Elsevier Editorial System(tm) for Energy and Buildings
Manuscript Draft

Manuscript Number: ENB-D-10-00047R1

Title: A Cooling Change-Point Model of Community-Aggregate Electrical Load

Article Type: Full Length Article

Keywords: Solar Radiation; Cooling Load Modeling; Energy Signature; Equivalent Thermal Parameters; Electric Load Modeling; Multivariate Regression; Change Point Model

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Abstract: Estimates of daily cooling load for a city of 800,000 are developed based on the relationship between weather variables and daily average electricity consumption over one year. The relationship is found to be nearly linear above a threshold temperature. Below the threshold, cooling is a progressively smaller fraction of that predicted by the linear model. Temperature and humidity were found to be the largest, at 59%, and second largest at 21% contributors to cooling load. Direct normal irradiation intercepted by a vertical cylinder, DNIsinθ, was found to be a useful explanatory variable when modeling aggregates of buildings without a known or dominant orientation. The best study case model used DNIsinθ and Diffuse Horizontal Irradiation as distinct explanatory variables with annual cooling load contributions of 9% and 11% each. Although the seasonal variation in cooling load is large, the combined direct and diffuse solar contribution is essentially flat through the year, a condition at odds with the common assumption that solar cooling can provide a good match between supply and demand. The final model gives a cooling load estimate for Abu Dhabi Island that corresponds to 41% of the total annual electrical load and 61% on the peak day.

16 January 2010

Prof. Branislav Todorović
Faculty of Mechanical Engineering ,
Belgrade University,
Kraljice Marije 16, 11120 Belgrade 35, Serbia,

Dear Professor Branislav Todorović,

I would like to submit the revised version of the paper which was assigned the manuscript number of ENB-D-09-00379 for publication to *Energy and Buildings*.

Title: *"A Cooling Change-Point Model of Community-Aggregate Electrical Load*".
Authors: *Muhammad Tauha Ali.*
Marwan Mokhtar.
Matteo Chiesa.
Peter R. Armstrong.

Thank you for your time and consideration. I look forward to discussing our contribution in more detail.

Yours faithfully,

Muhammad Tauha Ali
Masdar Institute of Science and Technology
P.O. 54224 Abu Dhabi, UAE
16 January 2009

Reviewer #2: This is a very interesting paper. Though this reviewer has been involved with such models at the individual building and campus level, the application to a whole city of 800,000 people is a first. The paper is well written, clear, uses convincing arguments, exhibits good familiarity with different analysis methods, and shows great competence in the use of regression and data analysis methods. I would accept the paper with the following minor comments:

a) The paper is rather long. Some of the analysis details could be removed without much loss in understanding the approach; for example, some of the multivariate correlation matrix tables

We have considered very carefully the comment of the reviewer. We tried to shorten the manuscript by moving some of the multivariate correlation table to the appendix but that has a negative impact in readability of the manuscript. For reading clarity we have decided to maintain the tables in the text.

b) I would suggest that the authors clearly present the methodology so that others could reproduce it in their own regions. Though applying it to Abu Dhabi is important as a credibility check, I would guess that the outdoor temperature range, humidity and solar insolation would be different in other locations throughout the world,a nd hence the need for an unambiguous methodology.

The methodology section is revised and re-written to eliminate any ambiguity. Results section has also been revised.

Methodology

Our analysis procedure, in outline, follows accepted practice: 1) formulate a set of candidate models, 2) identify transition regions or points, 3) test and refine the model. For aggregates of buildings it is advantageous to model a transition region, rather than a distinct change point and, because buildings are added during a study period that spans months or years, we must add a growth term. The use of more than two weather variables is also novel for change-point models with one-day or longer time steps.

The candidate models considered are multivariate linear and bi-linear combinations of weather, day-type and urban growth terms. Candidate solar irradiation terms include Global Horizontal Irradiance (GHI), Diffuse Horizontal Irradiance (DHI), Direct Normal Irradiance (DNI) on a vertical surface ($DNI\sin\theta$) and DNI on a horizontal surface ($DNI\cos\theta$) as shown in Figure 1.

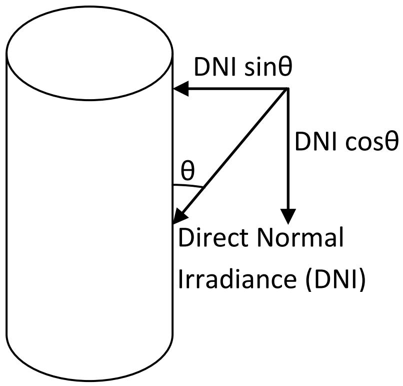

Figure 1: Components of Direct Normal Irradiation (DNI)

Other weather variables include ambient temperature and specific humidity. To account for growth in building stock during the relatively short period of one year, a linear growth model[1] is considered. The aggregate load model described above may be expressed as follows:

$$W_{electric} = (1 + C_0 * time) * (C_1 + C_2 * D_s + C_3 * D_f + C_3 * T + C_4 * w + C_5 * (DNI * sin\theta) + C_6 * DNI * cos\theta + C_7 * DHI + C_8 * GHI) \quad (1)$$

where,

$W_{electric}$ = average daily electrical load (MW)

Time= day of year

D_s = Saturday indicator variable,

D_f = Friday indicator variable,

T = daily mean outdoor dry-bulb temperature,

w = specific humidity (mass ratio of kg moisture per kg dry air),

DHI = diffuse horizontal irradiation (W/m^2),

DNI = direct normal irradiation (W/m^2),

θ = solar zenith angle (radian),

cosθ = ratio of direct irradiation on a horizontal surface to DNI,

sinθ = ratio of direct irradiation on a vertical surface to DNI,

GHI = global horizontal irradiation.

The use of daily time steps means that transient thermal response (lags) will have relatively little effect. Similar models have been used for whole-buildings and aggregates of buildings operating in conditions that require heating every day (i.e. depths of heating season) or cooling every day (depths of cooling season). Change point models with fewer weather terms (usually temperature only) have been widely used to model energy use through transition seasons as well as heating and/or cooling season response.

[1] Incorporation of the time term results in a model with bilinear terms. The least squares regression is accomplished by applying a Levenburg-Marquardt or partial least squares algorithm [38].

Although performance (COP) of cooling equipment is in fact a function of outdoor temperature, part load fraction and indoor conditions, its sensitivity is normally not very large. The result of this constant-COP assumption is a linear load model.

Equation (1), when applied to a single building, models the daily cooling load on days when conditions result in some amount of cooling and no heating. For aggregates of buildings we may relax the requirement by saying that some amount of cooling is required in *most* buildings equipped for cooling, provided that none are being heated. We refer to days that satisfy this condition as *cooling days* and to the locus of conditions on such days as the *linear region*. Since equation (1) applies only to the linear region, it is necessary to identify the transition region (usually modeled, for single buildings, as a change point) that is typically observed in swing seasons. We refer to the lower boundary of the linear region as a change point to be identified by an iterative process that may be described as successive filtering. Successive filtering has been used to find change points defined in terms of temperature only, temperature and humidity, and a linear combination of irradiation terms and temperature.

The simplest and most commonly chosen [5],[6],[9] threshold for the linear-to-transition region change point is temperature. This choice is consistent with the fact that cooling systems are thermostatically controlled. For the present case study we note that identification of the exact change point is not critical because the number of points in the linear region is ample.

The linear-to-transition region change point is estimated by plotting RMSE as a function of threshold value. Figure 2 indicates that for this data set, the linear region ends at 18.5°C. The average of the specific humidity at this temperature is 0.0085 kg of water/kg of dry air. Similar hot-climate temperature thresholds are reported in [6],[9] and also suggested in [5].

To establish the boundary between the base load[2] region and the transition region we could also use a simple temperature threshold. However, it is desirable to identify this change point as accurately as possible because it corresponds to the base load which, in turn, determines what fraction of the total annual electrical load may be attributed to cooling. Because the base load sample is small (7 days) each day in the sample has a large impact on the base load estimate. We therefore define an adjusted temperature (similar to sol-air temperature) as:

$$T_{adj} = T + (C_6 * DHI + C_7 * DNI sin\theta)/C_4 \quad (2)$$

The adjusted temperature corresponds to the outdoor temperature and solar radiation parts of the cooling load model identified for the linear region. This model accounts for the fact that thermostats will call for cooling when there are strong solar gains at a lower outdoor temperature than when there are not strong solar gains.

[2] There is undoubtedly some heating on cold days but not enough to reliably estimate a relation with temperature.

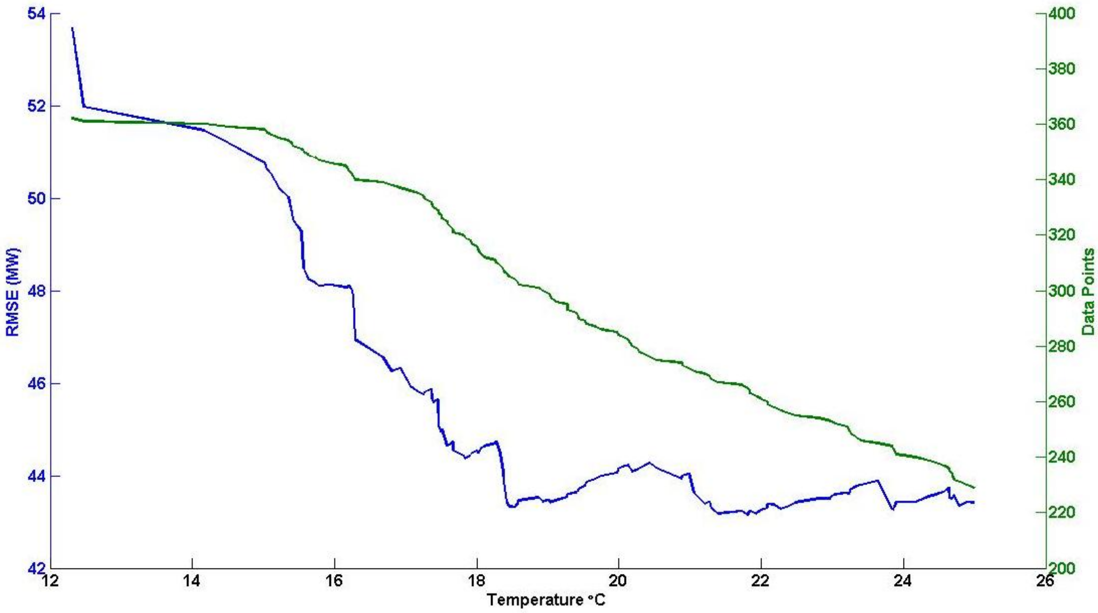

Figure 2: RMSE versus Temperature for linear-growth model with DHI and DNIsinθ terms (model 7, data set A)

Weekend and holiday electrical demands are presumed to exhibit behaviors different from the demand behavior of typical weekdays [5]. Therefore, day-typing was implemented to estimate this behavior [9],[16]. Possible day-types considered were Fridays, Saturdays, and holidays. UAE Schools and offices are generally closed on both Fridays and Saturdays. Shops are generally open on Saturdays but closed on Fridays. Holidays spanning a period of three days consecutively which are specific to Islam (30th September-2nd October and 8th-10th December in 2008) are also treated as Fridays. By setting C_0=0, eq. (1) reverts to a no-growth model and by setting C_2=C_3=0 it reverts to a model with no day-typing.

Ten combinations of the four solar terms mentioned above were investigated and the best model for the linear region was chosen based on least Root Mean Squared Error (RMSE), physical plausibility and standard errors of estimated coefficients.

The resulting regression models were used to estimate the daily-average electricity demand, a major component of which is supposed, in the study case, to be cooling demand. The data set was categorized in three data sets. Data set A comprises of all the data points. In order to assess the sensitivity of cooling load to weather in the linear region, cold days were excluded in data set B. While, in data set C weekends and holidays were also excluded.

In summary, the methodology as applied to the Abu Dhabi data proceeds as follows:

- Develop candidate models based on observed response to all plausible available independent variables, day types, and time.
- Compute the correlation matrix to identify possible co-linearity problems that may impact the later selection or elimination of variables in the model.
- Select model training and validation sets (not done in this study for lack of data).

- Identify change points in outdoor temperature (or linear combination of weather variables) by applying successive filtration. The data are sorted by daily electrical load and the regression is performed as each successive record is added. The transition region is identified when the rate of increase in RMSE becomes statistically significant.
- Test all combinations of explanatory variables. Select the best regression model based on RMSE, t-values and Durbin-Watson tests.
- In the case of base load change point, fit successive trend line to days with lowest cooling potential and apply Grubbs method [39] on the resulting data set with subsequent point for detection of outliers.

Having identified the change points and the coefficients of transition and linear region models, a further analysis can be performed to estimate the share of cooling load attributed to each weather variable.

c) The intent of the model is to have a predictive tool useful for electric utilities to forecast future load and to policy makers wishing to evaluate across-the-board policy changes in energy conversation for example. The authors should comment on how the model residuals can be interpreted as uncertainty for such purposes and whether the RMSE obtained can accomplish these objectives

The intent of the model is to estimate the share of cooling load in an area's electrical load given that weather dependent load comprise of only cooling load. On the uncertainty of energy savings estimation we have commented on it.

