

**METHODOLOGY TO DETERMINE THE MAXIMUM  
DEMAND OF MULTI CATEGORY BULK  
ELECTRICAL INSTALLATIONS**

S.A.C.Rajapaksa

119133P



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Degree of Master of Science

Department of Electrical Engineering

University of Moratuwa  
Sri Lanka

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Dissertation submitted in partial fulfillment of the requirements for the degree Master  
of Science

Department of Electrical Engineering

University of Moratuwa

Sri Lanka

May 2015

## DECLARATION

“I declare that this is my own work and this dissertation does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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(Dr. Asanka Rodrigo)

## ABSTRACT

Conventional method of maximum demand determination of a multi category bulk electrical installation at planning stage is done by using several rules of thumb, in which maximum demand and time at which maximum demand occurs cannot be estimated accurately. This incorrect maximum demand estimation caused for wrong transformer and backup power capacity estimation, wrong cable and switchgear selection, inefficient performance of transformer, incorrect statistics, etc.

In this research, a methodology is proposed to determine the maximum demand of multi category bulk electrical installation using its entire kVA profile. This entire kVA profile of multi category bulk electrical installation is generated through a database of kVA profiles in which averaged normalized kVA profile for each installation categories have been defined along with their electrical power loading characteristics.

Multi category bulk electrical installation can be considered as a combination of several single category bulk electrical installations. Hence, to determine the entire kVA profile of a multi category bulk electrical installation, averaged normalized common kVA profiles which represent each category will be added together with multiplying them by their individual calculated maximum demand.

To compile the database of averaged normalized common kVA profiles, kVA profiles (each contains kVA values of one month logging period with 15 minute intervals) of 500 numbers of single category bulk electrical installations have been considered as the sample. The sample is preprocessed, normalized and then clustered using Hierarchical Clustering Algorithm. By using square sum of error of each clusters and Knee point criterion, seventeen numbers of unique kVA pattern classes were identified. Then averaged normalized kVA profiles were derived for each pattern class and map them up with example single category bulk electrical installations and their characteristics to compile above said averaged normalized kVA profile database. Visual basic programming and Matlab software is used to execute above said research work.

This proposed methodology has been verified considering a multi category electrical installation and proposed methodology can be considered as an acceptable one to determine the maximum demand of multi category bulk electrical installations. This methodology can be further improved by compiling averaged normalized kVA profile database for each installation categories separately. Additionally, this research can be further improved as a required tool for load forecasting, demand-side management, system planning, distribution system loss estimation and better tariff design, etc.

Key words: kVA profile, Single category bulk electrical installations, multi category bulk electrical installations, Clustering, Hierarchical Clustering algorithm, Knee point criterion

## ACKNOWLEDGEMENT

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Data required for this research is not freely available and is not easily acquired with electricity distribution licensees. Need special permission and a little hard work to obtain them. Hence my sincere thank goes to Mr. Damitha Kumarasinghe; Director General of PUCSL, Mr. Gamini Herath; Deputy Director General of PUCSL who provided official support necessary to obtain required data from distribution licensees. And Mr. S.H.N. Somawardena; former Deputy General Manager of Colombo City distribution region of CEB, Mr. J. Meegoda; Deputy General Manager of Colombo City distribution region of CEB, Mr. C. Samarasinghe; Deputy General Manager of distribution region 2 WPN of CEB, Mr. N.W.Kumarasinghe, Deputy General Manager(C&C) of distribution region 3 of CEB, Dr. Narendra De Silva; Head of Engineering of LECO who granted permission to provide required data for this research. Also I would like to give my thank to Mrs. Janaki Rupasingha; Chief Engineer at CEB, Mr. Ravindra Gunathilake; Chief Electrical Engineer of CEB, Mr. Indika Samarasinghe; Electrical Engineer of CEB, Mr. Dulan Ranawaka; Electrical Engineer of CEB, Mr. Janaka Herath; Electrical Engineer of CEB, Mrs. O. K. Kokila; Electrical Engineer of CEB, Mr. Udayantha Wijesinghe; Test Engineer of LECO who dedicated their valuable time to download required kVA profiles for this research.

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## LIST OF ABBREVIATIONS

Abbreviation	Description
PUCSL	Public Utilities Commission of Sri Lanka
CEB	Ceylon Electricity Board
LECO	Lanka Electricity Private Limited
DR1	Distribution Region 1
DR2	Distribution Region 2
DR3	Distribution Region 3
DR4	Distribution Region 4
kVA	kilo-Volt-Ampere
kWh	kilo Watt Hour
kW	kilo Watt
PDF	Adobe Acrobat File Format
HC	Hierarchical Clustering
SSE	Square Sum of Error
BOC	Bank of Ceylon

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# CHAPTER 1

## INTRODUCTION

According to the IEE Wiring Regulations, an “Electrical installations” is defined as “an Assembly of associated electrical equipment to fulfill a specific purpose and having certain co-ordinated characteristics”.

“Electrical Equipment” corresponds to “any item for such purpose as generation, conversion, transmission, distribution or utilization of electrical energy, such as machines, transformers, apparatus, measuring instruments, protective devices, wiring materials, accessories and appliances”. The term “Assembly” indicates that the electrical equipment is not considered in isolation but as a complete set. Further this complete set has been assembled together for a specific purpose, and consists of equipment which has characteristics which are co-ordinated with each other.

Electrical installations which are used for utilization of electrical energy can be divided into several categories based on various points of view. In tariff point of view, those installations can be divided as “general purpose”, “hotel”, “industrial”, “domestic” and “religious”. By capacity point of view, there are mainly three categories called “1”, “2” and “3”. An electrical installation whose contract demand is less than 42 kVA is belonged to category “1”. An electrical installation whose contract demand is higher than 42 kVA and less than 1000 kVA is belonged to category “2” and an electrical installation whose contract demand is higher than 1000 kVA is belonged to category “3”. Electrical installations come under category “2” and “3” is also called as “bulk installations”. “Single category bulk installations” and “multi category bulk installations” are another means of categorizing electrical installations based on their category of installation which will be described in the coming section.

### 1.1 Single Category and Multi Category Bulk Installations

Bulk electrical installations can be mainly categorized into two groups. One is single category bulk electrical installations and other one is multi category bulk electrical installations. Single category bulk electrical installation means, bulk power supply is utilized only for one particular business purpose/requirement. In other way, total transformer power of that electrical installation is utilized only for one particular

business/requirement by single owner. Consider a hotel as an example. Electrical power supply for such kind of hotel installation should be provided by the dedicated bulk transformer and total power of that transformer is utilized only by that hotel. But there are some premises/electrical installations which are utilized for several business purposes by one or several owners. In this case one transformer has to cater the total power requirement of all these businesses. On the other hand, multi category bulk electrical installation is single premises but combination of separated several businesses which having various kVA loading profiles. As an example, consider a three story building which is powered by a transformer and in which first floor is a bank, second floor is a show showroom and third floor is a commercial office. In here instead of one type of business, three types of different businesses are together utilizing the power of that single transformer. Such kind of installation can be called as multi category bulk electrical installations. Refer figure 1.1. In general, single category bulk electrical installations are the one mostly available and multi category bulk electrical installations are few in number compared with single category bulk electrical installations.

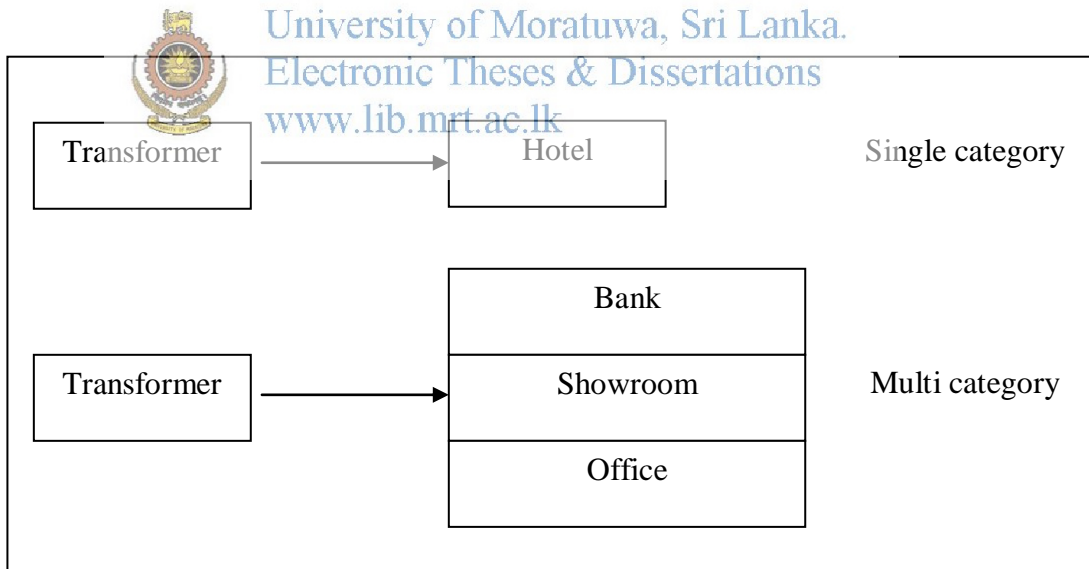


Figure 1.1: Single category and multi category installation

## 1.2 kVA Profile

kVA profile is a graph of measured kVA values of an electrical installation which is plotted against time. Typically 24 hour time period of 15 minute interval is considered for this KVA profile. Also kVA profile represents the loading pattern of various electrical loads belong to an electrical installation. Figure 1.2 shows an example kVA profile of a supermarket of a particular day.

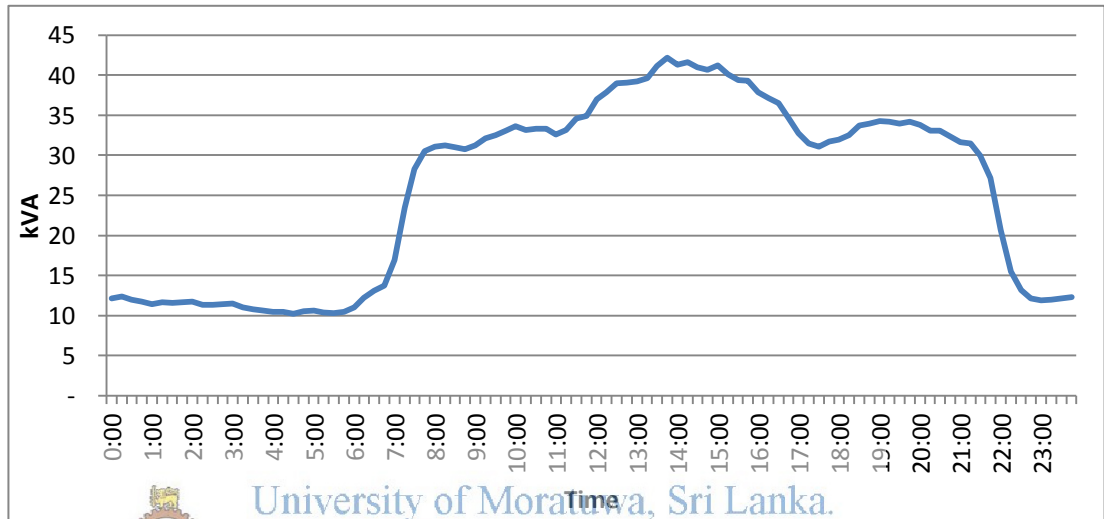


Figure 1.2. Sample kVA profile of a supermarket



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## 1.3 Maximum Demand Determination

### 1.3.1 Maximum demand determination of single category electrical installations

Conventional method of maximum demand (maximum kVA value) determination of a single category electrical installation is done by calculating kVA value based on various electrical loads of the installation and their loading pattern with considering various factors like diversity factor, simultaneous factor, etc. Few diversity factors which are used in demand calculations are tabulated in table 1.1.

Both single category and multi category electrical installations having its own kVA profile based on their functioning pattern. Pattern of this kVA profile of a single category electrical installation is predictable as single category electrical installations

are frequently available in the field and because of that, design engineers also much expert in maximum demand determination in such kind of assignments.

In design stage as an Electrical Engineer knows the application of his design, he has an approximation at what time its maximum demand occurs and based on that he calculate the maximum kVA demand requirement of that installation and based on that required transformer, backup generator, cables and switchgears are selected. Figure 1.3, Figure 1.4 and Figure 1.5 shows several example kVA profiles of bulk installations of various categories in Sri Lanka. As electrical designer is familiar with the inside operation of those installations and he calculates its loads to find the maximum demand during the time at which peak kVA demand occurs.

Table 1.1: Diversity factors used in maximum demand calculations

Type of final circuit	Category		
	Households	Small shops, stores, offices	Hotels, guest houses
Lighting	66% total demand	90% total demand	75% total demand
Heating and power	100% up to 10 A + 50% balance	$100\%X + 75\%(Y+Z)$	$100\%X + 80\%Y + 60\%Z$
Cookers	10 A + 30% balance + 5 A for socket	$100\%X + 80\%Y + 60\%Z$	$100\%X + 80\%Y + 60\%Z$
Instantaneous water heaters	$100\%X + 100\%Y + 25\%Z$	$100\%X + 100\%Y + 25\%Z$	$100\%X + 100\%Y + 25\%Z$
Standard circuits	$100\%X + 40\%(Y+Z)$	$100\%X + 50\%(Y+Z)$	$100\%X + 50\%(Y+Z)$
Sockets and stationary equip.	$100\%X + 40\%(Y+Z)$	$100\%X + 75\%(Y+Z)$	$100\%X + 75\%Y + 40\%Z$
X is the full load current of the largest appliance or circuit Y is the full load current of the second largest appliance or circuit Z is the full load current of the remaining appliances or circuits			

Source: <https://www.tlc-direct.co.uk/Book/6.2.3.htm>

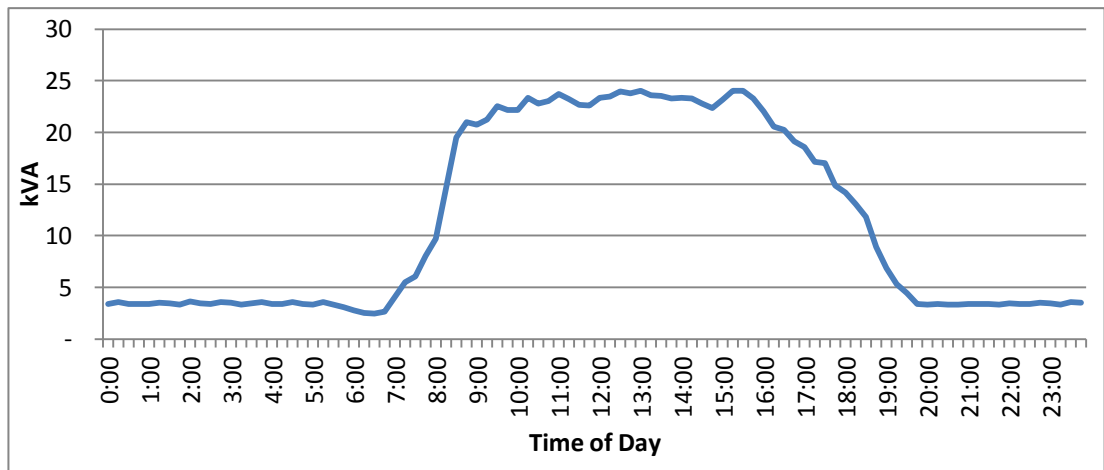


Figure 1.3: kVA profile of a bank

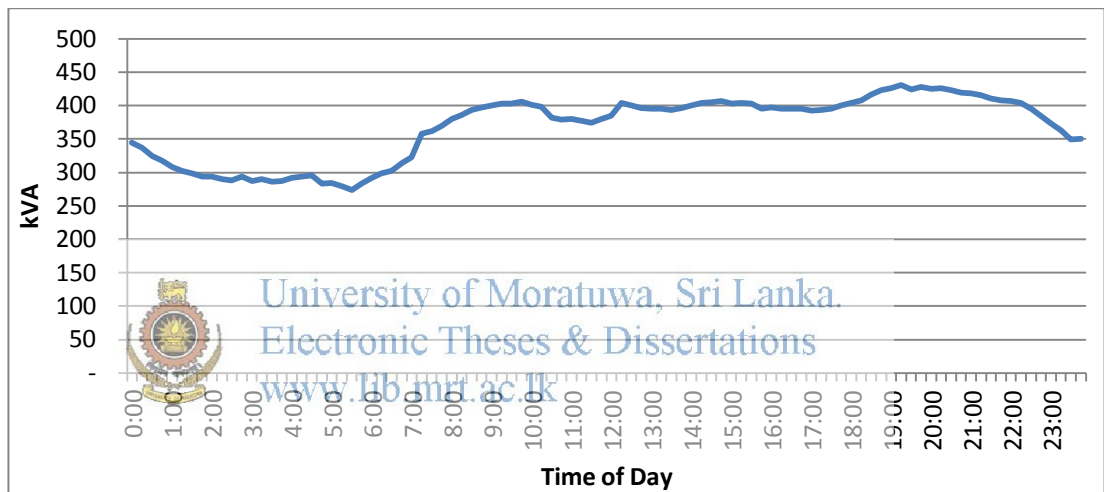


Figure 1.4: kVA profile of a hotel

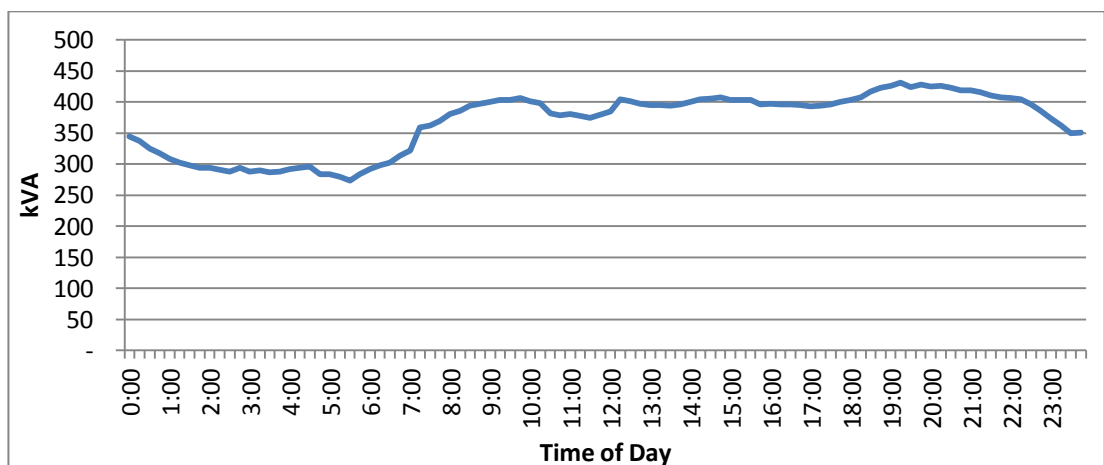


Figure 1.5: kVA profile of a consumer goods shop

### 1.3.2 Maximum demand determination of multi category electrical installations

Other than frequently available single category installations, there are multi category installations also available in the country. As an example there are some high rise buildings which consist of several banks, shopping moles, resident place. Hence they have different loading pattern/kVA profiles throughout the day. In such a case it's very difficult to identify at what time peak demand of that building occurs and value of that peak demand.

In such kind multi category electrical installation projects, to determine final maximum demand several rules of thumb are used. Several such kinds of rules of thumb are show in table 1.2.

Table 1.2: Rules of thumb

TABLE 1: Electrical supplies and loads				
Design area	Application	Other information	Rule of thumb	Ref
Electric supply	Electrical motors	Above 0.5 kW rating	3-phase supply	16
	Electrical motors	Up to and including 0.5 kW rating	Direct on-line starting	16
	Electrical motors	Above 4 kW rating	Assisted start	16
Electrical services load (per m <sup>2</sup> of building floor area)	Lighting		10 – 12 W/m <sup>2</sup>	16
	Small power		15 – 45 W/m <sup>2</sup>	16
	Air conditioning		60 W/m <sup>2</sup>	35
	Passenger lifts		10 W/m <sup>2</sup>	35
	Small computer room	Net area	200 – 400 W/m <sup>2</sup>	16
	Bespoke call centre	Net area	500 – 1000 W/m <sup>2</sup>	16
	<b>Total load (kVA)</b>	<b>Total building load</b>		<b>Total kW/0.8</b>
Design allowance for future expansion (%)	% increase in load		<b>Add 25% to existing capacity</b>	<b>35</b>

Source: Rules of Thumb BSRIA 2007

With that rule of thumb no exact estimate value can be calculated to determine maximum kVA demand requirement and no way to identify the exact time at which peak demand occurs of multi category electrical installations. This leads to transformer and backup power over estimation. This kind of overestimation is common in most of multi category electrical installations which caused to transformer losses, incorrect statistics, incorrect cable and switchgear selection, incorrect statistics etc.

Figure 1.6 shows kVA profile of a multi category installation in which several bank offices, one institute, government offices, and several private offices are available. In such a case kVA profile of total installation is unpredictable, as each one/installation operates in different way. Determination of kVA loading pattern of this whole installation and determination the time at which the maximum kVA demand is occurred in this whole installation is not possible with rules of thumb.

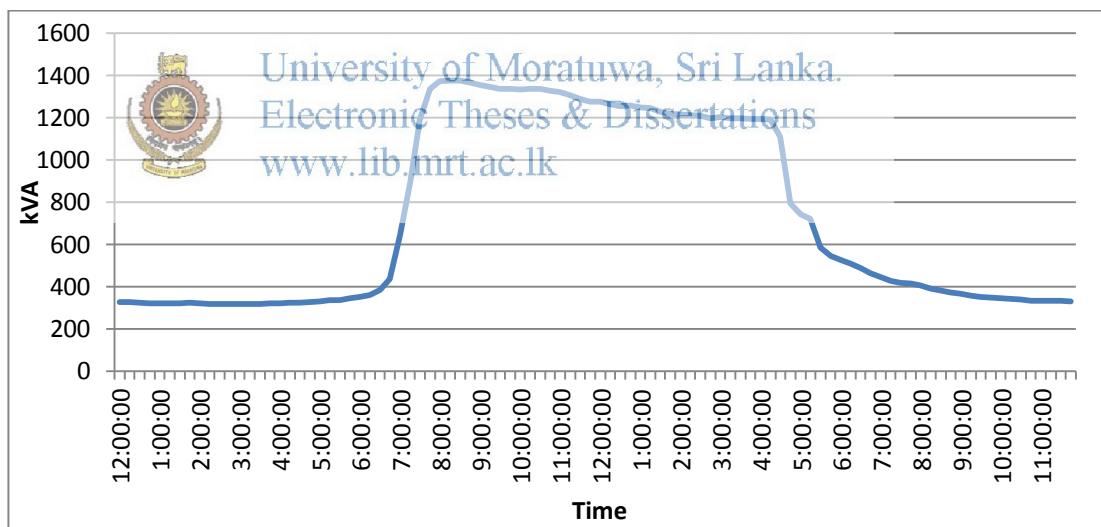


Figure 1.6: kVA profile of a multi category electrical installation

## CHAPTER 2

### RESEARCH OUTLINE

#### 2.1 Problem Identification

As described above, there is no accepted proper method to determine the maximum demand (kVA) of multi category electrical installations. Thumb rule which is described above for maximum demand determination is not an acceptable one and accurate method due to having several disadvantages as described in earlier pages. Hence purpose of this research is to propose a methodology to determine the maximum demand of multi category bulk electrical installations

#### 2.2 Objective

Propose a methodology to determine the maximum demand of multi category bulk electrical installations.

#### 2.3 Research Boundaries

The outcome of this research is only applicable for multi category bulk installations. This is not applicable for multi category electrical installations with industrial type sub installations. Also this is not applicable for multi category electrical installations which are consisted as retail type domestic, commercial and hotel electrical installations (electrical installations where its contract demand is below than 42 kVA). Also, this is not applicable the transformers which are used for distribution purposes.

This proposed methodology to determine the maximum demand of multi category bulk electrical installations is based on the maximum demand calculation of single category bulk electrical installations. Hence accuracy of existing methods of maximum demand determination of single category electrical installation is not considered for this research.



## 2.4 Literature Review

Numbers of research papers, journals, magazines, e books were referred to find out related similar work done on this topic and find out an approach to carry out this research. Most of the times, rules of thumb as described earlier has been used for maximum demand calculations of large scale installations irrespective of single category or multi category. No categorization was found like or similar to single category installations and multi category installations in referred researches.

There are some researchers done to find maximum demand of electrical installations based on the information like number of occupants, behavioral characteristic of them, electrical loads utilized, etc.[24]. But in many of researches, kVA profile concept has been used as a main tool in many areas in maximum demand determination or similar work as described below.

kVA profiles of consumers have been used to obtain demand pattern of consumers[4][14][15][16][18][21]. Those demand patterns will be an infrastructure for analyzing actual load behaviors on demand side, tariff design, load forecasting, load management, substation peak load estimation and system peak management. Sometimes these load forecasting may be short term but still requirement of kVA profile for them is essential [23]. Load modeling is useful for the long term planning of power distribution systems, economic analysis and operation and planning of distribution systems. kVA profile is essential tool for such kind of analysis work[17]. Also for some countries change of climate is causing the demand pattern of consumers and distribution system change adversely. kVA profiles are very much essential for analysis related with said circumstances [18]. Further, to determine many factors like diversity factors, simultaneous factors, loading factors which need in electrical demand calculations, contribution of kVA profiles is very essential [19]. kVA profile has been an essential tool to determine the household demand as well[22].

Base of most of above referred researches is kVA profile categorization. This kVA profile categorization has been done using many of clustering algorithms [1][2][3][5]. On top on that kVA profile categorizations, all other secondary findings which are describe above, have been performed.

## 2.5 Methodology

In this research, a methodology is proposed to determine the maximum demand of such kind of multi category bulk electrical installations. Based on the kVA data profiles obtained from 500 numbers of single category bulk electrical installations, set of normalized average kVA profiles for various categories/electrical installations have been compiled as a database. To determine the kVA profile of a multi category bulk electrical installation, select relevant normalized average kVA profiles appropriate for each category from said database, multiply each of them by the calculated maximum demand of relevant single installations and then add them up together to find the ultimate kVA profile of that multi category electrical installation. In brief, methodology of research as follows; [1] [2] [3]

1. Obtain daily kVA profiles of various single category bulk electrical installations/consumers throughout one month of time period
2. Preprocessing of those daily kVA profiles
3. Find the averaged normalized kVA profile for each bulk electrical installation/consumers
4. Categorize those averaged normalized kVA profile into various kVA profile pattern classes/clusters using a clustering algorithm
5. Derive a common averaged normalized kVA profile for each pattern class/cluster
6. Develop a database with derived common averaged normalized kVA profiles along with its corresponding characteristics
7. Use the kVA profiles in this database to determine the maximum demand of multi category electrical installations.

This database can be considered as the base to determine maximum demand of multi category bulk electrical installations. In order to determine the maximum demand of a multi category electrical installation, initially you have to find the various categories of electrical installations included in it and then find the appropriate well matching common kVA profile for those categories from this database. Then

multiply those common averaged normalized kVA profiles of each category by their calculated individual maximum demand and add them up together to find the kVA profile of entire installation which gives the expected pattern of that multi category bulk electrical installation. Then value of maximum demand and time at which this maximum demand occurs can be determined. Figure 2.1 shows the mathematical formula for maximum demand determination of multi category bulk electrical installations using proposed methodology.

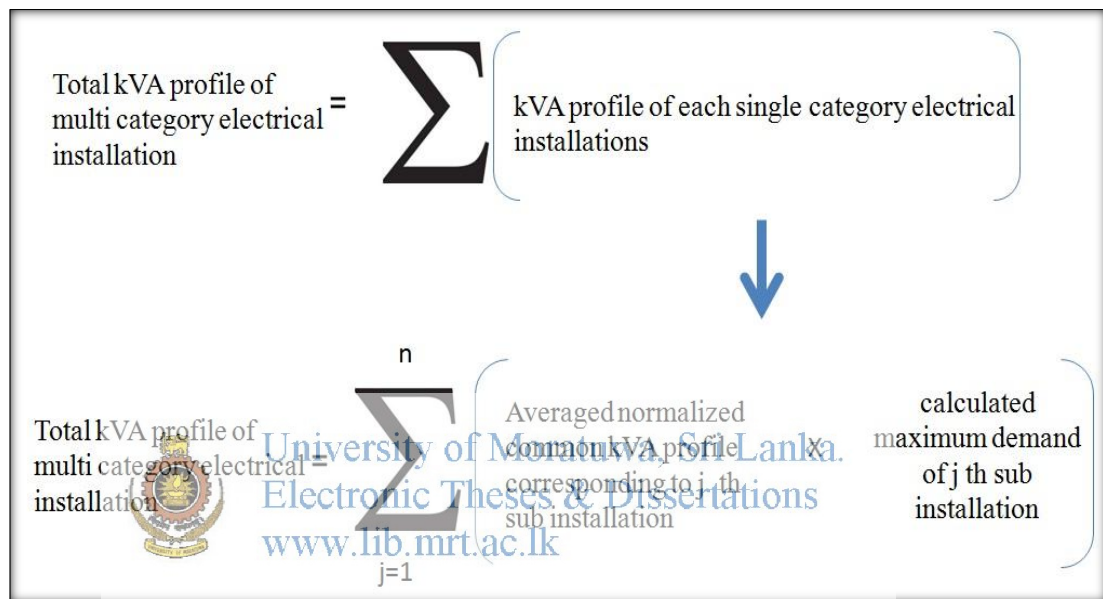


Figure 2.1: Determination of entire kVA profile

Consider below example, it is a high rise building located nearby Colombo city which having apartments and shopping complex together (Figure 2.2). Lower floors are allocated for shopping complex and upper floors are allocated for rented out apartments. Electrical power requirement for this high rise building is provided by a dedicated transformer. This is a multi category type electrical installation as two different types of installations are operating together with a single transformer. To find the kVA profile of this entire installation below mentioned steps have to be executed.

- Find the averaged normalized common kVA profile of each category (for apartment category and for shopping complex category) from prepared database. Figure 2.3 and figure 2.4
- Find the maximum demand of an apartment installation and shopping complex installation separately using normal engineering calculations
- Multiply each averaged normalized common kVA profile by corresponding maximum demand values taken up from above step
- Add multiplied kVA profiles together and that is the expected kVA profile of entire installation, in which value of maximum demand and time at which that maximum demand occurs can be easily determined.

