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# Climate change impact reliability of large electric power transformers in the Northeast United States

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# CLIMATE CHANGE IMPACT ON RELIABILITY OF LARGE ELECTRIC POWER TRANSFORMERS IN THE NORTHEAST UNITED STATES

BY

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# DEDICATION

This work is dedicated to my Mom, my Dad, Kalyan.

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# ABSTRACT

## CLIMATE CHANGE IMPACT ON RELIABILITY OF LARGE ELECTRIC POWER TRANSFORMERS IN THE NORTHEAST UNITED STATES

by

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University of New Hampshire, December, 2011

Global climate model simulations, when scaled to the Northeast U.S. region, indicate that New England will by 2100 experience many more days each summer of daily maximum temperatures in excess of $90°F$. Given the strong correlation between summer heat waves and electric power demand, the stresses placed on the components of the electric grid by prolonged, elevated power demand is of obvious concern.

In this thesis a standard thermal model for large transformers is coupled with a temperature-dependent electric power demand model to predict the frequency of transformer thermal overload events during the months of June, July, and August through the year 2099. The coupled demand/thermal model was driven by a projected daily maximum temperature time series extracted from the original datasets of the 2007 Northeast Climate Impacts Assessment of the Union of Concerned Scientists. The results of the calculations show that transformers loaded at 70% or less of their nameplate rating will not experience any significant increase in the frequency of thermal overload events even if New England's climate becomes substantially warmer. However, transformers loaded at 80% or more of their nameplate rating will experience an increasing frequency of thermal overload events in each of the summer months as time progresses to 2100. Ideas are presented for mitigating the increased likelihood of transformer thermal overload events.

# CHAPTER 1

# INTRODUCTION

## 1.1 Background of This Thesis

It is now widely believed by scientists that human activities have induced climate changes over the past three centuries. The combustion of fossil fuels, conversion of natural prairie to farmland, deforestation, urbanization and industrial growth have all contributed to increased carbon dioxide concentration in the atmosphere, and this increase is believed to be the predominant cause of increased average global temperature [1]. In particular, the growth of industrialization has increased the amount of greenhouse gases, specifically the emission and concentration of $CO_2(80\%)$ resulting in global warming. Global average temperature has increased by 1°F during the $20^{th}$ century. The ozone layer in the stratosphere, which protects earth from direct sun radiation, has developed a massive hole over the Antarctica region. The depletion of the ozone layer also has an adverse impact in the global climatic changes. Even though it was estimated that the ozone layer would recover by 2050, more recent analysis has revealed that its recovery might require a much longer time [2]. The increase in global average temperature causes changes in the earth's climatic system, resulting in more variable and extreme weather conditions; for example, sea level increases, increase in number of extreme storm events, changes in the levels of ice in the freezing zone in the North and South Poles and a decrease in snow cover periods, resulting in disruption of fresh water supplies, an increased demand for energy and impacts on many other natural areas in various parts of the world [3].

It appears very likely that human activities are poised to make a serious adverse impact on the global climate [1]. A number of companies, as well as national governments around the world, have begun to deliberate on the potential ramifications of a much warmer climate with prospectively more severe weather events that might affect their citizens and businesses. National Grid-USA is one among such companies, which is in the field of electric utility power distribution in the Northeast United States. National Grid USA approached the Department of Electrical and Computer Engineering at the University of New Hampshire, with a proposal for a study of potential impacts of long-term climate change on the reliability of the Northeast U.S. electric grid. The UNH research team, in co-ordination with National Grid staff engineers, identified a number of areas of potential concern both in the transmission and distribution segments of the electric grid. After further study, the UNH team focused its research on the thermal overload of transformers and transmission lines as a consequence of projected longer duration heat waves. The UNH research team proposed to couple simplified electric power demand models with projected daily maximum temperatures for the New England region that are derived from regionally down-scaled climate simulation data to estimate the frequency of thermal overloading events for transformers till 2100 (a standard endpoint for climate change simulations). It should be understood that the term "down-scaling" refers to a variety of methods for achieving finer geographic and/or time resolutions of atmospheric variables, including temperatures, than are typically used in global scale climate change models. However, the simulation outputs of the global models are the starting point for down-scaled models. In addition, the UNH team studied the likelihood of thermal overloading for overhead transmission lines under the same daily temperature projections, but this work was suspended to permit concentration on the transformer thermal overload analysis.

## 1.2 Prospective U.S. Northeast Climatic Changes

As global warming begins to affect our planet's climate more drastically, the Northeast U.S. will be no exception. The region's climate is characterized by its significant variations such as floods, droughts, heat waves, and severe storms. Recent research on the future Northeast U.S. climate indicates that we may expect earlier arrivals of summer, nearly three weeks earlier, and warm weather extending later into the fall, resulting in the overall expansion of summer weather duration [4].

In the higher emissions model considered by this study, the Northeast U.S. will experience daytime high temperatures above 90°F for more than 60 days a year and above 100°F temperatures during 1 to 2 days. In the lower emissions model, these effects would be reduced to half of that projected for the higher emissions model.

Winter average temperature is increasing gradually at the rate of 1.3°F per decade from 1970 to 2000. Noticeable changes were experienced in the number of snow covered days, lake ice duration, etc. If these trends continue for another few decades, increases in the winter average temperature by 2.5 to 4°F are expected across the region. In the higher emissions model, temperature increases in the range of 4 to 7°F are likely, while in the lower emissions model the increases in temperature would be 3.5 to 5°F. Under the lower-emissions model, the end-of-century temperatures are projected to rise on average by 5.8°F in winter and 5.1°F in summer compared with the 1961 to 1990 average. Under the higher-emissions model, end-of century temperatures are projected to average 9.8°F warmer in winter (ranging from 8 to 12°F warmer) and 10.6°F warmer in summer (ranging from 6 to 14°F warmer). Warmer winter temperatures result in less natural snow fall and thus a decline in the number of snow covered days in the Northeast U.S. states, which has obvious implications for both winter tourism-based businesses and drinking water supplies [4]. Because the Northeast U.S. climate already experiences short and long-term droughts, any reduction of the water supply has profound negative implications. Cities that today experience only a few days above 100°F each summer would average 20 such days per summer, while certain cities, such as Hartford and Philadelphia, would average nearly 30 days over 100°F. Short-term (one to three-month) droughts are projected to occur as frequently as once each summer in the Catskill and Adirondack Mountains, and across the New England states. Sea level in this region is projected to rise more than the global average. In the higher emissions model, the short-term droughts are expected to occur every year instead of once in 2 to 3 years, and the longer droughts are likely to increase and will occur every 6 to 10 years instead of once in 20 or 30 years as they occurred in the past. These changes in the climatic conditions leads to serious impacts on the ecosystem such as reduction of water supply, stress to agricultural production, and increased risks to wildlife. The Northeast is projected to face continued warming and more extensive climate-related changes, some of which could dramatically alter the region's economy, landscape, character, and quality of life [4].

## 1.3 Downscaling Analysis

Several research programs are focusing on the potential impacts of global warming and also are developing future action plans to reduce the emission of greenhouse gases and control global warming. To make appropriate decisions and develop action plans, the Global Climate Model (GCM), a computer simulation tool, is widely applied for understanding the Earth's climatic system and making projections of future climate changes [5]. While the GCM plays a vital role in simulating climate changes over a large area, downscaling techniques provide a better match between the scale of data and projections within a smaller region of interest. Therefore the prediction of climate changes by adopting downscaled models provides us some refined knowledge about future regional climate changes. With information in the appropriate scale to match the scale of a decision-maker's concerns, adaptation plans can more appropriately be developed, and cyclical or periodic evaluations of those adaptation plans can more easily be carried out. Regular use and revisions of downscaled projections can assist localities to better define their areas of most likely impact and highest vulnerabilities. Thus, use of downscaled climate change predictions gives better information for the purpose of thermal calculation for transformers[3].

## 1.4 Possible Impacts of Climate Change on the Reliability of the Electric Grid

Weather is a major determinant factor of energy demand. Both in the temporal as well as geographic pattern, climatic changes may alter the total energy demanded. The extreme weather events in the Northeast U.S. are hurricanes, ice storms, and extremes of hot and cold. These weather conditions are very drastic in nature and seriously affect the electric grid equipment and may cause failure of system operations. Electric power systems are designed for relatively stable climate conditions and slowly evolving loading patterns. However, these power system designs are strained by extreme weather events of the kinds previously mentioned. The increase in summer temperatures increases the usage of air conditioning equipment, which increases the system electrical loads. New England states' utility power demand records are invariably set on the $2^{nd}$ or $3^{rd}$ day of an extended heat wave, largely due to the expanded use of building air conditioning in a region that has not historically needed this infrastructure.

Utilities use demand forecasting models, which include both weather and econometric variables, to predict the electric power demand in response to severe heat waves. The increase in the electrical load impairs the proper functioning of equipment, deteriorates their performance through overheating, reduces equipment operational lifetime, and triggers premature equipment failure and power outages. Due to extreme cold weather such as ice storms, transmission lines are affected by the ice formation and there is often destruction of electrical equipment and power conductors. The most often affected components due to overloading are transformers and transmission lines.

## 1.5 Power Transmission and Distribution Systems

Effective and reliable functioning of the electric utility industry requires the proper functioning of both the power transmission and distribution networks. Each network is threatened by different secondary effects due to weather changes, and each one has different consequences. They are threatened directly by very high winds and ice storms. Transmission and distribution networks are subject to failure when elements are overheated by large transactions of power. Overheated transformers fail structurally, while wires can expand and sag into obstacles, causing short circuiting of the very high voltage present on transmission lines.

## 1.6 Power Transformers and Impacts of Climate Change

Power transformers play an important role in power delivery and the integrity of the power system network. Climatic changes may increase the peak demand for power and result in overloading of transformers. Transformers produce heat as a by-product during their normal operation. Overloading of transformers increases the internal operating temperatures, the oil coolant and winding temperatures, causes the deterioration of insulation in the transformer, and may result in premature failure of transformers. If frequent overloading occurs, it will weaken the insulation over a period of time and accelerate the transformer's loss-of-life, this term loss-of-life is language adopted in IEEE Std. C57.91-1995. Overloading can result in reduced transformer integrity and, in extreme cases, will result in thermal runaway conditions. The increase in demand for space cooling during a heat wave in turn results in greater heating of transformers. Transformer temperature rise is defined as the average temperature rise of the windings above the ambient temperature when the transformer is loaded at its nameplate rating. In general, more efficient transformers tend to have lower temperature rises, while less efficient transformers tend to have higher temperature rises. Large transformers are mostly located at substations and are often affected by overloading at the end of power transmission lines and along the distribution systems that deliver power to consumers. The increase in the number of hot days increases the peak load in summer-peaking regions and causes more stress on the power system components. Thermal limits on components are more likely to be experienced on hot days. If components are not de-rated to allow for this, they may fail more frequently, age faster, and require more maintenance and earlier replacement. Control equipment may require recalibrating to de-rate the equipment. Not all transformers have the opportunity to cool sufficiently at night, so they start with high temperatures the next day.

## 1.7 Power Conductors and Increase in Voltage Fault Conditions

Power conductors of overhead lines are energized at high voltage. High voltage power transmission lines also are affected by overheating caused by excessive electrical demand. As lines heat up, they stretch and sag. A sagging line may contact foliage and create a circuit fault to ground. Control equipment will then disconnect it from the transmission system. If a conductor's temperature remains high for an extended period of time, the strength of the conductor deteriorates and tensioned connectors may be expanded, thus resulting in mechanical failure during the next occurrence of ice or high wind loading. When more extreme wind gusts occur, they could cause tower and conductor damage and more electrical faults due to line "galloping" and trees falling across conductors. The increase in frequency and severity of icing and flooding events, as well as sea level rise, will make it necessary for utilities to adopt reinforced system designs and to consider shifting more resources to emergency planning and restoration.

## 1.8 Need to Focus this Thesis on Power Transformers

The main duty of the electric power industry is to provide the customers with a reliable, economically viable and acceptable quality of electric power. The reliability of the system depends on the functioning of the components. The change in the condition of the components and the environment directly affects the functioning of power system components, resulting in equipment failure. Power transformers play an important role in any power transmission and distribution system. Electrical utilities invest significant money in transformers, at least as much as they do in generating stations [6]. Thus, transformers are vital components in a power system, and a fault in this link causes considerable loss of revenue to the utility besides adversely affecting the system reliability. Transformers are expected to last from 20 to 30 years, and in many cases have been deployed even longer. Prospective climate changes may result in increased frequency and severity of hot and cold weather events, which cause growth in electric power demand. The consequent changes in loading patterns may cause overloading of transformers beyond their thermal limits. Transformer overloading causes deterioration of the internal insulation, increased internal temperatures, faster aging of the transformer, and premature equipment failure. Economic pressures also call for an extension of transformer service life. Therefore, it is important to study the effect of prospective climate changes on the aging of transformers to ensure reliable electric power transmission to the end users.

## 1.9 Need for Multiple Predictive Models

Multiple climate model predictions provide estimates for many of the climatic variables of importance to society. Hence, the model predictions provide a key framework for assessing the impacts of climate changes. Climate models employed by scientists have different characteristics and simplifications. These model predictions provide a scenario of possible future climates. The U.S. First Climate National Assessment [7] is based on a climate information strategy of providing a physically consistent climate foundation for regional and sector assessments to be utilized by every research team, with the opportunity for the teams to perform additional independent analyses.

The calculation of transformer loss-of-lifetime is described in several IEEE standards [8], and it involves the calculation of the hottest spot internal temperature for a given primary current and the calculation of the aging factor according to the Arrhenius theory. The thermal aging calculations require a more elaborate thermal model because the accelerated lifetime reduction is cumulative over time and thus depends on the temporal profile of the load. For the most accurate analysis of transformer aging one would ideally have a fine time scale set of both ambient temperature values as well as electric power demand values. Although downscaled temperature time series projected from global GCM models are available with a 3 hour interval, the temperature-sensitive electric power demand model available for this thesis research had only 1 day interval resolution. The simulated load profiles generated for this research best represent daily peak loads associated with the corresponding projected ambient daily maximum temperature.

## 1.10 Thesis Overview

The purpose of this thesis is to couple existing thermal models of transformers with the projected future ambient high temperature time series to determine how likely transformer overloading may occur under climate change scenarios. The thermal model used by the IEEE for aging calculation is modified here to accommodate temperature variation in the study of the aging of transformers. Chapter 2 describes the present IEEE standard model for thermal analysis based on top oil and hottest spot temperatures, includes the IEEE transformer aging theory, and presents an alternative method of thermal rating of transformers used by National Grid USA. The key variables required to run aging analyses are also described in this chapter. Chapter 3 develops the electric power demand sensitivity model and establishes a comparative baseline peak day demand under historic climate conditions. Chapter 4 describes the thermal analysis of transformers under climate change. Chapter 5 identifies and discusses the load in which the short term overload occurs and the frequency with which the transformers will exceed the maximum internal temperature limits. Recommendations are made for improvements in the thermal analysis of transformers.

# CHAPTER 2

# TRANSFORMER THERMAL MODELING

## 2.1 Transformers as an Essential Part of the Electric Power System

Electric power plays a vital role in the modern society. The basic function of an power distribution system is to supply customers with electric energy as economically as possible and with an acceptable degree of reliability. The age and condition of the system components, as well as the natural environment, directly affect the system condition, sometimes resulting in equipment failures. In particular, extreme weather events may cause difficulty in maintaining power supply reliability for varying durations.

