

ANALYZING INDUSTRIAL ENERGY USE THROUGH
ORDINARY LEAST SQUARES
REGRESSION MODELS

by

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ABSTRACT

Extensive research has been performed using regression analysis and calibrated simulations to create baseline energy consumption models for residential buildings and commercial institutions. However, few attempts have been made to discuss the applicability of these methodologies to establish baseline energy consumption models for industrial manufacturing facilities. In the few studies of industrial facilities, the presented linear change-point and degree-day regression analyses illustrate ideal cases. It follows that there is a need in the established literature to discuss the methodologies and to determine their applicability for establishing baseline energy consumption models of industrial manufacturing facilities.

The thesis determines the effectiveness of simple inverse linear statistical regression models when establishing baseline energy consumption models for industrial manufacturing facilities. Ordinary least squares change-point and degree-day regression methods are used to create baseline energy consumption models for nine different case studies of industrial manufacturing facilities located in the southeastern United States. The influence of ambient dry-bulb temperature and production on total facility energy consumption is observed. The energy consumption behavior of industrial manufacturing facilities is only sometimes sufficiently explained by temperature, production, or a combination of the two variables.

This thesis also provides methods for generating baseline energy models that are straightforward and accessible to anyone in the industrial manufacturing community. The methods outlined in this thesis may be easily replicated by anyone that possesses basic

spreadsheet software and general knowledge of the relationship between energy consumption and weather, production, or other influential variables. With the help of simple inverse linear regression models, industrial manufacturing facilities may better understand their energy consumption and production behavior, and identify opportunities for energy and cost savings.

This thesis study also utilizes change-point and degree-day baseline energy models to disaggregate facility annual energy consumption into separate industrial end-user categories. The baseline energy model provides a suitable and economical alternative to sub-metering individual manufacturing equipment. One case study describes the conjoined use of baseline energy models and facility information gathered during a one-day onsite visit to perform an end-point energy analysis of an injection molding facility conducted by the Alabama Industrial Assessment Center. Applying baseline regression model results to the end-point energy analysis allowed the AIAC to better approximate the annual energy consumption of the facility's HVAC system.

DEDICATION

This thesis is dedicated to everyone who helped me through my many years of study and guided me through the process of creating this manuscript. In particular, I dedicate this work to my advisor, family, and friends who stood by me and encouraged me throughout the time it has taken to complete this body of work.

LIST OF ABBREVIATIONS AND SYMBOLS

a	independent energy consumption
a_b	energy consumption at the change-point temperature
A	building envelope area
b	weather-dependent cooling slope
b_b	weather-dependent base level cooling slope (low temperature region)
$\beta_1, \beta_2, \beta_3$	independent variable regression coefficients
c	weather-dependent heating slope
c_b	weather-dependent base level heating slope (high temperature region)
CC	cooling coefficient or the cooling load
$cdd_i(T_{b,c})$	normalized cooling degree-days as a function of $T_{b,c}$ for the specified time interval
$cdd_i(T_{c,set})$	normalized cooling degree-days as a function of $T_{c,set}$ for the specified time interval
$CDD_i(T_{c,set})$	cooling degree-days as a function of $T_{c,set}$ over the specified time interval
COP_c	coefficient of (cooling) performance for conditioning system
c_p	specific heat of air
$CV-RMSE$	coefficient of variation of the root mean square error
E	total energy consumption
E_C	total (cooling) energy consumption
E_H	total (heating) energy consumption
f	fraction of the base energy consumption that is converted into heat

HC	heating coefficient or the heating load
$hdd_i(T_{b,h})$	normalized heating degree-days as a function of $T_{b,h}$ for the specified time interval
$hdd_i(T_{h,set})$	normalized heating degree-days as a function of $T_{h,set}$ for the specified time interval
L	heat loss coefficient of the building
\dot{m}	sum of ventilation and air infiltration mass flow rate
MSE	mean square error
n	number of observed values
η_h	efficiency of the heating system
N_i	number of days during the specified time interval i
p	number of regression parameters or coefficients
P_m	normalized total monthly quantity of units produced
Q_{base}	base (non-cooling and non-heating) energy consumption
$Q_{c,elec}$	cooling electrical energy consumption
$Q_{c,th}$	thermal cooling energy required
$Q_{c,total}$	total electrical energy consumption for cooling
Q_{free}	free heat provided by solar radiation and occupants within a building
Q_{gain}	thermal heat gain due to occupants, solar radiation, equipment, etcetera
$Q_{h,fuel}$	heating energy fuel consumption
$Q_{h,th}$	thermal heating energy required
$Q_{h,total}$	total energy consumption for heating
Q_{total}	total energy consumption
R^2	coefficient of determination
R^2_{adj}	adjusted coefficient of determination

RMSE root mean square error

SSE sum square of errors

SSR regression sum of squares

SST total sum of squares

T_{amb} ambient outdoor air temperature

$T_{amb,ij}$ average outdoor air temperature of the j^{th} day of time interval i

T_{bal} singular change-point or balance temperature

$T_{b,c}$ cooling balance-point or change-point temperature

$T_{b,h}$ heating balance-point or change-point temperature

$T_{c,set}$ interior cooling set-point temperature

$T_{h,set}$ interior heating set-point temperature

U overall building envelope conductance

X_1, X_2, X_3 independent variables

y_{act} observed value of the dependent variable

\bar{y}_{avg} mean of observed values

y_{mod} model value of the dependent variable

$(...)^+$ positive values within the parentheses are considered, otherwise the value is zero

$(...)^-$ negative values within the parentheses are considered, otherwise the value is zero

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CHAPTER 1: INTRODUCTION

Over the past few decades the topic of energy has become prominent in the sciences, politics, and the media. The ever-growing dependence on non-renewable energy sources, as well as the development, implementation, and application of renewable energy sources is a developing concern to many populations. Thus, it has become extremely important and relevant to understand the pathway of energy and to increase the end-use energy efficiency of existing residential, commercial and industrial facilities. In order to understand the energy consuming behavior of any building or facility, a baseline model must be established. Baseline energy models can help characterize end-user consumption, identify energy saving retrofit projects and estimate the savings of those proposed projects, calculate actual energy savings of retrofit projects after implementation, discover operating problems, forecast energy use, and compare energy consumption to similar buildings or operations in the residential, commercial, and industrial sectors.

The first objective of this thesis is to determine the effectiveness of simple inverse linear statistical regression models for establishing baseline energy consumption models for industrial manufacturing facilities. Extensive research using regression analysis or calibrated building simulations has been performed in order to create baseline energy consumption models for residential buildings and commercial institutions. However, few attempts have been made to discuss the applicability of these methodologies to generate baseline energy consumption models

for industrial manufacturing facilities. In the few studies of industrial facilities, the presented analysis illustrates ideal cases. It follows that there is a need in the established literature to discuss the methodologies and to determine their applicability for determining baseline energy consumption models of industrial manufacturing facilities. Without appropriate base-lining methodologies, or poor model fits, baseline energy models have no predictive ability or relevant applications to the energy consumption behavior of an industrial manufacturing facility.

The second objective of this thesis is to provide methods for generating acceptable and logical baseline energy models that are straightforward and accessible to anyone in the industrial manufacturing community. The analysis methods outlined in this thesis can be easily replicated by industrial facility personnel that possess basic spreadsheet software and general knowledge of the relationship between energy consumption and weather and production data. With the help of simple inverse linear regression models, or other inverse methods, companies may better understand their energy consumption and production behavior. In addition, employees can identify opportunities for retrofit projects where energy and cost savings may be realized.

The final objective of this thesis is to utilize baseline regression energy models to disaggregate facility energy consumption into separate end-user categories. Simple linear regression models subdivide facility total energy use into weather-dependent, independent, and production-dependent groupings. The baseline energy model provides a suitable and economical alternative to sub-metering individual manufacturing equipment. According to principles of lean manufacturing and production, any activity or energy consumed that does not directly add value to the finished product is considered waste. Understanding the amount of energy consumed by each end-user identifies energy savings opportunities and maximizes a facility's true production potential.

The literature review provided in Chapter 1 shows that significant research has been performed trying to discern the most accurate and appropriate process for establishing a baseline energy model. Simple ordinary least squares regression models, artificial neural network analysis, and detailed calibrated building models are among the most renowned proposed methods, and are discussed. However, it seems that accuracy and detail is sometimes sacrificed for the amount of effort and time required for the analysis. Nevertheless, simple statistical linear regression models have been presented as the most favorable method of analysis for understanding the basic characteristics of energy behavior, and were selected as the focus method of analysis for this thesis. Chapter 2 explains the specific methods contained in the analysis. Chapter 3 presents selected industrial facility case studies and discussion of the results. Chapter 3 also illustrates the conjoined use of baseline energy models and information gathered during a one-day onsite visit to perform an end-point energy analysis for an industrial manufacturing facility. Chapter 4 presents conclusions and outlines future work.

1.1 Background

The analysis of measured energy use and associated data is invaluable and endless, and involves many different parties associated with it. Production engineers and business executives are concerned with how much energy is being used to develop a product; energy auditors are concerned with identifying energy savings opportunities that are cost effective; and HVAC engineers are concerned with building characteristics, cooling load and occupancy schedule. Producing a relevant and meaningful baseline energy consumption model for any type of facility, whether it's residential, commercial, or industrial, provides immeasurable insight to those concerned with energy consumption. However, various different methodologies have been identified as the preferred procedure for obtaining a baseline energy model.

Published literature has presented numerous methods for analyzing and predicting energy use by using a correlation between utility bills and weather data or other determining factors. The practice of weather-normalizing facility energy use began with the variable-base degree-day PRISM method of Fels (1986) which analyzed residential energy consumption. Previously, weather normalization procedures were not documented when analyzing a baseline energy model, or when weather normalization was applied, polynomial fits of energy data to weather provided a poor physical basis for energy consumption (Claridge, 1998). The practice of weather normalization has since evolved into utilizing other various ordinary least squares models and takes on a more complicated approach in artificial neural network and calibrated forward models. One of the most cost- and time-effective ways to model baseline energy behavior is through simple statistical inverse modeling. However, more complicated methods have been shown to provide slightly more statistical accuracy, even if the physical basis behind the model is lacking.

The baseline energy methods presented in the established literature are separated by two commonly used basic ideas: forward models, and inverse models (Rabl, Norford, & Spadaro, 1992; Zhang, O'Neill, Wagner, & Augenbroe, 2013). Forward models, like calibrated building simulations, are intended to solve the “forward problem.” That is, forward models are best suited for designers concerned with calculating the peak and average loads on a building based on the design inputs. However, the inverse model, like data-driven regression analysis, may alternatively be used to solve the “inverse problem.” That is, one can learn about the building or facility characteristics by determining a baseline energy consumption model based on observed or measured energy use, obtained from utility bills or any other management system.

One can speculate that inverse models are advantageous over forward models when determining a baseline energy consumption model of an existing facility. Forward models often

require the re-creation of a building modeling project. This requires much information about the building that must be obtained from facility owners or building constructors, which may be incorrect or completely unobtainable. Furthermore, the time required for analysis is much greater, and may even require more skill. On the other hand, simple inverse models may be created directly from easily procurable weather data and utility bills which can effortlessly be provided by utility companies. There is no dispute that each of these base-lining methods will possess some sort of error from misuse of model application, model prediction errors, and incorrect correlating variables; but, it is up to the reviewer to determine the method relevant to the desired model specificity and amount of error.

The relevant questions and conclusions drawn from forward and inverse models using weather normalization are numerous. Rabl et al. (1992) propose many important questions that may be answered through the use of the inverse method. This includes comparing established and observed energy consumption with design criteria, or analyzing the adjustment of building thermostats or ventilation rate on the overall energy consumption. But perhaps the most widely used application of forward or inverse baseline energy models revolve around determining energy savings from retrofitting equipment or changing the operating profile, building shell, or structure of a facility. In fact, the measurement of savings from energy efficiency retrofits or operational changes is the most widespread analysis procedure being applied to measure building energy consumption today (Claridge, 1998). Energy savings were once documented by simple savings observed in monthly utility bills, although these savings are not always the sole result of a retrofit project. Weather normalization and accounting for other important variables allow for the differentiation between actual energy savings and observed or estimated energy savings that may be skewed by changes in progressive annual weather data or other variables. If these

changes are not accounted for between a pre- and post-retrofit period, then the energy savings are erroneous and misrepresented (Kissock, Reddy, & Claridge, 1998; Kissock & Eger, 2008). Therefore, determining an accurate baseline energy model is vital in developing accurate energy savings calculations and has been outlined in various protocols, such as ASHRAE Guideline 14-2002 which uses temperature based regression models to measure energy savings in the Whole Building Approach (ASHRAE, 2002).

Although much of the published literature describes the function of baseline energy models for calculating or estimating energy savings from a retrofit project, the focus of this thesis will not be on calculating energy savings. A main objective of this thesis is to evaluate the effectiveness of ordinary least squares regression models in providing feasible baseline energy models. Therefore, the case studies presented in this thesis utilize various forms of an ordinary least squares regression model. These models are physically meaningful, and thus can be useful in understanding building characteristics and industrial energy behavior. The inherent complexity of artificial neural network or calibrated simulation models prohibits their widespread use. Therefore, the use of artificial neural network and calibrated simulation models to describe energy use are not applied in this study; these methods are only presented in the literature review in this chapter for the sake of a comprehensive view of currently available baseline energy modeling methods.

1.2 Steady State Energy Balance

A simple energy balance of a building is a sufficient and significant starting point for understanding the correlation between energy consumption and outdoor air temperature. Both steady state and transient energy balances may be considered initially. Transient models may be used to evaluate warm-up and cool-down effects for changes in thermostat set-points, control of

HVAC equipment startup, and calculation of hourly peak loads (Rabl et al., 1992). However, transient analysis requires hourly data which is not often available or conveniently accessible. The methods utilized in the study presented in this thesis include the use of a steady state model and thus will be the primary focus.

The steady state energy balance of a building using energy to cool during warm summer months is presented first. Cooling energy consumption must address two components, sensible heat gain and latent heat gain. In most residential and commercial buildings the latent cooling is a small fraction of the sensible cooling consumption. However, this assumption may not be valid for large commercial or industrial facilities where latent cooling can be a significant portion of the total cooling energy (Katipamula, Reddy, & Claridge, 1994). Much of the latent load can be attributed to ventilation, which is a strong function of ambient dew-point temperature or relative humidity. This may be an important factor in industrial facilities located in the southeastern United States, where humidity levels are high during warm spring and summer months. However, studies have shown that in some cases latent and solar cooling loads are linearly related with outdoor air temperature, and are accounted for in simple linear regression models (Ruch, Chen, Haberl, & Claridge, 1993; Reddy, Kissock, & Ruch, 1998). This fact is further emphasized when monthly energy use is considered (Carpenter, Seryak, Kissock, & Moray, 2010). For the purposes of this study, the impact of latent heat loads will be disregarded. It is assumed that the latent cooling loads vary linearly with outdoor dry-bulb temperature.

For the purposes of this study, the total energy gain of the building includes the heat gain due to solar radiation, occupants, and operating equipment, as well as air infiltration and heat gain through the building envelope (Rabl et al., 1992). Based on the first law of thermodynamics the thermal cooling energy required to remove the heat from within the building must be

equivalent to the thermal energy gained. The steady state cooling energy balance of a particular building may be explained in Equation 1 below.

$$Q_{c,th} = Q_{gain} + L(T_{amb} - T_{c,set}) \quad (1)$$

where,

$Q_{c,th}$ = thermal cooling energy required,

Q_{gain} = thermal heat gain due to occupants, solar radiation, equipment, etc.,

L = heat loss coefficient of the building,

T_{amb} = ambient outdoor air temperature,

$T_{c,set}$ = interior cooling set-point temperature.

Electrical energy is the main consumer of cooling conditioning equipment. The amount of electrical energy consumed by the cooling equipment may be determined by the quotient of the required thermal cooling energy and the cooling coefficient of performance, COP_c , of the equipment, as shown in Equation 2.

$$Q_{c,elec} = \frac{Q_{c,th}}{COP_c} \quad (2)$$

where,

$Q_{c,elec}$ = cooling electrical energy consumption,

COP_c = coefficient of (cooling) performance for conditioning system.

The total electrical energy use of the building may be defined as the sum of the cooling electrical energy consumption and the base electrical energy consumption. The base electrical energy consumption includes the electricity used by all other non-cooling electrical equipment. The total electrical energy consumption of a building is defined in Equation 3.

$$Q_{c,total} = \frac{Q_{c,th}}{COP_c} + Q_{base} \quad (3)$$

where,

$Q_{c,total}$ = total electrical energy consumption for cooling,

Q_{base} = base (non-cooling and non-heating) energy consumption.

By substituting Equation 1 into Equation 3, the total electrical energy consumption may be redefined by Equation 4. It should be noted that due to the steady state assumption of the energy balance the values for heat gain, building heat loss coefficient, interior cooling set-point temperature, cooling coefficient of performance, and base level energy consumption are assumed to be constant values (Rabl et al., 1992). Equation 4 displays how electrical energy consumption correlates with outdoor air temperature by performing a steady state energy balance of a particular facility.

$$Q_{c,total} = \frac{[Q_{gain} + L(T_{amb} - T_{c,set})]}{COP_c} + Q_{base} \quad (4)$$

Rabl et al. (1992) further defines Q_{gain} , or the thermal heat gain due to solar radiation, occupants, and operating equipment, in Equation 5. The author states that the heat gained from operating equipment is equivalent to a fraction f of the energy consumption of all of the non-cooling and non-heating equipment, previously defined as the base level energy consumption, Q_{base} . The author also defines the heat gained from solar radiation and occupants within the facility as the free heat gain, or Q_{free} . Therefore the total internal heat gain of a facility is equal to the sum of a fraction f of the Q_{base} and Q_{free} .

$$Q_{gain} = fQ_{base} + Q_{free} \quad (5)$$

where,

f = fraction of the base energy consumption that is converted into heat,

Q_{free} = free heat provided by solar radiation and occupants within a building.

The steady state energy balance of a building using energy for heating during cool winter months may also be used to validate the correlation between energy use and outdoor air temperature. Based on the first law of thermodynamics, the thermal heating energy required to heat the interior of the building must be equal to the difference of the heat lost through the building envelope and the heat gained from solar radiation, occupants, and operating equipment. The steady state heating thermal energy balance equation is shown in Equation 6 below.

$$Q_{h,th} = L(T_{h,set} - T_{amb}) - Q_{gain} \quad (6)$$

where,

$Q_{h,th}$ = thermal heating energy required,

$T_{h,set}$ = interior heating set-point temperature.

Natural gas, oil, and electricity are the primary fuel sources used for space heating. The amount of fuel consumed by the heating system may be determined by the quotient of the thermal energy required to heat the building and the efficiency of the heating equipment, as presented in Equation 7.

$$Q_{h,fuel} = \frac{Q_{h,th}}{\eta_h} \quad (7)$$

where,

$Q_{h,fuel}$ = heating energy fuel consumption,

η_h = efficiency of the heating system.

The total energy consumption of the building may be defined as the sum of the heating energy consumption and the base level energy consumption of the non-heating equipment. The total heating energy consumption is described in Equation 8. It is important to note that if the same fuel source is used for both heating and cooling, Equation 4 and Equation 8 may be combined to find the total energy consumption used for simultaneous heating and cooling throughout an entire year.

$$Q_{h,total} = \frac{Q_{h,th}}{\eta_h} + Q_{base} \quad (8)$$

where,

$Q_{h,total}$ = total energy consumption for heating.

By rearranging Equation 6 and substituting it into Equation 8, the total energy consumption can be redefined Equation 9. Again, it is assumed that values for the heat gain, building loss coefficient, interior heating set-point temperature, heating efficiency, and base level energy consumption are constant due to the steady state assumption. Equation 9 displays how natural gas, oil, or electrical heating energy consumption correlates with outdoor air temperature by performing a steady state energy balance of a particular facility.

$$Q_{h,total} = \frac{[L(T_{h,set} - T_{amb}) - Q_{gain}]}{\eta_h} + Q_{base} \quad (9)$$

1.3 Ordinary Least Squares Regression Models

Statistical inverse approaches have been favored for selecting a baseline energy model due to the relative accuracy of the models and their clear interpretability, as well as the lesser amount of time required to complete the analysis in comparison to artificial neural networks or calibrated building simulations. Initially, the power of simple statistical regression methods

could not be fully demonstrated during the times the methods were initially employed by utility companies. However, with the advancement of technology, engineers and researchers can quickly perform computational analysis over multiple sets of large scale data. Hong, Gui, Baran, and Willis (2010) proclaim that in the case of applying regression analysis to a dataset containing four years of hourly electric load and ambient temperature data it takes less than five minutes to update model parameters of the proposed regression model with only 3.5GB RAM and 2.2GHz CPU, components that are found in most desktop computers.

Ordinary least squares regression has most often been the preferred way of correlating energy consumption and weather data. Regression analysis is the part of statistics that investigates the relationship between two or more variables related in a nondeterministic fashion (Devore, 2009). These variables may be related in a linear or nonlinear fashion. When establishing the relationship between two or more variables, an equation with specified parameters is assumed to describe the data. The object is to find a vector or correct model parameters using the principle of ordinary least squares that minimizes the sum of the error squared, or the squared deviation between the model and data points (Rao & Toutenburg, 1999).

Various baseline models have been considered when attempting to model facility energy use by way of ordinary least squares regression models. Change-point piecewise linear, variable-base degree-day, multivariate change-point piecewise linear, and multivariate variable-base degree-day models have all been utilized to characterize energy use patterns in residential, commercial, and industrial facilities. In fulfillment of the ASHRAE Research Project 1050-RP, Kissock, Haberl, and Claridge created the Inverse Modeling Toolkit (Kissock, Haberl, & Claridge, 2002). The Inverse Modeling Toolkit (IMT) develops methods for calculating linear, change-point linear, and multiple-linear inverse building energy analysis models, and addresses

elements of the change-point piecewise linear, variable-base degree-day, and multivariate inverse energy models. Much like the IMT, the following sections endeavor to detail the history, application, and methods behind the various types of inverse ordinary least squares regression models.

1.3.1 Change-point Models

Change-point models are piecewise linear regression models, which in effect piece together two or more linear regressions (Marsh & Cormier, 2002). They are also referred to as first order spline models, which provide superior approximation in comparison to low-order polynomial expressions for functions that have local, abrupt changes (Chapra, 2008). Change-point models that use linear and non-linear regression analysis are the preferred method of ordinary least squares regression analysis when creating a baseline energy model.

Most regression models have been found to be linear and of the first order due to the thermodynamic principles of energy flow in buildings and the simplicity of the statistics involving the formulation of the linear models (Haberl, et al., 1996). These ordinary least squares regression models are characterized by the number of regression parameters that each contains. For example, a three-parameter change-point model consists of three regression parameters, a four-parameter change-point model consists of four regression parameters, and a five-parameter change-point model consists of five regression parameters.

Change-point models developed as a derivative of the variable-base degree-day (VBDD) method when establishing a baseline energy model. Change-point models intend to establish a relationship between energy use and average outdoor air temperature; variable-base degree-day models intend to correlate energy use and cooling or heating degree-days. An extensive explanation of the variable-base degree-day methodology can be found in the following

Section 1.3.2. According to some authors (Kissock J. K., 1993; Kissock & Seryak, 2004), the variable-base degree-day method is not often the best statistical representation for buildings that have varying degrees of heating or cooling energy use. In order to correct some of the conceived faults within the VBDD model, Schrock & Claridge (1989) developed a four-parameter change-point regression model to provide a better statistical fit to a commercial grocery store's energy consumption. Following the introduction of the four-parameter change-point model, Kissock et al. (1994) developed the EModel software which compares energy use and ambient temperature in change-point models with one, two, three, or four regression parameters. A five-parameter change-point model was then created to describe simultaneous cooling and heating, as presented in Kissock et al. (2002).

Each of the varying types of change-point models as mentioned above have been applied to show correlation between energy use and weather data in residential, commercial, and industrial buildings. In general, the process of utilizing change-point models to establish baseline energy use involves two items: applying each of the varying-parameter change-point models and choosing the best model based on the goodness-of-fit, as well as having some basic knowledge of the facility's building characteristics, control schedules, or occupancy loads (Haberl, et al., 1998). Not only can change-point models be used to create a baseline model of energy use, they may also be used to calculate pre-retrofit to post-retrofit energy savings. In 1994, the Texas LoanSTAR program estimated energy savings in 19 of 89 institutional buildings, school districts, and energy plants by comparing pre- and post-retrofit regression models of one, two, three, and four-parameter change-point models (Haberl, et al., 1996). When determining an appropriate model, each varying-parameter change-point model was applied to the energy consumption data, whereupon the best model was chosen based upon the goodness-of-fit.

Typically, change-point models represent cooling and heating energy use as it corresponds to average ambient dry-bulb outdoor air temperature. Change-point models are effective in demonstrating cooling and heating energy use since there is typically a balance-point temperature where facility energy use increases or decreases based on the setting of a thermostat or HVAC system. Simple linear and change-point models can also statistically represent the thermostatic on-off behavior in many classes of buildings, as well as the internal-external cooling-heating patterns that are observed in many buildings (Haberl, et al., 1998). The thermostat control system present in most facilities is also the reason a spline fit linear model is chosen over a polynomial (Kissock & Eger, 2008). However, the effect to which the weather and other independent variables affect the energy consumption of a building may be described in each change-point model, and will be discussed in the following sections.

The previous utilization of change-point models when evaluating facility energy consumption has focused on the study of three-parameter cooling and three-parameter heating models, four-parameter heating and four-parameter cooling models, and five-parameter combined cooling and heating change-point models. One- and two-parameter linear models have also been analyzed, but have not been found to be extremely beneficial or accurate when correlating weather and energy consumption on their own. One parameter linear models solely represent weather-independent energy consumption, while two parameter models singularly represent weather-dependent energy consumption. Two parameter models have been found to be appropriate when evaluating sub-metered energy use in constant-air-volume systems without control features or high latent loads (Kissock et al., 1998; Kissock, Haberl, & Claridge, 2003). Because of their specificity, they are generally disregarded when evaluating an overall facility baseline energy consumption model. Because most of the published literature focuses on the use

of three-parameter, four-parameter, and five-parameter change-point models, emphasis and detail will be presented on these methods in the following sections.

1.3.1.1 Three-Parameter Cooling (3PC) and Three-Parameter Heating (3PH) Models

The title of the three-parameter cooling change-point model (3PC) and the three-parameter heating change-point model (3PH) derives from the fact that three regression parameters develop from the analysis: the constant weather-independent energy consumption, the weather-dependent cooling or heating slope, and the cooling or heating balance or change-point temperature. Typically, 3PC models display electrical energy use utilized for cooling and other electrical end users, while 3PH models display heating energy use in the form of gas or oil utilized for heating and other gas or oil end users. Many published resources have presented the validity of the three-parameter cooling and three-parameter heating models when evaluating the baseline energy consumption in residential, commercial, and some industrial settings. In fact, Sever, Kissock, Brown, and Mulqueen (2011) suggest that the weather dependence of energy consumption may be accurately described by three-parameter change-point models for most industrial facilities.

Figure 1 shows the graphical representation of the 3PC change-point model. In 3PC models, energy use remains constant up to the balance-point temperature, at which the energy use begins to linearly increase with rising temperature. Figure 2 shows the graphical representation of the 3PH change-point model. In 3PH models, energy use linearly decreases with increasing temperature up to the heating balance-point temperature, at which the energy use remains constant. The derivation and description of the 3PC and 3PH change-point models is expressed in the remainder of this section.

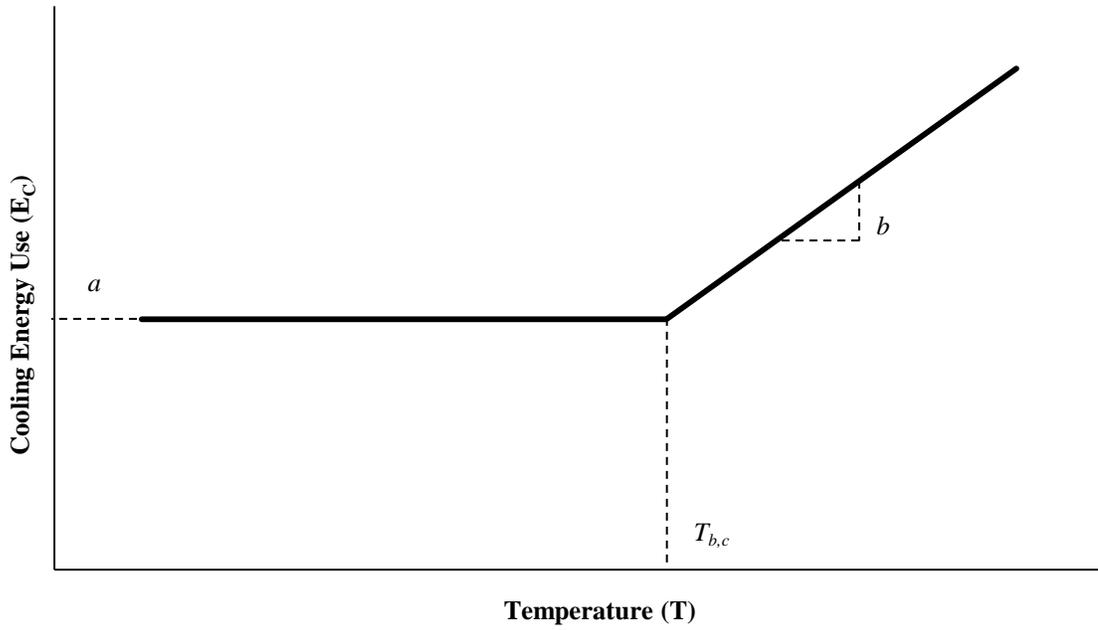


Figure 1. Three-parameter cooling change-point model (3PC).

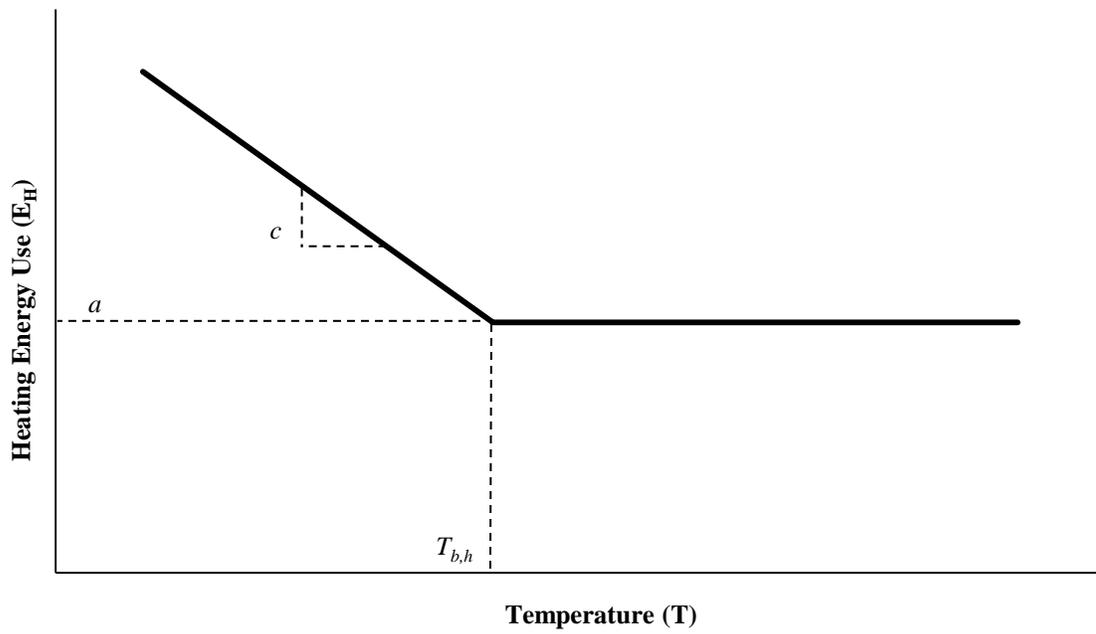


Figure 2. Three-parameter heating change-point model (3PH).

The mathematical formula representing the three-parameter cooling change-point model may be derived from Equation 4. First, the cooling balance-point temperature (also known as the change-point temperature) is established as the ambient outdoor air temperature at which no energy is required to cool the building (Kissock, 1993; Sever et al., 2011; Turner & Doty, 2007). In other words, the energy required to cool the space is equal to the sum of the internal heat gains (from occupants, equipment, and solar radiation) and the product of the overall building loss coefficient and the temperature difference between the outdoor air temperature and the facility set-point temperature. Using Equation 1 and setting $Q_{c,th}$ equal to zero, the interior cooling set-point temperature may be redefined in Equation 10.

$$T_{c,set} = \frac{Q_{gain}}{L} + T_{b,c} \quad (10)$$

where,

$T_{b,c}$ = cooling balance-point or change-point temperature.

The new definition of the interior cooling set-point temperature as described in Equation 10 may now be substituted into Equation 4. After simplifying, the total electrical energy consumption described by the cooling model may be represented in Equation 11. The “+” sign following the parentheses surrounding the temperature difference signifies that only the positive values of the difference are taken into account, otherwise the difference is equal to zero.

$$Q_{c,total} = \frac{L(T_{amb} - T_{b,c})^+}{COP_c} + Q_{base} \quad (11)$$

The heat loss coefficient of the building, L , is also referred to as the cooling load or the cooling coefficient, CC (Sever et al., 2011). The cooling load is considered the combined effect of the conductive heat gain through the building envelope and the sensible heat gain due to

ventilation and air infiltration. In effect, the heat loss coefficient or cooling load may be further defined in Equation 12.

$$CC = L = UA + \dot{m}c_p \quad (12)$$

where,

- CC = cooling coefficient or the cooling load,
- U = overall building envelope conductance,
- A = building envelope area,
- \dot{m} = sum of ventilation and air infiltration mass flow rate,
- c_p = specific heat of air.

Equation 11 may be further redefined in order to represent the typical form of the three-parameter cooling change-point model. The total energy consumed by the facility, $Q_{c,total}$, may be redefined by the variable E_C . The base level energy consumption, Q_{base} , may be redefined by the variable a . This base level energy consumption is also referred to as the non-weather-dependent, or independent energy consumption. This may be interpreted as the energy use that is used by a facility regardless of the outdoor air temperature. Finally, the variable b may be used to define the quotient between the heat loss coefficient and the cooling coefficient of performance (Sever et al., 2011). In other words, b is defined as the weather-dependent cooling slope, or the rate of increase in energy consumption that occurs as the average temperature rises. The linearity between the cooling slope and varying temperature is more pronounced in industrial facilities in comparison to residential and commercial buildings; high ventilation, combustion air and process infiltration loads are dominant in industrial facilities, and are strongly linearly related to outdoor air temperature (Kissock & Eger, 2008). The cooling change-point temperature can also represent the ambient temperature at which the energy use changes from weather-independent to

weather-dependent. Equation 13 summarizes the formula for a three-parameter cooling change-point model (Kissock et al., 2002). The units of energy use presented in Equation 13 are presented in kilowatt-hours (kWh) since electrical energy is the primary energy source used to provide cooling. The three-parameters a , b , and $T_{b,c}$ are determined by the regression analysis performed using a facility's monthly utility bills and average outdoor temperature data.

$$E_C = a + b(T_{amb} - T_{b,c})^+ \quad (13)$$

where,

E_C = total (cooling) energy consumption, kWh/day,

a = independent energy consumption, kWh/day,

b = weather-dependent cooling slope, kWh/day-°F.

It should be noted in Equation 13 that energy use is presented on a daily basis. The time interval of data presented in a typical regression model is often determined by the type of data that is available from the facility. While hourly or daily data may be used, most industrial facilities, which are the subjects of the case studies presented in this thesis, track energy consumption through analysis of monthly utility bills. Few industrial facilities have sub-metering available throughout the whole facility; sub-metering for the entirety of energy end-users can be expensive and provide copious amounts of unnecessary data. Individual industrial facility sub-systems can be sub-metered, such as compressed air systems and chilled water systems, but only represent fractions of the entire facility energy consumption. Therefore, for the purpose of this thesis, energy consumption will be expressed by daily averages.

Daily average energy use values result from the normalization of monthly utility bills, where the monthly energy use is divided by the number of days in the specified monthly time period. This removes variation of the energy consumption due to the variation in number of days

in each month. Furthermore, presenting energy consumption in a daily time period removes the effect of diurnal variation of internal heat gains and solar loads from the model (Kissock, et al., 1998). Internal heat gains and solar radiation are cyclical in nature, therefore their effect on energy consumption can be minimized by selecting a time period equal to or larger than the twenty-four hour cycle. In some studies, monthly-energy profiles have been proven to provide robust regression models similar to those generated by daily-energy data sets in residential and industrial buildings that observe consistent occupancy rates or operating profiles (Carpenter et al., 2010). Because of these reasons, the energy consumption and regression models described in this study will be represented by their daily values, as calculated from the monthly utility billing data.

Reddy et al. (1997b) presented the importance of corresponding utility bill read dates and associated monthly weather data when creating a baseline energy model. Their results indicated a noticeable difference in baseline model goodness-of-fit between energy consumption and weather data whose time periods agreed or disagreed. Though it may be unapparent to some observers, average monthly dry-bulb temperature measurements can vary significantly for monthly time periods starting at the beginning of the month or mid-way through the month. Therefore, in this thesis, care will be taken to insure that utility meter read dates coincide with appropriate weather data. More information about time boundaries is discussed in Chapter 2.

Similar to the 3PC change-point model, the formula representing the three-parameter heating change-point model may be derived from the steady state energy balance and Equation 9 described in Section 1.2. The heating balance-point, or change-point, temperature can be defined as the ambient air temperature at which no energy is required to heat the building (Kissock, 1993; Sever et al., 2011). In other words, the energy required to heat the space is equal to the

difference of the heat loss through the building envelope and from air infiltration and the internal heat gained from occupants, operating equipment, and solar radiation. Using Equation 6 and setting $Q_{h,th}$ equal to zero, the interior heating set-point temperature may be refined in Equation 14.

$$T_{h,set} = \frac{Q_{gain}}{L} + T_{b,h} \quad (14)$$

where,

$T_{b,h}$ = heating balance-point or change-point temperature.

The new definition of the interior heating set-point temperature as described in Equation 14 may now be substituted into Equation 9. After simplifying, the total heating fuel energy consumption described by the three-parameter heating change-point model may be represented in Equation 15.

$$Q_{h,total} = \frac{L(T_{b,h} - T_{amb})^+}{\eta_h} + Q_{base} \quad (15)$$

The heat loss coefficient of the building, L , may also be referred to as the heating load or the heating coefficient, HC , in terms of the 3PH change-point equation (Sever et al., 2011). Similar to the cooling load described in 3PC models, the heating load is considered as the combined effect of the conductive heat loss through the building envelope and the sensible heat loss due to ventilation and air infiltration. In effect, the heat loss coefficient or the heating load may be further defined in Equation 16.

$$HC = L = UA + \dot{m}c_p \quad (16)$$

where,

HC = heating coefficient or the heating load.

Equation 15 may be further rearranged and redefined in order to represent a three-parameter heating change-point model. The total energy consumed by the facility, $Q_{h,total}$, may be redefined by the variable E_H . The base level energy consumption, Q_{base} , may be redefined by the variable a . This may be interpreted as the non-weather-dependent or independent energy consumption. It should be noted that while the same variable a is used to describe the constant base level energy consumption in both the 3PC and 3PH model, the difference lies in the type of fuel consumption represented; electrical energy is the primary fuel source for 3PC models, while natural gas and oil are the primary fuel sources for 3PH models.

The variable c may be used to define the quotient between the heat loss coefficient and the overall space heating system efficiency (Sever et al., 2011). In other words, c is defined as the weather-dependent heating slope, or the rate of increase in energy consumption that occurs as the average temperature values decrease. The heating change-point temperature can also represent the ambient temperature at which the energy use changes from weather-dependent to weather-independent. Equation 17 summarizes the equation for a three-parameter heating change-point model (Kissock et al., 2002). Units of energy presented in Equation 17 are in units of MMBtu since natural gas is most often the primary fuel source represented by 3PH change-point models. Energy consumption in the 3PH model is also presented on a daily basis. Change-point models can be normalized by the daily average energy use in order to remove variation between the numbers of days in each month. The three-parameters a , c , and $T_{b,h}$ are determined by the regression analysis performed using a facility's monthly utility bills and average outdoor temperature data.

$$E_H = a + c(T_{b,h} - T_{amb})^+ \quad (17)$$

where,

- E_H = total (heating) energy consumption, MMBtu/day,
 c = weather-dependent heating slope, MMBtu/day-°F.

Average outdoor dry-bulb temperature data is most often the singular independent variable included in 3PC and 3PH change-point models when evaluating heating or cooling energy use. Multivariable change-point models that include additional independent variables other than outdoor air temperature may also be evaluated, and will be discussed in Section 1.3.3. However, the use of ambient temperature as the singular independent variable often eliminates statistical errors from multicollinearity while utilizing accurately measured and widely available data (Kissock et al., 1998).

1.3.1.2 Four-Parameter Cooling (4PC) and Four-Parameter Heating (4PH) Models

Schrock & Claridge (1989) first adopted the four-parameter cooling (4PC) and four-parameter heating (4PH) change-point models when analyzing the energy consumption at a commercial grocery store in Dallas, Texas. They came to justify the four-parameter model not only through a visual observation of the energy and temperature data, but also hypothesized that the behavior had a physical basis due to the increasing COP of the grocery store refrigeration equipment as the ambient temperature utilized for condenser cooling decreased (Ruch & Claridge, 1992). Furthermore, Haberl et al. (1996) and Reddy et al. (1997a) suggest that four-parameter change-point models explain the behavior of concurrent heating and cooling of the air supply stream in some commercial buildings. Large commercial buildings often have large air-handling units which may provide additional cooling or heating of the supply air from the main system. The authors also reason that latent loads present during humid and hot days as well as the fact that HVAC supply air is not always controlled linearly with ambient air temperature,

such as in constant-air-volume HVAC systems with economizers or variable-air-volume HVAC systems, may result in a four-parameter change-point model (Haberl, et al., 1996; Reddy, Kissock, Katipamula, Ruch, & Claridge, 1994; Kissock et al., 1998). Simply stated, four-parameter cooling change-point or four-parameter heating change-point models represent linear relationships for energy use that are weather depended both above and below a certain change-point temperature. Chronologically, the four-parameter change-point model was developed in response to disadvantages of the VBDD model. According to Kissock and Seryak (2004), VBDD models do not account for the instance where heating or cooling energy varies non-linearly with ambient temperature due to latent loads, or other system effects. Change-point models were thus developed to eliminate this variance.

Similar to the three-parameter change-point cooling and heating models, the four-parameter change-point models are named by the four regression parameters included in the model: the constant independent energy consumption, the weather-dependent heating or cooling slope, the weather-dependent base level cooling or heating slope, and the cooling or heating balance or change-point temperature. In four-parameter cooling change-point and four-parameter heating change-point models, the average outdoor air temperature is most often the singular independent variable, while energy consumption is the dependent variable. Both 4PC and 4PH models have two linear regions with varying slopes that are joined at a common point known as the change-point temperature. This is similar to the change-point temperature present in the 3PC and 3PH change-point models. 4PC models depict energy use linearly increasing with increasing outdoor air temperature, while 4PH models depict energy use linearly decreasing with increasing ambient air temperature. A graphical representation of the 4PC change-point model is shown in Figure 3. A graphical representation of the 4PH change-point model is shown in Figure 4.

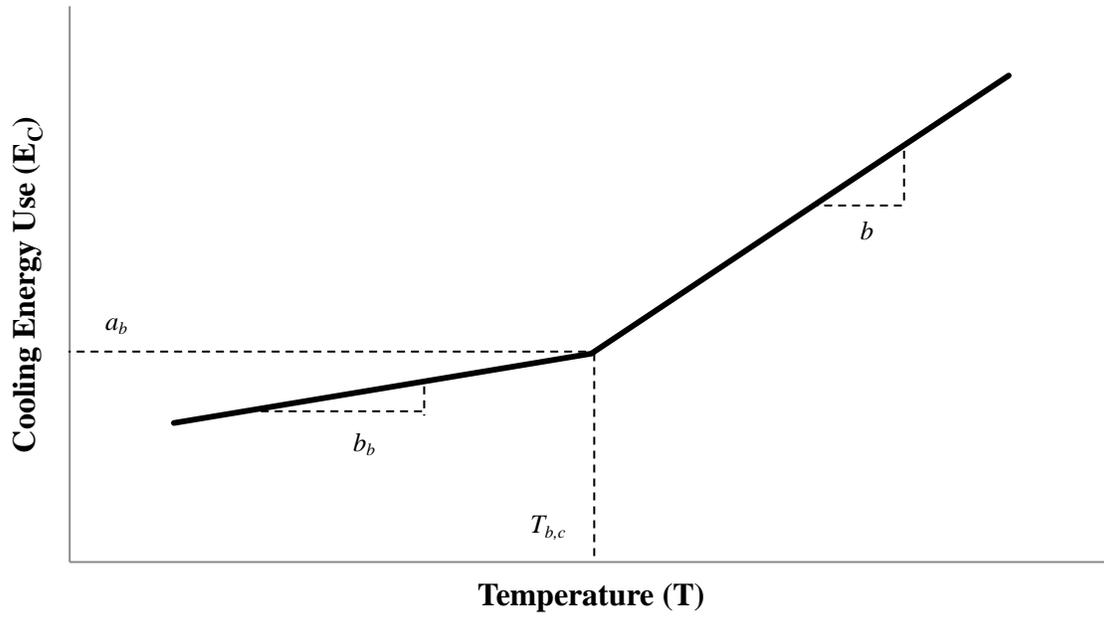


Figure 3. Four-parameter cooling change-point model (4PC).

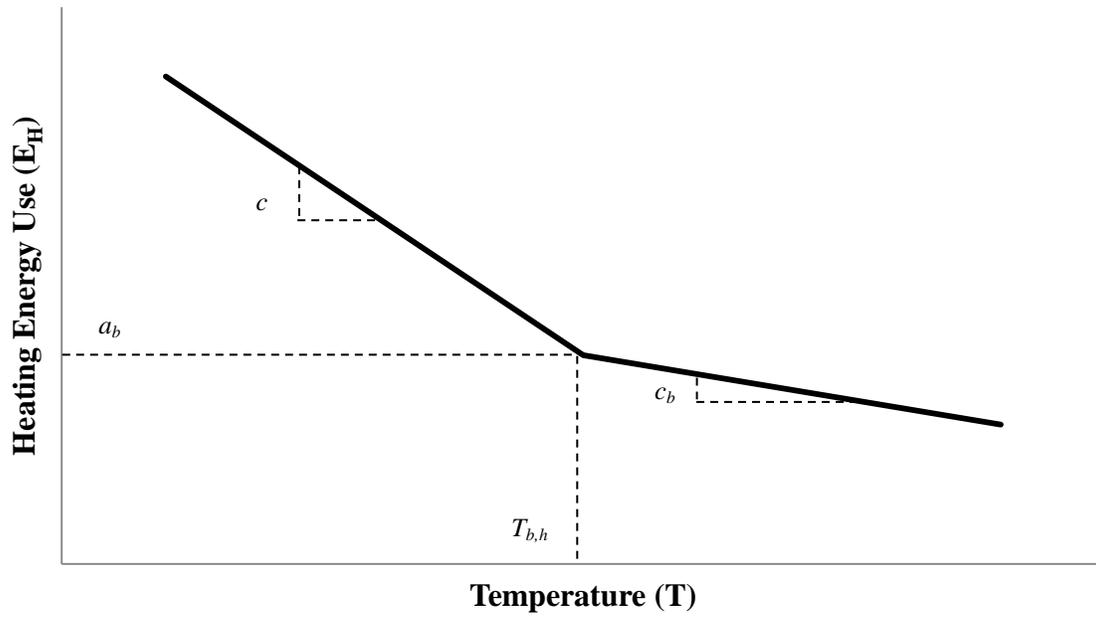


Figure 4. Four-parameter heating change-point model (4PH).

The equation for the four-parameter cooling change-point model may be derived from Equation 11 associated with the three-parameter cooling change-point model. Equation 11 shows that the total cooling fuel energy use is equal to the sum of the weather-dependent space cooling energy use and the constant base level energy consumption. Four-parameter cooling models suggest that the constant base level energy consumption only occurs at the balance-point temperature; instead, the overall facility energy consumption remains weather-dependent over the entire temperature range. This behavior could be due to refrigeration equipment, additional space conditioning systems, chillers, etc. In effect, the four-parameter cooling change-point model could be represented in Equation 18, similar to the formula presented by Ruch & Claridge (1992). The four regression parameters a_b , b , $T_{b,c}$, and b_b are determined by the regression analysis performed using a facility's monthly utility bills and average outdoor temperature data. The positive sign and negative sign following the brackets surrounding the temperature difference signify that only the positive difference or negative difference, respectively, are taken into account; otherwise the difference is equal to zero.

$$E_C = a_b + b(T_{amb} - T_{b,c})^+ + b_b(T_{amb} - T_{b,c})^- \quad (18)$$

where,

- a_b = energy consumption at the change-point temperature, kWh/day,
- b_b = weather-dependent base level cooling slope (low temperature region), kWh/day-°F.

Similar to a 3PC change-point model, the first regression coefficient a_b represents the energy use that occurs at the balance-point temperature. The second regression coefficient b represents the main cooling slope, or the rate of increase in energy use with increasing temperature in the high temperature region. The high temperature region is defined as the

temperature region above the balance-point temperature. The third regression coefficient $T_{b,c}$ represents the cooling balance or change-point temperature that joins the high temperature and low temperature linear sections together. The fourth regression coefficient determined is the base level cooling slope, b_b , or the rate of increase in energy use with the increase in temperature in the low temperature region. The low temperature region is defined as the temperature region below the cooling change-point temperature. Generally, the cooling slope in the high temperature region is larger than the base level cooling slope in the low temperature region. It should be noted that if the base level cooling slope is equal to zero, then the model takes the form of the three-parameter cooling change-point model.