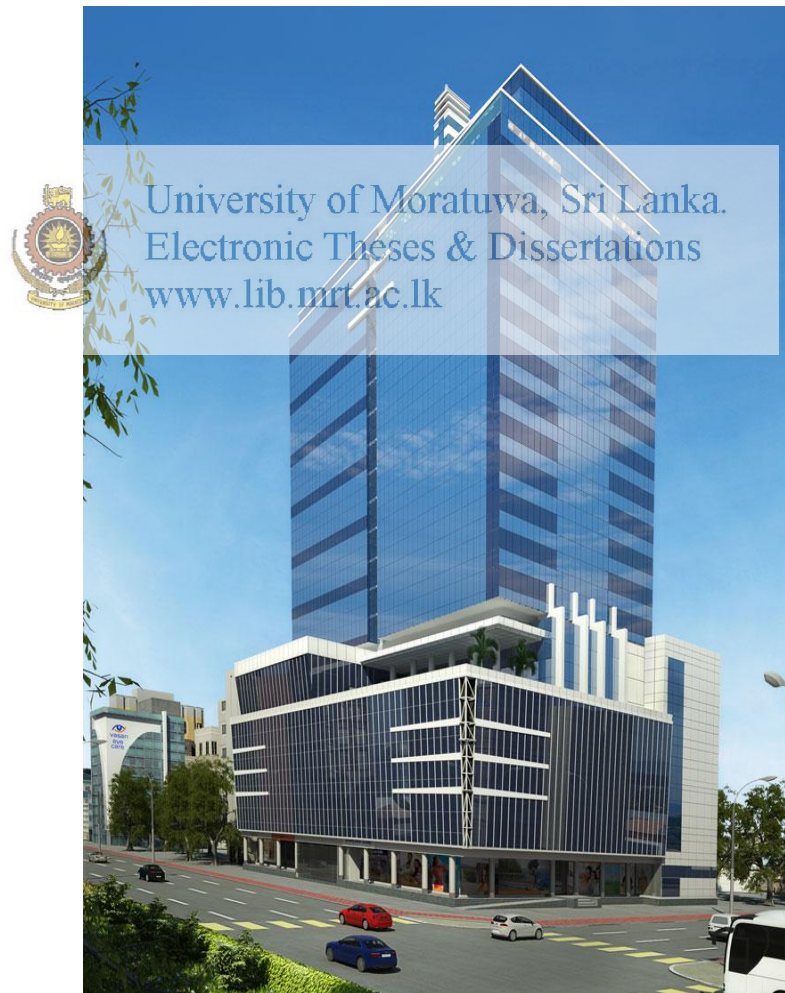


Figure 2.2: A multi category bulk electrical installation

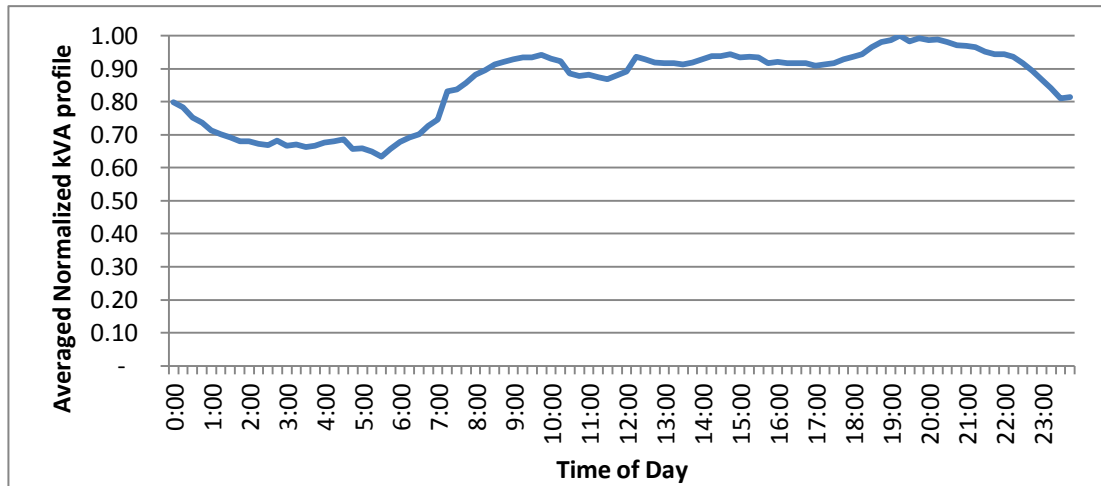


Figure 2.3: Averaged normalized common kVA profile of Apartment

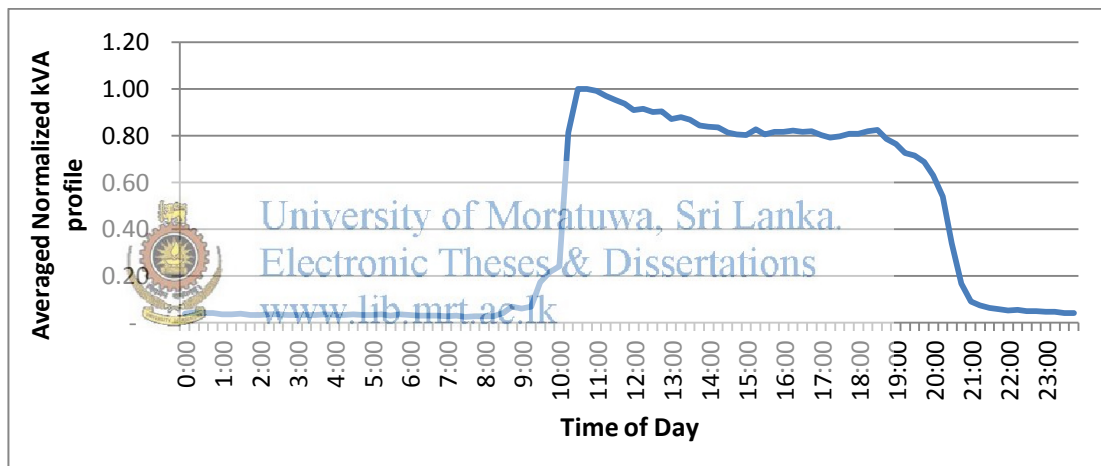


Figure 2.4: Averaged normalized common kVA profile of Shopping Complex

Below equation shows how to obtain the entire kVA profile of this entire installation

$$\begin{array}{l}
 \text{kVA profile of} \\
 \text{entire} \\
 \text{installation}
 \end{array}
 =
 \left( \begin{array}{l}
 \text{Averaged normalized} \\
 \text{common kVA profile of} \\
 \text{apartment building} \\
 \times \\
 \text{Calculated maximum} \\
 \text{demand of apartment} \\
 \text{buildings}
 \end{array} \right)
 +
 \left( \begin{array}{l}
 \text{Average normalized} \\
 \text{common kVA profile of} \\
 \text{shopping complex} \\
 \times \\
 \text{Calculated maximum} \\
 \text{demand of shopping} \\
 \text{complexes}
 \end{array} \right)$$

Let's assume calculated maximum demand of one apartment and one shopping complex is 50 kVA and 30 kVA respectively. Further number of apartments and number of shopping complexes in this entire installation is 15 and 10 respectively. Accordingly above equation will be modified as below and kVA profile of entire installation would be shown in figure 2.5. Based on that graphical representation maximum demand of entire installation can be determined as 977 kVA and which is occurring at 12:15 PM.

$$\text{kVA profile of entire installation} = \left( \begin{array}{c} \text{Averaged normalized} \\ \text{common kVA profile of} \\ \text{apartment building} \\ \times \\ 750 \end{array} \right) + \left( \begin{array}{c} \text{Average normalized} \\ \text{common kVA profile of} \\ \text{shopping complex} \\ \times \\ 300 \end{array} \right)$$



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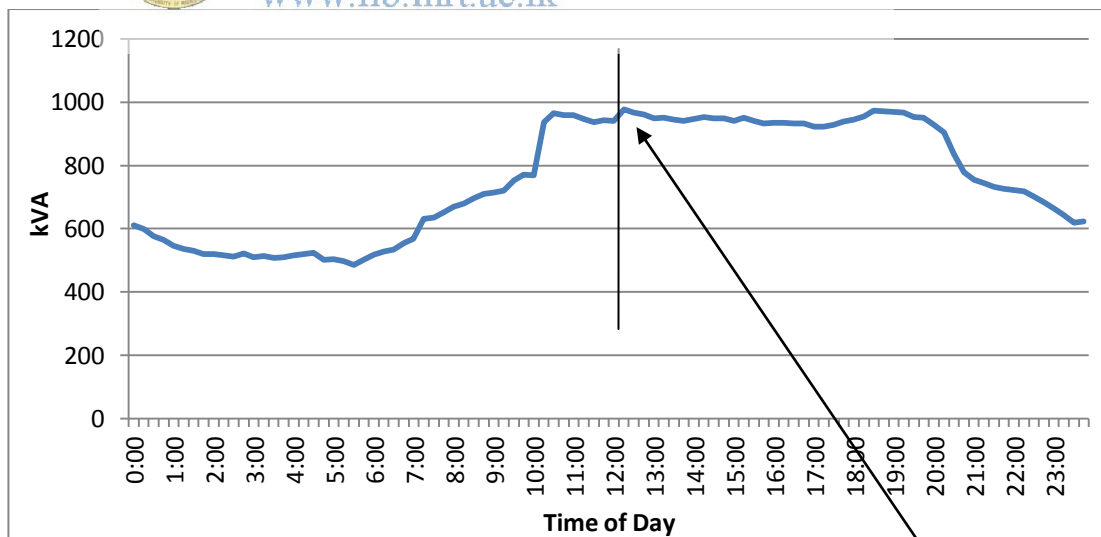


Figure 2.5: Entire kVA profile

Maximum demand

## CHAPTER 3

### KVA PROFILE SAMPLING AND PREPROCESSING

#### 3.1 kVA Profiles Sample

Electricity distribution of Sri Lanka is done by CEB and LECO together. Among these two distributors, CEB covers geographically more than 80% of distribution area in the country. CEB does its distribution under four distribution regions which are namely distribution region 1 (DR-1), distribution region 2 (DR-2), distribution region 3 (DR-3) and distribution region 4 (DR-4)

Total number of bulk installation under said two distribution licensees are tabulated in table 3.1. Sample size required to represent this total bulk installation population with 95% confident level and 5% error margin is 373.

Table 3.1: Bulk consumers in the country

Distribution licensee	Number of bulk installations
CEB	10,000
LECO	2,000

Table 3.2: kVA profiles obtained as sample

Distribution licensee	Number of kVA profiles
LECO	100
CEB- DR1	100
CEB- DR2	100
CEB- DR3	100
CEB- DR4	100

For this research 500 numbers of kVA profiles of single category bulk consumers were obtained from CEB and LECO as listed in table 3.2. kVA profiles of single category bulk installations can be downloaded from the bulk energy meter in pdf or

Microsoft excel format which includes measured data for below listed electrical parameters in each 15 minute interval throughout one month of period.

- System voltage
- Ampere consumption
- System frequency, power factor
- kWh consumption, kW value, kVAR value, kVA value

Annexure 01 and annexure 02 show sample few pages of such downloaded pdf format file and excel format file respectively. PDF to excel convertor is used to convert all data in each pdf file to excel sheet and visual basic program (Annexure 03) was compiled to extract kVA data.

kVA data measured in 15 minutes interval over one month of period of one consumer is available at CD as an excel sheet titled as “Measured kVA data of a consumer”. Accordingly, 2880 numbers of kVA readings are available for one bulk consumer per one month. (Per day 24 hours x 60 / 15 =96 readings and per month 96 x 30 =2880). At the end 500 numbers of excel sheets are available. Figure 3.1 shows the graphical representation of kVA profiles of each day over a period of one month belong to one consumer. Various colors represents each day of the month. At a glance it looks like a mesh of kVA patterns. But if you examine with closer look, three numbers of unique pattern of kVA profiles can be identified.

1. Six numbers of kVA profiles which are spreaded near to and parallel to the time axis
2. Four numbers of kVA profiles which are spreaded through the middle of the XY plane
3. Rest of all kVA profiles which are mostly spreaded through the upper part of the XY plane



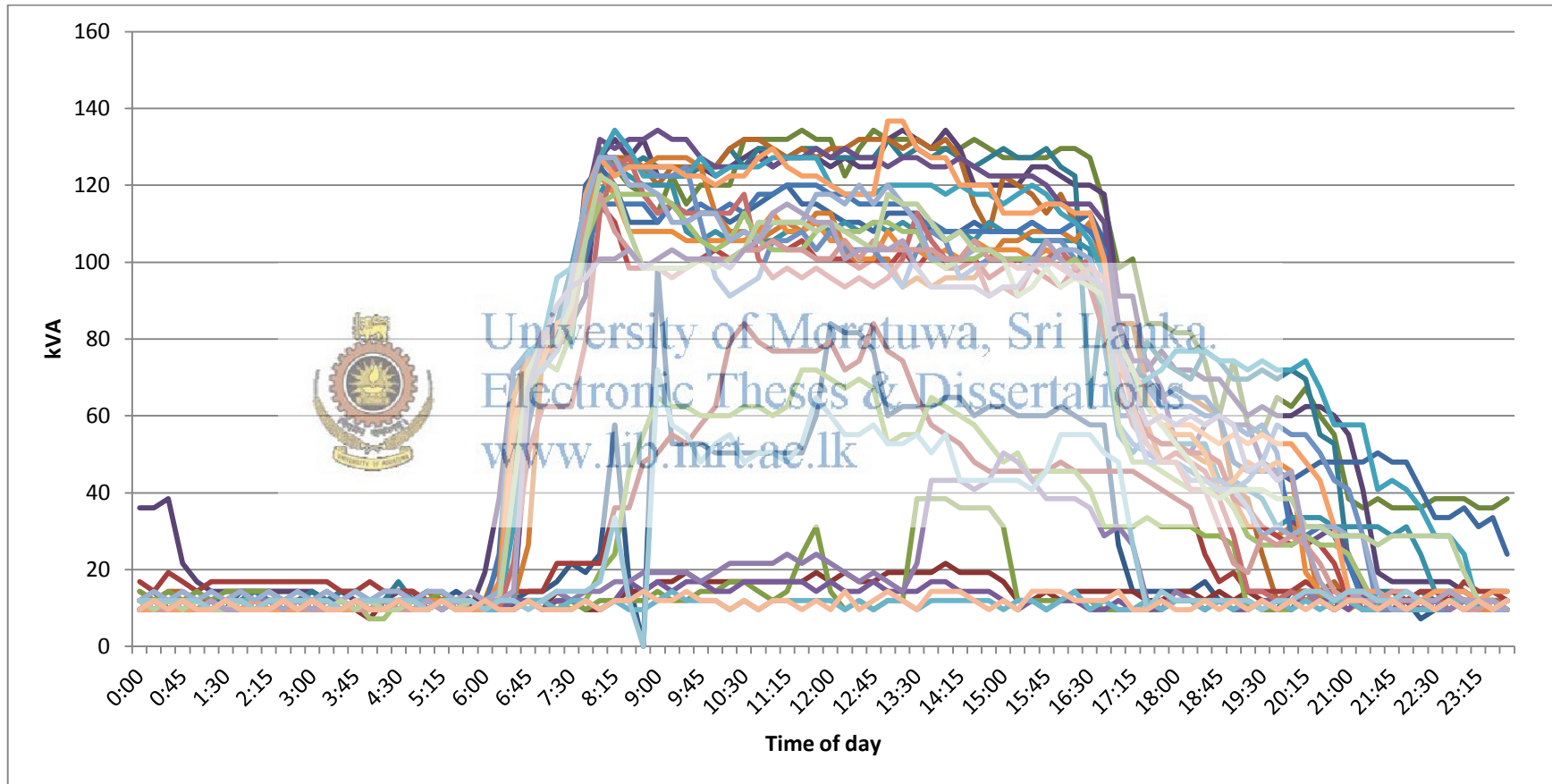


Figure 3.1: kVA profiles of a consumer over one month of period

### 3.2 Pre Processing of kVA Profiles

Now 500 numbers of kVA profiles of one month belong to 500 numbers of consumers/single category bulk installations are available. Main objective of this process is determining of an average kVA profile for each consumer/bulk installation. Prior to that, obtained raw data (set of kVA profiles of one month) has to be preprocessed. Steps for this preprocessing mechanism are listed below, [4] [5]

- Removal of error data, missing data from monthly kVA profiles
- Remove weekends from monthly kVA profiles(if applicable)
- Remove outliers from monthly kVA profiles
- Obtain the average kVA profile for each consumer
- Normalize the average kVA profile of each consumer

### 3.3 Removal of Error Data from kVA Profiles

After extracting required kVA data from downloaded pdf or excel files into a separate table as shown in annexure 4, some error marks (\*) can be observed among the data here and there instead of numerical kVA values. Those are because of communication errors which were occurring during downloading those data. If an error occurs while downloading data from energy meter at manual or through meter laboratory, that error is represented by this type of (\*) marks or minus (-) marks in downloaded pdf or excel files.

Such an example data set is attached in annexure 4. Such kind of error data has to be removed by using a preprocessing method. Such kind of preprocessing of the data is required to verify that only effective data is being used for analysis. Several rules used for this preprocessing task are given below. [4]

- Intervals with error records are exceeded 20% of the entire analyzing period of time, the date corresponding to the recorded will be discarded from the month.
- When considering kVA data of a particular day, if the continuous intervals less than two hours are missing, the missing part of the data will be estimated using linear interpolation.

- If the continuous intervals greater than two hours are missing, the missing part of the data will be estimated using the historical data. The historical data should be selected from the same type of day and time of that month.

### 3.4 Removal of Weekends from kVA Profiles

Base of this research is totally depending on the common average normalized kVA profiles which are generated for each installation category. Hence identification of common average normalized kVA profiles should be done in a much more accurate way. Therefore preprocessing of data like removing weekend data of some installations, removing outliers, etc. are have to be done very carefully and effectively.

When considering one month of time period, kVA profile of various consumers/installations is vary day by day depending on the nature of each day. As an example, government bank does not operate in weekends and bank holidays. But hotel operates all day irrespective of the date of week. While obtaining average kVA profile of each consumer/ installations this behaving nature is very important. kVA profile of a consumer/installation can be represented as an energy graph which shows the amount of energy consumed throughout the day in kWh. That graphical representation can be used to identify the consumers who do not work whole weekend, consumers who do not work only Sunday, etc. Figure 3.2 shows the kVA profiles of a bulk consumer who works mainly in weekdays throughout a month. It works weekends also, but not similar to weekdays. It clearly shows the operating pattern on weekdays and weekends. Before compiling an average kVA profile, all weekends of such kind of installations/consumers has to be removed. [3],[6].But in some installations/consumers like hotel, etc, above situation cannot be observed as they work in weekends also. Hence from such installations/consumers only holidays were removed prior to average kVA profile compilation.

After removing weekends and holidays (depending on the applicability) from each individual monthly kVA profile, still outliers may presence. Hence statistical method called modified Z score method was utilized to remove outliers.

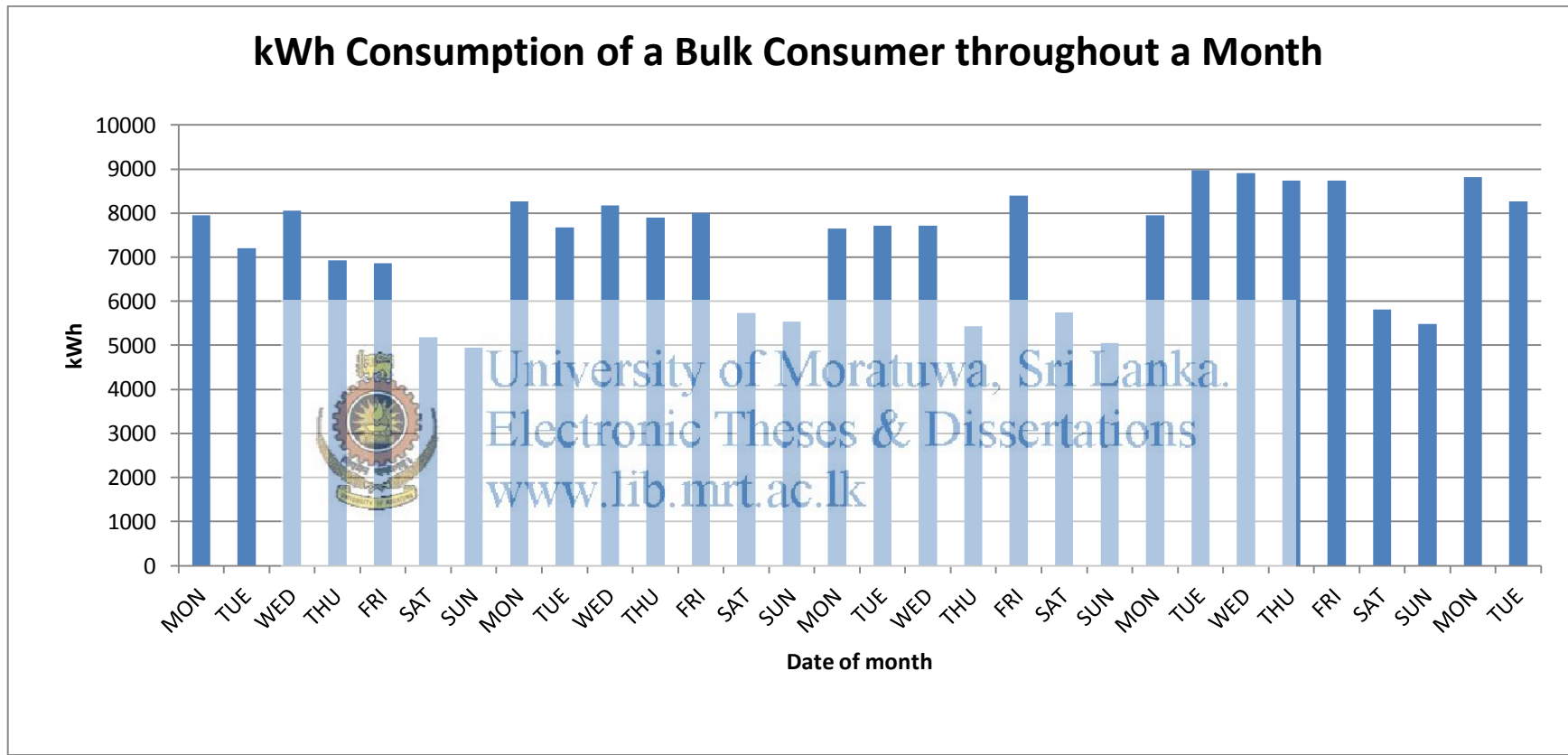


Figure 3.2: kWh consumption of a bulk consumer throughout a month

### 3.5 Removal of Outliers from kVA Profiles

In statistics, an outlier is an observation point that is distant from other observations. An outlier may be due to variability in the measurement or it may indicate experimental error; the latter are sometimes excluded from the data set.

There are many methods available to remove such kind of outliers in a data system. Figure 3.3 shows list of such outlier detection algorithm which is commonly used in statistics [7]. kVA profile of an installation can be considered as having normal distribution [8]. Accordingly Modified Z Score method is selected to remove outliers of kVA profiles.

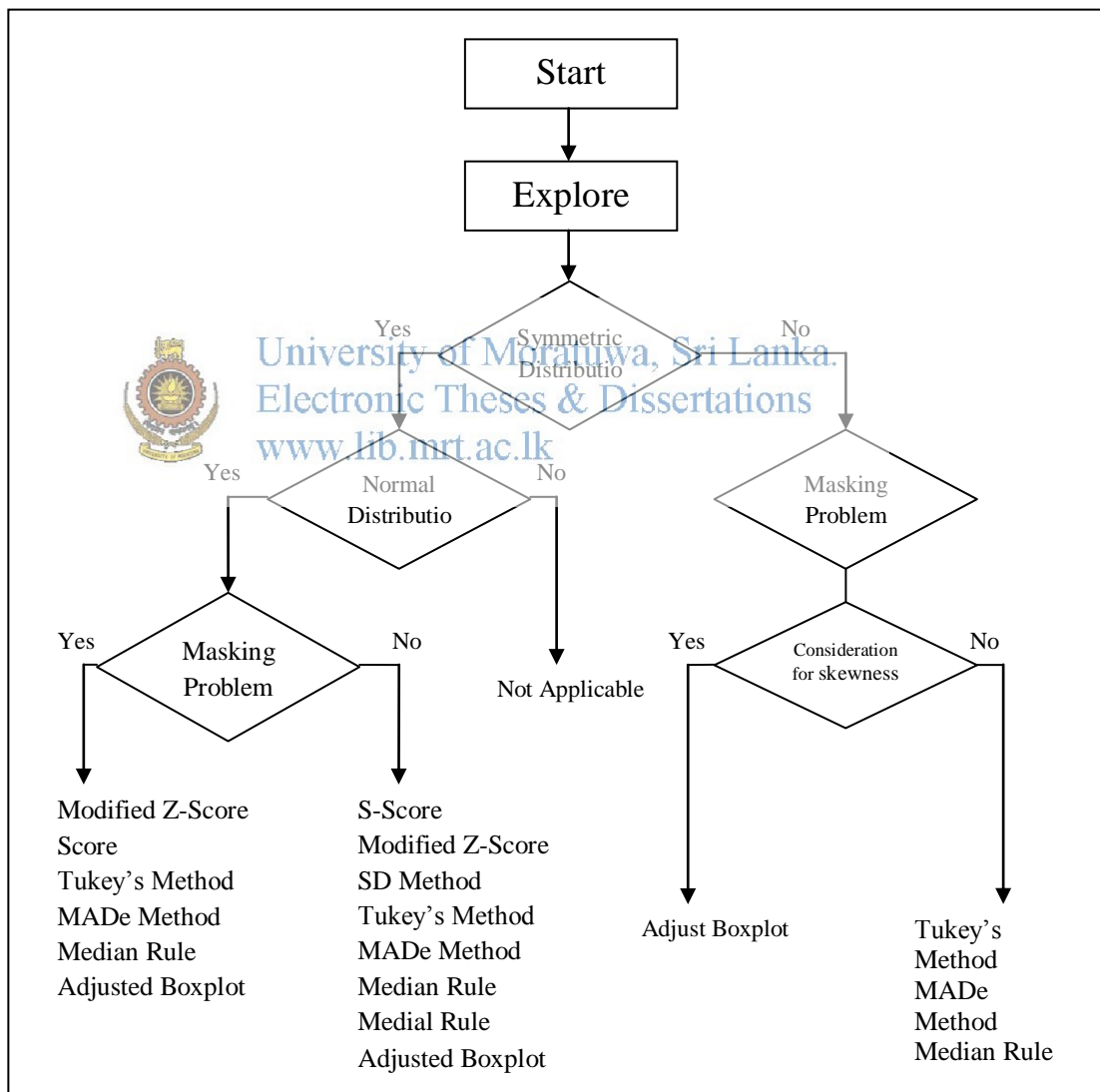


Figure 3.3: Outlier detecting methods

The basic idea of this rule is that if  $X$  follows a normal distribution,  $N(\mu, \sigma^2)$ , then  $Z$  follows a standard normal distribution,  $N(0, 1)$ , and  $Z$ -scores that exceed 3 in absolute value are generally considered as outliers. Limitation of this rule is that the standard deviation can be inflated by a few or even a single observation having an extreme value. Thus, it can cause a masking problem, i.e., the less extreme outliers go undetected because of the most extreme outlier(s), and vice versa. When masking occurs, the outliers may be neighbors. Hence this  $Z$  score method is modified as Modified  $Z$  Score and in here masking problem has been eliminated. Comprehensive explanation on Modified  $Z$  Score is attached in annexure 5. Modified  $Z$  Score method is coded (annexure 6) as a Matlab program and total kWh value of each days of a consumer are fed as a data sample in to Matlab program to detect outliers.

### 3.6 Average kVA Profile

As explained above, as summary, 30 numbers of kVA loading patterns (representing each day of month) can be obtained for a particular bulk consumer. One kVA loading pattern consists with 96 numbers of kVA values which were measured in each 15 minute intervals during 24-hours of a particular day. As our objective is finding the average kVA profile for a particular bulk consumer, kVA profiles corresponding to weekends (if not a working day) and holidays were removed. Then outlier detecting technique was used to remove outliers. Now considering remaining kVA loading patterns, average kVA loading pattern for a particular consumer can be obtained by obtaining average of those remaining kVA loading patterns. Above described steps have been illustrated in figure 3.4 to figure 3.7 as a graphical representation.