Transformers are essential elements of the electric power transmission and distribution system. A fault in a transformer interrupts the energy flow and may result in a major loss of revenue to the utility. Power transformers are one of the most valuable assets of the utility industry. Both economic and reliability considerations motivate utilities to extend the serviceable life of existing transformers and also reduce the cost of maintenance of transformers.

A transformer failure can occur due to various reasons, the most common reasons being design weakness, lightning and switching surges, fault short-circuits, lack of adequate protection, overloading, accidents, and environmental conditions. A transformer's rating is based on peak allowable load. The basic factor that limits the transformer load capability and service life is its thermal performance. The ability of the winding insulation to withstand repeated temperature cycling is the key factor in determining a transformers useful service life. In particular, the generation of gas bubbles within the oil coolant at high operating temperatures increases the water content of the coolant, and this adversely affects the insulation service life. The peak load rating method is imperfect, however, because it does not adequately account for the true relationships between transformer loading, ambient temperature and expected insulation lifespan. Transformers are expected to last 20 to 30 years, and some utilities have had transformers in service for more than 50 years [6]. Loading a transformer beyond its name plate rating increases its internal temperature, which accelerates the "loss of life". Overloading a transformer increases the temperature in its windings and oil coolant, which in turn affects the insulation between the windings. Frequent overloading weakens the insulation over a period of time. Overloads may also occur due to the failure of the system or operator events. To protect the transformer against these fault conditions, it is important to measure and record the top oil(TO) and hot spot(HS) temperatures under overload conditions and fault currents. The top oil temperature is the temperature of the cooling oil as measured at the top of the transformer tank and the hot spot temperature is the hottest temperature spot in the transformer winding. The transformer thermal model used in this thesis, which is defined by the IEEE C57.115 standard, does not require that one know the precise physical location of the hottest spot in order to estimate the hottest spot temperature. These temperature values help in planning the optimal loading and maintenance of transformers. Although this would ideally be done at each large transformer in the distribution system, it is in practice done only for the largest transformers at the interface between the high voltage transmission system and the lower voltage distribution system. Events of power demand in excess of a transformers nameplate rating are logged by utilities, and both the magnitude and duration of overload events are then used to estimate the remaining service life of a given unit.

## 2.2 Key Variables for Running Aging Analysis

In the analysis of transformer aging, the temperature as a function of time plays a major role in determining the aging factor. The three important temperatures to monitor the aging of the transformer are top-oil, hot-spot and ambient temperatures.

It is important to accurately determine these three temperatures for performing the aging calculation of the transformer.

## 2.3 IEEE Standard Model for Thermal Analysis Based on Top-Oil and Hottest-Spot Temperatures

There are several thermal models for predicting transformer internal temperatures. The IEEE/ANSI C57.115 standard serves as the starting point in this analysis. All of the variables and mathematical equations that appears in this section are obtained from IEEE Std. C57.115. The standard view of transformer internal temperatures is shown in Fig. 2.1.

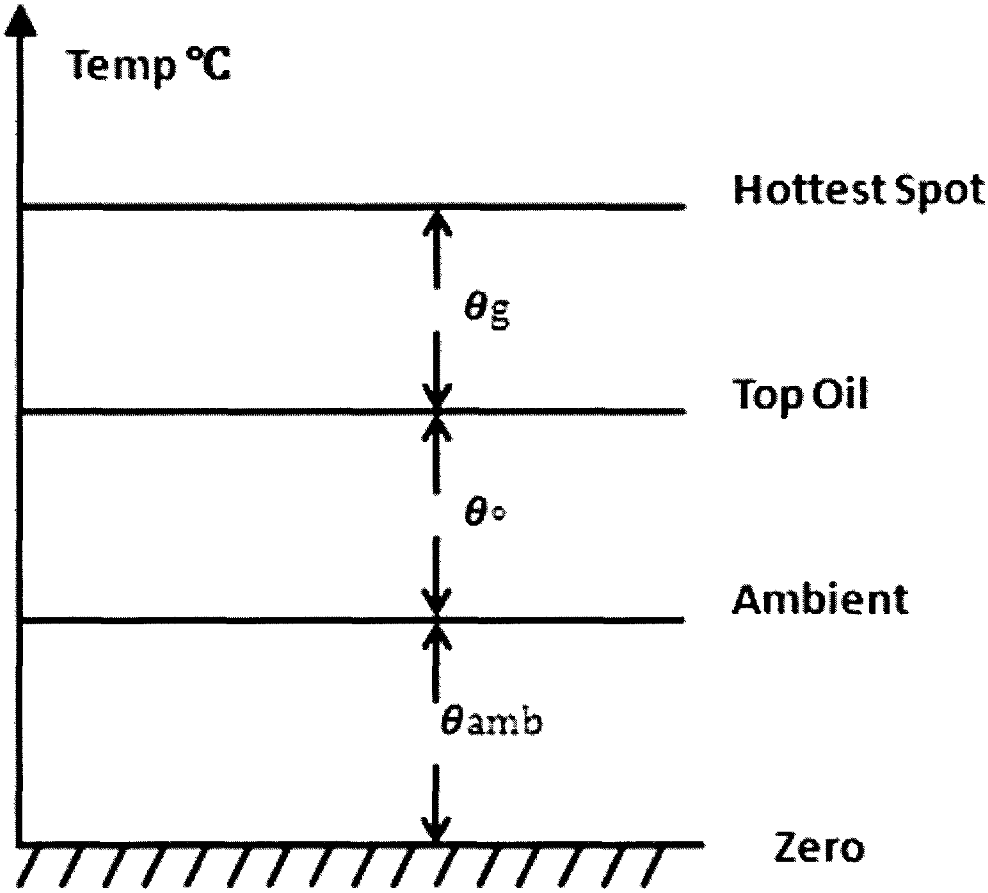


Figure 2.1: **Transformer Temperatures for Any Load Conditions**

$\theta_g$ represents the hot spot rise over the top oil temperature

$\theta_\circ$ represents the top oil rise over ambient temperature

$\theta_{amb}$ represents the ambient temperature

The variables $\theta_g$, $\theta_\circ$, $\theta_{amb}$ are functions of time.

### 2.3.1 Top-Oil Temperature

The transformer thermal model described in IEEE/ANSI C57.115 standard model for TO rise over ambient temperature is governed by the first order differential equation.

$$T_{\circ}\frac{d\theta_{\circ}}{dt} = -\theta_{\circ} + \theta_{u}, \tag{2.1}$$

where

$\theta_{\circ}$-top oil rise over ambient temperature in $^{\circ}C$

$\theta_{u}$- Ultimate top oil rise in $^{\circ}C$ for load L, defined in Equation [2.3]

$T_{\circ}$- Thermal Time constant at rated KVA (hr)

The solution of Equation [2.1], i.e., the temporal response for the top-oil rise over ambient temperature is given by

$$\theta_{\circ} = (\theta_{u} - \theta_{i})(1 - e^{(-t/T_{\circ})}) + \theta_{i}, \tag{2.2}$$

where

$\theta_{i}$- Initial top oil rise for t=0 in $^{\circ}C$

Here $\theta_{u}$ represents the top oil rise over ambient temperature that would be attained only asymptotically with time for a constant load.

$$\theta_{u} = \theta_{fl}\left(\frac{(K^{2}\cdot R+1)}{(R+1)}\right)^{n}, \tag{2.3}$$

where

$\theta_{fl}$- Top oil rise over ambient temperature at full rated load in $^{\circ}C$

n- Oil exponent

K- Ratio of load to full rated load

R- Ratio of load loss to no-load loss at rated load

Note that $\theta_{\circ}$ is the top oil rise over ambient temperature at an arbitrary load and is a function of time. $\theta_{fl}$ is the asymptotic value of $\theta_{\circ}$ when the transformer is operated at its full rated load, and is a constant independent of time.

The transformer thermal time constant may also be expressed in terms of the thermal capacitance and rated load power as shown in Equation [2.4]

$$T_{\circ} = \frac{C\theta_{fl}}{P_{fl}}, \tag{2.4}$$

where

$P_{fl}$- Full rated Load (MVA)

C- Transformer Thermal Capacity (Wh/$^{\circ}C$)

The top oil temperature is the temperature of the cooling oil as measured at the top of the transformer tank. The top-oil temperature increases approximately in proportion to the square of the current. Once Equation [2.1] is solved for $\theta_{\circ}$ (which is a function of time) the top oil temperature is calculated using

$$\theta_{top} = \theta_{\circ} + \theta_{amb}, \tag{2.5}$$

$$= (\theta_u - \theta_i)\left(1 - e^{-t/T_{\circ}}\right) + \theta_i + \theta_{amb}, \tag{2.6}$$

where

$\theta_{top}$- Top oil temperature in $^{\circ}C$

$\theta_{amb}$- Ambient air temperature in $^{\circ}C$

This model works well when $\theta_{amb}$ remains constant. It does not account for dynamic variations in the ambient temperature.

Lesieutre *et al*[14] proposed a modified top-oil model that accounts for dynamic variations in ambient temperature, and in this model we use top oil temperature in the place of top oil rise over ambient temperature. It is based on the differential equation that describes the TO temperature by

$$T_{\circ}\frac{d\theta_{top}}{dt} = -\theta_{top} + \theta_u + \theta_{amb}, \tag{2.7}$$

Solving we get

$$\theta_{top} = (\theta_u + \theta_{amb} - \theta_{topi})\left(1 - e^{-t/T_{\circ}}\right) + \theta_{topi}, \tag{2.8}$$

where $\theta_{topi}$ is the initial TO temperature for t = 0.

To estimate the unknown coefficients such as the thermal time constant, linear regression may be used against measured temperature and electrical loading data. To use linear regression, the defining equation must first be written in a discretized linear form. To achieve this, Lesieutre *et al*[14] applied the forward Euler discretizaton,

$$\frac{d\theta_{top}[k]}{dt} = \frac{\theta_{top}[k] - \theta_{top}[k-1]}{\Delta t}. \tag{2.9}$$

The discrete time equivalent to Equation [2.1] is given in Equation [2.10]

$$\begin{aligned} \theta_{top}[k] &= \frac{T_\circ}{T_\circ + \Delta t}\theta_{top}[k-1] + \frac{\Delta t}{T_\circ + \Delta t}\theta_{amb}[k] \\ &+ \frac{\Delta t \theta_{fl} R}{(T_\circ + \Delta t)(R+1)}\left(\frac{I[k]}{I_{rated}}\right)^2 + \frac{\Delta\theta_{fl}}{(T_\circ + \Delta t)(R+1)} \end{aligned} \tag{2.10}$$

where I[k] is the primary winding transformer current at time step index k.

Equation [2.10] can be re-written in a form amenable to linear regression with coefficients $k_1$, $k_2$, $k_3$ as

$$\theta_{top}[k] = k_1\theta_{top}[k-1] + (1 - k_1)\theta_{amb}[k] + k_2 I[k]^2 + k_3 \tag{2.11}$$

Replacing the $(1 - k_1)$ by another coefficient $k_4$ we get the following equation,

$$\theta_{top}[k] = k_1\theta_{top}[k-1] + k_4\theta_{amb}[k] + k_2 I[k]^2 + k_3 \tag{2.12}$$

Re-assigning the subscripts of the coefficients we get,

$$\theta_{top}[k] = k_1 I[k]^2 + k_2\theta_{amb}[k] + k_3\theta_{top}[k-1] + k_4 \tag{2.13}$$

The model represented by Equation [2.13] is known as a semi-physical model[14] because it is not directly derived from a thermal model of heat flow in the transformer, but it involves measurable physical variables such as the oil temperature, ambient temperature, and the primary winding current of the transformer.

### 2.3.2 Hot-Spot Temperature Prediction

One of the limiting factors in determining the maximum load on the transformer is the hot-spot temperature. The hot-spot temperature is defined as the hottest temperature spot in the transformer winding. The location of the winding's hottest spot is dependent on the physical design of the transformer. The IEEE Transformer Loading Guide equations use the TO rise over ambient temperature to determine the hot-spot temperature during an overload event. The IEEE Loading Guide equations are based on the assumption that the temperature of the oil exiting the winding ducts is the same temperature as the top-oil in the tank. The hot-spot temperature $\theta_{hs}$ is assumed to consist of three components given in the following equation,

$$\theta_{hs} = \theta_{\circ} + \theta_{amb} + \theta_{g}, \tag{2.14}$$

where

$\theta_{\circ}$- Top oil rise over ambient temperature in $^\circ C$

$\theta_{amb}$- Ambient air temperature in $^\circ C$

$\theta_{g}$- Hot-spot conductor rise over top-oil temperature in $^\circ C$

Alternatively the hot-spot temperature is given by

$$\theta_{hs} = \theta_{top} + \theta_{g}, \tag{2.15}$$

The ultimate hot-spot conductor temperature rise over top-oil temperature for a specified load is

$$\theta_{g} = \theta_{g(fl)} K^{2m}, \tag{2.16}$$

where

$\theta_{g(fl)}$- Hot spot conductor rise over top-oil temperature at full rated load,

K- Ratio of load to rated load,

m- Empirically derived winding exponent.

Therefore, substituting the $\theta_g$ in Equation [2.16] into Equation [2.15] we get,

$$\theta_{hs} = \theta_{top} + \theta_{g(fl)} K^{2m} \tag{2.17}$$

The parameter m is determined by the cooling mode used in the liquid filled transformer. For example,

m=0.8 for self-cooled(OA) or forced-air cooled(FA) operation or
non-directed forced Oil, forced-air cooled(FOA) or
forced oil, water cooled(FOW).

m=1 for directed flow forced-air, forced-oil cooled operation.

## 2.4 IEEE Transformer Aging Theory

The aging of a transformer refers to the thermal aging of the insulation of the transformer. The aging is a function of time and temperature. Increasing the transformer electrical load increases the temperature of the cooling oil, so loading above the name plate rating for an extended time involves some risk. Transformers are rated at a maximum oil temperature rise over ambient, with modern transformers rated at $65°C$ rise above ambient. The aging acceleration factor FAA, which indicates how fast the transformer insulation is aging, gives the relationship between oil temperature and transformer life expectancy. We calculate the insulation aging acceleration factor, FAA, for each time interval, $\Delta t$, as follows:

$$F_{AA} = exp\left[\frac{B}{(\theta_{H,R} + 273)} - \frac{B}{(\theta_H + 273)}\right], \tag{2.18}$$

where

$F_{AA}$- Insulation aging acceleration factor

B- Is a design constant, typically $15000,°C$

$\theta_{H,R}$ is the value of the hottest spot temperature $\theta_{hs}$ at full rated load. Two values of $\theta_{H,R}$ are typically used in aging analyses:

$95°C$ is used for transformers with average winding rise over ambient temperature of $55°C$ at rated load.

$110°C$ is used for transformers with average winding rise over ambient temperature of $65°C$ at rated load.

