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Citation for published version:
Parkpoom, S & Harrison, G 2008, 'Analyzing the Impact of Climate Change on Future Electricity Demand in Thailand', *IEEE Transactions on Power Systems*, vol. 23, no. 3, pp. 1441-1448. https://doi.org/10.1109/TPWRS.2008.922254

Digital Object Identifier (DOI):
10.1109/TPWRS.2008.922254

Published In:
IEEE Transactions on Power Systems

Analyzing the Impact of Climate Change on Future Electricity Demand in Thailand

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***Abstract*—The rise in temperatures induced by climate change may have important implications for Thailand's electricity demand. This paper investigates how changing climate will affect Thailand's daily, seasonal and long term electricity demand. Regression models are applied to capture daily load patterns across each month in the year. Temperature projections from the UK Hadley Centre climate model are then used to assess hourly sensitivity to changes in mean temperatures and diurnal temperature range. These are combined with four representative socio-economic scenarios from the Intergovernmental Panel on Climate Change Special Report on Emission Scenarios to project absolute changes in Thailand's electricity demand. The specific climate and socio-economic scenarios considered here indicate that mean annual temperatures in Thailand will rise by 1.74 to 3.43°C by 2080, implying increases in Thai peak electricity demand of 1.5–3.1% in the 2020s, 3.7–8.3% in the 2050s and 6.6–15.3% in the 2080s.**

***Index Terms*—Climate change, electricity demand, load forecasting, Thailand.**

I. INTRODUCTION

CLIMATE change is increasingly of popular and political concern. Growth in population and living standards is leading to increases in power consumption, transportation, and building construction which, in turn, are increasing emissions of carbon dioxide and other greenhouse gases (GHGs). The best estimates from the Intergovernmental Panel on Climate Change (IPCC) indicate an average global surface temperature rise of between 1.8 and 4.0°C by the end of the century [1].

Temperature has long been considered as a factor that drives electricity demand in the short term and a large body of literature is devoted to analysis of these effects and their use in forecasting demand. It is less well-known that temperature will increasingly become a driver in long-term demand as well as impacting much of the rest of the electricity industry including generation, transmission and distribution [2]. However, an increasing body of work is defining the potential changes.

Climate change is expected to lead to changes in ambient temperature, wind speed, humidity, precipitation and cloud cover. As electricity demand is closely influenced by these climatic variables, there is likely to be an impact on demand patterns. The potential impact of future changes in climate on electricity demand can be seen on a daily and seasonal basis through the fluctuation of weather patterns. The magnitude of the impact will depend on prevailing patterns of electricity use as well as long-term socio-economic trends. As developing countries improve their standard of living, their use of air conditioning and other weather-dependent consumption may increase their sensitivity to climate change.

The climate variables influence the requirement for air-conditioning and space heating as well as refrigeration and water pumping loads. Rising temperature will tend to reduce space heating demand whilst increasing cooling requirements. The impact on peak loading is particularly important, since occasions of extreme temperatures are likely to stress electricity systems in meeting demand. The 2003 heat wave in France was a good example where blackouts were threatened as soaring temperatures greatly increased air-conditioning at the very time that nuclear power station output was restricted by cooling limitations.

The work by Linder *et al.* [3] for the USA suggests climate change will drive extra demand of around 14 to 23% between 2010 and 2055. More recent analysis for Maryland, USA, suggests that residential summer electricity demand may increase by 24% by 2025 [4]. Mirasgedis *et al*. [5] found that for Greece, average annual demand would increase by around 3.6 to 5.5% by the 2080s although summer demand would increase by 13%. In Israel, it is estimated that an increase in temperature of 4°C would drive a 10% increase in summer peak demand [6].

Several studies have inferred demand impacts using changes in heating or cooling degree days (HDD and CDD, respectively). These are common in demand modeling, e.g., [7]-[8], as they account for human comfort by defining thresholds beyond which heating or cooling is required. Based on these, heating demand in Finland would reduce by 4% by 2020 and 14% by 2050 [9]. By 2030, cooling demand in Greece could increase by 15–28% while heating demand would fall by 5–10% [10]. Regional climate modeling of the UK [11] suggests significant changes in HDD and CDD although these were not translated into energy changes: warming would lower HDDs by up to 15% by the 2020s and 15–45% by the 2080s; and larger increases in cooling by 2080 with CDD in southern England increasing by 30–90% and doubling in colder Scotland.

As identified by Moreno and Skea [12] the literature mainly

Manuscript submitted May 19, 2007; revised September 13, 2007. This work was funded by a PhD scholarship awarded by the Energy Policy and Planning Office, Thailand. The authors are with the Institute for Energy Systems, Joint Research Institute for Energy, School of Engineering & Electronics, University of Edinburgh, Edinburgh EH9 3JL, UK, (emails: Gareth.Harrison@ed.ac.uk, S.Parkpoom@ed.ac.uk,).

relates to impacts in developed rather than developing nations. This paper begins to correct that by examining the potential changes in Thailand's electricity demand under a range of potential climate change scenarios within the broader context of economic growth and population changes.

