OPTIMAL PHOTOVOLTAIC SIZE ESTIMATION FOR A CAMPUS AREA CONSIDERING UNCERTAINTIES IN LOAD, POWER GENERATION AND ELECTRICITY RATES

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Approval of the Board of Graduate Programs

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This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

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ABSTRACT

OPTIMAL PHOTOVOLTAIC SIZE ESTIMATION FOR A CAMPUS AREA CONSIDERING UNCERTAINTIES IN LOAD, POWER GENERATION AND ELECTRICITY RATES

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The objective of this thesis is to develop simulation based optimization tools to determine the best strategy for photovoltaic (PV) installations at a campus environment (Middle East Technical University, Northern Cyprus Campus) with consideration of available risks and uncertainties in load, power generation and electricity rates. The first step is to accurately characterize the electricity consumption (load) pattern of the campus. Electricity demand is modeled using different forecasting models based on hourly, daily, monthly and yearly time scales. To minimize supply-demand mismatches, the second step of this study is to characterize the amount of solar power generation of a simple PV system. Probabilistic characterization is used for predicting electricity consumption and solar resources. Based on the forecasted values of electricity consumption and solar PV output for 20 years, economic feasibility analysis is performed using Monte Carlo simulation. For the entire lifetime (20 years) of PV system, two different options are analyzed economically; one time installation of 1 MW solar PV power plant, and stepwise installation of solar PV power plant (installing 1 MW after every 7 years). Both cases are analyzed for four different scenarios; constant electricity prices and increasing demand, increasing electricity prices and demand, constant prices and constant demand, and last increasing prices and constant demand. According to our results, although both the cases are feasible under all scenarios, the most feasible size for solar PV installation at METU NCC is between 2 MW – 3 MW.

Keywords: Solar PV; sizing; university; stochastic; optimization; Monte Carlo

ÖZ

BİR KAMPUS ORTAMINDA ENERJİ ÜRETİMİ, TÜKETİMİ VE FİYATLARINDAKİ BELİRSİZLİKLER DİKKATE ALINARAK OPTİMAL FOTOVOLTAİK SANTRAL KAPASİTESİ TAHMİNİ

Ali, Syed Muhammad Hassan
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Haziran 2015, 153 sayfa

Bu tezin amacı, enerji üretimi ve kullanımı sırasında var olan riskler ve belirsizlikler dikkate alınarak bir kampüs ortamında (Orta Doğu Teknik Üniversitesi, Kuzey Kıbrıs Kampüsü) fotovoltaik (PV) santral kurulumu için en iyi stratejiyi belirlemek üzere simülasyon tabanlı optimizasyon araçları geliştirmektir. İlk olarak kampüs elektrik tüketimi (yük) karakterize edilmiştir. Elektrik talebi, saatlik, günlük, aylık ve yıllık zaman ölçeklerinde farklı tahmin yöntemleri kullanılarak modellenmiştir. Çalışmanın ikinci aşamasını bir PV sisteminin güneş enerjisi üretim miktarını karakterize etmek oluşturmaktadır. Bu arz-talep uyumsuzluklarını en aza indirmek için önemlidir. Elektrik tüketimi ve güneş kaynakları tahmini için olasılık dağılımları oluşturulduktan sonra, ekonomik fizibilite analizi için Monte Carlo benzetim yöntemi kullanılmıştır. Yapılan çalışmada PV sisteminin ömrü olan 20 yıllık süre boyunca elektrik tüketimi ve güneş PV çıkışı saat bazında hesaplanmıştır. Geliştirilen azılım ile farklı kurulum seçenekleri ekonomik olarak karşılaştırılmıştır. Çeşitli kapasitelerde tek eferlik kurulum (1 MW – 6 MW) ve adım adım kurulum (her 7 yıl sonra 1 MW) analiz edilen seçeneklerdir. Bu kapasite seçenekleri olası elektrik fiyatı ve tüketim talep senaryoları için test edilmiştir. Bulunan sonuçlar ODTÜ KKK'da güneş PV kurulumu için en uygun apasitenin 2-3 MW arasında olduğunu göstermektedir.

Anahtar Kelimeler: Solar PV ; boyutlandırma ; üniversite ; stokastik ; optimizasyonu; Monte Carlo

DEDICATION

To my Beloved Grand Parents, Parents, Sisters and Fiancé.

For their unconditional support, trust and encouragement.

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NOMENCLATURE

L_t	Estimated smoothed level for period t
A_{PV}	Area of PV panels
b_1	Slope or regression coefficient for population
b_2	Y-intercept for linear regression with year
b_3	Slope or regression coefficient for year
b_o	Y-intercept for linear regression with population
C	Cooling needs
CDD	Cooling degree days
c_i	Capacity of Inverter (kW)
C_{IU}	Cost of Inverter module (200 USD kW^{-1})
c_p	Power Plant Capacity (kW)
C_{PV}	Cost of PV module (700 USD kW^{-1})
CS	Economic benefits or cost saved by reduction in electricity bills (USD)
DNI	Direct normal insolation (Wh m^{-2})
D_t	Trend estimate for daily change after each period or year p
E	Electricity consumption
EB_y	Net economic benefits in year y
E_D	Daily electricity consumption data generated as random data through probabilistic characterization
EG	Total energy generated and consumed on campus using Solar PV power plant (kWh)
E_H	Hourly electricity consumption
EPC	English preparatory school classes and exams
EP	Price of grid electricity (USD kWh^{-1})
E_{PV}	Electricity produced by PV panels
F_{t+p}	Forecast of p periods into the future
G	Standard irradiance for PV panels (1000 W m^{-2})
gap_{DS}	Gap between the demand and supply of electricity or shortage of supply (kWh)
gap_{SD}	Gap between the supply and demand of electricity or amount of supply exceeding demand (kWh)
GU	Graduate and undergraduate classes and exams
H	Heating needs
HDD	Heating degree days
$HECP_{i,k}$	Average hourly electricity consumption percentages for the hour i of month k
$HITP_{i,k}$	Average hourly tilted solar resource percentages for the hour i of month k
i	Interest rate (15%)

I_{bT}	Beam insolation on a tilted surface (Wh m^{-2})
IC_y	Insurance cost in year y (USD)
I_d	Amount of diffuse solar insolation available on a surface (Wh m^{-2})
I_{dT}	Diffused solar insolation on a tilted surface (Wh m^{-2})
IS_{cost}	Total cost of inverter system (USD)
I_T	Total solar insolation on a tilted surface (Wh m^{-2})
I_{TD}	Daily tilted solar resource data generated as random data through probabilistic characterization
I_{TF}	Forecasted hourly solar resources on tilted surface
K	Constant for multiple regression analysis
$LCOE$	Levelized Cost of Energy (USD kWh^{-1})
L_{loc}	Longitude of the location on which resources are to be measured
L_{st}	Local standard time meridian used in local time zone
L_t	Estimated smoothed level for period t
MAE	Mean absolute error
$MAPE$	Mean absolute percentage error
$MaxAPE$	Maximum absolute percentage error
MC_y	Maintenance cost in year y (USD)
NPV	Net present value
N_y	Year
OC	Opportunity cost
OR	Orientation and registration days
p	Periods to be forecasted into the future
pf	Performance factor
PP_{cost}	Power plant cost (USD)
P_{PV}	Rated power of the PV power plant
PV_{cost}	Total cost of PV system (USD)
RH	Average humidity of the day
$RMSE$	Root mean square error
$RMSPE$	Root mean square percentage error
s	Length of seasonality
SS	Summer school classes and exams
S_t	Seasonal estimate for period t
T_{avg}	Average temperature of the day
$TEC_{i,k}$	Total electricity consumption during hour i for the entire month k
TEC_k	Total electricity consumption during the entire month k
$TI_{i,k}$	Total solar resource on tilted surface during hour i for the entire month k
TI_k	Total solar resource on tilted surface during the entire month k
T_{ref}	Reference temperature at minimum electricity consumption

T_t	Estimated trend value for period t
W	Weekdays
WP	Excess production cost
X	Population
Y_t	Actual value of electricity consumption in period t
α	Smoothing constant for level (0-1)
β	Smoothing constant for trend (0-1)
β_a	Surface Tilt angle (degrees)
γ	Smoothing constant for seasonality estimate (0-1)
γ_s	Solar azimuth angle
δ	Declination angle
η_{PV}	PV panel efficiency
θ_z	Solar zenith angle
Φ	Latitude
ω	Hour angle

CHAPTER 1

INTRODUCTION

1.1. Motivation

Solar Photovoltaic (PV) electricity generation systems are largely affected by the intermittent nature of the solar resources. The solar irradiation is highly unstable and dependent on variety of factors such as climatic conditions, position of sun in the sky, orientation of PV panels, etc. The variable nature of solar resources induces a great risk of failure to grid connected solar PV systems. A remedy to this grid instability problem could be the use of energy storage systems together with solar PV systems. On the other hand, this increases the cost of PV systems significantly. Apart from the volatility in solar resources, it is essential to analyze the electricity consumption patterns of a possible unidirectional PV system to achieve sound supply-demand matching. Considering the lifetime of possible PV systems, the long term behavior of associated electricity demand (trend and seasonal fluctuations) should be modeled accurately. Moreover, short term behavior of the demand should also be analyzed in detail and inherited uncertainty of demand should be determined. In addition to demand and supply balance, grid electricity prices, which may not be stable based on the region, also have a tremendous effect on the economic feasibility of PV systems. Hence, it is crucial to incorporate various uncertainties during the design and planning phase of a possible solar PV power plant. On the other hand, given multiple uncertain elements and dynamic nature of the system, associated mathematical decision models become extremely complex leading a challenging design and analysis phase. Furthermore it becomes difficult to design and analyze such systems where a number of factors are uncertain. The motivation of this thesis is therefore to develop a versatile and effective simulation tool that can be adopted by decision makers to analyze such grid connected solar PV systems with multiple uncertainties. The simulation tool developed will be applied to analyze the feasibility of solar PV installation at METU NCC.

1.2. Power Sector of Northern Cyprus

KIB-TEK (The Cyprus Turkish Electricity Authority) is a local utility company that manages the generation, transmission and distribution of electricity in Northern Cyprus [1]. Fuel oil no. 6 is used for electricity generation due to financial constraints and lack of strict environmental policies. It has high sulfur content around 3.5% by weight, due to which utilization of this heavy oil poses serious threats to the environment. Table 1.1 gives the total power generation capacity of KIB-TEK and the power generated per station. It can be inferred from Table 1.1 that merely 0.37% of the total electricity is coming from solar photovoltaic plant. Moreover, it is also noteworthy that power generation is dependent on imported oil, which means that electricity production is expensive, unsustainable and results in dependency. Hence, in order to achieve sustainability and economic growth, dependency on imported oil should be reduced and a shift towards renewable energy is necessary, as renewable energy sources have least impact on environment.

Table 1.1 KIB-TEK Power stations and Capacities [2]

Power Stations	**Power**	**Total Power (MW)**
Teknecik	2 × 60 MW Steam Turbine	120
Teknecik	2 × 17.5 MW Diesel Generator	35
Teknecik	6 × 17.5 MW Diesel Generator	105
Dikmen	1 × 20 MW Gas Turbine	20
Kalecik	4 × 17.5 MW Diesel Generator	70
Serhatkoy	1.3MWp Photovoltaic	1.3
	Total Capacity	351.3

1.3. Solar Potential of Northern Cyprus

Cyprus is located in the north-eastern Mediterranean region in the south of Turkey at 35^{o}N of Equator and 33^{o}E of Greenwich. It is the third largest island with an area of 9251 km^2 in the Mediterranean Sea after Sicily and Sardinia. The northern part of Cyprus has an area of 3354 km^2; having a typical Mediterranean climate with an average temperature of 28^{o}C in summers and 11^{o}C in winters. According to Tariq and Baker [2], the Island enjoys long summer days of an average 12.5 hours, and short winter days of an average 5.5 hours. According to Erdil et al. [3], December and January receives an average daily radiation of 2.3 kWh m^{-2} and this may increase in June and July to reach 8.1 kWh m^{-2}. On average the daily global radiation is 5 kWh m^{-2}. With ample of solar resources available in Cyprus, a more sustainable option will be to generate electricity using solar Photovoltaic power plants.

1.4. METU NCC Initiatives for Sustainability

METU NCC has taken various measures to promote and create awareness regarding sustainability of the campus area and environment. Two of the most prominent measures are; ‘Green Campus Initiative’ and ‘Sustainable Environment and Energy Systems Program’. METU NCC Green Campus Initiative has been formed with the philosophy of sustainability and environmental friendliness. Within the agenda of national and international standard and related legal regulations; improving the efficiency of power production, transmission and consumption on the Campus, reducing of unconscious usage and waste, minimization of energy production costs, decreasing the greenhouse gas emission on Campus in order to cope with climate change, conservation and protection of natural resources with the help of the land use and rainwater harvesting plan, protecting environment from pollution with the waste management plan and creating and promoting awareness about the issue regarding energy and the environment are the necessary components of the Green Campus Initiative of METU NCC. This thesis serves for the Green Campus Initiative by reducing the cost of electricity, increasing the efficiency of energy production and reducing the emission associated with energy generation for METU NCC. The reason to select Solar PV is that it contributes to the concept of sustainability by reducing the emission from power generation and by reducing the amount payables to KIB-TEK in the form of electricity bill, as METU NCC will be generating its own electricity, moreover the large amount of solar potential of Northern Cyprus as discussed earlier can be utilized.

1.5. Literature on Campus Sustainability

Several studies on campus sustainability are present in the literature. Martin and Jo [4] assessed the feasibility of a utility-scale photovoltaic (PV) electricity generation system on Illinois State University's (ISU) campus. The capacity of PV system was estimated through analysis of the climate information and utilizing PV system modeling software. Eight utility-scale PV systems were modeled and simulated to determine three optimal systems for the university.

M. Drif et al. [5] did a performance analysis of UNIVER Project of its PV systems. It consists of four grid connected PV systems of 200kWp fully integrated into the Jaén University buildings. It provides the university campus with more than 8% of its electricity needs, i.e. 210 MWh/year. Kucuksari et al. [6] proposed a framework to integrate Geographical

Information Systems (GIS), mathematical optimization, and simulation modules to obtain the annual optimal placement and size of PV units in a campus area environment. A GIS module was developed to find the suitable rooftops and their panel capacity. An optimization module was used to maximize the long-term net profit of PV installations.

Gamage [7] worked on Ground Source Heat Pump (GSHP) systems for METU NCC. It provides an alternative energy source for residential and commercial space heating and cooling applications. It utilizes the favorable temperature profile at a certain depth under the ground surface. Pathirana and Muhtaroglu [8] performed a feasibility study of PV power plant for METU NCC. Analyses for grid-tied and standalone power plant was done. Their study used monthly solar resource and electricity demand data of the campus.

Tariq and Baker [2] completed a feasibility study for large scale PV penetration at the METU NCC. Sizing of PV panels considering unidirectional metering was done. One year hourly electricity demand and one year hourly solar resource data of campus was used for the analysis. He considered cost of electricity, maintenance and insurance to be constant.

It should be noted that the study done by Tariq and Baker [2] for METU NCC does not contain modeling of electricity consumption patterns for the campus and electricity prices are also considered constant and have not been modeled. Moreover uncertainties in electricity demand and prices are also not considered. These are important factors to consider while working on feasibility of large scale PV penetration at METU NCC. Because an underestimate of load could lead to capacity shortages, which would result in poor quality of service and may lead to higher electricity bills and an overestimate could lead to the authorization of a plant that may not be needed for several years.

1.6. Solar Energy Systems

Energy generation from solar resources has been increasing globally, with an average annual growth rate of 49.5% during 2006-2011 [9]. It is predicted by International Energy Agency (IEA), that 11% of the global electricity and 20% of world energy supply will come from solar energy by 2050. There was a record growth of 110% in 2008, when solar PV installation reached a record high of 5.95 GW [9].

During the year 2011 – 2012 there was an increase of approximately 44% in solar PV installations globally [2]. These growing rates of Solar PV installations are due to continuous increase in the efficiency of PV panels, minimal impact to the environment, continuous decrease in payback time and renewable nature of solar energy. The payback time for solar PV power plants has now reduced to 3-5 years, depending upon the available solar resources in that region [9]. Even though rapid growth is observed, it should be noted that electricity production from solar PV is negligible as compared to conventional fuels. This is not only due to the high cost associated with solar PV as compared to conventional fuels, but also due to the intermittent nature of solar energy resources. The essential intermittence characteristics of the solar PV significantly increase the complexity of operation of electrical systems. Research is being done in this area to increase the reliability of solar PV integrated electricity grids and solar PV stand alone systems and to reduce the cost of energy generation from solar PV.

As discussed earlier, the variable nature of solar resources reduces the use of solar PV for electricity generation. Solar irradiation depends on climatic conditions and surrounding atmosphere, due to high variability in solar resources the risk of grid failure increases. This problem can be countered by having storage with solar PV systems, but it significantly increases the cost. Another option is to improve solar PV output forecasts or incorporate uncertainties in solar resources while planning for solar PV installations, the work done in this thesis is based on the later approach.

There are two approaches for solar PV output forecasting that are most commonly used; indirect methods that are based on the sunshine intensity and direct methods that are based on the system output. Researchers have obtained many achievements for forecasting solar resources, widely applicable in agricultural production, construction, PV power generation, and other fields [10]. Different approaches for irradiance forecasting can be found in literature. One of the most recognized schemes is the use of time series modeling for irradiance forecasting.

Artificial Neural Network (ANN)-wavelet method which is one of the most popular time series method, is frequently employed for local predictions. Mellit et al. [11] used Continuous Wavelet Transform-Discrete Wavelet Transform (DWT) method for predicting daily solar radiations with Root Mean Square Error (RMSE) of 5.1%. Cao and Lin [12] used Diagonal Recurrent Wavelet Neural Networks (DRWNN) for hourly and daily solar irradiation predictions with RMSE of 8.3%. S. Cao and Cao [13] also employed the DWT method with a RMSE of 8.4%.

Yona et al. [14] used solar insolation forecasting at 24-hour-ahead for the power output forecasting of PV system. Three different Neural Network Methods used in their work are; Feed-Forwards Neural Networks (FFNN), Radial Basis Function Neural Network (RBFNN), and Recurrent Neural Network (RNN). Lorenz et al. [15] also presented PV power output predictions based on weather forecasts. They predicted PV output based on three days ahead forecast of weather provided by the European Centre for Medium-Range Weather Forecasts (ECMWF).

Tao et al. [16] proposed the use of NARX network based forecasting model for prediction of hourly power output for a PV system, eliminating the use of complex meteorological instrumentation. They used Hottel's radiation model to calculate the radiation of clear sky incident on the inclined surface, instead of using Numerical Weather Prediction (NWP) Models for meteorological data. Moreover they used weather forecast from public websites in order to characterize the variation in cloud status in future days. Kudo et al. [17] presented power generation forecast method for PV systems in an energy network. They used regression analysis and took weather information for forecasting of output of PV system installed in Expo 2005, Aichi Japan. Average forecasting error for their model was about 26% of the actual power. Boland [18] used Coupled Auto Regressive and Dynamical System (CARDS) solar forecasting tool for predicting solar radiation series at three different sites in Guadeloupe in the Caribbean. Forecast errors of these sites were tested for cross correlation. These correlations were taken into account in refining the forecast depending on their significance.

Even though a lot of research has been done on forecasting solar PV output and solar resources, not much work is found in the literature on incorporating uncertainties associated with solar resources in solar PV sizing and installation. This thesis aims to incorporate such uncertainties while planning for solar PV power plant installations.

1.7. Electricity Demand Modeling and Forecasting

In order to maintain grid stability and smooth supply of electricity, it is crucial to have demand match the supply. Earlier in this chapter uncertainties associated with solar resources and solar PV output were discussed, apart from that in order to have stable grid it is also important to account for uncertainties in electricity load or consumption. A number of different methods and techniques are present in the literature that can be used for developing prediction models of electricity consumption. These modeling techniques can be divided into two main categories; Parametric Methods and Artificial Intelligence Methods. In Parametric Methods we have; Trend Analysis, End-Use Models and Econometric Models. In Artificial Intelligence Methods we have; Artificial Neural Networks, Genetic Algorithms, Support Vector Machine, Fuzzy Logic Models, and Experts Systems. Apart from these traditional methods, some researchers have also used integrated methods in which they have combined two or more different methods for modeling electricity consumption. A review of electricity consumption modeling is presented by Jebaraj and Iniyan [24].

A case study for Dutch electricity distribution system operator was performed by Tanrisever et al. [19]. Relevant factors that were affecting electricity consumption were identified in their study. These factors were quantified in the prediction model. Electricity infeed was estimated one year in advance for hourly forecasting model.

Another study for University of California was done by Saima et al. [20] . In their study informatics approach was utilized for forecasting energy consumption patterns. They considered novel indirect indicators and energy use for daily and 15 minutes time interval was predicted. The used 3 year of sensor data for developing a forecasting model.

Bianco et al. [21] studied the effect of demographic and economic variables on electricity consumption in Italy. Using data of 38 years from 1970 till 2007, they developed different regression models for predicting long term electricity consumption depending upon independent variables of GDP (gross domestic product), GDP per capita (gross domestic product per capita) and population. On comparison with national forecasts, they found a deviation of $\pm 1\%$ – $\pm 11\%$, which they considered to be reasonable due to long term forecasts.

Mohamed and Bodger [22] also investigated the impact of economic and demographic variables on electricity consumption in New Zealand. They used 35 years of GDP, electricity price and population data of New Zealand from 1965 till 1999 for forecasting electricity consumption. They used multiple regression analysis to model and predict electricity consumption based on selected independent variables. On comparing their forecasts with national forecasts they found that for the initial years their forecasted electricity consumptions were close to national forecasts but for the later years their predictions started to deviate from the national forecasts.

Egelioglu et al. [23] studied the impact of economic variables on the annual electricity consumption for Northern Cyprus. They used historical electricity consumption and economic data from 1988 till 1997. Their multiple regression analysis suggested that there was high correlation between electricity consumption and number of consumers with an adjusted R – square value of 0.906.

The electricity consumption in METU NCC is increasing every year with increasing population. Since METU NCC has planned to install 1 MW solar PV power plant to satisfy most of its electricity needs, it has become extremely important to model and forecast electricity consumption for the campus. Forecasting models of different time scales are used in this thesis to predict hourly, daily, monthly and yearly predictions for the electricity consumption of METU NCC.

1.8. Uncertainties in Electricity Prices

For grid connected solar PV systems, the revenue is the savings from grid electricity usage. In such cases the revenue generated or savings made depends on grid electricity prices. Hence for such systems it is necessary to consider the uncertainties in electricity prices for analyzing their economic feasibility. Variation in electricity prices is another important factor that is considered in this thesis. Since, Fuel oil no. 6 is used for electricity generation and it is imported; therefore there lies huge uncertainty in electricity prices of Northern Cyprus. It can be inferred from Figure 1.1 that electricity prices in Northern Cyprus change every 4 – 5 months. Moreover the electricity prices in Northern Cyprus vary based on the customer type; METU NCC receives a 10% discount on its electricity prices, this adds more uncertainty in the economic assessment of grid connected solar PV systems in Northern Cyprus. Regardless of the upward trend, the frequent variation in electricity prices is an important factor to be considered as it will induce uncertainties in the economic assessment of a project.

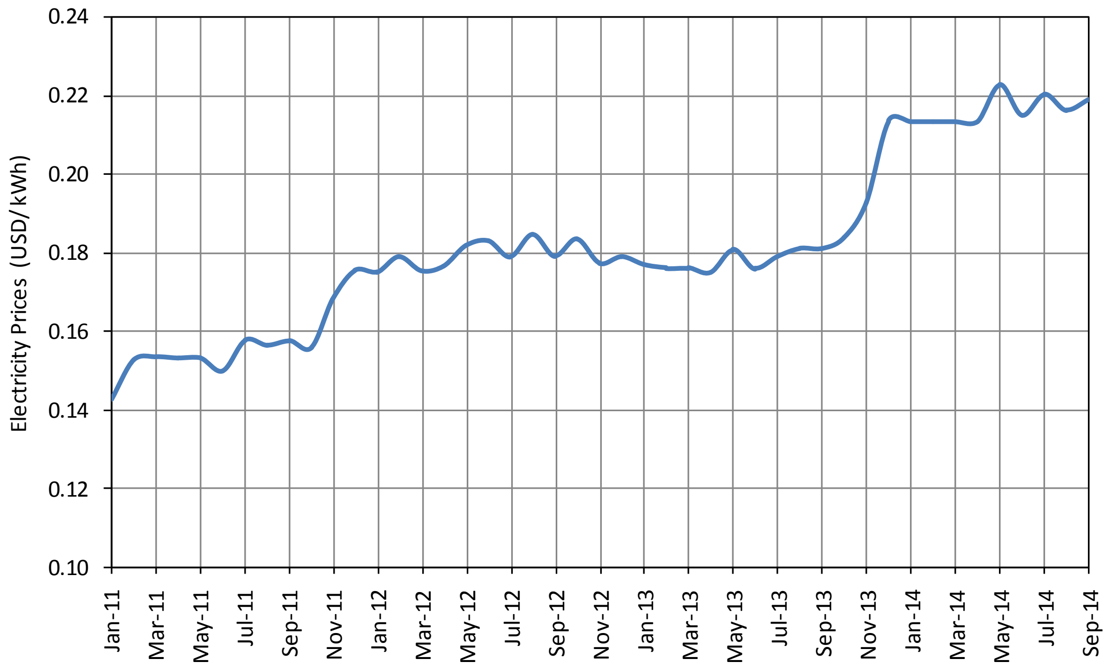

Figure 1.1 Time series of electricity prices per kilowatt hour in Northern Cyprus

1.9. Probabilistic Assessment of Solar PV System

In order to incorporate the uncertainties in electricity demand, supply and prices for the economic assessment of different solar PV installation sizes, Monte Carlo simulation is used in this project. Instead of generating point estimates of net present value (NPV), Monte Carlo simulation will generate outputs of NPV distributions, which will better represent the amount of associated risks in any option. Hence, probabilistic assessment of solar PV installation at METU NCC will give a more reliable result and a better understanding of associated uncertainties.

Several studies are present in the literature on the use of probabilistic modeling for sizing, design and optimization of solar PV systems. Cabral et al. [25] used stochastic method for standalone PV sizing. They analyzed energy storage and solar radiation using stochastic modeling, both Markov chain and Beta probability density functions are used in their study. They found that stochastic models provided more reliable results when compared to deterministic models.

Tina et al. [25] presented probabilistic modeling of long term performance assessment of hybrid solar/wind systems for both standalone and grid connected applications. They performed a reliability analysis by using energy index of reliability which is directly related to energy expected not supplied (EENS). Their analytical probability model when compared to time domain simulations such as Monte Carlo Simulation presented similar results, with a difference between 0.5% and 1.9%.

Arun et al. [26] proposed a methodology for optimizing the size of solar PV – battery systems for decentralized energy generation in remote or isolated areas considering uncertainties in solar insolation. Their methodology is based on design space approach which uses time series simulation of the entire system. They have used chance constrained programming approach for incorporating uncertainties in solar resources for sizing of solar PV – battery systems. They validated their methodology by using Monte Carlo simulation. Viawan et al. [27] used a probabilistic approach for the design of distributed PV systems and for analyzing its impact on low voltage feeder. They predicted solar radiation and load using Monte Carlo Simulation and used exact method to solve power flow.

1.10. Objectives

As discussed earlier in the motivation, the main object of this thesis is to develop a simulation tool that can be used to analyze the feasibility of grid connected solar PV systems based on uncertainties in solar resources, electricity consumption and electricity prices. A general model is developed for such analyses using Monte Carlo simulation, and it can be used for any grid connected system at any location. The main objectives of this thesis are;

- To develop simulation based optimization tool, which can determine the best strategy for grid connected solar PV installations.
- To consider available risks and uncertainties in electricity load, power generation and electricity prices for the economic assessment of solar PV installations.
- To consider different options for the entire life time of PV systems, and analyze them economically.

This general simulation model is applied to METU NCC for analyzing the economic feasibility of grid connected solar PV installations. Apart from this, the methodology used and the work presented in this thesis builds up directly on the work done earlier for METU NCC, such that different models for predicting electricity consumption of METU NCC on different time scales are presented in this thesis. An entirely new method is presented for predicting electricity consumption of METU NCC, by integrating multiple regression analysis and Holt's method of forecasting. Both electricity consumption and PV output are predicted based on probabilistic characterization of electricity demand and solar resource data. Different scenarios like constant electricity prices or increasing electricity prices are considered for economic assessment of different PV installation sizes at METU NCC. Monte Carlo simulation is used to generate distributions of net present value (NPV), levelized cost of electricity (LCOE), opportunity cost (OC) and excess production cost (WP) instead of point estimates, hence accounting for all the uncertainties and available risks for any installation size.

1.11. Overview of the Thesis

0 provides the details of methodology for modeling and forecasting electricity consumption of METU NCC. Different models for characterizing the trend and seasonality patterns of electricity consumption of METU NCC on different time scales are presented. A new method which is an integration of multiple regression analysis and Holt's method is also presented. These models are applied to METU NCC data and future electricity consumption predictions are developed. Annual, monthly and daily models are developed to study the electricity consumption patterns at METU NCC whereas for the simulation tool hourly electricity consumption models are presented. Chapter 3 presents a detailed model for calculating solar resources and solar PV output. The resources on tilted surface are characterized based on each month's fitted probability distributions, and 20 years of hourly tilted solar resources are predicted basted on fitted distributions. Chapter 4 provides economic feasibility model. Different parameters for analyzing the economic feasibility of any solar PV installation are discussed. A methodology to generate distributions of net present value (NPV), levelized cost of electricity (LCOE), opportunity cost (OC), and excess production cost (WP) using Monte Carlo simulation is presented. Chapter 5 describes the application of Monte Carlo simulation method for a possible PV system to be installed at METU NCC. Different cases are analyzed economically under four scenarios; constant electricity prices and demand, increasing electricity prices and demand, increasing electricity prices and constant demand, and constant electricity prices and increasing electricity demand. Chapter 6 presents the conclusions and future works.

CHAPTER 2

ELECTRICITY CONSUMPTION MODELING AND FORECASTING

This chapter illustrates different electricity demand forecasting models for Middle East Technical University Northern Cyprus Campus considering annual, monthly, daily and hourly time scale levels. A complete methodology of the data gathering, modeling and forecasting of electricity consumption is presented in this chapter. The chapter begins with the description of different types and scales of data used for modeling of electricity consumption of METU NCC. The chapter continues with the description of electricity demand or consumption models used for future predictions. Yearly models for forecasting annual trend in electricity consumption are followed by monthly model which include trend and seasonality components of electricity consumption data. Daily models based on multiple regression analysis which does not predict the increasing trend of electricity consumption is followed by a novel non-conventional model that predicts long term daily electricity consumption with trend. This model is an integration of multiple regression analysis and the trend component of Holt's method. Lastly, hourly prediction models for electricity consumption based on probabilistic characterization are presented.

2.1. Data Gathering and Management

The electricity consumption data used in this thesis is of four different time scales; yearly, monthly, daily and hourly. Yearly and monthly electricity consumption data were extracted from campus electricity bills obtained from METU NCC Administration. The annual electricity consumption, and the monthly electricity consumption data from January 2009 till December 2014 are used for annual and monthly electricity consumption prediction models.

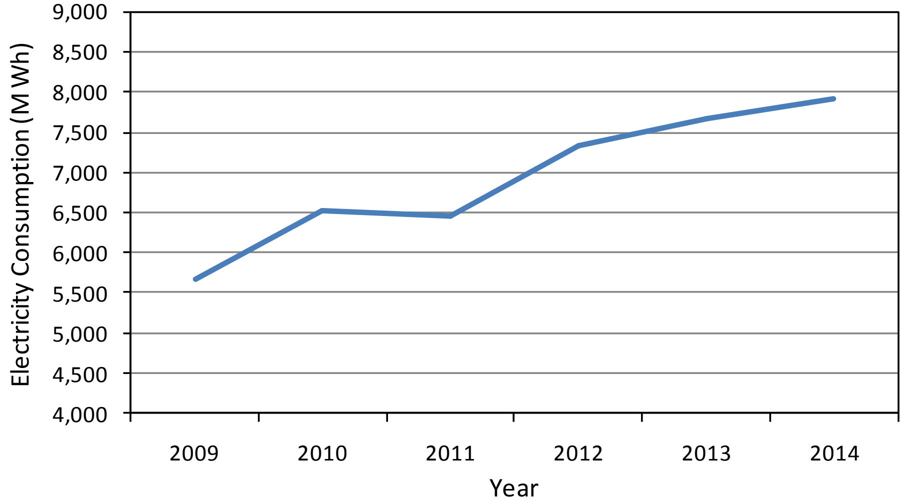

Figure 2.1 Annual electricity consumption of METU NCC

Figure 2.1 presents the annual electricity consumption, it can be inferred from the figure that there is an increasing trend. This increasing trend in electricity consumption will be addressed by the annual electricity consumption forecasting models.

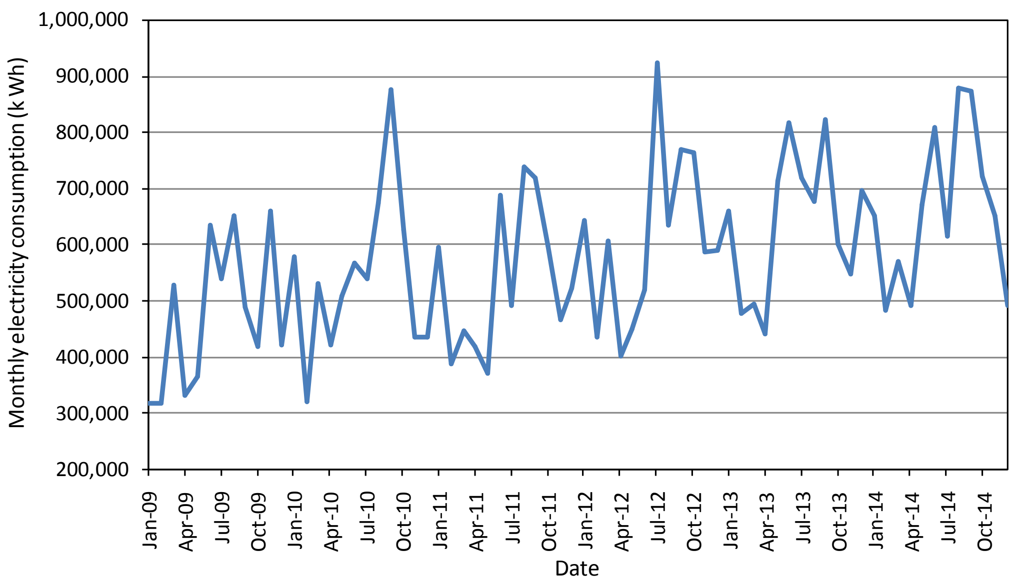

Figure 2.2 Monthly electricity consumption of METU NCC

The trend and seasonality components can be observed in monthly electricity consumption data as shown in Figure 2.2, it should be noted that during the month of September for each year considered, there is a sudden spike which is greater than the electricity consumption in rest of the months for that year. This is due to registration and orientation period when the electricity consumption increases due to orientation and registration activities of incoming students.

Hourly electricity consumption data from 1st June 2013 till 31st May 2014 is obtained from KIB-TEK. Daily consumption data is obtained by summing up the hourly electricity consumption data.

To model and forecast electricity consumption for different buildings at METU NCC, the monthly electricity consumption data for different buildings (blocks) of METU NCC was obtained from University administration. The monthly electricity consumption data obtained was from January 2009 till September 2014. METU NCC is divided into 16 different blocks; Education Facilities (Academic Block), School of Foreign Languages, Administration Building, IT Building, Health Facilities, Sports Facilities, Recreation Facilities, Dormitory 1, Dormitory 2, Dormitory 3, Residences, Cultural and Convention Center, Technical Facilities, Library, Infrastructure and Common Areas, and Guest House. Upon the analysis of the data a large number of uncertainties, errors and missing values were observed in the data. These issues increased the concern regarding the legitimacy of monthly electricity consumption data. The issues which were found are discussed below:

1. From January 2009 till December 2010 it was observed that for recreation facilities, dormitory 3, library and infrastructure and common areas electricity consumption values were missing.
2. The monthly electricity consumption values of each building (block) for January and February of year 2009 and 2010 were exactly the same, which is not possible.
3. Again the monthly electricity consumption values of each building (block) for July and August of 2009 and 2010 were exactly the same.
4. For January 2011 the electricity consumption values of all buildings (block) were missing.
5. For January 2014 and February 2014 there was no data for monthly electricity consumption for any building (block) of METU NCC.
6. Another significant issue which was found is that, from February 2011 till December 2013 the monthly electricity consumption values for each building (block) were forged. It was observed that fix percentages of total monthly electricity consumption of the campus were used to obtain building (block) wise monthly electricity consumption values. The percentages used for this purpose are given in Figure 2.3 below.

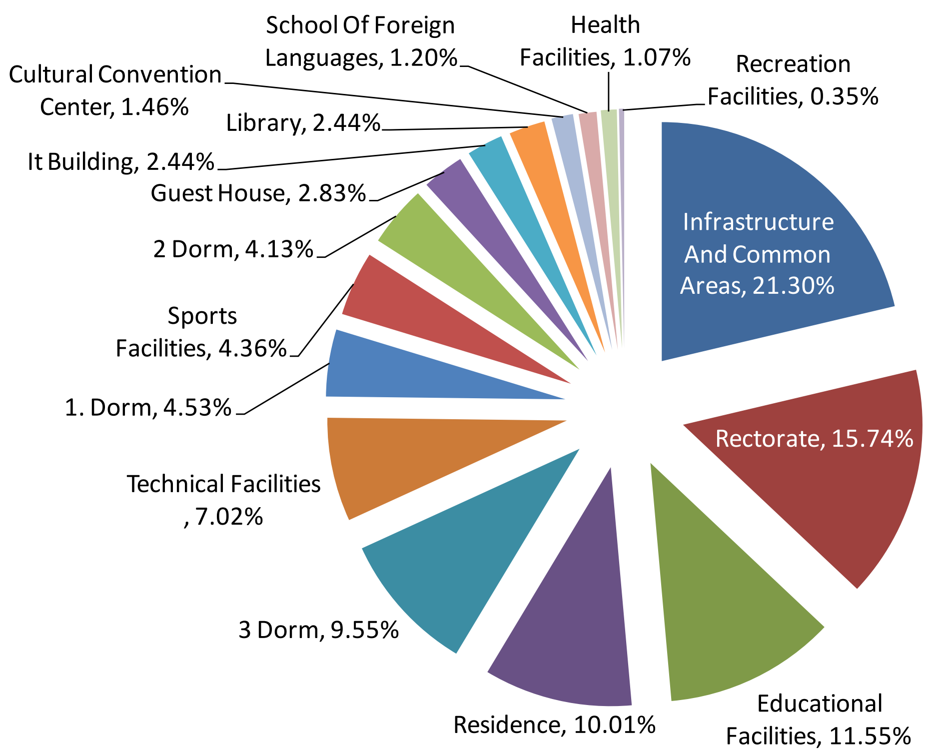

Figure 2.3 Percentages of electricity consumption at different buildings in METU NCC

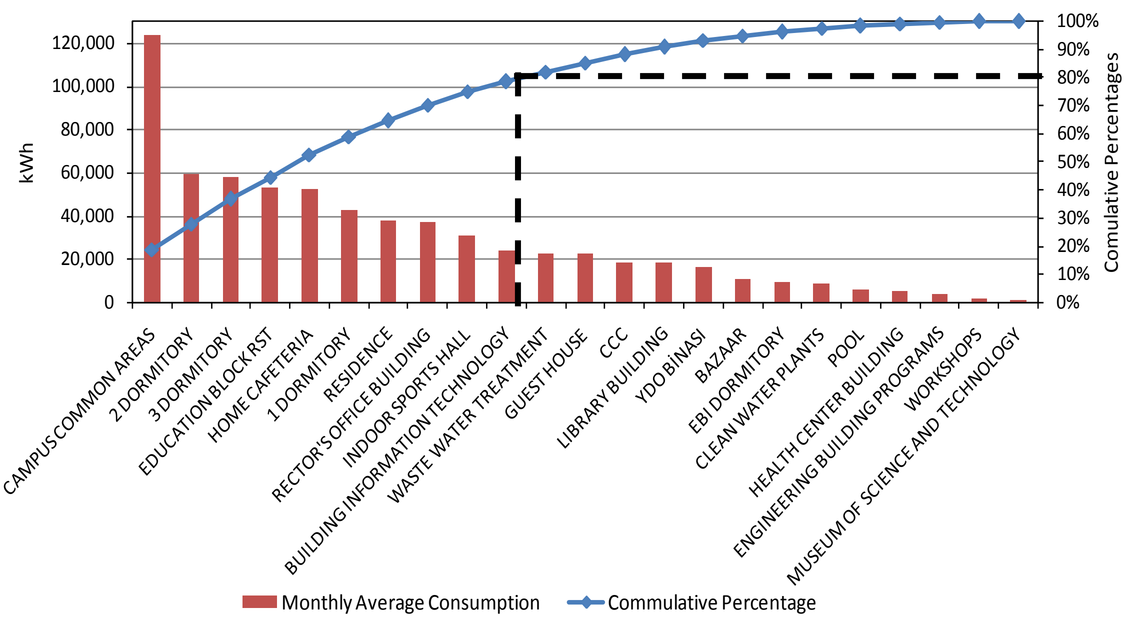

Figure 2.4 Pareto chart for building wise electricity consumption from March 2014 till September 2014 at METU NCC

Table 2.1 Cumulative consumption and percentages of different building at METU NCC

Cost Center Description	Monthly Average Consumption (kWh)	Cumulative Consumption (kWh)	Cumulative Percentage
Campus Common Areas	123,711.9	123,711.9	18.76%
2 Dormitory	59,474.3	183,186.1	27.77%
3 Dormitory	58,097.1	241,283.3	36.58%
Education Block R, S and T	52,800.0	294,083.3	44.59%
Home Cafeteria	52,085.7	346,169.0	52.49%
1 Dormitory	42,291.4	388,460.4	58.90%
Residence	37,447.0	425,907.4	64.57%
Rector's Office Building	37,280.0	463,187.4	70.23%
Indoor Sports Hall	30,657.1	493,844.6	74.88%
Building Information Technology	24,000.0	517,844.6	78.51%
Waste Water Treatment	22,422.9	540,267.4	81.91%
Guest House	22,291.4	562,558.9	85.29%
Cultural and Convention Center	18,400.0	580,958.9	88.08%
Library Building	18,285.7	599,244.6	90.86%
Preparatory School	15,885.7	615,130.3	93.26%
Market	10,254.9	625,385.1	94.82%
EBI Dormitory	9,457.1	634,842.3	96.25%
Clean Water Plants	8,748.6	643,590.9	97.58%
Pool	5,537.0	649,127.9	98.42%
Health Center Building	5,085.7	654,213.6	99.19%
Engineering Building Programs	3,814.3	658,027.9	99.77%
Workshops	1,085.7	659,113.6	99.93%
Museum Of Science And Technology	442.9	659,556.4	100.00%
Total Consumption	659,556.4		

The only period for which the electricity consumption data was correct and taken through actual readings, was from March 2014 till September 2014. Since it is a very short period, it was not feasible to develop prediction models for electricity consumption based on this monthly data. The data is used to develop Pareto analysis, which may be useful for demand side management and Green Campus Initiative of METU NCC. Pareto analysis which is also known as the 80-20 principle is a technique that can be useful in identifying those 20% of areas which can solve 80 % of the problem. In case of electricity consumption at METU NCC, 80% of it is due to campus common areas, student dormitories, academic blocks (R, S and T), Cafeteria, rectorate, residences sports center and IT block. Hence, if these key areas are managed to reduce electricity consumption significant results are possible. Table 2.1 gives the average monthly consumptions and cumulative percentages of electricity consumption for different buildings at METU NCC. Figure 2.4 shows the Pareto chart for electricity consumption at METU NCC and highlights those areas which contribute to 80% of the electricity consumption at METU NCC.

2.2. Annual Electricity Consumption Modeling and Forecasting

2.2.1. Holts Method

Also known as trend adjust exponential smoothing, this method is used when there is occasional change in the level of time series and a current level estimate is required. When the observed data have some trend and contain information that allows the prediction of future movements, a linear trend forecasting function is required. But when the data doesn't exhibit a fixed linear trend then an evolving linear trend over time is required. Holt's model allows local linear trends to be evolved in a time series.

An estimate of current slope and level is required to predict a trend in the time series. Holt's model uses different smoothing constants for level and slope. These smoothing constants helps in estimating level and slope that changes with time as new observations are available.

2.2.1.1. Data

The data used for trend adjusted exponential smoothing is obtained from university administration. Yearly electricity consumption of METU NCC from year 2009 till 2014 is used for modeling and forecasting purposes.

2.2.1.2. Model

The equations used in Holt's method are;

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{1}$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{2}$$

$$F_{t+p} = L_t + pT_t \tag{3}$$

Where;

L_t = Estimated smoothed level for period t

α = Smoothing constant for level (0-1)

Y_t = Actual value of electricity consumption in period t

β = Smoothing constant for trend (0-1)

T_t = Estimated trend value for period t

p = Periods to be forecasted into the future

F_{t+p} = Forecast of p periods into the future

Equation (1) is for estimating the level for period t, it contains a term T_{t-1}, which is the trend of previous period hence, properly updating the level for period t if a trend exists in period $t-1$. The current level L_t is calculated by weighted average of two level estimates; one estimate given by the current observationY_t, and the other estimate given by addition of previous trend $T_{\mathrm{t}-1}$ and previous smoothed level $L_{\mathrm{t}-1}$. Equation (2) is for estimating the trend for period t, using another smoothing constant β. The equation shows that the current trend T_t is the weight average of two trend estimates; one estimate is the change in level from time $t-1$ to t (i.e., $L_t - L_{t-1}$) and the other estimate is the smoothed trend for previous period $t-1$ (i.e., T_{t-1}). Equation (3) shows that the forecast for period p made at time t is calculated by multiplying the current trend T_t with the number of periods to be forecasted p and adding the product to current level L_t.

2.2.1.3. Results

The results of trend adjusted exponential smoothing model are given below. The smoothing constants for level and trend i.e. $\alpha = 0$ and $\beta = 0.19$ respectively are optimized by minimizing the mean square error value.

Table 2.2 Trend Adjusted Exponential Smoothing for METU NCC

$\boldsymbol{Year}$	$\boldsymbol{t}$	$\boldsymbol{Y_t}$ (kWh)	$\boldsymbol{L_t}$ (kWh)	$\boldsymbol{T_t}$ (kWh)	$\boldsymbol{F_t}$ (kWh)
	0		5,369,631	443,714	
2009	1	5,676,018	5,813,346	443,714	5,813,346
2010	2	6,511,175	6,257,060	443,714	6,257,060
2011	3	6,443,720	6,700,774	443,714	6,700,774
2012	4	7,327,260	7,144,488	443,714	7,144,488
2013	5	7,664,036	7,588,203	443,714	7,588,203
2014	6	7,913,593	8,031,917	443,714	8,031,917

Table 2.2 gives the actual electricity consumption (Y_t), level (L_t), trend (T_t) and forecasts (F_t) for each period (t). The actual and fitted total annual electricity consumptions from year 2009 till year 2014 for METU NCC are shown in Figure 2.5. The error summary is given in Table 2.3, with mean absolute percentage error (MAPE), mean absolute error (MAE), root mean square error (RMSE), root mean square percentage error (RMSPE) and maximum absolute percentage error (MaxAPE). With MAPE of 2.55%, the model can be considered reliable for yearly predictions. RMSPE and Max APE of 2.78% and 3.99% are also less indicating that the model in considerably accurate.

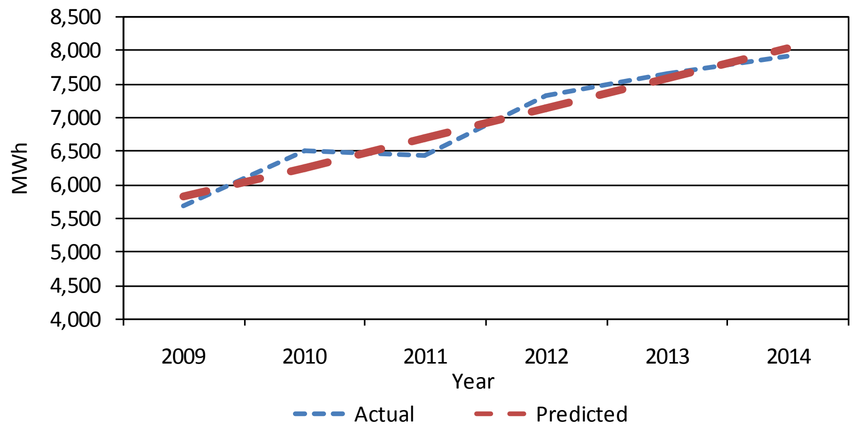

Figure 2.5 Actual and fitted annual electricity consumption using Holt's Model for METU NCC

Table 2.3 Error summary for Holt's model for annual electricity consumption predictions at METU NCC

Measurement	**Values**
MAPE	2.55%
MAE	170,904
RMSE	183,787
RMSPE	2.78%
MaxAPE	3.99%

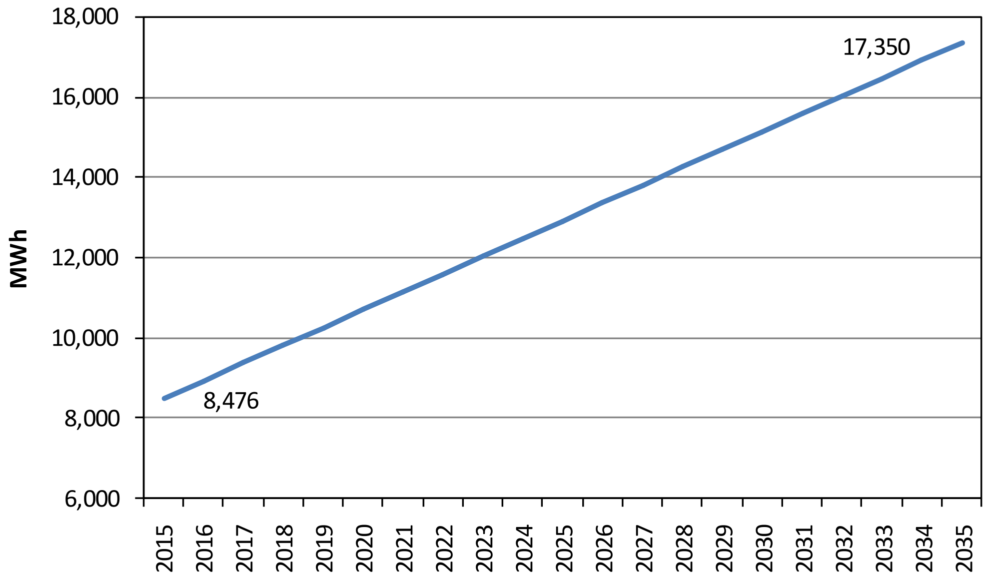

Figure 2.6 Forecast of annual electricity consumption for METU NCC using Holt's Method

Forecast from year 2015 till 2035 is shown in Figure 2.6. It is evident from Figure 2.6 that electricity consumption in year 2035 will be 17,349,914 kWh that is more than twice as compared to electricity consumption in 2014 which is 7,913,593 kWh. This forecast is based on linear growth assumption where the campus electricity consumption continues to increase every year with increasing population. It should also be noted here that the campus population will be stabilized at some point around 6,000; hence the electricity consumption will not show an increasing trend after that point.

2.2.2. Linear Regression with Population

A simple linear regression model develops a relationship between a dependent variable and an independent variable. On the basis of that relationship dependent variable values are forecasted. Here we try to develop a relationship between total annual electricity consumption and total campus population for that year.

2.2.2.1. Data

The data for total campus population for each year obtained from annual reports available on METU NCC website [28] and the total annual electricity consumption obtained from university administration from year 2009 till 2014 is used in this method.

2.2.2.2. Model

A simple linear regression model is developed with electricity consumption as dependent variable and population as independent variable. The regression model can be written as shown in Equation (4).

$$E = b_o + b_1 X \tag{4}$$

Here; E is the electricity consumption, b_o is the Y-intercept that will be obtained from regression analysis and b_1 is the slope or regression coefficient that will determine the relation between electricity consumption and population X.

2.2.2.3. Results

The regression analysis gives an R-square of 93% and adjusted R-square of 91% as shown in Table 2.4. The multiple R, R-square and adjusted R-square are the statistics obtained from the regression model. The closer these values are to 1 the better the model is in predicting the dependent variable (electricity consumption in this case).

Table 2.4 Linear regression statistics for electricity consumption at METU NCC

Observation	**Values**
Multiple R	0.96
R Square	0.93
Adjusted R Square	0.91

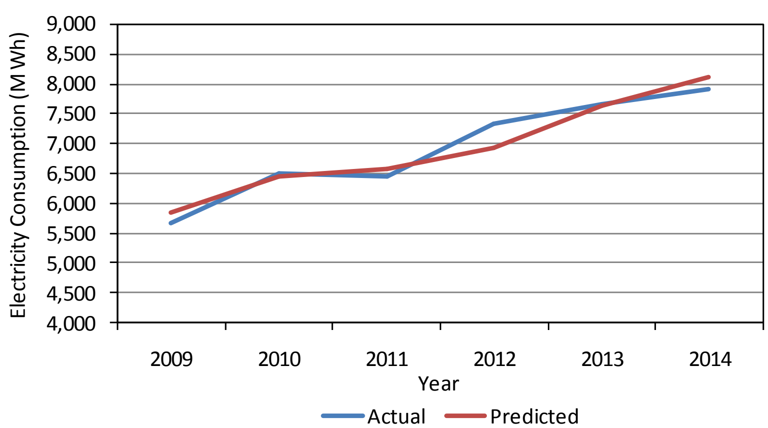

Figure 2.7 Actual and predicted annual electricity consumption using Linear Regression with population for METU NCC

The graph in Figure 2.7 shows the variation between actual and fitted electricity consumption. The error summary of the linear regression analysis is given in Table 2.5, with a MAPE of 2.4% the prediction model is reasonably accurate. Even though the observations are few in this model, it helps in understanding the relation of electricity consumption with population and the year by year changes in them. The T-statistics and P-values of regression coefficient and intercept are given in Table 2.6.

Table 2.5 Error summary for linear regression of annual electricity consumption predictions at METU NCC

Measurement	**Values**
MAPE	2.4%
MAE (kWh)	166,095.72
RMSE (kWh)	204,795.67
RMSPE	2.9%
MaxAPE	5.5%

Table 2.6 T-statistics and P-value for linear regression coefficient and intercept for electricity consumption at METU NCC

	Coefficients	**T-Stat**	**P-value**
Intercept	2,161,406.1	3.29	0.030
Population	2,540.7	7.35	0.002

The T-statistics is the ratio of coefficient of independent variable divided by its standard error. The larger this ratio is the less likely it is that the actual value of coefficient is zero, hence more certain is the impact of independent variable on dependent variable. Since the T-statistics values for the coefficient of population and for constant are large enough, they have considerable impact on the electricity consumption.

The P-value is the statistical test performed for the coefficient of each variable. A small P-value represent small probabilities, and imply that the coefficient of independent variable is not zero and is important to the regression model as it has significant impact on the dependent variable. Since the P-value of population is less than 0.05, it has a considerable impact on the electricity consumption. Equation (5) shows the relation between the annual electricity consumption of METU NCC and the average population of the campus. Considering that the campus population will keep increasing and will be stabilized at 6,000; based on Equation (5) the annual electricity consumption at that time will be around 17,405,606.1 kWh. This value is closer to the forecasted value of year 2035 in the Holt's method which is 17,349,914 kWh this means that campus population will not reach the level of 6,000 any sooner but it might reach in the year 2035.

$$Electricity\ Consumption\ (kWh) = 2{,}161{,}406.1 + 2{,}540.7 \times Population \quad (5)$$

2.2.3. Linear Regression with Year

Similar to linear regression with campus population, here linear regression with year is done. This may assist in such a way that if the campus population data is unknown then the electricity consumption can be predicted using the year value.

2.2.3.1. Data

Total annual electricity consumption from 2009 till 2014 obtained from university administration is used for testing and training this model.

2.2.3.2. Model

Similar to Section 2.2.2.2 a simple linear regression model is developed with electricity consumption as dependent variable and year number as independent variable. The regression model can be rewritten as shown in Equation (6).

$$E = b_2 + b_3 N_Y \quad (6)$$

Here; E is the electricity consumption, b_2 is the Y-intercept that will be obtained from regression analysis and b_3 is the slope or regression coefficient that will determine the relation between electricity consumption and year N_Y.

2.2.3.3. Results

The regression analysis gives an R-square of 94% and adjusted R-square of 93% as shown in Table 2.7, which means that the model presents a good fit for the dependent variable.

Table 2.7 Linear regression statistics for electricity consumption at METU NCC

Observation	Values
Multiple R	0.97
R Square	0.94
Adjusted R Square	0.93

The graph in Figure 2.8 shows the variation between actual and predicted electricity consumption.

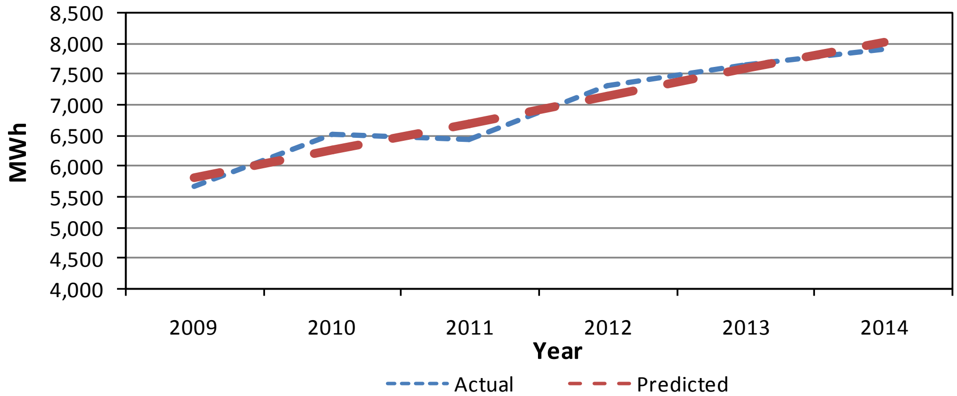

Figure 2.8 Actual and predicted annual electricity consumption using Linear Regression with year for METU NCC

Table 2.8 Error summary for linear regression of annual electricity consumption predictions at METU NCC

Measurement	Values
MAPE	2.6%
MAE (kWh)	170,904.32
RMSE (kWh)	183,787.45
RMSPE	2.8%
MaxAPE	4.0%

The error summary of the linear regression analysis is given in Table 2.8, with a MAPE of 2.6% the prediction model is reasonably accurate. Even though the observations are few in this model, it helps in understanding the relation of electricity consumption with year and the year by year changes in electricity consumption. The T-statistics and P-values of regression coefficient and intercept are given in Table 2.9. Since, the P-value of year is less than 0.05, it has a huge impact on the electricity consumption.

Table 2.9 T-statistics and P-value for linear regression coefficient and intercept for electricity consumption at METU NCC

	Coefficients	T-Stat	P-value
Intercept	-885,608,521.6	-8.18	0.001
Year	443,714.2	8.24	0.001

The forecasted electricity consumption from year 2015 till year 2035 is presented in Figure 2.9. It can be inferred from the figure that annual electricity consumption in the year 2035 will be around 17,349,918 kWh which is more than twice of the annual electricity consumption in 2015.

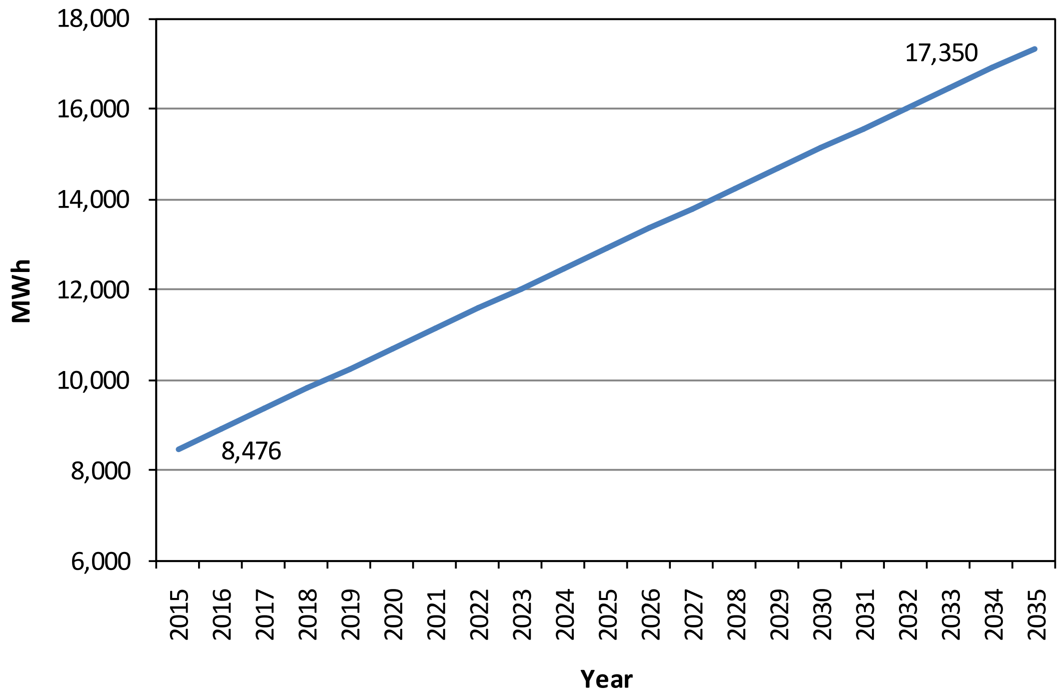

Figure 2.9 Forecasted annual electricity consumption for METU NCC using linear regression with year

2.2.4. Evaluation of Yearly Electricity Consumption Forecasting Models

For yearly electricity consumption forecasting three different models are used. The first model used is Holt's method presented in Section 2.2.1 followed by linear regression with population and linear regression with year presented in Section 2.2.2 and Section 2.2.3 respectively. All these models present comparable results with little variations in the forecasted values. The forecast generated from Holt's method for annual electricity consumption of year 2035 is 17,349,914 kWh which is very close to the forecast from linear regression with population that is 17,349,918 kWh. In the case of linear regression with population this value of annual electricity consumption is achieved when the campus population reaches around 6,000. With little variation between the forecasts of all these models, it is evident that the predictions are reliable.

2.3. Monthly Electricity Consumption Modeling

2.3.1. Winter's Method

Apart from yearly increasing trend there is seasonal component also in the electricity consumption data. These seasonal variations occur in a cycle across the time series. There may be daily, weekly or monthly seasonality factors in a time series. Until now annual electricity consumption models that only had trend component in them were discussed, this section illustrates monthly electricity consumption models that have trend as well as seasonality component in them. Also known as trend and seasonality adjusted exponential smoothing; Winter's model is an extension of Holt's model and might be better for representing the data with seasonal factor in the data. One additional equation is used to represent seasonality component in Winter's model.

2.3.1.1. Data

Monthly total electricity consumption data from January 2009 till December 2014 obtained from university administration is used for Winter's method.

2.3.1.2. Model

Winter's model can be developed using Equation (7) – Equation (10);

$$L_t = \alpha \frac{Y_t}{S_{t-s}} + (1-\alpha)(L_{t-1} + T_{t-1}) \tag{7}$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \tag{8}$$

$$S_t = \gamma \frac{Y_t}{L_t} + (1-\gamma)S_{t-s} \tag{9}$$

$$F_{t+p} = (L_t + pT_t)S_{t-s+p} \tag{10}$$

Where;

L_t = Estimated smoothed level for period t

α = Smoothing constant for level estimate (0-1)

Y_t = Actual value of electricity consumption in period t

β = Smoothing constant for trend estimate (0-1)

T_t = Estimated trend value for period t

γ = Smoothing constant for seasonality estimate (0-1)

S_t= Seasonal estimate for period t

p = Periods to be forecast into the future

s = Length of seasonality

F_{t+p} = Forecast of p periods into the future

Equation (7) gives smoothed level for period t. This is different from Equation (1) of holt's method in such a way that here Y_t is divided by S_{t-s}, which adjusts Y_t for seasonality, thus the seasonal effects are removed that might exists in Y_t. Equation (8) and (9) gives the trend and seasonality estimates respectively. The forecast is obtained using Equation (10), it is almost same as corresponding formula, Equation (3), in Holt's model for obtaining the forecast. The only difference is that here the estimate for future periods $t + p$, is multiplied by seasonal index S_{t-s+p}.

2.3.1.3. Results

The smoothing constants $\alpha = 0.004$, $\beta = 0.112$ and $\gamma = 0$ for level, trend and seasonality respectively are optimized by minimizing the value of mean square error. This approach of optimizing the smoothing constant is also novel and is not a common approach. Each month is considered as a separate season as it improves the forecasting accuracy of Winter's model in this case. Therefore, the length of seasonality (s) is taken as 12. Figure 2.10 gives the actual and fitted curves for monthly electricity consumption for METU NCC from January 2009 till December 2014.

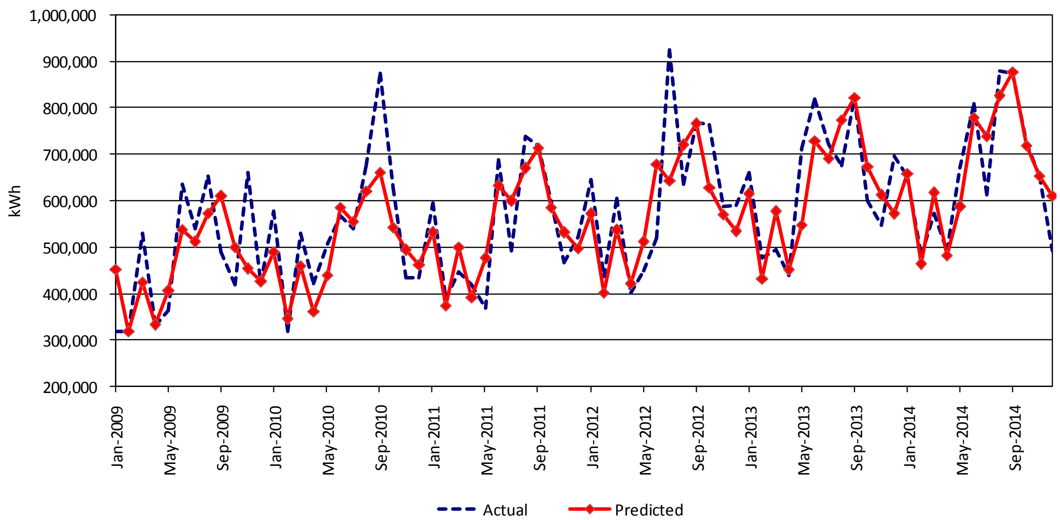

Figure 2.10 Actual and fitted monthly electricity consumption using Winter's Model for METU NCC

The error summary is given in Table 2.10, the inclusion of seasonality component decreases the forecasting accuracy but with MAPE of 11.22% the model gives reliable results.

Table 2.10 Error summary of Winter's model for monthly electricity consumption predictions at METU NCC

Measurement	**Values**
MAPE	11.22%
MAE (kWh)	64,037.27
RMSE (kWh)	84,305.49
RMSPE	14.35%
MaxAPE	42%

The monthly forecast represented by the solid black curve and trend of electricity consumption represented by the dashed black line from January 2015 till December 2020 are shown in Figure 2.11.

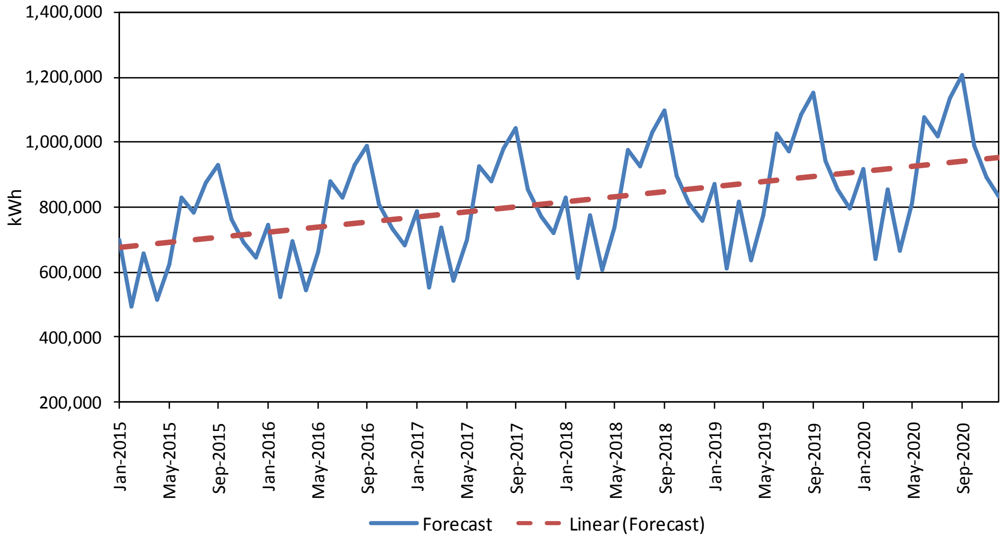

Figure 2.11 Monthly forecast of electricity consumption for METU NCC using Winter's method

2.4. Daily Electricity Consumption Modeling

2.4.1. Multiple Regression Analysis

In multiple regression analysis more than one independent variable are used for predicting a dependent variable. In simple linear regression model, the independent variable can be represented by X and the dependent variable can be represented by Y. In multiple regression models, the dependent variable is still represented by Y but the independent variables are represented by X's with subscripts or by any other symbol or letter. The mean response in multiple regression analysis is taken to be a linear function of the explanatory variables. In simple linear regression analysis the data consist of observations (X_i, Y_i) on the two variables. In multiple regression analysis the data for each case consist of an observation on each of the independent variable and on the response.

One of the most important problems in electricity demand modeling and forecasting was the presence of monthly seasonal patterns. In order to overcome this problem and improve the forecasting accuracy, separate daily regression models are developed for each month.

2.4.1.1. Data

Hourly electricity infeed data from 1st June 2013 till 31st May 2014 was collected from the utility company's SCADA system. Hourly data was converted into daily consumption data to train and test the forecasting model. A total of 12 regression models are produced each corresponding to a month. The independent variables tested in our case are taken from calendar data, meteorological data and demographic data.

2.4.1.1.1. Calendar Data

The variables that are considered in calendar data are weekdays (W), graduate and undergraduate classes and exams (GU), summer school classes and exams (SS), English preparatory school classes and exams (EPC), and the orientation and registration days (OR). The data was obtained from academic calendar available at the university website [29]. A simple 0 or 1 logic is used to incorporate these variables in the regression analysis which is discussed later in this chapter. If there is a working day then the variable is assigned a value of 1 and if there is a non-working day then the variable is assigned a value of 0.

Weekdays do not include national or other holidays, it only includes working days and non-working days that are weekends (Saturday and Sunday). The national, public and religious holidays are included in graduate and undergraduate classes and exams variable, summer school classes and exams variable and English preparatory school classes and exams variable.

The school has two semesters per year. The fall semester is the first semester and beginning of an academic year; hence the number of incoming students in fall semester is higher than that in spring semester. The fall semester classes starts from third/fourth week of September and the classes and exams end till second week of January. Since the fall semester is the start of an academic year and the number of incoming students are higher so the school organizes extensive orientation programs for incoming students usually in the second and third week of September, this is accounted for in the orientation and registration day variable. This is the reason for increased electricity consumption during the month of September as discussed earlier in Section 2.1. The spring semester then starts from second week of February and the classes and exams end till first week of June. The graduate and undergraduate class variable includes the above mentioned details as well as national, public and religious holidays, since the school is closed in these days.

The university organizes summer schools for students who wish to take additional courses during summer breaks in the month of July. Since the university is officially off and there are no graduate or undergraduate classes in summer breaks, summer schools account for most of the consumption in those months. The English preparatory school classes are organized by the university in parallel with the graduate and undergraduate classes. The university also arranges additional classes for students in July; hence the English proficiency classes are off only during the month of August and first two weeks of February.

2.4.1.1.2. Meteorological Data

The historical meteorological data is obtained from the website of Weather Underground [30]. The website provides data for Ercan airport which is at a distance of 49.3km from the campus; this can be considered sufficient for preliminary analysis and modeling. The variables used for regression analysis which is presented later in this chapter are; average temperature of the day (T_{avg}), average humidity of the day (RH), heating needs (H) and cooling needs (C).

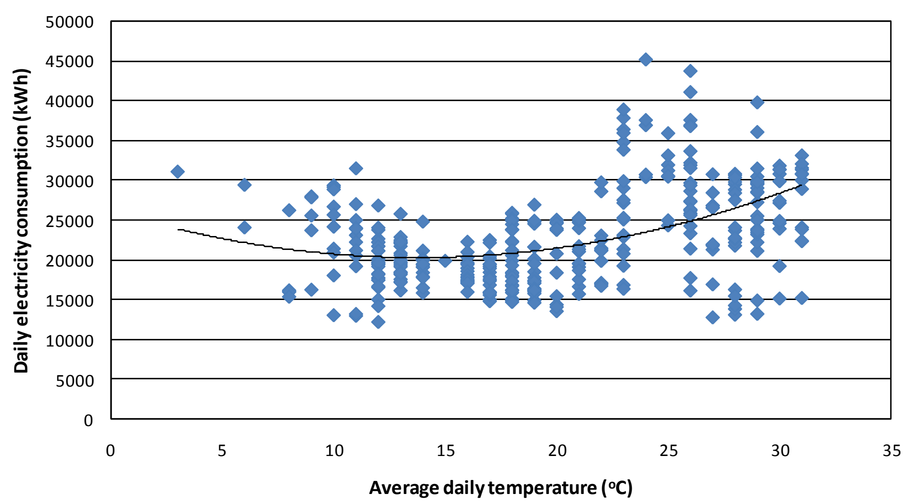

Figure 2.12 Relationship between daily electricity consumption and average daily temperature

The average daily temperature and humidity are obtained directly from the website whereas, the heating and cooling needs are calculated using Heating degree days (HDD) and Cooling degree days (CDD). In harmony of the existing literature, the relationship between the outdoor temperature and electricity consumption was found to be a U-shaped curve as shown in Figure 2.12. It can be inferred from Figure 2.12 that daily electricity consumption minimizes somewhere between average daily temperatures of 16 °C - 20 °C. For the sake of simplicity it is taken as average 18 ^{o}C (which is T_{ref}), this can be used to find HDD and CDD as shown below in Equation (11) and (12).

$$HDD = T_{ref} - T_{to} \tag{11}$$

$$CDD = T_{to} - T_{ref} \tag{12}$$

Here, T_{to} is the average outside temperature for any day. A simple 0 and 1 logic was used for incorporating heating needs H and cooling needs C in the regression analysis.

$$H = \begin{cases} 0, & HDD \le 0 \\ 1, & HDD > 0 \end{cases} \tag{13}$$

$$C = \begin{cases} 0, & CDD \le 0 \\ 1, & CDD > 0 \end{cases} \tag{14}$$

2.4.1.1.3. Demographic Data

The data for total campus population for each year is obtained from annual reports available on METU NCC website [28]. The campus population data includes total number of student registered, total number of academic staff and total number of administrative staff. This gives a rough estimate of the average campus population for a given year. Table 2.11 shows the average total population of METU NCC for a given year from 2009 till 2014.

Table 2.11 Average total population at METU NCC

Year	**Population**
2009	1452
2010	1689
2011	1736
2012	1875
2013	2151
2014	2341

2.4.1.2. Model

The regression model for each month containing the variables discussed earlier in Section 2.4.1.1 can be written as follows; for the sake of simplicity subscripts for months are not written.

$$E = K + \alpha(W_t) + \beta(GU_t) + \gamma(SS_t) + \delta(EPC_t) + \theta(OR_t) + \vartheta(T_{avg,t}) + \rho(RH_t) + \tau(H_t) + \psi(C_t) + \epsilon_t \quad (15)$$

Here; subscript t represents the day of a particular month, K is the constant term and α, β, γ, δ, θ, ϑ, ρ, τ, and ψ are the regression coefficients and ϵ_t is the residual term. The regression coefficients are generated automatically by the software packages, Microsoft Excel is used for this purpose.

2.4.1.3. Results

The results of all the regression models for each month are discussed below. The coefficients of significant variables are given in Table 2.12 for each month, at 5% significance level. The coefficients for weekdays suggest that they have a strong positive impact on the electricity consumption.

Table 2.12 Regression coefficients of significant variables for METU-NCC

	α	β	γ	δ	ϑ	ρ	θ	τ	ψ	K
June	6382.3	5818.5	2855.6	-1200.2	759.2	-63.4	0	0	0	4404.9
July	6050.0	0	0	1044.8	413.2	10.6	0	0	0	10669.3
August	8606.0	0	5529.5	0	1129.3	52.5	0	0	0	-19980.7
September	7249.6	10964.7	0	-3730.5	-768.8	-8.7	12987.9	0	0	41141.4
October	-2866.4	9250.4	0	0	619.7	188.5	0	0	0	-889.1
November	3151.2	7779.0	0	-7153.5	487.8	-82.4	0	0	0	16035.3
December	5079.9	0	0	0	-664.8	-39.8	0	0	0	30949.9
January	-3795.8	1265.4	0	5363.6	-210.7	39.7	0	0	0	19280.2
February	2450.7	730.4	0	733.6	257.2	57.8	0	0	0	7757.7
March	2054.6	0	0	0	-266.2	28.8	0	0	0	19182.8
April	1495.6	697.8	0	0	-190.9	-21.4	0	0	0	19577.7
May	2774.7	2583.9	0	-2817.1	2540.1	80.9	0	2115.9	-4963.3	-35400

For only January and October the coefficients of weekdays are negative due to incoming students behavior. October is more or less the start of an academic year, and hence the electricity consumption during weekends is more than during weekdays as it is the settling period of the newly enrolled students. In January the university has final exams for the first semester of an academic year. Hence, the electricity consumption of dormitories, library and increases during weekend as compared to weekdays. As thought the effect of graduate and undergraduate classes on the electricity consumption is positive. It is zero for the months of July and August as there are no classes during these months. And for the months of December and March it is zero because they have the same input values of zero and ones as weekdays due to no other holidays, and the regression analysis gives error if two input variable are same. Summer schools also have a positive effect on the electricity consumption. Summer schools are open during the months of June, July and August.

The coefficient for the month of July is zero because summer school has same set of input zeros and ones as the weekdays. Orientation and registration has a strong positive impact on the electricity consumption. Average outside temperature has both positive and negative effect on the electricity consumption. When the outside weather is cold or hot, the electricity consumption increases due to heating or cooling. But the consumption decreases, when the temperature is between 17^{o}C – 24^{o}C. Average outside humidity does not have a huge impact on the consumption but it is added in the models to improve the prediction accuracy. Heating and cooling needs also bring no considerable improvement in the accuracy of models except for the month of May when the outside temperature conditions are between 17^{o}C – 26^{o}C and weather starts to get warmer day by day.

Table 2.13 P-values of regression coefficients and intercept for METU-NCC

	W	**GU**	**SS**	**EPC**	**T_{avg}**	**RH**	**OR**	**H**	**C**	**K**
June	9×10^{-7}	1×10^{-7}	0.013	0.283	4×10^{-5}	0.136	-	-	-	0.365
July	4×10^{-5}	-	-	0.374	0.056	0.696	-	-	-	0.138
August	2×10^{-17}	-	4×10^{-10}	-	1×10^{-6}	0.022	-	-	-	0.001
September	7×10^{-5}	0.011	-	0.312	0.102	0.918	5×10^{-9}	-	-	0.009
October	0.066	2×10^{-7}	-	-	0.015	0.001	-	-	-	0.852
November	0.053	3×10^{-5}	-	0.002	0.004	0.004	-	-	-	0.000
December	5×10^{-7}	-	-	-	8×10^{-6}	0.266	-	-	-	0.000
January	0.001	0.119	-	7×10^{-5}	0.409	0.468	-	-	-	0.001
February	0.001	0.394	-	0.473	0.121	0.055	-	-	-	0.001
March	5×10^{-6}	-	-	-	6×10^{-4}	0.050	-	-	-	0.000
April	0.036	0.296	-	-	1×10^{-3}	0.144	-	-	-	0.000
May	0.225	0.384	-	0.436	7×10^{-8}	0.307	-	0.386	0.029	0.001

The P-values for all the regression coefficients are shown in Table 2.13. If P-value is less than 0.05 it means that the predicting variable has significant impact on the regression analysis and improves the model accuracy. If P-value is higher than 0.05, it means null-hypothesis showing that predicting variable has no effect on the response variable (or in our case the electricity consumption). The regression coefficients with P-value higher than 0.05, don't improve the modeling accuracy considerably.

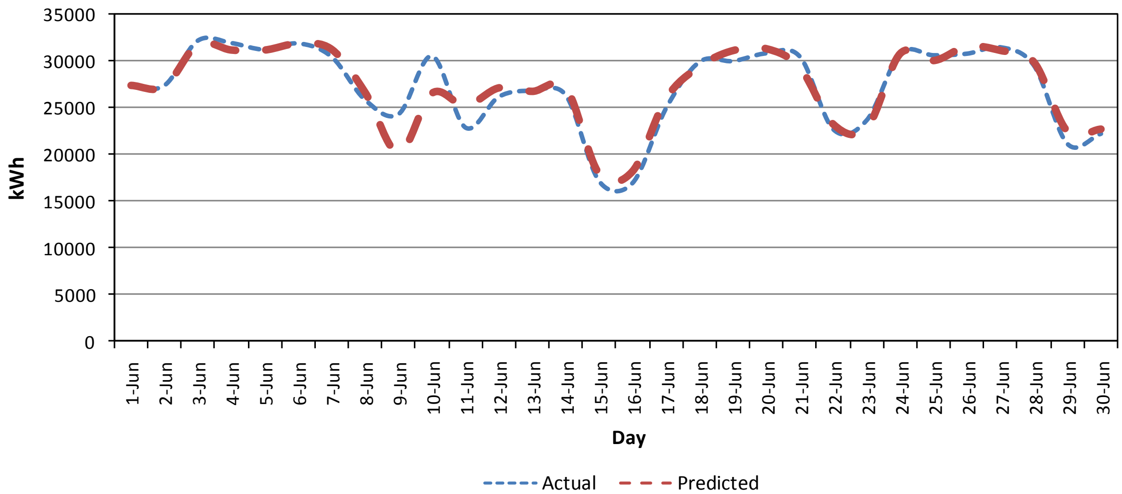

Figure 2.13 Actual and predicted consumption for June, 2013 at METU-NCC

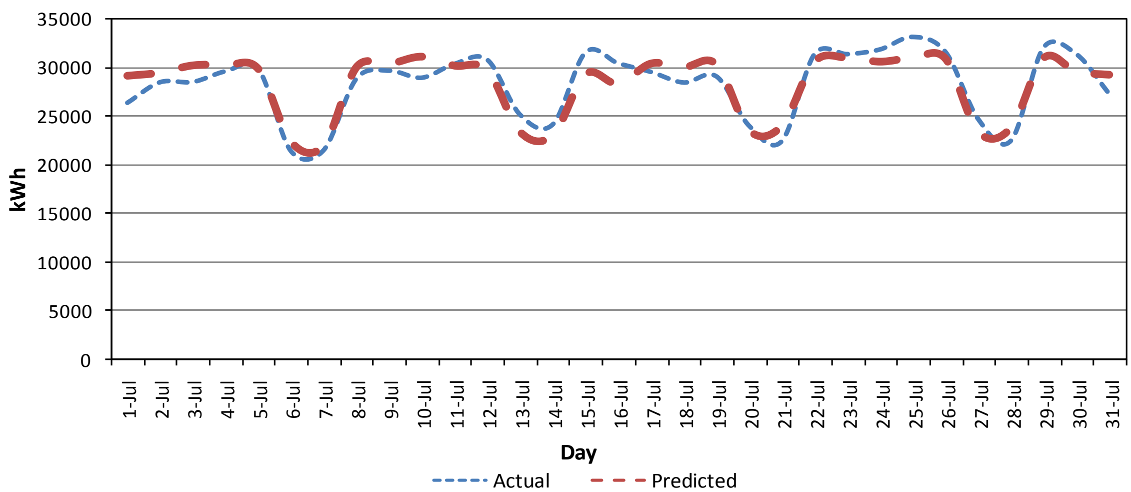

Figure 2.14 Actual and predicted consumption for July, 2013 at METU-NCC

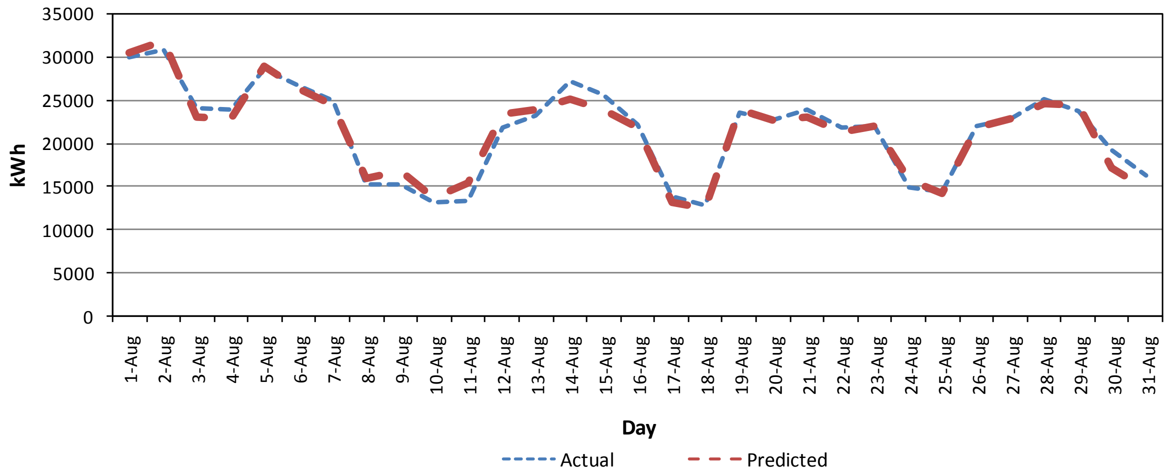

Figure 2.15 Actual and predicted consumption for August, 2013 at METU-NCC

Figure 2.13 to Figure 2.15 shows the fitted and actual daily electricity consumption for the back forecasts of each month from June, 2013 till August, 2013.

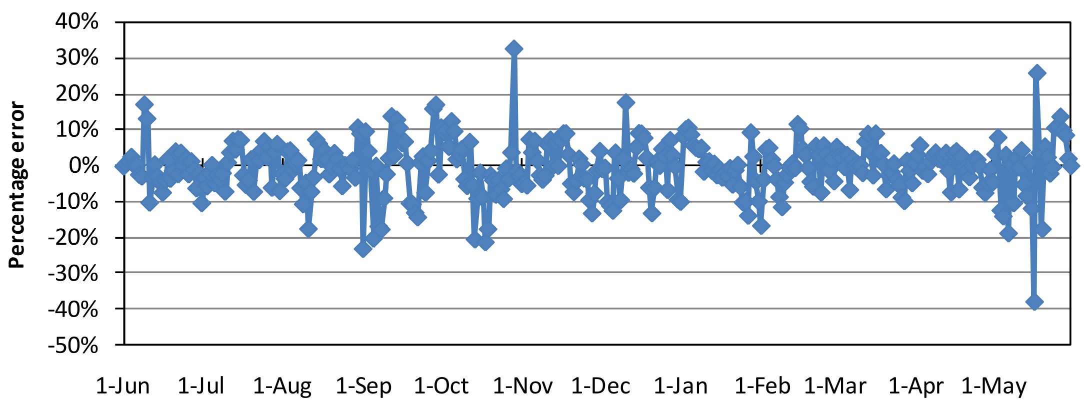

Figure 2.16 Percentage error of the multiple regression models for METU-NCC

It can be inferred from Figure 2.16 that the percentage errors are mostly varying from -15% to +15%, with only 29th Oct., 2013 at 32.59%, and 17th and 18th May, 2014 varying around -+30%. The R-square of the monthly regression models vary from 66% to 96% that makes them reasonably reliable for planning purposes of new facilities installations.

The Multiple R, R-square and adjusted R-square values for all the models are given in Table 2.14. The mean absolute percentage error (MAPE), mean absolute error (MAE), root mean squared error (RMSE), root mean squared percentage error (RMSPE), and maximum absolute percentage error (MaxAPE) values are given in Table 2.15. The MAPE for our back forecasts from June 2013 till May 2014 is 5.36%, which is quite low hence showing the reliability of our forecasting model.

Table 2.14 Regression Statistics for METU-NCC

	Multiple R	**R - Square**	**Adjusted R-Square**
June	0.95	0.90	0.88
July	0.91	0.83	0.80
August	0.98	0.96	0.95
September	0.92	0.86	0.82
October	0.88	0.78	0.75
November	0.87	0.76	0.70
December	0.88	0.77	0.74
January	0.87	0.75	0.70
February	0.91	0.82	0.78
March	0.81	0.66	0.62
April	0.88	0.78	0.75
May	0.91	0.83	0.78

Table 2.15 Summary of errors of regression models

Measurement	**Values**
MAPE	5.36%
MAE (kWh)	1,206.42
RMSE (kWh)	1,658.81
RMSPE	7.35%
MaxAPE	37.83%

2.4.2. Long Term Daily Electricity Consumption Modeling

For PV sizing daily electricity consumption should be predicted in order to achieve day by day supply and demand matching. Earlier models were based on yearly, monthly and daily demand. But the daily demand model (i.e. the multiple regression analysis) as presented in Section 2.4.1 does not account for an increasing trend in the electricity consumption due to unavailability of long term daily electricity consumption data of more than 5 years. In order to incorporate this increasing trend in electricity consumption, Holt's method is integrated with multiple regression analysis.

2.4.2.1. Data

This model depends upon the output of Holt's method and the output of multiple regression analysis. Holt's method uses annual electricity consumption data to predict the annual trend in electricity consumption. On the other hand, multiple regression analysis uses daily electricity consumption data and different predicting variables as discussed in Section 2.4.1.1 to generate forecast for daily electricity consumption. Annual electricity consumption data from 2009 till 2014 and daily electricity consumption data from 1st June 2013 till 31st May 2014 are used in this model.

2.4.2.2. Model

This model is a simple integration of Holt's method and multiple regression method. The trend estimate obtained from Holt's method is added to the output generated from multiple regression method. Since the annual increasing trend in electricity consumption is not incorporated in multiple regression method, therefore its output may be considered as a simple level estimate.

The equations used in this model are as follows;

$$F_{t+p} = E_t + pD_t \tag{16}$$

$$D_t = T_t/365 \tag{17}$$

Where;

F_{t+p} = Forecast of p periods into the future

E_t = Output of multiple regression method, taken as smoothed level estimate for period t.

p = Periods or years to be forecasted into the future

D_t = Trend estimate for daily change after each period or year p

T_t = Estimated trend value for period t

Equation (16) gives daily forecast by adding up the smoothed level E_t obtained from multiple regression method and the daily trend D_t obtained by dividing annual trend T_t by the number of days in a year as shown in Equation (17). It should be noted that E_t is obtained from Equation (15) of multiple regression analysis and T_t is obtained from Equation (2) of Holt's method.

2.4.2.3. Results

The model is divided into two parts, the first is the trend estimate which comes from Holt's method presented in Section 2.2.1 and the second part is the level estimate obtained from multiple regression analysis presented in Section 2.4.1. The predicted annual trend in electricity consumption considering 2014 as the base year is shown in Figure 2.17. This annual trend is converted to daily trend using Equation (17) and is shown in Table 2.16.

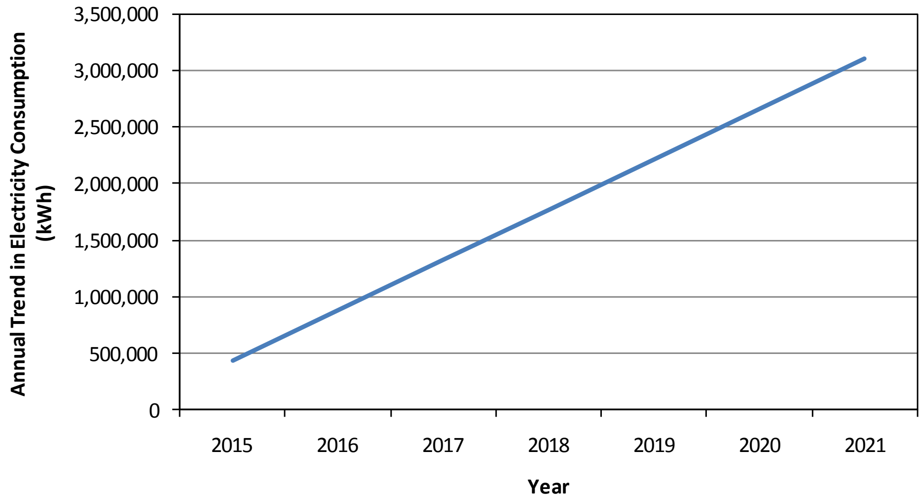

Figure 2.17 Annual increasing in electricity consumption with respect electricity consumption of 2014

Table 2.16 Annual and daily increasing trends in electricity consumption

Year	Annual increase in electricity consumption (kWh)	Daily increase in electricity consumption (kWh)
2015	443,714	1,215.7
2016	887,428	2,431.3
2017	1,331,142	3,647.0
2018	1,774,856	4,862.6
2019	2,218,570	6,078.3
2020	2,662,284	7,293.9
2021	3,105,998	8,509.6

As shown in Table 2.16 any day of the year 2016 will consume 2,431.3 kWh of electricity more than any day of the year 2014 hence, assuming that the annual increase in every year's electricity consumption is divided equally among all days of the year. This assumption may be considered valid due to unavailability of long term daily electricity consumption data because of which annual trend is used for estimating daily trend.

The level estimate comes from multiple regression analysis as shown in Section 2.4.1. These daily level estimates are added up with daily trend to generate daily electricity consumption forecasts with increasing trend as show in Figure 2.18. The blue line shows the daily electricity consumption forecasts whereas the black dashed line shows the increasing trend in electricity consumption each year.

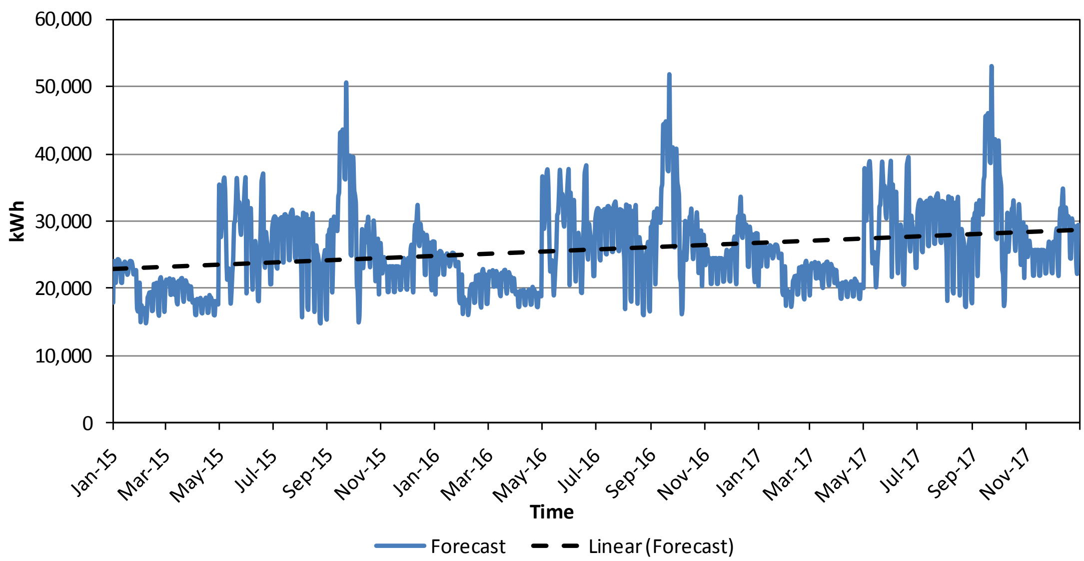

Figure 2.18 Long term daily electricity consumption forecast

2.5. Hourly Electricity Consumption Modeling

2.5.1. Probabilistic Characterization

In a grid connected solar PV system hourly electricity demand and supply matching is very important for the grid stability. Moreover, for analyzing the feasibility of any solar PV system it is necessary to have hourly electricity consumption data that can be used to obtain hourly shortages or excess supply of electricity. In this section hourly electricity consumption is predicted based on probabilistic characterization of daily electricity consumption data and average hourly electricity consumption percentages.

2.5.1.1. Data

The data used here are hourly electricity consumption data obtained from KIB-TEK's SCADA system from 1st June 2013 till 31st May 2014.

2.5.1.2. Model

The probability density function (pdf) of daily electricity data for each month is calculated and fitted into known probability distributions like Normal, Weibull and Extreme Value. Based on the best fit, for each month the parameters of fitted distribution are calculated. The pdfs of Normal, Weibull and Extreme value distributions are given in Equation (18) – (20) respectively.

$$f(x;\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{18}$$

$$f(x;a,b) = ba^{-b}x^{b-1}e^{-(\frac{x}{a})^b}, x \geq 0 \tag{19}$$

$$f(x;\mu,\sigma) = \sigma^{-1}e^{(\frac{x-\mu}{\sigma})}e^{-e^{(\frac{x-\mu}{\sigma})}} \tag{20}$$

Equation (18) represents the Normal distribution where pdf is dependent on mean (μ) and standard deviation (σ) of the data. Equation (19) represents pdf for a Weibull distribution, where associated parameters are scale parameter (a) and shape parameter (b). The pdf for Extreme Value distribution is given in Equation (20), where the associated parameters are location parameter (μ) and scale parameter (σ).

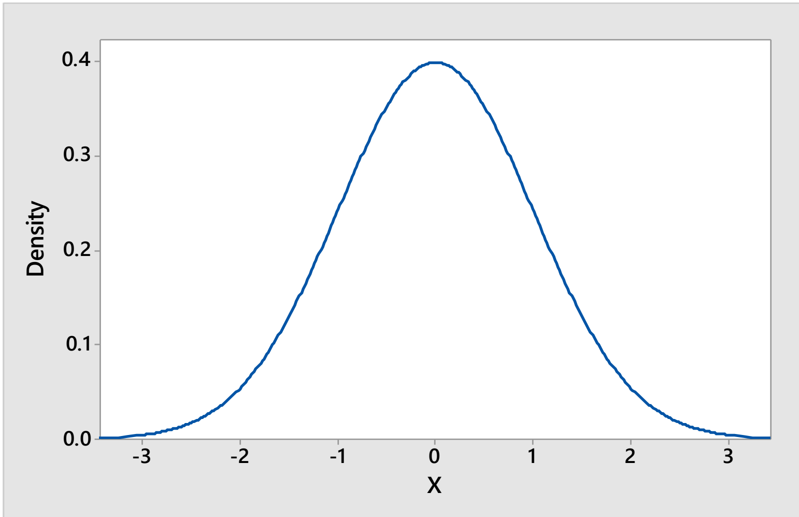

Figure 2.19 Standard normal probability density function with mean = 0 and standard deviation = 1

Normal distribution is the most common and most widely used distribution in statistics. Also known as the bell curve the probability density function of normal distribution is shaped like a bell as shown in Figure 2.19. Weibull distribution is another continuous distribution used commonly in statistics. Its density function changes very drastically with the changes in shape parameter as shown in Figure 2.20. Extreme value distribution is used as a limiting distribution for the maximum or minimum of a data set. The effect on density function of extreme value distribution due to variation in scale parameter is shown in Figure 2.21.

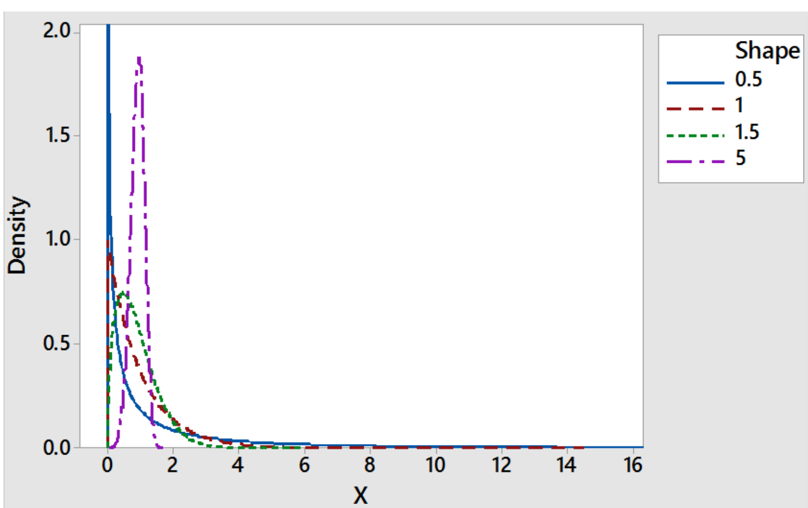

Figure 2.20 Probability density function of Weibull distribution for varying b and fixed a = 1

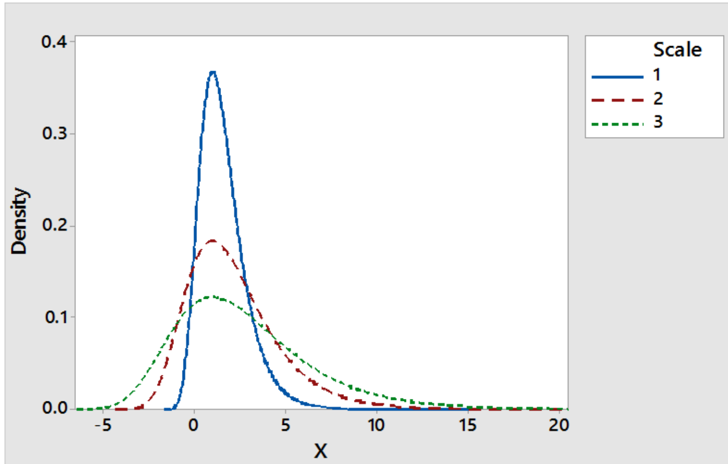

Figure 2.21 Probability density function of Extreme Value distribution with varying scale parameters

After identifying the probability distributions for each month which best fits the data, the associated parameters are calculated for each month's pdf. For months where Extreme Value distribution presents the best fit, the location parameter (μ) and scale parameter (σ) are calculated. Similarly, for month's which have Normal or Weibull distributions, their respective associated parameters are estimated. After finding each month's pdf and associated parameters, random data for daily electricity consumption is generated. In order to convert this daily electricity consumption data generated by probabilistic characterization to hourly electricity consumption data, it is multiplied by the average hourly electricity consumption percentages as shown in Equation (21).

$$E_H = E_D \times HECP_{i,k} \qquad (21)$$

$$HECP_{i,k} = \frac{TEC_{i,k}}{TEC_k} \qquad (22)$$

Where;

E_H = Hourly electricity consumption

E_D = Daily electricity consumption data generated as random data through probabilistic characterization

$HECP_{i,k}$ = Average hourly electricity consumption percentages for the hour i of month k.

$TEC_{i,k}$ = Total electricity consumption during hour i for the entire month k.

TEC_k = Total electricity consumption during the entire month k.

The Average hourly percentages of electricity consumption for each month are calculated separately. Equation (22) shows that average hourly percentage for any hour are calculated by dividing the total electricity consumption during that hour of the month by the total electricity consumption during the whole month. Now, Equation (21) gives the hourly electricity consumption data based on probabilistic characterization of each month's electricity consumption.

2.5.1.3. Results

For each month the probability distribution which best fits the daily electricity consumption data is identified by comparing their P-values and Anderson-Darling statistic (AD) values. P-values represent how good the data fits the distribution. A high P-value means a good fit whereas a low P-value (for example P-value < 0.05) means the data don not follow the distribution. AD is a statistical test which also helps in identifying the probability distribution which best fits the data. The Lower the AD value is, the better the fit is. On comparison the distribution with lowest AD value gives best fit. The P-values and AD values are automatically calculated by Minitab for any specified distributions that are to be tested to find the best fit for each month. Software package Minitab 17 is used for identifying the probability distributions that best fit to the electricity consumption data of each month.

Table 2.17 AD and P-values of different distributions for each month's electricity consumption data

	Normal Distribution		**Weibull Distribution**		**Extreme Value Distribution**	
Months	**P-value**	**AD**	**P-value**	**AD**	**P-value**	**AD**
January	0.067	0.683	>0.250	0.358	>0.250	0.316
February	0.076	0.659	0.225	0.483	>0.250	0.415
March	0.537	0.31	0.167	0.545	0.075	0.672
April	0.505	0.328	>0.250	0.265	>0.250	0.272
May	0.01	1.03	<0.01	1.065	0.217	0.492
June	0.006	1.094	0.01	0.997	0.019	0.908
July	<0.005	1.142	0.041	0.773	0.129	0.585
August	0.011	0.992	0.024	0.861	0.085	0.649
September	0.104	0.607	0.114	0.599	0.099	0.617
October	<0.005	1.222	<0.010	1.587	0.063	0.7
November	0.067	0.683	0.021	0.892	1.007	<0.01
December	0.637	0.275	>0.250	0.457	>0.250	0.332

Table 2.17 shows the P-values and AD values for Normal, Weibull and Extreme value distributions tested for electricity consumption data of each month. From the Table 2.17 it can be inferred that for January the AD is lowest for Extreme Value distribution and P-value is greater than 0.25 hence it presents better fit than other distributions. Also for February the Extreme value distribution has least AD and its P-value is also greater than the other two distributions hence it gives the best fit. In case of March, Normal distribution is the best for representing the electricity consumption data because its AD is less than the other two distributions and its P-value is also higher. Figure 2.22 - Figure 2.24 presents the probability plots of the selected probability distributions for January, February and March based of best fits. Figure 2.22 shows that all the data points of daily electricity consumption for the month of January are within the 95% confidence interval of estimated Extreme Value cumulative distribution curve. Similarly, Figure 2.23 and Figure 2.24 show that all the data points of electricity consumption in the months of February and March are within the confidence interval of Extreme Value and Normal cumulative distribution curves respectively.

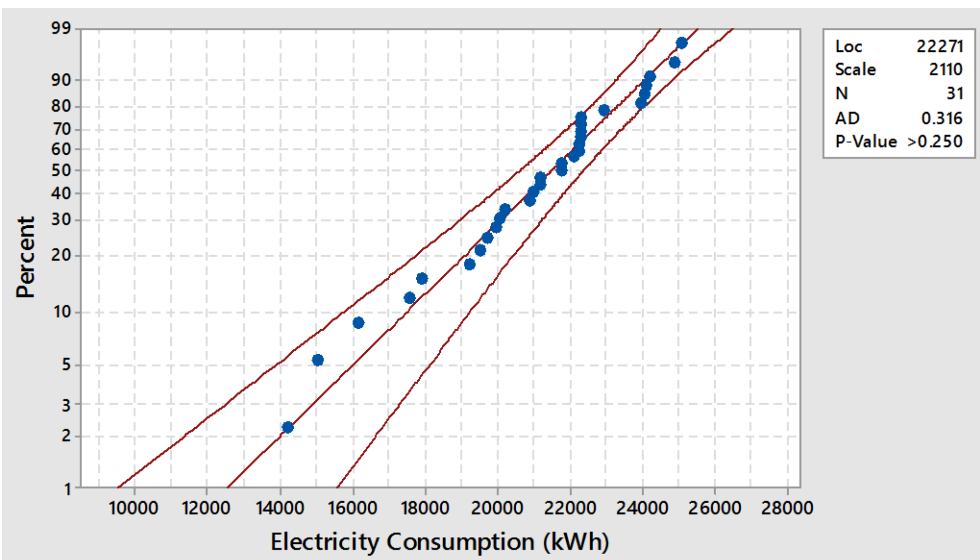

Figure 2.22 Fitted Extreme Value distribution for electricity consumption data of January

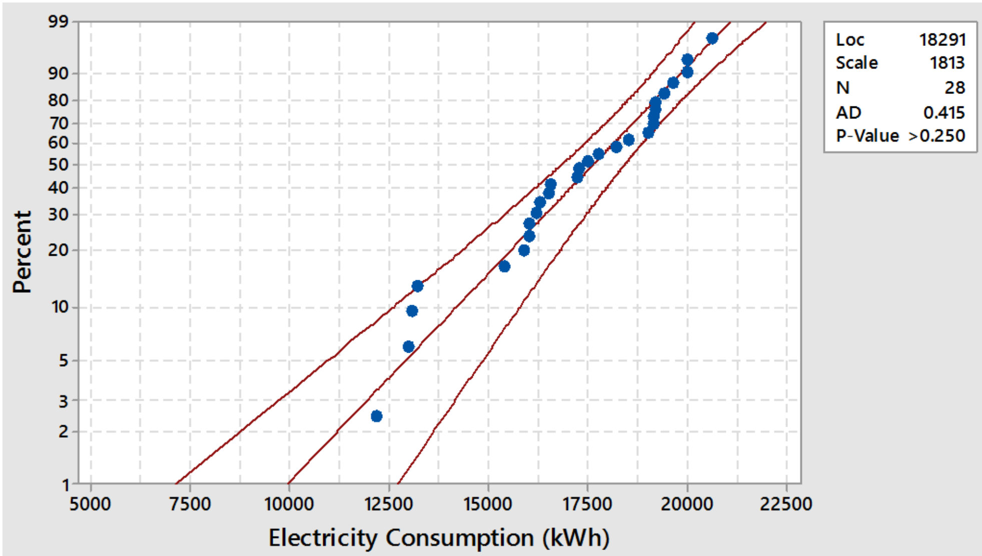

Figure 2.23 Fitted Extreme Value distribution for electricity consumption data of February

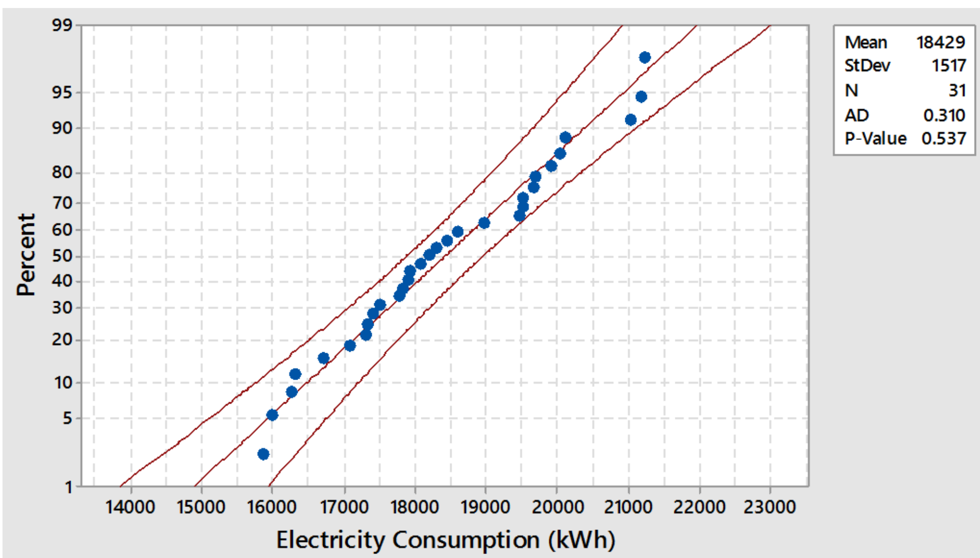

Figure 2.24 Fitted Normal distribution for electricity consumption data of March

After identifying the probability distributions that best fit the daily electricity consumption data for each month, the associated parameters for all the probability distribution are estimated. The estimated parameters for selected probability distributions for each month are given in Table 2.18.

Table 2.18 Associated parameters of identified distributions for each month's electricity consumption data

	Normal Distribution		Weibull Distribution		Extreme Value Distribution	
Months	**Mean**	**Std. Dev.**	**Shape**	**Scale**	**Location**	**Scale**
January	-	-	-	-	22271	2110
February	-	-	-	-	18291	1813
March	18429	1517	-	-	-	-
April	16370	1234	-	-	-	-
May	-	-	-	-	19054	4292
June	-	-	-	-	29199	2993
July	-	-	-	-	29845	2558
August	-	-	-	-	23940	4524
September	-	-	4.801	34480	-	-
October	-	-	-	-	20862	3700
November	21926	2679	-	-	-	-
December	24650	3796	-	-	-	-

After calculating the associated parameters of each month's fitted distribution, random data of daily electricity consumption is generated for 20 years. The random data generated for daily electricity consumption do not have yearly increasing trend, it may be considered as a simple level estimate of daily electricity consumption for 20 years. In order to incorporate the yearly increasing trend, the daily trend value D_t calculated in Equation (17) is added to the random data generated for daily electricity consumption. The random data can be easily generated using MATLAB. The random data of daily electricity consumption is then multiplied with each month's average hourly consumption percentages to obtain hourly electricity consumption data for 20 years. The average hourly percentages of electricity consumption during the day time for the months of January, February and March are shown in Figure 2.25 – Figure 2.27. Since storage is not considered for PV systems therefore hourly electricity consumption of day time is predicted using this model as night time consumption cannot be fulfilled without storage.

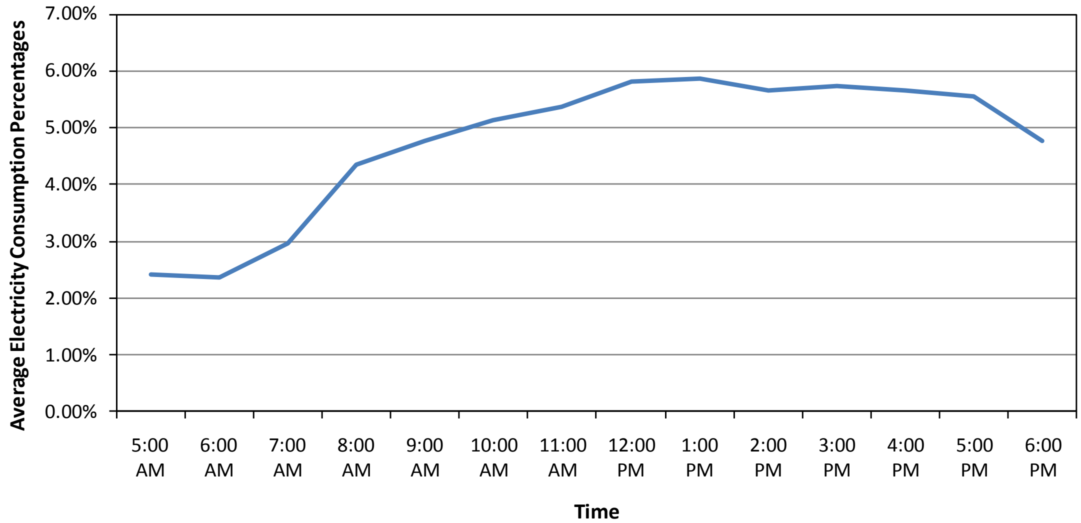

Figure 2.25 Average hourly electricity consumption percentages during the day time for January

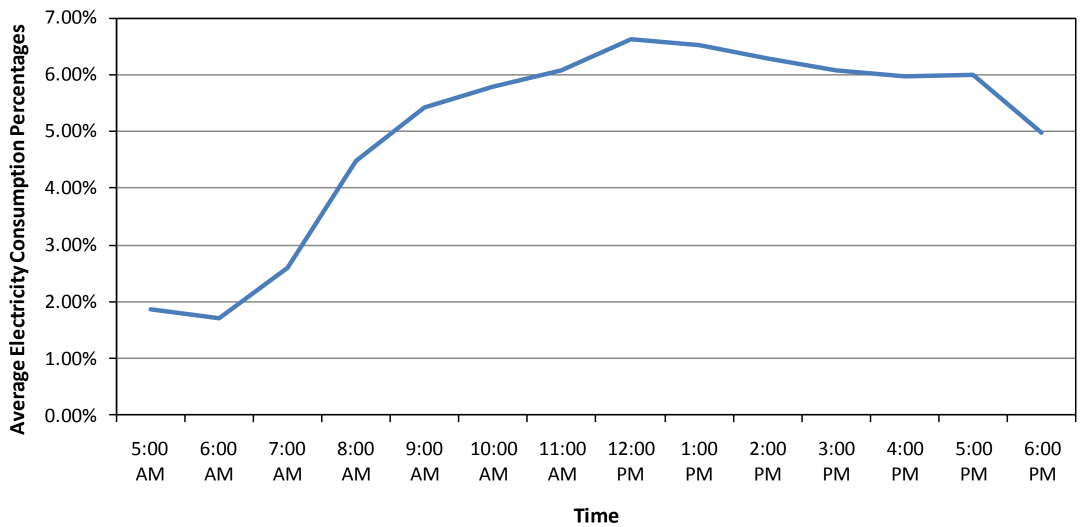

Figure 2.26 Average hourly electricity consumption percentages during the day time for February

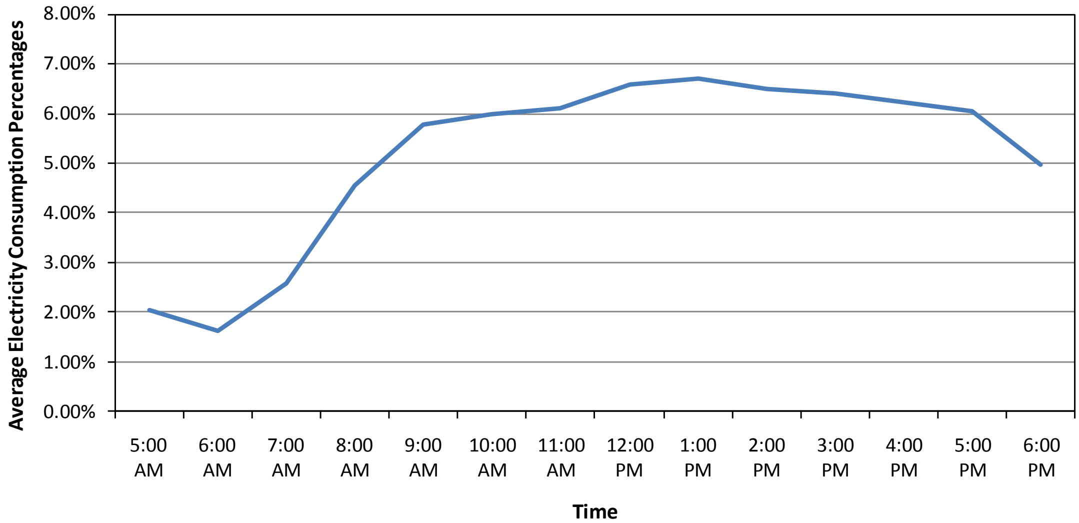

Figure 2.27 Average hourly electricity consumption percentages during the day time for March

2.6. Electricity Consumption Model Used in Simulation

In this chapter electricity consumption forecasting models of different time scales are presented. First annual electricity consumption models are presented that can be used for forecasting annual trends then monthly electricity consumption models are presented that can be used to analyze the monthly seasonal patterns in the electricity demand. This is followed by more detailed daily forecasting models for electricity consumption. At last hourly models are presented. Hourly models are based on probabilistic characterization of daily electricity consumption data and average hourly percentages of electricity consumption. Only day time electricity consumption is considered in hourly forecasting models because of no storage in the solar PV systems. Due to unavailability of storage night time demand cannot be fulfilled with solar PV systems. The Monte Carlo simulation model, used for analyzing the feasibility of solar PV systems that is presented in Chapter 4, considers hourly forecasting models for electricity consumption. Hourly forecasting models are considered because grid stability depends upon hourly demand and supply matching.

CHAPTER 3

SOLAR RESOURCE MODELING AND FORECASTING

As discussed earlier in Section 1.6 the intermittent nature of solar resources affects the usage of solar PV for electricity generation. Solar irradiation depends upon variety of factors such as climatic conditions, position of sun in the sky and orientation of PV panels etc, due to its high variability there exist a risk of grid failure. Energy storage systems with solar PV power plants are a good solution for improving grid stability but this increases the cost significantly. Another way to improve grid stability will be to have accurate forecast of output from PV systems and to incorporate uncertainties in the solar resources during the design or planning phase of solar PV power plant, this chapter presents a methodology based on the later approach. The chapter begins with an explanation on how solar resource data are gathered, followed by solar resource model to calculate the solar resources on tilted surface. Then, a solar resource prediction model is presented to forecast solar resources on tilted surface considering uncertainties in them. The last part of this chapter presents a simple model to calculate the amount of electricity generated from solar PV power plant based on solar resources forecasted.

3.1. Solar Resource Data

In order to calculate the amount of energy produced by solar PV system, hourly solar resource data is needed as an input. Measurements of the global horizontal irradiance and the direct normal irradiance are being made on-campus. In this study the actual hourly solar resource data from 1st June 2013 till 31st May 2014 is used for solar resource model. Average irradiance is being archived for every 10 minutes. This is averaged over an hour and repeated for the whole year to convert it into hourly data.

3.2. Solar Resource Modeling

The amount of solar energy received by the earth surface depends on the solar geometry that defines the position of sun in the sky and the angle with which solar radiations strike the earth surface. The equations presented here for solar resource model are taken from Duffie and Beckman [31].

Hour angle (ω), as shown mathematically in Equation (23) is the hourly angular displacement of the sun in a day by 15° per hour East or West.

$$\omega = (solar\ time - 12) \times 15° \tag{23}$$

The solar time in Equation (23) is different from standard time and is represented mathematically by Equation (24).

$$Solar\ time - Standard\ time = \frac{1}{60}\{4(L_{st} - L_{loc}) + E\} \tag{24}$$

Where;

L_{st} = Local standard time meridian used in local time zone

L_{loc} = Longitude of the location on which resources are to be measured

Solar time is defined as the passage of time based on the Sun's position in the sky. When Sun is at the highest position in the sky it is called local solar noon. Standard time is the local time with respect to Greenwich Mean Time (GMT). It should be noted here that for solar calculations standard time cannot be used, it is necessary to convert standard time to solar time. It is necessary to have constant correction for the difference in the meridian of local time and the observer's meridian. Another correction is for the time of sun crossing the observer's meridian which is affected by the deviation in earth's rotation. E can be mathematically obtained by Equation (25).

$$E = 229.2(0.000075 + 0.001868\cos B - 0.032077\sin B - 0.014615\cos 2B - 0.04089\sin 2B) \tag{25}$$

Here B is dependent on day number and can be found as shown in Equation (26).

$$B = (n-1)\frac{360}{365} \tag{26}$$

Where;

n = day number (i.e. for January 1, n is equal to 1 and for December 31, n is equal to 365).

Declination (δ) as shown mathematically in Equation (27) is the angle formed between the sun-earth line and equator and a vertical to the equator.

$$\delta = 23.45\, sin\left(360\,\frac{248+n}{365}\right) \tag{27}$$

It should be noted here that the declination angle becomes zero at spring and fall equinox i.e. March 21 and September 23 respectively. Whereas, it research a maximum value of 23.45° in the summer solstice i.e. June 21 and a minimum value of -23.45° in the winter solstice i.e. December 21.

The solar zenith angle (θ_z) represented by mathematical Equation (28) depends upon latitude ($\emptyset$), day number and time. It is the angle between the vertical line directly overhead from the reference point and the sun-earth line.

$$\cos\theta_Z = \cos\emptyset\cos\delta\cos\omega + \sin\emptyset\sin\delta \tag{28}$$

The solar azimuth angle (γ_s) defines the direction of sun. It is the angle measured from due south, such that the angles to the west of south are take positive and the angles to the east of south are taken negative. The solar azimuth angle is a function of zenith angle (θ_z), declination (δ) and latitude ($\emptyset$) as shown in Equation (29).

$$\gamma_s = sign(\omega)\left|cos^{-1}\left(\frac{cos\,\theta_Z\, sin\,\emptyset - sin\,\delta}{sin\,\theta_Z\, cos\,\emptyset}\right)\right| \tag{29}$$

The solar insolation from sun has two main components; beam and diffuse. The beam irradiation also known as direct insolation is defined as the solar insolation that travels in a straight line directly from the sun to the earth surface. On the other hand, the diffuse irradiation is that part of the solar insolation that has been scattered by the atmosphere before reaching the surface of the earth. The total irradiation on a tilted surface can be calculated as shown in Equation (30).

$$I_T = I_{bT} + I_{dT} \tag{30}$$

Where;

I_T = Total solar insolation on a tilted surface (Wh m^{-2})

I_{bT} = Beam insolation on a tilted surface (Wh m^{-2})

I_{dT} = Diffused solar insolation on a tilted surface (Wh m^{-2})

The beam insolation on a tilted surface can be mathematically represented as shown in Equation (31).

$$I_{bT} = DNI \cos\theta \tag{31}$$

Where;
DNI = Direct normal insolation (Wh m^{-2})

Equation (32) can be used to mathematically represent θ.

$$\cos\theta = \cos\theta_Z \cos\beta_a + \sin\theta_Z \sin\beta_a \cos(\gamma_s - \gamma) \tag{32}$$

The diffuse insolation on a tilted surface can be mathematically represented as shown in Equation (33).

$$I_{dT} = \left(\frac{1+\cos\beta_a}{2}\right) I_d \tag{33}$$

Where;
I_d= Amount of diffuse solar insolation available on a surface (Wh m^{-2})
β_a = Surface Tilt angle (degrees)

The solar resources on any surface at any part of the world during any hour of the day can be calculated using this model, if the DNI and diffuse horizontal solar resources are available.

3.3. Solar Resources Prediction

The solar resources on the tilted surface that are calculated using solar resource model as shown in Section 3.2, are now used for testing and training the prediction models for long term hourly forecasting of solar resources. The solar resources on tilted surface are forecasted using the probabilistic characterization technique.

The hourly solar resources on tilted surface calculated in Section 3.2 are converted to daily solar resources on tilted surface by simple summation. The probability density function of daily solar resources on tilted surface for each month is calculated and fitted into known probability distributions like Normal, Weibull and Extreme Value. Based on the best fit, for each month the associated parameters of fitted distribution are calculated. The pdfs of Normal, Weibull and Extreme Value distributions are given in Equations (18) – (20).

Equation (18) represents the Normal distribution, where pdf is dependent on mean (μ) and standard deviation (σ) of the data. Equation (19) represents pdf for a Weibull distribution, where associated parameters are scale parameter (a) and shape parameter (b). The pdf for Extreme Value distribution is given in Equation (20), where the associated parameters are location parameter (μ) and scale parameter (σ).

After identifying the probability distributions for each month which best fits the daily tilted solar resource data, the associated parameters are calculated for each month's pdf. For months where Extreme Value distribution presents the best fit, the location parameter (μ) and scale parameter (σ) are calculated. Similarly, for months which have Normal or Weibull distributions, their respective associated parameters are estimated. After finding each month's pdf and associated parameters, random data for daily solar resources on tilted surface are generated. In order to convert this daily tilted surface solar resource data generated by probabilistic characterization to hourly tilted surface solar resource data, it is multiplied by the average hourly tilted surface solar resource percentages as shown in Equation (34).

$$I_{TF} = I_{TD} \times HITP_{i,k} \tag{34}$$

$$HITP_{i,k} = \frac{TI_{i,k}}{TI_k} \tag{35}$$

Where;

I_{TF} = Forecasted hourly solar resources on tilted surface

I_{TD} = Daily tilted solar resource data generated as random data through probabilistic characterization

$HITP_{i,k}$ = Average hourly tilted solar resource percentages for the hour i of month k.

$TI_{i,k}$ = Total solar resource on tilted surface during hour i for the entire month of k.

TI_k = Total solar resource on tilted surface during the entire month of k.

The average hourly percentages of tilted solar resources for each month are calculated separately. Equation (35) shows that average hourly percentage for any hour are calculated by dividing the total tilted surface solar resources during that hour of the month by the total tilted surface solar resources during the whole month. Now, Equation (34) gives the hourly tilted surface solar resource data based on probabilistic characterization of each month's tilted surface solar resources.

3.4. Solar PV Output Model

The predicted solar resources on tilted surface calculated in Section 3.3 are utilized to determine the amount of electricity produced from Solar PV. The model presented here is taken from Ali et al. [31]. The amount of electricity generated from solar PV (E_{PV}) is dependent upon area of PV panels (A_{PV}), solar resources (I_{TF}), efficiency of the PV panel (η_{PV}) and the performance factor (pf) of the PV power plant as shown in Equation (36).

$$E_{PV} = I_{TF} \times A_{PV} \times \eta_{PV} \times pf \tag{36}$$

The area of the PV panels depends upon the rated power of the PV power plant, PV panel efficiency and the performance factor of PV power plant as shown in Equation (37).

$$A_{PV} = \frac{P_{PV}}{\eta_{PV} \times pf \times G} \tag{37}$$

Where;

P_{PV} = Rated power of the PV power plant

G = Standard irradiance for PV panels (1000 W m^{-2})

It should be noted here that the efficiency of PV panel decreases with increase in temperature this have an impact on the energy generated from PV panel, but for the sake of simplicity the PV panel efficiency is assumed to constant here. The model discussed in this section will give hourly output generated from PV panels taking predicted solar resources on tilted surface as input.

3.5. Results

3.5.1. Solar Resources

The solar resources are calculated based on the model presented in Section 3.2 for METU NCC. For a fixed surface, the maximum solar resources are received at a tilt angle around 24.67° facing due south. This is within the limit of 15° to 30° tilt angle facing due south for maximum solar resources, presented by Arsalan and Baker [2] for METU NCC. The average daily solar insolation for different characteristic surfaces for all the months is presented in Figure 3.1.

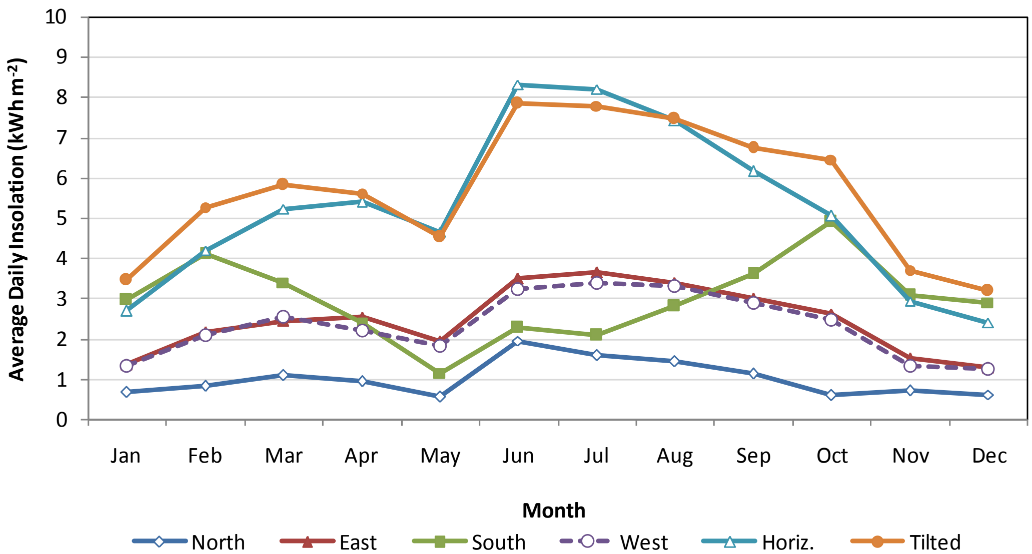

Figure 3.1 Trends in daily insolation for METU NCC. For the tilted surface $\beta=24.67^{o}$ and $\gamma=0°$.

It can be seen from Figure 3.1 that North facing wall obtains minimum solar insolation and east and west facing walls receives almost the same amount of insolation. This is because when the sun rises, eastern wall receives insolation until solar noon and when it is solar noon the western wall starts receiving insolation until sun sets and both walls receives almost equal amount of insolation in a day. Moreover Figure 3.1 shows that for horizontal and tilted surfaces, solar insolation increases from February and March and reaches maximum during June and July. For horizontal surface, June and July receives same (maximum) insolation, but it starts decreasing from July till December. Figure 3.1 also depicts that southern surface receives some insolation from January till March, but it starts decreasing from March till June due to summer solstice as the earth is below the plane of the sun. But for winter solstice it is above the plane of the sun so southern surface receives some insolation during winter months. It should be noted that there is a sudden decrease of solar insolation in May; this is an error because of the problems with the measuring instrument. But this error is not neglected and is considered in the analysis for the purpose of considering uncertainties.

Figure 3.2 represents daily beam normal and diffuse horizontal insolation for Guzelyurt, North Cyprus for the whole year. It can be inferred from Figure 3.2 that from January till April diffuse horizontal insolation is in significant amount as it is mostly cloudy during this period in Northern Cyprus; moreover it is rainy season during January to March. So due to more cloud the diffuse horizontal insolation is higher. Also, it is because of the fact that it is winter season and Earth is above the plane of the sun so direct normal insolation are least during this period. But from June till August the diffuse horizontal insolation is low as compared other months, this is because it is summer solstice and during summer season earth is below the plane of the sun so it receives maximum beam normal insolation and less diffuse horizontal insolation.

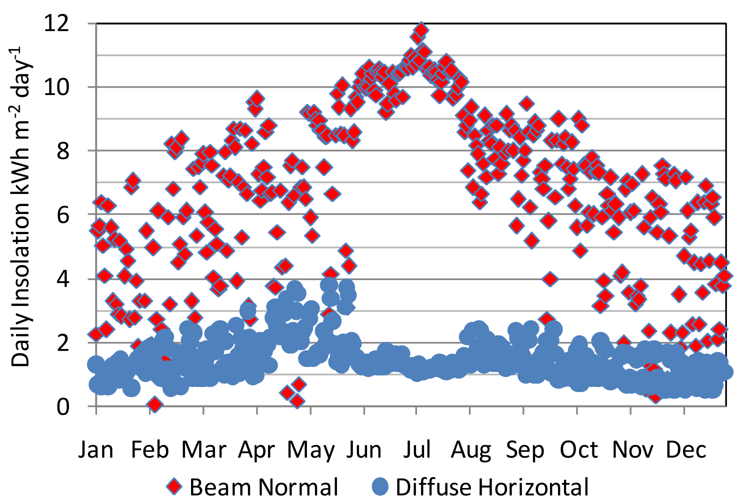

Figure 3.2 Daily beam (direct) normal and diffuse horizontal insolation for METU NCC

3.5.2. Solar Resources Forecast

The hourly solar resources on tilted surface obtained using the solar resource model presented in Section 3.2 are converted to daily solar resources. The daily solar resources on tilted surface for each month are characterized based on the probability distributions that best fits the data. The probability distribution that best fits the daily solar resource data for each month is identified by comparing the P-values and AD values as it is previously done for electricity consumption forecasting presented in Section 2.5.1.3. As stated earlier a high P-value means a good fit whereas a low P-value (for example P-value < 0.05) means the data don't follow the distribution and incase of AD, a lower value means a better fit. Table 3.1 shows the P-values and AD values for Normal, Weibull and Extreme value distributions tested for daily solar resources on tilted surface for each month.

From the Table 3.1 it can be inferred that for January the AD is 0.607 for Extreme Value distribution which is lower than the AD value of Normal and Weibull distributions and the P-value of Extreme Value distribution is 0.107 which is higher than the P-values of other two distributions hence, Extreme value distributions provides the best fit for January. Similarly for February and March the best fit is provided by Extreme Value distribution.

Table 3.1 AD and P-values of different distributions for each month's daily solar resources on tilted surface

	Normal Distribution		**Weibull Distribution**		**Extreme Value Distribution**	
Months	**P-value**	**AD**	**P-value**	**AD**	**P-value**	**AD**
January	0.006	1.108	<0.01	1.251	0.107	0.607
February	0.087	0.637	>0.250	0.391	>0.250	0.239
March	<0.005	1.221	<0.01	1.235	0.02	0.901
April	0.085	0.642	0.068	0.689	0.037	0.792
May	<0.005	1.572	<0.01	1.206	0.061	0.704
June	<0.005	1.216	0.088	0.641	0.081	0.659
July	0.16	0.533	>0.25	0.183	>0.25	0.174
August	0.816	0.221	>0.250	0.33	>0.250	0.37
September	<0.005	1.271	>0.250	0.453	>0.250	0.35
October	<0.005	1.469	0.085	0.651	0.224	0.485
November	0.136	0.558	0.116	0.598	0.218	0.491
December	0.219	0.479	0.037	0.789	0.229	0.48

Figure 3.3- Figure 3.5 presents the probability plots of the identified best fitted probability distributions for January, February and March. It can be inferred from Figure 3.3 that only on data point of daily solar resource on tilted surface for the month of January is outside the 95% confidence interval of estimated Extreme Value cumulative distribution curve. This means that data of solar resources on tilted surface can be represented by Extreme Value distribution. Similarly, Figure 3.4 and Figure 3.5 show that all the data points of daily solar resources on tilted surface in the months of February and March are within the confidence interval of Extreme Value distribution curve.

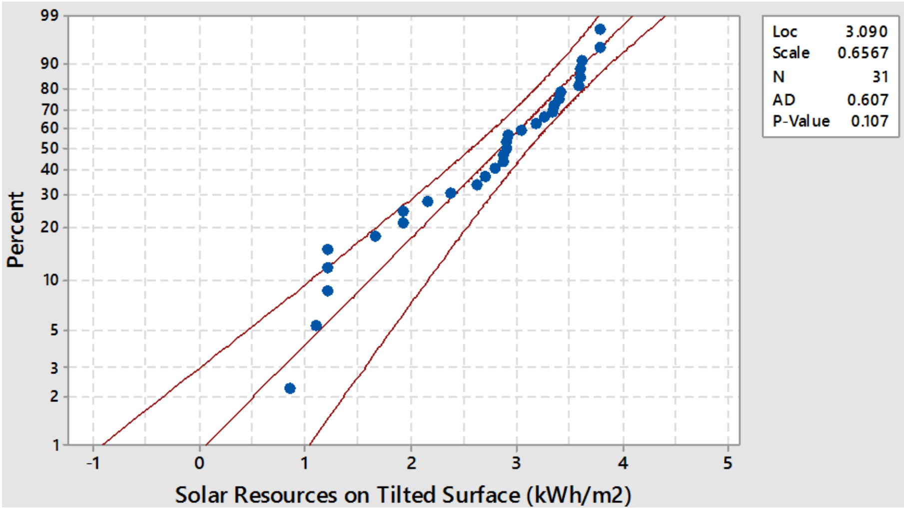

Figure 3.3 Fitted Extreme Value distribution for solar resources on tilted surface for January

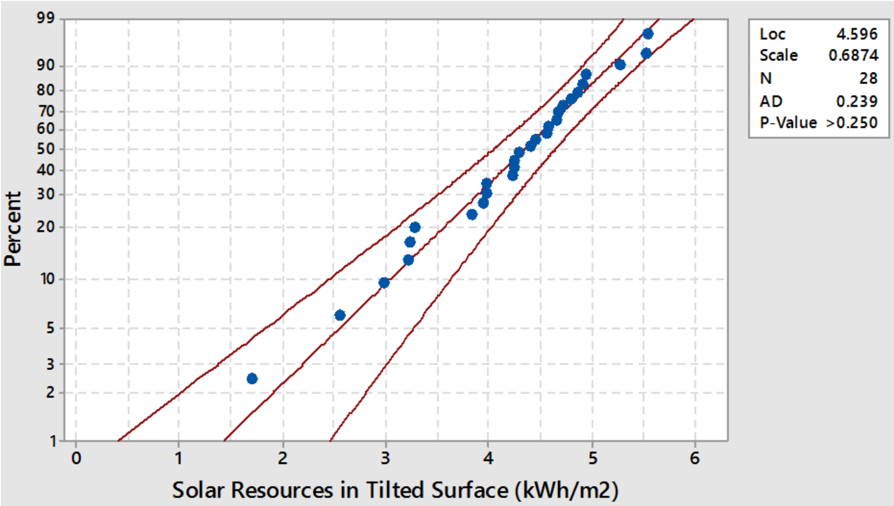

Figure 3.4 Fitted Extreme Value distribution for solar resources on tilted surface for February

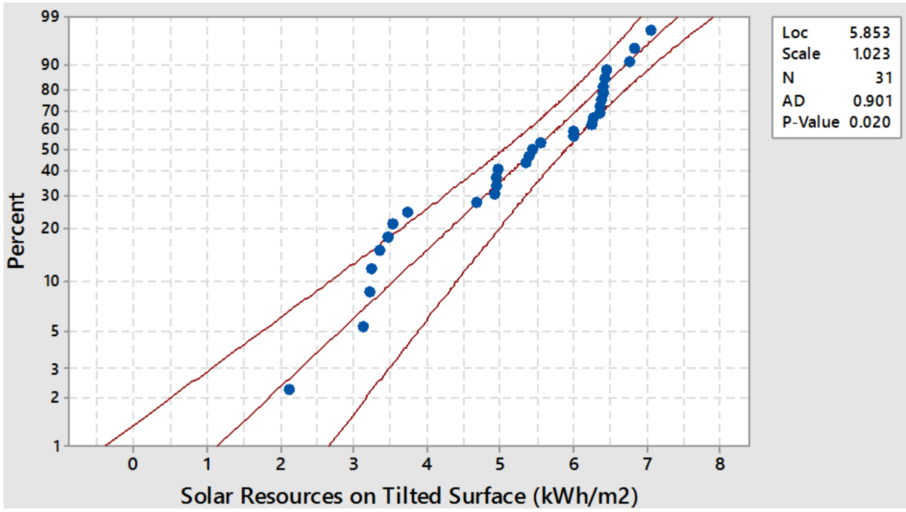

Figure 3.5 Fitted Normal distribution for solar resources on tilted surface for March

After identifying the probability distributions that best fit the tilted surface solar resources data for each month, the associated parameters for all the probability distributions are estimated. The estimated parameters for the selected probability distributions for each month are given in Table 3.2.

Table 3.2 Associated parameters of identified distributions for each month's tilted surface solar resource data

	Normal Distribution		**Weibull Distribution**		**Extreme Value Distribution**	
Months	**Mean**	**Std. Dev.**	**Shape**	**Scale**	**Location**	**Scale**
January	-	-	-	-	3.090	0.6567
February	-	-	-	-	4.596	0.6874
March	-	-	-	-	5.853	1.023
April	5.229	1.526	-	-	-	-
May	-	-	-	-	4.641	0.5735
June	-	-	22.11	8.055	-	-
July	-	-	-	-	7.872	0.1139
August	7.460	0.2598	-	-	-	-
September	-	-	-	-	6.942	0.3342
October	-	-	-	-	6.710	0.4368
November	-	-	-	-	4.219	0.8876
December	-	-	-	-	3.851	1.147

After calculating the associated parameters of each month's fitted distribution, random data of daily solar resources on tilted surface is generated for 20 years. The random data of daily solar resources on tilted surface is multiplied with each month's average hourly tilted solar resource percentages to obtain hourly electricity consumption data for 20 years. The average hourly percentages of solar resources on tilted surface for the months of January, February and March are shown in Figure 3.6 – Figure 3.8.

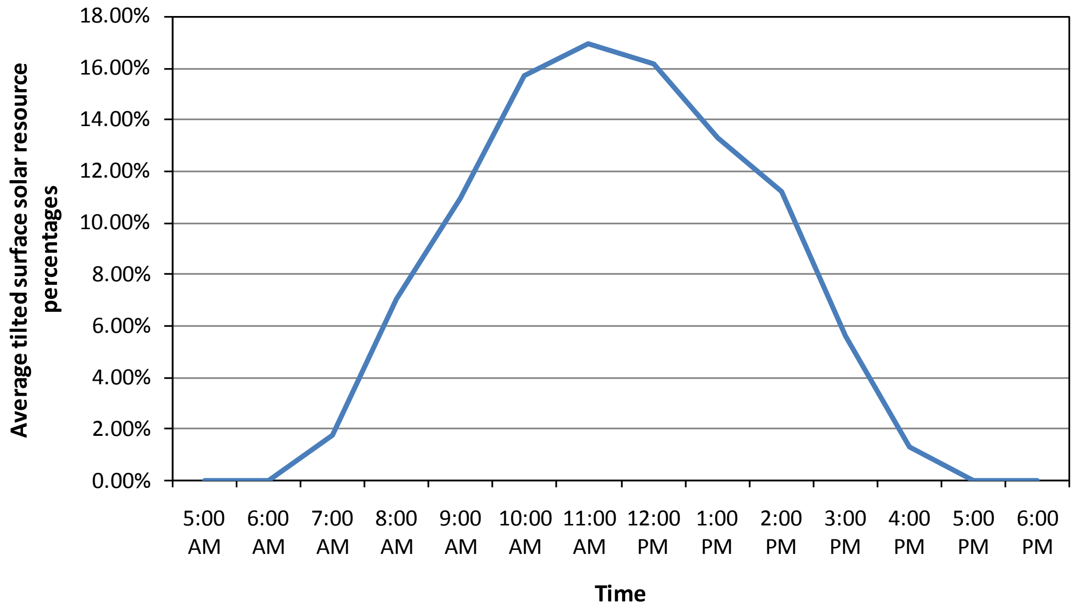

Figure 3.6 Average hourly percentages of solar resources on tilted surface for January

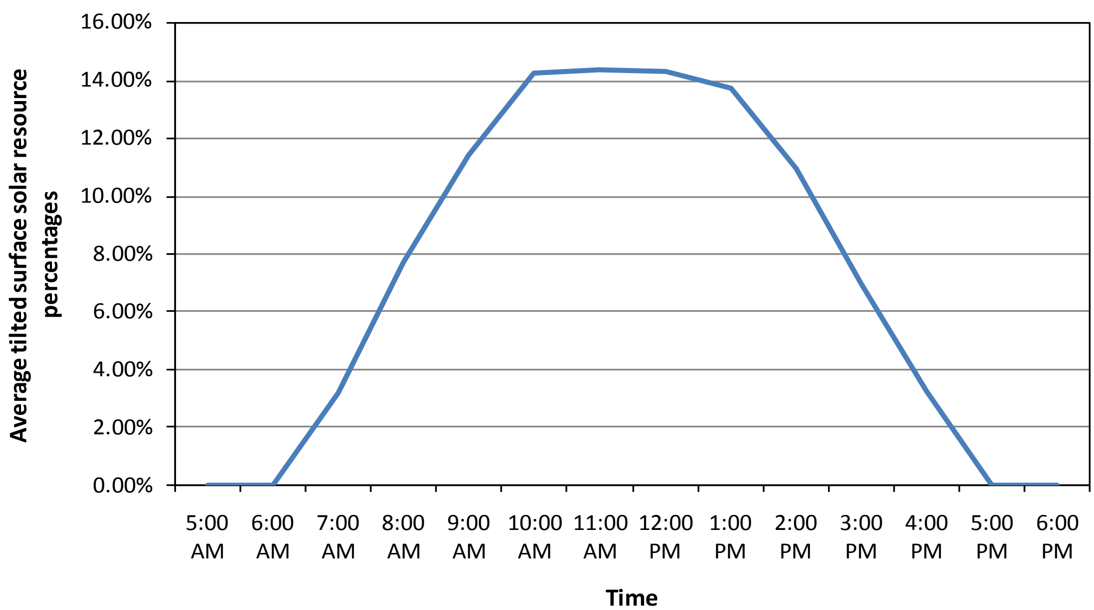

Figure 3.7 Average hourly percentages of solar resources on tilted surface for February

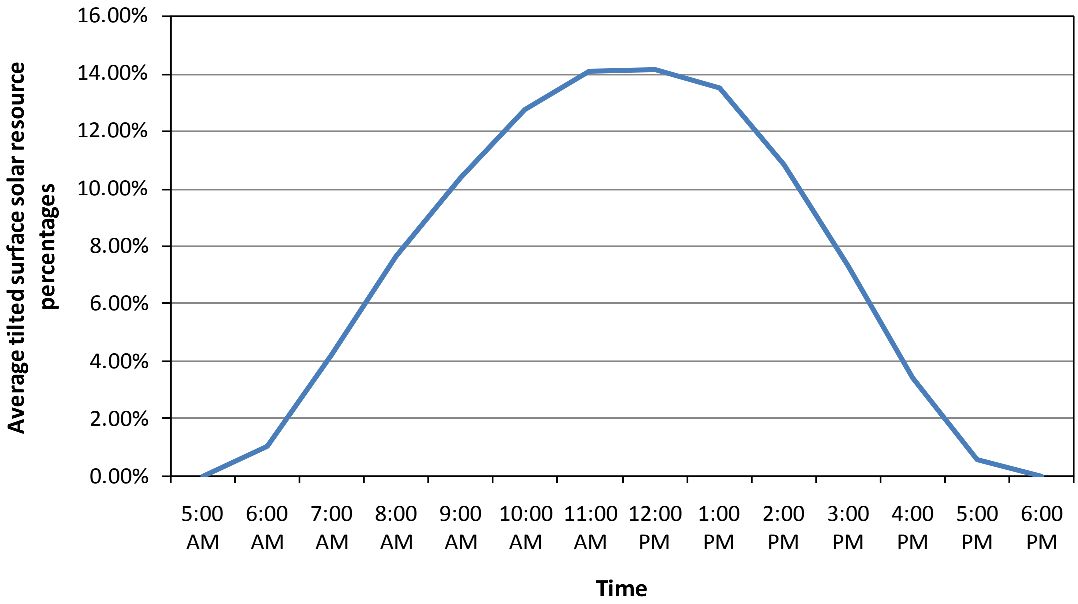

Figure 3.8 Average hourly percentages of solar resources on tilted surface for March

3.5.3. Solar PV Output

As presented earlier in Section 3.4, the electricity generated from solar PV power plant depends upon area of the solar panels, efficiency of the solar panels, performance factor of the solar PV power plant and the available solar resources. The efficiency of solar panel varies due to changes in temperature, as the temperature increases the efficiency decreases but for the sake of simplicity a constant efficiency is considered. SYP240S (polycrystalline) solar panel of Risen Energy Company limited is selected; it has an efficiency of 14.78% at Standard Test Conditions [31]. The performance factor of the PV power plant is considered to be 75% [31]. With these inputs and without considering uncertainties in solar resources, on average 5.62 MWh of daily electricity can be produced by 1 MW PV power plant with PV panel area equal to 9021 m^2. When the uncertainties in solar resources are considered as shown in Section 3.5.2 then the output varies widely. These variations are considered in the final feasibility analysis presented in the Chapter 5.

CHAPTER 4

ECONOMIC FEASIBILITY ANALYSIS USING MONTE CARLO SIMULATION

As discussed in the objectives of this thesis presented in Section 1.10, this chapter presents an economic model for assessing the feasibility of solar PV power plant with Monte Carlo simulation to add uncertainties in electricity consumption and solar resources. The first part of the chapter presents an economic model which contains the methodology for calculating net present value (NPV), Levilized cost of electricity (LCOE), opportunity cost (OC) and cost of excess production (WP). Then the methodology for Monte Carlo simulation is presented within which the uncertainties in electricity prices are discussed and different cases and scenarios for solar PV installations at METU NCC are presented.

4.1. Economic Model

The economic model estimates the NPV, LCOE, OC and WP for any PV system installation. These calculations will help the decision makers in selecting or analyzing the feasibility of any project.

4.1.1. Net Present Value

The sum of the present values of incoming and outgoing cash across a time line is called NPV. If the NPV is positive it means that the project can be accepted and it will incur profit but if the NPV is negative the project is not feasible as it will incur loss. The equations for economic model presented here are taken from Tariq and Baker [2] and Ali et al., [31]. The NPV can be mathematically obtained as shown in Equation (38).

$$NPV = \sum_0^y EB_y \times \frac{1}{(1+i)^y} - PP_{cost} \tag{38}$$

Where;

EB_y = Net economic benefits in year y

PP_{cost} = Power plant cost (USD)

i = Interest rate (15%)
y = Number of year (i.e. 1, 2, 3, 4, 5…)

The power plant cost is the fixed cost or capital cost incurred in the initial year of installation. It can be calculated as shown in Equation (39).

$$PP_{cost} = PV_{cost} + IS_{cost} \tag{39}$$

Where;
PV_{cost} = Total cost of PV system (USD)
IS_{cost} = Total cost of inverter system (USD)

The total cost of PV system can be obtained using Equation (40).

$$PV_{cost} = c_p \times C_{PV} \tag{40}$$

Where;
c_p = Power Plant Capacity (kW)
C_{PV} = Cost of PV module (700 USD kW^{-1})

The other portion of PP_{cost} that is IS_{cost} can be calculated as shown in Equation (41).

$$IS_{cost} = c_I \times C_{IU} \tag{41}$$

Where;
c_I = Capacity of Inverter (kW)
C_{IU} = Cost of Inverter module (200 USD kW^{-1})

It should be noted that the PV to inverter size ratio is assumed to be 1.2. The economic benefits can be considered as the amount of electricity generated from PV systems that reduces the electricity bills of campus since there is no revenue from the generated electricity because it is not being sold. Equation (42) shows the calculation for economic benefits in any given year.

$$CS = EG \times \mathrm{EP} \tag{42}$$

Where;
CS = Economic benefits or cost saved by reduction in electricity bills (USD)

EG = Total energy generated and consumed on campus using Solar PV power plant (kWh)

EP = Price of grid electricity (USD kWh^{-1})

The net economic benefits (EB_y) are calculated as shown in Equation (43).

$$EB_y = CS_y - IC_y - MC_y \tag{43}$$

Where;

EB_y = Net economic benefits in year y (USD)

IC_y = Insurance cost in year y (USD)

MC_y = Maintenance cost in y (USD)

It should be noted that insurance cost is considered 0.25% of the total fixed or capital cost as mentioned by Tariq and Baker [2]. And the maintenance cost is considered to be 1.5% of the total cost of PV system [2].

4.1.2. Levelized Cost of Electricity

LCOE is a measure that is used to compare different electricity generation sources; it can be used to calculate the cost of energy produced.

The levelized cost of electricity can be calculated as shown in Equation (44).

$$LCOE = \frac{PP_{cost} + \sum_{t=1}^{y}(IC + MC) \times \frac{1}{(1+i)^y}}{\sum_{t=1}^{y} EG \times \frac{1}{(1+i)^y}} \tag{44}$$

Where;

$LCOE$ = Levelized Cost of Energy (USD kWh^{-1})

EG = Total energy generated (kWh)

4.1.3. Opportunity Cost

OC represent the amount of cost that could be saved if demand and supply meets perfectly or in other words there is no shortage of supply and the demand is completely satisfied.

The opportunity cost (OC) can be calculated as shown in Equation (45).

$$OC = \sum_{t=1}^{y} \frac{gap_{DS} \times EP}{(1+i)^y} \tag{45}$$

Where;

gap_{DS} = Gap between the demand and supply of electricity or shortage of supply (kWh)

EP = Price of grid electricity (USD kWh^{-1})

4.1.4. Excess Production Cost

The excess production (WP) can be calculated in the same way as opportunity cost. The only difference between them is that supply-demand gap in opportunity cost represents shortage of supply whereas in excess production cost calculations it represent excess energy generated which is not used by the campus. Since storage is not considered in our calculation therefore excess production cost is important to calculate.

$$WP = \sum_{t=1}^{y} \frac{gap_{SD} \times EP}{(1+i)^y} \tag{46}$$

Where;

gap_{SD} = Gap between the supply and demand of electricity or amount of supply exceeding demand (kWh)

4.2. Monte Carlo Simulation

The main objective of this thesis is to develop a simulation based optimization tool that considers uncertainties in electricity consumption, solar resources and electricity prices to find the most feasible solution for solar PV installation. This section presents the methodology to develop such a simulation tool. Monte Carlo simulation is one of the most widely used techniques for considering uncertainties in any system or process. It has a broad class of computational algorithms that obtains numerical results from random number generation or random sampling.

Although there are many different ways of performing Monte Carlo simulation, the most general form can be written as;

1. Define a domain or a simulated set of possible inputs.

2. Generate random data for input based on probability distributions.
3. Calculate the output based on deterministic approach from the random input data.
4. Compile the results.

In this thesis Monte Carlo simulation is used to incorporate all the uncertainties in electricity consumption, solar resources and electricity prices. It takes into account probability distributions for generating random numbers rather than analytical calculations. Then based on random input generated it calculates distributions of output variables. The entire simulation is developed on MATLAB. It should be noted that the random input parameters taken for Monte Carlo simulation are daily electricity consumption data and daily tilted solar resource data, all other input parameters are non-random and do not depend upon any fitted probability distribution. This section illustrates the steps used to perform Monte Carlo simulation for generating distributions of NPV, LCOE, OC and WP. The Monte Carlo simulation method proposed in this thesis comprises of the following steps.

1. Generate random data for daily solar resources and electricity consumption for 20 years based on already known fitted probability distributions of each month's daily solar resources and electricity consumption data. Multiply the random data generated for daily electricity consumption and solar resources with known average hourly percentages of electricity consumption and solar resources, to convert daily data into hourly data for 20 years. The random data for hourly electricity consumption and solar resources are calculated using the method presented in Section 2.5.1 and Section 3.3.
2. Taking the predicted hourly solar resource data as input, calculate hourly electricity generated by predefined capacity of PV power plant that is to be analyzed for feasibility. Hourly electricity supply data is calculated using the equations presented in Section 3.4.
3. Calculate the NPV, LCOE, OC and WP for 20 years for the predefined capacity of PV power plant that is to be analyzed. These calculations are done for different cases that are presented in Results and Discussion Section. The calculations for NPV, LCOE, OC and WP are done as presented in Section 4.1. It should be noted that the values calculated in this step are point estimates.
4. Repeat steps 1 till 3 thousand times to generate probability distributions of NPV, LCOE, OC and WP for each case considered for entire 20 years. The probability distribution generated for NPV, LCOE, OC and WP are dependent upon the probability

distributions of electricity consumption and solar resources, hence accounting for all the uncertainties in them.

It should be noted that the number of iterations done for any simulation have an effect on the distributions of output variables. If the number of iteration is low the distribution results might not truly represent the uncertainties as the distribution will continue to change every time the simulation is run. If the number of iteration is higher than necessary it might result in spurious biases. The number of iterations for any simulation is chosen by checking the output distributions, if the output distributions are not changing the number of iteration for that simulation is correct.

The cases that will be run for economic feasibility analysis using Monte Carlo simulation are;

1. Installation of 1 MW PV power plant. This case will be analyzed first because METU NCC has received a license of installing 1 MW PV power plant, so it will be beneficial to do the analysis of 1 MW PV power plant first.
2. The second case is the stepwise installation of PV power plant. This means that after every 7 years the existing capacity of PV power plant at that time period will be increased. In other words, if a 1 MW PV power plant is installed in the first year then later after every seven years some capacity is added to the power plant. This case is analyzed as it seems logical to increase the supply after some time period due to increase in demand, so that supply continues to follow the increase in demand.

Both of these cases will be run for four different scenarios for the entire lifetime of PV systems (20 years). The first scenario is to consider constant electricity prices and increasing electricity demand. The second scenario is to consider increasing electricity prices and demand. The third scenario is to have constant electricity prices and demand, and the fourth scenario is to have increasing electricity prices but constant electricity demand. It should be noted that electricity prices in Northern Cyprus are highly variable. As discussed in Section 1.8 the electricity prices in Northern Cyprus are highly uncertain, this is largely due to the fact that electricity generation in Northern Cyprus is from imported fuel. This induces high risks due to dependency on imported oil and the prices are also elevated. It should be noted that METU NCC is receiving a special discount of 10% on the electricity prices, this induces the risks of having no discount which will suddenly increases the electricity prices, and hence any project which was feasible for reduced electricity prices might not be feasible for electricity prices without discount. The Figure 4.1 shows the time series plot of electricity prices.

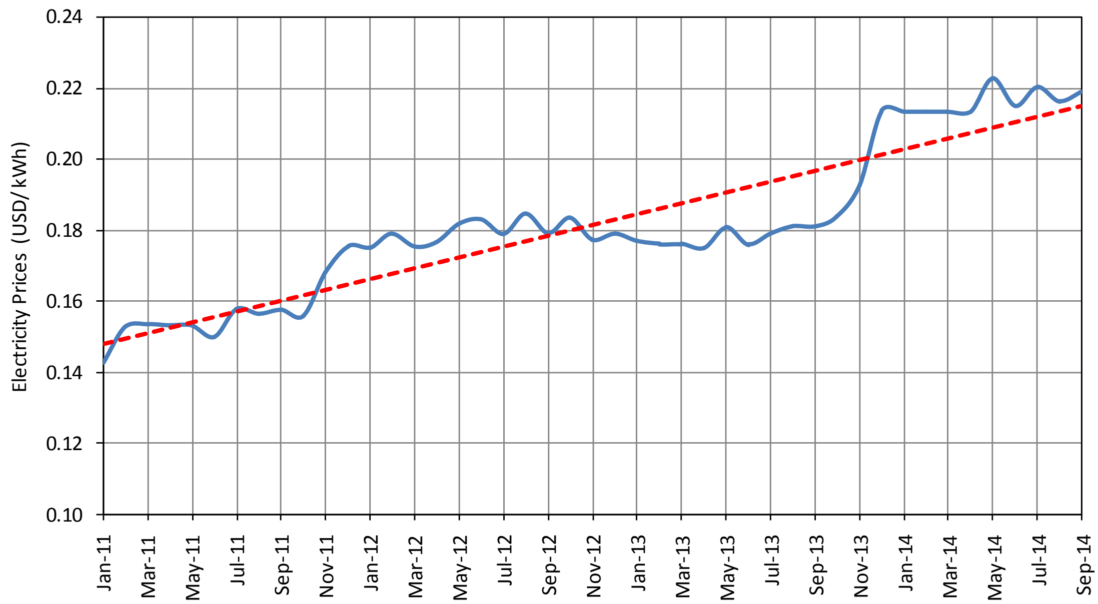

Figure 4.1 Time series plot and trend of electricity prices in Northern Cyprus

It can be inferred from the Figure 4.1 that electricity prices in Northern Cyprus changes every two to three months. There is either an increase or decrease in the electricity prices after every two or three months. Moreover there are sudden significant increases during the months of November 2013 till January 2014 and October 2011 till January 2012. In scenarios like this it becomes very difficult to predict electricity prices for the next 20 years. Hence, two simple scenarios are considered for electricity prices in order to have a better understanding. The first scenario is that electricity prices are fixed for the entire 20 years at the latest rate which is 0.22 USD/kWh. This scenario might not give realistic results as it is not possible to have constant electricity price for 20 years but it can be used for comparison purposes. Another scenario considered is increasing electricity prices. From the time series shown in Figure 4.1 it is calculated that on average there is an increase of 12% in the electricity prices every year. Hence the second scenario considered is to have an increment of 12% in electricity prices every year. Figure 4.2 shows the predicted electricity prices up till 2034 for an average of 12% increase every. It can be inferred from the Figure 4.2 that the predicted electricity prices in 2015 are 0.25 USD/kWh; in 2025 it will become 0.77 USD/kWh in 2025 and 2.12 USD/kWh in 2034. These predictions are based on time series and historical data, no external factor are taken into considerations. It is a very simple approach based on average annual increase in electricity prices.

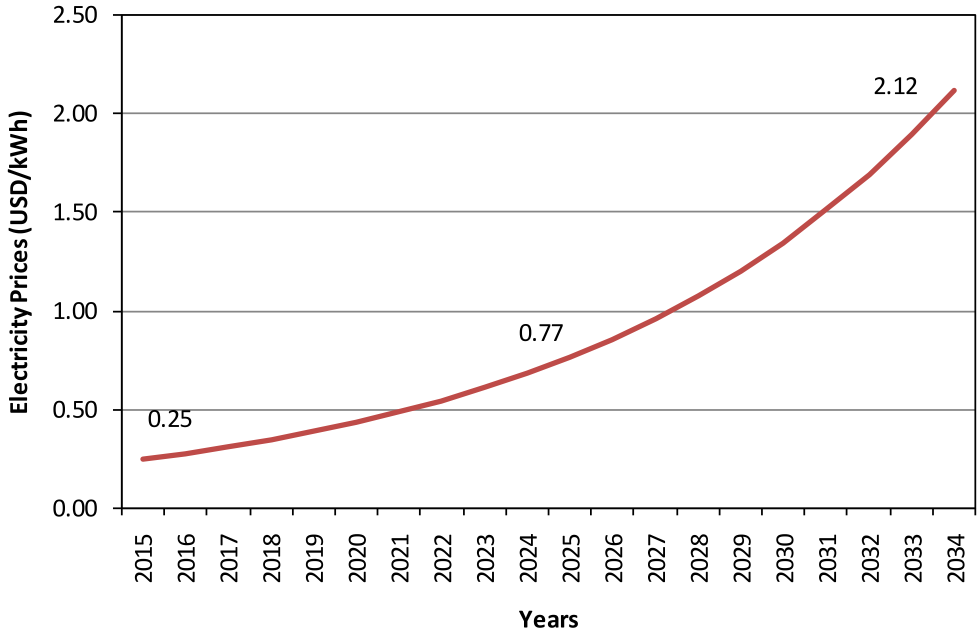

Figure 4.2 Electricity price forecast of 20 years for METU NCC

CHAPTER 5

RESULTS OF MONTE CARLO SIMULATION FOR PV POWER PLANT INSTALLATION AT METU NCC

This chapter presents the results of Monte Carlo simulation for calculating NPV, LCOE, OC and WP for different cases of solar PV power plant installations at METU NCC. The first case presented is of 1 MW power plant. METU NCC has received a license to install a 1 MW solar PV power plant that corresponds to an area of around 9000 m^2. The case will be analyzed for four different scenarios; constant electricity prices and demand, increasing electricity prices and demand, constant electricity prices but increasing electricity demand, and increasing electricity prices and constant electricity demand. The second case presented is of stepwise installation. In stepwise installation it is thought that supply will follow the increasing trend of demand. This case will also be analyzed for all the four scenarios mentioned earlier. A summary is presented at the end of this chapter that highlights the effect of size variations of solar PV power plant on NPV, LCOE, OC and WP. The summary also highlights the power plant size that is most feasible economically. The cost and other inputs considered for economic analyses of all the cases are presented earlier in Section 4.1.

5.1. One Time Solar PV Power Plant Installation at METU NCC

5.1.1. Constant Electricity Price and Increasing Demand

For a 1 MW solar PV power plant installation at METU NCC, considering electricity prices to be fixed at 0.22 USD/kWh for the entire lifetime of PV systems (i.e., 20years) and electricity demand to be increasing based on the model presented in Section 2.5.1, the LCOE, NPV, OC and WP distributions are presented in Figure 5.1 – Figure 5.4. It can be inferred from Figure 5.1 that LCOE varies between (0.09355 – 0.0955) USD/kWh with its mean at 0.0945 USD/kWh. It should be noted that both the maximum and minimum values of LCOE are lower than the electricity prices (0.22 USD/kWh) which means that electricity production from solar PV is cheaper than buying electricity from grid.

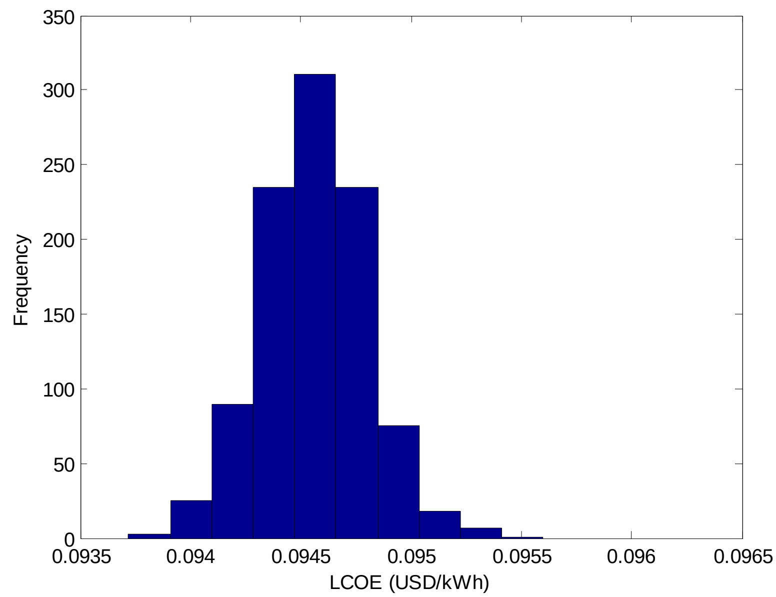

Figure 5.1 LCOE distribution for 1 MW solar PV plant at METU NCC with constant electricity prices

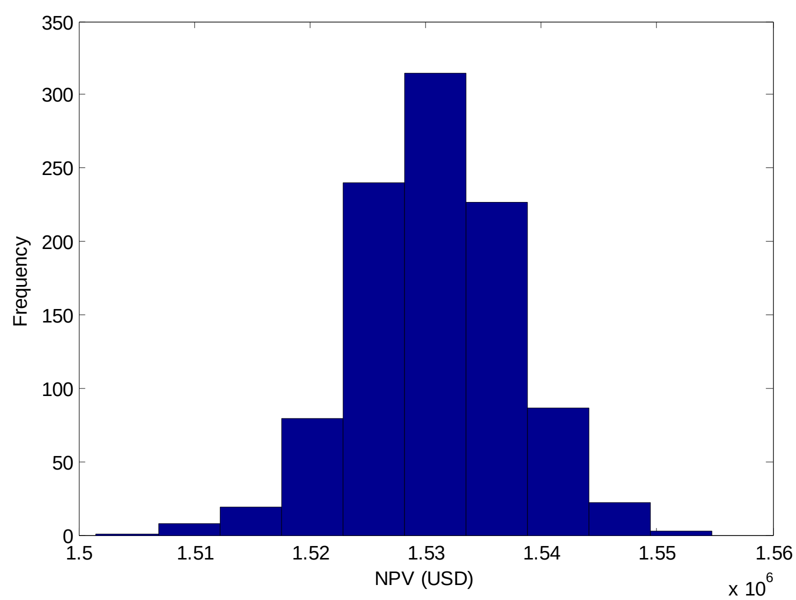

Figure 5.2 NPV distribution for 1 MW solar PV plant at METU NCC with constant electricity prices

Figure 5.2 shows the NPV distribution for a 1 MW solar PV power plant considering constant electricity prices and increasing electricity demand. It can be seen that the NPV varies more or less evenly around the mean of 1.53 million USD between the maximum value of 1.55 million USD and minimum value of 1.51 million USD.

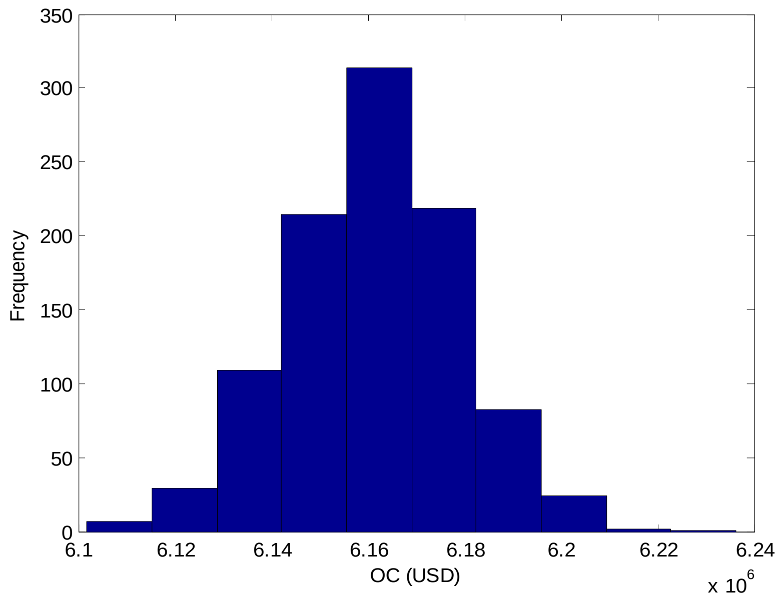

Figure 5.3 OC distribution for 1 MW solar PV plant at METU NCC with constant electricity prices

Opportunity cost distribution for a 1 MW solar PV power plant considering constant electricity prices and increasing electricity demand is presented in Figure 5.3. Opportunity cost refers to the amount of money that we could have saved but we did not. In other words, if a 1 MW solar PV power plant is installed at METU NCC then there will be some amount of electricity that we will still need from grid during the day time, this may be because of peak demands or low solar resources at that time. The amount of electricity that is taken from grid to meet the day time demand even though it should be met by electricity generated from solar PV is called as the opportunity cost because there is an opportunity to save that cost by having storage or other advance grid control systems for meeting day time demand. But since no such things are considered in the analysis therefore it may incur as an opportunity cost. The distribution of opportunity cost seems fairly even around the mean (6.16 million USD), with minimum value at 6.1 million USD and maximum value at 6.22 million USD. It should be noted here that the opportunity cost is high because the demand is increasing every year hence the demand supply gap is increasing every year.

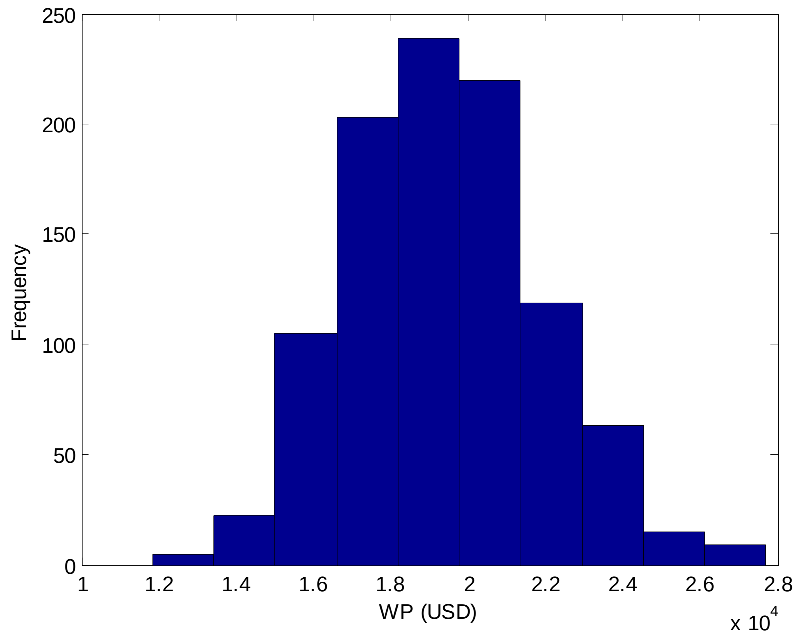

Figure 5.4 Distribution of WP for 1 MW solar PV plant at METU NCC with constant electricity prices

Figure 5.4 shows the distribution for cost of producing excess electricity for a 1 MW solar PV power plant at METU NCC. Excess production cost may incur when the demand is lower than the supply and the amount of electricity generated that is not used by the demand is wasted due to no storage. It should be noted that if storage is considered, both the excess production cost and opportunity cost can be reduced significantly by having more reliable and frequent supply demand matches. The distribution for the cost of excess production show little amount of right skewness which means that more data is on the right tail or upper end of the distribution. The mean is around 20,000 USD and the minimum value is 12,000 USD and the maximum value which is on the right tail side is 28,000 USD.

5.1.2.Increasing Electricity Price and Demand

In this section the prices of electricity are considered to be increasing with an annual rate of 12% and the electricity demand is also increasing. The distributions of LCOE, NPV, OC and WP for a 1 MW solar PV power plant are shown in Figure 5.5 – Figure 5.8. As shown in Figure 5.5 the mean of LCOE in this case is 0.0946 USD/kWh. The maximum value of LCOE is 0.0953 USD/kWh and the minimum value is 0.0938USD/kWh.

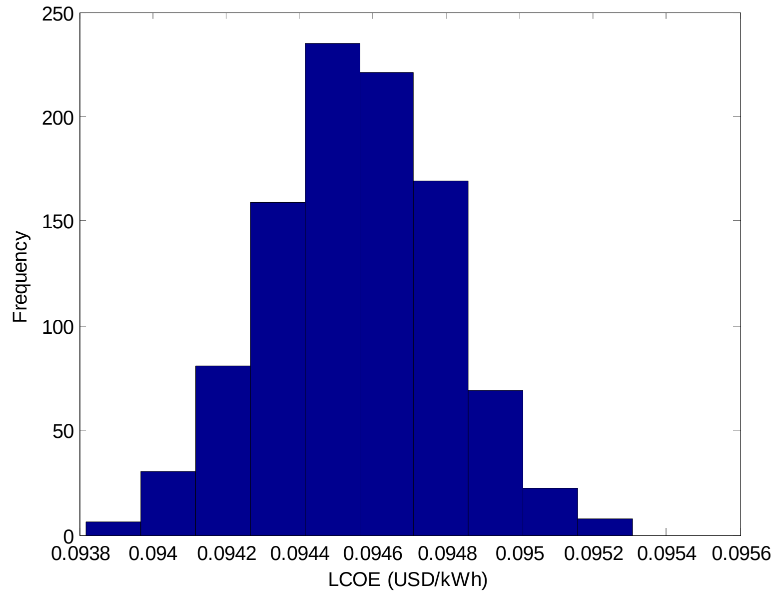

Figure 5.5 LCOE distribution for 1 MW solar PV power plant at METU NCC for increasing electricity prices at 12 % annual rate

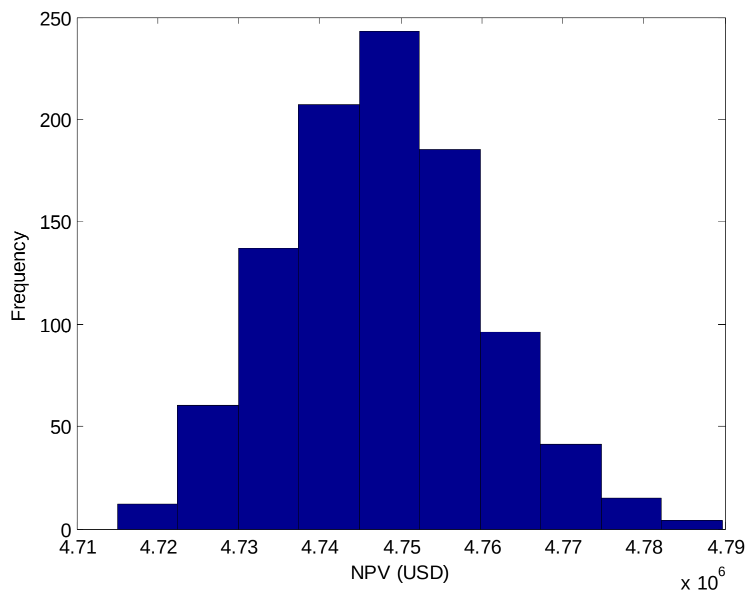

Figure 5.6 NPV distribution for 1 MW solar PV power plant at METU NCC for increasing electricity prices at 12 % annual rate

The distribution of NPV for a 1 MW power plant considering increasing electricity prices at an annual rate of 12% and increasing electricity demand is shown in Figure 5.6. It should be noted that the mean of NPV has increased to 4.74 million USD in this case. This means that on average for 12% annual increase in electricity prices the NPV increases by 200% as compared to the NPV with constant electricity prices presented in Section 5.1.1.

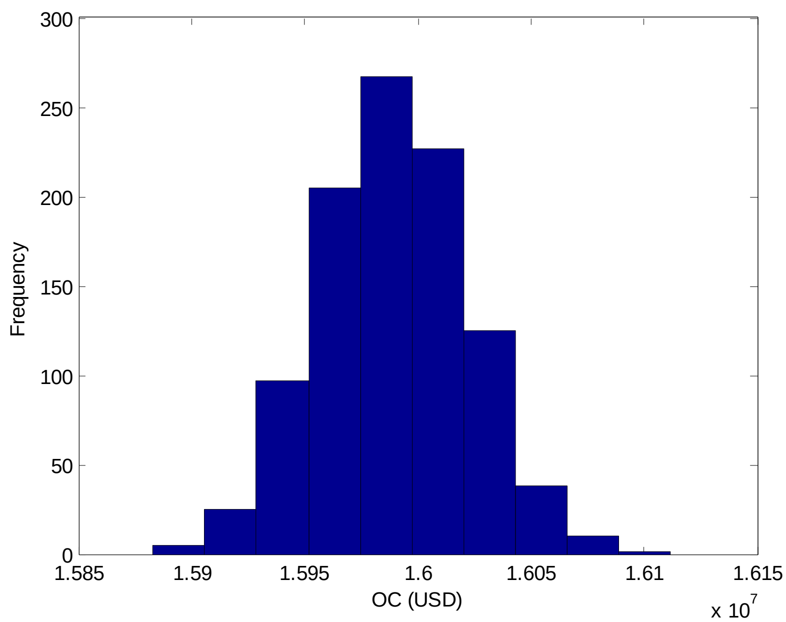

Figure 5.7 OC distribution for 1 MW solar PV power plant at METU NCC for increasing electricity prices at 12 % annual rate

The opportunity cost distribution for increasing electricity prices and increasing electricity demand is shown in Figure 5.7. The mean of opportunity cost is now 15.9 million USD and the maximum and minimum values are 16.1 million USD and 15.8 million USD respectively. It means that on average there is an increase of 150% in opportunity cost when increasing electricity prices are considered as compared to constant electricity prices. The distribution of excess production cost considering increasing electricity prices and demand is shown in Figure 5.8.The mean value of excess production cost in this scenario is 25,100 USD with a minimum value of 16,800 USD and a maximum value of 37,100 USD. This shows that the cost of excess production has increased by 25% due to increasing electricity prices.

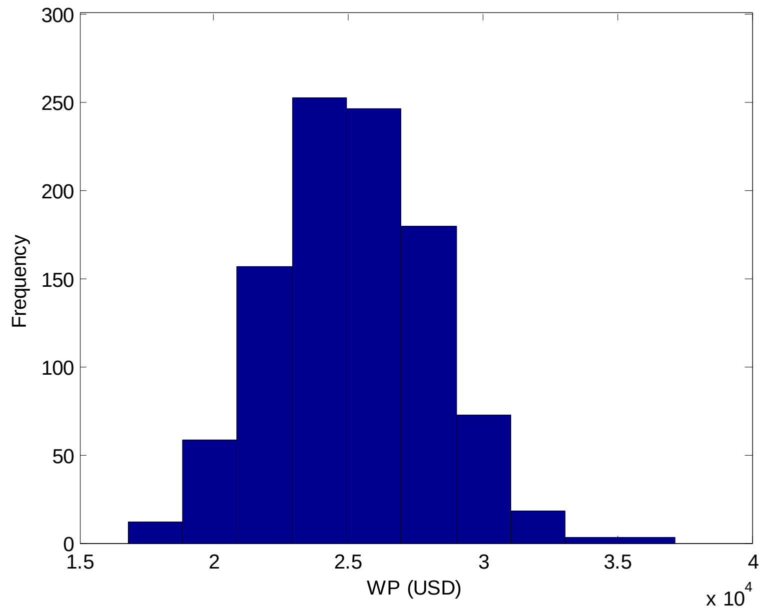

Figure 5.8 WP distribution for 1 MW solar PV power plant at METU NCC for increasing electricity prices at 12 % annual rate

5.1.3. Constant Electricity Price and Demand

The scenario considered in this section is to have fixed electricity prices and stagnant electricity demand. For a 1 MW solar PV power plant installation at METU NCC considering electricity prices to be fixed at 0.22 USD/kWh and electricity demand to be constant throughout the life time of PV system the distributions for LCOE, NPV, OC and WP are presented in Figure 5.9 – Figure 5.12. It can be inferred from Figure 5.9 that the distribution of LCOE is more or less evenly distributed around the mean value of 0.0961 USD/kWh with a minimum value of 0.0954 USD/kWh and a maximum value of 0.097 USD/kWh. On comparison with the constant electricity prices and increasing electricity demand scenario presented in Section 5.1.1, it should be noted that when the demand is considered to be constant the LCOE has increased by 1.6%. Moreover since this scenario is similar to the one considered by Tariq and Baker [2], on comparison there is a difference of 4% between the LCOE calculated by them and the mean value of LCOE calculated here. This account for the fact that simulation is giving correct results and the difference is due to uncertainties in electricity demand and solar resources considered in the simulation.

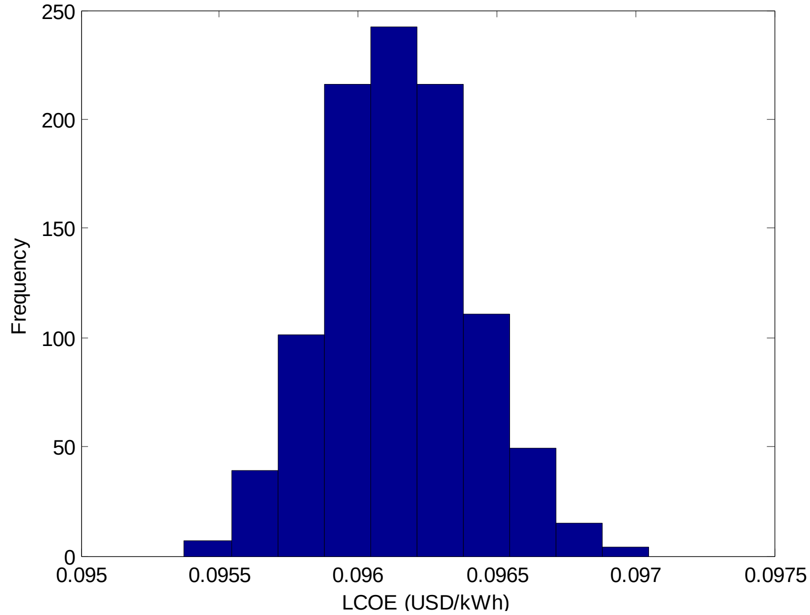

Figure 5.9 LCOE distribution for 1 MW solar PV power plant at METU NCC for constant electricity prices and demand

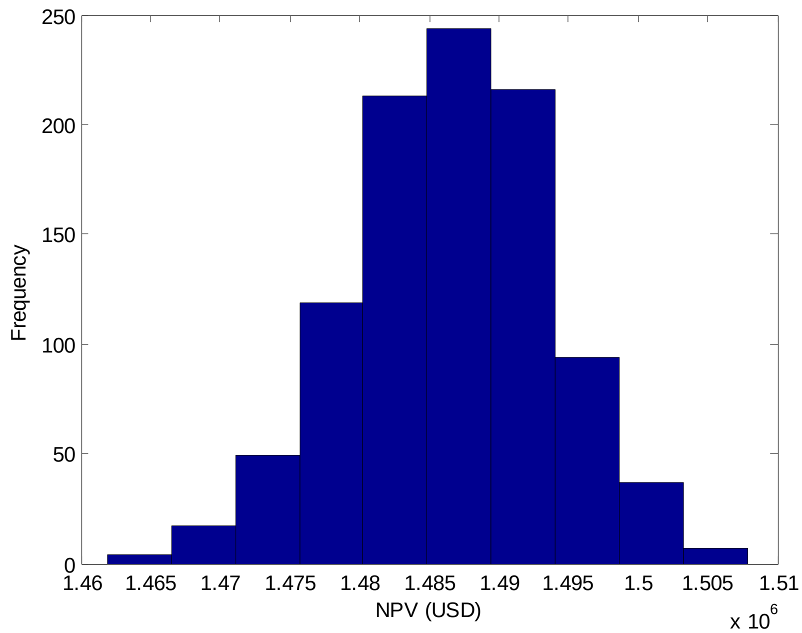

Figure 5.10 NPV distribution for 1 MW solar PV power plant at METU NCC for constant electricity prices and demand

For a 1 MW solar PV power plant considering constant electricity prices and demand, the distribution of NPV is presented in Figure 5.10. It can be inferred from the Figure 5.10 that the mean value of NPV is 1.4866 million USD with a minimum value of 1.4619 million USD and a maximum value of 1.5078 million USD. On comparison with constant electricity prices and increasing electricity demand, it should be noted that when the demand is considered constant the NPV decreases by 3.12%. The mean calculated by the simulation shows a deviation of 10% from the NPV calculated by Tariq and Baker [2] for the same scenario with the same inputs.

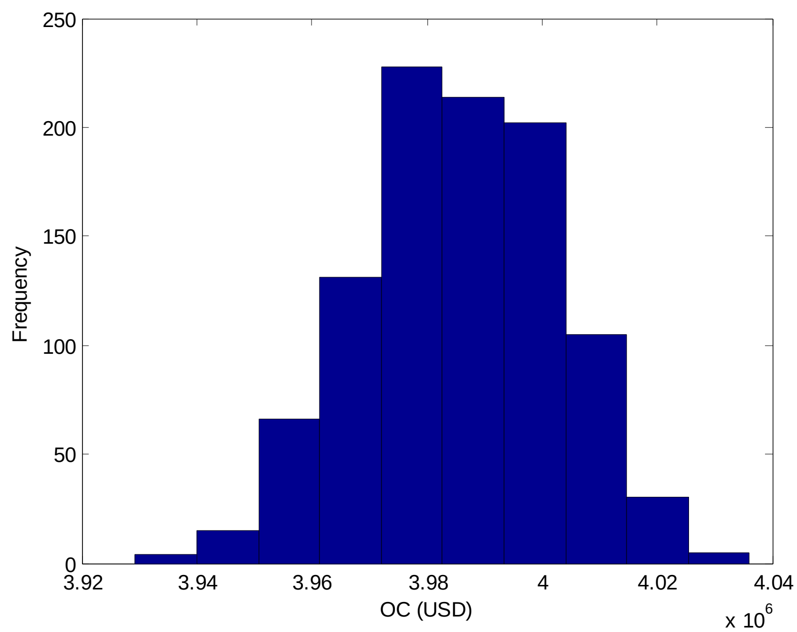

Figure 5.11 OC distribution for 1 MW solar PV power plant at METU NCC for constant electricity prices and demand

The distribution of OC for 1 MW power plant considering constant electricity prices and demand is presented in Figure 5.11. The mean of OC is 3.9853 million USD with the minimum value of 3.9294 million USD and maximum value of 4.0361 million USD. It should be noted here that more data is clustered on the right side of the mean. For constant electricity demand scenario the OC has reduced by 55% in comparison to increasing electricity demand scenario presented in Section 5.1.1. This means that increasing demand has huge impact on opportunity cost because as the demand increases with time and supply remains fixed, the demand supply gap increases significantly.

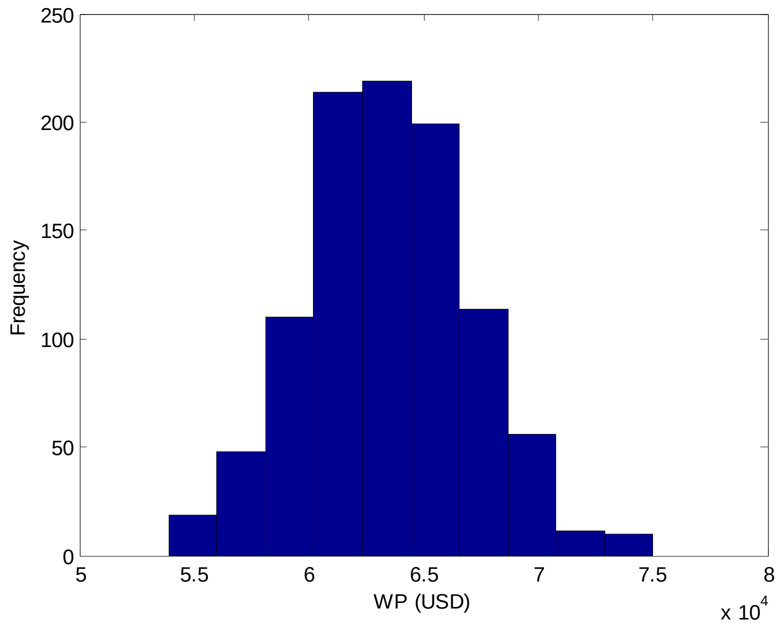

Figure 5.12 WP distribution for 1 MW solar PV power plant at METU NCC for constant electricity prices and demand

It can be inferred from Figure 5.12, that the cost of excess production has a mean value of 63,464 USD with a minimum value 53,895 USD and maximum value of 75,002USD. It should be noted here that the cost of excess production increases by 68% when constant electricity demand is considered in comparison to increasing electricity demand.

5.1.4.Increasing Electricity Price and Constant Demand

In this scenario the prices are assumed to be increasing with an annual rate of 12% but the electricity demand is assumed to be constant for a 1 MW solar PV power plant installation at METU NCC. The distributions of LOCE, NPV, OC and WP for this scenario are presented in Figure 5.13 – Figure 5.16. The LCOE has a mean value of 0.0961 USD/kWh with a minimum value of 0.0953 USD/kWh and a maximum value of 0.0971 USD/kWh as shown in the distribution presented in Figure 5.13. On comparison with the LCOE calculated in Section 5.1.2 for increasing electricity prices and demand the LCOE here has increased by an average of 1.6%.

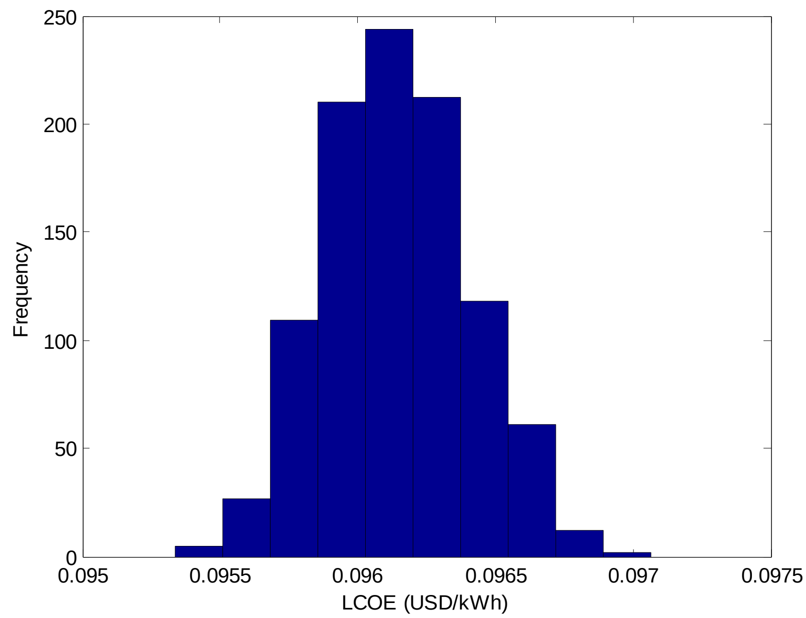

Figure 5.13 LCOE distribution for 1 MW solar PV power plant at METU NCC for constant demand and increasing electricity prices at 12 % annual rate

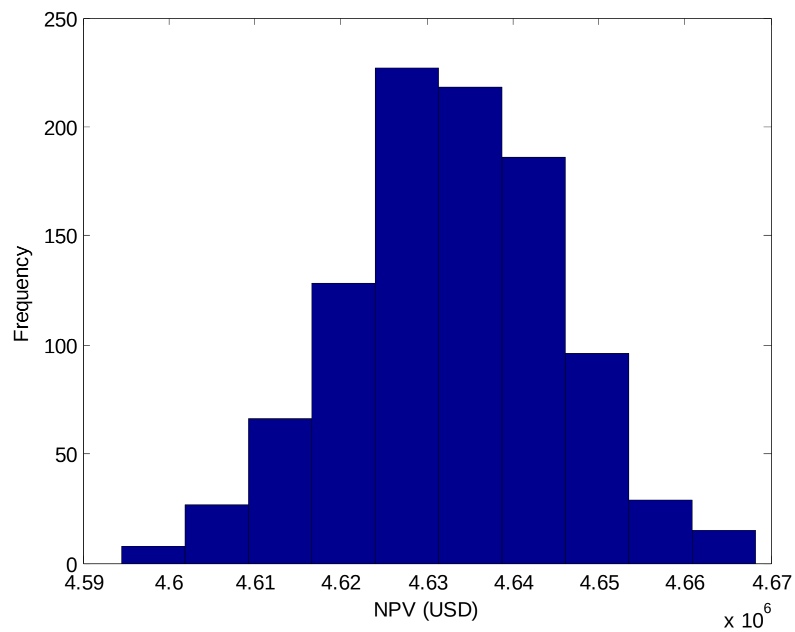

Figure 5.14 NPV distribution for 1 MW solar PV power plant at METU NCC for constant demand and increasing electricity prices at 12 % annual rate

The distribution of NPV for a 1 MW solar PV power plant installation at METU NCC considering constant electricity demand and increasing electricity prices is shown in Figure

5.14. It can be inferred from the figure that the mean of NPV is 4.633 million USD with a minimum value of 4.59 million USD and maximum value of 4.66 million USD. On comparison with the NPV calculated for increasing electricity prices and demand scenario presented in Section 5.1.2, the NPV in this scenario has decreased by 2%. This decrease seems reasonable because with constant demand the electricity generated by solar PV during hours when solar resources are high is not fully utilized but when the demand is continuously increasing with time the electricity generated during hours of high solar resources will be fully utilized.

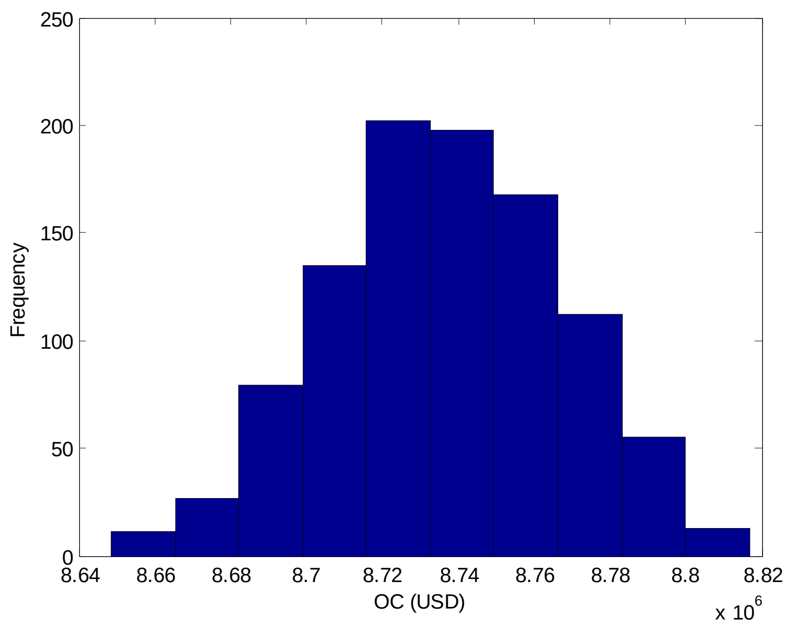

Figure 5.15 OC distribution for 1 MW solar PV power plant at METU NCC for constant demand and increasing electricity prices at 12 % annual rate

The distribution of OC for 1 MW solar PV power plant installation at METU NCC considering constant demand and increasing electricity prices is presented in Figure 5.15. The mean value of OC is 8.73 million USD with a minimum value of 8.64 million USD and a maximum value of 8.81 million USD. It should be noted that in comparison to the OC calculated for increasing electricity prices and demand presented in Section 5.1.2, the OC in this scenario has decreased by an average of 45%. This is because when the demand is not increasing, the opportunity to save more money by producing more from solar PV has decreased.

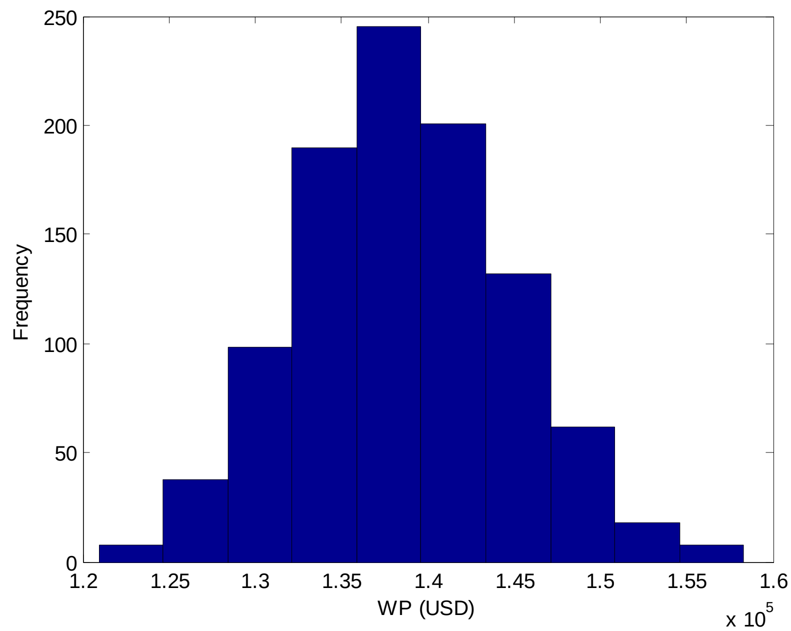

Figure 5.16 WP distribution for 1 MW solar PV power plant at METU NCC for constant demand and increasing electricity prices at 12 % annual rate

The distribution for the cost of excess production for 1 MW solar PV power plant considering constant demand and increasing electricity prices is shown in Figure 5.16. The mean value of WP is 138,600 USD with a minimum value of 120,000 USD and a maximum value of 158,000 USD. The OC here has increased by 450% as compared to increasing price and demand scenario as presented in Section 5.1.2. This is because when the demand is not increasing the number of hours when supply exceeds demand due to high solar resources has increased.

5.2. Stepwise Installation of PV Power Plant at METU NCC

5.2.1. Constant Electricity Price and Increasing Demand

As mentioned earlier in the beginning of this chapter the second case considered for the analysis is stepwise installation of solar PV power plant. Since, the demand is increasing every year, it will be necessary to increase solar PV plant capacity after some interval to fulfill the increasing demand. The case considered here is to install a 1 MW solar PV power plant at the first year then add another 1 MW to the solar PV power plant capacity after 7 years and then add another 1 MW to the solar PV power plant capacity after 14 years. The reason to consider 7 years of gap between additional capacities is that payback period of solar PV power plant is around 5 – 7 years. So, when the first plant is installed, its cost can be recovered in 7 years before more capacity is added. The amount of additional capacity i.e. 1 MW considered in this case is an arbitrary value and any capacity can be considered based on the growth and electricity demand of METU NCC. The graphs for the distributions of LCOE, NPV, OC and WP considering constant electricity prices and increasing electricity demand are presented in Figure 5.17 – Figure 5.20. It can be inferred from Figure 5.17 that LCOE for stepwise installation of solar PV power plant with constant electricity prices has reduced as compared to the LCOE of a single 1 MW solar PV power plant installation. The mean for the LCOE in this case is 0.0707 USD/kWh and the minimum and maximum values are 0.0702 USD/kWh and 0.0712 USD/kWh respectively.

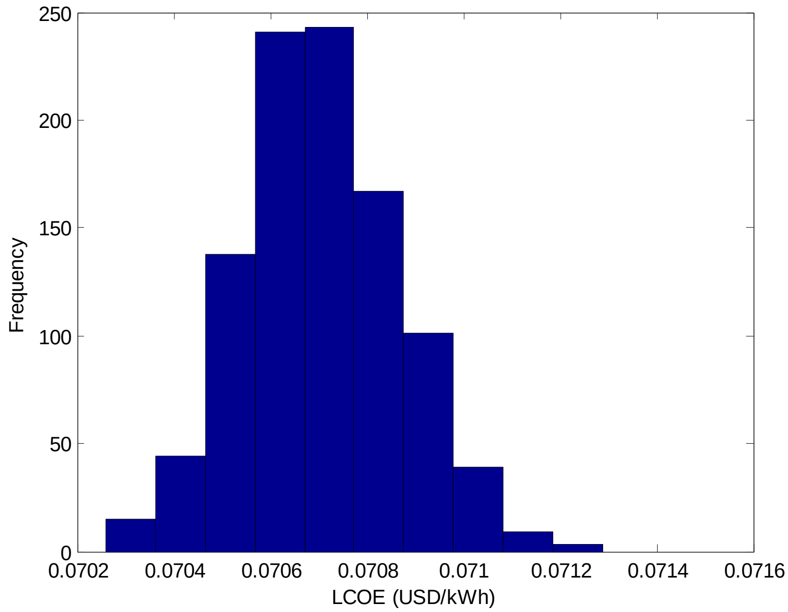

Figure 5.17 Distribution of LCOE for stepwise installation of solar PV plant at METU NCC with constant electricity prices

The NPV distribution shown in Figure 5.18 is for 20 years time period. It should be noted that the lifetime of first plant installed will end after 20 years but the life time of second plant will finish at the end of 27^{th} year and for third plant at the end of 34^{th} year. So, even after 20 years the plant will still be generating electricity with the capacities added in the 7^{th} and 14^{th} year. It should be noted that even though only 20 years are considered for calculating the NPV, the NPV in this case is higher than the NPV for a single 1 MW solar PV power plant installation for the same scenario considered. It can be seen from Figure 5.18 that the mean value of NPV is

2.56 million USD with minimum value 2.53 million USD and maximum value 2.58 million USD.

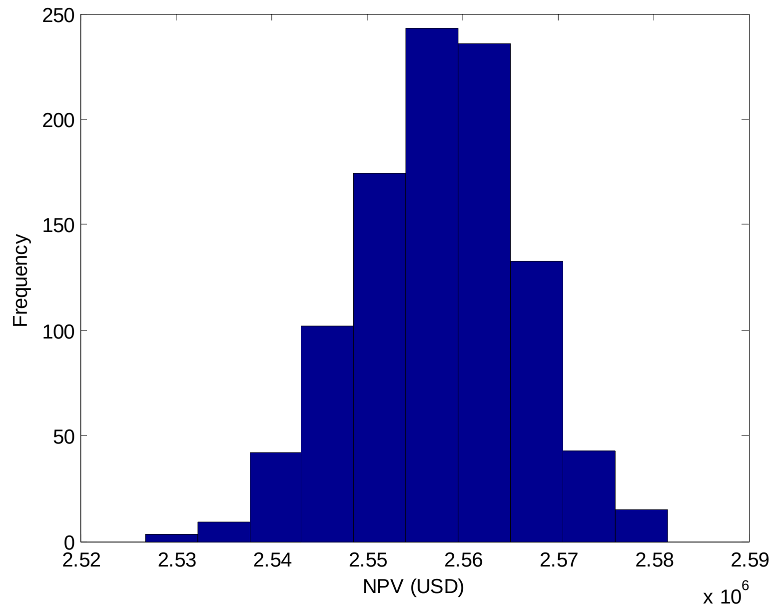

Figure 5.18 Distribution of NPV for stepwise installation of solar PV plant at METU NCC with constant electricity prices

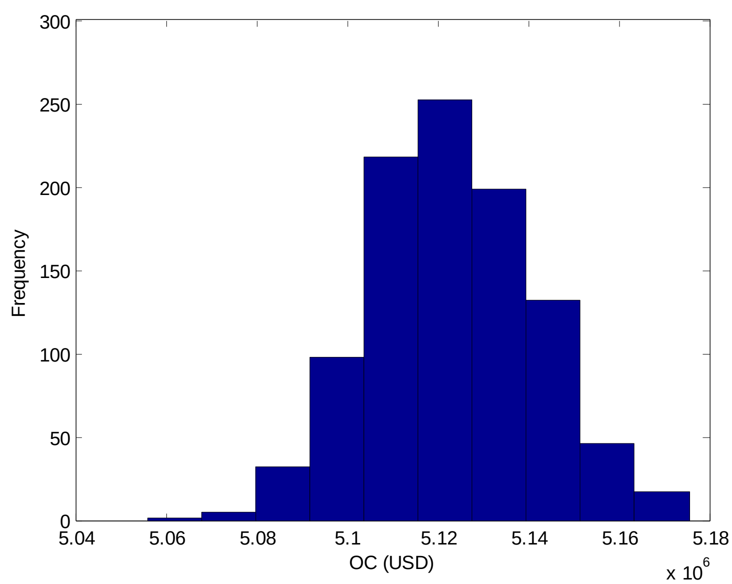

Figure 5.19 Distribution of OC for stepwise installation of solar PV plant at METU NCC with constant electricity prices

The distribution of opportunity cost for stepwise installation with constant electricity prices is presented in Figure 5.19. It is evident from the figure that the opportunity cost has reduced as compared the case of single 1 MW solar PV power plant installation presented in Section 5.1.1. The opportunity cost for stepwise installation is in the order of 5 million USD whereas for single 1 MW installation it was in the order of 6 million USD as shown in Figure 5.3. This is mainly due to the fact that in stepwise installation the supply is also increasing after 7 years and fulfilling the increased demand. The mean for the opportunity cost is 5.12 million USD with the minimum value 5.06 million USD and the maximum value 5.18 million USD.

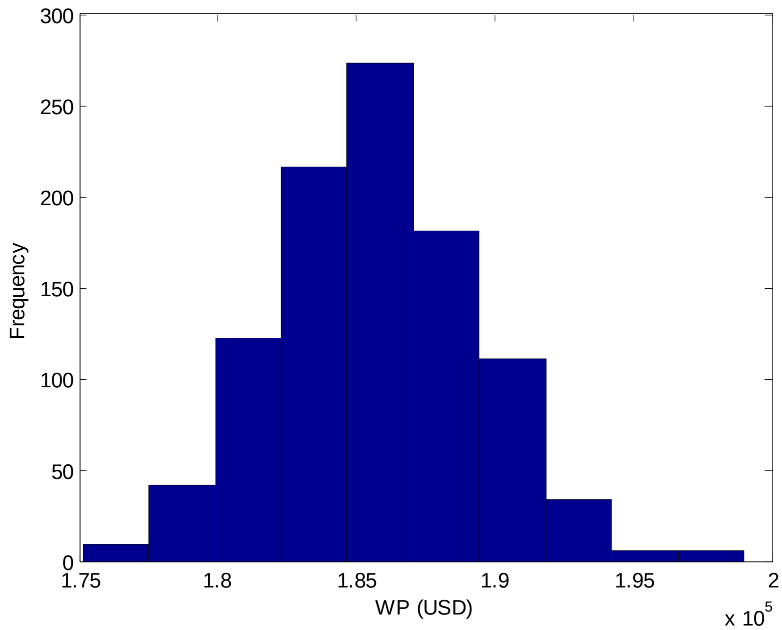

Figure 5.20 Distribution of WP for stepwise installation of solar PV plant at METU NCC with constant electricity prices

The distribution of the cost of excess production for stepwise installation with constant electricity prices is presented in Figure 5.20. It should be noted that cost of excess production has now increased as compared to the case of single 1 MW solar PV power plant installation considering the same scenario as presented in Section 5.1.1. The main reason of this increase is that the capacity is increasing in stepwise installation so the amount of excess electricity generated is higher. The mean for the cost of excess production in this case is 186,000 USD with a minimum value of 175,000 USD and a maximum value of 198,000 USD.

5.2.2. Increasing Electricity Price and Demand

The scenario considered earlier in this section was for constant electricity prices, but in this scenario it is considered that with the increase in electricity demand the electricity prices are also increasing at an average rate of 12% every year. The distributions for LCOE, NPV, OC and WP for this scenario are shown in Figure 5.21 – Figure 5.24. The mean for LCOE considering increasing electricity price is 0.0708 USD/kWh with a minimum value of 0.0702 USD/kWh and a maximum value of 0.0712 USD/kWh.

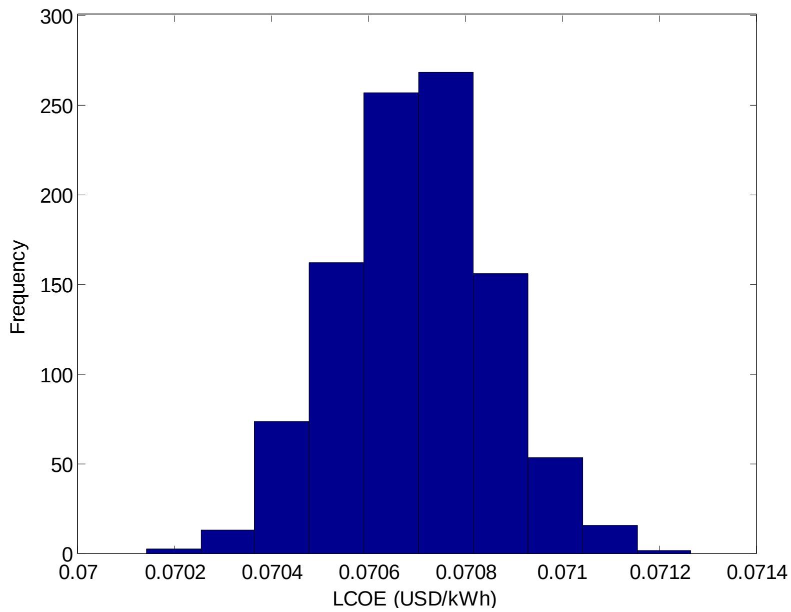

Figure 5.21 Distribution of LCOE for stepwise installation of solar PV plant at METU NCC with increasing electricity prices at 12% annual rate

The NPV distribution for stepwise installation considering increasing electricity prices with an annual rate of 12% and increasing electricity demand is shown in Figure 5.22. The mean in this case is 8.86 million USD with minimum value of 8.8 million USD and maximum value of 8.92 million USD. It should be noted here that for the same scenario for 1 MW solar PV power plant presented in Section 5.1.2, the mean value of the NPV was 4.74 million USD. This means that NPV has increased for stepwise installation.

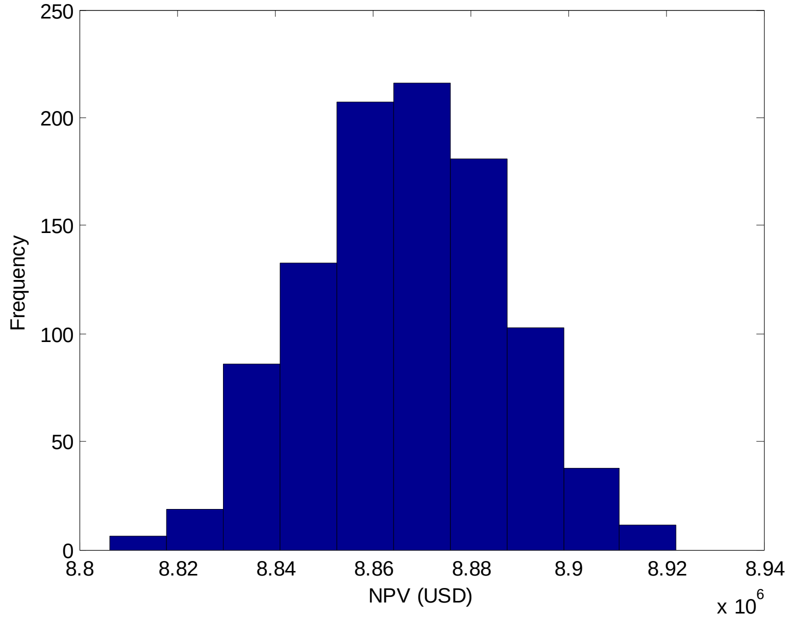

Figure 5.22 Distribution of NPV for stepwise installation of solar PV plant at METU NCC with increasing electricity prices at 12% annual rate

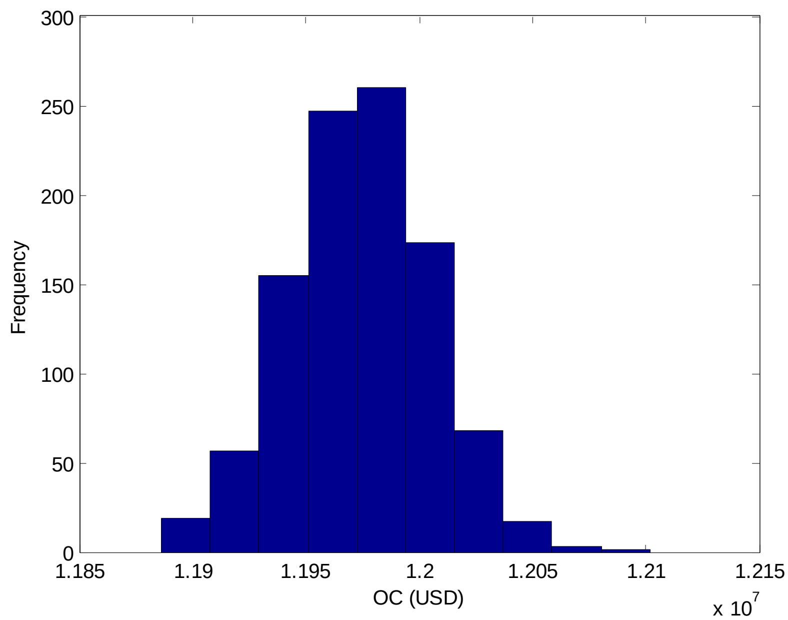

Figure 5.23 Distribution of opportunity cost for stepwise installation of solar PV plant at METU NCC with increasing electricity prices at 12% annual rate

The distribution of opportunity cost for stepwise installation considering increasing electricity prices is presented in Figure 5.23. The mean of opportunity cost is 11.9 million USD with minimum value of 11.8 million USD and maximum value of 12.1 million USD. On average there is an increase of 130 % in opportunity cost with increasing electricity prices as compared to opportunity cost with constant electricity prices presented in Section 5.2.1. Another fact that should be noted here is that OC for 1 MW power plant under the same scenario was in the region of 16 million USD as given in Section 5.1.2. This means that OC has reduced with stepwise installation. This is because; in stepwise installation the supply is increasing and chasing the increase in demand.

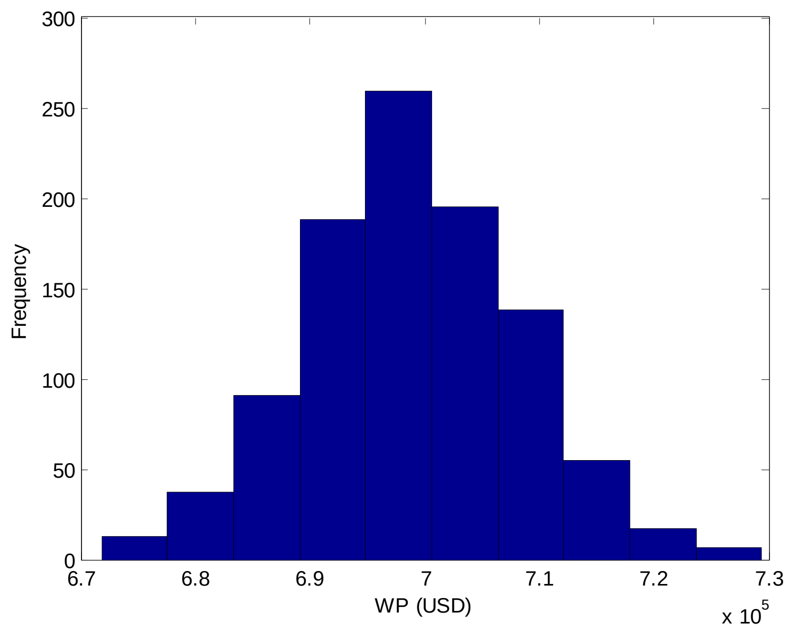

Figure 5.24 Distribution of cost of excess production for stepwise installation of solar PV plant at METU NCC with increasing electricity prices at 12% annual rate

The distribution of cost of excess production for stepwise installation considering increasing electricity prices and demand is shown in Figure 5.24. The mean for cost of excess production in this scenario is 698,000 USD with minimum value of 671,000 USD and maximum value of 729,000 USD. On average there is an increase of 270% in the cost of excess production with increasing electricity prices as compared to constant electricity prices scenario presented in Section 5.2.1. On comparison with 1 MW power plant under same scenario presented in Section 5.1.2, it should be noted that WP has increased for stepwise installation.

5.2.3. Constant Electricity Price and Demand

The scenario considered here is to have both the electricity prices and demand to be constant for the entire life time of PV system. The distributions of LCOE, NPV, OC and WP for stepwise installation of solar PV power plant at METU NCC are given in Figure 5.25 – Figure 5.28.

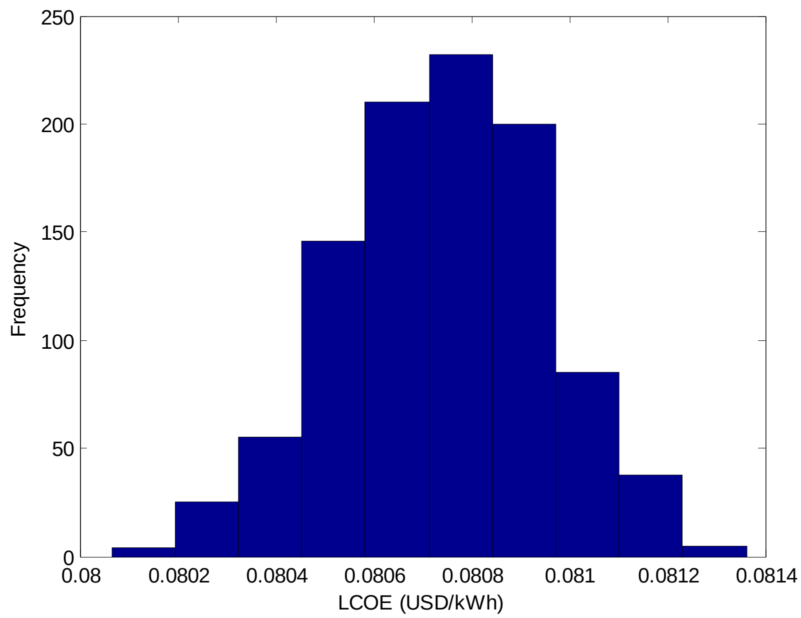

Figure 5.25 Distribution of LCOE for stepwise installation of solar PV plant at METU NCC with constant electricity prices and demand

The mean value of LCOE for stepwise installation for this case is 0.0807 USD/kWh with a minimum value of 0.0801 USD/kWh and a maximum value of 0.0814 USD/kWh as shown in Figure 5.25. The LCOE in this scenario has reduced by 12%, when compared to increasing electricity demand scenario presented in Section 5.2.1. On comparison with the LCOE of 1 MW power plant for the same scenario presented in Section 5.1.3, the LCOE for stepwise installation has decreased by 19%. The distribution of NPV for stepwise installation considering both the electricity demand and prices to be constant is presented in Figure 5.26. It can be inferred from the figure that the mean value of NPV is 2.0892 million USD with a minimum value of 2.0640 million USD and a maximum value of 2.117 million USD. On comparison with the increasing electricity demand scenario presented in Section 5.2.1, the NPV for constant electricity demand has decreased by 22%. Whereas, when it is compared to the NPV of 1 MW solar PV power plant installation at METU NCC for the same scenario presented in Section 5.1.3, the NPV for stepwise installation show an increase of 28%.

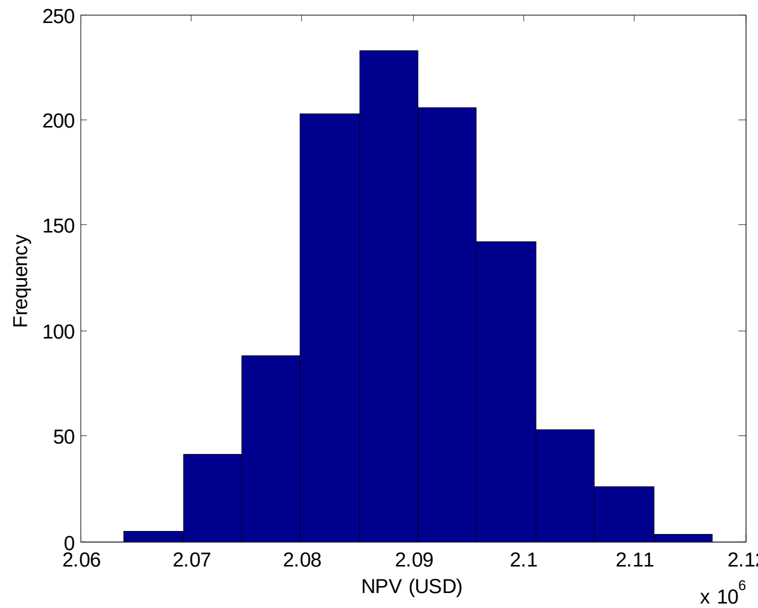

Figure 5.26 Distribution of NPV for stepwise installation of solar PV plant at METU NCC with constant electricity prices and demand

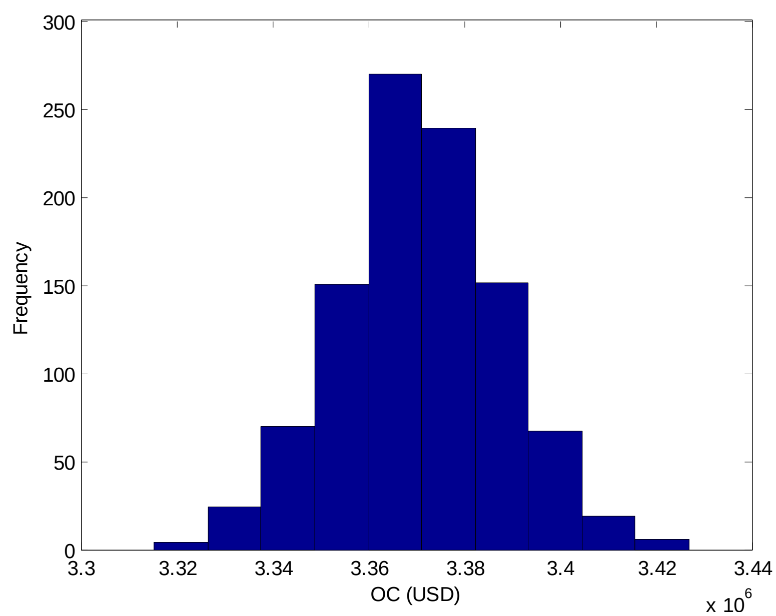

Figure 5.27 Distribution of OC for stepwise installation of solar PV plant at METU NCC with constant electricity prices and demand

The mean value of OC for stepwise installation at METU NCC considering constant electricity prices and demand is 3.3707 million USD, with a maximum value of 3.4269 million USD and minimum value of 3.3154 million USD as shown in Figure 5.27. The OC in this scenario has reduced by 34%, when compared to increasing electricity demand scenario presented in Section 5.2.1. On comparison with the OC of 1 MW power plant for the same scenario presented in Section 5.1.3, the OC for stepwise installation has decreased by 15%.

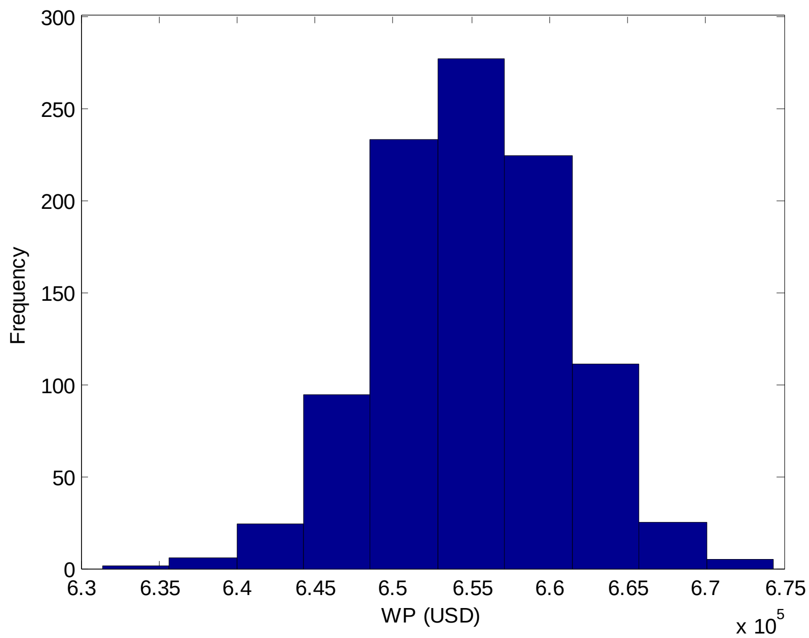

Figure 5.28 Distribution of WP for stepwise installation of solar PV plant at METU NCC with constant electricity prices and demand

When constant demand is considered the cost of excess production increase significantly, it can be inferred from the Figure 5.28 that the mean of WP is 655,100 USD with a minimum value of 631,390 USD and a maximum value of 674,320 USD. In this case the demand is considered to constant but the supply is increasing after every seven years, due to this fact the cost of excess production is high. On comparison with the constant prices and increasing demand scenario presented in Section 5.2.1, the excess production cost has increased by 250% in this case.

5.2.4. Increasing Electricity Price and Constant Demand

In this scenario it is assumed that the prices of electricity are increasing at a fixed rate of 12% every year and the demand of electricity is constant. The distributions of LCOE, NPV, OC and WP for stepwise installation at METU NCC for this scenario are presented in Figure 5.29 – Figure 5.32.

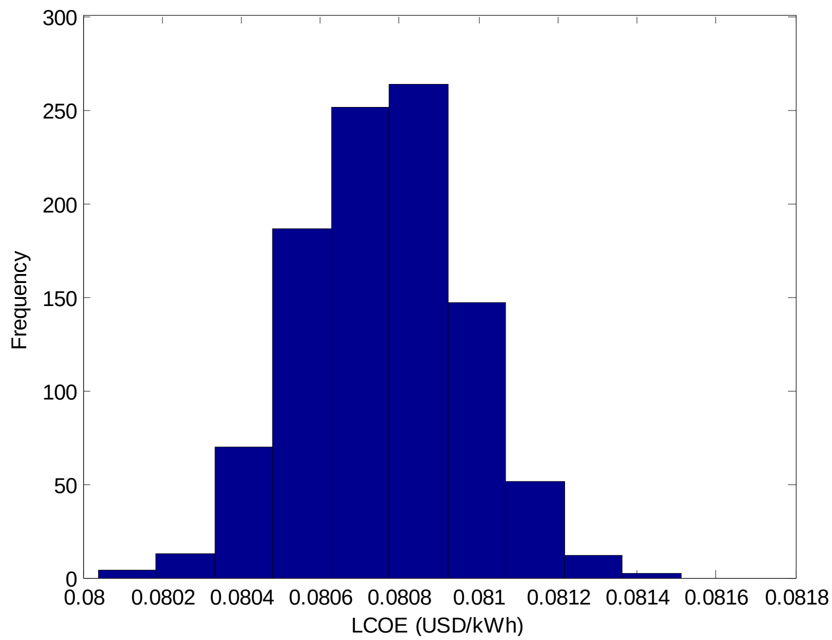

Figure 5.29 LCOE distribution for stepwise installation of solar PV power plant at METU NCC for constant demand and increasing electricity prices at 12 % annual rate

It can be seen from the distribution of LCOE in Figure 5.29, that the mean value of LCOE is 0.0808 USD/kWh and the maximum and minimum values are 0.0815 USD/kWh and 0.08 USD/kWh respectively. When compared to increasing electricity prices and demand scenario presented in Section 5.2.2, it can be seen that the LCOE in this scenario has increased by 12%. The mean of NPV for stepwise installation considering constant demand and increasing electricity prices is 6.95 million USD and the maximum and minimum values are 7.00 million USD and 6.89 million USD respectively as shown in Figure 5.30. The NPV in this case has decreased by 21% in comparison to the NPV for increasing prices and demand scenario presented in Section 5.2.2. This is due to the reason that demand is not increasing hence the increase in supply is not being utilized to increase cost savings.

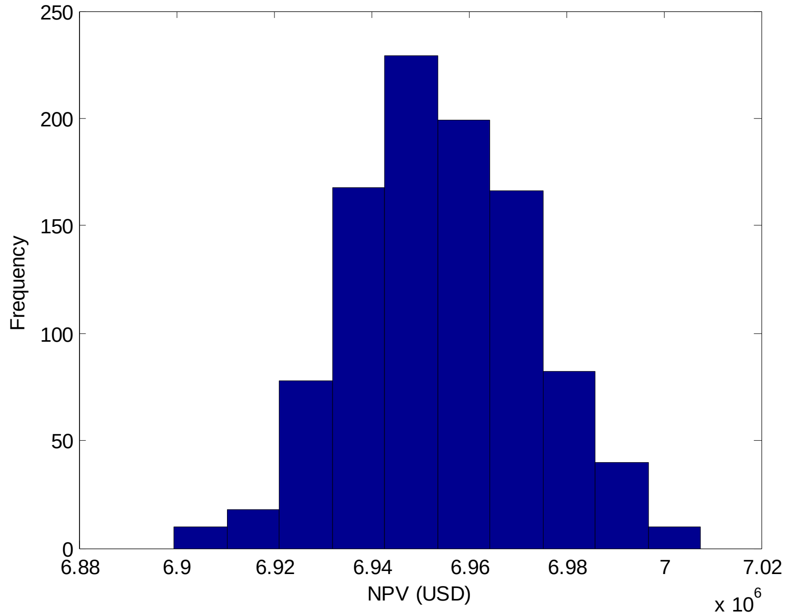

Figure 5.30 NPV distribution for stepwise installation of solar PV power plant at METU NCC for constant demand and increasing electricity prices at 12 % annual rate

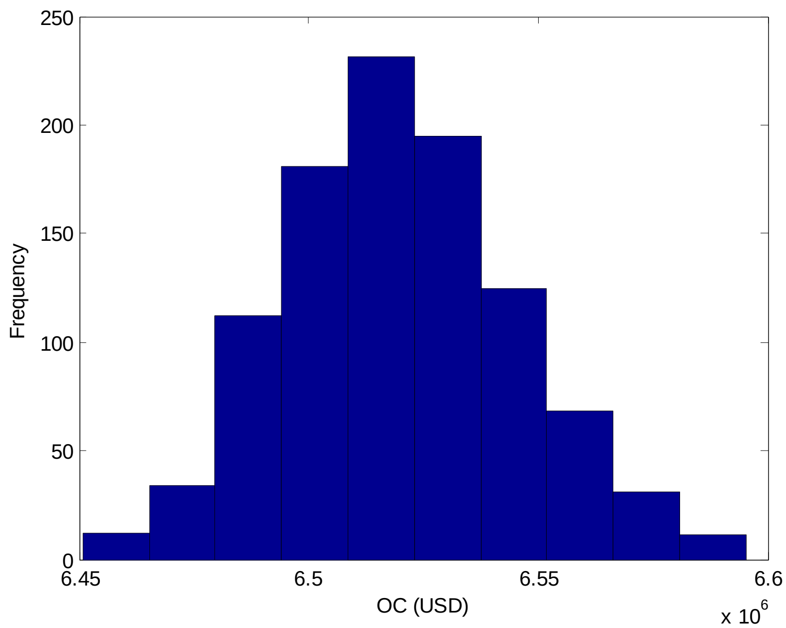

Figure 5.31 OC distribution for stepwise installation of solar PV power plant at METU NCC for constant demand and increasing electricity prices at 12 % annual rate

The mean value of OC for stepwise installation at METU NCC considering increasing electricity prices and constant demand is 6.52 million USD, with a maximum value of 6.59 million USD and minimum value of 6.45 million USD as shown in Figure 5.31. The OC in this scenario has reduced by 45%, when compared to increasing electricity prices and demand scenario presented in Section 5.2.2.

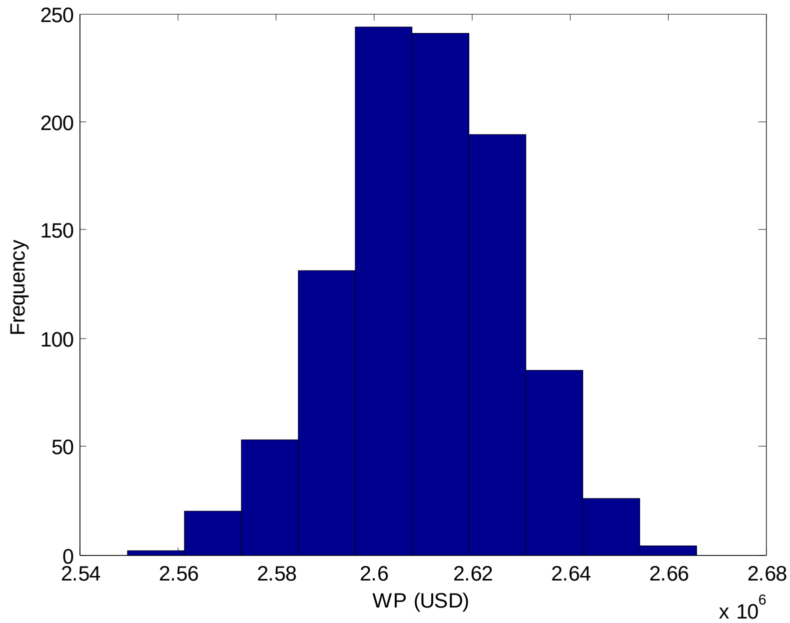

Figure 5.32 WP distribution for stepwise installation of solar PV power plant at METU NCC for constant demand and increasing electricity prices at 12 % annual rate

The distribution of cost of excess production for stepwise installation considering increasing electricity prices and constant demand is shown in Figure 5.32. The mean for cost of excess production in this scenario is 2.61 million USD with minimum value of 2.55 million USD and maximum value of 2.66 million USD. On average there is an increase of 270% in the cost of excess production with increasing electricity prices and constant electricity demand scenario as compared to increasing electricity demand and price scenario presented in Section 5.2.2. This increase is due to the reason that demand is constant and supply is increasing hence the amount of surplus energy in increasing.

5.3. Summary of Results

The simulation is run for different sizes to find the optimal size and understand the effect of size variation on LCOE, NPV, OC and WP. The results are summarized in Table 5.1 – Table 5.4 presenting the mean (μ) and standard deviation (σ) of the distributions of NPV, LCOE, OC and WP for different sizes under all four scenarios.

Table 5.1 Probability distribution summary of economic parameters considering constant price and increasing demand scenario for solar PV installations at METU NCC

Capacity (MW)	**LCOE (USD/kWh)**		**NPV (USD)**		**OC (USD)**		**WP (USD)**	
	μ	σ	μ	σ	μ	σ	μ	σ
1	0.0946	2.44×10^{-4}	1.53×10^{6}	1.33×10^{3}	6.16×10^{6}	1.18×10^{4}	1.94×10^{4}	2.37×10^{3}
2	0.1065	2.80×10^{-4}	2.45×10^{6}	1.25×10^{4}	4.19×10^{6}	1.54×10^{4}	5.37×10^{5}	8.20×10^{3}
3	0.1326	3.15×10^{-4}	2.28×10^{6}	1.36×10^{4}	3.24×10^{6}	1.32×10^{4}	2.08×10^{6}	1.42×10^{4}
4	0.1633	3.88×10^{-4}	1.6×10^{6}	1.47×10^{4}	2.78×10^{6}	1.17×10^{4}	4.11×10^{6}	2.03×10^{4}
5	0.1953	4.45×10^{-4}	7.3×10^{5}	1.48×10^{4}	2.51×10^{6}	1.06×10^{4}	6.33×10^{6}	2.57×10^{4}
6	0.2278	5.13×10^{-4}	-2.37×10^{5}	1.50×10^{4}	2.33×10^{6}	9.82×10^{3}	8.65×10^{6}	3.21×10^{4}

Table 5.2 Probability distribution summary of economic parameters considering increasing price and increasing demand scenario for solar PV installations at METU NCC

Capacity (MW)	**LCOE (USD/kWh)**		**NPV (USD)**		**OC (USD)**		**WP (USD)**	
	μ	**σ**	**μ**	**σ**	**μ**	**σ**	**μ**	**σ**
1	0.0946	2.53×10^{-4}	4.74×10^{6}	1.23×10^{4}	1.59×10^{7}	3.27×10^{4}	2.51×10^{4}	2.97×10^{3}
2	0.1065	2.72×10^{-4}	8.52×10^{6}	2.15×10^{4}	1.13×10^{7}	3.14×10^{4}	7.96×10^{5}	1.19×10^{4}
3	0.1326	3.38×10^{-4}	1.00×10^{7}	2.71×10^{4}	8.69×10^{6}	2.74×10^{4}	3.65×10^{6}	2.16×10^{4}
4	0.1634	3.97×10^{-4}	1.02×10^{7}	2.89×10^{4}	7.36×10^{6}	2.56×10^{4}	7.79×10^{6}	3.13×10^{4}
5	0.1953	4.59×10^{-4}	9.8×10^{6}	2.91×10^{4}	6.59×10^{6}	2.39×10^{4}	1.2×10^{7}	4.24×10^{4}
6	0.2278	5.20×10^{-4}	9.2×10^{6}	2.97×10^{4}	6.09×10^{6}	2.22×10^{4}	1.74×10^{7}	5.5×10^{4}

Table 5.3 Probability distribution summary of economic parameters considering constant price and constant demand scenario for solar PV installations at METU NCC

Capacity (MW)	LCOE (USD/kWh)		NPV (USD)		OC (USD)		WP (USD)	
	μ	σ	μ	σ	μ	σ	μ	σ
1	0.0961	2.63×10^{-4}	1.48×10^{6}	7.24×10^{3}	3.98×10^{6}	1.73×10^{4}	6.30×10^{4}	3.58×10^{3}
2	0.1204	3.41×10^{-4}	1.91×10^{6}	1.19×10^{4}	2.51×10^{6}	1.34×10^{4}	1.08×10^{6}	9.94×10^{3}
3	0.1607	4.65×10^{-4}	1.28×10^{6}	1.37×10^{4}	2.02×10^{6}	1.08×10^{4}	3.09×10^{6}	1.60×10^{4}
4	0.2032	5.64×10^{-4}	3.80×10^{5}	1.38×10^{4}	1.78×10^{6}	9.08×10^{3}	5.34×10^{6}	2.20×10^{4}
5	0.2465	6.66×10^{-4}	-6.20×10^{5}	1.39×10^{4}	1.64×10^{6}	8.59×10^{3}	7.69×10^{6}	2.72×10^{4}
6	0.29	7.69×10^{-4}	-1.67×10^{6}	1.39×10^{4}	1.54×10^{6}	7.81×10^{3}	1×10^{7}	3.29×10^{4}

Table 5.4 Probability distribution summary of economic parameters considering increasing price and constant demand scenario for solar PV installations at METU NCC

Capacity (MW)	LCOE (USD/kWh)		NPV (USD)		OC (USD)		WP (USD)	
	μ	σ	μ	σ	μ	σ	μ	σ
1	0.0961	2.77×10^{-4}	4.63×10^{6}	1.29×10^{3}	8.73×10^{6}	3.05×10^{4}	1.39×10^{5}	6.10×10^{3}
2	0.1204	3.47×10^{-4}	6.94×10^{6}	2.1×10^{4}	5.51×10^{6}	2.33×10^{4}	2.38×10^{6}	1.85×10^{4}
3	0.1606	4.67×10^{-4}	6.92×10^{6}	2.42×10^{4}	4.41×10^{6}	1.98×10^{4}	6.77×10^{6}	2.91×10^{4}
4	0.2032	5.69×10^{-4}	6.33×10^{6}	2.39×10^{4}	3.91×10^{6}	1.63×10^{4}	1.17×10^{7}	3.70×10^{4}
5	0.2465	6.86×10^{-4}	5.51×10^{6}	2.46×10^{4}	3.65×10^{6}	1.52×10^{4}	1.67×10^{7}	4.84×10^{4}
6	0.29	8.09×10^{-4}	4.58×10^{6}	2.44×10^{4}	3.39×10^{6}	1.42×10^{4}	2.21×10^{7}	5.68×10^{4}

Based on the results presented in Table 5.1 – Table 5.4, it can be inferred that the economically feasible size for solar PV power plant installation at METU NCC is between 2 MW – 3 MW. This is because under all scenarios except for increasing price and demand scenario, the NPV increases till 2 MW and it starts decreasing from 3 MW, this means that NPV become maximum between 2 MW and 3 MW. Moreover, the LCOE is lower than current price of grid electricity (i.e. 0.22 USD/kWh) for power plant sizes less than 4 MW. The LCOE tends to increase with increase in power plant size and it becomes higher than current grid electricity prices for a 5 MW solar PV power plant. The opportunity cost tends to decrease with increase in solar PV power plant size and on the other hand the excess production cost tends to increase. The opportunity cost and excess production cost become equal somewhere between 2 MW and 3 MW power plant sizes, highlighting the fact that the economically the most feasible size of solar PV power plant installation at METU NCC is between 2 MW – 3 MW. In case of increasing demand and price scenario, the NPV increase till 4 MW and then starts decreasing. Moreover, the LCOE for 4 MW is less than current price of grid electricity (0.22 USD/kWh) hence under this scenario installation of 4 MW power plant is most feasible economically.

CHAPTER 6

CONCLUSIONS AND FUTURE WORK

6.1 Conclusions

The manufacturing costs of solar PV are continuously decreasing and the efficiency of solar PV is also increasing which makes the future of this technology promising. With ample of solar resources in Northern Cyprus, solar PV can play an important role in decarbonisation and sustainability of the electricity sector in Northern Cyprus as it is explained in the introduction in Chapter 1. Several methodologies exist in the literature for the design and feasibility analysis of PV systems but no work has presented a tool that can directly analyze the feasibility of a project based on uncertainties in electricity consumption, solar resources and electricity prices.

Based on the objectives presented in Section 1.10, first the modeling and forecasting of electricity consumption at METU NCC is presented. Different models of different time scales are considered for forecasting of electricity consumption at METU NCC and are presented in 0. For forecasting annual trend in electricity consumption at METU NCC Holt's method is used. According to the Holt's forecasting model, the electricity consumption at METU NCC increases at average rate of 443,714 kWh every year. This means that the total annual electricity consumption at METU NCC will reach 17,349,914 kWh by the year by the year 2035. The other methods used for forecasting total annual electricity consumption are linear regression with population as independent variable presented in Section 2.2.2 and linear regression with year as independent variable presented in Section 2.2.3. For forecasting monthly electricity consumption at METU NCC, Winter's model is used. Both trend and seasonality component are considered in monthly forecasting of electricity consumption at METU NCC. Each month was considered as a separate season to have a more accurate and reliable forecast, with an MAPE of 11.22% the model give reliable results.

In case of daily forecasts, the first model that is presented is the multiple regression analysis presented in Section 2.4.1. In multiple regression analysis, electricity consumption is predicted based on a set of independent variables which influence the electricity consumption at METU NCC. The independent variables considered for multiple regression analysis are divided into three groups; calendar data, meteorological data and demographic data. In calendar data the variables considered are weekdays (W), graduate and undergraduate classes and exams (GU), summer school classes and exams (SS), English preparatory school classes and exams (EP), and the orientation and registration days (OR). The variables considered in meteorological data are; average temperature of the day (Tavg), average humidity of the day (RH), heating needs (H) and cooling needs (C). Twelve different regressions models are developed are to predict electricity consumption with increased accuracy, each model for each month. The results of the multiple regression analysis do not predict the yearly increasing trend in electricity consumption because the data available for testing and training the model was of one year only.

In order to present a daily forecasting model which also incorporates the yearly increasing trend in electricity consumption a new method is proposed and used as shown in Section 2.4.2. This novel and non-conventional model predicts long term daily electricity consumption with annual trend. This model is an integration of multiple regression analysis and the trend component of Holt's method. The trend estimate obtained from Holt's method is added to the output generated from multiple regression method. Since the annual increasing trend in electricity consumption is not incorporated in multiple regression method presented in Section 2.4.1, therefore its output may be considered as a simple level estimate in this model.

The last part of 0 presents hourly models for predicting electricity consumption at METU NCC. Probabilistic characterization technique is used for forecasting hourly electricity consumption. For each month the probability distribution which best fits the daily electricity consumption data is identified by comparing their P-values and AD values. Base on the indentified probability distributions for each month which best fits the data, the associated parameters are calculated for each month's pdf. For months where Extreme Value distribution presents the best fit, the location parameter (μ) and scale parameter (σ) are calculated. Similarly, for month's which have Normal or Weibull distributions, their respective associated parameters are estimated as shown in Section 2.5.1.3. After calculating the associated parameters of each month's fitted distribution, random data of daily electricity consumption is generated for 20 years. The random data are generated using MATLAB. The random data of daily electricity consumption are then multiplied with each month's average hourly consumption percentages to obtain hourly electricity consumption data for 20 years.

Chapter 3 presents detailed models for calculating and forecasting solar resources. The solar resources are calculated based on the model presented in Section 3.2 for METU NCC. For a fixed surface, the maximum solar resources are received at a tilt angle of 24.67° facing due south. This is within the limit of 15° to 30° tilt angle facing due south for maximum solar resources, presented by Arsalan and Baker [2] for METU NCC. The hourly solar resources are predicted for 20 years using probabilistic characterization technique in the same way as it is done for hourly forecasting of electricity consumption at METU NCC. The electricity generated from solar PV power plant depends upon area of the solar panels, efficiency of the solar panels, performance factor of the solar PV power plant and the available solar resources. The efficiency of solar Panel varies due to changes in temperature, as the temperature increases the efficiency decreases but for the sake of simplicity a constant efficiency is considered. SYP240S (polycrystalline) solar panel of Risen Energy Company limited is selected; it has an efficiency of 14.78% at Standard Test Conditions [31]. The performance factor of the PV power plant is considered to be 75% [31]. With these inputs and without considering uncertainties in solar resources, on average 5.62 MWh of daily electricity can be produced by 1 MW PV power plant with PV panel area equal to 9021 m^2.

The main objective of this thesis is to consider all the uncertainties in electricity consumption, solar resources and electricity prices in order to analyze the feasibility of any project. Based on this objective a general methodology and simulation tool (presented in Section 4.2) is developed in this thesis which is applicable to any location. Monte Carlo simulation is used for the economic analysis of the PV systems. Instead of having point estimates Monte Carlo simulation gives distributions for NPV, LCOE, OC and WP. For each case, thousand data values are calculated to generate a distribution. The cases considered for feasibility analysis and ran in the simulation developed are; installation of 1 MW solar PV power plant and stepwise installation of solar PV power plant (installing 1 MW after every 7 years). These cases are run for 20 years and their economic feasibility analysis is done. The distributions of NPV, LCOE, OC and WP generated for different cases accounts for all the uncertainties associated with the solar PV systems. Both the cases considered are run for four scenarios, the first scenario is to have constant electricity prices and increasing electricity demand, the second scenario is to have increasing electricity prices and demand, the third scenario is to have constant prices and demand and the last scenario is to have increasing electricity prices and constant electricity demand.

The novel methodology presented in this paper is a stochastic iterative technique that used Monte Carlo simulation for the feasibility analysis of solar PV installation. In conclusion, it should be noted that the simulation generated distributions instead of giving point estimates, hence accounting for all the uncertainties in electricity consumption and solar resources. The distributions generated by the simulation give realistic results and give an estimate of risk involved in any solar PV installation. Since, it is impossible to predict the precise value of NPV or LCOE or any other variable for solar PV power plant installation, the probability distributions generated by the simulation give realistic forecasts of NPV, LCOE, OC and WP based on uncertainties. Moreover, the scenario analysis presented allows the decision makers to have more insight knowledge of the possible outcomes. The proposed methodology is flexible as it can be used for analyzing the feasibility of solar PV power plant installation of any capacity at any location on earth for varying loads.

Based on the results of simulation it can be said that both 1 MW and stepwise installation options are feasible under all scenarios considering all the uncertainties. This is because of the positive NPV distributions that do not show any losses. Moreover, the LCOE for both the cases under all scenarios is coming lower than the current price of electricity. The most feasible power plant size economically is between 2 MW – 3 MW. With total capacity of 351 MW of the electricity grid of Northern Cyprus, it is highly unlikely that current regulations will allow higher capacity installations of solar PV at METU NCC. But if in future the electricity grid size of Northern Cyprus increases or it gets connected to the electricity grid of Turkey then the stepwise solar PV installation option may not be restricted.

6.2 Future Work

In this research different forecasting techniques are used for predicting electricity consumption and solar resources. These techniques and their forecasting accuracy can be improved if significant amount of historical data is available to train and test these models. Furthermore, in case of Monte Carlo simulation uncertainties in solar resources, electricity consumption and electricity prices are considered, this analysis can be enhanced if technological parameters are taken into account which may result in decrease in the cost of solar PV power plant in future. Moreover, a more general stochastic optimization model to find the optimal capacity of solar PV installation can be developed.

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APPENDIX A

ACTUAL AND PREDICTED ELECTRICITY CONSUMPTION USING MULTIPLE REGRESSION ANALYSIS

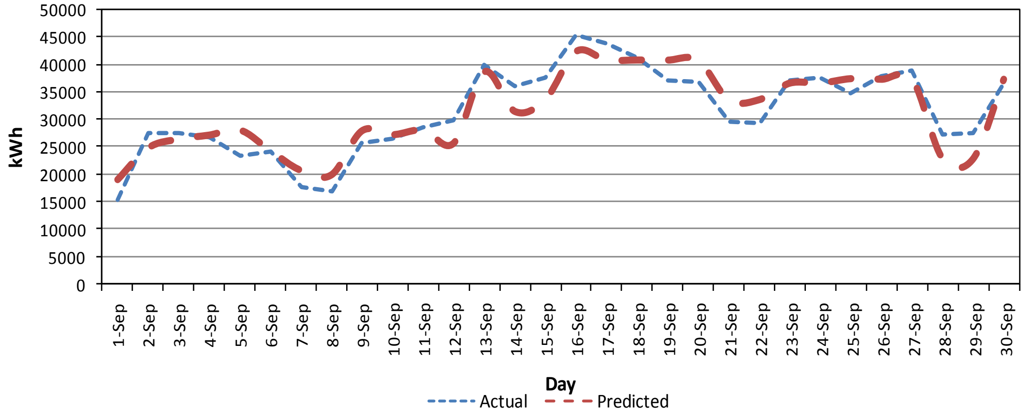

Figure A.1 Actual and predicted consumption for September, 2013 at METU-NCC

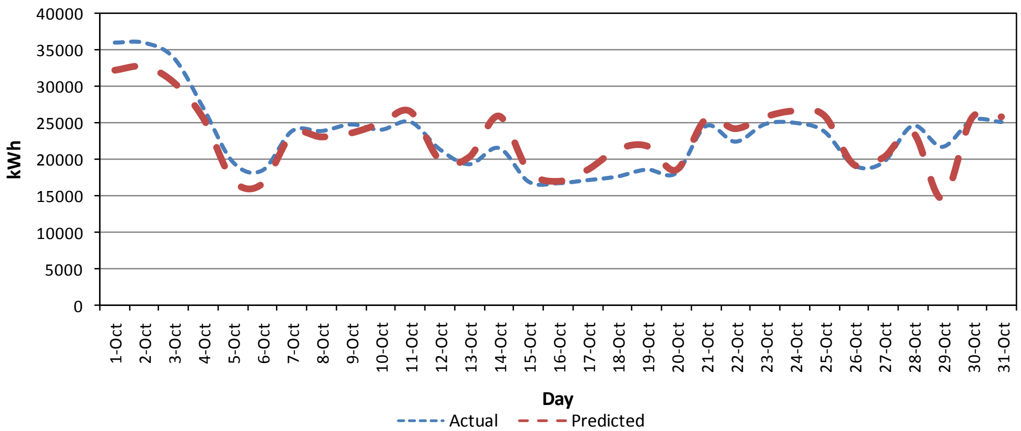

Figure A.2 Actual and predicted consumption for October, 2013 at METU-NCC

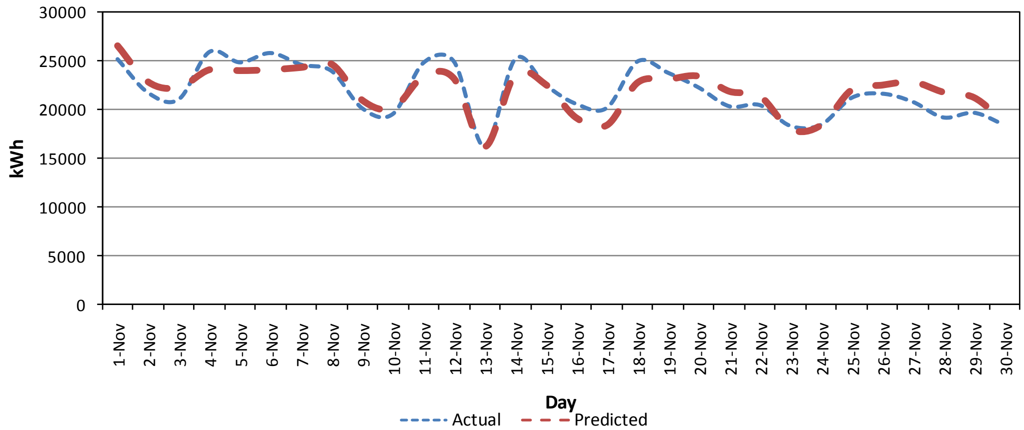

Figure A.3 Actual and predicted consumption for November, 2013 at METU-NCC

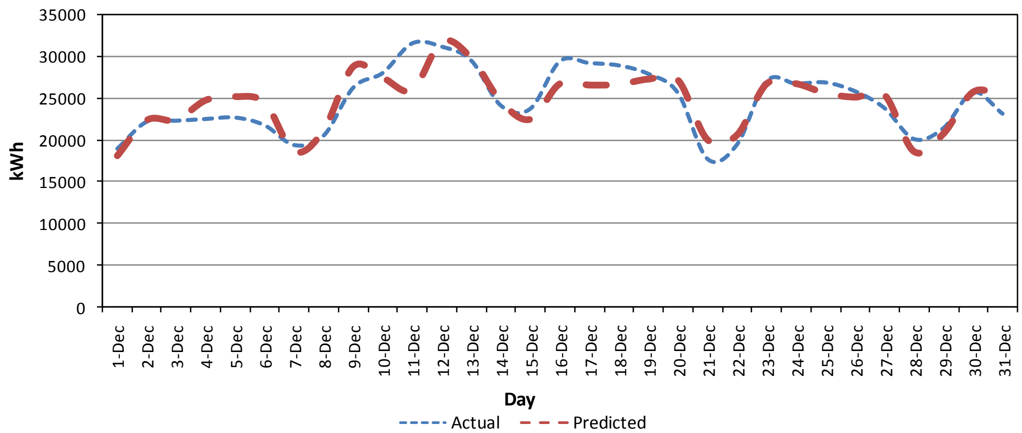

Figure A.4 Actual and predicted consumption for December, 2013 at METU-NCC

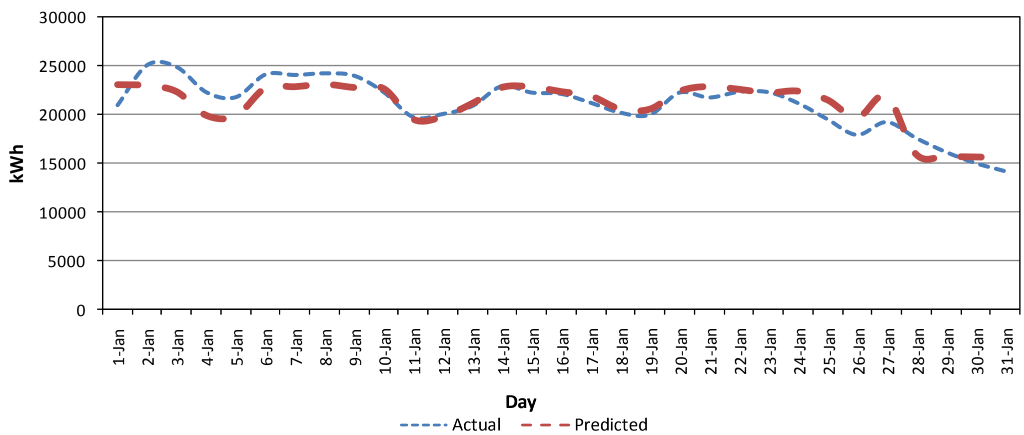

Figure A.5 Actual and predicted consumption for January, 2014 at METU-NCC

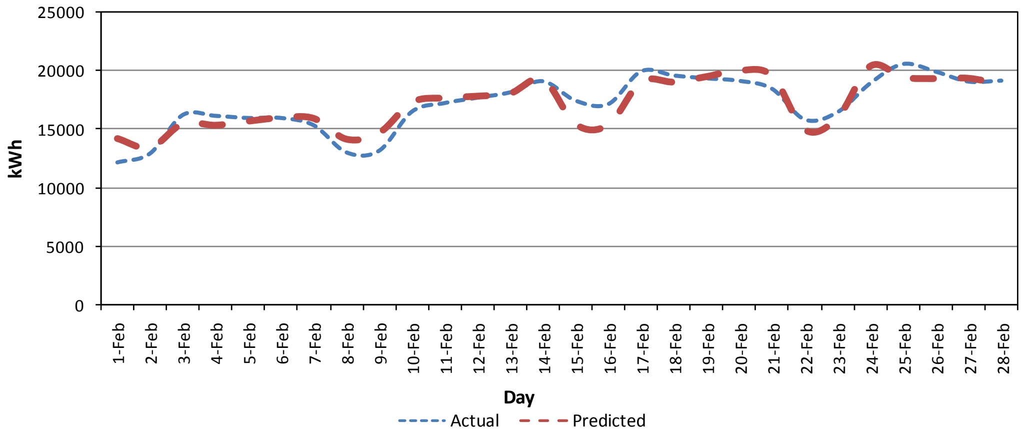

Figure A.6 Actual and predicted consumption for February, 2014 at METU-NCC

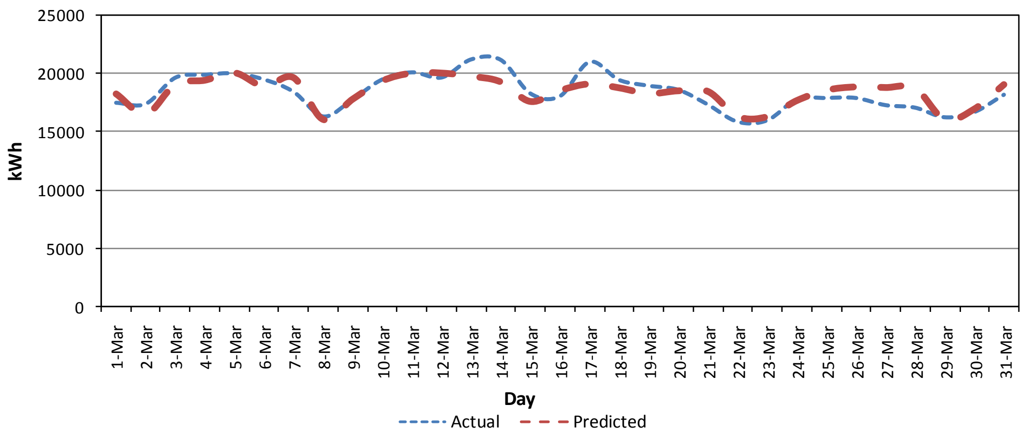

Figure A.7 Actual and predicted consumption for March, 2014 at METU-NCC

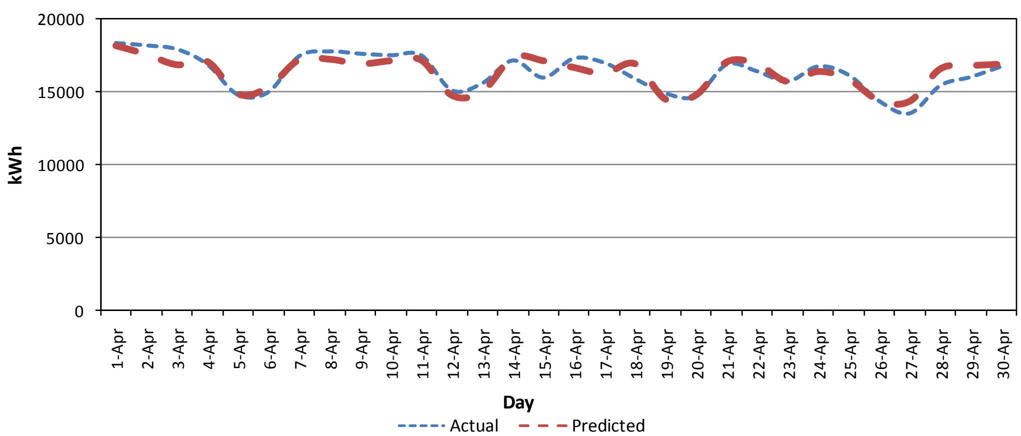

Figure A.8 Actual and predicted consumption for April, 2014 at METU-NCC

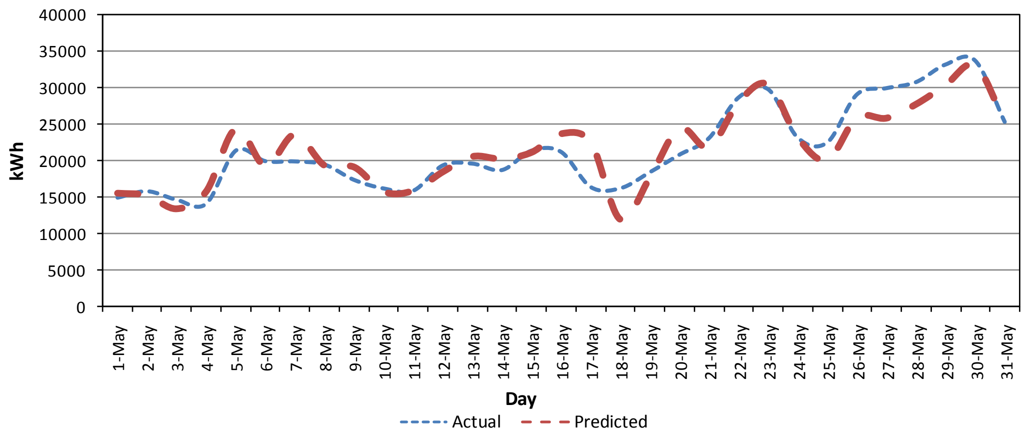

Figure A.9 Actual and predicted consumption for May, 2014 at METU-NCC

APPENDIX B

PROBABILITY PLOTS OF DAILY ELECTRICITY CONSUMPTION FOR EACH MONTH

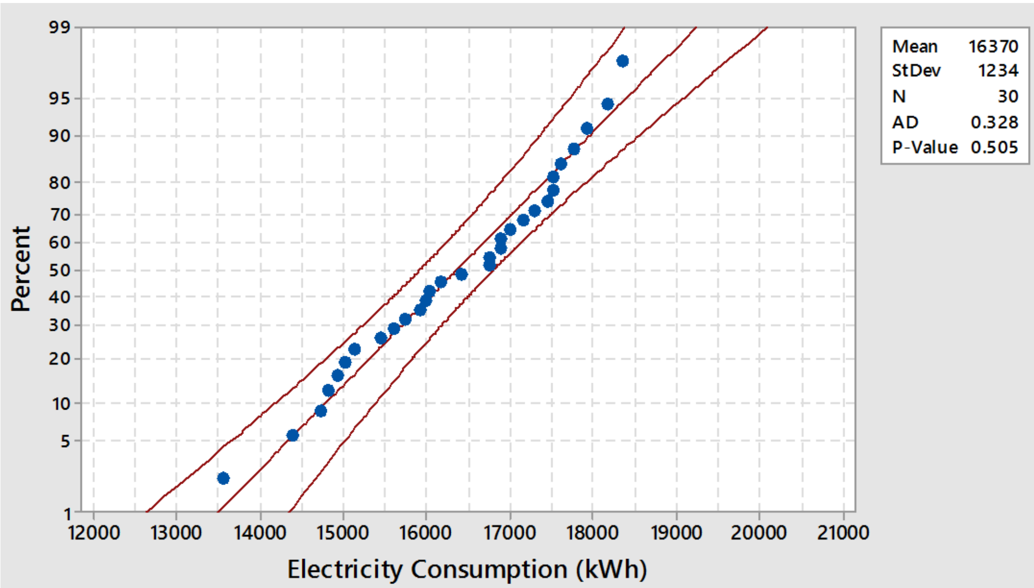

Figure B.1 Fitted Normal distribution for electricity consumption data of April

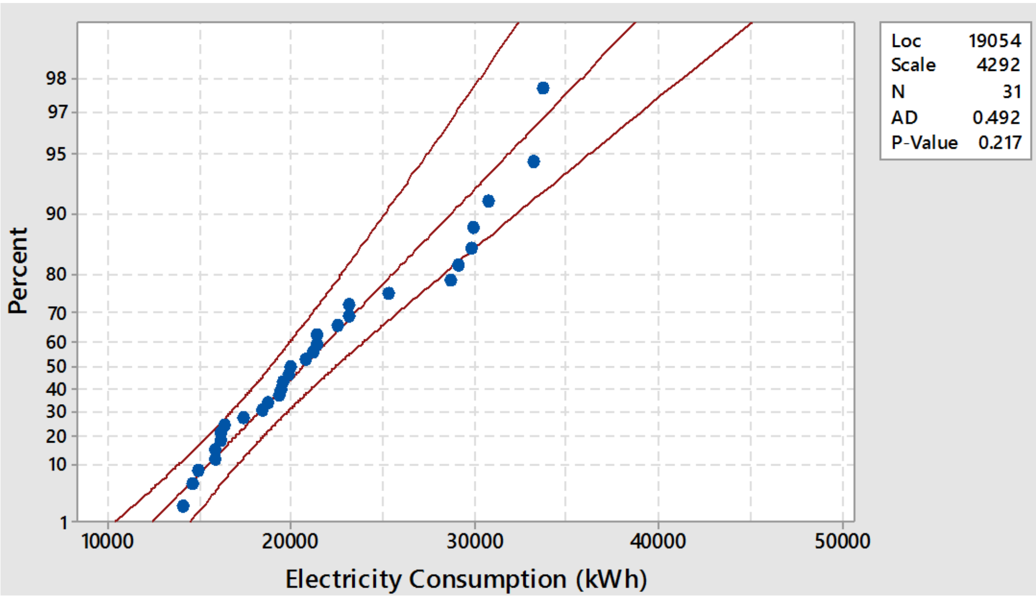

Figure B.2 Fitted Extreme Value distribution for electricity consumption data of May

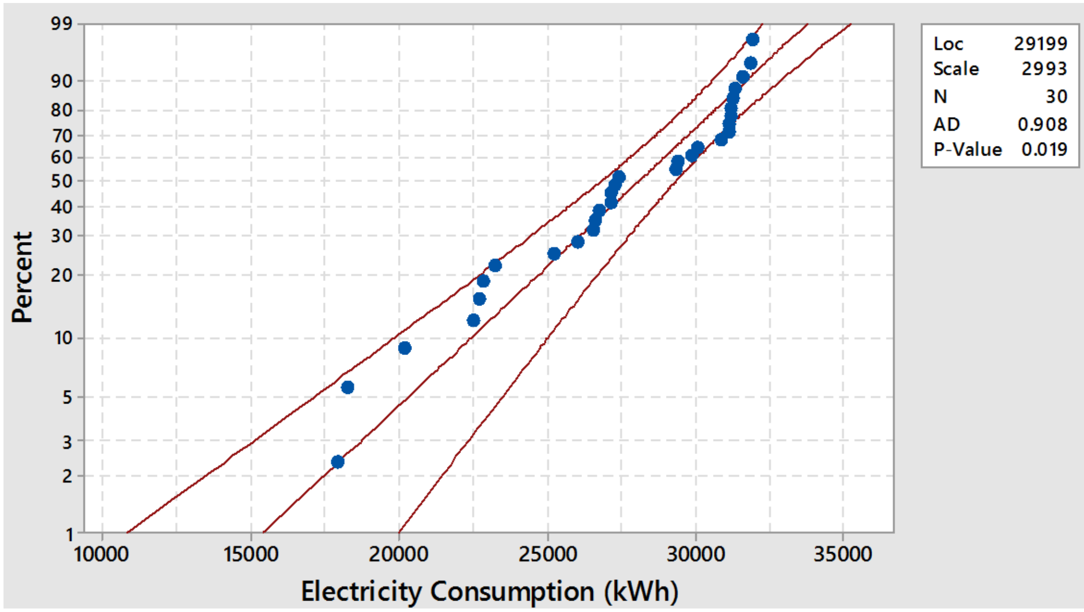

Figure B.3 Fitted Extreme Value distribution for electricity consumption data of June

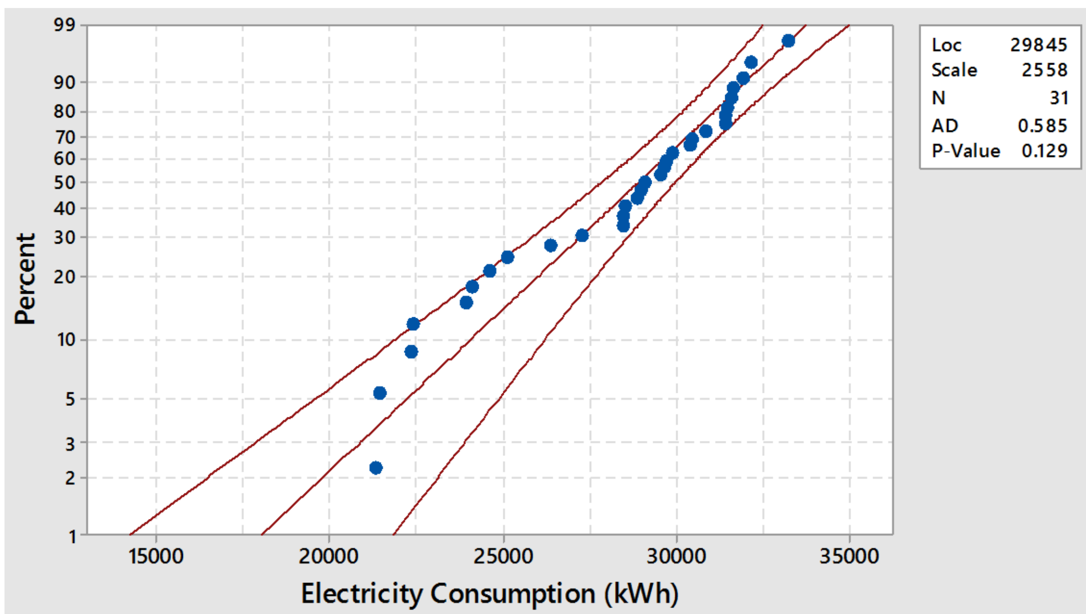

Figure B.4 Fitted Extreme Value distribution for electricity consumption data of July

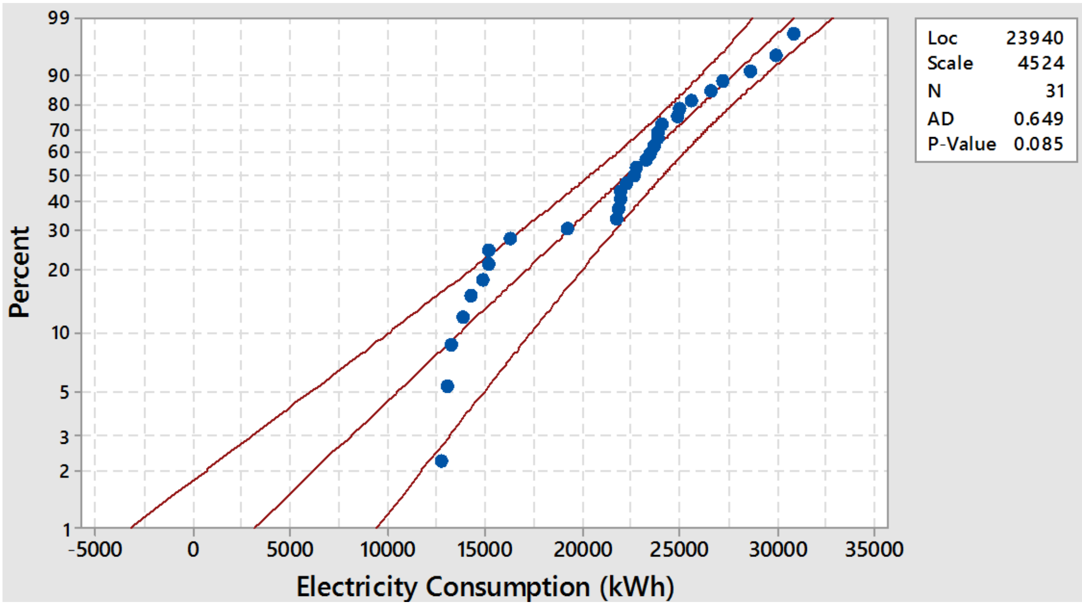

Figure B.5 Fitted Extreme Value distribution for electricity consumption data of August

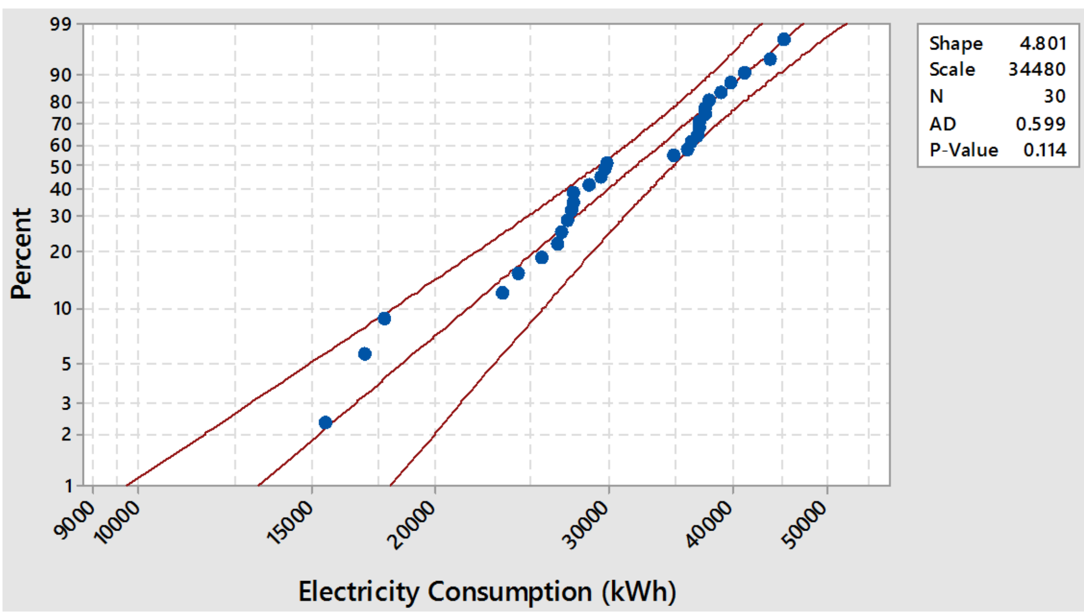

Figure B.6 Fitted Weibull distribution for electricity consumption data of September

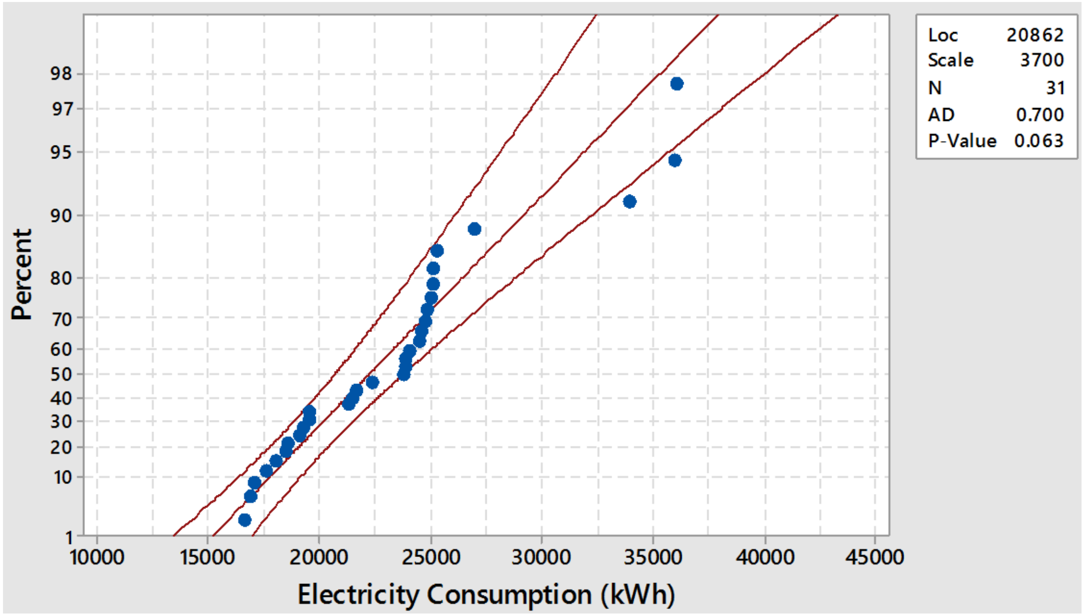

Figure B.7 Fitted Extreme Value distribution for electricity consumption data of October

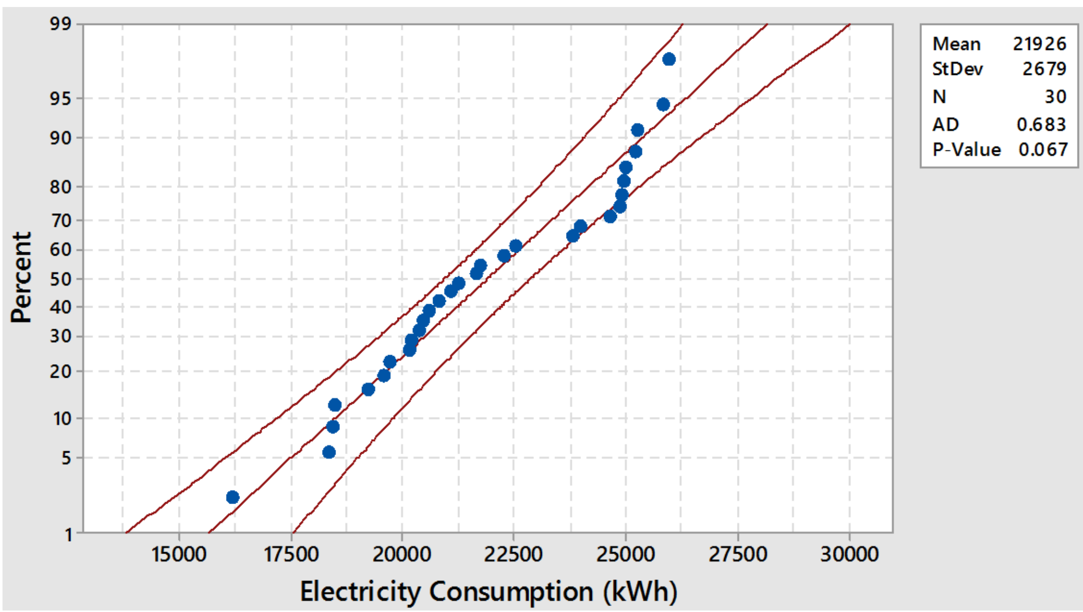

Figure B.8 Fitted Normal distribution for electricity consumption data of November

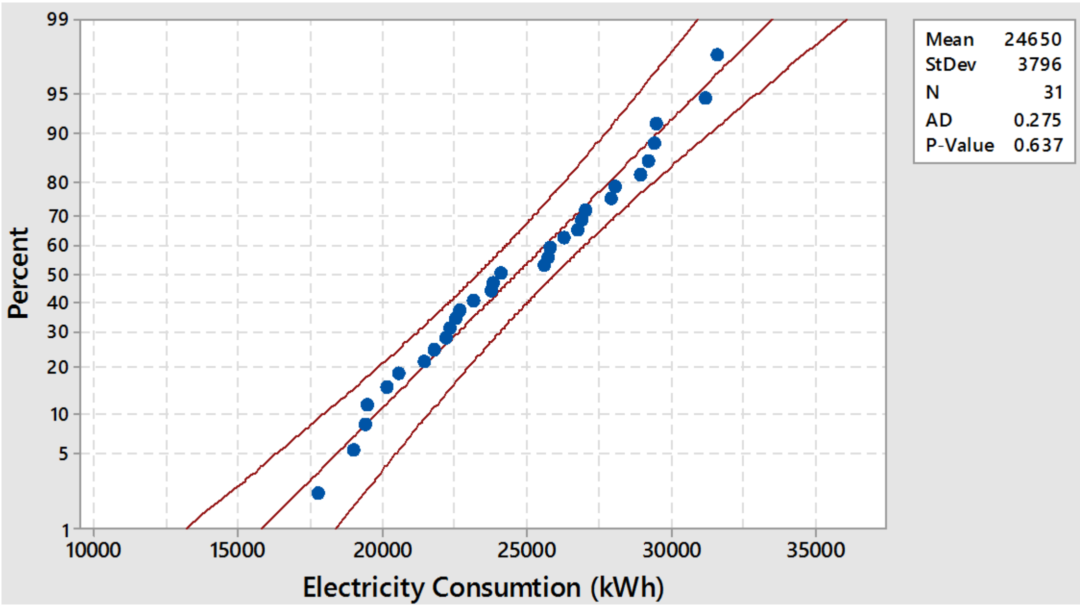

Figure B.9 Fitted Normal distribution for electricity consumption data of December

APPENDIX C

AVERAGE HOURLY PERCENTAGES OF ELECTRICITY CONSUMPTION FOR EACH MONTH

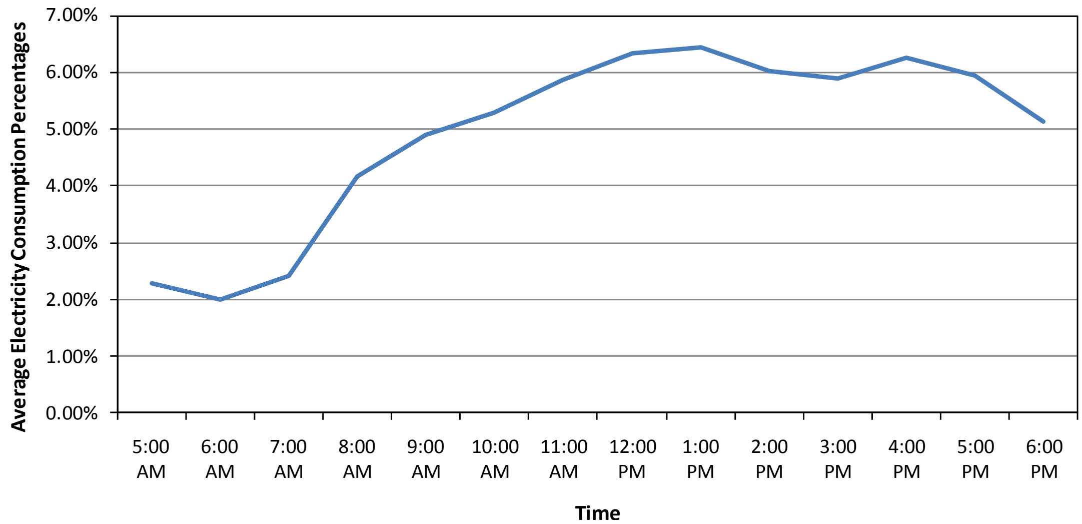

Figure C.1 Average hourly electricity consumption percentages during the day time for April

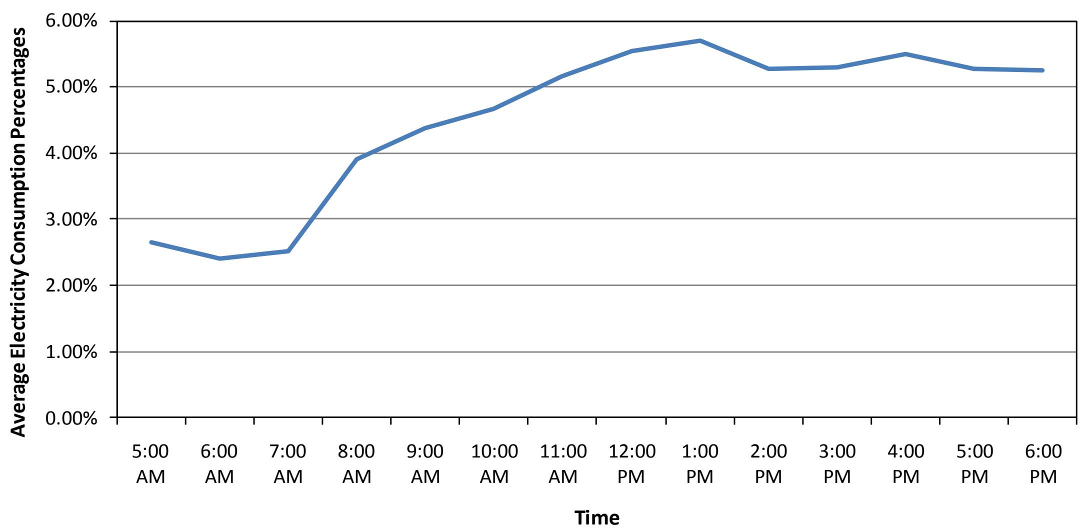

Figure C.2 Average hourly electricity consumption percentages during the day time for May

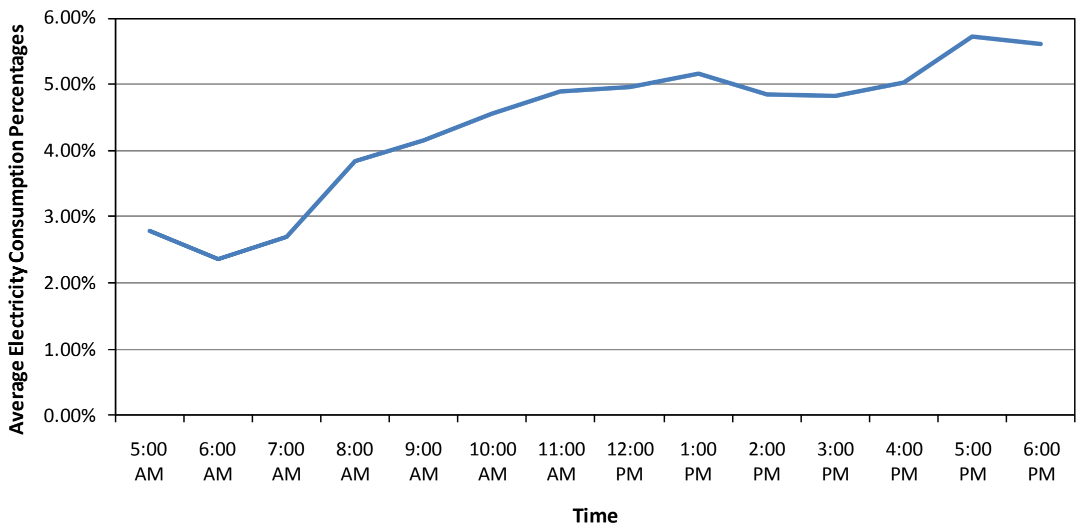

Figure C.3 Average hourly electricity consumption percentages during the day time for June

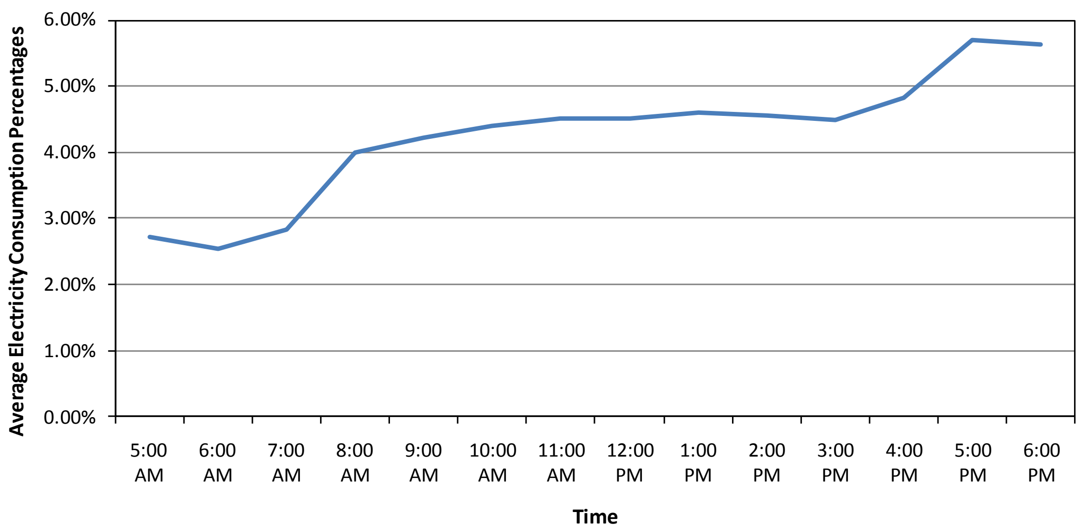

Figure C.4 Average hourly electricity consumption percentages during the day time for July

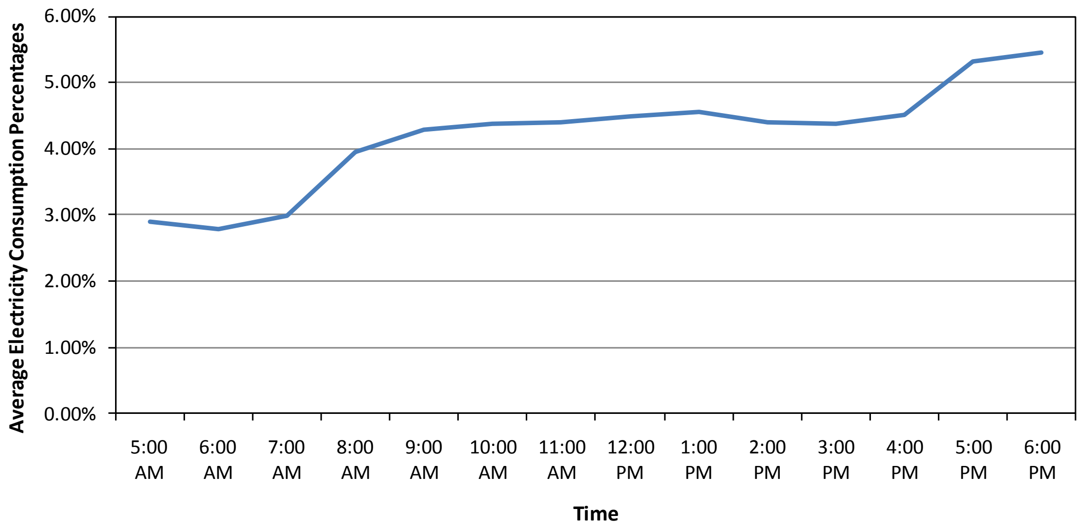

Figure C.5 Average hourly electricity consumption percentages during the day time for August

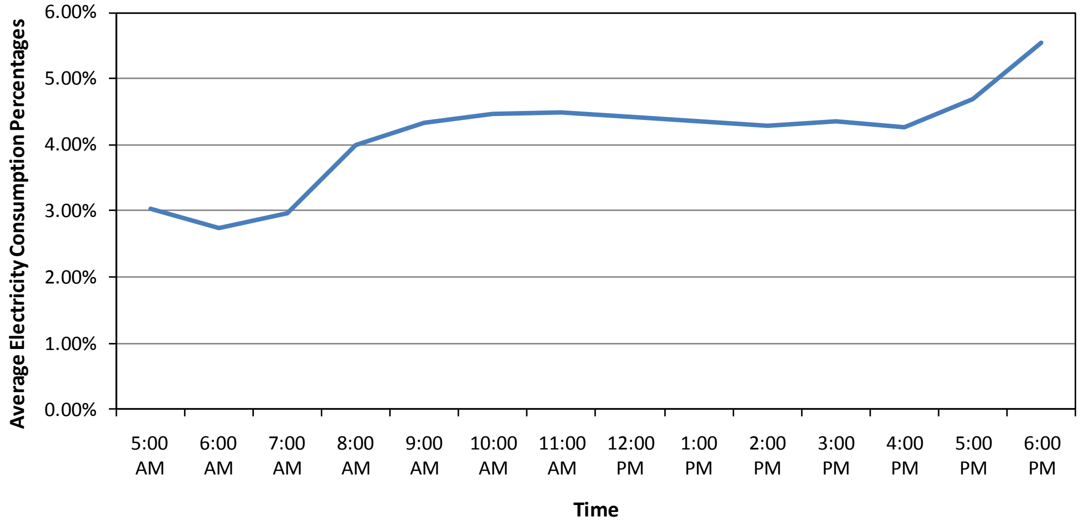

Figure C.6 Average hourly electricity consumption percentages during the day time for September

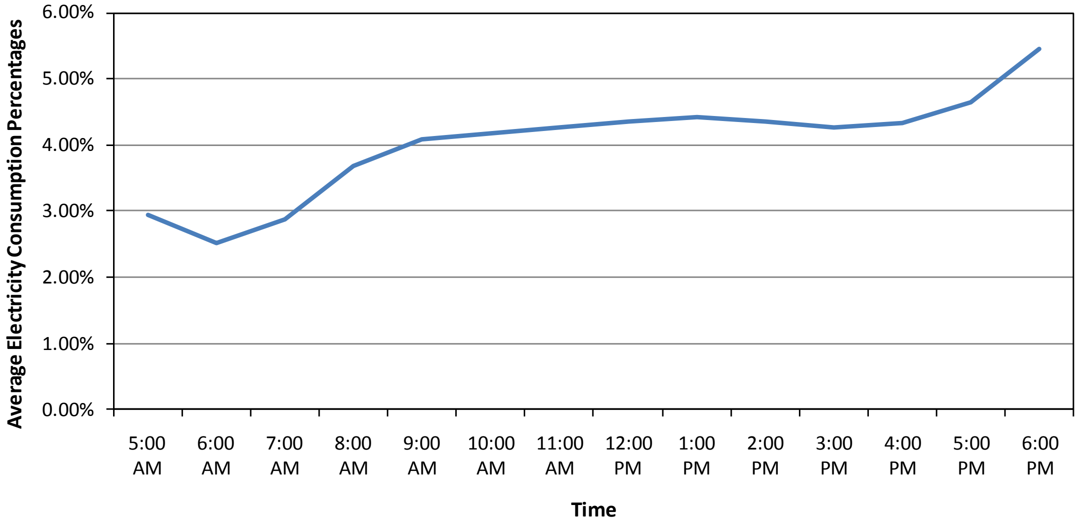

Figure C.7 Average hourly electricity consumption percentages during the day time for October

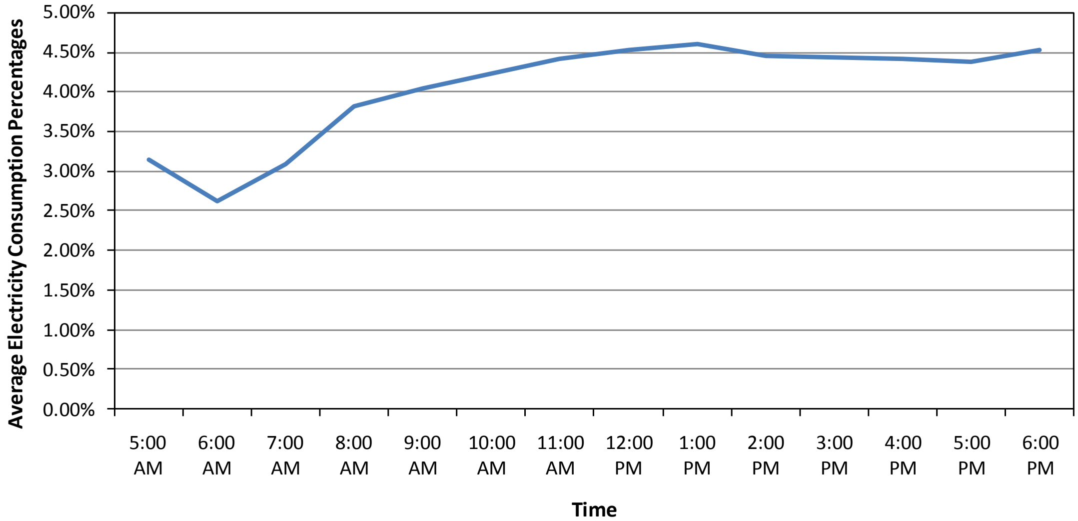

Figure C.8 Average hourly electricity consumption percentages during the day time for November

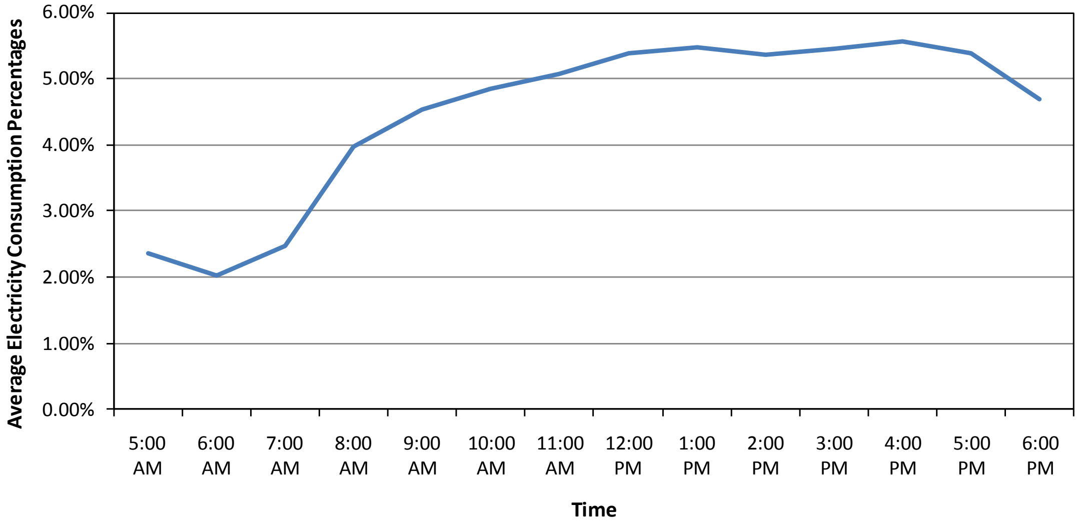

Figure C.9 Average hourly electricity consumption percentages during the day time for December

APPENDIX D

PROBABILITY PLOTS OF DAILY SOLAR RESOURCES ON TILTED SURFACE FOR EACH MONTH

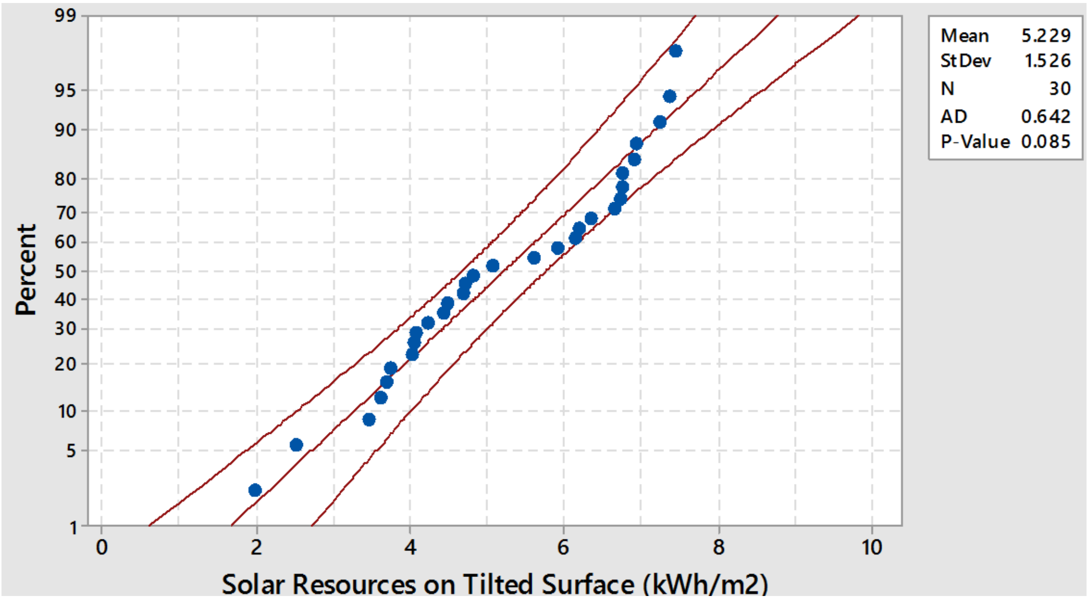

Figure D.1 Fitted Normal distribution for solar resources on tilted surface for April

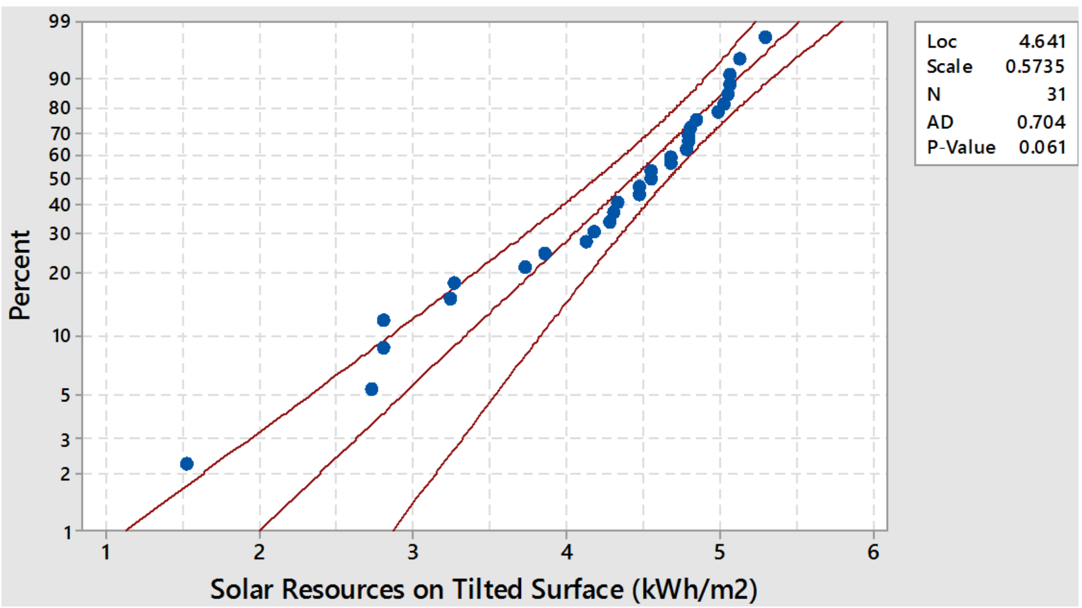

Figure D.2 Fitted Extreme Value distribution for solar resources on tilted surface for May

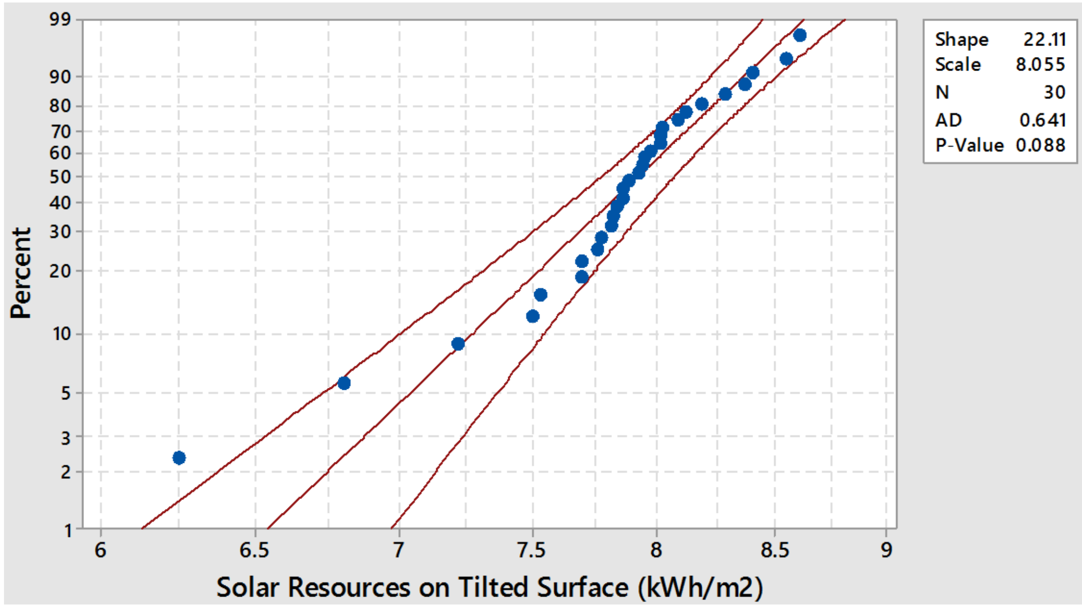

Figure D.3 Fitted Weibull distribution for solar resources on tilted surface for June

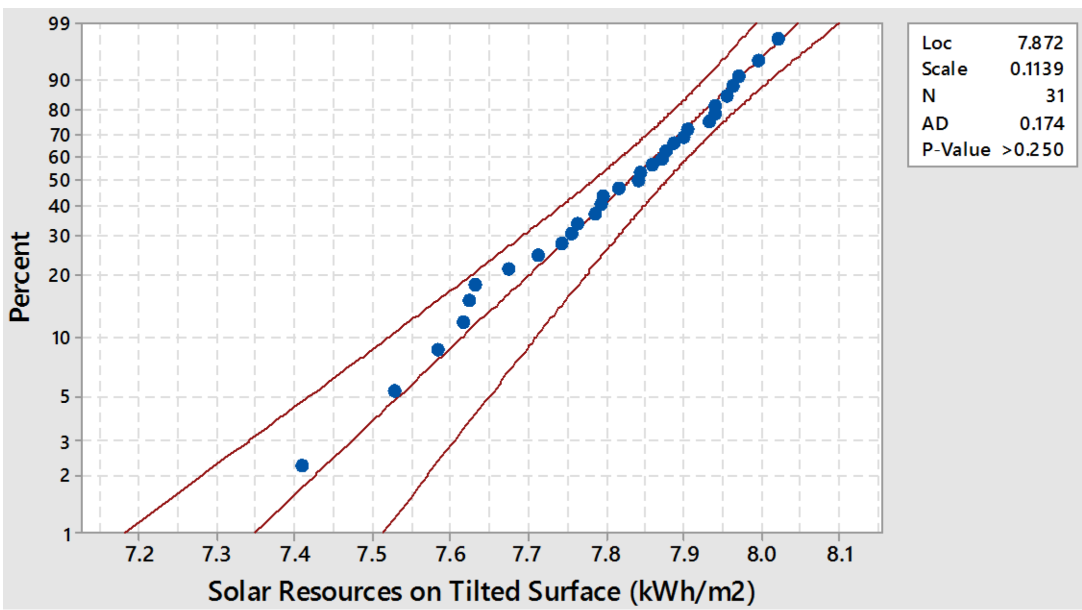

Figure D.4 Fitted Extreme Value distribution for solar resources on tilted surface for July

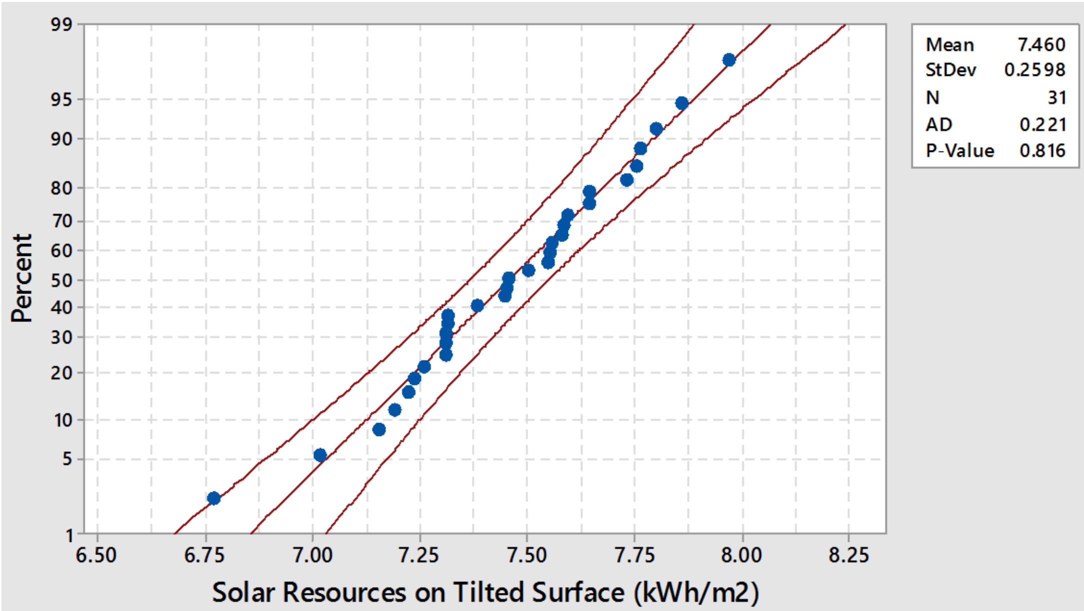

Figure D.5 Fitted Normal distribution for solar resources on tilted surface for August

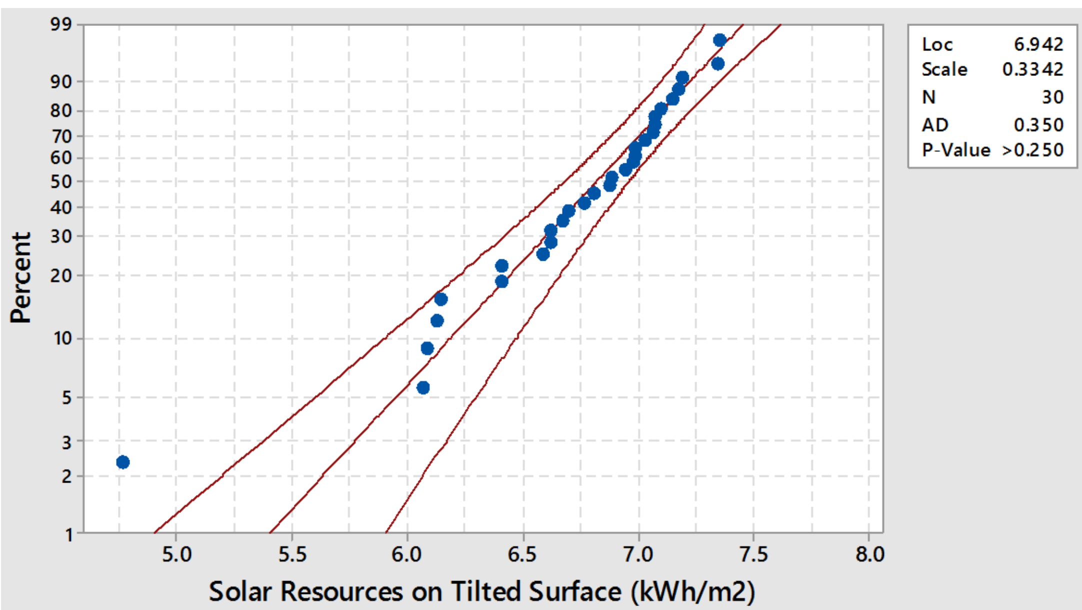

Figure D.6 Fitted Extreme Value distribution for solar resources on tilted surface for September

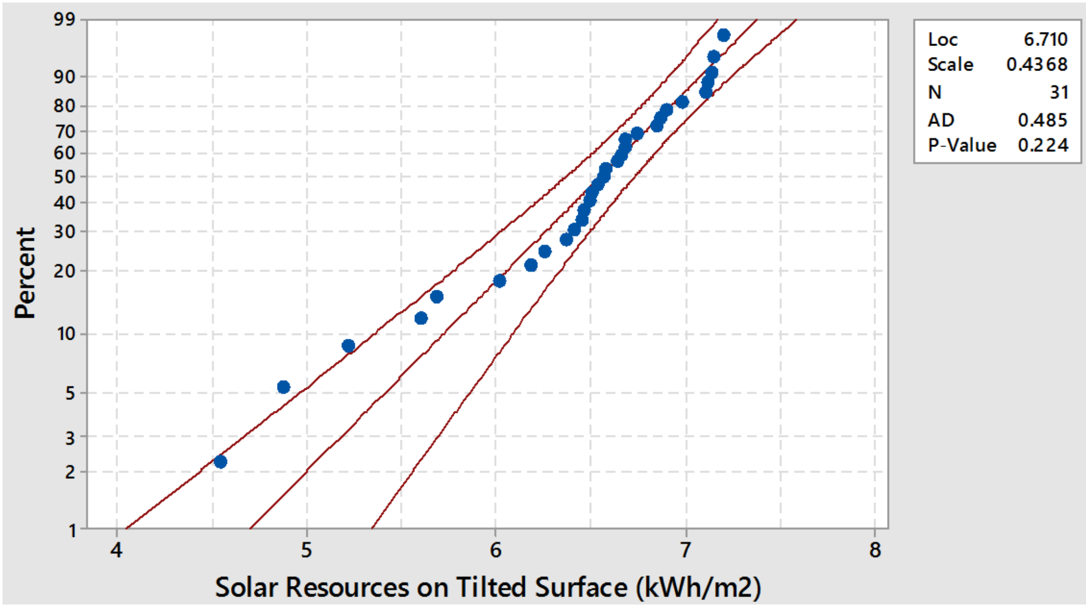

Figure D.7 Fitted Extreme Value distribution for solar resources on tilted surface for October

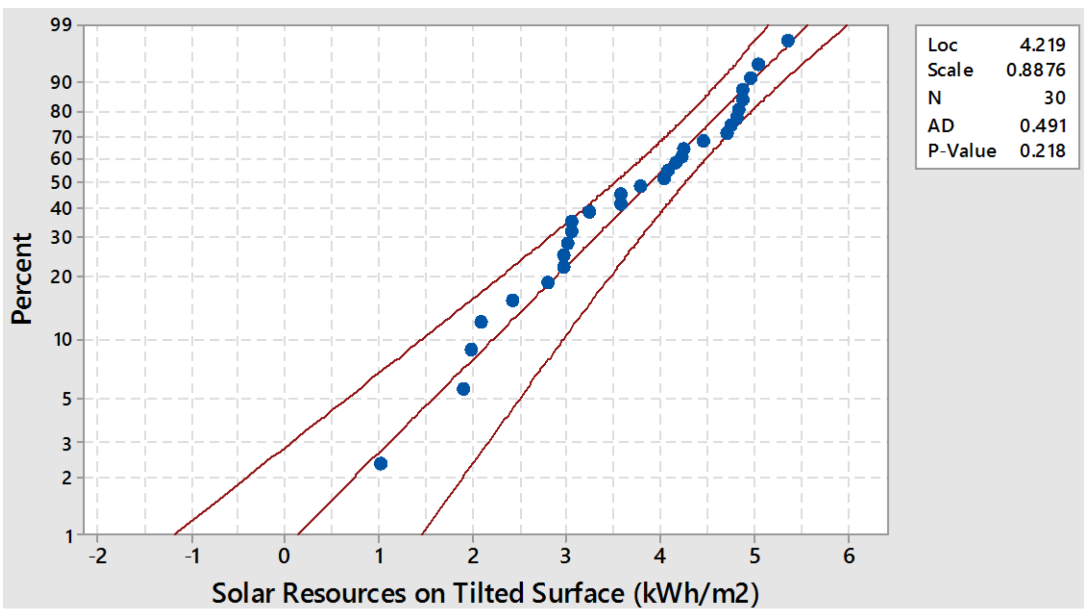

Figure D.8 Fitted Extreme Value distribution for solar resources on tilted surface for November

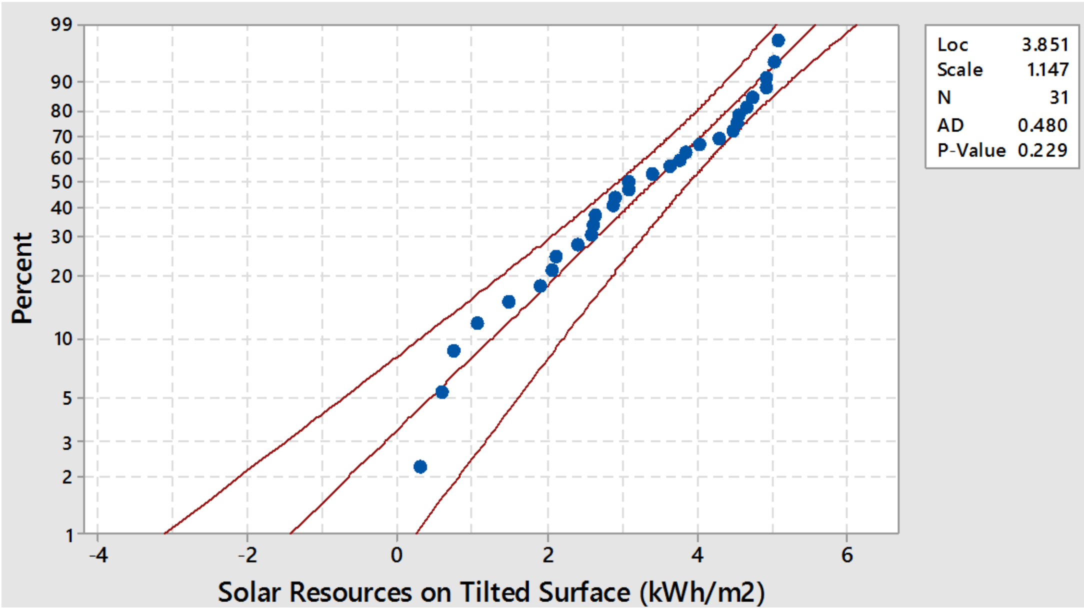

Figure D.9 Fitted Extreme Value distribution for solar resources on tilted surface for December

APPENDIX E

AVERAGE HOURLY PERCENTAGES OF SOLAR RESOURCES ON TILTED SURFACE FOR EACH MONTH

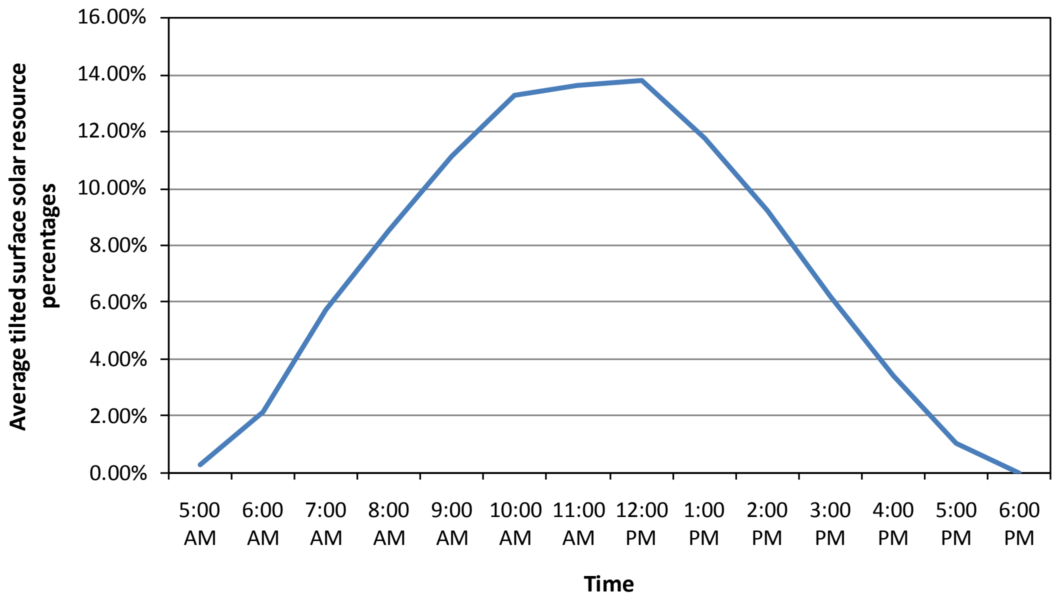

Figure E.1 Average hourly percentages of solar resources on tilted surface for April

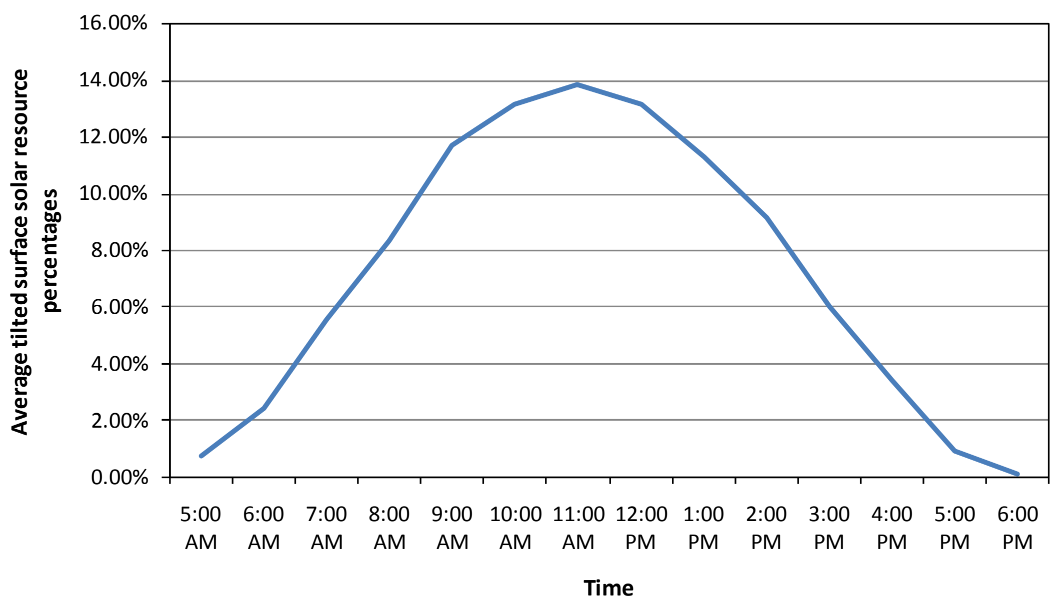

Figure E.2 Average hourly percentages of solar resources on tilted surface for May

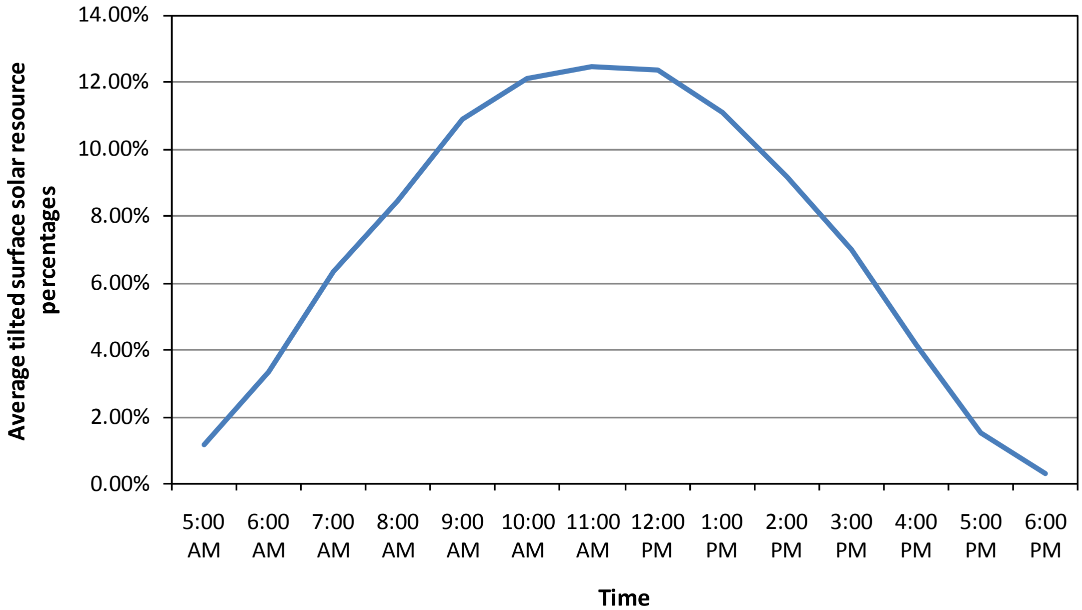

Figure E.3 Average hourly percentages of solar resources on tilted surface for June

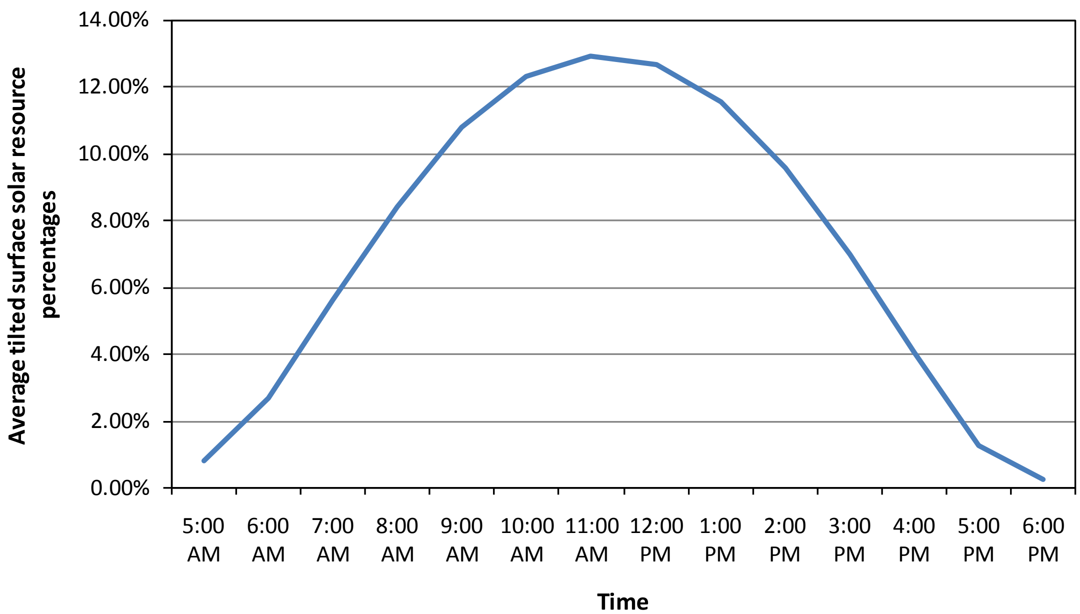

Figure E.4 Average hourly percentages of solar resources on tilted surface for July

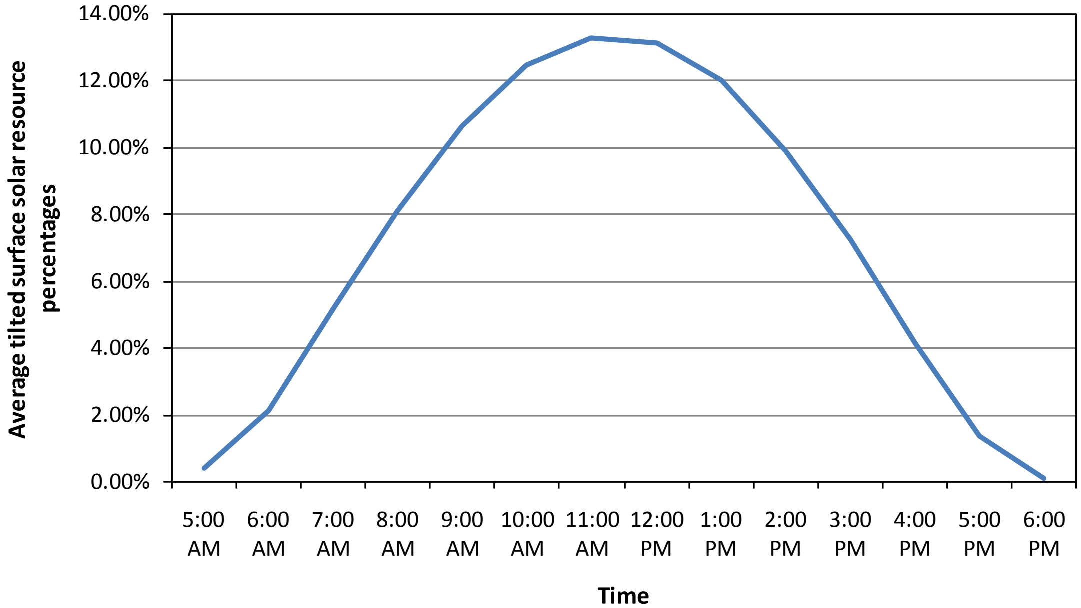

Figure E.5 Average hourly percentages of solar resources on tilted surface for August

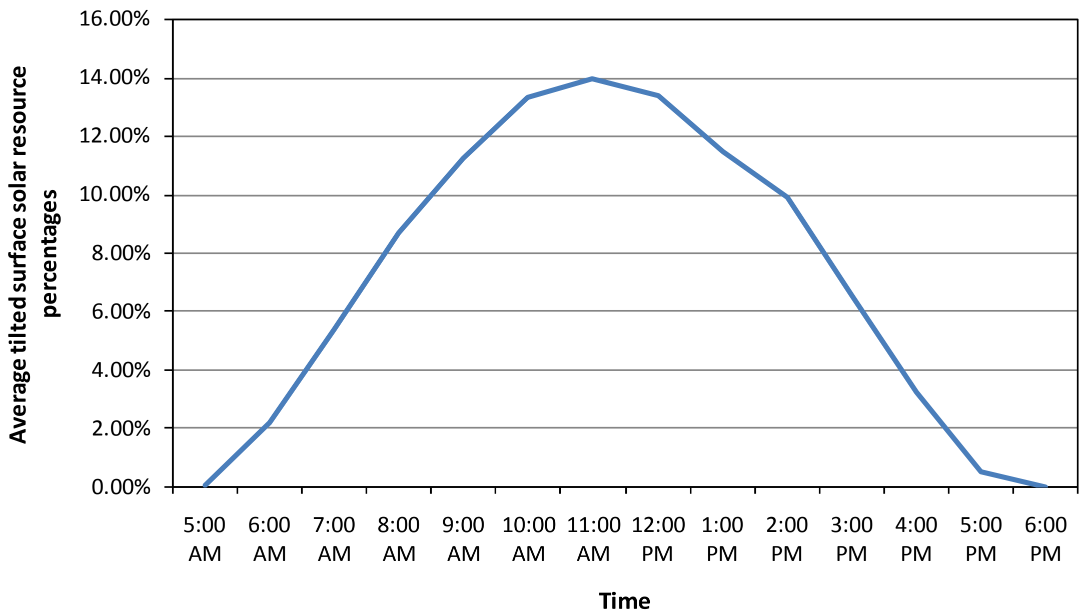

Figure E.6 Average hourly percentages of solar resources on tilted surface for September

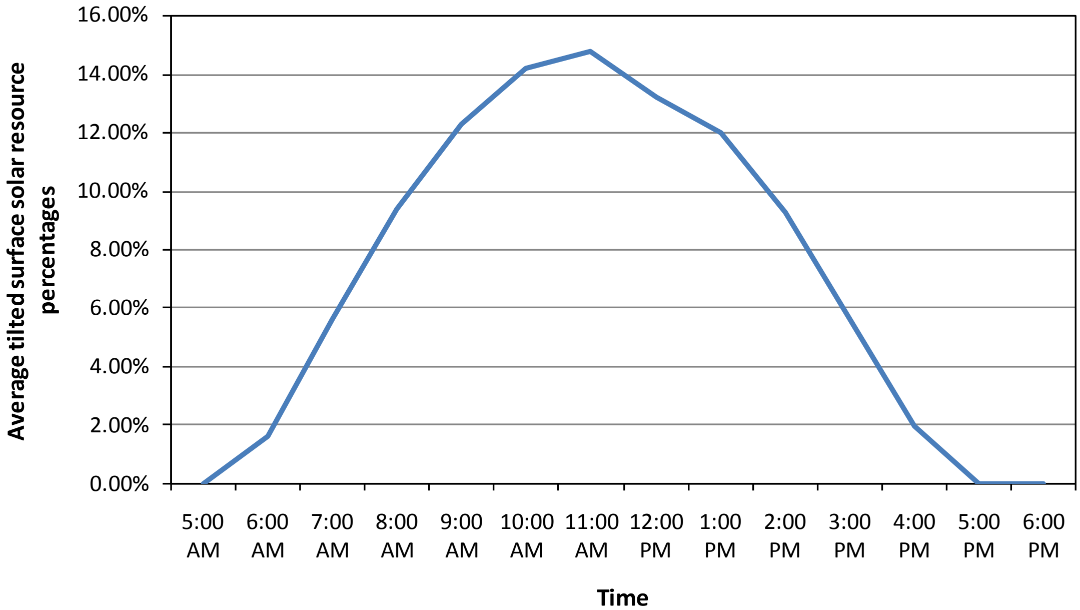

Figure E.7 Average hourly percentages of solar resources on tilted surface for October

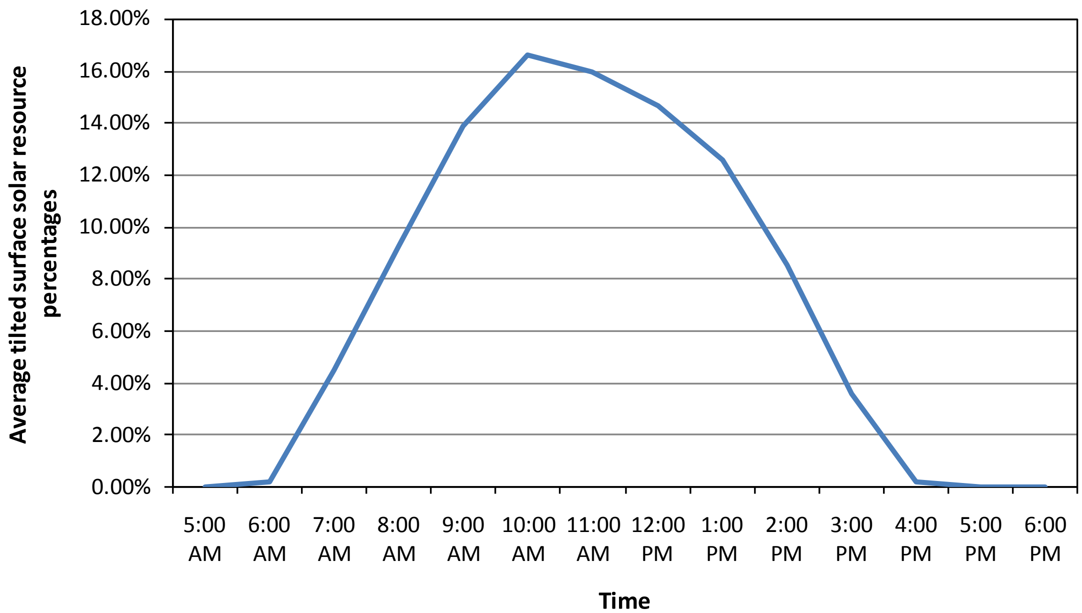

Figure E.8 Average hourly percentages of solar resources on tilted surface for November

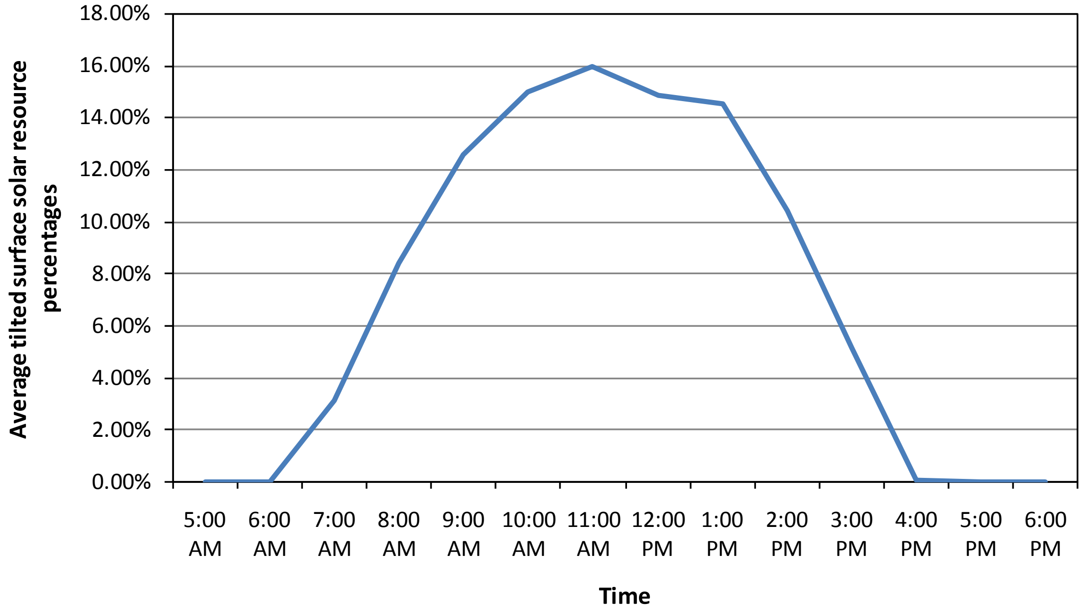

Figure E.9 Average hourly percentages of solar resources on tilted surface for December