### 2.4.1 Daily Rate of Loss of Life

Now we calculate the daily rate of loss of life (RLOL, percent loss of life per day) for a 24 hour period as follows:

$$RLOL = \frac{F_{EQA} \cdot 24}{ILIFE} \cdot 100\%, \tag{2.19}$$

where

RLOL = Rate of loss of life in percent per day

ILIFE = Expected normal insulation life in hours

The equivalent life at the reference hottest-spot temperature ($95°C$ or $110°C$) that will be consumed in a given time period for a given temperature cycle is:

$$F_{EQA} = \frac{\sum_{n=1}^{N} F_{AA} \cdot \Delta t_n}{\sum_{n=1}^{N} \Delta t_n} \tag{2.20}$$

where:

$F_{EQA}$- Equivalent insulation aging factor for a total time period

n- Index of the time interval,$\Delta t$

N- Total number of time intervals for the time period

$F_{AA_n}$- Insulation aging acceleration factor for the time interval

$\Delta t$- Time interval

During 24 hours, the total number of time intervals is:

$$N = \frac{24}{\left(\frac{\Delta t}{60}\right)} = \frac{1440}{\Delta t}, \tag{2.21}$$

where

$\Delta t$- Time interval in minutes.

Because the time intervals and the total time period used in the thermal model will be constant, we can simplify the calculation of $F_{EQA}$ to the following:

$$F_{EQA} = \frac{\sum_{n=1}^{N} F_{AAn}}{N} \tag{2.22}$$

### 2.4.2 Total Accumulated Loss of Life

An estimate of the total accumulated loss-of-insulation life in percentage of normal insulation life can be made by summing all of the daily RLOL values:

$$TLOL_d = RLOL_d + TLOL_{d-1}, \tag{2.23}$$

where

$TLOL_d$- Total accumulated loss of life, TLOL

$RLOL_d$- Most recent daily calculation

$TLOL_{d-1}$- Previous TLOL

Damage, or aging of insulation, roughly doubles with every 6 to $8°C$ of temperature rise above $95°C$ [6]. We can plan the approximate effects of hottest-spot temperature on insulation aging. Accumulated loss of life provides an indicator of the impact of operational overloads on the transformer. It is simply the integral over time of the accumulated aging, taking into account the effect of accelerated aging caused by elevated temperatures.

Moisture content in the cellulose insulation has a significant impact on insulation aging. If the moisture content increases from 0.5% to 1.0%, the rate of aging of the cellulose insulation at least doubles for a given temperature. Moisture in the insulation can be estimated by applying an appropriate algorithm to the measured water content in the oil. It is important to know the amount of water in the transformer oil because even an advanced temperature monitoring system cannot completely predict the perfect time to perform maintenance. Using the calculated moisture content to adjust the thermal aging factor of the insulation improves the ability to predict maintenance needs.

### 2.4.3 Alternative Methods Used by the Utilities to Determine the Age of Transformers

Every utility has its own methods and not all utilities necessarily adopt the IEEE C57.91-1995 standard[19] aging analysis. Some use more conservative methods than the standard aging calculation. Most transmission transformers in New England have been in service for at least 20 years. Loading criteria for transmission transformers are based on recommendations provided in the IEEE Loading Guide C57.91-1995, as well as several technical papers discussing the risk of transformer failure due to bubble evolution [9]. Utilities are free to adopt modified loading criteria, which are based on the IEEE standard but are not identical to it. For example, the IEEE loading guide recommends not overloading the transformer beyond twice the nameplate rating of the transformer, even if the top oil temperature and hot-spot limits have not been reached. Rather than perform extensive loss-of-life calculations for every transformer in its system, a utility may decide that a transformer's loading will not be allowed to exceed twice the nameplate rating for any operating condition. In this thesis we are not using the aging calculation as a factor to determine the aging of the transformer, since the utility which we worked with does not use this method.

# CHAPTER 3

# ELECTRIC POWER DEMAND SENSITIVITY MODELS

## 3.1 Brief Review of Short Term Models From The Literature: Weather and Econometric Variable Influences

Climate is a major determinant of energy demand. Changes in the climate may alter total energy as well as seasonal energy demand patterns. The daily routine weather conditions and the extremes of weather affect the electricity consumption patterns and the performance of the equipment, which in turn affect the cost and quality of the electrical energy supplied. Precise advanced knowledge of the varying weather's influence on the electric power system may help in reducing some of the most common and expensive social impacts of weather.

Modern utilities have various operation and planning procedures, which help the electric power system to meet the desired set of goals. The operations planning procedure involves methodologies and decision making processes which help the electric power system to meet the electric load within the specified time intervals in a reliable and economic manner. The operation planning procedure starts with a prediction of the demand for the electric load, i.e., load forecasting.

### 3.1.1 Load Forecasting

Load forecasting is the process of predicting the amount of electricity demand across a region or transmission network over a specified period of time. Accurate models for electric power load forecasting are essential to the operation and planning for a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development.

The basic requirement in the operation of power systems is to closely follow the system generation by the system load at all times. For economically efficient operation and for effective control, this must be accomplished over a wide range of time intervals. Accurate load predictions save cost by improving economic load dispatch, unit commitment and energy transfer scheduling. It also enhances the function of security control, such as effectively schedule spinning reserve allocation.

### 3.1.2 Load Forecasting Models from Literature

A large variety of mathematical methods have been developed for load forecasting. Depending on the application, load forecasting is classified as [16]

1. Short term
2. Medium term
3. Long term

### 3.1.3 Short Term Load Forecasting

Short term load forecasting is usually from 1 hour to 1 week. Medium term forecasts are usually from 1 week to a year, and long term forecasts are usually longer than a year. The forecasting methods are based on statistical, mathematical, econometric and other load models.

Short term load forecasting(STLF) plays a key role in the formulation of economic, reliable and secure operating strategies of the power system. The principal objective of the STLF function is to provide the load predictions for

1. Scheduling functions such as dispatching generators to dispatch load

2. Security of the power system

3. Demand response

The primary application of the short term load forecasting is to drive the scheduling function of the power system. The load forecasts help the system to determine the scheduling of the number of units for generation and the minimal hourly cost strategies for the start-up and shut down of units to supply the forecast load.

The short term load forecasting helps to provide a predictive assessment of the power system security. The load forecast, using the short term load forecasting method, helps in detecting the future conditions under which the power system may be vulnerable. This information helps dispatcher to prepare the necessary corrective actions to operate the power system securely. The other application of Short Term Load Forecasting is to provide system dispatchers with timely load information; the timely information includes the latest weather predictions and random behavior taken into account. This helps the dispatcher to operate the system economically and reliably.

The timeliness and accuracy of STLF have significant effects on power system operations and production costs. Thus by reducing the forecast error, reserve levels may be reduced without affecting the reliability and security of the system. In this way, the operating costs are reduced.

### 3.1.4 Factors Influencing Load Forecasting

The basic quantity of interest in STLF is, typically, the hourly integrated total system load. The system load is represented by the sum of all the individual demands at all the nodes of the power system. The system load behavior is influenced by a number of factors. We classify the factors into four major categories.

1. Economic

2. Time

3. Weather

4. Random effects

#### 3.1.4.1 Economic Factors:

The economy of the environment in which the utility operates has a clear impact on the electricity consumption pattern. Factors such as the level of industrial activity, the intensity and duration of electric appliance use, and the general level of business activity in a power supply area (i.e., a collection of distribution circuits in a given geographic area) all influence the demand profile. Although important in making longer term load projections, the econometric variables that represent the local economy are not included in short-term load forecasting models.

#### 3.1.4.2 Time Factors:

Time factors such as seasonal factors, depending on whether it's winter or summer, cause load to vary. The daily load cycle may vary from week to week depending on the electricity usage patterns in the business sectors served by the circuits of interest. Holidays also influence the load demand pattern. These factors have to be taken into account for load modeling.

#### 3.1.4.3 Weather Factors:

Changes in the weather patterns are responsible for significant variations in the load patterns. This is true because most utilities have large components of weather-sensitive load, such as those due to space heating, air conditioning and agricultural irrigation.

In many systems, temperature is the most important weather variable in terms of its effects on the load. For any given day, the deviation of temperature from a normal value may cause such significant load changes as to require major modifications in the generating unit commitment pattern. Humidity is a factor that may affect the system load in a manner similar to temperature, particularly in hot and humid areas. Other factors that impact load behavior are wind speed, precipitation and cloud cover.

## 3.2 Classification of Short Term Load Forecasting

The classification of the literature in STLF that follows is based on the type of the load model used. The classification considers two basic models: peak load and load shape models. The peak load models are basically of a single type. We have categorized the load shape models into two basic classes, each with its subtypes, namely:

1. Time of day

   a Summation of explicit time functions models

   b Spectral decomposition models

2. Dynamic models

   a Auto Regressive Moving Average (ARMA) models

   b State-space models

### 3.2.1 Peak Load Model

In this model the daily weekly load is modeled as a function of weather. The typical model is of the form

$$P = B + F(W) \tag{3.1}$$

where,

P-Peak load

B-Base load

F(W)-Weather dependent component

The advantages of a peak load model are its structural simplicity and its relatively low data requirements to initialize and to update. The disadvantage of these models is that they do not provide the time information at which the peak occurs.

### 3.2.2 Load Shape Models:

Such models describe the load as a discrete time series over the forecast interval. The load sampling time interval is typically one hour or one-half hour. Many load forecasting techniques describe load shape since this also includes the peak load. Basically there exist two types of load shape models,

1. Time-day models
2. Dynamic models

#### 3.2.2.1 Time-Day Models:

The time of day model defines the load z (t) at each discrete sampling time t of the forecast period of duration T by a time series {z (t) =1, 2.... T }.

In its simplest form, the time-of-day model stores T load values based on previously observed load behavior.

#### 3.2.2.2 Dynamic Models:

Dynamic load models recognize the fact that the load is not only a function of the time of day but also of its most recent behavior, as well as of weather and random inputs.

The basic dynamic models are,

1. ARMA models
2. State-space models

**3.2.2.2.1 ARMA Models:** The ARMA type model takes the general form

$$z(t) = Y_p(t) + y(t), \tag{3.2}$$

where $Y_p$(t) is a component that depends primarily on the time of day and on the normal weather pattern for the particular day. This component can be represented

by a periodic time function.
The term $y$ (t) is an additive load residual term describing influences due to weather pattern deviations from normal and random correlation effects.

Changes in the climate, especially the increase or decrease of average temperatures, alter the energy demand patterns. In United States, residential households devote 58%, commercial buildings 40%, and industrial facilities 6% of energy consumption to space conditioning requirements, so that around 22% of the end-use energy is utilized for space-conditioning purposes. The large quantity of energy devoted to heating and cooling suggests that climate change may have real and measurable effects on energy consumption.

In the previous section we have discussed the factors influencing the energy demand, on which weather has a significant impact. The weather variables that influence the energy use are daily average temperature, maximum temperature, minimum temperature, humidity and cloud cover.

Temperature serves as the main driving factor for load forecasting. Energy industries commonly use temperature for predicting the energy demand. The demand sensitivity analysis is done using the degree day methodology. Degree-days are common energy accounting practice for forecasting energy demand as a function of heating degree days and cooling degree days. The degree day is defined as each degree deviation from a predefined balance point temperature, the balance point temperature is the temperature at the bottom of the V-shaped temperature-energy consumption function, for the temperature extremes of that day. The degree day methodology presumes a V-shaped temperature-energy consumption relationship. At the balance point temperature, energy demand is at a minimum since outside climatic conditions produced the desired indoor temperature. The amount of energy demanded at the balance point temperature is the non-temperature-sensitive energy load. As the outdoor temperatures deviate above or below the balance point temperature, energy demand increases with temperature. Energy analyses commonly use a base temperature of $65°F$ as the balance point temperature of an energy system, but this value varies depending on the place-specific characteristics of the building stock and non-temperature weather conditions [15]. The monthly heating degree days and cooling degree days are derived from the daily temperature data.

## 3.3 Peak Day Demand Model Used by Northeast Utilities:

Load forecasting plays a vital role in the operation planning procedures of the electric utility industry. Load forecasting is especially important in the deregulated electricity markets to maintain the reliability of the electrical energy supply. The predicted weather information helps in decision-making in energy purchasing, load scheduling, the analysis of infrastructure development, etc. A large number of mathematical models are available for load forecasting. Demand for electric power typically depends on the temperature and several other weather factors. It also depends on the day of the week and the hour of the day. The northeast U.S. utilities forecasts are based on econometric models. In this method the economic information of the environment is combined with the statistical approach for the load forecasting of the electric energy in demand. A linear regression relationship between the energy consumption and the factors influencing the energy consumption is given by,

$$P_{demand} = \alpha + \beta X, \tag{3.3}$$

where

$P_{demand}$ is the Power Demand

$\alpha$ is Constant

$\beta$ is Coefficient of regression

X is Independent Variable

## 3.4 Construction of the Regression Model Time Series from the Independent Variable Temperature Series

In this method of analysis the first step is to find the influencing independent variable to determine the demand. While there are various factors influencing the energy forecast, this study mainly concentrates on the effect of climate change on the energy demand. The weather plays an important role in the energy forecast. There are several weather factors that influence the energy demand, such as wind, cloud cover, etc. In this study we have focused the impact of temperature on the energy demand; thus other weather variables are not modeled.

The second step is to construct time-series monthly maximum temperatures in June, July and August from the GCM simulation data sets from USC North East Climate Impacts Assessment by K. Hayhoe, C. Wake and collaborators [4]. The data set is a downscaled daily data for 7 Northeast urban areas, 8 different GCM models and 2 climate scenarios. Degree days are the common metric for forecasting energy demand consisting of heating and cooling degree days, and the constructed time series of maximum daily temperatures is used to calculate the degree days. These degree days calculated from the monthly maximum temperature data are used to study the historic sensitivity of the energy demand to temperature variations.

The third step is to use the demand sensitivity relationship (Equation [3.3]) to estimate the future energy consumption pattern under various climate scenarios. The regression model Equation [3.4] relating the temperature and the demand is a simplified model obtained from National Grid complicated model, which is not publicly available. The model represented in Matlab code as below,

$$\begin{aligned} Pdemand(j,:) &= (4.694 * maxcdd(j,:)) + (8.816 * cumincdd(j,:)) \\ &\quad +1248.873 - 702.945 \,, \end{aligned} \tag{3.4}$$

where

P*demand* is the power demand in MW

*maxcdd* is the maximum value of the cooling degree days in $^\circ C$

*cumincdd* is the cumulative cooling degree days in $^\circ C$

$j$ is the integer index signifying month

## 3.5 Examples of the Monthly Peak Day Demand Time Series Out to Year 2100

The model relates the historical monthly demands at the time of the utility peak, peak-day weather conditions and regional economic variables. The economic variables used in the analysis depend on the economic environment of the utility such as load, customer growth, employment, etc. The maximum and minimum temperature on the day of the peak and the day prior to the peak is taken as the peak weather condition.

Constructing the regression model's independent variable time series from predicted temperature time series involves the following steps:

1. Extraction of the peak day weather conditions from the temperature series.
2. Performing the degree day calculation using the extracted peak day weather conditions.
3. Forecasting the demand.

The downscaled weather simulation data for predicting the changes in the climate by Hayhoe and Wake [13] is used for extraction. Utilities use temperature for predicting the demand for a given period of time. The electric energy calculations are temperature sensitive, and the variations in the temperature cause the peaks in the electric power demand. The demand for the electric energy is given by the following equation,

$$E_{Demand} = C + y(CDDorHDD), \tag{3.5}$$

where

$E_{Demand}$ is the Electric Energy Demand

C is Constant

$y$ is the relationship between the temperature and demand.

The monthly peak demands calculated using the Equation [3.5] is shown in Fig. 3.1, Fig. 3.2, Fig. 3.3.