The paper is set out as follows. Section II provides a background to electricity use in Thailand, while Section III introduces a modeling methodology that allows the identification of the sensitivity of electricity demand to climate. Sections IV and V extend the method to provide robust estimates of changes in demand using socio-economic and climate model projections.

II. Electricity Demand in Thailand

The growth of electricity demand in Thailand is strongly influenced by the rapid increase in population and living standards (as measured by per capita Gross Domestic Product, GDP). Recent data indicates that electricity consumption in Thailand is rising at around 4.5%/year and this is forecast to continue into the medium term with annual increases of 4–7.5% up to 2016 [13]. It is anticipated that this and longer-term growth will be affected by the changes in weather patterns brought by climate change.

Thailand has a hot, humid climate with the 1996-2004 mean temperature being 31°C within an annual range of 22°C to 39°C. Electricity demand is much influenced by this variation with peak demand in summer 2004 exceeding the winter peak by around 4500 MW or around 32% of system peak demand [13]. The seasonality can be seen clearly in Fig. 1 which shows the daily consumption pattern in the three seasons: winter, summer and monsoon. The load pattern broadly reflects the daily temperature profile, which shows demand starting to increase around 8am up to the peak around 2pm before falling back and then picking up again in the evening. With a hot, humid climate, these differences reflect the hotter summer temperatures that lead people to spend more time indoors increasing in-house demand for air-conditioning and refrigeration.

III. Using Climate Variables to Project Demand

A. Modeling considerations

There are a range of considerations in developing an approach to estimate the influence of changing climate on electricity demand: which effects to consider, the degree of sectoral, spatial and temporal detail required and the climate variables of interest.

Given existing high temperatures in Thailand there is limited space heating requirement, particularly not in the Bangkok metropolitan area; this allows assessment to be restricted to cooling effects alone. The choice of which climate variables to apply depends on their relative influence: temperature is widely identified as the major factor [14]-[15] with other variables, e.g., humidity, having less effect [16]-[17].

Bottom-up demand models for each sector (e.g., domestic) require detailed meteorological, demographic and economic data as well as load characteristics like building construction, air-conditioning take-up, etc. As this information was not readily available for Thailand, top-down models such as regression models [3], [15] and neural networks [16] were investigated to empirically relate climate and demand. The use of a less-sophisticated top-down method is not believed to be a major shortcoming in an initial study, as Linder *et al.* [3] found that a regression-based model and a complex sectoral planning model gave comparable results.

The spatial detail required depends on the degree of homogeneity in the power system and availability of climate and demand data. Hourly meteorological data was available for Bangkok but coverage was limited elsewhere. Hourly aggregate system demand data was provided by the Electricity Generating Authority of Thailand (EGAT). With around 70% of Thailand's demand concentrated in the Bangkok metropolitan area, the hourly datasets were considered to be reasonably representative of the system as a whole.

The aim in this study was to provide as much temporal detail as possible to capture the effect of mean temperature changes and changes in diurnal temperature range (DTR, the difference between daily maximum and minimum temperature) in order to analyse changes in daily load profiles and particularly the relative response of peak and off-peak demand to temperature changes. Analysis of degree days could not provide this level of detail but the hourly weather and demand data available did allow such an assessment.

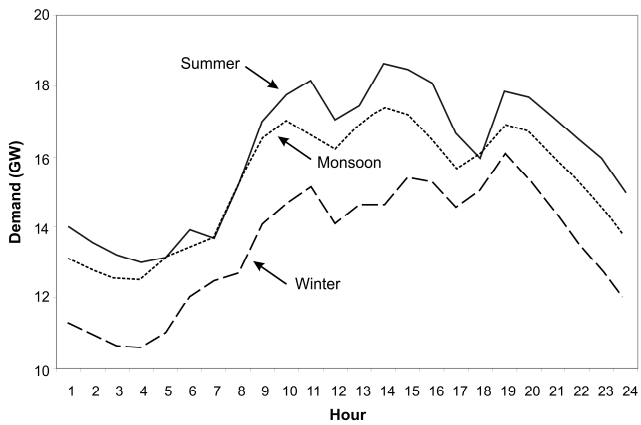

Fig. 1. Daily demand profiles in Thailand for 2004 [13]

B. Defining a Temperature-Demand Relationship

While neural networks can capture complex relationships, they require significant data volumes for training purposes, and the hidden nature of their relationships did not fit with the authors' desire to be able to 'see' the detail in order to interpret it. As such, a simpler regression approach was adopted. Broadly similar to that reported by Linder *et al.* [3] it uses regression models to link demand with temperature on a time-of-day and monthly basis. In making projections with such a model, there is an implicit assumption that the time-of-day relationships hold over time.