Results section paragraph 6:

"Figure 4 shows that, except for cold days identified by '+', the residuals are generally without structure. The cold-day residuals are positive. In the "linear region" of T > 18.5°C a small systematic variation of residuals with temperature is visible in Figure 4(a). In Figure 5 we see some temporal structure in the residuals. This can be quantitatively expressed by the Durbin Watson test [43]. The calculated value is below the threshold of 1.87 for a 95% confidence interval. This can be due to growth model inadequacy and can be rectified by developing the growth model using building stock data. The Coefficient of Variation (RMSE/W_{avg}) obtained for the best model is better or similar to the values obtained by other researchers using change point models on building level data [28],[44],[45]. Therefore, accuracy in estimation of cooling load from electrical load using the above model is good. However, the uncertainty in estimation of individual weather parameters share and prediction of electrical load due to structure present in residuals can be reduced by using longer data sets [39] and using building stock time series data to better explain load growth. Also, the savings achieved by a policy decision is difficult to estimate on a city level and depends on the level of market penetration. For example, a policy with small impact per building but high market penetration might be easier to detect on the community level than at the individual building level."

d) Small typos: page 15- what is the difference between D_s and D-f

We have corrected it.

Other modifications done:

- Introduction paragraph 4:

In this paper we will explore models based on the predominantly linear and non-interacting influences of four weather variables. The physical basis of such models is described. The idea of a change-point that is a linear combination of the explanatory variables is introduced and the need to model a transition *region*, rather than a discrete change *point*, is discussed. The analysis is applied to the electrical system load of a Persian Gulf city, Abu Dhabi, in which cooling load and solar resource are both substantial.

- Literature review is made part of introduction
- Data analysis is made part of results
- Results 1st paragraph:

"The negative coefficients are due to multicollinearity present between irradiation terms as can be seen in Table 1. Temperature and specific humidity are also correlated but the coefficients are seen in Appendix A to be much more stable, across models and data sets, than the coefficients of the solar irradiation terms. Therefore, elimination of irradiation terms, but not humidity, was undertaken to address collinearity problems [40],[41]."

- Results 4th paragraph:

"From Figure 3 and Table 3b, it can be seen that the linear growth model fits the data better than its no-growth counterpart. From Table 3a, we observe that the t-value, 0.01, is very low. The growth coefficient, C_0, identified by the model is therefore not reliable. For cooling dominated climates with practically no heating and a data set that begins and ends in the cold season, a manual adjustment of C_0 is possible based on matching the base loads at the beginning and end of the year. By this means, a physically reasonable growth constant was found without significant increase in RMSE (.75% for the best model in relation to the RMSE found by using regression to estimate the growth constant). The manually assigned 0.00035 growth/day corresponds to a 12.8% growth over the year while the regressed value corresponds to 16.2%/year, a large number even by UAE standards.   The acquisition of building stock time series data is a problem for modelers of large building populations that may have to be addressed in cases where the base load-matching adjustment used for this Abu Dhabi data set is not an option."

- Results 7th – 9th paragraph

"From Figure 6, one can see that the distribution of data set B residuals is nearly normal except in the positive (measured>modeled) tail. This may stem from eliminating (treating as non-cooling days) some days that really belong in set B or from the fact that the tail is artificially truncated at the change point. These would be days that are in the linear region as far as cooling load is concerned but appear not to be because they have an unusually high non-cooling load—i.e. large deviation from mean base load. It suggests, as does the thermodynamic basis of vapor-compression cooling [47] and as does the slight structure observed in Figure 3, that the assumption of linear variation of load with temperature is not completely justified. With a stationary data set (loads for parts of the community that are relatively free of demolition and construction) it is possible that a more physically realistic model with non-linear terms could be identified.

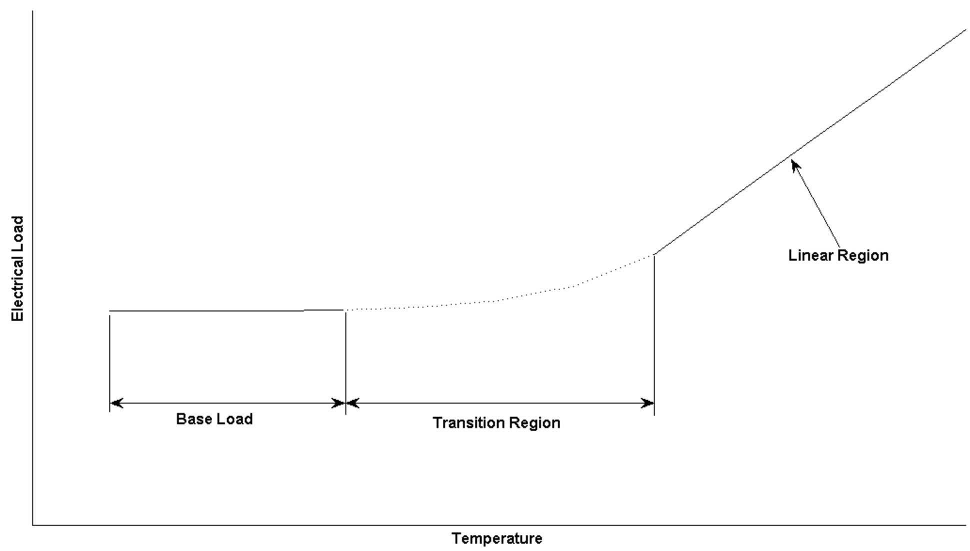

Figure 7: Three regions characterized by different behavior of electrical load with temperature

The linear model with temperature, humidity and solar irradiation terms works very well in the region above the 18.5°C threshold. Change point model practitioners usually use a temperature threshold to distinguish building-level cooling days from non-cooling days [45],[48]. We postulate that for aggregates of buildings there may not be a distinct change point in the cooling load behavior but rather, as illustrated in Figure 7, a transition region. Below this transition region we find a base load that can be estimated from the days with the lowest cooling potential where cooling potential, W_p, is defined as:

$$W_p = C_4 * T + C_5 * w + C_6 * DHI + C_7 * DNIsin\theta \quad (5)$$

Although the cooling load on these days may be so small as to be indistinguishable from random variations in the base load, equation (5) can be used to rank the ***potential*** for total daily cooling load. The most sensitive test is the one that considers each day in order of increasing cooling potential. A linear model was fitted to the successive data points representing the lowest cooling potential. The deviation of the subsequent data point from the linear model was computed. Grubbs outlier detection test [39] was applied to the resulting data set at the 95% confidence level. The first outlier was detected at the 8th point.

The t-statistic indicates that the trend of first 7 points is not significant. Therefore, the mean base load computed from the preceding 7 data points is 596.5MW."

- Results 12th paragraph

"When W_1 falls below the base load, W_1 is taken equal to base load. Each of the components from W_1 to W_5 are multiplied by an adjustment factor when $W_5<W_B$. This accounts for the difference in the base load (W_B) identified by the linear model and the base-load (W_{BL}) identified by outlier detection, as the mean of the 8 points that fall below the transition region. The adjustment is defined as:

Adjustment factor = $(W_1 - W_{BL})/(W_1 - W_B)$"

- Results 13th paragraph

"Estimates of the annual contributions to the total annual electrical demand of Abu Dhabi can now be evaluated by summing the appropriate W terms and taking the appropriate differences. The results of these calculations are presented in Table 4. The solar contribution to the electrical load is seen to represent a relatively small fraction, about 8% of total electrical load or 20% of the cooling load. While the combined effect of solar radiation components is remarkably flat over the year, the contribution of the direct solar component, DNISinθ, is seen to be much higher than the contribution of the diffuse solar component in the winter months. Around 21% of the annual electrical cooling load is associated with humidity which suggests that buildings are either leaky or the share of fresh air in supply air to the building is much higher than necessary. Temperature accounts for 23% of the total load or 59% of the cooling load. This does not fully explain the relative success of models that use temperature as the only weather variable. Rather it is probably the fact that there is also a strong correlation between humidity and temperature that makes temperature-only based models viable."

- Results paragraph 10th and 13th are moved from discussion section
- Discussion 4th paragraph

"Limitations of building level models

It is currently possible to process and fit a change-point or change-region models to every single building in a utility's service territory based on monthly billing data [52] and with advanced metering, a daily data feed is economically, as well as technically feasible so that such a process may be automated. But even with building-level data, the attribution of cooling load to temperature, on the one hand, and solar irradiation, on the other, becomes problematic at low temperatures. Moreover, we can begin to estimate that part of the cooling load tied to internal gains only after the base load is separated into building and non-building loads and the building base load further separated into indoor and outdoor loads. These details, if needed, are best (can, perhaps, only) be assessed by end-use metering."

A Cooling Change-Point Model of Community-Aggregate Electrical Load

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Mechanical Engineering Program, Masdar Institute of Science and Technology, Abu Dhabi, UAE

Abstract

Estimates of daily cooling load for a city of 800,000 are developed based on the relationship between weather variables and daily average electricity consumption over one year. The relationship is found to be nearly linear above a threshold temperature. Below the threshold, cooling is a progressively smaller fraction of that predicted by the linear model and for the 7 smallest daily loads there is essentially no variation of load with weather. Temperature and humidity were found to be the largest, at 59%, and second largest at 21% contributors to cooling load. Direct normal irradiation intercepted by a vertical cylinder, DNIsinθ, was found to be a useful explanatory variable when modeling aggregates of buildings without a known or dominant orientation. The best study case model used DNIsinθ and Diffuse Horizontal Irradiation as distinct explanatory variables with annual cooling load contributions of 9% and 11% each. Although the seasonal variation in cooling load is large—on peak summer days more than twice the winter base load—the combined direct and diffuse solar contribution is essentially flat through the year, a condition at odds with the common assumption that solar cooling can provide a good match between supply and demand. A linear short-term urban growth model indicates that growth rates of cooling load and base load are

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about equal. The final model gives a cooling load estimate for Abu Dhabi Island that corresponds to 41% of the total annual electrical load and 61% on the peak day.

Keywords: Solar Radiation; Cooling Load; Energy Signature; Equivalent Thermal Parameters; Electric Load Modeling; Multivariate Regression

Introduction

Models that predict energy use in the built environment have evolved along two largely independent paths—one primarily supplier oriented utility forecasting applications and the other building owner oriented towards building performance applications).   Utility forecasting models are not usually concerned with what happens more than a few time steps into the future. Pure time series models or models with just one weather variable, temperature, are prevalent. Building performance applications, on the other hand, often try to model response to weather and other factors in order to assign a weather-normalized building energy performance rating or so that annual energy impact of efficiency retrofits can be estimated. Perhaps the oldest supply side application—forecasting of customer fuel requirements by the heating degree day method—dates to 1930 or earlier[1]. Electric utilities now use short, medium and long term forecasts routinely for such varied applications as long-term planning (monthly time steps) and load dispatch (fraction of hour to one day). Load control (a form of dispatch) and day-ahead price setting are other important potential applications.

Building-level models are motivated by applications such as rating systems, fault detection, savings verification, retrofit and operational decision making, calculation of demand response credits, and model-based control. In fault detection, for example, deviations of model estimates from measured responses may indicate a fault and an associated change in one or more of the model parameters may indicate the type of fault. Models based on daily data are quite common although shorter (hourly) and longer (weekly and monthly) time steps have been used as well. Hourly and shorter time steps are used mainly for component-level fault detection and model-based control.

The present work is motivated by questions pertaining to both supply and demand-side policies. On the supply side, the potential for large (urban scale) solar powered cooling in hot, sunny climates is of interest. In order to properly size a solar district cooling plant, the aggregate cooling loads should be based on all of the significant load predictors--solar irradiation, humidity and temperature. Utilizability and optimal sizing are affected by seasonal variations of the solar resource, seasonal variations of the cooling load, and the phase relation of these variations. On the demand side, policy questions pertaining to things such as retrofit programs, energy codes, equipment efficiency standards and feed-in tariffs. These questions can be better answered when existing energy end-use intensities are fully understood.

In this paper we will explore models based on the predominantly linear and non-interacting influences of four weather variables. The physical basis of such models is described. The idea of a change-point that is a linear combination of the explanatory variables is introduced and the need to model a transition *region*, rather than a discrete change *point*, is discussed. The analysis is applied to the electrical system load of a Persian Gulf city, Abu Dhabi, in which cooling load and solar resource are both substantial.

Energy demand forecasting models are typically formulated as multivariate time series models that may include independent variables representing weather conditions and day type. For models with a one day or larger time step, the most often used weather variable is mean daily outdoor dry-bulb temperature or a variable related to outdoor temperature such as heating or cooling degree days with respect to a given base temperature[2] [1],[4-8]. A few electric load forecast models include

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[2] A *degree day* is a unit involving the difference between mean daily temperature and a temperature threshold or *degree day base* [2]. The sum of positive differences during a week, month or year is the cooling degree days for the period in question and the absolute value of the sum of negative differences is the heating degree days. Change point models typically estimate both the degree day base and ratio of heating or cooling load to temperature difference [3].

humidity and day-typing [9],[10]. Models that use only past loads [11],[12] and models that consider day typing and past loads without considering weather at all [13],[14] can give satisfactory results for one-step ahead forecasts. In [15], the importance of solar irradiation is demonstrated. The most common model forms are linear, linear with change-point, and artificial neural network. A review of utility forecasting methods and their application by different researchers is presented in [16]. Similar techniques are used to infer equivalent thermal parameters (ETP) or energy signatures (ES) of a building when applied on the building level [17].

The ES/ETP models may be used to forecast heating and cooling loads, heating or cooling plant input power, or whole building electric load. When used to forecast heating or cooling load on time steps of under one day, the models typically include transient terms [18],[19]. In [15],[20-24], regression[3]-based techniques are used while in [12],[25],[26] fuzzy logic and neural network techniques are used. Most of the efforts have been concerned with the heating loads of buildings. In [22], a model for variable internal gains is presented. In [26] among others, parameters accounting for both external and internal gains are considered for estimating the building energy signature. In [23], a detailed review of different models for heat load modeling of buildings is presented. In [27],[28], regression analysis is used to identify building ETP or response function models and develop controls for optimum operation of a chiller plant. In [29],[30], energy signatures are used to assess energy savings and financial feasibility of retrofit measures. A critical review of regression modeling applied on building level is presented in [17]. An exhaustive review of energy models and their applications in planning, forecasting, emission reduction etc.--from building level to utility service area--is given in [31].

The technique used for developing an energy signature, ETP, or other forecasting model depends on the amount and type of data available, application, and the simplifying assumptions that can or must

[3]*Regression model* here means a model based on observations of the variable to be forecast and any number of contemporaneous and past explanatory variables. It is a functional relationship between two or more correlated variables that is often empirically determined from data and is used especially to predict values of one variable when given values of the others

be made[25],[32]. In [33], comparison of fourteen regression models used for forecasting is presented and the need for more data with increasing model complexity is illustrated. In [12], a comparison of fuzzy logic, neural network and linear regression based modeling techniques is made and the data required to train a model is shown to be least for linear regression models because load-weather relationships are near linear and can therefore be identified with data that properly represent the extreme conditions and the average condition.

Building Load Data Availability and Characteristics

Residential and commercial building loads typically exhibit strong seasonal variation arising from operation of the electrical equipment that heats and cools the occupied spaces of these buildings. These are the so-called heating, ventilating and air-conditioning (HVAC) loads.

Non-HVAC loads do not vary much with weather. The non-HVAC loads include refrigeration, lighting, clothes and dish-washers, water heating[4], consumer and office electronics, and IT equipment. When considering the impacts of energy supply and demand-side policies, it is imperative to know how energy is used within a given population. The breakdown of electricity use varies from one region to another based on price, climate and economic activity. However, the energy consumption for heating and/or cooling of buildings is almost always significant, ranging from 10 to over 50% in most developing and developed countries [34]. Policies to reduce HVAC energy consumption may target the thermal loads, by introducing standards for the performance of building envelopes and equipment. Building codes may also target the energy impacts of HVAC systems and controls.

The most reliable way to assess energy end use is to measure it directly, but end-use metering is expensive and invasive. Because the variability among buildings is large, confidence that a given sample is representative of the underlying population can be achieved only with large samples i.e.,

[4] Water heating loads vary with water mains temperature, which typically lags (and blurs—i.e. low-pass filters) outdoor air temperature by months. For this study we assume the seasonal variation in water heating load is small.

End-Use Load and Consumer Assessment Program (ELCAP) [35]. ETP and ES methods can be applied to obtain large HVAC end use samples but with greater uncertainty at lower cost. A similar but less widely used approach involves identification of heating and cooling loads from the seasonal load variations observed in aggregates of buildings monitored at the feeder, substation, or higher level [36].

Both of these approaches are much less costly, per building, than end-use metering and they can be combined. A modest sample of building-level load observations can provide information about variance, while substation or higher level load observations provide estimates for a very large aggregate sample. The combination of community-level and building-level seasonal load analyses can thus address the sample size problem in a cost-effective way.

In this study we explore the community level by looking at the daily total energy delivered to a city. Abu Dhabi Island, a city of about 800,000 [37] comprised largely of commercial and residential buildings serves as the study case. The level of building type homogeneity, although uncommon at this scale, is quite common at the feeder or substation level. The methodology illustrated here can therefore provide useful assessments of heating and cooling loads at modest cost in many communities and urban areas. A method of change point identification for aggregates of buildings is developed and a multivariate regression model that uses all the physically meaningful explanatory variables (that can be applied at the building level as well as to large aggregates of buildings) serves to identify a community energy signature. The resulting model provides an estimate of the sensitivity of cooling load to each weather variable. To demonstrate the method, 2008 daily average electrical load data for the entire city were obtained from the Abu Dhabi Distribution Company (ADDC) and 2008 daily average weather data from a coastal weather station near Abu Dhabi served as the independent explanatory variables.

Methodology

Our analysis procedure, in outline, follows accepted practice: 1) formulate a set of candidate models, 2) identify transition regions or points, 3) test and refine the model. For aggregates of buildings it is advantageous to model a transition region, rather than a distinct change point and, because buildings are added during a study period that spans months or years, we must add a growth term. The use of more than two weather variables is also novel for change-point models with one-day or longer time steps.

The candidate models considered are multivariate linear and bi-linear combinations of weather, day-type and urban growth terms. Candidate solar irradiation terms include Global Horizontal Irradiance (GHI), Diffuse Horizontal Irradiance (DHI), Direct Normal Irradiance (DNI) on a vertical surface (DNIsinθ) and DNI on a horizontal surface (DNIcosθ) as shown in Figure 1.

Figure 1: Components of Direct Normal Irradiation (DNI)

Other weather variables include ambient temperature and specific humidity. To account for growth in building stock during the relatively short period of one year, a linear growth model[5] is considered. The aggregate load model described above may be expressed as follows:

$$W_{electric} = (1 + C_0 * time) * (C_1 + C_2 * D_s + C_3 * D_f + C_3 * T + C_4 * w + C_5 * (DNI * sin\theta) + C_6 * DNI * cos\theta + C_7 * DHI + C_8 * GHI) \quad (1)$$

where,

$W_{electric}$ = average daily electrical load (MW)

Time= day of year

D_s = Saturday indicator variable,

D_f = Friday indicator variable,

T = daily mean outdoor dry-bulb temperature,

5 Incorporation of the time term results in a model with bilinear terms. The least squares regression is accomplished by applying a Levenburg-Marquardt or partial least squares algorithm [38].

w = specific humidity (mass ratio of kg moisture per kg dry air),

DHI = diffuse horizontal irradiation (W/m^2),

DNI = direct normal irradiation (W/m^2),

θ = solar zenith angle (radian),

$\cos\theta$ = ratio of direct irradiation on a horizontal surface to DNI,

$\sin\theta$ = ratio of direct irradiation on a vertical surface to DNI,

GHI = global horizontal irradiation.

The use of daily time steps means that transient thermal response (lags) will have relatively little effect. Similar models have been used for whole-buildings and aggregates of buildings operating in conditions that require heating every day (i.e. depths of heating season) or cooling every day (depths of cooling season). Change point models with fewer weather terms (usually temperature only) have been widely used to model energy use through transition seasons as well as heating and/or cooling season response. Although performance (COP) of cooling equipment is in fact a function of outdoor temperature, part load fraction and indoor conditions, its sensitivity is normally not very large. The result of this constant-COP assumption is a linear load model.

Equation (1), when applied to a single building, models the daily cooling load on days when conditions result in some amount of cooling and no heating. For aggregates of buildings we may relax the requirement by saying that some amount of cooling is required in *most* buildings equipped for cooling, provided that none are being heated. We refer to days that satisfy this condition as *cooling days* and to the locus of conditions on such days as the *linear region*. Since equation (1) applies only to the linear region, it is necessary to identify the transition region (usually modeled, for single buildings, as a change point) that is typically observed in swing seasons. We refer to the lower boundary of the linear region as a change point to be identified by an iterative process that may be described as successive filtering. Successive filtering has been used to find change points defined in terms of temperature only, temperature and humidity, and a linear combination of irradiation terms and temperature.

The simplest and most commonly chosen [5],[6],[9] threshold for the linear-to-transition region change point is temperature. This choice is consistent with the fact that cooling systems are thermostatically controlled. For the present case study we note that identification of the exact change point is not critical because the number of points in the linear region is ample.

The linear-to-transition region change point is estimated by plotting RMSE as a function of threshold value. Figure 2 indicates that for this data set, the linear region ends at 18.5°C. The average of the specific humidity at this temperature is 0.0085 kg of water/kg of dry air. Similar hot-climate temperature thresholds are reported in [6],[9] and also suggested in [5].

Figure 2: RMSE versus Temperature for linear-growth model with DHI and DNIsinθ terms (model 7, data set A)

To establish the boundary between the base load[6] region and the transition region we could also use a simple temperature threshold. However, it is desirable to identify this change point as accurately as possible because it corresponds to the base load which, in turn, determines what fraction of the total annual electrical load may be attributed to cooling. Because the base load sample is small (7 days) each day in the sample has a large impact on the base load estimate. We therefore define an adjusted temperature (similar to sol-air temperature) as:

$$T_{adj} = T + (C_6 * DHI + C_7 * DNIsin\theta)/C_4 \quad (2)$$

The adjusted temperature corresponds to the outdoor temperature and solar radiation parts of the cooling load model identified for the linear region. This model accounts for the fact that thermostats will call for cooling when there are strong solar gains at a lower outdoor temperature than when there are not strong solar gains.

[6] There is undoubtedly some heating on cold days but not enough to reliably estimate a relation with temperature.

Weekend and holiday electrical demands are presumed to exhibit behaviors different from the demand behavior of typical weekdays [5]. Therefore, day-typing was implemented to estimate this behavior [9],[16]. Possible day-types considered were Fridays, Saturdays, and holidays. UAE Schools and offices are generally closed on both Fridays and Saturdays. Shops are generally open on Saturdays but closed on Fridays. Holidays spanning a period of three days consecutively which are specific to Islam (30th September-2nd October and 8th-10th December in 2008) are also treated as Fridays. By setting C_0=0, eq. (1) reverts to a no-growth model and by setting C_2=C_3=0 it reverts to a model with no day-typing.

Ten combinations of the four solar terms mentioned above were investigated and the best model for the linear region was chosen based on least Root Mean Squared Error (RMSE), physical plausibility and standard errors of estimated coefficients.

The resulting regression models were used to estimate the daily-average electricity demand, a major component of which is supposed, in the study case, to be cooling demand. The data set was categorized in three data sets. Data set A comprises of all the data points. In order to assess the sensitivity of cooling load to weather in the linear region, cold days were excluded in data set B. While, in data set C weekends and holidays were also excluded.

In summary, the methodology as applied to the Abu Dhabi data proceeds as follows:

- Develop candidate models based on observed response to all plausible available independent variables, day types, and time.
- Compute the correlation matrix to identify possible co-linearity problems that may impact the later selection or elimination of variables in the model.
- Select model training and validation sets (not done in this study for lack of data).
- Identify change points in outdoor temperature (or linear combination of weather variables) by applying successive filtration. The data are sorted by daily electrical load and the

regression is performed as each successive record is added. The transition region is identified when the rate of increase in RMSE becomes statistically significant.

- Test all combinations of explanatory variables. Select the best regression model based on RMSE, t-values and Durbin-Watson tests.
- In the case of base load change point, fit successive trend line to days with lowest cooling potential and apply Grubbs method [39] on the resulting data set with subsequent point for detection of outliers.

Having identified the change points and the coefficients of transition and linear region models, a further analysis can be performed to estimate the share of cooling load attributed to each weather variable.

Results

Least squares regression is used to estimate the coefficients for the linear regions of the different data sets and models considered. The day-type constants are removed from the models of data sets B and C from which weekends were eliminated. It can be seen from Appendix A that although the models containing three irradiation components have lower RMSE than models containing two, the former also have negative coefficients for some terms. Any model with a negative irradiation term is physically implausible because solar irradiation always contributes to the cooling load positively. The negative coefficients are due to multicollinearity present between irradiation terms as can be seen in Table 1. Temperature and specific humidity are also correlated but the coefficients are seen in Appendix A to be much more stable, across models and data sets, than the coefficients of the solar irradiation terms. Therefore, elimination of irradiation terms, but not humidity, was undertaken to address collinearity problems [40],[41].

Table 1: Correlation matrix (pair-wise R^2) for the 2008 daily mean electrical load and weather data

Note that in (1) only two of the three terms involving C_5, C_6 and C_8 are admissible in a given model because the associated random variables are related exactly by:

$$DHI = GHI - DNI * COS\theta \quad (3)$$

Therefore, when DHI is considered, either the GHI or DNIcosθ term can be included but not both. The solar terms for models with two and three irradiation terms are shown in Table 2 on the left and the equivalent two- and three-term groups are shown on the right. GHI appears usefully in only two of the equation (1) sub-models: one in which GHI is the only solar term and the other with DNIsinθ.

Table 2: Choice of solar irradiation terms from the 2-term and 3-term equivalent groups

For the linear region (cooling days) the best[7] physically plausible model was found to have the following form:

$$W_{electric} = (1 + C_0 * t) * \left(C_1 + C_2 * D_s + C_3 * D_f + C_4 * T + C_5 * w + C_6 * DHI + C_7 * DNIsin\theta\right) \quad (4)$$

From Figure 3 and Table 3b, it can be seen that the linear growth model fits the data better than its no-growth counterpart. From Table 3a, we observe that the t-value, 0.01, is very low. The growth coefficient, C_0, identified by the model is therefore not reliable. For cooling dominated climates with practically no heating and a data set that begins and ends in the cold season, a manual adjustment of C_0 is possible based on matching the base loads at the beginning and end of the year. By this means, a physically reasonable growth constant was found without significant increase in RMSE (.75% for the best model in relation to the RMSE found by using regression to estimate the growth constant). The manually assigned 0.00035 growth/day corresponds to a 12.8% growth over the year while the regressed value corresponds to 16.2%/year, a large number even by UAE standards. The acquisition of building stock time series data is a problem for modelers of large building populations

[7] lowest RMSE

that may have to be addressed in cases where the base load-matching adjustment used for this Abu Dhabi data set is not an option.

Table 3a: Statistics for best fit no-growth and linear growth models (data set B)

Table 3b: Statistics for best fit no-growth and linear growth models (data set B)

To check for an ill-conditioned data set, the regression analysis was repeated after normalizing the data and the same share of parameters in the electrical load and residuals were obtained.

Figure 3: Predicted electrical load from linear growth model 7 versus ADWEC data (data set A)

Figure 4 shows that, except for cold days identified by '+', the residuals are generally without structure. The cold-day residuals are positive. In the "linear region" of T > 18.5°C a small systematic variation of residuals with temperature is visible in Figure 4(a). In Figure 5 we see some temporal structure in the residuals. This can be quantitatively expressed by the Durbin Watson test [44]. The calculated value is below the threshold of 1.87 for a 95% confidence interval. This can be due to growth model inadequacy and can be rectified by developing the growth model using building stock data. The Coefficient of Variation (RMSE/W_{avg}) obtained for the best model is better or similar to the values obtained by other researchers using change point models on building level data [28],[45],[46]. Therefore, accuracy in estimation of cooling load from electrical load using the above model is good. However, the uncertainty in estimation of individual weather parameters share and prediction of electrical load due to structure present in residuals can be reduced by using longer data sets [40] and using building stock time series data to better explain load growth. Also, the savings achieved by a policy decision is difficult to estimate on a city level and depends on the level of market penetration. For example, a policy with small impact per building but high market penetration might be easier to detect on the community level than at the individual building level.

Figure 4: Plot illustrating random distribution of residuals with weather parameters of linear growth model 7(data set A)

Figure 5: Plot illustrating moderate structure in the residuals of linear growth model 7 (data set A)

Figure 6: Plot illustrating verification of normality of errors assumption in regression (data set B)

From Figure 6, one can see that the distribution of data set B residuals is nearly normal except in the positive (measured>modeled) tail. This may stem from eliminating (treating as non-cooling days) some days that really belong in set B or from the fact that the tail is artificially truncated at the change point. These would be days that are in the linear region as far as cooling load is concerned but appear not to be because they have an unusually high non-cooling load—i.e. large deviation from mean base load. It suggests, as does the thermodynamic basis of vapor-compression cooling [47] and as does the slight structure observed in Figure 3, that the assumption of linear variation of load with temperature is not completely justified. With a stationary data set (loads for parts of the community that are relatively free of demolition and construction) it is possible that a more physically realistic model with non-linear terms could be identified.

Figure 7: Three regions characterized by different behavior of electrical load with temperature

The linear model with temperature, humidity and solar irradiation terms works very well in the region above the 18.5°C threshold. Change point model practitioners usually use a temperature threshold to distinguish building-level cooling days from non-cooling days [45],[48]. We postulate that for aggregates of buildings there may not be a distinct change point in the cooling load behavior but rather, as illustrated in Figure 7, a transition region. Below this transition region we find a base load that can be estimated from the days with the lowest cooling potential where cooling potential, W_p, is defined as:

$$W_p = C_4 * T + C_5 * w + C_6 * DHI + C_7 * DNI sin\theta \quad (5)$$

Although the cooling load on these days may be so small as to be indistinguishable from random variations in the base load, equation (5) can be used to rank the ***potential*** for total daily cooling load. The most sensitive test is the one that considers each day in order of increasing cooling potential. A linear model was fitted to the successive data points representing the lowest cooling potential. The deviation of the subsequent data point from the linear model was computed. Grubbs outlier detection test [39] was applied to the resulting data set at the 95% confidence level. The first outlier was detected at the 8th point.

The t-statistic indicates that the trend of first 7 points is not significant. Therefore, the mean base load computed from the preceding 7 data points is 596.5MW.

Figure 8: Urban growth adjusted daily load versus solar irradiation adjusted outdoor temperature (data set A)

From Figure 8, it can be observed that the daily load of the lowest ranked 7 days is essentially invariant (mean=596.5MW, standard deviation=21.73MW) with the cooling potential.

Although a good deal of cooling equipment may be left running, the lack of any relation between load cooling potential is an indication that there is very little useful cooling in the lowest ranked 7 days. (Many commercial building cooling plants produce chilled water 24x7 even when there are no coil loads.)

The daily cooling load contributions may be evaluated as follows:

$W_T = C_4(T - T_{BASE})^+$; $W_w = C_5(w - w_{@TBASE})^+$; $W_{DHI} = C_6DHI$; $W_{DNI\_V} = C_7DNIsin\theta$

Where $(x)^+$ returns only positive values (i.e. x for x >0 and 0 otherwise). The trajectories plotted in Figure 9 are given by successive subtraction:

$W_1 = C_1+C_4*T+C_5*w+C_6*DHI+C_7*DNISin\theta$;

$W_2 = W_1 - W_T$;

$W_3 = W_2 - W_w$;

$W_4 = W_3 - W_{DHI}$;

$W_5 = W_4 - W_{DNI\_V}$;

$W_B = C_1 + C_2D_s + C_3D_f + C_4T_{BASE} + C_5w_{@TBASE}$

When W_1 falls below the base load, W_1 is taken equal to base load. Each of the components from W_1 to W_5 are multiplied by an adjustment factor when $W_5<W_B$. This accounts for the difference in the base load (W_B) identified by the linear model and the base-load (W_{BL}) identified by outlier detection, as the mean of the 8 points that fall below the transition region. The adjustment is defined as:

Adjustment factor = $(W_1 - W_{BL})/(W_1 - W_B)$

Figure 9 shows the daily contributions of weather to electricity consumption.

Figure 9: Contributions of different weather parameters for linear growth model 7 (data set A)

___ Weekdays ○ Fridays ☆ Saturdays

Table 4: Contributions of different model parameters in growth and day-type adjusted Electrical load for specified-growth model 7 with change points (data set A)

Estimates of the annual contributions to the total annual electrical demand of Abu Dhabi can now be evaluated by summing the appropriate W terms and taking the appropriate differences. The results of these calculations are presented in Table 4. The solar contribution to the electrical load is seen to represent a relatively small fraction, about 8% of total electrical load or 20% of the cooling load. While the combined effect of solar radiation components is remarkably flat over the year, the contribution of the direct solar component, DNISinθ, is seen to be much higher than the contribution of the diffuse solar component in the winter months. Around 21% of the annual electrical cooling load is associated with humidity which suggests that buildings are either leaky or the share of fresh air in supply air to the building is much higher than necessary. Temperature accounts for 23% of the total load or 59% of the cooling load. This does not fully explain the relative success of models that use temperature as the only weather variable. Rather it is probably the fact that there is also a strong correlation between humidity and temperature that makes temperature-only based models viable.

The average total load, 988.68MW, minus the estimated average base load, (366*596.5 – 52*17.332 – 57*58.475)/366 = 584.93MW, gives an estimated average cooling load of 404MW or 41% of the total. The fraction of the peak daily load that can be attributed to cooling is also of interest. The peak load of 1532.5MW occurs on a Sunday (workday in UAE) and this represents a cooling load that is (1532.5 – 596.5)/1532.5 = 61.1% of the peak-day average total load. This is a similar cooling load fraction found in the nearby UAE city Al-Ain [49].

Discussion

As reported by others [50],[51], we find that electrical load is strongly correlated with exposure of buildings to solar irradiation. However, in the case of Abu Dhabi, we have found that most of the large seasonal variation in electrical load may be attributed not to solar irradiation but to specific humidity and temperature. The annual solar contribution to cooling load is comparable to the annual humidity contribution but much flatter. Nevertheless, the day-to-day variations in electrical load are well, and to large extent, independently correlated with the two solar terms DHI and DNIsinθ. The coefficients of these two terms may be thought of as corresponding to aggregate equivalent aperture areas for the interception of diffuse and direct solar irradiation. The coefficients of the temperature term may be thought of as a sum of the aggregate envelope thermal conductance and aggregate ventilation thermal capacitance rate. The coefficient of the humidity term can be interpreted as an aggregate ventilation rate times the enthalpy of condensation per unit of ventilation air.

Limitations of the aggregate city level model

The impact that non-cooling electrical loads, such as lighting, have on cooling loads cannot be assessed from the models and data investigated here because the base load term includes not only the equipment and lighting inside buildings but also exterior lighting, street lighting, distribution losses, and other urban infrastructure loads such as communications, and water and sewer pumping stations. The interior non-cooling loads contribute to the thermal load which, in turn, increases the electrical cooling load, while the exterior loads non-cooling loads do not contribute to cooling load.

In general, each building has its own energy signature comprising a unique change region and base load intercept: 1) some buildings may follow a linear load-temperature curve to well below the threshold determined for the full sample, 2) after cooling ends, some buildings may begin to call for heating, 3) yet others may call for heating in some spaces while cooling is still called for in others, 4) use of reheat may be substantial in some buildings and 5) others may never call for heating at all. These behaviors have been identified historically by identifying ES/ETP models at the individual building level and there is reason to expect that, to the extent of local homogeneity in building thermal and use characteristics, feeder-level model identification will result in more clearly defined heating and cooling transition regions.

The effects of COP and saturation with outdoor temperature were not modeled. However with a stationary data set, e.g. load time series for a part of the community that is relatively free of demolition and construction, it is possible that these second order effects could be reliably identified.

Limitations of building level models

It is currently possible to process and fit a change-point or change-region models to every single building in a utility's service territory based on monthly billing data [52] and with advanced metering, a daily data feed is economically, as well as technically feasible so that such a process may be automated. But even with building-level data, the attribution of cooling load to temperature, on the one hand, and solar irradiation, on the other, becomes problematic at low temperatures.

Moreover, we can begin to estimate that part of the cooling load tied to internal gains only after the base load is separated into building and non-building loads and the building base load further separated into indoor and outdoor loads. These details, if needed, are best (can, perhaps, only) be assessed by end-use metering.

Conclusion

The analysis carried out suggests that the main characteristics of aggregate cooling load can be inferred approximately from electric utility system load time-series data and contemporaneous local weather when the building population in question is sufficiently homogeneous and the aggregate cooling load is a large fraction of the system load. For the case studied, we see that the decrease in electrical load is relatively small on weekends, suggesting that a substantial fraction of cooling equipment and/or other loads are in continuous operation. The significant contribution of humidity to cooling load suggests that ventilation retrofits could have a large impact. These might include weatherization, demand-controlled ventilation, dedicated outdoor air systems, enthalpy recovery and desiccant dehumidification.

Currently, building thermal inertia has not been modeled. For the one-day sampling time used in this analysis, thermal inertia effects are generally small. Other second order effects, including sol-air temperature (effect of wind and irradiation on building exterior surface temperatures), wind- and buoyancy-driven infiltration, and Coefficient of Performance variations with ambient dry-bulb and wet-bulb temperatures are not currently modeled. Saturation effects—when loads exceed cooling capacity of some buildings during extreme heat—are likewise not modeled. Further work should attempt to address these effects by using more detailed data sets, e.g. contemporaneous interval meter data from a sample of individual buildings, building stock time-series, street lighting schedules and system water use.

Acknowledgements

The authors are grateful for the load data provided by Mr. Mohammed Bin Jarsh Distribution Management System director Abu Dhabi Distribution Company (ADDC) and for the weather data provided by Dr. Afshin Afshari, Energy Management Department Head, MASDAR Initiative.

Appendix A

The results for all useful combinations of data filtering and model formulation are tabulated. Table A.1 describes the basic model formulations in terms of the random variables included in each model. Table A.2 describes each of the random variables used in one or more of the models.

Tables A.3 through A.5 present the results. Each table is formatted as follows.

The random variables listed in the leftmost column. Each model formulation is then represented by a pair of columns headed by the model# designation defined in Table A.1. Each model formulation has two variants, a no-growth (NG) formulation and a linear growth (LG) formulation thus creating the pair of columns for each model number. Each table is further divided into two sections: the coefficients are listed in the top section and the T-statistics are reported in the bottom section. Four additional rows are added at the very bottom to report the overall performance of each model in terms of the following three metrics:

1) RMSE
2) Correlation Coefficient R^2
3) Adjusted R^2
4) Durbin-Watson

The green cells identify the best models based on RMSE for each data set. The red cells identify the shortcoming of the other models over the best model. For the data set B with growth/day fixed to .00035, the best model is identified based on R^2 and Durbin-Watson test as RMSE variation among the possible models is small. The three tables, A.3-A.6, represent the three filtered data sets, defined as follows:

A) N= 363 (All data points)

B) N= 305 (Data points excluding cold days)

C) N= 217 (Data points excluding cold days, weekends and holidays)

In this section, the obtained coefficients, t-statistics, R^2, adjusted R^2 and RMSE are presented for all the models for comparison. Due to some bad records the total number of records is 363 instead of 366. The removed records are of days 14th January-16th January. In each model set ten combinations of parameters are considered according to the table below:

Table A.1 Possible Combination of Weather Parameters Considered

Model 1	Time	T	w	
Model 2	Time	T	w	GHI

Model 3	Time	T	w	DHI		
Model 4	Time	T	w	DNISinθ		
Model 5	Time	T	w	DNIcosθ		
Model 8	Time	T	w	GHI	DNISinθ	
Model 7	Time	T	w	DHI	DNISinθ	
Model 6	Time	T	w	DHI	DNIcosθ	
Model 10	Time	T	w	DNISinθ	DNIcosθ	
Model 11	Time	T	w	DHI	DNIcosθ	DNISinθ

Table A.2 Legend

Time	Day Number of Year	DHI	Diffuse Horizontal Irradiance
T	Ambient Temperature	DNIcosθ	Horizontal Component of Direct Normal Irradiance
w	Specific Humidity	DNISinθ	Vertical Component of Direct Normal Irradiance
GHI	Global Horizontal Irradiance	NG	No-Growth Model
LG	Linear Growth Model		

Table A.3 363 Records (Complete Data Set)

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8		Model 9		Model 10		Model 11	
Coefficients:	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG
Growth/day	—	0.000452	—	0.000566	—	0.000505	—	0.000480	—	0.000455	—	0.000691	—	0.000501	—	0.000836	—	0.000691	—	0.000887		0.000911
Constant	-452.355	-313.715	-427.849	-357.884	-444.508	-305.256	-510.580	-285.756	-462.694	-327.303	-420.360	-353.276	-513.333	-348.302	-478.123	-258.183	-420.360	-353.276	-524.714	-106.530	-546.862	-165.784
Saturday	-26.247	-21.793	-26.114	-21.214	-25.383	-21.957	-23.756	-22.441	-26.130	-21.599	-25.255	-21.330	-23.702	-20.928	-22.946	-23.862	-25.255	-21.330	-21.312	-27.824	-20.807	-26.340
Friday	-52.791	-50.681	-53.337	-48.827	-52.656	-50.432	-51.957	-50.751	-52.495	-50.351	-53.194	-47.983	-51.931	-50.097	-52.785	-47.389	-53.194	-47.983	-52.591	-47.847	-52.401	-47.275
T	32.145	31.644	33.233	28.269	33.517	30.580	33.010	31.281	31.901	31.317	34.586	25.759	32.972	30.298	35.232	23.510	34.586	25.759	35.467	23.538	35.246	22.668
W	60495.697	40609.442	58491.398	42338.054	59012.941	39717.450	61099.838	39384.849	61164.291	41387.300	57040.542	41207.527	61202.087	41135.676	57502.729	37824.367	57040.542	41207.549	58069.078	33482.363	58784.348	35086.740
GHI	—	—	-0.139	0.415	—	—	—	—	—	—		—	—	—	-0.258	0.768	-0.458	0.879	—	—	—	—
DHI	—	—	—	—	-0.322	0.228	—	—	—	—	-0.458	0.879	0.017	0.430	—	—	—	—	—	—	0.134	0.398
DNIsinθ	—	—	—	—	—	—	0.204	-0.071	—	—	—	—	0.212	0.129	0.250	-0.346	—	—	0.457	-0.883	-0.395	-0.692
DNIcosθ	—	—	—	—	—	—	—	—	0.068	0.094	-0.137	0.506	—	—	—	—	0.321	-0.373	-0.384	0.981	0.530	0.977
t-statistics:																						
Growth/day	—	0.0151	—	0.0181	—	0.0153	—	0.0144	—	0.0152	—	0.0200	—	0.0151	—	0.0219	—	0.0200	—	0.0216	—	0.0223
Constant	-18.174	-14.571	-13.986	-13.929	-17.935	-14.238	-16.975	-10.133	-16.876	-13.847	-13.832	-13.854	-10.613	-8.211	-14.683	-9.551	-13.832	-13.854	-17.444	-3.602	-11.167	-3.829
Saturday	-2.671	-2.587	-2.660	-2.589	-2.608	-2.621	-2.444	-2.659	-2.658	-2.569	-2.598	-2.652	-2.428	-2.486	-2.377	-3.020	-2.598	-2.652	-2.211	-3.507	-2.148	-3.327
Friday	-5.593	-6.262	-5.653	-6.198	-5.636	-6.266	-5.581	-6.270	-5.557	-6.229	-5.696	-6.206	-5.566	-6.220	-5.707	-6.262	-5.696	-6.206	-5.714	-6.337	-5.684	-6.297
T	29.731	33.869	24.824	25.110	28.642	30.308	30.093	32.832	28.618	32.588	24.612	21.228	27.186	28.970	25.057	18.819	24.612	21.228	26.351	19.205	25.155	18.068
W	13.946	10.469	12.796	10.925	13.648	10.299	14.272	9.994	13.895	10.545	12.530	10.830	13.566	10.105	12.815	10.144	12.530	10.830	13.368	9.110	12.996	9.243
GHI	—	—	-1.375	4.581	—	—	—	—	—	—	—	—	—	—	-2.499	7.410	-3.077	5.915	—	—	—	—
DHI	—	—	—	—	-2.899	2.160	—	—	—	—	-3.077	5.915	0.073	2.132	—	—	—	—	—	—	0.573	2.100
DNIsinθ	—	—	—	—	—	—	3.348	-1.213	—	—	—	—	1.655	1.154	3.956	-5.292	—	—	4.485	-7.182	-3.130	-4.304
DNIcosθ	—	—	—	—	—	—	—	—	0.900	1.460	-1.370	5.603	—	—	—	—	2.893	-3.620	-3.080	7.275	3.267	7.222
t-statistics significance:																						
Growth/day	—	0.988	—	0.986	—	0.988	—	0.989	—	0.988	—	0.984	—	0.988	—	0.983	—	0.984	—	0.983	—	0.982
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Saturday	0.008	0.010	0.008	0.010	0.009	0.009	0.015	0.008	0.008	0.011	0.010	0.008	0.016	0.013	0.018	0.003	0.010	0.008	0.028	0.001	0.032	0.001
Friday	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
T	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
W	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GHI	—	—	0.170	0.000	—	—	—	—	—	—	—	—	—	—	0.013	0.000	0.002	0.000	—	—	—	—
DHI	—	—	—	—	0.004	0.031	—	—	—	—	0.002	0.000	0.942	0.034	—	—	—	—	—	—	0.567	0.036
DNIsinθ	—	—	—	—	—	—	0.001	0.226	—	—	—	—	0.099	0.249	0.000	0.000	—	—	0.000	0.000	0.002	0.000
DNIcosθ	—	—	—	—	—	—	—	—	0.369	0.145	0.172	0.000	—	—	—	—	0.004	0.000	0.002	0.000	0.001	0.000
RMSE:	64.828	55.557	64.747	54.049	64.167	55.233	63.922	55.505	64.845	55.448	64.089	53.036	64.012	55.193	63.458	51.890	64.089	53.036	63.176	51.763	63.235	51.438
R-Square:	0.956	0.970	0.956	0.974	0.957	0.971	0.957	0.970	0.956	0.970	0.957	0.977	0.957	0.971	0.958	0.980	0.957	0.977	0.958	0.979	0.958	0.980
Adj. R-Square:	0.955	0.970	0.955	0.974	0.956	0.970	0.957	0.970	0.955	0.970	0.956	0.977	0.956	0.971	0.957	0.979	0.956	0.977	0.958	0.978	0.958	0.980
Durbin-Watson:	0.649	0.743	0.668	0.707	0.680	0.745	0.681	0.748	0.646	0.736	0.695	0.683	0.681	0.738	0.715	0.677	0.695	0.683	0.726	0.740	0.726	0.699

Table A.4 305 Records (Cold Days removed)

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8		Model 9		Model 10		Model 11	
Coefficients:	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG
Growth/day	—	0.000425	—	0.000624	—	0.000456	—	0.000410	—	0.000437	—	0.000740	—	0.000443	—	0.000827	—	0.000740	—	0.000837	—	0.000856
Constant	-611.978	-453.663	-599.639	-499.542	-605.234	-446.164	-704.067	-470.385	-635.036	-480.099	-597.121	-485.843	-803.220	-609.640	-681.176	-409.629	-597.121	-485.843	-717.811	-247.428	-849.552	-372.539
Saturday	-22.403	-19.386	-22.173	-20.257	-22.237	-19.253	-20.643	-19.255	-22.817	-19.870	-22.086	-20.022	-19.186	-16.870	-20.009	-21.376	-22.086	-20.022	-18.338	-24.327	-16.015	-22.099
Friday	-60.071	-56.845	-59.950	-56.422	-60.405	-56.509	-61.233	-57.092	-60.457	-57.258	-60.321	-55.443	-61.864	-57.625	-61.022	-54.568	-60.321	-55.443	-61.180	-53.818	-61.993	-54.258
T	36.299	35.077	36.818	30.033	37.803	34.467	37.642	35.304	35.812	34.431	38.133	27.848	36.718	33.759	38.916	26.549	38.133	27.848	39.813	27.130	39.007	26.177
W	63280.392	44100.867	62259.533	45526.554	61794.586	43465.071	64562.223	44826.102	64821.479	45586.720	61131.917	44068.546	68001.663	48709.027	62289.391	41451.123	61131.917	44068.537	61834.671	36907.867	65815.784	40313.098
GHI	—	—	-0.066	0.574	—	—	—	—	—	—	—	—	—	—	-0.152	0.791	-0.389	0.934	—	—	—	—
DHI	—	—	—	—	-0.348	0.118	—	—	—	—	-0.389	0.934	0.516	0.802	—	—	—	—	—	—	0.672	0.671
DNIsinθ	—	—	—	—	—	—	0.303	0.039	—	—	—	—	0.596	0.480	0.321	-0.244	—	—	0.530	-0.770	-0.390	-0.368
DNIcosθ	—	—	—	—	—	—	—	—	0.138	0.181	-0.044	0.647	—	—	—	—	0.345	-0.287	-0.329	0.891	0.953	0.855
t-statistics:																						
Growth/day	—	0.0134	—	0.0187	—	0.0130	—	0.0116	—	0.0140	—	0.0202	—	0.0129	—	0.0204	—	0.0202	—	0.0183	—	0.0192
Constant	-25.505	-22.121	-20.280	-21.771	-25.647	-21.784	-24.093	-16.599	-23.917	-21.592	-20.582	-21.535	-15.484	-13.542	-21.209	-15.869	-20.582	-21.535	-24.638	-8.036	-16.231	-7.902
Saturday	-2.546	-2.637	-2.516	-2.981	-2.577	-2.623	-2.440	-2.615	-2.605	-2.749	-2.555	-3.007	-2.278	-2.355	-2.371	-3.232	-2.555	-3.007	-2.191	-3.554	-1.931	-3.302
Friday	-6.972	-7.895	-6.951	-8.476	-7.150	-7.860	-7.397	-7.922	-7.049	-8.086	-7.129	-8.501	-7.523	-8.236	-7.394	-8.441	-7.129	-8.501	-7.499	-8.101	-7.696	-8.389
T	34.866	40.143	29.002	29.992	34.301	36.653	36.417	39.237	33.635	39.049	29.366	26.058	33.327	35.982	30.499	23.858	29.366	26.058	32.308	23.483	31.331	22.995
W	17.009	13.282	15.613	14.503	16.835	13.092	18.025	13.102	17.136	13.748	15.578	14.328	17.634	13.861	16.329	13.436	15.578	14.328	17.006	11.659	17.213	12.283
GHI	—	—	-0.715	7.093	—	—	—	—	—	—	—	—	—	—	-1.693	8.780	-3.040	7.434	—	—	—	—
DHI	—	—	—	—	-3.618	1.299	—	—	—	—	-3.040	7.434	2.306	4.198	—	—	—	—	—	—	3.012	3.739
DNIsinθ	—	—	—	—	—	—	5.124	0.677	—	—	—	—	4.256	3.995	5.360	-4.138	—	—	5.699	-6.542	-3.688	-2.229
DNIcosθ	—	—	—	—	—	—	—	—	1.986	3.157	-0.482	8.036	—	—	—	—	3.572	-3.435	-3.131	7.428	5.676	7.208
t-statistics significance:																						
Growth/day	—	0.989	—	0.985	—	0.990	—	0.991	—	0.989	—	0.984	—	0.990	—	0.984	—	0.984	—	0.985	—	0.985
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Saturday	0.011	0.009	0.012	0.003	0.010	0.009	0.015	0.009	0.010	0.006	0.011	0.003	0.023	0.019	0.018	0.001	0.011	0.003	0.029	0.000	0.054	0.001
Friday	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
T	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
W	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GHI	—	—	0.475	0.000	—	—	—	—	—	—	—	—	—	—	0.091	0.000	0.003	0.000	—	—	—	—
DHI	—	—	—	—	0.000	0.195	0.000	—	—	—	0.003	0.000	0.022	0.000	—	—	—	—	—	—	0.003	0.000
DNIsinθ	—	—	—	—	—	—	0.000	0.499	—	—	—	—	0.000	0.000	0.000	0.000	—	—	0.000	0.000	0.000	0.027
DNIcosθ	—	—	—	—	—	—	—	—	0.048	0.002	0.630	0.000	—	—	—	—	0.000	0.001	0.002	0.000	0.000	0.000
RMSE:	53.426	44.621	53.470	41.225	52.381	44.557	51.310	44.658	53.166	43.873	52.448	40.387	50.943	43.333	51.150	40.036	52.448	40.387	50.571	41.157	49.900	40.049
R-Square:	0.961	0.973	0.961	0.979	0.963	0.973	0.964	0.973	0.962	0.974	0.963	0.981	0.965	0.975	0.965	0.982	0.963	0.981	0.965	0.980	0.966	0.982
Adj. R-Square:	0.961	0.973	0.960	0.979	0.962	0.973	0.964	0.972	0.961	0.974	0.962	0.981	0.964	0.975	0.964	0.982	0.962	0.981	0.965	0.979	0.966	0.982
Durbin-Watson:	0.649	0.946	0.668	0.973	0.680	0.946	0.681	0.952	0.646	0.966	0.695	0.943	0.681	1.004	0.715	0.922	0.695	0.943	0.726	0.932	0.726	0.918

Table A.5 217 Records (Cold Days, Holidays and Weekends Removed)

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8		Model 9		Model 10		Model 11	
Coefficients:	**NG**	**LG**	**NG**	**LG**	**NG**	**LG**	**NG**	**LG**	**NG**	**LG**	**NG**	**LG**	**NG**	**LG**	**NG**	**LG**	**NG**	**LG**	**NG**	**LG**	**NG**	**LG**
Growth/day	—	0.000415	—	0.000616	—	0.000442	—	0.000389	—	0.000424	—	0.000718	—	0.000418	—	0.000781	—	0.000718	—	0.000767	—	0.000780
Constant	-579.167	-432.172	-570.344	-491.645	-577.436	-424.362	-689.933	-462.473	-611.926	-467.004	-575.305	-476.837	-826.284	-624.097	-670.043	-415.442	-575.305	-476.837	-699.097	-266.474	-863.082	-416.114
T	37.315	35.907	37.671	30.498	38.825	35.383	38.726	36.296	36.668	35.167	38.906	28.611	37.516	34.652	39.718	27.675	38.906	28.611	40.871	28.680	39.860	27.682
W	57659.362	40159.119	56921.931	42969.736	56773.575	39456.765	60046.730	41572.480	60049.630	42490.280	56597.633	41402.317	64617.437	46072.814	58163.675	39455.503	56597.633	41402.315	57032.572	35449.236	61869.331	39474.864
GHI	—	—	-0.045	0.609	—	—	—	—	—	—	—	—	—	—	-0.120	0.782	-0.376	0.925	—	—	—	—
DHI	—	—	—	—	-0.366	0.103	—	—	—	—	-0.376	0.925	0.705	0.907	—	—	—	—	—	—	0.838	0.784
DNIsinθ	—	—	—	—	—	—	0.338	0.067	—	—	—	—	0.745	0.575	0.349	-0.202	—	—	0.557	-0.678	-0.393	-0.199
DNIcosθ	—	—	—	—	—	—	—	—	0.172	0.198	-0.011	0.668	—	—	—	—	0.365	-0.257	-0.328	0.823	1.084	0.781
t-statistics:																						
Growth/day	—	0.0115	—	0.0165	—	0.0110	—	0.0095	—	0.0120	—	0.0175	—	0.0107	—	0.0170	—	0.0175	—	0.0145	—	0.0153
Constant	-21.399	-18.909	-16.520	-18.626	-21.834	-18.523	-20.418	-13.963	-19.724	-18.177	-17.033	-18.375	-13.961	-12.035	-17.661	-13.677	-17.033	-18.375	-20.885	-7.524	-14.640	-7.713
T	31.417	36.313	25.627	26.773	31.187	33.380	33.390	35.762	30.115	35.161	26.213	23.755	30.711	33.262	27.489	21.983	26.213	23.755	29.376	21.538	28.627	21.383
W	13.519	10.703	12.290	12.126	13.598	10.468	14.757	10.617	13.709	11.234	12.500	11.870	14.927	11.580	13.269	11.162	12.500	11.870	13.703	9.699	14.337	10.556
GHI	—	—	-0.413	6.491	—	—	—	—	—	—	—	—	—	—	-1.150	7.562	-2.570	6.550	—	—	—	—
DHI	—	—	—	—	-3.348	0.994	—	—	—	—	-2.570	6.550	2.786	4.202	—	—	—	—	—	—	3.343	3.829
DNIsinθ	—	—	—	—	—	—	5.034	1.007	—	—	—	—	4.649	4.156	5.149	-3.020	—	—	5.329	-5.000	-3.275	-1.053
DNIcosθ	—	—	—	—	—	—	—	—	2.107	2.957	-0.102	7.175	—	—	—	—	3.315	-2.740	-2.705	5.901	5.772	5.734
t-statistics significance:																						
Growth/day	—	0.991	—	0.987	—	0.991	—	0.992	—	0.990	—	0.986	—	0.991	—	0.986	—	0.986	—	0.988	—	0.988
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
T	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
W	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GHI	—	—	0.680	0.000	—	—	—	—	—	—	—	—	—	—	0.252	0.000	0.011	0.000	—	—	—	—
DHI	—	—	—	—	0.001	0.321	—	—	—	—	0.011	0.000	0.006	0.000	—	—	—	—	—	—	0.001	0.000
DNIsinθ	—	—	—	—	—	—	0.000	0.315	—	—	—	—	0.000	0.000	0.000	0.003	—	—	0.000	0.000	0.001	0.294
DNIcosθ	—	—	—	—	—	—	—	—	0.036	0.003	0.919	0.000	—	—	—	—	0.001	0.007	0.007	0.000	0.000	0.000
RMSE:	52.386	43.435	52.488	39.624	51.180	43.426	49.639	43.423	51.970	42.553	51.299	38.938	48.870	41.637	49.602	38.818	51.299	38.938	48.919	40.478	47.786	38.910
R-Square:	0.964	0.975	0.964	0.982	0.966	0.976	0.968	0.976	0.965	0.977	0.966	0.984	0.969	0.978	0.968	0.984	0.966	0.984	0.969	0.981	0.971	0.984
Adj. R-Square:	0.964	0.975	0.964	0.981	0.965	0.975	0.967	0.975	0.964	0.976	0.965	0.983	0.968	0.978	0.968	0.984	0.965	0.983	0.968	0.981	0.970	0.984
Durbin-Watson:	0.649	1.202	0.668	1.224	0.680	1.212	0.681	1.206	0.646	1.202	0.695	1.211	0.681	1.323	0.715	1.181	0.695	1.211	0.726	1.142	0.726	1.181

Table A.6 305 Records (Cold Days Removed with .00035 Growth/Day Constant)

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7		Model 8		Model 9		Model 10		Model 11	
Coefficients:	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG	NG	LG
Growth/day	—	0.00035	—	0.00035	—	0.00035	—	0.00035	—	0.00035	—	0.00035	—	0.00035	—	0.00035	—	0.00035	—	0.00035	—	0.00035
Constant	-611.978	-478.350	-599.639	-537.389	-605.234	-478.735	-704.067	-500.930	-635.036	-507.175	-597.121	-537.367	-803.220	-645.589	-681.176	-547.979	-597.121	-537.367	-717.811	-489.739	-849.552	-620.503
Saturday	-22.403	-19.886	-22.173	-21.043	-22.237	-19.898	-20.643	-19.453	-22.817	-20.420	-22.086	-21.041	-19.186	-17.332	-20.009	-20.770	-22.086	-21.041	-18.338	-21.356	-16.015	-19.065
Friday	-60.071	-57.402	-59.950	-57.977	-60.405	-57.381	-61.233	-57.666	-60.457	-57.880	-60.321	-57.983	-61.864	-58.475	-61.022	-58.104	-60.321	-57.983	-61.180	-57.755	-61.993	-58.454
T	36.299	35.271	36.818	32.741	37.803	35.174	37.642	35.625	35.812	34.678	38.133	32.763	36.718	34.333	38.916	33.013	38.133	32.763	39.813	33.825	39.007	33.066
W	63280.392	47170.068	62259.533	52127.313	61794.586	47270.120	64562.223	47418.351	64821.479	49047.017	61131.917	52108.024	68001.663	52335.362	62289.391	52112.505	61131.917	52108.025	61834.671	49719.680	65815.784	53587.944
GHI	—	—	-0.066	0.320	—	—	—	—	—	—	—	—	—	—	-0.152	0.310	-0.389	0.314	—	—	—	—
DHI	—	—	—	—	-0.348	0.022	—	—	—	—	-0.389	0.314	0.516	0.747	—		—	—	—	—	0.672	0.663
DNIsinθ	—	—	—	—	—	—	0.303	0.074	—	—	—	—	0.596	0.501	0.321	0.040	—	—	0.530	-0.109	-0.390	0.310
DNIcosθ	—	—	—	—	—	—	—	—	0.138	0.173	-0.044	0.320	—	—	—	—	0.345	0.006	-0.329	0.268	0.953	0.211
t-statistics:																						
Growth/day	—	0.011	—	0.010	—	0.010	—	0.010	—	0.011	—	0.009	—	0.010	—	0.008	—	0.009	—	0.007	—	0.007
Constant	-25.505	-23.185	-20.280	-22.188	-25.647	-23.165	-24.093	-17.623	-23.917	-22.623	-20.582	-22.070	-15.484	-14.235	-21.209	-19.522	-20.582	-22.070	-24.638	-14.826	-16.231	-12.176
Saturday	-2.546	-2.689	-2.516	-2.934	-2.577	-2.687	-2.440	-2.634	-2.605	-2.802	-2.555	-2.929	-2.278	-2.401	-2.371	-2.888	-2.555	-2.929	-2.191	-2.908	-1.931	-2.635
Friday	-6.972	-7.925	-6.951	-8.251	-7.150	-7.910	-7.397	-7.977	-7.049	-8.107	-7.129	-8.238	-7.523	-8.295	-7.394	-8.265	-7.129	-8.238	-7.499	-8.103	-7.696	-8.361
T	34.866	40.122	29.002	30.977	34.301	37.070	36.417	39.473	33.635	39.008	29.366	28.406	33.327	36.323	30.499	27.282	29.366	28.406	32.308	27.291	31.331	26.870
W	17.009	14.122	15.613	15.732	16.835	14.111	18.025	13.817	17.136	14.671	15.578	15.699	17.634	14.783	16.329	15.534	15.578	15.699	17.006	14.640	17.213	15.104
GHI	—	—	-0.715	3.741	—		—		—	—	—	—	—	—	-1.693	3.160	-3.040	2.319	—	—	—	—
DHI	—	—	—	—	-3.618	0.235	—	—	—	—	-3.040	2.319	2.306	3.885	—	—	—	—	—	—	3.012	3.419
DNIsinθ	—	—	—	—	—	—	5.124	1.281	—	—	—	—	4.256	4.143	5.360	0.630	—	—	5.699	-0.861	-3.688	1.736
DNIcosθ	—	—	—	—	—	—	—	—	1.986	2.989	-0.482	3.684	—	—	—	—	3.572	0.061	-3.131	2.085	5.676	1.642
t-statistics significance:																						
Growth/day	—	0.991	—	0.992	—	0.992	—	0.992	—	0.991	—	0.993	—	0.992	—	0.984	—	0.993	—	0.994	—	0.994
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Saturday	0.011	0.008	0.012	0.004	0.010	0.008	0.015	0.009	0.010	0.005	0.011	0.004	0.023	0.017	0.018	0.001	0.011	0.004	0.029	0.004	0.054	0.009
Friday	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
T	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
W	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
GHI	—	—	0.475	0.000	—	—	—	—	—	—	—	—	—		0.091	0.000	0.003	0.021	—	—	—	—
DHI	—	—	—	—	0.000	0.814	0.000	—	—	—	0.003	0.021	0.022	0.000	—	—	—	—	—	—	0.003	0.001
DNIsinθ	—	—	—	—	—	—	0.000	0.201	—	—	—	—	0.000	0.000	0.000	0.000	—	—	0.000	0.390	0.000	0.084
DNIcosθ	—	—	—	—	—	—	—	—	0.048	0.003	0.630	0.000	—	—	—	—	0.000	0.951	0.002	0.038	0.000	0.102
RMSE:	53.426	44.891	53.470	43.513	52.381	44.960	51.310	44.795	53.166	44.234	52.448	43.586	50.943	43.656	51.150	43.535	52.448	43.586	50.571	44.155	49.900	43.293
R-Square:	0.961	0.969	0.961	0.966	0.963	0.968	0.964	0.970	0.962	0.969	0.963	0.966	0.965	0.971	0.965	0.967	0.963	0.966	0.965	0.967	0.966	0.968
Adj. R-Square:	0.961	0.968	0.960	0.965	0.962	0.968	0.964	0.970	0.961	0.969	0.962	0.965	0.964	0.970	0.964	0.966	0.962	0.965	0.965	0.966	0.966	0.968
Durbin-Watson:	0.649	0.951	0.668	0.960	0.680	0.951	0.681	0.961	0.646	0.970	0.695	0.961	0.681	1.016	0.715	0.971	0.695	0.961	0.726	0.958	0.726	0.998

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— **Weekdays** ○ **Fridays** ☆ **Saturdays**

Table 1: Correlation matrix (pair-wise R^2) for the 2008 daily mean electrical load and weather data

	T	w	DNIsinθ	DNIcosθ	DHI	GHI	Load
T	1.000	0.874	-0.497	0.201	0.570	0.651	0.963
W	0.874	1.000	-0.455	0.094	0.452	0.452	0.916
DNIsinθ	-0.497	-0.455	1.000	0.582	-0.901	-0.132	-0.451
DNIcosθ	0.201	0.094	0.582	1.000	-0.394	0.686	0.180
DHI	0.570	0.452	-0.901	-0.394	1.000	0.398	0.508
GHI	0.651	0.452	-0.132	0.686	0.398	1.000	0.581
Load	0.963	0.916	-0.451	0.180	0.508	0.581	1.000

Table 2: Choice of solar irradiation terms from the 2-term and 3-term equivalent groups

Number of solar terms	Term used in the regression	Equivalent groups	
2	(DHI, DNIcosθ)	(GHI, DHI)	(GHI, DNIcosθ)
3	(DNIsinθ, DHI, DNIcosθ)	(DNIsinθ, GHI, DHI)	(DNIsinθ, GHI, DNIcosθ)

Table 3a: Statistics for best fit no-growth and linear growth models (data set B)

	Coefficient		t-value [42][41]		t-value significance	
	No-Growth	Linear	No-Growth	Linear	No-Growth	Linear
Growth/day	—	0.00035	—	0.010	—	0.992
Constant	-803.22	-645.59	-15.484	-14.235	$<10^{-3}$	$<10^{-3}$
Saturday constant	-19.186	-17.332	-2.278	-2.401	0.023	0.017
Friday constant	-61.864	-58.475	-7.523	-8.295	$<10^{-3}$	$<10^{-3}$
Temperature	36.718	34.333	33.327	36.323	$<10^{-3}$	$<10^{-3}$
Specific Humidity	68001	52335	17.634	14.783	$<10^{-3}$	$<10^{-3}$
DHI	0.516	0.747	2.306	3.885	0.022	$<10^{-3}$
DNI on Vertical Surface	0.596	0.501	4.256	4.143	$<10^{-3}$	$<10^{-3}$

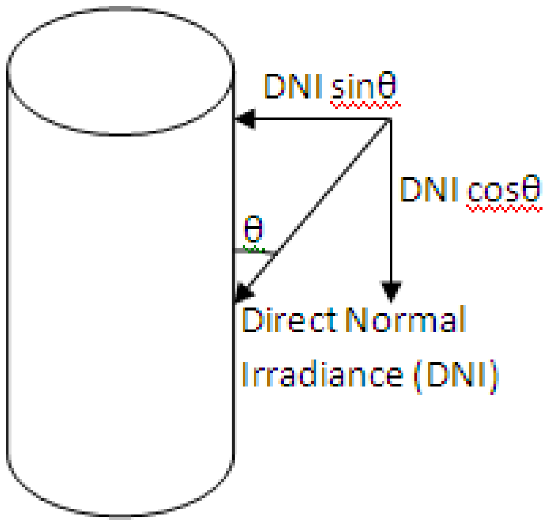
Table 3b: Statistics for best fit no-growth and linear growth models (data set B)

	RMSE	R^2	CV-RMSE	Adjusted	D-W
No-growth	50.943	0.965	4.53%	0.964	0.681
Linear growth	43.333	.975	3.86%	.975	1.004
Specified linear growth	43.656	0.971	3.89%	0.970	1.016

Table 4: Contributions of different model parameters in growth and day-type adjusted Electrical load for specified-growth model 7 with change points (data set A)

	Total (TWh)	Average (MW)	% of Total Load	% of Cooling Load
Temperature	2.0164	231.45	23.4	59.01
Specific Humidity	0.7215	82.81	8.4	21.12
DHI	0.3767	43.24	4.4	11.03
DNI on Vertical Surface	0.3021	34.68	3.5	8.84
Base Load	5.1954	596.50	60.3	–
Total Load	8.6121	988.68	100	–
Total Cooling Electrical Load	3.4167	392.18	40.3	100

Figure



Figure

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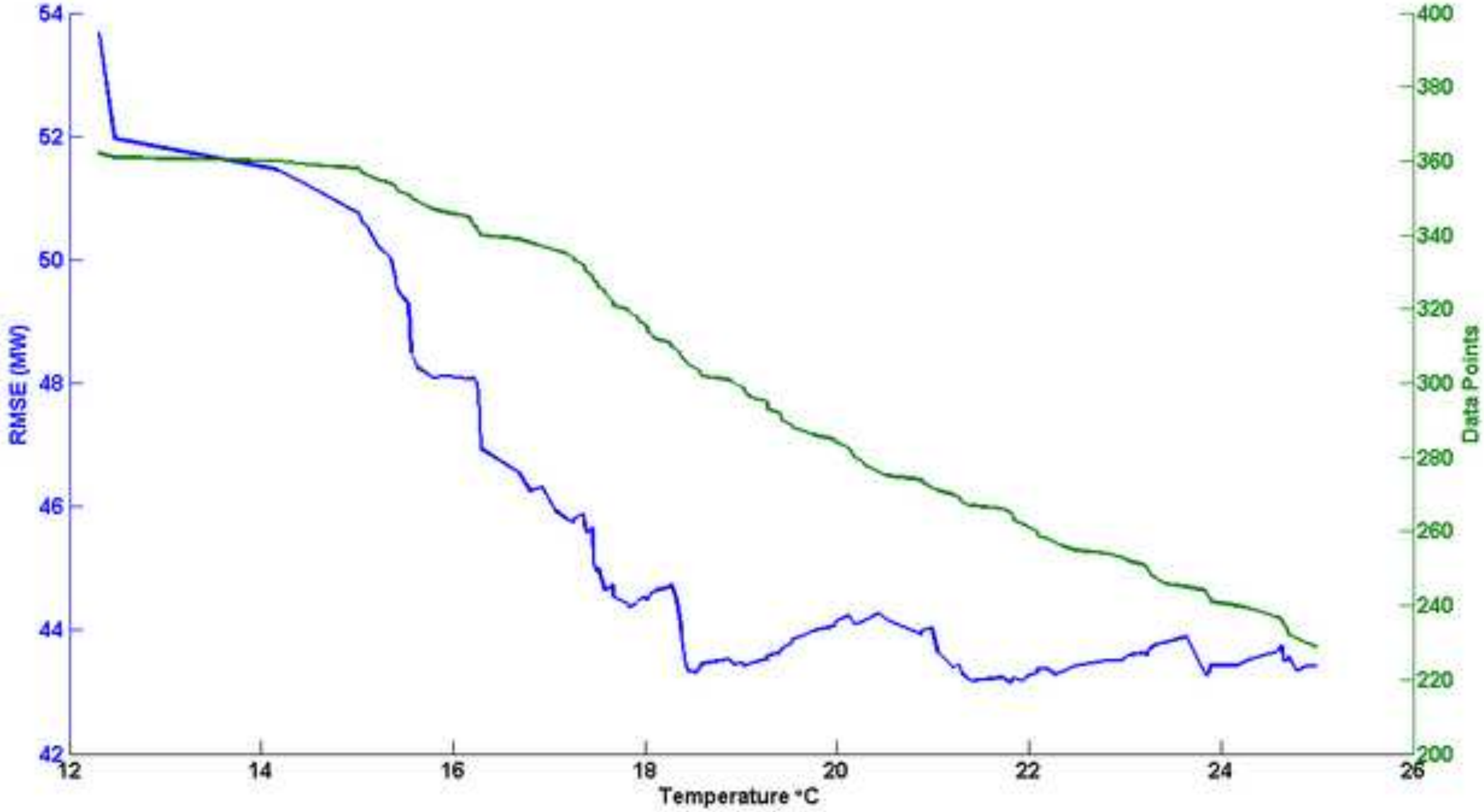

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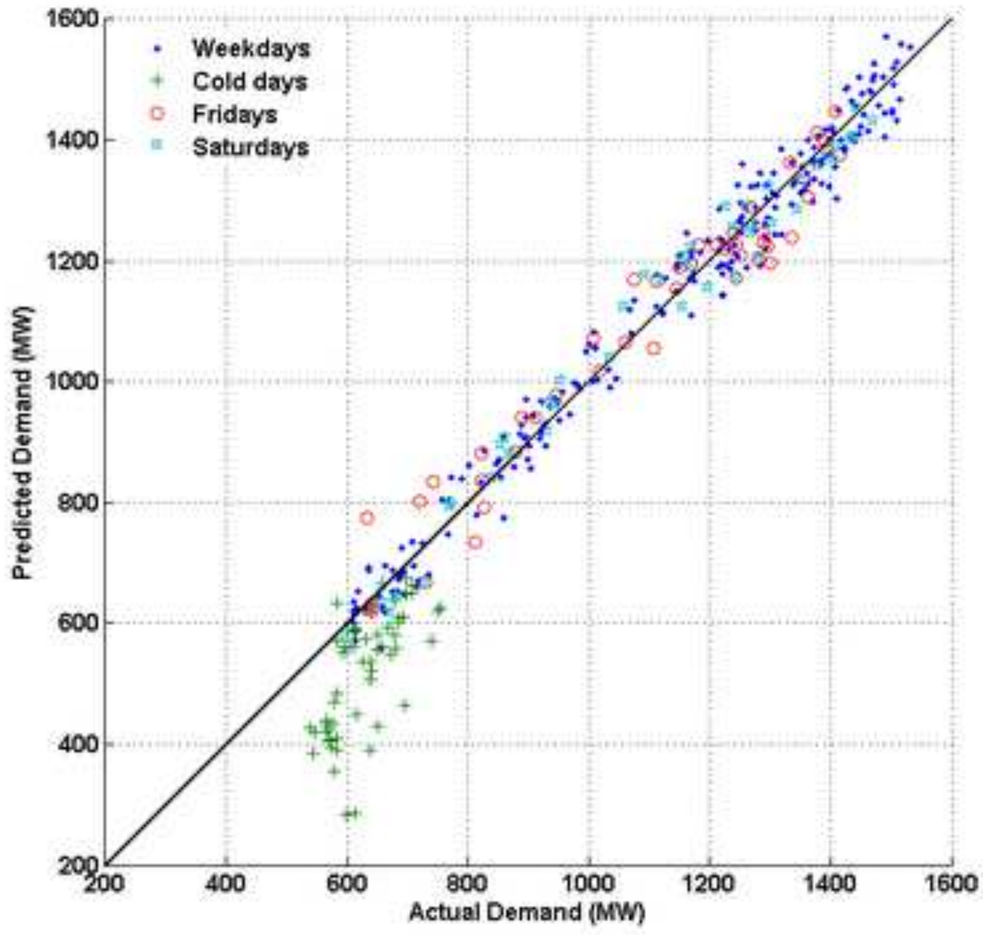

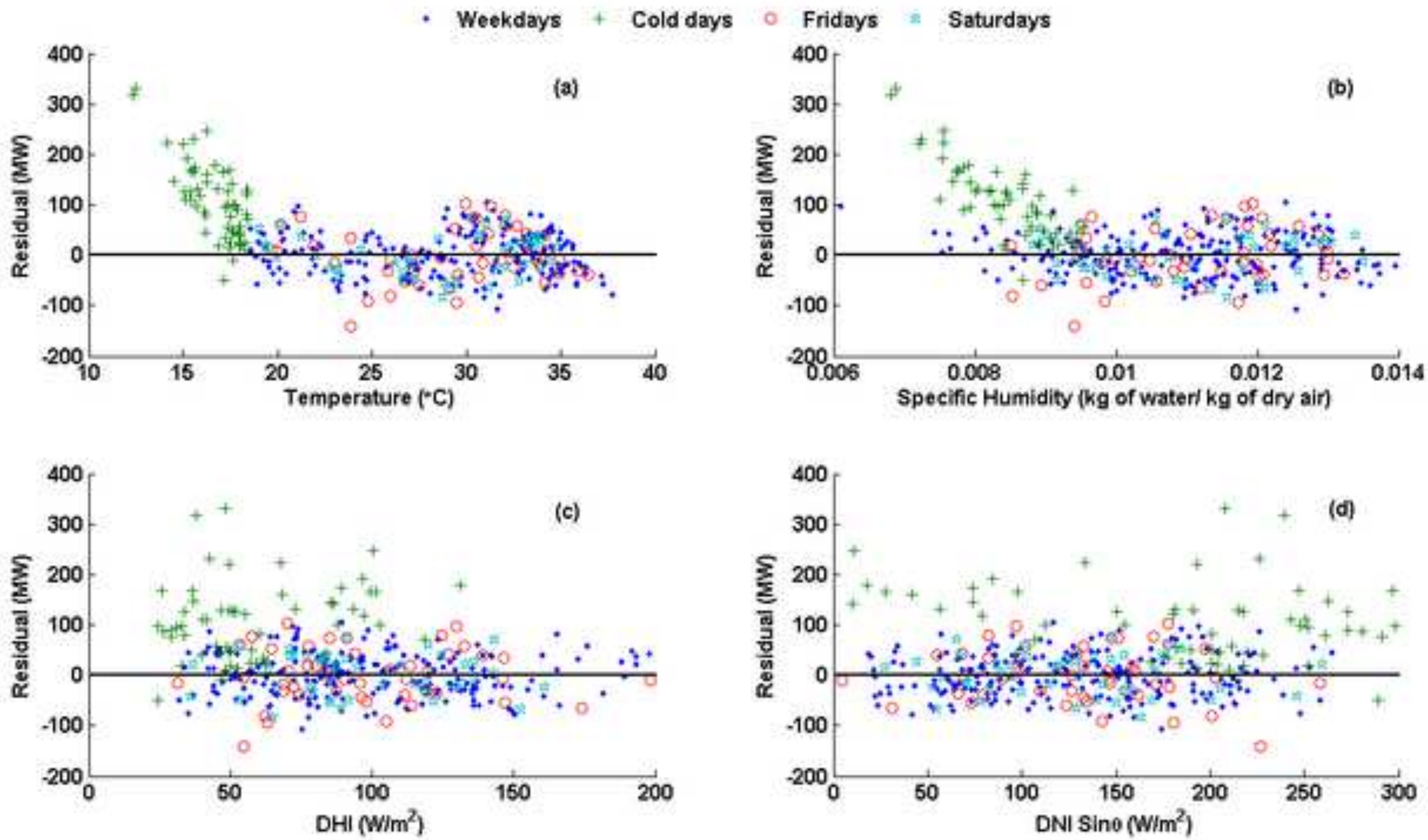
Weekdays
Cold days
Fridays
Saturdays
(a)
Residual (MW)
Temperature (°C)
(b)
Specific Humidity (kg of water/ kg of dry air)
(c)
DHI (W/m²)
(d)
DNI Sinθ (W/m²)

Figure
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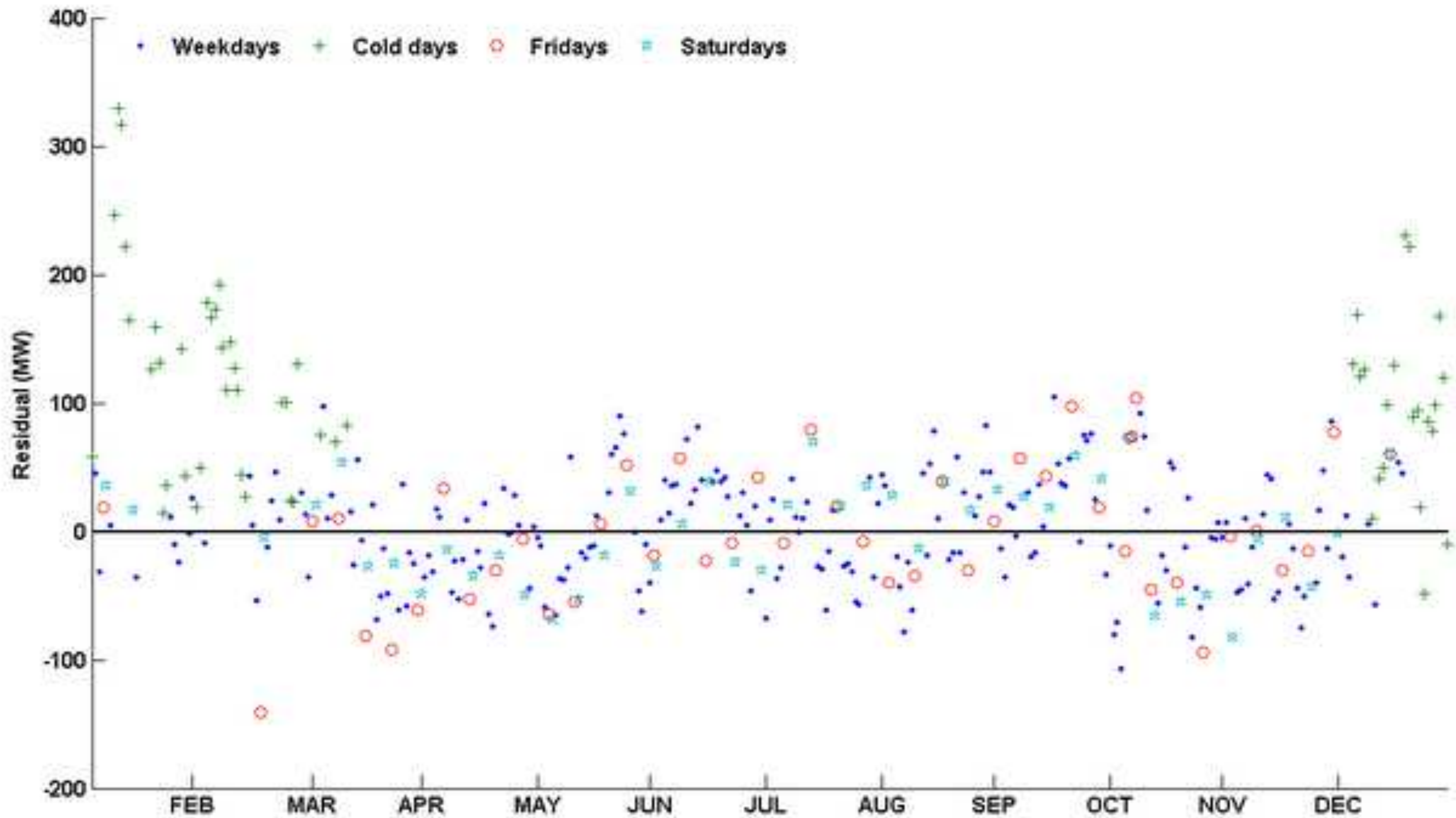

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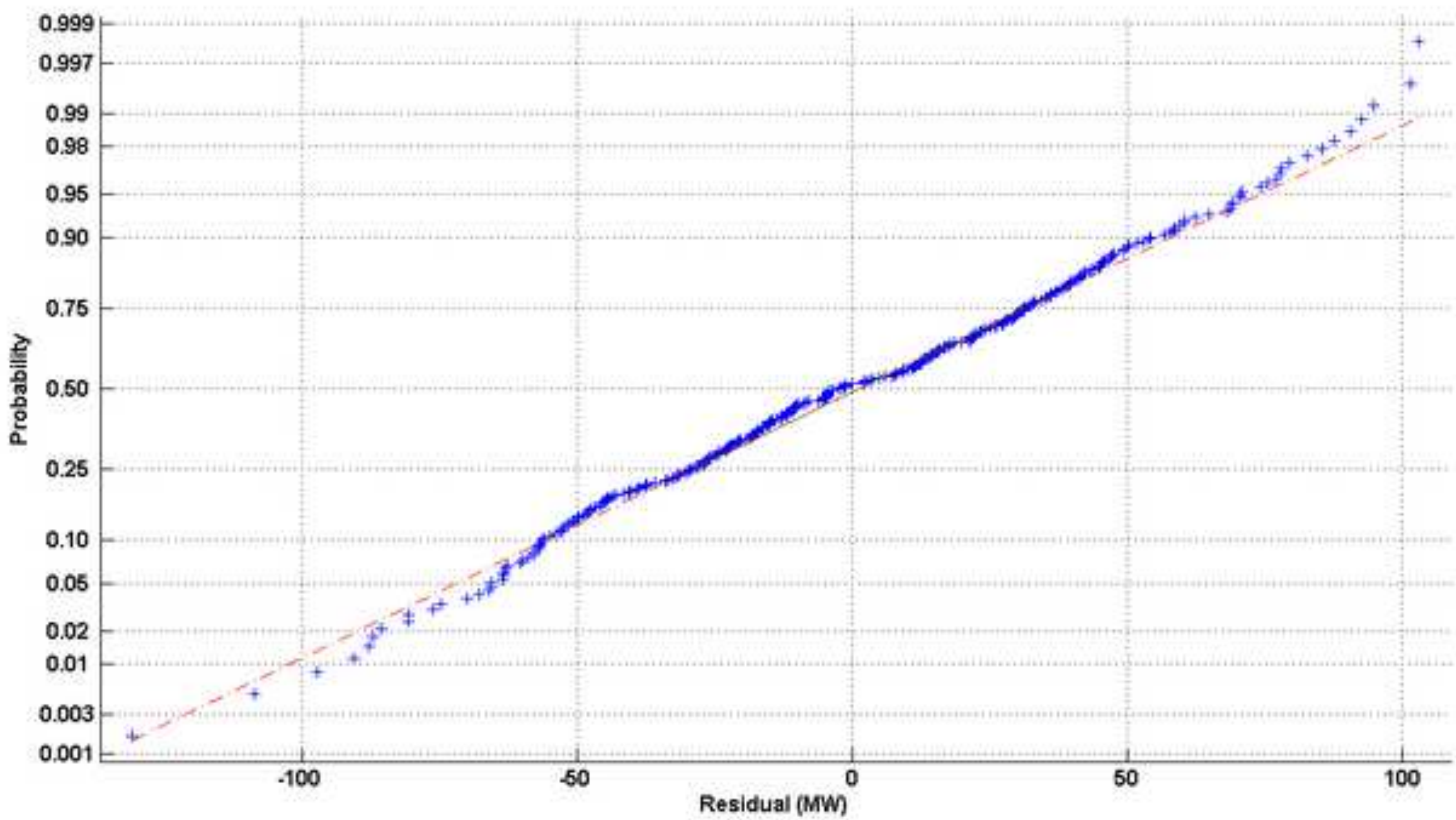

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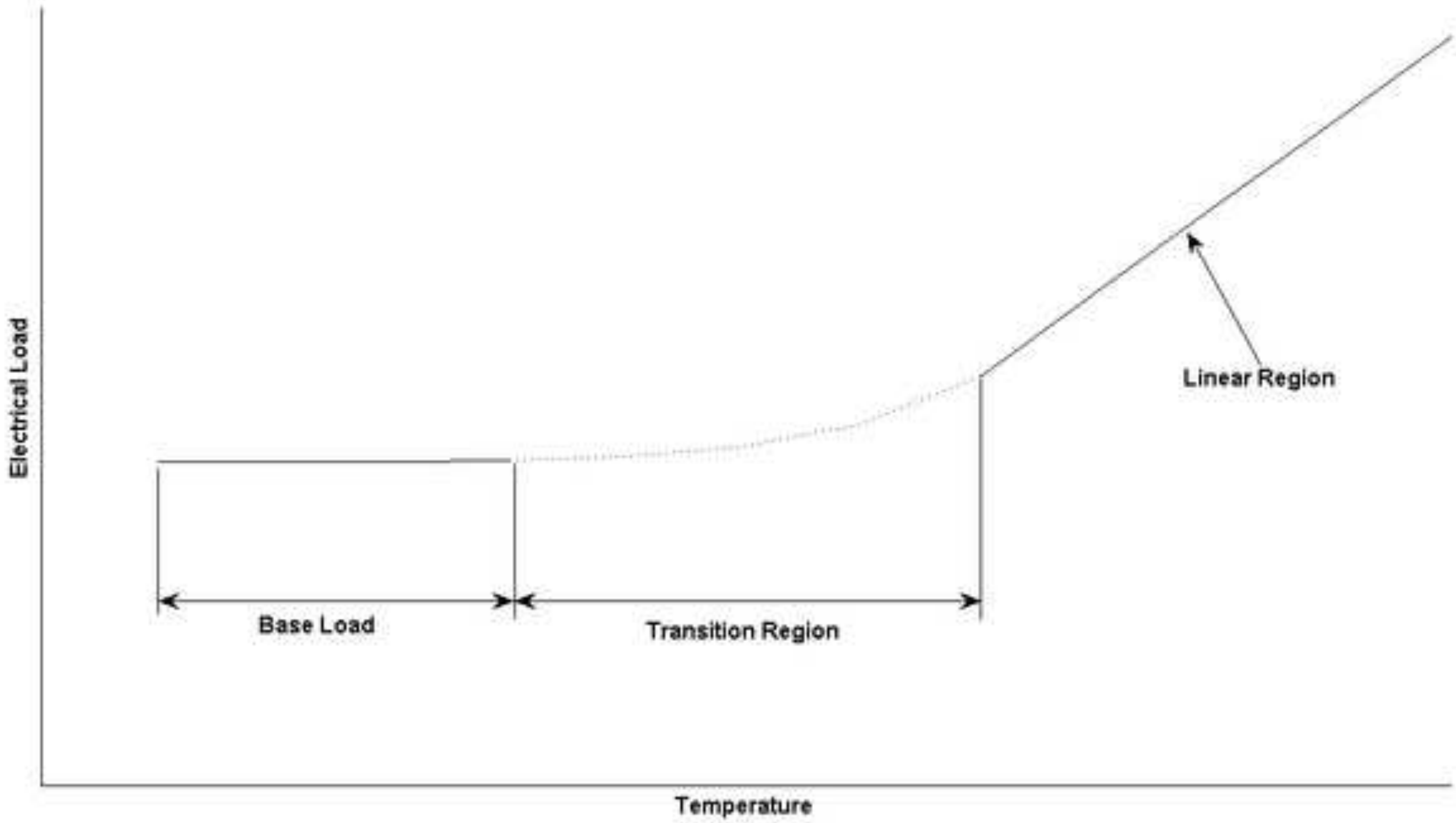

Figure

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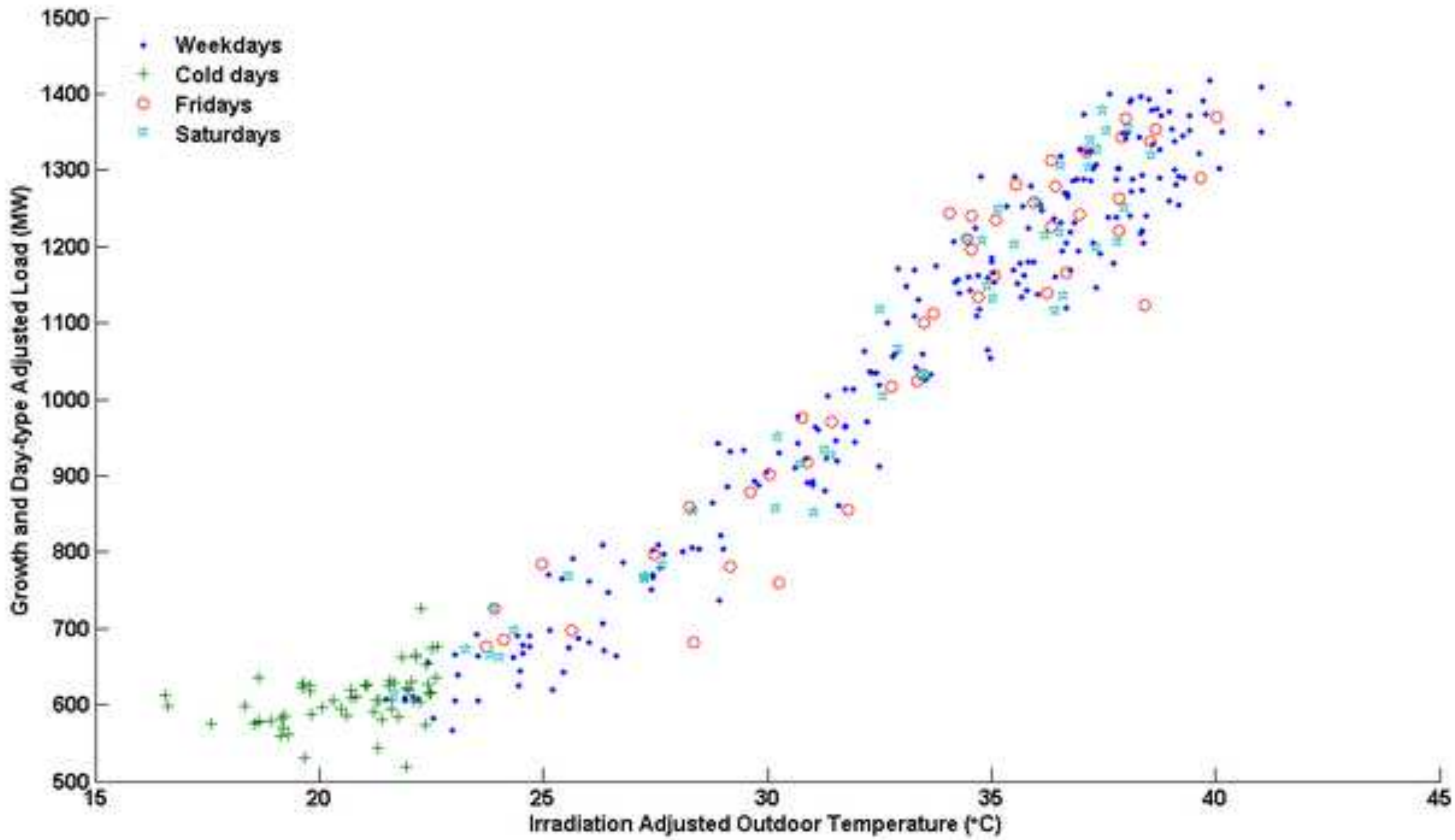

Figure
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