DEMAND SIDE MANAGEMENT:
LOAD PROFILE ANALYSIS FOR CAMPUS BUILDING

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering (Hons.) Electrical and Electronic Engineering

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DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have been duly acknowledged. I also declare that it has not been previously and concurrently submitted for any other degree or award at UTAR or other institutions.

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APPROVAL FOR SUBMISSION

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Specially dedicated to

my beloved family,

supervisor Mr. Chua Kein Huat,

and partners Mr. Teo Teck Cheong, Mr. Khor Wei Peng

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ABSTRACT

Demand side management (DSM) demonstrates means to improve energy efficiency, to converse energy and to provide responses toward changes in demand. The approaches of DSM are load reduction, load management and load conservation. In order to achieve these objectives, load profile analysis is required. In this project, load profile analysis is performed on SE block in Universiti Tunku Abdul Rahman. Data logging is conducted with the use of two power analysers. The collected data is then processed in a spreadsheet program, Microsoft Office Excel. The analysis is only conducted for weekdays which are the standard working days. The linear relationship of each weekday is proven using correlation coefficient for making comparison. Four sets data of each weekdays are compared to analyse their average power trends over 15-minute intervals. The analysis is further enhanced with the use of histogram to identify the occurrences of peak demand on each weekday. From the results, Thursday has the highest peak demand among the weekdays. A supply of energy from ESS could reduce that peak demand so as to avoid the surcharge of maximum demand from the utilities. Load distribution of tutorial rooms based on equipment types and actual timetable is discussed to provide alternate means on peak demand reduction which is to reduce the power consumption of air conditioner.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS / ABBREVIATIONS

kWh	kilowatts-hours
DSM	demand side management
DG	distributed generation
ESS	energy storage system
EE	energy efficiency
EC	energy conversation
DR	demand response
BESS	battery energy storage system
SVR	support vector regression
LS-SVR	least squares support vector regression
ANN	artificial neural network
AC	admission control
LB	load balancer
LF	load forecaster
DRM	demand response manager
HVAC	heating, ventilation and air conditioning
GUI	graphical user interface
TKWh	total power consumption
MD	maximum demand

INTRODUCTION

1.1 Background

The ever increasing electricity bills due to poor energy management has raised a concern among consumers who wish to cut down the electricity cost yet maintaining the productivity. It is rather crucial to identify the possible causes and to tackle them specifically to achieve desired results. There are more and more methods surfacing in the market nowadays on how to study the behaviour of energy usage so to implement efficient and effective solutions. It is no longer an issue of consumers whereby the utilities come into play to work together with customers in executing the best possible way to maintain power quality and stability.

One of the plausible and exciting methods will be demand side management (DSM). It applies largely to the energy usage in order to bring a significant reduction of cost to energy users. Demand side management provides opportunities to reduce energy demand. There are many low cost or even no cost approaches that most companies or individuals could learn to apply within a short period or long period, if good practices of energy management. Several case studies shows the promising potential of demand side management on saving costs and mitigating other power issues around the globe. Two DSM case studies are drawn below for reference, one from the United States and one from the Sultanate of Oman.

DSM programmes has been taken part by 459 large electricity utilities in the United States in 1999. 50.6 billion kilowatt hours (kWh) of energy generation by the large utilities was saved by these programme. This represented 1.5 % of the annual electricity sales of that year. Moreover, New York shows great potential in reducing demand by 1,300 MW in 2002 through DSM programmes. The amount is enough to supply power to 1.3 million homes (Cogeneration Technologies, n.d.).

By 2012, the electrical energy demands in Sultanate of Oman are expected to increase by about 60 % due to its fast growth in industrialization and country's multi-dimensional expansion activities. It has become vital for the government to look into the mutual benefit of both utility and the customer by regulating the energy demands and drafting suitable policies under DSM. A recommendation and implementation of suitable policies to regulate energy demands would result a total annual energy saving of 25.6% and a cost saving of $138,447 (Venkateswara, Parmal and Yousif, 2011).

1.2 Aims and Objectives

This project aims to integrate the application of demand side management to university campus buildings. The main objective of this project is to undertake a load profile analysis for a building in University Tunku Abdul Rahman, namely SE Block and make analysis on how energy costs could be reduced. To examine the possibility of the application of even load distribution and scheduling at reducing electricity bills and thus avoiding the maximum demand penalty from energy supplier.

The key elements of load profile analysis comprised of the following:

1) To identify the energy consuming unit;
2) To estimate the quantity of energy consumed by each unit;
3) To analyse energy consumption patterns;
4) To identify energy savings opportunities;
5) To recommend conservation measures

CHAPTER 2

LITERATURE REVIEW

2.1 Demand Side Management

Demand side management (DSM) has been regarded as means of reducing peak electricity demands so that utilities can delay the expansion of supply capacity. A concept deals with energy efficiency measures that adjust and reduce energy demand of end users. It introduces peak demand management which does not necessarily cut down total energy consumption but shed loads to achieve optimum energy demands. The adjustment applies not only to electricity loads but also to demands of all types of energy. The clear benefit here is reduced energy costs for a given output.

Nowadays, it has become essential to access power in an efficient and effective manner in order to save on cost. Demand side management is said to play an important role in delaying high investment costs in generation, transmission and distribution of power while still providing various practical benefits such as mitigating electrical system outbreaks, reducing system blackouts and increasing system reliability. Managing energy demands can substantially reduce dependency of expensive fuels import, reduce high energy prices and reduce harmful environmental impacts. All these in combination help to bring significant energy cost benefits.

Energy demands at wherever places can easily hit the peak load consumption without prior load management. This can tell when electricity bill each months is surcharged with an additional cost of maximum demand. It could be seen as a form of penalty that could have easily been avoided if the exact figure of load consumption is known. The two types of maximum demand surcharges are during peak period and off peak period according to the pricing and tariff by Tenaga Nasional Berhad.

On the other hand, DSM is greatly promoted with aims to provide cost reduction, social and environmental improvement and network and reliability issues. To save on the cost, DSM has introduced resources planning to reduce overall energy demands so to reduce cost. Less energy consumption leads to a cleaner environment because greenhouse gas emission and other environmental issues are reduced. Reduction in energy demands improves power system reliability in the immediate term. It also defers the need to upgrade power system which will save costs and maintain the reliability (Palensky and Dietrich, 2011).

2.1.1 DSM Concepts

There are three main concepts of demand side management which are energy efficiency (EE), energy conversation (EC) and demand response (DR). Each of these concepts has some particularities but they are complementary concepts as illustrated in Figure 2.1 below. Conflicts between each other may happen under bad design of DSM programmes. Thus, it is important to find the relevance between these three concepts to further improve the energy cycle (Boshell and Veloza, 2008).

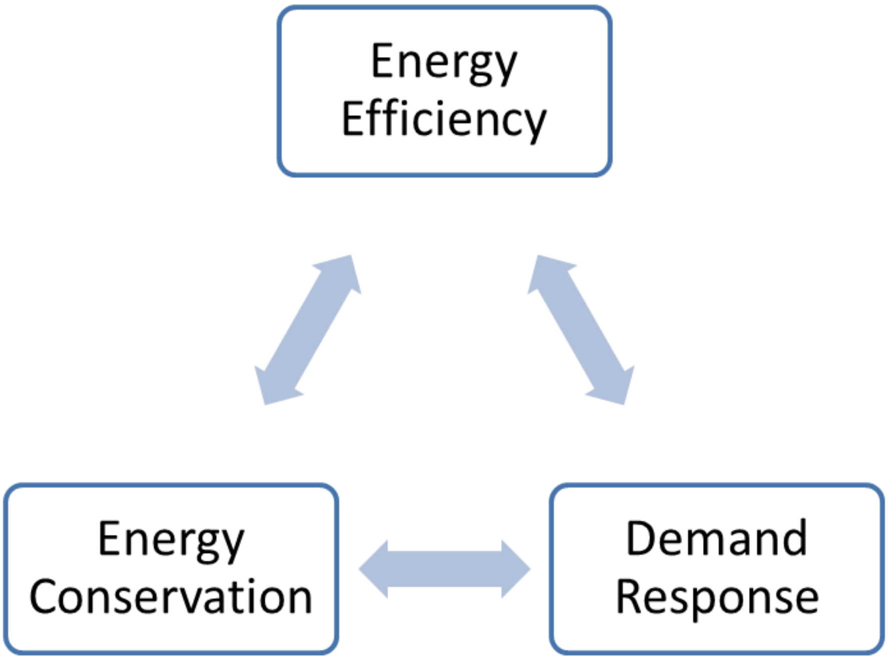


Figure 2.1: Three concept of DSM

In simpler terms, energy efficiency is related to solutions from technological advancements, whilst energy conversation is to achieve energy-saving through the study of consumer's behaviour, and finally demand response is based on the market demand on electricity and its changeable price. Since they are complementary and relevant to save energy, it is essential to promote adequate energy management programmes within an electricity liberalized community.

2.1.1.1 Energy Efficiency

Energy efficiency are introduced to eliminate energy losses in existing power system through the permanent installation of energy efficient technologies. The importance of energy efficiency is to reduce energy usage and not to compromise on the level of service provided.

Several approaches are promoted for better energy efficiency. It could be the replacement of incandescent light bulbs with compact fluorescent bulbs, the implementation of variable speed air conditioners that cool buildings using less energy than typical air conditioners or the maintenance on leaky compressed air networks.

2.1.1.2 Energy Conversation

Energy conversation promotes behavioural changes to use less resources in order to achieve energy-saving. The effect could be for a short term or may last for a long term as daily habits. It is a gradual change on the side of consumer’s behaviours to integrate an energy-saving lifestyle. More resources and energy could be conserved in the process and they could then be put into greater use in future.

It could a simple act like increasing cooling temperature from 16 ℃ to 24 ℃ for air conditioning system, waiting until the washing machine is fully loaded with clothes and wearing light clothes during hot seasons to cut down the use of air conditioners.

2.1.1.3 Demand Response

Demand response is often related to current market of electricity and its price. Consumers are exposed with two strategies which are load management and load shifting. Total loads are curtailed in response to signals received from the service provider to avoid surcharges. It is also possible to shift loads from peak periods to another time periods for a lower tariff of electricity cost.

Dynamic pricing is a new approach to load management which will induce customers to cut down power consumption at specific times or shift loads to other time periods, usually when the energy is at its highest price. Customers are made aware of their power consumptions and the related charges through demand response initiatives of information and communication technologies.

2.1.2 Types of DSM Approaches

2.1.2.1 Load Reduction

It aims to reduce demands through efficient processes, buildings and equipment. It mainly revolves around energy saving tips for the existing so-called household appliances. Most of them can be implemented at little or no cost, but some requires a significant capital investment due to their particular connection to industrial and commercial businesses.

A common practice to produce hot water and water with the use of relevant technology is perhaps a major activity for most enterprises. Inefficient steam systems and boiler operation represent a significant source of energy losses. Poor maintenance as well as poor original design could also incur significant losses. Performance improvement steps which are practical and at low cost are often considered. Adequate controls to adjust the configuration are required to routinely monitor conditions of the systems in order to keep the efficiency as high as possible.

Lighting often consumes 10% or more of electricity in industrial plant or 50% or more in commercial buildings. A great opportunity to save is possible in lighting system. The improvement could either be applied to a lesser or greater extent to the domestic sector. The common practice to improve lighting efficiency is to replace the existing type with energy efficient fluorescent tubes, CFL, and other low energy light sources. Other alternative is to consider using energy efficient electronic ballasts. The implementation of lighting control can set appropriate luminosity for different parts of the area. Perhaps, cleaning of fluorescent tube on a regular basic is essential to maintain the luminosity it can provide.

However, lighting system does not consume as much electricity as air conditioning system and laboratory machineries when referring to the university setting. In fact, major portion of electricity is spent on air conditioning system and followed by laboratory machineries. The energy saving tips for previous listed two items rely much on regular maintenances and services to keep them performed at high efficiency at all times. Laboratories machineries consist mostly motors and drive systems. These high power motors should be used properly and only run when needed. Electronic variable speed controls can be used where motor loads are variable in normal operation. Checking power factor regularly to ensure optimum operation of those machineries (REEEP/UNIDO Training Package, n.d.).