TABLE I: SAMPLE BI-HOURLY REGRESSION COEFFICIENTS AND PERFORMANCE BY SEASON FOR WEEKDAYS

Hour	Winter (January)			Summer (April)			Monsoon (July)		
	β_{CDH}	R^2	MAPE (%)	β_{CDH}	R^2	MAPE (%)	β_{CDH}	R^2	MAPE (%)
00-01	330	0.40	1.11	564	0.76	1.62	325	0.97	1.17
02-03	317	0.60	1.04	540	0.75	1.62	340	0.75	1.13
04-05	332	0.70	1.00	472	0.71	1.67	336	0.65	1.41
06-07	434	0.89	0.62	604	0.61	1.52	303	0.75	0.71
08-09	545	0.51	1.56	618	0.66	0.87	360	0.85	0.41
10-11	553	0.50	1.75	600	0.85	0.65	468	0.9	0.43
12-13	595	0.30	1.96	730	0.88	0.61	442	0.91	0.34
14-15	680	0.50	2.06	592	0.87	0.45	469	0.89	0.39
16-17	625	0.70	1.54	467	0.95	0.22	335	0.8	0.45
18-19	400	0.45	0.91	483	0.78	0.65	300	0.81	0.36
20-21	440	0.67	1.48	441	0.74	0.98	422	0.74	0.58
22-23	390	0.72	1.76	440	0.7	1.49	350	0.61	1.00

Following extensive assessment of weather variables and time-step combinations, temperature was found to be the most significant weather variable affecting Thai electricity demand. The most consistent and high quality regressions were based on Cooling Degree Hours (CDH), a short-term version of CDD, defined by:

$$CDH(T_h) = \begin{cases} \sum_{h=1}^{N}(T_h - T_b) & \text{for } T \geq T_b \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

Here N is the number of hours in the period of interest, T is the air temperature and T_b is the cooling threshold temperature, commonly taken to be 24°C in Thailand. To explore the impact of temperature on the daily load profile, one regression was performed for each hourly time-slice, e.g., 5–6pm in each month, of the form:

$$D = \beta_1 + \beta_{CDH}(CDH) + \varepsilon \quad (2)$$

Here D is the hourly electricity demand, β_1 is the intercept of the regression line on the demand axis, β_{CDH} is the gradient indicating the sensitivity of demand to cooling degree hours (in MW per CDH) and ε the random error.

From hourly temperatures and demand data for 2004, regressions were created for each hour in each month for weekdays, weekends and holiday periods (non-weekday regressions are inevitably less reliable due to lower sample sizes). Due to space limitations it is practical to present only a representative subset of the results: for weekdays in January (representing winter), April (summer) and July (Monsoon). Fig. 2 shows that the models provide a visually accurate representation of actual demand patterns across the seasons. This is reflected in the sample bi-hourly performance statistics in Table I. The full range of mean absolute percentage errors are 0.62–3.26% for January, 0.22–1.8% for April and 0.27–1.42% for July. January's R^2 values appear low as temperatures are often below the CDH threshold which results in demand variations being less well explained by CDH variations. Comparison with models based on data from earlier years indicated that they were consistent with the 2004 regressions. As such, the models were deemed to provide a defensible proxy for examining the relative sensitivity of each hour to changes in temperature.

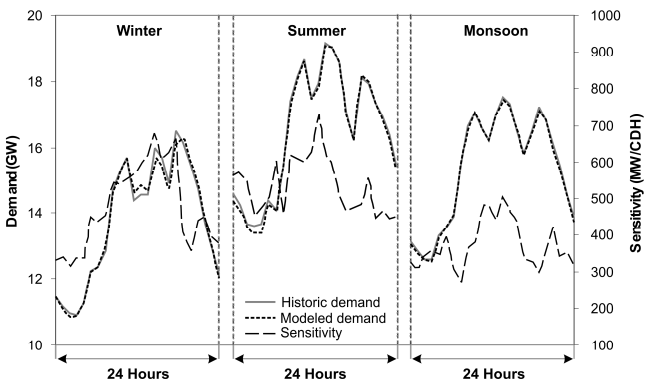

Fig. 2. Seasonal mean actual and estimated demand and demand sensitivity on weekdays during winter, summer and monsoon 2004.

C. Demand sensitivity

Fig. 2 and Table I also show the sensitivity of individual hourly demand (β_{CDH}) for each of the three seasons. It can be seen that the peak sensitivity tends to coincide with the peak demand. This is consistent with the higher temperatures during the working day when cooling of workplaces is needed, and during the evening when people return home and require cooling to reduce the heat accumulated during the day, particularly in summer. The coincidence implies that temperature rise from climate change will have a proportionally greater impact on peak demand levels.

The impact of uniform 1°C temperature changes on seasonal peak and mean demand is shown in Table II. As summer has the highest sensitivity coefficients it sees the largest increase in demand as temperature rises: a 1°C temperature increases raises peak and average demand by 4.6% and 3.8%, respectively, representing absolute increases of 810 MW and 577 MW at 2004 levels.

