Electricity Peak Demand Forecasting for Developing Countries

Amir Motaleb Mirlatifi

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Prof. Dr. Mustafa Tümer
Acting Director

I certify that this thesis satisfies the requirements as a thesis for the degree of Doctor of Philosophy in Mechanical Engineering.

Assoc. Prof. Dr. Hasan Hacışevki
Chair, Department of Mechanical Engineering

We 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 Doctor of Philosophy in Mechanical Engineering.

Prof. Dr. Fuat Egelioğlu
Co-Supervisor

Prof. Dr. Uğur Atikol
Supervisor

Examining Committee

1. Prof. Dr. Uğur Atikol
2. Prof. Dr. Fuat Egelioğlu
3. Prof. Dr. Adnan Sözen
4. Prof. Dr. Beşir Şahin
5. Assoc. Prof. Dr. Qasim Zeeshan

ABSTRACT

The current thesis aims to develop a peak demand forecast model suitable for developing countries based on their characteristic and availability of data. In this respect, we attempted to review a number of techniques used for energy forecasting and categorize them in terms of time ranges, the techniques used, and the cases in which they were employed. The advantages and disadvantages of each method were indicated and suitable approaches were devised to forecast the energy demand for small and large developing countries. We developed two different scenarios for small utilities depending on the availability of time series data. First, when considerable amount of time series data is available we proposed an econometric method to model the annual peak demand by which the key parameters affecting the electricity demand were discovered. The electricity demand was decomposed into weather sensitive demand and based demand to further examine the effect of extreme weather conditions on the peak demand. Second, when time series data is limited to merely annual peak demand records, an algorithm based on deterministic time series methods and fuzzy arithmetic was developed. These methods can be applied to forecast electricity demand of N. Cyprus and similar small islands. Thus, some advices were offered for electricity security plan of N. Cyprus. Finally, using the previously developed forecasting models, an approach was presented to forecast the peak demand of all developing countries based on their distinctive regional characteristic. The algorithm requires partitioning the country into smaller segments in which the previously developed forecast models for small utilities can be utilized.

Keywords: Decomposition, Econometric Method, Extension Principle, Fuzzy Arithmetic, Peak Demand Forecasting, Time Series Method, Transformation Method

ÖZ

Bu tez çalışması “ile” elde bulunan veriler doğrultusunda azami talebin gelişmekte olan ülkelere göre tahmin edilmesi amaçlanmıştır. Bu bağlamda çeşitli teknikler kullanılarak belirli zaman aralıklarında enerji taleplerinin kategorize edilmeleri yardımıyla sonuca varılmıştır. Avantajlar ve dezavantajlar, her bir yöntem ışığında, gelişmekte olan büyük ve küçük ülkelerin enerji talep ihtiyaçları tahminine göre oluşturulmuştur. Zaman serisi verileri kullanılarak iki farklı senaryo geliştirilmiştir.

Öncelikle, öngörülebilen zaman verisi ışığında yıllık en yüksek elektrik talep miktarı ekonometrik metot modeli ile kilit parametreler baz alınarak belirlenmiştir. Elektrik talebi mevsimsel olarak değişkenlik göstermekle beraber kötü hava koşullarında en yüksek elektrik talebine ulaştığı saptanmıştır.

İkinci olarak, zaman serisi verileri olarak sadece yıllık talep kullanıldığında saptanabilir zaman serisi metodu ve fuzi aritmetik modeli bağlı algoritma geliştirildi.

Bu yöntemler Kuzey Kıbrıs Türk Cumhuriyeti ve benzeri adalardaki elektrik taleplerin tahmini için kullanılabilir. Bununla beraber, Kuzey Kıbrıs Türk Cumhuriyeti’nin elektrik güvenliği için çeşitli planlar da tavsiye edilmiştir.

Sonuç olarak, geçmiş dönemlerde geliştirilmiş tahmin modellerini kullanarak gelişmekte olan ülkelerin en yüksek enerji talepleri o ülkelerin bulundukları coğrafi konumları göz önünde bulundurularak oluşturulmuştur. Bu algoritma daha önce geliştirilmiş tahmin teknikleri ile birlikte, ülkelerin küçük uygulama alanlarında kullanılabilinir.

Anahtar kelimeler: Ayrıştırma, Dönüşüm yöntemi, Ekonometrik yöntem, En yüksek talep tahmini, Fuzi aritmetik, Genişleme prensibi, Zaman serisi yöntemi.

This thesis work is dedicated to my parents. I am highly indebted to them, for their guidance, blessings, constant backing, and for providing the necessary support in completing this work.

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Finally, I dedicate this work to my son, Radin Mirlatifi. May you find the journey of knowledge to be a walk through deep valleys, rolling plains, strong rivers, and high mountains. However, knowledge is of no value unless you put it into practice.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AIC	Akaika’s Information Criterion
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
AR	Autoregressive Model
ARDL	Autoregressive Distributed Lag
ARMA	Autoregressive Moving Average
ARMAX	Autoregressive Moving Average with Exogenous Variables
ARIMA	Autoregressive Integrated Moving Average
BBO	Biogeography Based Optimization
BDR	Base Demand Ratio
BIC	Bayesian Information Criterion
BN	Bayesian Network
CCHP	Combined Cooling Heating and Power
CDD	Cooling Degree Days
DBN	Dynamic Bayesian Network
DSM	Demand Side Management
ECM	Error Correction Models
ES	Exponential Smoothing
ESN	Echo State Networks
EUNITE	European Network of Excellence on Intelligent Technologies
EXP	Energy Export
FLR	Fuzzy Linear Regression

FT	Fourier Transform
GA	Genetic Algorithm
GDP	Gross Domestic Product
GNN	Generalized Neural Network
GRNN	General Regression Neural Networks
GSR	Global Solar Radiation
HDI	Human Development Index
IMP	Energy Import
IPSO	Improved Particle Swarm Optimization
IRP	Integrated Resource Planning
LEAP	Long-range Energy Alternatives Planning System
MA	Moving Average
MAD	Mean Absolute Deviation
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Scaled Error
MMPF	Multi-Model Partitioning Filter
MSE	Mean Square Error
MW	Mega Watt
NN	Neural Network
NRMSE	Normalized Root Mean Square Error
OSeMOSYS	Open Source Energy Modeling System
PAM	Partial Adjustment Model
PCA	Principle Component Analysis
PSO	Particle Swarm Optimization

PRESS	Predicted Residual Sum of Squares
RBF	Radial Basis Function
RET	Renewable Energy Technology
RMSE	Root Mean Square Error
SA	Simulated Annealing
SARIMA	Seasonal Auto Regressive Integrated Moving Average
SARIMAX	Seasonal Auto Regressive Integrated Moving Average with Exogenous Input
SFL	Shuffled Frog-Leaping
SIDS	Small Island Developing State
STFT	Short Time Fourier Transform
STLF	Short-Term Load Forecasting
STSM	Structural Time Series Method
SVC	Support Vector Classification
SVM	Support Vector Machine
SVR	Support Vector Regression
TVP	Time Varying Parameter
TWh	Terawatt Hour
WNN	Weighted Nearest Neighbor
WSD	Weather-Sensitive Demand
WT	Wavelet Transform

LIST OF SYMBOLS

a	Left boundary value for each level of membership
A_i	Coefficients of regression
$\tilde{A}_i$	Fuzzy coefficients of regression
b	Right boundary value for each level of membership
β_i	Coefficients to be estimated
d_H	HAUSDORFF distance
e_t	Random disturbance
$\epsilon(t)$	White noise
$f(t)$	Fitting function vector of the process
h	Hour
${}^{k}\hat{z}^{(j)}$	k th element of fuzzy output array
m	Order of the equation
m	Number of intervals in fuzzy numbers
μ	Membership function
n	Number of fuzzy numbers
n	The number of series
$\tilde{P}$	Fuzzy numbers
$\tilde{q}$	Fuzzy output
Q	Fuzzy output in its decomposed form
S	Summation
t	Time, years
T	Transpose operator

T	total number of observation
V_i	Independent variables
w_l	Left width of fuzzy number
w_r	Right width of fuzzy number
X	Intervals for each level of memberships
$\hat{X}$	Fuzzy input array
y_t	Peak demand in the year t
y_t'	Estimated peak demand in the year t
$\tilde{y}$	Fuzzy peak demand
$\hat{Z}$	Fuzzy output array

Chapter 1

INTRODUCTION

1.1 Background

Modern life depends on a huge amount of energy and providing the future energy demand has always remained a challenge. Worldwide energy demand is rising due to the population growth and technological advances and it is predicted to reach more than twice as the current level by 2050. The less access to the modern energy, the less will be the economic and human development of countries [1].

Electricity as one of the most significant components in energy sources has become a basic necessity of life. It becomes the central source of daily life energy usage and it can be considered not only as a key element for economic development, but also political and social security of a country. Electricity differs from other energy resources; its storage is not practical and its demand may vary dramatically at different times, regions and sectors.

The time variation of electricity demand should be considered from the scale of milliseconds, seconds, up to time scale of years and decades[2], see Table 1. Electricity demand forecast is important for utility owners, power system managers, energy planners and system operators.

Table 1: Timescales in power systems management, planning and operation [2].

Time scale	Systems issues	Power systems tools
ms to s	Generator dynamics Motor load dynamics	Transient stability management Power - frequency regulation
Very short term min to1hour	Demand variations Power interchanges Maintain economic operation Frequency control System stability	Generation control Power flow economic dispatch Security analysis Fault analysis
Short term Hours /days/ up to a week	Weekly capacity planning	Demand Weather prediction Unit commitment
Medium term weeks/months	Seasonal capacity planning	maintenance scheduling market research Fuel provision
Long term years	Demand growth Plant retirement / overhaul Investment decisions Long term hydrological cycles	Generation expansion planning Reliability checks (maintenance) Scenario analysis Production cost modeling

The vast numbers of forecasting methods in the area of electricity demand forecasting indicate that there is still a need for developing more accurate and reliable forecasts. In this respect, peak demand forecasting is an important tool to ensure that the future electricity generations meet the future energy consumption. An accurate estimation requires abundant information and an appropriate budget. A 1% reduction of forecast error can save millions of dollars [3]. The information obtained from an appropriate forecast significantly reduces the cost of power generation and secure its supply.

Different sectors, such as residential, commercial, industrial, agricultural, transportation, use electricity for different purposes. This can substantially affect the peak demand patterns and it might be required to be examined in the forecasting models.

1.1.1 Uncertainty

Forecasting is always accompanied by several sources of uncertainty. Examples of uncertainty include uncertainties of data limitation and acquisition, and uncertainties as a result of idealization or simplification of the forecasted model. Uncertain data implies that information exhibit inaccuracy and questionability. The current study models these uncertainties by means of fuzziness. In Chapter 5 a model was suggested to deal with uncertainty.

1.1.2 Integrated Resource Planning

Utilities are always plan to reach the annual peak and energy demand forecast through the combination of supply side and demand side resources over a specified future period. This strategy is called Integrated Resource Planning (IRP), and despite the fact that it is time- and resource- intensive, it is quite beneficial. Not only utilities and consumers can benefit from IRP, it has also a positive environmental impact. Wilson and Biewald [4] indicated that IRP rules can be passed into law by government legislatures and utility commissions ought to put IRP regulations into action. The continuous rise in energy demand in N Cyprus and aging of the generation systems calls for initiation of a robust IRP process for adding or retiring power generating systems in the most cost-effective manner. Examining the addition of generation capacity (such as thermal, renewable, and etc.) and implementing energy efficiency are some IRP activities.

It is important for the power producers and policy makers to estimate the power demand and electricity consumption several years ahead in order to devise IRP programs. Figure 1 illustrates the steps taken in the creation of an IRP. It should be noted that the first step of a successful IRP process is to have a reliable long term peak demand forecast.

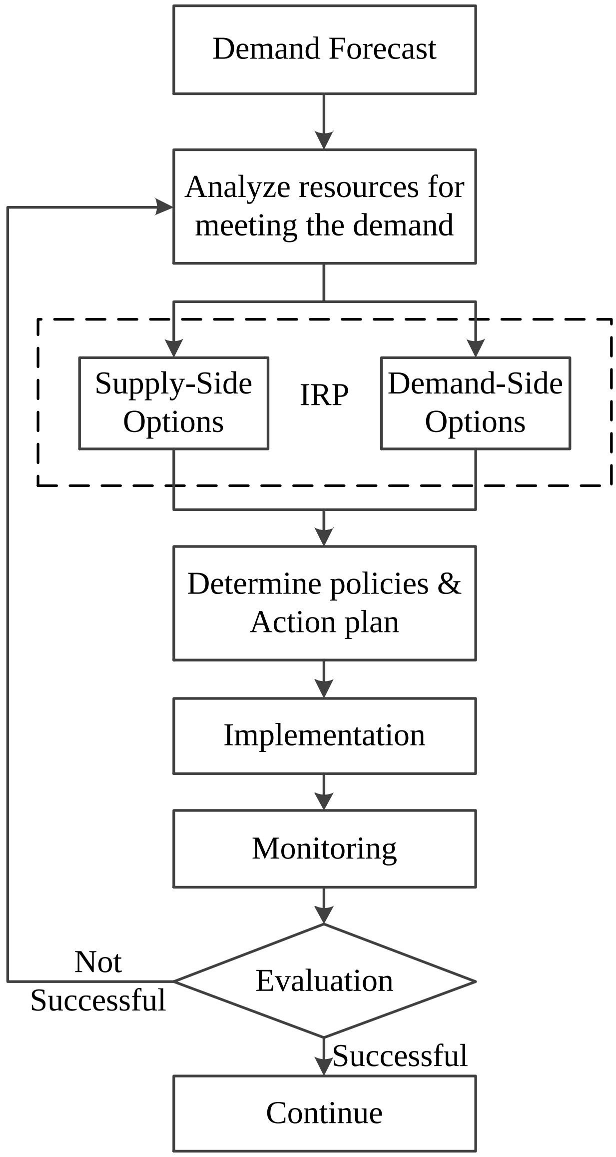

Figure 1: An Integrated Resource Planning Process [5].

1.1.3 Energy in Developing Countries

The developing economies can be generally distinguished from developed economies based on their human development index (HDI), which is associated with individual's education, health and income [6].

Developing countries play an important role in the world energy scene and they have a different energy feature from developed countries:

- Their development path can be unique and may not resemble more advanced countries.
- They suffer from severe power shortages and regional imbalances. Therefore, the need for additional generation capacities and investment is not the same for all economies. Developing economies require additional generation capacities for industrialization and rural electrification, whereas, it is the increase in use of electric appliances that imposes additional need for electricity generation in developed economies.
- Their structure and economic transition may change through time and their future may not follow the earlier trail
- A data limitation is another problem of developing countries which encounter the use of forecasting models with challenge.

These features, in fact, could differentiate their forecasting method from the industrialized countries.

Furthermore, there are slight variations in type of power plants used to generate electricity in developed and developing countries. Thermal, hydropower and geothermal plants are used in both developed and developing countries. However, developing countries usually install small scale renewable energy technologies for rural energy needs, such as solar thermal, photovoltaic, and biomass. Meanwhile, because of technological complications in nuclear power plants these power plants are seldom pursued in developing countries. Other alternatives of power generation are marine and wind power plants which have been used by developing countries in small scales.

1.1.4 Small Island Developing States (SIDS)

SIDSs are different from larger and landlocked developing countries and their energy provision may require more challenging approaches. Most SIDSs are extremely reliant on the import of fossil fuels for electricity generation. Their small sizes and remoteness can impose higher costs for fuel provision, higher risk for supply, chronic import/export imbalances and dependency on other economies[7]. Therefore, it is wise for SIDSs to decrease the import of energy and resort to renewable alternatives. In this regard, a robust energy plan and consequently an alternative energy forecasting are essential for these regions.

1.1.5 North Cyprus

Cyprus is one of the largest Mediterranean islands, with no preserved natural energy resources, and away from interconnected network of electricity and gas [8]. The island has been divided into north and south for more than four decades. Although, discovery of new fields of oil and gas near Cyprus may be promising, their extraction is not probable for couple of years and the fall of oil prices in the last year and geopolitical complications may further suspend using these resources.

At present, total generation capacity of N. Cyprus is 331.3 MW. KIB-TEK, as the state-owned utility firm, runs two oil fired steam power plants each with 60 MW capacity, has 6×17.5 MW Diesel cycles in Teknecik station, as well as a 1.3 MW Photovoltaic power plant in Serhatköy. The private utility company AKSA has 6×17.5 MW Diesel cycles in Kalecik station. All Diesel cycles use heavy oil No.6. The average annual growth rate in the annual peak demand between 1991 and 2013 was reported to be 6% [9][10][11]. The main driver of this growth was the development of tourism and construction industry. Currently KIB-TEK and AKSA have no attempt on the load management, despite the increase in generation costs and demand.

1.2 Scope and Objective of the Study

Utilities are usually reliant on the long term forecast models in order to devise suitable plans by considering the economy, climate, demography and other influential determinants. However, the scale of the load system, the budget of forecast, as well as the availability of data are important factors in selecting forecasting methods. The smaller the size of the system the easier it becomes to catch the information for an accurate forecast. In contrast, the larger the size of the system, the more sophisticated the forecast requires to be and the harder will be capturing the necessary information for a precise forecast. Therefore, it is appropriate to differentiate the modeling of a system with proper available data from a system with limited data. The current thesis attempts to tackle these problems through the following objectives:

1. to have a broad review on the energy and peak demand forecasting models,
2. to develop long-term base and weather sensitive demand models using econometric variables as regressors for small size utilities,
3. to develop long-term fuzzy regressions for small developing countries where data is limited to time series record of the peak demand,
4. to compare the results of the two methods and give some suggestions for energy security plan of N. Cyprus,
5. to develop a general approach of peak demand forecasting used for developing countries.

1.3 Organization of the Thesis

Chapter 2 presents a thorough literature review on the energy forecasting models. Chapter 3 is dedicated to the development of the forecasting models required for this study. Having sufficient data imply that statistical methods is suitable for the forecast. In this regard, chapter 4 presents an econometric method for small utilities to forecast the annual peak demand. Proper information of the key variables on energy and peak demand is not usually obtainable especially in the developing countries. That is, detailed data on different indicators is sometimes limited and only utility records are available. Consequently, chapter 5 attempts to deal with this scenario by means of a fuzzy arithmetic technique in forecasting. Chapter 6 introduces a partition-based peak demand forecasting that can be used in developing countries and finally chapter 7 concludes.

Chapter 2

LITERATURE REVIEW

2.1 Overview

Energy demand forecasting can be categorized from different views such as sourcewise- electricity, fossil fuel (coal, gas, oil), renewable energy (wind, solar) , sectorwise – residential, commercial, industrial, agricultural, transport, periodwise- long, medium, and short term, as well as, method-wise.

There are vast number of energy and peak demand forecasting models in the literature with their own cons and pros. The extensive number of research in modeling and forecasting energy and peak demand indicate the importance and complexity of energy forecasting and the need for developing more accurate models. Every method has its own advantages and disadvantages and none of them has supremacy over others [12]. An appropriate forecasting model for one region may not be appropriate for another region. Hence, it is necessary to choose the most suitable forecast for each case and situation. In the following sections an extensive review of literature is presented.

Based on the technique used in the forecasting model, it is possible to classify energy demand models as shown in Figure 2:

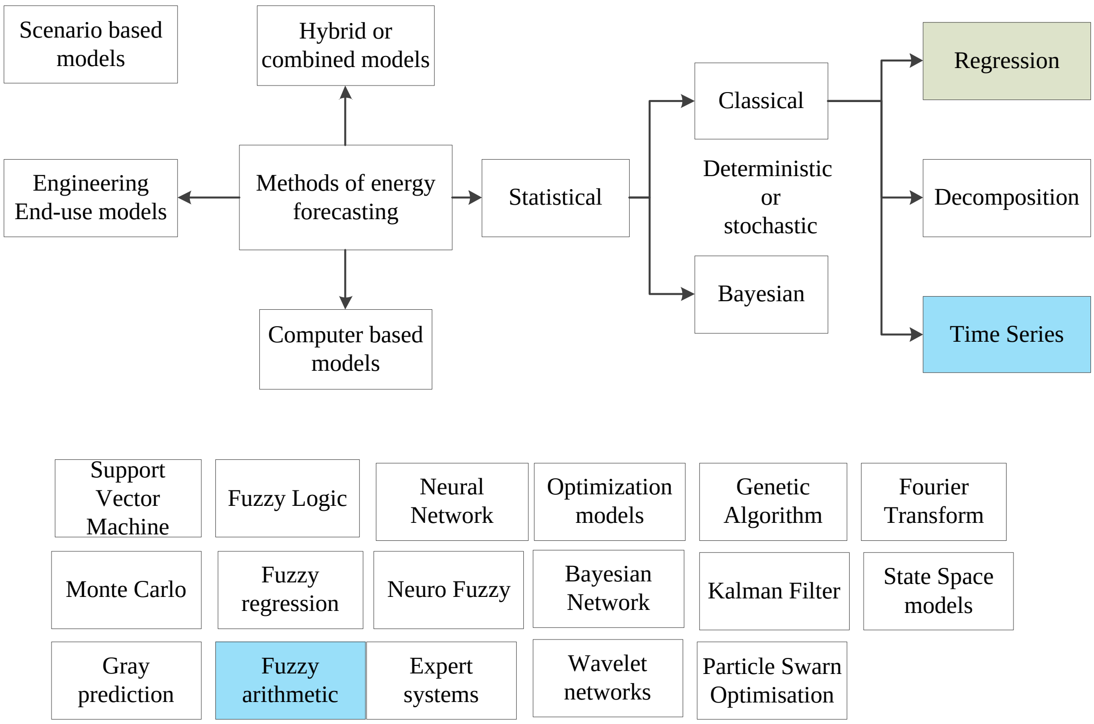

Figure 2: Different models used in energy demand forecasting

2.2 Time Series Methods

Time series methods assume that future electrical peak demand merely depends on historical demands. These models were originated first by deterministic characteristic and later stochastic models of time series were developed. Deterministic, autoregressive (AR), moving average (MA), autoregressive (integrated) moving average (ARIMA) , exponential smoothing (ES), and structural time series method (STSM) are some popular methods of time series that is explained in the following sub-sections.

2.2.1 Deterministic Methods

These models do not account for any of the underlying random components of the time series data. However, they have long been viewed as acceptable means of forecasting. They are of the simplest and fastest methods to apply [13]. The more data used in the model estimation, the more reliable the forecast model will be (provided that the historical data have been accurately collected). Two main categories of deterministic method are given as follows.

2.2.1.1 Linear Trend Model

The general form of the linear trend model is:

$$Y_t = \beta_1 + (\beta_2 \times t) \quad (1)$$

where t is year, and Y_t is energy demand at the year t. Coefficients β_1 and β_2 can be estimated using two alternatives; namely, simple average method and simple regression method. These methods are explained in detail in section 3.3.1.

2.2.1.2 Autoregressive Trend Model

The general form of the autoregressive trend model is:

$$Y_t = \beta_1 + (\beta_2 \times Y_{t-1}) \quad (2)$$

This model states that the current value simply depends on the previous value. The coefficients β_1 and β_2 can be estimated using three methods of straight average rate method, the compound average rate method, and the simple regression method, see section 3.3.1.

2.2.2 Autoregressive Methods

Autoregressive models can be utilized provided that the peak demand is assumed to be in a linear combination of previous peak demands [3]. The autoregressive equation of order m can be written as:

$$Y_t = -\sum_{i=1}^{m} \beta_{it} Y_{t-1} + e_t \quad , \beta_i = 1,2,\dots,m \quad (3)$$

where Y_t is the estimated peak demand at time t, e_t is the random disturbance, and β_i are unknown coefficients.