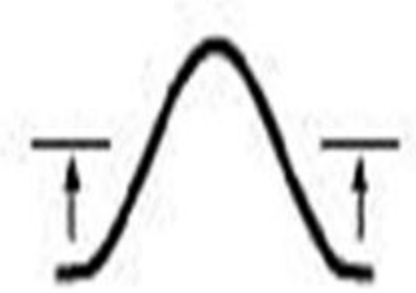
2.1.2.2 Load Management

Reducing demand at peak time and peak rates and varying the load pattern would definitely help in reducing electricity costs while having evenly distributed loads across the network. End-users can apply load management to achieve the redistribution of the demands and time of electricity usage under the influence of electricity suppliers. Normal production and operation generally will not be affected under the execution of load management programmes while having the utility to achieve a modified load curve. Load levelling, load control and tariff incentives and penalties are the types of load management techniques involved.

2.1.2.2.1 Load Levelling

Load levelling helps to regulate the base load of current generation without the need for additional supply to meet the peak demand periods. Table 2.2 below shows the classic forms of load levelling (Alyasin, et al., 1994).

Figure 2.2: Classic Forms of Load Levelling

	Peak clipping is a scenario where the peak demands during high demand periods are clipped and the load is reduced. Load management of this form does not affect demand much but focus on reducing peak demand.
	Valley filling is a scenario where the demand valleys during low demand periods are filled by having off-peak capacities. Load management of this form can be achieved by thermal energy storage that displaces fossil fuel loads.
	Load shifting is a scenario where loads are shifted from peak to valley to achieve both clipping and filling. The load is still present in the overall demand for shifting whereas it is removed for clipping. Some examples are storage water heating, storage space heating, coolness storage, and customer load shifting.

2.1.2.2.2 Load Control

Load control is where loads such as lighting, ventilation, heating and cooling can be switched on or off remotely depending on the situations. In a situation when the supply is cut off by the utility, customers may need back-up generators or energy storage system to face the electricity cut-off. Generally, they may have asked for a special rate from the utility on the interruption. Moreover, on-site generators could be called by the utilities to meet peak demand on the gird. This creates alternate means to deal with the peak demand and to reduce the heavy burden at utility side.

Rolling blackouts is one of the many ways to cut down demand when the demand exceeds the capacity. It is commonly practised in energy distribution industry. By definition, rolling blackouts are the systematic cutting off of supply to areas within a supplied region such that each area takes turns to lose supply. Prior announcements or schedule notices could be made so that companies and homes can plan their energy usage for that period. Effective communication is essential at both sides to prevent mass confusion, lost production and even lost goods.

2.1.2.2.3 Tariff Penalties

Utilities could use tariff penalties to warn customers a certain energy usage pattern at certain times to avoid the penalties. These include:

1. Maximum demand charges
   Utilities have different charges for maximum demand. Higher maximum demand charges would encourage a user to distribute loads in an even fashion to avoid the penalty.
2. Power factor charges
   Surcharges are applied if users are having power factors below a fixed threshold of 0.85.

2.1.2.3 Load Conservation and Growth

Since environmental health is at great dire, inevitably the world is turning to sustainable green solutions to conserve energy. Conventional methods which cause greenhouse gases emission will eventually be replaced with electric products which offer a switch from the use of polluting fuels to non-polluting electricity without sacrificing the performance factor.

Load conservation programmes are generally utility-stimulated and directed at consumption of end users. The programme is further enhanced by having a reduction in loads, a change in the pattern of energy usage and an improvement on efficiency of electrical appliances. Strategic conservation shown in Figure 2.3 below is the change of load shape which results from programmes stimulated by utilities directed at consumption of end users.

Figure 2.3: Strategic Load Conservation

Implementation of load growth programmes aims to improve customer productivity and environmental compliance while increasing the sale of power for the utilities. The market share of the utility increases and this enables an ability to increase peaks and fill valleys. These programmes can often divert unsustainable energy practices to better and more efficient practices such as the reduction of the use of fossil fuels and raw materials. Strategic load growth shown in Figure 2.4 below is the change of load shape which refers to a general sales increase beyond the valley filling.

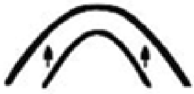


Figure 2.4: Strategic Load Growth

2.2 Peak Demand

Peak demand is the highest power consumption at any given time. The expensive infrastructural costs of extra power plants would be deferred with a reduction in peak demand. At the same time, this would help lower the generation cost and electricity prices. Energy storage system and a prediction model are proposed to achieve peak demand reduction.

Energy storage system offers a wide range of application besides the reduction of peak demand. It is largely used with distributed generation to store and dispatch energy. The latter one require an accurate prediction of peak and mean demand. The use of machine learning techniques are investigated to develop predictive model that uses observable characteristics such as past load values, day, time, season and weather associated with their occurrence, to predict the next peak demand. It is essential to model the expected behaviour of loads accurately in order to allow such system to operate efficiently.

2.2.1 Energy Storage System

Energy storage system (ESS) could be charged or discharged intelligently if the peak demand can be predicted, leading to a better power utilisation. Energy storage aims to reduce peak load by allowing the building to consume stored energy during peak hours. With the use of peak load prediction model, energy can be used in a way that serves the interests of grid while maximizing the consumer’s comfort.

Electricity generation based on renewable sources has become increasingly important for the sake of a greener and cleaner environment. Distributed generation (DG) is generally site generation that is closer to demands. There have been several DG settings put into operation around the globe in recent years. They include wind turbines, solar cells, and hydro plants. The dependency of DG could be inconsistent due to the unpredictable nature of the sources. Therefore, ESS is used in DG to store energy directly from the generation and dispatch energy to support the grid whenever necessary (Choi, Tseng, Vilathgamuwa and Nguyen, 2008).

One common ESS would be battery energy storage system (BESS). A battery uses chemical reaction of its electrochemical components to store electrical energy. When charging a battery, the energy is stored in chemical form due to reactions in the compounds. On the other hand, reverse chemical reactions can supply electricity out of the battery and back to the grid upon demand. The highlight of a battery would be its quick response as some batteries can respond to load changes in about 20ms. Depending on the types of electrochemical used and the frequency of cycle, the efficiency of batteries is in the range of 60 to 80% (Schainker, 2004).

2.2.2 Prediction Model

Singh, Peter and Daniel (2012) describes and employs regression based prediction. Different properties that drive peak load are studied through a set of five relevant features of each measured peak load value, y_t. Subsections below describe their definition, physical meaning and motivation.

2.2.2.1 Time of Day (x_t^1)

In a campus, occupancy and activities of consumer typically follows an underlying routine. For instance, students attend classes from the morning to the evening, use air conditioning and lighting throughout the sessions. This intrinsic pattern is likely to repeat across different days. In relation to hourly peak load, y_t, time of day (x_t^1) is defined as a feature, where $x_t^1 \in \{1,2 \dots 24\}$.

2.2.2.2 Day of week (x_t^2)

Consumer occupancy and activity patterns remain active on weekdays (Monday to Friday) as compared to weekend days (Saturday and Sunday). Thus, in addition to considering the time t of the peak load yt, the day of the week (x_t^2) is defined as a feature, where $x_t^2 \in \{1,2 \ldots 7\}$.

2.2.2.3 Ambient temperature (x_t^3)

Energy consumption is greatly affected by weather and seasonality. It has been used to model it. This is due to the use of air conditioners in hot weather. Extending this approach, x_t^3 is defined as the average ambient air temperature, and is used as a feature for the $(t+1)th$ hour because x_t^3 is not noticeable until the $(t+1)th$ hour.

2.2.2.4 Variance (x_t^4)

Most devices undergo a cycle of different modes of operation and varying consumption. Examples include using several types of machinery together. These different modes of operation result a large variation in the total load when in operation. Thus, the variance of measured load values is defined during the $(t-1)th$ hour as a feature of x_t^4 for hour t to capture consumer activity.

2.2.2.5 Last peak load (x_t^5)

The activity period of a user normally spans across hours. If the peak load of previous hour was high, a consumer is more likely to cause the hourly peak load to be high due to his activity. This is supported by the dataset which shows a high correlation of 0:52 between consecutive hours' peak load values.

2.2.2.6 Encoding

The following encoding is defined to encode the time of day (x_t^1) and day of week (x_t^2) features. Day of week (x_t^2) is encoded as $\tilde{x}_t^2$ = ($\tilde{x}_{t,1}^2;\tilde{x}_{t,2}^2;\tilde{x}_{t,3}^2;\tilde{x}_{t,4}^2;\tilde{x}_{t,5}^2;\tilde{x}_{t,6}^2;\tilde{x}_{t,7}^2$) where

$$\tilde{x}_{t,i}^2 = \begin{cases} 1, & if\ i = x_t^2 \\ 0, & otherwise \end{cases}$$

Hence, Monday is represented as $\tilde{x}_t^2 = (1;0;0;0;0;0;0)$. The hour of day ($x_t^1$) is encoded similarly. Such encoding decorrelates consecutive hours and days, allowing the model to predict from a wider range of values. Given the feature vector, $x_t = \{x_t^1, x_t^2, x_t^3, x_t^4, x_t^5\}$ of hour t, nonlinear regression based techniques are used to find a function $f(\cdot)$, such that $y_t \approx f(x_t)$. To obtain f, the following techniques are used:

1) Support Vector Regression (SVR)

   SVR expresses f as a nonlinear function of the input x_t together with a subset of support vectors taken from the dataset. A kernel function and its parameters define the nonlinear mapping. The loss criterion of SVR is insensitive of $\in$, which means the function is not penalized for training data that are predicted within $\in$ of their correct value.

2) Least Squares Support Vector Regression (LS-SVR)

   This approach operates in a manner similar to SVR but has two significant differences. First, it uses all of the training data as support vectors. Second, the loss criterion is the sum of squared differences between all observed and predicted peak loads.

3) Artificial Neural Networks (ANN)

   This non-linear regression method learns a function expressed in terms of hidden units that transform the input features to be used for pattern recognition.

Cross-validation errors are measured to evaluate the contribution of the physical features (x_t^1, x_t^2, x_t^3) and the history-based features (x_t^4, x_t^5) towards predictive accuracy.

2.3 Load Management

It has become essential to manage the loads of an existing system with in-depth analysis. A constant improvement is ensured to bring in a system design which could deliver an efficient management. By identifying the types of load, load distribution and scheduling could be performed to better integrate with the existing system.

2.3.1 System Architecture

Costanzo, Guchuan Zhu, Anjos and Savard (2012) illustrates that a system to manage the power consumption of multiple loads should consist of admission controller (AC), load balancer (LB), and a third layer composed by Load Forecaster (LF) and Demand Response Manager (DRM).

The bottom layer is the AC applying real-time load control by interacting with physical equipment. The middle layer is the LB coordinating admission control and demand response management using optimization that distribute the load to reduce the operational cost while considering capacity limits defined by DRM and operational constraints specified for each device. The LB provides also the DRM with information such as rejection rate and capacity utilization, which are among the basic performance parameters required for effective demand response management. The DSM system has the DRM as the entry point at the upper layer and functions as an interface to the grid. This module can process various pricing strategies such as maximum demand pricing and real time pricing. The LF provides the LB and the DRM with information to take advantage of the benefits from the pricing and the efficiency of power consumption.

Besides the proposed benefits of layered architecture, such as ease of integration, high interoperability, and modularity, the proposed framework highlights the following important characteristics:

1) Composability

   The utilities or energy whole sellers can implement the mechanism of pricing rules and demand response management for individual consumers or for group of users. A hierarchical organizing manner can be applied in the system to carry out the price bidding at different levels. Thus, coexistence of different pricing strategies in the same system is made possible through that integration.

2) Extensibility

   This system structure does not only integrate renewable resources and handle energy storage and exchange, but it is also suitable to be used for typical electricity load management. Incorporation of diverse objectives and constraints into the model of optimization and scheduling is made possible.