While the application of uniform warming across the year is useful in identifying the sensitivity of peak and average demand to temperature change, this is not a robust method for projecting realistic climate change impacts given that temperature changes will vary throughout the year and the diurnal temperature range will also alter.

TABLE II CHANGE IN PEAK AND MEAN DEMAND WITH 1°C UNIFORM TEMPERATURE RISE

Demand	Winter	Summer	Monsoon
Peak	4.2%	4.6%	2.8%
Mean	3.5%	3.8%	2.4%

IV. MODELING REALISTIC CHANGES IN DEMAND

As demand will rise in the future it is important from a system planning point of view to be able to relate potential demand changes to the generation and network capacity required. This requires potential changes in demand to be measured in absolute, i.e., MW terms rather than percentages. This in turn necessitates long-term demand forecasts to be made, typically from estimates of economic activity and population. To ensure that the climate-induced changes in demand are reasonable and defensible, any estimates of future demand levels must be consistent with future emissions levels by being based on the same socio-economic assumptions.

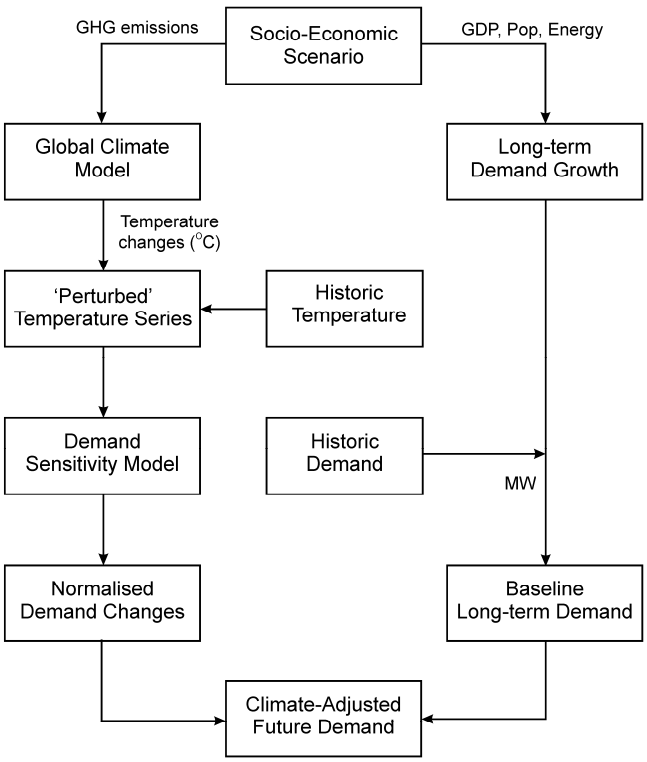

Fig. 3. Process for estimating future climate-induced demand changes.

With growth in both GHG emissions and electricity demand ultimately driven by the same socio-economic and technological patterns it was necessary to construct a series of linked components to capture these effects. As Fig. 3 shows, a scenario of economic growth and population gives rise to a particular pattern of GHG emissions. The emissions drive a climate model which provides estimates of changes in temperatures which are then added to the historic temperature series to create a scenario of future temperature. The demand sensitivity model developed in Section III then converts the temperatures into demand. The normalized changes (relative to historic demand) are converted into MW demand changes by projecting future demand levels from historic levels at growth rates derived from GDP and population scenarios. Each stage is outlined below.

A. *Long term socio-economic scenarios*

The IPCC Special Report on Emission Scenarios (SRES) [18] detailed a series of GHG emissions scenarios suitable for simulation in climate models as well as in impact assessments. The scenarios are based around four broad 'storylines' (referred to as A1, A2, B1 and B2) which describe the forces driving regional and global GHG emissions. The forces include demographic, social, economic, technological and environmental developments. The four storylines outline futures that are described in terms of economic or environmental values and being driven by increasing globalization or regionalization [18]:

- A1 is a future of strong economic growth, the introduction of efficient technologies and global population that peaks in the middle of the century.
- A2 is a regionally diverse world with increasing global population and regional economic growth.
- B1 is a world with the same global population as A1 but with rapid changes in economic structures and information and increasing resource-efficiency.
- B2 is a world in which the emphasis is on local solutions to sustainability, with continuously increasing population but at a lower rate than A2.

For each storyline, different scenarios were developed using six representative Economy-Energy-Environment (EEE) models. This was to capture the current range of uncertainties of future GHG emissions arising from different modeling approaches as well as those related to the driving forces [18]. A total of forty SRES scenarios were developed and each is regarded as equally valid. The results from the model runs are made available on the IPCC Data Distribution Centre (DDC) [19] website and consist of 10-yearly regional forecasts for population, GDP, energy use and production broken down by fuel, land-use and GHG emissions.