The equation for the four-parameter heating change-point model may be derived from Equation 15 associated with the three-parameter heating change-point model. Equation 15 shows that the total heating fuel energy use is equal to the sum of the weather-dependent space heating energy use and the constant base level energy consumption. However, the idea of the four-parameter heating model suggests that the constant base level energy consumption occurs only at the heating balance-point or change-point temperature; instead the overall facility energy use consumption of the heating fuel remains weather-dependent over the entire ambient temperature range. In effect, the four-parameter heating change-point model can be represented by Equation 19. The four-parameters a_b , c , $T_{b,h}$, and c_b are determined by the regression analysis performed using a facility's energy consumption data and average outdoor temperature records.

$$E_H = a_b + c(T_{b,h} - T_{amb})^+ + c_b(T_{b,h} - T_{amb})^- \quad (19)$$

where,

c_b = weather-dependent base level heating slope (high temperature region),
MMBtu/day-°F.

As in the 4PC change-point model equation, the first regression coefficient a_b represents the energy use that occurs at the balance-point temperature. Similar to a 3PH change-point model, the second regression coefficient c represents the main heating slope or the rate of increase in energy use as the temperature decreases. The main heating slope c is located in the low temperature region, or the temperature region below the heating change-point temperature. The third regression parameter $T_{b,h}$ represents the heating balance or change-point temperature that joins the high temperature and low temperature linear sections together. The fourth regression coefficient c_b is the base level heating slope or the rate of increase in energy consumption as the temperature decreases within the high temperature region. In general, the main heating slope present in the low temperature region is greater than the base level heating slope present in the high temperature region. It should be noted that if the base level heating slope is equal to zero, then the model takes the form of the three-parameter heating change-point model.

1.3.1.3 Five-Parameter Cooling and Heating (5PCH) Models

Five-parameter combined cooling and heating (5PCH) change-point models are used for analysis when one energy source is used simultaneously for cooling and heating. Unlike three-parameter and four-parameter change-point models, they include two change-point temperatures in which energy use increases as temperatures fall below the heating balance-point temperature and as temperatures rise above the cooling balance-point temperature. In between the heating and cooling change-point temperatures, the energy use remains at a constant value. Essentially, five-parameter cooling and heating change-point models resemble a combined three-parameter cooling model and three-parameter heating model. Five-parameter change-point models may only be used when the same energy source is used for both heating and cooling. Most commonly

this energy source is electricity, where the cooling energy is used for air conditioning while the heating energy is consumed by electric strip heat or heat pumps. A graphical representation of the 5PCH change-point model is shown in Figure 5.

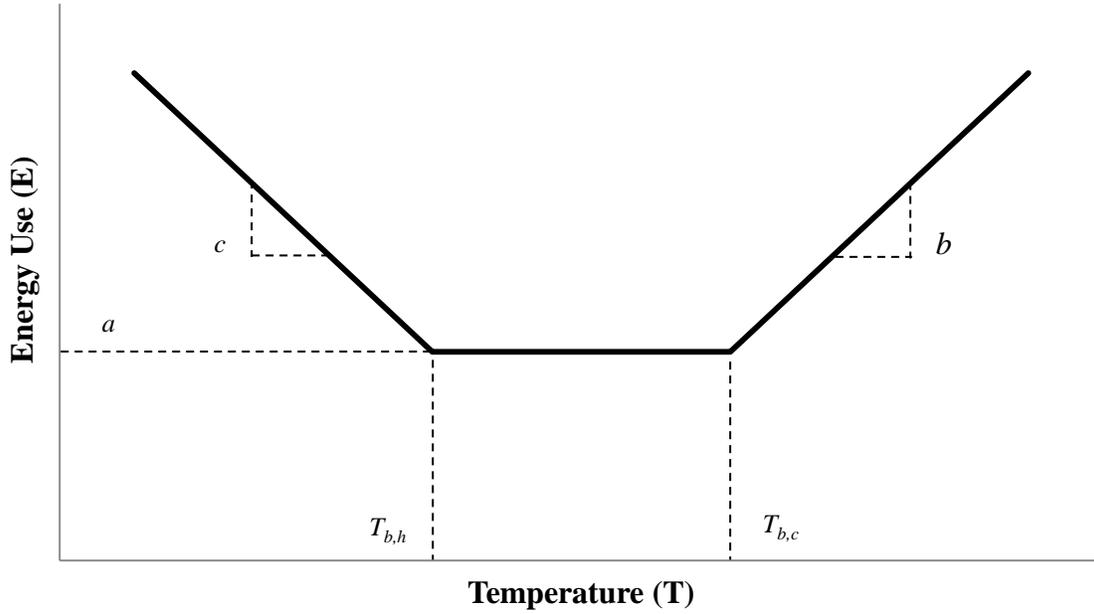


Figure 5. Five-parameter combined cooling and heating change-point model (5PCH).

The equation for the five-parameter combined cooling and heating model can be derived from Equation 4 and Equation 9. The total energy consumption of a facility can be attributed to the sum of the base level energy consumption, the weather-dependent cooling energy consumption, and the weather-dependent heating energy consumption. Equation 20 presents the total energy use represented in the 5PCH model.

$$Q_{total} = \frac{L(T_{h,set} - T_{amb}) - Q_{gain}}{\eta_h} + \frac{Q_{gain} + L(T_{amb} - T_{c,set})}{COP_c} + Q_{base} \quad (20)$$

where,

Q_{total} = total energy consumption.

As described in Section 1.3.1.1, the cooling balance-point temperature and the heating balance-point temperature are defined as the ambient temperatures at which no space conditioning is required. Using Equations 10 and 14 and substituting them into Equation 20, one can further simplify the expression for total energy consumption as shown in Equation 21.

$$Q_{total} = \frac{L(T_{b,h} - T_{amb})^+}{\eta_h} + \frac{L(T_{amb} - T_{b,c})^+}{COP_c} + Q_{base} \quad (21)$$

Using the same notation provided for the three-parameter cooling and three-parameter heating change-point models, Equation 21 may be redefined to represent the final equation for the 5PCH change-point model, as represented in Equation 22. The first regression parameter, a , represents the weather-independent energy consumption. This value remains constant between the heating and cooling balance-point temperature. The second regression coefficient is the heating slope c . The weather-dependent heating slope represents the rate of increase in energy use that occurs as the temperature decreases in the low temperature region. The third regression parameter $T_{b,h}$ is the heating change-point or balance temperature. This signifies when the energy use changes from weather-dependent to weather-independent. The fourth parameter is the cooling slope, b . The cooling slope represents the rate of increase in energy that occurs with increasing ambient temperature in the high temperature region. The fifth and final regression parameter $T_{b,c}$ is the cooling balance or change-point temperature. This is the temperature where the energy consumption transposes from weather-independent to weather-dependent. The units provided in the variable definitions are in terms of kWh since electrical energy is typically the primary source for combined heating and cooling. The five-parameters a , c , $T_{b,h}$, b , and $T_{b,c}$ are determined by the regression analysis performed using a facility's electrical energy consumption and average outdoor temperature data.

$$E = a + c(T_{b,h} - T_{amb})^+ + b(T_{amb} - T_{b,c})^+ \quad (22)$$

where,

E = total energy consumption, kWh/day.

5PCH regression models typically constitute ambient outdoor temperature as the single independent variable. However, multivariable models may be combined with the five-parameter model to account for other important independent variables. These multivariate models will be discussed in Section 1.3.3.

1.3.1.4 Four-Parameter Cooling and Heating (4PCH) Models

A supplementary change-point model can be derived from the combined cooling and heating five-parameter change-point model. Basic engineering principles and the physical basis of the five-parameter change-point model suggests that there is a defined temperature range where neither cooling nor heating energy is required. This notion is emphasized as the constant base level energy consumption of the facility, as defined by the variable a in the three-parameter, four-parameter, and five-parameter change-point equations. However, Reddy et al. (1997a) suggest that the base temperature range where neither cooling nor heating energy is required may be undetectable. Therefore, only one balance-point temperature exists where the energy consumption changes from heating to cooling. In this case, the base level energy consumption of the facility only occurs at the balance-point temperature, and only four regression parameters are evident. Essentially, the energy consumption is completely weather-dependent, as represented by 4PC and 4PH change-point models. However, in contrast to 4PC and 4PH regressions, the same fuel source is utilized for heating and cooling energy use and can be combined in the same equation. This combined cooling and heating four-parameter change-point model will be defined

as the 4PCH model for the purposes of this thesis. A graphical representation of the 4PCH change-point model is shown in Figure 6.

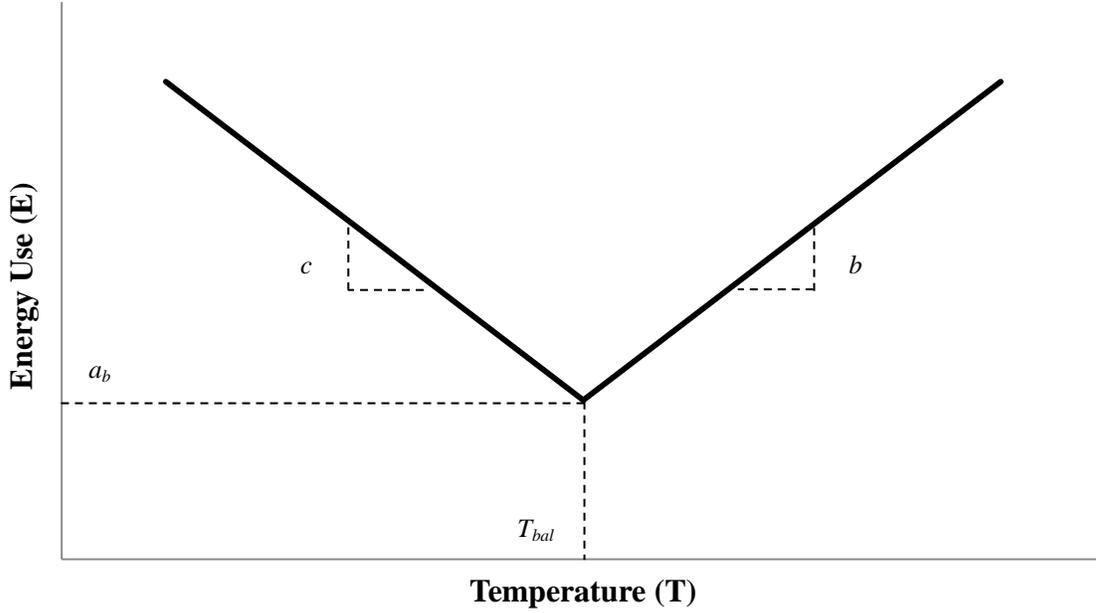


Figure 6. Modified four/five-parameter cooling and heating model (4PCH).

The equation for the 4PCH model can also be derived from the steady state energy balance referenced in Section 1.2. Thus, Equation 20 can also be used to define the total energy consumption of the facility. The single balance-point temperature can be defined as the ambient temperature at which no cooling or heating energy use is required. Equation 10 and Equation 14 may be redefined by using a singular balance-point temperature, T_{bal} , instead of a separate heating and cooling balance-point temperatures ($T_{b,c}$ and $T_{b,h}$). Substituting into Equation 20, the total energy consumption for a 4PCH model may be redefined in Equation 23.

$$Q_{total} = \frac{L(T_{bal} - T_{amb})^+}{\eta_h} + \frac{L(T_{amb} - T_{bal})^+}{COP_c} + Q_{base} \quad (23)$$

Using the same notation provided the previous change-point models, Equation 23 may be redefined to represent the final equation for the 4PCH change-point model, as represented in Equation 24. The first regression parameter, a_b , represents the base level energy consumption that occurs at the balance-point temperature. The second regression coefficient is the heating slope, c . The weather-dependent heating slope represents the rate of increase in energy use that occurs as the temperature decreases in the cold temperature region. The third regression parameter, T_b , is the singular balance-point or change-point temperature. The balance-point temperature is the ambient dry-bulb temperature at which the weather-dependent heating energy changes to weather-dependent cooling energy. The final regression coefficient is the cooling slope, b . The cooling slope represents the rate of increase in energy use that occurs with increasing ambient temperature in the high temperature region. The units provided in the variable definitions are in terms of kWh since electrical energy is typically the primary source for combined heating and cooling. The four-parameters a , b , T_{bal} , and c are determined by the regression analysis performed using a facility's electrical energy consumption and average outdoor temperature data.

$$E = a_b + c(T_{bal} - T_{amb})^+ + b(T_{amb} - T_{bal})^+ \quad (24)$$

where,

T_{bal} = singular change-point or balance-point temperature, °F.

1.3.2 Variable-Base Degree-Day Models

The introduction of variable-base degree-day (VBDD) models began the longstanding correlation between energy use and weather data. According to Claridge (1998), the traditional fixed-base degree-day formula was originally based on statistical analysis of residential gas use provided by the American Gas Association and the National District Heating Association. It was

observed that daily sales increased by an amount proportional to the amount by which the daily temperature was below 65°F. This original fixed-base degree-day method incorporated thermal characteristics of the housing envelope, and maintained a constant base temperature of 65°F for each regression analysis. Additional modification of the fixed-base degree-day formula considered the interior temperature of the house and heat gain from occupants, appliances and sunlight, and allowed the base temperature to vary based on a regression search algorithm. This method became known as the variable-base degree-day method (Kusuda, Sud, & Alereza, 1982).

This variable-base model was based on the physical observation that the heat gains within a building precluded the necessity for heating until the outdoor temperature fell below a balance-point temperature, which was lower than the thermostat set-point by an amount equal to the ratio of the heat gains to the loss coefficient of the building (Ruch & Claridge, 1992). The initial application of VBDD inverse models began with the development of the Princeton Scorekeeping method, also known as PRISM (Fels, 1986). The utilization of PRISM for creating a baseline energy model was introduced by Fels (1986), its original purpose to measure heating energy consumption and pre- to post- retrofit energy savings in residential buildings. The intention was to include weather normalization as a type of “scorekeeping” method – or measurement of actual energy savings – for heating energy use. PRISM proved to be a reliable and stable index of energy consumption, yet Fels (1986) cautioned that it is best used to describe the past behavior of energy use rather than the future. In later years, the PRISM VBDD model was also used to predict energy consumption in commercial buildings and at the campus level (Haberl, 1992).

Variable-base degree-day models utilize heating degree-days or cooling degree-days when analyzing energy consumption. Degree-days are calculated by summing the difference between a reference temperature and the average daily (or hourly) outdoor air temperature over a

specified time interval. The initial PRISM literature focused on the use of cooling degree-day models to describe cooling energy use, and heating degree-day models to describe heating energy use. In effect, PRISM heating degree-day and cooling degree-day models are special cases of three-parameter change-point inverse models in which monthly utility billing data are regressed against degree-days with the base temperature equal to the three-parameter change-point temperature (Kissock et al., 1998). Thus, cooling degree-day (CDD) and heating degree-day (HDD) models describe both the weather-dependent and weather-independent energy use over an entire range of temperatures. Like change-point models, they too are classified under the category of ordinary least squares regression models.

The introduction of a four-parameter change-point model concluded that energy consumption in commercial building may be temperature dependent over an entire range of outdoor air temperatures (Ruch & Claridge, 1992). However, CDD and HDD models only dictate the temperature dependence of energy over a certain range of outdoor air temperatures, while assuming that the energy use is constant over the remaining temperature range (Kissock & Seryak, 2004). Some of the published literature state that VBDD analysis is most suitable for shell-dominated buildings such as residences and small commercial buildings where the energy use is not strongly influenced by nonlinear energy use behavior associated with chillers, refrigeration equipment, and boilers (Reddy et al., 1997a). Therefore, the degree-day equivalent of a four-parameter change-point model has not yet been developed in publications up to this date.

In addition, the degree-day equivalent of a five-parameter change-point model for simultaneous heating and cooling has not been extensively discussed. Reddy et al. (1997a) introduced the idea of a combined cooling and heating degree-day model, which may be used to

describe electricity use that increases with both increases and decreases in ambient temperature, as in facilities that employ the use of heat pumps. However, Rabl & Rialhe (1992) suggest that VBDD models are not altogether reliable in representing energy consumption in commercial buildings where simultaneous heating and cooling occur using the same fuel source at the same point in time. The high heat gains and low heat losses of interior zones can cause the heating balance-point temperature to be much higher than the cooling balance-point temperature, resulting in a physically impossible energy model. Because most of the published literature focuses on the use of cooling degree-day, heating degree-day, and combined cooling and heating degree-day regression models, only these methods will be emphasized and detailed in the following sections.

1.3.2.1 Cooling Degree-Day (CDD) Models

Similar to the 3PC change-point model, the variable-base cooling degree-day (CDD) model provides three physical parameters: the weather or temperature-independent energy use, the weather-dependent cooling slope, and the cooling balance-point temperature. Energy consumption is compared to the number of cooling degree-days required by the facility based on the specified cooling balance-point temperature. Typically, CDD models represent electrical energy used for cooling and other electrical end users. Many published resources have presented the validity of the variable-base cooling degree-day model when evaluating the baseline energy consumption in residential, commercial, and some industrial settings. A graphical representation of the cooling degree-day model is shown in Figure 7.

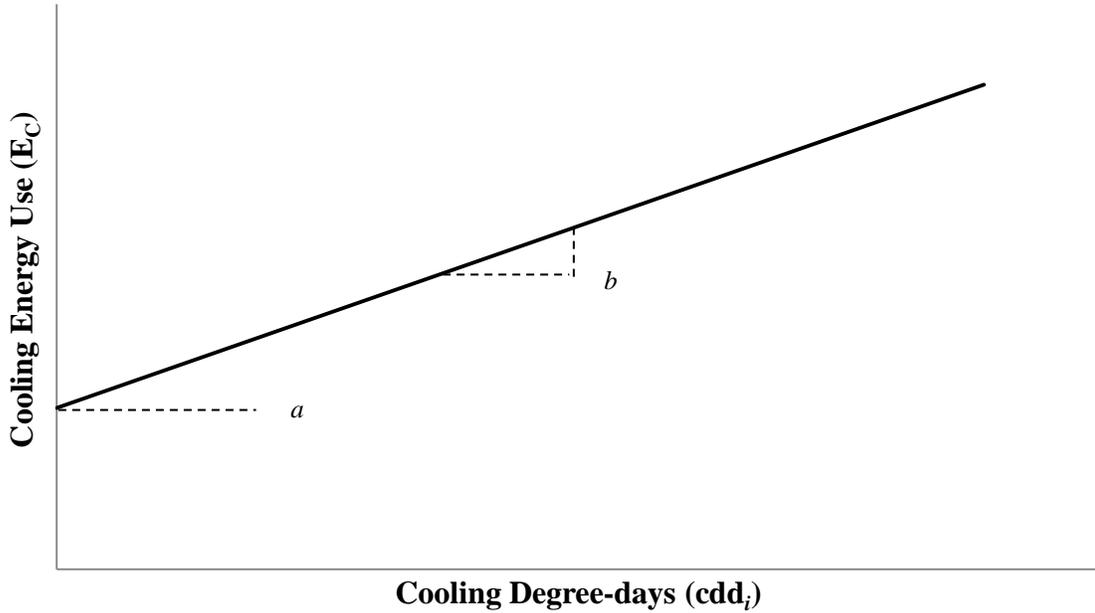


Figure 7. Variable-base cooling degree-day model (CDD).

In order to understand the behavior of the CDD model, one must first understand the application of the cooling degree-days. Cooling degree-days may be first defined as the sum of the temperature differences between the average daily ambient dry-bulb temperature and the indoor cooling set-point temperature of a facility over a given time interval, i , over a period of N_i days. In other words, it is a measure of how much and how long the outdoor air temperature was above a specified reference temperature. The equation for cooling degree-days as a function of the interior cooling set-point temperature is represented in Equation 25 (Fels, 1986). The “+” sign following the brackets represents that only the positive temperature differences are evaluated, otherwise the difference is equal to zero.

$$CDD_i(T_{c,set}) = \sum_{j=1}^{N_i} (T_{amb,ij} - T_{c,set})^+ \quad (25)$$

where,

$CDD_i(T_{c,set})$ = cooling degree-days as a function of $T_{c,set}$ over the specified time interval i , °F-day,

N_i = number of days during the specified time interval i , days,

$T_{amb,ij}$ = average outdoor air temperature of the j^{th} day of time interval i , °F.

Cooling degree-day inverse models have the ability to utilize hourly, daily, or monthly data. The time interval of data represented in the regression model is often determined by the type of data available from the facility. As noted in Section 1.3.1.1, most industrial facilities, and the case studies presented in this study, track energy through the analysis of monthly utility bills. The number of days in each month, and thus the number of days observed during each utility bill service period, varies throughout the year. In order to remove this variation, the degree-days are normalized by dividing by the observed number of days, N_i , during the time interval i . This way each variable is expressed by their daily average value. The normalized cooling degree-days as a function of the interior cooling set-point temperature may then be represented in Equation 26 (Fels, 1986). Normalized degree-days are the average degree-days each day during the observed time period, and are expressed in terms of degree-days per day.

$$cdd_i(T_{c,set}) = \frac{CDD_i(T_{c,set})}{N_i} = \frac{\sum_{j=1}^{N_i} (T_{amb,ij} - T_{c,set})^+}{N_i} \quad (26)$$

where,

$cdd_i(T_{c,set})$ = normalized cooling degree-days as a function of interior cooling set-point temperature for the specified time interval i , °F-day/day

Similar to Equation 4, Equation 27 demonstrates how total cooling energy consumption correlates with cooling degree-days through a steady state energy balance of a particular facility.

$$Q_{c,total} = \frac{\left[Q_{gain} + L \frac{\sum_{j=1}^{N_i} (T_{amb,ij} - T_{c,set})^+}{N_i} \right]}{COP_c} + Q_{base} \quad (27)$$

If the cooling balance-point temperature is defined as the ambient temperature for which no cooling energy is required, the cooling set-point temperature may be redefined as shown in Equation 10. If Equation 10 is substituted into Equation 26, the normalized degree-days as a function of the cooling balance-point temperature may be redefined by Equation 28.

$$cdd_i(T_{b,c}) = \frac{\sum_{j=1}^{N_i} (T_{amb,ij} - T_{b,c})^+}{N_i} \quad (28)$$

where,

$cdd_i(T_{b,c})$ = normalized cooling degree-days as a function of the cooling balance-point temperature for the specified time interval i , °F-day/day

Substituting Equation 28 into Equation 27, the total electrical energy consumption described by the cooling degree-day model may be represented in Equation 29.

$$Q_{c,total} = \frac{L \times cdd_i(T_{b,c})}{COP_c} + Q_{base} \quad (29)$$

Equation 29 may be further redefined in order to represent the typical variable-base cooling degree-day model. The total energy consumed by the facility, $Q_{c,total}$, may be redefined by the variable E_C . The base level energy consumption, Q_{base} , may be redefined by the variable a . This base level energy consumption is also referred to as the non-weather-dependent, or independent energy consumption. This may be interpreted as the energy use that is used by a facility regardless of the number of cooling degree-days. Finally, the variable b may be used to

define the quotient between the heat loss coefficient and the cooling coefficient of performance (Sever et al., 2011). In other words, b is defined as the weather-dependent cooling slope, or the rate of increase in energy consumption that occurs as the number of cooling degree-days increases. The definition of the cooling degree-days produces the third regression parameter of the cooling degree-day equation, the cooling reference or balance-point temperature. As the value of the daily average outdoor air temperature increases above the cooling balance-point temperature, the number of cooling degree-days increases and the energy consumption increases linearly. The actual values of the cooling balance-point temperature, as well as parameters a and b , are obtained by the best fit of the regression analysis (Sonderegger, 1998). Equation 30 summarizes the formula for the variable-base cooling degree-day model, similar to the linear model presented in Fels (1986).

$$E_c = a + b \left[cdd_i(T_{b,c}) \right] \quad (30)$$

It is important to note that the amount of cooling degree-days is the singular independent variable in the CDD energy equation. Furthermore, the amount of cooling degree-days is directly dependent upon the cooling balance-point reference temperature. Multivariable cooling degree-day models that include additional independent variables may also be evaluated. The inclusion of additional independent variables is discussed in Section 1.3.3.

1.3.2.2 Heating Degree-Day (HDD) Models

The variable-base heating degree-day (HDD) model is similar to the 3PH change-point model, but instead relates heating energy consumption to heating degree-days. The variable-base HDD model provides three physical parameters from the regression analysis: the weather or temperature-independent energy use, the weather-dependent heating slope, and the heating

balance-point temperature. The facility's energy consumption is compared to the number of heating degree-days required based on the specified heating balance-point temperature. Typically HDD models represent energy provided by natural gas or oil that is used for heating and other end users. Many published sources have presented the validity of the variable-base heating degree-day model when evaluating the baseline energy consumption in residential, commercial, and some industrial settings. A graphical representation of the heating degree-day model is shown in Figure 8.

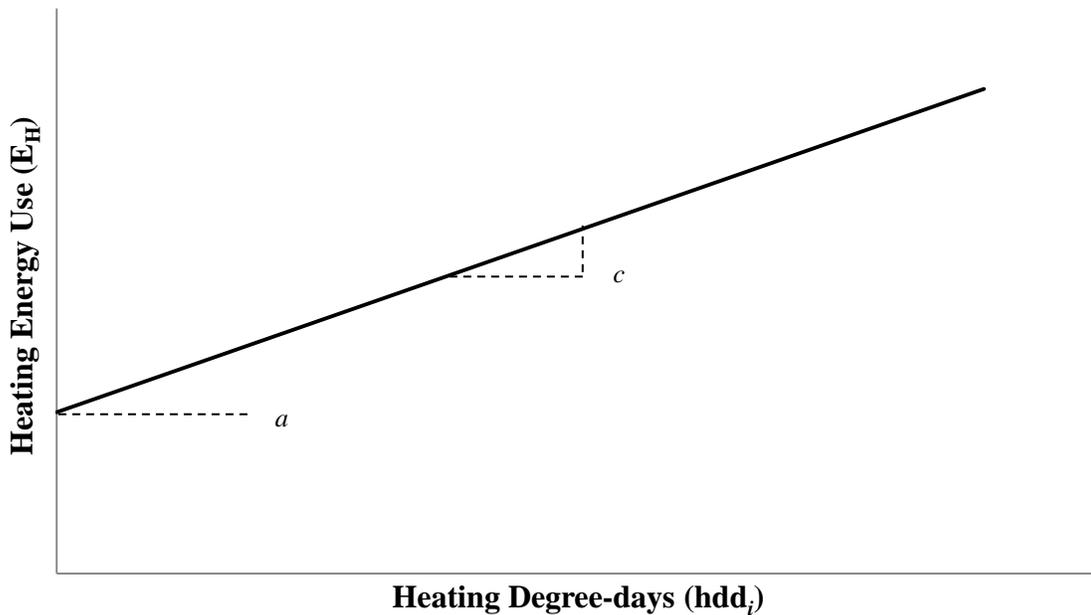


Figure 8. Variable-base heating degree-day model (HDD).

Heating degree-days must first be defined in order to understand the nature of the HDD model. Heating degree-days are calculated in a similar fashion to cooling degree-days, and may be defined as the sum of the temperature differences between the interior heating set-point temperature of a facility and the average daily outdoor dry-bulb temperature over a specified time interval, i , over a period of N_i days. In other words, it is a measure of how much and how

long the outdoor air temperature was below a specified reference temperature. In order to account for the variation in the number of days per month, the heating degree-days are normalized and presented by daily averages. The formula for heating degree-days is represented in Equation 31 (Fels, 1986).

$$hdd_i(T_{h,set}) = \frac{\sum_{j=1}^{N_i} (T_{h,set} - T_{amb,ij})^+}{N_i} \quad (31)$$

where,

$hdd_i(T_{h,set})$ = normalized heating degree-days as a function of interior heating set-point temperature for the specified time interval i , °F-day/day.

Similar to Equation 9, Equation 32 demonstrates how total heating energy consumption correlates with heating degree-days through a steady state energy balance of a particular facility.

$$Q_{h,total} = \frac{\left[L \frac{\sum_{j=1}^{N_i} (T_{h,set} - T_{amb,ij})^+}{N_i} - Q_{gain} \right]}{\eta_h} + Q_{base} \quad (32)$$

If the heating balance-point temperature is defined as the ambient temperature for which no heating energy is required, the interior heating set-point temperature may be redefined as shown in Equation 14. If Equation 14 is substituted into Equation 31, the normalized heating degree-days as a function of the heating balance-point temperature may be redefined in Equation 33.

$$hdd_i(T_{b,h}) = \frac{\sum_{j=1}^{N_i} (T_{b,h} - T_{amb,ij})^+}{N_i} \quad (33)$$

where,

$hdd_i(T_{b,h})$ = normalized heating degree-days as a function of the heating balance-point temperature for the specified time interval i , °F-day/day

Substituting Equation 33 into Equation 32, the total energy consumption described by the heating degree-day model may be represented in 34.

$$Q_{h,total} = \frac{L \times hdd_i(T_{b,h})}{\eta_h} + Q_{base} \quad (34)$$

Equation 34 may be further redefined in order to represent the typical variable-base heating degree-day model. The total energy consumed by the facility, $Q_{h,total}$, may be redefined by the variable E_H . The base level energy consumption, Q_{base} , may be redefined by the variable a . This base level energy consumption is also referred to as the non-weather-dependent, or independent energy consumption. This may be interpreted as the energy use that is used by a facility regardless of the number of heating degree-days (and therefore outdoor air temperature). Finally, the variable c may be used to define the quotient between the heat loss coefficient and the overall heating system efficiency (Sever et al., 2011). In other words, c is defined as the weather-dependent heating slope, or the rate of increase in energy consumption that occurs as the number of heating degree-days increases. It is a measure of “lossiness” of the facility (Fels, 1986). The definition of heating degree-days establishes the third regression coefficient, the heating balance-point temperature. The heating balance-point temperature can be defined as the temperature at which the internal heat gain of the facility balances the heat loss through the building envelope (Kissock et al., 2003). As the value of the daily average outdoor air temperature increases below the heating balance-point temperature, the number of heating degree-days increases and the energy consumption increases linearly. The actual values of the

heating balance-point temperature, as well as parameters a and c , are obtained by the best fit of the regression analysis (Sonderegger, 1998). Equation 35 summarizes the formula for the variable-base heating degree-day model, similar to the linear model presented in Fels (1986) .

$$E_H = a + c \left[hdd_i (T_{b,h}) \right] \quad (35)$$

It is important to note that the amount of heating degree-days is the singular independent variable in the CDD energy equation. Furthermore, the amount of heating degree-days is directly dependent upon the variable-base heating balance-point reference temperature. Multivariable heating degree-day models that include additional independent variables may also be evaluated. The inclusion of additional independent variables is discussed in Section 1.3.3.

1.3.2.3 Cooling and Heating Degree-Day (CHDD) Models

In the two previous sections, the methods for using cooling degree-day and heating degree-day models were described. Like their similar three-parameter cooling and three-parameter heating change-point model counterparts, they were used to describe electrical and natural gas or oil energy consumption used for base loads and space conditioning. For facilities in which the same fuel source is used for base loads, space cooling, and space heating throughout the year, five-parameter simultaneous heating and cooling change-point models can be used. Unfortunately, the published literature provides little information about the degree-day counterpart of the five-parameter cooling and heating change-point model. Many authors state that the variable-base degree-day method cannot be applied to facilities that have simultaneous heating and cooling (Rabl & Rialhe, 1992; Kisssock, 1993; Kisssock et al., 2002). However, it is implied that this reasoning applies to large multi-zone buildings that simultaneously heat and cool various parts of buildings throughout the entire year; in other words, the simultaneous

heating and cooling is not seasonal. This might include facilities with significant internal heat loads and buildings with poor thermal connection to the external environment. This can cause the heating balance-point temperature to be higher than the cooling balance-point temperature, leading to a physically impossible five-parameter model.

Sonderegger (1998) presents the baseline equation where cooling degree-days and heating degree-days may be used to describe the simultaneous and seasonal use of one fuel source to satisfy base loads, space cooling, and space heating loads throughout an entire year. Similar to the 5PCH change-point model, the combined cooling and heating variable-base degree-day (CHDD) model provides five physical parameters: the weather or degree-day-independent energy use, the weather-dependent heating slope, the heating balance-point temperature, the weather-dependent cooling slope, and the cooling balance-point temperature. Energy consumption is compared to the number of heating degree-days and cooling degree-days required by the facility based on the specified heating and cooling balance-point temperatures. The energy use is defined by a constant base level energy use, along with cooling energy based upon cooling degree-days, and heating energy based on heating degree-days.

The most efficient process for representing a CHDD model is shown in Figure 9. The graph shows that the total energy use is dependent upon both the heating and cooling degree-days. Cooling degree-days are displayed to the right of the y-axis, while heating degree-days are displayed to the left of the y-axis. This method provides clarity and separation when determining weather-dependent heating energy use and weather-dependent cooling energy use.

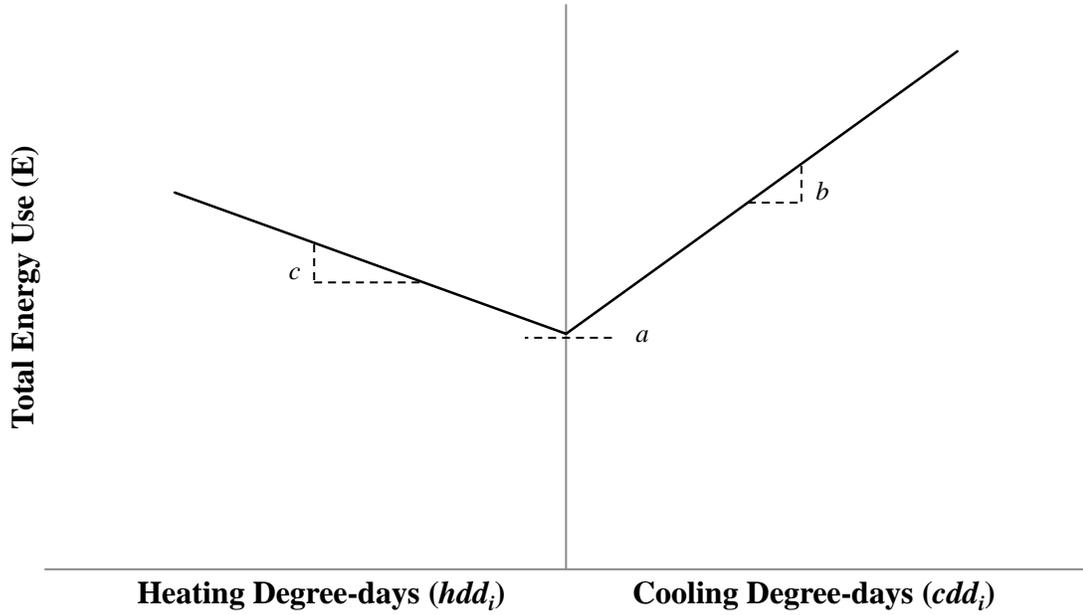


Figure 9. Combined cooling and heating variable-base degree-day model (CHDD).

The same definitions for normalized cooling degree-days and normalized heating degree-days, presented in Equation 28 and Equation 33, respectively, may be applied in the CHDD empirical model. Furthermore, if the same fuel source is used for space cooling and space conditioning, Equations 29 and 34 may be combined to describe the total energy consumption for the combined cooling and heating variable-base degree-day model, as presented in Equation 36.

$$Q_{total} = \frac{L \times hdd_i(T_{b,h})}{\eta_h} + \frac{L \times cdd_i(T_{b,c})}{COP_c} + Q_{base} \quad (36)$$

Using the same notation presented in the previous baseline energy models, Equation 36 may be redefined to represent the final equation for the combined cooling and heating variable-base degree-day model, as shown in Equation 32. The total energy consumed by the facility, Q_{total} , may be redefined by the variable E . The first regression parameter, a , represents the

degree-day or weather-independent energy consumption. The second regression coefficient, c , represents the degree-day or weather-dependent heating slope. The third regression parameter, $T_{b,h}$, is the heating balance-point temperature. The fourth regression parameter, b , represents the weather-dependent cooling slope. And finally, the fifth regression parameter, $T_{b,c}$, is the cooling balance-point temperature. The definition for cooling degree-days and heating degree-days produces values for $T_{b,h}$ and $T_{b,c}$ by the best fit of the regression analysis. As the value of the daily average outdoor air temperature decreases below the heating balance-point temperature, the number of heating degree-days increases and the energy consumption increases linearly. Likewise, as the value of the daily average outdoor air temperature increases above the cooling balance-point temperature, the number of cooling degree-days increases and the energy consumption increases linearly. The five-parameters a , c , $T_{b,h}$, b , and $T_{b,c}$ are determined by the regression analysis performed using a facility's electrical energy consumption and average outdoor temperature data. Equation 37 summarizes the formula for the combined cooling and heating variable-base degree-day model.

$$E = a + c \left[hdd_i(T_{b,h}) \right] + b \left[cdd_i(T_{b,c}) \right] \quad (37)$$

Unfortunately, the literature review does not provide graphical representation of the simultaneous CHDD model. This could be due to the seemingly misleading representation of “heating” degree-days and “cooling” degree-days. Although the model separates the use of degree-days into heating and cooling specifications, it is important to note that these are not considered as multiple independent variables; the terms “cooling” and “heating” only provide clarity. Both cooling degree-days and heating degree-days are still determined from one set of data: outdoor air temperature. Multivariate combined cooling and heating variable-base degree-day models that include additional independent variables can be considered, and are discussed in

Section 1.3.3. Cooling degree-days and heating degree-days are calculated using the heating and cooling balance-point temperature determined by the regression analysis. This explanation provides discussion over the desired method of visually representing the combined cooling and heating variable-base degree-day model in graphical form.

1.3.3 Multivariate Models

Many factors can affect the energy consumption of a building or group of buildings. The relative importance of each contributing component often depends on the type of facility considered: residential, commercial, or industrial. The process of evaluating the impact of more than one independent variable on total energy use is known as multiple or multivariate regression analysis. The goal of multivariate regression is to build a probabilistic model that relates the dependent variable to more than one independent or predictor variable (Devore, 2009). The complexity of employing multiple regression analysis to create a baseline energy use model lies in discerning which independent variables add value to the model and which do not.

Because most multivariate regression models are based on engineering principles which require knowledge of the HVAC system operation and its interactions with the other building systems, they are more difficult to develop (Katipamula, Reddy, & Claridge, 1998). Furthermore, as the building size, complexity of operation, and amount of equipment increases, the energy consumption becomes a more complicated mix of necessary factors. By and large, extensive studies show that outdoor dry-bulb temperature is the most important regressor variable in baseline energy models using ordinary least squares regression analysis, especially at monthly scales (Reddy et al., 1997a; Fels, 1986; Kissock, 1993; Katipamula et al., 1998).

Published analysis of residential, commercial, and industrial energy consumption attempts to evaluate the relevant independent variables necessary to create a baseline

multivariate inverse energy model. In general, climactic variables, building characteristics, building operation procedures, and end-user system characteristics can affect the overall energy consumption of a specific facility. Climactic variables that affect energy use may include weather variables such as ambient dry-bulb temperature, ambient wet-bulb temperature, relative humidity, wind speed, and solar radiation (Kissock et al., 1998; Katipamula et al., 1998). Building characteristics that affect energy use may include conditioned building floor area (Reddy et al., 1997a), building loss coefficients, heat capacity, and internal loads (Katipamula et al., 1998). Energy efficiency adjustments and operating schedules (Reddy et al., 1997a), population and number of occupants, as well as fresh air intake, ventilation, and air infiltration rates (Katipamula et al., 1998) are examples of building operation procedures that affect energy use. System characteristics such as the type of conditioning equipment utilized by a facility, the use of economizers, or the performance of weather-independent equipment also affect overall energy consumption of a facility (Katipamula et al., 1998). Whatever the affecting factor may be, the relative importance of each additional independent variable in a baseline energy model depends on the local climate and on the building's physical and operating characteristics (Kissock et al., 1998).

Theoretically, each of the aforementioned variables could be studied in a multivariable regression analysis when evaluating building energy consumption. However, some of these parameters are difficult to estimate or monitor in an actual building, and cannot be used explicitly as variables in a regression model (Katipamula et al., 1998). Therefore, one is limited to data and relevant parameters that are cost-efficient and available in terms of regression analysis. A significant amount of time and effort can be wasted attempting to include variables that have no real effect on an inverse baseline energy model.

Ruch et al. (1993) suggest that the most important environmental variables include ambient temperature, ambient humidity, and solar radiation when creating a baseline model for energy consumption. Building insulation (Ruch & Claridge, 1992) as well as conditioned area size and population (Reddy et al., 1997a) have also been suggested as additional predictive variables. However, these variables may not be altogether independent of one another. In fact, ambient temperature, humidity, and solar radiation are often linearly related to one another, and may cause multicollinearity within the baseline energy model (Ruch et al., 1993; Reddy et al., 1997a; Akbari & Konopacki, 1998). Multicollinearity suggests that predictor variables are inter-correlated. When this occurs, the results of the multivariable regression model may be misleading. The regression coefficients may be physically unreasonable or there may be great statistical instability of the model, meaning that the standard errors of each regression coefficient may be large (Ruch et al., 1993). The uncertainties of the parameters may be so large that their contribution does not provide an accurate model. The resulting coefficients may also inaccurately portray the relative importance of each of the independent variables (Kissock et al., 1998). Multicollinearity between may be adjusted through Principal Component Analysis presented by Ruch et al. (1993) such that multiple linear regression may be used without compromising the introduction of multiple independent variables.

In addition to the physical impossibility or the large uncertainty of the regression parameters, too many independent variables may cause an over-correction of the energy model. Unfortunately, with multivariate data there is no preliminary picture analogous to a scatter plot to indicate whether a particular multiple regression model is useful or not. The coefficient of determination or the “goodness-of-fit” value of R^2 is a good indicator, but may sometimes be deceptive because it may be greatly inflated by using a large number of predictors or

independent variables relative to the sample size (Devore, 2009). In general, including more variables in a regression analysis can increase the R^2 but decrease the significance of most individual coefficients (Sonderegger, 1998). As the relative uncertainty, or standard error, of each regression coefficient increases, so does the predictive value of the model (Kissock et al., 2002). Therefore, the importance and applicability of each independent variable must be analyzed in order to determine the value added to the baseline model. The number of independent variables should be small and concise enough such that there is a meaningful statistical relationship – otherwise the inverse energy model and provides no insight to the behavior of the facility. Sonderegger (1998) suggests that although it is theoretically possible, it is rare to find a statistically significant correlation in an equation that contains more than three or four independent variables. The use of the partial coefficient of determinations (Katipamula et al., 1998) may give an idea as to how much a specific variable explains the variation of data. Unfortunately, a rational and agreed upon procedure to normalize some of these multivariate parameters has not yet been established (Reddy et al., 1997a; Devore, 2009).

Katipamula et al. (1998) studied the effect of ambient dry-bulb temperature, dew point temperature, heating coil and cooling coil temperatures, air infiltration rate, hot and cold deck temperatures, solar radiation, internal sensible heat gains, and latent heat gains on the energy consumption of commercial buildings that utilized dual duct constant volume and variable volume air systems. The authors concluded that out of all the studied parameters, ambient dry-bulb temperature and ambient wet-bulb temperature accounted for more than 90 percent of the variation in the cooling energy use of each system type. However, they also conclude that it is up to the analyst to decide what additional variable should be added to the multivariate model and the additional cost or complexity that comes with those additional variables.

Katipamula et al. (1998) also consider the effect of different time scales when evaluating important multivariate variables and creating a baseline energy model. The authors conclude that the use of daily and hourly energy use models increase the significance of some variables like internal heat gain and air infiltration, while the use of monthly models suggest that only dry-bulb and wet-bulb ambient temperatures are significant. At low resolution time scales (monthly and daily), some of the information content is lost in the process of averaging the variables. Certain variables such as supply air temperatures and fresh air intake in the HVAC systems can vary from hour-to-hour, but are effectively constant day-to-day and even month-to-month. Therefore, their statistical contributions are minimal for models on a monthly or daily time scale. However, if the significance of these variables changes over time, monthly models may not be able to predict energy consumption accurately. In addition, the authors conclude that in general, monthly models have a higher coefficient of determination, R^2 , and a lower coefficient of variation, CV-RMSE, for the baseline model in comparison to daily and hourly models. However, daily and hourly models were found to be better predictors of energy use.

Reddy et al. (1997a) also considered the effects of additional independent variables besides outdoor air temperature when establishing baseline energy consumption models for Department of Defense facilities. In their study, the authors intended to capture the effect of the actual building conditioned floor area, population or number of occupants, and connected loads not associated with energy conservation and retrofit projects on the overall energy consumption of the DoD facilities. They concluded that there was no relation between the year-to-year change in annual energy use and the corresponding changes in population of the observed facilities. However, they suggested that the population could be connected to the overall conditioned area, and included the normalization of the energy use data based on the conditioned floor area of the

facility. Normalizing annual energy use to changes in building conditioned area was straightforward since previous publications consistently assumed a proportional relationship between the two variables. Yet, the authors were unable to reach any definite conclusions between the relationship of population and occupancy changes on the annual energy consumption. It was suggested that normalizing energy use for changes in population alone is not simple since a relationship must be statistically determined from data already available for similar types of buildings and facilities, which were lacking in the published literature at the time.

Multivariate models have not only been applied to formulate baseline energy consumption models, but to verify and measure actual energy savings between a pre- and post-retrofit time period (Kissock & Eger, 2008; Sever et al., 2011; Reddy et al., 1994). Proper measurement of savings requires the use of data from the baseline period to incorporate all parameters that significantly influence energy use. These baseline models normalize the data to account for changes in weather and other important operation parameters (Claridge, 1998).

The following sections introduce the application of multivariate regression analysis to the change-point and degree-day energy models. Change-point multivariate (CP-MVR) and variable-base degree-day multivariate (VBDD-MVR) models retain the ability to model energy use with change-point and balance temperatures, while including the effects of additional independent variables (Kissock et al., 2003). Although several variables have been analyzed in the literature review and may be of great importance, the basis of the change-point and variable-base degree-day models warrant the use of ambient air temperature as the most important and effective independent variable, while evaluating additional independent variables as appropriate. Weather and production have been proven as strong drivers of energy use in industrial facilities (Kissock

& Eger, 2008). Thus, ambient dry-bulb temperature and production will be the focus variables in the analysis of multivariate models presented in this thesis in Chapter 3.

1.3.3.1 Change-point Multivariate (CP-MVR) Models

Change-point multivariate models have the capability of evaluating baseline energy consumption through the use of temperature data and heating and cooling change-point temperatures, while including the application of additional independent variables. Three-parameter cooling, three-parameter heating, four-parameter cooling, four-parameter heating, and five-parameter combined cooling and heating change-point models may include additional independent variables other than average dry-bulb temperature. For the purposes of this thesis, the only additional variable considered other than ambient dry-bulb temperature is production. The total number of units produced significantly influences facility energy consumption in many industrial manufacturing industries. However, other variables such as solar radiation, total area of facility space, humidity, and occupancy schedules may be important additions when evaluating a baseline energy model.

Equations 38 through 42 show the change-point multivariate models for a varying number of regression parameters, similar to the change-point models presented in the Inverse Modeling Toolkit (Kissock et al., 2002). Three additional independent variables other than temperature have been shown in the empirical formulas, but the number of additional variables is dependent upon the desire of the operator and their relevance to the dependent variable. The three-parameter cooling change-point multivariate (3PC-MVR) model is shown in Equation 38.

$$E_C = a + b(T_{amb} - T_{b,c})^+ + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \quad (38)$$

where,

$\beta_1, \beta_2, \beta_3 =$ independent variable regression coefficients,

$X_1, X_2, X_3 =$ independent variables.

The three-parameter heating change-point multivariate (3PH-MVR) model is shown in Equation 39.

$$E_H = a + c(T_{b,h} - T_{amb})^+ + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \quad (39)$$

The four-parameter cooling change-point multivariate (4PC-MVR) model is shown in Equation 40.

$$E_C = a_b + b(T_{amb} - T_{b,c})^+ + b_b(T_{amb} - T_{b,c})^- + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \quad (40)$$

The four-parameter heating change-point multivariate (4PH-MVR) model is shown in Equation 41.

$$E_H = a_b + c(T_{b,h} - T_{amb})^+ + c_b(T_{b,h} - T_{amb})^- + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \quad (41)$$

The five-parameter combined cooling and heating change-point multivariate (5PCH-MVR) model is shown in Equation 42.

$$E = a + c(T_{b,h} - T_{amb})^+ + b(T_{amb} - T_{b,c})^+ + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \quad (42)$$

1.3.3.2 Variable-Base Degree-Day Multivariate Models

Variable-base degree-day multivariate models have the capability of evaluating baseline energy consumption through the use of temperature data and cooling and heating degree-days, while including the application of additional independent variables. Cooling variable-base degree-day, heating variable-base degree-day and combined cooling and heating variable-base degree-day models may include additional independent variables other than cooling and heating degree-days calculated from average dry-bulb temperature data. Equation 43 through 45 show

the variable-base degree-day multivariate models for cooling, heating, and combined cooling and heating annual energy use. These presented equations are similar to the empirical forms presented in the Inverse Modeling Toolkit (Kissock et al., 2002). Three additional independent variables other than temperature have been shown in the equations, but the number of additional variables is dependent upon the desire of the operator and their relevance to the dependent variable.

The cooling variable-base degree-day multivariate (CDD-MVR) model is shown in Equation 43.

$$E_C = a + b \left[cdd_i(T_{b,c}) \right] + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \quad (43)$$

The heating variable-base degree-day multivariate (HDD-MVR) model is shown in Equation 44.

$$E_H = a + c \left[hdd_i(T_{b,h}) \right] + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \quad (44)$$

The combined cooling and heating variable-base degree-day multivariate (CHDD-MVR) model is shown in Equation 45.

$$E = a + c \left[hdd_i(T_{b,h}) \right] + b \left[cdd_i(T_{b,c}) \right] + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 \quad (45)$$

1.4 Artificial Neural Network Models

Artificial neural networks (ANNs) have been used in many different fields to break down a complex system into simple elements. There are many different types of networks, but they are all characterized by the following components: a set of nodes, and the connections between nodes (Gershenson, 2003). An artificial neuron is a computational model inspired by natural neurons found in biological elements such as the human brain. Artificial neural networks combine networks of artificial neurons in order to process information through inputs, hidden

function layers, and outputs. The input layer receives information or data, and the output layer shows the response of the analysis. The hidden layer is first trained by a set of data to adapt to a certain already-known structure that relates the inputs and the responses. This is known as the learning phase. By conducting the learning phase, the ANN can be trained to analyze complex relationships between sets of data and to recognize patterns between input and output variables. This allows the model to be extremely flexible and to discover the possible linear or nonlinear relationship between the independent and dependent variables. Because ANNs are trained by a set of measured or simulated data the method is considered an inverse solution. Artificial neural network analysis is not utilized in the case studies presented in this thesis. Details are presented in this section for purposes of background information on baseline energy modeling methodology.

Artificial neural networks have been used to describe the dependence of energy consumption for a variety of different factors. Although the approach may seem complex and convoluted to those unexperienced with the method, Claridge (1998) suggests that it is appropriate to view ANNs as a set of powerful non-linear regression tools. Among the artificial intelligence approach for modeling energy use, artificial neural networks have been favored by several major vendors or utilities in the power industry because of its flexibility and the advantage of handling nonlinearity between datasets (Hong et al., 2010). In addition, ANNs have had success in modeling the current behavior of commercial and office building energy consumption (Kissock, 1994; Karatasou, Santamouris, & Geros, 2006), as well as predicting whole building electrical energy use, hot water use, and chilled water use (Feuston & Thurtell, 1994; Ohlsson, Peterson, Pi, Rognvaldsson, & Soderberg, 1994; MacKay, 1994) and overall energy consumption for a complex institutional building (Anstett & Kreider, 1993) without the

use of data acquisition system. Like ordinary least squares regression methods, artificial neural networks have also been applied to measure actual energy savings between a pre- and post-retrofit period (Curtiss, Shavit, & Kreider, 1996; Krarti, Kreider, Cohen, & Curtiss, 1998; Zhang et al., 2013; Yalcintas & Akkurt, 2005).

In comparison to ordinary least squares regression models, artificial neural networks are highly complicated systems that require extensive knowledge of the analysis process. However, ANNs have been capable of producing more accurate baseline energy models than the more simplified methods of analysis since they have the ability to consider multiple independent variables and complex model relationships. But, the lack of physical interpretability and over-fitting of the resulting ANN baseline energy model is also a concern (Hong et al., 2010). Overall, the consensus for applying artificial neural networks to produce a baseline energy model is that the complexity of the technique must be weighed against the accuracy gained by including analysis between multiple independent variables and the time taken to produce the results.

1.5 Calibrated Simulation Models

Calibrated simulation models constitute another category of methods for creating baseline energy use models. These models replicate the characteristics of a building and the energy consuming equipment within the building. Calibrated building simulation models are often used by architects or engineers for building design. These users are often concerned with the “forward problem,” as specified by Rabl et al. (1992); they have the description and characteristics of the building in the design phase, and want to calculate the average and peak energy consumption loads. The software for calibrated building simulation model can range from sophisticated whole building modeling, such as DOE-2 (JJH, LBNL, USDOE, 2014), eQuest (eQuest, 2014), and EnergyPlus (EnergyPlus, 2013), to simplified HVAC-concentrated modeling, such as ESim

(Kissock, 2012). Not only have calibrated simulation models been used to create baseline energy models of buildings (Katipamula & Claridge, 1992), but they have also been used to measure energy savings between pre- and post-retrofit periods (Katipamula & Claridge, 1993; Willson, 1998). Calibrated building simulation or forward analysis is not utilized in the case studies presented in this thesis. Details are presented in this section for purposes of background information on baseline energy modeling methodology.

After the basic building characteristics of a building are known, a simulated building model can be fine-tuned with utility bills or other measured information to calibrate the model to represent the current energy consumption behavior. Overall, calibrated forward models are not ideal for creating baseline energy models. Detailed information about the building characteristics may not be available from facility owners. Furthermore, the process of inputting building characteristics and fine tuning the energy use of equipment based on utility bills into the simulation software is time intensive and laborious. Fels (1986) suggests that the dynamic calibrated simulation models are overly complicated for basic scorekeeping of energy consumption data, which in the simplest form of analysis only requires long-term averages of energy consumption, data that are readily available for large numbers of building in general. Therefore, calibrated simulation models are not often the choice method for creating baseline energy consumption models. Although calibrated simulation models can help describe complex interactions between weather data and building energy consumption behavior, the added value of the analysis must be weighed against the time and cost required for the analysis and the complexity of the method.

CHAPTER 2: METHODS

The methods presented in this thesis use single variable piecewise and multivariable piecewise linear regression models to develop baseline energy consumption models for manufacturing industrial facilities using monthly utility billing data, weather data, and monthly production values from a one year period. This chapter explains the method of data analysis using author-developed programming in Microsoft Excel (Microsoft, 2010) to define the baseline energy consumption models presented in Chapter 3. Once a desired model type and facility location is chosen, one full calendar year of utility bill and production data is inserted into the program. A regression analysis for each model type is then performed through the application of the Solver Excel feature. The regression parameters and baseline energy equations are established, and the models' statistical goodness-of-fit values are reported. A discussion on the statistical values that are used to determine a model's goodness-of-fit is also provided.

2.1 Choosing an Appropriate Model

The first requirement for establishing a baseline energy consumption model is to determine the appropriate type of model to use in the analysis. As described in Chapter 1, there are numerous methods for modeling energy consumption as a function of weather data and additional independent variables. The case studies presented in this thesis utilize change-point piecewise linear regression models as well as degree-day linear regression models to characterize energy use. Both advantages and disadvantages between the change-point and degree-day

methods have been presented in published literature. It has been suggested that no single model type is universally the best; rather, the appropriate model choice depends on what one wants to calculate and what data are available (Rabl et al., 1992). Thus, it is upon the discretion of the analyst to determine the appropriate methods.

The case studies of industrial manufacturing facilities that are presented in this thesis were executed with the use of Microsoft Excel, Visual Basic for Applications (VBA) programming, and the imbedded Solver function found in basic Microsoft Excel packages. By answering a series of questions in the author-developed Excel program, the user has the ability to analyze energy use data for a given facility using change-point models by the way of average monthly temperature data, or to analyze the data using degree-day models by the way of TMY3 data files, or to compare and contrast both methods. Based on the energy use and fuel use characteristics of the facility, the user can create three-parameter cooling-only or heating-only change-point models with or without production values as an additional independent variable (3PC, 3PH, 3PC-Prod, 3PH-Prod). The user can also create five-parameter combined cooling and heating change-point models with or without production values as an additional independent variable (5PCH, 5PCH-Prod). The user also has the ability to create cooling-only degree-day, heating-only degree-day, or combined cooling and heating degree-day models with or without production values as an additional independent variable (CDD, HDD, CHDD, CDD-Prod, HDD-Prod, CHDD-Prod). The user may also choose to evaluate all of the listed methods in order to compare and contrast baseline model results and goodness-of-fit. It is apparent that the ability to evaluate the multivariate models in the Excel program relies on the procurement of production data from the observed facility; otherwise, only the single variable regression methods may be evaluated.

While the basic relationship between cooling energy consumption or heating energy consumption and weather data is known, the regression analysis often requires that the modeler have some basic knowledge or understanding of the physical and logical relationships between the independent and dependent variables. Although the model type or regression equation with the best fit is sometimes used as the most appropriate model, this may not always be the case. The correct model choice is sometimes ambiguous. Trial and error procedures and basic inspection of the present data can be used, but the results of the baseline energy model may rely upon the skill and intuition of the modeler (Fels, Kissock, & Marean, 1994). Although Fels et al. (1994) developed a type of screening for determining the initial type of regression, model selection may be performed by the user by physically examining the energy consumption data in terms of outdoor air temperature, number of degree-days, and even monthly production values. For example, the analyst may observe that a facility using only electrical energy for space cooling and space heating may experience larger amounts of energy consumption during the summer and winter months; as a result, the user may choose to evaluate a five-parameter change-point model or a combined cooling and heating degree-day model. Overall, it may be concluded that the reviewer must obtain some basic knowledge of the analysis methods and the physical relationships between variables.

2.2 Data Sources

Once the appropriate regression model type or method is selected, data obtained from the facility may be inserted into the Excel program. The source data for the development of the models are monthly electricity and natural gas use, which should be obtained from monthly utility billing data. Electrical billing data is used for cooling-only or combined cooling and heating analyses, while natural gas billing data is used for heating-only analyses. If a multivariate

analysis is to be performed, monthly production data should be obtained from the facility. Monthly production data is typically recorded in most manufacturing industries, and can be readily obtained from facility personnel. The recorded units of the provided production data are trivial; the recorded production units need only be in the same format for each reported month.

The production data provided by the facility must correspond with the same time period as the monthly utility billing data. One year of data has been proven to be sufficient for establishing a baseline energy consumption model (Seryak & Kissock, 2005; Eger, 2006). In most cases, one year of data will include one complete weather and operational cycle. Establishing a baseline energy model from short data sets, or data observed over a period shorter than one year, questions the base-lining and predictive ability of the resulting regression model (Kissock, 1993). The case studies presented in this thesis utilize one full year of utility bill energy consumption, production data, and weather data to create a baseline energy model.

2.3 Weather Data

Once regression model types are chosen and the utility bill energy consumption data and production data are inserted in to the Excel program, the user has the ability to select the location of the facility. A complete list of available areas in the Excel program is presented in Table 1. After a location is selected, the actual weather data or normalized weather data for the specified region is automatically inserted into the Excel program to be used in the regression analysis. The user should select the exact city in which the facility is located, or the city that has the closest geographical proximity to the facility.

Table 1

Selected Locations for Regression Analysis in Microsoft Excel Program

Alabama	Georgia	Mississippi
Anniston	Albany	Biloxi
Auburn	Athens	Columbus
Birmingham	Atlanta	Greenville
Dothan	Columbus	Greenwood
Enterprise	Macon	Hattiesburg
Gadsden	Rome	Jackson
Huntsville	Savannah	McComb
Mobile		Meridian
Mobile-Downtown		Natchez
Montgomery		Tupelo
West Montgomery		
Muscle Shoals		
Troy		
Tuscaloosa		

The temperature data referenced in the Excel program and used in the regression analysis is dependent upon the designated model type. For change-point model analysis, actual mean monthly temperature values should be obtained for the same time period specified by the provided utility bill data. Actual monthly mean ambient temperatures are used so that the baseline models represent the behavior of the actual energy consumption data obtained from the facility’s utility bills. Monthly temperature data can be obtained from government websites such as the National Climatic Data Center (NOAA) or the U.S. EPA Average Daily Temperature Archive (U.S. EPA & The University of Dayton, 2007), or from privately owned websites such as Weather Underground (The Weather Channel, LLC). The change-point baseline energy models presented in this thesis employ actual weather data obtained from Weather Underground. This resource tracks historical weather data from government owned weather stations and local airport weather stations, and compiles the data in a user-friendly interface.

In addition to inserting actual monthly mean outdoor temperature values, the user also retains the ability to use normalized weather data in the Excel program. Normalized weather data represents the average weather conditions observed in a typical year. Data files for the typical meteorological year (TMY) were inserted in the Excel program for a variety of locations in the southeastern U.S., as shown in Table 1. Typical meteorological year 3 (TMY3) data files were obtained from the National Renewable Energy Lab (NREL). These data include 24 hour sets of meteorological elements, such as ambient temperature values, for 365 days in a one year period. Measured values from local weather stations from 1991-2005 have been averaged to create the TMY3 data files. Additional typical meteorological year data are also available, such as TMY2 data files which use average weather measurements from 1961-1990.

Actual temperature data should be used when establishing change-point energy consumption models so the baseline model represents the actual behavior of the obtained energy consumption data. When using change-point regression analysis to perform savings estimates, normalized temperature data is used to calculate or predict energy savings for a proposed retrofit project, or to perform a normalized savings analysis from existing pre-retrofit and post-retrofit energy consumption data. Normalized savings analysis uses the normalized annual consumption, or NAC, instituted by Fels (1986), representing annual energy consumption based on average weather conditions. Actual savings analysis may also be performed from existing pre-retrofit and post-retrofit energy consumption data. Actual weather data from the post-retrofit period is used to calculate energy savings between the pre-retrofit baseline model and actual post-retrofit energy data. Advantages, disadvantages, and discussions of normalized savings analyses and actual savings analyses have been examined in many of the published reference materials (Fels, 1986; Ruch & Claridge, 1993; Reddy et al., 1997a; Kissock et al., 1998; Kissock et al., 2002).

Furthermore, the impact of using measured data versus TMY data in building energy simulations has also been discussed (Haberl, Bronson, & O'Neal, 1995).

In contrast to the change-point baseline energy models presented in this analysis, the degree-day baseline energy models use normalized weather data in the form of TMY3 data files. The arrangement of the TMY3 hourly ambient dry-bulb temperature data allows for the simple calculation of degree-days based on the cooling or heating balance point temperature found by the regression. It is a fact that actual weather data may also be applied in degree-day regression analyses. However, other referenced weather data resources did not provide a widespread selection of geographical facility locations, delivered lower-resolution time scales by providing only daily or monthly average temperature values, or required excessive effort and time to prepare the weather data into acceptable form for the Excel program regression analysis. It was also concluded that the TMY3 hourly weather data might provide more insight into the hourly, daily, and seasonal temperature fluctuations observed in many southeastern states, the location of all case studies presented in this thesis. Average monthly mean temperatures, as applied in the change-point baseline methodology, do not expose these fluctuations which have the ability to alter the baseline energy consumption model.

2.4 Utility Bill Meter Read Dates

The developed Excel regression analysis program also has the ability to analyze temperature data based on the utility bills' recorded service dates. Reddy et al. (1997b) presented the importance of corresponding utility bill read dates and associated monthly weather data when creating a baseline energy model. The study applied a statistical procedure for identifying suitable baseline energy consumption models when utility bill meter dates were not explicitly

known. The results indicated a noticeable difference in baseline model goodness-of-fit between energy consumption and weather data whose time periods agreed or disagreed.

Depending on an industrial facility's utility provider, bill meter read dates can extend from the beginning of one calendar month to the beginning of the next calendar month, or from the middle of one calendar month to the middle of the next calendar month. Furthermore, utility providers often distribute the facility's monthly billing statement two weeks to one month following the final meter read date. Consequently, the baseline model analyst must take care to match the utility bills' recorded service dates to the appropriate monthly temperature and weather data. The Excel program has the ability to adjust built-in TMY3 average weather data for meter read dates that occur at the beginning of the month or the middle of the month. If the initial meter read date occurs at the beginning of the month, TMY3 weather data spanning the first to last day of each calendar month is reported. If the initial meter read date occurs near the middle of the month, weather data from the 15th day of the initial month to the 14th day of the following month is reported for the calendar year. Though it may be unapparent to some observers, average monthly dry-bulb temperature measurements can vary significantly for monthly time periods starting at the beginning of the month or mid-way through the month.

2.5 Use of Microsoft Excel Solver

After choosing the appropriate regression model type, selecting specifics for weather data and facility location, and inserting monthly energy consumption and production data into the Excel program, the user must perform the regression analysis through the use of the Microsoft Excel Solver feature. Through rudimentary observation of the relationship between the supplied energy, production (if applicable), and weather data, the user must insert initial values for each regression coefficient. The sum square of errors, the SSE, or the sum of the squared differences

between actual and predicted data points, is presented in the Excel program. Using the principle of ordinary least squares and the Excel Solver feature, the SSE value is set to a minimum by adjusting the cell values of each regression parameter. The values resulting from the Solver analysis provide the regression parameters for the final baseline energy consumption model.

The bundled version of the Microsoft Excel Solver program represents the low end of the range of spreadsheet functionality, having the ability to support 200 independent decision variables in one analysis. More powerful Solver versions are available, but are often used to solve more complicated problems in industry, supporting almost 32,000 decision variables in their programming (Fylstra, Lasdon, Watson, & Waren, 1998). Since the baseline energy model analysis in this study only contains a maximum of six regression parameters, or decision variables, the basic built-in Excel Solver package is sufficient for use in this analysis.

The Microsoft Excel Solver program has three different solving methods that can be selected for optimization problems. The first is the Simplex method, which is used for solving linear problems. The second is the GRG Nonlinear method, which is used for solving nonlinear problems. The third is the Evolutionary method, which uses genetic algorithms to find solutions, and is useful for nonlinear or smooth nonlinear Excel formulas and functions. The GRG Nonlinear Solver method was selected for use in this analysis. GRG stands for the generalized reduced gradient method, and is defined by the GRG2 code (Lasdon, Waren, Jain, & Ratner, 1978). Although the baseline regression equations are considered linear, it was unclear how the piecewise change-point model behavior would affect the use of the Simplex Solver method. Furthermore, GRG2 has a reputation for robustness, compared to other nonlinear optimization methods, for difficult problems that are not continuously differentiable or present other numerical difficulties (Fylstra et al., 1998).

The GRG Nonlinear Solver method uses an inconstant Jacobian matrix of partial derivatives of the problem function with respect to the decision variables (Fylstra et al., 1998). This Jacobian matrix is approximated by the use of finite differences. In effect, the GRG Nonlinear Solver uses the finite difference method, an iterative numerical procedure where the values of each regression parameter are adjusted slightly and the rate of change of the value of the sum square of errors is observed. The finite difference approach was selected by Microsoft for use in the Excel Solver program because it has the ability to support all of Excel's built-in functions as well as user-written functions. The Excel user has the ability to choose between forward differencing and central differencing for approximations of derivatives. Central differencing can lead to more accurate derivatives, but requires twice as many calculations of the worksheet at each new trial solution (Frontline Systems, Inc., 2014a). Calculating finite differences and using the central differencing option can result in more computing time; Fylstra et al. (1998) caution that Excel recalculates every formula on the current worksheet during the use of the Solver feature, including those cells that are not involved in the optimization model. However, it was observed during the analysis for this thesis that the assessment using the GRG Nonlinear Solver with central differencing was concluded in a matter of seconds, and proved the warning to be negligible.

In earlier versions of Microsoft Excel, the starting values for the decision variables, or the regression parameters, have slightly more significance to the Solver solution than in more recent versions of Excel (2010 and greater). In the earlier Excel versions, the specific path taken by the GRG2 algorithm to form a solution is dependent upon the initial values of the decision variables. Some problems can contain multiple locally optimum points where partial derivatives of the optimum cell are zero. In this case, Solver will converge to a single solution close to the initial

starting point, but will have no sure way of knowing if a more plausible solution is some distance away (Microsoft Support, 2011). In order to modify this feature, more recent versions of Excel Solver include the Multistart option for global optimization.

The Multistart method automatically runs the GRG Nonlinear method from a number of different starting points and will display the best of severally locally optimal solutions found, resulting as the most probable optimal solution (Frontline Systems, Inc., 2014b). The Multistart option can use anywhere from 10 to 200 different starting points, also known as population size, for the decision variables. For the analysis presented in this thesis, the Multistart method was used with a population size of 100. The use of the Multistart method provides a safeguard for final solutions that may differ greatly from the initial regression parameter values that are inserted by the Excel user. Although the Multistart option can be used to find the global optimum, most Solver support references still suggest beginning with values that are representative of the expected optimal solution rather than with arbitrary values. Including the Multistart option in the Solver analysis can also require more computing time; however, during this study it was observed that including the use of the Multistart option did not have a negative effect on computation time when performing the baseline model regression analysis.

Various other search algorithms to find baseline energy model coefficients are used in other versions of energy modeling software. For example, the search algorithm in the Inverse Modeling Toolkit (Kissock et al., 2002) uses a two stage grid search to develop change-point and degree-day baseline energy models. The algorithm identifies the interval between minimum and maximum temperature values, and separates it into ten subsequent intervals. The model is regressed to find the coefficients and goodness-of-fit at each of the ten steps, and the value that produces the lowest RMSE is selected as the initial change-point temperature. The method is

then repeated using a finer grid search centered around the initial change-point temperature. This process is the same for single or multivariate analysis, finding all of the regression coefficients simultaneously. However, some researchers, such as Sonderegger (1998), suggest finding multivariate baseline energy models by initially regressing energy consumption against only weather data to find the best fit balance temperature, and then using those regression parameters to solve the multivariate model equation. Although other search algorithms have been proven successful for energy analysis, the methods presented in this chapter utilize the Solver feature to find all regression parameters simultaneously. Detailed information on additional search algorithms used in other energy software can be found in most of the referenced materials (Fels, 1986; Ruch & Claridge, 1992; Kissock, 1993; Kissock et al., 1998).

Many forms of energy modeling software are available for use by researchers and the general public, aside from the Microsoft Excel program developed for use in this thesis study. However, many existing software programs do not have the ability to easily compare and contrast change-point and degree-day baseline energy models, or are more applicable when calculating energy savings for retrofitting projects. Energy Explorer (Kissock, 2000) was developed to create various parameter change-point baseline energy models. EModel (Kissock, et al., 1994) and ETracker (Kissock J. K., 2003), as well as PRISM (Fels, Kissock, Marean, & Reynolds, 1995) and Metrix (Abraxas Energy Consulting, 2013) were developed to calculate energy savings between pre- and post-retrofit periods through the use of change-point and degree-day models, respectively. Although additional software, complicated search algorithms, and more robust optimization programs are available to most energy consumers, one of the goals of this analysis is to provide methods for creating acceptable and logical baseline energy models that are straightforward and accessible to anyone in the industrial manufacturing community.

Thus, the methods described in this chapter can be easily reproduced by many individuals in the manufacturing industry that possess a basic Microsoft Excel package and general knowledge of the relationship between energy consumption and weather and production data.

2.6 Statistical Goodness-of-fit: R² Versus CV-RMSE

The goodness-of-fit of a statistical model helps describe the discrepancy between observed values and values calculated by the statistical model. It can also determine how well a statistical model will predict a future set of observations. There are multiple ways of determining a model's goodness-of-fit in statistical analysis. Unfortunately, there are no general guidelines for selecting an appropriate goodness-of-fit method. Furthermore, one goodness-of-fit test may suggest one specific model selection, while another goodness-of-fit test may suggest another. Goodness-of-fit test selection may be based on statistician preference or may be determined by the model application and intent, and is somewhat arbitrary.

The coefficient of determination, R², and the coefficient of variation of the root mean square error, CV-RMSE, are two primary tests used when determining baseline energy model goodness-of-fit and modeling strength. The significance of R² and CV-RMSE can be explained by first understanding the method of least squares. The least squares estimate poses the relationship between the total sum of squares (SST), the sum square of errors (SSE), and the regression sum of squares (SSR). The total sum of squares, or the variability in the target variable, can be found as the sum of the regression sum of squares and the sum square of errors, as depicted in Equation 46.

$$SST = SSE + SSR \quad (46)$$

The regression sum of squares is defined as the variability of the data set accounted for by the regression analysis. The sum square of errors is defined as the variability remaining after

the regression (Chatterjee & Simonoff, 2013). The total sum of squares, the sum square of errors, and the regression sum of squares are defined by Equation 47, 48, and 49. To find an appropriate baseline energy model using the method of least squares, the sum square of errors is minimized through regression and the model equation parameters are found.

$$SST = \sum (y_{act} - \bar{y}_{avg})^2 \quad (47)$$

$$SSE = \sum (y_{act} - y_{mod})^2 \quad (48)$$

$$SSR = \sum (y_{mod} - \bar{y}_{avg})^2 \quad (49)$$

where,

y_{act} = observed value of the dependent variable,

\bar{y}_{avg} = mean of observed values,

y_{mod} = model predicted value of the dependent variable.

The ratio of the sum square of errors and the total sum of squares is the proportion of the total variation of the measured data that is not explained by the regression model (Devore, 2009). Thus, the coefficient of determination, R^2 , shown in Equation 50, explains the proportion of variation of the measured data that is explained by the regression model. In other words, the coefficient of determination represents the fit of measured data to the regression model compared to the fit of measured data to the mean value of the data. It is the population proportion of variability in the dependent variable that is accounted for by the best linear combination of the predictors (Chatterjee & Simonoff, 2013).

$$R^2 = 1 - \frac{SSE}{SST} \quad (50)$$

Also known as the squared correlation coefficient, R^2 is represented as a value between zero and one. An R^2 value equal to 1.0 indicates a perfect fit between the measured data and the

regression model. An R^2 value equal to 0.0 indicates that the regression model provides no better fit than the mean of the measured data (Kissock et al., 2003). It is a direct measure of how similar the observed and fitted target values are (Chatterjee & Simonoff, 2013). The closer the R^2 value is to 1.0, the closer the regression model is to predicting the behavior of the dependent variable.

The coefficient of determination can become overinflated as the number of regression coefficients and the number of predictive or independent variables are increased in a linear regression model. Introducing additional regression coefficients will always increase the value of R^2 even if the terms are insignificant to the model equation. Thus, the adjusted coefficient of determination is applicable for measuring statistical goodness-of-fit when including additional explanatory variables. Since the adjusted coefficient of determination, R^2_{adj} , concerns itself with variances and not variation, this eliminates the incentive to include additional variables in a model which have little or no explicative power (Reddy, 2011). Equation 51 provides the formula for the adjusted coefficient of determination (Devore, 2009).

$$R^2_{adj} = 1 - \left[\frac{(n-1) SSE}{(n-p) SST} \right] \quad (51)$$

where,

n = number of observed values,

p = number of regression parameters or coefficients.

Statistical references do not specify criterion for the use of R^2 or R^2_{adj} when determining a regression model's goodness-of-fit. Chatterjee & Simonoff (2013) state that unless the number of predictors or independent variables is large relative to the sample size, then R^2 and the adjusted R^2 will be relatively close to each other, and the choice of which to use is a minor concern. In

relation to creating baseline energy models, Kissock et al. (2003) suggest that the adjusted coefficient of determination compensates for the effect of additional regression coefficients resulting from additional independent variables. Therefore, the presented analysis will include values of the adjusted coefficient of determination for multivariate regression analysis where weather and production are included as independent variables. Values for R^2 will be presented for models which include weather as the single independent variable.

There is some debate as to if the coefficient of determination is the best test of goodness-of-fit for linear regression models (Draper & Smith, 1998). The mean square error, MSE, is a statistical alternative to determine the goodness-of-fit of a baseline energy model. The mean square error, or the residual mean square, describes the mean variance of the errors, or the average variance between the measured and model values. The mean square error can be described by Equation 52. The square root of the mean square error, or the root mean square error, RMSE, is a measure of the scatter or deviation of the measured data around the regression model. The RMSE is defined by Equation 53.

$$MSE = \frac{SSE}{(n - p)} \quad (52)$$

$$RMSE = \sqrt{\frac{SSE}{(n - p)}} \quad (53)$$

A normalized measure is often appropriate when evaluating a model's goodness-of-fit. The coefficient of variation of the root mean square error, CV-RMSE, can be used to assess the strength of a regression model. The CV-RMSE is the ratio of the root mean variation of the dependent variable that is not explained by the regression model and the mean value of the observed data, as shown in Equation 54. The values are provided as percentages. For example, a CV-RMSE of 7.2% denotes that the root mean value of the unexplained variance in the

dependent variable is 7.2% of the mean value of the dependent variable. Thus, a smaller CV-RMSE value is desired in a goodness-of-fit evaluation.

$$CV-RMSE = \frac{RMSE}{\bar{y}_{avg}} \quad (54)$$

It is unclear in the established literature which statistical test, R^2 or CV-RMSE, is more appropriate for determining the goodness-of-fit of a baseline energy model. Some analysts prefer emphasizing the R^2 (Akbari & Konopacki, 1998; Carpenter et al., 2010), while others prefer emphasizing the CV-RMSE (Haberl, et al., 1998). Turner & Doty (2007) suggest that a buildings thermal “weight” may be characterized by the value of R^2 . Reddy et al. (1997b) concluded in a study of energy consumption of various Department of Defense buildings that the R^2 statistic is misleading in three-parameter change-point heating models and suggest using CV-RMSE for determining goodness-of-fit for baseline energy models. Both methods are unit-less measures that are indicative of model fit, but they define model fit in two different ways. The CV-RMSE evaluates the relative closeness of the predictions to the measured values. The R^2 evaluates how much of the variability in the measured values is explained by the model (IDRE UCLA).

It is also unclear as to what numerical values for R^2 or CV-RMSE constitute a “good-fit” regression model. Sonderegger (1998) suggests that the coefficient of determination should be no less than 0.75. Reddy et al. (1997b) suggest that a CV-RMSE of 5% or less is an excellent model, 10% or less is a good model, 15% or less is a mediocre model, and greater than 20% is a poor model. Regardless of the selection criteria, Ruch & Claridge (1993) recommend using multiple statistical tests for verifying a model’s goodness-of-fit. It is apparent that the methods and requirements of what defines a linear regression model’s goodness-of-fit is quite arbitrary and varies from reference to reference. It may be concluded that it is up to the analyst to

determine the selection standards. The analysis presented in this thesis will include R^2 , R^2_{adj} , and CV-RMSE values for comprehensiveness and discussion.

CHAPTER 3: RESULTS

This chapter presents the selected case studies of industrial manufacturing facilities including discussion of results. A total of nine case studies observing various types of industrial manufacturing facilities are examined. Each facility is located in the southeastern section of the United States, in Alabama or Georgia. The presented case studies intend to evaluate the effectiveness of simple inverse linear statistical regression models for establishing baseline energy consumption models for industrial manufacturing facilities. This chapter also illustrates the use of a baseline energy model to assist in the development of an end-point energy analysis for one of selected case studies.

Inspiration, funding, and data for this thesis project were provided by the Alabama Industrial Assessment Center (AIAC). The AIAC is one of twenty-four centers sponsored by the Department of Energy's Energy Efficiency and Renewable Energy (EERE) division. The center is comprised of faculty members and engineering students of the University of Alabama. The role of the AIAC is to assist manufacturers and industrial facilities with energy conservation, waste reduction, and productivity enhancement, while providing training and on-hand experience to the engineers-of-tomorrow. The industrial sector uses almost half of the world's total delivered energy, at about 200 quadrillion Btu in 2010. This value is expected to grow to nearly 307 quadrillion Btu by 2040 (U.S. Energy Information Administration, 2013). The Industrial

Assessment Centers located throughout the United States attempt to minimize this growth by providing no-cost assessments of industrial manufacturing facilities.

The AIAC student and faculty teams perform a one-day onsite assessment of selected industrial manufacturing facilities located in Alabama and some surrounding states. The AIAC teams have a 60 day period to produce a comprehensive report and deliver it to the client. One goal of the comprehensive report is to provide clients with energy and cost savings recommendations, which are justified on the basis of a simple payback economic analysis. The second goal of the comprehensive report is to perform an end-point energy analysis for the client. The end-point energy analysis is compiled using information gathered during the initial site visit and the subsequent two-month report production period.

The end-point energy analysis provides industrial manufacturing clients with an estimated breakdown of energy consumption for each major end-user. Due to the one-day onsite visit constraint, the amount of detailed information gathered by the AIAC is fairly limited. Many assumptions regarding equipment use and operating procedures are oftentimes made when completing the end-point energy analysis. With the help of simple inverse linear regression models, or other inverse methods, the AIAC hopes to define baseline energy models for industrial facilities in order to help companies understand their energy consumption and production behavior and to identify energy and cost saving opportunities.

Each case study presented in this chapter utilizes real information obtained by AIAC members from facility personnel during the initial onsite visit and succeeding report production period. The names of individual companies are withheld due to confidentiality agreements, but are identified in accordance to the reference number assigned by the AIAC. Facility location, manufactured product, and basic information are provided.

3.1 Case Study UA0094

Facility UA0094 is an industrial manufacturing facility located in Cedartown, Georgia. The company manufactures office furniture such as desks, office chairs, and file cabinets. The facility uses electricity to supply energy for motors, compressed air, lighting, air handling, space cooling, and other manufacturing processes. The building is approximately 570,000 square feet. This area includes the production space, warehouse, and office space in one large, metal frame building with a white reflective roof. This case study will examine the use of three-parameter cooling change-point and variable-base cooling degree-day regression methods to establish a baseline energy model for the facility's electrical energy use.

To compensate for a high internal heat load, the production floor and office areas are cooled year-round with two large chillers, various air handling units, and eight air conditioning units. Thus, it is expected that the facility's electrical energy consumption will vary with outdoor ambient dry-bulb temperature. The facility operates 24 hours per day, five to six days per week, for 52 weeks each year. Energy consumption data was obtained for November 2011 through October 2012. Production data was not provided by facility personnel during the initial AIAC site visit. Electricity is not used for space heating or process heating at the facility.

Using the methods and Microsoft Excel program described in Chapter 2, a three-parameter cooling change-point regression analysis was performed for facility UA0094. Actual monthly average mean dry-bulb temperature data for Cedartown, GA (in the Dallas Paulding County Region) was obtained from the Weather Underground website for the 3PC analysis. Electrical service dates for this facility range from the beginning of one month to the beginning of the next calendar month. Initial starting values for the regression parameters a , b , and $T_{b,c}$ were 60,000 kWh/day, 700 kWh/day-°F, and 60.0°F, respectively. Following the regression

analysis using the Excel Solver feature, the final regression parameters for a , b , and $T_{b,c}$ are 58,830 kWh/day, 1,006 kWh/day-°F, and 61.3°F, respectively. The 3PC change-point baseline energy model for UA0094 is shown in Equation 55. The R^2 value is 0.71, and the CV-RMSE is 8.2%. This suggests that ambient dry-bulb temperature is an influential variable and that the 3PC change-point model is a good baseline energy consumption model for facility UA0094.

$$E_c = 58,830 \frac{kWh}{day} + 1,006 \frac{kWh}{day \cdot ^\circ F} (T_{amb} - 61.3^\circ F)^+ \quad (55)$$

Figure 10 depicts the actual monthly energy use and the monthly energy use as modeled by the 3PC change-point regression. A plot of energy versus time of year is a good starting point for evaluating industrial facility energy use. It shows whether ambient temperature is a significant factor (Rabl et al., 1992). If the simple time plot shows that energy consumption is not weather-dependent, the relationship can be ruled out and other independent variables, such as production, may be analyzed.

The figure shows that the electrical energy use is slightly higher from May through September when average monthly outdoor dry-bulb temperatures are greatest and space cooling loads increase. During the winter and fall months, electrical energy use declines but remains fairly constant. Thus, the electrical energy use is weather-independent during this time period; the electricity consumption during these months is sufficient to condition the production and office areas from the internal heat load of the facility, and to supply energy for production-dependent and production-independent manufacturing processes. The graph indicates that the 3PC baseline energy model sufficiently reflects the weather dependency of facility UA0094's electricity consumption.

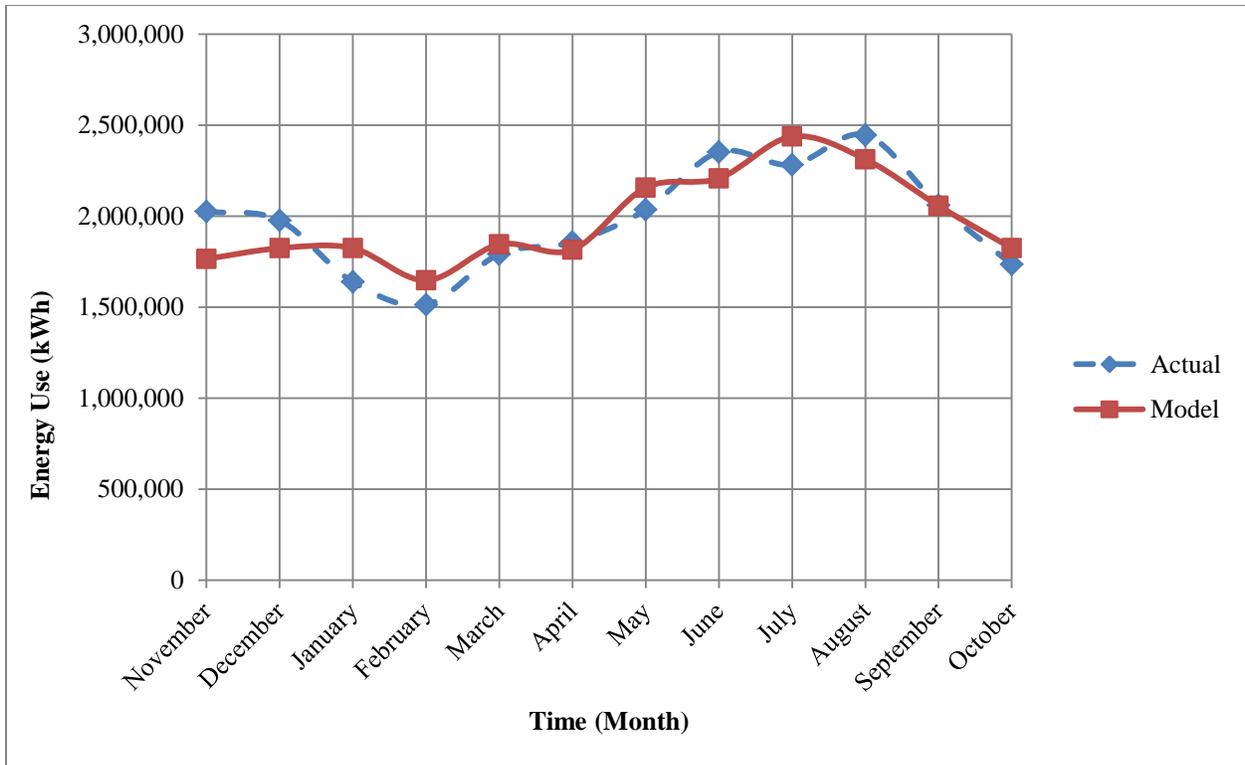


Figure 10. Actual and 3PC model predicted monthly electricity use for facility UA0094.

Figure 11 shows the 3PC change-point model for facility UA0094. The graph also shows the increase in energy consumption during the summer months. The independent energy consumption is 58,830 kWh/day. Therefore, the baseline model implies that 91.4% of the facility's total electrical energy consumption is weather-independent. The percentage of energy that is weather-independent or weather-dependent is calculated through the regression model between the maximum and minimum temperatures from the observed data. The cooling slope is 1,006 kWh/day-°F and the cooling change-point temperature is 61.3°F. Therefore, the weather-dependent energy consumption is 8.6% of the facility's total electrical energy use. The difference between the model calculated annual energy use and the billed annual energy use is -0.9%, which signifies the model is only slightly under-predicting electrical energy consumption.

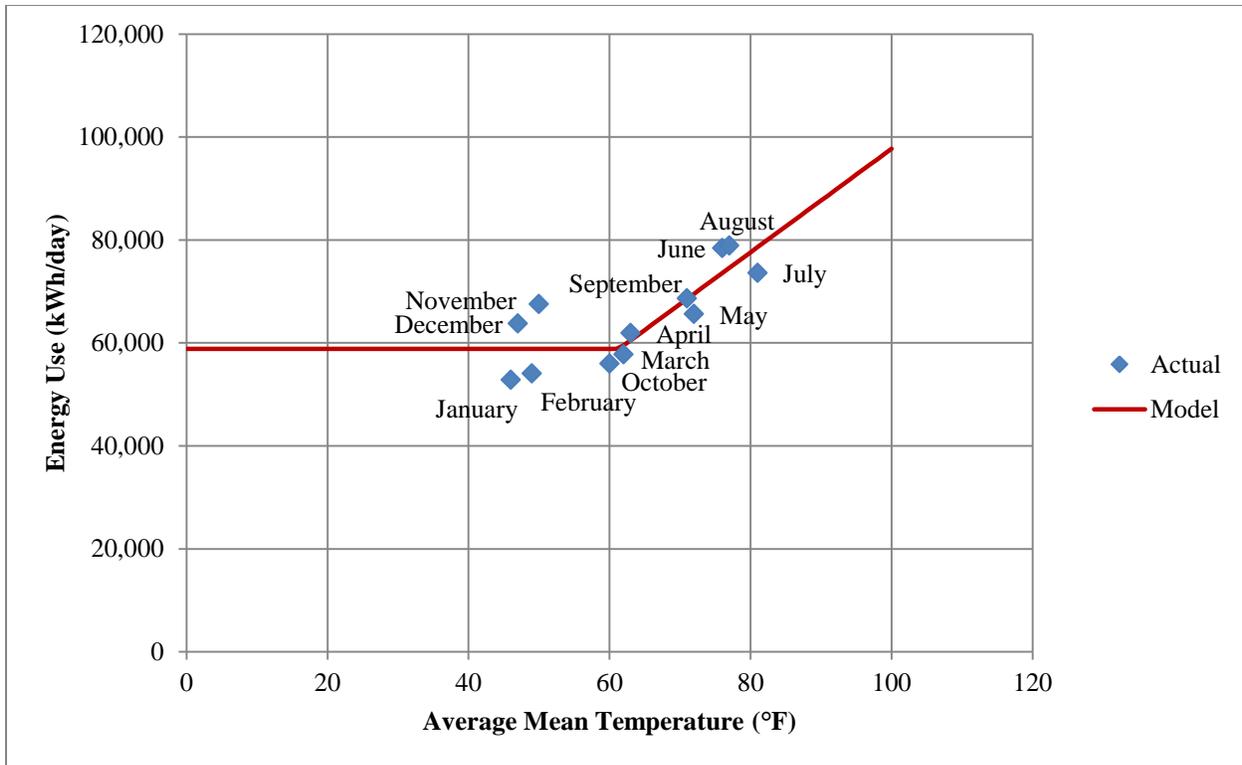


Figure 11. 3PC change-point model of monthly electrical energy use for facility UA0094.

A variable-base cooling degree-day (CDD) regression analysis was also performed for facility UA0094. Cedartown, GA is approximately 20 miles south of Rome, GA. Therefore, normalized TMY3 weather data for Rome, GA was selected for the CDD analysis. Similar to the 3PC change-point analysis, the initial starting values for the regression parameters a , b , and $T_{b,c}$ were 60,000 kWh/day, 700 kWh/day-°F, and 60.0°F, respectively. Following the regression analysis using the Excel Solver feature, the final CDD regression parameters for a , b , and $T_{b,c}$ are 59,165 kWh/day, 2,387 kWh/day-°F, and 72.6°F, respectively. The CDD baseline energy model for UA0094 is shown in Equation 56. The R^2 value is 0.68, and the CV-RMSE is 8.5%. These goodness-of-fit values indicate that ambient temperature is an influential variable and that the

CDD change-point model is also a good baseline energy consumption model for facility UA0094.

$$E_C = 59,165 \frac{kWh}{day} + 2,387 \frac{kWh}{day \cdot ^\circ F} [cdd_i(72.6^\circ F)] \quad (56)$$

Figure 12 depicts the actual monthly energy use and the monthly energy use as modeled by the CDD regression. Similar to the 3PC model, the CDD sufficiently explains the increase in electrical energy during the summer months as ambient dry-bulb temperatures increase, and the relatively constant energy consumption in the winter and fall months. Figure 13 shows the facility's electrical energy use a function of cooling degree-days as explained by the CDD empirical model. The independent energy consumption is 59,165 kWh/day. The cooling slope is 2,387 kWh/day-°F. The calculation of degree-days is based on the cooling balance temperature of 72.6°F. The CDD model indicates that 86.6% of the total electrical energy use is weather-independent, and 13.4% of the total electrical energy use is weather-dependent. The difference between the CDD model calculated annual energy use and the billed annual energy use is +5.1%, indicating the model is over-predicting electrical energy consumption.

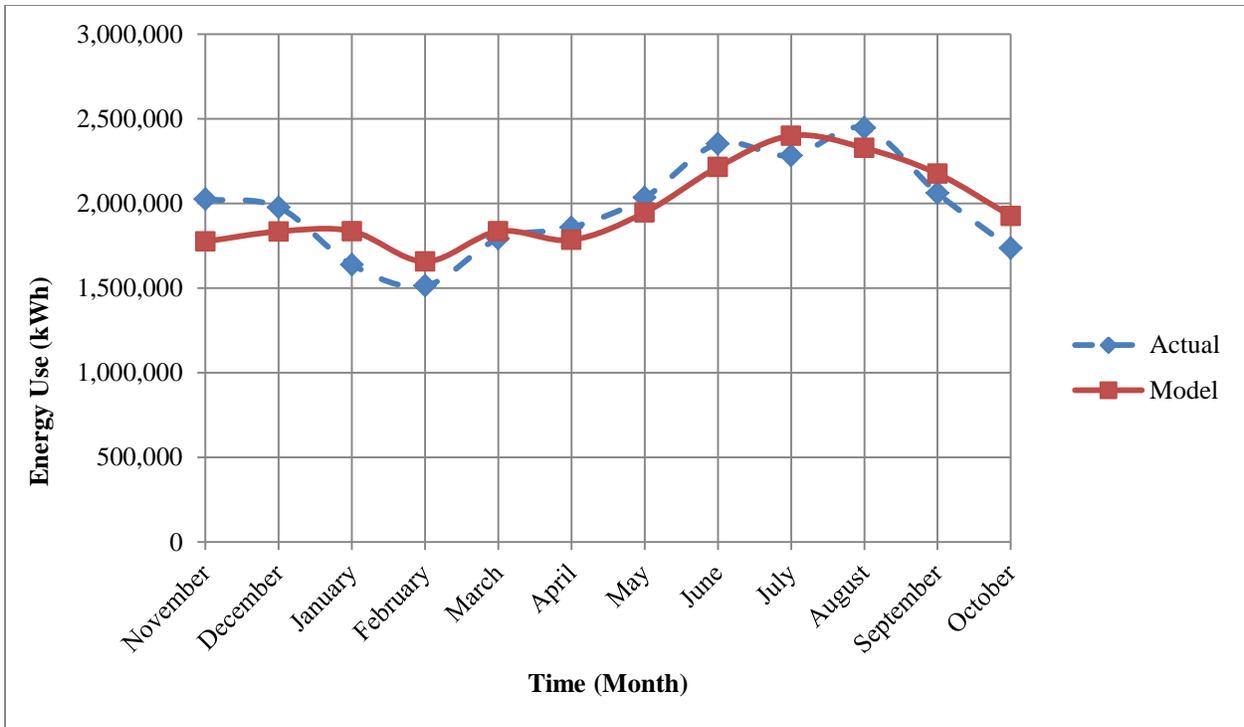


Figure 12. Actual and CDD model predicted monthly electricity use for facility UA0094.

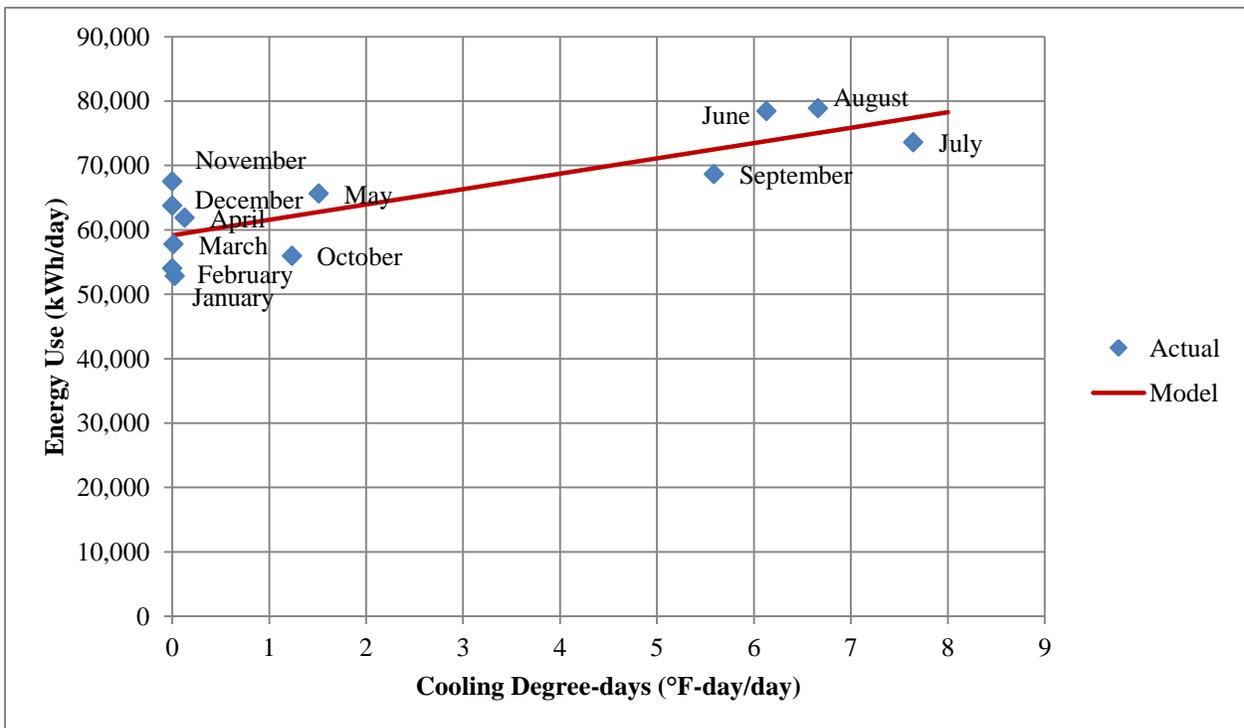


Figure 13. CDD model of monthly electrical energy use for facility UA0094.

The 3PC change-point and CDD regression analyses proved to be sufficient baseline energy consumption models for facility UA0094. The 3PC change-point model possessed slightly better goodness-of-fit values than the CDD model. However, the difference in values for R^2 and CV-RMSE were not large enough to provide conclusions as to which model type provides a better fit. The independent energy consumption parameters were similar for both model types. However, the cooling slope and balance point temperature values for the CDD model were larger than the values for the 3PC change-point model. Furthermore, in comparison to the 3PC change-point model the CDD model indicated that a larger percentage of the total energy use was weather-dependent. These differences may be a result from the variance in dry-bulb temperature data sources. 3PC change-point models utilize average mean monthly temperature values, while CDD models use TMY3 hourly temperature data files. Although differences between the 3PC change-point and CDD model types are evident, both regression models sufficiently indicated the temperature dependency of the electrical energy consumption for facility UA0094.

It is also important to note the significance of initial parameter values in the case study of UA0094. Chapter 2 explained the use of the GRG Nonlinear Multistart Solver option for finding a globally optimum solution during the regression analysis. However, this case study proved the importance of selecting reasonable starting values, as the Multistart Solver option is limited by finding the probable globally optimum solution. In fact, the verbiage of the Solver solution box explains that the “GRG engine has *probably* found a globally optimal solution.” Selecting unreasonable initial values for the regression parameters resulted in illogical baseline energy models for the 3PC change-point model type.

Multiple 3PC change-point regression trials and their initial regression parameter values are summarized in Table 2. The first trial included reasonable starting values for parameters a , b , and $T_{b,c}$. The first trial resulted in a logical 3PC change-point baseline energy model, and was used as the final solution. The second trial utilized very low starting values for a , b , and $T_{b,c}$, at 20,000 kWh/day, 100 kWh/day-°F, and 40.0°F, respectively. The results from the second trial developed a 3PC model with an unreasonable cooling change-point temperature of 31.0°F. The third trial inserted large initial starting values for a , b , and $T_{b,c}$, at 100,000 kWh/day, 2,000 kWh/day-°F, and 70.0°F, respectively. The results from the third trial developed a 3PC model with reasonable regression parameter values. However, the R^2 value was 0.00 and the CV-RMSE was 15.2%, indicating that the regression model does not adequately represent the relationship between temperature and electrical energy consumption. In conclusion, it is essential to provide reasonable initial regression parameter estimates in order to achieve satisfactory baseline energy models.

Table 2

3PC Regression Trials with Varying Initial Parameter Values

	Coefficient	Trial 1	Trial 2	Trial 3
Initial	a	60,000	20,000	100,000
	b	700	100	2,000
	$T_{b,c}$	60.0	40.0	70.0
Final	a	58,830	47,840	64,924
	b	1,006	536	1,679
	$T_{b,c}$	61.3	31.0	84.0
	R^2	0.71	0.57	0.00
	CV-RMSE	8.2%	9.9%	15.2%

3.2 Case Study UA0084

Facility UA0084 is an industrial manufacturing facility located in Gadsden, Alabama. The company produces interior automotive panels from plastics and foam using injection molding. The building is approximately 270,000 square feet. This area includes production space, storage, and office space in one large sectioned building. Due to the internal heat load, most of the facility is cooled year-round with electricity. However, the facility also uses natural gas for space heating in the office areas and in some of its curing processes. Thus, it is expected that the facility's natural gas consumption will vary with outdoor dry-bulb temperature. This case study will examine the use of three-parameter heating change-point and variable-base heating degree-day methods to establish a baseline energy model for the facility's natural gas usage.

The facility's production schedule spans over three shifts for 24 hours per day, five to six days per week, and 50 weeks per year. Natural gas consumption data was obtained for the facility from April 2011 through March 2012. Utility bill read dates occur from the middle of the month to the middle of the next calendar month. Production data was not provided by facility personnel during the initial AIAC site visit. Natural gas is not consumed for space cooling or any sort of process cooling at the facility.

Using the methods and described in Chapter 2, a three-parameter heating change-point regression analysis was performed for facility UA0084. Actual monthly average mean dry-bulb temperature data for Gadsden, AL was obtained from the Weather Underground website. Care was taken to verify that the average mean temperature values were evaluated from the middle of one month to the next, to ensure that the temperature data corresponded to the natural gas utility bill read dates. Initial starting values for the regression parameters a , c , and $T_{b,h}$ were 2.00 MMBtu/day, 0.50 MMBtu/day-°F, and 65.0°F, respectively. Following the regression analysis

using the Excel Solver feature, the final regression parameters for a , c , and $T_{b,h}$ are 1.96 MMBtu/day, 0.58 MMBtu/day-°F, and 61.1°F, respectively. The 3PH change-point baseline energy model for UA0084 is shown in Equation 57. The R^2 value is 0.80, and the CV-RMSE is 45.6%. The CV-RMSE value is large for the 3PH model; CV-RMSE values were observed to be large in other studies of heating baseline energy models (Reddy et al., 1997b). Based on the R^2 goodness-of-fit test, the baseline model adequately portrays the relationship between ambient dry-bulb temperature and natural gas consumption for facility UA0084.

$$E_H = 1.96 \frac{\text{MMBtu}}{\text{day}} + 0.58 \frac{\text{MMBtu}}{\text{day} \cdot ^\circ\text{F}} (61.1^\circ\text{F} - T_{amb})^+ \quad (57)$$

Figure 14 depicts the actual monthly natural gas use and the monthly natural gas use as modeled by the 3PH change-point regression. The graph shows that the natural gas consumption increases from the months of October through February when average monthly dry-bulb temperatures are lowest space heating requirements increase. Thus, the natural gas consumption during this time period is weather-dependent. During the spring and summer months, natural gas energy use declines and remains fairly constant. Thus, the natural gas consumption during this time period is weather-independent. The graph indicates that the 3PH baseline energy model is a relatively good model for depicting baseline natural gas energy use for facility UA0084.

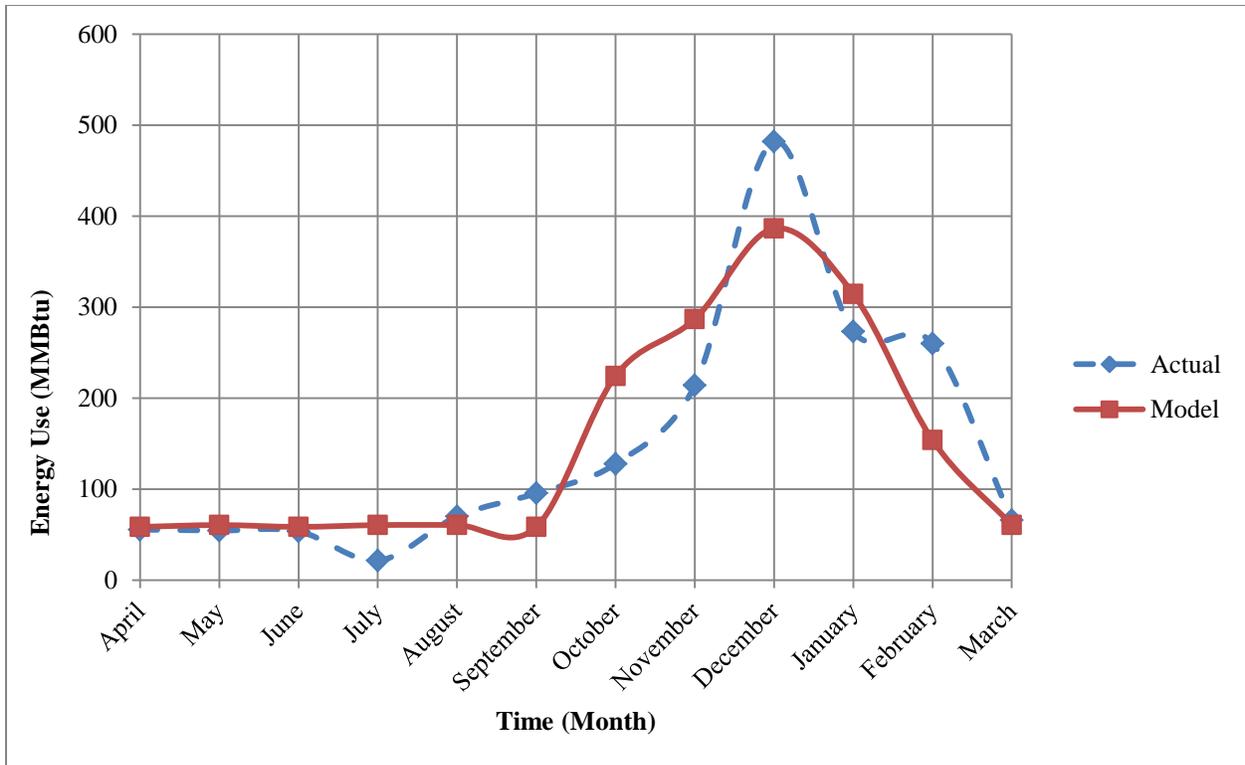


Figure 14. Actual and 3PH model predicted monthly natural gas use for facility UA0084.

Figure 15 shows the 3PH change-point model for facility UA0084. The graph also shows the increase in energy consumption during the fall and winter months. The independent natural gas consumption is 1.96 MMBtu/day. The baseline model indicates that 42.5% of the facility's total natural gas consumption is weather-independent. The heating slope is 0.58 MMBtu/day-°F and the heating change-point temperature is 61.1°F. The weather-dependent energy consumption is 57.2% of the facility's total annual natural gas consumption. The difference between the model calculated annual energy use and the billed annual energy use is -5.4%, suggesting that the model is under-predicting natural gas energy consumption for facility UA0084.

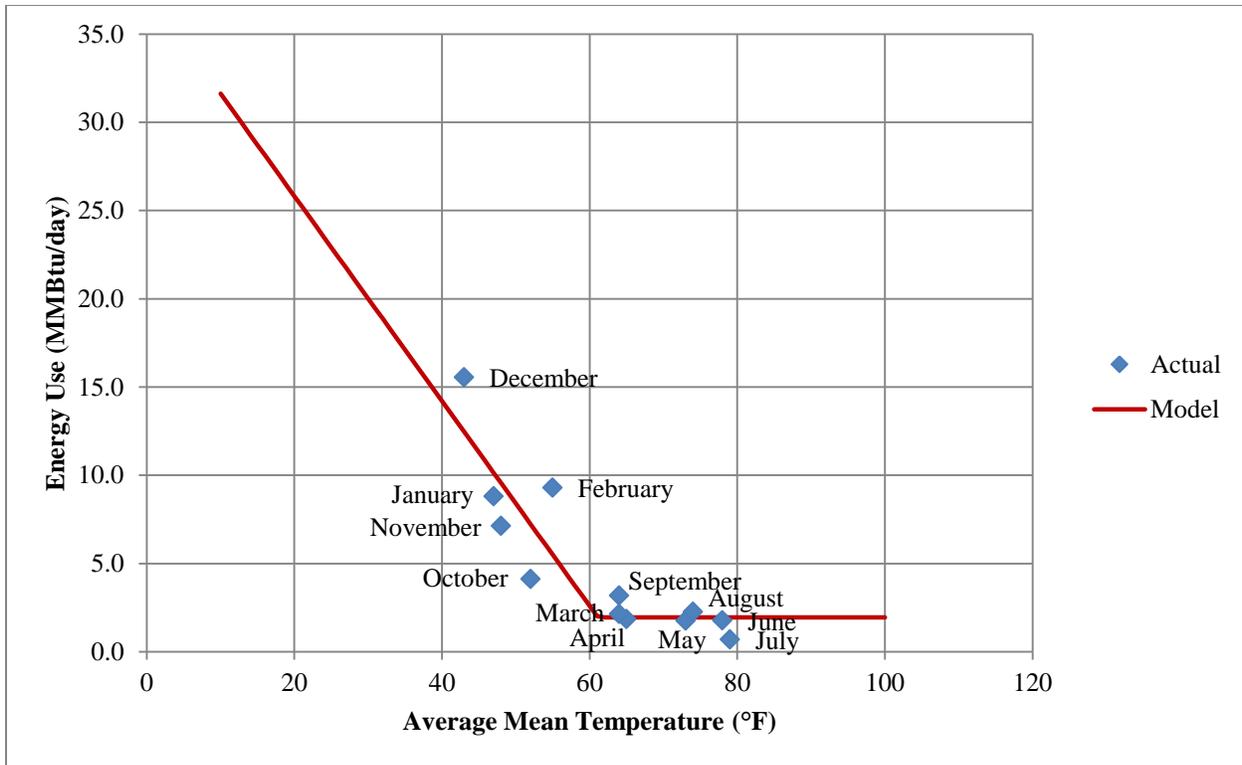


Figure 15. 3PH change-point model of monthly natural gas use for facility UA0084.

A variable-base heating degree-day (HDD) regression analysis was also performed for facility UA0084. TMY3 weather data for Gadsden, AL was selected for HDD analysis. Similar to the 3PH change-point analysis, the initial starting values for the HDD regression parameters a , c , and $T_{b,h}$ were 2.00 MMBtu/day, 0.50 MMBtu/day-°F, and 65.0°F, respectively. Following the regression analysis using the Excel Solver feature, the final regression parameters for a , c , and $T_{b,h}$ are 1.60 MMBtu/day, 0.67 MMBtu/day-°F, and 55.4°F. The HDD baseline energy model is shown in Equation 58. The R^2 value is 0.83, and the CV-RMSE is 41.4%. Based on the R^2 goodness-of-fit test, the baseline model adequately portrays the relationship between ambient dry-bulb temperature and natural gas consumption for facility UA0084.

$$E_H = 1.60 \frac{\text{MMBtu}}{\text{day}} + 0.67 \frac{\text{MMBtu}}{\text{day} \cdot ^\circ\text{F}} \left[hdd_i (55.4^\circ\text{F}) \right] \quad (58)$$

Figure 16 depicts the actual monthly energy use and the monthly energy use as modeled by the HDD regression. As seen from the graph, the HDD model attempts to explain the increase in natural gas consumption during the winter and fall months as ambient dry-bulb temperatures decrease, and the relatively constant energy use in the spring and summer months. Figure 17 shows the facility's natural gas use as a function of heating degree-days as explained by the HDD empirical model. The independent energy consumption is 1.60 MMBtu/day. The heating slope is 0.67 MMBtu/day-°F. The calculation of heating degree-days is based on the heating balance point temperature of 55.4°F.

The HDD estimates that 22.5% of the total natural gas energy use is weather-independent, and 77.5% of the total annual natural gas use is weather-dependent. It is reasonable that a large majority of the model predicted annual energy use is weather-dependent, since most of the natural gas consumption for facility UA0084 is used for space heating in the office areas. The difference between the HDD model calculated annual energy use and the actual billed natural gas use is +46.1%. The HDD is greatly over-predicting the annual natural gas consumption for the facility. The cause of this may be due to the small amount of overall natural gas consumption for the facility, or the use of typical weather data.

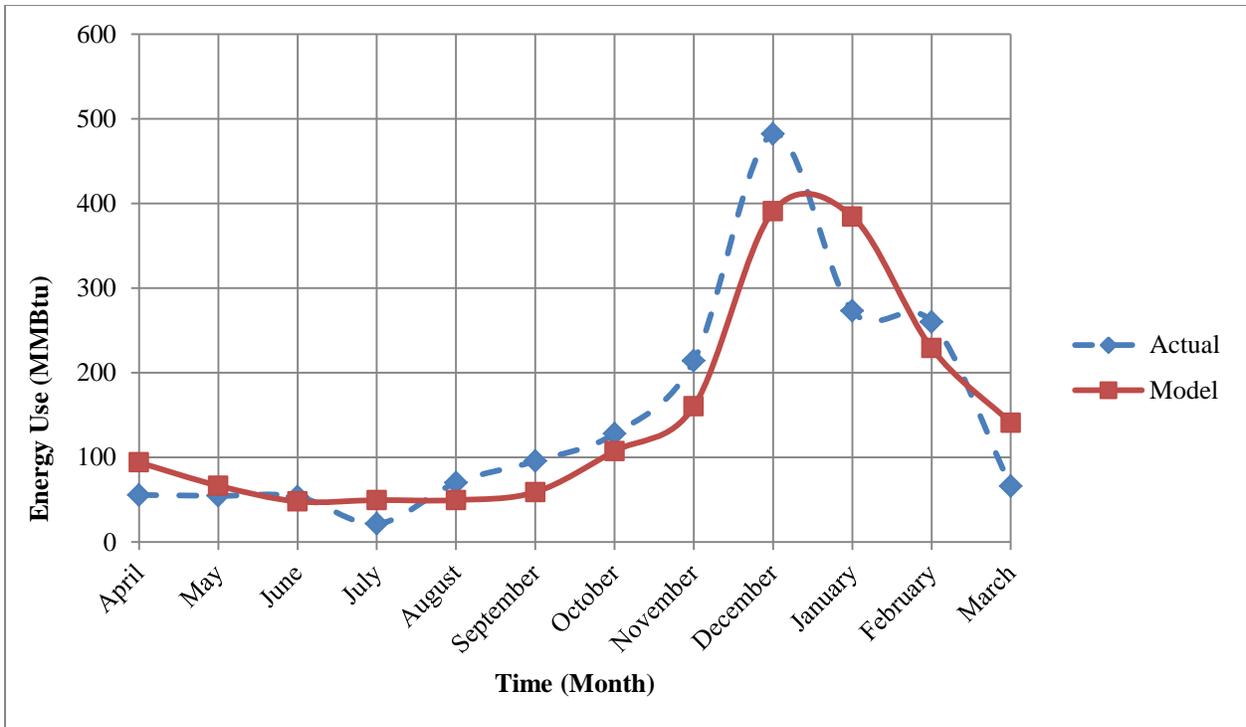


Figure 16. Actual and HDD model predicted monthly natural gas use for facility UA0084.

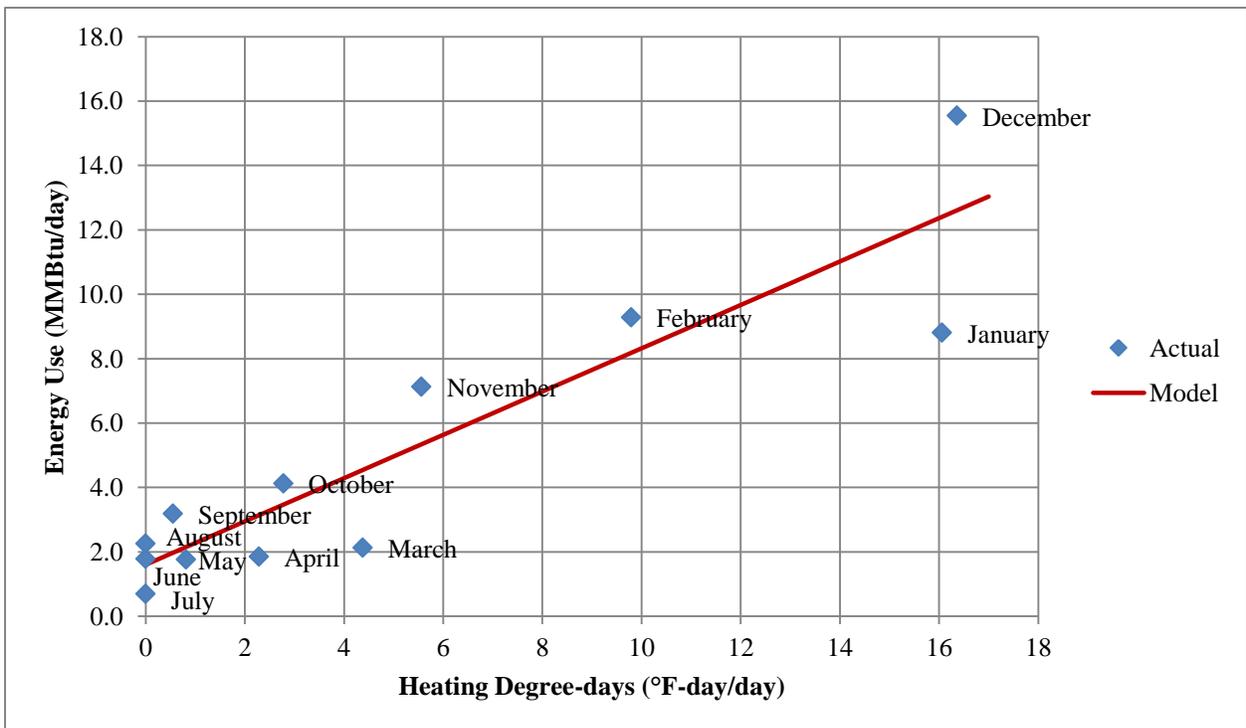


Figure 17. HDD model of monthly natural gas energy use for facility UA0084.

The 3PH change-point and HDD regression analyses proved to be adequate baseline energy consumption models for facility UA0084. In contrast to case study UA0094, the variable-base heating degree-day model possessed slightly better goodness-of-fit values than the 3PH change-point model. However, the difference between the goodness-of-fit for each model type is not large enough to provide conclusions as to which model type provides a better fit for the facility. The 3PH change-point model suggests that about half of the facility's natural gas consumption is weather-dependent and the remaining half of the facility's natural gas consumption is weather-independent. The HDD model suggests that a majority of the facility's annual natural gas consumption is weather-dependent and the remainder is weather-independent. The facility reported that most of the natural gas is utilized for space conditioning in the office areas. Therefore, it may be hypothesized that the heating degree-day model provides a more reasonable description of the natural gas consumption behavior for facility UA0084.

3.3 Case Study UA0103

Facility UA0103 is an industrial manufacturing facility located in Eastaboga, AL. The company manufactures complete sets of automotive seats. The facility's singular fuel source is electricity, used to supply energy for space cooling, space heating, lighting, compressed air, production heaters and steamers, fans, and other manufacturing processes. The building is approximately 120,500 square feet, which includes the main production area, office area, and warehouse in one large building structure. This case study will examine the use of five-parameter cooling and heating change-point and variable-base cooling and heating degree-day regression methods to establish a baseline energy model for the facility's electrical energy use.

Due to manufacturing specifications, the entire facility must be conditioned year-round. The facility uses thirteen rooftop air conditioning units with electric strip heat to cool the

production and office areas during warmer months and heat the areas during colder months. Thus, it is expected that the facility's electrical energy consumption will vary with outdoor dry-bulb temperatures. During the initial site visit, AIAC estimated that the energy consumed by the space conditioning equipment comprised more than half of the total annual electrical energy consumption for the facility.

The facility operates 10 hours per day, four to five days per week, for 50 weeks in a typical year. The facility has a sophisticated system for programming the thermostat set-point at the facility, but it was not being used at the time of the AIAC assessment; manual controls were enabled for adjusting the thermostat system. Energy consumption data was obtained from the facility for November 2011 through October 2012. Utility bill read dates occur from the beginning of one calendar month to the beginning of the next calendar month.

Since one fuel source (electricity) is used for space heating and space cooling, a five-parameter cooling and heating change-point model and a cooling and heating degree-day model are appropriate for creating a baseline energy consumption model for facility UA0103. Using the methods described in Chapter 2, a five-parameter cooling and heating (5PCH) change-point regression analysis was performed. The facility is located in Eastaboga, AL, which is approximately 15 miles to the southwest of Anniston, AL. Actual monthly average mean dry-bulb temperature data for Anniston, AL was obtained from the Weather Underground website. Initial values for the regression parameters were as follows: $a = 7,300$ kWh/day, $b = 80.0$ kWh/day-°F, $T_{b,c} = 70.0$ °F, $c = 100.0$ kWh/day-°F, $T_{b,h} = 50.0$ °F. Using the Excel Solver feature to carry out the regression analysis, the final regression parameters are as follows: $a = 7,462$ kWh/day, $b = 60.1$ kWh/day-°F, $T_{b,c} = 64.0$ °F, $c = 100.0$ kWh/day-°F, $T_{b,h} = 47.5$ °F. The 5PCH change-point baseline energy model for UA0103 is shown in Equation 59.

$$E = 7,462 \frac{kWh}{day} + 60.1 \frac{kWh}{day \cdot ^\circ F} (64.0^\circ F - T_{amb})^+ + 100.0 \frac{kWh}{day \cdot ^\circ F} (T_{amb} - 47.5^\circ F)^+ \quad (59)$$

The R^2 value for Equation 59 is 0.44, and the CV-RMSE is 7.4%. Although the R^2 value does not suggest that the 5PCH model is a good fit, the CV-RMSE value suggests otherwise. A very low CV-RMSE percentage of 7.4% is considered a good fit in other baseline energy model analyses. Although the statistical goodness-of-fit test indicates that the 5PCH model describes the relationship between the ambient temperature and electrical energy consumption, a visual representation of the model proves the opposite.

Figure 18 shows the actual monthly electrical energy use and the monthly electrical energy use as modeled by the 5PCH change-point regression. The graph shows that the regression model attempts to follow the same seasonal energy consumption pattern that the actual data exhibits. Figure 19 depicts the 5PCH change-point model for facility UA0103 and includes the actual data points for comparison. The weather-independent energy consumption is 7,462 kWh/day. The cooling slope is 61.1 kWh/day-°F, and the heating slope is 100.0 kWh/day-°F. The cooling change-point temperature is 64.0°F and the heating change-point temperature is 47.5°F.

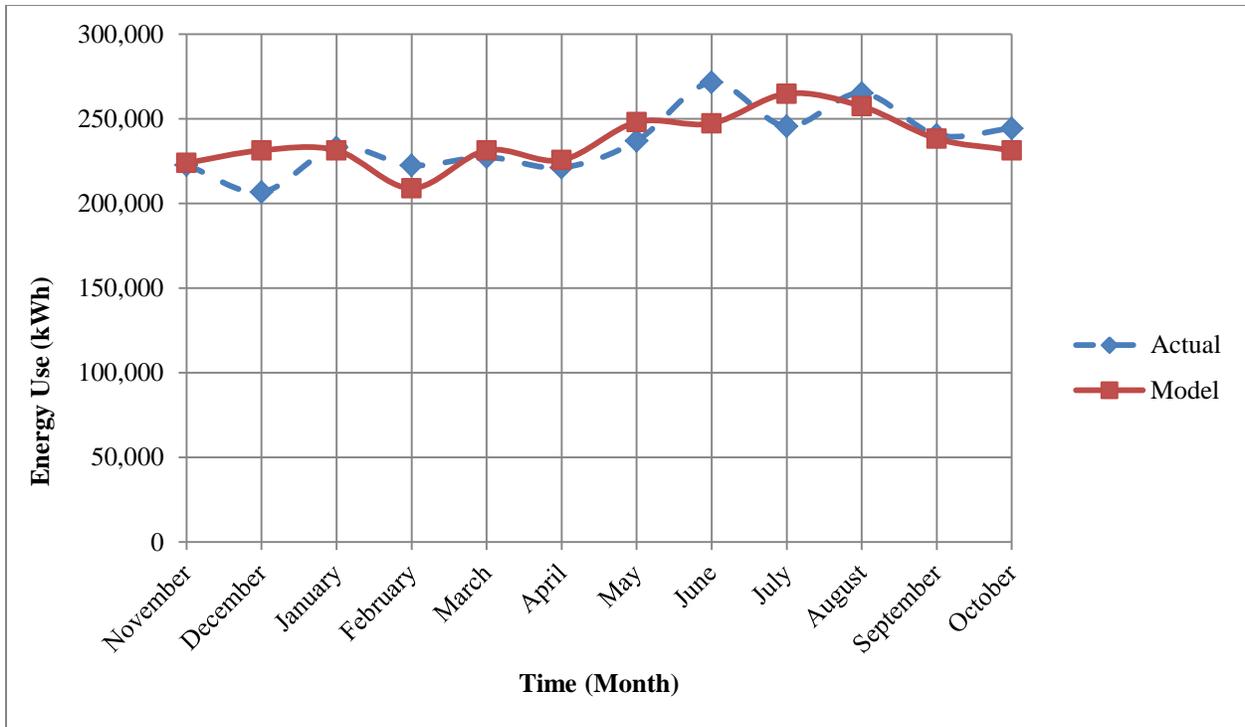


Figure 18. Actual and 5PCH model predicted monthly electricity use for facility UA0103.

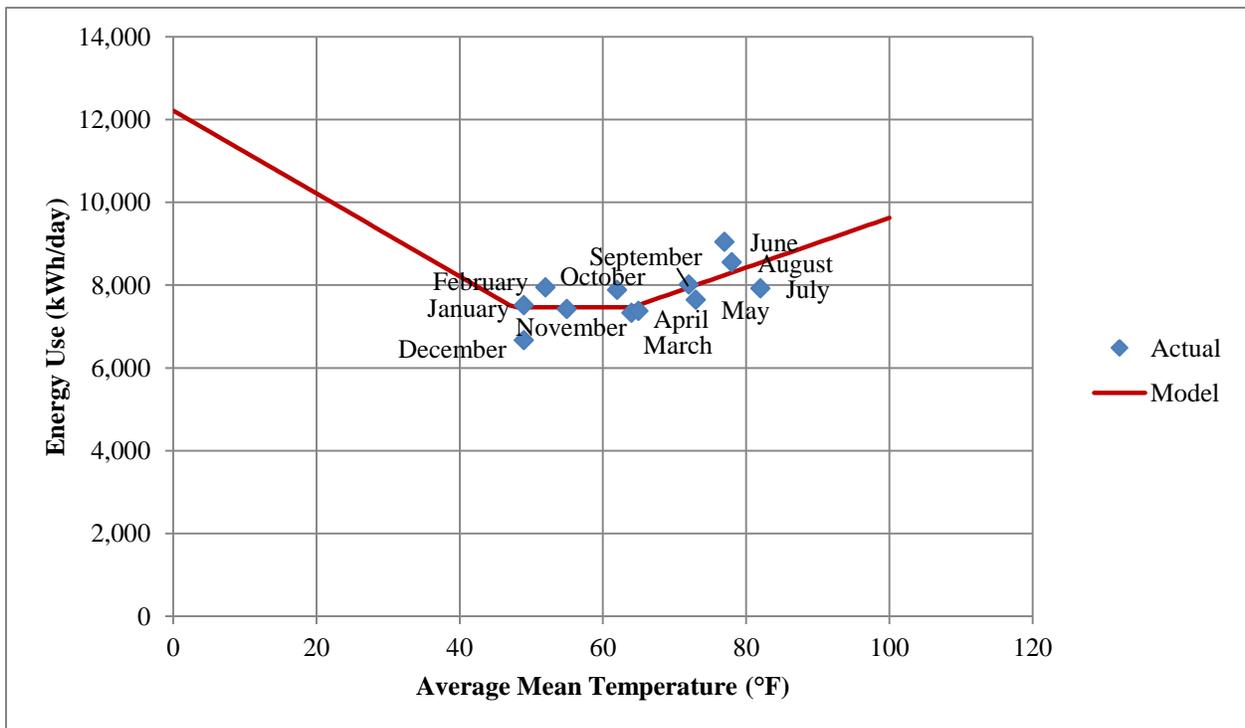


Figure 19. 5PCH model of monthly electrical energy use for facility UA0103.

Figure 19 shows that all of the observed data points have temperature values larger than the heating change-point temperature. In fact, the constant independent energy consumption seems to occur during the winter months when ambient temperatures are lowest and electrical energy consumption is fairly constant. Because none of the observed data points actually occur below the regression calculated heating change-point temperature, the parameters found for the heating slope and the heating change-point temperature during the regression analysis are quite arbitrary and somewhat insignificant. In addition, the value for the heating slope did not change before and after the regression analysis.

The model and observed data suggests that the 5PCH change-point model may not be an accurate representation of the relationship between ambient temperature and electrical energy consumption for the facility. Although the cooling change-point temperature is reasonable, the heating change-point temperature is unreliable since no observed data occurs below this point. One possibility for this model behavior could result from the fact that the internal heat loads of the facility are quite large, and very little electrical energy is required to heat the production area; only small amounts of electricity may be required for space heating in the office areas, which is only a small portion of the overall facility. Therefore, the heating weather-dependent energy is almost nonexistent, and the facility's energy behavior is more representative of a three-parameter cooling change-point model.

The 5PCH baseline energy model suggests that 93.8% of the facility's electrical energy consumption is weather-independent, and 6.2% of the facility's total electrical energy consumption is cooling weather-dependent. These percentages are calculated from the 5PCH model and the maximum and minimum average mean monthly temperatures observed by the facility; therefore, the model suggests that 0.0% of the total annual electrical energy consumption

is heating weather-dependent. The difference between the model calculated annual energy use and the billed annual energy use is +2.3%, suggesting that the model is slightly over-predicting the electrical energy consumption for facility UA0103.

Although a large majority of the facility's total electrical energy use is estimated to be weather-independent, some of this energy consumption may be dedicated to conditioning the plant floor year-round to satisfy manufacturing specifications or humidity requirements. Internal heat gains from production equipment, lighting, and occupants are energy sources consistently present in the facility throughout a typical production year. Therefore, a large percentage of the weather-independent energy consumption and the weather-dependent energy consumption depicted by the 5PCH model may be dedicated to the facility's space conditioning equipment.

A variable-base cooling and heating degree-day (CHDD) regression analysis was also performed for facility UA0103. TMY3 weather data for Anniston, AL was selected for CHDD analysis. The initial parameter values for the CHDD regression were as follows: $a = 7,500$ kWh/day, $b = 100.0$ kWh/day-°F, $T_{b,c} = 70.0$ °F, $c = 50.0$ kWh/day-°F, $T_{b,h} = 50.0$ °F. Using the Excel Solver feature to carry out the regression analysis, the final regression parameters are as follows: $a = 7,456$ kWh/day, $b = 1,055$ kWh/day-°F, $T_{b,c} = 82.0$ °F, $c = 0.0$ kWh/day-°F, $T_{b,h} = 50.0$ °F. The 5PCH change-point baseline energy model for UA0103 is shown in Equation 60.

$$E = 7,456 \frac{kWh}{day} + 1,055 \frac{kWh}{day \cdot ^\circ F} [cdd_i(82.0^\circ F)] + 0.0 \frac{kWh}{day \cdot ^\circ F} [hdd_i(50.0^\circ F)] \quad (60)$$

The R^2 value for Equation 60 is 0.66, and the CV-RMSE is 5.7%. The R^2 value suggests that the CHDD model is mediocre; however, the CV-RMSE value suggests that the CHDD model is a great fit for a baseline energy equation. Like the 5PCH model, although the goodness-of-fit tests indicates a good fit, analysis of the regression parameters and the visual representation of the model suggests otherwise. Figure 20 illustrates the actual monthly electrical energy use

and the monthly electrical energy use modeled by the CHDD regression. The graph portrays the regression model’s attempt to mirror the seasonal effects of the facility’s electrical energy consumption.

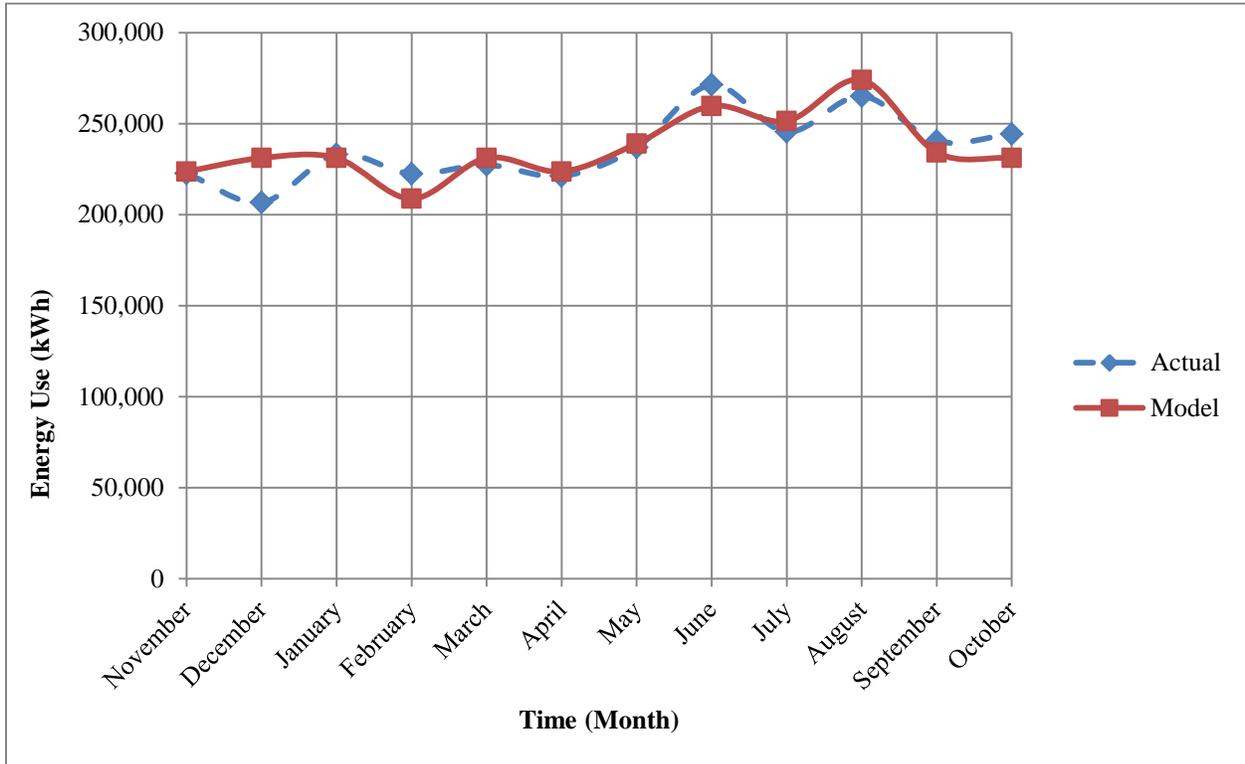


Figure 20. Actual and CHDD model predicted monthly electricity use for facility UA0103.

Figure 21 illustrates the CHDD model for facility UA0103. The weather-independent energy consumption is 7,456 kWh/day. The cooling slope is 1,055 kWh/day-°F and the heating slope is 0.0 kWh/day-°F. The cooling balance point temperature is 82.0°F and the heating balance point temperature is 50.0°F. The value for the heating balance point temperature did not change before and after the regression analysis. The CHDD baseline model indicates that for the facility’s total annual electrical energy use, 98.8% is weather-independent, 1.2% is cooling

weather-dependent, and 0.0% is heating weather-dependent. The difference between the model calculated annual energy use and the billed annual energy use is -2.9%, suggesting that the model is slightly under-predicting the electrical energy consumption for facility UA0103.

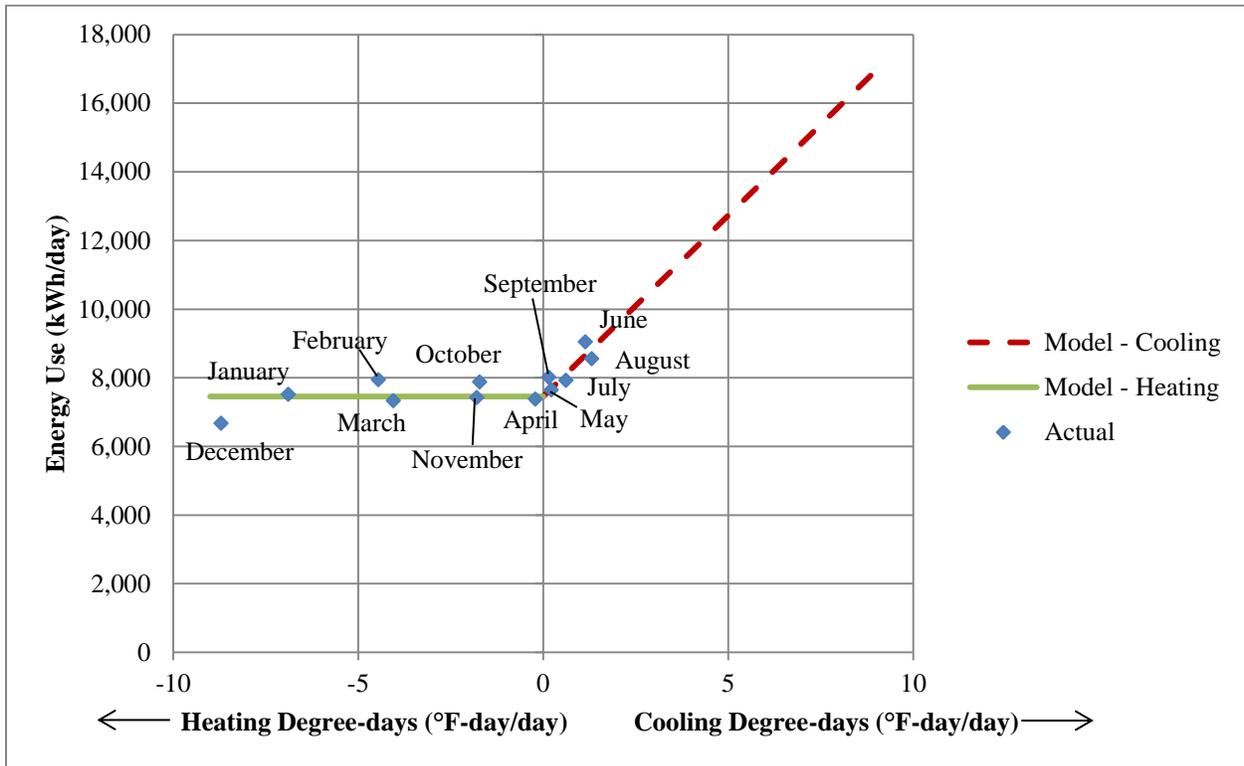


Figure 21. CHDD model of monthly electrical energy use for facility UA0103.

The CHDD regression results propose that the CHDD model may not be an accurate representation of the electrical energy consumption for the facility. Similar to the 5PCH baseline model, the CHDD results allude that no electrical energy is required for space heating. The heating slope is zero, indicating that there is no weather-dependence of the electrical energy consumption in respect to heating. The facility's energy consumption behavior implies that most of the energy use is dedicated to production processes and space cooling. In fact, the cooling

degree-day model could more accurately portray the relationship between electrical energy consumption and ambient temperature.

The independent energy consumption parameters for the 5PCH change-point and CHDD analyses resulted in very similar values. The cooling slope of the 5PCH analysis is much smaller than the CHDD analysis. In addition, the cooling change-point temperature of the 5PCH analysis is much smaller than the cooling balance point temperature for the CHDD analysis. Although the regression parameters varied, the CV-RMSE goodness-of-fit tests between the two results were not extremely different between the two model types. While the CV-RMSE values suggest that the models are moderate fits for the facility's baseline energy consumption, it is not enough to suggest that the five-parameter cooling and heating change-point or the variable-base cooling and heating degree-day models are sufficient for explaining the energy consumption behavior of facility UA0103. Other parameters that influence energy use, such as production, may be more accurate in describing the fluctuations in annual electrical energy use.

3.4 Case Study E3028

Facility E3028 is an industrial manufacturing facility located in Florence, AL. The company produces flooring tiles from raw and recycled materials. The building is approximately 400,000 square feet, which includes the main production area, packaging area, warehouse space, and offices. About 50,000 square feet is devoted to the office areas. Only the office spaces are conditioned at facility E3028; the production, warehouse, and packaging areas are not heated or cooled. Although only a small space of the facility is conditioned, it is still expected that the electrical energy consumption will vary somewhat with outdoor dry-bulb temperature. This case study will examine the use of multivariate three-parameter cooling change-point and multivariate

variable-base cooling degree-day regression methods to establish a baseline energy model for the facility's electrical energy use.

The facility uses electricity to supply energy to process equipment, air compressors, electric furnaces, chillers, lighting, and space cooling. The facility also uses electricity for some space heating in the office areas. However, the amount of energy consumed for space heating is considered to be a very small portion of the facility's overall electrical energy consumption (1%-2% or less). Therefore, the impact of electrical energy used for space heating is ignored for this case study and regression analysis. Operating hours for the facility range from 10 to 20 hours per day, four to five days per week, for 49 weeks each year. Energy consumption data and production data were obtained from the facility from April 2012 through March 2013. Utility bill read dates occur from the beginning of one calendar month to the beginning of the next calendar month. Production data also correlates with the beginning of each calendar month, and was reported in terms of square feet of tile produced per month.

Energy consumption and production values are very strongly correlated for facility E3028. Figure 22 shows monthly electricity use and the number of units produced (in square feet) by the facility during the specified time frame. The two variables seem to be greatly correlated, rising and falling in unison. Using a simple linear curve fit, the relationship between electrical energy use and production is explained by Equation 61. The variable P_m indicates the total monthly quantity of units produced, normalized by the number of days in the month. The coefficient of determination R^2 for the energy versus production model is 0.93, indicating that production significantly influences the electrical energy consumption. These results justify the inclusion of production as an appropriate additional independent variable for multivariate 3PC-Prod change-point and CDD-Prod regression analyses.

$$E_c = \left(0.236 \frac{kWh}{ft^2} P_m \right) + 9,120 \frac{kWh}{day} \quad (61)$$

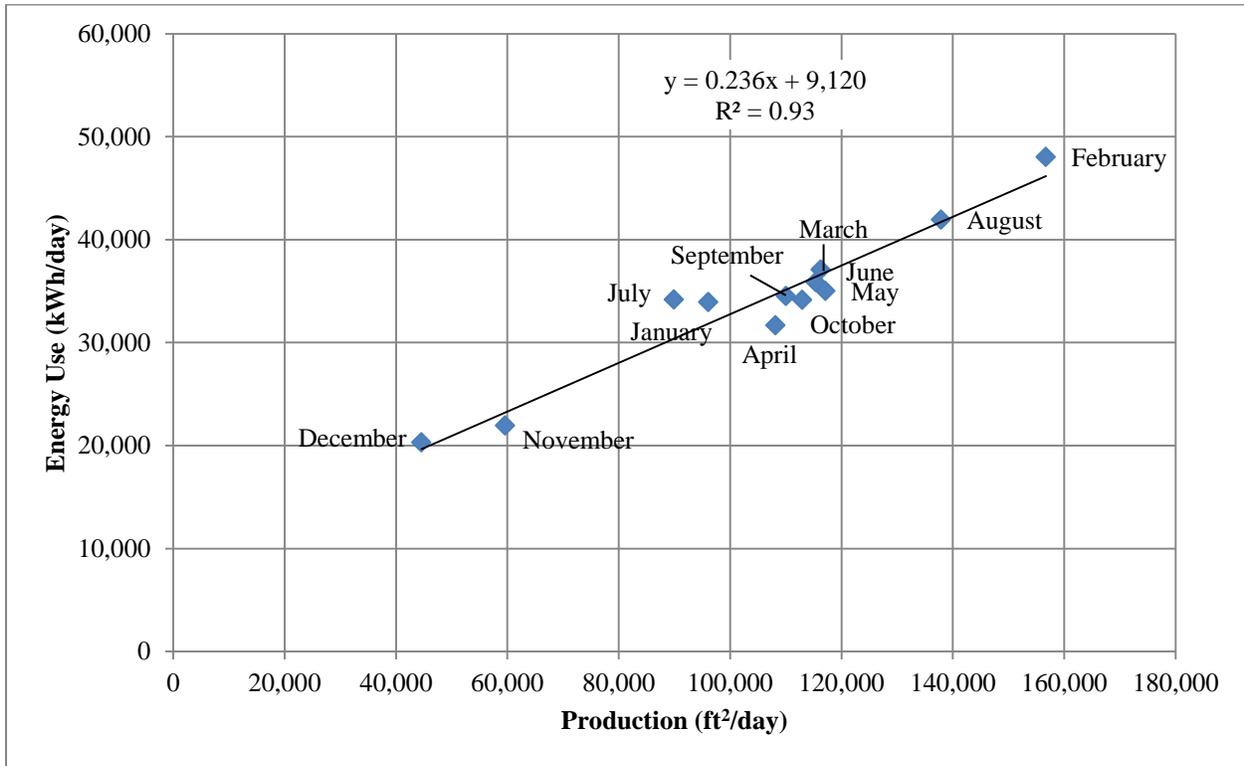


Figure 22. Monthly electricity use and number of units produced for facility E3028.

A multivariate three-parameter cooling change-point regression analysis was performed for facility E3028. Actual monthly average mean dry-bulb temperature data for Muscle Shoals, AL was obtained from the Weather Underground website. Muscle Shoals, AL is located only 5 miles south of Florence, AL, across the Tennessee River. Initial values for the 3PC-Prod analysis were as follows: $a = 8,000$ kWh/day, $b = 500$ kWh/day-°F, $T_{b,c} = 70.0$ °F, $P = 0.240$ kWh/ft². The initial value for the production parameter, P , was taken from the simple linear curve fit between energy use and production. Using the Excel Solver feature to carry out the regression analysis, the final regression parameters are as follows: $a = 8,201$ kWh/day, $b = 953$ kWh/day-°F, $T_{b,c} = 79.5$ °F, $P = 0.242$ kWh/ft². The 3PC-Prod change-point baseline energy model is shown in

Equation 62. The R^2_{adj} value for Equation 62 is 0.95, and the CV-RMSE is 5.1%, suggesting that the 3PC-Prod model is an excellent baseline energy model for facility E3028.

$$E_C = 8,201 \frac{kWh}{day} + 953 \frac{kWh}{day \cdot ^\circ F} (T_{amb} - 79.5^\circ F)^+ + 0.242 \frac{kWh}{ft^2} P_m \quad (62)$$

Figure 23 illustrates the actual monthly energy use and the monthly energy use as depicted by the 3PC-Prod change-point regression. The graph shows that the electrical energy use varies throughout the year. The electrical energy consumption decreases during the winter months, but it is unclear whether this decrease is due to production or ambient temperature, as both temperature and production values decrease during these time periods. The graph indicates that the 3PC-Prod baseline energy model adequately reflects the monthly energy consumption behavior of facility E3028 throughout the observed production year.

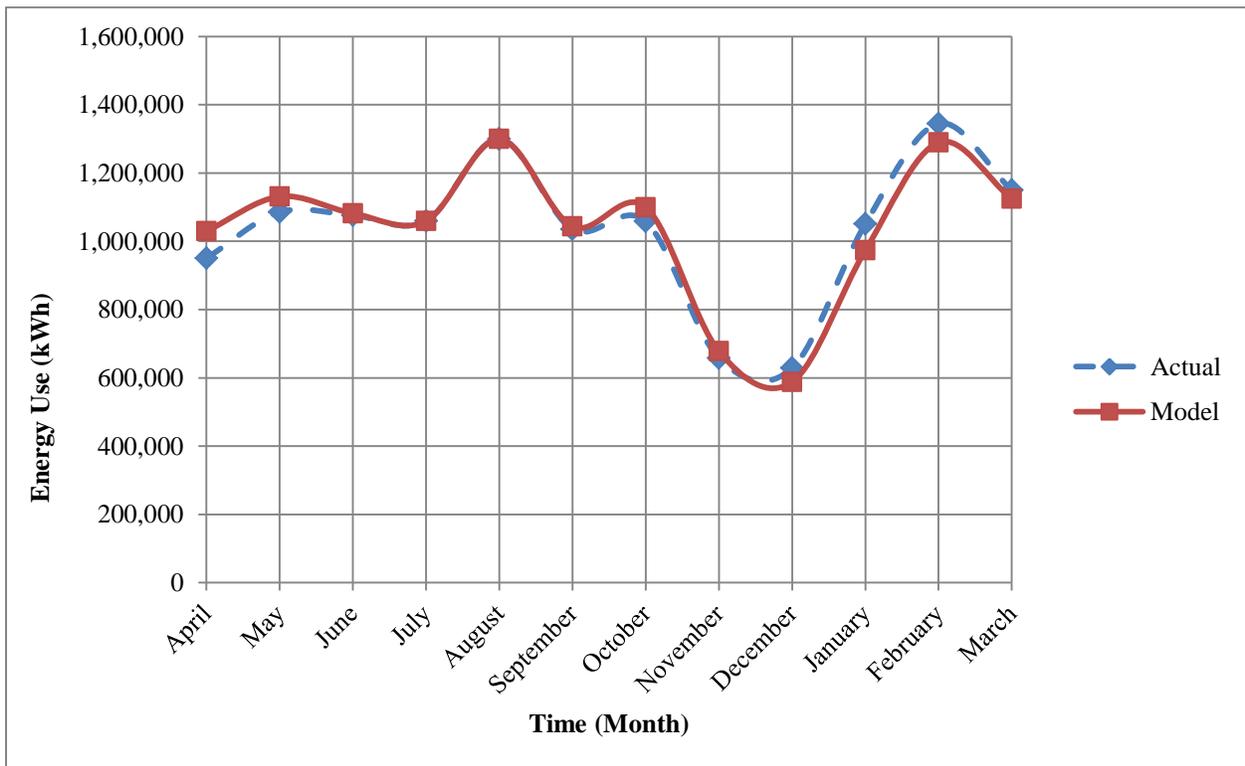


Figure 23. Actual and 3PC-Prod model predicted monthly electricity use for facility E3028.

Figure 24 shows the 3PC-Prod change-point model for facility E3028. The graph illustrates the energy consumption is sporadic in relation to ambient outdoor dry-bulb temperature, indicating that there may not be a strong relationship between energy consumption and temperature alone. The weather and production-independent energy consumption is 8,201 kWh/day. The cooling slope is 953 kWh/day-°F and the cooling change-point temperature is 79.6°F. The production regression coefficient is 0.242 kWh/ft². The 3PC-Prod baseline equation suggests that 24.2% of the facility’s total annual electrical energy consumption is weather and production-independent, 0.7% is weather-dependent, and 75.1% is production-dependent. The baseline model is a great predictor of annual energy consumption, only under-predicting the billed annual electricity use by -0.2%.

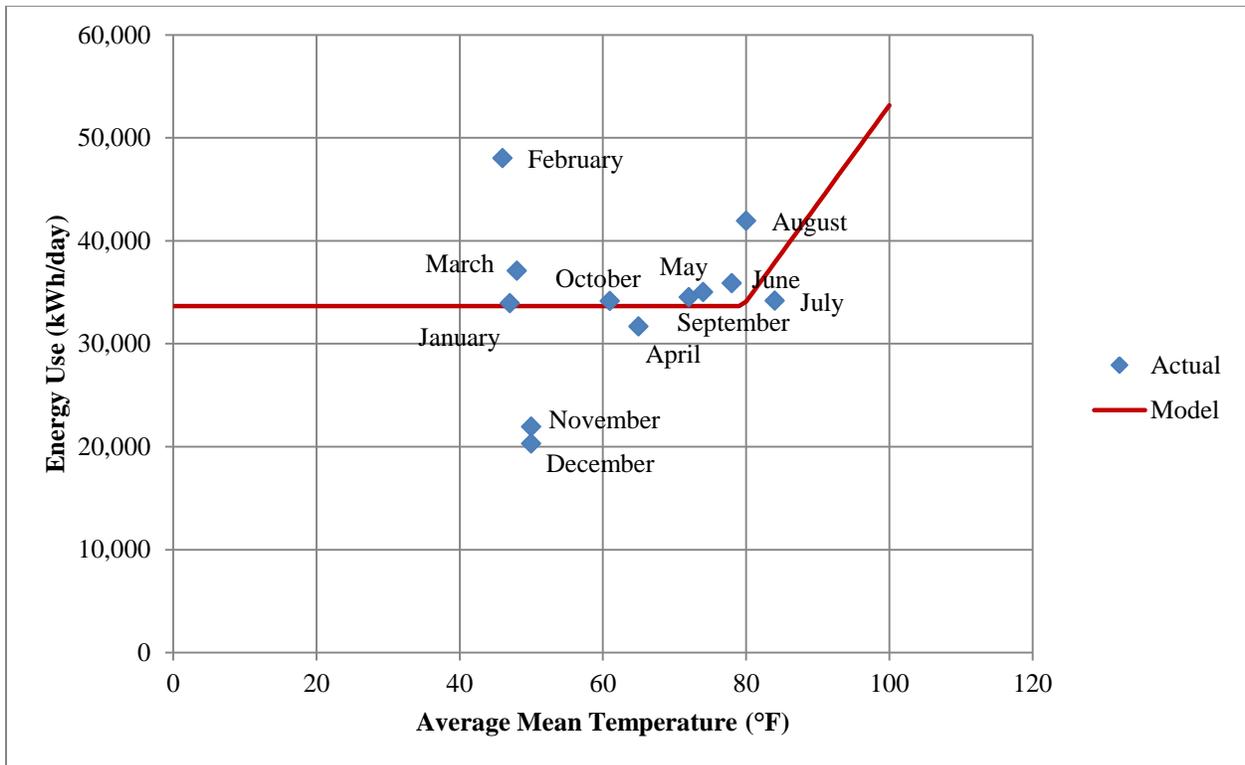


Figure 24. 3PC-Prod model of monthly electrical energy use for facility E3028.

The 3PC-Prod baseline energy model suggests that a majority of the facility's electrical energy use is production-dependent. This result is justified by the strong singular correlation between energy use and production values alone. The 3PC-Prod model results also prove that both temperature and production are significant variables that influence electrical energy consumption. The coefficient of determination for the energy and production model displayed in Equation 61 is 0.93. The adjusted coefficient of determination for the 3PC-Prod model is 0.95. Increasing the number of regression coefficients will always increase the unadjusted R^2 value. However, even adjusting the coefficient of determination for the additional independent variable of production, the R^2_{adj} value for the 3PC-Prod model is larger than the R^2 value for Equation 61, signifying that both production and temperature are influential variables in the baseline energy model.

Production-dependent energy use insists that the electrical energy consumed is directly related to the creation of the facility's product. For instance, the energy may be consumed by process equipment used to cut the tile to specified dimensions, by motors servicing packaging and shipping devices, or by air compressors delivering compressed air to pneumatic manufacturing equipment. From an energy management standpoint, this result is a desired effect of operation control. One goal for industrial manufacturing industries should be to devote the largest fraction of their total energy consumption to the production of their product. Weather-dependent and independent energy consumption does not contribute to the development of the product, and should be limited in order to reduce overhead energy costs.

A multivariate variable-base cooling degree-day (CDD-Prod) regression analysis was also performed for facility E3028. TMY3 weather data for Muscle Shoals, AL along with facility supplied monthly production data. The initial parameters for the CDD-Prod regression were as

follows: $a = 8,000$ kWh/day, $b = 500$ kWh/day-°F, $T_{b,c} = 70.0$ °F, $P = 0.240$ kWh/ft². Using the Excel Solver feature to carry out the regression analysis, the final regression parameters for the CDD-Prod baseline model are as follows: $a = 8,452$ kWh/day, $b = 4,567$ kWh/day-°F, $T_{b,c} = 86.9$ °F, $P = 0.238$ kWh/ft². The CDD-Prod baseline energy model is shown in Equation 63. The R^2_{adj} value is 0.93, and the CV-RMSE value is 5.6%, suggesting that the CDD-Prod model is also an excellent baseline energy model for facility E3028.

$$E_c = 8,452 \frac{\text{kWh}}{\text{day}} + 4,567 \frac{\text{kWh}}{\text{day} \cdot \text{°F}} [cdd_i (86.9^\circ F)] + 0.238 \frac{\text{kWh}}{\text{ft}^2} P_m \quad (63)$$

Figure 25 displays the actual monthly energy use and the monthly energy use as described by the CDD-Prod regression. The graph indicates that the CDD-Prod baseline energy model sufficiently reflects the monthly energy consumption behavior of facility E3028 throughout the observed production year. Figure 26 shows the CDD-Prod baseline model. Similar to the 3CP-Prod baseline equation, the figure shows that there may not be a strong relationship between dry-bulb ambient temperature and energy consumption alone. The weather and production-independent energy consumption is 8,452 kWh/yr. The cooling slope is 4,567 kWh/day-°F and the cooling balance point temperature is 86.9°F. The production regression coefficient is 0.238 kWh/ft².

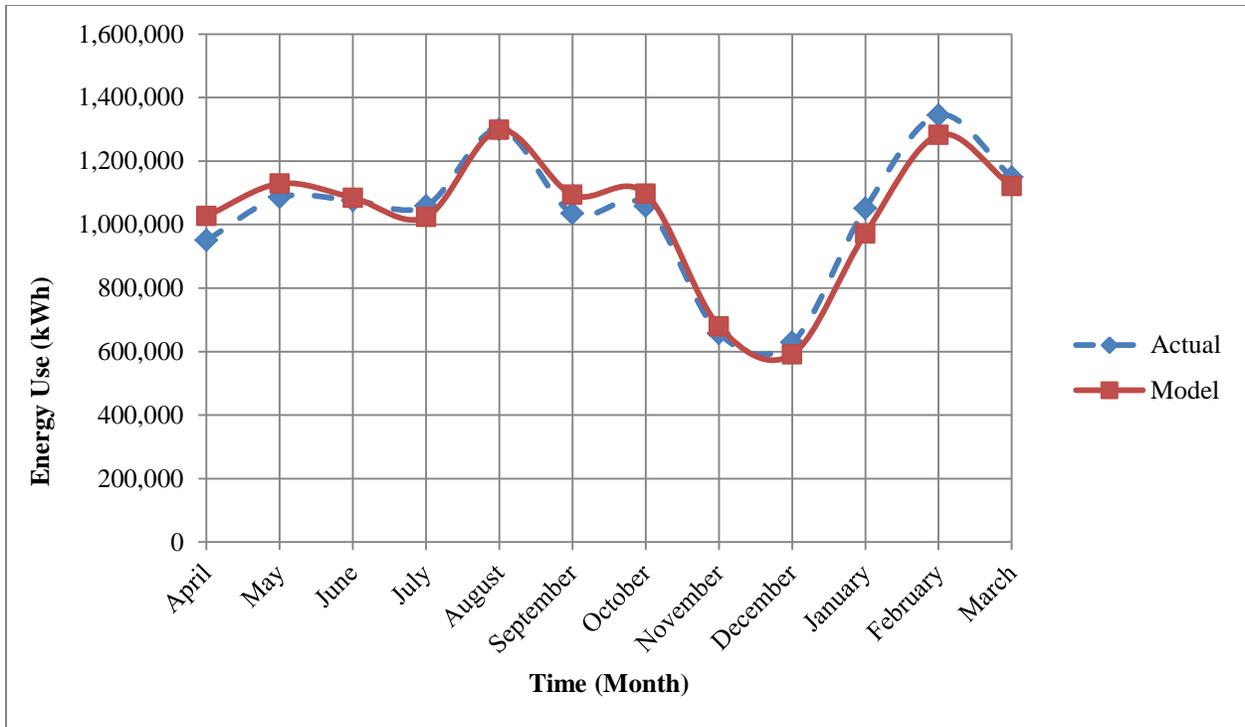


Figure 25. Actual and CDD-Prod model predicted monthly electricity use for facility E3028.

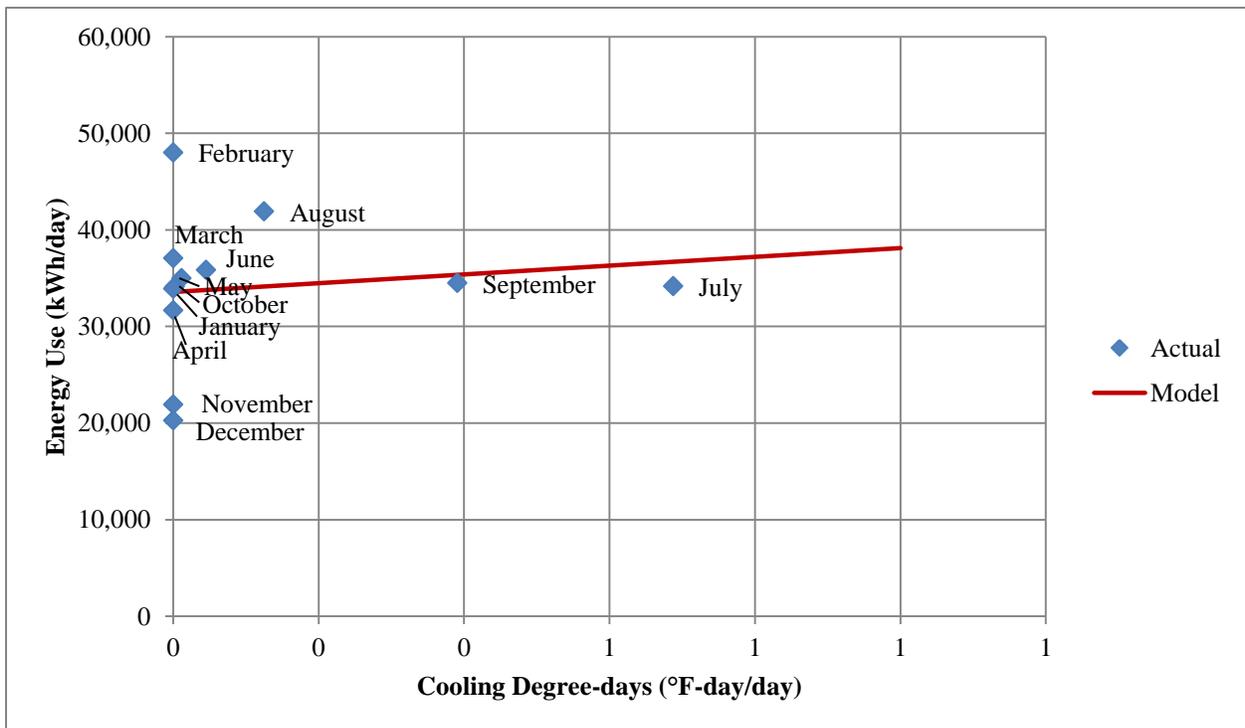


Figure 26. CDD-Prod model of monthly electrical energy use for facility E3028.

The CDD-Prod baseline energy model suggests that 24.0% of the facility's total annual electrical energy consumption is weather and production-independent, 4.5% is weather-dependent, and 71.5% is production-dependent. The difference between the model calculated annual energy use and the billed annual energy use is +3.4%, indicating the CDD-Prod baseline model is slightly over-predicting annual energy use. As predicted, the CDD-Prod baseline equation indicates a large portion of the facility's total energy use is production-dependent. In contrast to the 3PC-Prod model, the CDD-Prod baseline model suggests that a larger percentage of the total annual energy use is weather-dependent. In addition, the cooling slope and cooling balance point temperature of the CDD-Prod model are larger than the 3PC-Prod model. These differences could be an effect of the temperature data referenced by each model. The 3PC-Prod model uses actual temperature data, and cooler temperatures may have been observed during the specified time period in relation to the typical meteorological year. Goodness-of-fit values for the 3PC-Prod model are slightly better than the CDD-Prod model; therefore, using actual weather data may provide a more acceptable fit for the baseline energy model in the case of facility E3028.

It is also important to note the magnitude of the significance of including production as an additional independent variable in the present case study. The actual monthly energy use and the monthly energy use as described by a 3PC regression model are shown in Figure 27. The 3PC model, displayed in Figure 28, only evaluates temperature as the singular independent variable in the facility's baseline energy model. A simple visual comparison between the 3PC and 3PC-Prod baseline models proves that temperature alone does not sufficiently explain the behavior of the facility's annual energy use. Furthermore, the R^2 and CV-RMSE of the 3PC model are 0.07 and 23.4%, respectively, demonstrating a poor baseline model fit. Therefore, it is

important to consider the impact of multiple variables and their effect (or incapacity) when developing an industrial facility's baseline energy consumption model. In the case of facility E3028, it is obvious that the inclusion of production as an additional independent variable is necessary to establish a baseline energy model.

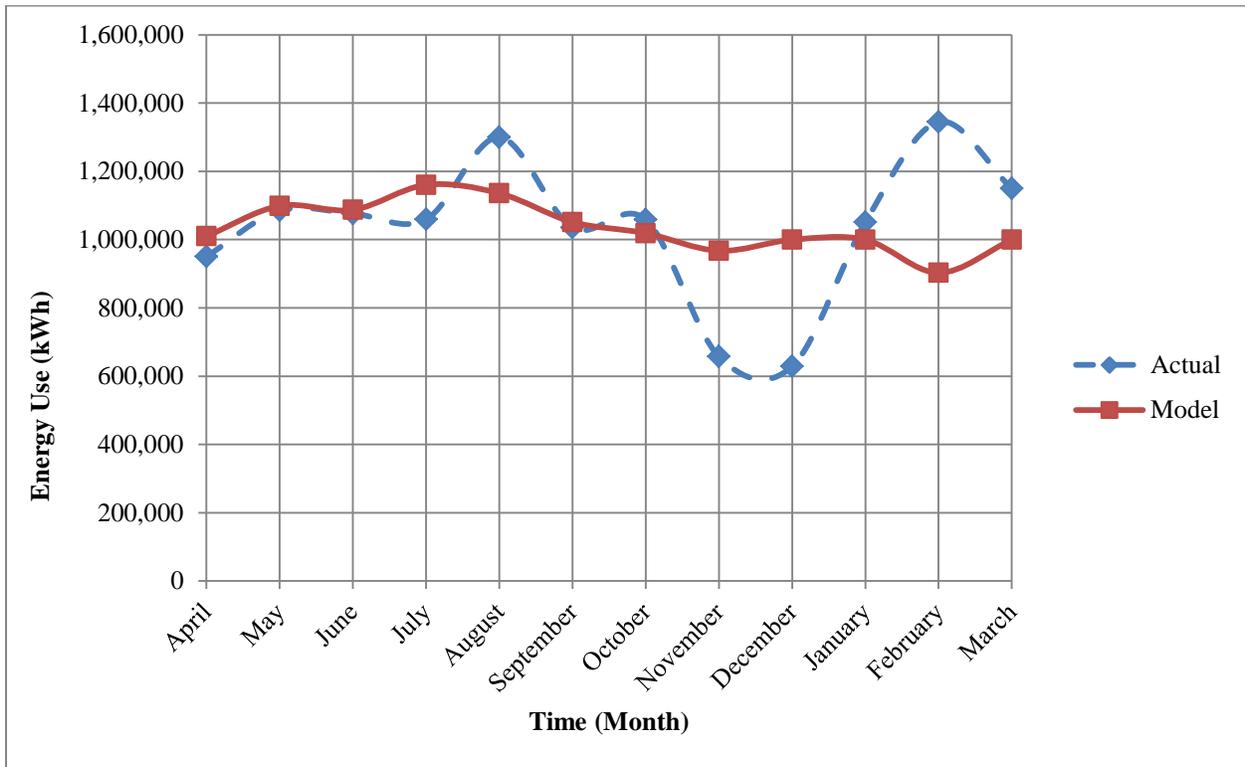


Figure 27. Actual and 3PC model predicted monthly electricity use for facility E3028.

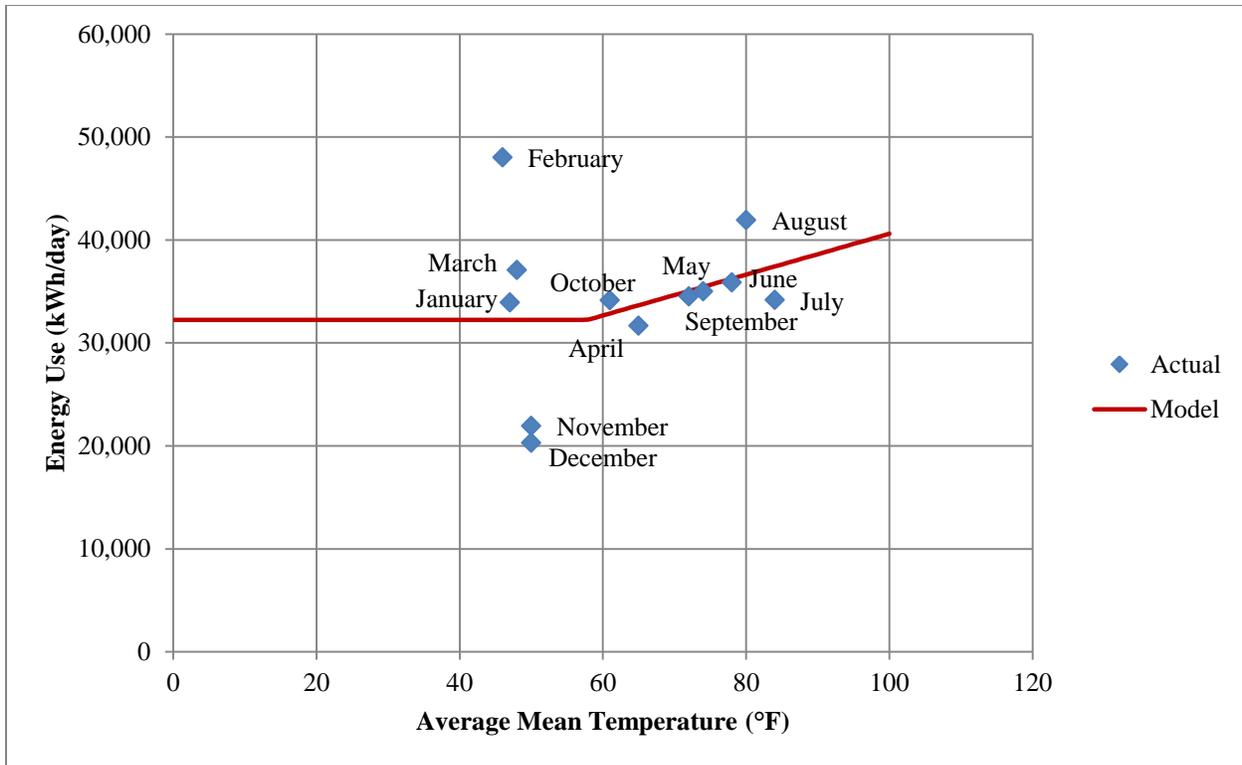


Figure 28. 3PC model of monthly electrical energy use for facility E3028.

3.5 Case Study UA0104

Facility UA0104 is an industrial manufacturing facility located in Tuscaloosa, AL. The company assembles axle sets for use in the assembly of luxury brand automobiles. The building spans approximately 165,000 square feet, and includes the main production area, warehouse, office spaces, storage and inspection area, oven room, and shipping space. All areas are conjoined in one large building structure. Electricity is used for space cooling, lighting, and other manufacturing processes, and natural gas is primarily used for space heating and the facility’s paint-drying ovens. This case study will examine the use of change-point and degree-day regression methods to develop a baseline energy model for the facility’s natural gas use.

The entire facility, including the production area, is conditioned year-round by 23 rooftop HVAC units that utilize electricity for cooling and natural gas for heating. The facility is divided

into seven separate conditioning zones. Each zone is comprised of various numbers and sizes of conditioning equipment. Furthermore, thermostat controls range from programmable to conventional in each conditioned zone. These thermostats have diverse cooling and heating set-points. In addition, some of the set points (specifically in the office areas) are altered during non-production hours in order to save energy. Although energy is used for space conditioning in various capacities throughout the plant, it is expected that the facility's natural gas consumption should vary with outdoor air temperature.

The facility operates 24 hours per day, five to six days per week, for 50 weeks each year. Natural gas energy use and production data from March 2012 through February 2013 was obtained for facility UA0104. Total monthly production values were reported in pounds (lbs). Actual natural gas utility bills were not provided; however a spreadsheet summary of natural gas usage was supplied by plant personnel. The facility-created spreadsheet did not specify actual utility meter read dates. Therefore, it is assumed that the utility read dates occur at the beginning of each calendar month. It is also assumed that the reported production data provides total units produced during each calendar month.

Figure 29 shows facility UA0104's monthly natural gas use in relation to the total monthly production units. It is clear that there is not a strong correlation between the two variables. In fact, the simple linear curve fit shown in the figure mathematically indicates that there is a negative relationship between total units produced and natural gas usage. During the initial AIAC facility interview, facility personnel stated that a large natural gas paint-drying oven was installed July 2012. Previous to this installation, natural gas was only consumed for space heating.

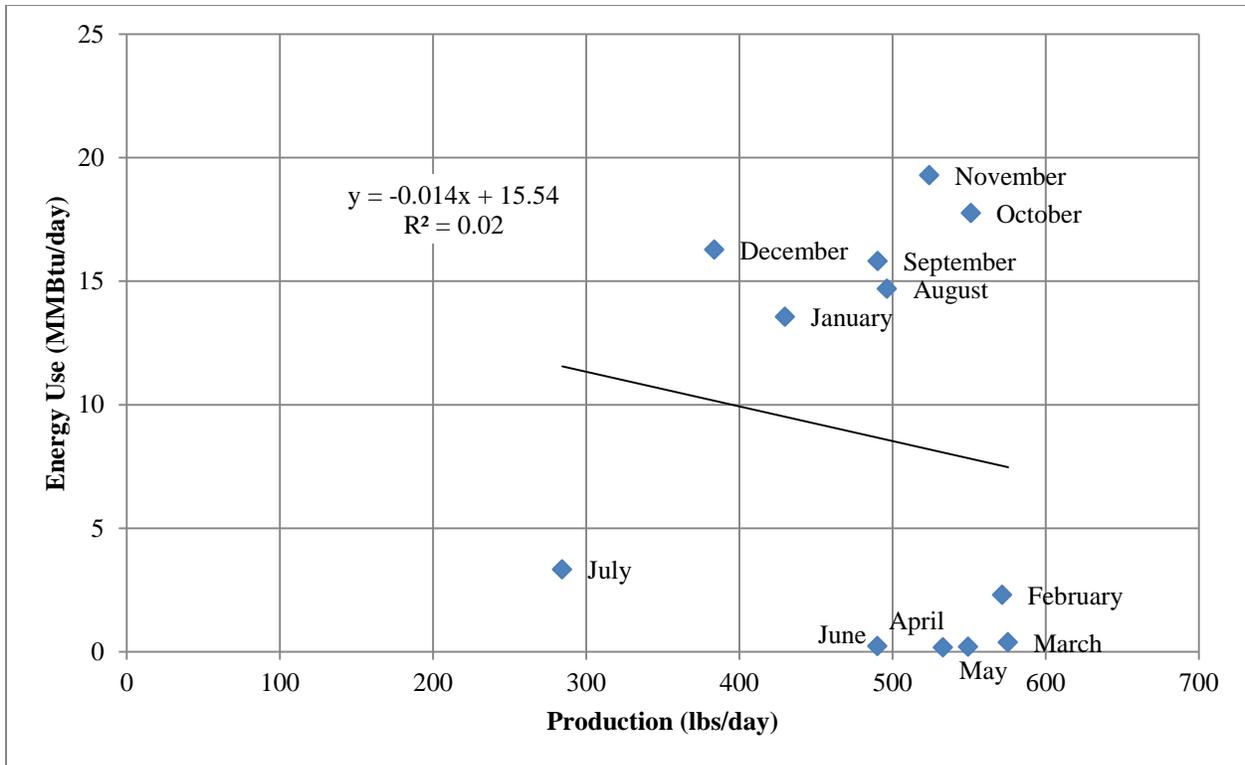


Figure 29. Monthly natural gas use and number of units produced for facility UA0104.

Based on billing data, a large increase in natural gas use coincides with the addition of the new oven to the production line. Natural gas usage seems to correlate with production in the months following the oven installation, except for the month of February 2013. The billing history data shows a dramatic decrease in usage between the months of January 2013 and February 2013. This decrease in natural gas use is not correlated with production values, as monthly production values for February followed similar trends from the previous months. Facility personnel also reported no changes in production behavior during February after the irregularity in the natural gas consumption was brought to their attention.

Figure 30 illustrates the facility's monthly natural gas use versus total monthly production after the natural gas oven was installed. The graph also eliminates the month of

February 2013 due the inexplicable decline in natural gas use. In contrast to Figure 29, this graph shows a positive correlation between natural gas use and units produced. This is a logical relationship if most of the natural gas consumption is dedicated to the production-dependent paint-drying oven. A simple linear curve fit of the energy and production data for the shortened data set is explained by Equation 64. The model exhibits an R^2 value of 0.29. This result indicates that the correlation between natural gas consumption and total units produced is not strong. Other factors, like ambient temperature, may better explain the facility's natural gas consumption.

$$E_H = 0.018 \frac{\text{MMBtu}}{\text{lbs}} P_m + 7.66 \frac{\text{MMBtu}}{\text{day}} \quad (64)$$

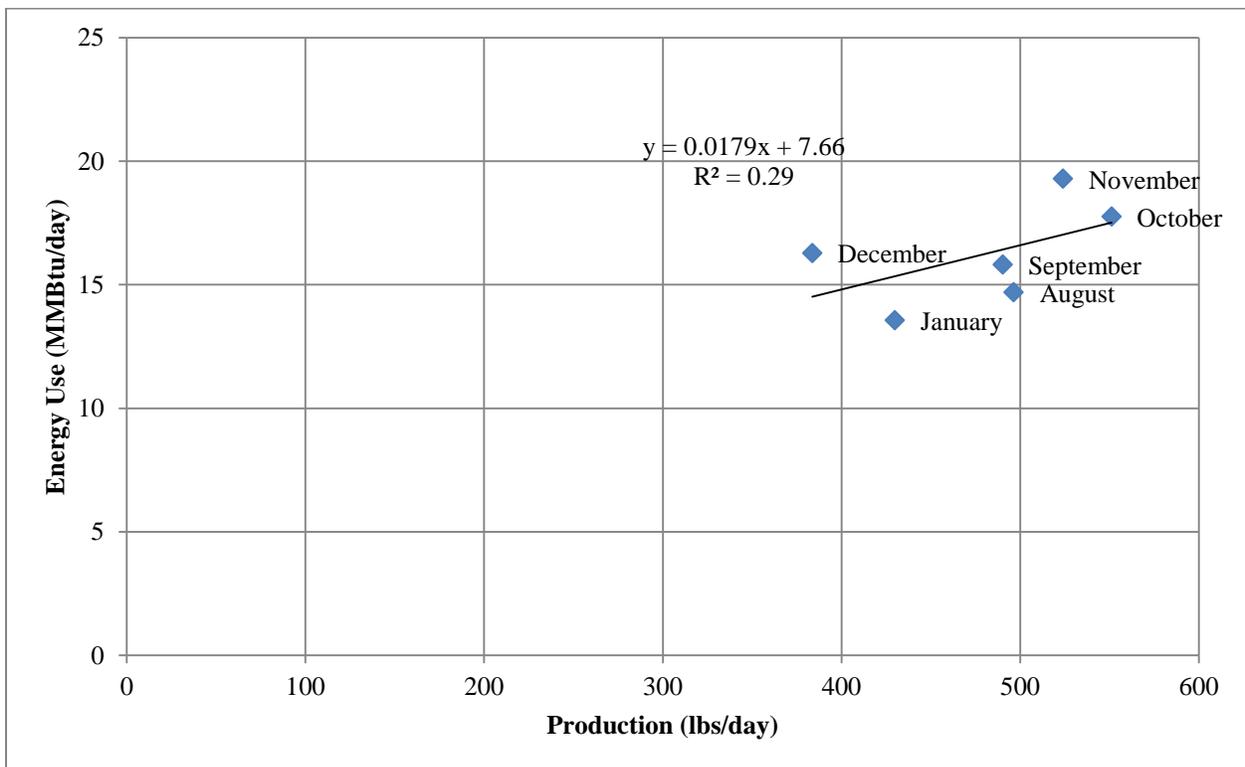


Figure 30. Monthly natural gas use and production units for August 2012 through January 2013 for facility UA0104.

The AIAC performed a building energy analysis using eQUEST (eQuest, 2014) software prior to the regression analysis. The eQUEST (QUick Energy Simulation Tool) software is a building energy simulation tool developed to allow engineers and architects the opportunity to conduct detailed energy analysis for the entire building (Alabama Industrial Assessment Center, 2013). Some specifications for building dimensions and building materials were obtained from mechanical and architectural drawing provided by facility personnel. The remaining details not obtained from the facility were assumed and inserted into the eQUEST software. Estimations for lighting density, equipment power draw, air infiltration rates, and occupation schedules were also implemented into eQUEST. Air infiltration rates and equipment power consumption were adjusted in the software program until the building simulation energy consumption profiles paralleled the observed billing data.

Figure 31 (Alabama Industrial Assessment Center, 2013) shows the eQUEST model results for natural gas energy consumption versus actual natural gas billing history. The graph indicates the sharp increase in natural gas use after the paint-drying oven was installed. The eQUEST model was somewhat able to resemble this behavior, but does not exactly match the natural gas billing data. Some of these differences can be contributed to variations between the actual weather during the observed time period and the bin weather data used by the eQUEST program. Also, many simplifications were made in the software building wall construction, and generalizations were made with thermostat set points in the office locations. The eQUEST model also had some difficulty rectifying the irregularity in energy use for the month of February 2013. Due to the addition of the paint-drying oven, the generalizations made for building construction, and the unexplained decrease in natural gas use in the last observed month, the eQUEST analysis was only able to produce a mediocre baseline energy model for facility UA0104.

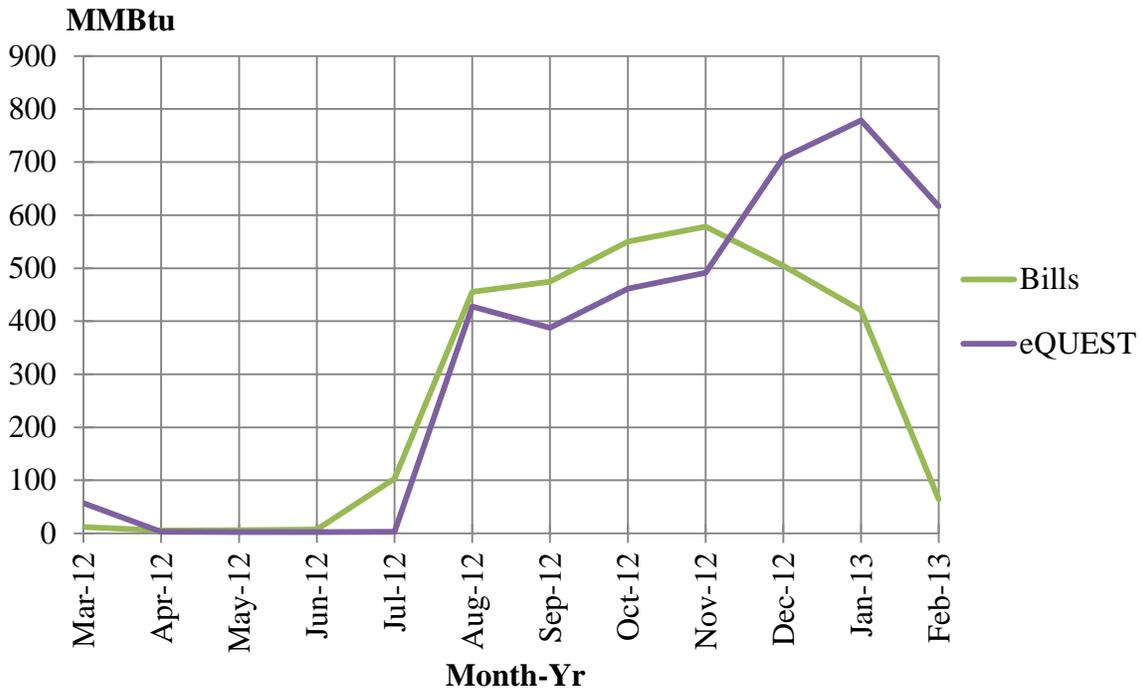


Figure 31. Actual bill data versus AIAC developed eQUEST model natural gas energy use
(Alabama Industrial Assessment Center, 2013).

In addition to the eQUEST modeling, a multivariate three-parameter heating change-point regression analysis was performed for facility UA0104. Actual monthly average mean dry-bulb temperature data for Tuscaloosa, AL was obtained from the Weather Underground website. Initial values for the 3PH-Prod analysis were as follows: $a = 3.00$ MMBtu/day, $c = 0.200$ MMBtu/day-°F, $T_{b,h} = 70.0$ °F, $P = 0.010$ MMBtu/lbs. The initial value for the production parameter, P , was taken from the simple linear curve fit between energy use and production for the short data set shown in Figure 30. Using the Excel Solver feature to carry out the regression analysis, the final regression parameters are as follows: $a = 5.88$ MMBtu/day, $c = 0.257$ MMBtu/day-°F, $T_{b,h} = 75.0$ °F, $P = 0.00$ MMBtu/lbs. The resulting 3PH-Prod change-point baseline energy model is shown in Equation 65.

$$E_H = 5.88 \frac{\text{MMBtu}}{\text{day}} + 0.257 \frac{\text{MMBtu}}{\text{day} \cdot ^\circ\text{F}} (T_{\text{amb}} - 75.0^\circ\text{F})^+ + 0.00 \frac{\text{MMBtu}}{\text{lbs}} P_m \quad (65)$$

The adjusted coefficient of determination, R^2_{adj} , for Equation 65 is -0.21. The CV-RMSE is 102.3%. Both values indicate that the 3PH-Prod baseline equation provides a very poor fit to the observed data. The resulting multivariate 3PH-Prod model does not represent the relationship between natural gas consumption and production and ambient temperature in any capacity. A visual relationship between the 3PH-Prod model and observed data is depicted in Figure 32. The graph illustrates the actual monthly energy use and the monthly energy use as expressed by the 3PH-Prod change-point regression.

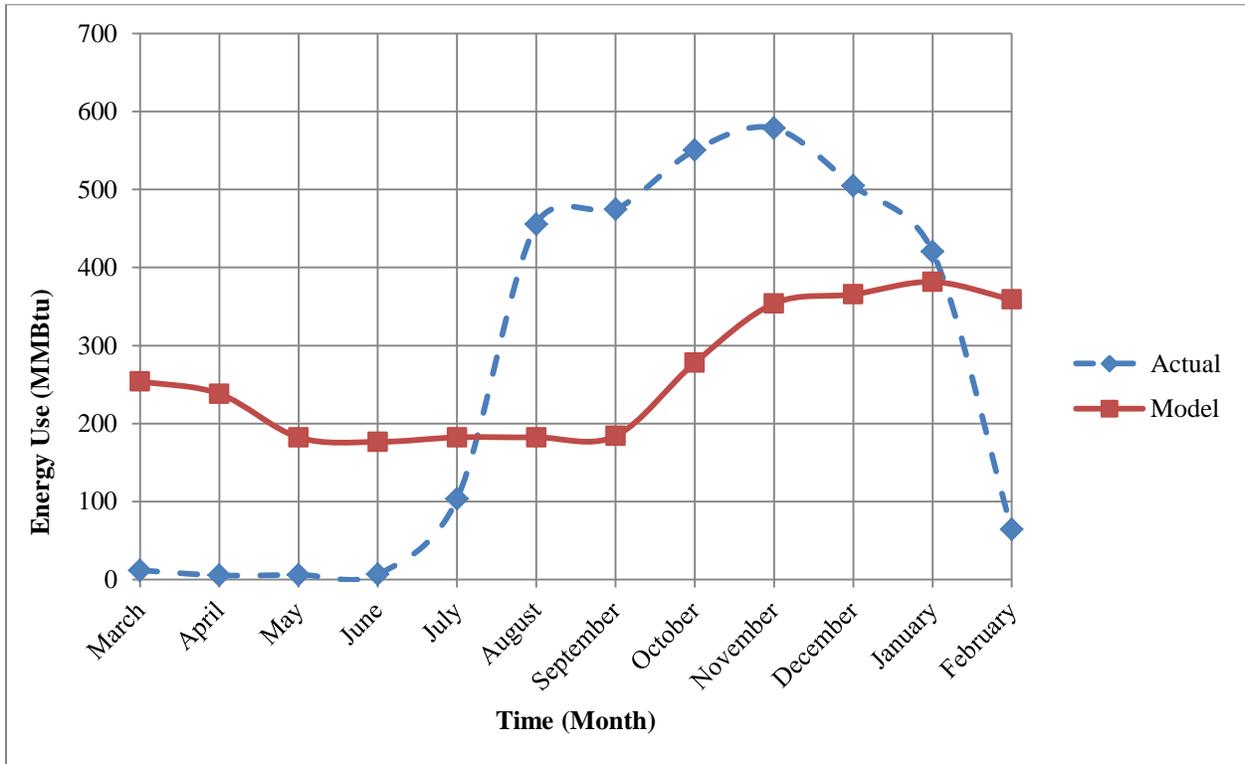


Figure 32. Actual and 3PH-Prod model predicted monthly natural gas use for facility UA0104.

Figure 33 includes the 3PH-Prod change-point model for facility UA0104. The weather-independent energy consumption is 5.88 MMBtu/day. The heating slope is 0.257 MMBtu/day-

°F, and the heating change-point temperature is 75.0°F. The production regression coefficient is 0.00 MMBtu/lb. Figure 33 justifies that the 3PH-Prod does not explain the natural gas usage behavior for the automotive manufacturing facility. It is evident that neither production nor ambient temperature influence natural gas energy consumption for the one-year observed period. The production regression coefficient is zero, indicating that 0.0% of the facility’s total annual natural gas use is production-dependent. The 3PH-Prod baseline model also suggests that 69.3% of the total annual energy use is weather and production-independent, and 30.7% is weather-dependent.

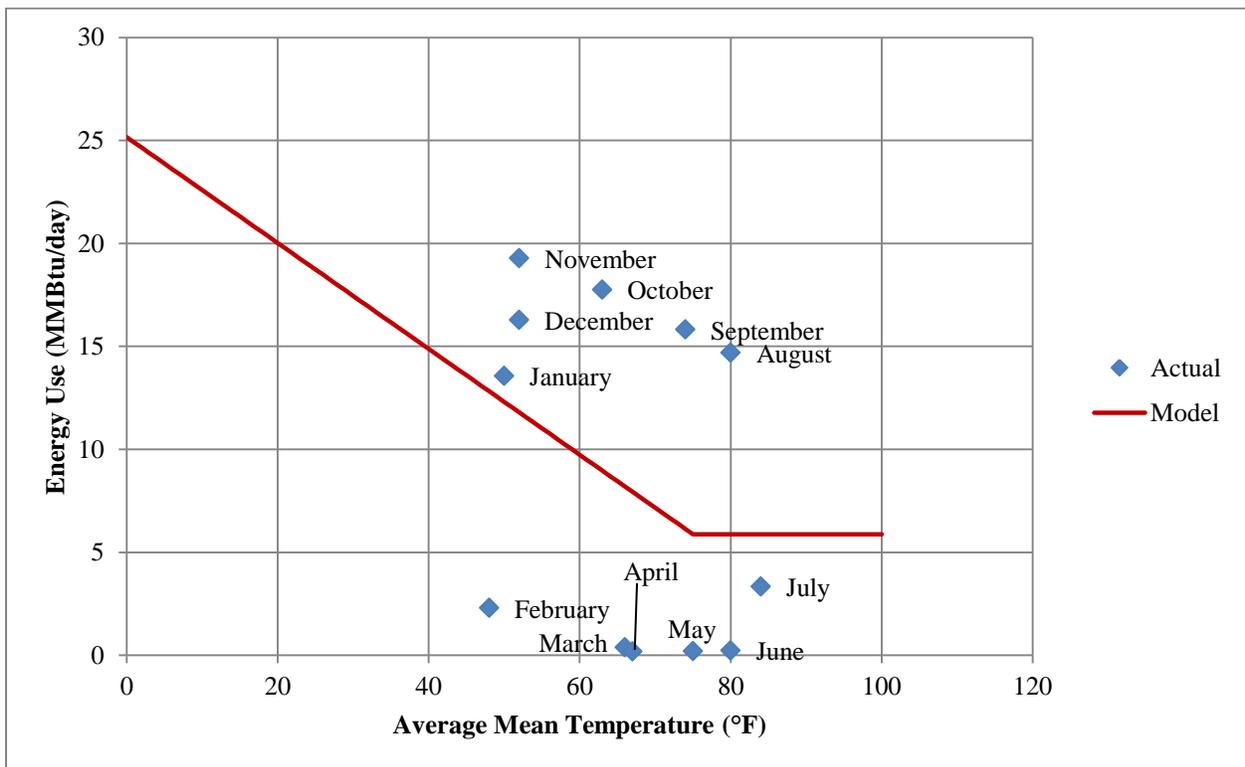


Figure 33. 3PH-Prod model of monthly natural gas energy use for facility UA0104.

One reason for the poor baseline model fit could be attributed to the installation of the new natural gas paint-drying oven in the middle of the observed data period. Large alterations in

facility production behavior or the addition of new equipment will undoubtedly alter overall energy consumption. A baseline energy model is best determined by a set of data that observes typical operating processes throughout the entire observed time period. A better baseline fit may be found if the short term data set after the installation of the new oven is considered. Other case studies discourage the use of short term data sets in establishing baseline energy models (Kissock, 1993; Katipamula et al., 1994). However, even if the data prior to August 2012 is rejected from the analysis, values for the month of February 2013 remain an irregularity. When evaluating the short term data, the 3PH-Prod regression provides a poor fit to the natural gas energy consumption.

The poor fit of the 3PH-Prod baseline model could also be attributed to the variation in thermostat set-points. The facility is separated into seven conditioned zones, each supplied by multiple rooftop HVAC units. The thermostats controlling these units have differing heating and cooling set-points between each zone. Some of these set-points are controlled through programmable thermostats, and are adjusted throughout the day. The variation in thermostat set-points for the HVAC units could have an effect on the heating change-point temperature for a steady-state model. Separate steady-state models for set-points during the production and non-production hours could be developed and provide more clarity to the temperature dependence of the baseline model. Transient energy models may also provide a better understanding of energy consumption when facilities have varying parameters throughout the observed time period.

In addition to the change-point regression, a multivariate variable-base heating degree-day regression analysis was also performed for facility UA0104. TMY3 dry-bulb temperature data for Tuscaloosa, AL was selected for the HDD-Prod analysis. The initial parameter values for the HDD-Prod regression were as follows: $a = 3.00$ MMBtu/day, $c = 0.200$ MMBtu/day-°F,

$T_{b,h} = 70.0^{\circ}\text{F}$, $P = 0.010$ MMBtu/lbs. Using the methods described in Chapter 2, the final regression parameters are as follows: $a = 6.80$ MMBtu/day, $c = 0.253$ MMBtu/day- $^{\circ}\text{F}$, $T_{b,h} = 64.0^{\circ}\text{F}$, $P = 0.00$ MMBtu/lbs. The HDD-Prod baseline energy model for UA0104 is shown in Equation 66.

$$E_H = 6.80 \frac{\text{MMBtu}}{\text{day}} + 0.253 \frac{\text{MMBtu}}{\text{day} \cdot ^{\circ}\text{F}} [\text{hdd}_i (64.0^{\circ}\text{F})] + 0.00 \frac{\text{MMBtu}}{\text{lbs}} P_m \quad (66)$$

The R^2_{adj} value for the HDD-Prod baseline model is -0.28 and the CV-RMSE is 105.3%. Similar to the 3PH-Prod model, both goodness-of-fit tests indicate that the HDD-Prod model provides a very poor fit to the observed data. It does not represent a significant relationship between natural gas consumption and production and ambient temperature. Figure 34 illustrates the actual monthly natural gas use and the monthly natural gas use modeled by the HDD-Prod regression. Figure 35 shows the HDD-Prod model for facility UA0104.

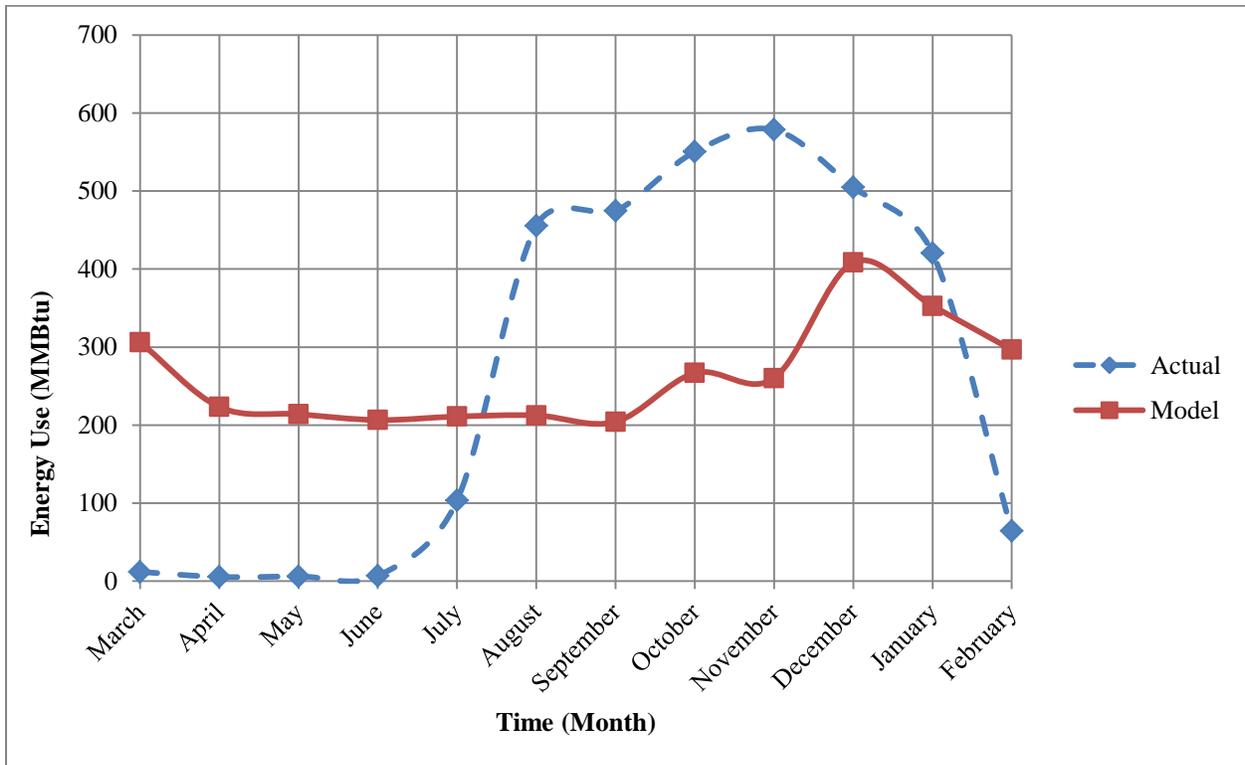


Figure 34. Actual and HDD-Prod model predicted monthly natural gas use for facility UA0104.

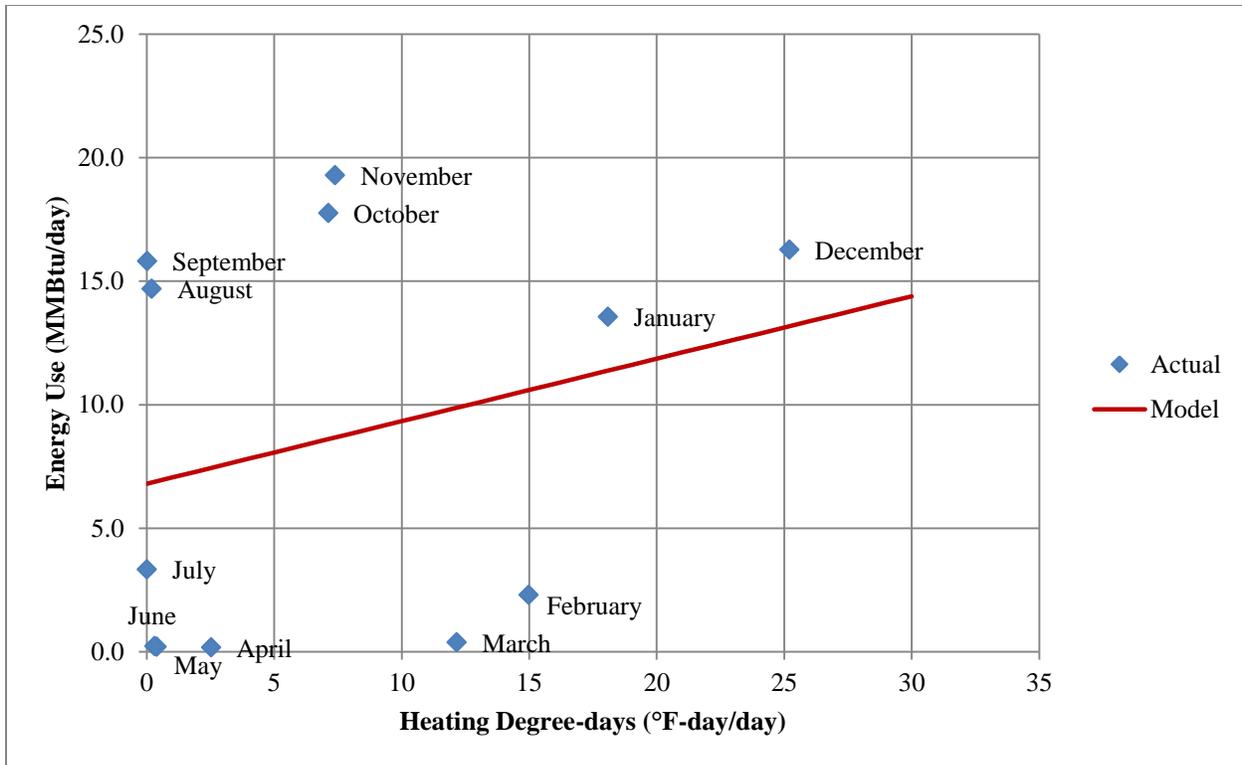


Figure 35. HDD-Prod model of monthly natural gas energy use for facility UA0104

Both figures indicate the poor representation of the model in comparison to the actual data. The independent energy consumption is 6.80 MMBtu/day. The heating slope is 0.253 MMBtu/day-°F, and the heating balance point temperature is 64.0°F. The production regression coefficient is zero, indicating the baseline model defines 0.0% of the facility’s total annual natural gas use as production-dependent. The model also predicts 68.1% of the facility’s total natural gas consumption is independent of weather and production, and 31.9% is weather or temperature dependent.

The 3PH-Prod and HDD-Prod baseline energy models were both poor indicators of the relationship between facility UA0104’s natural gas energy consumption and weather and production data during the observed one-year period. The addition of new production equipment

in conjunction with data irregularities provided challenges for characterizing the facility's baseline natural gas usage. A separate set of natural gas utility bills and production data could be obtained for a one-year period after the large paint-drying natural gas oven was installed in the facility. A reasonable baseline model could be developed from a new data set where the oven has been in steady use for some time and production and operational procedures become more streamlined in the facility.

These results of this case study indicate that blind application of a change-point or degree-day multivariate regression model would not properly describe the baseline energy used by facility UA0104. Ordinary least squares regression methods alone are not always the perfect solution for describing the energy usage of industrial manufacturing facilities. Manufacturing facilities have many intricate and complicated components that contribute to their overall energy consumption. Knowledge of the facility's history and understanding of their operational procedures are imperative when analyzing an industry's energy use. These observations and the regression analysis should be used in conjunction with one another in order to fully describe baseline energy behavior.

3.6 Case Study UA0108

Facility UA0108 is an industrial manufacturing facility located in Anniston, AL. The company fabricates large plastic barrels, or intermediate bulk containers (IBCs), for commercial and industrial use. The building spans 82,000 square feet, and includes office areas, the main production floor, air compressor room, testing room, and a shipping and warehouse space. All areas are conjoined in one large building structure. Electricity is the only energy source, and is used for process equipment, compressed air, chillers, lighting, pumps, fans, and space cooling and heating. This case study will examine the use of multivariate five-parameter cooling and

heating change-point and multivariate variable-base cooling and heating degree-day regression methods to establish a baseline energy model for the facility's electrical energy use.

Currently only the office areas and personnel break room are heated and cooled by 9 air conditioning units. The thermostats are set at varying set-points throughout the facility. Because the facility uses electricity for space heating and cooling, it is expected that the facility's electrical energy use varies with outdoor air temperature. The facility's production area operates 24 hours per day, 6 days per week, for 52 weeks each year. The office area operates 9 hours per day, 5 days per week, for 52 weeks each year. Electrical energy use for May 2012 through April 2013 was provided by facility UA0108. Utility bill meter read dates ranged from the middle of the calendar month to the middle of the next calendar month.

Production units were also provided for each calendar month. Values were recorded in total number of IBCs produced. It was assumed that these dates ranged from the beginning of each calendar month to the end of the same calendar month. In order to obtain recorded production dates that coincide with the utility bill meter read dates, the production values must be time-shifted. Sonderegger (1998) suggests that time-shifting may be done by proportional weighting of two consecutive production values by the fraction of the time their period overlaps that of the utility bill. The formula provided by Sonderegger (1998) for time-shifting of production values is displayed in Equation 67.

$$\bar{V}_i = \sum_{j=1}^M V_j * \frac{[\text{Min}(D_i, S_j) - \text{Max}(S_{j-1}, D_{i-1})]^+}{(S_j - S_{j-1})} \quad (67)$$

The author also provides a visual example of the time-shift, shown in Figure 36.

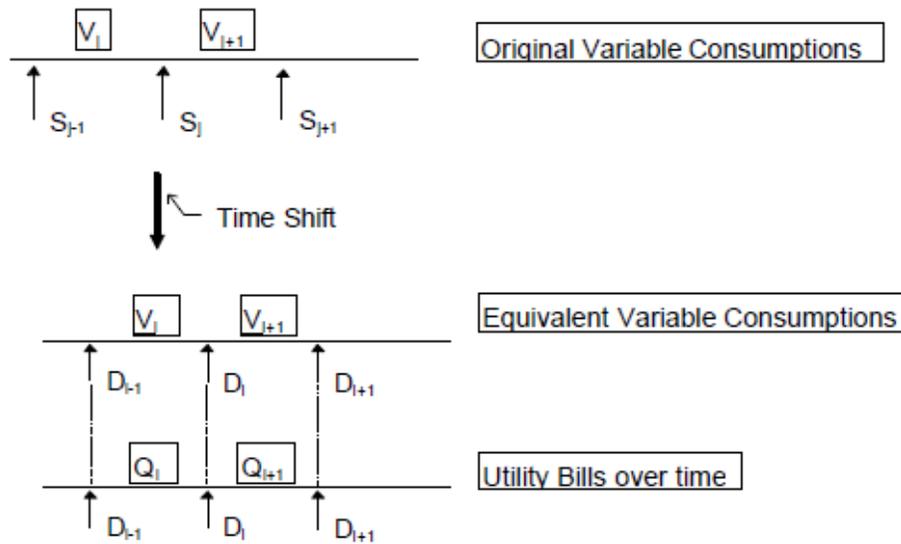


Figure 36. Time-shift of variables to fit utility bill date intervals (Sonderegger, 1998).

Energy consumption and production values are fairly correlated for facility UA0108. Figure 37 shows monthly electricity use and the total number of units produced by the facility during the specified billing periods. Using a simple linear curve fit, the relationship between electrical energy use and production is explained by Equation 68. The equation suggests that the independent energy consumption is a negative value. Although this result is illogical, the model produces an R^2 value of 0.85, indicating a fair model fit. The electrical energy consumption increases with increasing normalized production values, suggesting that production influences the facility's energy usage. These results justify the inclusion of production as an appropriate additional independent variable for multivariate 5PCH-Prod and CHDD-Prod regression analyses.

$$E = -961 \frac{kWh}{day} + 25.3 \frac{kWh}{unit} P_m \quad (68)$$

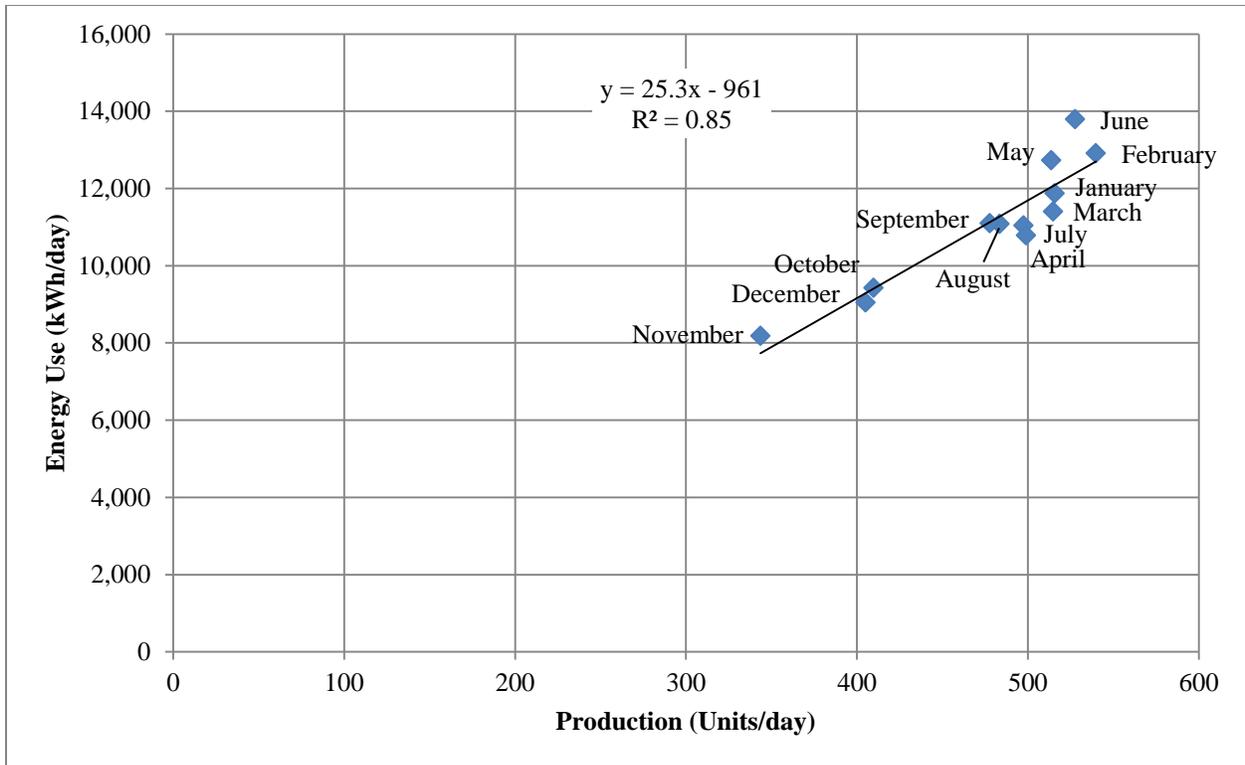


Figure 37. Monthly electricity use and production units for facility UA0108.

Since one fuel source (electricity) is used for space heating and space cooling, a multivariate 5PCH-Prod model or a CHDD-Prod model is appropriate for establishing a baseline energy consumption model for facility UA0108. Using the methods described in Chapter 2, a multivariate five-parameter cooling and heating change-point regression analysis was performed. Actual monthly average mean dry-bulb temperatures for Anniston, AL were obtained from the Weather Underground website. Initial values for the regression parameters were as follows: $a = 500$ kWh/day, $b = 200$ kWh/day-°F, $T_{b,c} = 60.0$ °F, $c = 1,000$ kWh/day-°F, $T_{b,h} = 50.0$ °F, $P = 18.0$ kWh/unit. The final regression parameters are as follows: $a = 471$ kWh/day, $b = 108$ kWh/day-°F, $T_{b,c} = 49.1$ °F, $c = 1,306$ kWh/day-°F, $T_{b,h} = 49.0$ °F, $P = 18.1$ kWh/unit. The 5PCH-Prod change-point baseline energy model for UA0108 is shown in Equation 69.

$$E = 471 \frac{kWh}{day} + 108 \frac{kWh}{day \cdot ^\circ F} (T_{amb} - 49.1^\circ F)^+ + 1,306 \frac{kWh}{day \cdot ^\circ F} (49.0 - T_{amb})^+ + 18.1 \frac{kWh}{unit} P_m \quad (69)$$

The R^2_{adj} value for Equation 69 is 0.39, and the CV-RMSE is 11.5%. The R^2_{adj} goodness-of-fit test does not suggest that the 5PCH-Prod model is a good fit, while the CV-RMSE suggests that the baseline equation provides a moderate fit to the data. Figure 38 shows the actual monthly electrical energy use and the monthly electrical energy use as modeled by the 5PCH-Prod change-point regression. The graph shows that electrical energy consumption varies throughout the year. Figure 39 depicts the 5PCH-Prod change-point model for facility UA0108 and includes actual data points for reference. The weather and production-independent energy consumption is 471 kWh/day. The cooling slope is 108 kWh/day-°F and the heating slope is 1,306 kWh/day-°F. The cooling change-point temperature is 49.1°F and the heating change-point temperature is 49.0°F. The production regression coefficient is 18.1 kWh/unit.

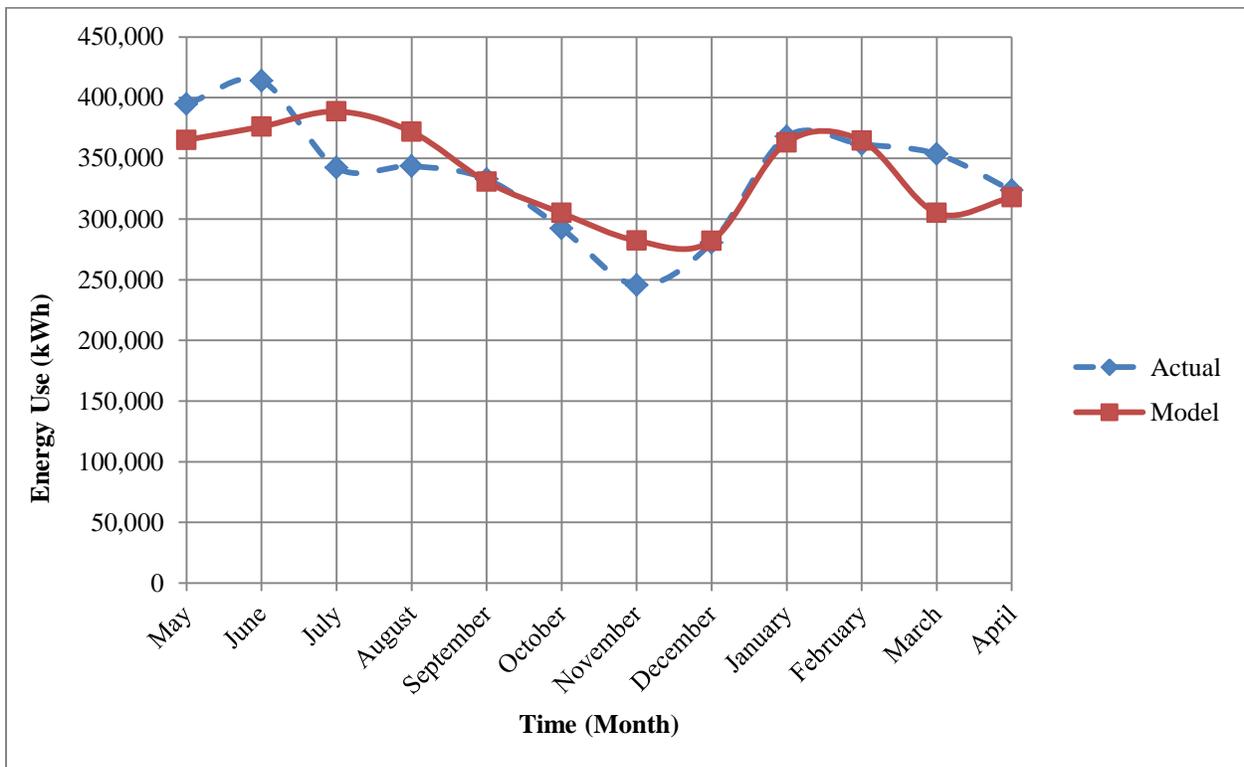


Figure 38. Actual and 5PCH-Prod model predicted monthly electricity use for facility UA0108.

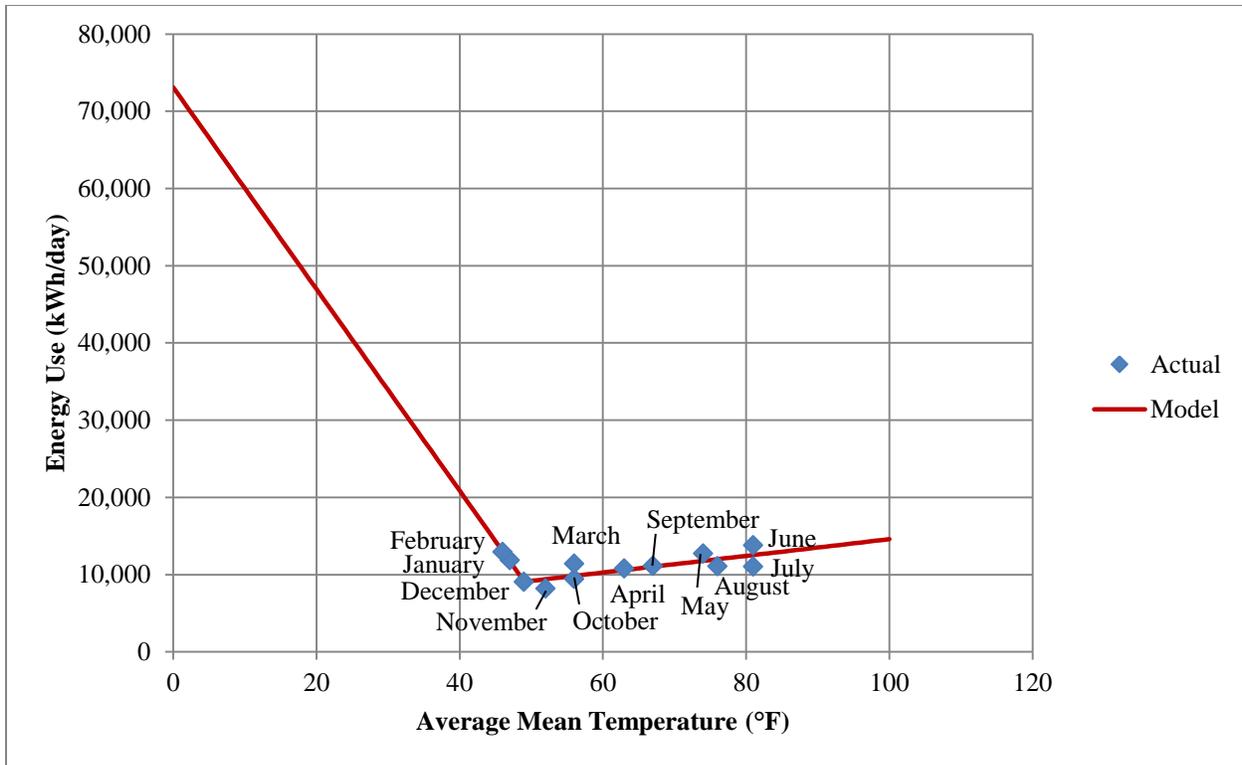


Figure 39. 5PCH-Prod model of monthly electrical energy use for facility UA0108.

Figure 39 shows the increase in electrical energy consumption during the cool winter months of December, January, and February, and the warm summer months of June, July, and August. However, the cooling change-point temperature of 49.1°F is extremely close to the heating change-point temperature of 49.0°F. As a result, the fall and spring months do not seem to exhibit a steady constant weather-independent value. In fact, the difference between the heating and cooling change-point temperatures is so small, the values may be considered equivalent. If the cooling and heating change-point temperatures are equivalent, the 5PCH-Prod model more closely resembles that of the multivariate four-parameter cooling and heating change-point model (4PCH-Prod).

A 4PCH-Prod change-point model indicates that the base temperature range where neither cooling nor heating energy is required is undetectable. Therefore, only one balance-point temperature exists where the energy consumption changes from heating to cooling. Essentially, the energy consumption is weather-dependent across the entire temperature range. Reddy et al. (1997a) believe that this result can occur when evaluating commercial buildings or energy use across several buildings of different types in one campus. The 4PCH-Prod behavior of facility UA0108 could be attributed to the conditioning operation at the facility. Only the office spaces and personnel break room are conditioned throughout the year. Furthermore, the thermostats are set to varying set-point temperatures throughout these areas. Therefore, it may be complicated to detect the overall facility change-point temperatures where heating and cooling energy use is not required.

These results may also indicate that the relationship between production and energy use is stronger than the relationship between ambient temperature and energy use. Although the resulting 5PCH-Prod change-point model more closely represented the behavior of a 4PCH-Prod change-point model, the baseline equation still portrays the strong relationship between facility UA0108's electrical energy consumption and the monthly production units. Based on Equation 69, the 5PCH-Prod baseline denotes that 79.6% of the facility's total annual electrical energy consumption is production-dependent, 4.4% is weather- and production-independent, 14.5% is cooling weather-dependent, and 1.5% is heating weather-dependent. These divisions are reasonable if only a small portion of the facility is conditioned year-round.

A multivariate CHDD-Prod regression analysis was also performed for facility UA0108. TMY3 dry-bulb temperature data for Anniston, AL was selected for the procedure. The initial parameter values for the CHDD-Prod regression were as follows: $a = 500$ kWh/day, $b = 600$

kWh/day-°F, $T_{b,c} = 70.0^\circ\text{F}$, $c = 300 \text{ kWh/day-}^\circ\text{F}$, $T_{b,h} = 55.0^\circ\text{F}$, $P = 15.0 \text{ kWh/unit}$. The initial value for the production coefficient, P , was estimated using the simple linear curve fit between energy use and production. The final regression parameters after evaluation are as follows: $a = 0.0 \text{ kWh/day}$, $b = 521 \text{ kWh/day-}^\circ\text{F}$, $T_{b,c} = 82.4^\circ\text{F}$, $c = 0.0 \text{ kWh/day-}^\circ\text{F}$, $T_{b,h} = 44.7^\circ\text{F}$, $P = 23.0 \text{ kWh/unit}$. The CHDD-Prod baseline energy model for UA0108 is shown in Equation 70.

$$E = 0.0 \frac{\text{kWh}}{\text{day}} + 521 \frac{\text{kWh}}{\text{day} \cdot ^\circ\text{F}} [cdd_i(82.4^\circ\text{F})] + 0.0 \frac{\text{kWh}}{\text{day} \cdot ^\circ\text{F}} [hdd_i(44.7^\circ\text{F})] + 23.0 \frac{\text{kWh}}{\text{unit}} P_m \quad (70)$$

The R^2_{adj} value for Equation 70 is 0.76, and the CV-RMSE is 7.2%. Both goodness-of-fit tests indicate that the CHDD-Prod model is a good fit for a baseline energy equation. However, closer inspection of the CHDD-Prod regression parameters reveals that the model suggests that there is no production- or weather-independent energy use. This cannot be true if the facility is using electrical energy for lighting or running office equipment. Furthermore, the heating slope is zero, indicating that the facility uses no electrical energy for space cooling. These results may suggest that the proportion of electrical energy dedicated to space heating and independent end-users may contribute to a very small portion of the facility's overall electrical energy consumption. Figure 40 illustrates the actual monthly electrical energy use and the monthly electrical energy use as modeled by the CHDD-Prod regression. Figure 41 shows the CHDD-Prod model for facility UA0108.

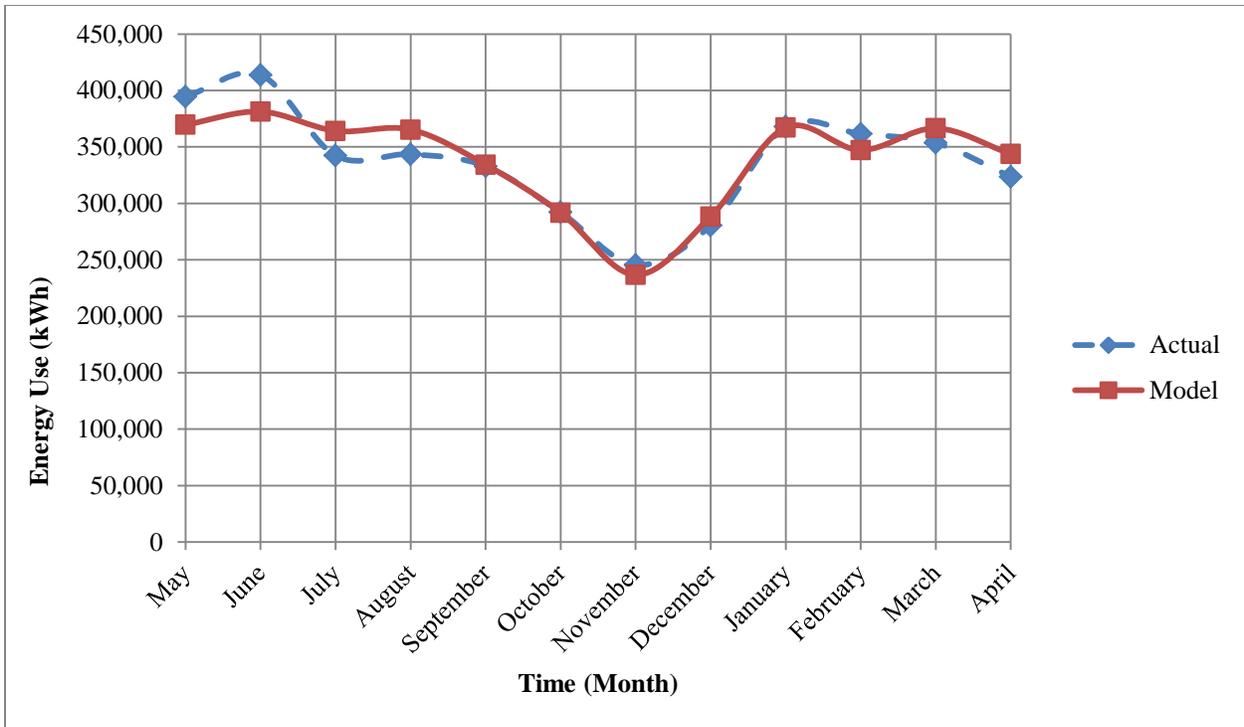


Figure 40. Actual and CHDD-Prod model predicted monthly electricity use for facility UA0108.

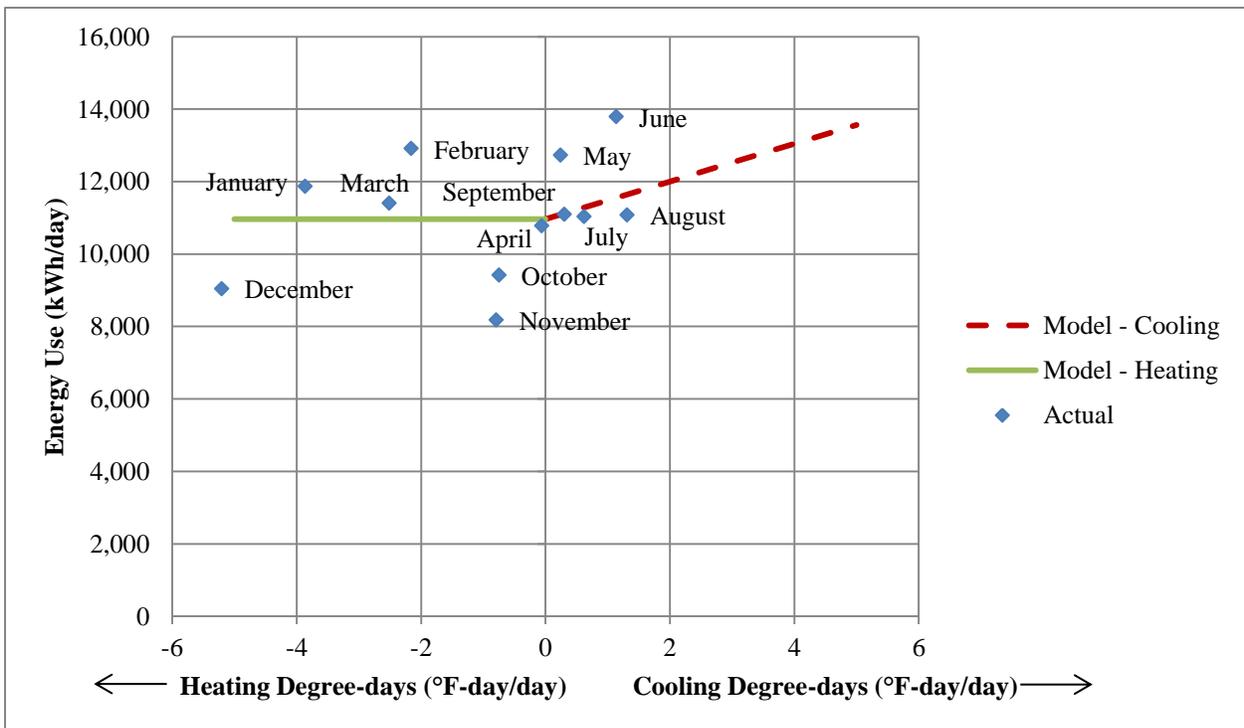


Figure 41. CHDD-Prod model of monthly electrical energy use for facility UA0108.

The CHDD-Prod baseline model indicates that the production- and weather-independent energy consumption and the heating slope are zero. The cooling slope is 521 kWh/day-°F. The cooling balance point temperature is 82.4°F and the heating balance point temperature is 44.7°F. According to the CHDD-Prod baseline model, 99.4% of the facility's total annual energy consumption is production-dependent, and the remaining 0.6% is cooling weather-dependent. In contrast to the 5PCH-Prod model, the CHDD-Prod model indicates that the facility has a cooling and heating balance point temperature. This fact may be hard to verify since the 5PCH-Prod change-point and CHDD-Prod models utilize differing temperature data resources. In comparison to the 5PCH-Prod change-point model, the CHDD-Prod model does indicate the strong relationship between electrical energy use and production values.

Neither the 5PCH-Prod nor the CHDD-Prod model seemed to adequately describe the energy consumption behavior of facility UA0108. The 5PCH-Prod change-point baseline model exhibited more behaviors of a 4PCH-Prod model. The CHDD-Prod model had statistically better goodness-of-fit values in comparison to the 5PCH-Prod change-point model. However, the CHDD-Prod model indicated that no electrical energy was dedicated to weather- and production-independent end-users or for space heating. Based on the results of the regression analyses, the electrical energy consumption of the facility seems to have a stronger relationship with monthly production in comparison to outdoor dry-bulb temperature data. This is a plausible result since the facility only conditions the office space and break room, which contribute a small percentage of the overall facility building area. Production may be the more influential variable than outdoor dry-bulb temperature for facility UA0108.

3.7 Case Study UA0105

Facility UA0105 is an industrial manufacturing facility located in Demopolis, AL. The company produces grain feed for various types of livestock. The 25,000 square foot facility is composed of several attached metal frame buildings with metal roofs. These include production areas as well as shipping and receiving areas. There are also smaller separate buildings for the maintenance shop, storage house, and boiler room. The facility uses electricity for process equipment, compressed air, lighting, space cooling, space heating, and fans. The facility also supplies natural gas to its boiler and drying ovens. This case study will examine the use of single variable and multivariate change-point and degree-day methods to establish baseline energy models for the facility's electrical energy use. The study will also examine the importance of production as an additional independent variable and the effect of the facility's operation schedule on the baseline model results.

A very small portion of the overall facility is conditioned throughout a typical production year. The office areas, break room, and control room are conditioned by three small outdoor units. Additional window units also provide conditioning for individual offices in the production area. In total, the units provide less than 20 tons of cooling (or heating) throughout the year. Because the amount of energy dedicated to space heating was estimated to be very small, three-parameter cooling change-point and variable-base cooling degree-day regression models were chosen for this analysis. Initial evaluation of the utility bills showed an increase in energy use during summer months, while exhibiting a strong decline in winter months. Therefore, it was expected that the facility's electrical energy use varied with outdoor temperature.

The facility operates 24 hours per day, 4 to 6 days per week, for 50 weeks each year. Electrical energy use and production data from February 2012 through January 2013 was

obtained from facility UA0105 personnel. Total monthly production values were reported in pounds of feed produced. Utility bill meter read dates occurred approximately from the beginning of one calendar month to the beginning of the next calendar month. The reported production data was provided in total units produced during each calendar month.

The first regression analysis performed on data received from facility UA0105 included a three-parameter cooling change-point model. Demopolis, AL is located approximately 100 miles due west of Montgomery, AL. Historical data for Demopolis, AL was unobtainable using the Weather Underground website. Therefore, actual monthly average mean dry-bulb temperature data for Montgomery, AL was selected for use in the 3PC analysis. Initial starting values for the regression parameters a , b , and $T_{b,c}$ were 5,000 kWh/day, 500 kWh/day-°F, and 60.0°F, respectively. Using the Excel Solver feature, the final regression parameters for the 3PC model are 5,081 kWh/day, 507 kWh/day-°F, and 58.8°F, respectively. The 3PC change-point baseline energy model for UA0105 is shown in Equation 71.

$$E_C = 5,081 \frac{kWh}{day} + 507 \frac{kWh}{day \cdot ^\circ F} (T_{amb} - 58.8^\circ F)^+ \quad (71)$$

Figure 42 depicts the actual monthly energy use and the monthly energy use as modeled by the 3PC change-point regression. The graph shows the increase in electrical energy use during the warmer summer months, and the steep decline in energy consumption during the cooler winter months. Upon initial observation, it would appear that the electrical energy consumption is strongly weather-dependent. Figure 43 illustrates the 3PC change-point model. The graph also shows the increase in energy consumption during the warmer summer months. The 3PC model suggests that the independent energy use is 5,081 kWh/day, the cooling slope is 507 kWh/day-°F, and the cooling change-point temperature is 58.8°F. The 3PC model and gathered data

indicate that 50.6% of the facility's total annual electrical energy use is weather-independent, and the remaining 49.4% is cooling weather-dependent.

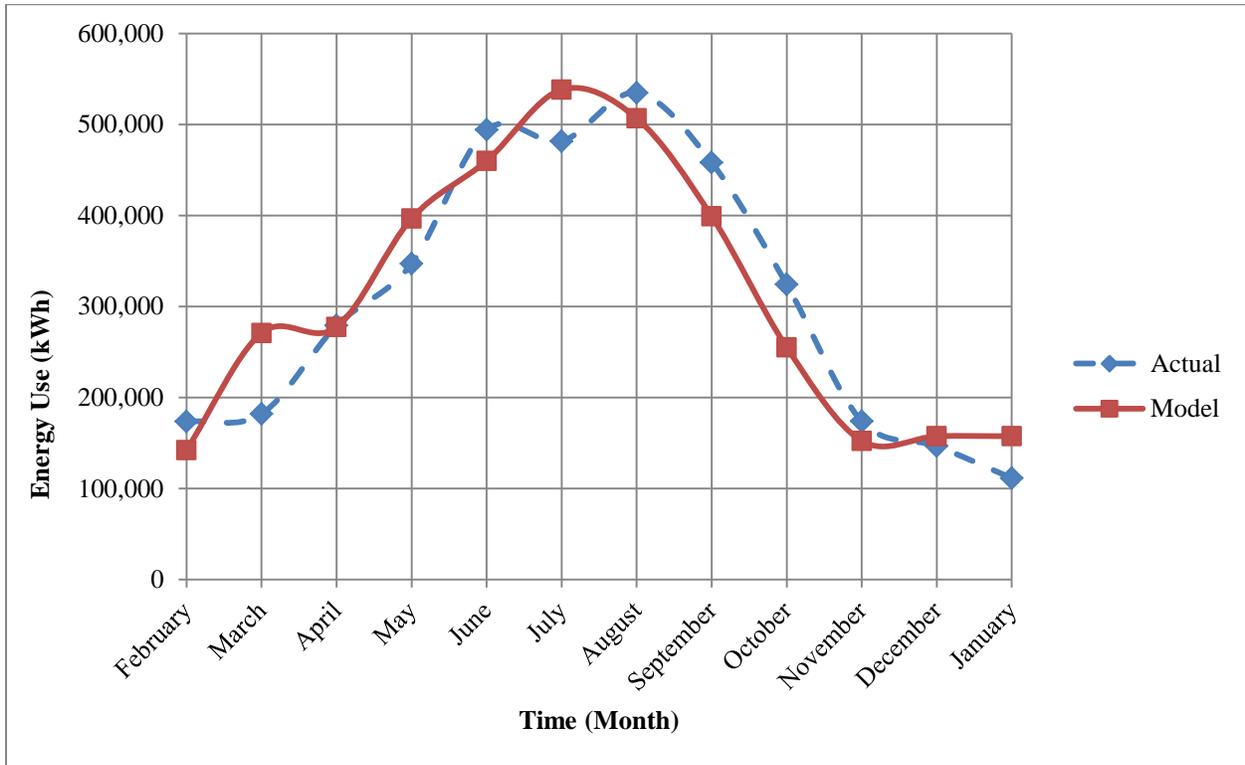


Figure 42. Actual and 3PC model predicted electricity use for facility UA0105.

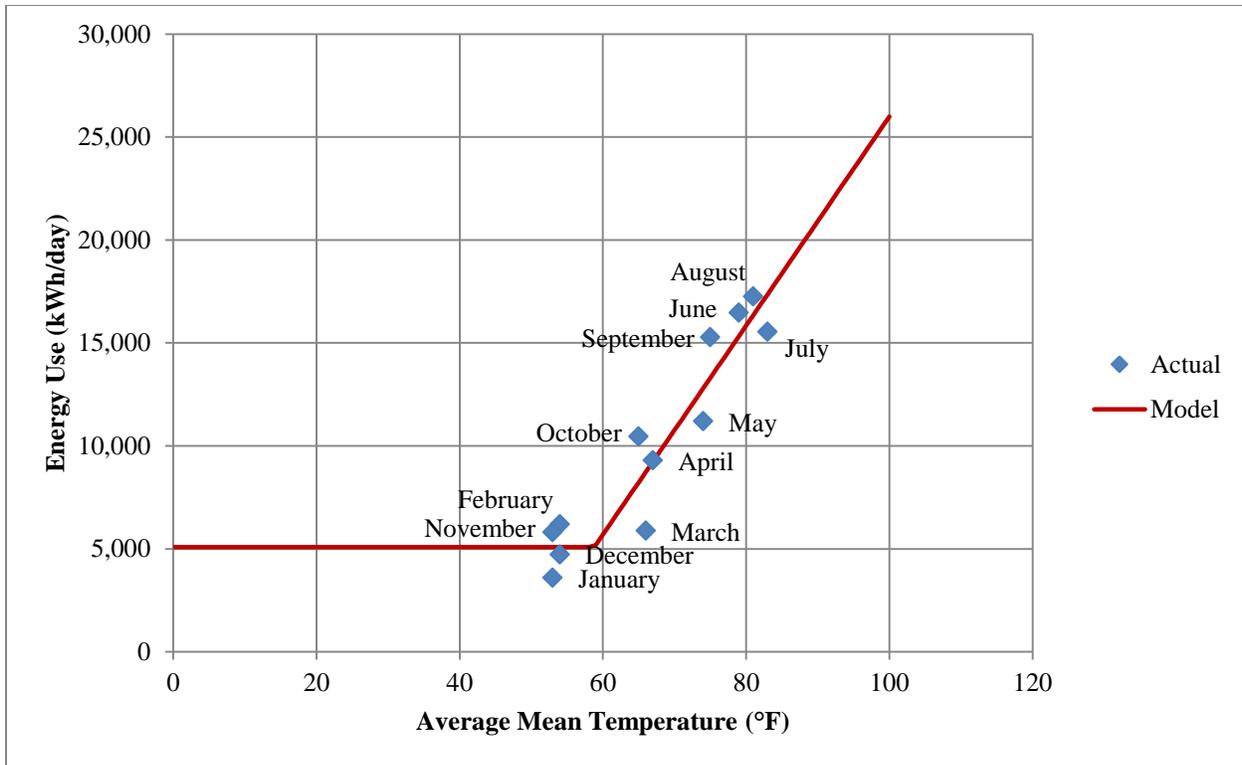


Figure 43. 3PC model of monthly electrical energy use for facility UA0105.

The R^2 value of Equation 71 is 0.89, and the CV-RMSE is 17.8%. Although the CV-RMSE indicates a poor model fit, the R^2 value indicates that the model is a good fit. Furthermore, Figure 42 and Figure 43 indicate that 3PC change-point model provides an adequate baseline for facility UA0105's electrical energy use. However, further inspection of the facility's production behavior reveals that the 3PC modeling the singular relationship between facility UA0105's electrical energy use and ambient dry-bulb temperature is not satisfactory.

During the initial site visit with the AIAC, facility personnel provided details about their seasonal operational schedule. The facility operates year-round to produce various types of livestock feed. However, the facility increases its production hours during the summer months when the demand for one particular type of livestock feed greatly increases. Original inspection

of the facility's utility bills shows that the electrical energy consumption increased during the summer months. Based on this information and the results of the 3PC baseline equation, it is unclear whether the increase in electrical energy consumption is due to an increase in ambient temperatures, or due to the increase in production values.

The relationship between electrical energy consumption and production for facility UA0105 is displayed in Figure 44. A simple linear curve fit of the two variables shows that they are very strongly correlated. Equation 72 explains the mathematical relationship between the facility's electrical energy use and production values. The coefficient of determination R^2 for the energy versus production model is 0.99, indicating that the model is almost a perfect fit to the actual data points. The goodness-of-fit test justifies the notion that production values significantly affect the facility's total electrical energy consumption. Therefore, production should be included in a multivariate regression analysis to greatly understand facility UA0105's energy consumption behavior.

$$E_C = 868 \frac{kWh}{day} + 0.0339 \frac{kWh}{lb} P_m \quad (72)$$

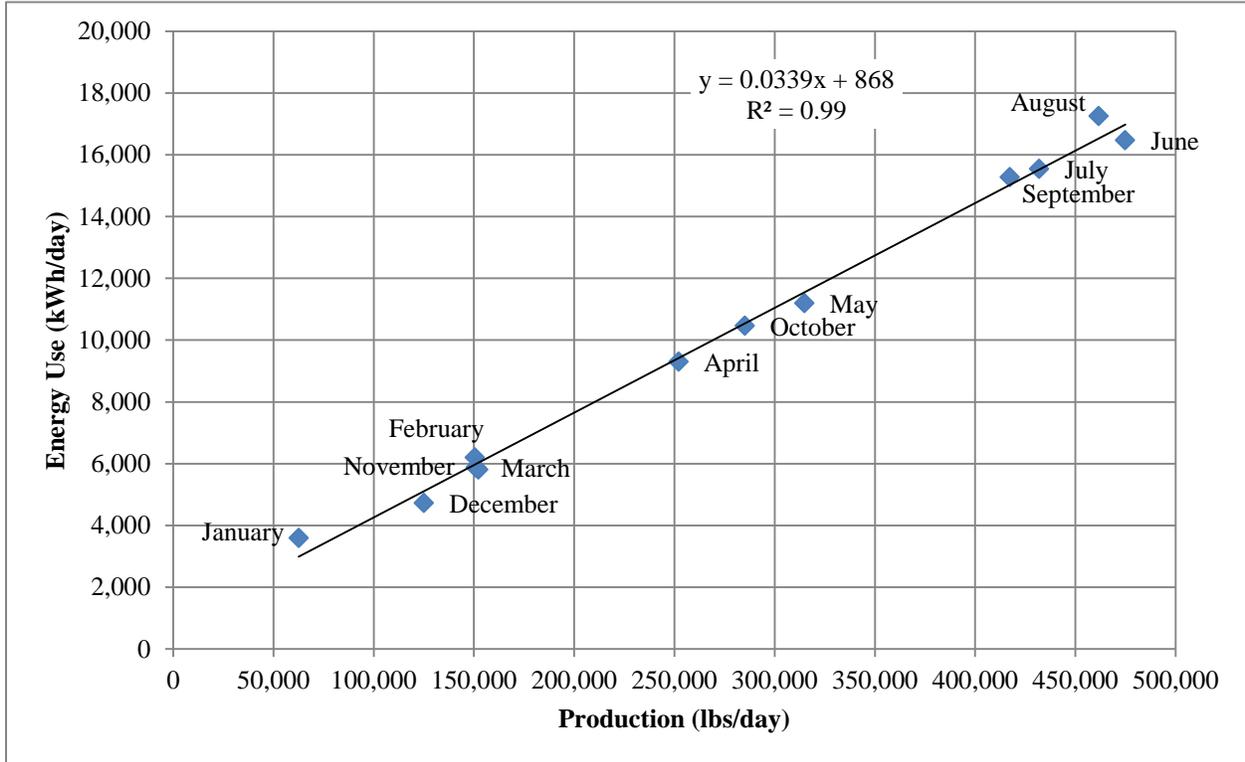


Figure 44. Monthly electricity use and number of units produced for facility UA0105.

Using the provided utility bills and production data, a multivariate three-parameter cooling change-point model was performed for facility UA0105. Actual monthly average mean dry-bulb temperature data for Montgomery, AL was obtained from the Weather Underground website. Initial values for the 3PC-Prod analysis were as follows: $a = 870$ kWh/day, $b = 500$ kWh/day-°F, $T_{b,c} = 70.0$ °F, $P = 0.034$ kWh/lb. The initial values for the production coefficient, P , and the independent energy consumption, a , were selected from the simple linear curve fit between energy use and production. Using the Excel Solver feature to carry out the regression analysis, the final regression parameters are as follows: $a = 868$ kWh/day, $b = 513$ kWh/day-°F,

$T_{b,c} = 83.1^{\circ}\text{F}$, $P = 0.0339 \text{ kWh/lb}$. The 3PC-Prod change-point baseline energy model is shown in Equation 73.

$$E_c = 868 \frac{\text{kWh}}{\text{day}} + 513 \frac{\text{kWh}}{\text{day} \cdot ^{\circ}\text{F}} (T_{amb} - 83.1^{\circ}\text{F})^+ + 0.0339 \frac{\text{kWh}}{\text{lb}} P_m \quad (73)$$

Figure 45 depicts the actual monthly electrical energy use and the monthly electrical energy use as predicted by the 3PC-Prod change-point regression. The graph shows that the 3PC-Prod model accurately replicates the electrical energy increase during the warming spring and summer months and the decrease during the cooler fall and winter months. Figure 46 shows the 3PC-Prod change-point model for facility UA0105. The R^2_{adj} value for the 3PC-Prod model is 0.99, and the CV-RMSE is 4.4%. These goodness-of-fit tests indicate that the 3PC-Prod change-point regression is an excellent fit for a baseline energy model. However, further inspection of the regression parameters proves that the model should not be used as a baseline energy consumption indicator.

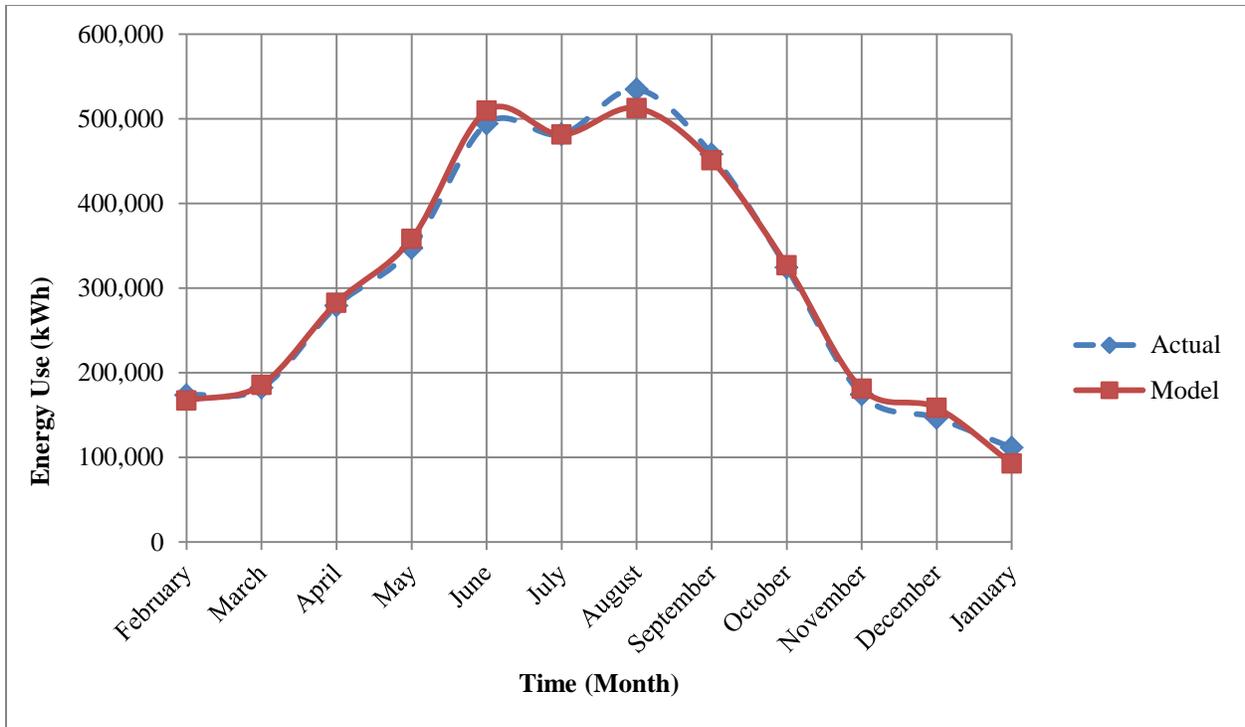


Figure 45. Actual and 3PC-Prod model predicted electricity use for facility UA0105.

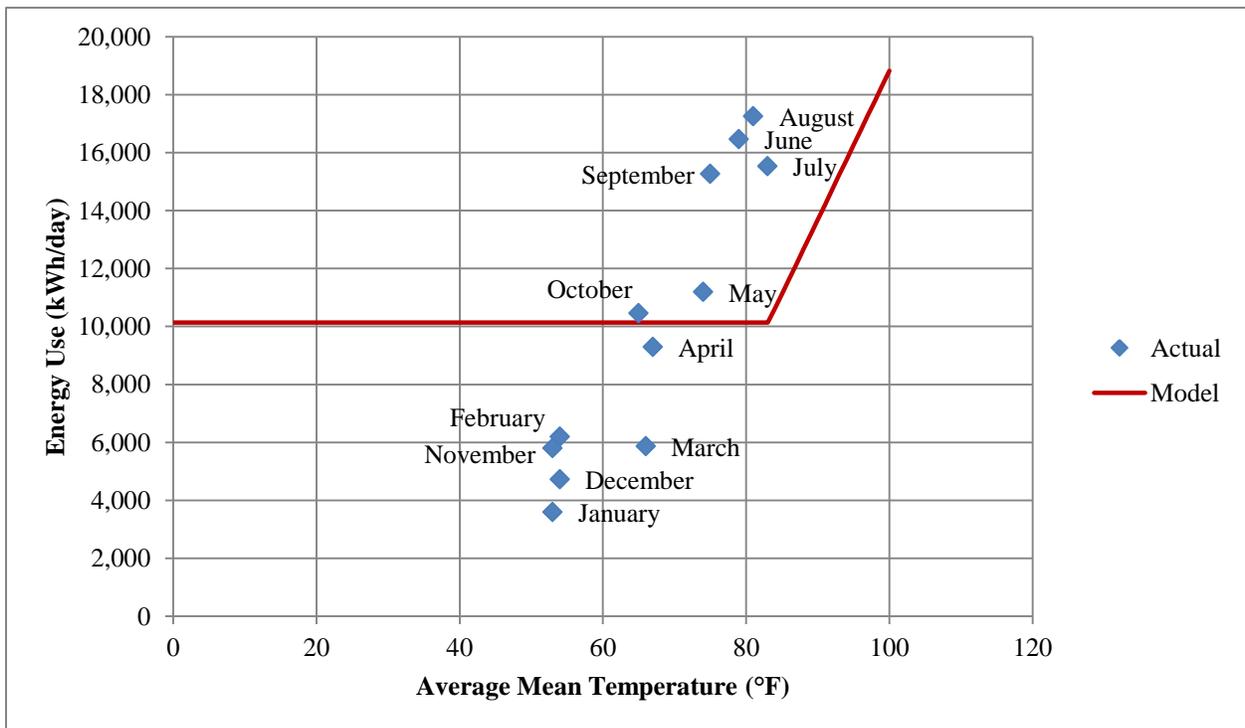


Figure 46. 3PC-Prod model of monthly electrical energy use for facility UA0105.

The 3PC-Prod model's cooling change-point temperature of 83.1°F is larger than the maximum ambient monthly average mean temperature value in the given data set. Therefore, the final regression parameters for the cooling change-point temperature and cooling slope are arbitrary, and indicate that 0.0% of the facility's total annual electrical energy use is weather-dependent. Furthermore, the regression coefficients for the production parameter and the independent energy consumption from the 3PC-Prod are equivalent to the parameters found in the energy versus production model. It is clear that production is the more influential variable in comparison the ambient temperature when establishing a baseline energy model for facility UA0105.

A CDD-Prod degree-day model was also observed in this case study. The model results are almost identical to that of the 3PC-Prod model. The CDD-Prod baseline energy model is shown in Equation 74. The values for independent energy use and the production coefficient are equivalent to those found in the energy versus production model. The cooling slope of the CDD-Prod model is zero and the cooling balance point temperature of the CDD-Prod model is larger than the maximum ambient average mean temperature in the given data set. Even with the application of typical weather data for the West Montgomery, AL area, the CDD-Prod model results indicate that production is the singular influential variable for determining the baseline electrical energy model for facility UA0105.

$$E_c = 868 \frac{kWh}{day} + 0.0 \frac{kWh}{day \cdot ^\circ F} [cdd_i (90.4^\circ F)] + 0.0339 \frac{kWh}{lb} P_m \quad (74)$$

Figure 47 illustrates the actual monthly energy use and the monthly energy use as described by the CDD-Prod regression. Due to the independent energy use and production parameter regression coefficients, the model accurately replicates the facility's electrical energy use throughout the observed year. Figure 48 shows the CDD-Prod model for facility UA0105.

The R^2_{adj} value for the CDD-Prod model is 0.99. The CV-RMSE is 4.4%. Although these goodness-of-fit tests indicate that the CDD-Prod model is a good fit to the data, production has proved to be the more influential independent variable in comparison to temperature data.

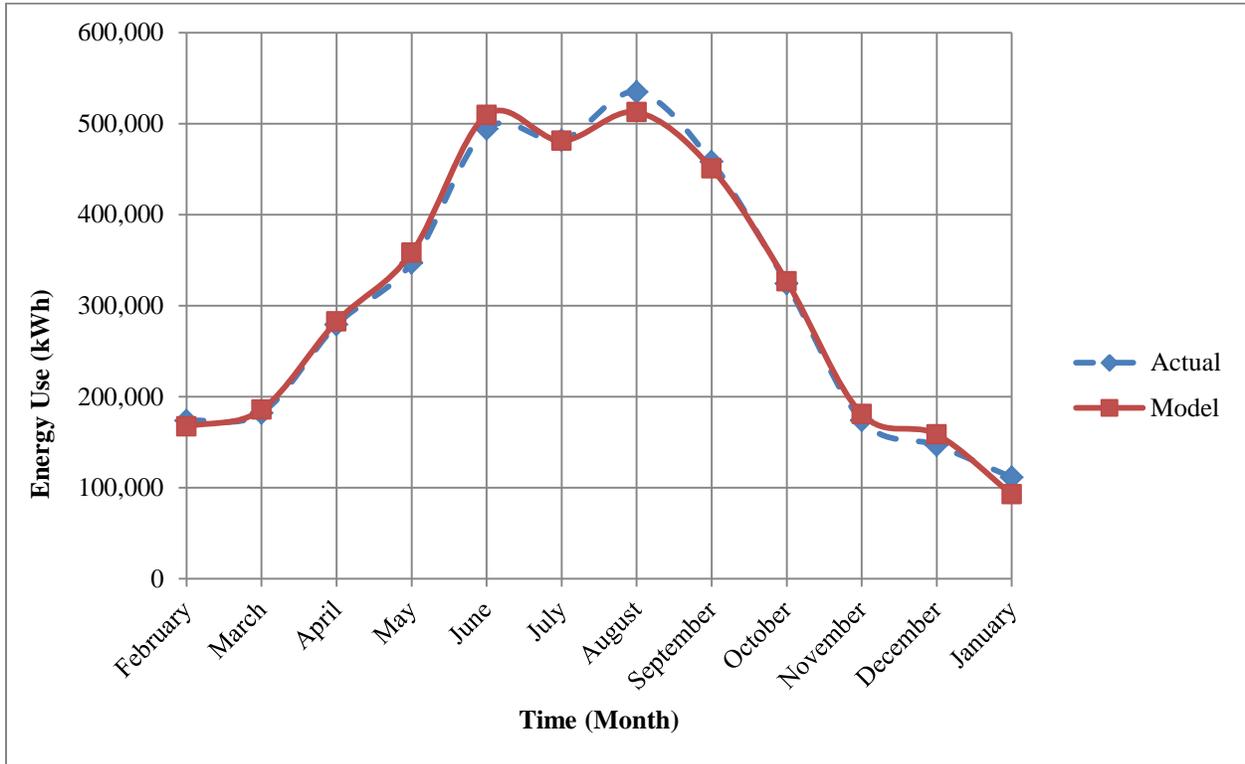


Figure 47. Actual and CDD-Prod model predicted electricity use for facility UA0105.

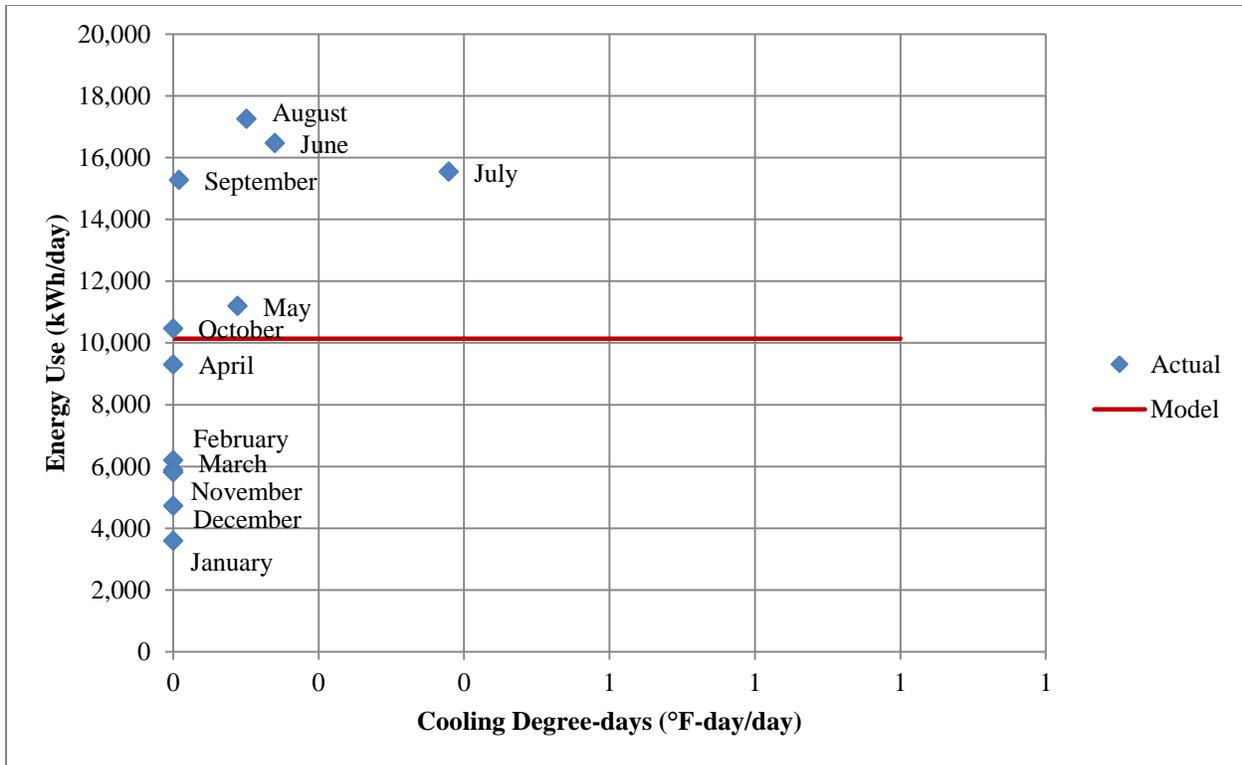


Figure 48. CDD-Prod model of monthly electrical energy use for facility UA0105.

The results of the energy versus production model, the 3PC-Prod model, and the CDD-Prod model indicate that approximately 90% of facility UA0105's total annual electrical energy is production-dependent. This means only 10% of the facility's annual energy is consumed by equipment that does not directly contribute to the manufacturing of the facility's product. From an energy management standpoint, this shows great control of the facility's resources. Production is clearly the most influential independent variable for facility UA0105's electrical energy use. This outcome is conceivable since the amount of energy that varies with outdoor air temperature and is delivered to the space conditioning equipment is extremely small in relation to the total amount of electricity consumed by the plant. Initially assuming that ambient temperature is the singular influential variable is misleading due to the seasonal production schedule of the facility.

3.8 Case Study E3031

Facility E3031 is an industrial manufacturing facility located in Northport, AL. The company is a lumber mill that fabricates different sizes and qualities of pine wood lumber for commercial, residential, and some commercial use. The facility spans 100,000 square feet, and is separated into two centralized locations each composed of several individual buildings. The first main area includes the saw mill, maintenance shop, raw material storage area, production lines, and office buildings. The second main area includes the boiler room, finishing lines, sales office, and drying kilns. The facility uses electricity for process equipment, compressed air, fans, pumps, lighting, and space heating and cooling. The facility also uses natural gas for space heating. It is assumed that the energy use of the facility varies with outdoor air temperature. This case study will observe the differences between using cooling- and heating-only models and combined cooling and heating models when establishing baseline energy models that use multiple fuel sources for space heating or space cooling.

A very small portion of the facility is conditioned throughout a typical production year. These areas include the main office space, other small office areas, maintenance shop, and kiln control room. Seven separate air-conditioning units of various sizes service the aforementioned spaces. Some of the units utilize natural gas for heating, while other units use electric strip heat or heat pumps for space heating. Only electricity is used for space cooling. Due to the use of natural gas and electricity for space heating, it is unclear whether a combined cooling and heating regression model or a set of cooling-only and heating-only regression models is appropriate for establishing the baseline energy consumption for facility E3031. The correct baseline model choice can sometimes be ambiguous, especially when a heating or cooling signal is only marginally clear. In addition, occasional data anomalies, from incorrect meter readings,

for example, or sporadic behavioral changes in the occupants, may lead to an erroneous model choice (Fels et al., 1994). The use of multiple fuel sources for space heating or space cooling is a common occurrence in many industrial manufacturing companies.

The facility operates 8 to 10 hours per day, five days per week, for 51 weeks each year. Electricity and natural gas utility bills were obtained from September 2012 through August 2013. Electrical utility bill meter read dates occur from the beginning of one calendar month to the beginning of the next calendar month. Natural gas utility meter read dates occur from the end of one calendar month to the end of the next calendar month. Total monthly production values, in units of board feet (bft), for each calendar month in the utility bill time period were also provided by facility E3031. Plant personnel stated that production values for the observed time period were not necessarily representative of a typical production year; economic demand for lumber was fairly low for some time during the observed period, and thus facility personnel decreased production.

The first regression analysis performed for facility E3031 included the use of three-parameter cooling-only and heating-only change-point models. It was estimated that the amount of electrical energy dedicated to space heating was relatively small in comparison to the facility's overall electrical energy usage. Therefore, it was assumed that 3PC-Prod and 3PH models could be created to explain the production and weather dependency of the facility's electricity and natural gas use. Production was not included in the three-parameter cooling change-point analysis because facility personnel stated that the single use of natural gas was for space heating in office areas and other buildings throughout the plant.

The relationship between electrical energy use and production for facility E3031 is shown in Figure 49. A simple linear curve fit of the two variables shows that electrical energy is

somewhat correlated with total production. Equation 75 explains the mathematical relationship between facility's electrical energy use and production values. The coefficient of determination R^2 for the energy versus production model is 0.44, indicating the simple linear model is only a mediocre fit to the data. Although electrical energy use does not exhibit an extremely strong correlation with production, production will remain as an additional independent variable in the following 3PC-Prod analysis.

$$E_C = 3,965 \frac{kWh}{day} + 0.182 \frac{kWh}{bft} P_m \quad (75)$$

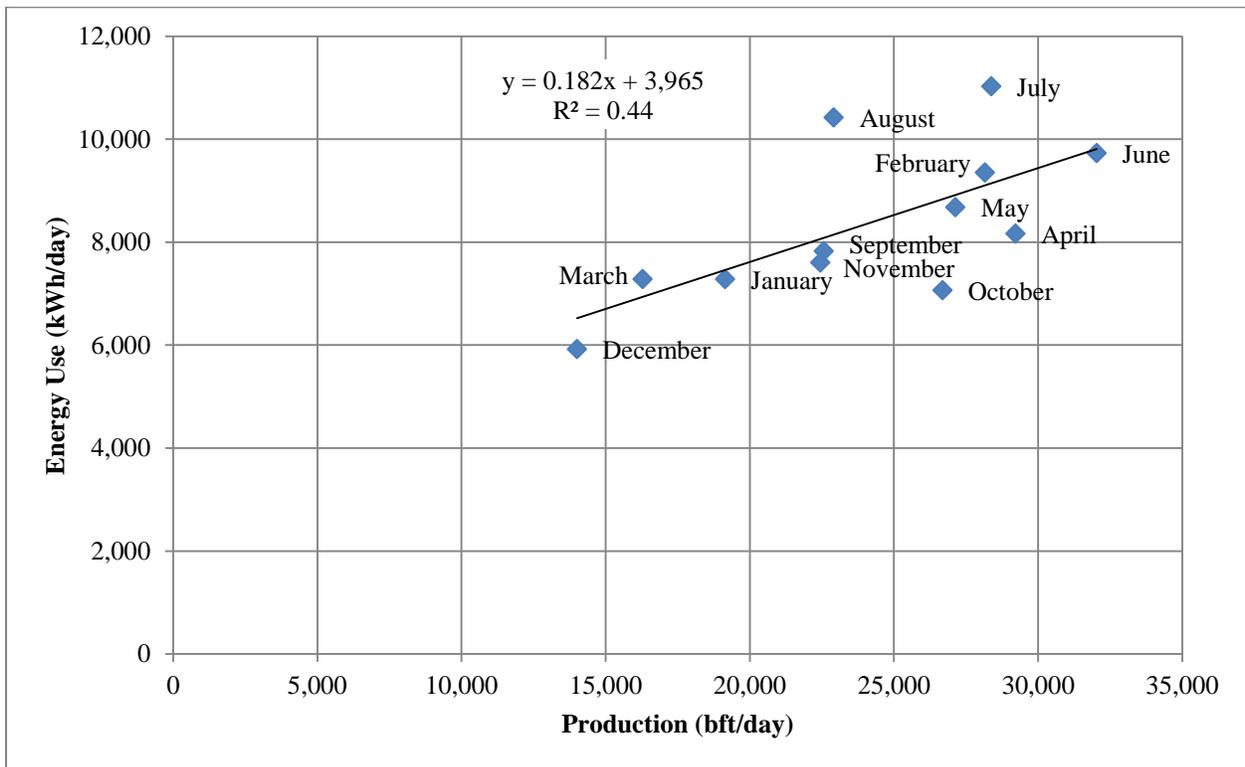


Figure 49. Monthly electricity use and total production units for facility E3031.

Actual monthly average mean dry-bulb temperature data for Tuscaloosa, AL was selected from the Weather Underground website for use in the 3PC-Prod and 3PH analysis. Tuscaloosa, AL is located only two miles south of the city of Northport, AL. Initial values for the 3PC-Prod

analysis were as follows: $a = 3,500$ kWh/day, $b = 300$ kWh/day-°F, $T_{b,c} = 70.0$ °F, $P = 0.180$ kWh/bft. The initial parameters for regression coefficients a and P were estimated using the simple linear curve fit described by Equation 75. Using the methods described in Chapter 2, the final regression parameters were found: $a = 5,022$ kWh/day, $b = 323$ kWh/day-°F, $T_{b,c} = 73.6$ °F, $P = 0.112$ kWh/bft. The resulting 3PC-Prod change-point baseline energy model is shown in Equation 76. The R^2_{adj} value is 0.73, and the CV-RMSE is 9.4%, indicating the 3PC-Prod change-point model is a sufficient baseline electrical energy model for facility E3031.

$$E_C = 5,022 \frac{kWh}{day} + 323 \frac{kWh}{day \cdot ^\circ F} (T_{amb} - 73.6^\circ F)^+ + 0.116 \frac{kWh}{bft} P_m \quad (76)$$

Figure 50 shows the actual monthly energy use and the monthly energy use as modeled by the multivariate 3PC-Prod change-point regression. The graph shows that the electrical energy use varies throughout the entire year, and slightly increases during the summer months of June, July, and August. These increases in electrical energy consumption do not necessarily coincide with production values. Figure 51 illustrates the 3PC-Prod change-point model for the facility. The increase in electrical energy use coincides with the increase in average mean dry-bulb temperature values of the facility location. Thus, it is concluded that some of the electrical energy consumed by facility E3031 is weather-dependent. Electrical energy use does not increase with the decrease in ambient temperature during cooler winter months. Therefore, the exclusion of electrical energy use attributed to space heating is justified.

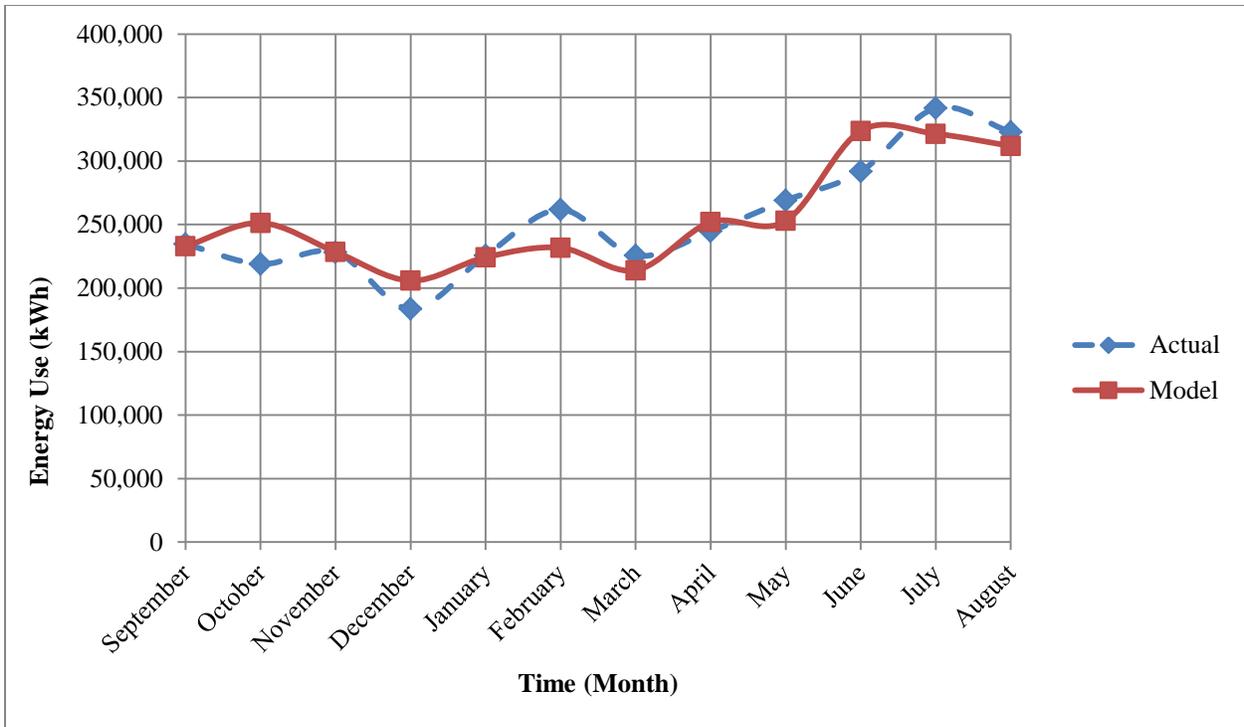


Figure 50. Actual and 3PC-Prod model predicted electrical energy use for facility E3031.

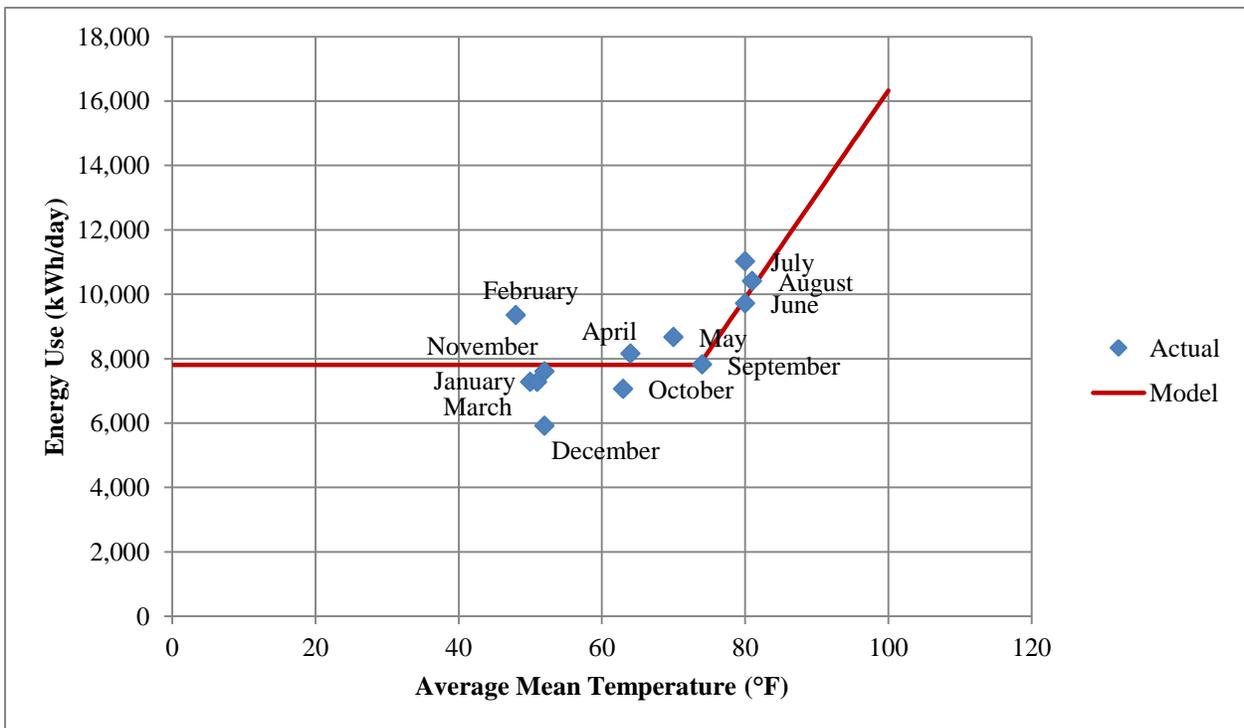


Figure 51. 3PC-Prod change-point model of electrical energy use for facility E3031.

A 3PH change-point regression analysis was also performed to characterize the natural gas consumption behavior of facility E3031. Initial values for the 3PH analysis were as follows: $a = 0.050$ MMBtu/yr, $c = 0.025$ MMBtu/day-°F, $T_{b,h} = 60.0$ °F. Using the methods described in Chapter 2, the final regression parameters were found: $a = 0.010$ MMBtu/yr, $c = 0.031$ MMBtu/day-°F, $T_{b,h} = 58.1$ °F. The resulting 3PH change-point baseline natural gas energy model is shown in Equation 77. The R^2 value for the 3PH model is 0.87, and the CV-RMSE is 49.1%. Disregarding the high value for CV-RMSE, the coefficient of determination suggests that the 3PH model is a sufficient baseline natural gas consumption model for facility E3031.

$$E_H = 0.010 \frac{\text{MMBtu}}{\text{day}} + 0.031 \frac{\text{MMBtu}}{\text{day} \cdot ^\circ\text{F}} (58.1^\circ\text{F} - T_{amb})^+ \quad (77)$$

Figure 52 shows the actual monthly natural gas consumption and monthly natural gas use as modeled by the 3PH change-point regression. The graph illustrates the increase in natural gas use during the cooler fall and winter months. Natural gas use during the warmer spring and summer months is nearly zero due to the lack energy use for space heating. Figure 53 depicts the 3PH change-point model for the facility. The increase in natural gas use coincides with the decrease in average mean dry-bulb temperature for the facility location. The 3PH model verifies the fact that most of the natural gas consumption is used for space heating in various buildings throughout the facility.

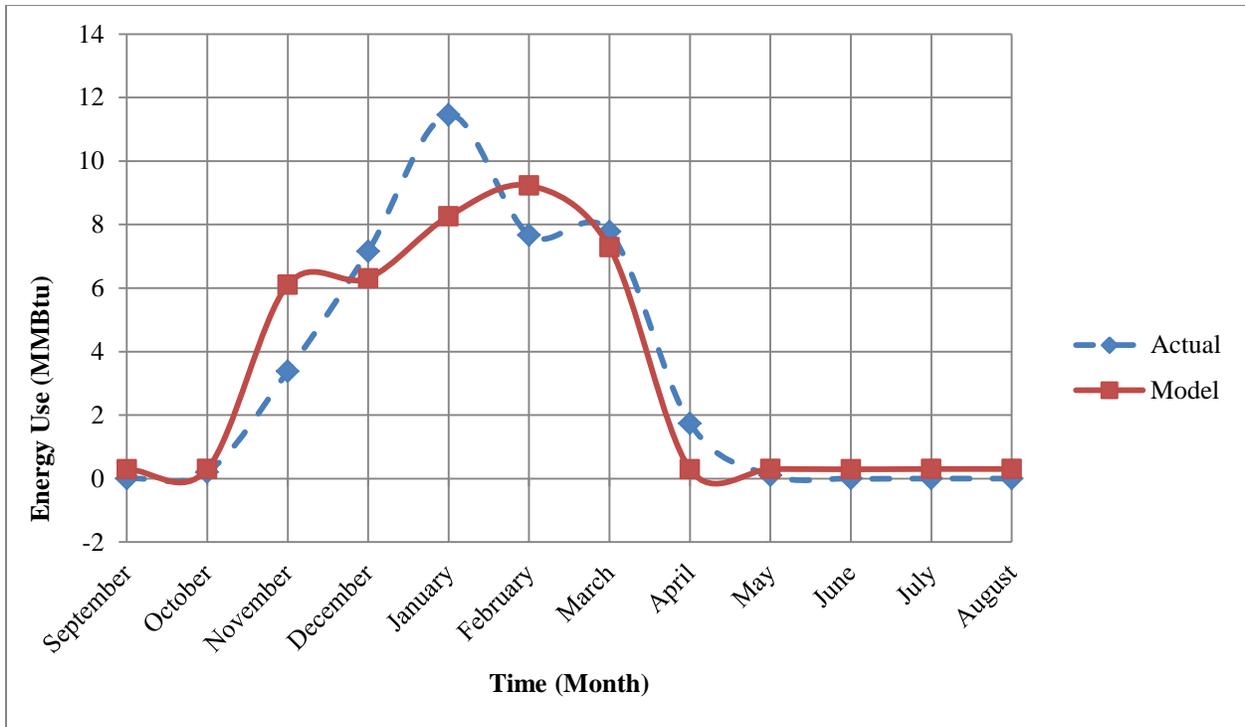


Figure 52. Actual and 3PH model predicted monthly natural gas use for facility E3031.

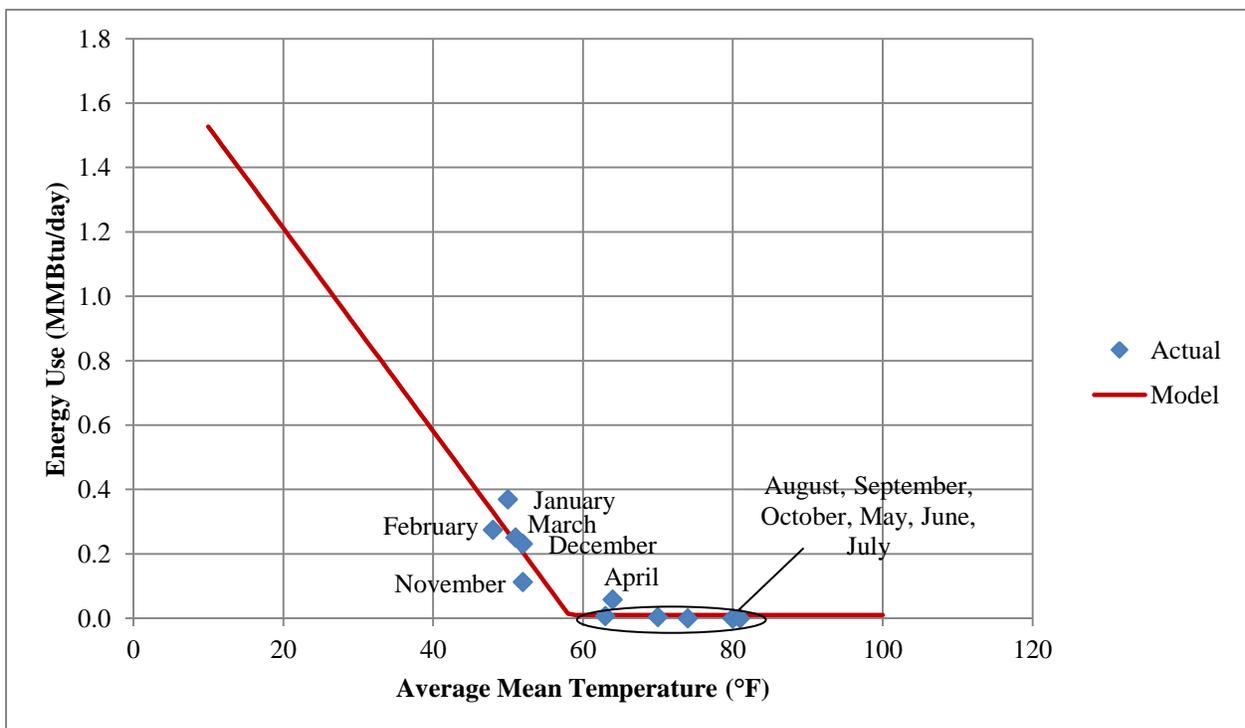


Figure 53. 3PH change-point model of natural gas use for facility E3031.

During the initial site visit of facility E3031, the AIAC noted air-conditioning units that used electricity and natural gas to provide space heating in certain buildings. In general, five-parameter cooling and heating change-point regression models (and cooling and heating degree-day models) are used to form the baseline energy model when the same fuel source is used for space cooling and space heating. The 3PC-Prod model described earlier negated the electrical energy devoted to space heating. The application of a multivariate five-parameter cooling and heating change-point model will be created to compare and contrast the cooling- and heating-only and combined cooling and heating change-point models.

Actual monthly average mean dry-bulb temperature data for Tuscaloosa, AL was also selected for use in the 5PCH-Prod change-point regression analysis. Initial values for the 5PCH-Prod analysis were as follows: $a = 3,000$ kWh/day, $b = 200$ kWh/day-°F, $T_{b,c} = 70.0^\circ\text{F}$, $c = 100$ kWh/day-°F, $T_{b,h} = 50.0^\circ\text{F}$, $P = 0.180$ kWh/bft. Using methods described in Chapter 2, the final regression parameters were found: $a = 3,060$ kWh/day, $b = 214$ kWh/day-°F, $T_{b,c} = 67.6^\circ\text{F}$, $c = 100$ kWh/day-°F, $T_{b,h} = 45.5^\circ\text{F}$, $P = 0.185$ kWh/bft. Equation 78 describes the 5PCH-Prod change-point baseline electrical energy model for facility E3031. The R^2_{adj} value is 0.33, and the CV-RMSE is 14.8%, indicating that the 5PCH-Prod model provides a poor fit to the observed electrical energy consumption data for facility E3031.

$$E = 3,060 \frac{\text{kWh}}{\text{day}} + 214 \frac{\text{kWh}}{\text{day} \cdot ^\circ\text{F}} (T_{\text{amb}} - 67.6^\circ\text{F})^+ + 100 \frac{\text{kWh}}{\text{day} \cdot ^\circ\text{F}} (45.0^\circ\text{F} - T_{\text{amb}})^+ + 0.185 \frac{\text{kWh}}{\text{bft}} P_m \quad (78)$$

Figure 54 shows the actual monthly electrical energy consumption and monthly electrical energy consumption as modeled by the 5PCH-Prod change-point regression. The graph illustrates the model's wavering prediction of electrical energy use. Figure 55 depicts the multivariate 5PCH-Prod change-point model for the facility's electrical energy use. The increase in energy use coincides with the increase in average ambient temperatures during the warm

summer and spring months. However, the model fails to capture any sort of increase in electrical energy use as ambient temperatures decrease as ambient temperatures decrease. The heating change-point temperature is smaller than the minimum average mean dry-bulb temperature for the facility location. The resulting regression parameters for the heating slope and the heating change-point temperature are arbitrary since all of the observed data points occur at temperatures above the heating change-point temperature. This result indicates that the 5PCH-Prod change-point regression model is not necessarily the most suitable method for establishing a baseline electrical energy model for facility E3031.

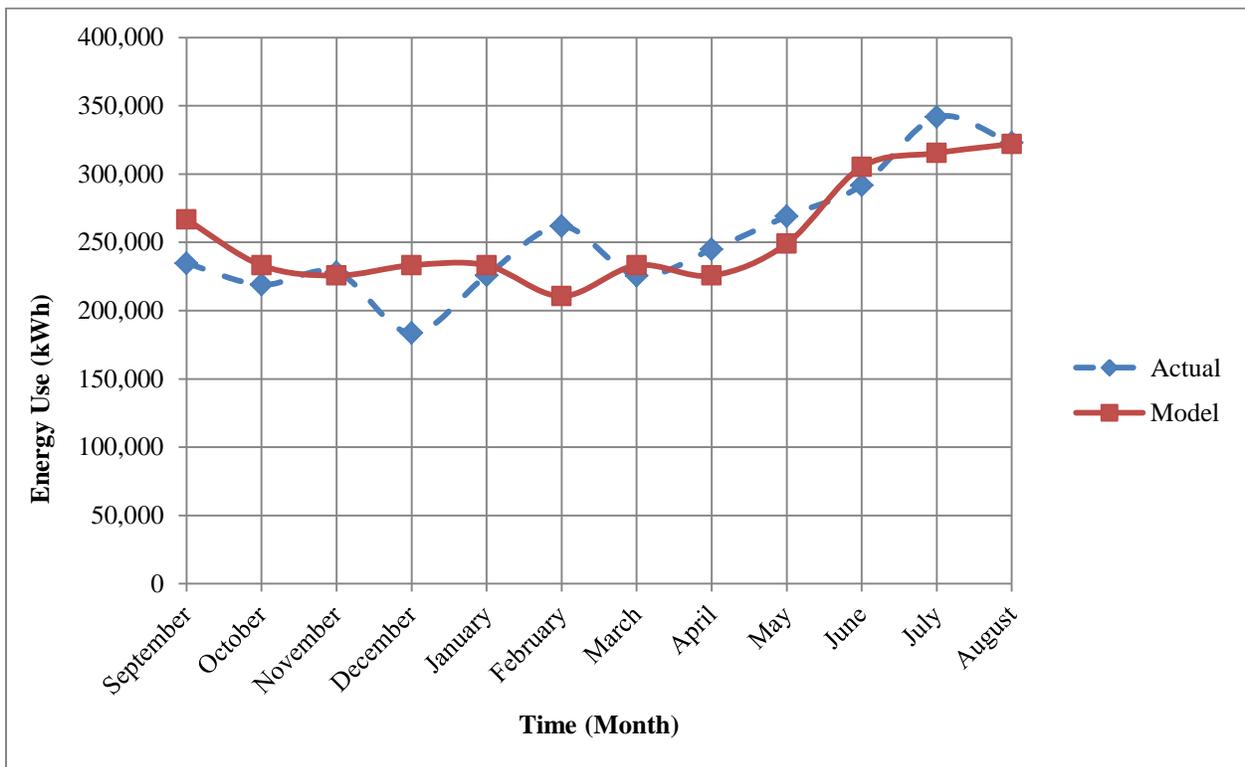


Figure 54. Actual and 5PCH-Prod model predicted monthly electricity use for facility E3031.

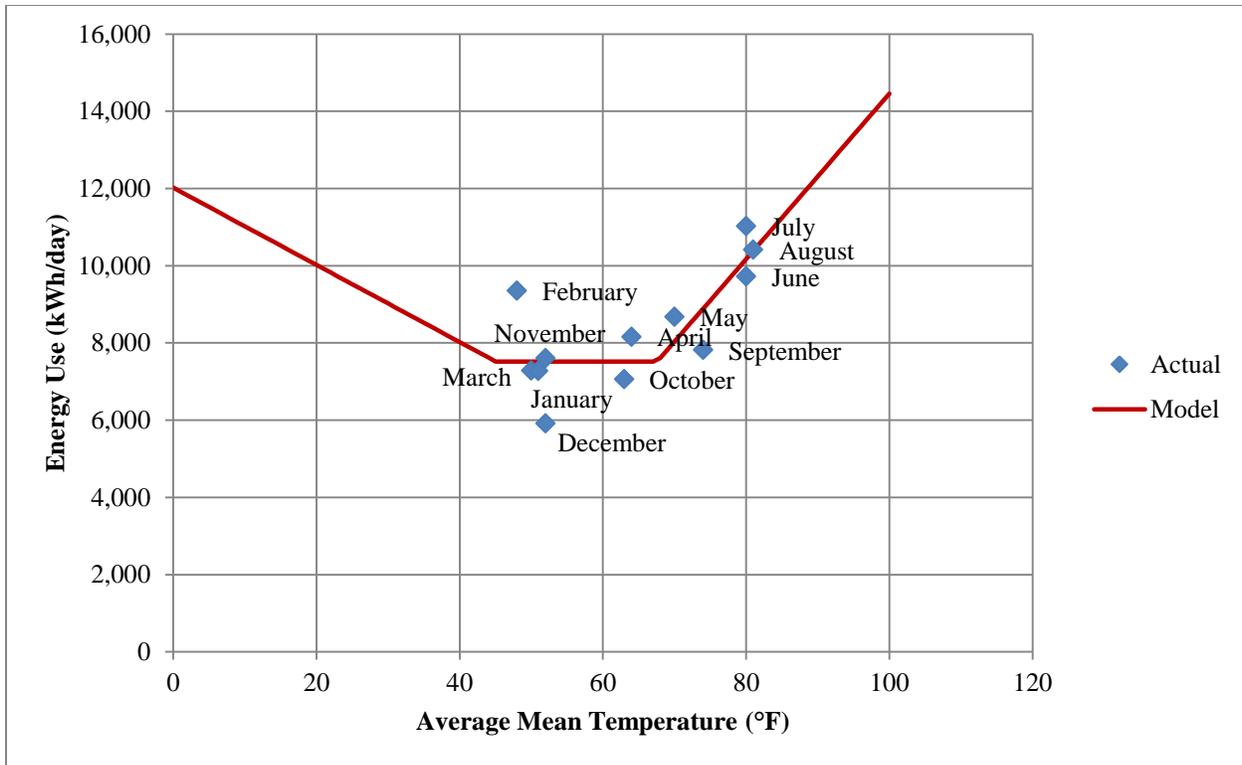


Figure 55. 5PCH-Prod change-point model of electrical energy use for facility E3031.

As previously noted, the utility bill history does not indicate that the electrical energy consumption increases with decreasing ambient temperature values. The results of this case study indicate that the 3PC-Prod cooling-only change-point and the 3PH heating-only change-point models best represent the electrical and natural gas energy consumption of facility E3031. The 5PCH-Prod combined cooling and heating change-point baseline model does not provide an acceptable fit to the observed electrical energy data. The energy consumed by the electrical conditioning equipment is very small in comparison to the total annual energy consumption of the overall facility. Therefore, it may be concluded that the amount of electrical energy consumed by the conditioning equipment for space heating is negligible when establishing a baseline energy model.

When multiple energy sources are used for heating or cooling, one should approach each building energy analysis with caution. Gathering as much information regarding the facility and its operation is critical. Energy use versus temperature or production factors may be plotted in several different ways to gain an understanding of the facility's energy consumption behavior. During AIAC assessments of industrial facilities, not every piece of heating or cooling equipment is observed. Even if equipment information is supplied by facility personnel, incorrect model number or sizes may be reported; correct heating or cooling fuel sources may not be obtained. Even if HVAC equipment specifications are correct, energy consumption data may be inconsistent with suspected heating and cooling signals (Fels et al., 1994). Therefore, it is best to identify many possible influences on facility energy consumption before determining the most appropriate baseline model choice. This case study proves the importance of analyzing multiple regression methods, and understanding facility energy consumption and operating behaviors in order to determine accurate baseline energy models.

3.9 Case Study UA0117

This section describes the Alabama Industrial Assessment Center's application of a baseline energy regression model to perform an end-point energy assessment for facility UA0117. Evaluating the amount of energy consumed by each end-user at a large manufacturing facility can be a cost- and time-intensive process. Sub-metering projects are very costly and often difficult to justify. In addition, industrial equipment is often located on the same electrical circuit or natural gas supply line, making it difficult to separate. Analytical energy disaggregation techniques have been proven to be promising alternatives, requiring readily available data such as monthly utility bills.

Methods for disaggregating industrial facility energy use have already been applied in published literature. Akbari & Konopacki (1998) use the End-use Disaggregation Algorithm (EDA), which decomposes short interval energy consumption of the whole building into the major end uses of a facility. The EDA uses statistical analysis with the help of computer simulations. It performs a regression analysis based on facility hourly energy data, with the single independent variable identified as outdoor dry-bulb temperature. The estimated whole building energy load calculated by the regression is subdivided into weather-dependent and weather-independent loads.

Next, the weather-independent and weather-dependent energy use is divided into fractions of energy use for each major facility end-user. The weather-dependent load is considered to include space conditioning. The remaining weather-independent loads are subdivided based on a computer simulated building energy use program that was formulated using an on-site survey of the industrial facility. The estimated end uses from the combined regression analysis and computer simulation are then slightly adjusted to match the actual total measured facility energy use. Data analyzed for each observed hour are averaged together to create monthly load profiles as well as seasonal load profiles.

A major goal of the AIAC is to provide industrial manufacturing facilities with an end-point energy analysis detailing the amount of energy consumed by each major end-user. Currently, AIAC teams utilize data gathered during the initial site visit along with operational and equipment information supplied by facility personnel to create the end-point energy analysis. Due to the one-day onsite visit constraint, the amount of detailed information gathered is fairly limited. Many assumptions regarding equipment use and manufacturing procedures are often made when completing the end-point energy analysis. The application of a baseline energy

model and an analytical method for disaggregating total facility energy use can greatly increase the accuracy of estimates performed by AIAC personnel when completing an end-point energy analysis.

The EDA analysis introduced by Akbari & Konopacki (1998) is disadvantageous for AIAC purposes. The EDA method requires high resolution energy consumption data, computer building simulations, and other detailed facility and equipment information. The AIAC does not have access to hourly energy consumption data for an entire facility. Most electrical and natural gas utility companies do not provide hourly consumption data to their industrial clients. Some facilities may track hourly energy use, but only observe individual energy systems (e.g. compressed air). The AIAC must rely on monthly utility bills for analysis.

The AIAC cannot heavily rely on the use of detailed computer building energy simulations when performing an end-point energy analysis. As explained in case study UA0104, the AIAC applied eQuest (2014) software to model whole facility energy usage, but the simulation only provided a mediocre model fit to the actual data. Computer simulations require extensive amount of building and operational information, which even facility personnel cannot provide. In addition, computer simulations require energy consumption profiles for each type of energy consuming equipment in the facility, which can vary significantly throughout a typical production year. AIAC personnel do not have the ability to observe every piece of equipment during the one-day onsite visit. Performing computer energy simulations is also time-consuming; the AIAC has only sixty days to deliver a comprehensive report to each client.

Case study UA0117 exhibits the AIAC's utilization of ordinary least squares baseline energy regression models as a simple and straightforward method for disaggregating total annual energy use into major energy consuming components. Baseline linear regression models have

already been used to disaggregate industrial facility energy use into production-dependent, weather-dependent, and independent categories (Kissock & Seryak, 2004; Eger & Kissock, 2007; Kissock & Eger, 2008). The AIAC wishes to further develop this disaggregation process and use the baseline model in the formation of the AIAC end-point energy analysis. Industrial manufacturing facilities may then establish their own baseline energy models to perform individualized end-point energy analyses.

3.9.1 Regression and End-Point Energy Analysis

Baseline energy models developed through statistical regression analysis are valuable tools for disaggregating facility energy consumption into individual end-user categories. The ordinary least squares regression models presented in the previous case studies separate industrial manufacturing facility total energy use into weather-dependent, independent, and production-dependent divisions. The Alabama Industrial Assessment Center intends to use the baseline energy models along with information gathered during the one-day onsite visit to perform an end-point energy analysis for industrial manufacturing facilities. This section outlines basic ideology for dividing the baseline energy model into individual end-user categories. The following Section 3.9.2 details the use of a baseline energy model to determine the end-point energy analysis for facility UA0117.

A facility's total energy use can be disaggregated into weather-dependent, independent, and production-dependent components by using the facility's developed baseline energy equation. Both change-point and degree-day cooling- and heating-only or combined cooling and heating baseline models can be used to separate the energy use into appropriate categories. Figure 56, Figure 57, and Figure 58 seen on the following pages provide visual representations of the energy-use-breakdown for a multivariate 3PH-Prod change-point model, multivariate

5PCH-Prod change-point model, and multivariate CHDD-Prod degree-day energy model, respectively.

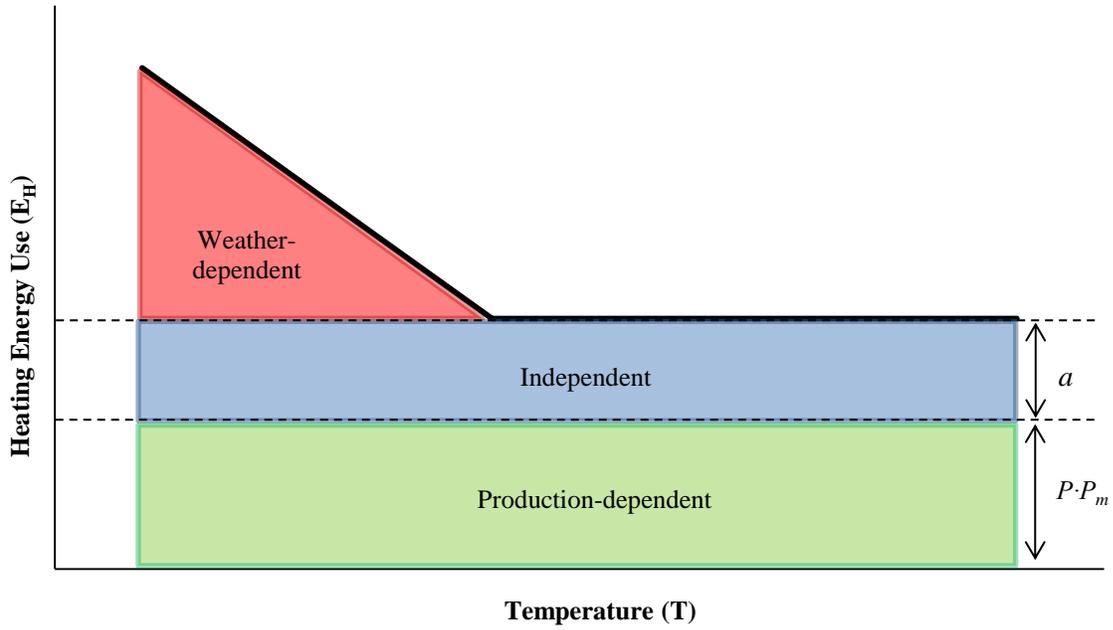


Figure 56. Energy separation for 3PH-Prod change-point baseline model.

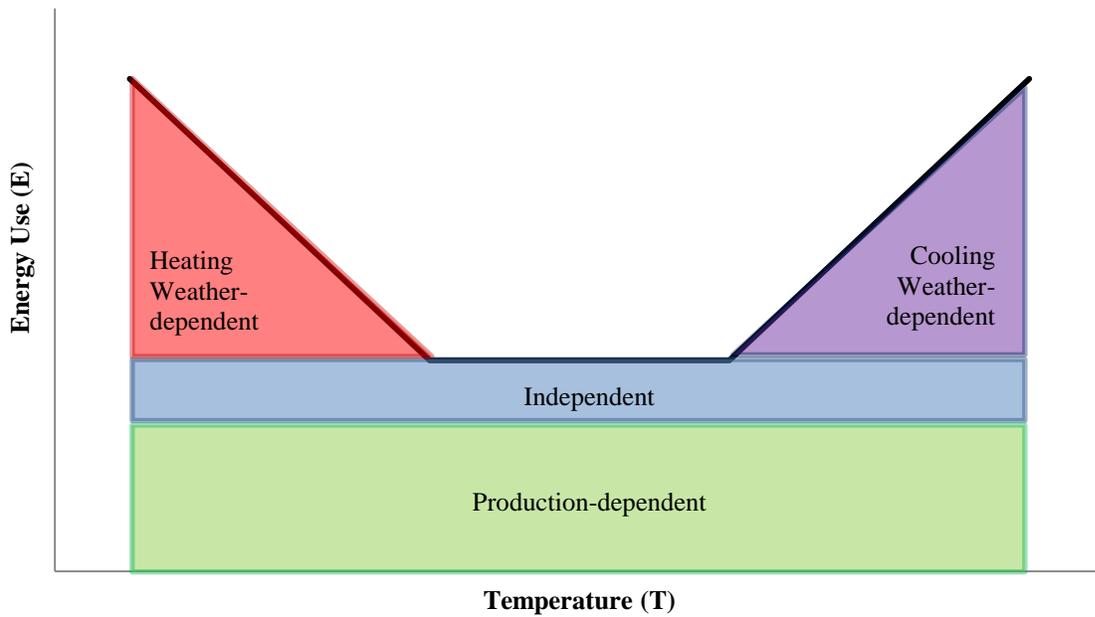


Figure 57. Energy separation for 5PCH-Prod change-point baseline model.

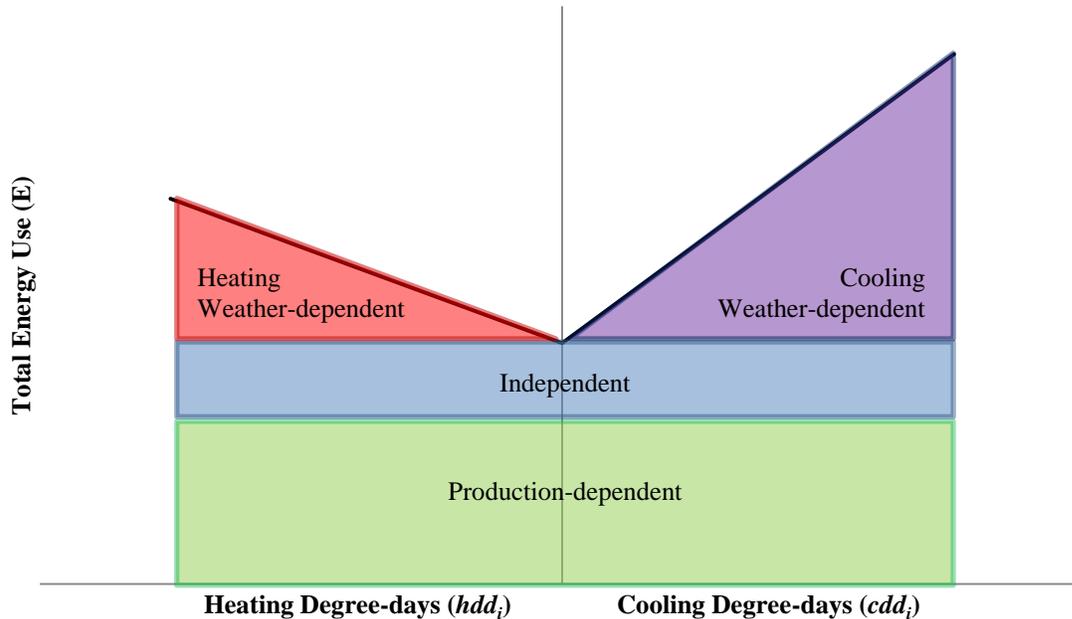


Figure 58. Energy separation for CHDD-Prod degree-day baseline model.

The division of overall facility energy use into production-dependent, independent, and weather-dependent categories allow for the further separation into estimates of energy consumption for each major industrial end-user. Unfortunately, the separation of major end-user energy consumption into weather-dependent, production-dependent, and independent categories can be quite challenging for industrial facilities. Oftentimes, the energy consumed by a major end-user can be considered as independent, production-dependent, or weather-dependent, or even any combination of the three categories. For example, energy delivered to fans used to cool a product line may be considered production-dependent when operating during production hours; their electrical energy consumption should vary with production values. However, if those fans are not turned off during non-production hours, their energy use will not correlate with units of production; the energy used by the fans could be considered independent of production and temperature (Kissock & Seryak, 2004).

Seryak & Kissock (2005) use “Lean Energy Analysis” statistical methods, such as the change-point or degree-day regression model, to help divide industrial facility energy use into separate components. The authors define the constant individual energy use regression parameter, a , as “facility” energy use. From the lean manufacturing perspective, facility energy use does not add value to the product or to the plant environment and can be considered waste. Wasted energy sources can include friction losses, air infiltration, oversized and part-loaded equipment, and idling equipment. Ideal control or proper management of the facility’s overall energy consumption would lead the facility energy use to reach zero, or nearly zero; all energy would be consumed for space conditioning or would be proportional to production. The first goal in identifying energy savings is to reduce the facility energy use.

The independent or “facility” energy consumption can be defined as any energy consumed that is unrelated to space conditioning or production. End-users that contribute to the independent energy consumption of an industrial facility may include lighting, fans, pumps, air compressors, and motors. Energy attributed to lighting is independent of weather and production; typically, the number of widgets produced by a manufacturing facility has no effect on the energy consumed directly by the lighting system. In addition, fans, pumps, or motors that are not turned off during non-production hours could be classified as an independent energy consumer. Energy used by air compressors whose singular application of compressed air is for cleaning maintenance shop floors, or dusting off employees’ clothes could also be included in the independent energy consumption category.

Production-dependent energy consumption is defined as the energy directly related to the process of manufacturing the finished product. When determining if the energy consumed by a specific end-user falls within the production-dependent energy use category, facility personnel

may pose the following question: If the piece of equipment was turned off, can the product still be manufactured? If the answer is no, then the end-user is most likely production-dependent. If the answer is yes, the end-user most likely falls within the independent or weather-dependent category. For example, lighting systems and HVAC equipment may be considered a part of the independent and weather-dependent energy use categories; lights and space conditioning of the facility is used for employee visibility and comfort. The energy consumed by these end-users has no direct correlation with the energy consumed to manufacture a finished product.

Examples of production-dependent equipment include fans, pumps, motors, air compressors, boilers, ovens and furnaces, and various other types of process equipment. Some of these specific end users were also described as independent energy consumers. However, the application and use of the equipment ultimately decides the appropriate classification. One example of a production-dependent energy consumer could include a large motor used by injection molding facility UA0108 to grind flash material to be recycled back into the process line. An increase in production results in an increase the amount of flash material; more flash material increases the use of the flash grinding motor. This causes an increase in production-dependent energy use. Another example of a production-dependent energy consumer could include an air compressor producing compressed air for use in pneumatic production machinery.

For the case studies presented in this thesis, weather-dependent energy consumption is defined as the energy consumption that is influenced or dependent upon the increase or decrease in ambient dry-bulb temperature. End-users that contribute to the weather-dependent energy consumption of an industrial facility may include HVAC units, cooling towers, chillers, and even boilers, fans, and pumps. As ambient dry-bulb temperatures increase or decrease, more energy must be consumed by an air conditioning unit in order to cool or heat a serviced area. Energy

consumed by chillers, cooling towers, and boilers may also be considered weather-dependent if HVAC units are water-cooled or steam-heated.

At first consideration, the entirety of energy consumed by an industrial facility HVAC system may be categorized as weather-dependent. However, arguments may be made that categorize fractions of the overall HVAC energy consumption as independent and even production-dependent. Some industrial facilities, like case study UA0094, must cool the entirety of the plant year-round due to internal heat loads or to satisfy production requirements. The energy used to cool the facility due to the constant presence of the internal heat load, given off by production equipment, occupants, etc., could be classified as a fraction of the facility's independent energy consumption. Energy must be consumed to cool the facility to the required specifications, regardless of outdoor temperature values.

Akbari & Konopacki (1998) also address the independent and production-dependency of HVAC energy consumption. As a facility increases its production, more energy is consumed by production-dependent equipment. In theory, as more energy is consumed by production-dependent equipment, more heat energy is expelled inside the facility, thus increasing the internal heat load. Increasing the internal heat load would require more space cooling in a fully conditioned facility. Thus, some of the production-dependent energy consumption as explained by the baseline energy model could be attributed to operating the HVAC system. The separation of HVAC energy consumption into weather-dependent, independent, and production-dependent categories will be further explored in case study UA0117, found in the next section.

The process of addressing the energy consumption of major facility end-users into the appropriate weather-dependent, independent, and production-dependent categories is challenging for industrial facilities. Each manufacturing facility's energy use profile is a unique complicated

web made up of numerous types of process equipment, operating schedules, and maintenance procedures. The breakdown of energy consumption for each major facility end-user must be performed on a case-by-case basis; each separation profile is non-transferrable. Detailed information about facility equipment and operating procedures must be acquired in conjunction with a baseline energy model to estimate the breakdown of total facility energy consumption into distinct parts.

3.9.2 Case Study UA0117: End-Point Energy Analysis

Facility UA0117 is an industrial manufacturing facility located in Rainsville, AL. The company uses injection molding to create plastic parts used in the assembly of automobiles. The facility covers a total of 296,000 square feet, and is enclosed in one large building structure. The facility includes the main production area, maintenance area, and office spaces. The facility uses electricity to supply energy to injection modeling machines, air conditioning units (for space cooling), chillers, pumps, lighting, air compressors, fans, and additional process equipment. The facility also uses natural gas to supply energy to paint-drying ovens, air conditioning units (for space heating), and other process equipment. Due to the use of electricity and natural gas for space cooling, it is assumed that the facility's energy consumption varies with outdoor temperature. This case study will observe the use of a three-parameter cooling change-point and a variable-base cooling degree-day baseline energy model in an end-point electrical energy analysis for facility UA0117.

The entire facility is conditioned year-round by 29 rooftop air-conditioning units. Each unit uses electricity for space cooling and natural gas for space heating. The units provide a total of 736 tons of conditioning to the plant. The facility operates 24 hours per day, 5 days per week, 50 weeks each year. Electricity utility bills and production data were obtained from facility

personnel for the period of January 2013 through December 2013. Electrical utility bill meter read dates occur from the beginning of one calendar month to the beginning of the next calendar month. Production data for each calendar month was provided in total assemblies or units produced.

Energy consumption and monthly production values are not strongly correlated for facility UA0117. Figure 59 shows monthly electricity use and the number of units produced by the facility from January 2013 through December 2013. The data points are highly scattered. Using a simple linear curve fit, the relationship between electrical energy use and production is explained by Equation 79. The R^2 value for the energy versus production model is 0.017, indicating a very poor fit to the observed data. The total number of units manufactured does not significantly influence the total electrical energy consumption. For this reason, a multivariate change-point or degree-day method was not utilized in the production of the end-point energy analysis.

$$E_c = 49,266 \frac{kWh}{day} + 0.215 \frac{kWh}{unit} P_m \quad (79)$$

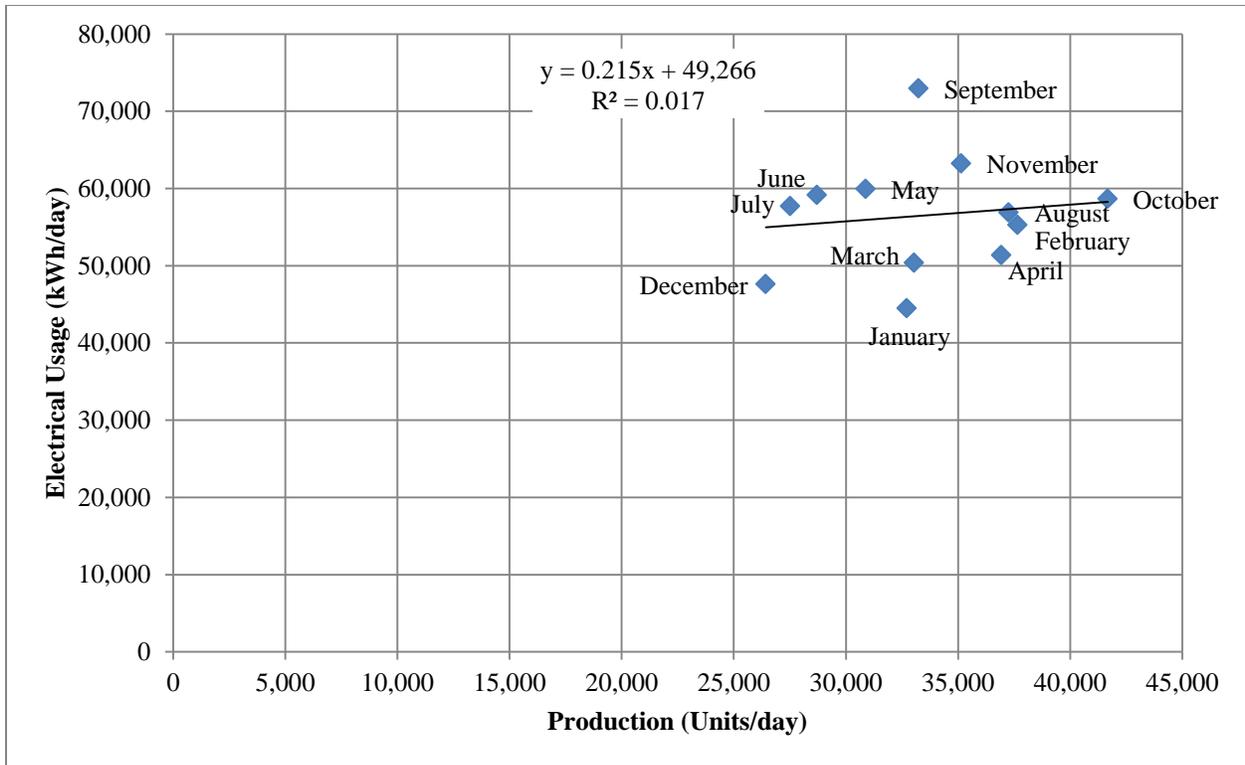


Figure 59. Monthly electricity use and production units for facility UA0117.

With the elimination of production as a significant independent variable, a three-parameter cooling change-point regression analysis was performed for facility UA0117. In contrast to the other case studies presented in this thesis, actual weather data was not used in the 3PC analysis. TMY3 weather data for the city of Gadsden, AL was used for the 3PC change-point analysis. The purpose of the application of TMY3 weather data was to closely compare and contrast the results of the 3PC and CDD analysis for use in the end-point energy analysis.

Initial values for the 3PC change-point analysis were as follows: $a = 45,000$ kWh/day, $b = 400$ kWh/day-°F, $T_{b,c} = 50.0$ °F. Using the Excel Solver feature to carry out the regression analysis, the final regression parameters are as follows: $a = 48,856$ kWh/day, $b = 347$ kWh/day-°F, $T_{b,c} = 38.1$ °F. The 3PC change-point model is shown in Equation 80. The R^2 value for

Equation 80 is 0.37, and the CV-RMSE is 11.8%. Although the R^2 value does not indicate a strong model fit, the CV-RMSE indicates that there is a relationship between dry-bulb temperature and electrical energy consumption.

$$E_c = 48,856 \frac{kWh}{day} + 347 \frac{kWh}{day \cdot ^\circ F} (T_{amb} - 38.1^\circ F)^+ \quad (80)$$

Figure 60 illustrates the actual monthly energy use and the monthly energy use as depicted by the 3PC change-point regression. The graph shows that the electrical energy use varies throughout the year. The electrical energy consumption slightly increases during some of the summer and fall months. Figure 61 shows the 3PC change-point model for facility UA0117. Although the data is somewhat scattered, the graph does indicate an increase in electrical energy use as ambient dry-bulb temperatures increase.

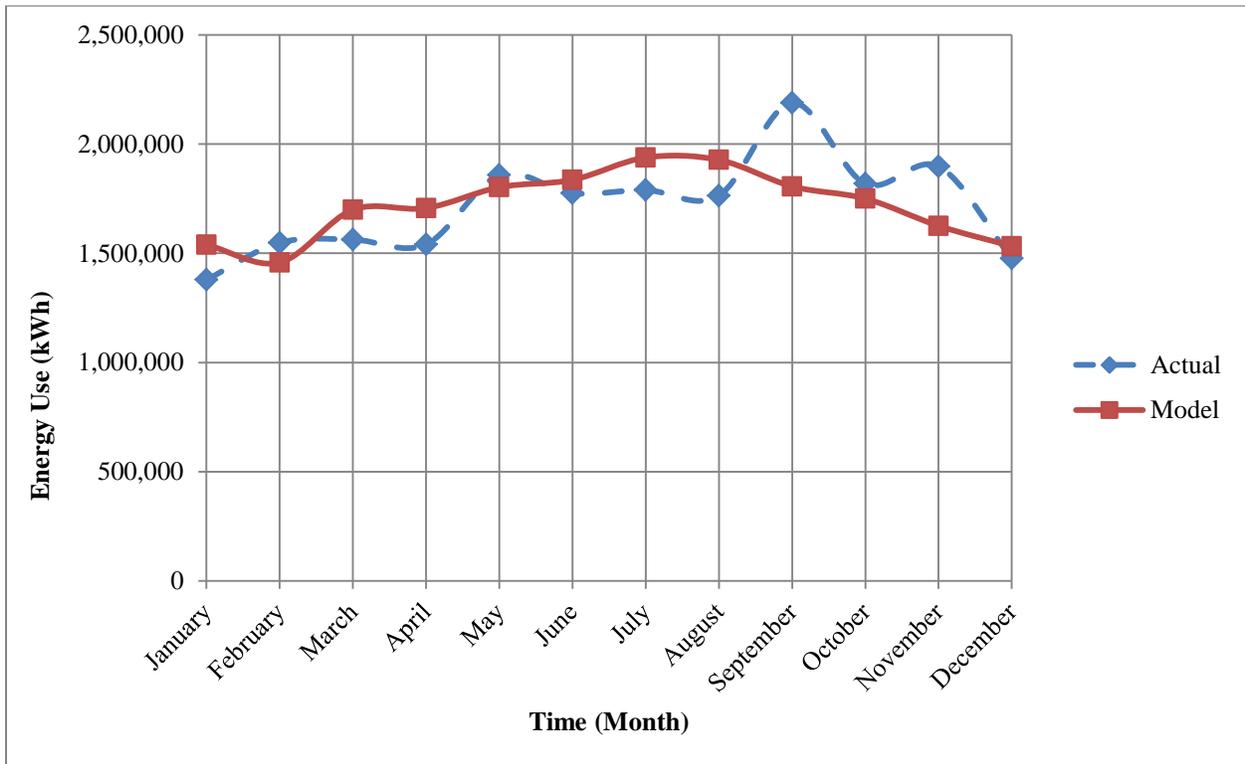


Figure 60. Actual and 3PC model predicted electrical energy use for facility UA0117.

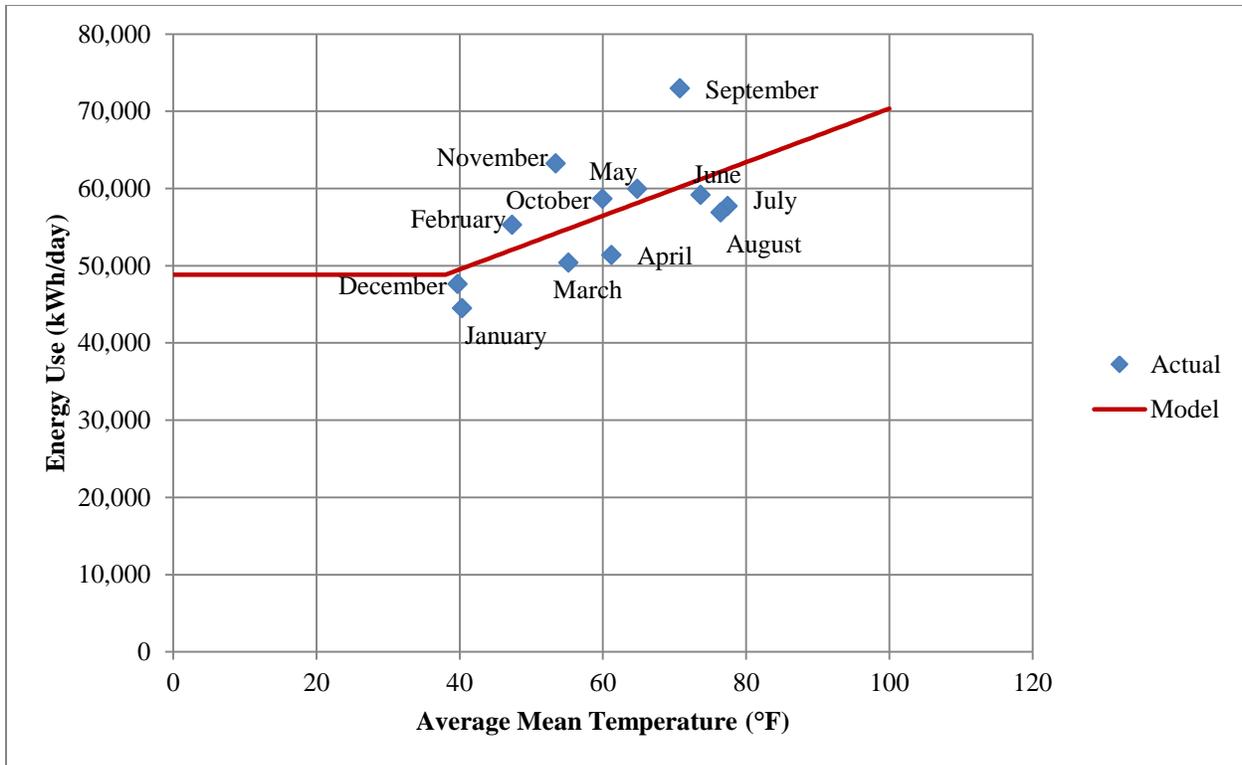


Figure 61. 3PC change-point model of electrical energy use for facility UA0117.

A cooling degree-day regression analysis was also performed for facility UA0117. TMY3 weather data for the city of Gadsden, AL was used in the CDD analysis. Initial parameter values for the cooling degree-day analysis were identical to the initial values presented in the 3PC case. Using the methods presented in Chapter 2, the final regression parameters were found: $a = 41,045$ kWh/day, $b = 347$ kWh/day-°F, $T_{b,c} = 15.6^\circ\text{F}$. The CDD model is shown in Equation 81. The R^2 value is 0.37, and the CV-RMSE is 11.8%, identical to the 3PC model. In addition, the CDD developed cooling slope is identical to the 3PC cooling slope. These similarities could be a result of applying TMY3 data to both model types. The CV-RMSE indicates that there is a relationship between electrical energy consumption and ambient dry-bulb temperature.

$$E_c = 41,045 \frac{\text{kWh}}{\text{day}} + 347 \frac{\text{kWh}}{\text{day} \cdot ^\circ\text{F}} \left[cdd_i (15.6^\circ\text{F}) \right] \quad (81)$$

Figure 62 illustrates the actual monthly energy use and the monthly energy use as depicted by the CDD regression. Figure 63 shows the cooling degree-day model for facility UA0117's electrical energy consumption. Although the data remains somewhat scattered, the CDD model replicates the increase in electrical energy use as the number of cooling degree-days increases. The cooling slope parameters obtained from the analyses are identical for the change-point and degree-day cooling models. The independent energy consumption values are also relatively similar. The cooling change-point and balance point temperatures are relatively low for cooling-only baseline models.

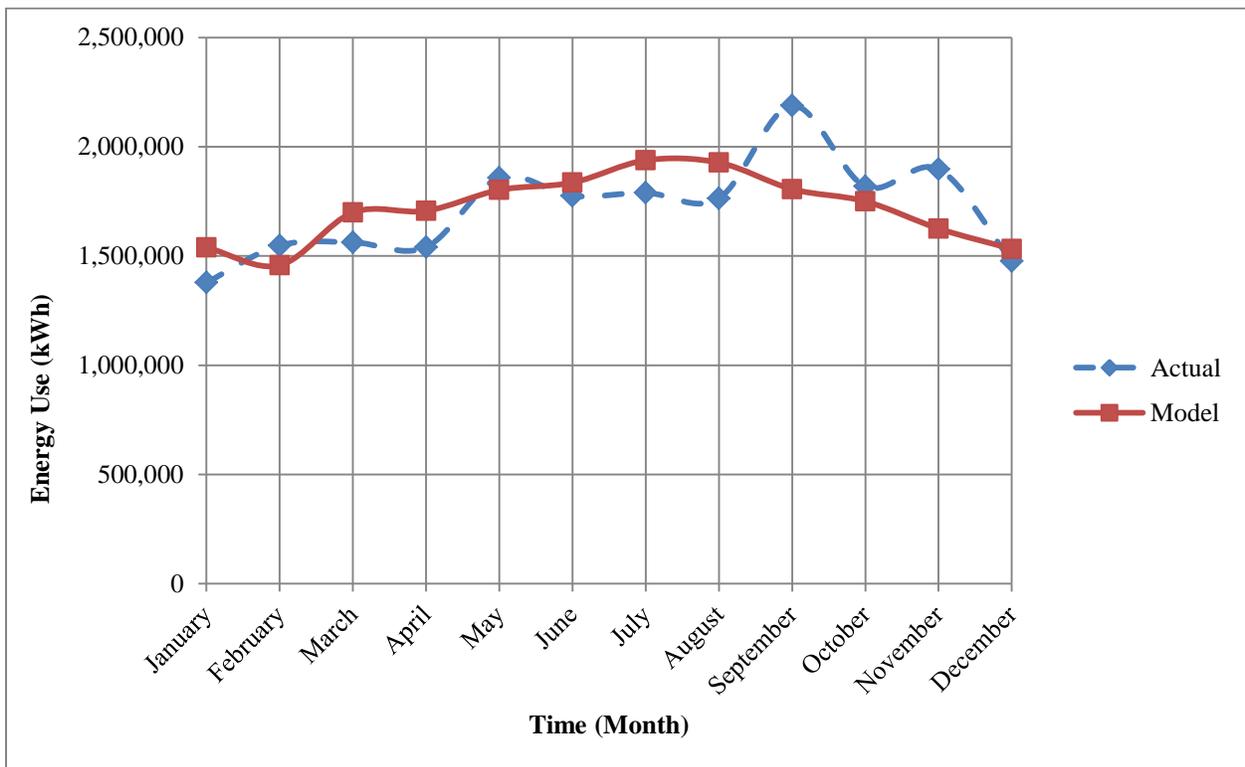


Figure 62. Actual and CDD model predicted monthly electrical energy use for facility UA0117.

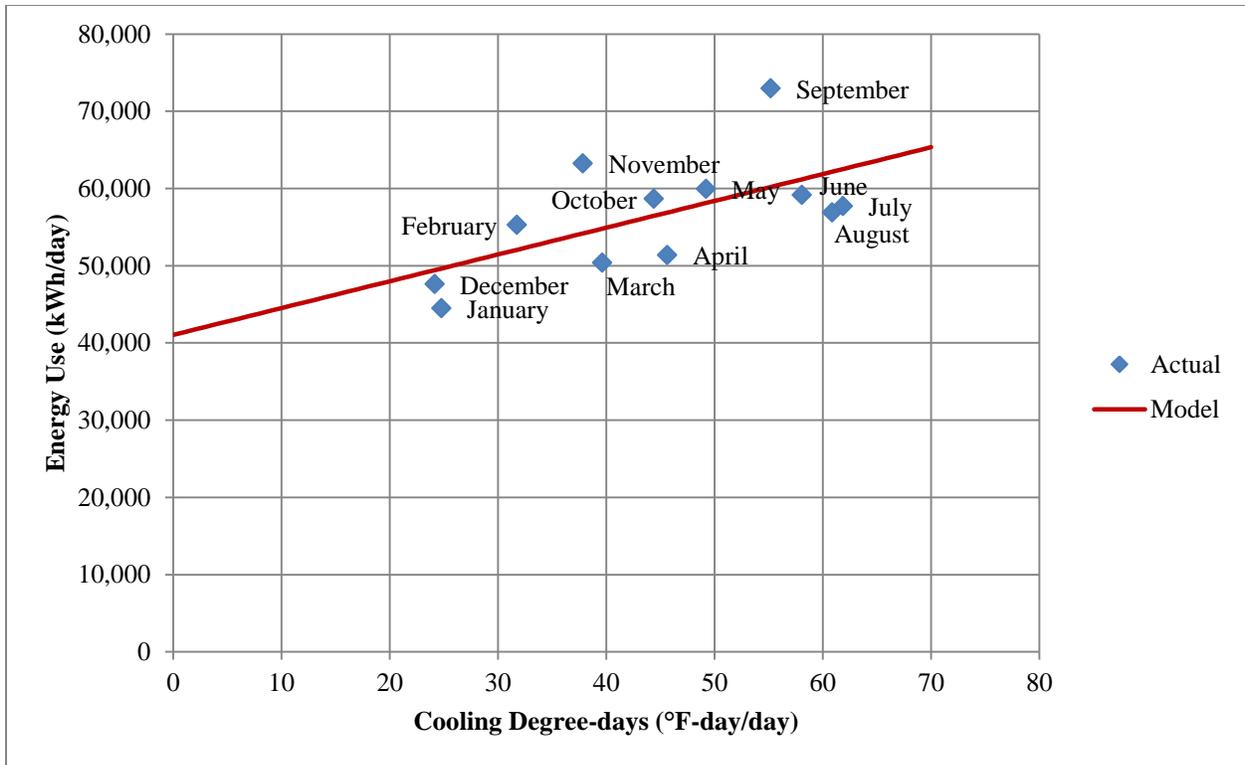


Figure 63. CDD model of electrical energy use for facility UA0117.

Prior to the establishment of a baseline energy regression model, the AIAC assessment team assigned to facility UA0117 experienced some difficulty in estimating the annual energy consumption of the HVAC system when performing the end-point energy analysis. The AIAC used the results of the cooling degree-day and change-point cooling models to guide their calculations in the end-point energy analysis. Estimated average load factors for the HVAC system and process equipment in the end-point energy analysis were slightly adjusted until the energy consumption of the HVAC system calculated in the end-point energy analysis equaled the total weather-dependent and weather-independent energy consumption estimated by the baseline regression model.

As described in the previous Section 3.9.1, the weather-dependent energy consumption outlined in the baseline model is not necessarily equivalent to the total energy consumed by an industrial facility’s HVAC system. If the entire facility is conditioned year-round or significant internal heat loads from process equipment, occupants, or solar radiation are present, the facility must continuously operate the HVAC system to remove the facility’s internal heat gain regardless of outdoor temperature. Thus, a fraction of the base load or independent energy consumption in addition to the weather-dependent energy use outlined in the baseline equation is equivalent to the total energy consumed by the HVAC system. Figure 64 provides a visual representation of the energy separation for a cooling-only degree-day model. Facility UA0117 conditions the facility year-round. For the purposes of this case study, the energy consumption included in the independent baseline model category is denoted as the “weather-independent” energy consumption.

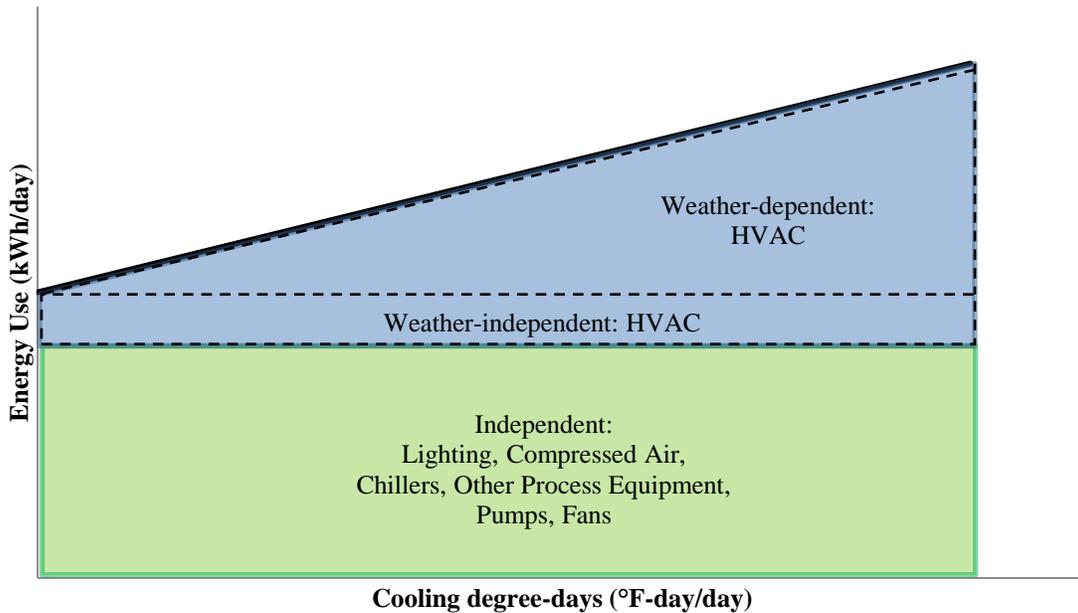


Figure 64. Separation of HVAC weather-dependent and weather-independent energy use.

A combination of Equation 27, Equation 28, and Equation 5 divides the total electrical energy consumption of facility UA0117 into the weather-independent and weather-dependent HVAC energy use and the remaining base load consumed by lighting, air compressors, and other electrical equipment. The total electrical energy use is described by Equation 82.

$$Q_{c,total} = b \left[cdd_i (T_{c,set}) \right] + \frac{fQ_{base} + Q_{free}}{COP_c} + Q_{base} \quad (82)$$

The first term calculates the weather-dependent energy consumption of the facility. The HVAC system is the only weather-dependent energy end-user for facility UA0117. The weather-dependent energy use is found by multiplying the cooling slope developed by the CDD (or 3PC) regression model and the facility's annual cooling degree-days. The annual required cooling degree-days are a function of the average interior thermostat set-point temperature of a facility, and may be calculated using bin-weather data. The cooling slope of facility UA0117 was found to be 347 kWh/day-°F. The annual cooling degree-days based on the average interior thermostat set-point temperatures of facility UA0117 were found to be 881 °F-day/yr.

The second term of Equation 82 describes the weather-independent energy consumption of the HVAC system. Rabl et al. (1992) define the facility internal heat gain, Q_{gain} , from solar radiation, occupants, and operating equipment in Equation 5. The total internal heat gained from operating equipment is equivalent to a fraction f of the energy consumption of all other non-cooling and non-heating equipment, Q_{base} . The total heat gained from occupants and solar radiation is defined as Q_{free} . The amount of electrical energy required to remove the internal heat gain is equivalent to the quotient of Q_{gain} and the average cooling coefficient of performance of the facility's HVAC system, COP_c .

The AIAC initially estimated load factors for facility process equipment to calculate the energy consumed by non-cooling electrical operating equipment and the internal heat gain of the

facility. The sum of end-point estimated electrical energy consumption for all process equipment located within conditioned spaces of the facility comprised Q_{base} . The fraction f was considered to be 1. Theoretically, 100% of the electrical energy consumed by non-cooling production equipment inside the facility is not converted into heat. However, this fraction accounts for additional heat gain due to occupants and solar radiation that was not observed by the AIAC. To find the weather-dependent energy consumption of facility UA0117's HVAC system, the AIAC divided the estimation for internal heat gain by the average cooling coefficient of performance of the HVAC system. The average COP_c was assumed to be 3.0.

The AIAC's initial estimation of energy consumed by the facility's HVAC system was calculated as the sum of the weather-dependent and weather-independent energy consumption based on results from the CDD baseline equation and initial end-point process equipment energy estimates. Estimated average load factors for the HVAC system and process equipment in the end-point energy analysis were slightly adjusted until the energy consumption of the HVAC system calculated in the end-point energy analysis equaled the total weather-dependent and weather-independent energy consumption estimated by the baseline regression model.

Applying baseline regression model results to an end-point energy analysis allowed the AIAC to better approximate the annual energy consumption of the facility's HVAC system. The AIAC estimates that 21% of facility UA0117's total annual electrical energy use is consumed by the HVAC system. This value is reasonable given that the facility provides over 700 tons of space conditioning year-round throughout the entire facility.

In addition to estimating the energy consumed by the HVAC system, the AIAC was also able to approximate the energy consumed by the facility's lighting system. The AIAC performed a comprehensive lighting survey of the entire facility during the one-day onsite visit. Rated

power draw, bulb type, number of bulbs, and annual operating hours were recorded for each light fixture. The amount of detailed information allowed the AIAC to estimate the total annual energy use of the lighting system with great confidence. The division of energy use for facility UA0117 is shown in Figure 65. Using the process outlined by the AIAC, the energy consumed by each major category of electrical equipment may be extracted from the baseline energy model to perform an end-point energy analysis and disaggregate whole industrial facility energy consumption.

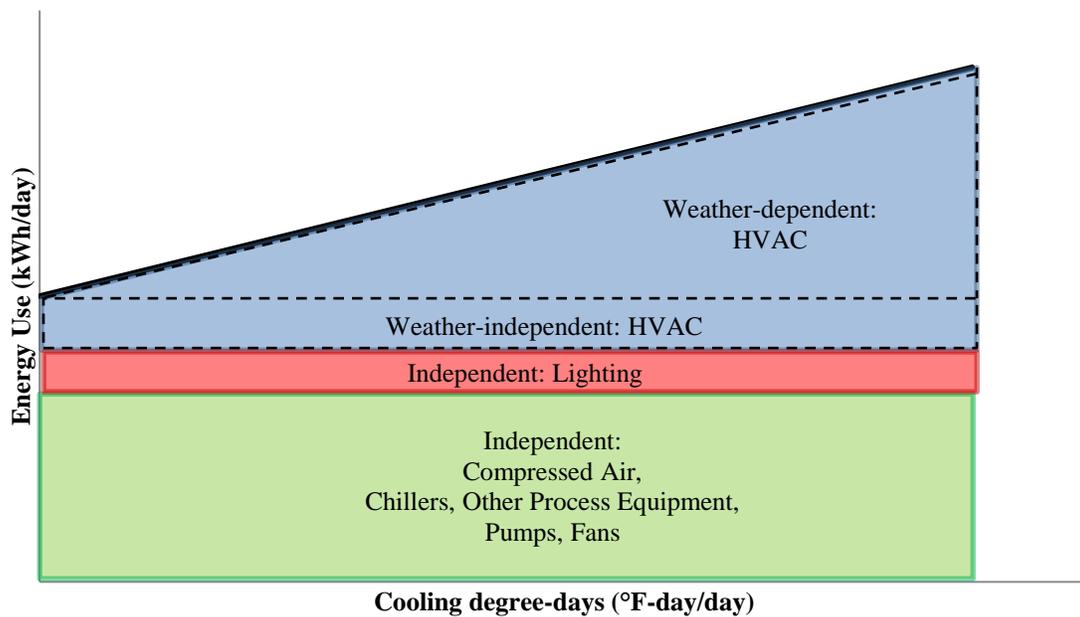


Figure 65. Separation of electrical energy use for facility UA0117.

The use of simple linear regression energy models allowed the AIAC to more accurately estimate an end-point energy analysis for facility UA0117. This case study observed the use of baseline energy models to begin disaggregating total energy use between each major industrial facility end-user. Energy consumed by lighting systems and air conditioning systems may be easily determined from a baseline regression model and one-day site visit to the facility. More

research is needed to develop methods for disaggregating industrial facility energy use for additional energy end-users.

CHAPTER 4: CONCLUSIONS

Chapter 1 provided a literature review of some of the methods used to establish baseline energy consumption models. These methods included ordinary least squares regression, artificial neural network, and calibrated simulation analyses. Chapter 2 explained the specific methods used in the analysis of the presented case studies. Chapter 3 summarized the results of nine selected industrial facility case studies. Chapter 3 also illustrated the conjoined use of a baseline energy model and information gathered during a one-day onsite visit to perform an end-point energy analysis for an industrial manufacturing facility. This chapter provides a summary of conclusions that may be drawn from the analysis presented in this thesis, and details further development opportunities.

4.1 Summary

The first objective of this thesis is to determine the effectiveness of simple inverse linear statistical regression models for establishing baseline energy consumption models for industrial manufacturing facilities. Nine case studies of various types of industrial manufacturing facilities were presented. In some of the case studies, ordinary least squares regression models proved to be effective in demonstrating the energy consumption behavior of the industrial facility. In other cases, the energy consumption behavior of the industrial facility could not be substantially explained by production, ambient dry-bulb temperature, or a combination of both variables.

Many conclusions may be drawn from the nine case studies of industrial manufacturing facilities presented in Chapter 3. First, the results between the change-point and degree-day

models can be compared to determine if either method provides a better fit. Previous publications advocate the use of the change-point regression model over the use of the degree-day method (Reddy et al., 1997b; Haberl, et al., 1998; Kissock & Seryak, 2004). Likewise, other studies advocate the use of degree-day regression models over the use of the change-point method (Fels, 1986; Sonderegger, 1998). The results of the first four case studies do not suggest that either method should be preferred over the use of the other. Case studies UA0094 and E3028 suggest that the change-point method provides a better fit to the observed data, while case studies UA0084 and UA0103 indicate that the degree-day method provides a better fit. When evaluating each case study, the differences of the goodness-of-fit values between the change-point and degree-day are not large enough to provide a definitive conclusion as to which model type is superior.

Perhaps it is unfair to compare the change-point and degree-day analyses of each facility to discern which method provides a better fit to the observed data. The change-point methodology used in this thesis utilizes actual temperature data. The degree-day methodology used in this thesis utilizes typical weather data obtained from TMY3 data files. Without the use of actual weather data, degree-day models may be unable to characterize the energy behavior of a facility that experiences atypical hot or cool weather patterns during the observation period. It may be more appropriate to compare and contrast the application of change-point or degree-day models if comparable weather data is referenced. Actual weather data should always be included in the baseline analysis when available; this will allow the baseline model to adequately reflect any changes in energy consumption that are a result of weather abnormalities.

The results of this study also indicate the importance of selecting appropriate initial parameter values when performing the regression analysis. As explained in case study UA0094,

the use of the GRG Nonlinear Multistart option in Microsoft Excel Solver does not guarantee a globally optimum solution. Only the probable globally optimum solution is found. Selecting unreasonable initial values for each regression parameter may result in uncharacteristic baseline energy models.

Case study UA0104 also summarized the importance of obtaining a full year of data that illustrates a typical production year. The addition of a natural gas oven during the middle of the observed data period prohibited the formation of a reliable baseline energy model. Even the use of a short term data set could not establish a relationship between the facility's energy use and temperature or production values. Transient baseline energy models may better explain the energy consumption behavior in industrial facilities that exhibit major production alterations. Steady-state baseline energy regression models are best determined by a set of data that observe typical operating procedures and energy consumption behaviors throughout the entire surveyed time period.

The results presented in this thesis also indicate the importance of understanding facility production, operating behaviors, and applications of specific fuel sources when selecting an appropriate baseline energy model. The use of one or multiple fuel sources for heating or cooling may lead one to believe a certain model type should be applied. However, the actual energy consumption data may exhibit the behavior of another model. For instance, facility UA0103 uses electricity for seasonal heating and cooling of their facility. However, the amount of electricity dedicated to space heating is too small in comparison to the amount of electricity providing energy to other equipment; the relationship between energy use and ambient temperature is better represented by a cooling-only model. In addition, initial evaluation of facility UA0108 suggested the application of a multivariate 5PCH-Prod model. However, the energy consumption

was best described as a 4PCH-Prod model, as the base temperature where neither heating nor cooling was required was undetectable. Variable thermostat set-points throughout the interior of the building may have led to this result.

The selected case studies also prove that temperature, production, or a combination of both variables influence energy consumption of industrial facilities. Manufacturers that exhibit good control of their operations, such as facility UA0103, or that do not use large amounts of energy to heat and control their buildings, such as facility UA0108, are more influenced by production. In some cases, as in case study E3028, temperature and production are good indicators of energy use. The baseline model results should not always be taken at face value. Due to its summer seasonal production schedule, facility UA0105 disguised its strong energy and production correlation as a significant relationship between energy and ambient temperature. The selection of significant energy influencers must be judged on a case-by-case basis for each company. Multiple evaluations of energy consumption behavior and influential variables are necessary to fully understand the energy consumption behavior of an industrial facility.

The evaluation of other variables may prove useful in models where temperature and production could not explain the energy consumption behavior of certain industrial facilities. For example, high latent heat loads may have an effect on energy consumption in some of the case studies presented in this thesis. Wet-bulb temperature values and relative humidity may have a significant impact, especially since all of the studied facilities are located in the warmer climates of the southeastern United States. Additional variables that may affect the definition of a baseline energy model are addressed in the next section, as suggestions for consideration in future work.

A facility's geographical location did not affect the baseline model fit of each facility in this study. In addition, the type of manufacturing industry had no effect on the baseline model fit

for each facility. The overall area covered by each facility did not affect the fit of a baseline model. However, facilities that condition their entire building tended to have more weather dependency than facilities where only a portion of the facility is heated or cooled.

The second objective of this thesis is to provide methods for generating acceptable and logical baseline energy models that are simple and accessible to anyone in the industrial manufacturing community. The methodology presented in this thesis is straightforward and easy to reproduce. The analysis methods outlined may be applied to all different categories of manufacturing industries. Facility personnel that possess basic spreadsheet software and general knowledge of energy principles may use the simple linear regression models to understand the relationship between energy consumption and weather and production data for their own company. In addition, employees can identify opportunities for retrofit projects where energy and cost savings may be realized.

Baseline energy models can also be used to describe the energy breakdown between major industrial energy end-users. The application of a three-parameter change-point baseline energy model was extremely useful when performing an end-point energy analysis for facility UA0117. The model was proven extremely useful when estimating the total energy consumed by the HVAC system. More research is needed to understand the application of a baseline energy model when disaggregating the remaining energy use between other industrial energy end-users.

In conclusion, simple inverse linear statistical regression models may not provide the most accurate insight into the energy consumption behavior of an industrial manufacturing facility. Industrial facilities are complex and utilize intricate production, heating, and cooling systems, so they correspondingly require more complex methods for baseline energy use establishment. However, change-point and degree-day baseline energy models have the potential

to provide useful approximations using simple data readily available and recorded by most manufacturers. Basic understanding of a facility's operating profile can be used in conjunction with simple linear regression analysis to fully describe industrial manufacturing energy behavior. Most industrial facility personnel can replicate the methods used in this thesis using basic knowledge of spreadsheets and energy consumption relationships. Ordinary least squares regression models may also provide additional insight into the breakdown of energy consumption between major industrial facility energy end-users.

4.2 Future Work

This thesis explores the application of change-point and degree-day simple linear regression models to establish baseline energy consumption of industrial manufacturing facilities. This study can be expanded by further development. The following list describes topics that may be considered for future work.

- Evaluation of the degree-day method should include the use actual weather data when available. Discernable differences or advantages between the change-point and degree-day methodologies may be established if comparable temperature resources are used. The scarcity of degree-day models in published literature may be a result of the inaccessibility of actual temperature data in an appropriate form for convenient degree-day calculations.
- Baseline energy models may be compared with industrial facility sub-metered energy consumption data to evaluate the effectiveness of the model.
- Longer observation periods could be evaluated. Small data sets can decrease the likelihood of a good baseline model fit if the observed data is not representative of a typical production year. Lengthier observations periods may allow data anomalies to be excluded during the regression analysis.

- Include the effects of latent heat loads in the evaluation of industrial manufacturing facilities located in humid climates. Large latent heat loads can cause noisiness in the relationship between energy consumption and ambient temperature. Including factors such as wet-bulb temperature and relative humidity may provide more insight into the energy consumption behavior of some manufacturing facilities.
- Include the effect of air infiltration and fresh air intake in the regression analysis. Many industrial facilities experience high traffic through loading and dock doors. Some industries leave these doors open at all times, even if the surrounding areas are conditioned. The high levels of air infiltration may lead to high internal heat gain or heat loss. Studies have shown correlation between energy use and the times loading or dock doors remain open.
- In cases where energy consumption behavior cannot be explained by temperature or production, other additional variables should be evaluated to determine their usefulness in establishing a baseline energy model for industrial manufacturing facilities. Some variables for consideration include, but are not limited to: total building area, total conditioned area, occupancy or operating schedules, varying heating and cooling set-points within the facility, use of programmable thermostats, wind, solar radiation, internal heat capacity, building materials and loss coefficients, and use of economizers.
- Methods for disaggregating whole facility energy use into separate industrial energy end-users can be further developed. Baseline energy models may be used to evaluate total energy consumed by categories of industrial equipment other than the HVAC or lighting systems.

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