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Power System Load Modeling Using A Weighted Optimal Linear Associative Memory (Olam)

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POWER SYSTEM LOAD MODELING USING A WEIGHTED OPTIMAL LINEAR ASSOCIATIVE MEMORY (OLAM)

by

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DEDICATION

This thesis is dedicated to my wife, Sailay Eesiah, my father, Mr. James Z. Eesiah, my mother, Kebbeh Saygbe, my grandmother, Soni Jallah, my sons, all of my brothers, sisters, uncles, aunts, and all those who helped me arrive at this milestone, for their love and encouragement.

BIOGRAPHICAL SKETCH

Morlue Samukai Eesiah was born on June 30, 1980, in Monrovia, Liberia to Mr. James Z. Eesiah and madam Kebbeh Bendu Saygbe. He is the youngest of Josephine Clarke, Fatta Kargba, Edward Eesiah, Deddeh Dixon, and Branda Eesiah. He is the eldest of Francis Eesiah and Malay Eesiah.

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ABSTRACT

Eesiah, Morlue Samukai. POWER SYSTEM LOAD MODELING USING A WEIGHTED OPTIMAL LINEAR ASSOCIATIVE MEMORY (OLAM). **(Major Professor: Dr. Gary L. Lebby)**, North Carolina Agricultural and Technical State University.

Power system load models are very powerful tools, which have a wide range of applications in the electric power industry. These uses include scheduling system maintenance, monitoring load management policies, helping with the generator commitment problem by providing short-term forecasts, and aiding system planning [4].

Further, Power System Load Modeling is a technique used to model a power system and other essentials for the assessment of stability. In today's datacenters, power consumption is a major issue. Storage usually typically comprises a large percentage of a datacenter's power. Therefore, without mentioning that managing, understanding, and reducing storage, power consumption is an essential aspect of any efforts that address the total power consumption of datacenters. Moreover, according to [16], power system load models have a wide range of applications in the electric power industry including load management policy monitoring, such as aiding with system planning by providing long-term forecasts, short-term forecasts, and others including assisting with the generator commitment problem.

The direct impact that population growth and technological development have on the electric demand load cannot be under estimated. This thesis partly served as a reminder that through data and research that the direct proportional relationship between

population growth and demand load, and technological development and demand load makes up the entire concept of electric power generation and the entire electric power system that is a part of our daily lives. Since they are a part of our daily lives, power system engineers should and must derive mathematical models, namely, Traditional Least Squares, Truncated Fourier series, the use of artificial neural networks, and the Optimal Linear Associative Memory (OLAM) to capture these impacts on demand load.

CHAPTER 1

INTRODUCTION

Power or electric utility companies must be knowledgeable of at least the minimum demand load to set into place or coordinate energy storage procedures or maintenance. Being aware of this drives my sincere passion, among other things, to model a utility company's collection of power system load data implementing the weighted Optimum Linear Associative Memory (OLAM). Electric utility companies also have to be cognizant of rising demand load and ready to serve during peak demand load comfortably. Therefore, a portion of the data modeled was obtained from the Randolph Electric Membership Corporation, which is an Electric Power corporation operating in an area surrounding Asheboro, North Carolina [7]. In addition to discussing the importance of the three central tendency models (Linear, Quadratic, and Cubical), a large section of this thesis developed a scalable power modeling method by implementing artificial neural network's OLAM. The OLAM estimates or forecasts the power consumption of storage power system loads.

Additionally, the art of applying an explanatory data analysis (EDA) to the power system load utilizing load models is critical. To this end, a compilation of power system load over a span of three years was modeled using linear functions and estimating the unknown model parameters from data. With the aid of OCTAVE, a free version of MATLAB, this huge collection of power system load data was manipulated. Therefore, this thesis presented a detailed algorithm developed and implemented to mimic the definition of the weighted OLAM. In addition to having a power system load forecast or model, this definition outlines a comparison of hourly, daily, weekly, monthly, and yearly extractions of the load data. Each model shows the **growth rate** and **base load**. How do we know for sure that the linear, quadratic, or cubical model is our best choice? The OLAM's capabilities allow one to estimates or models the daily Randolph Power System Load Data and the weekly Randolph power system load data to show the cubical central tendency models of each case, and the best curvature that at least mimics or follows the trajectory of an original plot.

The general chronological order of this research begins with a detail explanation of the importance of electric power system load modeling to both utility companies and our lives. This thesis then moves on to discuss the entire electric power system, from generation to the customer or utilization. Then, a detailed history is given of power system load modeling and load management concerns, which is linked to the history of ANN, and its huge impact in power system load modeling. The role of some of ANN's sub networks are described, namely, Radial Basis Function Generalized Regression Neural Network (RBFGRNN) and the feed forward network, and the OLAM. Further, this thesis includes rising electric demand load in a power system. This research then showed the effects of biological patterns, natural, and seasonal cycles on the very electric power system that is a huge part of our daily lives. Discussions and proofs are given the fact that demand load growth is indeed impacted by the increasing population and increasing technological developments.

Therefore, one of the crusts or nucleus of this thesis is to emphasize that electric demand load and modeling these loads are indeed a part of our daily lives, which must be important to both electric power system engineers and to everyone else as well. As this case cannot be ignored or swept under the carpet because engineers must be able to use mathematical models to capture these impacts on demand load. With all these human realities and chain effects affecting the electric power system, this simply means that such occurances are indeed a part of us as humans that do affect our daily activities. Since the population and electric demand load are related, it is imperative that power system engineers derive mathematical models or use mathematical models to capture impacts on electric demand load. Consequently, these impacts do lead to the concepts of the Traditional Least Squares Model (Unweighted OLAM), Truncated Fourier Series Model, the Weighted OLAM three central tendency model. Besides the OLAM and many other methods that can be explored to come up with good power system load models, the scope of this thesis only allows for brief discussions of the Radial Basis Function Generalized Regression Neural Network (RBFGRNN) method.

CHAPTER 2

ELECTRIC POWER SYSTEM

2.1 Generation

An electric power system is mainly concerned with the generation, transmission, distribution, and utilization of electric power. Paramount to this definition is any power system must be economical, reliable, safe, and accommodative to the environment. A power system can have subdivisions, namely, generation, transmission, sub-transmission, distribution, sub-distribution, and loads [1]. Figure 2.1 is a visual of an entire power system that shows different sources of electric power. Conveyed also are concepts of generation, transmission, distribution, and utilization from the demand end. One can also glean from Figure 2.1 how different climatic or weather conditions affect the entire power system.

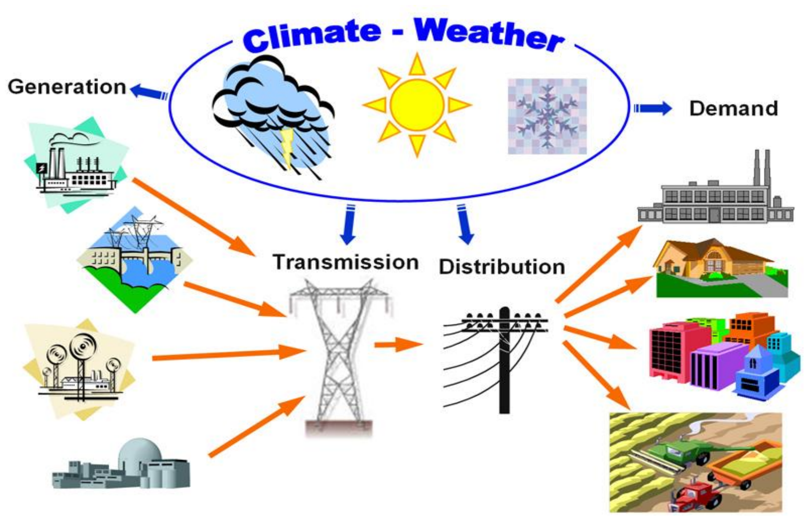

Figure 2.1: **Typical Electrical Power System**

Utility companies do generate electricity in a variety of ways. One of the most common methods is the energy of running water to power a generator. Power created in this way is termed hydroelectricity. In order to generate such a massive energy of flowing water, a dam may be built across a narrow gorge in a river or somewhere at the head of a man-made lake. All the water that backs up behind this dam's force-bay, is then allowed to flow through a submerged passage (Penstock) in a controlled release manner. Now, the massive flow of this elevated water spins the generator's giant turbines as it falls, producing electricity. Remember that electrical power produced in this way is called AC power or alternating current. Basically, it can be considered as the use of ac generators with rotating rectifiers known as brushless excitation systems. The generator excitation system not only maintains generators voltage, but also controls the reactive power flow. AC generators do generate high power at high voltages [2, pg 232]. Further, [12] adds that generators are usually built in the range of 18-24 KV with some at slightly higher rated voltages.

2.2 Transmission

An electric transmission system can be defined as the interconnection of the electric energy producing power plants or generating stations including the loads. Figure 2.2 depicts the interconnections involved with transmissions lines. Shown also in the upper right hand corner of the figure is a basic electric power system with the power plant as the generation unit and shows transmission lines and substations involved with the interconnections until it reaches the load, which is the house in Figure 2.2.

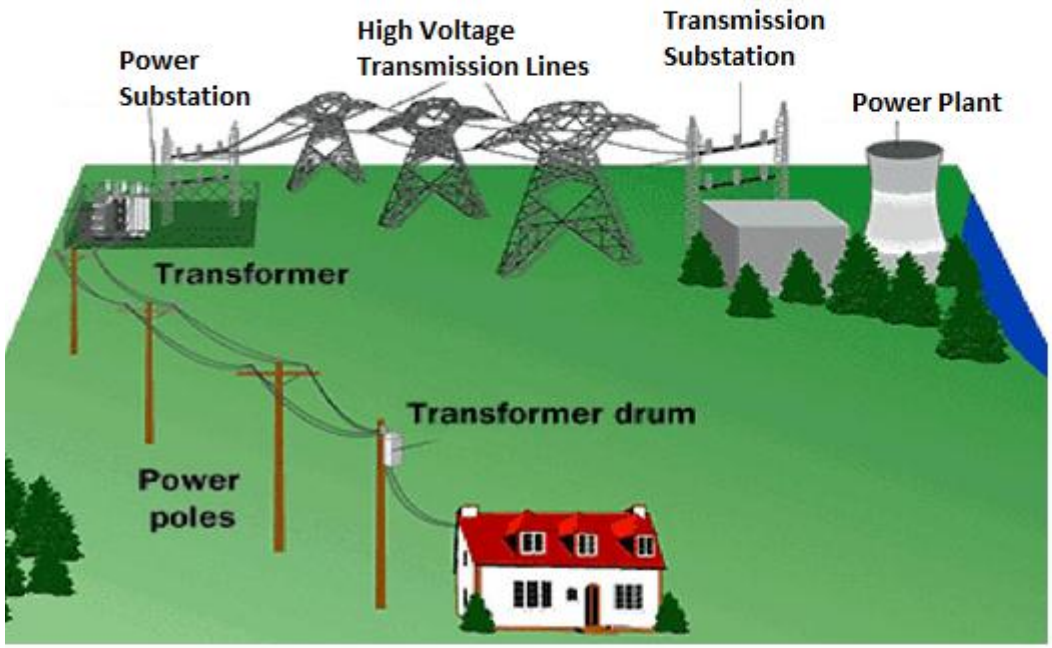

Figure 2.2: **Typical Transmission Lines and Substations**

According to [12], transmission lines operate at nominal voltages up to 765 KV line to line. A three-phase AC system is used for most transmission lines with an operating frequency of 60Hz (US) and 50Hz (Europe, Australia, and other parts of Asia and Africa [3]. After a utility company produces electricity, the power company must then be able to transmit the electricity through many miles of transmission lines so the power can reach the end users or customers. To ensure ease of transmission, the electrical power is raised to many thousands of volts and conducted over high-voltage transmission lines to the utility company's regional switching stations. Once at the regional stations, the utility company steps down the power to a lower voltage for transmission to substations. This procedure is continued until the power reaches your home. A typical transmission starts at 230,000 volts, is stepped down to 69,000 volts at a switching station, it is again stepped down further at a substation to 13,800 volts. By the time it reaches your home, it is reduced to 240 volts through utility transformers [2, pg. 232].

An electric transmission system is the interconnection of the electric energy producing power plants or generating stations with the loads. A three-phase AC system is used for most transmission lines. A three-phase AC system, operating frequency of 60 Hz (United States) and 50 Hz (Europe, Australia, and other parts of Asia), is used for most transmission lines.

2.3 Transformers

Simply stated, a transformer not only steps up or steps down electric energy or voltage, it can be considered as a device that carries or transfers electric energy from one circuit to the other basically through conductors that are inductively coupled. Figure 2.3 is an image of a utility transformer at a switching station where very high voltages are stepped down to be tranmitted further over long distances. The receiving end and the sending end of the transformers are seen in the image. In-fact, [12, pg 41] rightly puts states: Transformers are the link between the generators of the power system and the transmission lines, and between lines of different voltage levels. Transformers also lower the voltages to distribution levels and finally for residential use at 240/120 V. They are highly (nearly 100%) efficient and very reliable.

Figure 2.3: **Typical Utility Transformer at a Substation**

For the case of the IDEAL Transformer, [12] explains that transformers consist of two or more coils placed so that they are linked by the same magnetic flux. In a power transformer, the coils are placed on an iron core for confinement purposes so that almost all of the flux linking any one coil links all others. Several coils may be connected in series or parallel to form one winding, the coils of which may be stacked on the core alternately with those of the other winding or windings. Figue 2.4 shows an image obtained during research that depicts the basic transformer winding concept in a typical step-up transformer.

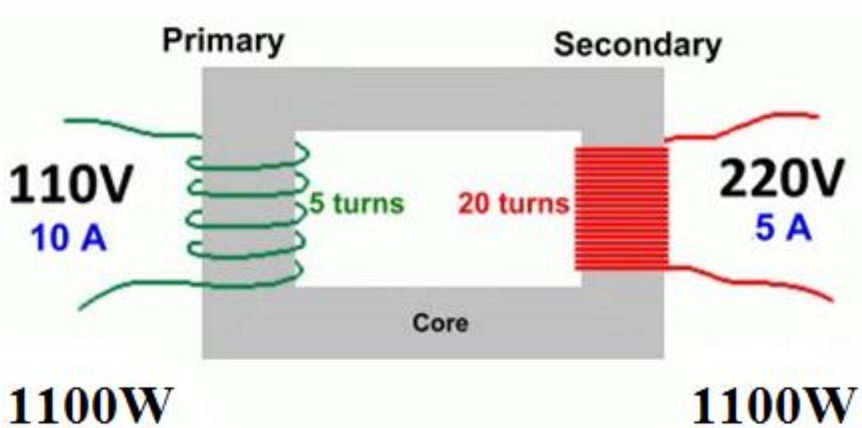

Figure 2.4: **A Basic Transformer Concept**

2.4 Distribution

Remember that within a power plant, a number of AC generators generally operate in parallel. For a smooth and economic operation of the plant, the total load must be appropriately shared by the generating units [1]. A power distribution system is the part that the sub-transmission lines typically deliver their power to locations called substation, when stepped-down transformers are used to reduce the high voltage to a level usable by customers. The voltage of the distribution system is usually between 4.6KV and 25KV [3]. Figure 2.5 shows a typical configuration of electric distributions and how they form a major part of the power system network. Figure 2.5 also shows how the distribution line at the secondary end receives the dropped or stepped down voltage from the step-down transformer hanging on the electric pole. The other end of the stepped-down transformer is the primary side that has higher voltage from the substation. The voltage level, 240 volts, on the secondary end is ready to be utilized by homes.