B. *Applying climate model temperature projections*

Temperature projections for future periods are determined from General Circulation Models (GCMs), complex numerical models of the atmosphere and oceans that provide information on a wide range of climate variables. The transient GCM simulations used in the SRES are driven by GHG concentrations that vary with time: observed concentrations were used for the period from 1860 to 1990 with increases thereafter up to 2100 as defined by the GHG emissions

scenario in question. To minimise the effect of bias within GCMs it has been common practice to use the 'perturbation' method rather than use GCM output directly. Perturbation adjusts historic values by the difference between GCM-modelled values for a future period and a baseline 'current' climate (typically 1961-1990). The future periods are 30 year averages corresponding to the 2020s (covering the years 2011-2040), the 2050s (2041-2070) and the 2080s (2071-2100). Each GCM has a different structure, spatial resolution and range of processes modeled; this gives rise to different climate outcomes although there is good agreement on temperature trends. The SRES therefore used several GCMs with the same GHG trends to capture the model variability.

Early impact studies made use of changes in mean temperature alone. However, to capture the potentially important changes in diurnal temperature range, the changes in mean ($\Delta TMEAN$), minimum ($\Delta TMIN$) and maximum ($\Delta TMAX$) temperatures are required (all are available from the IPCC DDC [19]). A method termed as 'morphing' was developed by Belcher *et al.* [20] to adjust historic temperature series by the amounts implied by the GCM. The simple process applies a vertical shift in the mean temperature as well as stretching the range of temperatures according to the change in DTR. For each hour, the temperature adjusted for climate change, T_{cc}, is given by [20]:

$$T_{cc} = T_{act} + \Delta TMEAN + \alpha(T_{act} - t_{mean}) \quad (3)$$

where T_{act} is the historic temperature in the base year and t_{mean} was the historic average daily temperature in each month. The scaling factor, α, provides the stretch required to capture changes in DTR:

$$\alpha = \frac{(\Delta TMAX - \Delta TMIN)}{(t_{max} - t_{min})} \quad (4)$$

where t_{max} and t_{min} are the historic mean monthly maximum and minimum temperatures, respectively (°C).

The altered temperature profile is applied to the demand sensitivity model to provide an estimate of demand levels at elevated temperatures. These are compared with the original modeled demand to indicate the normalized demand changes.

C. Long-term demand projections

The absolute changes in demand implied by climate change require realistic baseline estimates of future demand levels. As long-term demand growth is driven by GDP and population, a common approach has been to use regression models, e.g., [21]. A difficulty with such methods is that they do not explicitly consider structural/technical changes or economic factors (e.g., relative fuel prices) that influence choices. These effects are, however, accounted for in the EEE models used in the SRES. These provide energy consumption estimates for fuels including electricity (in EJ) at 10 year intervals making it possible to extract the growth rates consistent with GDP, population and GHG emissions, and to use them to inflate demand levels (MW). This requires assumptions on the relationship between average (energy) and peak demand; here a constant load factor has been assumed. The baseline demand is then combined with the normalized changes to estimate the absolute changes in demand implied by climate change.

V. Future Demand Changes in Thailand

A. Socio-economic changes

While it is beyond the scope of this paper to explore the full range of electricity demand outcomes implied by all SRES scenarios, a subset of them is used to illustrate potential changes. To ensure consistency between socio-economic assumptions between each storyline only one of the SRES EEE models has been applied here: the Asian Pacific Integrated Model (AIM) [22]. AIM is a large-scale simulation model for analyses of emissions and the impacts of global warming in the Asia-Pacific region. It provides global estimates with greater detail and emphasis for the Asian-Pacific zone. The model groups similar countries together whose development is assumed to progress at the same rate. As such, the growth rates applicable to the region containing Thailand should be applicable to Thailand itself.

The AIM results for four scenarios (A1, A2, B1 and B2) have been selected to cover the broad spread of socio-economic possibilities. Table III provides a sample of the socio-economic indicators and electricity growth rates for the decades prior to 2020, 2050 and 2080. It is apparent that there are significant differences in GDP and population growth rates throughout the century, particularly in later years. The divergence in scenarios means that while growth rates for electricity demand are broadly similar up to 2020 there are large changes towards 2050 and beyond. Applying the AIM growth rates to Thailand's peak electricity demand from 2004 onwards results in Fig. 4 where this divergence can be seen: the spread of values is around 9 GW in 2020, 70 GW in 2050 and 320 GW in 2080.

TABLE III: SAMPLE ANNUAL GROWTH PROJECTIONS [19]

Decade prior to	Indicator	AIM Scenario			
		A1	A2	B1	B2
2020	GDP	7.8	4.2	6.1	6.3
	Population	0.8	1.3	0.9	0.9
	Electricity	5.8	4.2	6.3	5.7
2050	GDP	4.5	1.7	4.3	3.1
	Population	0.1	0.5	−0.1	0.3
	Electricity	5.0	3.0	1.5	2.8
2080	GDP	2.4	4.2	2.0	1.6
	Population	−0.8	0.8	−0.7	0.1
	Electricity	2.3	1.5	−0.5	2.0

The AIM-based demand values were compared with two sets of growth forecasts based on multiple linear regression models. The first, a forecast to 2016 by the Thai utility EGAT [13] lies within the AIM results range (Fig. 4). A second model was constructed by the authors from recent historical demand, GDP and population data. When driven by the AIM GDP and population growth rates, there was good agreement for the A1 scenario but a poor fit with B2. This perhaps relates to recent growth better matching the economically-driven development of the A1 scenario rather than the ecologically-driven scenarios which imply major structural changes.