2.2.3 Autoregressive (Integrated) Moving Average

Auto regressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) are extensions of previously explained methods. These models are the combination of autoregressive (AR) coefficients multiplied by past values of the time series and moving average (MA) coefficients multiplied by past random shocks. Various criteria were devised to find the order of the time series with their own cons and pros, such as Akaika's information criterion (AIC), multi-model partitioning filter (MMPF), Bayesian information criterion (BIC) and etc. Meanwhile, a good ARIMA model can be found using the three-stage procedure introduced by Box and Jenkins [14]. These stages are identification, estimation, and diagnostic checking.

By the advent of computers, ARMA or ARIMA methods became popular in all disciplines such as energy and peak demand forecasting. Badri et al. [15] introduced a load forecast model based on various time series method to provide near-optimal statistical models of electric peak demand in United Arab Emirates. ARMA model were used for modeling the electricity demand loads in Greece [16]. A univariate Box-Jenkins ARIMA analysis was used to estimate the monthly electricity consumption of eastern province of Saudi Arabia [17]. Six forecast models including ARIMA were applied to forecast radiation over short time horizons in six places of North America [18]. SARIMA formula contains both a seasonal pattern and non-seasonal parts. In addition, ARMAX [19] or SARIMAX [20] are the extensions of the time series models by containing exogenous variables in the model. That is, another time series can be incorporated into the time series to improve the performance predictions.

2.2.4 Exponential Smoothing

An extensive review of exponential smoothing (ES) methods was given by Everette and Gardner [3] in which exponential smoothing methods were considered as a special case of ARIMA and more extensively, a state space method. Exponential smoothing initiated in 1959 [21] and has been utilized as one of the traditional methods of peak demand forecasting [3]. It is modeled using a fitting function and it can be expressed as [22]:

$$y(t) = \beta(t)^T f(t) + \epsilon(t) \tag{4}$$

where $f(t)$ is fitting function vector of the process, $\beta(t)$ is the coefficient vector, $\epsilon(T)$ is white noise, and T is the transpose operator. Exponential smoothing were used in a demand response algorithm to predict the required energy of appliances [23]. Exponential smoothing outperformed Neural Network (NN), ARIMA and Principle Component Analysis (PCA) methods in forecasting the daily peak demand of Rio de Janeiro [24].

2.2.5 Structural Time Series Method (STSM)

Unlike the traditional ARIMA models, the basic concept of STSM approach is to decompose a time series into unobserved components [25], such as trends and irregularities. This process allows for direct interpretations and it is similar to regression analysis. “As a result, the model selection methodology associated with structural models is much closer to econometric methodology”, [26]. STSM can be formulated based on either stochastic or deterministic trends. The method is the expansion of the co-integration technique which resulted in time series econometric modeling coupled with co-integration technique. The method were compared with other time series method to forecast the electricity price for a German utility [27].

2.3 Regression Analysis

Regression is the most commonly used method mainly due to its simplicity and ease of use. It relates different influential variables with the independent variable, which is mostly the energy demand. A linear regression was used for long term electricity consumption forecasting of Italy [28]. A functional regression was used to forecast the peak demand of a district [29].

2.4 Decomposition Methods

For the peak demand analysis of Australia, Wang et al [12] decomposed the electricity demand data into diurnal, seasonal, and yearly components. They specified simple trend lines for each element and subsequently they projected annual average peak electricity up to 2020. South Africa's daily peak demand was predicted by decomposing the SARIMA model into point forecast and volatility forecast [30].

2.5 Fourier Transform

In classical statistical approaches, data is presumed to be stationary. However, if data shows fluctuation, mathematical transformation is one way to cope with non-stationarity. At times, the time domain may not reveal the necessary information and as a result the frequency domain is used. Fourier transform (FT) is a commonly used method of transformation in many areas of engineering. However, the effect of time cannot be traced through it and thereby the short time Fourier transform (STFT) is used as one solution to the problem. STFT divides the signal into smaller parts so that each segment is considered stationary. In this respect, a windows function is selected. The window should be small to the extent that the stationarity remains valid and a good frequency resolution achieves. FT were used along with exponential smoothing to account for the weekly load demand [31]. FT was also used to forecast the periodic behavior of Spanish electric energy demand. Thus, the accuracy of the forecast based on NN was improved [32]. FT was used to cancel the nonlinearity in the short term load forecasting of a province in Netherland [33].

2.6 Wavelet Transform

In order to deal with resolution problems, wavelet transform (WT) was developed as an alternative method to STFT [34]. The proper resolution can be reached by automatic adaptation of window size. Wavelet offers a proper compromise between wavelength and smoothness resulting in appropriate behaviors. In general, two types of wavelet transform is defined; continuous transform and discrete transform [35].

Wavelet analysis was used in peak demand forecasting by decomposing load data into smaller frequency components. Each component can be analyzed and the forecast accuracy can be improved. In order to have a successful model, proper wavelet functions should be selected.

WT were used to improve the accuracy of the short term load forecast based on generalized neural network (GNN) [36]. In the process of short term load and temperature forecasting, WT were used to decompose temperature and load time series [37]. In a NN method for electricity peak demand forecasting, a de-noisy WT was employed to remove a random noise from the time series and to obtain better performances [35].

2.7 Neural Network

Neural network (NN) models were extensively used for short term load forecasting and a few studies utilized NN for long term peak demand forecasting. The basic principle of NN stems from neuron activities of the brain. By mimicking the operations of human brain, scientists utilized various combinations of networks to solve practical problems. In the design of NN, it is essential to decide on the type, size, and the number of neural being used. In addition, the network architecture and method of training is to be determined so that the most suitable network can be formed.

The excellent scheduling capabilities of Artificial Neural Network (ANN) make them popular in the short term load forecasting. However, neural network may be accompanied by skepticism [38]. A general overview of electrical load forecasting using artificial intelligence (AI) was presented and various ANN based techniques were reviewed to attain the concept of smart grids and smart buildings [39]. It was argued that network complexity, forecast accuracy, convergence rate, and training algorithm are needed to be addressed in the future. In an attempt to overcome the over-fitting problem and curse of dimensionality effects in neural network, a novel radial basis function (RBF) training algorithm was proposed by Wilamowski et al [40]. ANN based on back-propagation was presented for forecasting the daily load consumption of a large building [41]. ANN were also used to forecast heating, cooling and electrical load up to 24 hours in a large scale district [42] and it was used to forecast peak electricity demand up to 1 hour for a large government building [43]. Some well-known ANN algorithms were reviewed for 24 h electric load forecasting [40]. In order to project the short term load demand of northern areas of Vietnam, feed-forward neural network with a back-propagation algorithm was used [44]. Using ARIMA models and ANN structures, Lo and Wu [45] proposed a method to evaluate the risk that the supply industry in UK faces. They found no strong correlation between local demand and weather for the sample of data analyzed.

2.8 Support Vector Machine

Support vector Machine (SVM) is a supervised machine learning procedure. It was invented in 1963 and it was later developed to handle different types of problems. Support Vector Classification (SVC) deals with classification problems and Support Vector Regression (SVR) is used for modeling and prediction. In SVM the data maps into a space with higher dimensions so that the solution can be reached more conveniently than in the original space. The training of the data is done in an iterative fashion and it is possible to increase the training data set to achieve better performances.

SVM was applied for short term electrical load forecasting [46]. It was also used for time series predictions for midterm electric load forecasting [47]. In Italy electricity demand was predicted in the medium term using seasonal climate forecast of temperature [48]. SVR were used for long term prediction of Turkey's energy consumption [49]. The global solar radiation (GSR) in Iran was forecasted for designing and implementation of solar power systems. It was found that SVR outperforms fuzzy linear regression (FLR). SVM were used to forecast the Taiwanese electricity load using simulated annealing algorithm [50]. In utilizing a hybrid approach based on WT for short term load forecasting, SVM showed better performances than ANN methods [51].

2.9 Fuzzy Models

Fuzzy set theory was first presented by Lotfi A. Zadeh in 1965 [52] and since then became a major field in dealing with problems carrying uncertainty. A fuzzy set is an extension of the classical set in which each member may carry a degree of membership. Fuzzy set theory extends to many subdomains such as fuzzy logic, fuzzy pattern recognition, fuzzy regression, fuzzy control and fuzzy arithmetic. Fuzzy based models were extensively used in energy models and forecasting. Suganthi et al [53] attempted to categorize fuzzy based models into fuzzy models, hybrid models and multi criteria decision models. However, it is more appropriate to review fuzzy models as follows.

2.9.1 Fuzzy Logic

Fuzzy logic is an intelligent based technique mimicking human or animal ways of dealing with every day's tasks. It can handle imprecision and uncertainty where discrete logic can fail. In contrast with Boolean logic which is confined within true or false, fuzzy logic allows for some degrees of truth. That is, apart from the availability of 0 and 1 in discreet logic, the degree of truth in fuzzy logic can vary from 0 to 1. Therefore, the antecedents and consequences of "if and then" rules in fuzzy logic are fuzzy propositions.

A fuzzy logic approach was used to forecast the electric load in Bahia state of Brazil [20]. Also, yearly electricity demand of Turkey was forecasted through fuzzy logic method [54].

2.9.2 Fuzzy Regression

Fuzzy linear regression was first formulated by Tanaka in 1982 [55]. The general equation is written as:

$$\tilde{Y} = \tilde{A}_0 V_0 + \tilde{A}_1 V_1 + \cdots + \tilde{A}_n V_n \tag{5}$$

where the regression coefficients $\tilde{A}_j$, $j = 0, \dots, n,$ as well as the dependent variable $\tilde{Y}$ are fuzzy and base on the feature of the problem independent variables V_n are considered either fuzzy or crisp.

Fuzzy linear regression were used for predicting the solar radiation in Iran [56]. Also, it was used as part of an intelligent algorithm to model energy consumption of Iran [57].

Möller and Reuter [58] propose a number of forecasting models based on an alternative left-right (LR) discretization technique as a class of fuzzy set theory. However, this method has not gain much attention to date.

2.9.3 Fuzzy Arithmetic

Fuzzy set theory forms the mathematical basis for fuzzy numbers and fuzzy variables. Fuzzy arithmetic is associated with the algebraic operation of fuzzy numbers. Hanss [59] introduced a well-organized and systematic method in which the arithmetic of fuzzy numbers were significantly enhanced. The current thesis aimed to implement this algorithm in the area of peak demand forecasting.

2.10 Bayesian Methods

Bayes' theorem was used to calculate the probability of demand power in appliances as part of a demand response algorithm [23]. Bayesian methods can be applied to all time series models as a model selection criterion [14], [16]. The method can also be used in artificial intelligence to tackle problems with uncertainty. This technique is called Bayesian Networks (BNs) and it deals with problems with uncertainty, randomness or both. The method were applied in renewable energy area and mostly for wind energy and hydroelectricity [60]. Dynamic Bayesian Network (DBN) were used to forecast the wind power of a wind farm in Mexico for a time horizon of 5 hours [61].

2.11 Kalman Filter

Kalman filter is a recursive procedure for calculating the optimal estimator of the state vector given all the information available at initial time. The procedure is applied in reference [62] to find the electricity demand of industrial and residential sectors in Turkey. It also used as part of a Multi Model Partitioning filter (MMPF) to model the electricity load of Greece [16]. Wind speed and wind energy were forecasted using kalman filtering [63].

2.12 State Space Method

State space form of equation is the main tool for estimating many computational techniques. Many models such as STSM [25], SVM, PSO [64], and etc. can be written in a well-posed method of state space method.

2.13 Grey Prediction Models

Grey models can be used when data is limited or shows chaotic features. Grey prediction models were utilized to forecast the demand of electricity in Turkey [65] and nonresidential electricity consumption of Romania [66].

2.14 Optimization

Optimization can be used for optimal design of various models such as regression based models, ANN models [6] and etc. A comparison of optimized regression and ANN models was presented for long-term electrical energy consumption of developing and developed economies [6].

Electricity system models are mostly based on optimization in order to minimize the cost, or to reach the environmental or financial goals [67]. Open Source Energy Modeling System (OSeMOSYS) as a full-fledged system optimization model was used for long-run energy planning. Welsch et al [68] introduced a long term energy system model by using short term constraints. An integrated model was developed for power generation planning of Tokyo area using optimization[69].

Due to the complexity of energy systems, traditional optimization methods may encounter with impractical computation time. Therefore, approximate methods such as metaheuristic techniques were developed in recent decades. A review of over two hundred optimization methods applied to renewable energy was concluded that optimization methods increased dramatically in recent years [70]. Therefore, some nature-inspired metaheuristic approaches were used in the area of energy forecasting which are given in the following sub-sections.

2.14.1 Genetic Algorithm (GA)

Genetic Algorithms (GA) was initially introduced in 1975 by Holland [71] and later it was used in optimization problems. GA is a numerical optimization technique, which depends on the mechanism of natural evolution such as crossover, mutation, and selection. Solution in conventional nonlinear optimization models can be reached by gradual variations from a single solution. However, GA maintains the population of solutions and subsequently they can attain better results. Nevertheless, convergence issues and prolonged run are some limitations of genetic algorithms.

A genetic algorithm was used to forecast annual electricity demand [72].

2.14.2 Particle Swarm Optimization (PSO)

PSO is a metaheuristic optimization technique introduced first in 1995. It is a population based stochastic algorithm and unlike evolutionary methods, is not based on selection process. In PSO a number of n-dimensional vectors (particles) move around the search space and attempt to cluster together in optimal places of the search space. This process has been used in long term electric load forecasting of Kuwaiti and Egyptian networks, [64].

2.14.3 Shuffled Frog-Leaping (SFL)

SFL is a meta-heuristic optimization technique that was introduced in 2008. This algorithm mimics the way frogs search for food in places with high amount of food. The optimized solution is the location that each frog may possess.

shuffled frog-leaping (SFL) and improved particle swarm optimization (IPSO) algorithms were used for optimal ANN models in order to forecast the energy consumption of the U.S. while the effects of DSM were considered [73]. A modified SFL algorithm were used to optimize a short term load and temperature forecasting [37].

2.14.4 Biogeography-Based Optimization (BBO)

BBO was Introduced in 2008 by Dan Simon [74], is a stochastic optimization technique for solving multi-modal optimization problems. A hybrid model involving ANN and bio-geography based optimization was utilized to predict the electricity demand of each sector in India [75].

2.15 Scenario Based Analysis

One way to deal with the uncertainties of future demand is employment of scenario based analysis. The method can be used in long term electricity planning and design. It may outweigh optimization approaches in developing countries [67]. A scenario based analysis was used to shed light on the complicated electric energy system of Canada [76].

2.16 Hybrid Approaches and Combined Methods

Hybrid approaches and combined methods were developed to benefit from the strength of several models. Since there is no one best approach, a proper linear combination of several methods may outperform each individual methods [77].

Various hybrid approaches of forecasting electricity demand were proposed for china [77], Finland [34], California, Spain [78], and Iran [51], [79]. A hybrid genetic-based adaptive neuro-fuzzy inference system (GBANFIS) was presented and compared with several methods to estimate the Iranian monthly electricity demand [80]. An integrated algorithm based on Fuzzy regression and ARMA was introduced for the energy consumption estimation of Iran and China [57]. A combined model based on data pre-analysis and cuckoo search optimization was proposed to forecast the electricity demand in Australia [81].

Based on the availability of data various approaches can be classified for energy forecasting, Figure 3.

- Extrapolation: Models merely based on a single time series data.
- Top-down approaches: Models that rely on the history of dependent data and all the necessary independent variables.
- Expert systems: Models with no time series data which use expert knowledge.
- Bottom-up approaches: Models with no time series data yet various end use data.
- Integrated models: the combination of various approaches forms comprehensive approaches in energy demand.

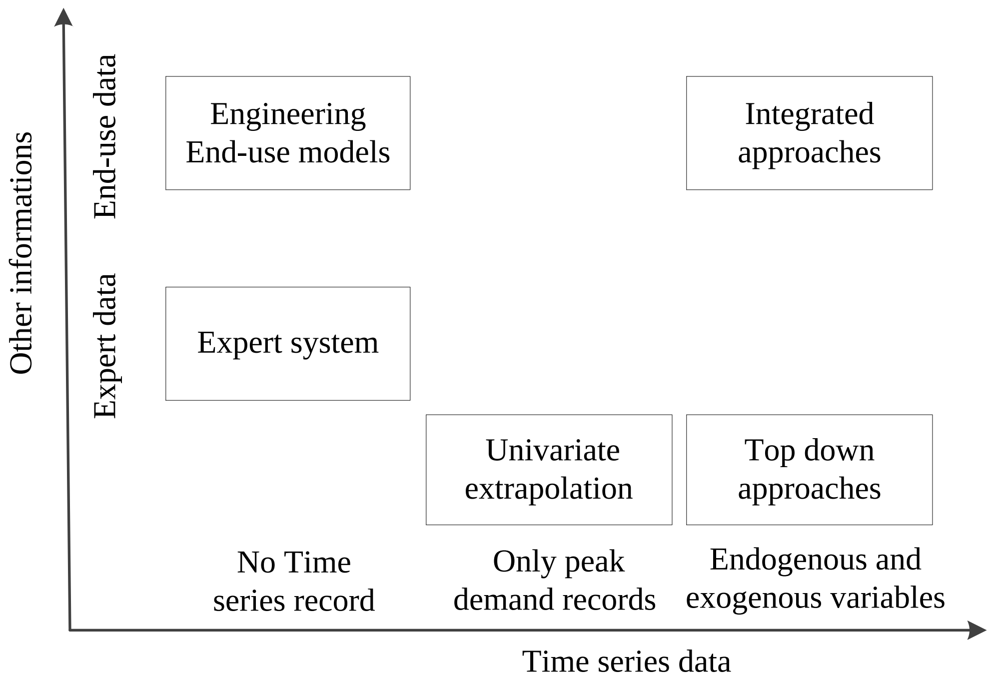

Figure 3: energy forecast models based on the data requirements

2.17 Top Down Approaches

2.17.1 Econometric Methodology

The econometric methodology also known as top-down approach estimates the peak and energy demand by considering the influence of endogenous and exogenous parameters. Therefore, it requires extensive amount of data and it demands capturing all the related variables for the estimations. A fail in catching the impact of exogenous effects in previous Turkish energy demand forecasts was resulted in an erroneous estimations [25].

In the literature, a number of various techniques have been used in energy demand estimation and modeling. Some categories of econometric methods are 1.Co-integration, and 2. Error correction models (ECM) 3.trans-log wave, and etc.

In terms of influential parameters, constant parameter approach and time varying parameters (TVP) [62] are two approaches of forming the equations.

The formulation can be based on regression methods, Bayesian methods, and etc.A regression based econometric method was discussed in chapter 4.

2.18 Bottom-Up Approaches

The bottom-up approaches extrapolate the estimated energy consumption of a representative set of individual houses to the regional and national levels.

A long-term bottom-up model of electricity consumption was presented for the commercial class of Brazil, [82]. Using bottom-up load methods new demand side management (DSM) strategies were developed to reduce the daily peak loads [83] or to model the residential energy demand [84]. A bottom-up load model was also used for small-scale energy consumers to predict the consumption and shift the time usage of appliances for the peak power reduction purposes [85].

Table 2 illustrate an extensive review of models in the literature as well as the case that they were used and Table 3 shows their advantage and disadvantage.

A comparison of optimized regression and ANN models were presented for long-term electrical energy consumption of developing and developed economies [6]. A classification of long term electricity forecast was proposed by Esteves et al [86]; after a systematic review of all the related articles, it was found that the most commonly used methods in a descending order were statistical, computer intelligence, end-use, hybrid and other approaches. Statistical techniques consist of Bayesian [23] or traditional methods [13].

Table 2: Summary of models used in the literature for energy and electricity peak demand forecasting.

	Method	Activity	Time	Case - Sector	remarks
1.	Univariate ARMA method using multi model partitioning filter (MMPF) [16].	An electricity demand load model	Long term	Greece	The current ARMA used Akaike Corrected Information Criterion and a Kalman based filter.
2.	Univariate ARIMA based on Box-Jenkins [17]	Electricity consumption forecast	monthly	Saudi Arabia – eastern region	ARIMA features: data requirements are low, relatively simple, and accurate. It is not dependent on other variables. The model used a transfer function to overcome the effect of sudden changes in weather parameters
3.	Six models including ARIMA[18]	Forecast solar radiation	Short term	North America	Six models were compared and the ARIMA in logs, with time varying coefficients showed better performance.
4.	ARIMAX[19]	Forecast cooling heating and electrical load	Short term-hourly	Hypothetical building in Victoria, Canada	Forecast were used to design a CCHP system Exogenous variable: dry- bulb temperature
5.	Exponential smoothing [23]	Price based demand response	Short term	smart home	This technique can significantly reduce or even eliminate peak energy demand.
6.	Exponential Smoothing, Principle component analysis (PCA) [24]	Comparing six univariate models for electricity forecasting	short term	Rio de Janeiro and England and Wales.	Exponential smoothing outperformed NN, ARIMA and PCA methods.
7.	Structural time series model (STSM) [25]	electricity consumption model	Long term	Turkey - residential	Variables: expenditure and electricity prices In 2020 the range of residential electricity consumption is estimated to be between 48 and 80 TWh.

Table 2: Summary of models used in the literature for energy and electricity peak demand forecasting (continued).

	Method	**Activity**	**Time**	**Case - Sector**	**remarks**
8.	Various Time series models [27]	Forecast electricity price	Short term	Germany – a utility	STSM, AR and ARMA with various situations were investigated.
9.	Econometric model based on Linear regression model [28]	electricity consumption	Long-term	Italy	Variables: electricity consumption record, GDP, GDP per capita and population.
10.	Functional regression [29]	peak load forecasting	Short-term (24h)	a district heating system in Turin, Italy	The current technique generalizes the classical multiple regression model.
11.	Decomposition [12]	forecasting of regional electricity demand	Medium and long term	Queensland, Victoria, and South East Queensland, Australia	Simpler models can be used. Better insight can be reached by knowing the type of the day and season.
12.	Decomposition based on SARIMA model [30]	Peak electricity demand	Short term (daily)	South Africa	The problem is decomposed into point and volatility forecasting. This model outperforms piecewise linear regression.
13.	neural networks and Fourier series [32]	electricity demand forecasting	Medium term (monthly)	Spain	The accuracy of forecast based on NN was improved when Fourier transformation was used.
14.	GNN and WT [36]	Load forecasting	Short term	A substation in India	WT improves the accuracy of GNN method

Table 2: Summary of models used in the literature for energy and electricity peak demand forecasting (continued).

	Method	**Activity**	**Time**	**Case - Sector**	**remarks**
15.	Echo state networks (ESN) based on WT and SFL optimization [37]	Load forecasting and weather forecasting	Short term (1h and 24 h)	North American electric utility	WT were used as the first step for decomposition of temperature and load time series.
16.	ANN [41]	Electrical consumption forecasting	from a few minutes to several days	Large buildings (Hospital facilities)	Data: load, weather, time of the day, type of day such as weekday or holiday,
17.	NN with recursion [42]	Load forecast for an energy system	Hourly up to a day	A large campus with 70000 students and employees	Weather (temperature and humidity) and time variables are the exogenous input data
18.	ANN [43]	Forecast peak demand	Short term	United States – government building	Forecast can be used to reduce the charging for end-use peak electrical demand
19.	ANN [44]	Electric load forecasting	short term	Northern areas of Vientnam	A feed-forward neural network with a back-propagation algorithm was used Large data set were used for training. The results are satisfactory and comparable to other models
20.	Support vector Machine [46]	electric forecasting	Short term	Eastern Saudi Arabia	Contrary to AR or NN models, the training data is not limited in SVM
21.	Support vector Machine [47]	electric load forecasting	Medium term	EUNITE European network	Appropriate segmentation of data improved the performance. Imprecise weather data forecast give rise to erroneous results.

Table 2: Summary of models used in the literature for energy and electricity peak demand forecasting (continued).