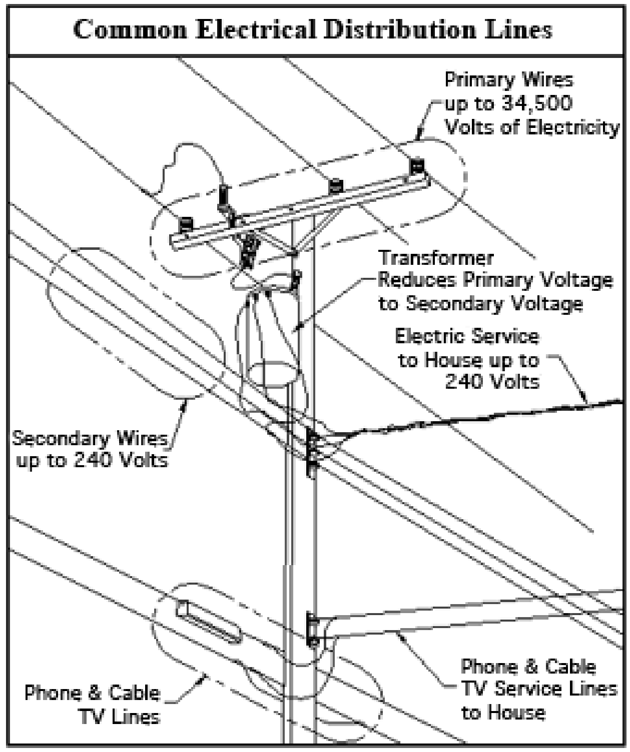

Figure 2.5: **Typical Image of Electric Distribution Lines**

2.5 Load

A load can be regarded as the electricity demand of consumers or customers for power. It is basically the "burden" that customers put on utility companies. Loads of the power systems are classified into industrial, commercial, residential, and others. Residential customers are domestic users whereas commercial and industrial customers are business and industrial users. Among other customer classifications are municipalities, state and federal government agencies, electric corporations, and educational institutions [3].

2.6 The Randolph Power System Load Data

The Randolph Electric Membership Corporation is an Electric Power Corporate operating in the area surrounding Ashboro, North Carolina. The original Randolph Power System Load data used for this thesis is residential load data whose size is 1369 by 24 (1369 days by 24 hours). The Randolph Corporation collected these data from their load centers from 1990 through 1993. Table 2.1 is a truncated version of the entire Randolph load data that only shows the first seven days and the first ten hours.

Table 2.1: Truncated Table of the Randolph Power System Load Data

DAYS	HOURS (Hour # 1 through hour # 10)									
(Days 1 thru 7)	5237	4961	4759	4759	5115	5747	6581	7768	9052	9777
	9072	9449	9655	9999	10619	12272	13017	13280	13069	11984
	8870	8614	8813	9040	9643	11344	12531	12434	11283	10052
	7497	7278	7136	7193	7727	9339	10404	10429	9692	9262
	6225	5954	5958	6035	6654	8294	9659	9874	9177	8728
	6768	6314	6209	6213	6456	6691	7132	7849	9011	10129
	6950	6597	6610	6541	6691	6921	7424	8659	10562	11020

2.7 Importance of Power System Load Modeling

Before preceeding with some of the importance of power system load modeling, the author must stress that although there are several methods used in modeling power system load data, this study do not want to restrict anyone’s ability to investigate any of the mechanisms that power system engineers can use to model power system load data.

Power system load modeling is significant in that both outside and inside the power industry. There is an increasing appreciation of the dire need to account for how much customers value the power supply they consume and also to account for their expectations. This is where load modeling comes into play and becomes even more important especially with regards to near-future forecasting to ensure system maintenance. Power system load modeling aids power engineers when it comes to putting into place operating strategies, maintenance schedules, and reinforcements.

Besides applications involving load management policy monitoring, aiding with system planning by providing long term forecasts, providing short term forecasts, and many more including assisting with the generator commitment problem. According to [8], a load model is very important to improve the accuracy of stability analysis and study load flow in power systems.

2.8 History of Power System Load Modeling and Load Management Concerns

As the power system load becomes the new area of research within power system stability, repeated evidence of the current trajectory shows load modeing has certainly gained attention. Studies have shown that there is a need to discover more accurate load models other than those already used traditionally (e.g. All constant impedance or all constant power).

Remember, voltage collapses only took several minutes in the past "real-world" cases, the older modeling works focused on induction machines, which were critical in the range of some seconds after a disturbance. The load response was taken as a fuction of voltage [20]. In addition, the use of dynamic load models has increasingly become popular compared to static load models. Although knowledge has been acquired from a power system load in recent years, it is one of the most difficult and unknown areas of study in the midst of the power system models. This is because of the diverse and complex load components, the high distribution and variation during the time of day and year, weather, and lack of information for the load. New techniques such as this thesis' implementation of the OLAM and truncated Fourier series do also result in a better understanding of the load and a better representation of the load in simulations of a power system. This helps in having a positive impact for the control, operation, and reliability of the power system. Remember that accurate load models and even a real-time monitoring application do help to introduce more competitiveness for the electric industry and contribute to the development of a smart grid information structure [21].

The ability to functionally express variations in the power system load over time is an important attribute, especially to those concerned with load management. Load management primarily deals with techniques that in the long run determine the shape of the daily load curve. In general, the best means to observe the effects of load management techniques is to have an apparatus that gives as output a typical daily load curve in a particular week.

A desire to have a mathematical expression of the power system load is not limited to those connected with a load management program. Modeling of a power system load has applications in a dispatching environment where knowing the shape of the load at a particular hour may be as important as knowing the actual magnitude itself.

This indeed can be seen in the unit commitment problem. This problem has enough generating units on-line when they are needed. Remember, in the unit commitment problem, there must be adequate time between identification of the need and the actual need in order to have additional generating units on-line. An in-depth knowledge of the shape of the daily load curve in conjunction with the load magnitude becomes important in determining how many generating units to have ready on-line. It is well established that in the early morning hours, the power system load experiences a rapid rate of increase due to people waking up in the morning to begin their daily routines. In order to know how the power system load behaves during this period could allow dispatchers to plan with a greater efficiency of how many on-line generating units to allocate.

From the time of the energy disruptions of the 1970s, predictable demand in conjunction with a flexible low-cost supply became harder to achieve. Since then, there has been a nationwide push aimed at controlling the shape of the daily load curve. One of the primary aims of those in load management is to flatten out the daily load curve so that it will conform to some pre-determined curve, which is economically optimum and system dependent. One could easily visualize the daily load curve as being obviously constructed of peaks and valleys. The goal is to fill in the valleys and clip off the peaks of the daily load curve in such a manner that the total energy consumed remains undiminished, yet still the resultant curve approaches the ideal system load curve. One primary reason behind forcing the power system load to some economically system load curve is to decrease the capital investment (generating units and their maintenance), while still maintaining an acceptable level of demand. Remember, there must be enough generating units to service the peak demand and the level of demand must be such that the outputs from the generating units are used efficiently. Load control schemes are put into place in situations such as these.

The sincere effort to influence the daily load is not a new development. In the infancy of electric utility, a large portion of the demand was due to night-time lighting. There evolved a management campaign to shift some of the load to daylight hours by smart advertisers who promoted day-time usage. This is clearly an example of demand-side planning. The important lesson here is that all demand-side planning does not just involve load reduction or load construction, but it can also involve the redistribution of load or a combination of all three.

Even though there are many different ways one could modify the load shape, there are still five different general types of changes that embodies them all [22]. The following five load management techniques are not necessarily mutually exclusive, yet it is suitable to cover all of them for clarity. Another point to establish is in general, a given load management technique consists of a combination of all five in a kind of varying degree. Out of the five load management techniques, the first three are classical, whereas the last two are the less used approaches.

The first technique is to clip the peaks, which reduces the system peak load. As it is obvious, clipping the peak load by itself is not acceptable to the power industry since this result in lower demand, which is a direct reflection of lost revenue. This peak clipping can be accomplished in the residential sector by having the customer accept direct control over appliances such as air conditioners and it can be accomplished in the commercial sector by having customers subscribe to interruptible power at lower rate as an incentive. The impacts of these load management techniques are still evolving.

The second load management technique is to fill the valleys. Remember that valleys are off-peak hours and filling them in can be accomplished by creating new reasons for added load to exist at those hours. As it is typical with most changes involving human nature, there must be some incentive involved to encourage the required modification. Next, some common valley-filling techniques by sectors are described.

- In the residential sector, valley filling can be accomplished by having the customer use off peak water heating; whereas in the commercial sector, the customer could store hot water to augment space heating requirements.
- The industrial customer could be given incentives to add night-time operations. Obviously, the residential load in the form of water heating is being shifted from some other period of time, preferably from an on-peak region, since hot water is a constant necessity of everyday living. <u>A component of growth encouragement is embedded in the current valley filling technique used for the industrial sector.</u>
- It has already being assumed above that the space heating requirement is a major contributor to the load associated with the commercial sector. If this is indeed the case, then a portion of the commercial space heating load is being transferred to the commercial water heating load in a manner that will increase the commercial water heating load due to intended heat loss.

The third technique in actuality is a combination of techniques one and two with a restriction that there is not a loss of overall demand. Load shifting is the third technique.

Its principle is to move demand from on-peak to off-peak periods. For instance, the residential customer could subscribe to time-of-use rates, while the industrial customer could shift more of their day-time activity to nighttime. These three examples can be referred to as the classics in load management. The remaining techniques (fourth and fifth) are not very common.

The fourth technique is to invoke strategic conservation. Probably, this technique is not popular because it typically reduces the total energy usage and peak load. From the stand point of the electric utility, the load management technique's purposed is not to reduce revenue. Notwithstanding, in the residential sector, this could be realized by increasing home insulation; whereas, the commercial customer could reduce lighting usage and the industrial customer could install more efficient energy-saving processes.

Strategic load growth is the fifth type of change. Basically, this technique target areas where sales can be beneficial. If the growth is targeted for the valley areas of the daily load curve, then the load management aspect of this technique can be realized. In effect, the residential customer would switch from gas to electric water heating. The commercial customer would be somehow persuaded to have heat pumps installed, while the industrial customer would be persuaded to convert from gas to electric process heating.

Remember any uncertainty occurred after implementing a chosen load management policy will fade away gradually once a load mechanism is put into place; wherein the effectiveness of a load management program is enhanced after assessing the power system load (PSL) before and after the policy has been in efect. One has to look at the subtle changes in the PSL, noting how the shape of the PSL changes over several fixed intervals of time. Figure 2.6 is an illustration of how the daily load curve is made up of peaks and valleys.

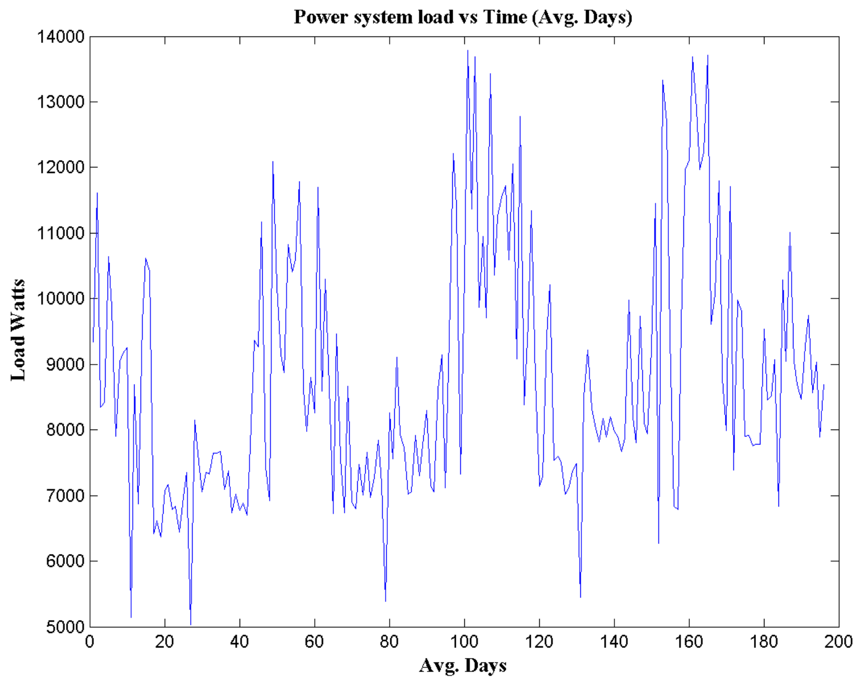

Figure 2.6: **Power System Load Model of Average Days of Randolph Power System Load Data**

CHAPTER 3

ARTIFICIAL NEURAL NETWORKS

3.1 General Overview

In the human brain, neurons send signals that activate each other. All of the activations and interconnections create intelligent thoughts. Humans make decisions based on factors believed to be important based on whatever tasks are at hand. A certain level of importance may be attached to these tasks. In the process of coming up with a solution, these factors has a certain level of importance based on previous experiences of the present task and any generalizations that may be obtained from other instances, which maybe applicable. Once obtained, the solutions can be distributed, impartially, as a factor to any task that conceiveably might hold some significance. The result may well be a dynamic and complexed network of reasoning built from a learning paradigm that makes use of both historical and environmental data. In a general sense, this identical process can occur at the biological level considering how scientists believe the human brain works. This thesis can safely mention that the brain can be described as a complexed, parallel computer, which is composed of trilliions of processing units known as neurons [5].

There are four basic components in the composition of a neuron, namely, axon, dendrites, synapses, and the soma located in the neuclus (see Figure 3.1). As shown in Figure 3.1, the dendrites do provide input channels to the nucleus connecting to the soma, which provides input and creates output to be received by the axon. The axons carry signals away. They carry the output to the synapses, which transmit the information to other neurons [20]. Recall as [5] precisely stated, the neuron is capable of storing acquired knowledge for future use while obtaining new knowledge to be processed. It is clear that massive biological neural networks of immense complexity can be created within the brain based on the neuron's capabilities and its simplistic architecture.

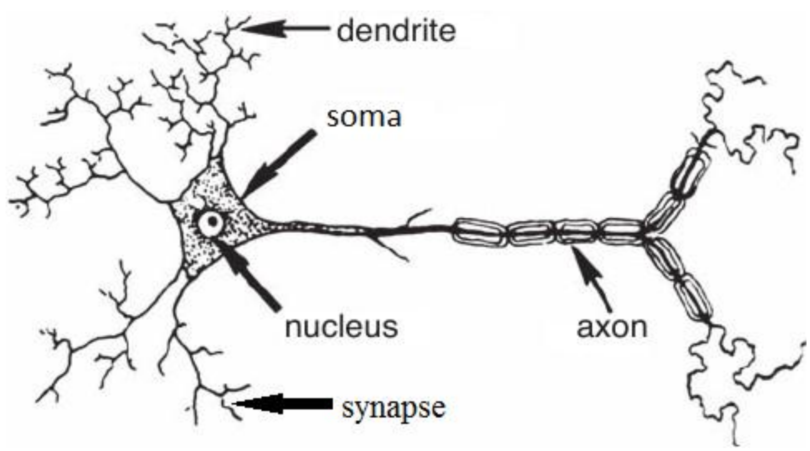

Figure 3.1**: Biological Neuron**

Artificial Neural Networks (ANN) are algorithms that emulate biological networks created within the brain utilizing a mathematical model of the neuron as a building foundation. Figure 3.2 depicts the first mathematical representation of a neuron known as a single-layer perception neural network (SLPNN). SLPNN represents an input vector whose characteristics are examined for importance by the weight vector, W.