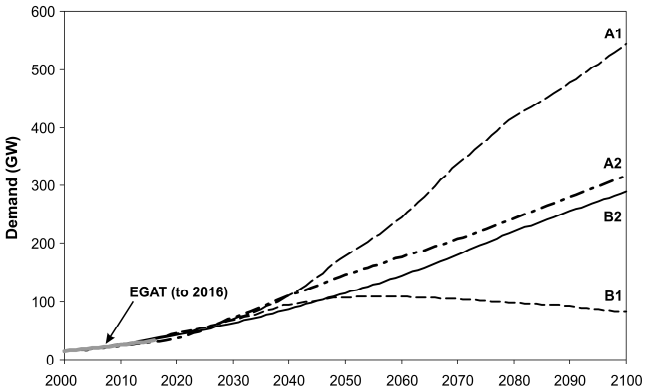

Fig. 4. Projected demand to 2100 for AIM and EGAT scenarios.

B. Temperature changes

To keep the presentation simple only the temperature projections from a single GCM are used here. The UK Met Office Hadley Centre HadCM3 GCM [23] has a spatial resolution of 2.5° latitude by 3.75° longitude. At this scale several grid squares cover or partially cover Thailand but only the cell covering the Bangkok metropolitan area has been selected. With demand and temperature data also based on this area this level of resolution is reasonable and avoids the need to 'downscale' the data to a higher resolution. Table IV shows the projected changes in mean, maximum and minimum annual temperatures for the four scenarios for the 2020s, 2050s and 2080s. It can be seen that mean annual temperatures rise by up to 1.74−3.43°C in 2080. The temperature rise reflects the development scenario, with the higher emissions A1 scenario warming more than the 'greener' scenarios. It is also clear in most cases, that the diurnal temperature range is projected to increase as rises in maximum temperatures outstrip changes in the minimum. Although not shown, winter tends to warm more than summer, reducing overall seasonal differences.

C. Demand changes

The historic temperature series were 'morphed' using the Hadley Centre projections and applied to the demand sensitivity model. The resulting changes in seasonal peak and mean demand are shown in Table V. Despite greater warming in winter than summer, summer demand increases are the most significant across all emissions scenarios and time periods. Summer peak demand rises more than mean demand as summer afternoons possess the highest demand sensitivity coefficients. This results in significant changes in summer peak demand of 1.5 to 3.1% in the 2020s, 3.7 to 8.3% in the 2050s and 6.6 to 15.3% in the 2080s. Fig. 5 shows the normalized demand profiles for summer for each scenario. The greater change in mid-afternoon demand can be seen clearly, particularly in the 2080s. The monsoon sees a similar pattern of change albeit smaller in magnitude, while in winter, mean demand rises more than peak for most scenarios.

Absolute changes in demand in each time slice were estimated by multiplying the long-term demand by the percentage change in demand (Table V). Table VI shows the resulting changes in peak summer demand. It is apparent that there are similar, modest, increases in peak demand across the 2020s scenarios. By the 2080s, however, the range of potential

TABLE IV: AVERAGE ANNUAL CHANGES IN MEAN, MAXIMUM AND MINIMUM TEMPERATURES FROM HADLEY CENTRE GCM.

Scenario	Variable	Temperature rise from present (°C)		
		2020s	2050s	2080s
A1	Mean	0.62	1.93	3.43
	Max	0.67	1.78	3.62
	Min	0.66	1.88	3.50
A2	Mean	0.62	1.37	2.87
	Max	0.49	1.41	2.88
	Min	0.46	1.47	2.89
B1	Mean	0.62	1.18	1.74
	Max	0.49	1.22	1.78
	Min	0.46	1.27	1.67
B2	Mean	0.62	1.18	1.93
	Max	0.67	1.22	1.96
	Min	0.66	1.06	1.88

TABLE V: CHANGE IN SEASONAL PEAK AND MEAN DEMAND FOR EACH SCENARIO

Period and Demand		**Winter**				**Summer**				**Monsoon**			
		A1	**A2**	**B1**	**B2**	**A1**	**A2**	**B1**	**B2**	**A1**	**A2**	**B1**	**B2**
2020s	Peak	1.8%	1.2%	1.6%	1.0%	3.1%	1.5%	1.8%	2.0%	1.6%	1.6%	1.2%	1.6%
	Mean	1.9%	1.3%	1.5%	1.0%	2.1%	0.9%	1.6%	2.1%	1.5%	1.5%	1.1%	1.5%
2050s	Peak	3.7%	2.9%	3.2%	2.0%	8.3%	4.0%	4.2%	3.7%	4.7%	3.7%	2.8%	3.6%
	Mean	4.0%	3.1%	3.1%	2.2%	6.5%	3.0%	3.6%	3.4%	3.8%	3.3%	2.6%	2.9%
2080s	Peak	6.8%	5.6%	3.7%	3.3%	15.3%	12.2%	8.1%	6.6%	7.9%	6.5%	3.4%	5.1%
	Mean	7.3%	6.2%	3.6%	4.0%	12.1%	9.6%	6.6%	5.3%	7.0%	6.1%	3.1%	4.2%