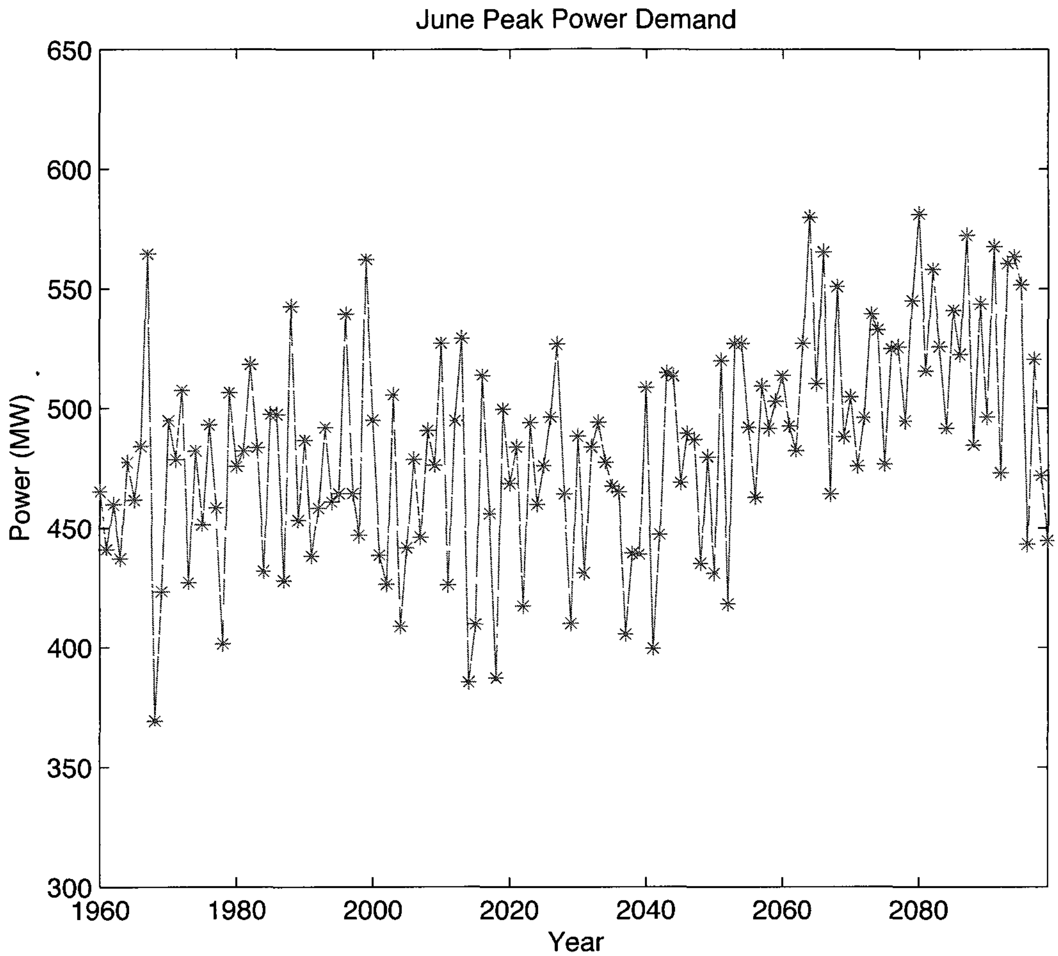
June Peak Power Demand
Power (MW)
Year
650
600
550
500
450
400
350
300
1960
1980
2000
2020
2040
2060
2080

Figure 3.1

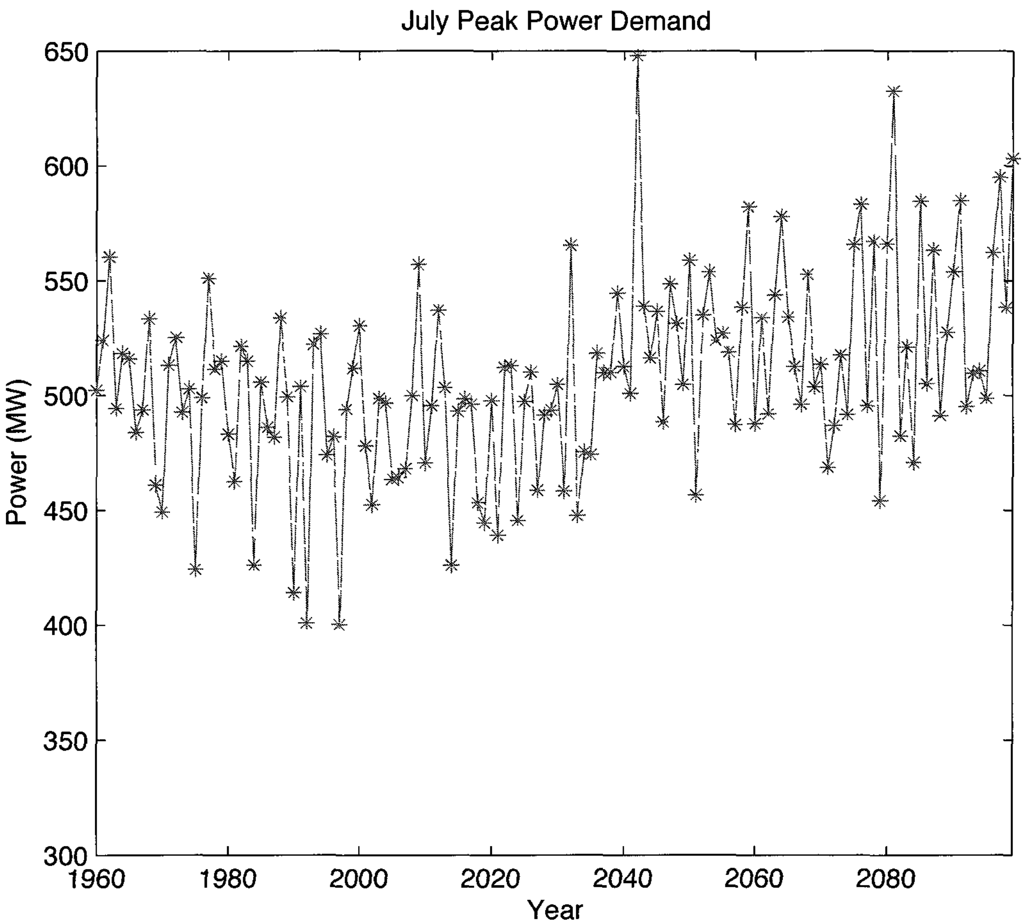
July Peak Power Demand
Power (MW)
Year
650
600
550
500
450
400
350
300
1960
1980
2000
2020
2040
2060
2080

Figure 3.2

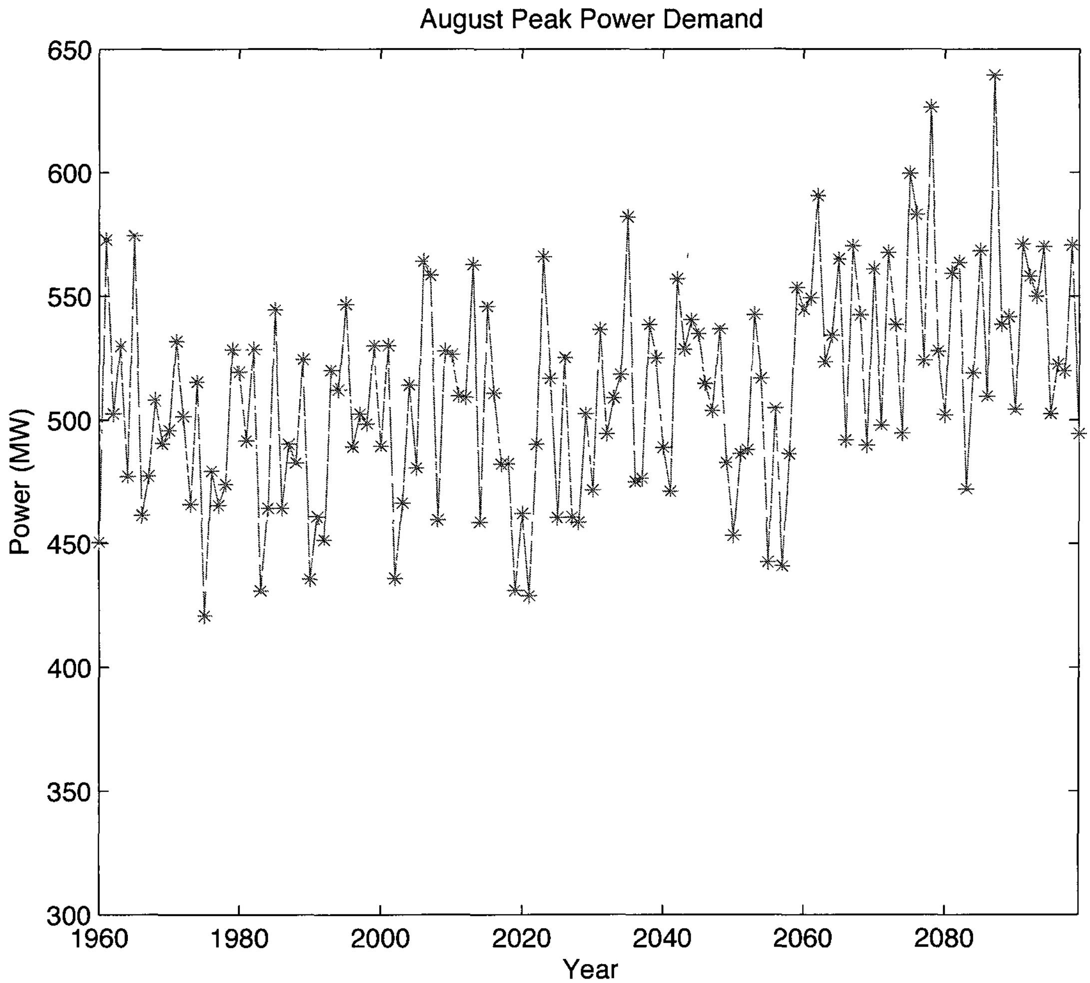
August Peak Power Demand
650
600
550
500
450
400
350
300
Power (MW)
1960
1980
2000
2020
2040
2060
2080
Year

Figure 3.3

## 3.6 Comparative Baseline Peak Day Demand for Historical Temperature Time Series

The method adopted in this thesis for estimating transformer internal temperatures under simulated future temperature time series requires the assumption of a baseline, or reference, power demand value. The justification is that specific transformer characteristics and an associated set of historical power demand data were not available. However, reasonable sets of transformer operating characteristics may be found in the IEEE standards documents dealing with transformer thermal analysis. A regression model for peak day power demand (over a power supply area rather than a single transformer) as a function of a number of independent variables, including temperature-related variables, was available. If one assumes an historical peak day power demand value, then simulated future power demands may be described by a series of demand factors with respect to the assumed baseline power demand, and the transformer thermal model variables may be recast in terms of the demand factor and the baseline power demand values.

There are numerous methods by which one could choose to establish a baseline power demand value for the calculation of future demand factors. Rather than describe all of the prospective methods that might be considered, only the method used in this thesis is described here and an argument is given for its validity. The ready availability of historical temperature time series for a region enables one to calculate the number of cooling degree days in a given summer month (the season of most interest in this study) and to apply a power demand regression model to estimate the monthly peak day demand for the area associated with the model. Rather than select the average of all peak day demand values for that month in the historical period as baseline historical power demand for a given month, the baseline value was chosen as the $90^{th}$ percentile value of the histogram of historical peak day demand values for the given month. Both the maximum and average values of historical demand data are known to be sensitive to outliers, and it was decided that a more realistic picture of future demand estimates would be obtained if a conservative historical baseline power demand value was selected as the basis for computation of future demand factors. The histogram $90^{th}$ percentile value is much less sensitive to the presence of extreme maximum values (outliers) than the maximum itself, and the use of the $90^{th}$ percentile value establishes a relatively higher, and thus more conservative, baseline demand value than would the use of the average peak day demand. The transformer thermal study conducted in this thesis is intended to reveal potential future problems with accelerated transformer aging due to presumptive climate changes, and the use of a conservative historical baseline power demand value is believed to be necessary.

The computation of cooling degree days (CDD) for a month requires the assumption of a balance point temperature Tbal, and the number of cooling degree days is simply the sum of the quantities T(i)-Tbal for those days on which the difference is positive, where T(i) represents the peak temperature on day (i) of the month. For the purposes of this study, the value of Tbal was selected to be that used for the construction of the power demand regression model, which was $65°F$, for calculating the maximum CDD and $60°F$ for cumulative minimum of cooling degree days(cumin CDD). The cooling degree days were calculated separately for the months of June, July and August from the historical temperature time series for the years 1960-2000, and the corresponding peak day power demands for those months were found from the peak day demand regression equation. A histogram of peak day demands for a single month over the time interval was constructed, and the $90^{th}$ percentile value of the histogram was used as the baseline demand value for that month. The baseline demand values obtained by this procedure were 562 MW, 580 MW and 573 MW for the months of June, July and August. July is the historically highest baseline demand. These are the values used in predicting the overload events.

# CHAPTER 4

# TRANSFORMER THERMAL ANALYSIS UNDER CLIMATE CHANGE

Power transformers are an important part of a transmission and distribution system. They are valuable assets of a power system, and thus it is important to extend as much as possible the service lifetimes of the transformers. The transformer operation involves the transfer of electrical energy between circuits; part of the energy is converted into heat which increases the internal temperature of the transformer. This limits the amount of power transfer through the transformer. Thermal impact leads not only to long-term oil/paper insulation degradation; it is also a limiting factor for transformer operation [10]. The thermal analysis of the transformer involves the prediction of top-oil and hottest-spot temperatures. Thus it is important to know the transformer temperatures.

In this thesis we examine the effect of predicted long-term climate change on the reliability of transformers in the Northeast U.S. by studying the variation in the internal temperatures of the transformer using simulated ambient temperature time series through the year 2100. One of the main objectives of the thesis is to predict the top oil and hot spot temperatures. The top oil and hot spot temperatures were calculated based on the IEEE/ANSI C57.115 standard by incorporating the peak demand in the calculation of the temperatures for different baseline demands as a percentage of the nameplate rating. In this thesis, we provide a template for transformer temperature calculations rather than an analysis of any specific transformer in an existing power system. The analysis presented here may be made specific for any given transformer once its baseline load and nameplate rating data are used. Thus for the percentage of the name plate load rating (typically in kVA or MVA) we indicate normalized values such as 0.2, 0.3, 0.5, 0.80, 0.90 and 1 which represent 20%, 30%, 50%, 80%, 90% and 100% of the nameplate rating of the transformer. This method of normalized analysis enables us to present results on future transformer reliability that are not unique to any given transformer in an existing power system, but are reflective of broad impacts across any system.

The analysis is done for the summer months June, July and August over the period of the temperature time series through the year 2100. The peak demand for the months of June, July and August are shown in Fig. 3.1 through Fig. 3.3. The demand calculated shows the upward trend in the energy demand in the future. The transformer parameters used for these simulations are shown in Table 4.1 and Table 4.2.

The transformer internal temperatures are calculated using the predicted temperature series[13] as the ambient temperature and the calucated peak demand for the months respectively. The count of number of days in which the top oil and the hot spot temperature over $65°C$ and over $120°C$ respectively is calculated to predict the frequency of the overloading events of the transformer in the future.

These predictions are shown in Fig. 4.1 through Fig. 4.17 for normalized baseline loads of 80%, 90% and 100% of the nameplate rating. Calculations were also performed for normalized loadings of 20% and 30% and 50% but the results show zero days in which the internal temperatures exceed their allowable limits. In particular for a normalized load of 80% in the month of June the calculation for hot spot temperature exceeding over $120°C$ resulted in zero days. As for the calculation of number of days in which the top oil temperature threshold is exceeded, it was found that lightly loaded transformers (20%, 30%, 50% of the nameplate rating) were not at risk for hot spot temperature exceeding the $120°C$ threshold in any year for the months of June, July and August.

Table 4.1: Number of Days where Top Oil Temperature Exceeds 65°$C$ for the Summer Months of June, July and August

| **Month** | **% of Nameplate Rating** | **Number of days/Fig.No.** |
|---|---|---|
| June | 20%,30%,50% | 0 |
| June | 80% | Fig. 4.1 |
| June | 90% | Fig. 4.2 |
| June | 100% | Fig. 4.3 |
| July | 20%,30%,50% | 0 |
| July | 80% | Fig. 4.4 |
| July | 90% | Fig. 4.5 |
| July | 100% | Fig. 4.6 |
| August | 20%,30%,50% | 0 |
| August | 80% | Fig. 4.7 |
| August | 90% | Fig. 4.8 |
| August | 100% | Fig. 4.9 |

Table 4.2: Number of Days where Hot Spot Temperature Exceeds 120°$C$ for the Summer Months of June, July and August

| **Month** | **% of Nameplate Rating** | **Number of days/Fig.No.** |
|---|---|---|
| June | 20%, 30%, 50%, 80% | 0 |
| June | 90% | Fig. 4.10 |
| June | 100% | Fig. 4.11 |
| July | 20%,30%,50% | 0 |
| July | 80% | Fig. 4.12 |
| July | 90% | Fig. 4.13 |
| July | 100% | Fig. 4.14 |
| August | 20%,30%,50% | 0 |
| August | 80% | Fig. 4.15 |
| August | 90% | Fig. 4.16 |
| August | 100% | Fig. 4.17 |

## 4.1 Excessive Top Oil Temperature Days

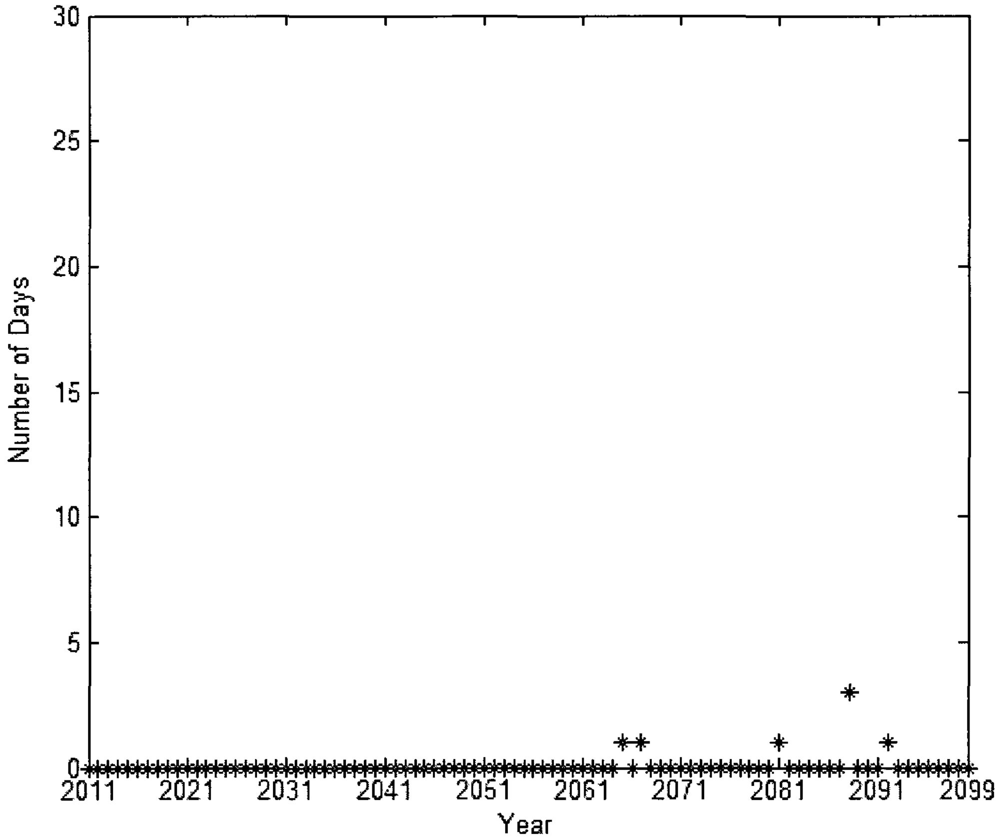


Figure 4.1: Number of Days in June where Top Oil Temperature Exceeds 65°$C$ Loading at 80% of Nameplate Rating

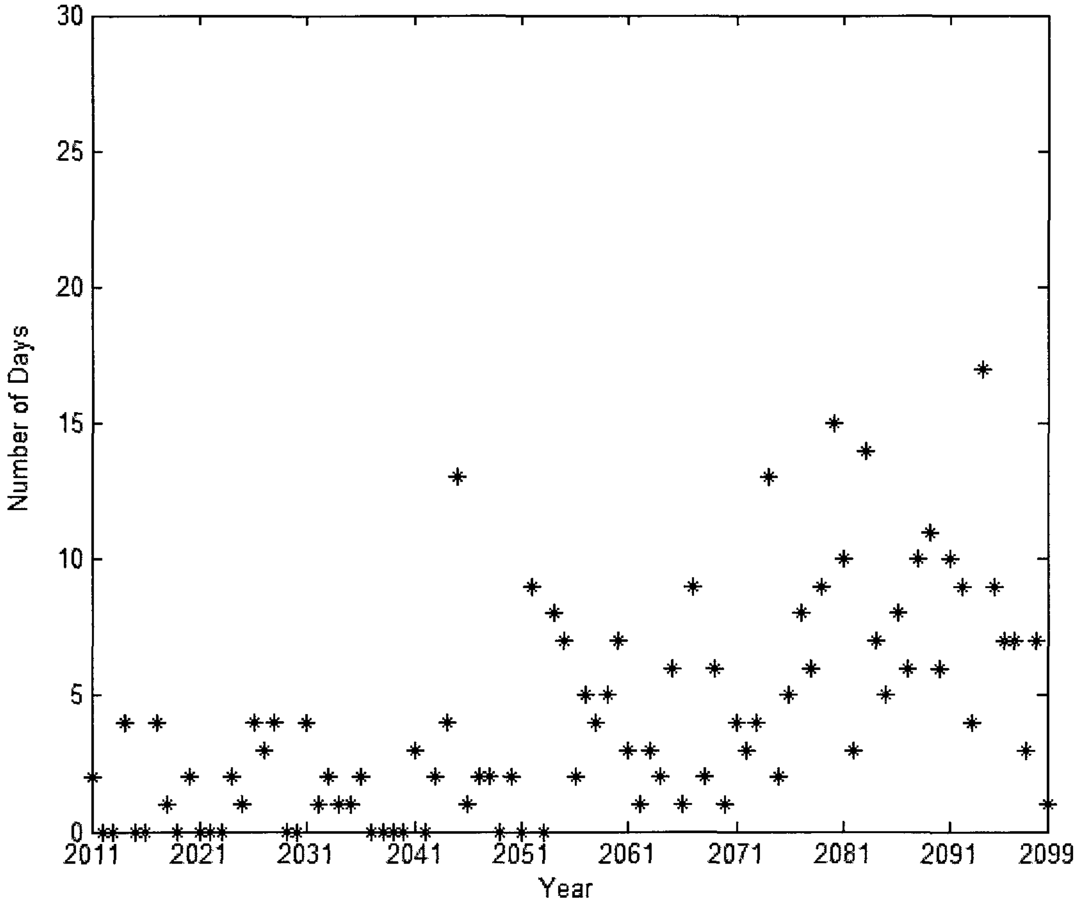


Figure 4.2: Number of Days in June where Top Oil Temperature Exceeds 65°$C$ Loading at 90% of Nameplate Rating

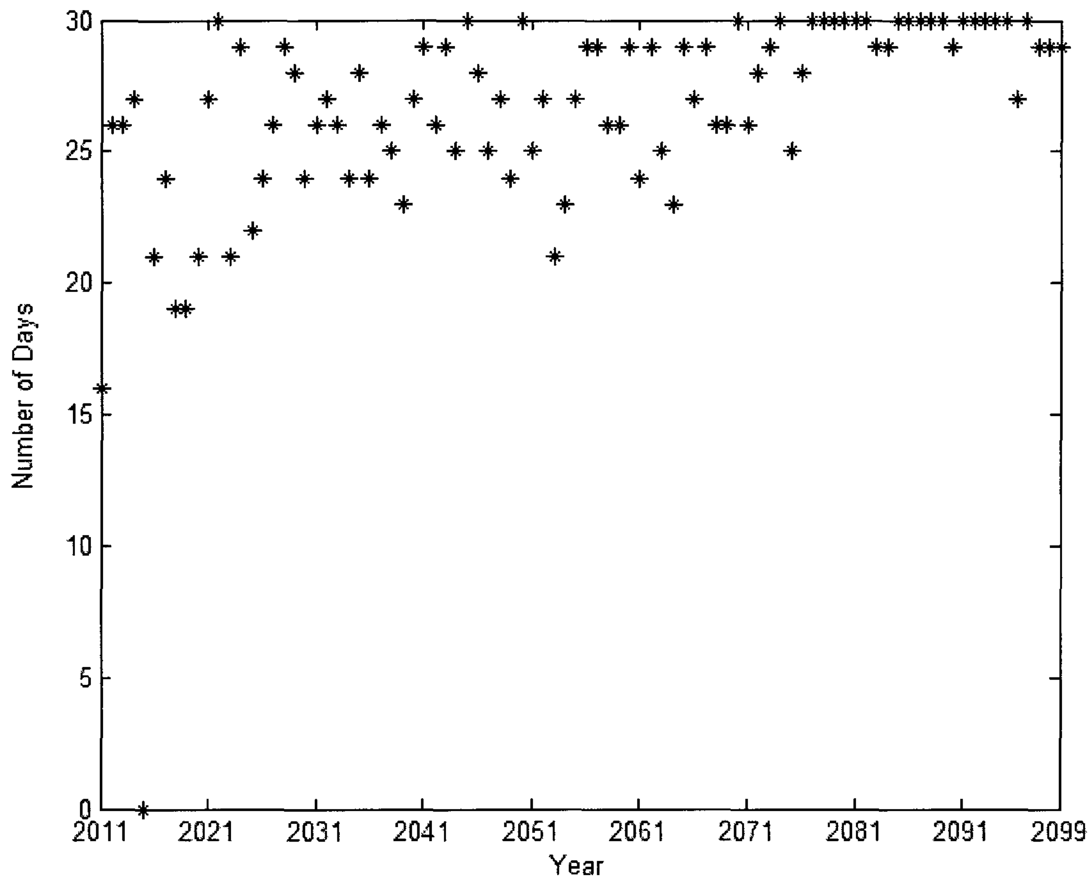


Figure 4.3: Number of Days in June where Top Oil Temperature Exceeds 65°$C$ Loading at 100% of Nameplate Rating

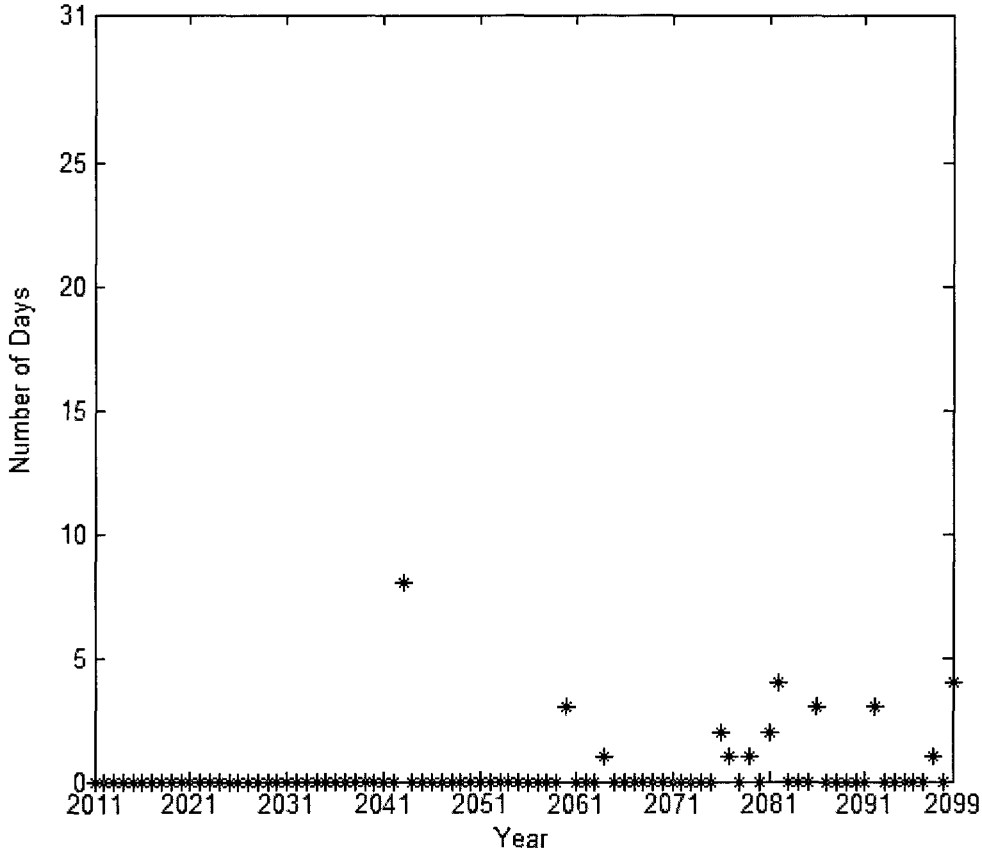


Figure 4.4: Number of Days in July where Top Oil Temperature Exceeds 65°$C$ Loading at 80% of Nameplate Rating

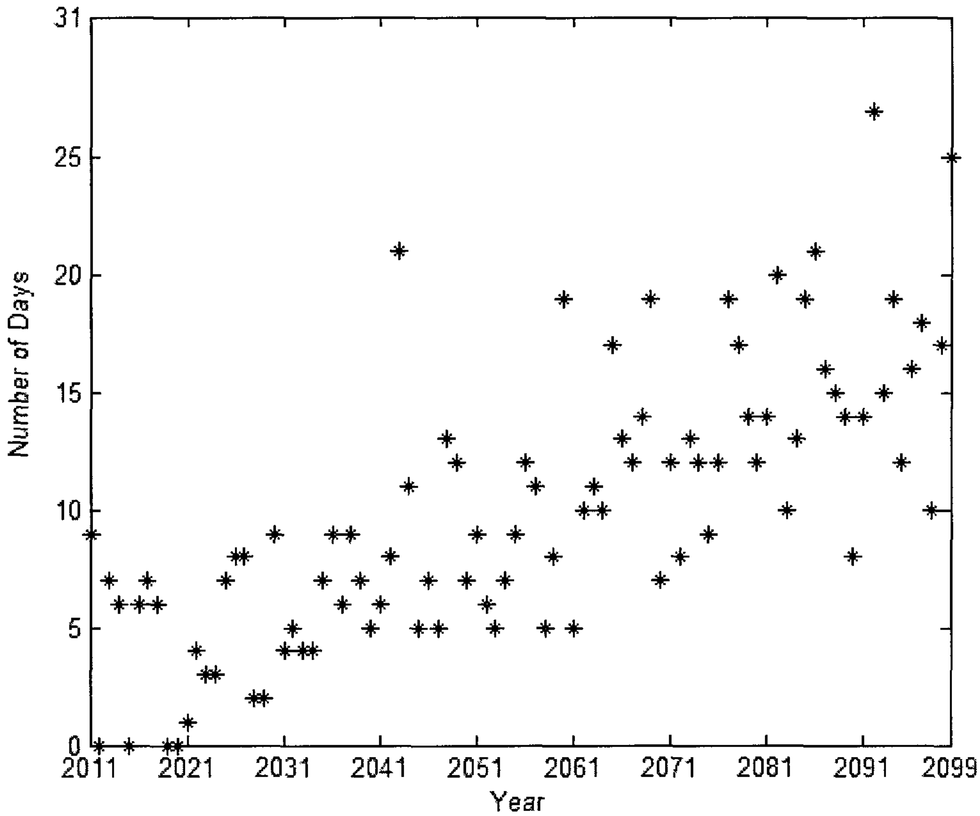


Figure 4.5: Number of Days in July where Top Oil Temperature Exceeds 65°$C$ Loading at 90% of Nameplate Rating

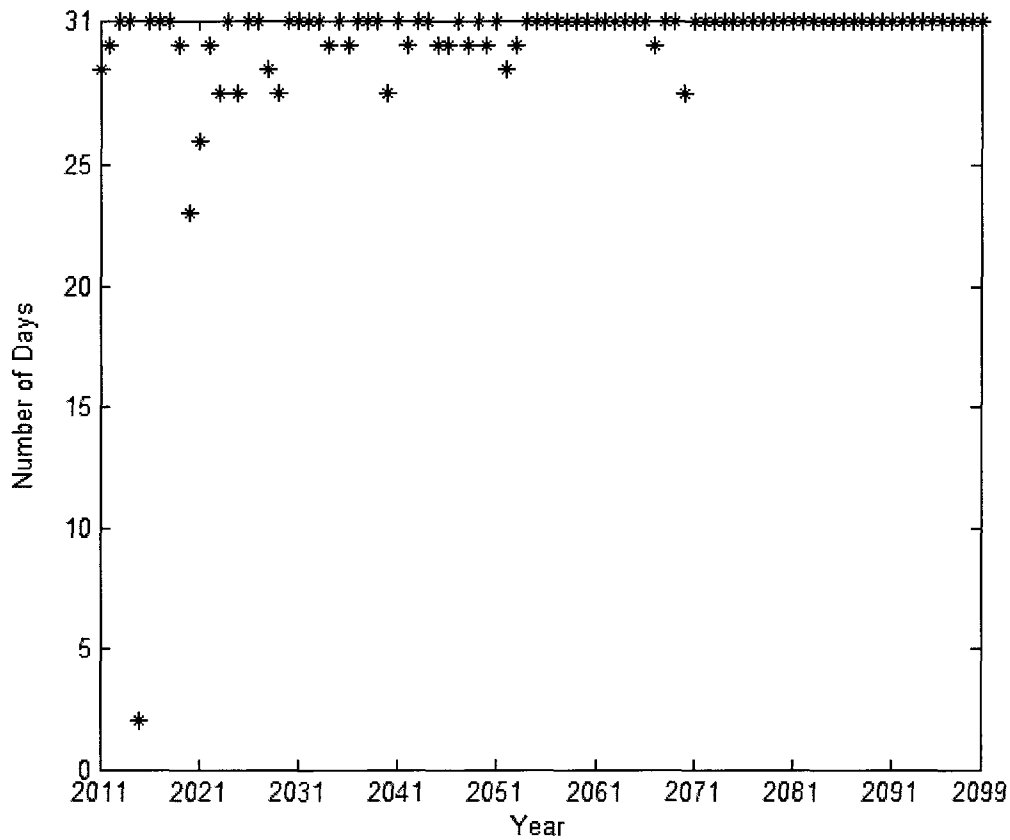


Figure 4.6: Number of Days in July where Top Oil Temperature Exceeds 65°$C$ Loading at 100% of Nameplate Rating

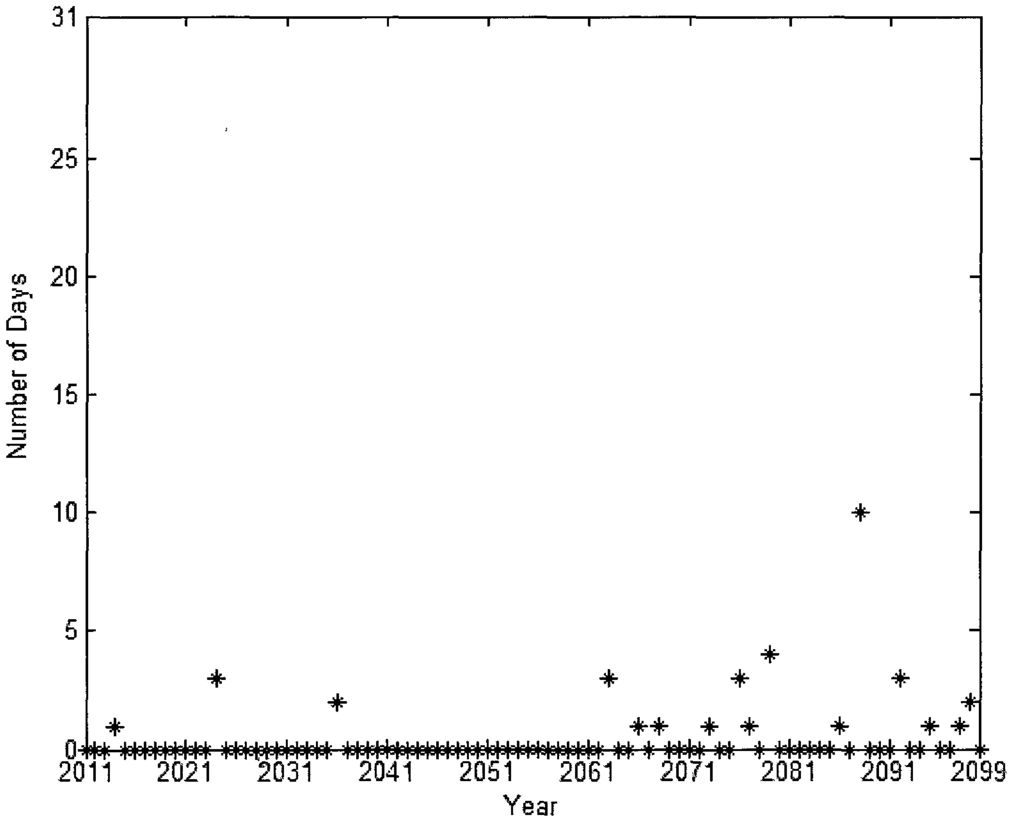


Figure 4.7: Number of Days in August where Top Oil Temperature Exceeds 65°$C$ Loading at 80% of Nameplate Rating

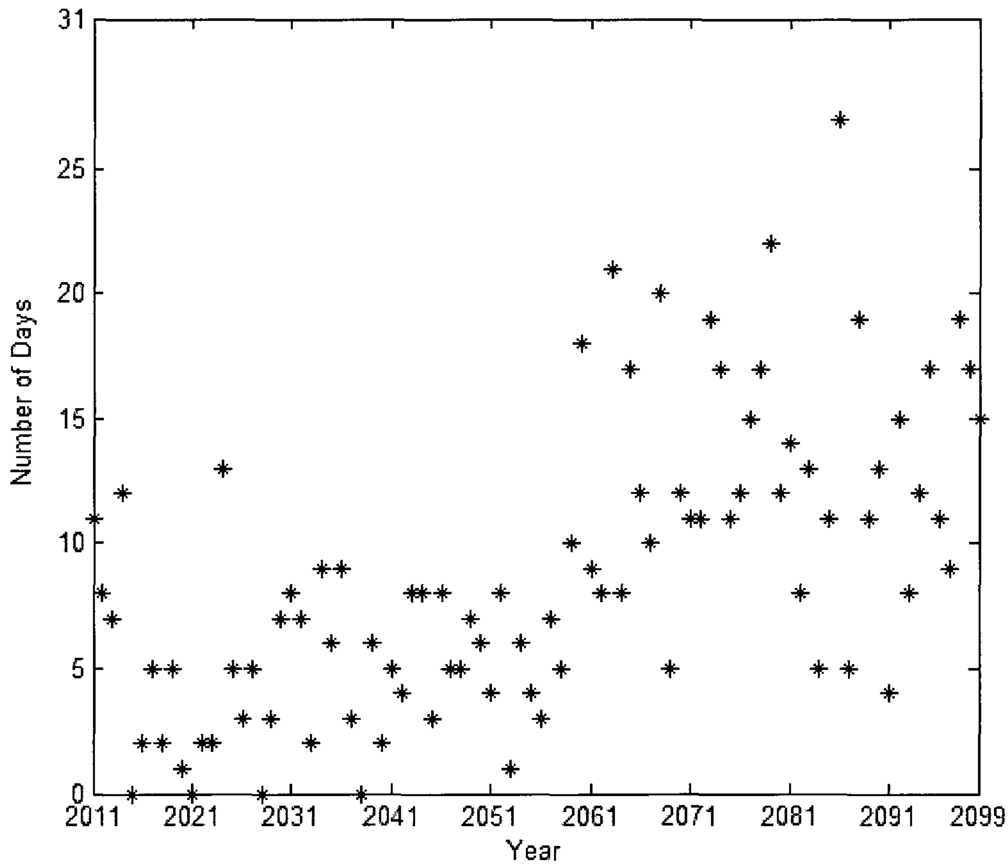


Figure 4.8: Number of Days in August where Top Oil Temperature Exceeds 65°$C$ Loading at 90% of Nameplate Rating

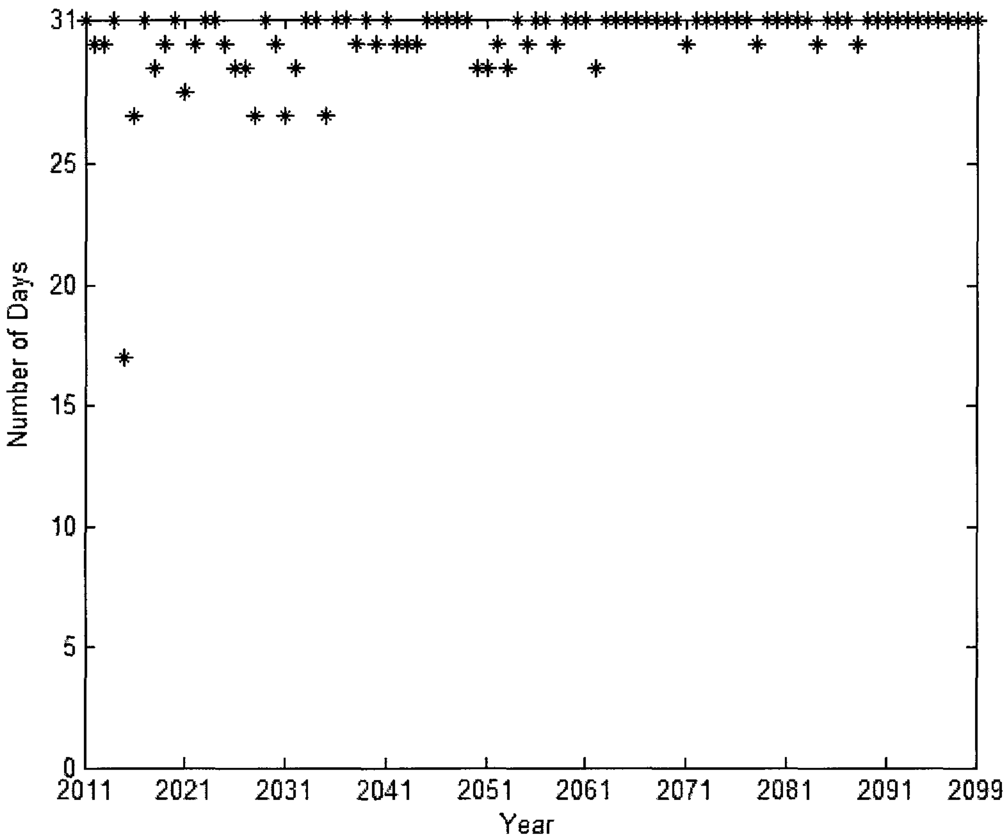


Figure 4.9: Number of Days in August where Top Oil Temperature Exceeds 65°$C$ Loading at 100% of Nameplate Rating

## 4.2 Excessive Hottest Spot Temperature Days

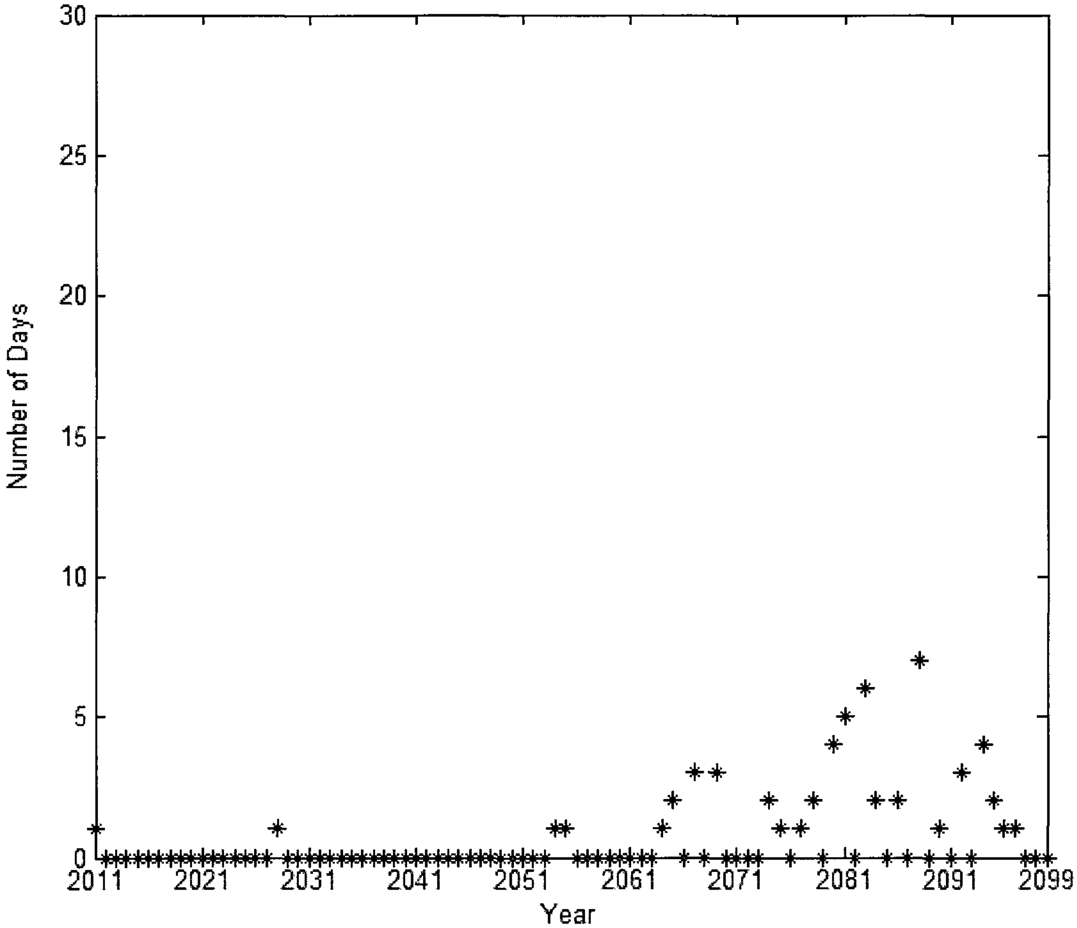


Figure 4.10: Number of Days in the June where Hot Spot Temperature Exceeds $120°C$ Loading at 90% of Nameplate Rating

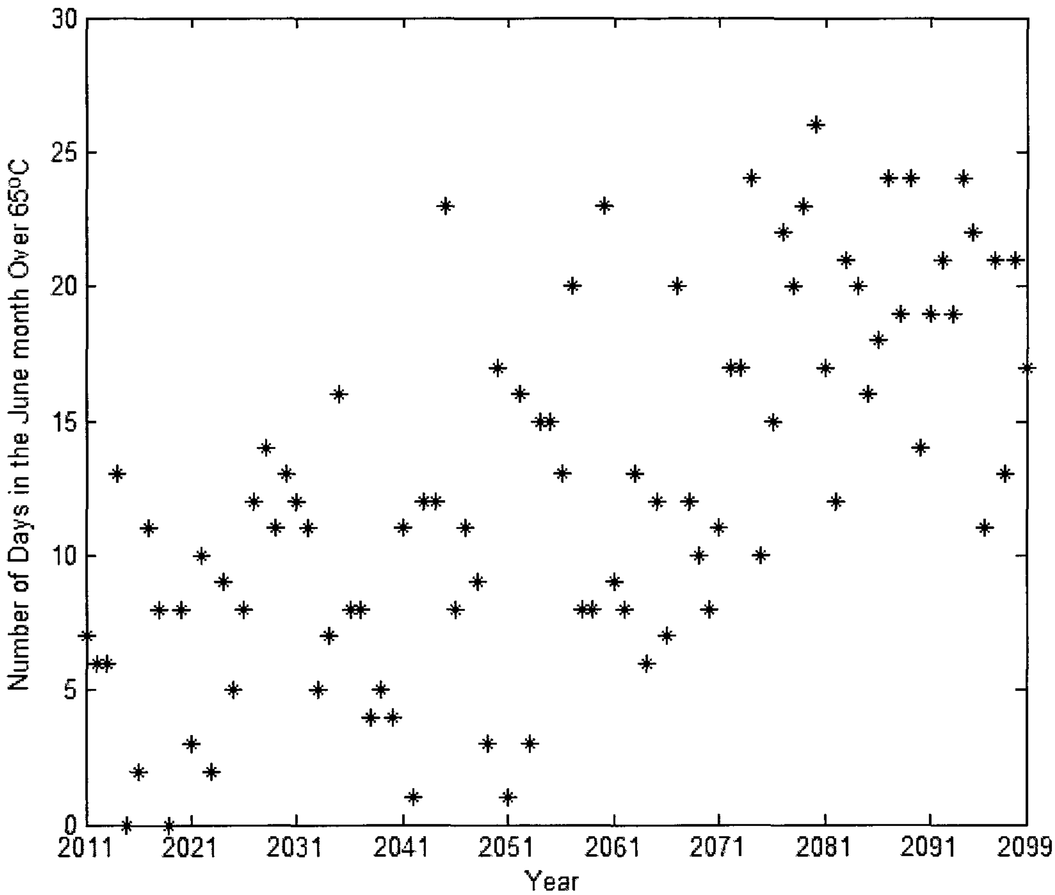


Figure 4.11: Number of Days in the June where Hot Spot Temperature Exceeds $120°C$ Loading at 100% of Nameplate Rating

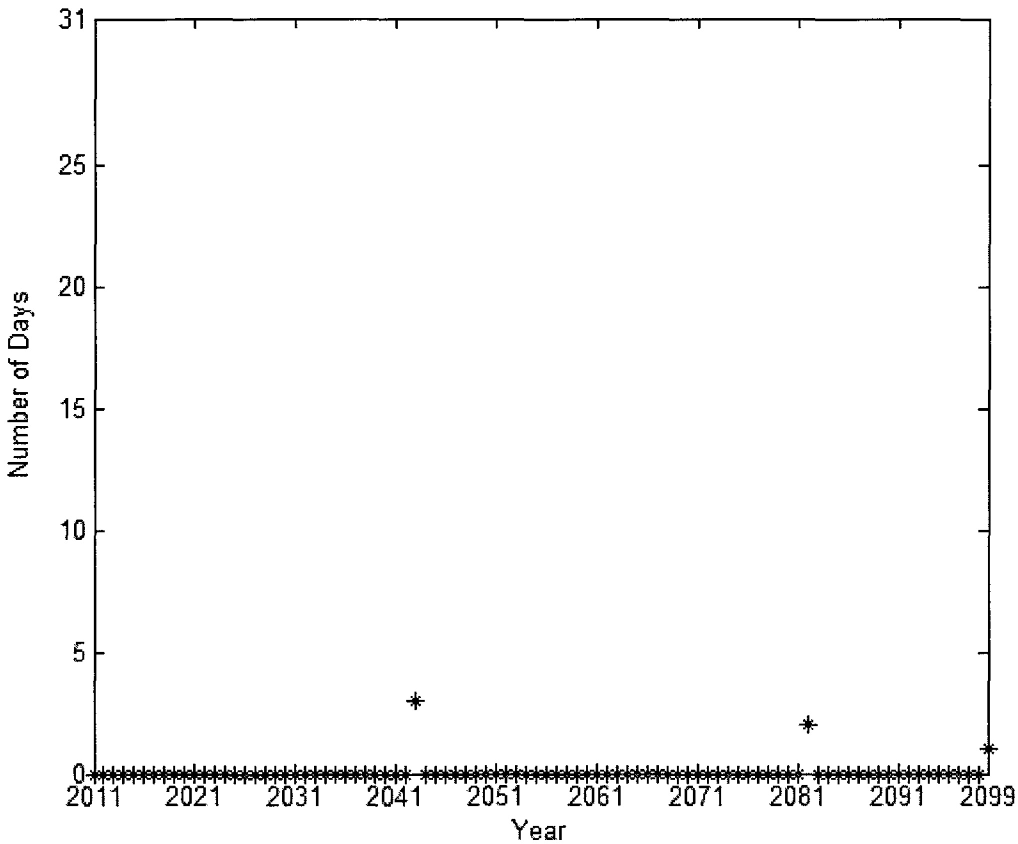


Figure 4.12: Number of Days in the July where Hot Spot Temperature Exceeds $120°C$ Loading at 80% of Nameplate Rating

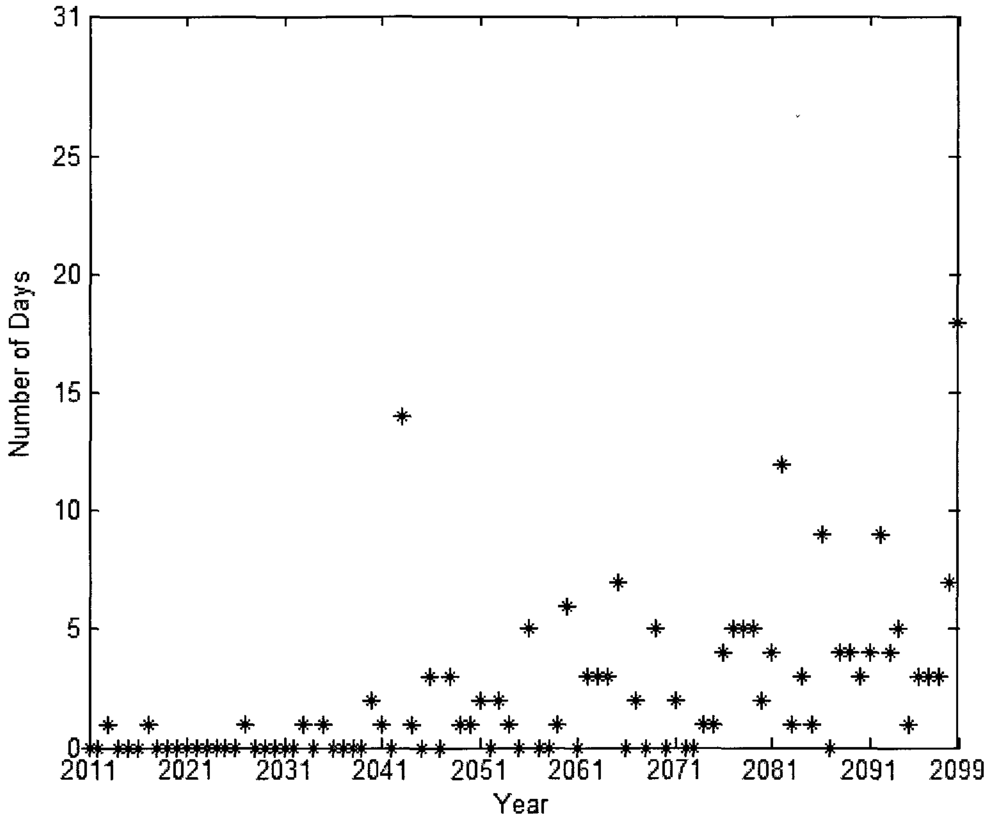


Figure 4.13: Number of Days in the July where Hot Spot Temperature Exceeds $120°C$ Loading at 90% of Nameplate Rating

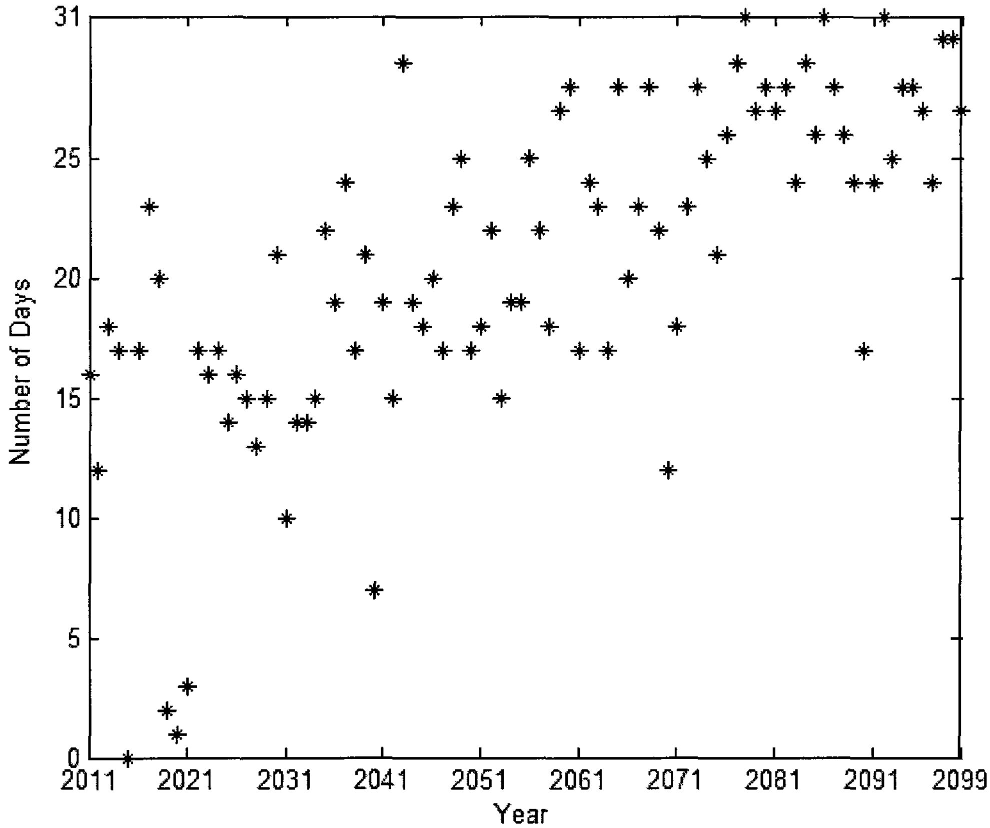


Figure 4.14: Number of Days in the July where Hot Spot Temperature Exceeds $120°C$ Loading at 100% of Nameplate Rating

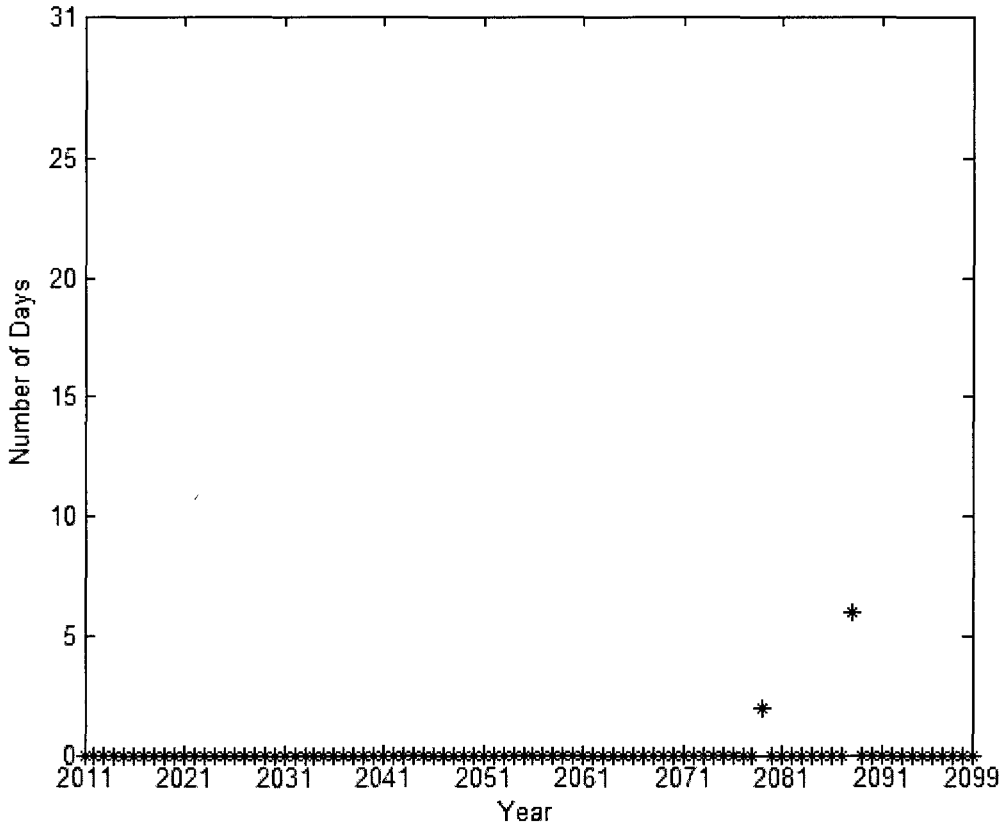


Figure 4.15: Number of Days in the August where Hot Spot Temperature Exceeds $120°C$ Loading at 80% of Nameplate Rating

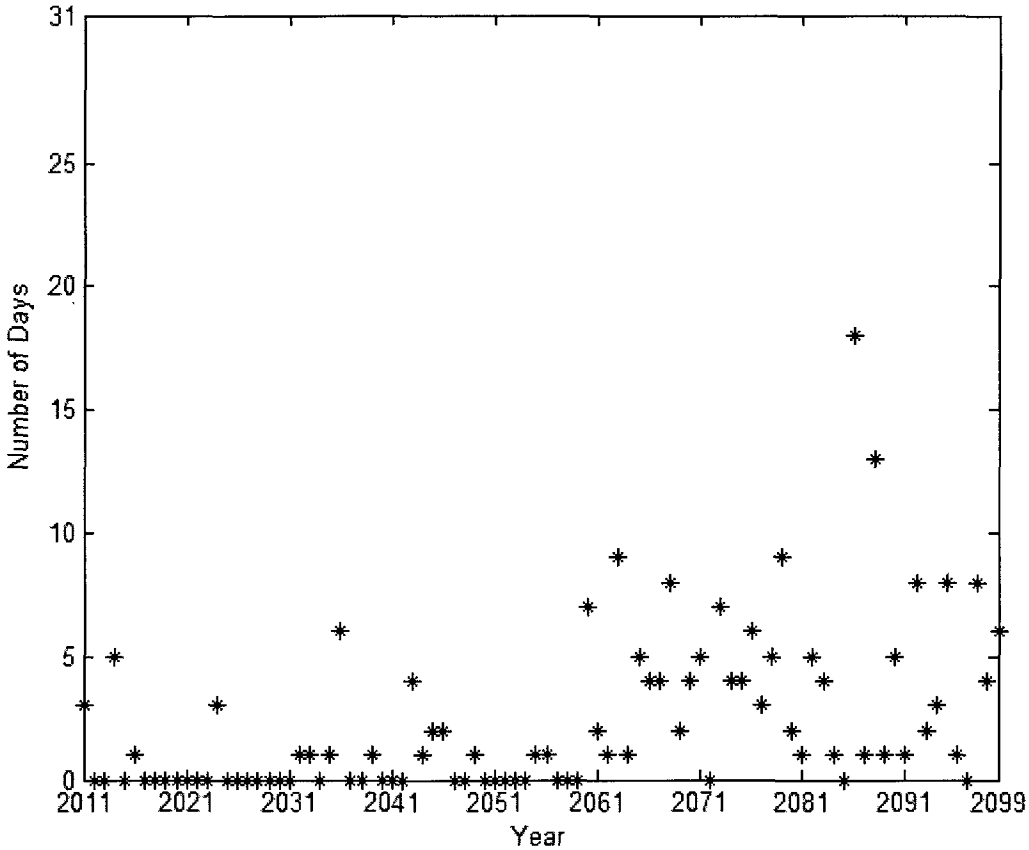


Figure 4.16: Number of Days in the August where Hot Spot Temperature Exceeds $120°C$ Loading at 90% of Nameplate Rating

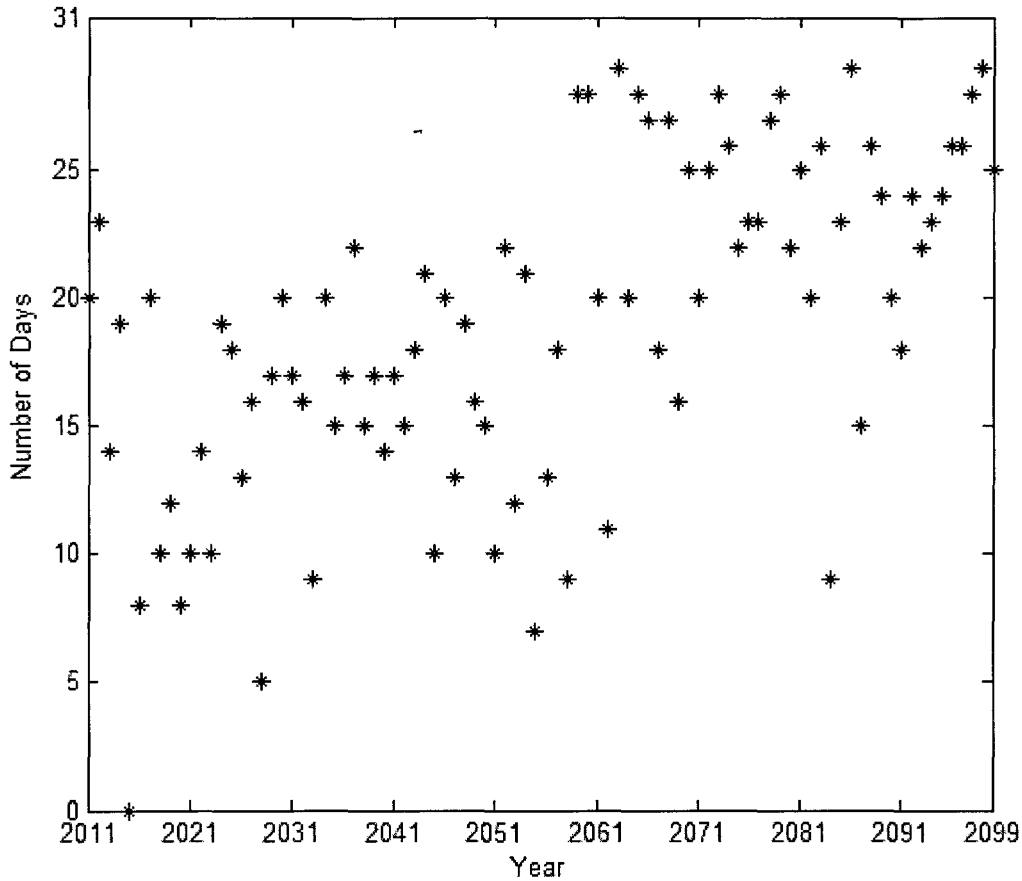


Figure 4.17: Number of Days in the August where Hot Spot Temperature Exceeds $120°C$ Loading at 100% of Nameplate Rating

The data presented in Fig. 4.1 through 4.17 enable two conclusions to be drawn about the relative frequency of transformer thermal overload events under projected New England climate change through 2100. It was found that transformers loaded at 70% or less of their nameplate rating will experience no thermal overload events due to prolonged, elevated daily maximum temperatures in the summer months of June, July and August. However, transformers loaded at 80% or more of their nameplate rating will experience an increasing frequency of thermal overload events as time progresses to 2100. Utility engineers have informed us [17] that many transformers are already operating close to their nameplate ratings during the summer months, and thus the results depicted in the top oil and hottest spot graphs for normalized loads of 90% and 100% indicate that thermal overload will occur on 10 or more days of each summer month as we near the end of this century. The present analysis does not reveal the duration of each isolated overload event, but that would be of interest because utilities use both overload frequency and duration to estimate the aging of a transformer[17].

# CHAPTER 5

# CONCLUSION AND SUGGESTED FUTURE WORK

## 5.1 Conclusion

The impact of long term prospective climate change on the reliability of large electric power transformers in the Northeast United States was successfully analyzed in this thesis. Downscaled GCM simulated temperature time series through the year 2100 were used together with standard transformer thermal models to predict the future peak power demand for the summer months and for the calculation of the transformer temperatures with respect to variation in the climate. In this thesis we performed a proportionality analysis, where this program serves as a template for the calculation of the transformer temperature, i.e., this analysis is not done in specific for a particular transformer rating. The program is simple enough that the variable values can be modified as desired, and it can be used for different transformer ratings. The final code enables the user to perform both the prediction of transformer temperature for the peak demand and the percentage of name plate rating analysis. The program that has been written for this thesis work provides utilities with an effective way of managing the operation planning procedure for the utility. The code also helps the user to predict the changes that take place in the transformer due to variation in the climate. The code is adaptable to different types of transformer, and requires a few minor changes to be implemented on any other network. The results that are inferred from the temperature graphs show how likely the transformer temperatures will exceed the internal temperature limits under future climate change scenarios.

## 5.2 Future Work

The study was mainly performed to analyze the impact of climate change on the transformers reliability in the Northeast United States. This can be used in the future for the following purposes

### 5.2.1 Ways to Improve These Analyses

1. Identify transformer base load at which relative frequency of short term overload events begins to increase significantly:

   In the previous chapter, we specified the base load as a percentage of name plate rating. One could actually infer from the graphs Fig. 3.1 through Fig. 3.3 the peak of the month and year and perform a detailed analysis of that data set of the temperature series. This helps the utility to plan for the demand in load and perform wiser operation planning procedures and decision making processes.

2. Three hour time interval GCM Data set:

   The GCM data sets are publicly available [11]. The three-hour interval temperature series data from GCM data sets can be used for a finer scale of analysis. These data sets are not locally defined; hence one must use a downscaling process to use it for the area of interest.

3. Extending monthly peak day demand model to daily peak day demand model:

   In this thesis we have calculated the monthly peak day demand for the Northeast U.S. using a monthly peak day demand model. This can be further extended to use daily peak day demand model.

4. Downscaling of Temperature series:

   In the future work the downscaling of the GCM temperature time series could be extended to the spatial scale that is commensurate with the utility power supply area. This would permit more refined results to be obtained for regions of the size that are important in utility planning processes.

5. Reliability of transformers in the power supply area:

   There are different kinds and sizes of transformers in the utility network. This model serves as a template that can be used to perform reliability projections across an entire utility of transmission and distribution networks, thus reducing the time and effort to perform individual analysis and extending this study from reliability of a single transformer to reliability of transformers over the entire network.

6. Use STLF(1-3 hours) models:

   Use short term load forecasting models together with transformer dynamic thermal models to obtain better estimates of day the counts for transformer internal temperature threshold exceedance. Standard short term load forecasting models use the ambient temperature and humidity index to more accurately predict likely power demand.

# Appendix

Matlab Code for the Month of June

```
A=xlsread('Vinayaka');% Load data set
B=A(:,4); Reading Tmax from the data file
c=A(:,1); Reading Year from the data file
D=A(:,3); Reading day of the month from the data file.
j=A(:,2); Reading Month from the data file
i=1;
for pt=5
May_Index=find(j==pt);
X1=A(May_Index,:);
for Year1=1960:2099
Index2=find(X1(:,1)==Year1);
Index2;
[MinTemp_5((Year1-1960+1),1:31)]=X1(Index2,6);
end
end
for m=6
June_Index=find(j==m);
X=A(June_Index,:);
for Year=1960:2099
Year_Index=find(X(:,1)==Year);
Year_Index;
[Max_Temp((Year-1960+1),1:30)]=(X(Year_Index,4));
[Min_Temp((Year-1960+1),1:30)]=X(Year_Index,6);
MinPrior_Temp((Year-1960+1),2:30)= Min_Temp((Year-1960+1),1:29)
[MinPrior_Temp((Year-1960+1),1)]= MinTemp_5((Year-1960+1),30);
```

```
ct=1;
for ct=1:30
if (Max_Temp((Year-1960+1),ct)<=18.34)
MaxCDD(Year-1960+1,ct)=0;
else
MaxCDD(Year-1960+1,ct)=(Max_Temp((Year-1960+1),ct)-18.34);
end
if (Min_Temp((Year-1960+1),ct)<=15.56 || MinPrior_Temp((Year-1960+1),ct
)<= 15.56)
CumMinCDD(Year-1960+1,ct)=0;
else
CumMinCDD(Year-1960+1,ct)=0.7*(Min_Temp((Year-1960+1),ct)-15.56)+
                              0.3*(MinPrior_Temp((Year-1960+1),ct)-15.56);
end
Pdemand((Year-1960+1),ct)=(4.694*MaxCDD((Year-1960+1),ct))+
                             (8.816*CumMinCDD((Year-1960+1),ct))+1248.873-702.945;
ct=ct+1;
end
Meanofmonths((Year-1960+1))=mean(Pdemand((Year-1960+1),:));
Maxofmonths((Year-1960+1))=max(Pdemand((Year-1960+1),:));
Minofmonths((Year-1960+1))=min(Pdemand((Year-1960+1),:));
MADD((Year-1960+1))=(Maxofmonths((Year-1960+1))-Minofmonths((Year-1960+1)))/20;
Mhist((Year-1960+1),:)=Pdemand((Year-1960+1),:)+MADD((Year-1960+1));
for xt=1:30
DFJune((Year-1960+1),xt)=Pdemand((Year-1960+1),xt)/562;
ADJune((Year-1960+1),xt)=(DFJune((Year-1960+1),xt))*(562/150)*(150/187);
K1((Year-1960+1),xt)=ADJune((Year-1960+1),xt);
xt=xt+1;
end
end
length(Min_Temp);
i=i+1;
```

```
end
AT1=Max_Temp; Ambient Temperature for the month of June
R=3.2;  Ratio of load loss to no-load loss
tTO=3.5; Old thermal time constant for rated load
t=1;  time interval
m=0.8; Exponent of loss function vs. top-oil rise
n=0.8; Exponent of load squared vs.winding gradient
DTr=65;  Top oil rise over the ambient temperature at rated load
DTi=0;Top oil rise over ambient temperature at start time of interval
TOP=50; Assumed Previous Top Oil  temperature
DHr=50; Hot spot rise over ambient temperature
DHi=0; Initial Hot spot rise over top oil temperature at start time of
the interval
Ths=0.08; Winding time constant of the hottest spot in hours
C=1.43; Transformer thermal capacity,Watt-hours/degree.
Pr=776; Total loss in Watts at rated load.
Ref_load=[0.2,0.3,0.5,0.8,0.9,1];
for r= 1:6
i=50;
for rt=1:30
DTUJune(rt,:) =((((DFJune(i,rt)*Ref_load(r)*R)+1)/(R+1))^n)*DTr;
end
rt=0;
DTUiJune(r,:)=DTUJune;
end
Ref_load=[0.2,0.3,0.5,0.8,0.9,1];
GG=1;
countofdays=0;
hsscountofdays=0;
for r= 1:6
Ref_load(r);
for i=51:140
```

```
for mct=1:30
DTu(i,mct)=((((DFJune(i,mct)*Ref_load(r)*R)+1)/(R+1))^n)*DTr;
DTui=DTu(i,mct);
TO(i,mct)= DTu(i,mct);
TOP=TO(i,mct);
DHU(i,mct)=((DFJune(i,mct)*Ref_load(r))^(m))*DHr;
HS(i,mct)=TO(i,mct)+DHU(i,mct);
tTOR=C*(DTr/Pr);
test=(DTu);
end
end
DTUU(GG)={DTu};
TOO(GG)={TO};
DHUU(GG)={DHU};
HSS(GG)={HS};
GG=GG+1;
end
for tcnt=1:6
for yct=51:140
for dct=1:30
if((DTUU{1,tcnt}(yct,dct))>=65)
dDTUU{1,tcnt}(yct,dct)=DTUU{1,tcnt}(yct,dct);
countofdays=countofdays+1;
else
dDTUU{1,tcnt}(yct,dct)=0;
end
if((HSS{1,tcnt}(yct,dct))>=120)
dHSS{1,tcnt}(yct,dct)=HSS{1,tcnt}(yct,dct);
hsscountofdays=hsscountofdays+1;
else
dHSS{1,tcnt}(yct,dct)=0;
end
```

```
end
ctday(tcnt,yct)= countofdays;
hctday(tcnt,yct)= hsscountofdays;
countofdays=0;
hsscountofdays=0;
end
end
for ctld=1:6
figure;
ctday(ctld,:)
plot(51:140,ctday(ctld,(51:140)),'*');
ylabel('Number of Days');
xlabel('Year');
pause;
hctday(ctld,:)
plot(51:140,hctday(ctld,(51:140)),'*');
ylabel('Number of Days');
xlabel('Year');
pause;
end
```

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