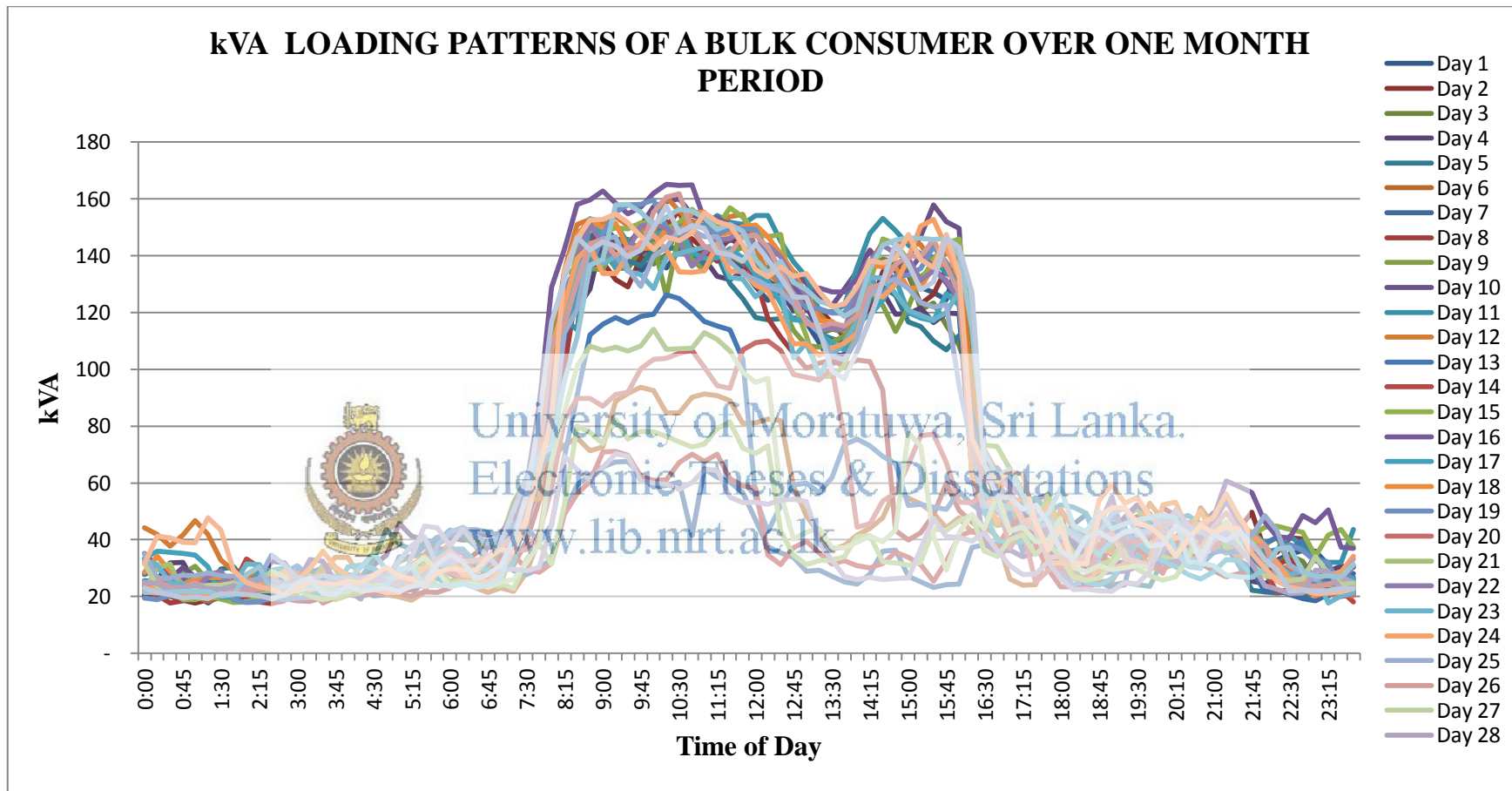


Figure 3 : kVA profiles of a bulk consumer over one month of period

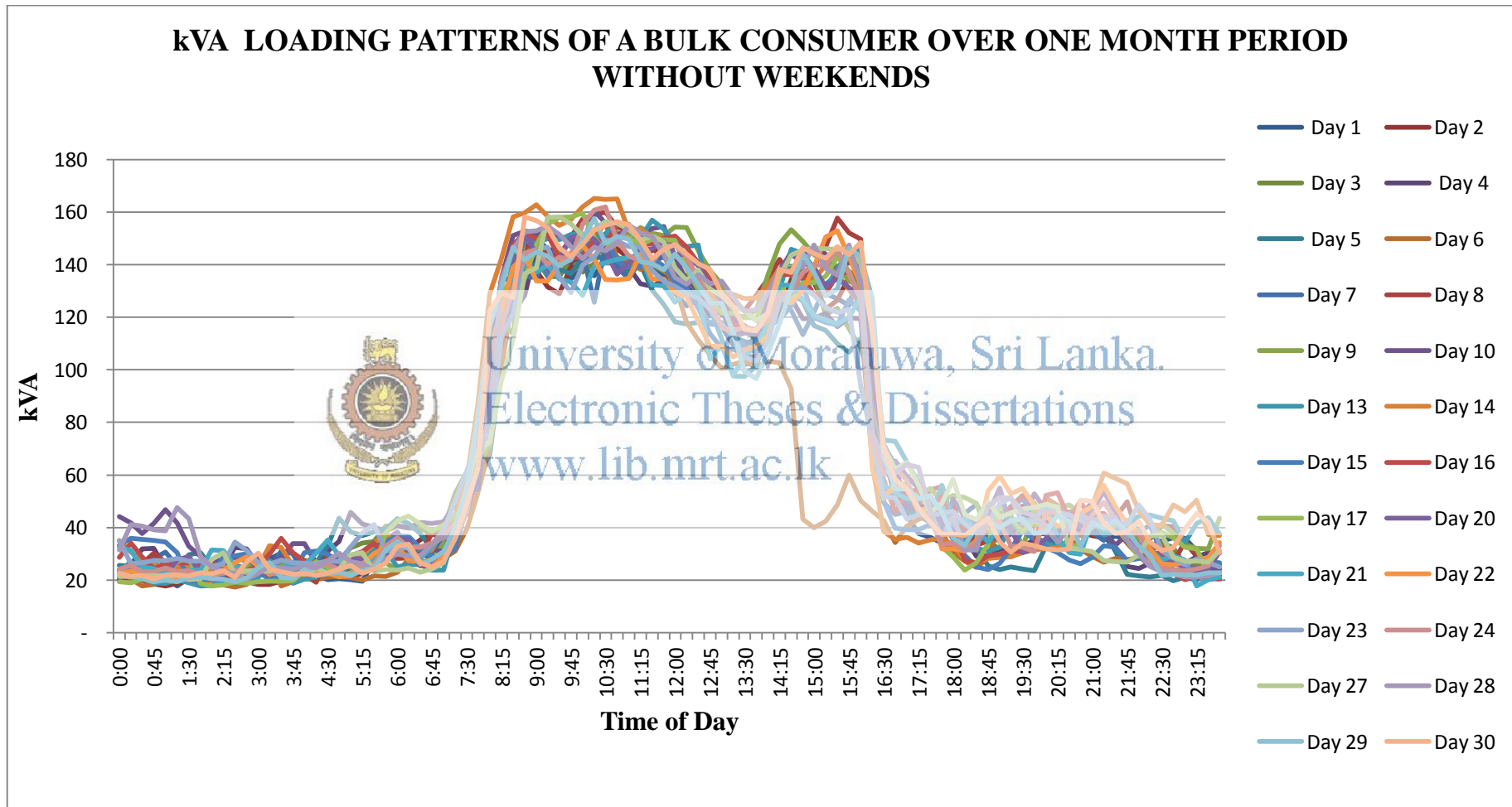


Figure 3.5: kVA profiles after removing weekend kVA profiles



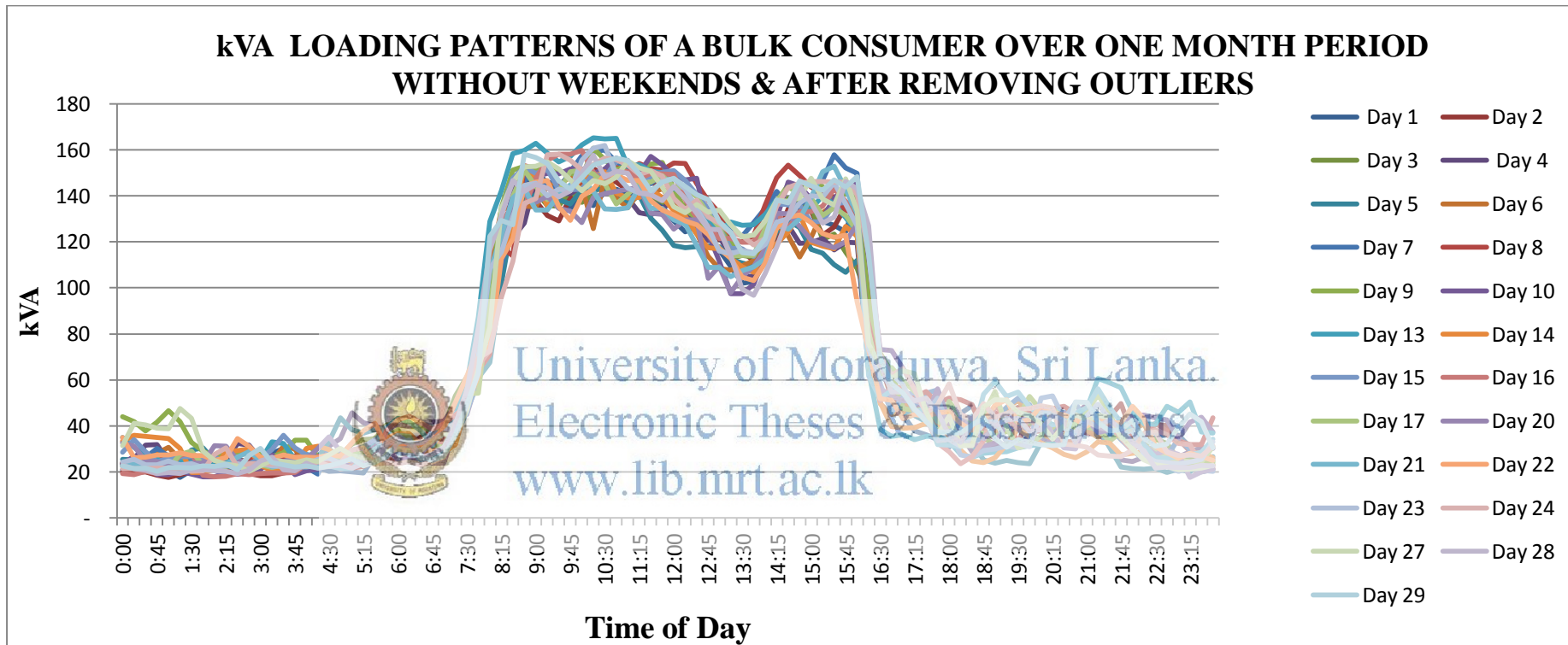


Figure 3.6: kva profiles without weekends & after removing outliers

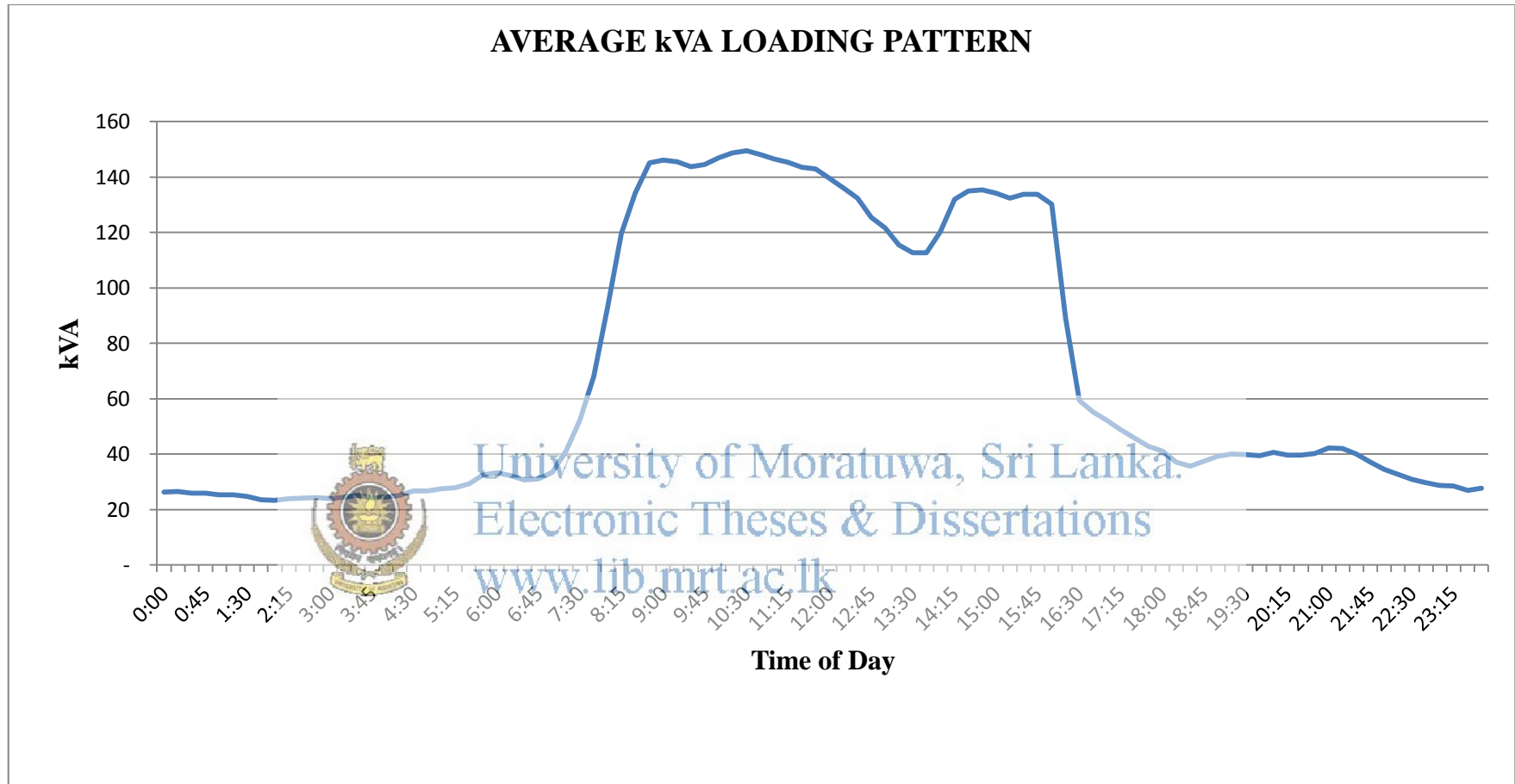


Figure 3.7 Average kVA loading pattern

## CHAPTER 4

### CLUSTERING

With the removal of weekends, holidays and further remaining outliers, now 404 numbers of kVA profiles are available for consumer/installation. Figure 3.6 illustrated in above is one such example which represents the daily kVA profiles of a bulk consumer over one month of period after removing weekends, holidays and outliers. Next step is finding average kVA profile for each consumer/installation. For this purpose, normal average of daily kVA load profiles can be used. Figure 3.7 shows one example for this. With this now 404 numbers of average kVA profiles belong of 404 numbers of installations/consumers are available. Those each average kVA profiles were normalized by dividing their maximum kVA values [1],[9]. Then 404 numbers of normalized average kVA profiles of bulk installations are available.

#### 4.1 Clustering Techniques

Next step is classify these normalized average kVA profiles in to classes where having similar patterns. For this pattern identification task, clustering algorithm has to be used. Classification using clustering methods forms groups of similar measured load profiles. In other words Cluster analysis is a term used to describe a family of statistical procedures specifically designed to discover classifications within complex data sets. Clustering methods can be divided, in general, into hierarchical, nonhierarchical, geometric, and others. The main purpose is to compare units that represent load profiles, and to gather them progressively in coherent groups in a way that the profiles in the same group are similar and the profiles in different groups are distinct. There are few such kinds of clustering algorithms are being used mostly in pattern identification.[10],[11],[12],[13]. They are

- Hierarchical clustering algorithm
- K means clustering algorithm
- Fuzzy K-means algorithm
- Follow the leader algorithm
- Fuzzy relation algorithm

Table 2.1: Pros and Cons of Clustering Methods

Clustering algorithm	Number of clusters is predetermined	Creates boundaries between data sets
Hierarchical clustering	No	Yes
K means clustering	Yes	Yes
Fuzzy K-means	Yes	No
Follow the leader	If necessary	Yes
Fuzzy relation	If necessary	No

Above table 4.1 shows the comparison of each algorithm [10]. One purpose of this research is to identify similar kVA profiles which belong to different consumers/installations and separate them in to unique groups. Hence at beginning, number of such groups has not known. Hence Hierarchical clustering is the most suitable method to cluster kVA loading patterns into classes in this research.

#### 4.2 Hierarchical Clustering

The main purpose is to compare load profiles, and to gather them progressively in coherent groups in a way that the profiles in the same group are similar and the profiles in different groups are distinct. This procedure can be carried out using the following steps. [1]

- Determination of dissimilarity between profiles

Normalized profiles are organized in a matrix in such a way that each row of matrix X is referred to as a particular consumer's load profile. Then a distance  $D(x_k, x_i)$  between pairs of profiles k and I is computed. For a data set S, made up of m profiles  $\frac{m(m-1)}{2}$  distances are computed.

- Grouping the units into hierarchical cluster tree

Distances generated in the first step are used to determine proximity of load profiles to each other. After that, they are gathered into the new cluster C. As objects are paired into binary clusters, the newly formed clusters are

grouped into larger clusters until a hierarchical tree is formed. In one clustering step, clusters  $C_i$  and  $C_j$  are gathered into new cluster  $C_k = C_i \cup C_j$ . After that, the distances  $d(C_k, C_l)$  to all other clusters are computed and clusters with the smallest distance are grouped together. The process is repeated until only one-cluster remains. In a data set  $S$ , made up of  $m$  load profiles,  $m-1$  steps are needed. The rate of the distortion of the classification represented in steps 2 and 3 is measured by Pearson's correlation coefficient  $r$ , which gives the relation between the distances  $D(x_k, x_l)$  and  $d(C_k, C_l)$ . The value of  $r$  is in the interval  $[0, 1]$ . The higher the value of  $r$ , the more coherent are the load profiles in the same cluster.

- Division of the hierarchical cluster tree into coherent groups

In this step, the hierarchical cluster tree is divided into coherent groups by cutting it at an arbitrary point. The final number of groups is determined by the maximum threshold value of the inconsistency coefficient. The higher the value of this coefficient less similar are the load profiles in the same cluster.

#### 4.3

#### Hierarchical Clustering in Matlab

Now 404 numbers of normalized average kVA profiles of bulk consumers/installations are available and need to cluster them with Hierarchical clustering (HC) method into groups. Originally measured kVA values and averaged normalized kVA values measured in each 15 minute interval of those consumers are available in an excel sheet of CD titled as "Averaged normalized kVA profiles of sample consumers". Above said Hierarchical clustering algorithm is inbuilt function of Matlab software. Annexure 7 has described how Hierarchical clustering algorithm is used in Matlab software with an example.

According to HC algorithm, 404 numbers of normalized averaged kVA profiles are loaded in to excel sheet as a matrix. It indicates as a matrix of 404 numbers of rows and 96 numbers of columns. In simple dimension of that matrix is  $404 \times 96$ . After executing HC in Matlab final received dendrogram is shown in figure 4.2.

Next step is to determine the cutting point of this dendrogram which determine the number of clusters of this set of kVA profiles.

#### 4.4 Determination of Number of Clusters

The accuracy of load profiles could be increased by increasing the number of customer classes. However, in practice, a compromise between the accuracy and number of customer classes has to be made. Here, the desired number of clusters was selected on the basis of the knee-point criterion [5], [14]. The knee-point criterion helps to find the optimal number of clusters. To choose the optimal number of clusters, first plot square sum of error (SSE) against number of clusters. Then you look for the "elbow" in the plot (knee point), and that is the number of clusters to be used as illustrated in figure 4.1.

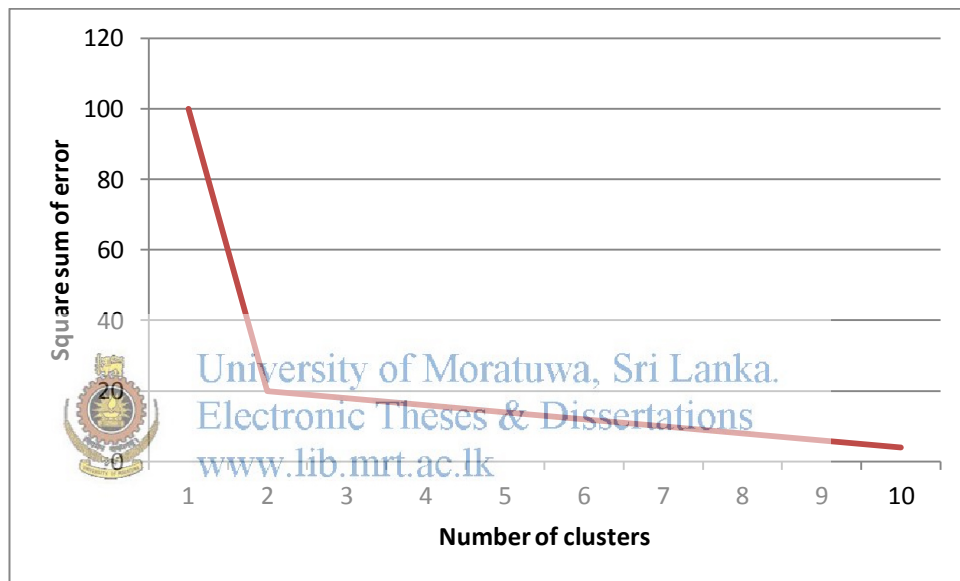


Figure 4.1: Knee point criterion

Given the number of clusters  $K$ , HC approximately minimizes the within-cluster square sum of errors (SSE).

$$SSE = \sum_{k=1}^K \sum_{C(i)=k} |X_i - \bar{X}_k|^2$$

Where  $\bar{X}_k$  is the average of points in group  $k$ ,  $\bar{X}_k = \frac{1}{n_k} \sum_{C(i)=k} X_i$

Calculated SSE values of clusters up to 100 numbers are tabulated in Table 4.2. To calculate SSE for each number of clusters a Matlab code is used and that code is attached in annexure 8.

Figure 4.3 shows how the square sum of errors (SSE) between the cluster centers and the measurements depends on the number of the clusters. In that graph, exact knee point/ elbow cannot be identified visually at a glance. To determine knee point/ elbow accurately, a Matlab “knee\_pt” function is used. The “knee\_pt” function operates by walking along the curve one bisection point at a time and fitting two lines, one to all the points to left of the bisection point and one to all the points to the right of the bisection point. The knee is judged to be at a bisection point which minimizes the sum of errors for the two fits. That specific “knee\_pt” matlab code is annexed in annexure 9. It gives the best knee point/ elbow at 17. It means that all 404 numbers of averaged normalized kVA profiles can be optimally divided into 17 clusters.



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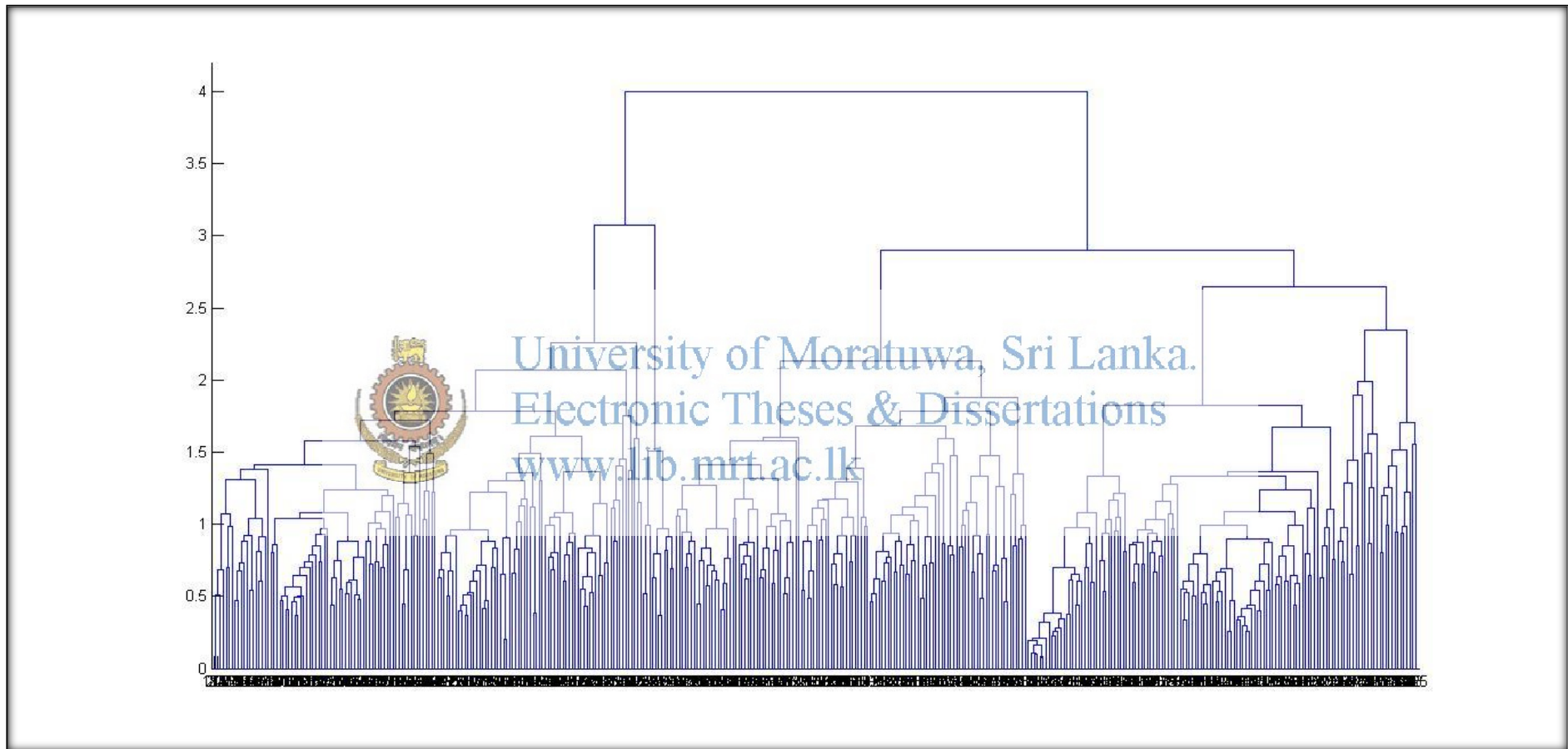


Figure 4.2: Dendrogram



Table 4.2: Calculated SSE of each clusters

Number of Clusters	SSE	Number of Clusters	SSE	Number of Clusters	SSE
2	1,112	35	266	68	164
3	1,034	36	265	69	163
4	702	37	264	70	160
5	613	38	261	71	159
6	591	39	259	72	158
7	582	40	247	73	157
8	513	41	240	74	156
9	498	42	238	75	155
10	490	43	236	76	154
11	488	44	234	77	153
12	478	45	232	78	152
13	429	46	232	79	151
14	411	47	225	80	148
15	366	48	224	81	148
16	363	49	221	82	147
17	356	50	219	83	146
18	354	51	218	84	144
19	334	52	216	85	143
20	324	53	206	86	142
21	323	54	204	87	141
22	304	55	197	88	139
23	302	56	193	89	139
24	301	57	188	90	136
25	296	58	187	91	136
26	294	59	183	92	134
27	286	60	182	93	134
28	285	61	181	94	133
29	283	62	179	95	132
30	280	63	175	96	131
31	276	64	174	97	130
32	275	65	173	98	129
33	273	66	172	99	129
34	271	67	167	100	124

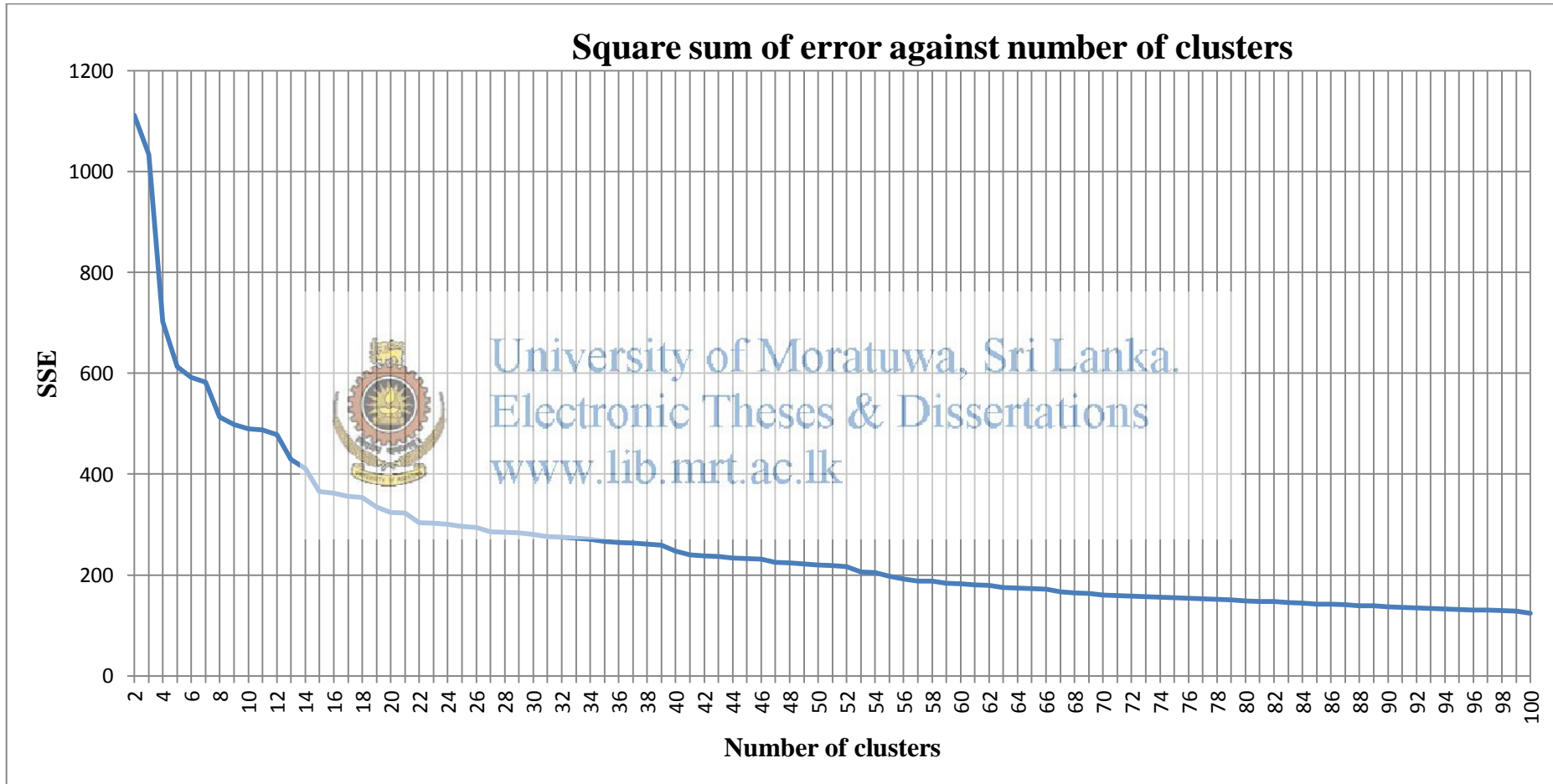


Figure 4.3: SSE against number of clusters

#### 4.5 Clusters and Common Averaged Normalized kVA profiles

Table 4.3: Number of kVA profiles belongs to each cluster

Cluster	Number of profiles	Cluster	Number of profiles
1	5	10	6
2	70	11	1
3	2	12	8
4	6	13	5
5	58	14	42
6	17	15	3
7	53	16	13
8	34	17	11
9	70		

Table 4.3 shows the number of kVA profiles belong to each cluster after clustering using HC algorithm. Cluster number 3, 11 and 15 are not rich clusters compare with others due to there is not an adequate number of kVA profiles in the selected sample. If the sample is increased more, then there are will be more matching kVA profiles for those clusters. But compare with those three, other clusters are very rich. As an example, cluster number 2 having 70 numbers of kVA profiles which follow almost same pattern. Figure 4.3 and figure 4.5 shows all kVA profiles which represent cluster number 2 and cluster 5 respectively along with their common averaged normalized profile which are represented in figure 4.4 and figure 4.6 respectively. Rests of the clusters and their average kVA profiles are attached in annexure 10. With this exercise 404 numbers of kVA profiles belong to single category electrical installations are clustered in to 17 distinct classes which represent different installation types. Such example installation related to each cluster is tabulated in table 4.4. With this, a database of Common Averaged Normalized kVA profiles can be compiled.