	Method	Activity	Time	Case - Sector	remarks
22.	Linear regression model and SVM [48]	electricity demand forecast	Medium term	Italy	seasonal climate forecast of temperature were used
23.	Support vector regression (SVR) [49]	modeling and prediction of electricity consumption	Long term	Turkey	Turkish electricity consumption was predicted until 2026. Data used: 1975 to 2006
24.	SVM [50]	Forecast electricity load	Short term	Taiwan	The parameters were selected through simulated annealing (SA) algorithms and then they were used in SVM model. The model outperforms ARIMA and GRNN
25.	WT +SVM & WT+NN [51]	Load forecasting	Short term	Iran	WT+SVM outperformed WT+NN
26.	Fuzzy logic [54]	Annual electricity demand forecast	Long term	Turkey	GDP affects the annual electricity demand
27.	Econometric analysis using time varying regression [62]	Estimation of the price and income elasticity of electricity demand	Long term	Turkey – industrial and residential	The problem is stated in space state form and Kalman filter were used for optimization. Electricity price hardly affect the consumption since electricity is vital.
28.	Forecast of wind energy using Kalman filter [63]	Wind energy forecast.	Very short term	Varese Ligure wind farm, Italy	Kalman filter improved the prediction of numerical weather prediction software.
29.	Particle swarm optimization [64]	Electric peak load forecasting.	Long term	Kuwait & Egypt	The state space form was used to describe the problem and the error is minimized using PSO. It performed better than many conventional optimizations such as LSE.
30.	Grey prediction model with Holt- winters ES [66]	electricity consumption forecast	Long term	Romania - nonresidential	Linear logarithmic regression was used with data as electricity consumption, GDP and electricity price

Table 2: Summary of models used in the literature for energy and electricity peak demand forecasting (continued).

	Method	**Activity**	**Time**	**Case - Sector**	**remarks**
31.	Probabilistic [33]	Peak electricity demand forecasting	Short term	A province of Netherland	Peak demand is related with: day of the week, yearly seasonality, holidays, and temperature, wind speed and luminosity
32.	econometric techniques based on time series [87]	Electricity demand forecasting	Long term	Sri lanka	Forecast based on all six time series do not vary significantly
33.	Multiplicative SARIMA [88]	peak demand of electricity	Monthly (medium term)	India	Multiplicative SARIMA model performs better that official reports
34.	A system dynamic approach [76]	A comprehensive view on the electricity generation	Long term	Canada	The Interaction between the supply and demand was modeled via a scenario analysis
35.	An econometric approach using Autoregressive distributed lag and particle adjustment [89]	electricity demand forecast	Long and short term	Ghana	Income is the main factor to influence the demand
36.	An econometric approach based on Structural time series model [90]	Electricity demand forecast	Long term	Turkey	Influential factors: electricity price, GDP, and demand trend.
37.	An econometric method based on Adaptive neuro-fuzzy network [91]	Electricity demand	Long term	Ontario province - Canada	The effect of, population, GDP, CDD and HDD, and housing was trivial compare to employment. That is, employment is the main driver for electricity demand.
38.	Scenario analysis using an electricity system model [92]	Three electricity demand and supply scenarios	Long term	Japan	Future work: impact of renewable energy generation

Table 2: Summary of models used in the literature for energy and electricity peak demand forecasting (continued).

	Method	**Activity**	**Time**	**Case - Sector**	**remarks**
39.	LEAP: Bottom up accounting and scenario based analysis [93]	energy alternatives planning	Long range	Turkey	Two scenarios were studied in which demand of electricity and CO_2 emissions will increase
40.	Review traditional, NN, GA, Fuzzy rules and wavelet network methods [94]	Review electric load demand forecasting	long-term	-----	Some load forecasting methods were discussed with their advantages and disadvantages
41.	ANN [95]	energy use forecast in wheat production of arable lands	Long term	Canterbury province, New Zealand - agriculture	ANN outperforms multiple linear regression models. The main sources of energy consumption in wheat industry are electricity, fuel and fertilizer.
42.	A simple optimization model [96]	Prediction of heat demand	Short term	District heating systems	Simple models can outperform more advanced ones. Heating systems has similarities with electrical power systems.
43.	Univariate Abductive Network [97]	energy demand forecasting	Medium-term (monthly)	A Power utility, US	Abductive network methods were defined to overcome the shortcomings of NN methods. Namely, they select effective inputs and can be simpler than neural network models.
44.	Abductive network [98]	electric energy consumption	Medium-term (monthly)	Eastern Saudi Arabia	Monthly average weather data gave better results than yearly average.
45.	Fuzzy logic [20]	forecast the electric load	Long term	Bahia state of Brazil	Exogenous input: the number of customers, rainfall, and temperature SARIMAX and FIS were compared
46.	DBN [61]	Wind power forecast	Short term	Wind farm in Mexico	History of the wind speed was used as the input data

Table 2: Summary of models used in the literature for energy and electricity peak demand forecasting (continued).

	Method	**Activity**	**Time**	**Case - Sector**	**remarks**
47.	Hybrid method [78]	load forecasting	Short term	California, Spain	Hybrid Model is based on WT, triple ES and weighted nearest neighbor (WNN)
48.	Hybrid approach[79]	peak load forecasting	Short term (Day ahead)	Iran	wavelet decomposition, ANN, and GA optimization
49.	Hybrid approach based on WT, SARIMA, and NN [34]	Forecast electricity demand and price	Short term	Finland	WT, ARIMA, and NN an appropriate forecast requires a trade-off between wavelength and smoothness.
50.	Hybrid procedure [77]	electricity demand forecasting	Medium Term (Seasonal)	China	Hybrid model based on MA, combined and adaptive PSO
51.	Integrated procedure[57]	Electricity consumption estimation	Medium Term	Iran and China	Integrated method is based on fuzzy regression and ARMA
52.	Neuro-fuzzy [80]	electricity load forecasting	Short term	Iran	genetic-based adaptive neuro-fuzzy inference system
53.	Combined method [81]	Forecast electrical power	Short term	Australia	Cukoo search optimize the weight coefficients in the combined method
54.	Scenario based optimization model [69]	Integrated power generation plan model	long term	Tokyo area, Japan	Optimization and hourly simulation were used for planning future smart electricity systems.
55.	A bottom-up model[84]	Energy demand model	Long term	US	The effect of new technologies on the energy usage pattern of a community was studied
56.	A bottom up approach [83]		Long term		
57.	Bottom up model[85]		Long term		

Table 2: Summary of models used in the literature for energy and electricity peak demand forecasting (continued).

	Method	**Activity**	**Time**	**Case - Sector**	**remarks**
58.	Hybrid approach based on ANN and BBO [75]	Sector-wise Electrical Energy Forecasting	Long-term	India	Data: population, per capita GDP The accuracy of forecast was improved, local optima trapping resolved, the number of iterations were reduced and converged to the lowest MSE.
59.	Genetic Algorithm (GA) [72]	electricity demand forecast	Long term	Turkey, industrial sector and total.	Total electricity consumption is related with Population, import, export, and GNP. Industrial electricity consumption is related with import, export, and GNP.
60.	SVR and fuzzy linear regression (FLR) [56]	Global solar radiation prediction	long-term	Iran	Global solar radiation (GSR) prediction is required to design and construct the solar power plants. SVR noticeably outperforms FLR.
61.	ANN based on IPSO and SFL [73]	Investigate the effect of DSM on electric energy forecasting	Long term	US	IPSO – ANN shows better results. Data: electric energy consumption, GDP, IMP, EXP, POP
62.	Energy plus software [99]	Impact of weather on peak demand and energy consumption	Long term	Three types of office building in 17 climate zones	weather variations affect electricity demand more than energy consumption
63.	OSeMOSYS [68]	energy system model	Long term with short term constraints	A simple system	It is beneficial to consider short term constraints in long term models

Table 2: Summary of models used in the literature for energy and electricity peak demand forecasting (continued).

	Method	**Activity**	**Time**	**Case - Sector**	**remarks**
64.	FORECAST-Tertiary (Bottom up approaches), [82]	electricity consumption	Long term	Brazil - commercial class	Consumption for commercial class is growing faster than that of the other classes.

Table 3: Advantages and disadvantages of models used in electric demand forecasting

Method	**Advantage**	**disadvantage**
Exponential Smoothing [22] [24]	• Robustness • Simplicity • It is quick to implement	• Difficulty in identification of the best exponential smoothing model.
Time series method	• Relatively high performance in short term • Minimal cost • Less data need • Relatively quick • Most simplest of models [100]	• Hard to interpret error sources • Hard to deal with seasonality and nonlinearity [81] • fail to deal with data with noise or errors [16] • It produces only one result • Model selection is challenging
Expert system	• It benefits from the knowledge of experienced people with low price. • It can be used when no time series data is available [101]	• Strong dependency on knowledge data base.[81] • Informed source may not be available. • Opinions sometimes biased. • At times opinions are contradictory
Bottom-up (end use) method	• It does not demand high skill • Ability to obtain clear engineering view on the results. • The only feasible method that can estimate the energy for a sector even without having historical time series data [84]. • They are capabel to model technological changes. [82]	• Extensive detailed data requirements about the consumers or their appliances and different sectors [83]. • Data acquisition is difficult and costly • Hard to assess the technological variation. • Relationship between energy demand and end-use can vary by time • Wrong assumptions about consumer behavior can result in inaccurate conclusions
Regression based Econometric methods	• They provide detailed information on future levels of electricity demand • They model distinctly nonlinear relationships by linear devices • Models can be readily re-estimated	• Extensive data required for detailed disaggregated model • Models developed in one region may not be used in other regions. • Exogenous determinants are hard to determine, and their accurate data may not be accessible. [97]

Table 3: Advantages and disadvantages of models used in electric demand forecasting (continued)

Method	**Advantage**	**disadvantage**
Decomposition methods [12] [24]	• Reducing the dimension of multivariate data sets simplify the problem • It is relatively easy for implementation • It can provide the knowledge of planning for base load generation and network upgrades.	• Decomposition may be accompanied by some bias. • The components may not be easily decomposable
Particle swarm optimization (PSO) [64]	Advantage over conventional optimization algorithms • Reducing the computational complexity • Easily incorporated with other optimization tools • Ability to escape local minima. • Less sensitive to a good initial solution Compare to other evolutionary methods: • Easy programming • Less computational time and memory • Less parameters tuning • Promising convergence characteristics	

Table 3: Advantages and disadvantages of models used in electric demand forecasting (continued)

Method	**Advantage**	**disadvantage**
Neural Networking (NN) [95]	• They can solve nonlinear problems in a flexible and adaptable manner • They are able to model complex systems by using prior information • Their application are simple and their results are robust • Capability for universal function approximation • Resistance to noisy or missing data • Good generalization ability • Excellent scheduling capabilities is a reason to use it for STLF.[40]	• Large computation time • Slow convergence rate [75] • difficulty in determining optimum network topology and training parameters [97]. • They are prone to returning solutions which are locally but not globally optimal [81] • Finding the best model is time intensive and depends on many factors: such as number of layers, number of neurons, activation functions, learning parameters, neural network architectures, and learning methods.
Wavelet networks	• It provides powerful and flexible tool to decompose and analyze peak demand data. • It is more accurate than multilayer NN [94]	• There is no general rule in selecting the proper wavelet function. • Border distortion problem can distort the forecast
Abductive Neural network [97], [98]	• They select effective inputs and can be simpler than neural network models. • Reduction of over-fitting and improving generalization in applications	• Selecting suitable independent variables are difficult and it requires labor-intensive iterations.
Neuro- fuzzy	• It is more accurate than regression models • It is more robust than NN methods in extrapolation of future estimates. • Minimal data requirements • It can deal with nonlinearity	• Model development is time consuming compared to regression methods. • The accuracy and the interpretability of the obtained model are contradictory properties directly depending on the learning process and/or the model structure.[80]
Fuzzy logic	• Minimal data requirements • Ability to deal with uncertainty	• Difficulty in forming the “if-then” rules.

Table 3: Advantages and disadvantages of models used in electric demand forecasting (continued)

Method	**Advantage**	**disadvantage**
Fuzzy set theory (LR discretization) [58]	• Minimal data requirements • Ability to treat the uncertainty to some extent.	• Uncertainty is considered with underestimation.
Fuzzy set theory (extension principle) [59]	• Minimal data requirements • Ability to fully cover the uncertainty.	• Limiting the forecast horizon due to the propagation of uncertainty
Kalman filter [62]	• Ability to handle measurements that change with time because of the recursive procedure [64]	
Support vector Machine (SVM)	• The training data set in SVM can be larger than AR model, NN methods or GA. This can improves the accuracy of SVM	• Network parameter selection can be problematic [64]
Conventional nonlinear Optimization	• Easy to implement	• They make incremental changes to a single solution to the problem rather than maintaining the whole database of solutions.
Genetic Algorithm (GA)	• Robustness • It is suitable for parallel implementation[72] • Despite the incremental changes to a single solution of problems in conventional optimization, GA search by maintaining a population (or database) of solutions from which better solutions are created	• Convergence issues and prolonged run are some limitations of genetic algorithms • Computational cost of GA can increase as the binary string gets longer for higher degree of precision [72] • Training data set should be decreased because some data is needed for testing the performance.
Grey forecasting model	• Simplicity • Easier to use compared with Box-Jenkins methods.	• For an accurate results they can only combine with exponential growth trend [81]

2.20 Error Estimation Methods

In order to measure the performance of the forecast various estimation methods were used in the literature. Some commonly used estimators are as follows:

Mean Absolute Error (MAE)

$$MAE = \frac{1}{T}\sum_{t=1}^{T} |y_t - y_t'| \tag{6}$$

Mean Square Error (MSE)

$$MSE = \frac{1}{T}\sum_{t=1}^{T} (y_t - y_t')^2 \tag{7}$$

Root Mean Square Error (RMSE) [16]

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} (y_t - y_t')^2} \tag{8}$$

Normalized root mean square error (NRMSE) [50]

$$NRMSE = \sqrt{\frac{\sum_{t=1}^{T} (y_t - y_t')^2}{\sum_{t=1}^{T} y_t}} \tag{9}$$

Mean Absolute Percentage Error (MAPE) [57]

$$MAPE = \frac{1}{T}\sum_{t=1}^{T} \left|\frac{y_t - y_t'}{y_t}\right| \tag{10}$$

2.21 Concluding Remarks

The extensive review of forecast methods on the energy demand indicates that while a plethora of techniques is presented in the literature, there are still a number of gaps on many areas of energy forecasting. Some of the areas needed to be studied are models based on the size of the system, the uncertainty of the energy forecast due to lack of data, the method which is best suited for the country, the performance measurement methods, and having more comparative studies. The current thesis attempted to have a view on some of these problems.

Chapter 3

PROPOSED METHODOLOGIES FOR PEAK DEMAND FORECASTING

3.1 Introduction

This chapter describes the methodologies used to forecast the annual peak demand for small utilities. The appropriate method can be selected depending on the availability of data. If historical data is rich and all the necessary key variables in defining the system of interest exist, econometric methods have the supremacy over any other methods. Chapter 4 is devoted to an econometric method for annual peak demand of small utilities such as N. Cyprus. On the other hand, when the necessary variables are limited or missing, a fuzzy peak demand forecasting model were utilized for the estimations, see Figure 4. Chapter 5 discusses the method by providing an algorithm to forecast the peak demand. The rest of the chapter discusses the econometric method used for small utilities. Subsequently, the Fuzzy Arithmetic Approach used to forecast the peak demand in developing countries was elaborated.

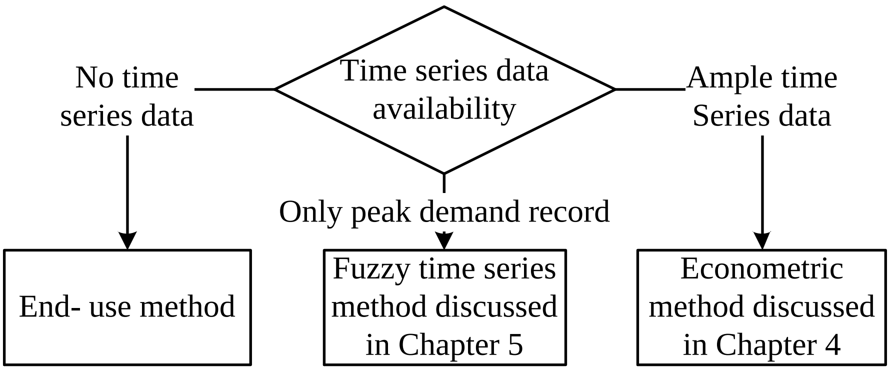

Figure 4: Chapters and Methodologies

3.2 Adoption of the Econometric Method for Small Utilities

The econometric approach describes the connection between energy demand and the economic variables. It can be referred to as a top-down approach since it is dealt with aggregate values. The yearly values of various parameters which may influence the load system can be gathered. Applying econometric theory, generally involves two types of variables, namely, endogenous and exogenous variables. Endogenous variables are the parameters associated with the utility's internal environment while exogenous variables are factors influenced by the utility's external environment. Some important economic variables which may be considered in the formulations are listed in Table 4.

Table 4:Typical exogenous and endogenous variables used in econometric method

Endogenous Variables	**Remarks**	**Reference**
Electricity prices	The prices should change during the historical period, otherwise its relation with electricity demand cannot be determined	
Number of customers	Although there is a relation between population and number of customers, Number of customers are the people who has electricity meters and they are different than the population	[20]
Incentive program levels	Incentive programs are the measures done by utilities to influence the electricity consumption. These programs could be either encouraging or discouraging	

Table 4:Typical exogenous and endogenous variables used in econometric method (continued)

Exogenous Variables	**Remarks**	**Reference**
Price of Competing Products	The competing products affect electricity consumption to some extent. For instance, if the price of oil, natural gas, solar panels, wind generation and etc. are cheap, they might be consider as an alternative means of energy consumption	
Population	The number of residence has an important influence on the electric energy consumption	[6][28]
Per Capita Income	The amount of money each person earns in the service territory can affect the consumption	
Gross domestic product (GDP)	The total economic activities of a nation in terms of all goods and services may have an effect on the energy demand.	[6] [89] [28]
GDP per capita		[28]
Unemployment rate	High unemployment rates can be associated with a weak economy. It may indicate low economic activities or high residential consumption. Because more people may stay at home	
Degree of Urbanization		[89]
Energy import		[6]
Energy export		[6]
Retail sales	High retail sales may result in higher commercial and residential demand for electricity	
Housing Starts	The more homes being built, the more commercial activity as well as residential customer is expected.	
New Businesses	An increment in the number of businesses may lead to additional commercial or industrial activities or even more residence moving into the service area.	
Industry output		[89]
Tourism	The number of visitors to the community each year may have a considerable impact on the amount of electricity consumption.	
Temperature	By knowing the weather patterns in the area	

Table 4:Typical exogenous and endogenous variables used in econometric method (continued)

Exogenous Variables	Remarks	Reference
	of the interest, the impact of the temperature on the consumption of electricity can be realized. The maximum and minimum temperatures are important especially when electric heating or air conditioning is necessary. Also HDD or CDD quantify the number of hours required to use heating or cooling equipment.	[20] [19][33] [41] [42]
Humidity		[42]
Wind speed		[33]
Luminosity		[33]
precipitation	The amount of daily rainfall may affect the energy demand especially in tropical areas.	[20]
Type of day	Electricity demand can change dramatically during holidays and weekdays.	[33][41]
Time of day	Electricity reaches to its peak in a specific time of the day. This information can be required for short term forecasting	[41][42] [33]

3.2.1 Econometric Method in Small Utilities

Energy forecast for large sized systems may call for sophisticated techniques. As an example, for larger systems with vast geographical variations temperature can be quite diverse in different regions and considering a single temperature value for the whole system may result in an erroneous outcome. However, temperature might be more uniform for smaller systems and considering a single value is reasonable.

3.2.2 Adoption of Relevant data

The variables used in econometric methods should be initially selected based on the experience and judgment of forecaster. In another words, the parameters affecting the energy demand can vary from country to country and case to case. For example, an industrial country has different influential parameters than a country which relies more on tourism or agriculture. As another example, changing the energy prices in a country with high per capita income brings about small variation in energy consumption, while a change in electricity rate in a poor community imposes dramatic changes in energy pattern.

3.2.3 Data Acquisition

Collecting quality data is the key to a successful econometric load forecast. Data acquisition can be a labor-intensive and prolonged process. Yearbooks and reports of statistical departments can be one source of data. It may also require obtaining information from the electricity, meteorological, and statistical departments. Meanwhile, some data might be missing or very expensive to obtain. Moreover, multiple customer classes such as residential, industrial, commercial, and etc may call for further information.

3.2.4 Analysis of Variance (ANOVA)

After gathering the parameters that have the potential to affect the energy demand, a statistical procedure is needed to determine which variables to select and which variables to omit. In this regard, ANOVA can be utilized to distinguish the significance of each variable on the energy demand and remove the parameters which are insignificant. In this procedure some variables might be highly correlated with other variables. This situation is called multicollinearity and mistakenly can cause elimination of significant variables from the equations.

3.2.5 Multiple Regression Model

A multiple regression model describes the relationship between the dependent variable and the independent variables. For different systems different independent variables might be related; therefore, independent variables must be selected carefully regarding the characteristic of the system. It is advantageous to use linear regression models, especially in developing countries. Also, the independent variables are not linearly interrelated with each other; that is multicollinearity does not exist. Several software packages can be used to find the coefficients of the regression model, such as Minitab or SPSS.

3.2.6 Model Selection and Performance Evaluation

Various methods can be used to evaluate the appropriateness of the best model. Relying on only one method may cause erroneous conclusions in accepting the best model. Plotting the graph of the predicted values versus real values is always the first step of verification, since "a picture is worth a hundred words." Statistical factors such as R^2, adjusted R^2, F-ratio, t-statistic and Predicted Residual Sum of Squares (PRESS) are other elements for measuring the performance. These statistical indicators can provide adequate confidence for the accuracy of the results.

MAPE and MASE can be used to measure the performance of the models. In order to ensure that the selection of in-sample and out-of-sample data does not affect the results, MAPE and MASE were calculated by sliding the in-sample and out-of-sample data.

3.2.7 Multiple Regression Model Forecast

After determining the coefficients of the regression model and selecting the best model, the econometric model can be used to forecast energy demand into the future. In this regard, the behavior of the independent variables must first be projected.

Predicting the behavior of the independent variables may require the knowledge of the experts. For instance, specialists who work in the utility may have a good idea of what will be happening to rates, at least in the near future. Another way of estimating the independent variables is to forecast each independent variable using an appropriate model such as deterministic time series method. Subsequently, the energy demand can be forecasted by simply using the regression model.

3.3 Development of the Fuzzy Arithmetic Approach for Developing Countries

When the variables influencing the energy demand are absent or uncertain, applying econometric method is impossible. Therefore, employing simpler methods like univariate extrapolation may be one solution. univariate models benefit from being reliant on single time series data especially when exogenous variables are unknown or hard to acquire [97]. The simplifications of models can give rise to further uncertainties. Fuzzy arithmetic can be used when data is missing and models are simplified.

3.3.1 Deterministic Time Series Methods

As discussed in section 2.2.1 deterministic models are the fastest and easiest methods to apply in forecasting, especially when uncertainty exists. In order to find the parameters β_1 and β_2 of linear trend models, Eq. (1), two methods of simple average, Eq. (11) and simple regression, Eq. (12) can be used as follows:

$$\beta_1 = Y_1 \quad and \quad \beta_2 = \sum_{t=2}^{T} \frac{\beta_{2t}}{T-1}, \qquad \text{where} \qquad \beta_{2t} = Y_t - Y_{t-1} \tag{11}$$

where T is the total number of the time series and β_{2t} is the differences of peak demands in the interval t. Similarly:

$$\beta_2 = \frac{T * S_{Yt} - S_Y * S_t}{T * S_{t^2} - {S_t}^2} \qquad S_t = \sum_{t=1}^{T} t \,, \qquad S_Y = \sum_{t=1}^{T} Y_t,$$

$$\beta_1 = (S_Y - \beta_2 * S_t)/T \qquad \text{where} \qquad S_{Yt} = \sum_{t=1}^{T} tY_t \,, \; and \quad S_{t^2} = \sum_{t=1}^{T} t^2 \tag{12}$$

Moreover the parameters β_1 and β_2 in Eq. (2) can be found through the following formulas:

For Straight Average Rate method:

$$\beta_1 = 0 \; and \; \beta_2 = \sum_{t=2}^{T} \frac{\beta_{2t}}{T-1} \tag{13}$$

where $\beta_{2t} = \frac{Y_t}{Y_{t-1}}$ for interval t. For Compound Average Rate method

$$\beta_1 = 0 \quad and \quad \beta_2 = \left(\frac{Y_t}{Y_{t-1}}\right)^{\frac{1}{T-1}}. \tag{14}$$

For Simple Regression method:

$$\beta_2 = \frac{T * S_{Yt} - S_Y * S_t}{T * S_{t^2} - {S_t}^2} \qquad \text{where} \qquad S_t = \sum_{t=2}^{T} Y_{t-1} \,, \qquad S_Y = \sum_{t=2}^{T} Y_t \,,$$

$$\beta_1 = (S_Y - \beta_2 * S_t)/T \qquad S_{Yt} = \sum_{t=2}^{T} Y_t \times Y_{t-1} \,, and \;\; S_{t^2} = \sum_{t=2}^{T} (Y_{t-1})^2 \tag{15}$$

3.3.2 Advanced Fuzzy Arithmetic Procedure

In the literature various operations were defined to carry out the arithmetic of fuzzy numbers. Transformation method of Hanss [59] was selected as a well-organized and systematic approach to deal with arithmetic of fuzzy numbers. The transformation method which was used in this study is briefly explained in the following sub-sections.

3.3.2.1 Decomposition of the Input Fuzzy Numbers

Fuzzy numbers (such as peak demands) $\tilde{P}_i \,, i = 1,2, \dots, n$ can be segmented into finite sequences of their α-cuts denoted by $cut_\alpha(\tilde{P}_i)$, with $\alpha \in [0,1]$. Thus, it is convenient to generate m intervals of length $\Delta\mu = \frac{1}{m}$ on the membership function, μ, with μ_j given by

$$\mu_j = \frac{j}{m}, \quad j = 0, 1, \dots, m \tag{16}$$

where $\mu_0 = 0$, and $\mu_m = 1$ and m is known as decomposition number. Therefore

$$\mu_{j+1} = \mu_j + \Delta\mu, \quad j = 0, 1, \dots, m-1\ . \tag{17}$$

Hence, the i^{th} fuzzy number $\tilde{P}_i$ can be represented in its decomposed form by the set

$$P_i = \left\{X_i^{(0)}, X_i^{(1)}, \dots, X_i^{(m)}\right\}, \qquad i = 1, 2, \dots, n \tag{18}$$

of $(m+1)$ intervals, where

$$X_i^{(j)} = \left[a_i^{(j)}, b_i^{(j)}\right] = cut_{\mu_j}(\tilde{P}_i), \ \ a_i^{(j)} \le b_i^{(j)}, \qquad j = 1, 2, \dots, m \tag{19}$$

$$X_i^{(0)} = \left[a_i^{(0)}, b_i^{(0)}\right] = \left[w_{l_i}, w_{r_i}\right] \ with \quad]w_{l_i}, w_{r_i}[= supp(\tilde{P}_i) \tag{20}$$

where $X_i^{(j)}$ are intervals and $a_i^{(j)}$and $b_i^{(j)}$ are the boundary values for each level of membership μ_j, $j = 0,1, \dots, m$, and for all fuzzy numbers, $i = 1,2, \dots, n$, and $supp(\tilde{P}_i)$ are the support of the fuzzy set which include all the values with nonzero degree of membership. Figure 5 displays a fuzzy number with its decomposition procedure.

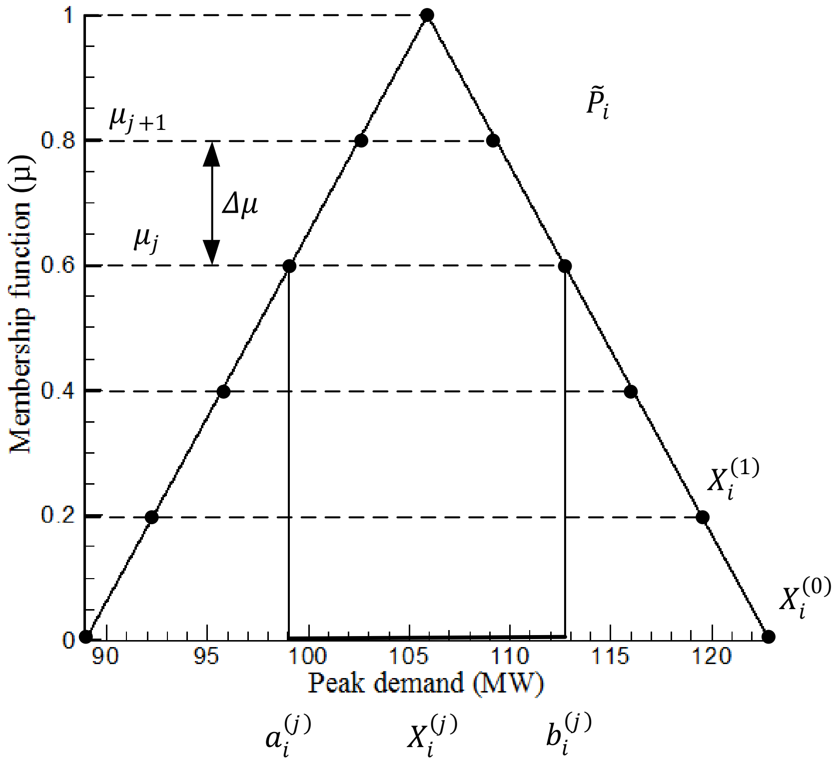

Figure 5: Decomposition of a typical peak demand as a fuzzy number.

3.3.2.2 Transformation of the Input Intervals

The reduced form of transformation method was used because the general trend of peak demand as the function of the problem $F(\tilde{P}_1, \tilde{P}_2, \ldots, \tilde{P}_n)$ is expected to act monotonically. The intervals $X_i^{(j)}$, found in the previous step can be transformed into arrays $\hat{X}_i^{(j)}$ of the form

$$\hat{X}_i^{(j)} = \left(\overbrace{\left(\alpha_i^{(j)}, \beta_j^{(j)}\right), \left(\alpha_i^{(j)}, \beta_j^{(j)}\right), \ldots, \left(\alpha_i^{(j)}, \beta_j^{(j)}\right)}^{2^{i-1} pairs} \right) \tag{21}$$

with

$$\alpha_i^{(j)} = \left(\underbrace{a_i^{(j)}, \ldots, a_i^{(j)}}_{2^{n-i}\ elements} \right), \quad \beta_i^{(j)} = \left(\underbrace{b_i^{(j)}, \ldots, b_i^{(j)}}_{2^{n-i}\ elements} \right), \tag{22}$$

where $a_i^{(j)}$ and $b_i^{(j)}$ are the left and right boundaries of the intervals $X_i^{(j)}, i = 1,2,\ldots,n$, $j = 0,1,\ldots,m$. For example, using the reduced transformation method, and given the membership $\mu = 0$, for n=3 fuzzy numbers, Eqs. (20) and (22) can be written as:

$$X_1^{(0)} = \left[a_1^{(0)}, b_1^{(0)}\right], \qquad X_2^{(0)} = \left[a_2^{(0)}, b_2^{(0)}\right], \qquad X_3^{(0)} = \left[a_3^{(0)}, b_3^{(0)}\right] \tag{23}$$

$$\begin{aligned}
\hat{X}_1^{(0)} &= \left(a_1^{(0)}, a_1^{(0)}, a_1^{(0)}, a_1^{(0)}, b_1^{(0)}, b_1^{(0)}, b_1^{(0)}, b_1^{(0)}\right), \\
\hat{X}_2^{(0)} &= \left(a_2^{(0)}, a_2^{(0)}, b_2^{(0)}, b_2^{(0)}, a_2^{(0)}, a_2^{(0)}, b_2^{(0)}, b_2^{(0)}\right), \\
\hat{X}_2^{(0)} &= \left(a_2^{(0)}, a_2^{(0)}, b_2^{(0)}, b_2^{(0)}, a_2^{(0)}, a_2^{(0)}, b_2^{(0)}, b_2^{(0)}\right),
\end{aligned} \tag{24}$$

The process can be shown geometrically by a nested cuboid in Figure 6 where Eq. (24) with $\mu = 0$ are the vertices of the outermost cuboid and $\mu = 1$ is the dot in the center of all cuboids.

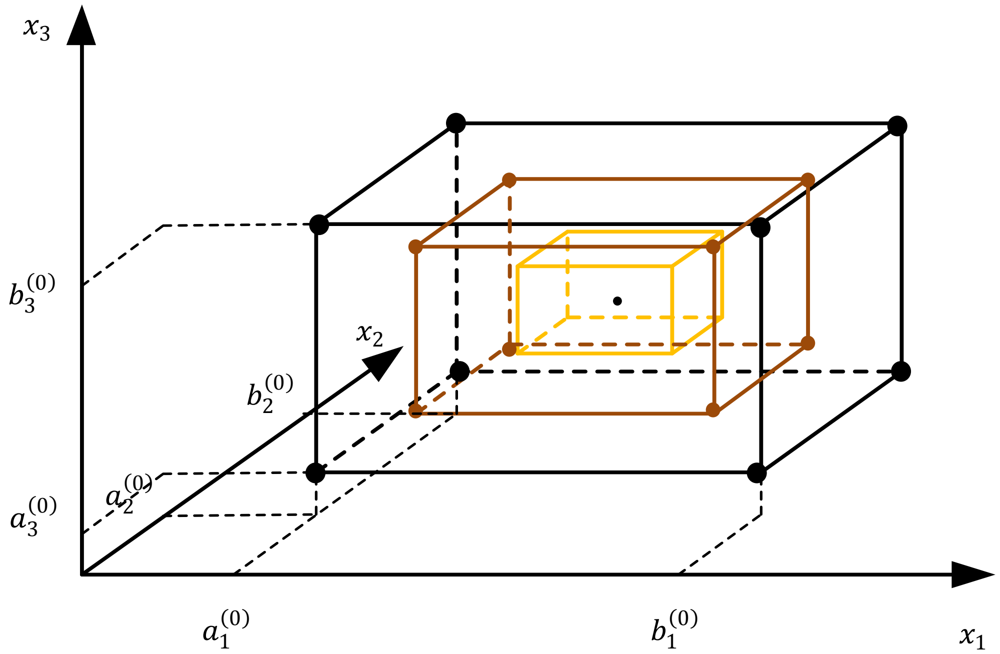

Figure 6: Reduced form of transformation method when three fuzzy variables are used [59].

3.3.2.3 Model Evaluation

At each of the columns of the arrays, the fuzzy-parameterized model can be determined through the standard arithmetic for ordinary numbers. That is, the kth element ${}^{k}\hat{z}^{(j)}$ of the output array, $\hat{Z}^{(j)},\ j = 0,1,\dots,m$, can be found by

$$ {}^{k}\hat{z}^{(j)} = F\left({}^{k}\hat{x}_1^{(j)}, {}^{k}\hat{x}_2^{(j)}, \dots, {}^{k}\hat{x}_n^{(j)}\right) \tag{25}$$

where F can be any functional expression, and ${}^{k}\hat{x}_i^{(j)}$stand for the kth element of array $\hat{X}_i^{(j)}$.

3.3.2.4. Retransformation of the Output Array

As a result of the application of fuzzy arithmetic, the output value can be obtained through the retransformation of the arrays $\hat{z}(j)$ using the recursive formulas

$$a^{(j)} = \min_k\ (a^{(j+1)},\ {}^{k}\hat{z}^{(j)}) \tag{26}$$

$$b^{(j)} = \max_{\mathrm{k}}(b^{(j+1)},\ {}^{k}\hat{z}^{(j)}), j = 0,1,\dots,m-1 \tag{27}$$

with

$$a^{(m)} = \min_k\ (\ {}^{k}\hat{z}^{(m)}) = \max_k\ (\ {}^{k}\hat{z}^{(j)}). \tag{28}$$

Therefore, the output, $\hat{q}$, can be expressed in its decomposed representation with $(m+1)$ intervals as

$$Q = \left\{Z^{(0)}, Z^{(1)}, \dots, Z^{(m)}\right\} \tag{29}$$

where

$$Z^{(j)} = \left[a_i^{(j)}, b_i^{(j)}\right] = cut_{\mu_j}(\tilde{\mathrm{q}}),\ \ a_i^{(j)} \le b_i^{(j)}, \qquad j = 1, 2, \dots, m \tag{30}$$

$$Z^{(0)} = \left[a_i^{(0)}, b_i^{(0)}\right] = \left[w_{l_i}, w_{r_i}\right] \ with \quad]w_{l_i}, w_{r_i}[= supp(\tilde{q}) \tag{31}$$

3.3.2.5 Recomposition of the Output Interval

Finally, the output fuzzy number, $\tilde{q}$, can be obtained through recomposition of the intervals $Z^{(j)},\ j = 0, 1, \dots, m$, of Q regarding their levels of membership μ_j.

The output fuzzy number is the result of the forecast model and it is a fuzzy value.

3.3.3 Evaluating the Performance of Fuzzy Forecast

The first step in determining the best model for forecasting is employment of graphical visualization against time. This can reveal the characteristics of models and data. It should be noted that techniques for model evaluation of fuzzy numbers are different than ordinary numbers. Instead of only one value, a range of values with different possibilities are to be dealt with. Therefore one way to cope with the problem is defining the fuzzy distances. Subsequently, MAPE can be calculated over the fuzzy distance, see section 5.3.3.

Chapter 4

ECONOMETRIC MODEL FOR ANNUAL PEAK DEMAND FORECASTING IN SMALL UTILITIES

4.1 Introduction

It is essential to utilize forecast models for estimating both the energy consumption and the peak demand to produce consistent plans. For example, when energy models are not coupled with demand models it is difficult to decide whether a base load unit or a peak load unit would be more appropriate for power expansion. Also, successful implementation of clean energy projects and assessing their impact on the electric power systems can be realized more easily with the developed forecast models [102], [103]. For electricity forecasting, there are no universally accepted guidelines that prescribe which variables should be specified in which equations, [104]. Egelioglu et al [105] studied the N. Cyprus yearly electric energy consumption, using a multiple regression model based on economic variables and temperature. However, this study alone is not sufficient for planning the future generation system as demand forecasting was not considered.

Electric energy demand can be modeled by determining the relationship between historical demand and other influential factors such as social, economy, demography, and climate. This kind of modeling is known as econometric method which is a common practice in electricity demand forecasting. Suganthi and Samuel [100] in their review paper classified energy models for demand forecasting into twelve groups and among 364 papers that they cited, fifty of them used econometric methods in various applications of energy and for different cases.

Providing STSM to estimate Turkish aggregate electricity demand, Dilaver et al [90] argued that the previous electricity demand forecasts were unsuccessful in Turkey. The reason was failure in selecting the main economic drivers. This can underline the importance of capturing the appropriate variables in econometric approaches.

In order to forecast electricity demand of Ghana, Adom and Bekoe [89] employed two econometric approaches; auto regressive distributed lag (ARDL) and partial adjustment model (PAM). They examined the determinants of electric energy demand and in long and short-term. They concluded that industry, urbanization, and income surpass the negative efficiency effects and thereby electric energy consumption increases.

In order to design the pricing policy in Turkey, Arisoy and Ozturk [62] urged on the necessity to study the main determinants of electric energy demand. They estimated the price and income elasticity of electricity demand. It was revealed that the change in price of electricity was not seriously affecting the residential and industrial electricity demands because electricity usage is crucial.

Hyde et al. [106] presented an automated short term electricity forecast in Ireland, based on weather sensitive and weather insensitive load components. Hippert et al [38] in their review paper stated that although load systems exhibit nonlinearity, linear regression models and models that decompose the load into basic and weather-dependent components are still agreeable; because, they allow engineers to understand their behavior. They argued that neural network may outperform standard forecasting and therefore it may be accompanied by skepticism. Pardo et al. [107] developed linear regression and AR models for electricity demand. The developed long term forecast was able to analyze the effects of exogenous determinants and anomalous events in Spain. Tabatabaie et al [108] studied the relationship between energy consumption and yield in producing two cultivars of plum through econometric models using structured questionnaire method.

The larger the system is the more intricate and costly the process of obtaining and distinguishing the independent variables become. In Canada, Zahedi et al [91] estimated electric energy demand using adaptive neuro-fuzzy network. It was concluded that among six parameters which were used numbers of employment have the greatest impact on electricity demand. Also, they proposed using simpler approaches like regression methods or Fourier series for systems in which non-linearity is negligible or laborious methods are not desirable.

By examining the impact of weather on both the peak demand and energy consumption of buildings in 17 cities around the world, Hong et al [99] concluded that the change in yearly weather condition affects the peak demand more than energy consumptions in buildings.

A model used for one place may not be applicable in others. The model developed in this chapter is simple and it is especially suitable for small utilities (i.e., utilities having capacities less than 1000 MWe) that provide services to small geographical areas, such as N. Cyprus and many similar islands. These utilities are far away from the interconnected grid and they require an appropriate peak demand forecasting.

Similarly, many SIDSs are in the same vein and they require a full scale forecasting [7].

For a long term planning (i.e., ten to thirty years) utilities need to develop electrical demand and consumption models, which directly account for the impact of economic variables upon energy consumption [13]. Despite the rich literature on the energy and demand models, relatively few studies consider the scale of the load system. Large utilities provide electricity for usually a vast geographical area with different classes of customers and climatic conditions which make sophisticated load forecasts a necessity for them. However, in smaller sized utilities the parameters affecting the electricity consumption may not diverge substantially and subsequently they can use less time and labor intensive methods to prepare accurate load forecast. In this chapter we introduce an algorithm to estimate the peak demand of small-sized utilities. Using this method, it is expected that planners and investors who will plan or invest in small utility projects around the world will benefit the most. For instance, many SIDS which require distinct energy forecast [7] can use the model. Also, the impact of extreme weather conditions and climate change on energy and peak demand (e.g. [109], [110], [111]) can be monitored through estimation of base and weather sensitive demand.

The remainder of the chapter is organized as follows. In section 2 the method of the current study is delineated and the statistical procedure is elaborated. Section 3 discusses and presents the best model for the utility planning of N. Cyprus. Section 4 contains the concluding remarks.

4.2 Approach

The approach of the present study is illustrated in Figure 7. The methodology employed is based on the econometric method. The econometric methods yield acceptable forecasts when extensive information about the system together with the necessary data are available [112]. Therefore, effective parameters on the load system must be distinguished first and a substantial amount of data is to be collected.

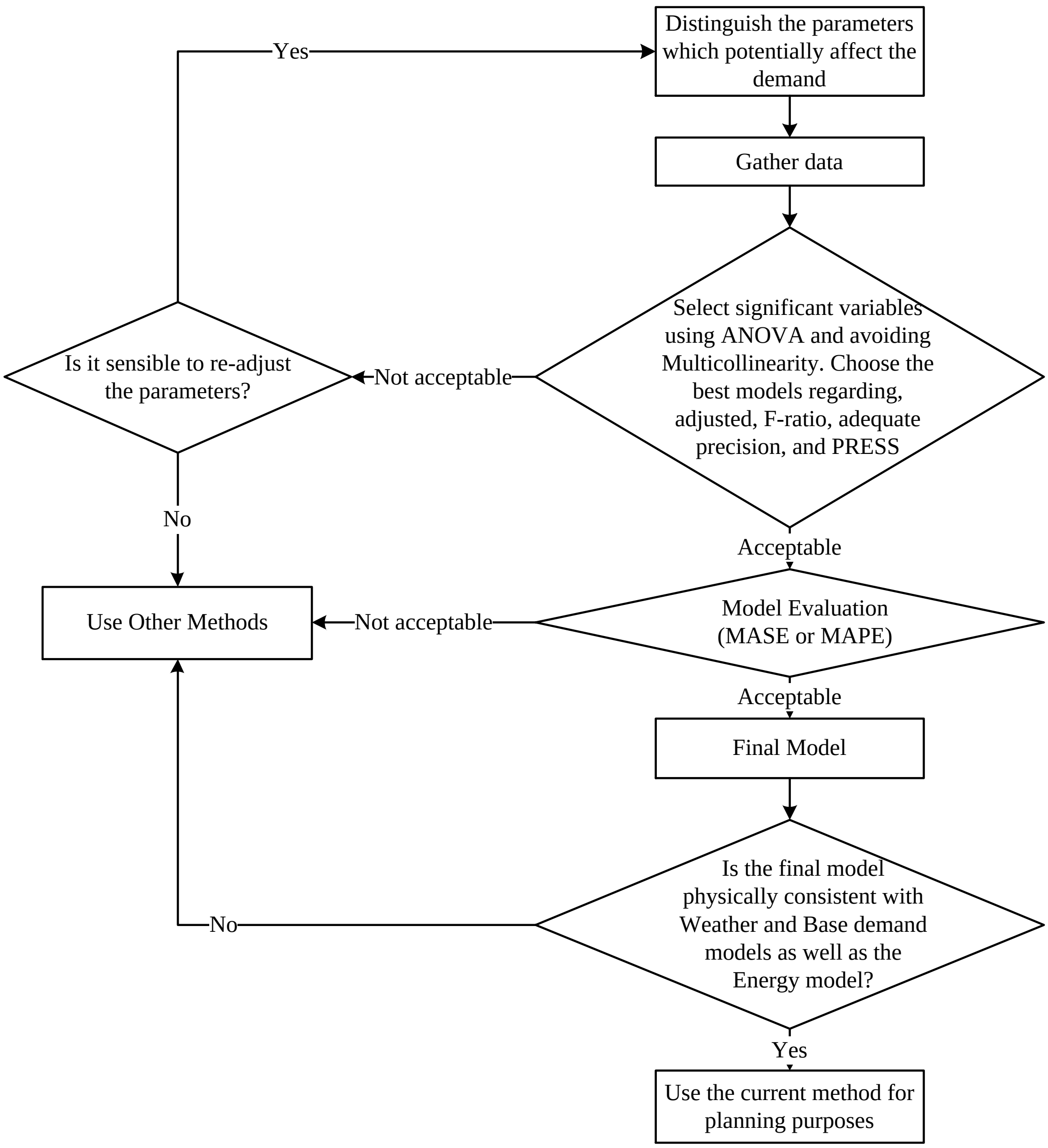

Figure 7: Schematic of the Econometric Forecast Method for Small Utilities.

The final demand forecasting model can be developed by conducting the analysis of variance and performing statistical examination. Historical data (in-sample data) covered the period from 1992 to 2010 and for testing the model data from 2011 to 2013 (out-of-sample data) were compared to the actual data. Furthermore, the accuracy of the results was assessed by regenerating the models using in-sample and out-of-sample data for five consecutive years. In order to have a comprehensive projection of the future supply, the current model is proposed to be coupled with the base and weather sensitive components of the annual peak demand as well as the annual energy consumption forecast.

4.2.1 Data Acquisition

the history of peak demand (*L*), the number of customers (electricity meters) (*C*) and electricity prices (*P*) were gathered for the period of 1992-2013, from annual reports [9], [10], and [11]. population (*N*), per capita income (*PCI*), and the number of tourists (*T*) were available on the yearly bases [113]. Finally, heating degree day (*HDD)* was estimated from the hourly temperatures [114].

4.2.2 Explanation of the Technique

The utilities' internal and external variables were linked through the multiple regression analysis and via the formula:

$$Y = A_0 + A_1V_1 + A_2V_2 + A_3V_3 + A_4V_4 + A_5V_5 + A_6V_6 + e \qquad (32)$$

where, *Y* represents the annual peak demand, A_i are the coefficients of regression and e is the residuals or error. V_i are the independent variables that may be associated with *Y* such as *P*, *T* ,*C*, *PCI*, *N*, and *HDD*. The internal and external variables also known as endogenous and exogenous parameters are the determinants that are influenced by the utility's internal or external environment. These variables are usually varies from case to case because of the dissimilarities in structure of the load system. The effect of all variables on the peak demand should be examined and appropriate variables should be selected in order to form the final regression model.

4.2.2.1 Base Demand

Base demand is associated with normal day-to-day activities. Base demand is independent of very hot or very cold weather and can be calculated by considering the climate of the region for each year. In the Mediterranean weather of Cyprus usually during four months of the year cooling or heating units are used at their lowest demand and it can be said that the demand is free from the extreme weather conditions. Consequently, the average base demand for a year is calculated from the following equation [13].

$$Average\ Base\ Demand = \frac{\sum_{i=1}^{4} MW_i}{4} \tag{33}$$

where MW_i is the i^{th} lowest monthly peak demand of each year. May and June in spring, as well as September and October in fall have the lowest electricity demand in N. Cypurs. The base demand ratio (*BDR*) for the j^{th} year is defined as

$$BDR_j = \frac{Average\ Base\ Demand\ (\mathrm{MW})}{Annual\ Peak\ Demand\ (\mathrm{MW})} \tag{34}$$

the base demand for each year was determined from:

$$Base\ Demand_j = Peak\ Demand_j \times BDR_j \tag{35}$$

where *j* is the year, and “base demand $_j$” and “peak demand $_j$” are the base demand and peak demand at that year, respectively.

4.2.2.2 Weather-Sensitive Demand

Weather-sensitive demand (WSD) is the demand that is affected by the extreme weather conditions. Weather sensitive demand is the difference between the annual peak demand and the base demand. WSD is sensitive to the local weather pattern. In very cold or very hot weather electricity demand increases dramatically. In N. Cyprus, where in summer, air conditioning and in winter, electric water heaters are common, weather sensitive demand is expected to be highly significant.

4.2.3 Data Analysis

In N. Cyprus four sectors are benefited from electricity such as industrial, commercial, residential, and agricultural. The price of electricity is different for each sector based on the utilities' policies. In order to have a single value for the price, the electricity rates for all the customer classes were combined through the following equation [13]

$$P = \frac{\sum_{i=1}^{N} GWh_i \times Rate_i}{\sum_{i=1}^{N} GWh_i} \tag{36}$$

where GWh_i is the amount of electric energy consumed by the i^{th} rate class, and $Rate_i$ is the price of the electricity of the i^{th} rate class. Figure 8 illustrates the average historical electricity prices for all sectors.

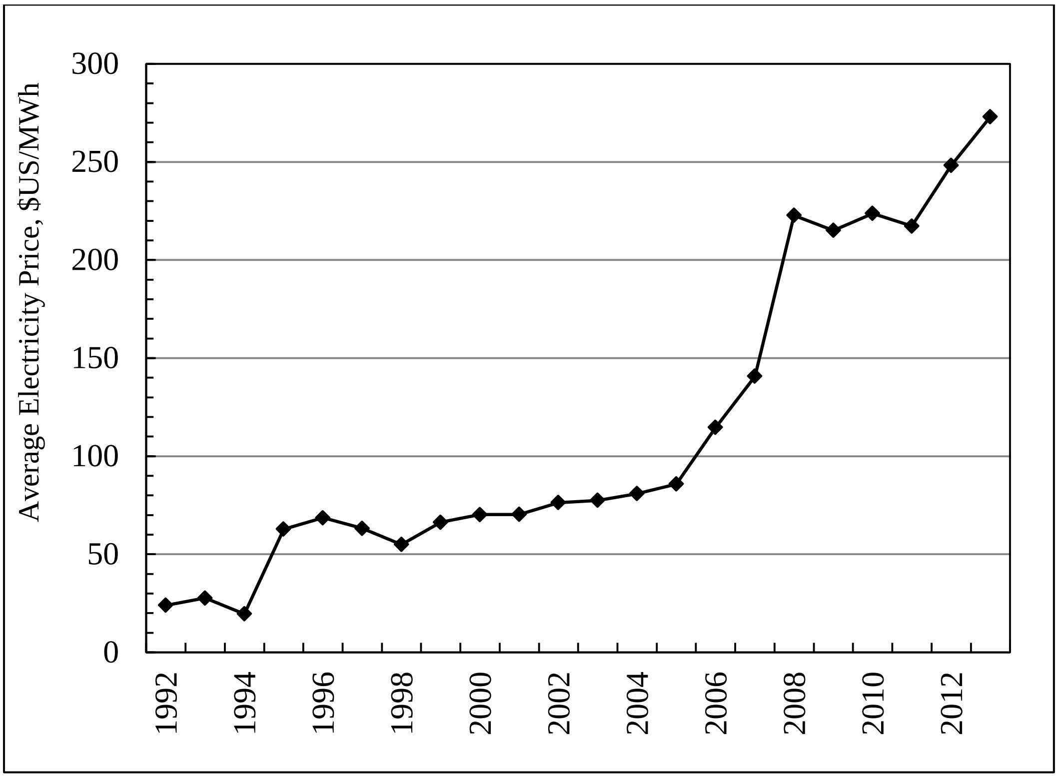

Figure 8: Weighted average electricity rate.

Until 1995, electricity was imported from S. Cyprus free of charge due to a joint contract. Thus, the electricity prices in N. Cyprus were trivial. In 1995, KIB-TEK started to generate most of the energy consumed in N. Cyprus and raised the electricity prices to cover the generation cost. Also, due to the revaluation of the Turkish lira, and the rising fuel costs, a noticeable growth of tariff followed between 2006 and 2008.

Figure 9 represents the annual peak demand between 1992 and 2013. It is evident that the peak demand has increased dramatically except in 1995, 2001, and 2013. After examining the data, it was observed that in 1994 there was a power shortage due to a major accident at one of the steam power units accompanied by reduction in the power supplied by S. Cyprus after mid-1994. In order to cover the generation costs, in 1995 the rates were increased by 220% and towards the end of 2000 there was a serious economic recession causing decreases in the growth of annual peak demand in 1995 and 2001 respectively. In 2013, the country experienced the highest winter temperatures of the past few decades. Meanwhile, the electricity prices continued to rise in 2013 causing a remarkable decrease in the peak demand in 2013.

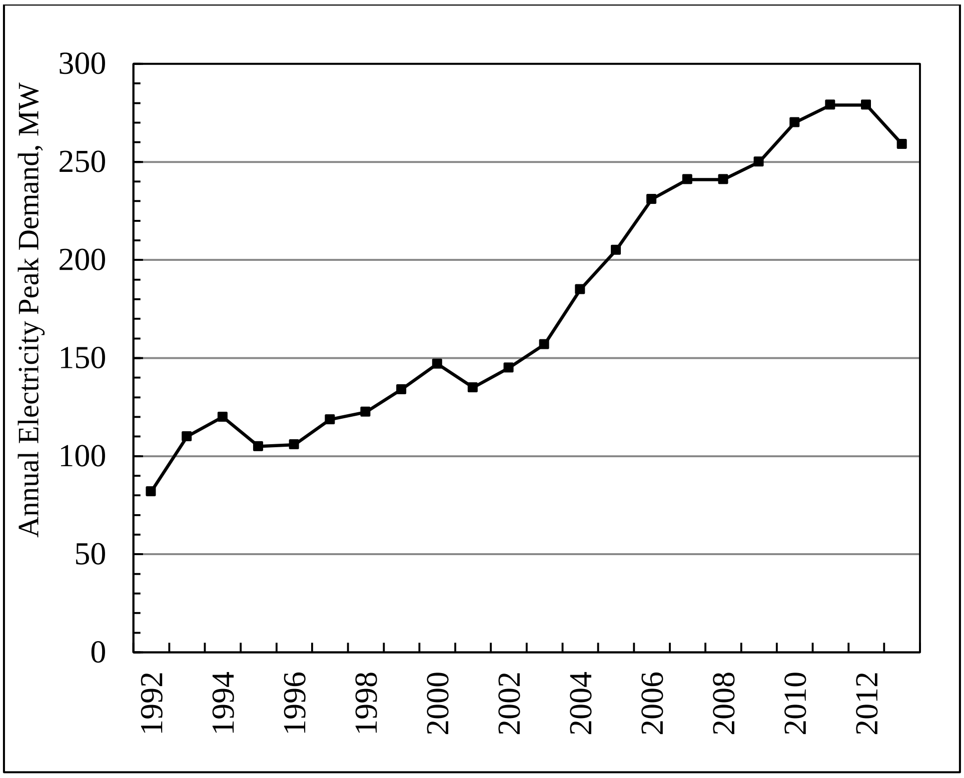

Figure 9: Annual peak demand in N. Cyprus.

Figure 10 illustrates the historical time series for the number of tourists and per capita income (PCI) in logarithmic scale. The number of tourists and PCI increased almost at the same rate. They are highly correlated with each other.

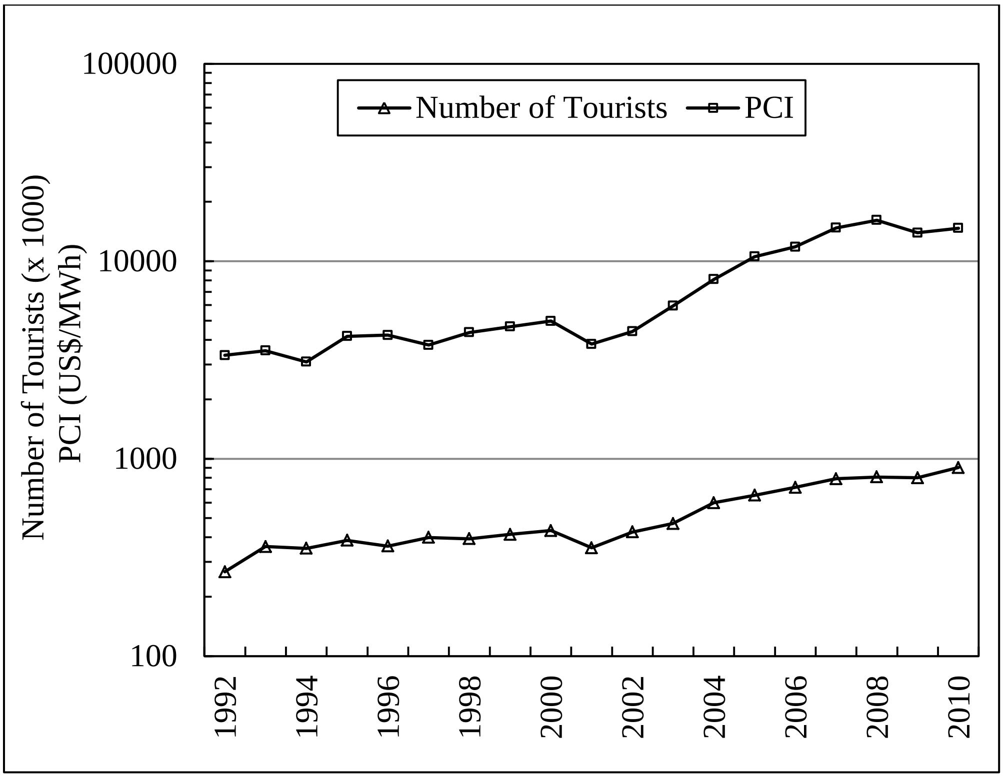

Figure 10: Time plot of number of Tourists and Per capita Income (PCI)

There is a strong linear relationship between the numbers of tourists and PCI. Normally, if two independent variables strongly correlate it is necessary to remove one of the variables to avoid multicollinearity. Number of tourists and PCI are strongly correlated. Although they are treated as independent variables in the developed models, PCI were removed later.

Figure 11 shows the scatter plots of independent variables versus annual peak demand to visualize the relations between peak demand and other determinants.

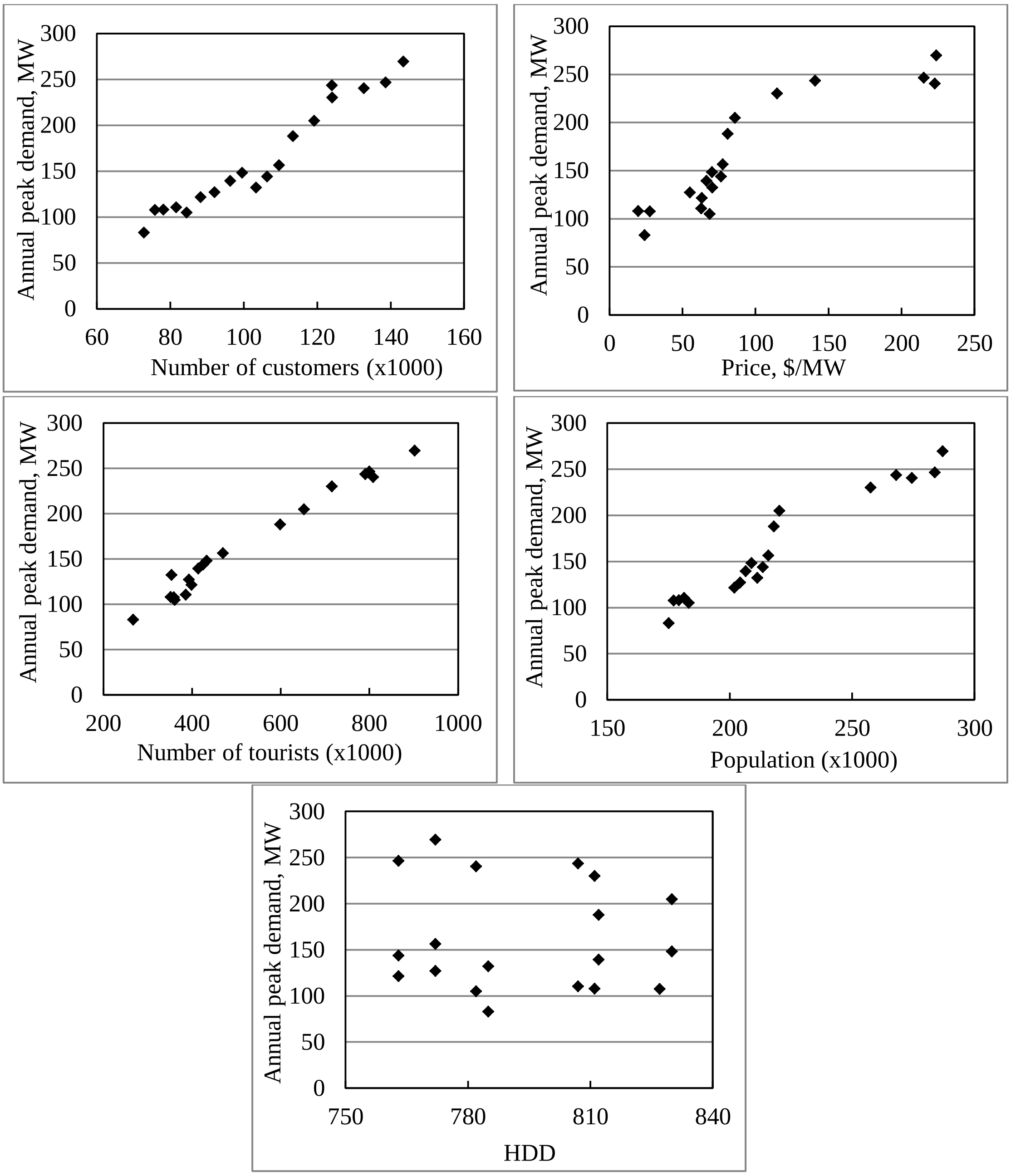

Figure 11: Scatter plots of annual peak demand vs independent variables.

The historical data between 1992 and 2010 were used to calculate the coefficients of regression in Eq. (32). In order to assess the appropriateness of the developed models, ANOVA, graphical method, adjusted R^2, F-test, PRESS and the scatter plot of residuals were used.

In the evaluation process of the econometric model both the Linear and exponential trend models were utilized. The linear trend model for the peak demand is given by:

$$Y_t = A_1 + A_2 t \tag{37}$$

where t is the time, and A_1 and A_2 are constants. Parameter A_1 is the peak demand corresponding to the first year while A_2 is the annual increase in maximum peak. Similarly, exponential trend equation is

$$Y_t = A_1 Exp(A_2 t) \tag{38}$$

where A_1 and A_2 are the unknown constants to be found. Historical data of annual peak demand is used to estimate the unknown parameters A_1 and A_2 in Eqs. (37) and (38).

The base and weather-sensitive components of the annual peak demand are identified by using Eqs. (33) , (34) and (35). Figure 12 shows the base demand, WSD and annual peak demand between 1992 and 2013. It indicates that the general trend for both base demand and WSD are increasing.

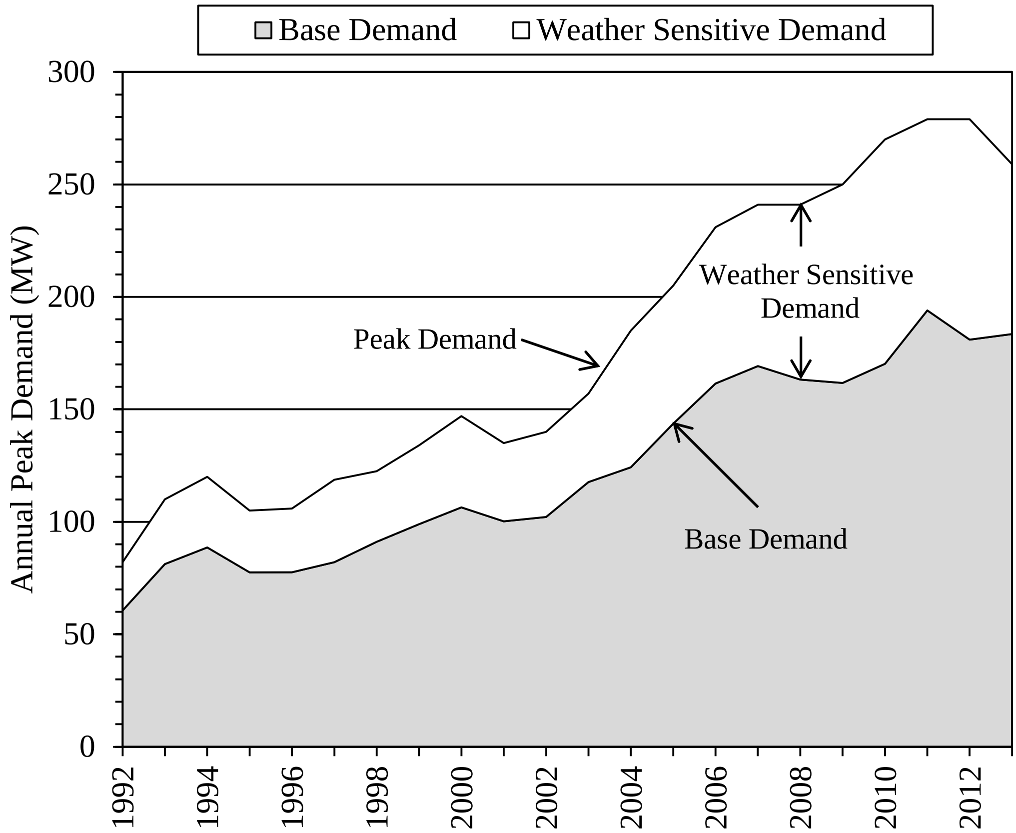

Figure 12: Annual electricity peak demand, base demand and WSD.

Finally, in order to test the model obtained by the in-sample data, out-of-sample data from 2011 to 2013 (representing the future) are used. Also, MASE and MAPE for various successive in-sample and out-of-sample data were calculated to ensure the accuracy of the final model [115],[116].

4.3 Model Selection and Discussions

Since the size of the load system in N. Cyprus is relatively small, discerning its features and data gathering processes remain undemanding. Therefore, as aforementioned it is suitable to choose econometric method in describing the whole system [117].

Analysis of variance for all variables was carried out and the results of the regression are presented in Table 5. Superficially, in model 1 both the HDD and PCI are not statistically significant at the 5% level. Therefore, it could be deduced that model 2 with four variables is an appropriate model. However, the strong correlation between the number of tourists and PCI causes multicolinearity, which only resolved after removing PCI from the equations. Removing PCI from the equations, it appears that HDD became significant at the 5% level. Consequently, the proposed model can be reduced to model 3 with five independent variables, and its features are presented in Table 5.

Table 5: Annual peak demand model summary and corresponding parameters to check the adequacy of models * Predicted Residual Sum of Squares

Model		Coefficients	R^2	Adjusted R^2	P-value (95%)	F-Ratio	t-statistic	PRESS*
1	Constant	-213.897	0.995	0.993	0.006	441.757	-3.315	515.540
	C*1000	0.796			0.003		3.646	
	P($/MWh)	-0.154			0.035		-2.370	
	T*1000	0.172			0.001		4.452	
	PCI($)	5.102E-06			0.997		0.004	
	N*1000	0.144			0.016		2.814	
	HDD	0.477			0.064		2.043	
2	Constant	-90.74	0.994	0.992		565.019		626.157
	C*1000	0.78			0.003			
	P($/MWh)	-0.22			0.003			
	T*1000	0.21			0.000			
	N*1000	0.39			0.042			
3	Constant	-213.966	0.995	0.994	0.003	574.28	-3.614	498.268
	C*1000	0.796			0.001		4.049	
	P($/MWh)	-0.154			0.024		-2.558	
	T*1000	0.173			0.000		6.915	
	N*1000	0.477			0.010		3.013	
	HDD	0.144			0.048		2.181	
4	A_1	63.83	0.916	-	-	-	-	-
	A_2	9.96						
5	A_1	83.64	0.942	-	-	-	-	-
	A_2	0.06						

Models 1, 2, and 3 consist of six, four, and five variables, respectively. Their values of R^2 are not distinctly different. Therefore, to determine the most appropriate model adjusted R^2, F-ratio and PRESS were used and model 3 was chosen as the best model; so the final regression model is as follows:

$$Y = -213.956 + 0.796C - 0.154P + 0.173T + 0.477N + 0.144HDD \qquad (39)$$

The F-ratio for model 3 is 574.28, is much greater than the critical value of F = 3.03 for degrees of freedom (5, 13) at 5% level of significance. This indicates that the model is highly significant. Figure 13 shows the actual and predicted annual peak demand of electricity in N. Cyprus. The figure shows that models 1, 2 and 3 have strong predictive ability. Model 4 is the time series model obtained from Eq. (37) and model 5 is the exponential trend from Eq. (38). Models 4 and 5 were used to evaluate the performance of the econometric models.

It is crucial to evaluate the forecasting performance of the final model using in-sample and out-of-sample data of various years. Table 6 shows the MASE and the MAPE for three out-of-sample data.

Likewise, Figure 13 illustrates MAPE and MASE of regenerated models for several years. The results indicated that the regression model with 5 parameters has the best performance among all the other models especially when the in-sample data increases.

Many researchers such as Armestrong [2] advised to use the longest possible in-sample data for model training. Meanwhile, out-of-sample data is also necessary for evaluation of the forecast. However, KIBTEK utility was established in 1995 and the electricity records are only available from 1991 onward and because of the scarcity of data in N. Cyprus the attempt was to make a trade-off between the number of out-of-sample data and in-sample data.

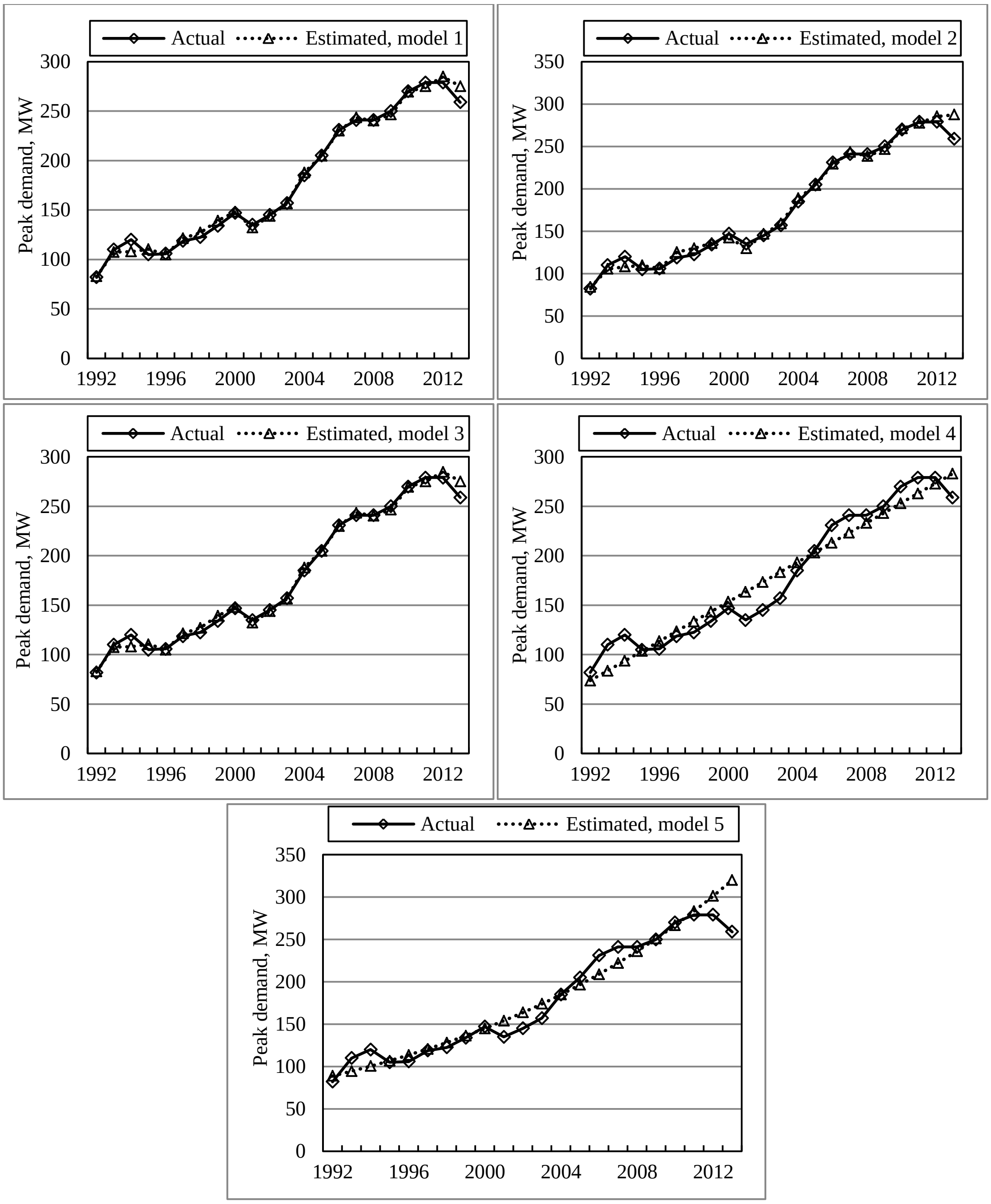

Figure 13: Actual and predicted annual electricity peak demand in N. Cyprus.

Table 6: Measurement for the performance of models *Mean Absolute Scaled Error **Mean Absolute Percentage Error (%)

Type of Error	model 1	model 2	model 3	Linear	Exponential
MASE* (In-Sample)	0.214	0.287	0.214	1.417	0.958
MASE (out-of-Sample)	1.042	2.208	1.041	1.537	1.634
MAPE** (In-Sample)	2.025	2.642	2.025	9.427	6.828
MAPE (out-of-Sample)	3.259	4.575	3.256	5.709	10.464

Also, it is necessary to examine the model through WSD and base demand in order to deal with weather condition's abnormal fluctuation. For example, in 2013 apart from the increase in tariff, the decrease in the peak demand is attributable to uncommon decrease in the HDD in that year. This can also be seen in Figure 12. Although the base demand was slightly increased in 2013 compared to the previous year, WSD decreased substantially. Furthermore, the base demand ratio is calculated to be 0.71 in 2013 compared to 0.65 of 2012. That is, despite the slight increase in base demand from 181 MW in 2012 to 184 MW in 2013, WSD dropped substantially from 98MW to 76 MW.

Figure 15 shows the residuals plotted against the five explanatory variables after fitting model 3. The other two panels display the residuals plotted against the fitted values. Randomly scattered residuals are the signs of an acceptable regression model.

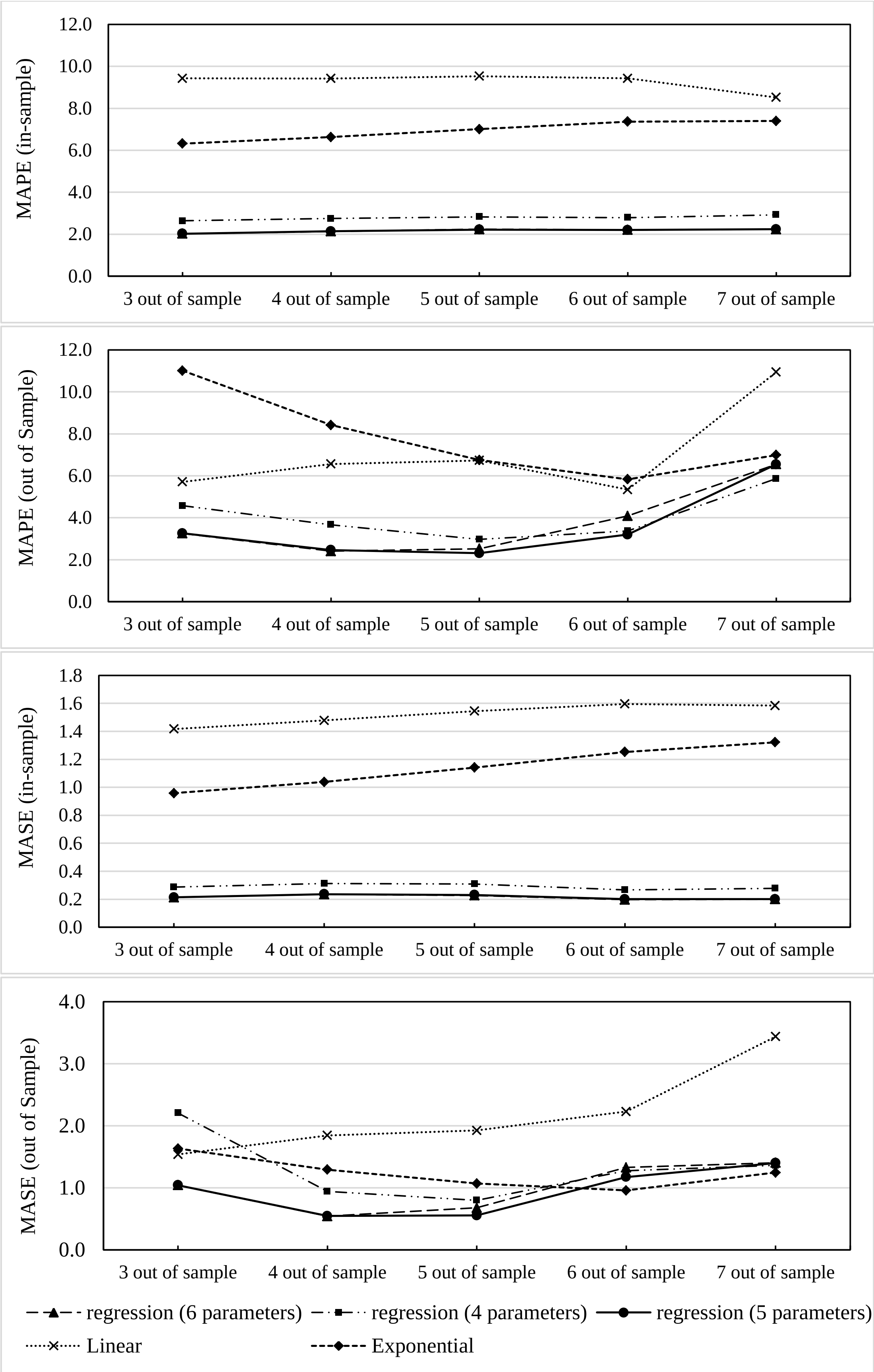

Figure 14:MASE and MAPE for five consecutive in samples and out of samples

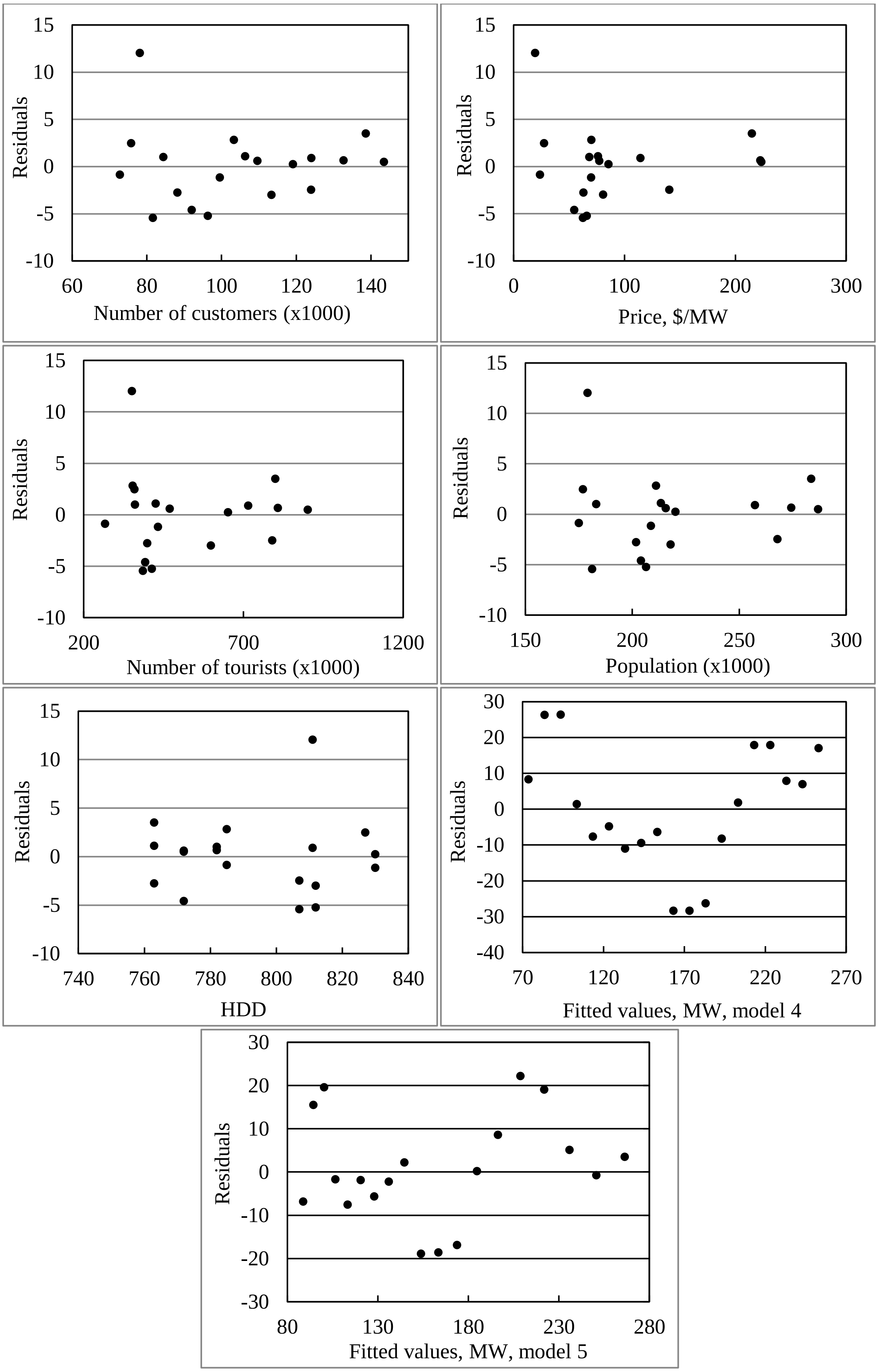

Figure 15: Residuals when annual peak demand is regressed against number of customers, electricity price, population, number of tourists, and heating degree days (HDD).

The econometric load forecasting method is based on econometric theory, thus a hypothesis that describes the relationship between peak demand or energy consumption and economic variables should be formed. Two types of variables i.e., internal and external variables can affect the electricity peak demand. Internal variables include electricity prices, number of people connected with meters and incentive program levels. Utilities in N. Cyprus do not have incentive program levels so this variable was not considered in load forecasting. External variables are the factors influenced by the utility's external environment. External variables include price of competing products (i.e. oil and gas and etc.), PCI, GDP, population, unemployment rate, tourism, import and export, HDD, CDD and maximum/minimum temperatures and etc. that was discussed in section 3.2.3. The econometric method requires a large, accurate historical database. It is important to determine the reliability and the availability of the required data. The developed model will be sufficient (i.e., reasonably accurate and satisfies the load forecast objectives) if more and reliable data are used.

Large size utilities have larger total service areas and several types of customers. A large size utility should consider doing separate load forecast for customer class and may need to divide its service area as discussed in chapter 6. Large size utilities may need to perform short-term load forecasting (hourly, daily, weekly and etc.) for optimization reasons. The forecast method depends on the objective of the load forecaster. Also, large size utilities prepare detailed load forecasts in order to produce a complete integrated resource planning. Large utilities also analyze environmental externalities, risks, uncertainties and also conduct a complete public involvement for resource planning.

4.4 Conclusive Comments

In the present study a long-term base and weather sensitive demand model was presented using econometric variables as regressors for small size utilities. Regions like N. Cyprus in which forecasting on the peak demand has never practiced before, are advised to use the current method, provided that sufficient data is available. Also, the current approach can be used as a benchmark to evaluate more advanced techniques in the future.

The results suggest that among the six chosen variables the model which uses price of electricity, number of customers, tourists, population and HDD as variables, is the most suitable model for estimating future peak demand of N. Cyprus. The performance of this model was evaluated by regenerating models and recalculating their MASE and MAPE for five different in-sample and out-of-sample intervals.

Determination of WSD and base demand is necessary to better examine the effect of weather conditions on the power demand requirements. In addition, energy models must be linked with peak demand models to provide a better vision for the forecaster.

Using ANOVA analysis eases the regression process by avoiding the conventional need to calculate all possible regression models. Other models are not necessarily produce the optimal results [118]. However, relying on only one method may result in inaccurate conclusion.

The better is the knowledge of the forecaster about the system the better predictions are expected. For an accurate forecast model, accurate and relevant parameters are required. The model can be compared with different forecasting models for further validation.

In the process of decision making for IRP, forecasting is the first step. The current forecast method is beneficial since physical meanings of variables can assist planners to have a better sense about the system and make better decisions on the system with higher certainty. For example, by forecasting the future independent parameters used in the peak demand model the period for power expansion can be estimated.

Nevertheless, many unknown factors can bring about uncertainty and accordingly, it might be suitable to use more compelling approaches such as Bayesian probability or fuzzy arithmetic. The former needs to be practiced further in the area of load forecasting and the latter is the future work of authors.

Chapter 5

FUZZY PEAK DEMAND FORECASTING MODEL FOR SMALL DEVELOPING COUNTRIES

5.1 Introduction

In the present chapter a fuzzy peak demand forecast model was developed to estimate the future power requirements of small developing countries. An accurate long term forecast requires extensive data and an appropriate budget for forecasting. However, many developing countries suffer from lack of information and budget. This impairs a straightforward solution for the estimations. In this respect, engineering end-use models mostly suffer from data deficiency and huge data gathering [119] and econometric approaches inadequately capture the developing countries features [67] due to data mismanagement. The uncertainties due to lack of data as well as small budget of forecast highlight a requisite for developing an effective method of forecasting used in developing countries.

A plethora of forecasting techniques are available in the literature and forecasting models were classified from different views. In general, forecasting was categorized into two schemes of judgmental and statistical and the best method was chosen by means of a selection tree [120]. Based on the forecast horizon, forecasting can be categorized into short, medium, and long ranges [121]. Energy and demand models were also classified as simple and complex approaches [119]. At times results of simple methods can be as accurate as complicated schemes especially when measured data is limited and uncertainty exists [96].

In many developing countries institutional framework for governing the energy issues are not widely established [122]. Many statistical data which are readily available in developed countries may not be available in developing countries. Therefore, it is hard for the utilities to devise detailed forecasting models that are employed in developed countries. Although the utilities usually encounter difficulties attaining the required statistical data it is a common practice to keep a record of the maximum peak demand. The present work attempts to develop a new algorithm where the demand history is utilized as the only available data for demand forecasting. While forecasting is always accompanied by various sources of uncertainty, the focus of the current study is to deal with uncertainty due to data limitation and model simplification. One way to circumvent uncertainty is the employment of simple approaches, (eg. [119], [96]). However, to the best of authors' knowledge no systematic approach have been developed to employ simple methods and at the same time undertake uncertainties related with data limitations and model simplifications. Therefore, the current work tried to benefit from the simplicity of the time series methods and simultaneously the possible uncertainty was quantified and treated by a well-organized fuzzy arithmetic analysis.

The rest of the chapter is organized as follows: Section 2 provides the case of N. Cyprus and section 3 presents the methodology of the study. An algorithm was utilized to deal with data inadequacy. Triangular fuzzy numbers were defined for the annual peak demand and classical univariate time-series extrapolations were employed to estimate the future peak demand using the fuzzy arithmetic and the extension principle introduced by Lotfi A. Zadeh. In order to minimize the overestimation of uncertainty and at the same time reaching to an acceptable result, the transformation method of Hanss was used. In section 4 the results were given and discussed. The most precise model was selected and verified through graphical representation and by iteratively calculating MAPE over the fuzzy distance defined in the literature. The annual peak demand was forecasted for the next ten years. Chapter 5 presents some concluding remarks. The obtained results showed that the developed model is accurate enough and can be used for policy advice in uncertain situations.

5.2. Case of N Cyprus

The case of the current chapter is chosen to be N Cyprus with small geographic variations. The attempt is to look into the electricity demand in N Cyprus, in which small utilities have been utilized for electricity generation. The country is seeking to implement cost-effective methods for forecasting the electricity consumption and demand. Many parameters such as economic, environmental or political situation can affect the demand. They are categorized as endogenous and exogenous parameters [13]. For example, an increase of temperature in a summer day can elevate the peak demand or increase in the electricity prices can adversely affect the use of electricity. These fluctuations may imply that the electricity record could be different to some extent, provided that the influential factors would be different. Usually, the impacts of these variations are not easily traceable, especially when necessary data is unavailable. In order to deal with these probable fluctuations peak demand can be considered as a fuzzy variable. Therefore, appropriate fuzzy numbers can be used for the annual peak demand.

In chapter 4 peak demand of N. Cyprus was modeled using an econometric method [5]. It was found that the current peak demand is highly correlated with five influential parameters; namely, Price, HDD, number of tourists, customers and population. However, obtaining these data is not always possible and in situations that only historical consumption is available, provided that a change in any of these parameters was occurred, peak demand was expected to be transformed. Figure 16 illustrates the peak demand estimation based on the variation of HDD around the standard deviation. Annual peak demand due to weather variations using standard deviation is estimated to vary about 10 MW. Likewise, variation in other independent parameters could bring about differences in the annual peak demand record. In fact, in many developing countries necessary data is not available for sophisticated forecasting and the peak demand may be affected from different variables. Consequently, it is impossible to predict the peak demand by tracing their influential parameters. The aim is to let the peak demand to change to a certain degree so that it covers the uncertainties related with missing parameters and model simplifications.

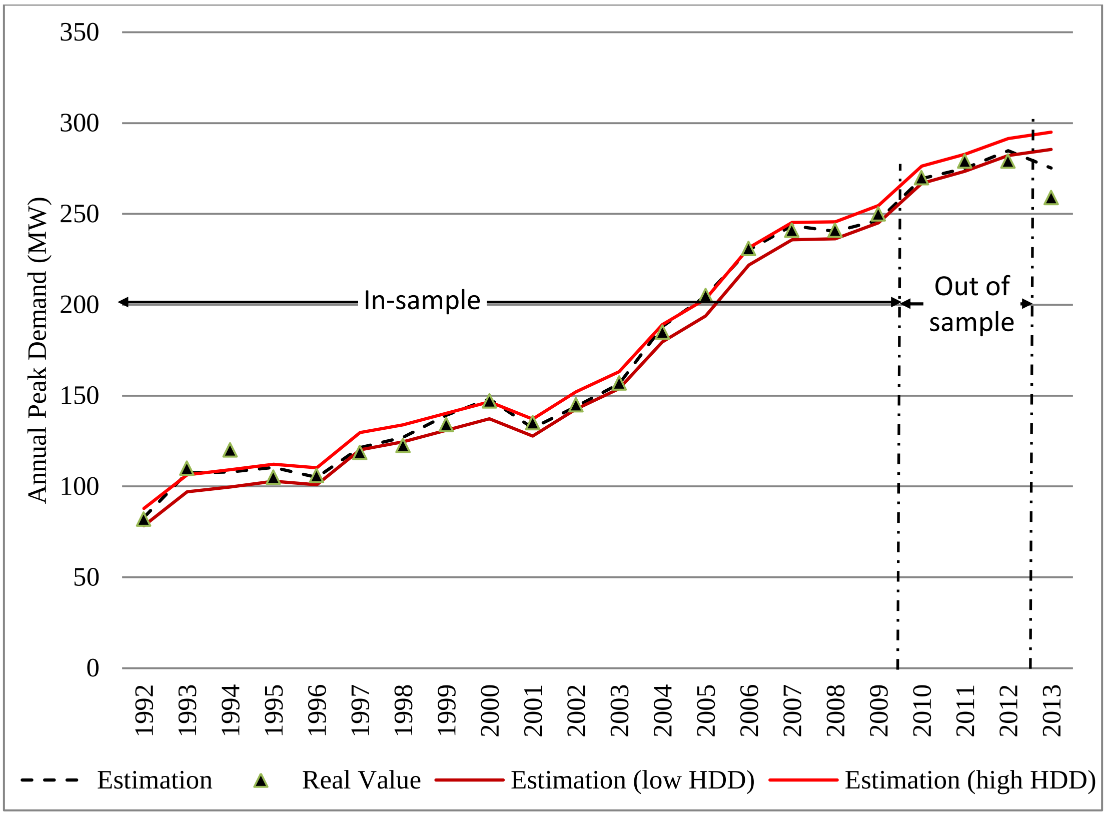

Figure 16: Peak demand estimation using econometric method for the high and low HDD considering the standard deviation

5.3. Methodology for Fuzzy Peak Demand Forecasting

In this chapter an algorithm was proposed to forecast the annual peak demand of North Cyprus, as presented in Figure 17. The only data used was the annual peak demand from 1992 to 2013. Conventional univariate time-series extrapolations were integrated with Hanss' fuzzy arithmetic approach [59] grounded on Zadeh's extension principle [123]. The effects of uncertainties were quantified using membership functions and fuzzy arithmetic analysis was utilized to mitigate the uncertainties related with absence of data (i.e. data other than historical peak demand).

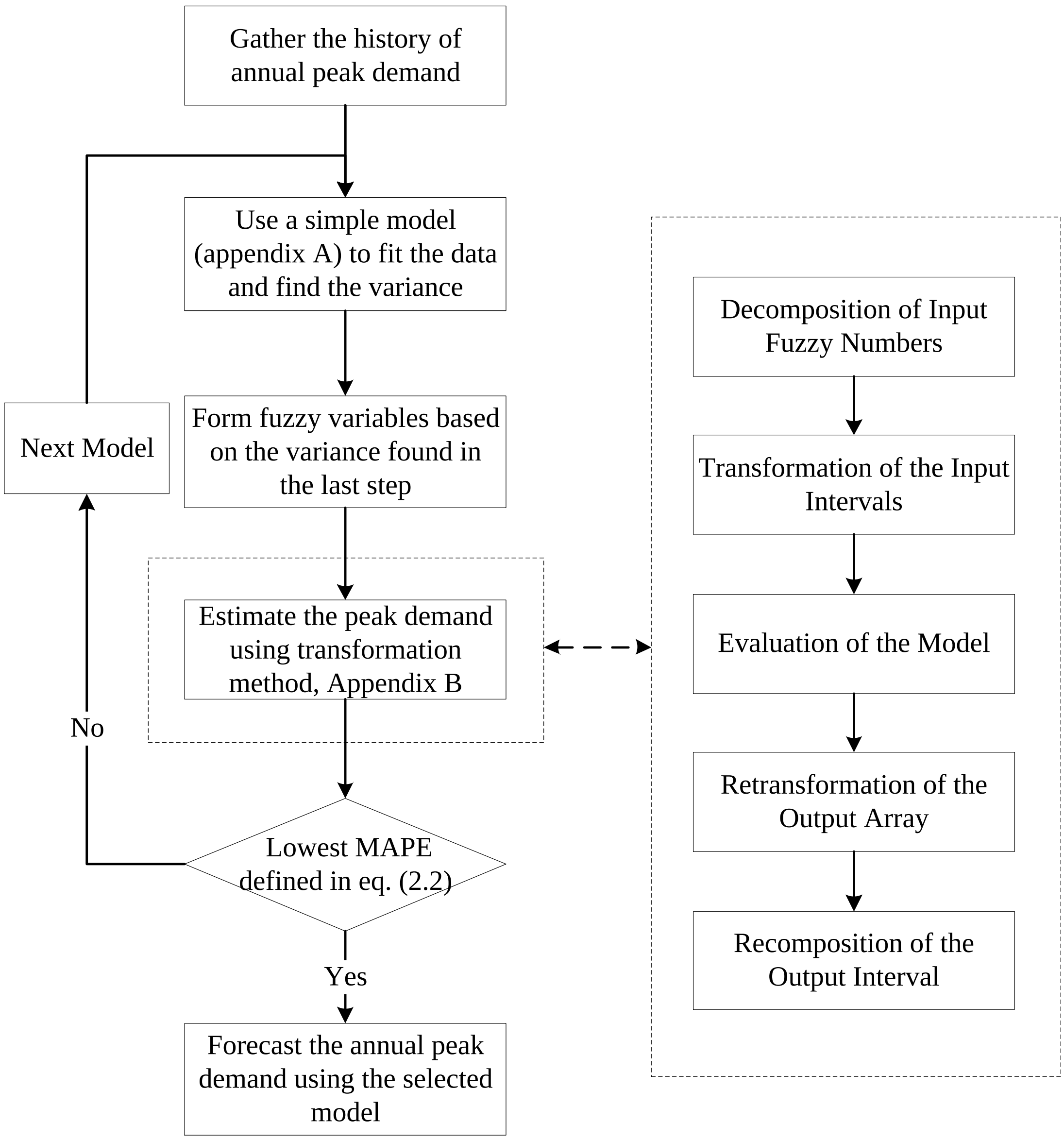

Figure 17: the algorithm used for the forecast of annual peak demand

The historical record of peak demand was utilized and fuzzified and its behavior was extrapolated for the future. Linear trend models (i.e. simple average method and simple regression method), eq (40) , and auto regressive models (i.e. straight average, compound average, and Autoregressive regression methods), eq (41), were fitted to historical peak demand values in order to find the best model in describing the historical pattern and future peak demand forecast.

$$\tilde{Y}_t = \tilde{\beta}_1 + \tilde{\beta}_2 * t \tag{40}$$

$$\tilde{Y}_t = \tilde{\beta}_1 + \tilde{\beta}_2 * \tilde{Y}_{t-1} \tag{41}$$

Where $\tilde{Y}_t$ is the fuzzy demand at time t and $\tilde{\beta}_1$and $\tilde{\beta}_2$ are fuzzy coefficients to be estimated. In order to estimate the parameters $\tilde{\beta}_1$ and $\tilde{\beta}_2$, five aforementioned methods were selected which are explained in section 3.3.1.

5.3.1 Fuzzification

Fuzzy peak demands can be introduced by allowing the peak demands to belong to a fuzzy number rather than to entirely belong or not to belong to a specific number. For the description of fuzzy numbers, a membership function $\mu_{\tilde{P}}$ for a fuzzy number $\tilde{P}$ can be introduced, which has a mapping of the form

$$\mu_{\tilde{P}}: X \longmapsto [0,1] \tag{42}$$

It is suitable to use a triangular membership function of the form:

$$\mu_{\tilde{P}} = \begin{cases} 0 & \text{for} \quad x \leq \bar{x} - \alpha_l \\ 1 + (x - \bar{x})/\alpha_l & \text{for} \quad \bar{x} - \alpha_l < x < \bar{x} \\ 1 - (x - \bar{x})/\alpha_r & \text{for} \quad \bar{x} \leq x < \bar{x} + \alpha_r \\ 0 & \text{for} \quad x \geq \bar{x} + \alpha_r \end{cases} \tag{43}$$

where $\mu_{\tilde{P}}$ is the membership function, x denotes the energy consumption or peak demand, $\bar{x}$ is the modal value of fuzzy number, and σ_l or σ_r are the left and the right hand worse case deviations. The deviations σ_l or σ_r were selected equally for each membership function depending of their variation from the fitted values. For each time series model, the standard deviation from the real values was calculated. These standard deviations were used to form the triangular fuzzy peak demands. A triangular membership function for peak demand is illustrated in the Figure 18.

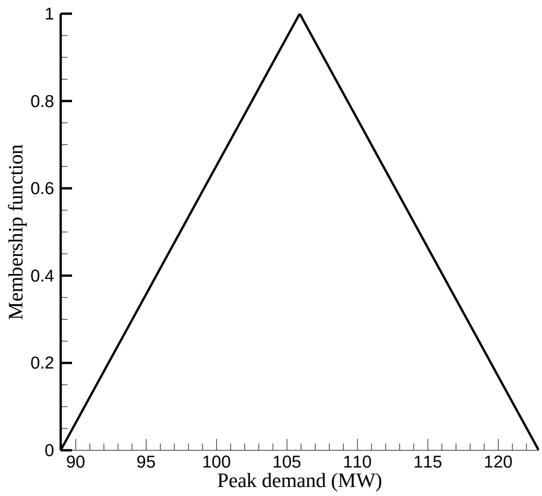

Figure 18: A typical triangular Membership Function for peak demands (MW).

In order to deal with fuzzy numbers, advanced fuzzy arithmetic was employed in this study and it is explained in brief in the following section.

5.3.2 Advanced Fuzzy Arithmetic

Various operations for the fuzzy arithmetic analysis exist in the literature which have their own strengths and drawbacks, such as extension principle, Hukuhara [124], $l_\alpha r_\alpha$ operations [125], and etc. One well-posed structured method is to apply extension principle of Zadeh [123].with the aid of transformation method of Hanss [59]. The five steps of the aforementioned method were briefly elaborated in section 3.3.2. In order to implement fuzzy arithmetic calculations, reduced form of transformation method of Hanss were programmed, since the estimated functions are expected to behave as monotonic.

5.3.3 Model Selection

The performance of the models was evaluated using graphical representation and after comparing their MAPE defined as:

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{d_F(\tilde{y}_t, \tilde{y}'_{\mathrm{t}})}{\tilde{y}_t}\right| \tag{44}$$

where $\tilde{y}_{\mathrm{t}}$ and $\tilde{y}'_{\mathrm{t}}$ represent the actual and estimated peak demands and $d_F(\tilde{y}_t, \tilde{y}'_{\mathrm{t}})$ is the distance between estimated peak demand $\tilde{y}'$, and the real value $\tilde{y}$ at time t. It is defined through HAUSDORFF distance [58] and in line with the notation of the current thesis it can be written as:

$$d_F(\tilde{y}_t, \tilde{y}'_{\mathrm{t}}) = \sum_{j=0}^{m}\frac{max\left\{\left|b_2^{(j)} - b_1^{(j)}\right|, \left|a_2^{(j)} - a_1^{(j)}\right|\right\}}{m+1} \tag{45}$$

where $a_i^{(j)}$ and $b_i^{(j)}, j = 0,1,\ldots,m$, are the left and right boundaries of fuzzy numbers $\tilde{p}_i$ for the level of membership μ_j , see Figure 19.

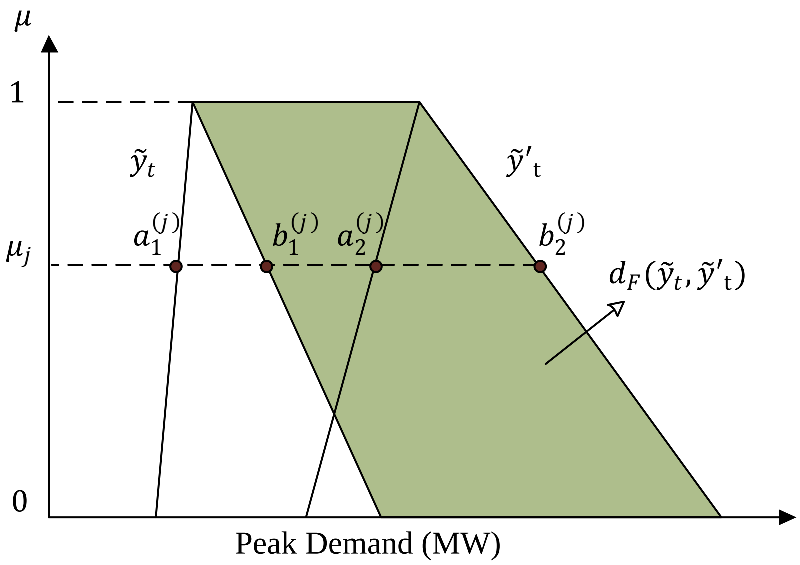

Figure 19: distance between the two fuzzy numbers, $\tilde{y}_{\mathrm{t}}$ and $\tilde{y}'_{\mathrm{t}}$.

In order to compare the models, the first 15 years (1992-2006) were used for the estimation of the next seven years (2007-2011). Meanwhile, to assure that the outcomes are reliable and independent from the initial sample values, the calculations were repeated by increasing the in-sample data (i.e. decreasing the out of sample data). Eventually, the best model was selected to forecast the peak demand for the next 10 years.

5.4. Forecast Models and Discussion

Fortran 90 was used to carry out all the computations of the codes for the transformation algorithm and some conventional time series methods in an attempt to estimate the annual peak demand for N. Cyprus.

Figure 20 to Figure 24 illustrate the results of forecast for five simple models. 17 in-samples data were used to train the data and 5 out-of-samples data were used to evaluate the performance of each model. Real values were also plotted and compared with the estimated values. The most adequate model was selected using the graphical representation and through calculating MAPE. Despite the fact that models 3 and 5 demonstrate a good fit for higher values of membership, μ, they show substantial overestimation in lower membership values. In order to evaluate the forecasting performance MAPE were calculated for five consecutive in-sample and out-of-sample data, see Table 7.

Table 7: Measurement for the performance of models for various in samples and out-of-samples *Mean Absolute Percentage Error

Type of Error	Model 1	Model 2	Model 3	Model 4	Model 5
15 In-samples & 7 Out-of-samples					
MAPE* (In-Sample)	0.152	0.098	0.284	0.087	0.508
MAPE (out-of-Sample)	0.073	0.157	1.185	0.284	3.193
16 In-samples & 6 Out-of-samples					
MAPE (In-Sample)	0.142	0.107	0.262	0.075	0.358
MAPE (out-of-Sample)	0.075	0.119	1.073	0.248	1.693
17 In-samples & 5 Out-of-samples					
MAPE (In-Sample)	0.116	0.108	0.228	0.071	0.220
MAPE (out-of-Sample)	0.052	0.105	0.904	0.155	0.646
18 In-samples & 4 Out-of-samples					
MAPE (In-Sample)	0.108	0.107	0.219	0.073	0.189
MAPE (out-of-Sample)	0.058	0.100	0.833	0.129	0.431

It can be seen from the table that model 1 has the lowest out-of-sample error with relatively high in-sample error, and model 4 has the lowest in-sample error but with a relative high out-of-sample error. However, model 2 is always stands second in rank in both in-sample and out-of-sample measurements and it can be selected as the best model among the others for the projection of power demand of N. Cyprus. Figure 20 to Figure 24 illustrate the comparison of models with 17 in-sample and 5 out-of-sample data.

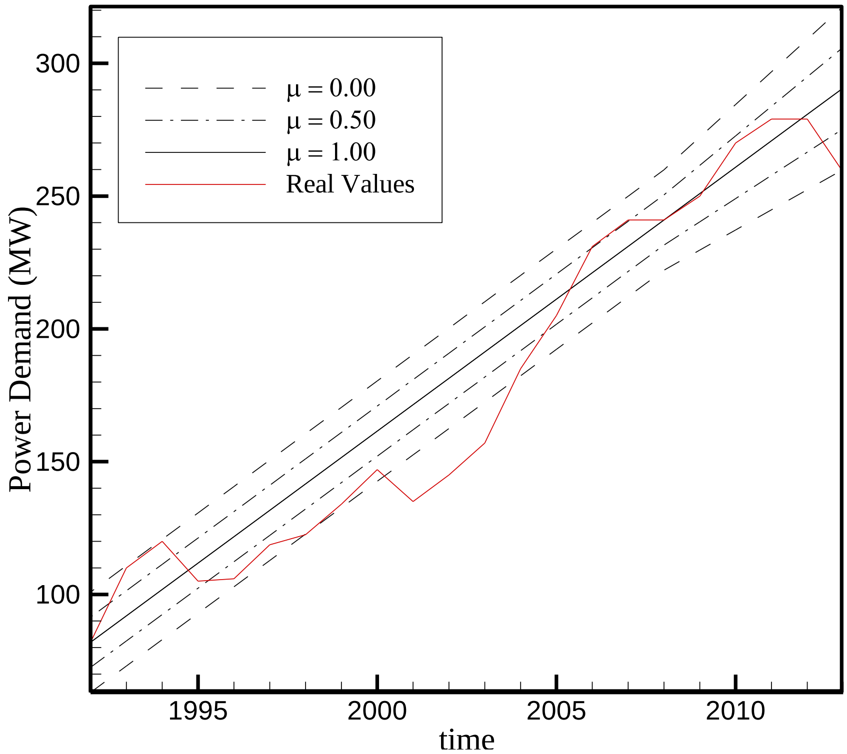

Figure 20. Model 1: Simple Average Method with 17 in-sample and 5 out-of-sample data

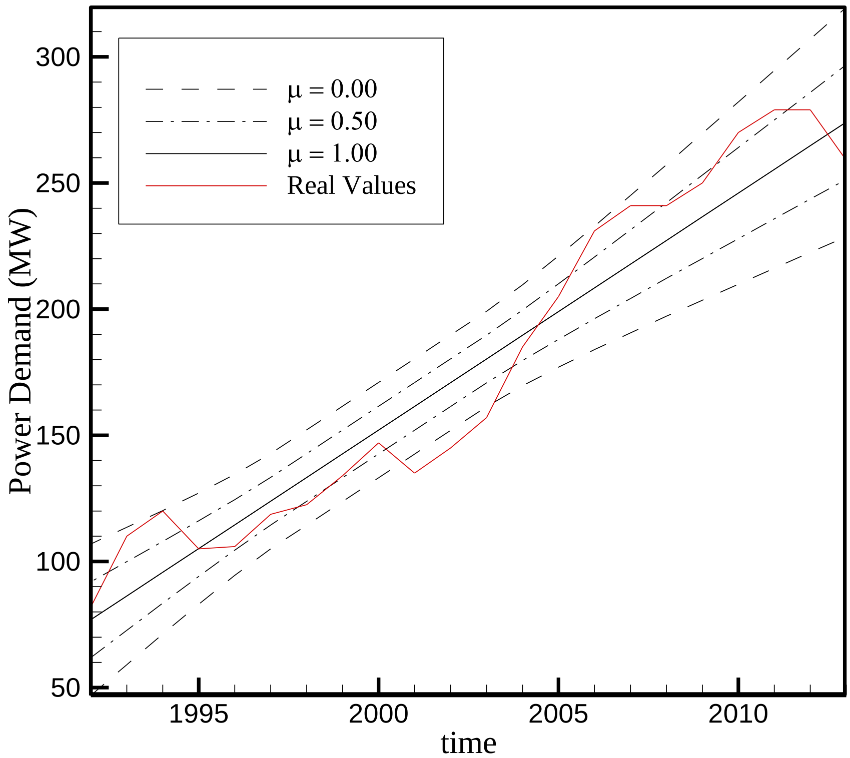

Figure 21. Model 2: Simple Regression Method with 17 in-sample and 5 out-of-sample data

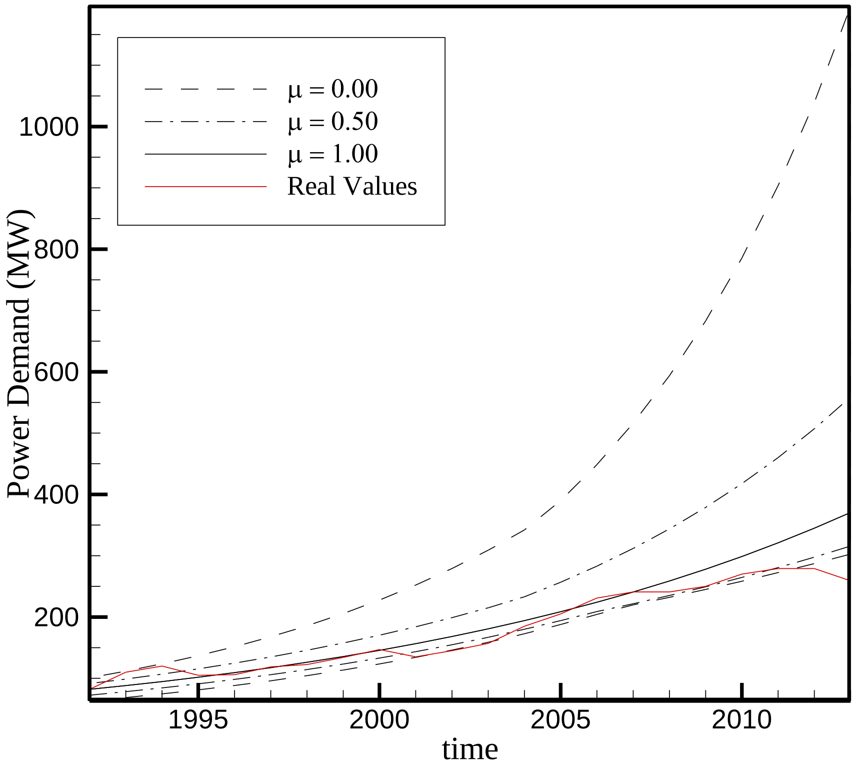

Figure 22. Model 3: Straight Average Method with 17 in-sample and 5 out-of-sample data

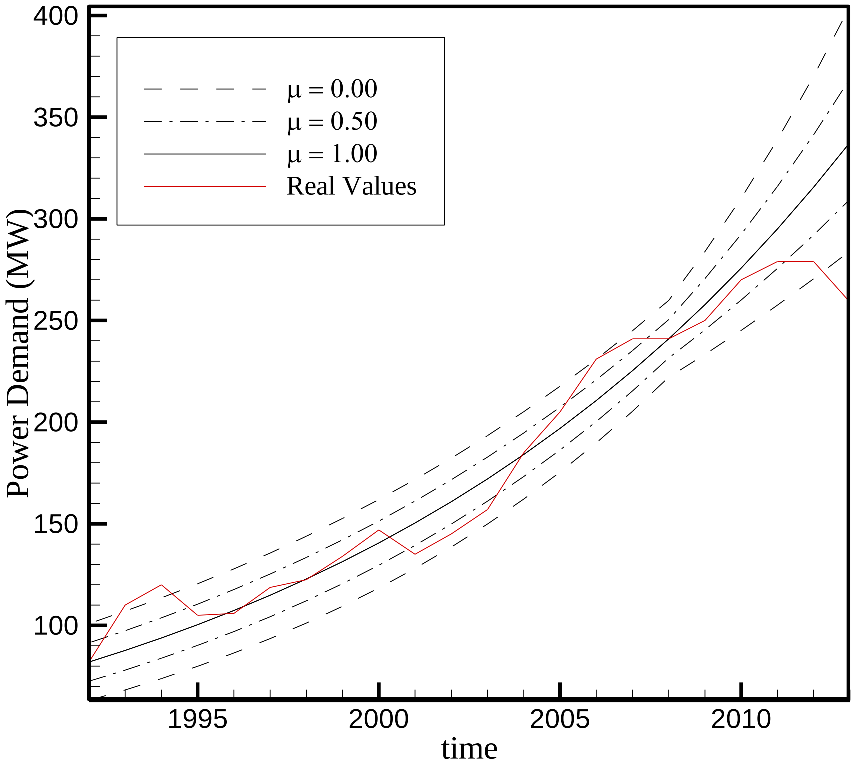

Figure 23. Model 4: Compound Average Method with 17 in-sample and 5 out-of-sample data

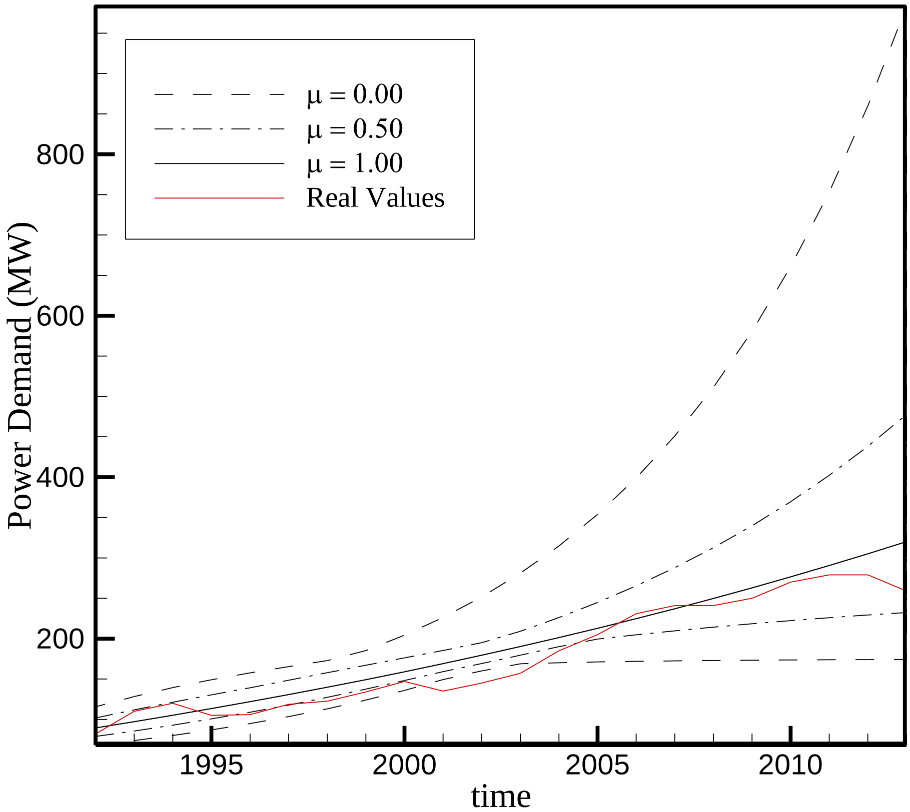

Figure 24. Model 5: Autoregressive Regression Method with 17 in-sample and 5 out-of-sample data

Figure 25 illustrates the projection of peak demand for 2023 using model 2. It can be seen that the forecasted results showed conformity with the econometric method described in ref [5] especially when $\mu = 0.6$.

Usually, the results of all forecasts differ from the real values to some extend and we cannot be confident to select the econometric method over the current method nor do we assure to select the current approach over the econometric models. However, unlike traditional forecasts which merely present a single value, the outcome of the current forecast provides a wider range and higher flexibility for planners in deciding for the future.

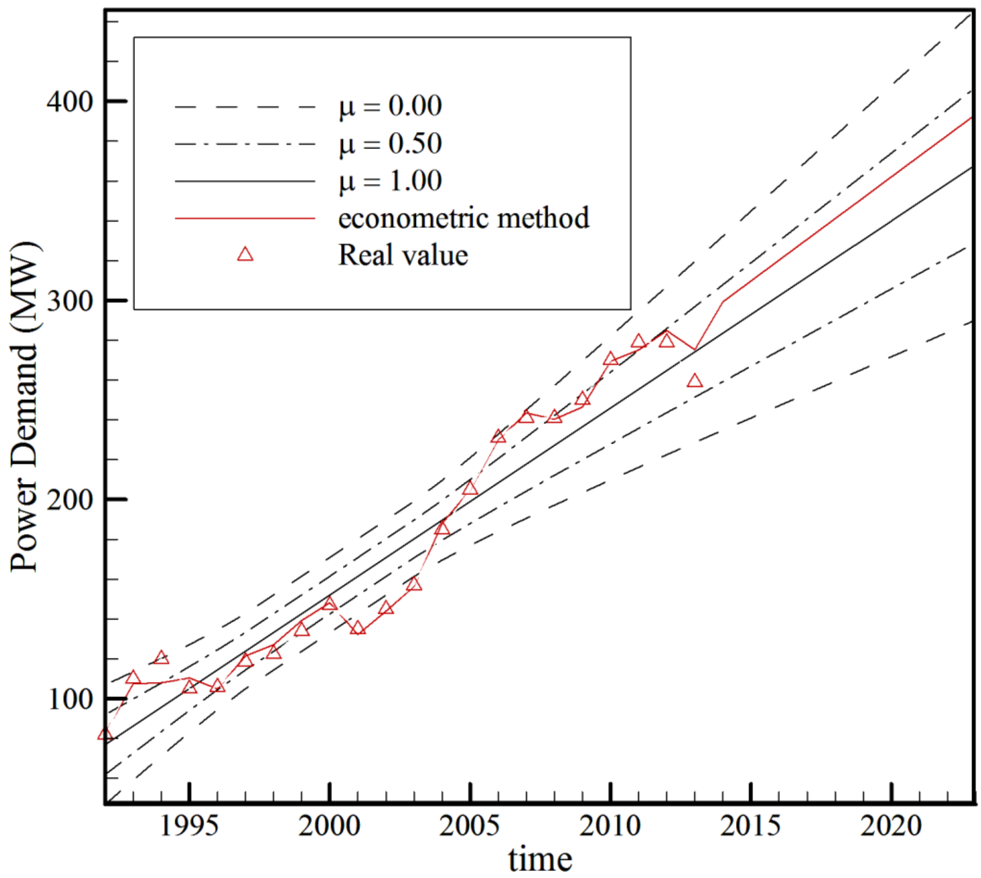

Figure 25: N. Cyprus peak demand forecast for 2023: a comparison between fuzzy peak demand and the econometric method

It has been shown that using simple schemes can generate useful results in forecasting future peak demands with less number of data. These methods are inexpensive and can be easily utilized in the developing countries. However, simplification always increases the uncertainty and as a result advanced fuzzy arithmetic was used to deal with uncertainty.

Due to advances of renewable energy in recent years, application of clean energy technologies seems to be an indispensable alternative for power generation. The investors need to decide how to finance the projects. This requires a sensible technique of forecasting. Underestimation of the demand can result in failure of the system and overestimation may call for costly generators and would be a press on clean energy investments. As a result of the current practice, insufficient data by no means should prevent attending to forecast for the future, and decision makers will have a better idea as to how to postpone the investments of establishing expensive generators for the advantage of giving renewable energy generation more chances.

Smallness and remoteness of an island like Cyprus imposes more energy costs than larger countries. The increase of cost is largely due to fuel transport, and lack of storage and distribution facilities. These island-specific attributes requires different way of development and consequently different approach of planning and policy formulation [7].

In order to prevent blackout and secure the electricity provision, a number of reliability criteria were designed in power plant management. In N-1 criterion the planned system capacity minus the largest generator is greater than peak load and N-2 criterion calls for the system to be able to withstand the loss of two largest generators which can support the system even if a generator requires planned maintenance work and another is accidentally unavailable.

In N. Cyprus the active power capacity is 293MW and it can rise to the full capacity of 331 MW using old and expensive generators. Meanwhile, the current annual peak demand record is 280 MW which is 50 MW below the full capacity. It is clear that a fail in any 60 MW steam generators can cause a blackout and it is evident that even at present the capacity is 10MW less than N-1 security criterion.

In 2023 the power demand of N. Cyprus is expected to be raised to 390 MW using the econometric method and it is estimated to be in the range of 330-410 MW by

50% possibility using the fuzzy arithmetic approach, see Figure 26. The future uncertainties call for the employment of the fuzzy arithmetic approach rather than relying on a single value of econometric method. Clearly, with the existence of two 60 MW steam generators the current capacity should be augmented. Therefore, according to N-1 criteria the existing capacity of 330 MW should be elevated by a range of 60 to 140 MW. This requirement would be decreased remarkably if small generators were utilized. For example, having used 17.5 MW diesel generators as the largest generator the N-1 security criterion would be met by increasing the capacity between 16 MW and 96 MW. Provided that the lower scenario occurs, that is, only 16 MW increment would be needed, renewable energy could be an adequate source for power expansion.

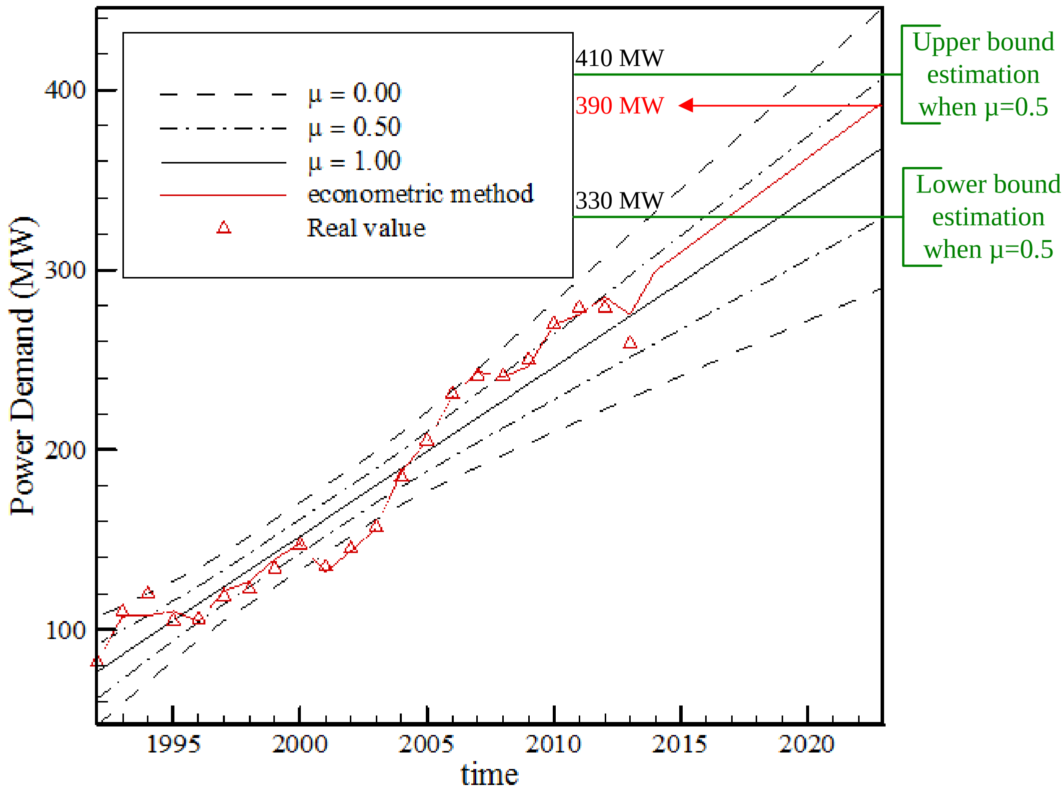

Figure 26: Future power requirement of N. Cyprus

Nevertheless, for the current situation, a trade-off is needed between reaching economies of scale and at the same time ensuring security of supply. Having two large steam power generators resulted in a higher need of installed capacity to ensure reliability under the N-1 or N-2 criteria. This calls for the increment of the cost of power production or simply endangers the security of the supply. Therefore, it is vital to allow for small generators for the future power expansions and resort to reliance on S. Cyprus grid until the retirement of those big generators. The plan of connection to Turkey's grid through the Mediterranean Sea is seen as another alternative of having a reliable system. However, its long term efficiency, cost, and geopolitical effect should be studied and be compared with indigenous renewable energy generation.

It is evident that the electricity demand improves the economy and GDP growth all over the world. Therefore, some developing countries try to lower the cost of electricity generation by subsidizing the costs. This makes the least-cost method of electricity generation as an incorrect approach for meeting the future energy demands. Having a single public utility or few utilities makes the decision on the electricity tariff setting a political choice.

N. Cyprus electricity generation is highly dependent on the import of fossil fuels. This imposes not only a huge economic burden, financial risks, and dependency, it can also bring about environmental setbacks. At the moment, the country demands a substantial financial aid each year and it is expected that the growth in the future demand will impose serious financial difficulties and macroeconomic stresses.

Interestingly, there is an endless amount of renewable energy sources in N. Cyprus, which makes it possible to cut the price of current modes of electricity generations. These indigenous recourses can reduce the dependency on the fossil fuel imports. Since renewable energy technologies (RETs) are particularly competitive in small-scale applications, it is necessary to promote RETs in the energy plans and policies.

5.5. Conclusive Comments

The purpose of the present study is to develop a new algorithm in forecasting annual peak demand especially for the developing countries in which necessary data may not be available for sophisticated demand forecasting methods. Using the annual peak demand as the only available data, the future possibilities of power demand were estimated and were validated with the real values of N. Cyprus. The case study results exhibited the possible ranges of peak demand for N. Cyprus up to 2023. These possibilities should be viewed carefully by policy makers in order to develop medium to long term action plans for the future peak demand.

The ranges of the future possibilities get wider as the forecast horizon increases. The growth of uncertainty attributes to fuzziness in the values of previous years and it is different than prediction interval, which can be presented by fan charts, [126]. This may imply that increasing the forecast horizon is accompanied by more fuzziness and it may give a wide spread of possibilities for the future peak demand. Therefore, forecasting using the current fuzzy arithmetic may be more appropriate for ranges up to ten years.

Chapter 6

A GENERALIZED APPROACH FOR PEAK DEMAND FORECASTING IN DEVELOPING COUNTRIES

6.1 Introduction

Developing countries suffer from regional imbalances and they usually face rapid structural and economic transitions [127]. These variations can intensely affect the regional electricity demands in the long term and it can adversely affect the overall peak demand projection of a country. For example, an industry may thrive in one region of a country and as a result the local demand of electricity for that part escalates dramatically. In addition, population may rush to a city or migrate from one region to another region to seek better opportunities. A peak demand model which simply ignores these variations can slip into fallacies due to fail in capturing the appropriate exogenous effects [25].

Apart from the abovementioned problems, the climatic condition of a large country may vary dramatically from one region to another region [99]. That is, the weather profile of a country can be segregated into different regions with moderately similar weather pattern. For example, while the country usually enjoys the warmth of the weather in some regions at a particular time of the year, it may be under extreme cold weather in some other areas. Thus, in order to correctly forecast the electricity peak demand of the country, a model is required to be developed in dealing with regional weather variations.

Therefore, spatial variation of influential variables on the peak demand forecasting has been seldom dealt with in previously developed forecast models; thereby the previous estimations of peak demand for the whole country are by no means problem free, because regional characteristic were usually overlooked through their application.

The current chapter attempts to tackle these problems by introducing a suitable forecast model through partitioning the country into smaller regions with unique characteristic. Subsequently, electricity demand can be forecasted for each region in order to deal with structural changes as well as diverse climatic variations. Also, the total electricity demand of the country can be forecasted by accumulating the estimated peak demand of all regions.

The proposed model of partitioning the country into characteristically similar regions can be used in all developing countries and it is an extension of the previously developed forecasting models used for small utilities. That is, in addition to small utilities, peak demand in larger countries with diverse climatic conditions and regional features can also be forecasted by combining the previously developed methods.

6.2 Partitioning the Country into Characteristically Similar Zones

In dividing the country into characteristically similar zones it is essential to consider the similarities or distinctive characters of each region such as climate features, economy, demography and other influential factors that can affect the peak demand. This procedure can be carried out by an expert who is familiar with the unique characteristic of different regions. Figure 27 can be prepared as a typical schematic of a country with diverse regional structures.

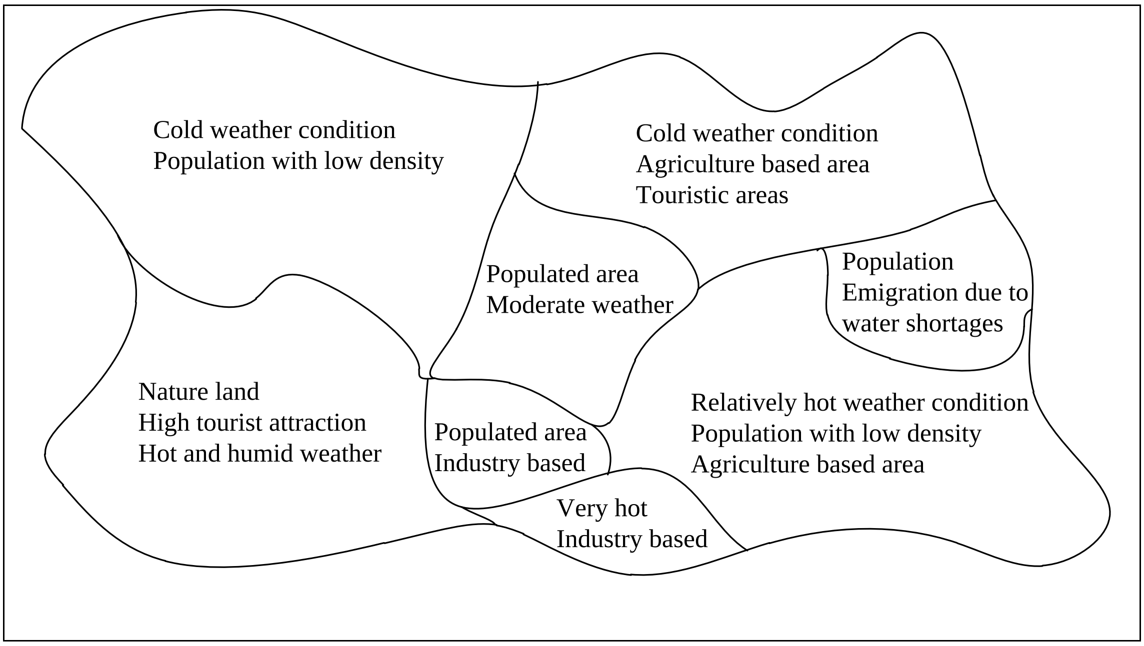

Figure 27: Typical partitioning of a representative country based on its major distinctive attributes

All these regions have distinctive structures. For example, while one region has less population, with a lot of tourists and a hot weather profile, another region might be densely populated, with lack of tourist attraction and moderate weather condition. Therefore, for each region dissimilar parameters might be correlated with the electricity peak demand, which can makes the calculations more accurate.

In partitioning the county into several distinctive zones, it is better to use normal weather conditions and to avoid weather anomalies. It might be necessary to take several years of weather data in order to assure about the normality of weather conditions.

Due to the scarcity of databases in some regions, the available data may be limited to the history of the peak demand. Also, the scales of the divisions are not very small compared to the spatial load forecasting studies which aim at small scale grid and equipment allocation purposes [128].

6.3 Methodology for Partition-Based Peak Demand Forecasting

Figure 28 illustrates an algorithm to forecast the peak demand for all developing countries by considering the distinguished characteristic of different regions. Provided that some distinctive features can be found in different locations, the entire country can be divided into smaller regions with relatively similar electricity pattern. Consequently, peak demand in these small partitions can be forecasted based on the availability of time series data. If necessary data in defining the load system is available for a region, the use of econometric method, developed in chapter 4, is preferable. However, if the peak demand records are the only existing data, the preference is with the fuzzy peak demand models, developed in chapter 5.

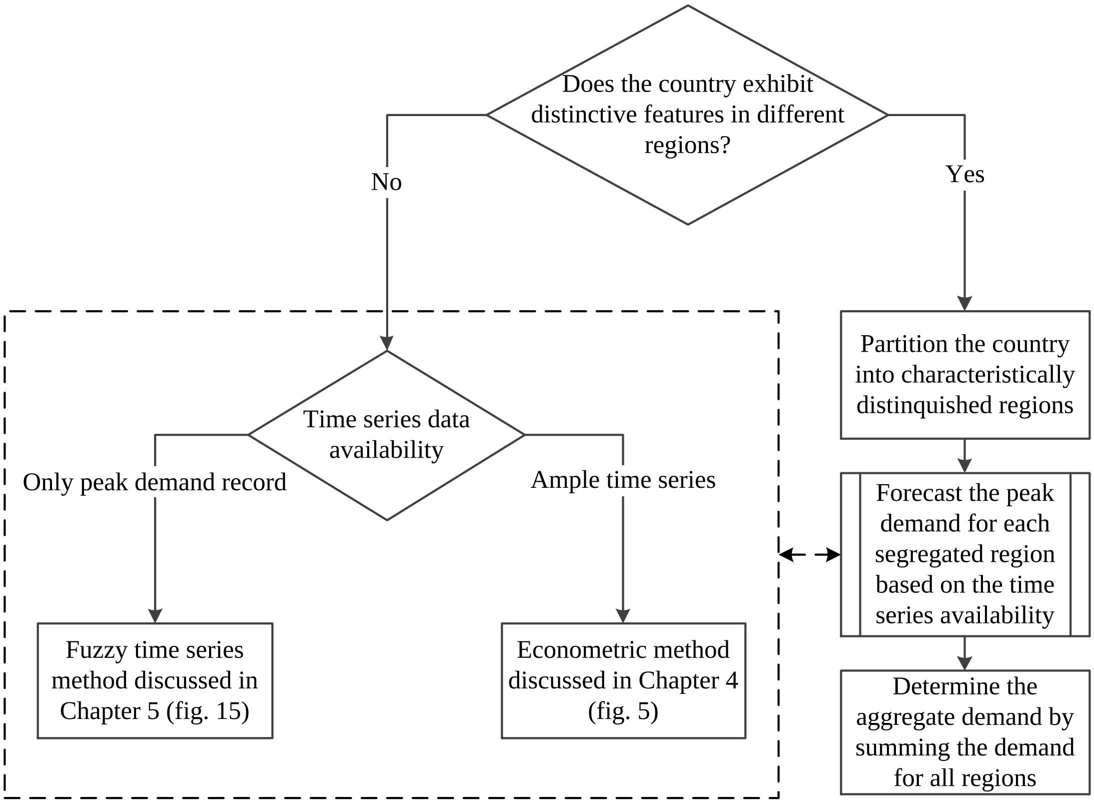

Figure 28: Peak demand forecasting for developing countries based on the geographical characteristic variation and data availability

6.4 Discussions and Conclusive Remarks

Availability of data for each region such as provincial electricity demand, existence of weather stations, and other statistic and demographic variables related to that region can improve the accuracy of the forecast. If necessary data is available in a region econometric methods are superior, while if data is limited to simply the peak demand records, fuzzy arithmetic approach is the alternative. The total peak demand will be the summation of peak demands for all the divisions.

The effect of regional characteristic and weather variations on the provincial load distribution can also be investigated in the long run to assure preventing regional power shortages and for the safe and effective provision of electricity for all the regions. Due to the large scale of weather variation and geographical features, the scale of the current approach is quite larger than special load forecasting techniques in which different cellular types is used in quite smaller scales [128].

Each region may have its own distinguished pattern in using electricity and thereby the demand of electricity in different regions might be correlated with dissimilar parameters. As an example, electricity demand in a touristic place is highly dependent on the number of tourists coming to that area, while the peak demand in an industrial region might be more related with the export of the goods. As another example, some areas of a country might usually have a very cold or hot climate compared to other regions. A model that correlates average values of parameters to the peak demand of the entire country can possibly fail to capture the correct exogenous effects. Hence, in order to estimate the peak demand of a large county, it is recommended to partition the county into smaller zones with similar features and determine the peak demand of each region.

The current approach highlights the requisite to seek for a regional and more extensive data acquisition process through the whole country. Since this procedure is a top-down approach, the feature of the time series data used in this model is different than end-use data. The first can be recorded in local or provincial databases, while the latter can be determined through observation, surveys or questionnaires. However, obtaining end-use data is more expensive and labor-intensive and at times, the availability or the quality of the end use data might be questionable in the developing countries.

Chapter 7

CONCLUSION

In this study some algorithms were presented to forecast the energy demand of developing countries based on their size and data availability. In this regard some suitable approaches of energy demand forecasting were reviewed in different countries and for various cases; subsequently, the advantages and disadvantages of each model were listed.

Energy peak demand forecasting was shown as a first step of a successful IRP. However, the differences in the traits of developing and developed countries highlighted a requisite to devise alternative forecasting approaches for developing countries and especially for SIDSs.

We demonstrated the use of multivariate regression-based econometric method and univariate fuzzy arithmetic based time series models for long-term energy demand forecasting of N. Cyprus as an example of a SIDS.

First, when necessary data is available an econometric method was used. Various endogenous and exogenous variables were tabulated for different cases and it was found that price of electricity, number of customers, tourists, population and HDD are the five determinants of electricity peak demand of N. Cyprus. The decomposition of the peak demand into the WSD and base demand provides an engineering view on the effect of extreme weather condition on the electricity peak demand.

Second, when data is limited to merely the historical annual peak demand, deterministic time series models were used with the aid of advanced fuzzy arithmetic. An algorithm was presented which provides a range for the possible peak demand for the future. Accordingly, the future capacity can be planned with more flexibility and it can promote RETs in the energy plans and policies.

In practice, multivariate forecasts rely on the forecast of their external variables and usually, the forecast of independent variables compound the forecasting efforts and it ends up with more uncertainty. On the other hand, univariate forecasts do not depend on additional external parameters that are often unknown or hard to obtain. Therefore, the advantage of univariate models is that they are only reliant on a single time series data especially when other exogenous determinants are unavailable or hard to obtain.

Finally, a generalized peak demand forecasting algorithm was proposed to forecast the peak demand for developing countries. The model is suitable for the large countries that exhibit distinctive characteristic in different regions. Each region can be studied separately and energy demand forecast models are developed based on the availability of data for each case.

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