3) Scalability

The proposed system provides an architecture which covers a wide range of consumers, ranging from homes to buildings, commercial centres, campuses, factories, military bases, and even micro-grids. The components come with different complexity, while the system structure remains the same.

2.3.2 Types of Load

Appropriate classifications of power consumption modes are essential for efficient load management, loads are divided into three types based on their intrinsic characteristics (Costanzo, Guchuan Zhu, Anjos and Savard, 2012).

1) Baseline Load

This type of load must be served immediately at any time or maintained on standby. Baseline loads include lighting, projectors, computers and network devices. Baseline load should be considered while computing the available capacity to balance loads and control admission. Power consumption and operation mode of these loads could be recorded and retrieved by central management system with the use of smart meters,

2) Burst Load

This types of load is required to start and stop its operation within a fixed amount of given time. Burst loads include motors, air compressors and machineries in laboratories. Accumulation of burst loads could easily result an increase of peak demand. It is a critical issue to carefully manage a burst load to avoid high power consumption and energy cost.

3) Regular Load

This type of load is always in running mode for a long period of time. Regular loads include heating, ventilation and air conditioning system (HVAC), refrigerator and water heater. Regular load allows sporadic interruption on its operation which could be managed through admission control. Such characteristic makes burst load a particular case for regular load.

2.3.3 Load Distribution

Out of the big picture of DSM, load distribution by customers affects greatly the monthly electricity bill payment. To further study the topic, commercial building model is considered with the implementation of load scheduling.

Commercial building is undoubtedly one of the major energy consumption building blocks with complete lighting and air conditioning system. It is however operated at a fixed interval of hours per day. It could be the case for most office buildings but more factors are to be considered for research based buildings. University is one type of those commercial buildings which consist laboratories with high power equipment. If all these function together, the cost in fact will suffer from high penalty of maximum demand due to improper load distribution.

In energy demand management simulation, Ying Guo, Rongxin Li, Poulton and Zeman (2008) proposed that there are various components for electricity consumption. They include controllable load component, non-controllable load component and human behaviour component. Each components interacts with one another in different level of details. Load distribution profile for controllable load component could be shaped according to demand on request. Direct control is possible for this component. Non-controllable load component vary greatly depending on the type of load. Average profile of power consumption is taken to derive variance to create a load distribution profile. It is very difficult to produce a precise human behaviour model because it is very dependent on the content level of users. Conditions of controllable loads becomes the determining factor for user satisfaction.

2.3.4 Load Scheduling

Load scheduling can help to shape a better energy demand graph as the expected load consumption of specific time frame is obtained and studied so that heavy loads could be relocated or redistributed. This is to avoid the maximum demand penalty while maintaining a good energy usage practice. An integration of programme to bring up the capability to perform load profile matching.

Load profile is a compilation of overall consumption of each item listed with their specific power rating and the total amount of each item. It provides an overview of load distribution map across the network. The programme will sort of the best combination of different types of loads to avoid hitting the maximum demand which will later incur additional charges. A piece of intelligent programme that will provide the best scenario of how each specific load is distributed across a time period without overlapping each other while maintaining the freedom to choose from all the available combination suggestion list generated by the programme.

2.4 Adaptive Energy Forecasting

A smart system that can react to user inputs on the types of load available within the campus which is the subject used to collect the real power data series. The system must exhibit dynamic, distributed and data intensive (D3) characteristics along with an always-on paradigm to support operational needs. Instrumental tools such as Smart Power Meter and Phasor Measurement Units have been deployed across the transmission and distribution network of electric network. Smart grids are an outcome of instrumentation. Sensors of these tools provide utilities with enhanced real time electricity usage by individual consumers, and the information of power quality and stability of the transmission network (Yogesh, et al., 2012).

Demand response optimization (DR) is one of the highlighted characteristic applications of Smart Grids. The goal here is to use the power consumption time series data from the instrumentation process to reliably forecast the future consumption profile for individual consumers, and to use this information to detect any potential demand-supply mismatch. Then, such detection should trigger load curtailment strategies at the consumer side to shape, shift or shed load during the predicted peak period to avoid blackouts. Investigation on scalable software to support DR applications in a larger scale. The software will be deployed and tested on the DR components and algorithms, with the intent to scale these applications to be used in university campus setting.

Specifically, DR software must be able to address the:

- Adaptive scalability required by the information integration pipeline to continuously ingest sensor data
- Ensemble scaling required to train machine learned forecasting models on accumulated sensor data

The former utilizes the continuous data flow engine to scale on private Cloud services to dynamically meet application quality of service needs. Meanwhile, the later utilizes OpenPlanet, an open-source implementation of the PLANET regression tree algorithm on the Hadoop MapReduce framework using a hybrid approach for ensemble training in a cluster. The integrated information and training models are accessible through web portal for decision support to the microgrid operations and for information diffusion in the community for energy awareness

2.5 Demand Response Management

The DR application is decomposed into three phases:

1. Information ingest
2. Data analytics
3. Information Diffusion

2.5.1 Information Integration Pipelines

The DR application uses a variety of information sources that characterize the Smart Grid for improved situation awareness and analytics. These sources pass through an information processing pipeline that retrieves data from real time sources, parses the response into a canonical data structure, annotates the data tuple with semantics, and inserts the RDF triples into semantic respiratory. Semantics help manage the information complexity of diverse entitles that affect energy use, such as the power grid, electrical equipment, building, academic and facility schedules, organizational details and weather.

The information integration pipelines need to adapt several forms of dynamism. Real time sources are the primary data source in the microgrid and include power analysers in individual buildings and floors. In the current campus setting, the possible integration will be lightning report, operational status and Heating, Ventilation and Air Conditioning (HVAC) units emitting set point and ambient temperature. The collective data are monitored at a point in time depend on the current DR application needs. During peak load time period, additional sources to be monitored. The sampling rate of the analyser is set at one minute and the data is collected throughout the day for a week period. These information is later retrieved from the memory of analyser and is used for DR application to optimize resource usage and operations.

2.5.2 Machine Learned Demand Forecasting Models

The robust forecasting of power demand over time within the DR application is required as the microgrid behaviour changes. The approach here is to adopt machine learned forecasting models that indirect indicators for power usage prediction. Specifically, regression tree learning is used to predict building and campus level power consumption at daily granularities. The model operates on features like power consumption, academic semester, weekday/holiday and building type to make the forecast on the load distribution graph.

The regression tree model construction requires training on historical time series data. The data itself is extracted from the semantic repository being updated by the pipeline. A huge set of training data of the buildings on campus and using specific time granularities to achieve the accuracy. Moreover, distinct models can be constructed for different combinations of spatial collections (individual building, collection of buildings, the whole campus), temporal granularities (minute, hour, day) and combinations of features to determine the ones that offer the best prediction accuracy. The ability to perform ensemble runs of training is required whenever newer sets of data is accumulated.

2.5.3 Information Diffusion Portal

There are three primary types of consumer information within the campus microgrid which are campus facility operations, power data series analysts and the faculty staff and students. The system visualize the realtime information in the repository and energy forecasts to decide on the operational changes such as initiating direct energy curtailment in specific building by reducing its loads. Analyst evaluate the effectiveness of different forecasting models to select appropriate one for use. Users within the campus will have access to the current energy profile of buildings through web portal servers for information diffusion. They can then voluntarily take action to limit their energy impact for sustainability.

CHAPTER 3

METHODOLOGY

3.1 Site Investigation

To research on demand side management, Universisti Tunku Abdul Rahamn Setapak branch campus has been chosen to conduct a series of raw power data collection. The inside out electrical power point distribution of each buildings is analysed through field trips to the place. Several types of major electrical loads including lighting, air-conditioner, computer and laboratory machinery are taken into account to calculate the expected load consumption.

Each building layout is surveyed thoroughly to obtain the total items being connected to the grid. Specific power rating of each load is taken to compute the total power consumption of the building. The detailed load distribution map of every floors is carefully sketched. This is to obtain separate load profile according to the type of facilities. With that, specific adjustment (load shedding or load scheduling) could be made to that particular section without affecting the whole operation. It also helps to identify potential loads which suffer from poor efficiency and cause energy loss. Upon investigating the load distribution pattern, better load graph could be shaped to avoid hitting maximum demand penalty and to reduce the likelihood of any unforeseen power crisis. Substantial effort will be taken towards loads identified with great contribution to the overall power consumption. The data is also used to plot a graph of expected load consumption to be matched with the load graph plotted with real time power data.

3.2 Data Logging

In order to collect real time power data series, a power analyser which is capable of tapping real time voltage and current is installed in each existing building within the campus. The model is TES-3600 3P4W Power Analyser as shown in Figure 3.1. The display of the power analyser is completed with real power, reactive power and also neutral current besides showing the fed in three phase voltages and currents. A functional power analyser has four crocodile clips and four clamps which are for voltage and current instrumentation respectively. The supported operating modes are 1P2W, 1P3W, 3P3W2M and 3P3W. It also comes with internal memory to store up a maximum of 10,000 sets of data at any given time interval.

Figure 3.1: TES-3600 3P4W Power Analyser

Before proceeding to switchyards to deploy power analysers, permission from utility personnel is a must to bring the device along with a laptop to read the data in graphical form through a user interface designed using NI LabVIEW. All the four clamps are clamped onto wires directly for current readings while having live busbars clipped with the crocodile clips to obtain voltage readings. Both sets of instrumentation must come together so that the device can properly register the values. The power analyser will be placed inside the switchyard for roughly a week in order to fill up its maximum capacity. The data is retrieved by connecting the device to any computer supported with RS232 port and can be saved into any readable spreadsheet format. It not only consists of current and voltage readings, but also a comprehensive list of other useful parameters.

The complete setup of data logging process is shown in Figure 3.2 which includes a unit of laptop and two units of power analysers. There will be a total of 10080 (60 x 24 x 7) sets of data. Since the collection of data is limited to 10,000 per unit of power analyser, we have placed in two units of power analysers to record the extra 80 sets. The two analysers are initiated at two different time so to cover the extra sets for each other. Power analyser is able to operate without an active connection to a computer unit. A computer unit is only required upon the collection of data from the power analyser. The retrieval of data could also be done after the disconnection of power analyser from the live busbar because the device has its own internal memory to store the data even it is not powered on. The use of two power analysers allows us to perform a check on the data if any one set of the data is not correctly recorded. One of them could always serve as a backup to the other if one of them fails to operate.

Figure 3.2: Complete Setup of Data Logging Process

There are four current clamps and four voltage crocodile clips on each unit of power analyser. The first three pairs of clamp and clip are used to measure three phase power, namely phase A, phase B and phase C. The reading of neutral current is taken using the last pair of clamp and clip. In order to measure power, both clamp and clip must be installed together. Each of them is put onto live busbars with extreme care to prevent short circuit within the busbars as shown in Figure 3.3. Wearing insulating rubber gloves is a must under normal proceedings.

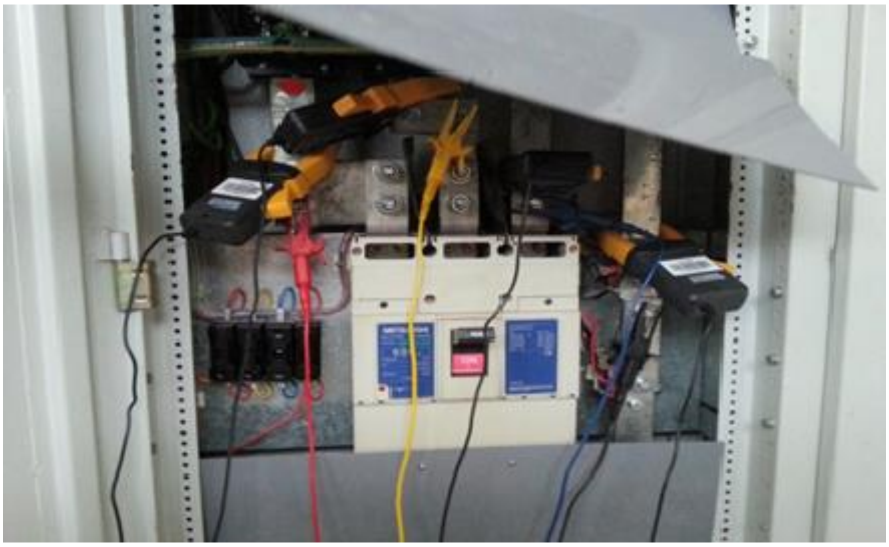


Figure 3.3: Clamping Onto Live Busbars

Two analysers are used simultaneously to ensure a complete set of readings is taken. All pairs of clamp and clip from both power analysers are also connected to live busbars in close proximity as shown in Figure 3.4. That is to ensure that both set of readings are in a low degree of variation to improve the accuracy. Each crocodile clip come in four different colours which include red, yellow, blue and black for each phase. In addition, all the clamps are labelled with phase number and they are used together with the crocodile clips as in pairs. Properly sorting out the cables allows easy removal work and to prevent people from tripping over the cables. Extra precautions steps are taken throughout the course of measurement as the equipment is operated in high power and safety is our utmost concern. We provide adequate and sufficient warning notices to raise awareness in the operating compound.

Figure 3.4: Two Power Analysers in Action

Some important functions of power analyser is highlighted as shown in Figure 3.5. The measurement will start once all pairs of clamp and clip are properly connected and the device is powered on. A suitable operating mode must be selected through mode selection button to ensure the device operates in optimum condition. In our case, 3P4W mode is selected. As shown in Figure 3.5, the screen gives the readings of powers, voltages and currents for each phase. All three phase voltage and current are displayed simultaneously whereas three phase power is displayed separately for each phase. Total power could also be read by browsing the power button.

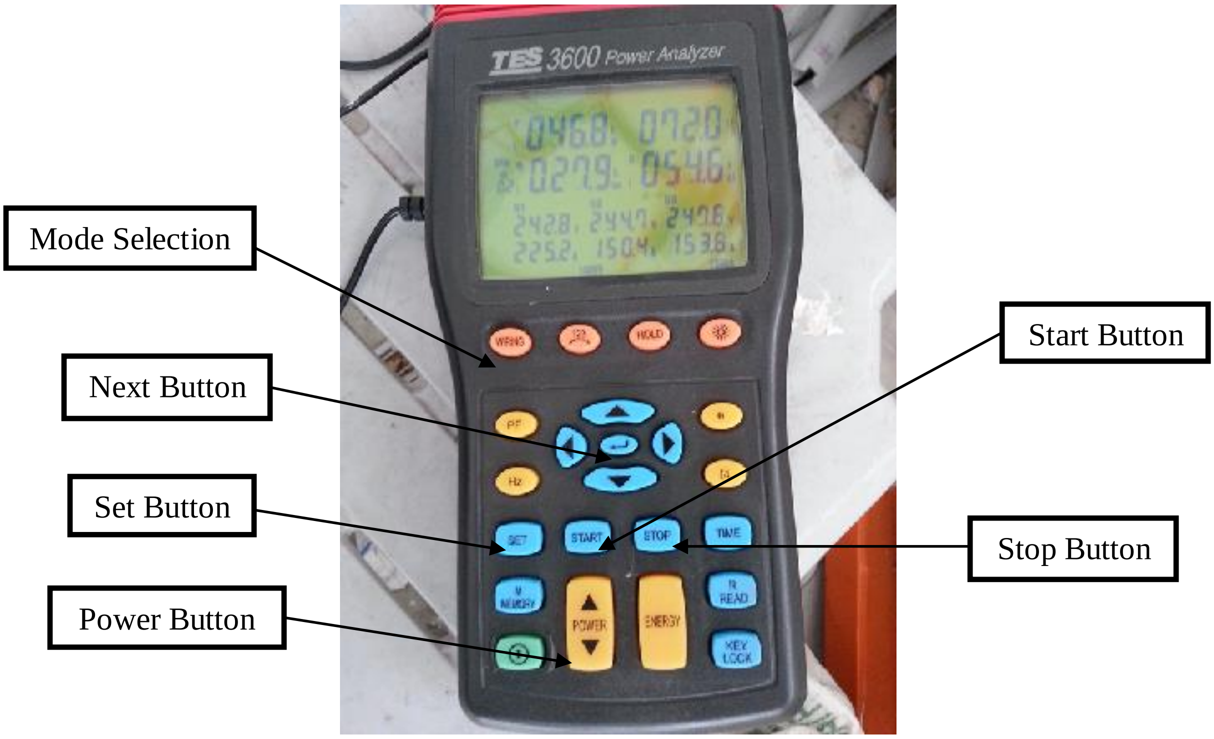


Figure 3.5: Close up View of Power Analyser

Power analyser does not start logging data after connecting to the power source but it requires a fair bit of setup to initiate the data logging sequence. Set button is first pressed to enter into time confirmation screen where we can set the exact year, date and time for the first set of reading. Subsequently by pressing the next button, we will be setting the interval of time between each set of data. This available intervals to choose from are 5 seconds, 30 seconds and 1 minute. 1 minute is ideal for our study and this is also to retain a near complete one week worth of data which is about 10,000 sets of readings. After setting up, the start button is pressed to initiate the data logging sequence and the process is interruptible with the stop button. The data logging session will continue on until next interruption or the data storage threshold is hit.

Figure 3.6 shows the graphical user interface (GUI) of power analyser. It is a LabView based GUI that provides an intermediate showcase of all the current readings on the first tab and also the mode that the device is currently in. There are four tabs to browse through and each of them comes with a specific function. They are Real Time, Graphic Signal, Datalogger and Saved File. We access only two tabs which are Real Time and Datalogger in our project. The former provides the insight on three phase power measurements either in graphical or text form. The latter is datalogger which shows the status of internal memory and it will be discussed in next paragraph.

Figure 3.6: Graphical User Interface of Power Analyser

Under Datalogger tab shown in Figure3.7, one would see a battery-like block and a similar graphical and text based display. The block indicates the status of internal memory with two different colour which are blue and red. Blue tells the free memory available while red tells the used memory. The memory capacity is usually 512kB and it allows multiple sets of reading to be stored at once and to be retrieved in later time. However, each set of reading is limited to only 10,000 sets. There could be losses on each set because we have to initiate the device again for next set of reading. Therefore, it is recommended to use two power analysers at once to fill in the missing gap. The data logging session will be interrupted automatically if the read data sequence is initiated and the reading process normally takes about 10 minutes for 10,000 sets of record. Once the retrieval is complete, we could save the file to a desired location for later use.

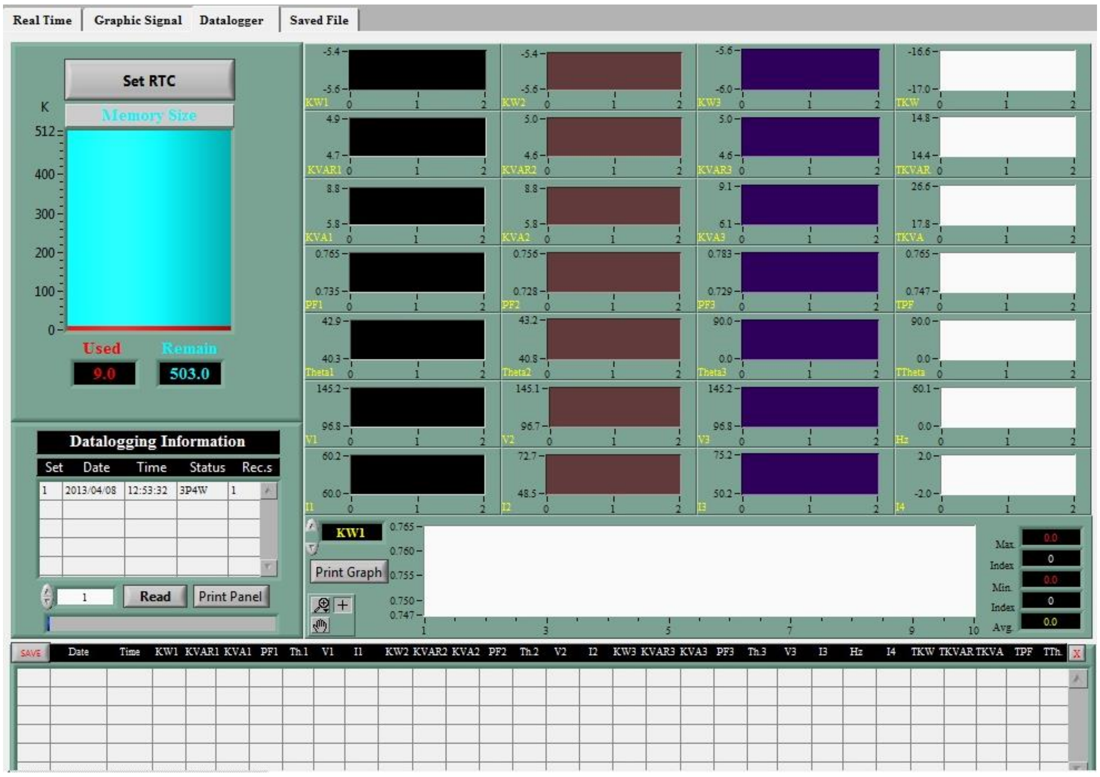


Figure 3.7: Status of Internal Memory

The first time connection of power analyser to a computer unit, we need to identify the right port before the communication could be made. Trial and error approach is used in this process for the specific port number is always random on each computer unit. The ease of this GUI is its compatibility with all power analysers of same model, one could just install the GUI on a computer in order to communicate with the rest of power analysers. The GUI has a clean and friendly layout to display the necessary information in a clear and direct manner. It covers a wide range of power parameters to be analysed with and they are also presented in high resolution.

As a conclusion, the operating mode must be 3P4W for the supply side provides three phase power. The date and time stored in power analysers are corrected to keep an accurate data logging period. Meanwhile, the time interval is set to read the values every one minute until it reaches 10,000 sets of records. All the readings of each parameter will then be converted to graphical form in excel spreadsheet to study their trends.

3.3 Graph Tools

All the data are eventually loaded into a spreadsheet program which is Micros to be processed. The expected outcome would be analysis in tabular or graphical form. Several approaches are introduced to deal with such large amount of data. All data are loaded in spreadsheet format where they are divided and arranged by rows and columns. To sort and organize the data systematically, filter function is applied. As shown in Table 4.1, we could selectively view the data on a specific date or group them in a particular order. The presentation of data is clearer with the use of filter function as our main focus is to sort the data according to the date. The trend of power consumption could then be analysed and studied accordingly.

Table 3.1: Data Filtered According to Date

Date	Time	KW1	KVAR1	KVA1	PF1	Theta1	V1	I1
3/11/2013	0:00:17	8	4.5	9.2	0.869	29.6	248	37.1
3/11/2013	0:01:17	8.2	4.1	9.2	0.893	26.8	248.2	37
3/11/2013	0:02:17	8.2	4.2	9.2	0.888	27.3	248.1	37.2
3/11/2013	0:03:17	8.4	4.4	9.5	0.886	27.6	248.1	38.2
3/11/2013	0:04:17	8.4	4.4	9.5	0.885	27.7	248.4	38.2
3/11/2013	0:05:17	8.3	4.5	9.5	0.877	28.7	248.4	38.1

However, there are 1440 sets of data point recorded for each day for the time interval set between data is 1 minute. To further reduce the data points, we consider to find the average of every 15 sets of data points. The resultant amount of data point would be 96 sets which is greatly reduced down from the original 1440 sets. The reduction is to find relevance of data points to the analysis later. The average of every 15 sets or 30 sets could then be used to study the occurrence peak demand which is the highest amount of electricity used within any consecutive period of thirty minutes.

The average of every 15 sets of data points is calculated with the use of the spreadsheet program's built in formula function. The precise calculation of the average is performed on the 1440 sets of data points for each day. The resultant 96 sets of data points are calculated with ease with the formula shown below. The formula is built upon the basic math function of average which is provided within the spreadsheet program. It is modified to start reading the column, C2 to the end and display the result in the column, D2. The specific interval of the average is stated at the end.

=AVERAGE(OFFSET(C$2,(ROW()-ROW(D$2))*15,,15,)) (3.1)

Correlation coefficient is used to tell the linear relationship between two sets of variable whether they could be put together for comparison. The correlation coefficient is automatically calculated by selecting the data by columns or by rows. Meanwhile, histogram is used to find out the occurrence frequency for a given range of value. The range of value is categorized into several groups with an increment of 5kW, starting from 0 to 140kW. The frequency of each group is displayed in both tabular and graphical forms. Both of these analytical function could be accessed from Data Analysis packs provided within the spreadsheet program.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

A month of raw power data is logged using the power analyser. The load profile analysis is performed solely on the total power consumption. They are processed in Microsoft Excel to obtain an average reading of every 15 minute for each weekday. Correlation coefficients on each weekday are tabulated along with a combined graph to show the strong relation between weekdays.

Furthermore, the processed data are presented in histogram to identify the frequencies of peak power consumption on each successive day. The result consists only the occurrence of peak power on weekdays because the total power consumption on weekend falls below the average. Maximum demand surcharges could be avoided by supplying the calculated required energy. Besides, a regulation on the power consumption of air conditioning could also save on electricity bills.

4.2 Total Power Consumption

Total power consumption (TKWh) is of importance in the load profile analysis because the occurrence of maximum power is observed from the total power consumption. It is the sum of average powers from all three phases. A total of 1440 sets of data were taken through power analyser at the time interval of 1 minute.

In order to scale down the data size, the data recorded at the interval of 1 minute are further reduced by taking the average of every 15 sets of the overall data. There are a total of 96 sets of data are used for the load profile analysis on each day. Four sets of data are collected for each weekday and their average are taken to do the comparison on their power consumption trends.

4.3 Weekdays Analysis

4.3.1 Correlation Coefficient and Graph

Table 4.1 shows the correlation coefficient between any two days of weekdays. It is defined as the measure of the strength of the straight-line or linear dependency of two variables or sets of data. The correlation coefficient takes on a number between 1 and -1 calculated. A strong positive linear relationship is expected when the values fall between 0.7 and 1.0.

4.3.1.1 Correlation Coefficient of Mondays

Table 4.1 shows the correlation coefficient of four Mondays. Each pair of them has strong positive linear relationship with correlation coefficients all above 0.7 as calculated using the spreadsheet program, ranges from 0.9539 to 0.9842. This allows us to combine all four sets into a set by finding their average.

Table 4.1: Correlation Coefficients of Mondays

Monday	March 11	March 18	March 25	April 1
March 11	1.0000			
March 18	0.9765	1.0000		
March 25	0.9539	0.9824	1.0000	
April 1	0.9661	0.9807	0.9715	1.0000

As shown in Figure 4.1, each Monday possesses a fairly similar graph trend of average power over 15-minute intervals. These average powers rises gradually starting from 8am to 6pm, the standard working hours. They are also known as peak hours whereas other time slots are off-peak hours. The highest peak power recorded is 141.55kW among the four Mondays. The variations of average powers over 15-minute intervals are mainly caused by the combination of different loads.

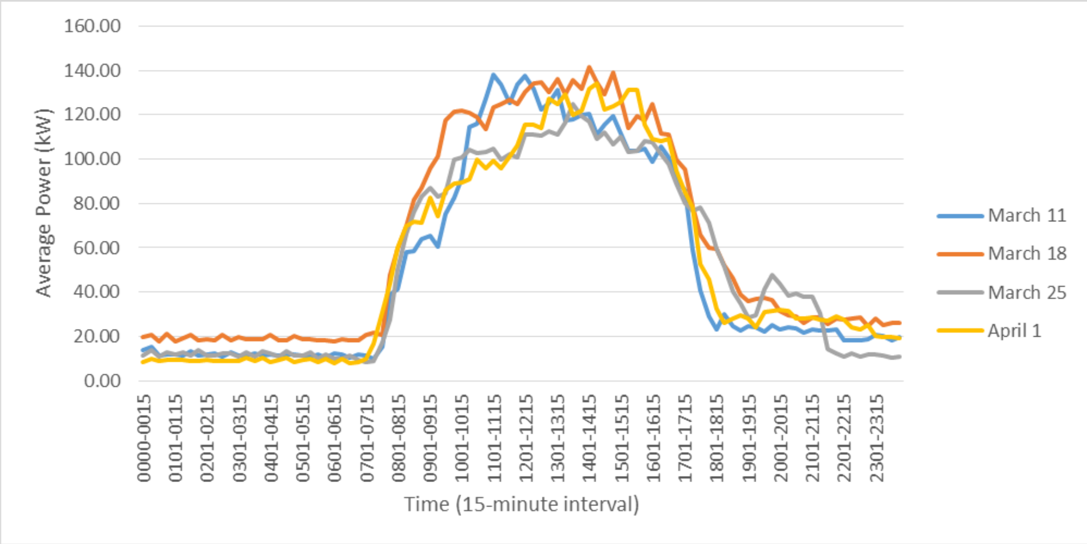


Figure 4.1: Average Power over 15-Minute Intervals on Mondays

4.3.1.2 Correlation Coefficient of Tuesdays

Table 4.2 shows the correlation coefficient of four Tuesdays. Each pair of them has strong positive linear relationship with correlation coefficients all above 0.7 as calculated using the spreadsheet program, ranges from 0.9813 to 0.9902. This allows us to combine all four sets into a set by finding their average.

Table 4.2: Correlation Coefficients of Tuesdays

Tuesday	March 12	March 19	March 26	April 2
March 12	1.0000			
March 19	0.9878	1.0000		
March 26	0.9834	0.9902	1.0000	
April 2	0.9813	0.9889	0.9855	1.0000

The graph trends of the four Tuesdays shown in Figure 4.2 do not vary much as they share more or less the same average power trends over 15-minute intervals on that particular weekday. The slight increment or decrement of average powers on the four Tuesdays result a close match of their average power trends over 15-minutes intervals. The highest peak power is 139.77kW among the four Tuesdays.

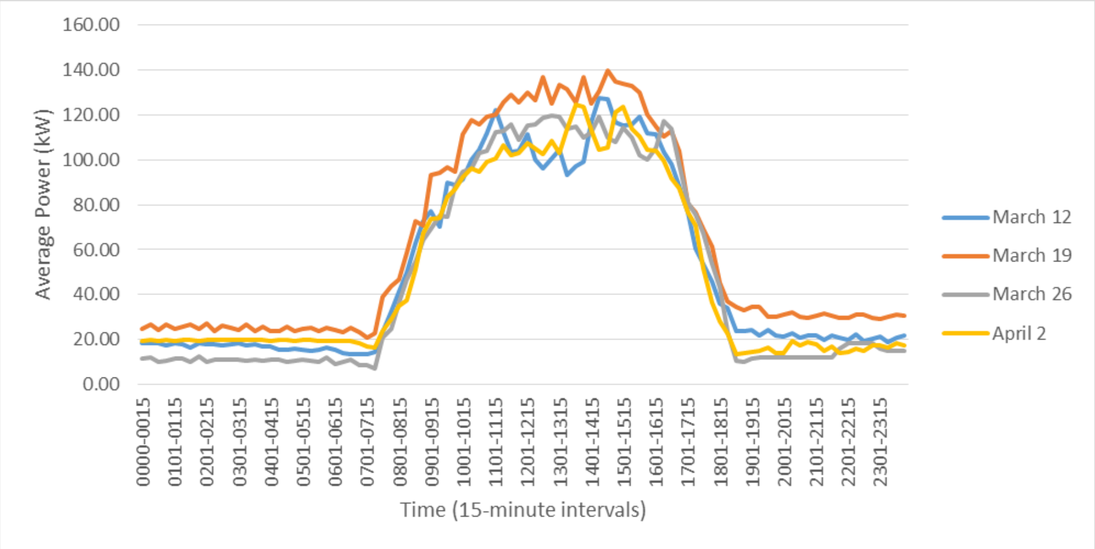


Figure 4.2: Average Power over 15-Minute Intervals on Tuesdays

4.3.1.3 Correlation Coefficient of Wednesdays

Table 4.3 shows the correlation coefficient of four Wednesdays. Each pair of them has strong positive linear relationship with correlation coefficients all above 0.7 as calculated using the spreadsheet program, ranges from 0.9578 to 0.9837. This allows us to combine all four sets into a set by finding their average.

Table 4.3: Correlation Coefficients of Wednesdays

Wednesday	March 13	March 20	March 27	April 3
March 13	1.0000			
March 20	0.9733	1.0000		
March 27	0.9837	0.9807	1.0000	
April 3	0.9578	0.9797	0.9651	1.0000

A close match between each average power trends over 15-minute intervals on Wednesdays is expected as shown in Figure 4.3. The gradual increment on average power starts from 8am and the peak is hit around noon time. The gradual fall comes after and ends at 6pm. This type of trend is shared the all four Wednesdays. The highest recorded value for peak power is 145.18kW among the four Wednesdays.

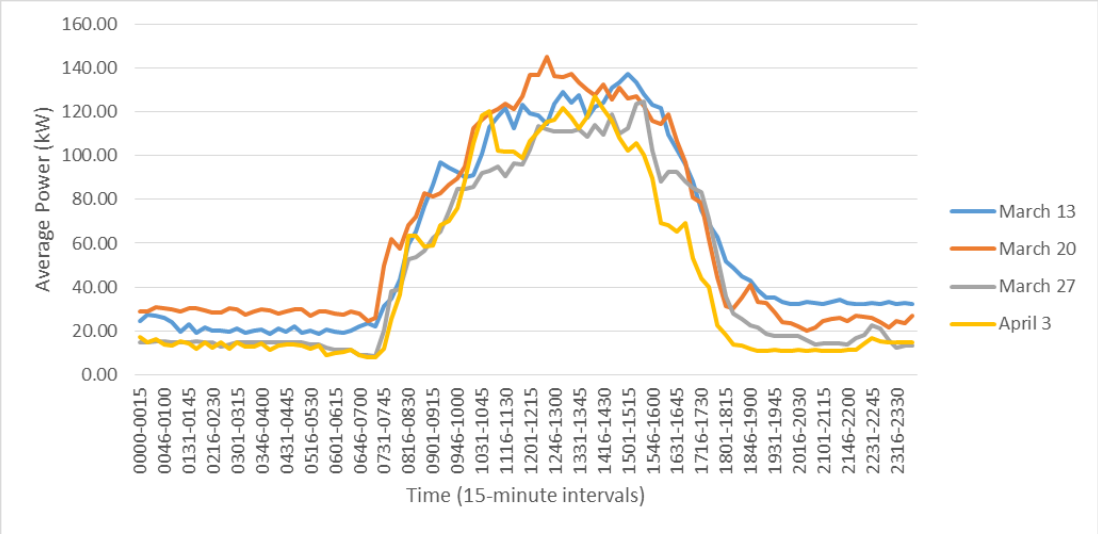


Figure 4.3: Average Power over 15-Minute Intervals on Wednesdays

4.3.1.4 Correlation Coefficient of Thursdays

Table 4.4 shows the correlation coefficient of four Thursdays. Each pair of them has strong positive linear relationship with correlation coefficients all above 0.7 as calculated using the spreadsheet program, ranges from 0.9718 to 0.9896. This allows us to combine all four sets into a set by finding their average.

Table 4.4: Correlation Coefficients of Thursdays

Thursday	March 14	March 21	March 28	April 4
March 14	1.0000			
March 21	0.9825	1.0000		
March 28	0.9718	0.9866	1.0000	
April 4	0.9896	0.9860	0.9726	1.0000

Average powers over 15-minute intervals of four Thursdays have been put together in a graph as shown in Figure 4.4 to study on their graph trends. They matches closely as in align with the calculated correlation coefficient. The occurrence of peak power happens at about the same time among the all four Thursdays which is from 3pm to 4pm. The highest recorded value for peak power is 152.23kW among the four Thursdays.

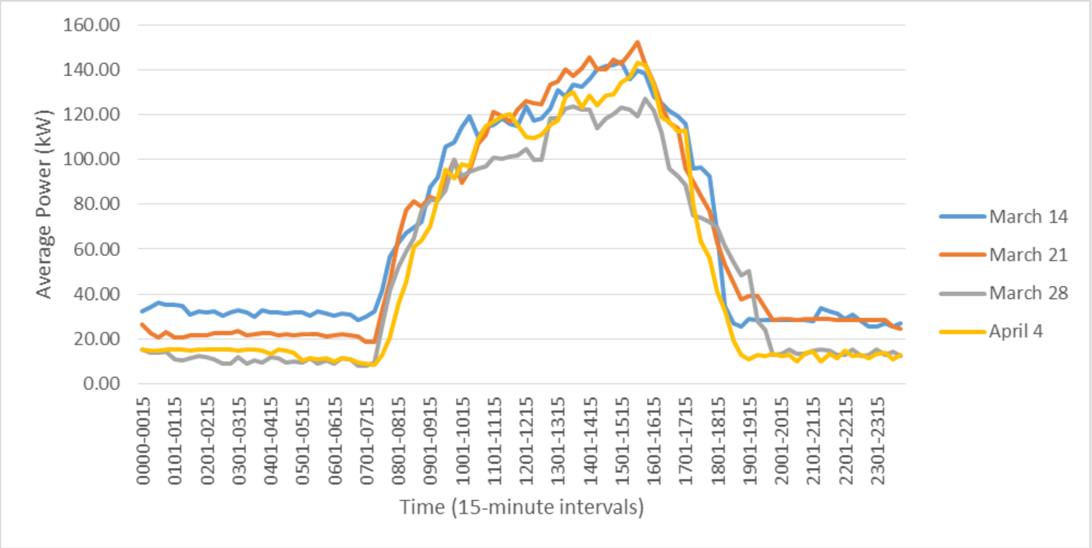


Figure 4.4: Average Power over 15-Minute Intervals on Thursdays

4.3.1.5 Correlation Coefficient of Fridays

Table 4.5 shows the correlation coefficient of four Fridays. Each pair of them has strong positive linear relationship with correlation coefficients all above 0.7 as calculated using the spreadsheet program, ranges from 0.9274 to 0.9846. This allows us to combine all four sets into a set by finding their average.

Table 4.5: Correlation Coefficients of Fridays

Friday	March 15	March 22	March 29	April 5
March 15	1.0000			
March 22	0.9841	1.0000		
March 29	0.9846	0.9757	1.0000	
April 5	0.9560	0.9724	0.9346	1.0000

Four Fridays share a close match on their average power trends over 15-minute intervals as shown in Figure 4.5. The trend rises from 8am and falls in the afternoon. The occurrence of peak power is expected to be about the same time slot as the Thursdays which is also from 3pm to 4pm. The lower peak power on the one of the Fridays is due to the reduction of total loads connected to the grid. The highest recoded of peak power is 145.92kW among the four Fridays.

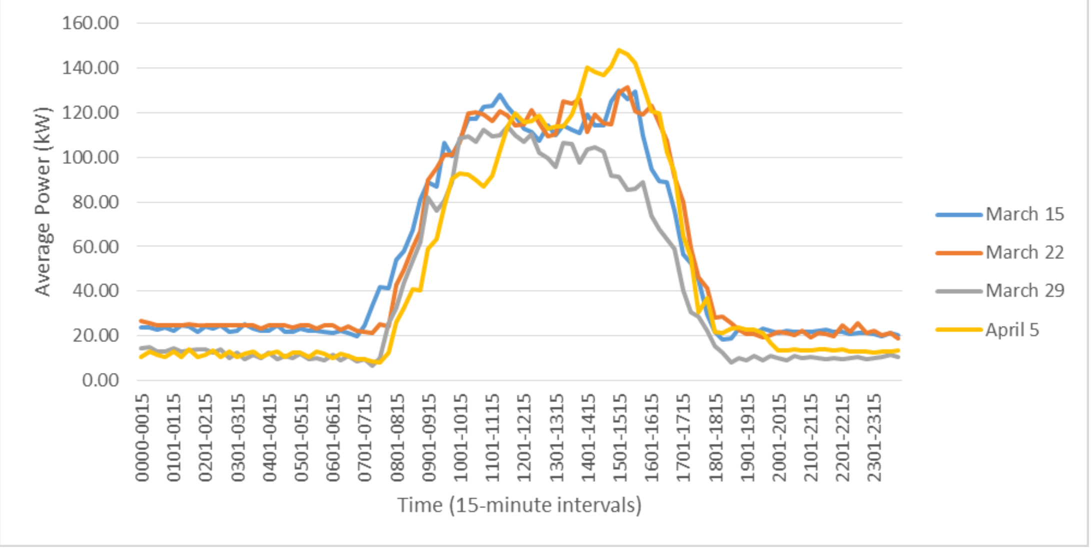


Figure 4.5: Average Power over 15-Minute Intervals on Fridays

4.3.1.6 Correlation Coefficient of Weekdays

The average of each of weekdays is calculated to have only a total of five sets from Monday to Friday for the weekday analysis. Correlation coefficients between the days shown in Table 4.6 are close to the value of 1 which indicates a strong positive linear relationship. This tells that each day share a similar graph trend of total power consumption. Any increment or decrement on any day will also result the same to the other days because they are closely related under the linear rule.

Table 4.6: Correlation Coefficient of Weekdays

Day	Monday	Tuesday	Wednesday	Thursday	Friday
Monday	1.0000				
Tuesday	0.9903	1.0000			
Wednesday	0.9881	0.9951	1.0000		
Thursday	0.9808	0.9870	0.9901	1.0000	
Friday	0.9760	0.9840	0.9778	0.9580	1.0000

The combined graph shown in Figure 4.6 shows a fairly similar trend of average power over 15-minute intervals on weekdays. The uprising trend starts at about 8 in the morning and ends at around 6 in the evening. That period of time is the standard operating hours for a campus based commercial buildings. Similar adaptation applies throughout the week. The average power increases gradually over time and saturates after the noon time. The saturation contributes to the peak demand whereby the highest peak recorded is on Thursday at 138.59kW around 1530. The peak demands on other days mostly fall around 120kW or more.

The average power trends over 15-minute intervals on weekdays are very much affected by the timetable of each day. A day packed with both lab sessions and tutorial classes will result in higher average powers and also high peak demands due to the operation of machineries and air-conditioner over long hours. This effect is prominent on Thursday because it has the highest peak demand across the week. This analysis could lead to a predictable point of occurrence of peak demand if enough data points are collected and studied over a several weeks under normal circumstances.

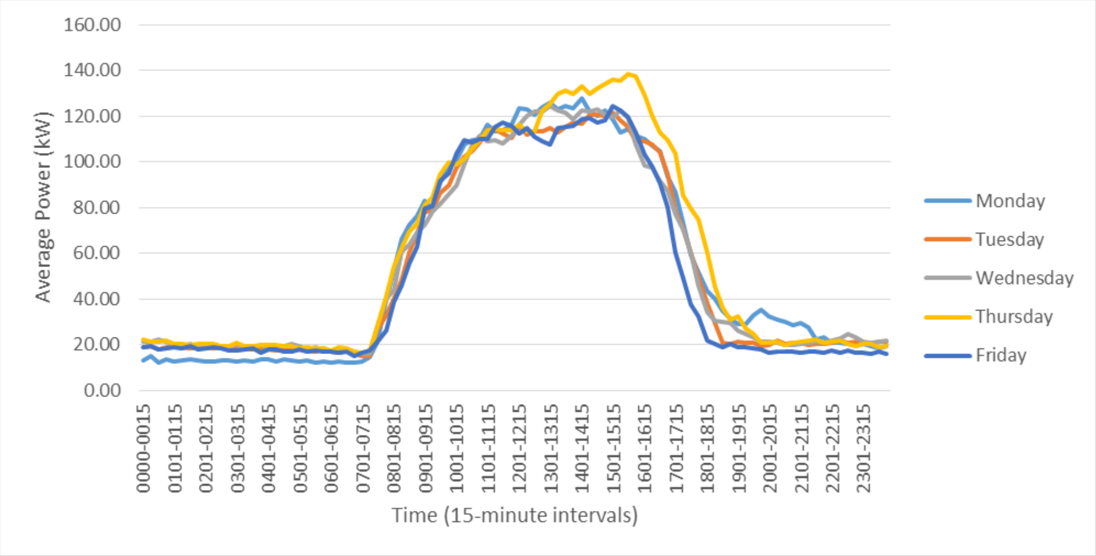


Figure 4.6: Average Powers over 15-Minute Intervals on Weekdays

4.4 Occurrence of Peak Demand

4.4.1 Use of Histogram

Histogram is an estimate of probability distribution of a continuous variable data. It is used to find the frequency of the occurrence of peak power consumption. Histogram allows the power consumptions to be grouped in a particular range from the lowest to the highest. Every 5kWh of power consumption is bundled as a group with their frequencies determined. Peak demand analysis is performed on each weekday by finding the highest value of power consumptions for each day. Relatively, the occurrence frequency of peak demand is taken to calculate the energy required to avoid maximum demand surcharges from the utility. Those power consumption ranges follow after the peak demand are also considered to calculate their money saving potential if the required amount of energy could be supplied.

The calculated average of weekdays from the previous studies are used. The peak demand is determined among the weekdays and the value of its power consumption is used to determine the amount of energy required to avoid maximum demand surcharges. The calculation is as follow:

Energy Required = Occurrence Frequency x 5kWh (4.1)

Potential Saving = Energy Required x RM25.90/kWh (4.2)

4.4.1.1 Histograms of Weekdays

Power consumption of weekdays are categorised with their occurrence frequencies specified. These power consumption groups are set in the range of 0kWh to 140kWh with a step of 5kWh for each group.

Histograms shown in Figure 4.7, Figure 4.8, Figure 4.9, Figure 4.10 and Figure 4.11 show the occurrence frequency of each power consumption group from Monday to Friday. This is to provide the ease of comparing the highest power consumptions among the weekdays. The relative occurrence frequency is used to calculate the energy required to save from maximum demand surcharges.

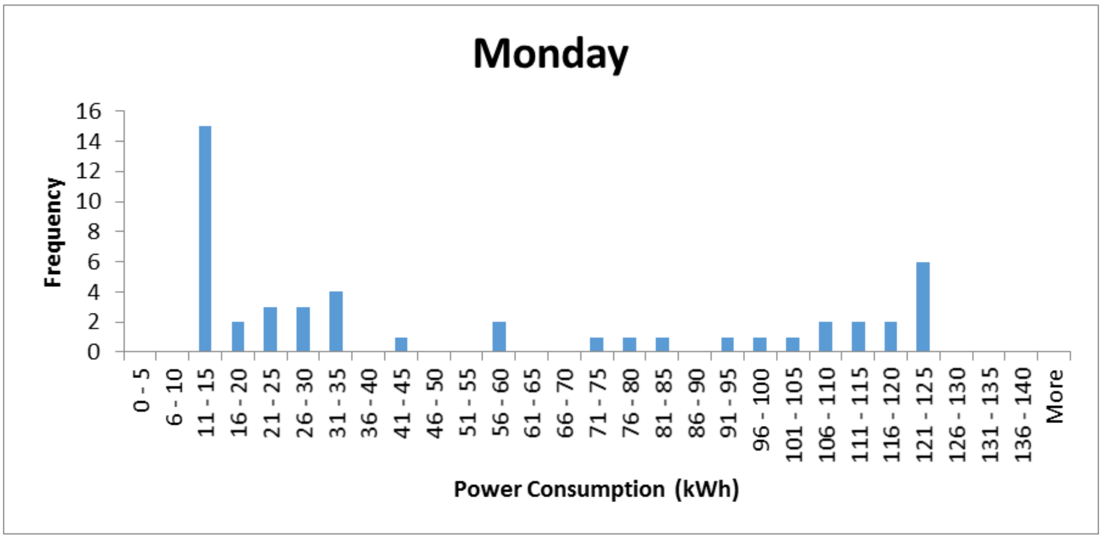


Figure 4.7: Histogram of Monday

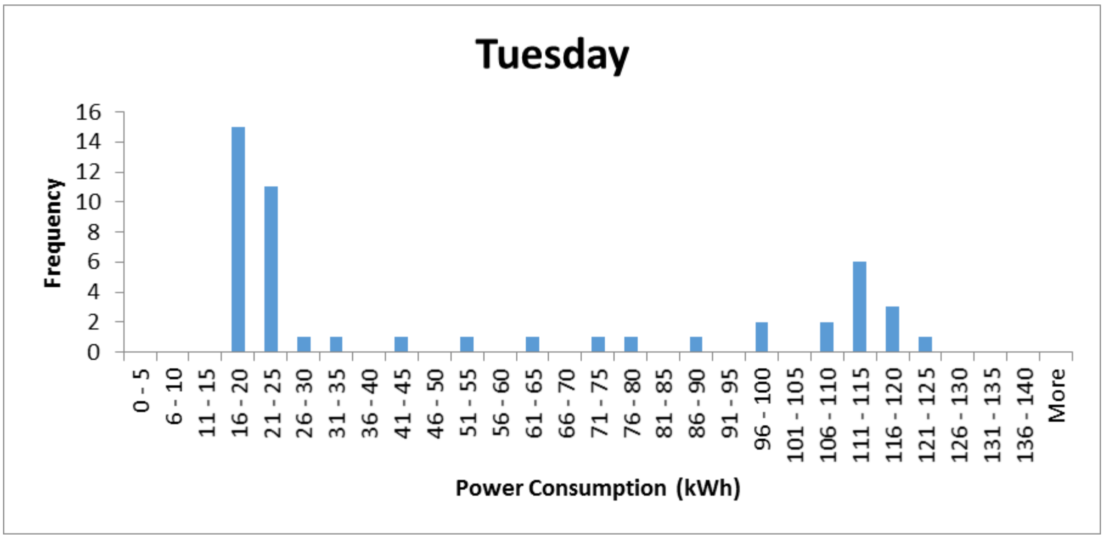


Figure 4.8: Histogram of Tuesday

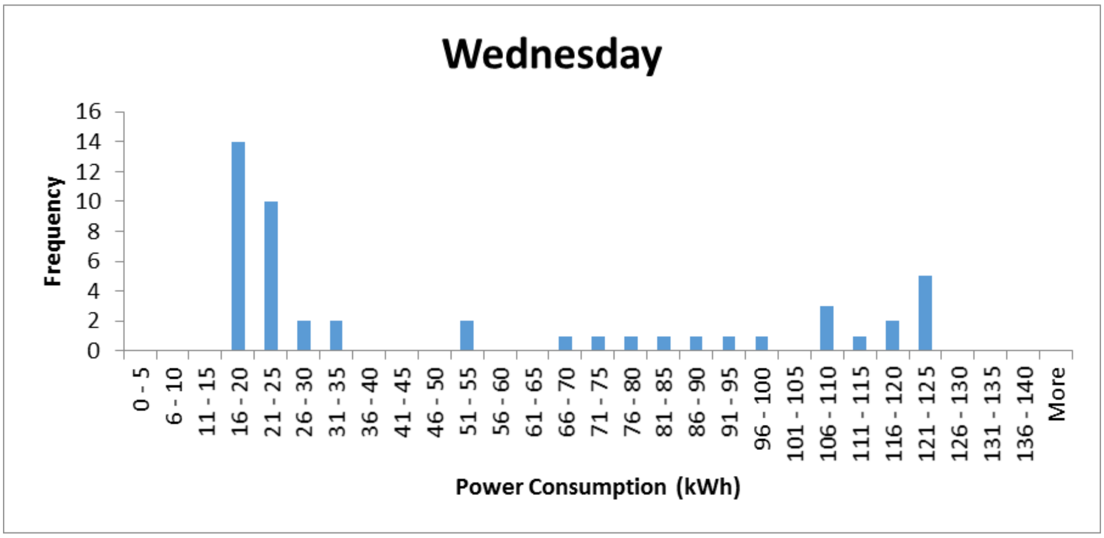


Figure 4.9: Histogram of Wednesday

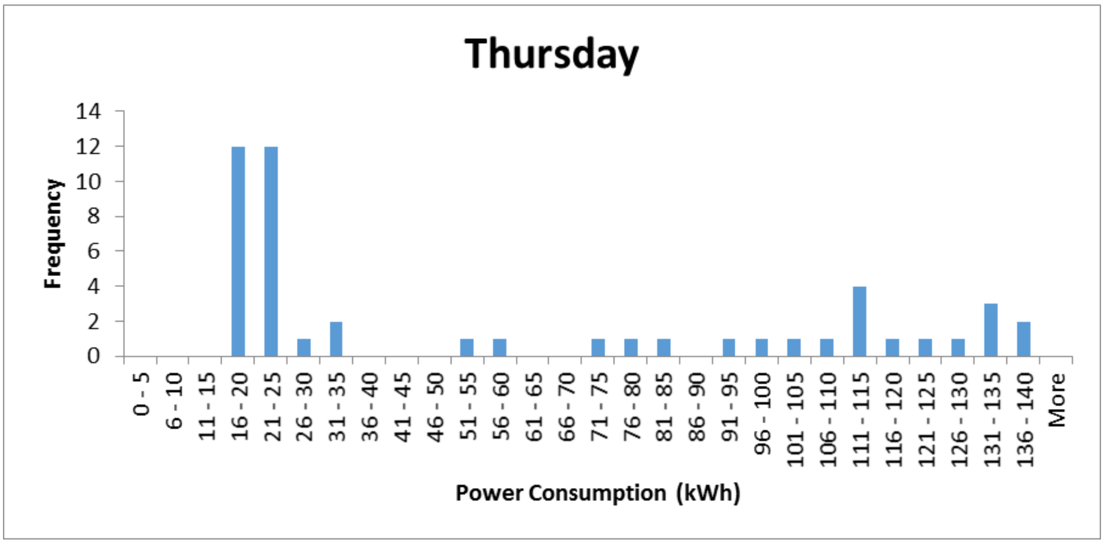


Figure 4.10: Histogram of Thursday

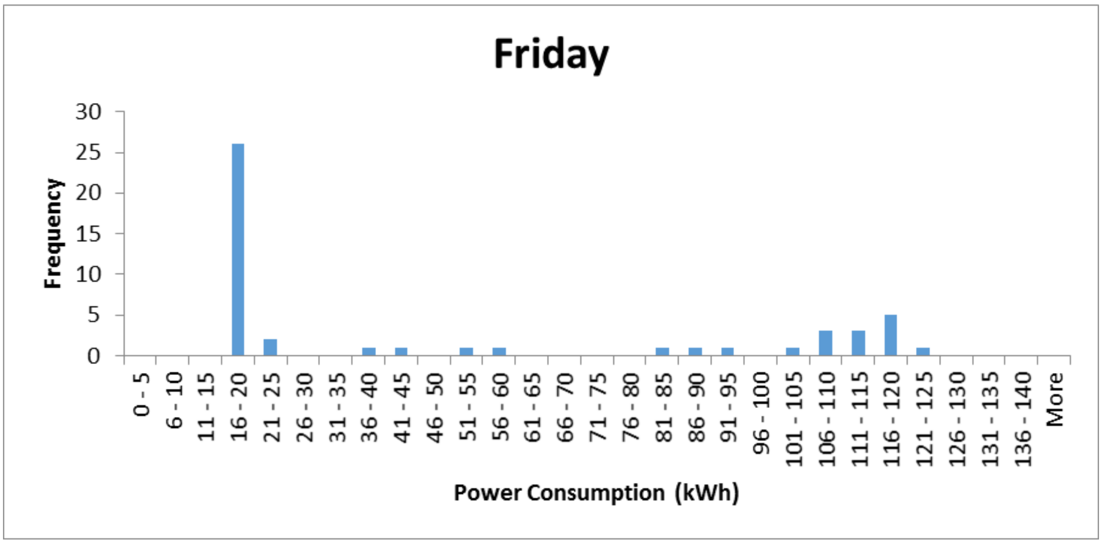


Figure 4.11: Histogram of Friday

Thursday has the highest peak demand among all and it is within 136-140kWh as identified in Figure 4.10 while the rest of the peak demands are within 121-125kWh for Monday, Tuesday, Wednesday and Friday. The maximum demand surcharge is applied towards the highest power consumption of the month.

In order to avoid that maximum demand surcharge, peak demand on Thursday could be brought down from 136-140kWh to 131-135kWh. Whenever the power consumption of that day falls between 136-140kWh, 5kWh of energy will be supplied to bring down the power consumption from 136-140kWh to 131-135kWh. The occurrence frequency of peak demand on Thursday is 2 where energy is supplied for that two occurrences of peak demand.

Energy Required = 2 x 5kWh = 10kWh

Potential Saving = 10kWh x RM25.90/kWh = RM259.00

The amount of energy required to avoid peak demand is 10kWh. By bringing down the power consumption from 136-140kWh to 131-135kWh, we can avoid the maximum demand surcharge and achieve a potential saving of RM259.00.

4.4.1.2 Combined Histogram of Weekdays

The histogram in Figure 4.12 shows a combined occurrence frequency of each power consumption range on weekdays. Each day shares a relatively high frequency of power consumption from 11kWh to 20kWh. These power consumptions occur mainly during the off-peak period and they appear to be uniform across weekdays. The power consumption within 136-140kW is considered to be the peak demand. From the combined histograms, Thursday has proven to have the highest peak demand as compared to the other days.

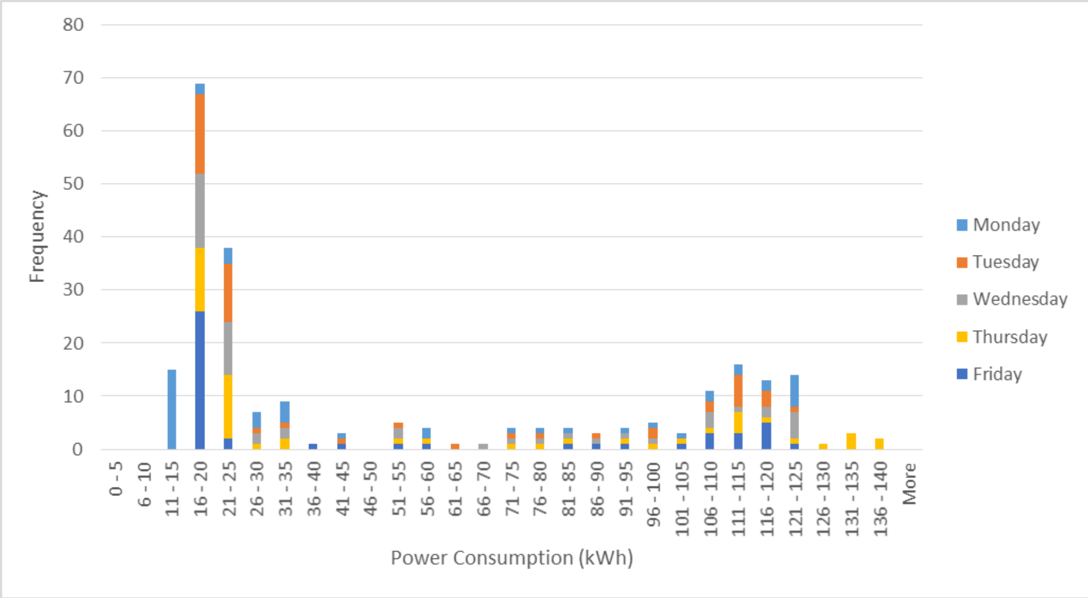


Figure 4.12: Occurrence Frequency of Power Consumption on Weekdays

With the use of histogram, power consumption is divided into groups. The supply of energy is performed whenever the power consumption falls into the group which constitutes the occurrence of peak demand. Energy is supplied whenever the power consumption falls within the group which is labelled as the occurrence of peak demand. On the other hand, by knowing the exact value of peak demand, the energy is only supplied whenever the peak demand is hit to avoid maximum demand surcharge for that instance.

4.5 Load Distribution of Tutorial Rooms in SE Block

Another effective way to study the power consumption of a building over a specific period of time is to breakdown the power consumption onto specific load types. Each type of load will have different load profile which will result in a different amount of power consumption. In every session, there will be several types of load being put together to bring upon the optimum operation.

4.5.1 Types of Load

The pie chart shown in Figure 4.14 shows the percentage of load distribution which includes lighting, computer, air-conditioner, ceiling fan and projector. This is specifically used for the tutorial rooms where no machineries are involved. Machineries bring upon a high degree of variation on power consumption as according to its mode of operation. To show fair justification on load distribution, common loads with consistent load profile are considered to study their accumulative power consumption over a specific period of time which is based on the standard operating hours from 0800 to 1800 hours.

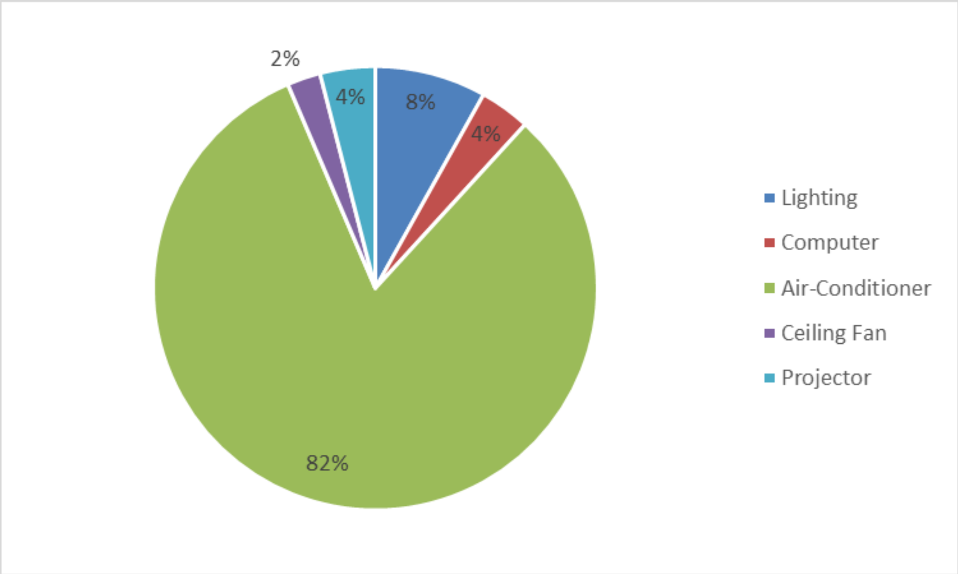


Figure 4.13: Load Distribution of Tutorial Rooms

Air conditioner has taken up the major portion of the load distribution with its high power rating. Therefore, a potential reduction could be expected from the power consumption of air-conditioner. The rest of the loads are also closely tied to the air conditioner for they will all be used the same time during each tutorial or lecture hour. Though the other loads do not contribute a significant power consumption as compared to the air conditioner, they could still be regulated and controlled to further the energy efficiency.

4.5.2 Power Consumption Based on Timetable

Figure 4.15 shows total power consumptions of tutorial rooms in SE block on each weekday. The values taken are hourly based and derived from actual timetable. The power consumptions are based on the exact operating capacity of tutorial rooms from 8am to 8pm. The operating capacity is referred to the occupancy of tutorial rooms throughout the day with the optimum use of loads. The highest power consumption during peak hours is 73.5kWh. The gradual rise and fall happen after 7am and 6pm respectively for each weekday. It is found out that the power consumption varies greatly from day to day due to the inconsistent usage pattern of tutorial rooms.

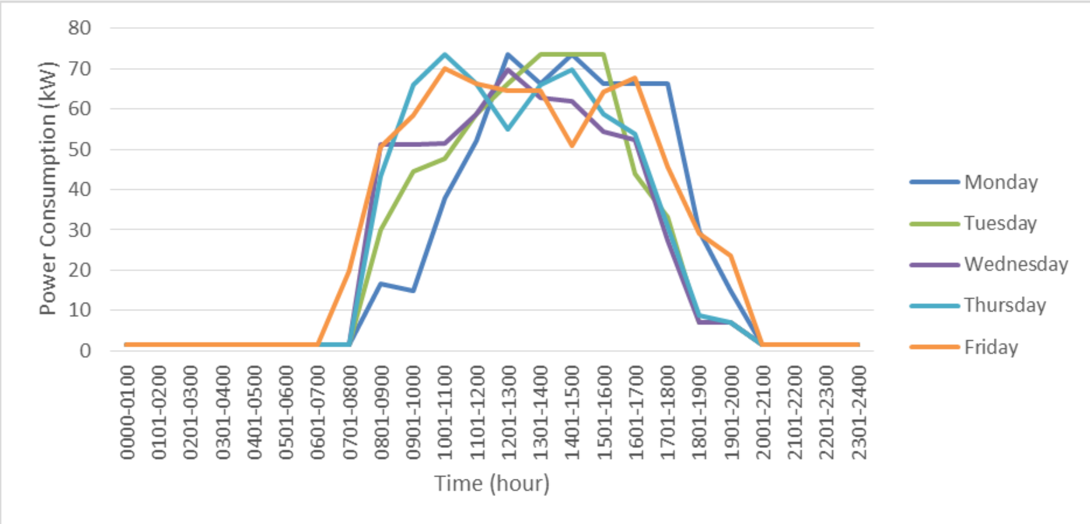


Figure 4.14: Total Power Consumption of Tutorial Rooms on Weekdays

4.6 Load Shedding

There are multiple ways to achieve energy saving for a building. One of them would be load shedding. Loads are normally made up of different pieces of equipment with various power rating. With proper management of loads, we could easily divide loads into two types which are essential loads and non-essential loads.

4.6.1 Essential and Non-essential Loads

Essential loads require active power source to maintain its optimum operation and they are normally non-interruptible. Non-essential loads are turned on when there is a demand over a particular period of time. So, essential loads will always be prioritized over non-essential loads under normal circumstances.

Load shedding scheme has put emphasis on shedding non-essential loads. For an instance, air-conditioners and lighting in tutorial rooms should be turned off whenever the rooms are not in use. Non-essential loads can provide immediate relief towards reduction in power consumption for their characteristics. Essential loads would also be arranged in such that no two essential loads operate at their maximum capacities the same time because there is high chance to hit above the maximum demand threshold. The solution would be to shift the loads to off-peak periods or to alternate the essential loads to take turn running in their full capacities.

Turning on and off loads based on the requirements would greatly reduce the power consumption because predictable pattern could be observed to always have the optimum power consumption. With certain degree of prediction, the loads could be efficiently scheduled or shed to avoid peak power consumption especially during peak hours. The unnecessary surcharges could be only avoided if we could have seen it coming. Nevertheless, loads should be monitored and regulated to operate at their optimum conditions to achieve better energy efficiency.

4.6.2 Alternate Mean to Reduce Peak Demand

Air conditioner is one of the major power consuming units in overall. This is due to its high power rating and a large number of units to be installed within a building. The main purpose is to keep a closed space cool under a certain a low temperature. Lower temperature setting would require an active exchange of air to bring down the room temperature and maintain the low temperature. This has in fact made up a higher power consumption over time.

Load shedding could be performed on air conditioner by reducing its power consumption accordingly. The necessity to power on all units of air conditioner could be avoided through proper load management. Whenever a class ends, air conditioner should be switched off to converse the energy. In a small class setting, turning on one air conditioner would be sufficient instead of more to achieve in reduction of overall power consumption. In practical, the real power consumption according to the timetable varies from 45kWh to 50kWh from Monday to Friday. The difference of the variation provides the possible amount of money could be saved from the maximum demand surcharges through a reduction in total power consumption of air conditioner. The reduction could help reduce the peak power and avoid hitting the maximum demand threshold.

As the power consumption of air conditioner varies from 45kWh to 50kWh, the maximum possible energy reduction is 5kWh. The energy reduction could be performed in the step of 1kWh until it reaches the maximum. The reduction will directly help lower the peak demand of any day. For an instance, an energy reduction of 5kWh can reduce the peak demand of 136.93kWh on Thursday to 131.93kWh. Thus, the amount of maximum demand surcharge to be avoided is RM RM3546.49.

4.7 Maximum Demand Surcharge

The occurrence of peak demand within any consecutive period of thirty minutes in a month will incur a surcharge of maximum demand. By all means, the surcharge is to be avoided in order to save on the electricity bill. Maximum demand is measured in kilowatts, and it is calculated as double the highest amount of electricity used (kWh) within any consecutive period of thirty minutes in a month (Tenaga Nasional Berhad, n.d.).

As identified in the combined graph of weekdays, Thursday shares the most occurrence of peak demand and also the highest peak demand in value. The surcharge of maximum demand could be avoided through the clipping of peak demand. To be specific, the power consumption is maintained below the specific maximum demand threshold. The additional power demand is supplied by a separate power grid either from a distributed generator (DG) or a micro-grid. The system to perform all those is regarded as energy storage system (ESS). It does not only help prevent maximum surcharge, but also as a backup supply during power outages. It gives an output of energy to prevent the occurrence of peak demand.

On the other term, the amount of electricity to be penalised would in fact be the highest power consumption within a specific period. For an example, the amount of energy required to lower the peak demand would be dependent on the size of ESS. The surcharge of maximum demand is calculated as RM25.90 per kilowatts-hour of electricity. Thus, 10kWh of energy is supplied to avoid the maximum demand of 136.93kWh on Thursday. The potential saving will be RM259.00. It would be a large amount to pay if the occurrence of peak demand is taken on every building. By injecting power to the grid during peak hours with energy storage system would save much on the electricity cost in long term. The accumulative amount of surcharges could also be diverted through proper load management by shifting the major loads to operate during off peak hours.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The analysis presented is considered to be straightforward after having the data points reduced to its minimum amount. The analysis started off by looking into the correlation coefficients between any two days because much studies are taken from the comparison of any two sets of data. Graphical and tabular forms are largely used to analyse load profiles of SE block where the main focus is on the average powers trends over 15-minute intervals of weekdays. Load distribution of tutorial rooms is investigated based the types of load and their power consumption trends.

The occurrence of peak demand is observed through the trend of power consumption on weekdays. This could be resulted from the packed timetable on that day and the loads used are with high power rating. The possible occurrence of peak demand could be predicted based on the past occurrence of peak demand pattern. The occurrence frequency of peak demand on each weekday is also determined with the use of histogram. From the results, possible reduction in peak demand is performed in a step of 5kWh. The uniform power consumption of 11kWh to 20kWh has the highest frequency for all weekdays which is during off-peak periods.

The peak demand is later suggested to be reduced with the use of energy storage system to avoid the surcharge of maximum demand. A weekday analysis is conducted on each weekday to learn the occurrences of peak demand which would later be used to determine the highest peak demand. We can save on the maximum demand surcharge if we are able to clip away the peak demand by supplying required energy to maintain the peak demand below the maximum demand threshold. Possible reduction in power consumption of air conditioner is also investigated to bring down the peak demand so to avoid maximum demand surcharges.

5.2 Recommendations

Currently, the data logging is limited to manual collection after each session. The data logged in the power analyser is also restricted to only 10,000 sets. It requires consistent labour work to check the condition of power analysers on site and to collect the data manually through a computer unit which has to be brought around during each session. The recommendation here is to bring the data logging to next level whereby everything could be done remotely and automatically without moving much of the existing device.

A central management system would be useful to constantly monitor and regulate the data logging process remotely. The measurements on three phase power could be retrieved in real time and monitored from a distant computer unit. This removes the requirement of consistent visit to the site to check the condition of power analyser. Consistent health checking signal can be sent to the device from time to time. If a problem is identified through remote monitoring, immediate action could be taken right after. This in fact ensures the continuity of data logging process and to retrieve data at ease. By implementing advanced control algorithms, the system could perform self-regulation towards external stimuli. For an instance, the system would know when to raise an alert to the consumer if the power consumption has hit a certain limit which would incur surcharges. This smart system is reconfigurable to suit the needs of consumer towards multiple scenarios. On a higher level, controls could be exerted from the central management system to solve the problem without the need to alert consumers. However, the activity of the system would still be monitored by the consumer to ensure an optimum operation.

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