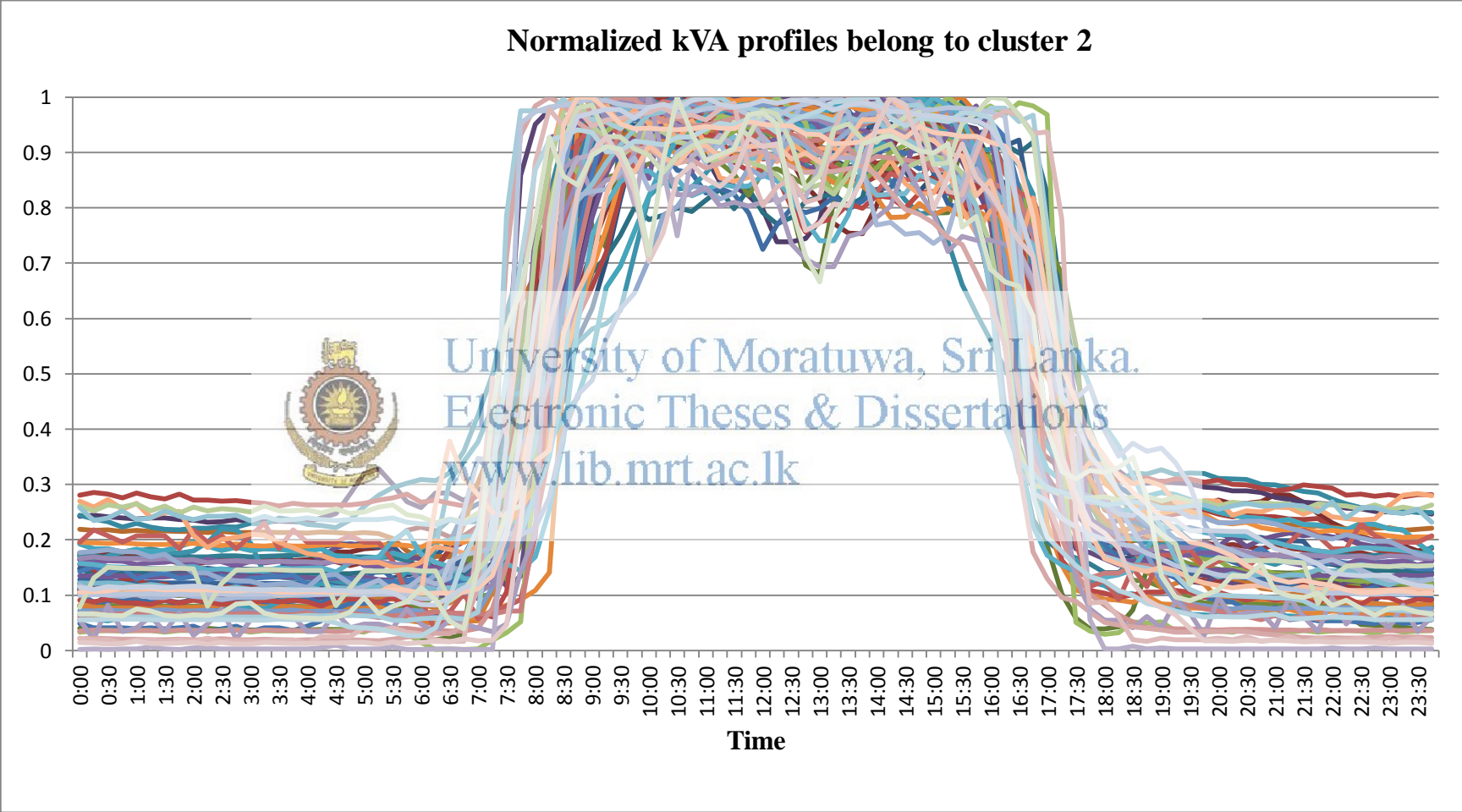


Figure 4.4: Normalized kVA profiles belong to cluster 2

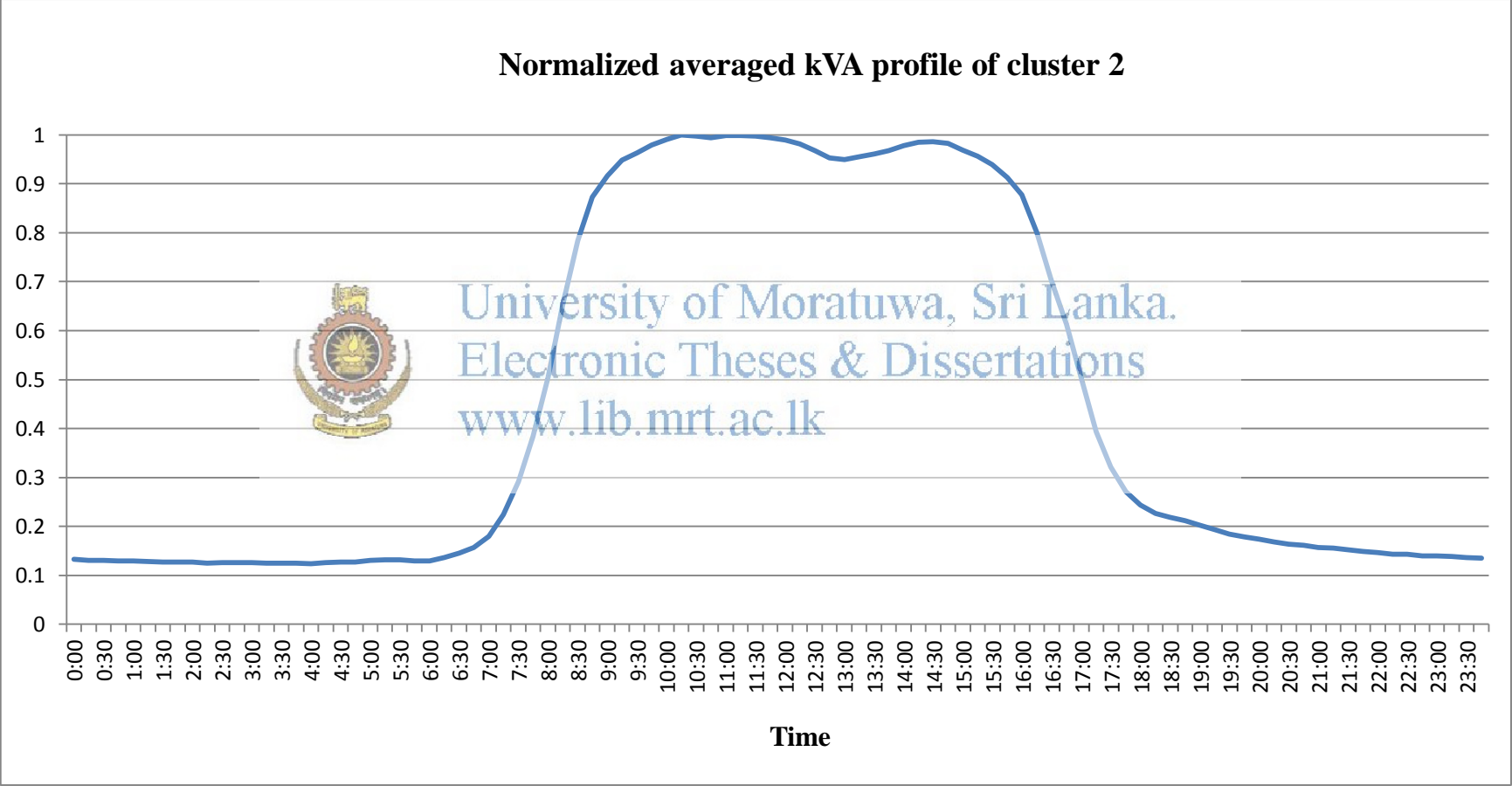


Figure 4.5 Normalized averaged kVA profile of cluster 2

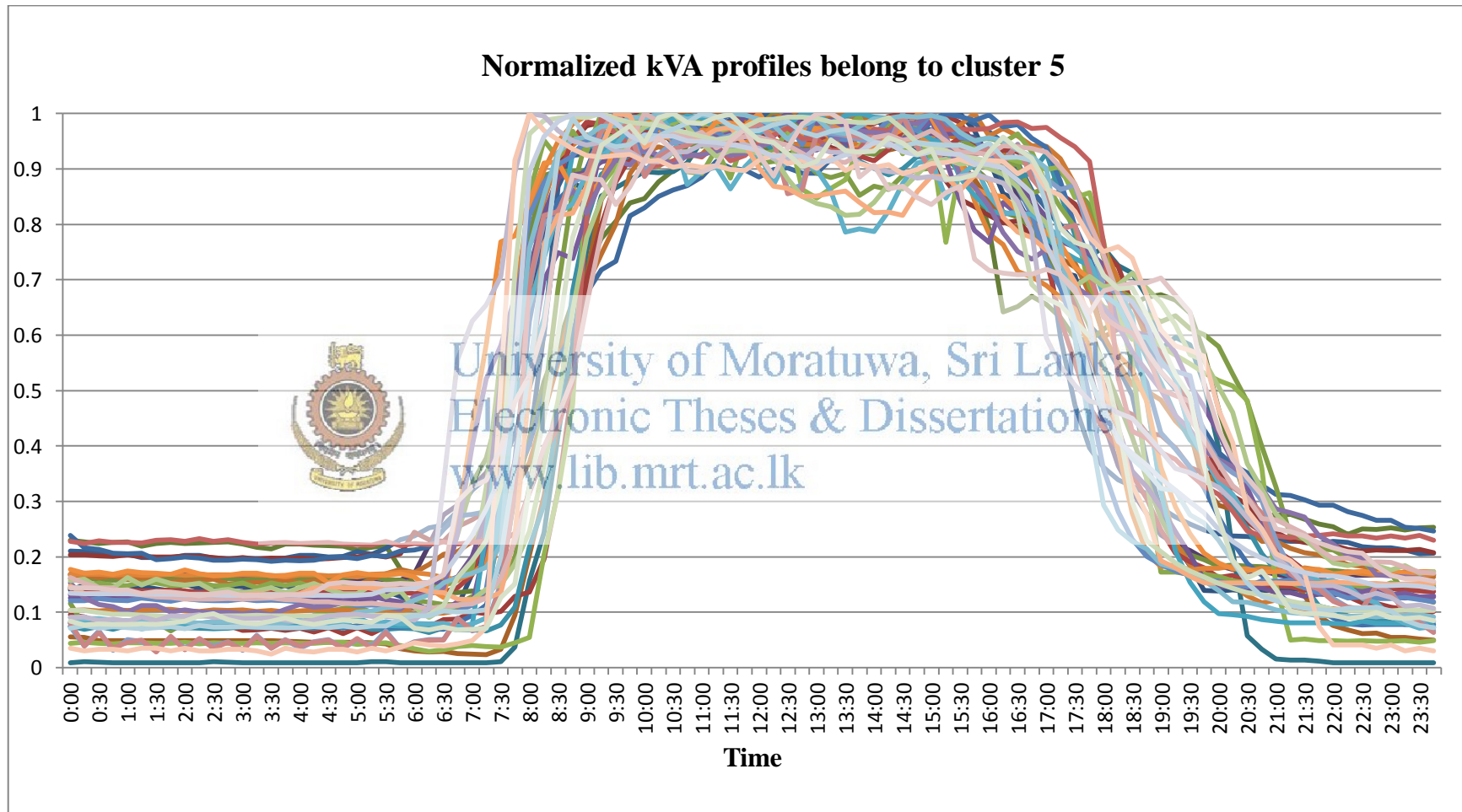


Figure 4.6: Normalized kVA profiles belong to cluster 5

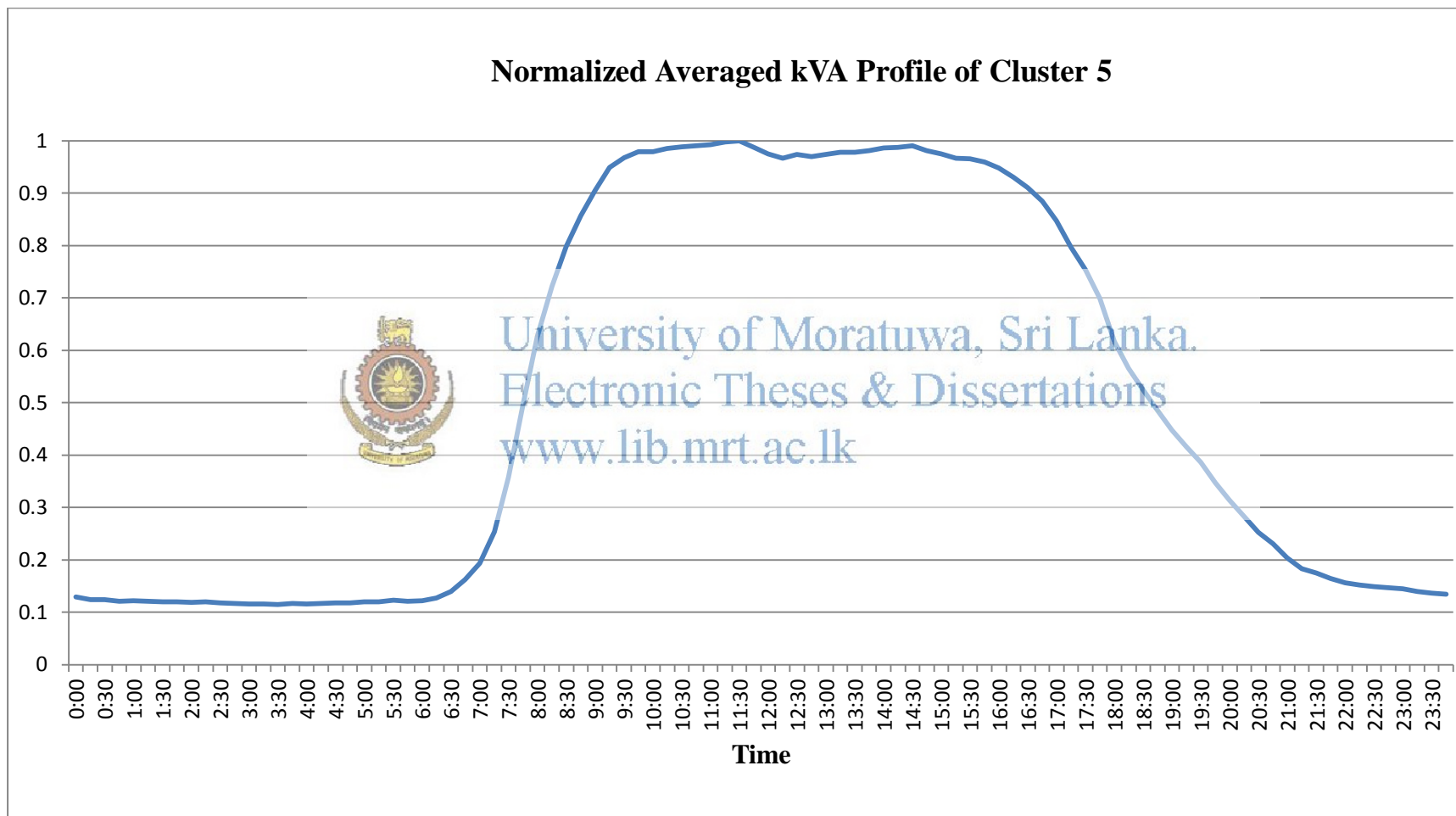


Figure 4.7: Normalized average kVA profile of cluster 5

Table 4.4: Example installations for each cluster

<b>Cluster</b>	<b>Example installations</b>
Cluster 1	No similar type consumers
Cluster 2	Government banks, Government offices, University faculty , Educational Institute type 1 , Embassy offices type 1, High commissioner's offices, Municipal Councils,
Cluster 3	Not a significant cluster
Cluster 4	Financial institute office, Fashion Outlets type 1,
Cluster 5	Private banks, Private company offices type 1, Insurance offices,
Cluster 6	Show rooms(shoes), Apartments
Cluster 7	Hospitals type 1, Embassy office type 2, Institute type 2, Private
Cluster 8	Utility service officers, Hotel type 1
Cluster 9	Hotels type 2, Hospitals
Cluster 10	No similar type consumers
Cluster 11	Not a significant cluster
Cluster 12	Hotels type 3
Cluster 13	Prisons,
Cluster 14	Super markets(consumer goods, electrical items), Food outlets, Fashion
Cluster 15	Not a significant cluster
Cluster 16	Railway Stations, Hotel type 4
Cluster 17	Fashion Outlets type 3, Private company office type 3,



## CHAPTER 5

### VERIFICATION

To verify the proposed methodology, a multi category type bulk installation was considered. This considered multi category electrical installation is a high rise building called BOC Merchant Tower with 19 stories located in Colombo 03. It contains several kinds of office premises and institutes which can be considered as multi categories. Maximum demand of each individual floor is calculated using normal engineering calculations. That information is tabulated in below table 5.1.

Table 5.1: Calculated maximum demand of each floor

Floor	Floor Detail		Calculated Maximum Demand/(kW)
	Organization / Load	Installation category	
Basement	Water pump, Fire Pump		47.520+27.5
Ground	MBSL	Private Bank	33
1st floor	BOC	Government Bank	38.5
	MBSL	Private Bank	31.9
2nd floor	BOC	Government Bank	77
3rd floor	Parking/Maintenance office		12
4th floor	Parking/Chiller/Chill pumps		107.49
5th floor	Parking		5.5
6th floor	PUCSL	Government office	36.3
7th floor	CESTA	Private office	52.8
	WATAWALA	Private office	42.9
8th floor	MBSL	Private Bank	35.2
	BOC	Government Bank	41.8
	INTERGRATED	Private office	27.5
9th floor	SLIIT	INSTITUTE	68.2
10th floor	MCSL	FINANCE/INSURANCE	28.6
11th floor	MCSL	FINANCE/INSURANCE	60.5
12th floor	SLIIT	INSTITUTE	69.3
13th floor	SLIIT	INSTITUTE	60.5
14th floor	MCSL	FINANCE/INSURANCE	52.8
15th floor	SLIIT	INSTITUTE	66
16th floor	SLIIT	INSTITUTE	60.5
17th floor	American Insurance	FINANCE/INSURANCE	44
18th floor	MBSL	Private Bank	58.3
19th floor	Air force Unit	Other	5.5
	Cooling Towers, Lift Rooms		125
Common Area			8
Floor wise AHUs			28.5

## 5.1 Additional Information

There is few additional information and assumptions have been considered in calculation process and those are listed out below.

- Chiller operating time 8:00AM to 5:00 PM. But chiller is not considered in this calculation as air conditioning is inbuilt in average normalized kVA profiles
- Water pumps are operating throughout 6:00 AM to 8:00PM (20 kW) and stop when water is filled into tanks. As no information is available on their loading pattern only half of full load is considered.
- There are two lifts (30kW each) which are used to bring passenger vehicles from basement to floor 3,4 and 5 for parking purpose. Peak time for this car lifts are from 7:30AM to 9:00 AM in the morning and in the evening it is 4:30PM to 5:15PM. As no proper trace is available with these car lift's operation in other times, it is ignored for this calculation
- There are four passenger lifts (26kW each) and one service lift available. Peak times for passengers' lifts are from 7:00AM to 9:00 AM in the morning, 12:00NOON to 1:00 PM and in the evening it is 4:00PM to 5:00PM. As no trace is available assume one lift is in operation in other times. Hence assume one lift is in operation all the time except peak times.
- As no proper trace is available with service lift, it is ignored for this calculation. But it has a considerable amount of contribution for the loading pattern as it is used as a normal passenger lift when availability of existing passenger lifts are less in the morning time
- Two escalators are used in ground floor. It is operated from 8:00AM to 3:00PM. It is 19kW
- Common area lighting of all floors is 8kW
- Power factor is considered as 0.9 for calculation

## 5.2 Determination of kVA Profile based on Proposed Methodology

According to table 5.1 it can be identified that similar type of electrical installations are available. By adding maximum demand of those similar types of installations together, ultimate multiplication factor can be found as tabulated below table 5.2.

Table 5.2: Multiplication factor for each category

Normalized Average kVA pattern	Multiply factor
Private Bank	158
Government Bank	151
Government office	36
Private office	123
Institute	325
Finance/Insurance	133

Then final equation to determine entire kVA profile of BOC merchant tower according to proposed methodology would be =

$$\left( \text{Normalized Averaged common kVA profile of (private bank x 158 + government bank x 151 + government office x 36 + private office x 123 + Insurance/finance company x 133 + institute type 2 x 325) + additional load} \right)$$

Detailed calculation of this is attached in annexure 11.

## 5.3 Estimated and Actual kVA Profile

Based on above calculations estimated and actual kVA profile is plotted as follow in figure 28. Actual kVA profile is obtained from Ceylon Electricity Board. It is also obtained for a period of one month and same preprocess which was described in early chapters was applied to obtain average kVA profile. And actual one and estimated one plotted together to compare as figure 28 shows.

#### 5.4 Observation

- When comparing estimated kVA profile which was generated through proposed methodology and actual kVA profile of BOC merchant tower, it can be said that the estimated kVA profile follows the same pattern similar to actual one.
- In actual kVA profile, it can be observed that a considerable amount of base load is available throughout the off day time and the peak is taken place in the morning. Then the peak decrease gradually in small amount till the evening and then it decreased rapidly till its base load within two hours of time period. And same behavioral pattern can be observed from the estimated kVA profile which is generated through proposed methodology. Hence it nearly shows the time at which peak demand is taken place.
- When considering the maximum demand point of view, proposed one is not exactly same with the actual one. Actual peak is 1400 kVA and peak demand shown by the proposed methodology is 1250 kVA. There are few loads (water pumps, service lift) which were not considered for this calculation of proposed one due to non availability of their loading details properly. Mainly that is the reason for this difference of 150 kVA.



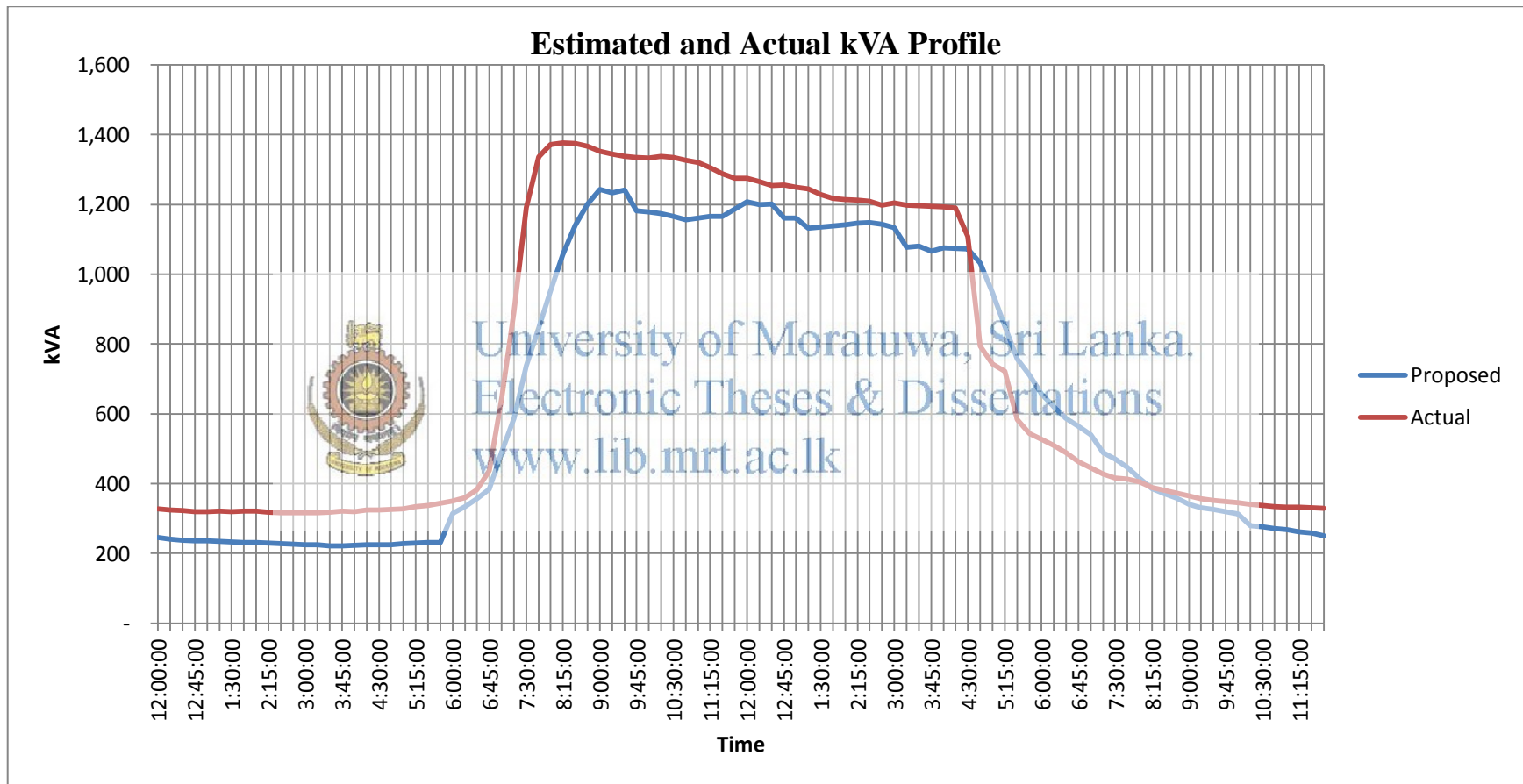


Figure 5.1: Estimated and actual kVA profile

## CHAPTER 6

### DISCUSSION

Above verification proves that proposed methodology is an acceptable methodology to determine the maximum demand of the bulk electrical installations. The most important component of this proposed methodology is the averaged normalized common kVA profile database. Higher the diversity of the database means higher the accuracy of the methodology. On the other hand, database of higher diversity shall have unique averaged normalized common kVA profile to represent any kind of bulk electrical installation.

To build up this proposed methodology, all bulk installations of the country were considered as one population and sample size was determined accordingly. Out of that selected sample, seventeen numbers of unique, distinguished kVA profile clusters were generated by the used clustering algorithm (Hierarchical clustering). Then the sample kVA profiles were divided into each corresponding clusters and example bulk installations were identified for each cluster.

Bulk electrical installations can be categorized into various types based on their operation. Banks, Super markets, Fashion outlets, offices are such examples. Diversity of this averaged normalized common kVA profiles database can be improved in great extent by considering samples of various bulk installation types separately for clustering. Then averaged normalized common kVA profile databases can be generated separately for each type of bulk installations. As an example, consider only the bulk electrical installations of banks in the country. By considering all banks (bulk installations) in the country as one population, a sample of kVA profiles can be obtained. That sample can be used for clustering. Then at the end, an averaged normalized common kVA profile database is available specifically for bank sector in the country. In that database, there may be clusters which represent bank branches, bank super branches, bank head offices, bank regional offices, ATM less bank branches, etc. Similarly databases for other types of bulk installations can be

compiled. With that the diversity of the database can be improved which leads to improve the accuracy of this proposed methodology.

KVA profiles of this research study were obtained from meter laboratories of distribution licensees. Only 404 numbers of kVA profiles out of 500 were qualified to be used for clustering and rest of kVA profiles were removed at the preprocessing stage. Main reason for this is availability of missing data or error data of those kVA profiles due to communication error. Presence of communication error (missing data/error data) cannot be observed or detected at their downloading process. As considerable numbers of steps have to be followed to extract kVA data of a consumer from downloaded file, presence of communication error can only be found at stage just before the preprocessing. As adequate sample size is available for the study, re downloading of those kVA profile (kVA profiles with communication error) didn't execute.

KVA profiles of bulk consumers were provided by distribution licensees for the request made as a requirement of this research. Even though the request was made to obtain kVA profiles of bulk consumers belonged to particular one month, the requirement was not fulfilled as requested due to various practical difficulties. All five distribution licensees gave kVA profiles which were belonged to various months of the year. That may have a slight effect for final outcome. Depending on the temperature variations, air conditional loads also vary. Air condition load contributes a significant kVA amount for load profile. Hence for a considering two consumers, who are having approximately same parameters but kVA profiles belonged into different months, may have slightly different load profiles. That difference may cause to cluster those two consumers into two separate clusters even though both of them having same loading parameters. As Sri Lanka doesn't have adverse climatic changes like in other countries, this difference month scenario was neglected.

To determine the kVA profile a multi category bulk electrical installation, each averaged normalized common kVA profile has to be multiplied by their corresponding maximum demand values. This maximum demand calculation is done by conventional methods as described in table 1.1. Accuracy of this calculation is

directly caused for the accuracy of the proposed methodology. As diversity factors listed in table 1.1 are not very much accurate, this calculation part should be done by an experienced engineer to ensure the maximum demand of each sub installation is done very accurately. Inaccuracy of that calculation may also be one reason for having a difference between actual kVA profile and estimated kVA profile of above verification example. In addition to that, there may be some special loads which have to be added separately (indicated as “additional load”) in multi category electrical installations. Service lift, water pump, escalator and passenger lifts are few of them in associated with above verification example. Those special loads were not represented in kVA profiles of averaged normalized common kVA profile database which is generated through a sample of single category bulk installations. That is the reason to add them as additional loads. But data related to those loads such as loading patterns of them, is not available in great detail is another huge issue which leads to make this proposed methodology less accuracy. Due to lack of data, some assumptions had to be made in those calculations and that may also be another reason for having a difference between actual kVA profile and estimated kVA profile of above verification example. Hence proper analysis has to be done separately which elaborate how to use those additional data in a very accurate manner.



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Hierarchical clustering algorithm plays a vital role in this proposed methodology. There are few disadvantages associated with this hierarchical clustering algorithm (when compare with other algorithms) as listed below

- No provision can be made for a relocation of objects that may have been “incorrectly” grouped at an early stage. The result should be examined closely to ensure it makes sense.
- Use of different distance metrics for measuring distances between clusters may generate different results. Need to perform multiple experiments and comparing the results is required to find most suitable distance matrices
- Difficult to identify the correct number of clusters by the dendogram. Hence need to use knee point/L bow point method to find it. Sometimes it also may be difficult and in such a case Matlab has to be used to determine the knee point..



Even though there are many clustering algorithms available with advance features, hierarchical clustering algorithm is the only method which can be used for this proposed algorithm due to number of clusters is unknown at initial stage.

KVA profile clustering can be used in greater extent in number of disciplines as described below. kVA profile and clustering of consumers can be used to obtain demand patterns of consumers. Those demand patterns will be an infrastructure for analyzing actual load behaviors on demand side, tariff design, load forecasting, load management, substation peak load estimation and system peak management. Sometimes these load forecasting may be short term, but still requirement of kVA profile pattern for them is essential. Load modeling is useful for the long term planning of power distribution systems, economic analysis and operation and planning of distribution systems. kVA profile is essential tool for such kind of analysis work. Further, to determine many factors like diversity factors, simultaneous factors, loading factors which need in electrical demand calculations, the contribution of kVA profiles clustering is very essential.



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## CHAPTER 7

### CONCLUSIONS

- This research was done to propose a methodology to determine the maximum demand of multi category bulk electrical installations.
- According to the proposed methodology to determine the maximum demand of a multi category bulk electrical installation, initially a database of averaged normalized common KVA profiles, which represent each installation category has to be compiled considering a sample of existing single category bulk installations. Then identify the each installation category of the multi category installation of which the maximum demand is going to be determined. Next find the appropriate well matching averaged normalized common kVA profile for each category from above said database. After that multiply those averaged normalized common kVA profiles of each category by their calculated individual maximum demand and add them up together to find the kVA profile of entire installation which gives the expected pattern of that multi category bulk electrical installation. Then the value of maximum demand and time at which this maximum demand occurs can be determined.
- 500 numbers of kVA profiles of single category bulk electrical installations were selected as the sample and seventeen number of kVA profile patterns/clusters were generated by using hierarchical clustering algorithm. Then the averaged normalized common kVA profiles which represent each profile patterns/clusters were generated as the database.
- Proposed methodology was verified by using a multi category bulk electrical installation. With that it can be concluded that, this proposed methodology to determine the maximum demand of multi category bulk installation can be considered as an acceptable one. But further improvement is needed for this proposed methodology to meet the expected results.

## CHAPTER 8


### FUTURE WORK

- This proposed methodology to determine the maximum demand of multi category bulk installation can be further developed by improving the density of the averaged normalized common kVA profile database. For that, other than considering entire bulk installations as one population, bulk installations of each category can be sampled and clustered as separate populations. By doing so, the availability of best suit averaged normalized common kVA profile for any behavioral (loading pattern) requirement will be increased.
- The existing technology of communication system and infrastructure system associated with meter laboratories of distribution licensees shall be improved, so then it allows downloading error free kVA profiles in a very efficient way.
- The distribution licensee shall implement a meter laboratory based dynamically updating and recording data base system of kVA profiles of their consumers. Which enables the path for plentiful of studies like demand forecasting, demand side management, load management, tariff design, distribution peak estimation, consumer behavior identification, etc. for utilities. Other than utility, that data will provide best statistics for researchers and regulators as well.
- Further, distribution licensees shall introduce digital energy meters/smart meters (which having data recording facility) for their non bulk consumers. With that another (or same) database of averaged normalized common kVA profile can be developed (improved). With that, this proposed methodology can be applied for multi category electrical installations which include non bulk consumers and distribution purpose transformers also.

## REFERENCES


- [1] Gerbec, D. ; Gasperic, S. ; Smon, I. ; Gubina, F.,”A methodology to classify distribution load profiles”, Transmission and Distribution Conference and Exhibition 2002: Asia Pacific. IEEE/PES, Page(s): 848 - 851 vol.2,2002
- [2] Gerbec, D. ; Gasperic, S. ; Gubina, F.,” Determination and allocation of typical load profiles to the eligible consumers”, Power Tech Conference Proceedings, 2003 IEEE Bologna, Volume:1, 2003
- [3] Gerbec, D. ; Gasperic, S. ; Smon, I. ; Gubina, F.,” Determining the load profiles of consumers based on fuzzy logic and probability neural networks”, Generation, Transmission and Distribution, IEE Proceedings-Volume:151,Issue: 3, Page(s): 395 - 400,2004
- [4] In Hyeob Yu ; Jin Ki Lee ; Jong Min Ko ; Sun Ic Kim ,” A method for classification of electricity demands using load profile data “Computer and Information Science, 2005. Fourth Annual ACIS International Conference on ,Page(s): 164 - 168, 2005
- [5] Mutanen, A. ; Ruska, M. ; Repo, S. ; Jarventausta, P. ,”Customer Classification and Load Profiling Method for Distribution Systems”,Power Delivery, IEEE Transactions on Volume: 26, Issue: 3, Page(s): 1755 - 1763, 2011
- [6] Gerbec, D. ; Gasperic, S. ; Smon, I. ; Gubina, F. ,”An approach to customers daily load profile determination”,Power Engineering Society Summer Meeting, 2002 IEEE Volume:I, Page(s): 587 - 591 vol.1 ,2001
- [7] Seo, Songwon,” A Review and Comparison of Methods for Detecting Outliers in Univariate Data Sets”, Master’s Thesis, University of Pittsburgh,2002
- [8] Ahmad, Arfah ; Azmira, I. ; Ahmad, S. ; Apandi, Nur Ilyana Anwar ,”Statistical distributions of load profiling data”,Power Engineering and Optimization Conference (PEDCO) Melaka, Malaysia, 2012 IEEE International,Page(s): 199- 203,2012
- [9] Gerbec, D. ; Gasperic, S. ; Smon, I. ; Gubina, F.,”Consumers” load profile determination based on different classification methods”, Power Engineering Society General Meeting, 2003, IEEE Volume:2,2003
- [10] Prahastono, I. ; King, D. ; Ozveren, C.S. ,”A review of Electricity Load Profile Classification methods”,Universities Power Engineering Conference, 2007. UPEC 2007. 42nd International ,Page(s): 1187- 1191,2007

- [11] G. J. TSEKOURAS<sup>1</sup>, F.D. KANELLOS<sup>1</sup>, V.T. KONTARGYRI<sup>1</sup>, E.S. KARANASIOU<sup>1</sup>, A.D. SALIS<sup>1</sup>, N. E. MASTORAKIS, "Power System Typical Load Profiles Using A New Pattern Recognition Methodology", 12th WSEAS International Conference on CIRCUITS, Heraklion, Greece, July 22-24, 2008
- [12] Chicco, G. ; Napoli, Roberto ; Piglionne, Federico , "Application of clustering algorithms and self organising maps to classify electricity customers", Power Tech Conference Proceedings, 2003 IEEE Bologna , Volume:1,2003
- [13] Elena C. BOBRIC, Gheorghe CARTINA, "Clustering Techniques in Load Profile Analysis for Distribution Stations", Advances in Electrical and Computer Engineering, Volume 9 , Number 1, 2009
- [14] Cliff Walton, Sarah Carter , "S E C O N D A R Y S U B S T A T I O N L O A D P R O F I L I N G – I D E N T I F I C A T I O N A N D V I S U A L I S A T I O N O F C H A N G E S S" , 22nd International Conference on Electricity Distribution Stockholm, 10-13 June 2013
- [15] Prahastono, I. ; King, D.J. ; Ozveren, C.S. ; Bradley, D., "Electricity load profile classification using Fuzzy C-Means method" , Universities Power Engineering Conference, 2008. UPEC 2008. 43rd International , Page(s): 1- 5 , 2008
- [16] Yen-Ting Chao, Sheng-Ta Lee, Hong-Chan Chang, "An improvement project for distribution transformer load management in Taiwan", Power Engineering Society General Meeting, 2003, IEEE , Volume:1,2003
- [17] Nazarko, J. ; Styczynski, Z.A. , "Application of statistical and neural approaches to the daily load profiles modelling in power distribution systems", Transmission and Distribution Conference, 1999 IEEE , Volume:1, Page(s): 320 - 325 vol.1 , 1999
- [18] Ching-Lai Hor ; Watson, S.J. ; Majithia, S., "Daily Load Forecasting and Maximum Demand Estimation using ARIMA and GARCH" , Probabilistic Methods Applied to Power Systems, 2006. PMAPS 2006. International Conference on, Page(s): 1- 6 , 2006
- [19] David E. Claridge, Ph.D., "Electricity Diversity Profiles for Energy Simulation of Office Buildings"
- [20] Queiroz, L.M.O. ; Roselli, M.A. ; Cavellucci, C. ; Lyra, C. , "Energy Losses Estimation in Power Distribution Systems", Power Systems, IEEE Transactions on , Volume: 27, Issue: 4, Page(s): 1879- 1887 , 2012

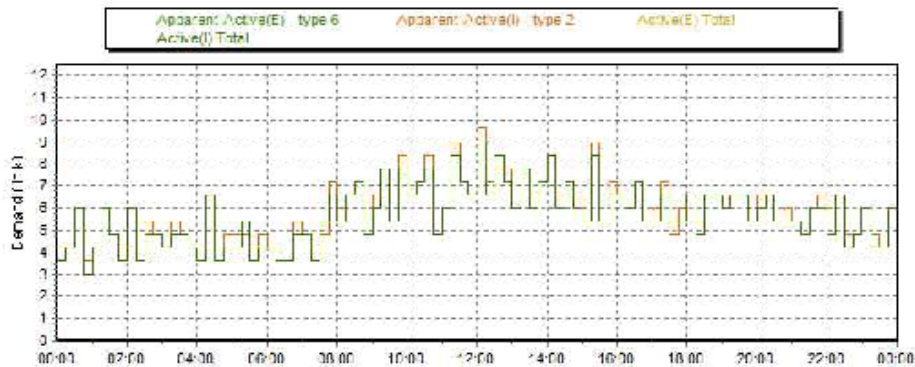
- [21] Broadwater, R.P. ; Sargent, A. ; Yarali, A. ; Shaalan, H.E. ; Nazarko, J. , "Estimating substation peaks from load research data", Power Delivery, IEEE Transactions on , Volume: 12, Issue: 1, Page(s): 451- 456 ,1997
- [22] Karmacharya, S. ; Putrus, G. ; Underwood, C. ; Mahkamov, K., "Evaluation of domestic electrical demand and its effect on low voltage network", Universities Power Engineering Conference (UPEC), 2012 47th International, Page(s): 1- 4,2012
- [23] Clifford A. Cathers, Gary D. Thompson, "Forecasting Short-Term Electricity Load Profiles", 2006
- [24] Ihab, A.M. ; Rajamani, H.S. ; Abd-Alhameed, R.A. ; Jalboub, M.K. , "Statistical predictions of electric load profiles in the UK domestic buildings", Energy, Power and Control (EPC-IQ), 2010 1st International Conference on , Page(s): 345- 350,2010
- [25] "MATLAB Language Reference Manual", Volume 5[online], available: [http://ub.cbm.uam.es/publications/teaching/master\\_biofisica\\_2011\\_2012/MATLAB\\_REFBOOK.pdf](http://ub.cbm.uam.es/publications/teaching/master_biofisica_2011_2012/MATLAB_REFBOOK.pdf)
- [26] "Learning Matlab 7", Matlab and Simulink Student Version[online], Available:
- [27]  [www.lib.mrt.ac.lk](http://www.lib.mrt.ac.lk) [http://www.mathworks.com/academia/student\\_versions/matlab\\_sp3.pdf](http://www.mathworks.com/academia/student_versions/matlab_sp3.pdf)
- [28] "Excel VBA - Reference Guide"[online], available : <http://www.excel-spreadsheet.com/vba/vba.htm>
- [29] Eran Eden, Weizmann, " Introduction to Matlab & Data Analysis"[online], available: <http://www.weizmann.ac.il/midrasha/courses/MatlabIntro/>
- [30] Xiaoli Li ; Bowers, C.P. ; Schnier, T., "Classification of Energy Consumption in Buildings With Outlier Detection", Industrial Electronics, IEEE Transactions on , Volume: 57, Issue: 11, Page(s): 3639- 3644,2010
- [31] Manoj K, Senthamarai Kannan K, "Comparison of methods for detecting outliers", International Journal of Scientific & Engineering Research, Volume 4, Issue 9, September-2013

# ANNEXURE 1

## SAMPLE PDF FORMAT OF DATA DOWNLOADED FROM BULK METERS

	<b>09102793 - Load Survey</b>	EMF (Applied)		
	Source: 091027932013100120131031.emd	Voltage	Current	Energy
	Read on: 08/10/2013 11:06:46 AM	1.00	1.00	1.00

**08/09/2013 : Demand**



Param 1 : Apparent-Active(E) - type 6


Param 2 : Apparent-Active(I) - type 2

Param 3 : Active(E) Total

Param 4 : Active(I) Total

Interval	Param 1 (kVA)	Param 2 (kVA)	Param 3 (kW)	Param 4 (kW)
00:00-00:15	0.00	1.00	0.00	0.00
00:15-00:30	0.00	1.00	0.00	0.00
00:30-00:45	0.00	6.00	0.00	6.00
00:45-01:00	0.00	3.60	0.00	3.60
01:00-01:15	0.00	4.20	0.00	4.20
01:15-01:30	0.00	6.00	0.00	6.00
01:30-01:45	0.00	4.80	0.00	4.80
01:45-02:00	0.00	4.20	0.00	4.20
02:00-02:15	0.00	6.00	0.00	6.00
02:15-02:30	0.00	3.60	0.00	3.60
02:30-02:45	0.00	5.40	0.00	4.80
02:45-03:00	0.00	4.80	0.00	4.80
03:00-03:15	0.00	4.20	0.00	4.20
03:15-03:30	0.00	5.40	0.00	4.80
03:30-03:45	0.00	4.80	0.00	4.80
03:45-04:00	0.00	4.20	0.00	4.20
04:00-04:15	0.00	4.20	0.00	3.60
04:15-04:30	0.00	6.60	0.00	6.60
04:30-04:45	0.00	3.60	0.00	3.60
04:45-05:00	0.00	4.80	0.00	4.20
05:00-05:15	0.00	4.80	0.00	4.20
05:15-05:30	0.00	4.80	0.00	5.40
05:30-05:45	0.00	4.20	0.00	3.60
05:45-06:00	0.00	4.80	0.00	4.20
06:00-06:15	0.00	4.20	0.00	4.20
06:15-06:30	0.00	3.60	0.00	3.60
06:30-06:45	0.00	3.60	0.00	3.60
06:45-07:00	0.00	5.40	0.00	4.80
07:00-07:15	0.00	4.80	0.00	4.80
07:15-07:30	0.00	4.20	0.00	3.60
07:30-07:45	0.00	4.80	0.00	5.40
07:45-08:00	0.00	7.20	0.00	6.60
08:00-08:15	0.00	6.00	0.00	5.40
08:15-08:30	0.00	6.60	0.00	6.60
08:30-08:45	0.00	7.20	0.00	7.20
08:45-09:00	0.00	4.80	0.00	4.80
09:00-09:15	0.00	6.60	0.00	6.00
09:15-09:30	0.00	7.80	0.00	7.80
09:30-09:45	0.00	5.40	0.00	5.40
09:45-10:00	0.00	8.40	0.00	7.80
10:00-10:15	0.00	6.60	0.00	6.60
10:15-10:30	0.00	7.20	0.00	7.20

# ANNEXURE 1

		<b>09102793 - Load Survey</b>			EHF (Applied)		
		Source: 091027932013100120131031.amd			Voltage	Current	Energy
Read on: 08/10/2013 11:06:46 AM				1.00	1.00	1.00	
10:30-10:45	0.00	8.40	0.00	7.80			
10:45-11:00	0.00	4.80	0.00	4.80			
11:00-11:15	0.00	6.00	0.00	6.00			
11:15-11:30	0.00	9.00	0.00	8.40			
11:30-11:45	0.00	7.20	0.00	7.20			
11:45-12:00	0.00	6.60	0.00	6.60			
12:00-12:15	0.00	9.60	0.00	9.00			
12:15-12:30	0.00	7.20	0.00	6.60			
12:30-12:45	0.00	7.80	0.00	8.40			
12:45-13:00	0.00	7.80	0.00	7.20			
13:00-13:15	0.00	6.00	0.00	6.00			
13:15-13:30	0.00	7.80	0.00	7.80			
13:30-13:45	0.00	6.60	0.00	6.00			
13:45-14:00	0.00	7.20	0.00	7.20			
14:00-14:15	0.00	8.40	0.00	8.40			
14:15-14:30	0.00	6.60	0.00	6.00			
14:30-14:45	0.00	7.20	0.00	7.20			
14:45-15:00	0.00	6.60	0.00	6.00			
15:00-15:15	0.00	5.40	0.00	5.40			
15:15-15:30	0.00	9.00	0.00	8.40			
15:30-15:45	0.00	5.40	0.00	5.40			
15:45-16:00	0.00	7.20	0.00	6.60			
16:00-16:15	0.00	6.60	0.00	6.60			
16:15-16:30	0.00	6.00	0.00	6.00			
16:30-16:45	0.00	7.20	0.00	7.20			
16:45-17:00	0.00	5.40	0.00	5.40			
17:00-17:15	0.00	6.00	0.00	5.40			
17:15-17:30	0.00	7.20	0.00	6.60			
17:30-17:45	0.00	4.80	0.00	5.40			
17:45-18:00	0.00	6.00	0.00	5.40			
18:00-18:15	0.00	8.60	0.00	8.60			
18:15-18:30	0.00	5.40	0.00	4.80			
18:30-18:45	0.00	8.60	0.00	8.60			
18:45-19:00	0.00	6.60	0.00	6.60			
19:00-19:15	0.00	6.60	0.00	6.00			
19:15-19:30	0.00	6.60	0.00	6.60			
19:30-19:45	0.00	6.60	0.00	6.60			
19:45-20:00	0.00	5.40	0.00	5.40			
20:00-20:15	0.00	6.60	0.00	6.00			
20:15-20:30	0.00	6.60	0.00	6.60			
20:30-20:45	0.00	5.40	0.00	5.40			
20:45-21:00	0.00	6.00	0.00	5.40			
21:00-21:15	0.00	4.80	0.00	4.80			
21:15-21:30	0.00	4.80	0.00	4.80			
21:30-21:45	0.00	6.00	0.00	6.00			
21:45-22:00	0.00	6.00	0.00	6.00			
22:00-22:15	0.00	4.80	0.00	4.80			
22:15-22:30	0.00	6.00	0.00	6.60			
22:30-22:45	0.00	4.80	0.00	4.20			
22:45-23:00	0.00	4.80	0.00	4.80			
23:00-23:15	0.00	6.00	0.00	6.00			
23:15-23:30	0.00	4.80	0.00	4.20			
23:30-23:45	0.00	4.20	0.00	4.20			
23:45-00:00	0.00	6.00	0.00	6.00			
<b>Maximum</b>	<b>0.00</b>	<b>9.60</b>	<b>0.00</b>	<b>9.00</b>			
<b>Minimum</b>	<b>0.00</b>	<b>3.60</b>	<b>0.00</b>	<b>3.00</b>			



**SAMPLE EXCEL FORMAT OF DATA DOWNLOADED FROM BULK METERS**

**09102793 - Load Survey**

Source: 091027932013100120131031.m Voltage Current Energy  
 Roadno: 08/10/2013 11:06:46 AM 1 1 1

**08/09/2013 : Demand**

Param 1 : Apparent-Active(E) - type 6  
 Param 3 : Active(E) Total  
 Param 2 : Apparent-Active(I) - type 2  
 Param 4 : Active(I) Total

Interval	Param 1 (kVA)	Param 2 (kVA)	Param 3 (kW)	Param 4 (kW)
00:00-00:15	0	4.2	0	3.6
00:15-00:30	0	4.2	0	4.2
00:30-00:45	0	6	0	6
00:45-01:00	0	3.6	0	3
01:00-01:15	0	4.2	0	4.2
01:15-01:30	0	6	0	6
01:30-01:45	0	4.8	0	4.8
01:45-02:00	0	6	0	6
02:00-02:15	0	6	0	6
02:15-02:30	0	3.6	0	3.6
02:30-02:45	0	5.4	0	4.8
02:45-03:00	0	4.8	0	4.8
03:00-03:15	0	4.8	0	4.2
03:15-03:30	0	5.4	0	4.8
03:30-03:45	0	4.8	0	4.8
03:45-04:00	0	4.2	0	4.2
04:00-04:15	0	4.2	0	3.6
04:15-04:30	0	6.6	0	6.6
04:30-04:45	0	3.6	0	3.6
04:45-05:00	0	4.8	0	4.2
05:00-05:15	0	4.8	0	4.2
05:15-05:30	0	4.8	0	5.4
05:30-05:45	0	4.2	0	3.6
05:45-06:00	0	4.8	0	4.2
06:00-06:15	0	4.2	0	4.2
06:15-06:30	0	3.6	0	3.6
06:30-06:45	0	3.6	0	3.6
06:45-07:00	0	5.4	0	4.8
07:00-07:15	0	4.8	0	4.8
07:15-07:30	0	4.2	0	3.6
07:30-07:45	0	4.8	0	5.4
07:45-08:00	0	7.2	0	6.6
08:00-08:15	0	6	0	5.4
08:15-08:30	0	6.6	0	6.6
08:30-08:45	0	7.2	0	7.2
08:45-09:00	0	4.8	0	4.8
09:00-09:15	0	6.6	0	6
09:15-09:30	0	7.8	0	7.8
09:30-09:45	0	5.4	0	5.4
09:45-10:00	0	8.4	0	7.8
10:00-10:15	0	6.6	0	6.6
10:15-10:30	0	7.2	0	7.2

1 of 187 Generated on: 08/10/2013 11:15:18 AM Keyz Not Available

ANNEXURE 2

The screenshot displays the Microsoft Excel 2010 interface. The ribbon includes tabs for Home, Insert, Page Layout, Formulas, Data, Review, View, and Developer. The Home tab is active, showing options for Clipboard (Cut, Copy, Paste, Format Painter), Font (Arial, size 10, Bold, Italic, Underline, Color, Background Color), and Alignment (Wrap Text, Merge & Center). The spreadsheet shows a table with the following data:

Row	Time Interval (B)	Value (C)	Value (E)	Value (F)	Value (H)
5	10:30-10:45	0	8.4	0	7.8
6	10:45-11:00	0	4.8	0	4.8
7	11:00-11:15	0	6	0	6
8	11:15-11:30	0	9	0	8.4
9	11:30-11:45	0	7.2	0	7.2
10	11:45-12:00	0	6.6	0	6.6
11	12:00-12:15	0	9.6	0	9
12	12:15-12:30	0	7.2	0	6.6
13	12:30-12:45	0	7.8	0	8.4
14	12:45-13:00	0	7.8	0	7.2
15	13:00-13:15	0	6	0	6
16	13:15-13:30	0	7.8	0	7.8
17	13:30-13:45	0	6.6	0	6
18	13:45-14:00	0	7.2	0	7.2
19	14:00-14:15	0	8.4	0	8.4
20	14:15-14:30	0	6.6	0	6
21	14:30-14:45	0	7.2	0	7.2
22	14:45-15:00	0	6.6	0	6
23	15:00-15:15	0	5.4	0	5.4
24	15:15-15:30	0	9	0	8.4
25	15:30-15:45	0	5.4	0	5.4
26	15:45-16:00	0	7.2	0	6.6
27	16:00-16:15	0	6.6	0	6.6
28	16:15-16:30	0	7.2	0	7.2
29	16:30-16:45	0	6	0	6
30	16:45-17:00	0	5.4	0	5.4
31	17:00-17:15	0	6	0	5.4
32	17:15-17:30	0	7.2	0	6.6
33	17:30-17:45	0	4.8	0	5.4
34	17:45-18:00	0	6	0	5.4
35	18:00-18:15	0	6.6	0	6.6
36	18:15-18:30	0	5.4	0	4.8
37	18:30-18:45	0	6.6	0	6.6
38	18:45-19:00	0	6.6	0	6.6
39	19:00-19:15	0	6.6	0	6
40	19:15-19:30	0	6.6	0	6.6
41	19:30-19:45	0	6.6	0	6.6
42	19:45-20:00	0	5.4	0	5.4
43	20:00-20:15	0	6.6	0	6
44	20:15-20:30	0	6.6	0	6.6
45	20:30-20:45	0	5.4	0	5.4
46	20:45-21:00	0	6	0	5.4
47	21:00-21:15	0	5.4	0	5.4
48	21:15-21:30	0	4.8	0	4.8
49	21:30-21:45	0	6	0	6
50	21:45-22:00	0	6.6	0	6
51	22:00-22:15	0	4.8	0	4.8
52	22:15-22:30	0	6.6	0	6.6
53	22:30-22:45	0	4.8	0	4.2
54	22:45-23:00	0	4.8	0	4.8
55	23:00-23:15	0	6	0	6
56	23:15-23:30	0	4.8	0	4.2
57	23:30-23:45	0	4.2	0	4.2
58	23:45-00:00	0	6	0	6
59	Maximum	0	9.6	0	9
60	Minimum	0	3.6	0	3

The status bar at the bottom shows 'Ready' and the taskbar with various application icons. A watermark for 'University of Moratuwa, Sri Lanka. Electronic Theses & Dissertations www.lib.mut.ac.lk' is overlaid on the spreadsheet.

**VISUAL BASIC CODE USED TO FORMULATE kVA DATA OF  
CONSUMER**

Sub Button1\_Click()

Sheets("Sheet 1").Range("B33:B74").Copy

Destination:=Sheets("acc").Range("B3:B44")

' above code used to copy data in cell range B33 to B74 of Sheet 1 in to cell range of B3 to B44 of sheet "acc"

Sheets("Sheet 2").Range("B9:B62").Copy

Destination:=Sheets("acc").Range("B45:B98")

Sheets("Sheet 1").Range("F10:F10").Copy

Destination:=Sheets("acc").Range("C2:C2")

Sheets("Sheet 1").Range("E33:E74").Copy

Destination:=Sheets("acc").Range("C3:C44")

Sheets("Sheet 2").Range("E9:E62").Copy

Destination:=Sheets("acc").Range("C45:C98")

Sheets("Sheet 7").Range("F10:F10").Copy

Destination:=Sheets("acc").Range("D2:D2")

Sheets("Sheet 7").Range("E33:E74").Copy

Destination:=Sheets("acc").Range("D3:D44")

Sheets("Sheet 8").Range("E9:E62").Copy

Destination:=Sheets("acc").Range("D45:D98")

Sheets("Sheet 13").Range("F10:F10").Copy

Destination:=Sheets("acc").Range("E2:E2")

Sheets("Sheet 13").Range("E33:E74").Copy

Destination:=Sheets("acc").Range("E3:E44")

Sheets("Sheet 14").Range("E9:E62").Copy

Destination:=Sheets("acc").Range("E45:E98")

Sheets("Sheet 19").Range("F10:F10").Copy

Destination:=Sheets("acc").Range("F2:F2")

Sheets("Sheet 19").Range("E33:E74").Copy

Destination:=Sheets("acc").Range("F3:F44")

Sheets("Sheet 20").Range("E9:E62").Copy

Destination:=Sheets("acc").Range("F45:F98")

Sheets("Sheet 25").Range("F10:F10").Copy

Destination:=Sheets("acc").Range("G2:G2")

Sheets("Sheet 25").Range("E33:E74").Copy

Destination:=Sheets("acc").Range("G3:G44")

Sheets("Sheet 26").Range("E9:E62").Copy

Destination:=Sheets("acc").Range("G45:G98")

Sheets("Sheet 31").Range("F10:F10").Copy

Destination:=Sheets("acc").Range("H2:H2")

Sheets("Sheet 31").Range("E33:E74").Copy

Destination:=Sheets("acc").Range("H3:H44")

Sheets("Sheet 32").Range("E9:E62").Copy

Destination:=Sheets("acc").Range("H45:H98")



### ANNEXURE 3

Sheets("Sheet 37").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("I2:I2")  
Sheets("Sheet 37").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("I3:I44")  
Sheets("Sheet 38").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("I45:I98")  
Sheets("Sheet 43").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("J2:J2")  
Sheets("Sheet 43").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("J3:J44")  
Sheets("Sheet 44").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("J45:J98")  
Sheets("Sheet 49").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("K2:K2")  
Sheets("Sheet 49").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("K3:K44")  
Sheets("Sheet 50").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("K45:K98")  
Sheets("Sheet 55").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("L2:L2")  
Sheets("Sheet 55").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("L3:L44")  
Sheets("Sheet 56").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("L45:L98")  
Sheets("Sheet 61").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("M2:M2")  
Sheets("Sheet 61").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("M3:M44")  
Sheets("Sheet 62").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("M45:M98")  
Sheets("Sheet 67").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("N2:N2")  
Sheets("Sheet 67").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("N3:N44")  
Sheets("Sheet 68").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("N45:N98")  
Sheets("Sheet 73").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("O2:O2")  
Sheets("Sheet 73").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("O3:O44")  
Sheets("Sheet 74").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("O45:O98")  
Sheets("Sheet 79").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("P2:P2")

## ANNEXURE 3

Sheets("Sheet 79").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("P3:P44")  
Sheets("Sheet 80").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("P45:P98")  
Sheets("Sheet 85").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("Q2:Q2")  
Sheets("Sheet 85").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("Q3:Q44")  
Sheets("Sheet 86").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("Q45:Q98")  
Sheets("Sheet 91").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("R2:R2")  
Sheets("Sheet 91").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("R3:R44")  
Sheets("Sheet 92").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("R45:R98")  
Sheets("Sheet 97").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("S2:S2")  
Sheets("Sheet 97").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("S3:S44")  
Sheets("Sheet 98").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("S45:S98")  
Sheets("Sheet 103").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("T2:T2")  
Sheets("Sheet 103").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("T3:T44")  
Sheets("Sheet 104").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("T45:T98")  
Sheets("Sheet 109").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("U2:U2")  
Sheets("Sheet 109").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("U3:U44")  
Sheets("Sheet 110").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("U45:U98")  
Sheets("Sheet 115").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("V2:V2")  
Sheets("Sheet 115").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("V3:V44")  
Sheets("Sheet 116").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("V45:V98")  
Sheets("Sheet 121").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("W2:W2")  
Sheets("Sheet 121").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("W3:w44")

## ANNEXURE 3

Sheets("Sheet 122").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("W45:W98")  
Sheets("Sheet 127").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("X2:X2")  
Sheets("Sheet 127").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("X3:X44")  
Sheets("Sheet 128").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("X45:X98")  
Sheets("Sheet 133").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("Y2:Y2")  
Sheets("Sheet 133").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("Y3:Y44")  
Sheets("Sheet 134").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("Y45:Y98")  
Sheets("Sheet 139").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("Z2:Z2")  
Sheets("Sheet 139").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("Z3:Z44")  
Sheets("Sheet 140").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("Z45:Z98")  
Sheets("Sheet 145").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("AA2:AA2")  
Sheets("Sheet 145").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("AA3:AA44")  
Sheets("Sheet 146").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("AA45:AA98")  
Sheets("Sheet 151").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("AB2:AB2")  
Sheets("Sheet 151").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("AB3:AB44")  
Sheets("Sheet 152").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("AB45:AB98")  
Sheets("Sheet 157").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("AC2:AC2")  
Sheets("Sheet 157").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("AC3:AC44")  
Sheets("Sheet 158").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("AC45:AC98")  
Sheets("Sheet 163").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("AD2:AD2")  
Sheets("Sheet 163").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("AD3:AD44")  
Sheets("Sheet 164").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("AD45:AD98")

### ANNEXURE 3

```
Sheets("Sheet 169").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("AE2:AE2")  
Sheets("Sheet 169").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("AE3:AE44")  
Sheets("Sheet 170").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("AE45:AE98")  
Sheets("Sheet 175").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("AF2:AF2")  
Sheets("Sheet 175").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("AF3:AF44")  
Sheets("Sheet 176").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("AF45:AF98")  
Sheets("Sheet 181").Range("F10:F10").Copy  
Destination:=Sheets("acc").Range("AG2:AG2")  
Sheets("Sheet 181").Range("E33:E74").Copy  
Destination:=Sheets("acc").Range("AG3:AG44")  
Sheets("Sheet 182").Range("E9:E62").Copy  
Destination:=Sheets("acc").Range("AG45:AG98")  
End Sub
```



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## OVERVIEW OF M Z SCORE OUTLIER DETECTION METHOD Z-SCORE

Another method that can be used to screen data for outliers is the Z-Score, using the mean and standard deviation.

$$Z_i = \frac{x_i - \bar{x}}{sd}, \text{ where } X_i \sim N(\mu, \sigma^2), \text{ and } sd \text{ is the standard deviation of data.}$$

The basic idea of this rule is that if  $X$  follows a normal distribution,  $N(\mu, \sigma^2)$ , then  $Z$  follows a standard normal distribution,  $N(0, 1)$ , and Z-scores that exceed 3 in absolute value are generally considered as outliers. This method is simple and it is the same formula as the 3 SD method when the criterion of an outlier is an absolute value of a Z-score of at least 3. It presents a reasonable criterion for identification of the outlier when data follow the normal distribution. According to Shiffler (1988), a possible maximum Z-score is dependent on sample size, and it is computed as  $(n-1)/\sqrt{n}$ . The proof is given in Appendix B. Since no z-score exceeds 3 in a sample size less than or equal to 10, the z-score method is not very good for outlier labeling, particularly in small data sets<sup>21</sup>. Another limitation of this rule is that the standard deviation can be inflated by a few or even a single observation having an extreme value. Thus it can cause a masking problem, i.e., the less extreme outliers go undetected because of the most extreme outlier(s), and vice versa. When masking occurs, the outliers may be neighbors. Table 3 shows



a computation and masking problem of the Z-Score method using the previous example data set, X.

**Table 3: Computation and Masking Problem of the Z-Score**

<i>i</i>	Case 1 ( $\bar{x}=5.46, sd=3.86$ )		Case 2 ( $\bar{x}=4.73, sd=2.82$ )	
	$x_i$	Z-Score	$x_i$	Z-Score
1	3.2	-0.59	3.2	-0.54
2	3.4	-0.54	3.4	-0.47
3	3.7	-0.46	3.7	-0.37
4	3.7	-0.46	3.7	-0.37
5	3.8	-0.43	3.8	-0.33
6	3.9	-0.41	3.9	-0.29
7	4	-0.38	4	-0.26
8	4	-0.38	4	-0.26
9	4.1	-0.35	4.1	-0.22
10	4.2	-0.33	4.2	-0.19
11	4.7	-0.26	4.7	-0.01
12	4.8	-0.17	4.8	0.02
13	14	<b>2.21</b>	14	<b>3.29</b>
14	15	<b>2.47</b>	-	-

For case 1, with all of the example data included, it appears that the values 14 and 15 are outliers, yet no observation exceeds the absolute value of 3. For case 2, with the most extreme value, 15, among example data excluded, 14 is considered an outlier. This is because multiple extreme values have artificially inflated standard deviations.

### THE MODIFIED Z-SCORE

Two estimators used in the Z-Score, the sample mean and sample standard deviation, can be affected by a few extreme values or by even a single extreme value. To avoid this problem, the median and the median of the absolute deviation of the median (MAD) are employed in the

modified Z-Score instead of the mean and standard deviation of the sample, respectively (Iglewicz and Hoaglin, 1993).

$MAD = median\{|x_i - \tilde{x}|\}$ , where  $\tilde{x}$  is the sample median.

The modified Z-Score ( $M_i$ ) is computed as

$$M_i = \frac{0.6745(x_i - \tilde{x})}{MAD}, \text{ where } E(MAD) = 0.675 \sigma \text{ for large normal data.}$$

Iglewicz and Hoaglin (1993) suggested that observations are labeled outliers when  $|M_i| > 3.5$  through the simulation based on pseudo-normal observations for sample sizes of 10, 20, and 40.<sup>21</sup> The  $M_i$  score is effective for normal data in the same way as the Z-score.

**Table 4: Computation of Modified Z-Score and its Comparison with the Z-Score**

$i$	$x_i$	Z-Score	modified Z-Score
1	3.2	-0.59	-1.80
2	3.4	-0.54	-1.35
3	3.7	-0.46	-0.67
4	3.7	-0.46	-0.67
5	3.8	-0.43	-0.45
6	3.9	-0.41	-0.22
7	4	-0.38	0
8	4	-0.38	0
9	4.1	-0.35	0.22
10	4.2	-0.33	0.45
11	4.7	-0.20	1.57
12	4.8	-0.17	1.80
13	14	<b>2.21</b>	<b>22.48</b>
14	15	<b>2.47</b>	<b>24.73</b>

Table 4 shows the computation of the modified Z-Score and its comparison with the Z-Score of the previous example data set. While no observation is detected as an outlier in the Z-Score, two extreme values, 14 and 15, are detected as outliers at the same time in the modified Z-Score since this method is less susceptible to the extreme values.

## MATLAB CODE FOR M ZSCORE OUTLIER DETECTION METHOD

```

function [mzscore maxmz outlier outlier_num] = mzscore(x, x_date, thresh, dist)

% if (nargin < 2) || (nargin > 4)
% error('Requires two to four input arguments.')
%end
% Define default values
% if nargin == 2,
%   thresh = 3.5;
%   dist = 0;
% elseif nargin == 3,
%   dist = 0;
%end
% Normal transformation
% if dist == 1,
%   x = log(x);
%end
% Check for validity of inputs
% if ~isnumeric(x) || ~isreal(x) || ~iscellstr(x_date),
%   error('Input x must be a numeric array, x must be positive for log-normality, and
x_date must be a string table.')
%end
[n, c] = size(x);
mad = median(abs((x-repmat(median(x),n,1)))));
mzscore = 0.6745*(x-repmat(median(x),n,1))./repmat(mad,n,1);
[i,j] = find(abs(mzscore) > thresh)
maxmz = (n-1)/sqrt(n);
if ~isempty(i),
%outlier = [x_date(i) cellstr(strcat('Series', num2str(j)))];
outlier_num = [i j]
else
outlier = ('No outliers have been identified!');
outlier_num = ('No outliers have been identified!');
end
end

```

## HIERARCHICAL CLUSTERING IN MATLAB

Hierarchical clustering groups data over a variety of scales by creating a cluster tree or dendrogram. The tree is not a single set of clusters, but rather a multilevel hierarchy, where clusters at one level are joined as clusters at the next level. This allows you to decide the level or scale of clustering that is most appropriate for your application. The Statistics and Machine Learning Toolbox™ function `clusterdata` supports agglomerative clustering and performs all of the necessary steps for you. It incorporates the `pdist`, `linkage`, and `cluster` functions, which you can use separately for more detailed analysis. The `dendrogram` function plots the cluster tree.

### 1.1 Algorithm Description

To perform agglomerative hierarchical cluster analysis on a data set using Statistics and Machine Learning Toolbox functions, follow this procedure:

1. Find the similarity or dissimilarity between every pair of objects in the data set. In this step, you calculate the *distance* between objects using the `pdist` function. The `pdist` function supports many different ways to compute this measurement.
2. Group the objects into a binary, hierarchical cluster tree. In this step, you link pairs of objects that are in close proximity using the `linkage` function. The `linkage` function uses the distance information generated in step 1 to determine the proximity of objects to each other. As objects are paired into binary clusters, the newly formed clusters are grouped into larger clusters until a hierarchical tree is formed.
3. Determine where to cut the hierarchical tree into clusters. In this step, you use the `cluster` function to prune branches off the bottom of the hierarchical tree, and assign all the objects below each cut to a single cluster. This creates a partition of the data. The `cluster` function can create these clusters by detecting natural groupings in the hierarchical tree or by cutting off the hierarchical tree at an arbitrary point.

### 1.2 Similarity Measures

You use the `pdist` function to calculate the distance between every pair of objects in a data set. For a data set made up of  $m$  objects, there are  $m*(m - 1)/2$  pairs in the data set. The result of this computation is commonly known as a distance or dissimilarity matrix.

There are many ways to calculate this distance information. By default, the `pdist` function calculates the Euclidean distance between objects; however, you can specify one of several other options.

## ANNEXURE 7

For example, consider a data set, X, made up of five objects where each object is a set of x,y coordinates.

- Object 1: 1, 2
- Object 2: 2.5, 4.5
- Object 3: 2, 2
- Object 4: 4, 1.5
- Object 5: 4, 2.5

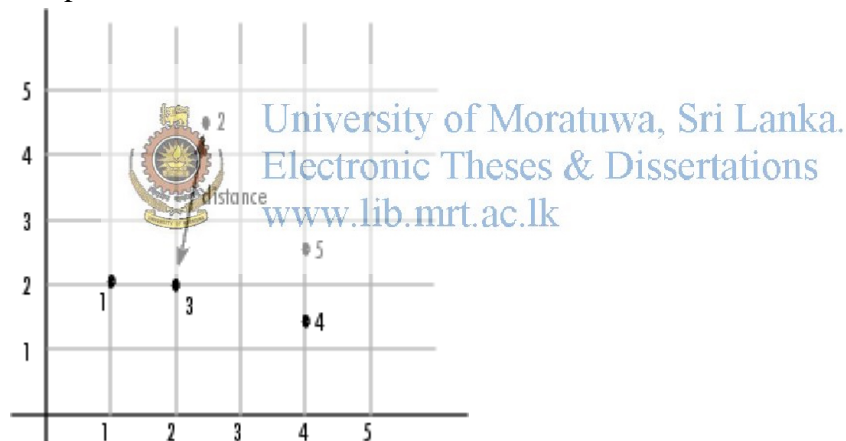
You can define this data set as a matrix

```
rng default; % For reproducibility
```

```
X = [1 2;2.5 4.5;2 2;4 1.5;...
```

```
4 2.5];
```

and pass it to pdist. The pdist function calculates the distance between object 1 and object 2, object 1 and object 3, and so on until the distances between all the pairs have been calculated. The following figure plots these objects in a graph. The Euclidean distance between object 2 and object 3 is shown to illustrate one interpretation of distance.



### 1.3 Distance Information

The pdist function returns this distance information in a vector, Y, where each element contains the distance between a pair of objects.

```
Y = pdist(X)
```

```
Y =
```

```
Columns 1 through 7
```

```
2.9155 1.0000 3.0414 3.0414 2.5495 3.3541 2.5000
```

```
Columns 8 through 10
```

```
2.0616 2.0616 1.0000
```

To make it easier to see the relationship between the distance information generated by `pdist` and the objects in the original data set, you can reformat the distance vector into a matrix using the `squareform` function. In this matrix, element  $i,j$  corresponds to the distance between object  $i$  and object  $j$  in the original data set. In the following example, element 1,1 represents the distance between object 1 and itself (which is zero). Element 1,2 represents the distance between object 1 and object 2, and so on.

```
squareform(Y)
ans =
```

```

    0  2.9155  1.0000  3.0414  3.0414
  2.9155    0  2.5495  3.3541  2.5000
  1.0000  2.5495    0  2.0616  2.0616
  3.0414  3.3541  2.0616    0  1.0000
  3.0414  2.5000  2.0616  1.0000    0
```

#### 1.4 Linkages

Once the proximity between objects in the data set has been computed, you can determine how objects in the data set should be grouped into clusters, using the `linkage` function. The `linkage` function takes the distance information generated by `pdist` and links pairs of objects that are close together into binary clusters (clusters made up of two objects). The `linkage` function then links these newly formed clusters to each other and to other objects to create bigger clusters until all the objects in the original data set are linked together in a hierarchical tree.

For example, given the distance vector `Y` generated by `pdist` from the sample data set of  $x$ - and  $y$ -coordinates, the `linkage` function generates a hierarchical cluster tree, returning the linkage information in a matrix, `Z`.

```
Z = linkage(Y)
Z =
```

```

  4.0000  5.0000  1.0000
  1.0000  3.0000  1.0000
  6.0000  7.0000  2.0616
  2.0000  8.0000  2.5000
```

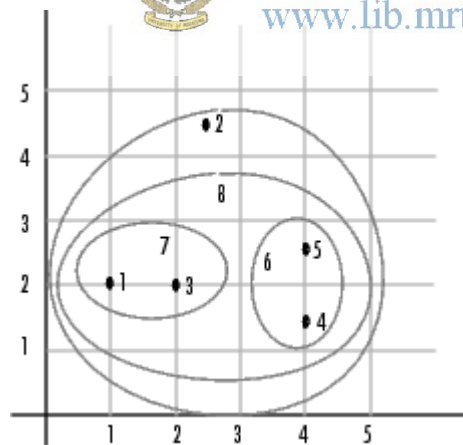
In this output, each row identifies a link between objects or clusters. The first two columns identify the objects that have been linked. The third column contains the distance between these objects. For the sample data set of  $x$ - and  $y$ -coordinates,

the linkage function begins by grouping objects 4 and 5, which have the closest proximity (distance value = 1.0000). The linkage function continues by grouping objects 1 and 3, which also have a distance value of 1.0000.

The third row indicates that the linkage function grouped objects 6 and 7. If the original sample data set contained only five objects, what are objects 6 and 7? Object 6 is the newly formed binary cluster created by the grouping of objects 4 and 5. When the linkage function groups two objects into a new cluster, it must assign the cluster a unique index value, starting with the value  $m + 1$ , where  $m$  is the number of objects in the original data set. (Values 1 through  $m$  are already used by the original data set.) Similarly, object 7 is the cluster formed by grouping objects 1 and 3.

linkage uses distances to determine the order in which it clusters objects. The distance vector  $Y$  contains the distances between the original objects 1 through 5. But linkage must also be able to determine distances involving clusters that it creates, such as objects 6 and 7. By default, linkage uses a method known as single linkage. However, there are a number of different methods available. See the linkage reference page for more information.

As the final cluster, the linkage function grouped object 8, the newly formed cluster made up of objects 6 and 7, with object 2 from the original data set. The following figure graphically illustrates the way linkage groups the objects into a hierarchy of clusters.

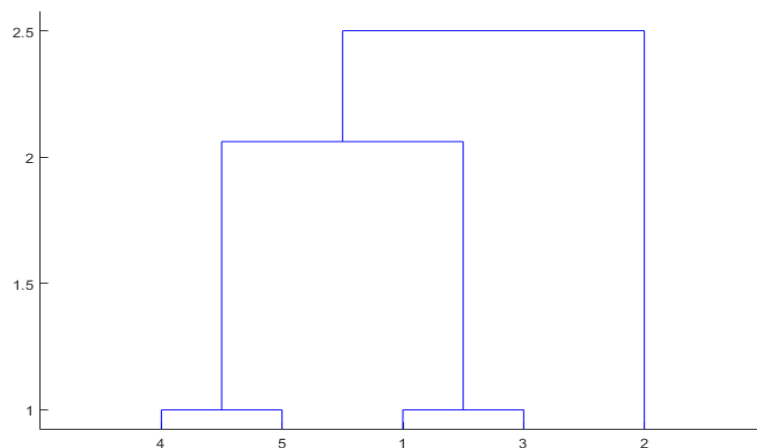


### 1.5 Dendrograms

The hierarchical, binary cluster tree created by the linkage function is most easily understood when viewed graphically. The Statistics and Machine Learning Toolbox function `dendrogram` plots the tree as follows.

```
dendrogram(Z)
```





In the figure, the numbers along the horizontal axis represent the indices of the objects in the original data set. The links between objects are represented as upside-down U-shaped lines. The height of the U indicates the distance between the objects. For example, the link representing the cluster containing objects 1 and 3 has a height of 1. The link representing the cluster that groups object 2 together with objects 1, 3, 4, and 5, (which are already clustered as object 8) has a height of 2.5. The height represents the distance linkage computes between objects 2 and 8.

### 1.6 Verify the Cluster Tree

After linking the objects in a data set into a hierarchical cluster tree, you might want to verify that the distances (that is, heights) in the tree reflect the original distances accurately. In addition, you might want to investigate natural divisions that exist among links between objects. Statistics and Machine Learning Toolbox functions are available for both of these tasks, as described in the following sections.

### 1.7 Verify Dissimilarity

In a hierarchical cluster tree, any two objects in the original data set are eventually linked together at some level. The height of the link represents the distance between the two clusters that contain those two objects. This height is known as the *cophenetic distance* between the two objects. One way to measure how well the cluster tree generated by the linkage function reflects your data is to compare the cophenetic distances with the original distance data generated by the `pdist` function. If the clustering is valid, the linking of objects in the cluster tree should have a strong correlation with the distances between objects in the distance vector. The `cophenet` function compares these two sets of values and computes their

correlation, returning a value called the *cophenetic correlation coefficient*. The closer the value of the cophenetic correlation coefficient is to 1, the more accurately the clustering solution reflects your data.

You can use the cophenetic correlation coefficient to compare the results of clustering the same data set using different distance calculation methods or clustering algorithms. For example, you can use the cophenet function to evaluate the clusters created for the sample data set.

```
c = cophenet(Z,Y)
```

```
c =
```

```
0.8615
```

Z is the matrix output by the linkage function and Y is the distance vector output by the pdist function.

Execute pdist again on the same data set, this time specifying the city block metric. After running the linkage function on this new pdist output using the average linkage method, call cophenet to evaluate the clustering solution.

```
Y = pdist(X,'cityblock');
```

```
Z = linkage(Y,'average');
```

```
c = cophenet(Z,Y)
```

```
c =0.9047
```



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The cophenetic correlation coefficient shows that using a different distance and linkage method creates a tree that represents the original distances slightly better.

### 1.8 Verify Consistency

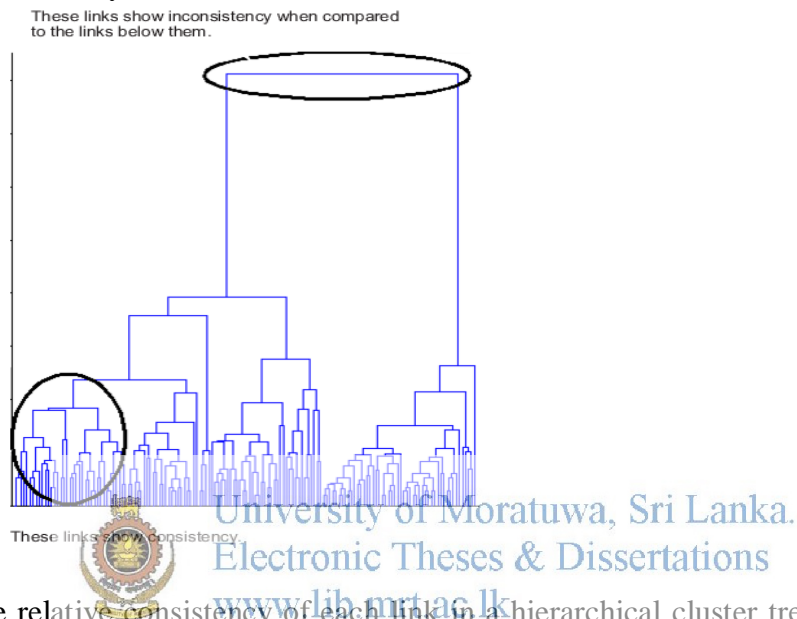
One way to determine the natural cluster divisions in a data set is to compare the height of each link in a cluster tree with the heights of neighboring links below it in the tree.

A link that is approximately the same height as the links below it indicates that there are no distinct divisions between the objects joined at this level of the hierarchy. These links are said to exhibit a high level of consistency, because the distance between the objects being joined is approximately the same as the distances between the objects they contain.

On the other hand, a link whose height differs noticeably from the height of the links below it indicates that the objects joined at this level in the cluster tree are much farther apart from each other than their components were when they were joined. This link is said to be inconsistent with the links below it.

In cluster analysis, inconsistent links can indicate the border of a natural division in a data set. The cluster function uses a quantitative measure of inconsistency to determine where to partition your data set into clusters.

The following dendrogram illustrates inconsistent links. Note how the objects in the dendrogram fall into two groups that are connected by links at a much higher level in the tree. These links are inconsistent when compared with the links below them in the hierarchy.



The relative consistency of each link in a hierarchical cluster tree can be quantified and expressed as the *inconsistency coefficient*. This value compares the height of a link in a cluster hierarchy with the average height of links below it. Links that join distinct clusters have a high inconsistency coefficient; links that join indistinct clusters have a low inconsistency coefficient.

To generate a listing of the inconsistency coefficient for each link in the cluster tree, use the `inconsistent` function. By default, the `inconsistent` function compares each link in the cluster hierarchy with adjacent links that are less than two levels below it in the cluster hierarchy. This is called the *depth* of the comparison. You can also specify other depths. The objects at the bottom of the cluster tree, called leaf nodes, that have no further objects below them, have an inconsistency coefficient of zero. Clusters that join two leaves also have a zero inconsistency coefficient.

For example, you can use the `inconsistent` function to calculate the inconsistency values for the links created by the linkage function in `Linkages`.

## ANNEXURE 7

First, recompute the distance and linkage values using the default settings.

$Y = \text{pdist}(X);$

$Z = \text{linkage}(Y);$

Next, use `inconsistent` to calculate the inconsistency values.

$I = \text{inconsistent}(Z)$

$I =$

```

1.0000    0  1.0000    0
1.0000    0  1.0000    0
1.3539  0.6129  3.0000  1.1547
2.2808  0.3100  2.0000  0.7071

```

The `inconsistent` function returns data about the links in an  $(m-1)$ -by-4 matrix, whose columns are described in the following table.

Column	Description
1	Mean of the heights of all the links included in the calculation
2	Standard deviation of all the links included in the calculation
3	Number of links included in the calculation
4	Inconsistency coefficient

In the sample output, the first row represents the link between objects 4 and 5. This cluster is assigned the index 6 by the linkage function. Because both 4 and 5 are leaf nodes, the inconsistency coefficient for the cluster is zero. The second row represents the link between objects 1 and 3, both of which are also leaf nodes. This cluster is assigned the index 7 by the linkage function.

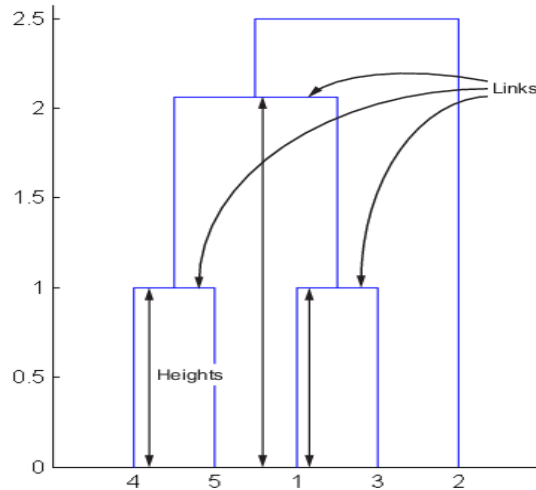
The third row evaluates the link that connects these two clusters, objects 6 and 7. (This new cluster is assigned index 8 in the linkage output). Column 3 indicates that three links are considered in the calculation: the link itself and the two links directly below it in the hierarchy. Column 1 represents the mean of the heights of these links. The `inconsistent` function uses the height information output by the linkage function to calculate the mean. Column 2 represents the standard deviation between the links. The last column contains the inconsistency value for these links, 1.1547. It is the difference between the current link height and the mean, normalized by the standard deviation.

$(2.0616 - 1.3539) / .6129$

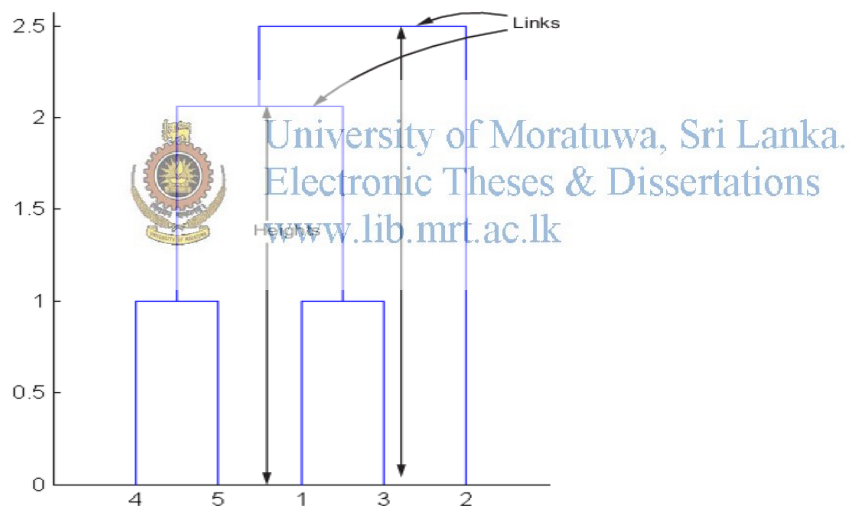
ans =

1.1547

The following figure illustrates the links and heights included in this calculation.



Row 4 in the output matrix describes the link between object 8 and object 2. Column 3 indicates that two links are included in this calculation: the link itself and the link directly below it in the hierarchy. The inconsistency coefficient for this link is 0.7071. The following figure illustrates the links and heights included in this calculation.



### 1.9 Create Clusters

After you create the hierarchical tree of binary clusters, you can prune the tree to partition your data into clusters using the cluster function. The cluster function lets you create clusters in two ways, as discussed in the following sections:

#### 1.10 Find Natural Divisions in Data

The hierarchical cluster tree may naturally divide the data into distinct, well-separated clusters. This can be particularly evident in a dendrogram diagram created from data where groups of objects are densely packed in certain areas and not in others. The

## ANNEXURE 7

inconsistency coefficient of the links in the cluster tree can identify these divisions where the similarities between objects change abruptly. (See Verify the Cluster Tree for more information about the inconsistency coefficient.) You can use this value to determine where the cluster function creates cluster boundaries.

For example, if you use the cluster function to group the sample data set into clusters, specifying an inconsistency coefficient threshold of 1.2 as the value of the cutoff argument, the clusterfunction groups all the objects in the sample data set into one cluster. In this case, none of the links in the cluster hierarchy had an inconsistency coefficient greater than 1.2.

```
T = cluster(Z,'cutoff',1.2)
```

```
T =
```

```
1  
1  
1  
1  
1
```

The cluster function outputs a vector, T, that is the same size as the original data set. Each element in this vector contains the number of the cluster into which the corresponding object from the original data set was placed.

If you lower the inconsistency coefficient threshold to 0.8, the cluster function divides the sample data set into three separate clusters.

```
T = cluster(Z,'cutoff',0.8)
```

```
T =
```

```
3  
2  
3  
1  
1
```

This output indicates that objects 1 and 3 are in one cluster, objects 4 and 5 are in another cluster, and object 2 is in its own cluster.

When clusters are formed in this way, the cutoff value is applied to the inconsistency coefficient. These clusters may, but do not necessarily, correspond to a horizontal slice across the dendrogram at a certain height. If you want clusters corresponding to a horizontal slice of the dendrogram, you can either use the criterion option to specify

that the cutoff should be based on distance rather than inconsistency, or you can specify the number of clusters directly as described in the following section.

### 1.11 Specify Arbitrary Clusters

Instead of letting the cluster function create clusters determined by the natural divisions in the data set, you can specify the number of clusters you want created.

For example, you can specify that you want the cluster function to partition the sample data set into two clusters. In this case, the cluster function creates one cluster containing objects 1, 3, 4, and 5 and another cluster containing object 2.

```
T = cluster(Z,'maxclust',2)
```

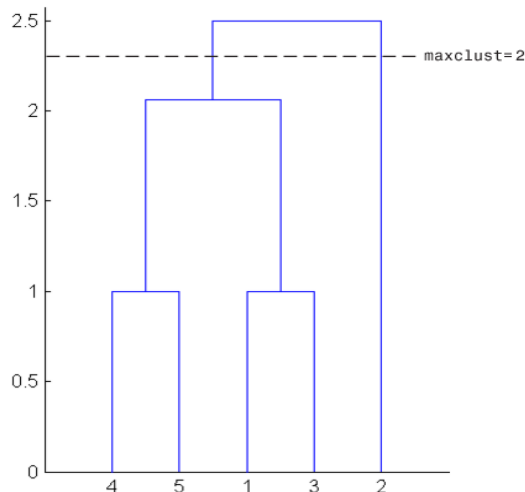
```
T =
```

```

2
1
2
2
2

```

To help you visualize how the cluster function determines these clusters, the following figure shows the dendrogram of the hierarchical cluster tree. The horizontal dashed line intersects two lines of the dendrogram, corresponding to setting 'maxclust' to 2. These two lines partition the objects into two clusters: the objects below the left-hand line, namely 1, 3, 4, and 5, belong to one cluster, while the object below the right-hand line, namely 2, belongs to the other cluster.



## ANNEXURE 7

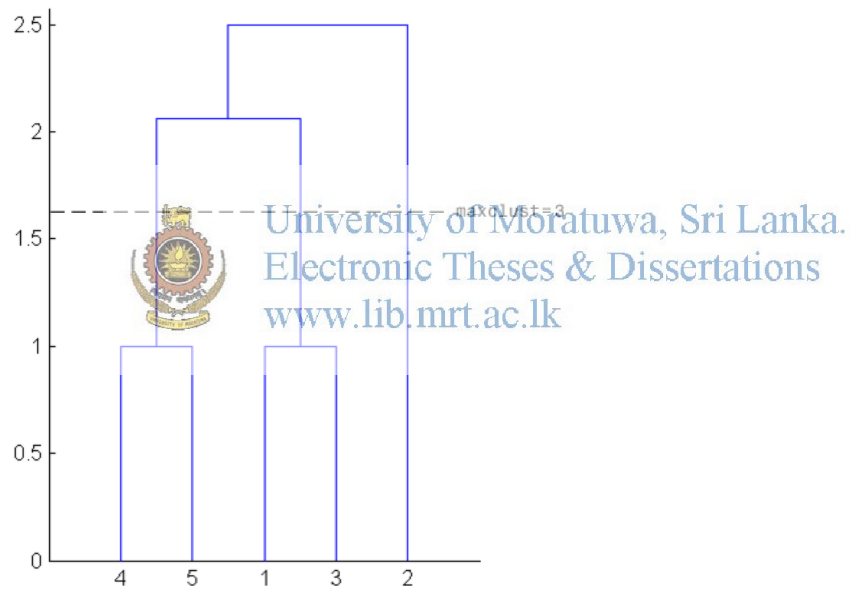
On the other hand, if you set 'maxclust' to 3, the cluster function groups objects 4 and 5 in one cluster, objects 1 and 3 in a second cluster, and object 2 in a third cluster. The following command illustrates this.

```
T = cluster(Z,'maxclust',3)
```

```
T =
```

```
2  
3  
2  
1  
1
```

This time, the cluster function cuts off the hierarchy at a lower point, corresponding to the horizontal line that intersects three lines of the dendrogram in the following figure.





## MATLAB CODE TO FIND SSE

```

% read the normalized 480 numbers of clusters( 500 x 96 matrix)
D = xlsread('kVA profiles after removing profiles which dont have clear
cluster.xlsx','Sheet1');
% read the frequency of load profiles in each clusters
E = xlsread('frequency.xlsx','Sheet2');
% break the D in to small matrices which dimension is = number of profiles per
cluster x 96
F= mat2cell(D, E, [96,0]);
% value of final index of array E
G=numel(E);

% create spare array to fill error values
L=[];

% startin value of error value
M=0;

for i=1:G
    if E(i) == 1 % if number of profiles per a cluster is one, there is problem of getting
mean value of that profile, for such cases take F{i,q} directly as mean
        H=F{i,1};
    else
        H = mean(F{i,1});
    end

    I=F{i,1}-repmat(H,E(i),1); % find the error of each cluster by getting diffrance
between matrix of load profiles of a cluster with its mean matrix. mean is re arranged
using repmat() function to tally with the dimension of the cluster matrix
    %J= abs(I); % convert minus value of error matrix in to positive

    J=I.^2; % obtain the squire of error

    K=sum(J(:)); % obtain the sum of all elements of the error matrix
    M=M+K; % add error or each clusters together to find total error

end

```

## MATLAB INBUILT FUNCTION TO DETERMINE KNEE POINT

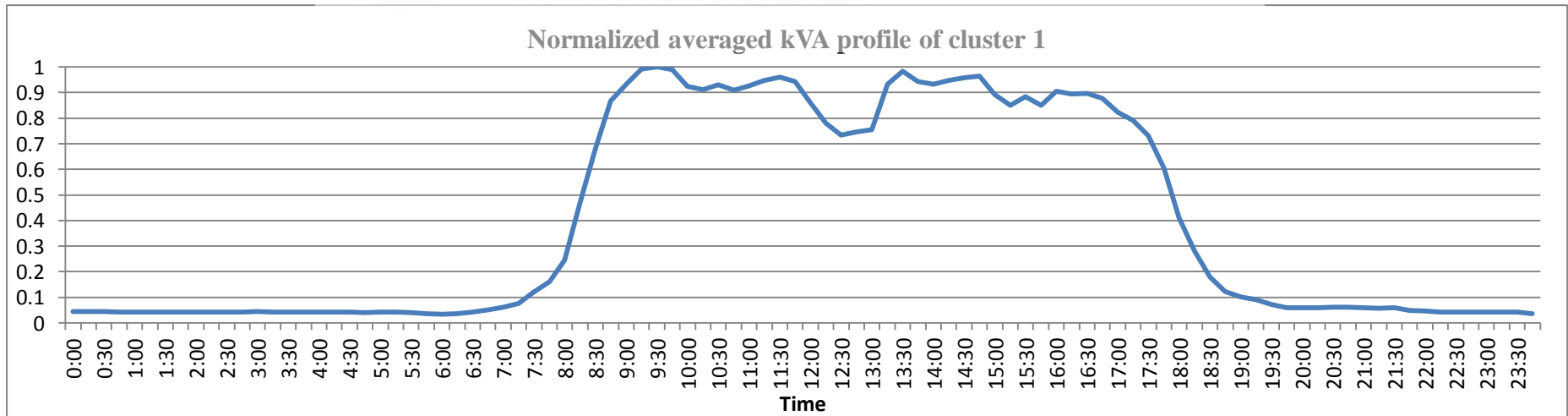
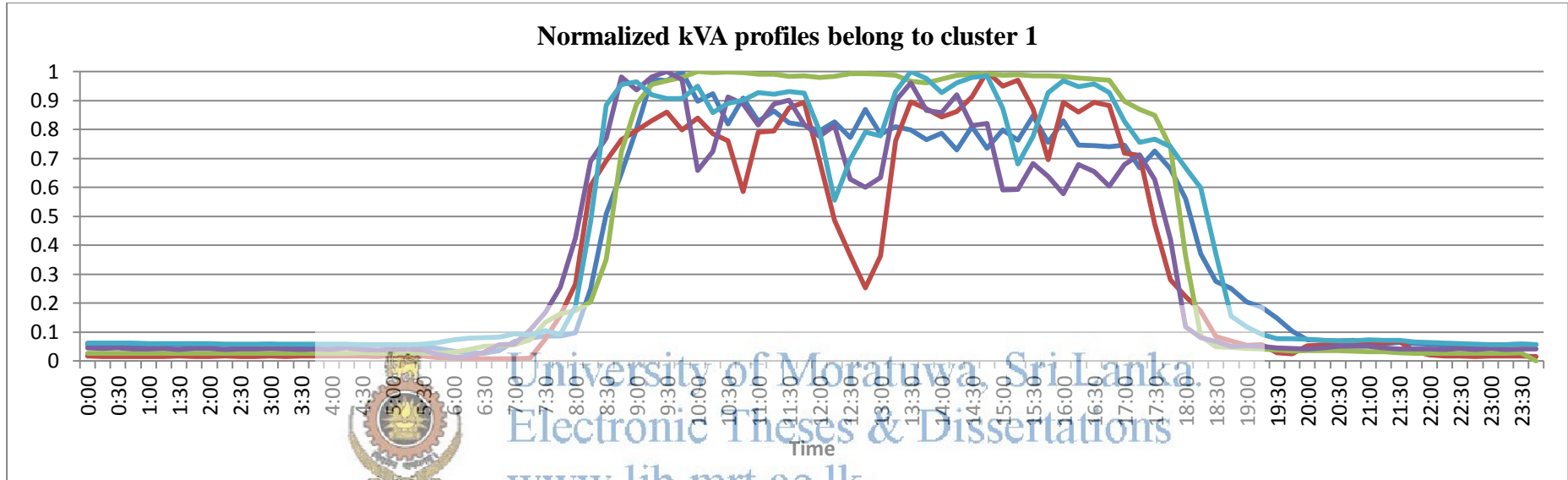
```

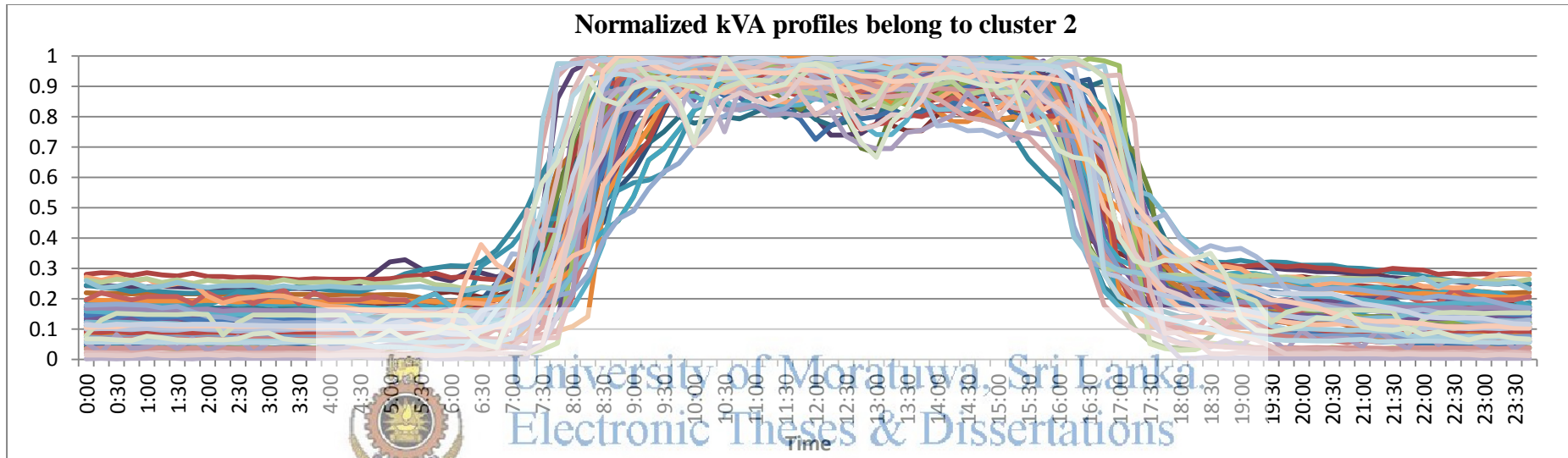
function [res_x, idx_of_result] = knee_pt(y,x,just_return)
[i,ix]=knee_pt([30:-3:12,10:-2:0]) %should be 7 and 7
knee_pt([30:-3:12,10:-2:0]) %should be 7
knee_pt(rand(3,3)) %should error out
knee_pt(rand(3,3),[],false) %should error out
knee_pt(rand(3,3),[],true) %should return Nan
knee_pt([30:-3:12,10:-2:0],[1:13]) %should be 7
knee_pt([30:-3:12,10:-2:0],[1:13]*20) %should be 140
knee_pt([30:-3:12,10:-2:0]+rand(1,13)/10,[1:13]*20) %should be 140
knee_pt([30:-3:12,10:-2:0]+rand(1,13)/10,[1:13]*20+rand(1,13)) x = 0:.01:pi/2; y =
sin(x); [i,ix]=knee_pt(y,x) %should be around .9 and around 90
[~,reorder]=sort(rand(size(x)));xr = x(reorder); yr=y(reorder);[i,ix]=knee_pt(yr,xr)
knee_pt([10:-1:1]) %degenerate condition -- returns location of the first "knee" error
minimum: 2
issue_errors_p = true;
if (nargin > 2 && ~isempty(just_return) && just_return)
    issue_errors_p = false;end
res_x = nan;
idx_of_result = nan;
if (isempty(y))
    if (issue_errors_p)
        error('knee_pt: y can not be an empty vector');
    end
    return;
end
if (sum(size(y)==1)~=1)
    if (issue_errors_p)
        error('knee_pt: y must be a vector'); end
    return;end
y = y(:);
if (nargin < 2 || isempty(x))
    x = (1:length(y))';
else
    x = x(:);end
if (ndims(x)~= ndims(y) || ~all(size(x) == size(y)))
    if (issue_errors_p)
        error('knee_pt: y and x must have the same dimensions'); end
    return;end
if (length(y) < 3)
    if (issue_errors_p)
        error('knee_pt: y must be at least 3 elements long');
    end
    return;
end
end

```

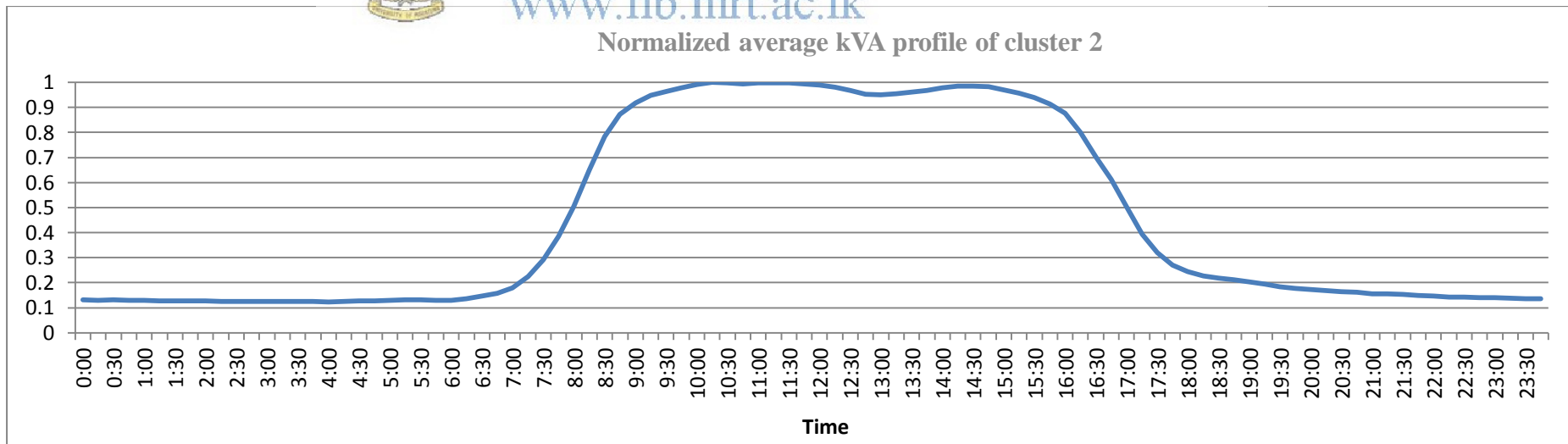


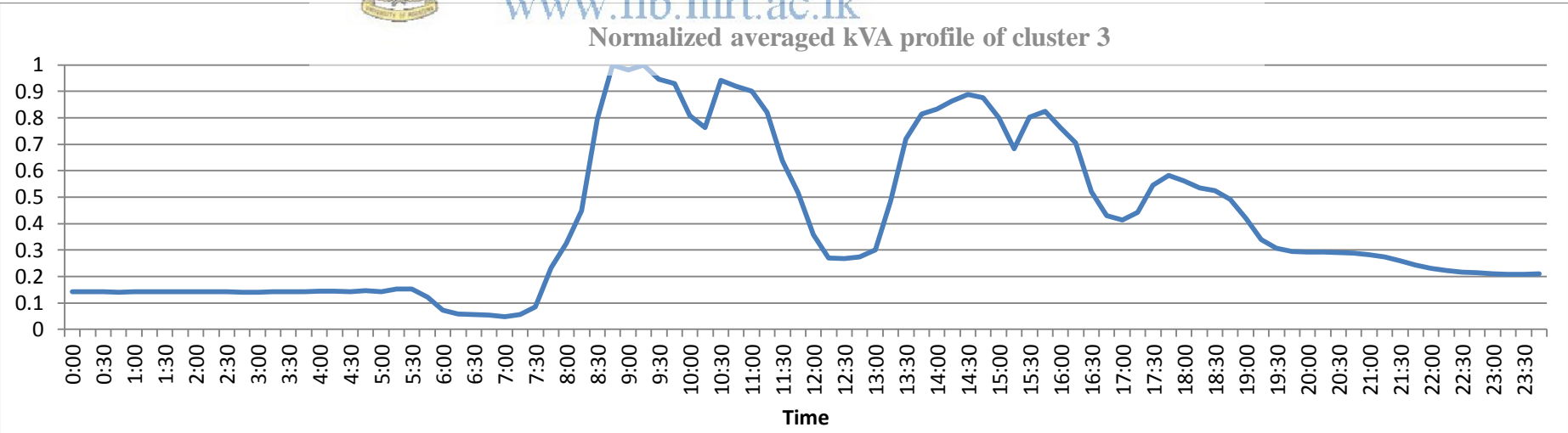
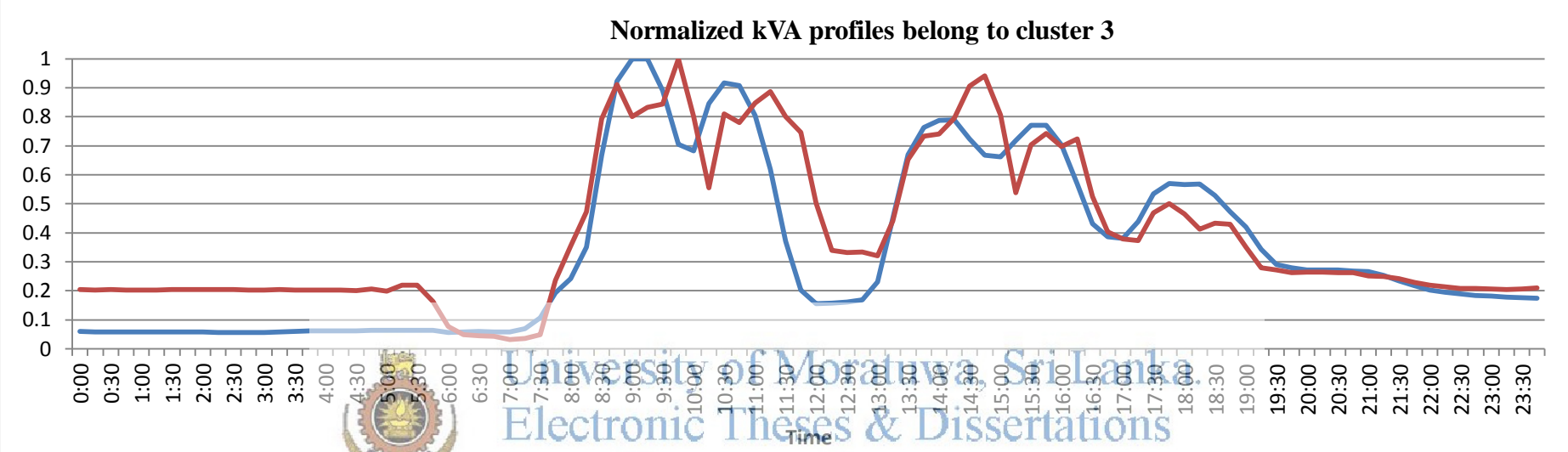
**17 NUMBERS OF CLUSTERS WITH THEIR NORMALIZED KVA PROFILES AND AVERAGED  
NORMALIZED KVA PROFILE**

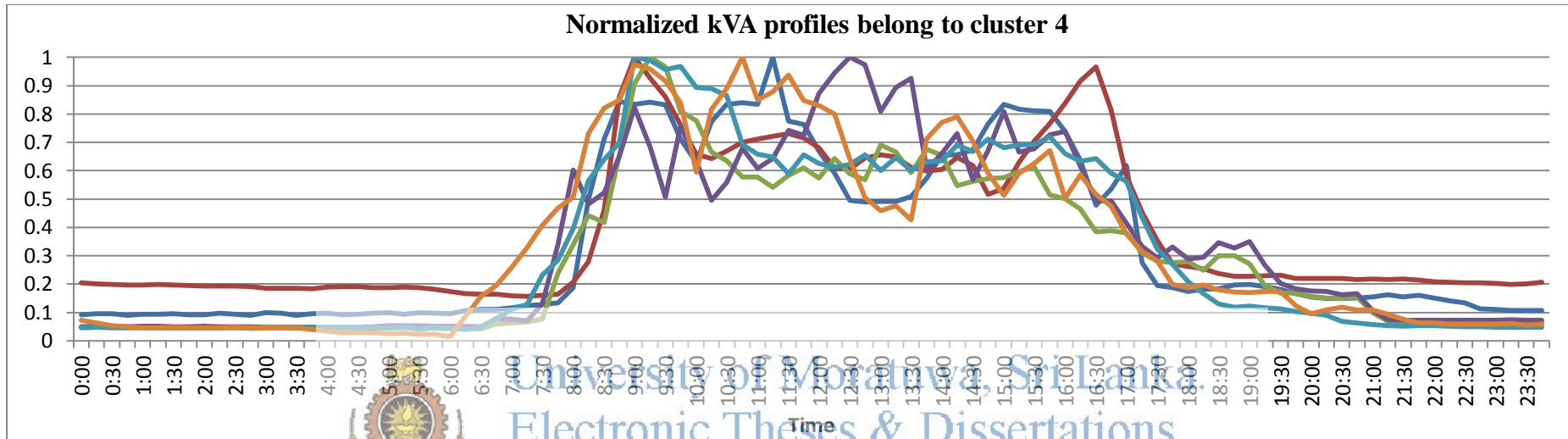




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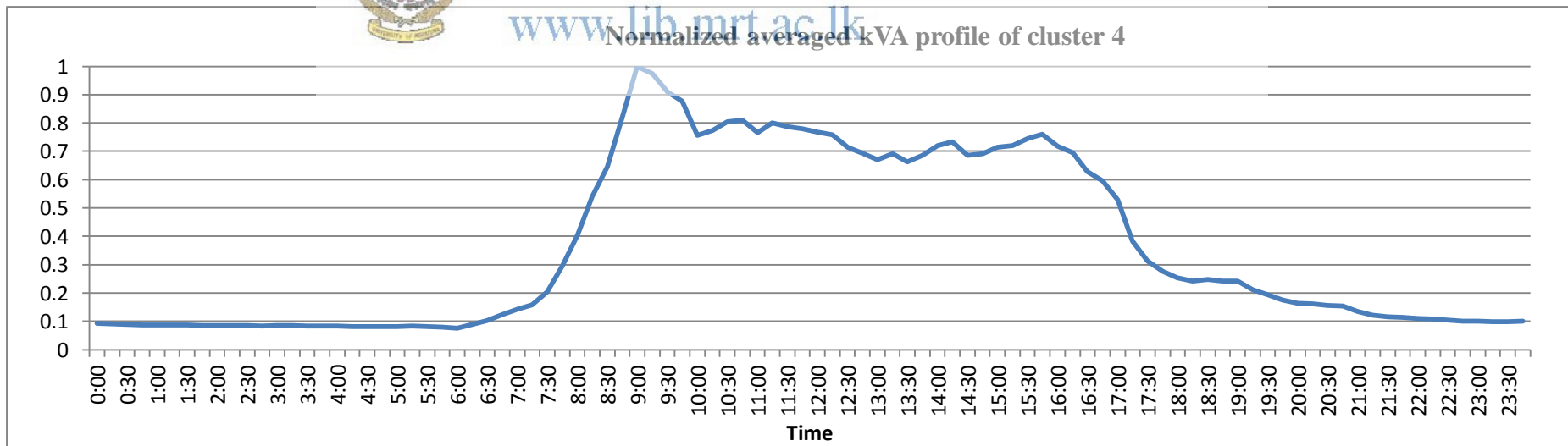


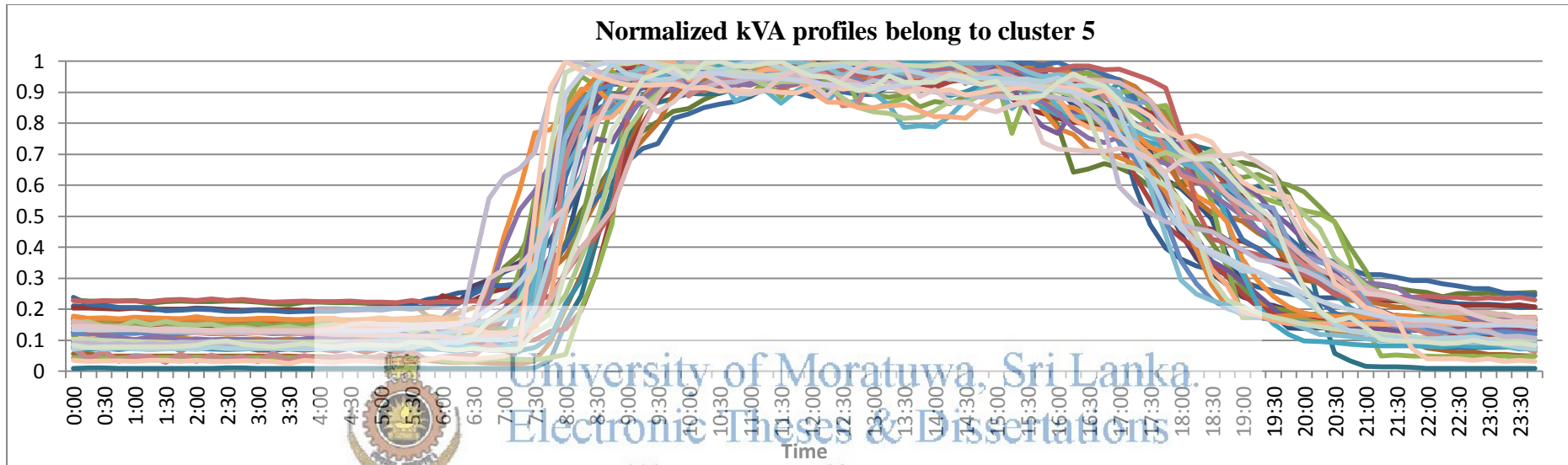




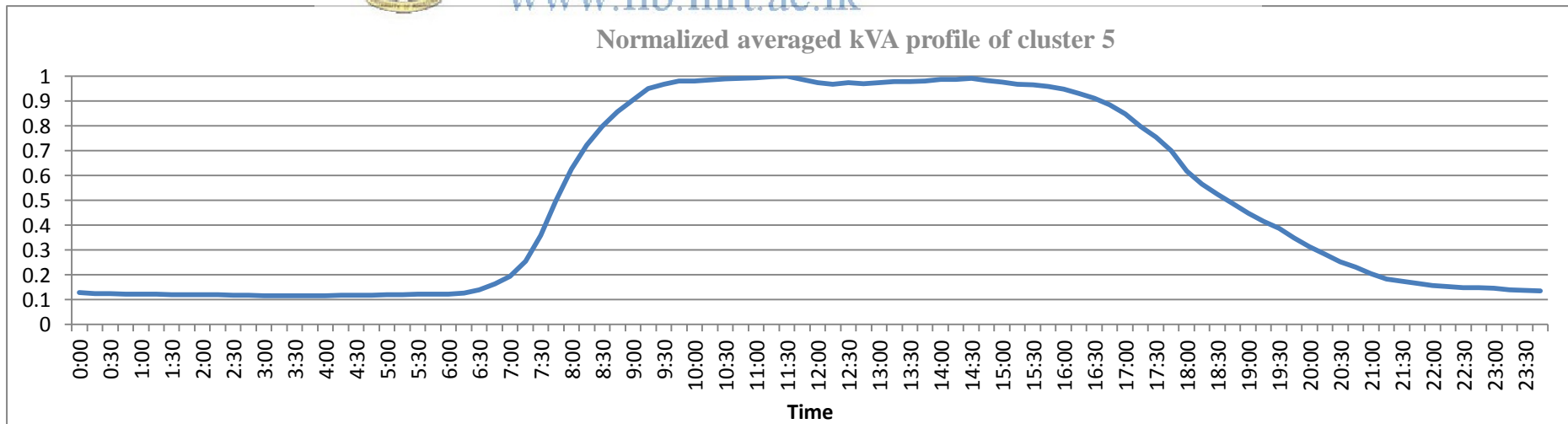
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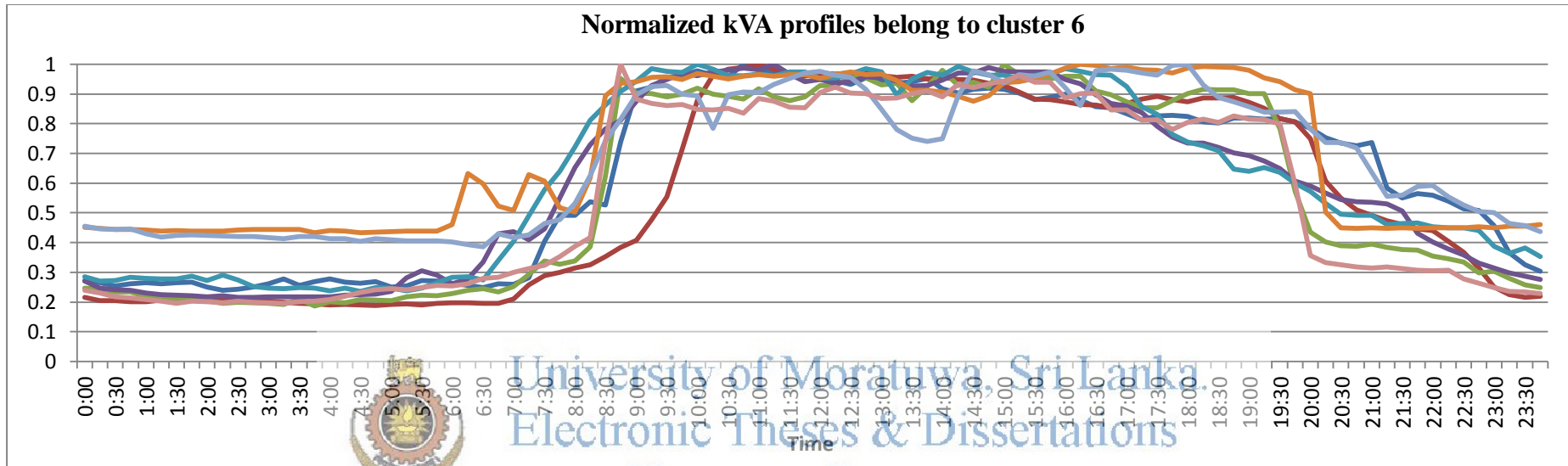
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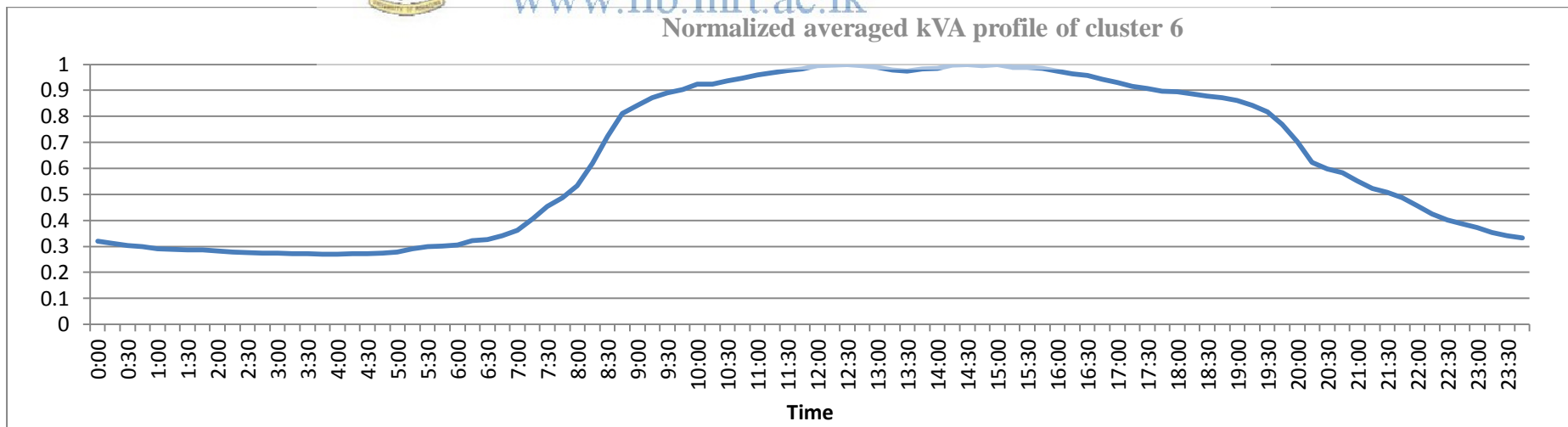


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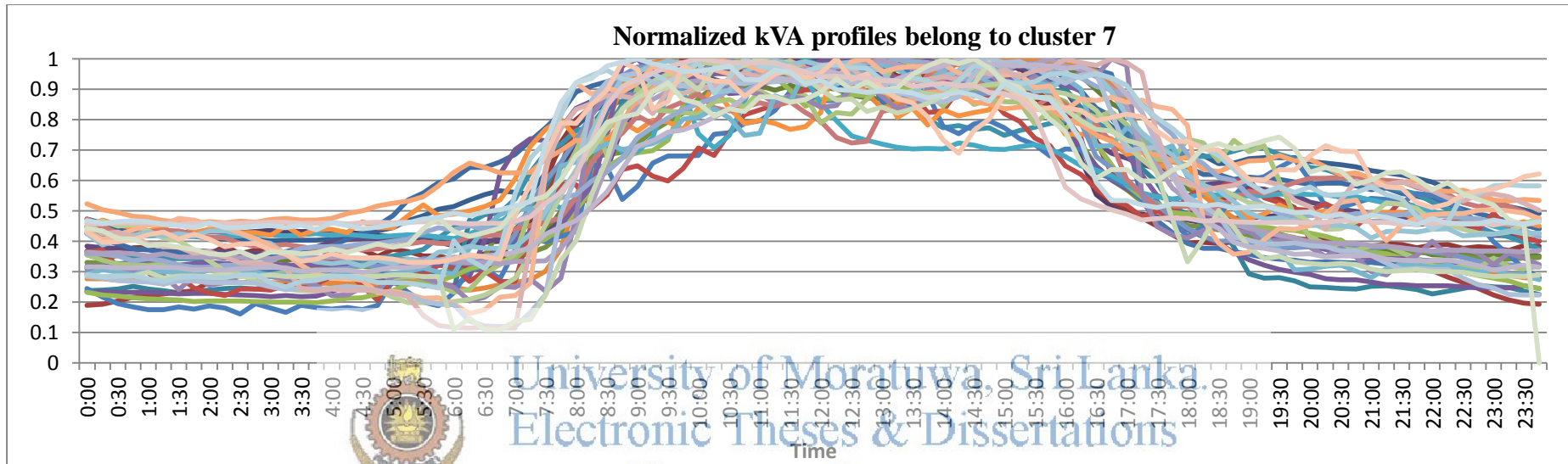




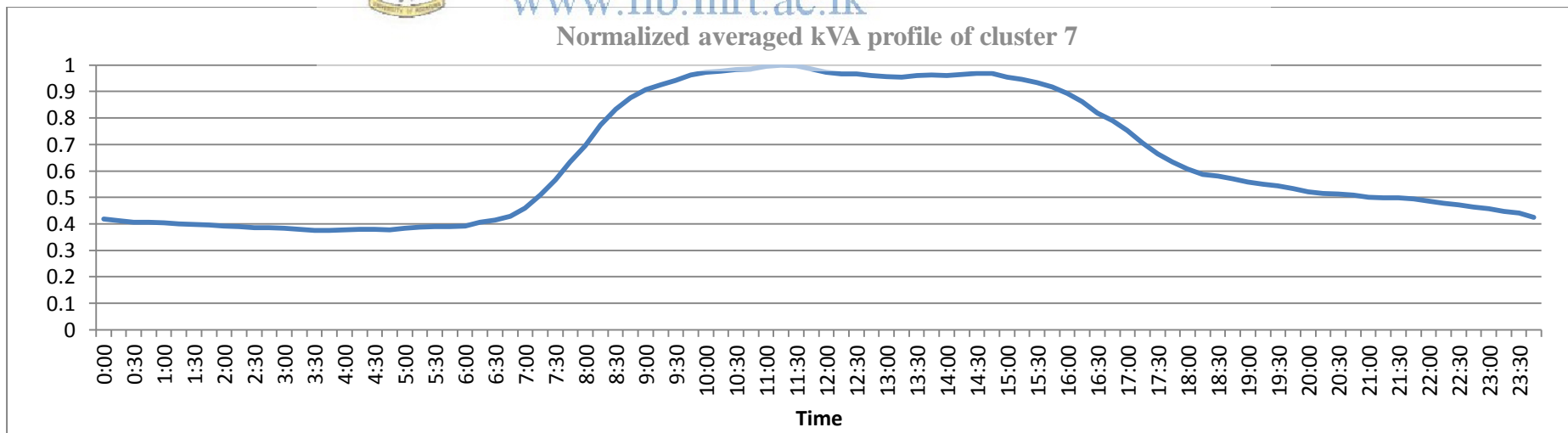
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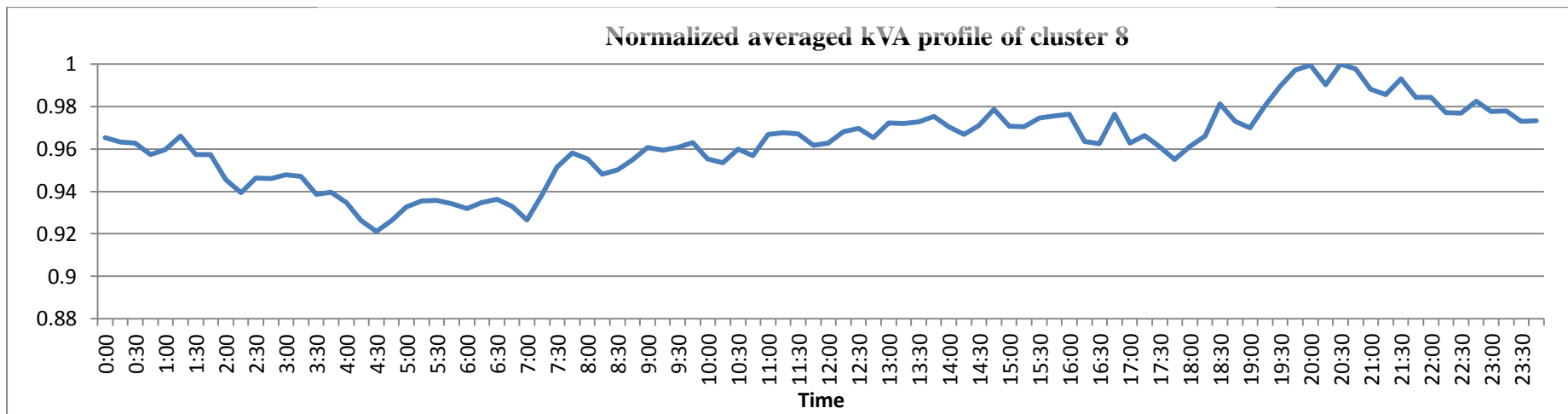
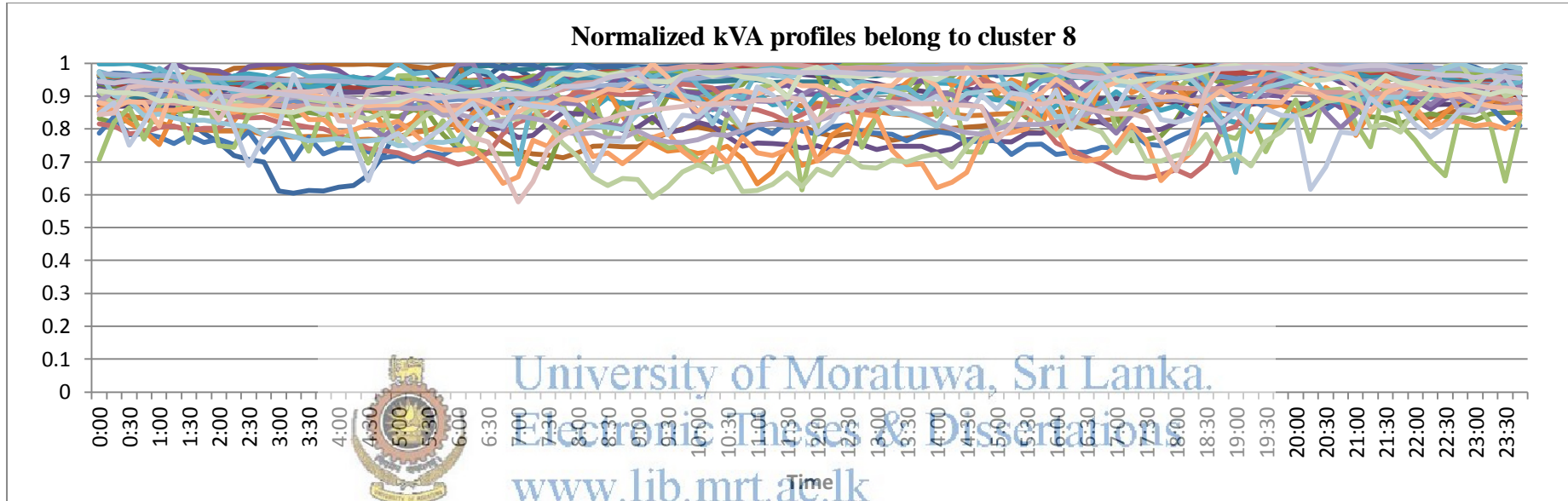


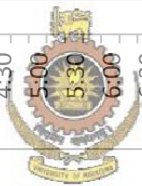
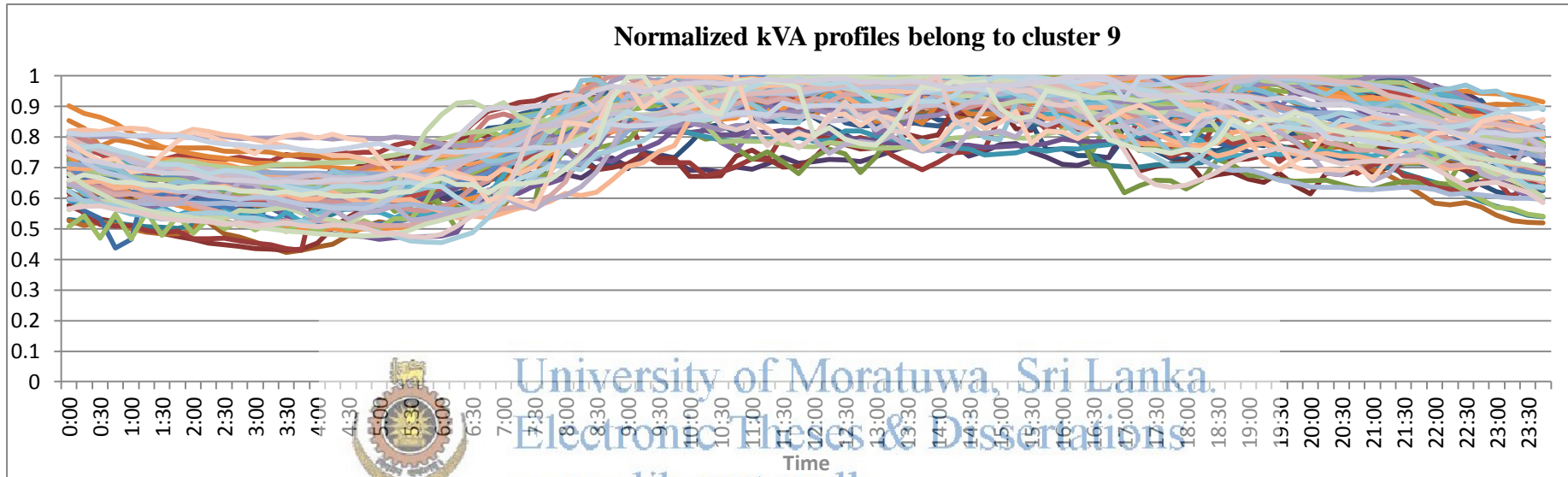




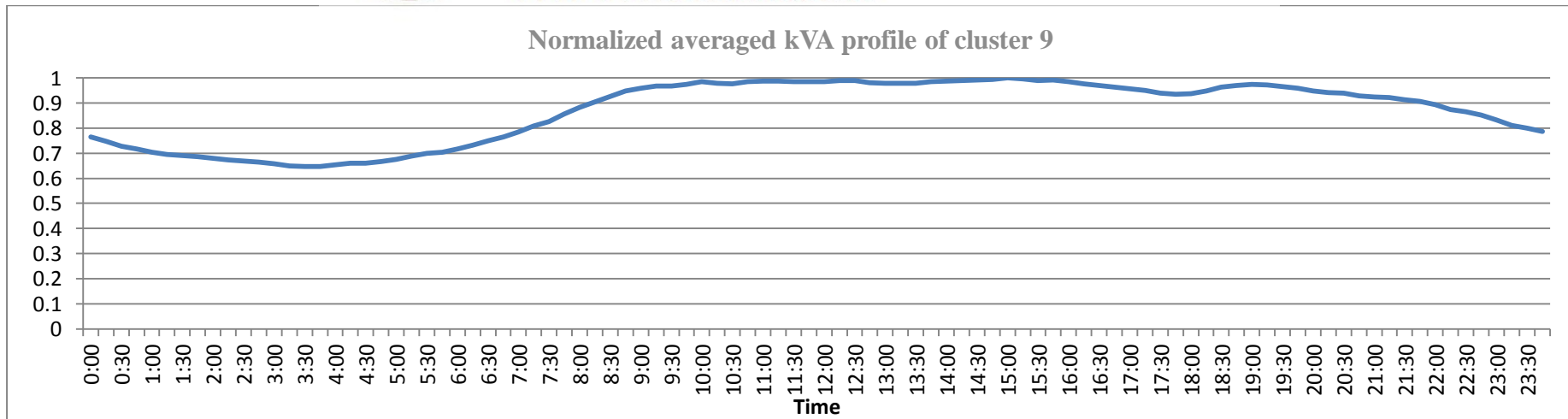
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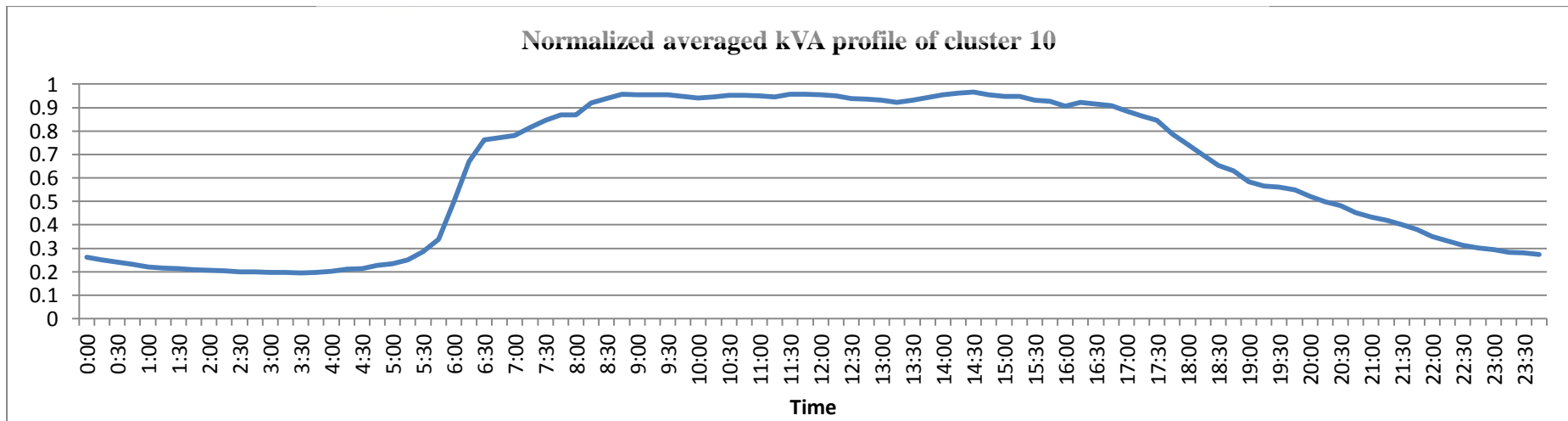
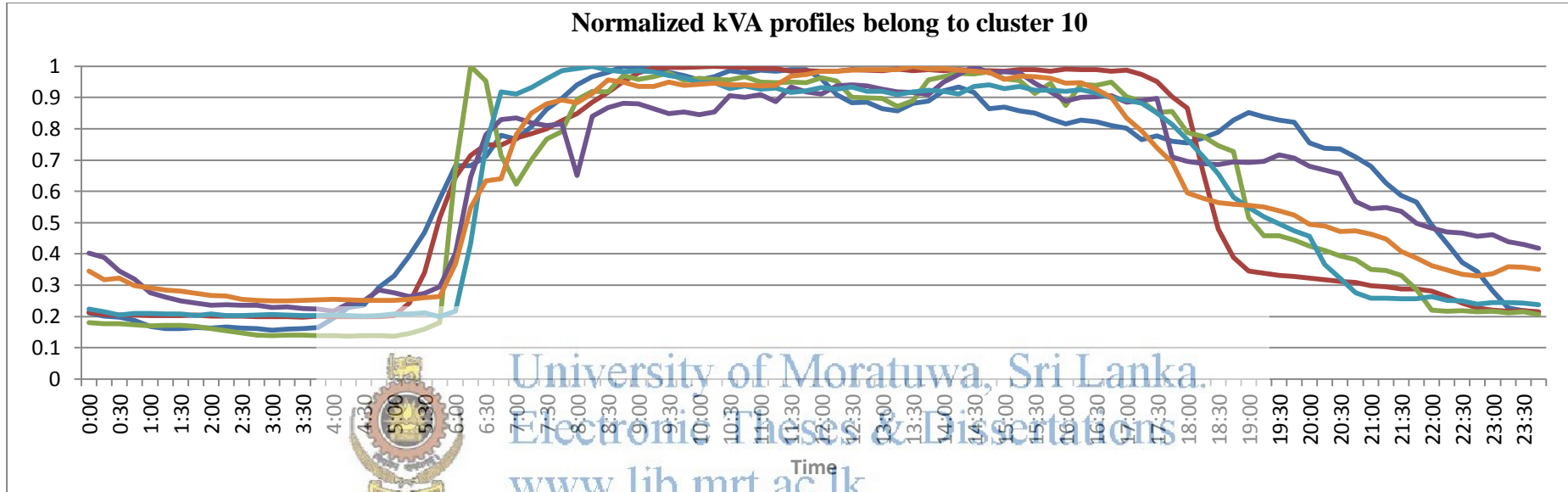


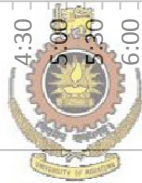
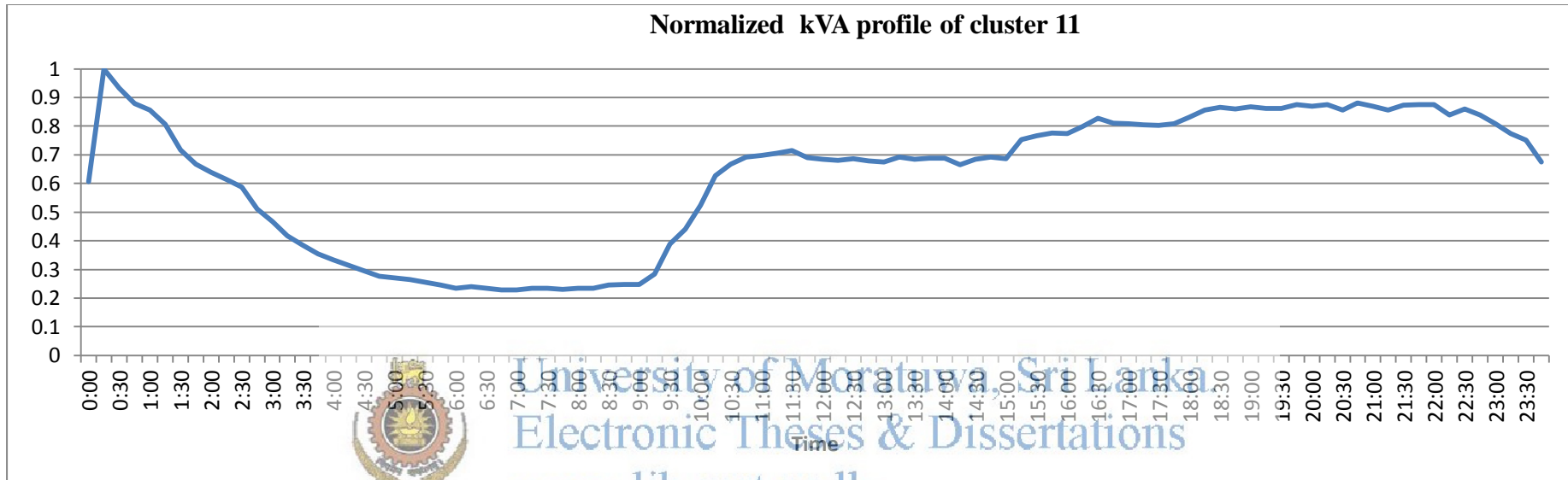




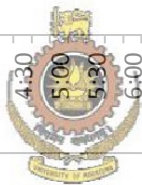
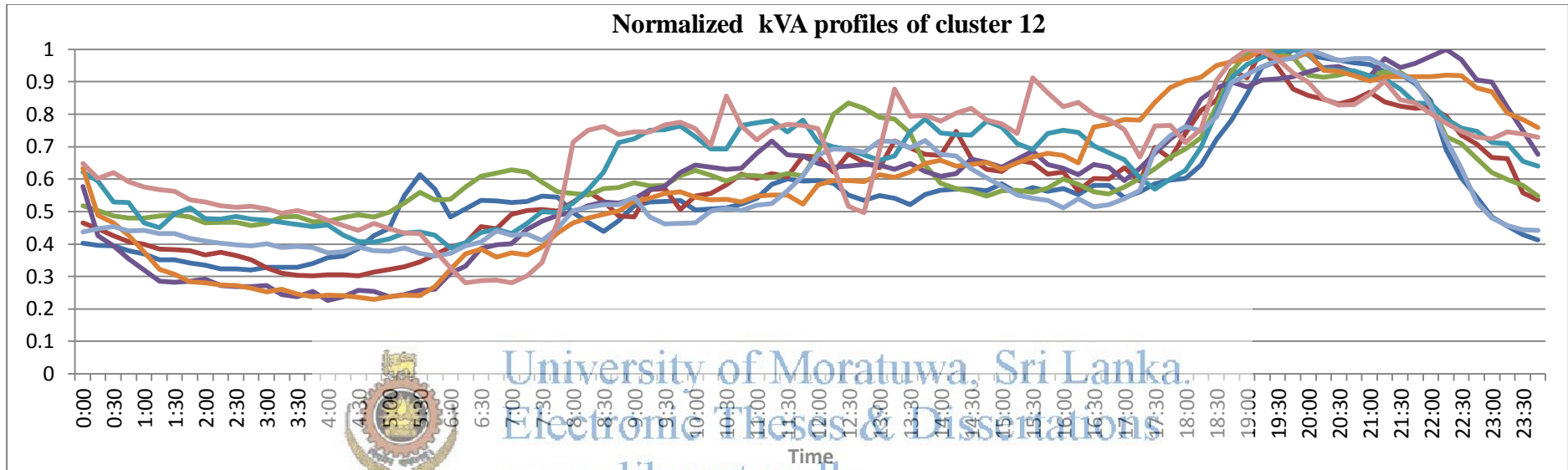
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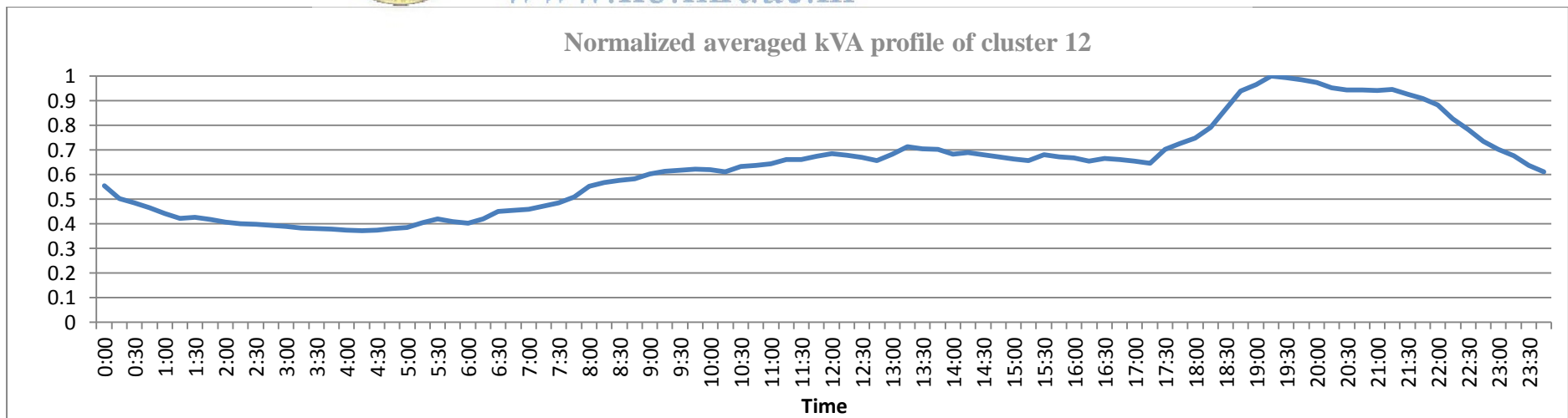


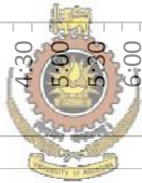
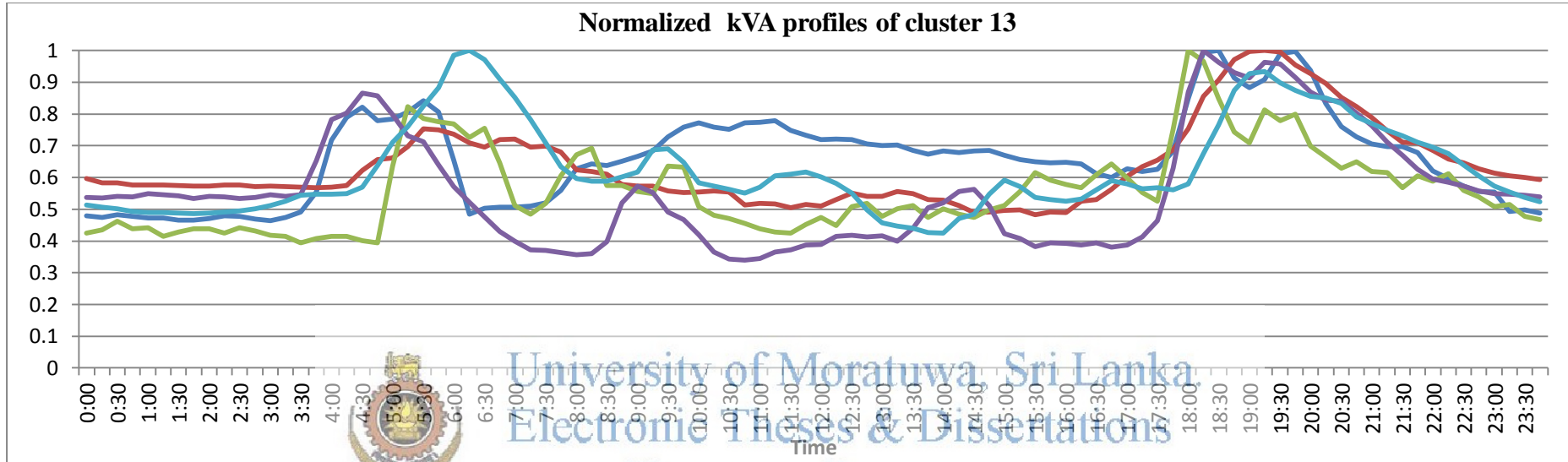


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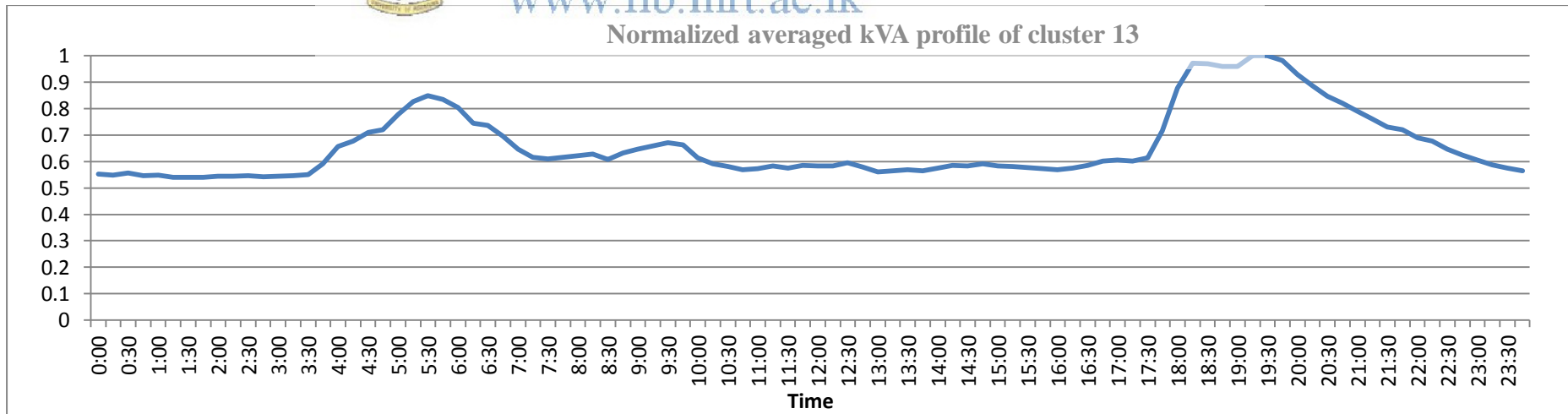


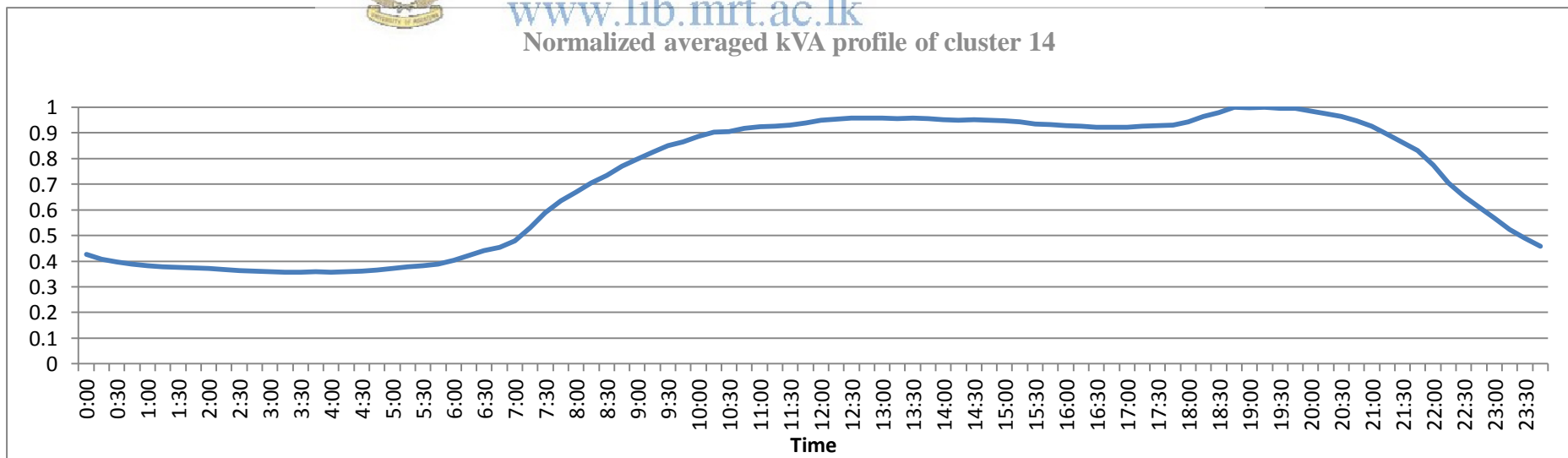
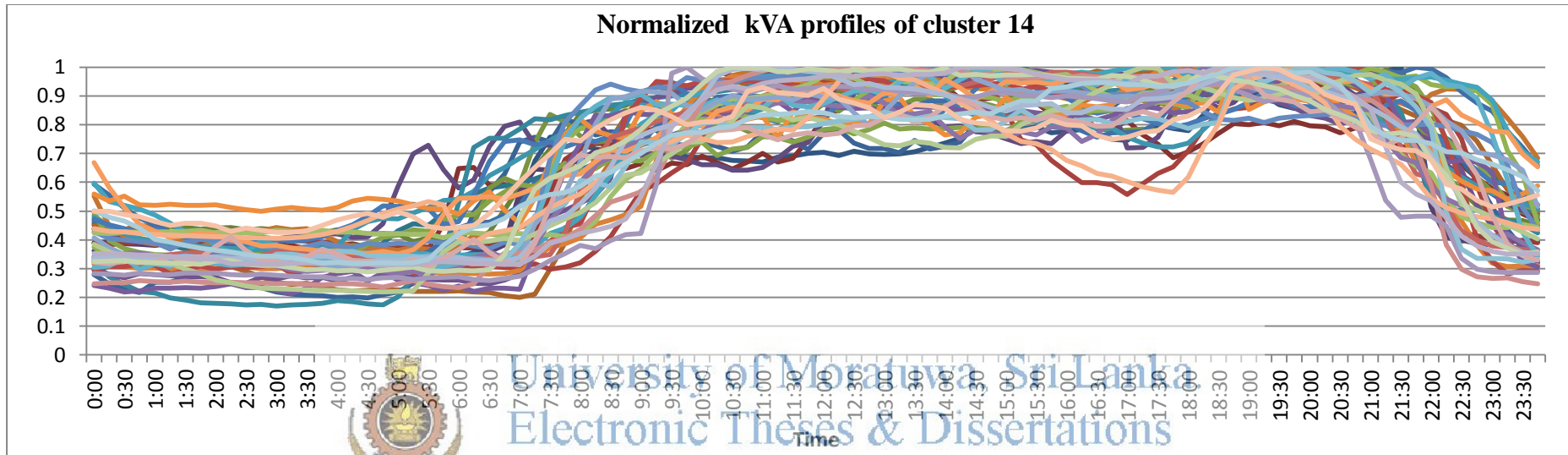
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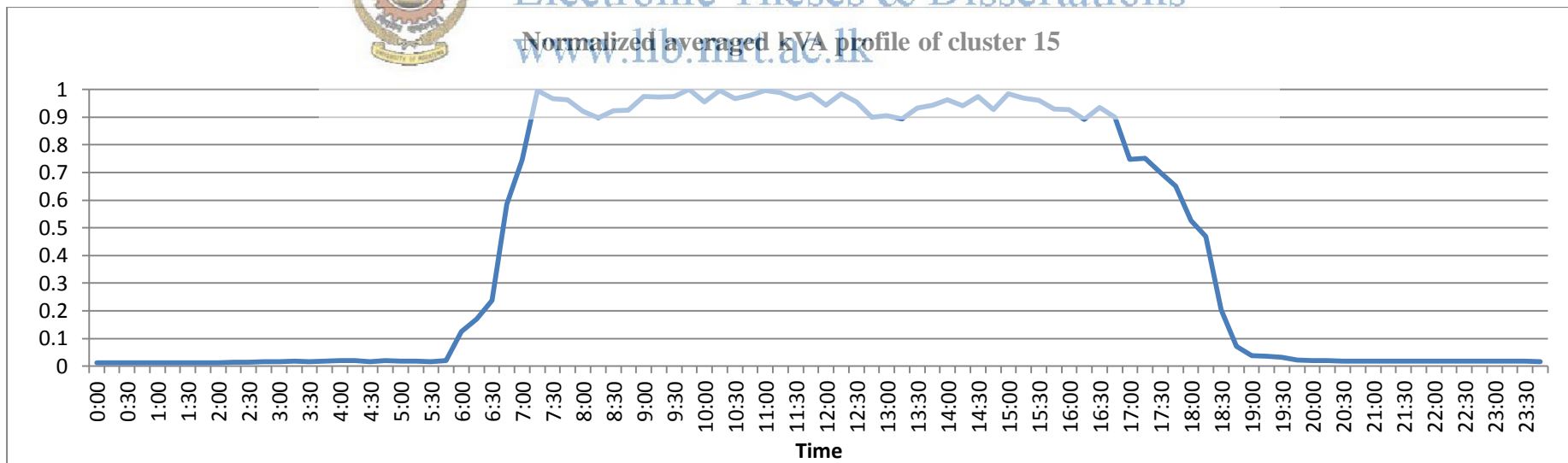
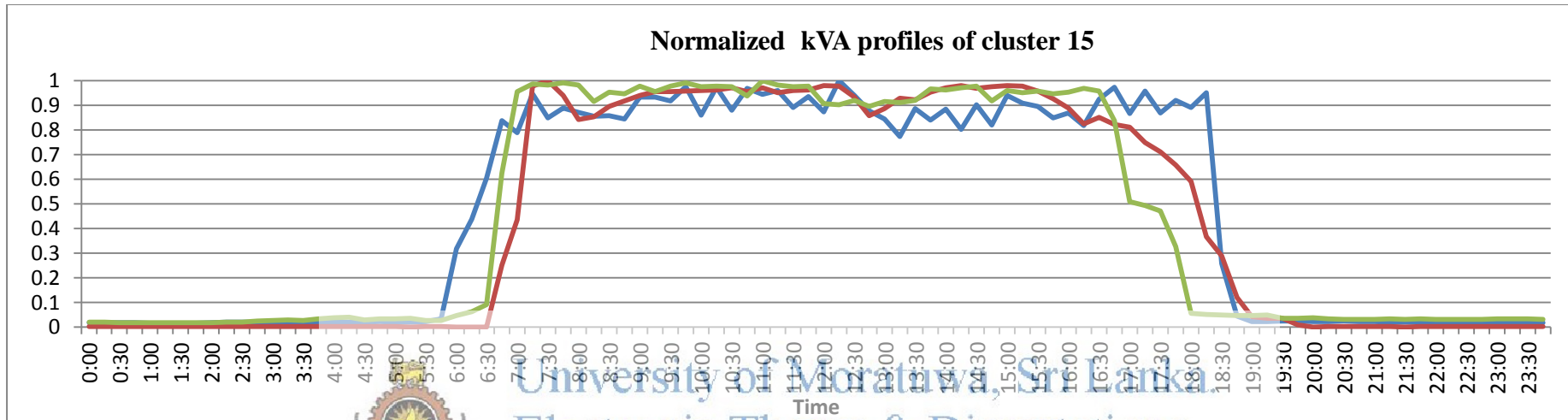


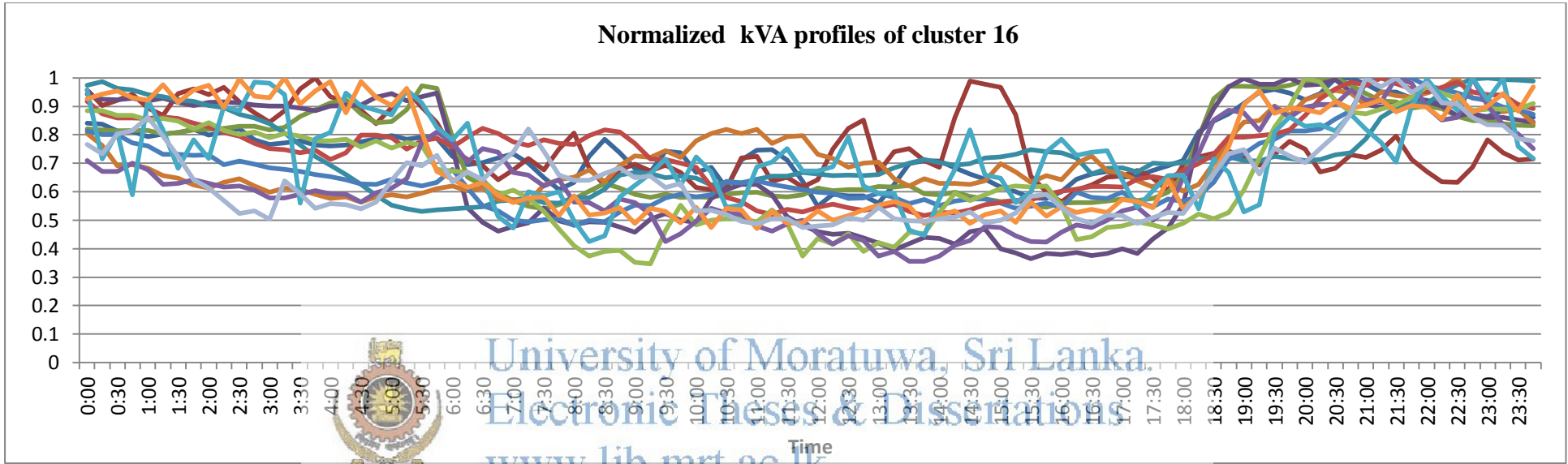
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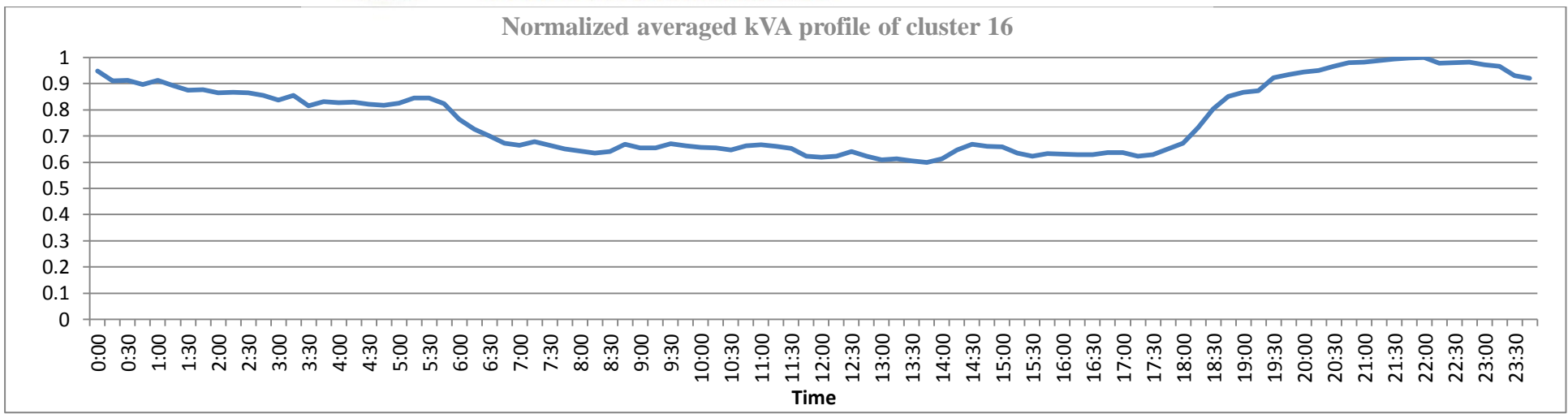


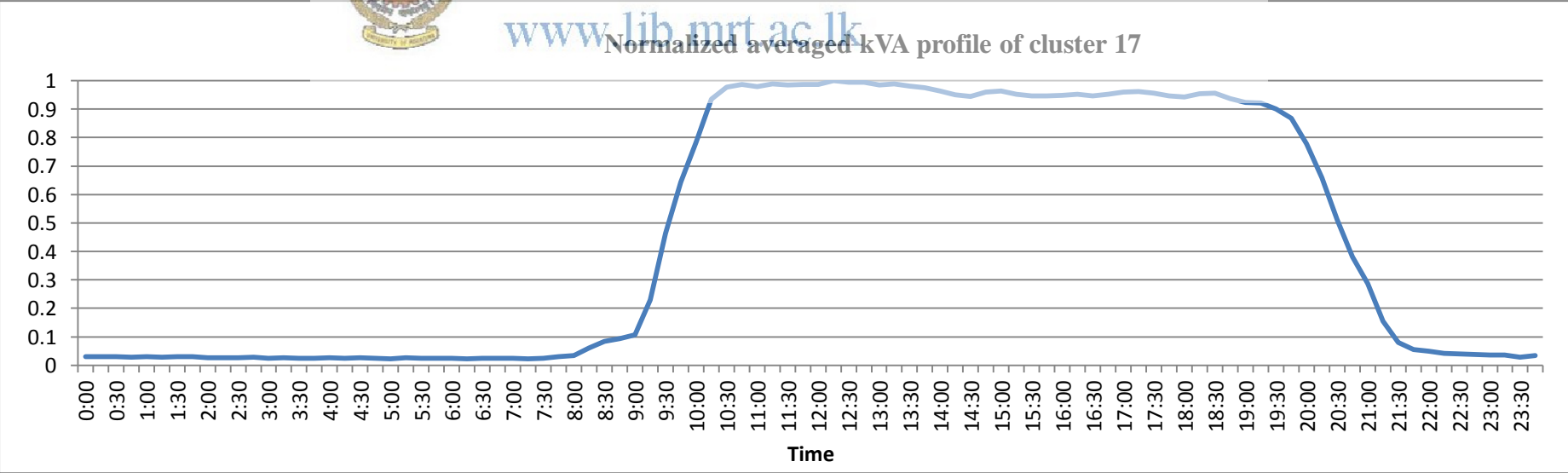
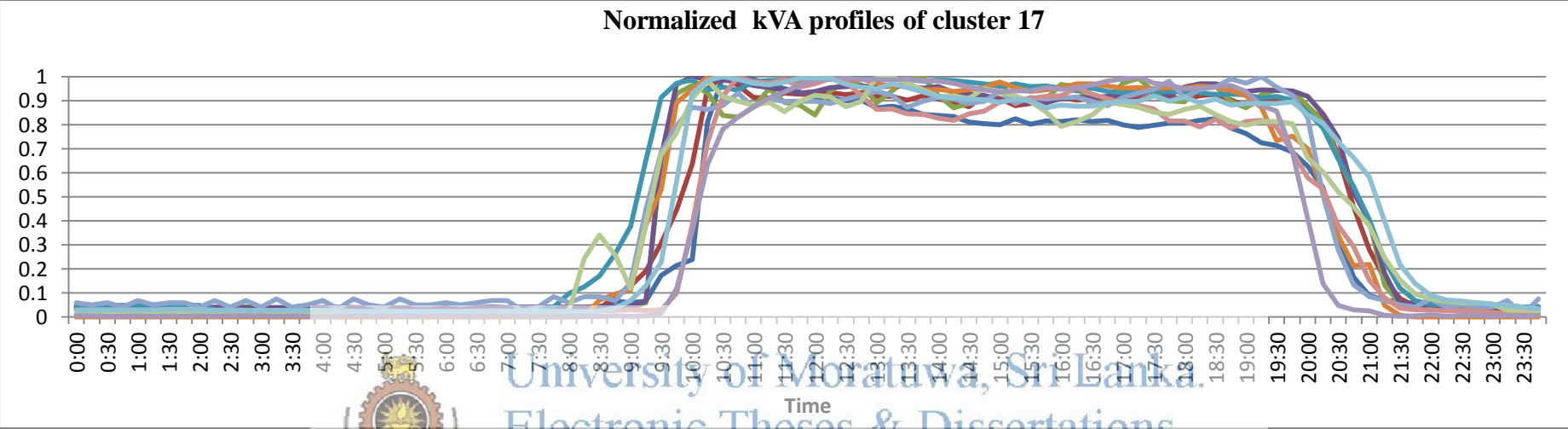






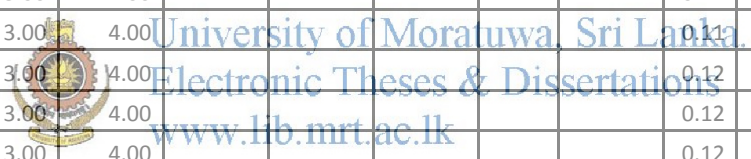
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Time	Car lifts/kw	Security office of ground floor /kw	ground floor and ground floor bathroom/kw	Escallator/kw	water Pump/kw	Parking/MO/kw	Common Areas/kw	Lifts/kw	PVT BANK/kw		GV BANK/kw	
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1:30:00		3.00	4.00						0.12	158.40	0.13	150.70
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GV OFFICE/kw		PVT OFFICE/kw		INSTITUTE/kw		INSURANCE/kw		Total Estimated/kVA			
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```

if (nargin > 1 && any(diff(x)<0))
    [~,idx]=sort(x);
    y = y(idx);
    x = x(idx);
else
    idx = 1:length(x);
end
sigma_xy = cumsum(x.*y);
sigma_x = cumsum(x);
sigma_y = cumsum(y);
sigma_xx = cumsum(x.*x);
n = (1:length(y))';
det = n.*sigma_xx-sigma_x.*sigma_x;
mfwd = (n.*sigma_xy-sigma_x.*sigma_y)./det;
bfwd = -(sigma_x.*sigma_xy-sigma_xx.*sigma_y) ./det;
% figure out the m and b (in the y=mx+b sense) for the "right-of-knee"
sigma_xy = cumsum(x(end:-1:1).*y(end:-1:1));
sigma_x = cumsum(x(end:-1:1));
sigma_y = cumsum(y(end:-1:1));
sigma_xx = cumsum(x(end:-1:1).*x(end:-1:1));
n = (1:length(y))';
det = n.*sigma_xx-sigma_x.*sigma_x;
mbck = flipud((n.*sigma_xy-sigma_x.*sigma_y)./det);
bbck = flipud(-(sigma_x.*sigma_xy-sigma_xx.*sigma_y) ./det);
error_curve = nan(size(y));
for breakpt = 2:length(y-1)
    delsfwd = (mfwd(breakpt).*x(1:breakpt)+bfwd(breakpt))-y(1:breakpt);
    delsbck = (mbck(breakpt).*x(breakpt:end)+bbck(breakpt))-y(breakpt:end);
    % disp([sum(abs(delsfwd))/length(delsfwd), sum(abs(delsbck))/length(delsbck)])
    if (use_absolute_dev_p)
        % error_curve(breakpt) = sum(abs(delsfwd))/sqrt(length(delsfwd)) +
sum(abs(delsbck))/sqrt(length(delsbck));
        error_curve(breakpt) = sum(abs(delsfwd))+ sum(abs(delsbck));
    else
        error_curve(breakpt) = sqrt(sum(delsfwd.*delsfwd)) +
sqrt(sum(delsbck.*delsbck));
    end
end

 [~,loc] = min(error_curve);
res_x = x(loc);
idx_of_result = idx(loc);
end

```