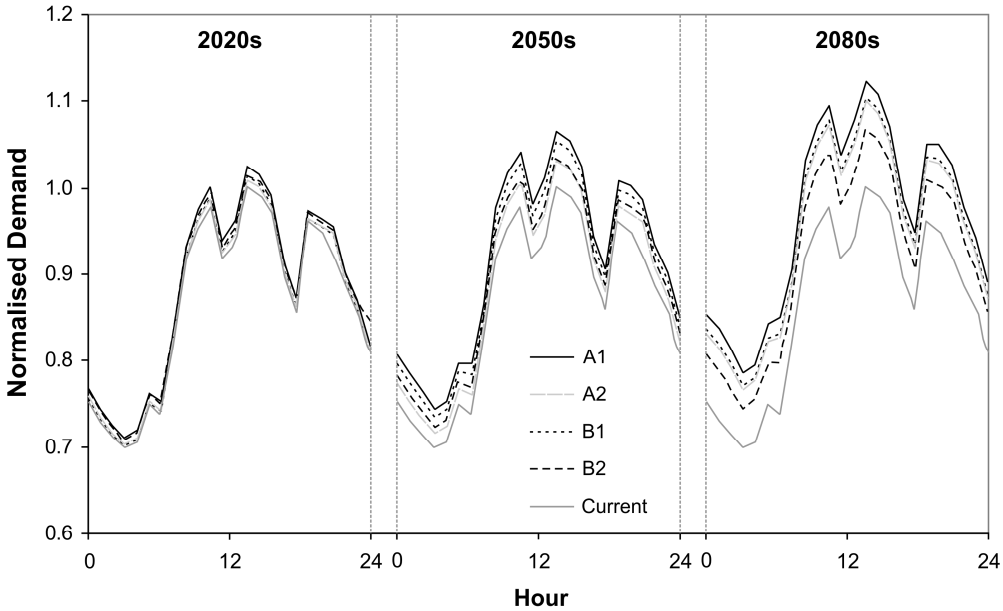

Fig. 5. Normalized demand profiles for 'current' climate (2004) and the four SRES scenarios.

changes is very large indeed (over 55 GW) while the 2050s see a large but less extreme spread. The larger spread arises from the divergence in both baseline demand and normalized demand changes.

TABLE VI: ABSOLUTE CHANGES IN SUMMER PEAK DEMAND (GW)

Period	A1	A2	B1	B2
2020	1.4	0.6	0.8	0.7
2050	14.8	5.8	4.9	2.6
2080	64.0	29.5	7.9	8.5

VI. DISCUSSION

This work represents a first step in exploring the potential impacts of climate change on Thailand's electricity sector. It has followed best practice in using multiple socio-economic scenarios to explore the potential range of future demand as driven by population change, increasing standards of living and the effect of increasing GHG emissions.

The approach allowed daily and seasonal demand profiles to be examined. The key result is that the highest changes in temperatures occur in summer which coincides with the peak demand and temperature sensitivity. The potential changes in demand are significant across all time periods and scenarios, with even the more modest increases for the 2020s representing significant investment in additional peaking and base load plant and/or transmission capacity. It is apparent that the Thai utility EGAT needs to incorporate such climate change effects within its load forecasting and system planning regime.

The changes are broadly in line with other studies particularly that of Mirasgedis *et al.* [5] for Greece using a regression method driven by OECD socio-economic projections and a version of the HadCM3 model. They are less extreme than those of Ruth and Lin [4] for Maryland which probably reflects the fact that Thailand's climate is already hot and humid and not subject to the extremes of the US eastern seaboard.

It is important to emphasize that the demand changes suggested here are indications and should *not* be interpreted as forecasts for specific calendar years. The absolute changes in GW therefore illustrate the scale of possible change rather a forecast of the amount of extra generation or transmission capacity required.

The range of demand outcomes across the four scenarios applied here is large and serves to underline the significant uncertainty associated with such projections. Indeed, as only a single GCM and socio-economic model are used here, the expectation would be that the range of possible outcomes would be higher. However, it is not possible at this stage to estimate the level of uncertainty and further work is required.

The approach used a relatively simple regression model which was justified by the preliminary nature of the work, limitations on available data and the concentration of demand in the Bangkok area. However, there are several possible limitations. Firstly, the regressions are based on only a single year of data and a single variable; although the relationships were similar to recent years they do not capture the full range of climate or demand conditions. Secondly, no account has been made of the effect of changing rates (or saturation) in ownership in temperature-sensitive appliances like air conditioning; this risk is tempered as use of air conditioning is already extensive within urban and semi-urban areas. Finally, the demand projections assume that the load factor and demand patterns remain the same far into the future: they do not account for the effect of energy efficiency or micro-

generation employed to mitigate climate change which will not only significantly change demand profiles but also affect the response of demand to rising temperatures.

Overall, the paper demonstrates the assessment method and, in doing so, shows the scope for climate change to significantly raise Thailand's electricity demand. The magnitude of the changes necessitate that more detailed work should follow, incorporating modeling of building stock response to changing conditions alongside demographics and greater spatial detail.

VII. Conclusions

This paper examined the implications for Thailand's electricity demand that may arise from changes in temperature driven by climate change. Regression models were applied to capture daily load patterns across each month in the year. Four representative socio-economic scenarios from the IPCC Special Report on Emission Scenarios were used to estimate future demand. These were combined with the corresponding temperature projections from the UK Hadley Centre climate model to assess hourly demand response to changes in mean temperature and diurnal temperature range. The specific climate and socio-economic scenarios considered here project that mean annual temperatures in Thailand will rise by 1.74 to 3.43°C by 2080 and, in doing so, will significantly increase Thailand's peak electricity demand: by 1.5–3.1% in 2020, 3.7–8.3% in 2050 and 6.6–15.3% in 2080. It is apparent that the Thai utility needs to incorporate climate change effects within its load forecasting and system planning regime.

VIII. Acknowledgement

The authors wish to thank the Energy Policy and Planning Office and the Electricity Generating Authority of Thailand for providing data on electricity demand. The authors acknowledge the support of the Scottish Funding Council for the Joint Research Institute with Heriot-Watt University as part of the Edinburgh Research Partnership.

References

[1] Intergovernmental Panel on Climate Change (IPCC), *Climate Change 2007 The Physical Science Basis - Summary for Policymakers*, Cambridge, UK: Cambridge University Press, 2007.

[2] F. Stern, "Energy", in *Handbook on Methods for Climate Change Impact Assessment and Adaptation Strategies*, J. F. Feenstra, L. Burton, J. B. Smith, and R. S. J. Tol, Eds., Nairobi and Amsterdam: UNEP and Institute for Environmental Studies/Vrije Universiteit, 1998.

[3] K. P. Linder, "National impacts of climate change on electric utilities", in: *The Potential Effects of Global Warming on the United States*, J. B. Smith and D. A. Tirpak, Eds., Washington, D.C.: Environmental Protection Agency, 1990.

[4] M. Ruth and A.-C. Lin, "Regional energy demand and adaptations to climate change: Methodology and application to the state of Maryland, USA", *Energy Policy*, vol. 34, pp. 2820–2833, 2006.

[5] S. Mirasgedis, Y. Sarafidis, E. Georgopoulou, V. Kotroni, K. Lagouvardos and D.P. Lala, "Modeling framework for estimating impacts of climate change on electricity demand at regional level: Case of Greece", *Energy Conversion and Management*, vol. 48, pp. 1737–1750, 2007.

[6] M. Segal, H. Shafir, M. Mandel, P. Alpert and Y. Balmor, "Climatic-related evaluations of the summer peak-hours' electric load in Israel", *J. Applied Meteorology*, vol. 31, no. 12, pp. 1492–1498, 1992.

[7] A. Satman and N. Yalcinkaya, "Heating and cooling degree hours for Turkey", *Energy*, vol. 24, no. 10, pp. 833-840, 1999.

[8] K. Papakostas and N. Kyriakis, "Heating and cooling degree hours for Athens and Thessaloniki, Greece", *Renewable Energy*, vol. 30, no. 12, pp. 1873-1880, 2005.

[9] A. Venäläinen, B. Tammelin, H. Tuomenvirta, K. Jylhä, J. Koskela, M. A. Turunen, B. Vehviläinen, J. Forsius and P. Järvinen, "The influence of climate change on energy production and heating energy demand in Finland", *Energy and Environment*, vol. 15, no. 1, pp. 93-109, 2004.

[10] C. Cartalis, A. Synodinou, M. Proedrou, A. Tsangrassoulis and M. Santamouris, "Modifications in energy demand in urban areas as a result of climate changes: An assessment for the southeast Mediterranean region", *Energy Conversion and Management*. Vol. 42, No. 14, pp. 1647-1656, Sept. 2001.

[11] M. Hulme, G.J. Jenkins, X. Lu, J.R. Turnpenny, T.D. Mitchell, R.G. Jones, J. Lowe, J.M. Murphy, D. Hassell, P. Boorman, R. McDonald and S. Hill, *Climate Change Scenarios for the United Kingdom: The UKCIP02 Scientific Report*, Norwich, UK: Tyndall Centre for Climate Change Research, 2002.

[12] R. A. Moreno and J. