PV capacity factors.

From analyzing the LCOE of the different case studies performed with Model 2, the one-year prosumer models are the ones with the lowest LCOE values due to its large energy generation and sales to the main grid. Comparison of the one-year prosumer model to and island model shows that the prosumer model has a lower expected cost and a lower LCOE than the island model even though it implemented a higher renewable energy technology than the island model. This is because the prosumer model, generated a lot of energy which is sold to make profit contributing to reduce the total expected cost of the model.

This study contributes to reducing the use and emission of fossil fuels and other harmful gases into the atmosphere since manufacturing industries consume one third of the energy generated in the United states. It is well known that a stochastic model performs better than a deterministic one as it considers the variability of wind and the uncertainty of product demand but it is important for a decision maker to know the magnitude of the cost difference in a particular production setting. The main research questions answered in this thesis were: (1) what is the cost impact of considering energy requirements in the production systems studied? , (2) what is the LCOE difference if running the production systems with wind and solar energy and implementing battery instead of purchasing energy to the main grid?, (3) is it feasible and cost-effective to run the production system studied using only the microgrid energy generated and battery storage? (4) what is the benefit of solving the proposed stochastic models instead of using deterministic models?, (5) what are good approaches to solve the MSSP models over short-term and long-term time horizons without growing the scenario trees excessively and how tractable are those approaches?, and (6) what are the energy costs elements in the model (i.e. renewable energy equipment costs, price from purchasing energy from the grid, revenues from selling energy to the grid) that affect the most its total expected cost and are there any significant interactions in these cost elements?

The future research will consider implementing this model in a particular industry and extend the model to include other practical constraints. Another interesting future work to be considered is implementing mirrors in the microgrid system (Budiyanto and Fadliondi, 2017) to help turn solar energy into extreme heat and generate more energy since the PV only generates energy for only half of the day.

APPENDIX SECTION

Appendix A: Capacity Factors

Table A1.1: Solar PV daily capacity factors for the city of Amarillo (Day 1-68)

Day	2013	2014	2015	Day	2013	2014	2015
1	0.201	0.170	0.170	35	0.355	0.178	0.178
2	0.442	0.210	0.210	36	0.247	0.157	0.157
3	0.272	0.264	0.264	37	0.194	0.527	0.527
4	0.279	0.206	0.206	38	0.301	0.252	0.252
5	0.093	0.316	0.316	39	0.283	0.053	0.053
6	0.071	0.337	0.337	40	0.209	0.122	0.122
7	0.154	0.115	0.115	41	0.341	0.062	0.062
8	0.145	0.220	0.220	42	0.363	0.055	0.055
9	0.239	0.124	0.124	43	0.402	0.088	0.088
10	0.066	0.095	0.095	44	0.459	0.097	0.097
11	0.259	0.223	0.223	45	0.332	0.084	0.084
12	0.164	0.329	0.329	46	0.178	0.159	0.159
13	0.246	0.136	0.136	47	0.310	0.137	0.137
14	0.257	0.346	0.346	48	0.565	0.152	0.152
15	0.257	0.274	0.274	49	0.352	0.206	0.206
16	0.164	0.442	0.442	50	0.301	0.092	0.092
17	0.476	0.338	0.338	51	0.276	0.124	0.124
18	0.271	0.478	0.478	52	0.134	0.270	0.270
19	0.287	0.480	0.480	53	0.333	0.173	0.173
20	0.295	0.446	0.446	54	0.369	0.267	0.267
21	0.344	0.264	0.264	55	0.309	0.242	0.242
22	0.281	0.277	0.277	56	0.202	0.177	0.177
23	0.151	0.174	0.174	57	0.368	0.316	0.316
24	0.070	0.355	0.355	58	0.391	0.179	0.179
25	0.099	0.495	0.495	59	0.401	0.300	0.300
26	0.236	0.107	0.107	60	0.306	0.341	0.341
27	0.135	0.317	0.317	61	0.249	0.187	0.187
28	0.325	0.319	0.319	62	0.296	0.479	0.479
29	0.189	0.147	0.147	63	0.102	0.196	0.196
30	0.196	0.108	0.108	64	0.413	0.135	0.135
31	0.429	0.102	0.102	65	0.132	0.149	0.149
32	0.405	0.089	0.089	66	0.129	0.080	0.080
33	0.516	0.226	0.226	67	0.320	0.137	0.137
34	0.264	0.519	0.519	68	0.151	0.306	0.306

Table A1.2: Solar PV daily capacity factors for the city of Amarillo (Day 69-136)

Day	2013	2014	2015	Day	2013	2014	2015
69	0.193	0.235	0.235	103	0.166	0.391	0.391
70	0.122	0.099	0.099	104	0.163	0.201	0.201
71	0.195	0.132	0.132	105	0.122	0.243	0.243
72	0.337	0.140	0.140	106	0.569	0.472	0.472
73	0.423	0.137	0.137	107	0.569	0.472	0.472
74	0.355	0.446	0.446	108	0.321	0.470	0.470
75	0.215	0.513	0.513	109	0.348	0.250	0.250
76	0.328	0.193	0.193	110	0.295	0.372	0.372
77	0.346	0.193	0.193	111	0.264	0.316	0.316
78	0.202	0.411	0.411	112	0.456	0.201	0.201
79	0.191	0.323	0.323	113	0.334	0.332	0.332
80	0.274	0.351	0.351	114	0.354	0.257	0.257
81	0.230	0.369	0.369	115	0.606	0.219	0.219
82	0.143	0.261	0.261	116	0.647	0.212	0.212
83	0.126	0.626	0.626	117	0.425	0.496	0.496
84	0.134	0.315	0.315	118	0.546	0.358	0.358
85	0.339	0.241	0.241	119	0.635	0.407	0.407
86	0.627	0.583	0.583	120	0.666	0.316	0.316
87	0.424	0.439	0.439	121	0.363	0.286	0.286
88	0.452	0.295	0.295	122	0.332	0.537	0.537
89	0.232	0.356	0.356	123	0.254	0.187	0.187
90	0.168	0.429	0.429	124	0.219	0.342	0.342
91	0.182	0.384	0.384	125	0.139	0.429	0.429
92	0.167	0.579	0.579	126	0.347	0.190	0.190
93	0.341	0.343	0.343	127	0.517	0.088	0.088
94	0.152	0.196	0.196	128	0.430	0.361	0.361
95	0.216	0.183	0.183	129	0.622	0.138	0.138
96	0.166	0.165	0.165	130	0.660	0.408	0.408
97	0.216	0.215	0.215	131	0.659	0.610	0.610
98	0.200	0.088	0.088	132	0.585	0.516	0.516
99	0.139	0.286	0.286	133	0.242	0.563	0.563
100	0.105	0.418	0.418	134	0.252	0.389	0.389
101	0.158	0.290	0.290	135	0.165	0.193	0.193
102	0.224	0.214	0.214	136	0.215	0.285	0.285

Table A1.3: Solar PV daily capacity factors for the city of Amarillo (Day 137-204)

Day	2013	2014	2015	Day	2013	2014	2015
137	0.151	0.197	0.197	171	0.343	0.332	0.332
138	0.211	0.209	0.209	172	0.240	0.492	0.492
139	0.274	0.385	0.385	173	0.184	0.303	0.303
140	0.314	0.350	0.350	174	0.142	0.457	0.457
141	0.457	0.184	0.184	175	0.334	0.517	0.517
142	0.402	0.090	0.090	176	0.457	0.461	0.461
143	0.308	0.301	0.301	177	0.372	0.319	0.319
144	0.376	0.474	0.474	178	0.357	0.319	0.319
145	0.143	0.399	0.399	179	0.362	0.323	0.323
146	0.225	0.407	0.407	180	0.347	0.517	0.517
147	0.400	0.335	0.335	181	0.157	0.260	0.260
148	0.340	0.424	0.424	182	0.330	0.292	0.292
149	0.597	0.194	0.194	183	0.362	0.364	0.364
150	0.477	0.296	0.296	184	0.361	0.354	0.354
151	0.413	0.194	0.194	185	0.549	0.508	0.508
152	0.342	0.216	0.216	186	0.599	0.332	0.332
153	0.391	0.316	0.316	187	0.128	0.352	0.352
154	0.349	0.261	0.261	188	0.190	0.192	0.192
155	0.264	0.148	0.148	189	0.158	0.347	0.347
156	0.157	0.235	0.235	190	0.173	0.199	0.199
157	0.225	0.415	0.415	191	0.261	0.424	0.424
158	0.126	0.261	0.261	192	0.292	0.189	0.189
159	0.177	0.324	0.324	193	0.408	0.169	0.169
160	0.147	0.338	0.338	194	0.642	0.352	0.352
161	0.414	0.321	0.321	195	0.606	0.349	0.349
162	0.641	0.320	0.320	196	0.396	0.217	0.217
163	0.537	0.640	0.640	197	0.201	0.461	0.461
164	0.342	0.320	0.320	198	0.426	0.439	0.439
165	0.436	0.306	0.306	199	0.461	0.378	0.378
166	0.320	0.308	0.308	200	0.560	0.238	0.238
167	0.324	0.295	0.295	201	0.366	0.400	0.400
168	0.419	0.284	0.284	202	0.323	0.450	0.450
169	0.408	0.271	0.271	203	0.323	0.346	0.346
170	0.375	0.264	0.264	204	0.323	0.335	0.335

Table A1.4: Solar PV daily capacity factors for the city of Amarillo (Day 205-272)

Day	2013	2014	2015	Day	2013	2014	2015
205	0.308	0.324	0.324	239	0.170	0.353	0.353
206	0.288	0.256	0.256	240	0.132	0.370	0.370
207	0.222	0.328	0.328	241	0.144	0.211	0.211
208	0.356	0.329	0.329	242	0.461	0.144	0.144
209	0.392	0.332	0.332	243	0.333	0.225	0.225
210	0.333	0.364	0.364	244	0.358	0.451	0.451
211	0.296	0.211	0.211	245	0.337	0.253	0.253
212	0.213	0.142	0.142	246	0.288	0.341	0.341
213	0.302	0.417	0.417	247	0.244	0.317	0.317
214	0.370	0.196	0.196	248	0.271	0.314	0.314
215	0.351	0.196	0.196	249	0.424	0.327	0.327
216	0.457	0.288	0.288	250	0.484	0.317	0.317
217	0.327	0.386	0.386	251	0.345	0.290	0.290
218	0.345	0.355	0.355	252	0.326	0.342	0.342
219	0.196	0.327	0.327	253	0.396	0.305	0.305
220	0.195	0.197	0.197	254	0.279	0.327	0.327
221	0.367	0.365	0.365	255	0.404	0.325	0.325
222	0.373	0.207	0.207	256	0.344	0.385	0.385
223	0.298	0.205	0.205	257	0.341	0.295	0.295
224	0.175	0.310	0.310	258	0.173	0.157	0.157
225	0.344	0.596	0.596	259	0.335	0.284	0.284
226	0.372	0.559	0.559	260	0.184	0.349	0.349
227	0.262	0.319	0.319	261	0.178	0.250	0.250
228	0.329	0.337	0.337	262	0.254	0.214	0.214
229	0.329	0.321	0.321	263	0.395	0.250	0.250
230	0.311	0.353	0.353	264	0.388	0.434	0.434
231	0.380	0.350	0.350	265	0.404	0.544	0.544
232	0.274	0.335	0.335	266	0.179	0.351	0.351
233	0.142	0.378	0.378	267	0.389	0.345	0.345
234	0.132	0.318	0.318	268	0.288	0.319	0.319
235	0.168	0.198	0.198	269	0.245	0.356	0.356
236	0.299	0.198	0.198	270	0.314	0.314	0.314
237	0.429	0.192	0.192	271	0.626	0.310	0.310
238	0.342	0.215	0.215	272	0.359	0.315	0.315

Table A1.5: Solar PV daily capacity factors for the city of Amarillo (Day 273-340)

Day	2013	2014	2015	Day	2013	2014	2015
273	0.426	0.284	0.284	307	0.433	0.315	0.315
274	0.310	0.213	0.213	308	0.319	0.228	0.228
275	0.316	0.189	0.189	309	0.280	0.332	0.332
276	0.185	0.436	0.436	310	0.375	0.514	0.514
277	0.265	0.307	0.307	311	0.512	0.299	0.299
278	0.188	0.319	0.319	312	0.509	0.145	0.145
279	0.122	0.398	0.398	313	0.253	0.152	0.152
280	0.122	0.336	0.336	314	0.504	0.161	0.161
281	0.129	0.333	0.333	315	0.251	0.186	0.186
282	0.187	0.198	0.198	316	0.394	0.253	0.253
283	0.427	0.230	0.230	317	0.264	0.263	0.263
284	0.576	0.383	0.383	318	0.261	0.296	0.296
285	0.483	0.371	0.371	319	0.246	0.353	0.353
286	0.170	0.277	0.277	320	0.073	0.310	0.310
287	0.073	0.117	0.117	321	0.134	0.146	0.146
288	0.325	0.173	0.173	322	0.097	0.409	0.409
289	0.497	0.278	0.278	323	0.250	0.252	0.252
290	0.405	0.102	0.102	324	0.301	0.144	0.144
291	0.410	0.102	0.102	325	0.275	0.302	0.302
292	0.572	0.396	0.396	326	0.103	0.306	0.306
293	0.332	0.393	0.393	327	0.331	0.358	0.358
294	0.445	0.344	0.344	328	0.171	0.333	0.333
295	0.367	0.171	0.171	329	0.292	0.278	0.278
296	0.190	0.132	0.132	330	0.468	0.140	0.140
297	0.475	0.186	0.186	331	0.466	0.134	0.134
298	0.493	0.461	0.461	332	0.215	0.406	0.406
299	0.506	0.549	0.549	333	0.401	0.399	0.399
300	0.546	0.546	0.546	334	0.460	0.315	0.315
301	0.542	0.542	0.542	335	0.363	0.459	0.459
302	0.539	0.524	0.524	336	0.232	0.329	0.329
303	0.252	0.325	0.325	337	0.206	0.287	0.287
304	0.344	0.314	0.314	338	0.151	0.204	0.204
305	0.448	0.309	0.309	339	0.342	0.203	0.203
306	0.526	0.263	0.263	340	0.332	0.301	0.301

Table A1.6: Solar PV daily capacity factors for the city of Amarillo (Day 341-365)

Day	2013	2014	2015	Day	2013	2014	2015
341	0.292	0.328	0.328	354	0.273	0.121	0.121
342	0.110	0.226	0.226	355	0.389	0.107	0.107
343	0.273	0.203	0.203	356	0.443	0.044	0.044
344	0.181	0.133	0.133	357	0.435	0.389	0.389
345	0.154	0.085	0.085	358	0.270	0.386	0.386
346	0.343	0.278	0.278	359	0.161	0.416	0.416
347	0.237	0.153	0.153	360	0.169	0.424	0.424
348	0.214	0.293	0.293	361	0.399	0.246	0.246
349	0.151	0.118	0.118	362	0.381	0.375	0.375
350	0.133	0.133	0.133	363	0.075	0.309	0.309
351	0.054	0.094	0.094	364	0.381	0.089	0.089
352	0.081	0.080	0.080	365	0.156	0.080	0.080
353	0.094	0.192	0.192				

Table A1.7: WT daily capacity factors for the city of Amarillo (Day 1-40)

Day	2013	2014	2015	Day	2013	2014	2015
1	0.465	1.000	0.083	21	0.226	0.648	1.000
2	0.290	0.426	0.039	22	0.310	0.631	1.000
3	0.112	1.000	0.271	23	0.101	1.000	0.202
4	0.852	1.000	0.852	24	0.194	0.700	0.631
5	0.980	1.000	1.000	25	0.300	0.354	0.507
6	0.439	0.377	0.122	26	1.000	0.980	0.567
7	1.000	1.000	1.000	27	1.000	1.000	0.235
8	0.426	1.000	1.000	28	1.000	0.140	0.536
9	1.000	0.598	0.552	29	1.000	1.000	0.957
10	0.552	0.812	1.000	30	1.000	1.000	0.389
11	1.000	0.439	0.235	31	0.598	0.439	0.332
12	0.936	1.000	1.000	32	1.000	0.631	1.000
13	0.218	0.465	0.235	33	0.166	0.754	0.893
14	0.332	1.000	0.122	34	1.000	1.000	0.452
15	0.067	0.914	0.310	35	0.736	0.567	1.000
16	0.439	0.522	1.000	36	0.426	1.000	0.343
17	0.244	0.507	1.000	37	1.000	0.631	0.793
18	1.000	0.754	1.000	38	1.000	1.000	0.401
19	0.754	1.000	0.134	39	1.000	0.252	0.507
20	0.536	1.000	0.615	40	1.000	0.552	0.736

Table A1.8: WT daily capacity factors for the city of Amarillo (Day 41-108)

Day	2013	2014	2015	Day	2013	2014	2015
41	1.000	0.271	0.567	75	1.000	1.000	1.000
42	0.615	0.173	1.000	76	0.522	1.000	1.000
43	0.665	0.648	0.413	77	0.893	1.000	0.134
44	0.079	0.648	0.262	78	0.665	0.377	0.872
45	0.493	0.936	1.000	79	0.872	1.000	0.101
46	0.252	0.893	1.000	80	1.000	1.000	0.166
47	0.365	0.957	0.852	81	1.000	1.000	0.235
48	0.598	1.000	0.582	82	1.000	0.736	0.310
49	1.000	1.000	0.146	83	1.000	1.000	0.754
50	1.000	0.773	1.000	84	0.112	1.000	1.000
51	0.793	1.000	1.000	85	1.000	1.000	0.598
52	1.000	0.582	0.615	86	1.000	1.000	0.202
53	0.117	0.128	1.000	87	0.218	0.321	0.290
54	0.682	0.936	0.507	88	0.290	1.000	1.000
55	1.000	0.598	0.507	89	0.280	1.000	0.754
56	1.000	0.812	1.000	90	0.914	1.000	0.271
57	0.252	0.736	1.000	91	1.000	1.000	1.000
58	1.000	0.980	0.957	92	1.000	1.000	0.936
59	0.235	1.000	0.452	93	1.000	1.000	1.000
60	0.354	1.000	0.117	94	0.226	0.343	1.000
61	0.271	1.000	0.736	95	1.000	1.000	1.000
62	1.000	0.389	1.000	96	1.000	0.300	1.000
63	1.000	0.700	1.000	97	0.271	1.000	0.700
64	0.479	1.000	0.389	98	0.852	0.872	1.000
65	1.000	0.754	0.552	99	1.000	1.000	1.000
66	1.000	1.000	0.426	100	1.000	1.000	0.365
67	1.000	1.000	0.218	101	0.465	0.377	1.000
68	1.000	0.465	0.202	102	0.936	1.000	1.000
69	1.000	0.872	0.056	103	1.000	1.000	1.000
70	0.343	1.000	0.180	104	1.000	1.000	0.041
71	0.872	1.000	0.479	105	1.000	1.000	1.000
72	1.000	1.000	0.812	106	1.000	1.000	0.536
73	0.290	1.000	0.682	107	1.000	1.000	0.226
74	0.202	1.000	0.226	108	1.000	1.000	0.507

Table A1.9: WT daily capacity factors for the city of Amarillo (Day 109-176)

Day	2013	2014	2015	Day	2013	2014	2015
109	0.354	1.000	1.000	143	1.000	0.332	1.000
110	1.000	1.000	0.262	144	1.000	0.648	1.000
111	0.507	0.465	0.377	145	1.000	0.682	0.832
112	1.000	1.000	1.000	146	1.000	0.793	0.166
113	1.000	1.000	1.000	147	1.000	0.465	1.000
114	0.226	1.000	1.000	148	1.000	0.146	1.000
115	1.000	1.000	1.000	149	1.000	0.202	0.552
116	1.000	1.000	1.000	150	1.000	0.343	0.812
117	0.226	1.000	1.000	151	0.262	0.773	0.665
118	0.665	0.893	0.832	152	1.000	1.000	1.000
119	1.000	1.000	0.112	153	1.000	0.522	1.000
120	1.000	1.000	1.000	154	1.000	1.000	1.000
121	1.000	0.893	1.000	155	0.754	1.000	1.000
122	1.000	0.354	1.000	156	1.000	1.000	1.000
123	0.682	1.000	1.000	157	0.280	1.000	1.000
124	0.465	1.000	0.793	158	1.000	1.000	1.000
125	0.166	1.000	0.754	159	1.000	1.000	0.087
126	1.000	1.000	1.000	160	0.413	1.000	0.343
127	1.000	1.000	0.936	161	1.000	0.493	1.000
128	1.000	1.000	0.718	162	1.000	1.000	1.000
129	1.000	0.718	1.000	163	1.000	1.000	1.000
130	0.552	0.852	0.507	164	1.000	1.000	0.210
131	0.479	1.000	0.426	165	1.000	1.000	0.832
132	1.000	1.000	1.000	166	1.000	1.000	0.321
133	1.000	1.000	0.648	167	1.000	1.000	0.140
134	1.000	0.700	0.754	168	0.567	1.000	0.128
135	1.000	0.321	1.000	169	0.321	1.000	0.389
136	0.426	1.000	0.479	170	1.000	1.000	0.682
137	0.914	0.736	0.452	171	1.000	1.000	1.000
138	1.000	1.000	0.773	172	1.000	1.000	1.000
139	0.665	1.000	1.000	173	1.000	1.000	1.000
140	1.000	1.000	1.000	174	1.000	1.000	1.000
141	0.936	1.000	0.582	175	1.000	1.000	1.000
142	1.000	1.000	0.754	176	1.000	1.000	1.000

Table A1.10: WT daily capacity factors for the city of Amarillo (Day 177-244)

Day	2013	2014	2015	Day	2013	2014	2015
177	0.832	1.000	0.567	211	0.567	0.718	0.332
178	1.000	1.000	0.079	212	0.310	0.413	0.648
179	1.000	1.000	0.536	213	0.957	0.262	0.465
180	0.631	1.000	0.377	214	1.000	0.101	0.598
181	0.389	1.000	0.365	215	0.893	0.194	0.700
182	0.180	1.000	1.000	216	0.536	0.936	0.493
183	0.053	0.507	0.194	217	1.000	1.000	0.262
184	0.812	0.665	0.631	218	1.000	0.365	0.631
185	1.000	1.000	0.365	219	0.682	0.493	0.754
186	1.000	1.000	1.000	220	0.452	0.615	0.852
187	1.000	1.000	1.000	221	0.507	0.893	0.567
188	1.000	0.567	1.000	222	0.173	0.128	0.354
189	0.718	0.401	0.354	223	0.507	0.262	0.522
190	1.000	1.000	1.000	224	0.413	0.146	0.736
191	0.465	1.000	1.000	225	0.252	0.872	0.567
192	0.536	1.000	1.000	226	0.754	1.000	0.290
193	0.980	1.000	0.582	227	0.166	1.000	0.665
194	0.832	0.452	0.479	228	0.793	0.665	0.980
195	1.000	0.507	0.493	229	1.000	0.087	0.793
196	0.426	0.812	1.000	230	1.000	0.389	0.598
197	0.290	1.000	0.522	231	1.000	0.493	1.000
198	0.682	0.389	1.000	232	1.000	1.000	0.936
199	0.615	0.226	1.000	233	1.000	1.000	1.000
200	1.000	1.000	0.957	234	0.754	1.000	0.754
201	0.914	1.000	0.615	235	0.439	1.000	1.000
202	1.000	1.000	0.280	236	0.567	1.000	0.202
203	1.000	0.210	1.000	237	0.536	1.000	0.389
204	0.980	0.117	0.832	238	1.000	0.507	0.343
205	1.000	0.700	0.893	239	0.700	0.832	1.000
206	1.000	1.000	0.872	240	1.000	0.413	0.280
207	0.980	1.000	0.773	241	1.000	0.166	0.187
208	1.000	0.648	1.000	242	0.493	0.439	0.083
209	1.000	1.000	1.000	243	0.682	1.000	1.000
210	1.000	0.700	0.343	244	0.401	0.582	1.000

Table A1.11: WT daily capacity factors for the city of Amarillo (Day 245-312)

Day	2013	2014	2015	Day	2013	2014	2015
245	0.377	0.736	1.000	279	0.187	0.218	0.957
246	0.567	1.000	1.000	280	0.321	0.134	0.166
247	0.413	1.000	1.000	281	1.000	0.321	0.000
248	0.401	1.000	0.872	282	1.000	0.479	0.439
249	0.452	0.773	0.700	283	1.000	1.000	1.000
250	0.377	0.000	0.582	284	1.000	0.321	0.452
251	0.567	1.000	0.310	285	0.493	1.000	0.413
252	1.000	1.000	0.280	286	1.000	1.000	0.235
253	1.000	1.000	0.536	287	1.000	0.365	0.377
254	1.000	0.452	0.893	288	1.000	0.465	0.536
255	0.321	1.000	0.793	289	0.152	0.682	1.000
256	1.000	0.439	1.000	290	0.244	0.290	1.000
257	1.000	1.000	1.000	291	1.000	0.202	1.000
258	0.389	1.000	1.000	292	0.401	0.852	1.000
259	0.413	0.087	1.000	293	0.682	0.075	1.000
260	0.773	0.354	1.000	294	0.493	0.465	0.389
261	1.000	0.401	1.000	295	0.377	1.000	0.700
262	1.000	0.262	0.914	296	0.793	0.536	1.000
263	0.700	0.079	1.000	297	1.000	0.210	0.290
264	0.522	0.682	0.832	298	0.812	0.914	0.039
265	1.000	0.957	1.000	299	0.648	1.000	0.754
266	0.852	1.000	1.000	300	0.452	0.736	0.426
267	0.134	1.000	0.047	301	1.000	0.117	1.000
268	1.000	0.413	0.071	302	0.507	0.718	0.682
269	1.000	0.479	0.112	303	1.000	0.736	1.000
270	1.000	1.000	0.465	304	1.000	0.321	0.310
271	0.957	0.736	0.615	305	0.598	1.000	0.210
272	0.793	1.000	0.134	306	0.522	1.000	0.665
273	0.252	1.000	0.493	307	1.000	1.000	1.000
274	0.401	0.218	1.000	308	0.957	0.413	1.000
275	0.852	1.000	1.000	309	1.000	0.047	0.936
276	1.000	0.812	1.000	310	0.244	0.235	0.582
277	1.000	0.452	0.252	311	0.773	1.000	0.244
278	1.000	0.210	0.552	312	1.000	0.479	1.000

Table A1.12: WT daily capacity factors for the city of Amarillo (Day 313-365)

Day	2013	2014	2015	Day	2013	2014	2015
313	0.452	1.000	1.000	340	0.354	0.202	0.244
314	0.117	1.000	1.000	341	0.493	0.536	0.389
315	1.000	1.000	1.000	342	1.000	0.354	0.235
316	1.000	1.000	0.262	343	0.187	0.479	0.682
317	1.000	0.310	0.980	344	1.000	0.044	0.507
318	0.736	1.000	1.000	345	0.439	0.079	0.552
319	0.980	1.000	1.000	346	1.000	1.000	1.000
320	1.000	1.000	1.000	347	1.000	1.000	1.000
321	1.000	0.343	1.000	348	1.000	1.000	0.465
322	0.365	0.536	0.718	349	0.152	0.957	1.000
323	1.000	0.354	0.536	350	0.041	0.343	0.134
324	0.290	0.180	1.000	351	0.262	1.000	0.615
325	1.000	0.146	1.000	352	1.000	0.262	0.682
326	1.000	0.832	0.202	353	1.000	0.117	1.000
327	0.631	1.000	1.000	354	0.980	0.631	1.000
328	0.202	0.140	1.000	355	0.280	0.493	0.465
329	1.000	0.754	1.000	356	0.310	1.000	1.000
330	0.343	0.452	1.000	357	0.452	1.000	0.754
331	0.377	1.000	1.000	358	1.000	1.000	0.452
332	0.365	1.000	0.439	359	0.567	1.000	1.000
333	1.000	1.000	0.041	360	0.465	0.872	1.000
334	0.134	1.000	0.262	361	0.152	0.280	1.000
335	0.097	0.852	0.226	362	0.936	0.218	1.000
336	0.226	0.552	0.194	363	1.000	0.465	0.493
337	1.000	0.452	0.280	364	0.718	1.000	0.300
338	1.000	0.332	1.000	365	1.000	0.159	0.159
339	0.700	0.479	1.000				

Appendix B: Glossary

Electric vehicle energy intensity rate:

Amount of battery energy consumed to move 1kg object across 1 km at a specific speed (Pham et al, 2019). The electric vehicle energy intensity rate is notated as q_v and computed as $q_v = \frac{E_{EV}}{md_{\max}}$ where E_{EV} is the battery capacity in MWh, $d_{\max}$ is the driving range at speed *v* measured in km and *m* is the vehicle gross weight including the payload.

For example, the battery capacity of a Condor e-truck is 0.05 MWh (or 50 kWh), the driving range of a fully charged Condor can reach up to 160 km at 100km/h and the gross weight of this vehicle is approximately 2630 kg. At v=100 km/h, q_{100} is computed as follows:

$$q_{100} = \frac{0.05}{2630*160} = 1.19\text{x}10^{-7} \text{ MWh/kg/km}$$

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