Equation 3.1 generates the output of the neuron, and passes the weighted summation to the transfer function. Equation 3.2 is a function that determines whether or not the neuron will activate, and depending on the slope parameter, α, this equation may perform as a hard limiter or a soft limiter. Better still, it can be removed from the network completely.

$$X = \sum_{j=1}^{N} W_j I_j \tag{3.1}$$

$$T(X) = \frac{1}{1+e^{-\alpha I}} \tag{3.2}$$

Eventhough, there are a number of different ANNs, the scope of this thesis briefly discuss three of these networks, namely, the Radial Bassis Function Generalization Regression Neural Network, the Backpropagation Neural Network and the sub feed-forward network, and the Optimal Linear Associative Memory (OLAM).

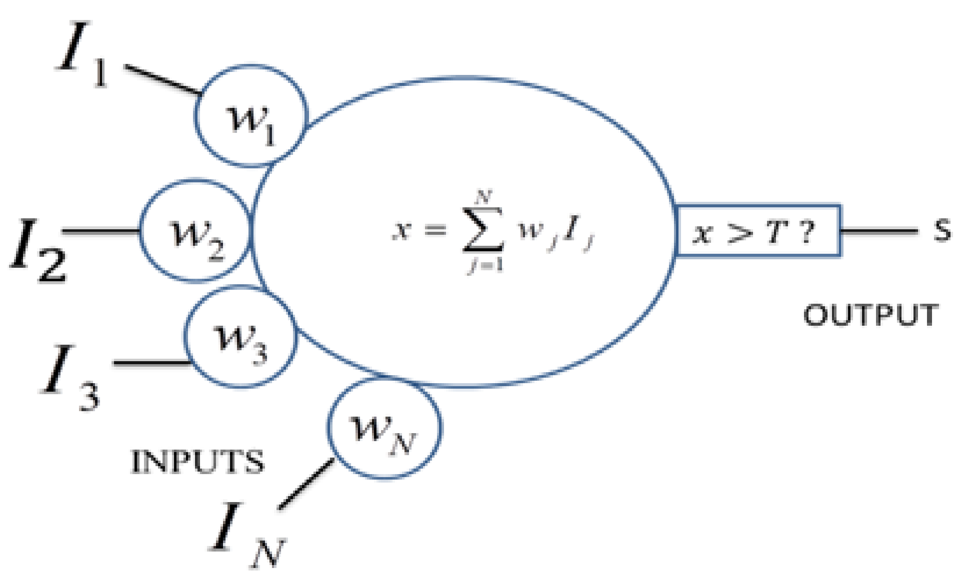

Figure 3.2: **Single Layer Perceptron Neural Network**

3.2 A Brief History of Artificial Neural Networks

Remember that the Optimal Linear Associative Memory (OLAM) is a subset of Artificial Neural Network's feed-forward networks. A thorough, 100%, or a complete literature of this powerful and huge area of artificial neural networks is completely out of the reach or beyond the scope of this thesis. Therefore, it is fitting to at least mention a few historical studies mentioned in the literature. According to [9], the history of neural networking arguably started in the late 1800s with scientific attempts to study the workings of the human brain. In 1890, William James published the first work about brain activity patterns. We begin our look at neural network history in the Age of Camelot with perhaps the greatest American psychologist who ever lived, William James. James also taught, and thoroughly understood physiology. It has been almost exactly a century since James published his "Principles of Psychology," and its condensed version, "Psychology (Briefer Course)" James was the first to publish a number of facts relative to the brain's structure and function. For example, he was first to state some of the basic principles of correlational learning and associative memory [18, pg.15].

The human brain has neurons that send signals that activate each other, and implies interconnections (see Figure 3.3). All of the activations and interconnections create intelligent thoughts. Particularly, [6] continued McCulloch's and Pitts' work on neural networks published in 1943, which still is a cornerstone in the theory of neural networks. They made an attempt to understand and describe the brain's functions by mathematical means. McCulloch and Pitts used their neural networks to model logical operators. Contemporary developments in the field of computer science were closely related.

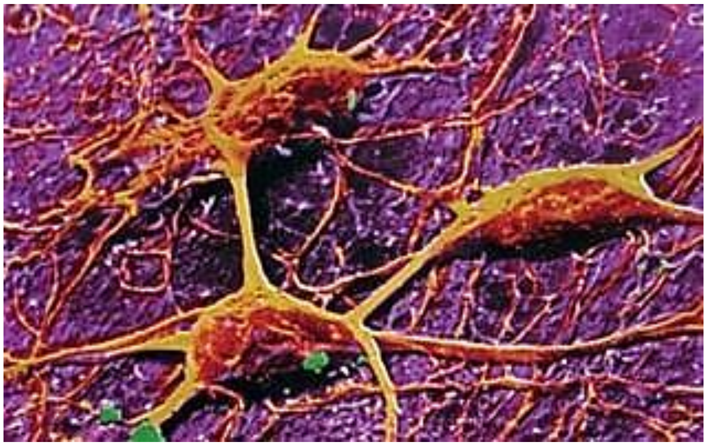

***Figure 3.3*: Human Brain Neurons Interconnections**

For this thesis, there is a systematic and intentional use of several references to highlight the coherence in these historical developments. Therefore, [5] made similar accounts as [6] states, the study of the human brain dates back thousands of years. However, it has only been with the dawn of modern day electronics that man has begun to attempt and emulate the human brain and its thinking processes. The modern era of neural network research is credited with the work of neuro-physiologist, Warren McCulloch and the young mathematical prodigy, Walter Pitts, in 1943. McCulloch had spent 20 years of his life thinking about the "event" in the nervous system that allowed us to think, feel, and so on. When the two joined forces, they wrote a paper on how neurons might work, and they designed and built a primitive artificial neural network using simple electric circuits. They are credited with the McCulloch-Pitts Theory of Formal Neural Networks. (Haykin, 1994, pg. 36) (http://www.helsinki.fi)."

The next major development in neural network technology arrived in 1949 in a book entitled, “The Organization of Behavior” by Donald Hebb. The book supported and further reinforced McCulloch-Pitts's theory about neurons and how they work. A major point brought forward in the book described how neural pathways are strengthened each time they were used. Likewise, this is true of neural networks, specifically in a training network. (Haykin, 1994, pg. 37) (http://www.dacs.dtic.mil) [5].

Between 1959 and 1960, Bernard Wildrow and Marcian Hoff of Stanford University in the United States developed the ADALINE (ADAptiveLINear Elements) and MADELINE (Multiple ADAptiveLINear Elements) models. These were the first neural networks that could be applied to real problems. The ADALAINE model is used as a filter to remove echoes from telephone lines. In 1969, Minsky and Papert published several documents, including their book, ‘Perceptron.’ They showed how neural networks of the time were severely limited, and due to the opinion of these two influential men, research into neural networks decreased drastically [5].

In 1982, John Hopfield of Caltech presented a paper to the scientific community. He stated the approach to AI should not be purely to imitate the human brain but instead to use its concepts to build machines that could solve dynamic problems. He showed what such networks were capable of and how they would work. It was his articulate, likeable character and his vast knowledge of mathematical analysis that convinced scientists and researchers at the National Academy of Sciences to renew interest into the research of AI and neural networks. His ideas gave birth to a new class of neural networks that over time became known as the Hopfield Model. (http://www.dacs.dtic.mil) (Haykin, 1994, pg: 39).

At about the same time at a conference in Japan on neural networks, Japan announced that they had again begun exploring possibilities of neural networks. The United States feared that they would be left behind in terms of research and technology and began almost immediately funding AI and neural network projects. (http://www.dacs.dtic.mil). Moreover, [11] adds an important concept during this period: Adaptive Resonance Theory (ART) was first introduced by Carpenter and Grossberg in 1983. The development of ART has continued and resulted in the more advanced ART II and ART III network models.

Broomhead and Lowe first introduced Radial Basis Function (RBF) networks in 1988. Although the basic idea of RBF was developed 30 years ago under the name "method of potential function," the work by Broomhead and Lowe opened a new frontier in the neural network community. According to [10], in 1985, the American Institute of Physics hosted the first annual meeting on Neural Networks for Computing, and by 1987, the Institute of Electrical and Electronic Engineers (IEEE) the first International Conference on Neural Networks drew more than 1,000 attendees. This interest has more or less continued to present day and artificial neural networks have now found uses in everything from medical diagnosis equipment to speech recognition software. The year 1986 saw the first annual Neural Networks for computing conference that drew more than 1800 delegates. In 1986 Rumelhart, Hinton, and Williams reported on the developments of the back-propagation algorithm. The paper discussed how back-propagation learning had emerged as the most popular learning set for training of multi-layer perceptrons [5].

3.3 Radial Basis Function Generalization Regression Neural Network

The RBFGRNN is a nonlinear mapping and linear separation network with a cluster-based module comprised of KSOM and DIANA. The RBFGRNN employs a curve fitting approach whose learning process searches an optimal fitting surface in a multidimensional space. Remember, the neurons in the hidden layer of the radial basis function neural network (RBFNN) are offered a radial basis function set, which builds a discretion space. It must be mentioned that the radial function was introduced to solve the real multi-variable interpolation problems in the beginning. Figure 3.4 depicts that in the typical architecture of a RBFGRNN, the adjustable weights are only present in the output layer. The connections from the input layer to the hidden are fixed to unit weights.

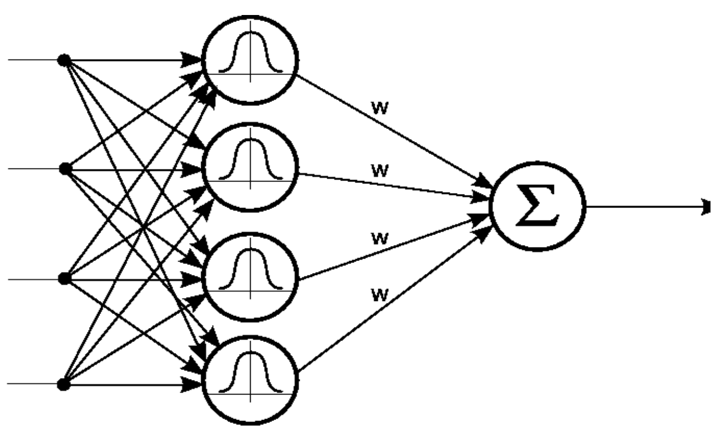

Figure 3.4: **Radial Basis Function Network**

3.4 Back Propagation Neural Network

The BPN is a network that uses a recursive technique. In fact, according to [5], Paul John Werbos established the back-propagation algorithm in his dissertation in 1974 and proposed the concept of hidden layers. Unfortunately, his work went largely ignored and was revived in the late 1980s. In their training style, the generalized delta rule, James L. McClelland and David E. Rinehart made the BPN popular. Remember that the weight adjusting type of back propagation neural network is divided into two parts, the forward propagation and back propagation. Basically, the structure of forward propagation is the same as multi-layer perception. Figure 3.5 is a clear depiction of the back-propagation multilayer feed forward network. It shows how errors, $\delta_1 = W_{14}\delta_4 + W_{15}\delta_5$ (Sigma, which is the difference between desire and expected output) are fed back again to the input layer so that again they can be weighted and a new set of weights can be achieved. Signal e is the adder output signal, which is basically the sum of product X and W.

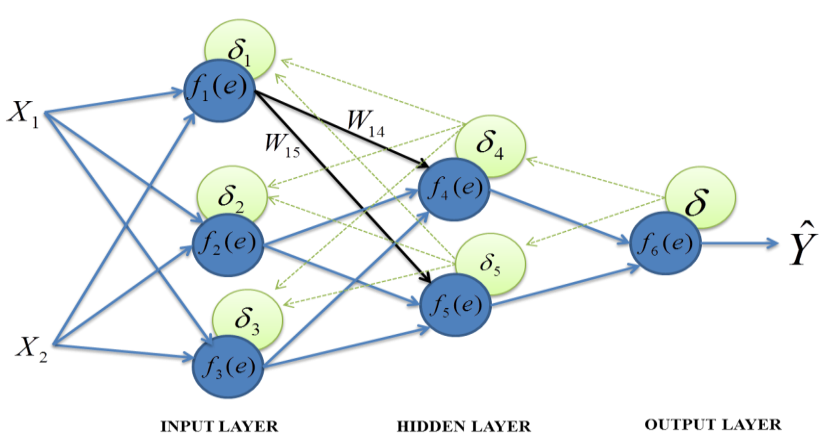

Figure 3.5: **A Fully Connected Multilayer Feed Forward Back Propagation Network**

CHAPTER 4

RISING OF LOAD DEMAND IN POWER SYSTEM

4.1 Effects of Biological Patterns, Natural, and Seasonal Cycles on an Electric Power System

Decisions are made by human beings based on a number of given factors that can be considered to a certain task at hand. It must be noted that an electric power system load is composed of two types of loads, random and regular. The regular load portion is what brings in the biological patterns, natural, and seasonal cycles. These do decribe the periodical variations caused by daily life activities, seasonal changing, working schedule, and so forth. Eventhough an electric power system is affected by biological patterns, natural, and seasonal cycles, it must be emphasized that within certain operational constraints, the basic goal of any modern electric power distribution system is essentially to satisfy the growing and changing system demand load during planning periods. This can be done safely, reliably, and economically especially when optimized decisions are made on the following: servicing areas, voltage levels of the distribution network, sizes, locations, scheduled expansions of substations, conductor types, routes, building and load schedules of sub-transmission lines and feeders, load reliability level, and locations of switching devices, etc.

Since decision makers of a modern electric power system are basically interested in knowing or having a basic idea of what the electric load will be at a certain future time interval of interest, these same decision makers must also be cognizant of the fact that load modelling or load forecasting becomes an even difficult task to perform partly due to these biological pattens, natural, and seasonal cycles. These factors do make load forecasting an intricate task. Two of the many factors are:

Weather Factor: noticeably, electric power load has a definite correlation to weather in general, especially to temperature. Temperature is the most influential factor in electric load forecasting. When a change in temperature occurs, its impact becomes important. For instance, during the summer when temperature rises, more power is needed for air conditioning and cooling systems, or during the winter when the temperature is lower, more power is needed for the heating system. Also, a number of factors such as wet and dry temperatures, dew point, wind, precipitation, and humidity do impact the amount of power needed.

Time Factor: time factors do have an important effect on electric load pattern. This may include holidays, hour of the day, and day of the week. For example, the consumption of electric power during week days is quite different from the weekend or a seasonal effect can be the number of daylight hours in a season. Holidays do also have a different and important effect on load patterns. Holiday loads will mostly depend on geographical location and cultural attributes of each country. For instance, typical holiday load models in India and the United States would be quite different.

4.2 Load Demand Growth Due To Increasing Population

Electric power is a little like the air one breathes or better still like the water one drinks. The general population will not think about it until it is no longer available or until it is missed. In these mordern times, a substantial amount of the human population put a lot of constraint or demand on electric power utility companies as a result of human dire needs for heating, cooling, lighting, refrigeration, cooking, entertainment, sound computation, etc. So, without electricity, life somehow becomes cumbersome. Since electricity is usually provided around the clock in the industrialized world, this along with the steady increase in the human population will definitely show a typical demand load verses population plot with an ascending trend.

Overwhelming evidence and repeated research have shown healthy economies and expanding populations are taxing electric grids and could force certain countries or subregions or states to cut into their emergency power reserves during times of peak use in the very near future. Growing demand for electricity especially during the hottest times of the year are treatening to outstrip new power supplies. For instance, in order to buttress the fact that electric demand load is directly proportional to population growth, [23] stresses that on a yearly basis, it can be concluded that as the population estimates increase, the electric power generated, annual average load demand and instanteous annual peak load values do change dynamically. Since the crust of [23]'s research is based on electric generation and demand trend of Nigeria from 1973 to 2006, its subsequent study revealed that power demand or energy demand and supplies are growing at an annual exponential rate of 18.56% while the electric load factor for the period under review is 0.595.

In this thesis, it must be stated that beyond all reasonable doubts that as population increases, demand load is bound to increase, and as such, a consequent effect would be for utility companies to increase electric power generation. With all these human realities and chain effects affecting the electric power system simply means that such occurances are indeed a part of humans; they do affect our daily activities. Since population and electric demand load are related, it is imperitive that power system engineers derive mathematical models or use mathematical models to capture these impacts on electric demand load. Thus, leading to the crust of this thesis' next chapter.

Table 4.1 shows data beginning in 1973 through 2006, the corresponding power generation, the average demand load, and the population estimate in the Nigerian State of Osogbo. A clear proportionality can be seen between demand load and population. For graphing purposes and to minimize data congestion, Table 4.2 was used to generate the graph in Figure 4.1. Table 4.2 and Figure 4.1 shows the first two years and skip two years. Figure 4.1 shows a direct proportionality among population growth, power generation (P), and Demand Load (DL).

Table 4.1: Annual Electric Generation, Demand Trend, And Population in Osogbo, Nigeria

Year	Power Generated (GW)	Average Demand Load (MW)	Population
1973	2493	285	54226
1974	2780	318	55865
1975	3322	379	57500
1976	3750	428	59143
1977	4195	479	60782
1978	4359	498	62421
1979	5151	588	64060
1980	5724	654	65699

Table 4.1: ***Cont.***

Year	Power Generated(GW)	Average Demand Load (MW)	Population
1981	6766	773	67782
1982	7102	811	69865
1983	8456	966	71948
1984	8927	1020	74031
1985	10156	1160	76115
1986	10665	1218	78198
1987	11141	1272	80281
1988	11147	1310	82364
1989	12700	1450	84447
1990	13364	1526	86530
1991	14212	1623	89263
1992	15066	1721	92057
1993	14617	1669	94934
1994	14557	1663	97900
1995	15793	1804	100959
1996	15971	1824	104095
1997	15416	1760	107286
1998	16235	1856	110532
1999	16291	1860	113829
2000	17227	1738	117171
2001	17637	2014	120481
2002	21544	2460	123791
2003	22612	2582	127101
2004	24132	2756	130412
2005	24177	2759	133722
2006	23300	2761	137032

Table 4.2: Truncated Version of Table 4.1 For Graphing Purpose

Year	P(GW)	DL(MW)	Population
1973	2493	285	54226
1974	2780	318	55865
1977	4195	479	60782
1978	4359	498	62421
1981	6766	773	67782

Table 4.2: ***Cont.***

Year	P(GW)	DL(MW)	Population
1982	7102	811	69865
1985	10156	1160	76115
1986	10665	1218	78198
1989	12700	1450	84447
1990	13364	1526	86530
1993	14617	1669	94934
1994	14557	1663	97900
1997	15416	1760	107286
1998	16235	1856	110532
2001	17637	2014	120481
2002	21544	2460	123791
2005	24177	2759	133722
2006	23300	2761	137032

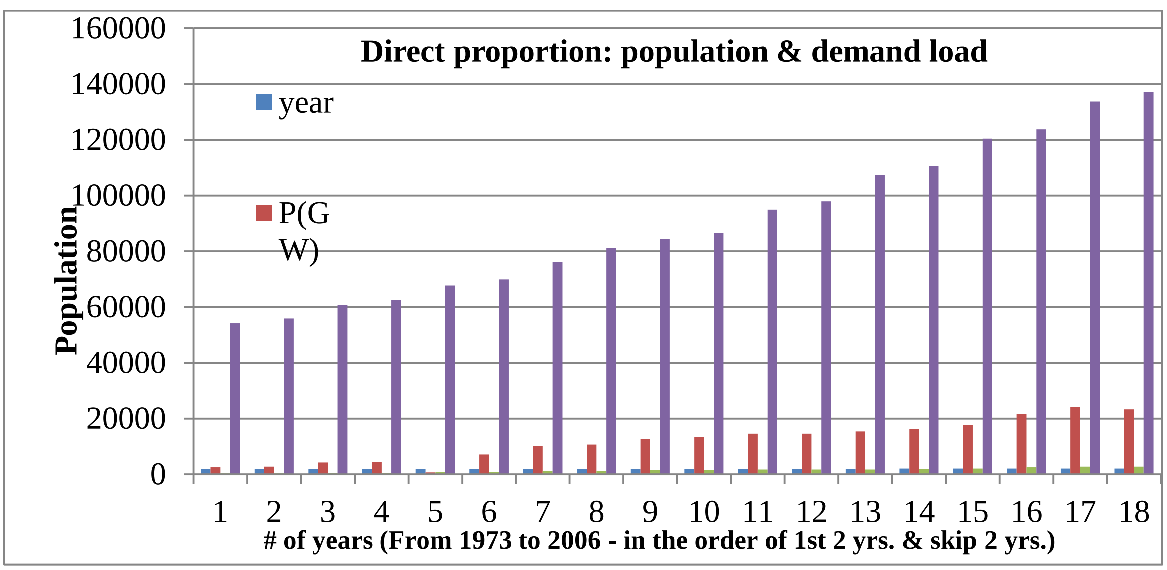

Figure 4.1: **Graph Showing Direct Proportion Among Population Growth, Power Generation, And Demand Load**

4.3 Load Demand Growth Due To Increasing Technological Development

This thesis also argues that there is a direct correlation between demand load growth and increasing technological development. Most rural areas do not have technologically advance electronic gadgets and high-level power-consuming equipments compared to urban and metropolitan areas. Remember that most Americans do live in urban areas, forming huge hot spots of energy consumption. Indeed electric demand loads do increase as a result of heating, air conditioning, business machines, higher light intensities, and appliances. Evidently, urban metropolitan areas are more technologically advanced and do possess the best power-consumming appliances, which are factors that increase electric demand load.

Advancement in technology can be generally linked to an increase in electric load density partly because more, and more components are packed in the same space, thus drawing more power. According to [24], these two factors, building function and equipment technology are interrelated. The researcher maintains that certain types of buildings are more prone to load growth than others due to the task being performed and the ongoing advancement of the equipment technology being used. Lab and hospital equipment continue to become more electronic with the need to store and access substantial amounts of information. Data center equipment continues to become more compact with higher power use in a smaller space. Since more of the types of buildings listed in Table 4.3 found in urban areas, [24] adds that Table 4.3 depicts projected load growth factors for different types of building functions based on a 10- to 15-year period.

Table 4.3: Building Type And Percentage of Load Growth

Building Type	% of Load Growth
Data center	50% to 200%
Laboratory Building	15% to 35%
Hospital	15% to 35%
Office Building	5% to 15%

CHAPTER 5

THE USE OF MATHEMATICAL MODELS TO CAPTURE THESE IMPACTS ON DEMAND LOAD

5.1 Traditional Least Squares Model (Unweighted OLAM)

The Traditional Least Squares Model cannot easily be explained without mentioning Regression or Curve Fitting. Remember that field data such as the Randolph power System Load data is often accompanied by noise. It is evident that all control parameters such as the independent variables do remain constant, but the resultant outcomes such as the dependent variables do vary. Therefore, it is only necessary to have a process called Regression or Curve fitting to quantatively estimate the trend of the outcomes.

Least squares analysis is one of the most widely used methods of fitting trends to data. Several researches have shown that the method of least squares is a good method of fitting data to a model equation. Basically, this is all about fitting the best trend curve to data. The sum of square error needs to be at a minimum. Regression analysis is implemented by means of least squares. One important note is that the presence of outliers is critical because they do affect the fit as a whole. The least squares method is indeed sensitive to outliers.

Among the many assumptions that can be made in linear modeling after the statement of the model, only two will be mentioned for the scope of this thesis. The first assumption is the independent variables are linearly independent or simply the rank assumption. Since this is also about a problem of uniqueness of solution, the second assumption is there are more data available then parameters to be determined. There must be some reason behind why the least squares is used or favored. The following three properties could be partly the reasons:

1. The least squares estimator is unbiased. Meaning that the value of the unknown population parameter is the espected value of the estimator.
2. Linearity is another property of the least square estimator. That is, the least squares estimator for a sum of vectors of data on the dependent variable is indeed the sum of the least squares estimator for each separate vector.
3. The estimator is efficient. Meaning the bias and variance are taken into account by efficiency. If one estimator is a smaller spread about the true value of the population than another then it is more efficient.

5.2 Truncated Fourier Series Model

Glancing at the Randolph power system load data, it is evident that the daily variations are basically in relationship between the days of the week. Comparing it to another day of the week of the same hour, such relationships can be as simple as just one day of the week having a larger load on average at a certain hour. Weekly variations in the power system load (PSL) is handled by its explicit inclusion in the mathematical form of each daily and hourly model.

Remember that such time-varying load is composed of a base load, a growth that is related to the load, and a seasonal component. In this thesis, the characteristics used to model the power system load are achieved by plotting, and then observing obvious trends in a given historical average weekly load data spanning over a period of about four years. Summer cooling peaks and winter heating peaks are recognizable characteristics that happens in approximately 24 week intervals. According to [25], in electric power utilities located in the southeastern part of the United States, the peaks are due to the summer cooling loads in the hot months and the winter heating loads in the cold months. This pattern occurs every year (see Figure 5.1); hence, is the reason for the labeling, seasonal load effect. Additionally, [26] adds that the seasonal weather load is traditionally modeled as a truncated Fourier series. Equation 5.1 describes the load model used in this thesis.

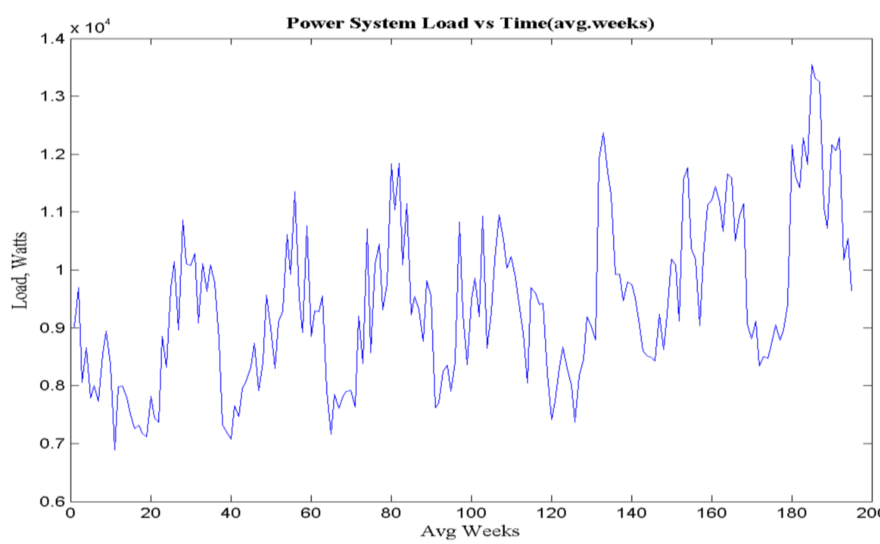

***Figure 5.1*: Average Weekly Power System Load**

$$\widehat{PSL(w)}\text{=BaseLoad + GrowthRate*w + Seasonal(w)} \tag{5.1}$$

The assumptions made in this thesis are the base load and growth rate are indeed linear functions of the weekly variable (w). Equation 5.2 defines the fundamental frequency, whereas Equation 5.3 describes the expression of the seasonal weighted component as having embedded components such as sinusoids and the fundamental frequency. Figure 5.2 is a plot of the truncated Fourier series model showing the OLAM estimate and the actual PSL data.

$$\omega_0 = \frac{\pi}{26} \tag{5.2}$$

$$Seasonal(w) = \sum_{i=1}^{N} A(i)\cos(\omega_0 iw)\, B(i)\sin(\omega_0 iw) \tag{5.3}$$

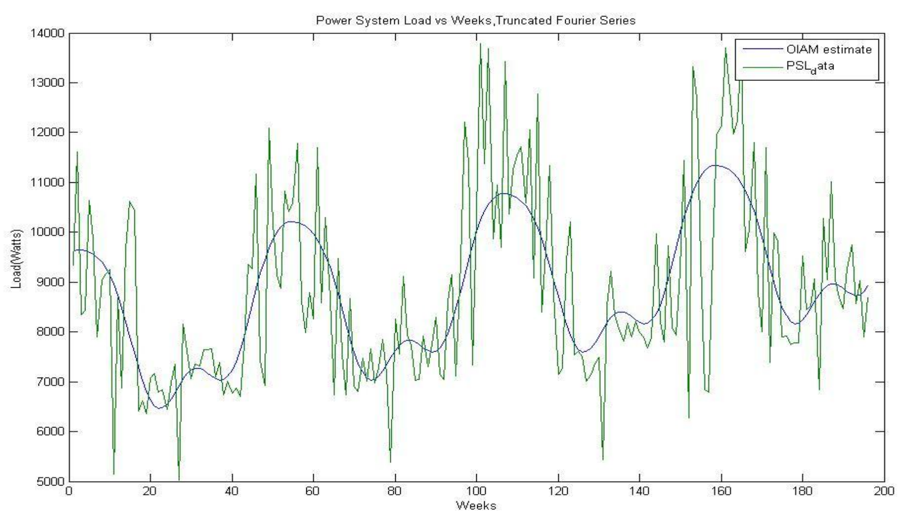

Figure 5.2: **Truncated Fourier Series Model With OLAM Application**

As the number of unknown constants in a typical problem grows, the direct application of solving the normal equations for the least square problems become much more cumbersome and tedious. Equation 5.4 gives a general estimate or output expression of the problem.

$$y = w_0 x_0 + w_1 x_1 + \cdots + w_n x_n \tag{5.4}$$

We can include Equation 5.5 if considering many discrete events, for instance P, and then assume x_0 can be written as,

$$\tilde{y} = \widetilde{w} \cdot \tilde{X} \tag{5.5}$$

5.3 The Weighted OLAM

In 1984 professors Teuvo Kohonen and Mikko J. Ruohonen developed the OLAM based on an earlier work in 1973, which involved correlation matrix memories. The weights of the OLAM guarantee perfect retrieval of stored memories given the columns of both X and Y fields are linearly independent. An assumption can also be made that the columns of X and Y are linearly independent. Both fields, X and Y, can be separated into a training set and a testing set [5].

In this thesis, the concept of the weighted OLAM is an attribute and a sense of focus on the fact that in the hidden layer section of the feed-forward structure, there are indeed weights or better still, adjusted weights that do contribute to the final forecast or output or prediction or estimate of our power system load model. Note that the OLAM is a feed-forward network, thus making it a very essential tool in predicting or forecasting power system loads and the ability to provide enough simple processing neurons, which does prove advantagous when it comes to time series.

5.4 Definition of The Weighted OLAM

Remember that the Optimal Linear Associative Memory is basically a linear regression, which is an approach to modeling the relationship between a scalar variable, Y, and one or more variables denoted by X. Recall that a linear regression line has an equation of the form $\boldsymbol{Y = a + bX}$, where $\boldsymbol{X}$ is the explanatory variable and $\boldsymbol{Y}$ is the dependent variable. The slope of the line is $\boldsymbol{b}$, and the intercept is $\boldsymbol{a}$ (the value of $\boldsymbol{y}$ when $\boldsymbol{x}$ = 0). X is the input matrix, W being the Weight or interconnection matrix, and Y is the output matrix.

Figure 5.3, depicts a simple OLAM conceptual diagram wherein the analogy is that the Randolph Power system load data over three yeas represent the input field, X, which gets fed into the feed-forward network wherein weights, W, are readjusted, manipulated, pre-processed and then sent out as Y, the output, as a forecast or estimate. The stimulus term (Xk), in some cases can be refered to as the KEY pattern, and that of the response term (Yk) can be refered to as the Stored pattern, both are data-containing vectors. Remember also that positive and negative values can be assumed by elements or contents of Yk and Xk. Equation 5.6 shows contents of the typical interconnection matrix wherein the contribution of each input relative to its position index is shown, and after weight adjustment, the estimates are then sent as y, output.

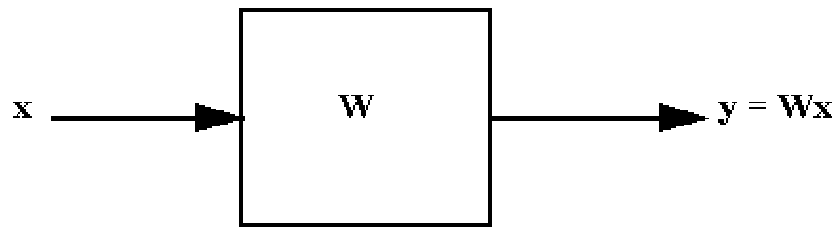

Figure 5.3: **Simple Weighted OLAM Architecture**

$$W=\begin{bmatrix} w_0^1\ w_0^2 & \cdots & w_0^k \\ w_1^1\ w_1^2 & \cdots & w_1^k \\ \vdots & \ddots & \vdots \\ w_n^1\ w_n^2 & \cdots & w_n^k \end{bmatrix} \tag{5.6}$$

Remember, it is very important to point out that the OLAM is a feed-forward network, thus making it a very essential tool in predicting or forecasting power system loads and the ability to provide enough simple processing neurons, which does prove advantagous when it comes to time series. "Feed-forward network has the capacity to complex non-linear cue because of its ability to provide many simple processing neurons of the composite role, …. " [14, pg. 329].

This thesis stresses the point that there is no doubt that there exists a link or correlation when it comes to the human brain's interconnected neurons and that of the OLAM's structure with regards to the input neurons and the internections and contributions of each weight toward the final output or result, which does lead to forecasting or load modeling. One contributor of Neural Networks even stresses the assertion of this thesis. In stating what he called his Elementary Principle, James wrote: "Let us then assume as the basis of all our subsequent reasoning this law: *When two elementary brain processes have been active together or in immediate succession, one of them on reoccurring, tends to propagate its excitement into the other."* This is closely related to the concepts of associative memory and correlational learning. James seemed to foretell the notion of a neuron's activity being a function of the sum of its inputs, with past correlation history contributing to the weight of interconnections, when he wrote: "The amount of activity at any given point in the brain cortex is the sum of the tendencies of all other points to discharge into it. Such tendencies being proportionate to the number of times the excitement of each other point may have accompanied that of the point in question; to the intensity of such excitements; and to the absence of any rival point functionally disconnected with the first point into which the discharges might be diverted" [18, pg. 15]. Unlike other earlier associative memory networks or models like the correlation memory, the OLAM also makes optimal use of the Linear Associative Memory (LAM) weights that are interconnected.

OPTIMIZATION of the Linear Associative Memory is one of its distintive characteristics. The optimization basically refers to the fact that stored memories can be perfectly recovered or retrieved. All of this is only possible as long as the set of associations is linearly independent. This is the technique that basically makes the LAM to be Optimal. The number of links or associations must be based on the size of the weight matrix.

The MEMORY aspect is also very important and distinctive because it becomes just as simple as recognizing the fact that memory will be a complete nonentity without changes and alterations. Also, if memory cannot be linked or if it is not accessible by another subset or branch or by another link, then memory is not useful. This is the neucleus of this thesis. The Optimal Linear Associative Memory (OLAM)'s memory or the contents of the OLAM's memory have to be reachable or accessible because those contents have within them the manipulated power system load data or the weighted average. The contribution of each input neuron to the entire output is needed so that future behavior can be influenced or models like the power system load model can be derived.

A discussion of learning tasks, particularly the task of pattern association, leads us to think about *memory* naturally. In a neurobiological context, memory refers to the relatively enduring neural alterations induced by the interaction of an organism with its environment. Without such a change there can be no memory. Furthermore, for memory to be useful, it must be be accessible to the nervous system in order to influence future behavior. However, an activity pattern must initially be stored in memory through a learning process. Memory and learning are intricately connected. When a particular activity pattern is learned, it is stored in the brain where it can be recalled later when required. Depending on the retention time. memory may be divided into "short-term" and "long-term" memory. *Short-term memory* refers to a compilation of knowledge representing the "current" state of the environment. Any discrepancies between knowledge stored in short-term memory and a "new" state are used to update the short-term memory. *Long-term memory*, on the other hand, refers to knowledge stored for a long time or permanently [5, pg. 75]. The following characteristics must be mentioned about the OLAM:

- Data that are in a stimulus (Key) helps determine a path link or address so that those data can be retrieved.
- Contents of a stimulus also helps determine the storage location of those data in memory.
- Interactions between distinct and individual patterns that are stored in the memory do exist, assuming the memory is not exceptionally large.
- If there is a possibility for data patterns being stored in isolation, the likelihood of error occuring in memory during a recall proceeding.
- The distribution of memory is a fact.
- Across a huge number of neurons, data can be stored in memory by establishing a pattern of neural activities that is spatial. Figure 5.4 gives a structural visualization of a multi-layered feed-forward network wherein inputs are received and adjustments and readjustments are done within the hidden layers and then released as outputs or estimates.

5.5 Applications Of The OLAM

The OLAM is a very powerful feed-forward artificial neural network, which is why this network is at the neucleous of this thesis. Among the OLAM's other applications, it is also used to predict, give a trojectory, or forecast of a power system load data. If the intent is to forecast, avoid difficulties with regards to learning prototypes that are sort of related, avoiding the growth of weight matrices that are not constrained or take advantage of the OLAM's storage capacity. Then, the OLAM should be the choice. Remember that the use of artificial neural networks or specifically one of its networks especially in power system load modeling is to ensure that making assumptions are avoided. Neural network enables load forecasting engineers to derive accurate models. Even [19, pg. 341] mentions that "ANNs are used in a wide variety of data processing applications where real-time data analysis and information extraction are required. One advantage of the neural network approach is that most intense computation takes place during the training process. Once the ANN is trained for a particular task, operation is relatively fast and unknown samples can be rapidly identified in the field."

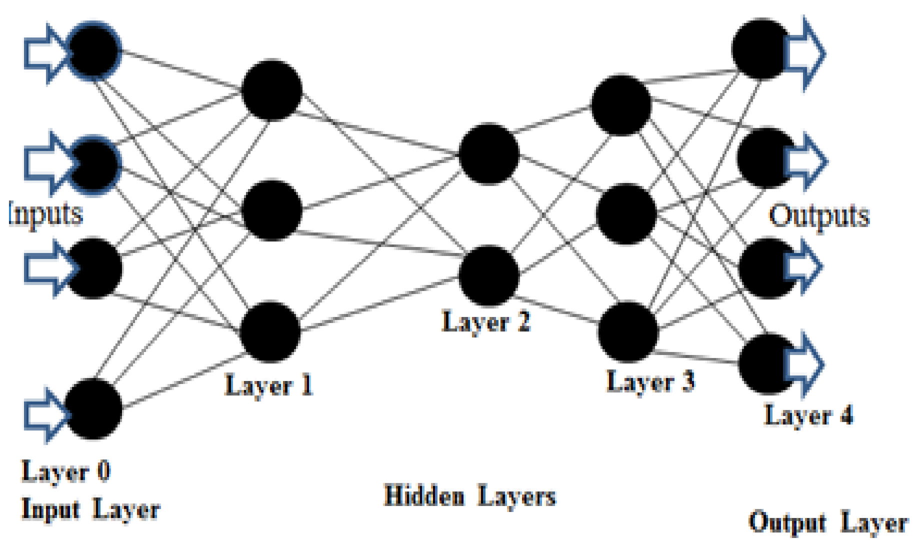

Figure 5.4: **Architecture of a Typical Feed Forward Network**

In fact, [15, pg. 1393] gives a better explanation: “To overcome those difficulties [mentioned above], different learning algorithms were proposed. The most popular solution uses a weight matrix that converges to an optimal linear associative memory (OLAM) based on the pseudo-inverse. The pseudo-inverse of a matrix was,….proposed as a neural network leaning algorithm by Kohonen…… and applied to the Hopfield network by Personnaz and Guyon…. and Kanter and Sompolinsk.”

For even more heightened insight into the importance of the OLAM with regards to historical and chronological sequence of events from the first works on associative matrix memories or better still, correlation matrix memories to the OLAM, please see [16] in detail.

In fact, [16] hightlights additional reasons why the OLAM is important when it comes to crosstalks that appeared among input patterns of activity. To overcome this degradation effect on performance, several learning strategies were proposed, such as the Optimum Linear Associative Memory (OLAM), which uses the pseudo-inverse for storage… and also on matrix memories deal with efficient representation of input/output associations onto the weight matrix space [16, pg. 51].

The OLAM is also very important compared to other networks with regards to its role in the linear problem. In fact, [13] comments that, unlike the BAM (Bidirectional Associative Memory), which lacks the ability to perform nonlinear classification such as solving the well-known XOR problem, the OLAM (Optimal Linear Associative Memory) does have the ability to solve linear problems.

5.6 Prelude To The OLAM and Data Pre-Processing

For the scope of this thesis, Figure 5.5 is presented as a visual of how the OLAM models actually looks along with the individual base load and growth relate of each model. Before proceeding to the daily and weekly OLAM implementation of this thesis, the next subsections examines and mimics this typical power system load model. A relative explanation is given of how the OLAM and the concept of the pseudo-inverse play a huge part in each of these next subsections on implementing the OLAM. The constant, b0 is the base load and the other constant, b1 is the growth rate. Remember, this thesis makes every effort so that these power system load model figures and equations will serve as prototypical explanations into how the results of the next subsections originated.

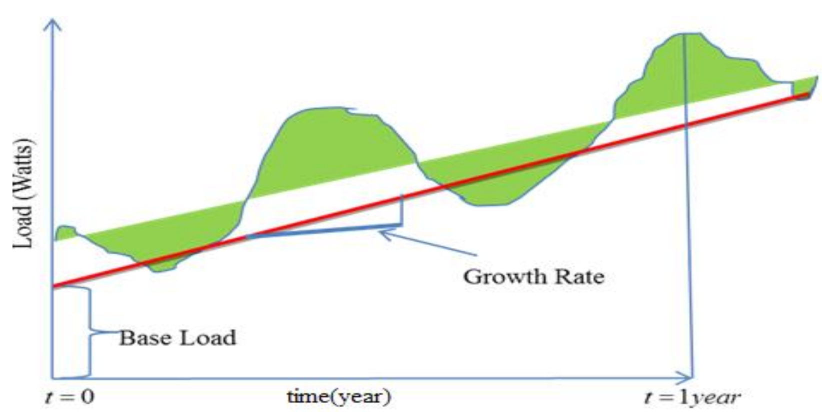

Figure 5.5: **Typical OLAM Power System Model**

Therefore, the first two columns of Equation 5.7, referred to as the "E" matrix equation, do represent the output and input fields. For this thesis, the input field is indeed the power system load data over a span of three years of the Randolph Power coorperation represented by X, while Y represents the output of our feed-forward network. Since X and Y do represent the input and output respectively, this thesis can safely relate the fact that by a simple Weighted Optimal Linear Associative Memory (OLAM) relation, the input and output can be mapped linearly using this pseudo-inverse operations in Equations 5.8 and 5.9. Then, Equation 5.10 is the typical equation to express the power system load.

$$E = \begin{bmatrix} 1 & 1 & | & PSL_1 \\ 1 & 2 & | & PSL_2 \\ \vdots & \vdots & | & \vdots \\ 1 & N & | & PSL_N \end{bmatrix} \tag{5.7}$$

$$\begin{pmatrix} \widehat{b_0} \\ \widehat{b_1} \end{pmatrix} = (X^T X)^* X^T Y \tag{5.8}$$

$$\hat{\beta} = (X^T X)^{-1} X^T Y \tag{5.9}$$

$$PSL = b_0 + b_1 w_1 \tag{5.10}$$

Therefore, with serious consideration of the above figures and equations related to the implementation of the OLAM, the b0 and b1 (base load and growth rate respectively) do represent the forecast or projection or estimate of the power system load data [4].

In the next OLAM implementation subsections, the growth rate will indeed be likely and expected as in most of power system load modeling, the series of the load or the load series do show an ascending trend. Trying to increase the sample size by aggregating data from years way back in the past may not be feasible because in most places, the load series show a very clear and upward trend [17, pg. 50].

Furthermore, before the next subsection, the idea or need to have data pre-processing or data manipulation or the rearranging of our original power system load data is very important. In order to avoid the appearance of unwanted data or outliers in the final data set and also for normalization purposes, the biasing concept is applied and in a separate column with a bias of “1” is applied to each daily and weekly use of the OLAM modeling. [17, pg. 49] could not emphasize the importance of pre-processing any better: “before data are ready to be used as input to a NN, they may be subjected to some form of pre-processing, which usually intends to make the forecasting problem more manageable. Pre-processing may be needed to reduce the dimension of the input vector, in order to avoid the “curse of dimensionality” (the exponential growth in the complexity of the problem that results from an increase in the number of dimensions). Pre-processing may also be needed to “clean” the data by removing outliers, missing values or any irregularities, since NNs are sensitive to such defective data.”

This thesis used the Randolph power system load data, which is a three-year residential load data that has been used to impliment the OLAM in order to derive different models for each OLAM modeling for the next subsections. The Randolph data used by this thesis is of size 1369 by 24. This is basically the length of time over which this data was cumulated (1369 days, 24 hours a day). The power system load model of the entire Randolph power system load data for average days before implementation of the OLAM is shown in Figure 5.6, where as the weekly pre-OLAM Randolph load data is plotted in Figure 5.7.

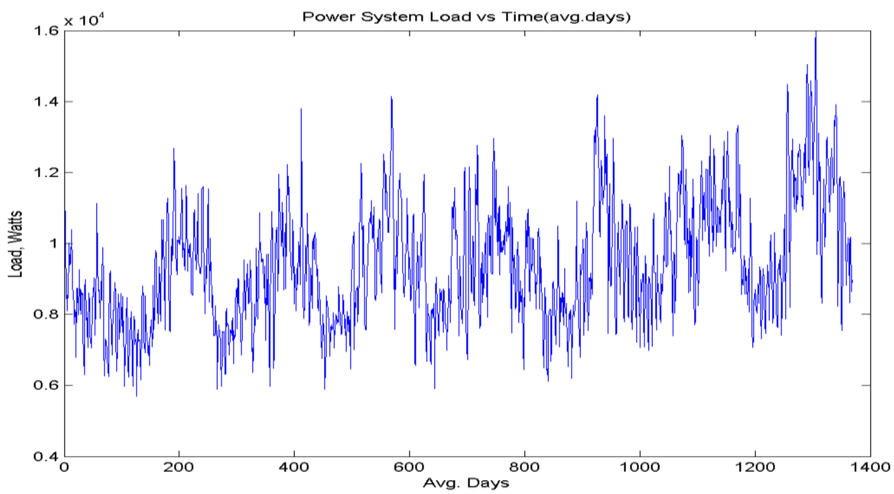

Figure 5.6: **Pre-OLAM Daily Randolph Load Plot**

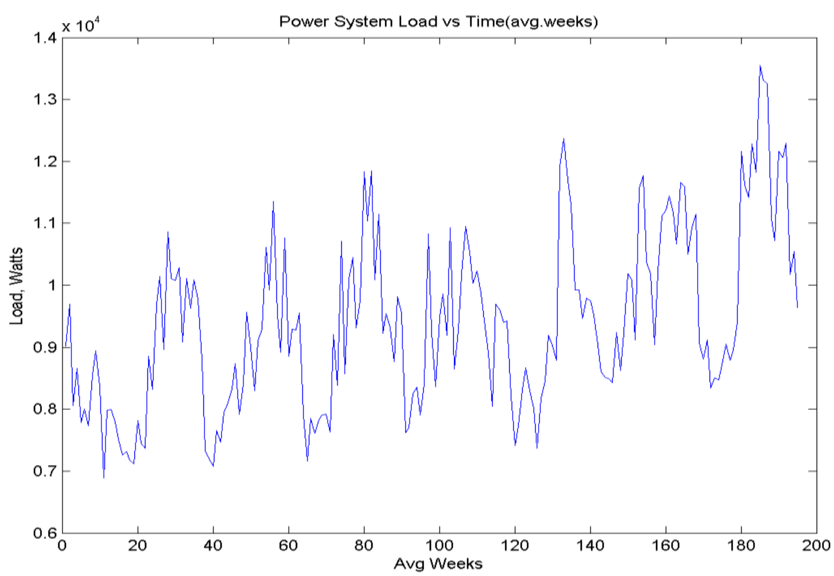

Figure 5.7: **Pre-OLAM Weekly Randolph Load Plot**

Equation 5.11 shows the link between the "E" matrix and base load and that of the growth rate, wherein Y is the Power System Load Data and X is the Week Data. Equations 5.12, 5.13, and 5.14 are the OLAM estimation equations for the Linear, Quadratic, and Cubical central tendency models, respectively.

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} 1 & X_1 \\ 1 & X_2 \\ \vdots & \vdots \\ 1 & X_n \end{bmatrix} \cdot \begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix} \tag{5.11}$$

$$\widehat{Y_\iota} = b_0 + b_1 x_i \tag{5.12}$$

$$\widehat{Y_\iota} = b_0 + b_1 x_i + b_2 x_i^2 \tag{5.13}$$

$$\widehat{Y_\iota} = b_0 + b_1 x_i + b_2 x_i^2 + b_3 x_i^3 \tag{5.14}$$

5.7 Short-term Load Modeling Using The OLAM

Eventhough hourly load modeling can be categorized as short, the weekly load model is relatively short as well. The weekly load term is affected greatly by weather. As a whole, seasonal changing regularities do affect the model outcome. Industrial, agricultural, commercial, and load composition do affect the load model. Figure 5.8 shows plots of the three outputs of the testing data after the sliding window data had been formed.

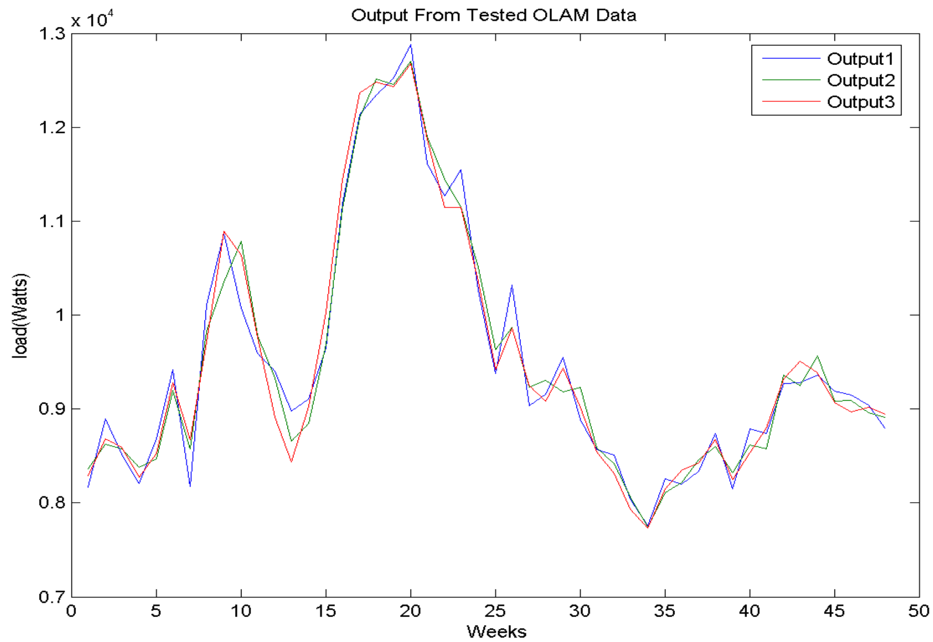

Figure 5.8: **Three Outputs From The Tested OLAM Data**

Figure 5.9 shows the results of the three outputs from the trained OLAM data. Figure 5.10 is the result of the short term power system load modeling mechanism in which the sliding window process was used to arrive at the tested predictions or estimates that closely resembles the three outputs previously viewed. Figure 5.11 shows the error plot that was generated as a result of the training and testing process of the sliding window data.

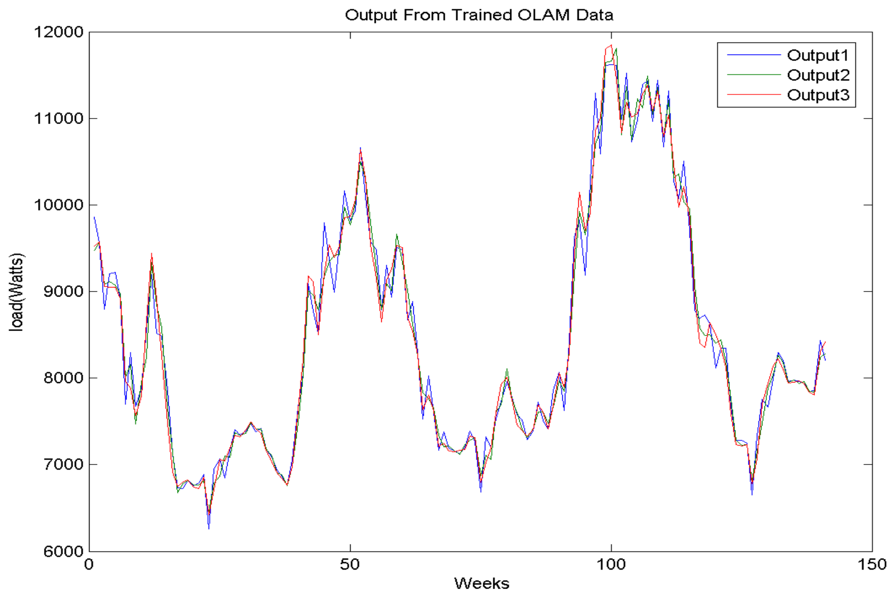

Figure 5.9: **Three Outputs From The Trained OLAM Data**

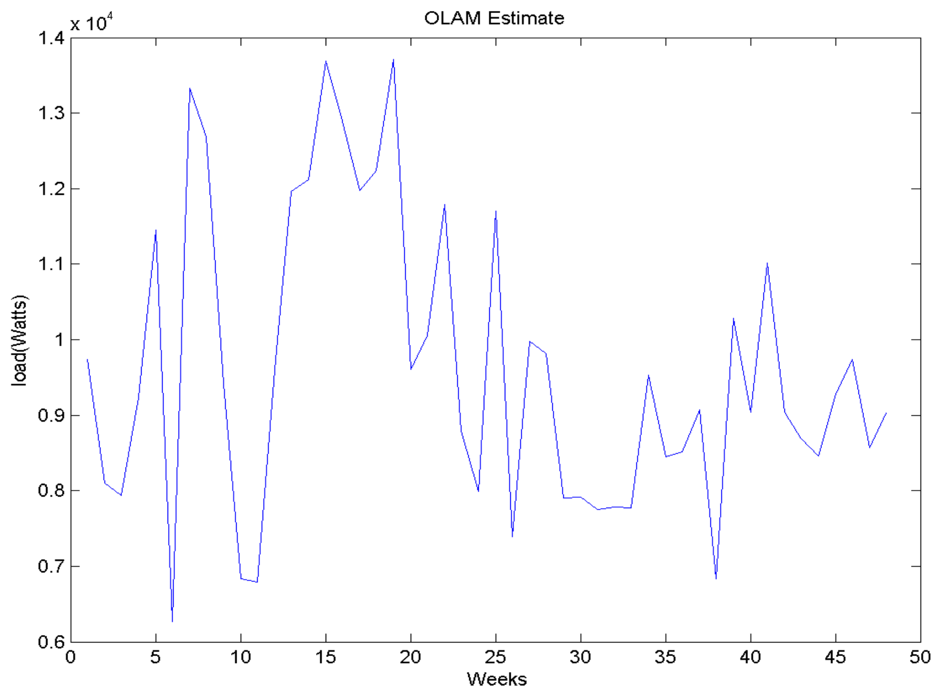

Figure 5.10: **OLAM Estimate of The Tested Data**

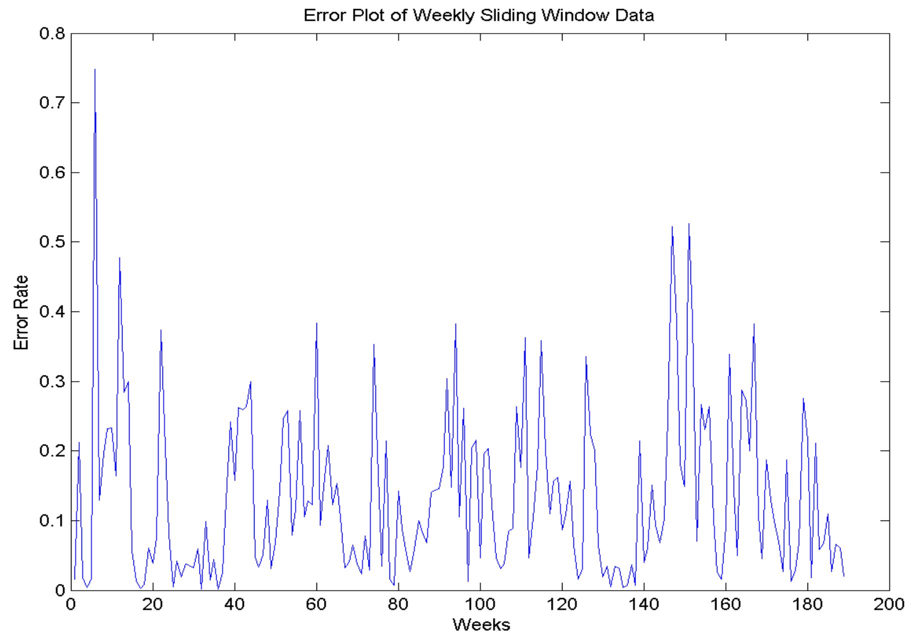

Figure 5.11: **Error Plot of Weekly Sliding Window Data**

5.8 Three Central Tendency Models Using The Daily OLAM Data

In the following sections of this research, the OLAM is used to model and show comparisons among the three central tendencies: Linear, Quadratic, and cubical. These three central tendencies are relevant and important partly because each tendency gives some meaning to the power system load model with regards to the base load and growth rate. The tendency of each model to stay with some close vacinity of the base load does matter. How far does each model deviate from the base load? Additionally, the fact that the cubical central tendency model has even more terms and more seasonal effects does partly make its model mimic or follow much closely the trojectory of the original power system load model.

Modeling daily load uses certain characteristics that would depend on the observations of obvious trends of daily load curve in a month. Observing the daily OLAM models, noticeable obvious trends such as the first periodic occurrence occurs a little over every 200 days. A second periodic occurrence kicks in as a weekly load composition every 52 weeks and so on (refer to Figures 5.12 through 5.14).

Figures 5.12 through 5.14 also show the Linear, Quadratic, and Cubical daily models with central tendency obtained after implementing the OLAM. In each model, a section in the code was also used to obtain the individual base load and growth rate as shown in each central tendency model. Remember that in the PSL equation used, it is worth reiterating that in the Randolph power system load data used to implement the OLAM, the relavant equation does have a weather component. Therefore, in electric power system load modeling, not only time sequence load itself should be considered because the influence of weather factors should also be considered.

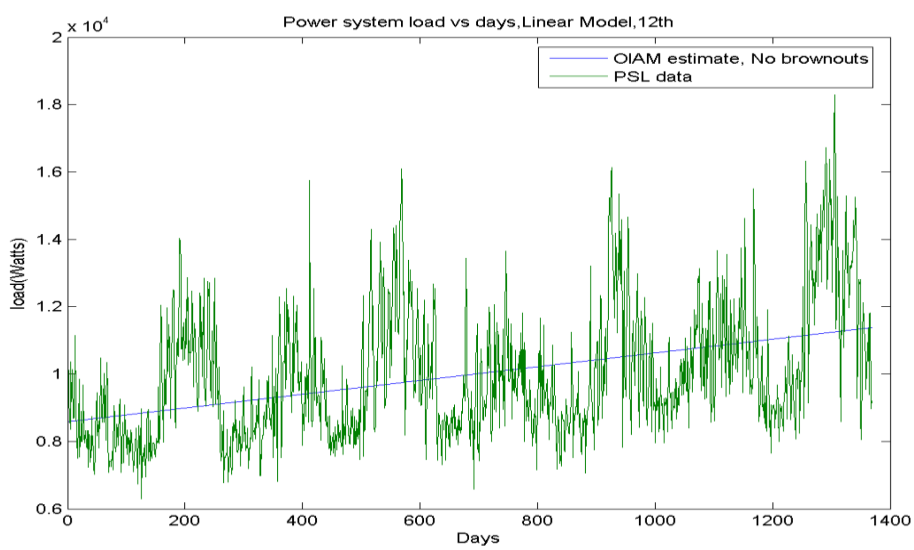

Figure 5.12: **Linear Model of 12th Hour of The Randolph Power System Load Data With Central Tendency**

Base Load and Growth Rate of LINEAR MODEL are*

bhat =

8583.4124
2.0431

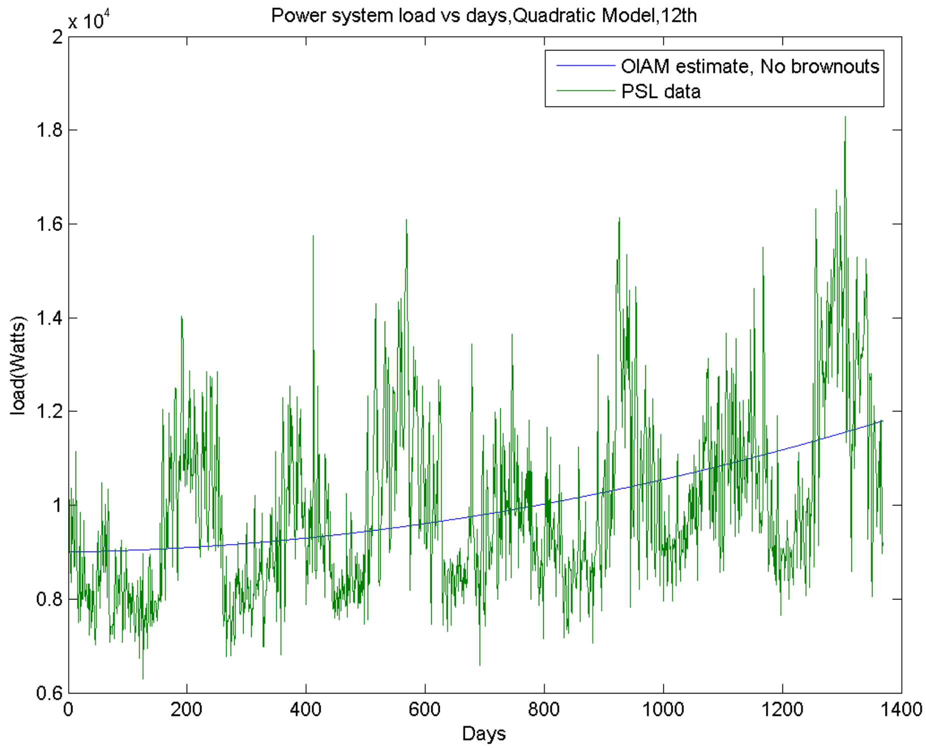

***Figure 5.13*: Quadratic Model of 12th Hour of The Randolph Power System Load Data With Central Tendency**

Base Load and Growth Rate of Quadratic MODEL are*
bhat =

9.0025e+03
2.0915e-01
1.3386e-03

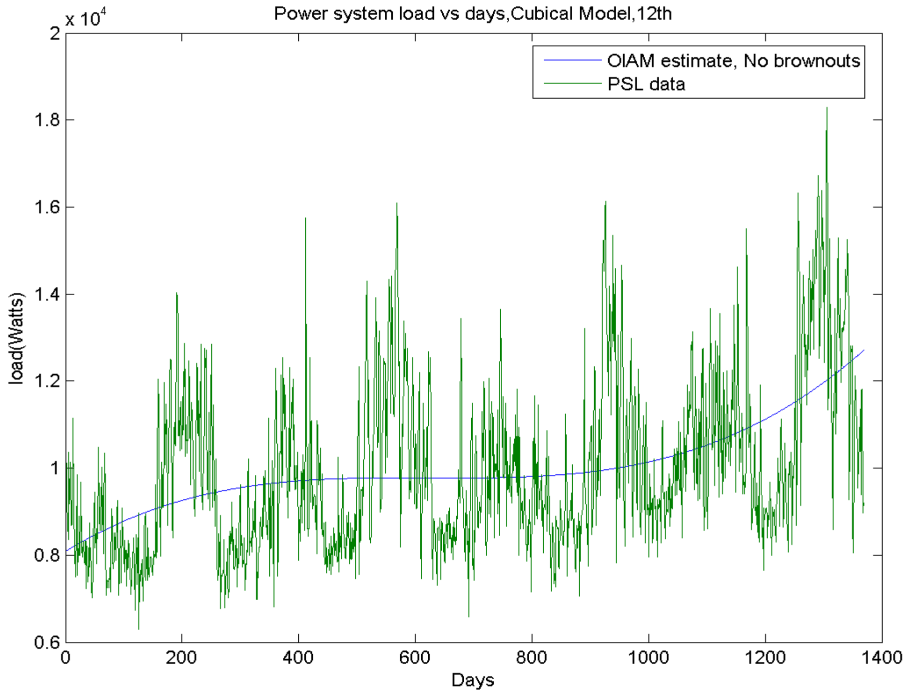

Figure 5.14: **Cubical Model of 12^{th} Hour of The Randolph Power System Load Data With Central Tendency**

Base Load and Growth Rate of Cubic MODEL are*
bhat =

8.0822e+03
8.2555e+00
-1.3339e-02
7.1424e-06

5.9 Three Central Tendency Models Using The Weekly OLAM Data

The Randolph power system load data somehow improved the simulation's fidelity. The weekly load prediction can be categorized as middle-term load prediction. It does have a seasonal changing regularity. It is hugely affected by load composition, weather features, agricultural, industrial, and commercial proportions. Certain characteristics used to model the OLAM weekly load do depend on the observations of trends weekly load curve over a span of almost four years (1990 to 1993). Observing each of the models (Figures 5.15 through 5.17), the fundamental load has a noticeable period of 52 weeks (about a year). The second periodic occurance from peak to peak (summer to summer or winter to winter) is about 26 weeks, while the third periodic occurance seems to swing somehow in correlation to the seasons, which would be approximately 12 to 13 weeks.

Figures 5.15 through 5.17 are aslo the Linear, Quadratic, and Cubical weekly central tendency models obtained after implementing the OLAM, respectively. In each model, a section in the code was also used to obtain the individual base load and growth rate as shown in each model.

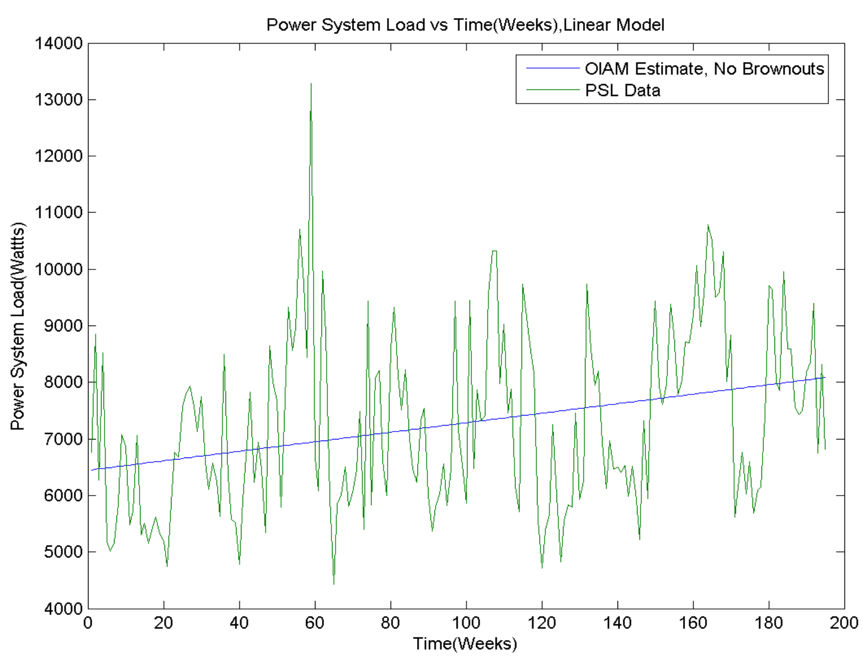

***Figure 5.15*: Linear Model of Sixth Hour of Every Seventh Day With Central Tendency**

Base Load and Growth Rate of Linear MODEL are*

bhat =

6444.4188
8.4072

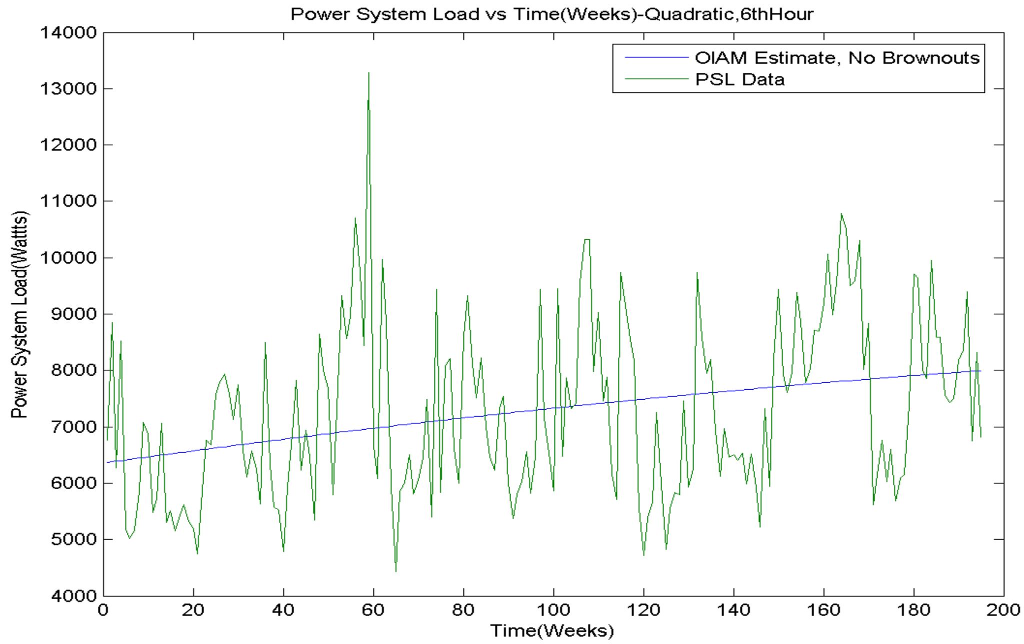

Figure 5.16 **Quadratic Model of Sixth Hour of Every Seventh Day With Central Tendency**

Base Load and Growth Rate of Quadratic Model are*
bhat =

6.3547e+03
1.1141e+01
-1.3949e-02

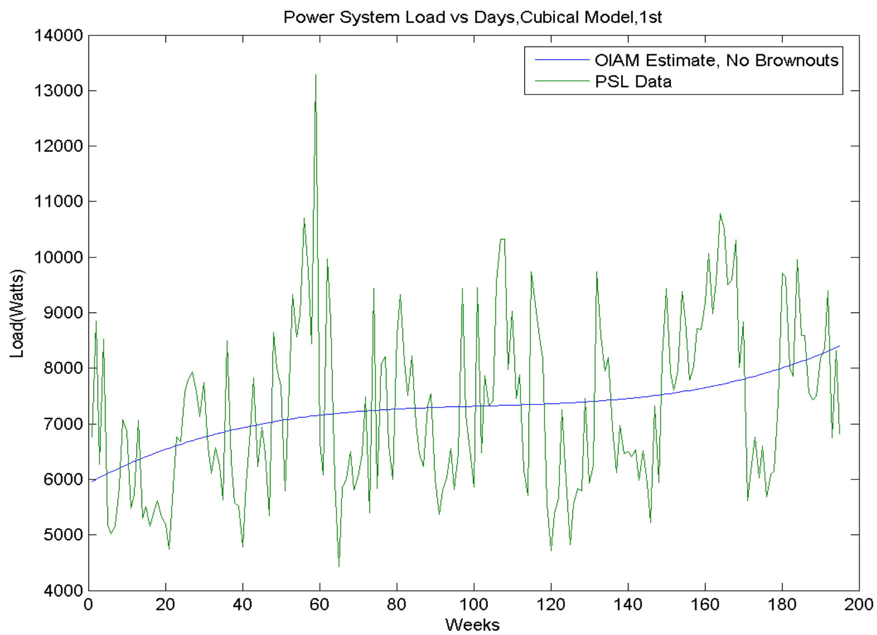

Figure 5.17: **Cubical Model of Sixth Hour of Every Seventh Day With Central Tendency**

Base Load and Growth Rate of Cubic MODEL are*
bhat =

5.9255e+03
3.7082e+01
-3.4399e-01
1.1226e-0

CHAPTER 6

CONCLUSION

Good and accurate electric power system load modeling is very essential to electric energy utilities for several reasons, namely, energy management, grid operating mode selection, maintenance scheduling, power plant construction planning, generation cost reduction, economical and reasonable arrangements of a generator group start-up and shut-down, keeping the grid operationg safe and stable, and many more. Recall the PSL equation. It is worth reiterating the Randolph power system load used to implement the OLAM with central tendencies, the relavant equation does have a weather component. Therefore, in electric power system load modeling, not only should time sequence load be considered but also weather factors influences should be considered, as well.

The OLAM being a feed forward network and a good tool used in this thesis to model power system load. Every section of the data under consideration was factored in as weights and then manipulated and adjusted and summed up and fed forward to form a part of the final estimate or model. Further, it must be mentioned that certain important factors do increase the accuracy of the neural network prediction, namely, seasonal changes, human daily activities, weather conditions, etc. A reasonable selection of these variables influenced the accuracy of the forecasted results. This was clearly shown in the OLAM daily and weekly power system load models whereas the Linear, Quadratic, and Cubic central tendency models were shown for each category (daily and weekly). Looking at each model objectively, it is clear that the cubical central tendency model has more curvature and the cubical equation does have more terms (more weights and weather factor involved). The Mean Average Deviation (MAD) is the selection criteria for the best model of choice. Among the models, Linear, Quadratic, and Cubical, the model with the least MAD became our model of choice or our best model for the scope of this thesis. Table 6.1 shows that in both the daily and weekly OLAM central tendency models, the cubic central tendency model had the least MAD.

Table 6.1: Mean Average Deviation Comparison of Central Tendency Models

	Daily OLAM Model	**Weekly OLAM Model**
Linear	1413.9	1208.1
Quadratic	1403.5	1207.4
Cubic	1368.3	1207.1

To crown it all, this research explained the OLAM in detail and showed the power of the OLAM in electrical power system load modeling. Artificial Neural Networks are great modeling tools because, among input variables, of their ability to model multivariate problems basically without making assumptions that are complexed and also dependent. One observation was instead of relying on human experience, ANN's attempted to draw links between sets of input and output data. This thesis also stressed another core theme. Since population and electric demand load are related, it is imperative that power system engineers derive mathematical models or to use mathematical models to capture these impacts on electric demand load. Consequently, these led to the concepts of the Traditional Least Squares Model (Unweighted OLAM), Truncated Fourier Series Model, the Weighted OLAM, and other neural network models, which were also discussed.

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APPENDIX A

THESIS CODES

The Code For Average Days and Average Weeks For The Randolph Power System Load Data

```
## Copyright (C) 2012 Eesiah

##Thesis: Average Days and Average Weeks of Randolph data

## Author: Morlue Eesiah <Morlue@ubuntu>

function [  ] = thesisDaysWeeks ()

## Load three-year Randolph power system load data

data=load('-ascii','RANDOLPH.DAT');

[R C] =size(data);

daily=zeros(R,1);

for i=1:R

##Find daily average (average of each row)

daily(i)=mean(data(i,:));

end

figure(1)

plot(daily')

title("Power system load vs time(avg.days)")

xlabel("avg days")

ylabel("load, Watts")
```

```
print -dpng thesisdaily.png
figure(2)
count=0;
##start incrementing every seven rows (weekly)
for i=1:7:1365
	count=count+1;
weekly(count)=mean(daily(i:i+6,:));
end
plot(weekly)
title("Power system load vs time(avg.weeks)")
xlabel("avg weeks")
ylabel("load, Watts")
print -dpng thesisweekly.png
##avgD=mean(data,2);
##plot(avgD);
Endfunction
```

Below is The Code For The Power System Load Model, Implementing The OLAM ,

For the 12th Hour of The Randolph Power System Load Data, The Central Tendencies:

```
## Copyright (C) 2012 Morlue
## Author: Morlue S. Eesiah <Morlue@ubuntu>
##Power system load model of the 12th hour
function [ ret ] = thesis12thHour ()
```

```
dataY=load('-ascii','RANDOLPH.DAT');

twelvethHour=dataY(:,12);

printf('\n*****LINEAR MODEL******\n');

b0=ones(1369,1);

weeks=[1:1369]';

x=[b0 weeks];

printf('\n**Base Load and Growth Rate of LINEAR MODEL are***\n');

bhat=pinv(x)*twelvethHour

yhat=(x*bhat)';

for i=1:1369

error(i)=(twelvethHour(i)-yhat(i))^2;

endfor

sse=sum(error)

##Begin to find Mean Average Deviation

for i=1:1369

##obtain difference in magnitude between desired output

##and estimated output

mad(i)=abs(twelvethHour(i)-yhat(i));

endfor

MAD=sum(mad)/1369

################

figure(1)
```

```
plot(weeks, yhat, weeks,twelvethHour)

legend('OlAM estimate, No brownouts', 'PSL_data');

title("Power system load vs days,Linear Model,12th")

xlabel(" Days")

ylabel("load(Watts)")

print -dpng thesis12HourLinear.png

printf('\n****QUADRATIC******\n');

##square element-by-element of the second column of our OLAM input matrix

q=x(:,2).^2;

x=[x q];

printf('\n**Base Load and Growth Rate of Quadratic MODEL are***\n');

##find pseudo inverse

bhat=pinv(x)*twelvethHour

yhat=(x*bhat)';

for i=1:1369

error(i)=(twelvethHour(i)-yhat(i))^2;

endfor

sse=sum(error)

for i=1:1369

mad(i)=abs(twelvethHour(i)-yhat(i));

endfor

MAD=sum(mad)/1369
```

```
#################
figure(2)
plot(weeks, yhat, weeks,twelvethHour)
legend('OlAM estimate, No brownouts', 'PSL_data');
title("Power system load vs days,Quadratic Model,12th")
xlabel(" Days")
ylabel("load(Watts)")
print -dpng thesis12HourQuad.png
printf('\n****CUBIC******\n');
##cube element-by-element of the second column of our OLAM input matrix
c=x(:,2).^3;
x=[x c];
printf('\n**Base Load and Growth Rate of Cubic MODEL are***\n');
bhat=pinv(x)*twelvethHour
yhat=(x*bhat)';
##Begin to find Sum Square Error (SSE)
for i=1:1369
error(i)=(twelvethHour(i)-yhat(i))^2;
endfor
sse=sum(error)
for i=1:1369
mad(i)=abs(twelvethHour(i)-yhat(i));
```

```
endfor
MAD=sum(mad)/1369
figure(3)
plot(weeks, yhat, weeks,twelvethHour)
legend('OlAM estimate, No brownouts', 'PSL_data');
title("Power system load vs days,Cubical Model,12th")
xlabel("Days")
ylabel("load(Watts)")
print -dpng thesis12HourCubic.png
endfunction
```

Below is the Code Used To Generate The Truncated Fourier Series Model

```
data = load('-ascii','RANDOLPH.DAT');
[r c]=size(data)
n=[1:r]';
HourType=6;                    %choosen hour of the day
DayType=4;
idx=find(mod(n,7)==DayType);  %Finds the specified day out of the week
Dat=data(idx,HourType);
sizeIDX=size(Dat)
A=[];
plot(Dat)
##define omega or frequency
```

```
w=2*pi/52;
for t=1:196
row=[1 t cos(w*t) sin(w*t) cos(w*2*t) sin(w*2*t) cos(w*3*t) sin(w*3*t)];
A=[A;row];
end
SizeA=size(A)
weeks=[1:196]'
bhat=pinv(A'*A)*A'*Dat
yhat=A*bhat
plot(weeks,yhat,weeks,Dat)
legend('OlAM estimate', 'PSL_data');
title("Power system load vs Weeks,Truncated Fourier Series")
xlabel(" Weeks")
ylabel("load(Watts)")
print -dpng thesisFourierWeeks.png
t=1:196;
y=x(1)+x(2)*t+x(3)*cos(w*t)+x(4)*sin(w*t)+x(5)*cos(2*w*t)+x(6)*sin(2*w*t)+x(7)*co
s(3*w*t)+x(8)*sin(3*w*t)
figure;plot(t,Dat)
```

Below is the Code Used To Generate The First, Second, and Third Trained OLAM Output, The First, Second, and Third Tested OLAM Output, and Also The OLAM Estimate:

```
data = load('-ascii','RANDOLPH.DAT');
[r c]=size(data);
n=[1:r]';
HourType=6;                    %choosen hour of the day
DayType=4;
Events=thesisSlidingWin (data,DayType,HourType);
[R C]=size(Events);
TrSz=floor(R*.75);
delta_w=0;beta=.10;alpha=.25;
%%Input Data
Xtr=Events(1:TrSz,1:5);
Xts=Events(TrSz+1:R,1:5);
%%Output Data
Ytr=Events(1:TrSz,6:8);
Yts=Events(TrSz+1:R,6:8);
weights=pinv(Xtr'*Xtr)*Xtr'*Ytr;
%%Trainig
YhatTr=Xtr*weights;
plot(YhatTr)
legend('Output1','Output2', 'Output3');
title(''Output From Trained OLAM Data'')
xlabel('' Weeks'')
```

```
ylabel("load(Watts)")

print -dpng thesisTrainOutput.png

%%Testing

YhatTs=Xts*weights;

figure;plot(YhatTs)

legend('Output1','Output2', 'Output3');

title("Output From Tested OLAM Data")

xlabel(" Weeks")

ylabel("load(Watts)")

print -dpng thesisTestedOutput.png

%% Validation  (Averaging to calculate Yhat)

for i=1:rows(Yts)-2

Yhat(i,:)=mean([Yts(i+2,1) Yts(i+1,2) Yts(i,3)]);

end

YEst=[Yts(1,1) Yts(1,2) Yhat'] ;

figure;plot(YEst)

title("OLAM Estimate")

xlabel(" Weeks")

ylabel("load(Watts)")

print -dpng thesisEstimate.png
```

APPENDIX B

SLIDING WINDOW DATA

Below is The Result of The Generated Sliding Window Data During The Process of Short Term Load Modeling Using The OLAM.The Weights,W, are at The End of This 189 by 8 Data. Five Inputs, Three Outputs.

```
octave-3.2.4.exe:6> ThesisBuildDataSet

DataSet =

 9339   11607    8343    8424   10643    9874    7906    9044
  11607    8343    8424   10643    9874    7906    9044    9173
   8343    8424   10643    9874    7906    9044    9173    9250
   8424   10643    9874    7906    9044    9173    9250    5139
  10643    9874    7906    9044    9173    9250    5139    8687
   9874    7906    9044    9173    9250    5139    8687    6877
   7906    9044    9173    9250    5139    8687    6877    9651
   9044    9173    9250    5139    8687    6877    9651   10619
   9173    9250    5139    8687    6877    9651   10619   10425
   9250    5139    8687    6877    9651   10619   10425    6415
   5139    8687    6877    9651   10619   10425    6415    6614
   8687    6877    9651   10619   10425    6415    6614    6367
   6877    9651   10619   10425    6415    6614    6367    7079
   9651   10619   10425    6415    6614    6367    7079    7164
  10619   10425    6415    6614    6367    7079    7164    6784
```

10425	6415	6614	6367	7079	7164	6784	6832
6415	6614	6367	7079	7164	6784	6832	6444
6614	6367	7079	7164	6784	6832	6444	6986
6367	7079	7164	6784	6832	6444	6986	7355
7079	7164	6784	6832	6444	6986	7355	5026
7164	6784	6832	6444	6986	7355	5026	8149
6784	6832	6444	6986	7355	5026	8149	7634
6832	6444	6986	7355	5026	8149	7634	7059
6444	6986	7355	5026	8149	7634	7059	7355
6986	7355	5026	8149	7634	7059	7355	7322
7355	5026	8149	7634	7059	7355	7322	7646
5026	8149	7634	7059	7355	7322	7646	7650
8149	7634	7059	7355	7322	7646	7650	7667
7634	7059	7355	7322	7646	7650	7667	7096
7059	7355	7322	7646	7650	7667	7096	7379
7355	7322	7646	7650	7667	7096	7379	6743
7322	7646	7650	7667	7096	7379	6743	7019
7646	7650	7667	7096	7379	6743	7019	6776
7650	7667	7096	7379	6743	7019	6776	6881
7667	7096	7379	6743	7019	6776	6881	6703
7096	7379	6743	7019	6776	6881	6703	7752
7379	6743	7019	6776	6881	6703	7752	9360
6743	7019	6776	6881	6703	7752	9360	9262
7019	6776	6881	6703	7752	9360	9262	11174

6776	6881	6703	7752	9360	9262	11174	7436
6881	6703	7752	9360	9262	11174	7436	6926
6703	7752	9360	9262	11174	7436	6926	12089
7752	9360	9262	11174	7436	6926	12089	10182
9360	9262	11174	7436	6926	12089	10182	9141
9262	11174	7436	6926	12089	10182	9141	8878
11174	7436	6926	12089	10182	9141	8878	10822
7436	6926	12089	10182	9141	8878	10822	10413
6926	12089	10182	9141	8878	10822	10413	10595
12089	10182	9141	8878	10822	10413	10595	11781
10182	9141	8878	10822	10413	10595	11781	8618
9141	8878	10822	10413	10595	11781	8618	7979
8878	10822	10413	10595	11781	8618	7979	8797
10822	10413	10595	11781	8618	7979	8797	8262
10413	10595	11781	8618	7979	8797	8262	11696
10595	11781	8618	7979	8797	8262	11696	8590
11781	8618	7979	8797	8262	11696	8590	10299
8618	7979	8797	8262	11696	8590	10299	8663
7979	8797	8262	11696	8590	10299	8663	6731
8797	8262	11696	8590	10299	8663	6731	9469
8262	11696	8590	10299	8663	6731	9469	7565
11696	8590	10299	8663	6731	9469	7565	6743
8590	10299	8663	6731	9469	7565	6743	8671
10299	8663	6731	9469	7565	6743	8671	6901

8663	6731	9469	7565	6743	8671	6901	6800
6731	9469	7565	6743	8671	6901	6800	7468
9469	7565	6743	8671	6901	6800	7468	7011
7565	6743	8671	6901	6800	7468	7011	7655
6743	8671	6901	6800	7468	7011	7655	6970
8671	6901	6800	7468	7011	7655	6970	7278
6901	6800	7468	7011	7655	6970	7278	7841
6800	7468	7011	7655	6970	7278	7841	7185
7468	7011	7655	6970	7278	7841	7185	5382
7011	7655	6970	7278	7841	7185	5382	8262
7655	6970	7278	7841	7185	5382	8262	7561
6970	7278	7841	7185	5382	8262	7561	9113
7278	7841	7185	5382	8262	7561	9113	7930
7841	7185	5382	8262	7561	9113	7930	7731
7185	5382	8262	7561	9113	7930	7731	7023
5382	8262	7561	9113	7930	7731	7023	7051
8262	7561	9113	7930	7731	7023	7051	7910
7561	9113	7930	7731	7023	7051	7910	7298
9113	7930	7731	7023	7051	7910	7298	7764
7930	7731	7023	7051	7910	7298	7764	8294
7731	7023	7051	7910	7298	7764	8294	7144
7023	7051	7910	7298	7764	8294	7144	7051
7051	7910	7298	7764	8294	7144	7051	8618
7910	7298	7764	8294	7144	7051	8618	9149

7298	7764	8294	7144	7051	8618	9149	7116
7764	8294	7144	7051	8618	9149	7116	9400
8294	7144	7051	8618	9149	7116	9400	12211
7144	7051	8618	9149	7116	9400	12211	11409
7051	8618	9149	7116	9400	12211	11409	7331
8618	9149	7116	9400	12211	11409	7331	10396
9149	7116	9400	12211	11409	7331	10396	13782
7116	9400	12211	11409	7331	10396	13782	11368
9400	12211	11409	7331	10396	13782	11368	13681
12211	11409	7331	10396	13782	11368	13681	9870
11409	7331	10396	13782	11368	13681	9870	10943
7331	10396	13782	11368	13681	9870	10943	9704
10396	13782	11368	13681	9870	10943	9704	13426
13782	11368	13681	9870	10943	9704	13426	10360
11368	13681	9870	10943	9704	13426	10360	11255
13681	9870	10943	9704	13426	10360	11255	11547
9870	10943	9704	13426	10360	11255	11547	11717
10943	9704	13426	10360	11255	11547	11717	10587
9704	13426	10360	11255	11547	11717	10587	12057
13426	10360	11255	11547	11717	10587	12057	9084
10360	11255	11547	11717	10587	12057	9084	12778
11255	11547	11717	10587	12057	9084	12778	8388
11547	11717	10587	12057	9084	12778	8388	9619
11717	10587	12057	9084	12778	8388	9619	11336

10587	12057	9084	12778	8388	9619	11336	8760
12057	9084	12778	8388	9619	11336	8760	7140
9084	12778	8388	9619	11336	8760	7140	7290
12778	8388	9619	11336	8760	7140	7290	9437
8388	9619	11336	8760	7140	7290	9437	10214
9619	11336	8760	7140	7290	9437	10214	7541
11336	8760	7140	7290	9437	10214	7541	7602
8760	7140	7290	9437	10214	7541	7602	7513
7140	7290	9437	10214	7541	7602	7513	7015
7290	9437	10214	7541	7602	7513	7015	7140
9437	10214	7541	7602	7513	7015	7140	7375
10214	7541	7602	7513	7015	7140	7375	7488
7541	7602	7513	7015	7140	7375	7488	5443
7602	7513	7015	7140	7375	7488	5443	8509
7513	7015	7140	7375	7488	5443	8509	9222
7015	7140	7375	7488	5443	8509	9222	8327
7140	7375	7488	5443	8509	9222	8327	8072
7375	7488	5443	8509	9222	8327	8072	7817
7488	5443	8509	9222	8327	8072	7817	8169
5443	8509	9222	8327	8072	7817	8169	7893
8509	9222	8327	8072	7817	8169	7893	8201
9222	8327	8072	7817	8169	7893	8201	7979
8327	8072	7817	8169	7893	8201	7979	7902
8072	7817	8169	7893	8201	7979	7902	7671

7817	8169	7893	8201	7979	7902	7671	7885
8169	7893	8201	7979	7902	7671	7885	9979
7893	8201	7979	7902	7671	7885	9979	8201
8201	7979	7902	7671	7885	9979	8201	7804
7979	7902	7671	7885	9979	8201	7804	9736
7902	7671	7885	9979	8201	7804	9736	8096
7671	7885	9979	8201	7804	9736	8096	7942
7885	9979	8201	7804	9736	8096	7942	9234
9979	8201	7804	9736	8096	7942	9234	11449
8201	7804	9736	8096	7942	9234	11449	6269
7804	9736	8096	7942	9234	11449	6269	13325
9736	8096	7942	9234	11449	6269	13325	12685
8096	7942	9234	11449	6269	13325	12685	9424
7942	9234	11449	6269	13325	12685	9424	6840
9234	11449	6269	13325	12685	9424	6840	6792
11449	6269	13325	12685	9424	6840	6792	9599
6269	13325	12685	9424	6840	6792	9599	11968
13325	12685	9424	6840	6792	9599	11968	12118
12685	9424	6840	6792	9599	11968	12118	13693
9424	6840	6792	9599	11968	12118	13693	12887
6840	6792	9599	11968	12118	13693	12887	11972
6792	9599	11968	12118	13693	12887	11972	12235
9599	11968	12118	13693	12887	11972	12235	13709
11968	12118	13693	12887	11972	12235	13709	9611

12118	13693	12887	11972	12235	13709	9611	10060
13693	12887	11972	12235	13709	9611	10060	11794
12887	11972	12235	13709	9611	10060	11794	8784
11972	12235	13709	9611	10060	11794	8784	7995
12235	13709	9611	10060	11794	8784	7995	11705
13709	9611	10060	11794	8784	7995	11705	7387
9611	10060	11794	8784	7995	11705	7387	9983
10060	11794	8784	7995	11705	7387	9983	9813
11794	8784	7995	11705	7387	9983	9813	7902
8784	7995	11705	7387	9983	9813	7902	7914
7995	11705	7387	9983	9813	7902	7914	7752
11705	7387	9983	9813	7902	7914	7752	7784
7387	9983	9813	7902	7914	7752	7784	7776
9983	9813	7902	7914	7752	7784	7776	9534
9813	7902	7914	7752	7784	7776	9534	8452
7902	7914	7752	7784	7776	9534	8452	8513
7914	7752	7784	7776	9534	8452	8513	9072
7752	7784	7776	9534	8452	8513	9072	6832
7784	7776	9534	8452	8513	9072	6832	10287
7776	9534	8452	8513	9072	6832	10287	9040
9534	8452	8513	9072	6832	10287	9040	11016
8452	8513	9072	6832	10287	9040	11016	9040
8513	9072	6832	10287	9040	11016	9040	8695
9072	6832	10287	9040	11016	9040	8695	8465

6832	10287	9040	11016	9040	8695	8465	9275
10287	9040	11016	9040	8695	8465	9275	9740
9040	11016	9040	8695	8465	9275	9740	8566
11016	9040	8695	8465	9275	9740	8566	9032
9040	8695	8465	9275	9740	8566	9032	7893
8695	8465	9275	9740	8566	9032	7893	8687

sizeDataset =

189 8

W =

0.10747	0.20029	0.13030
0.15871	0.10506	0.20461
0.20464	0.19589	0.14911
0.17553	0.22477	0.21285
0.34655	0.26462	0.29330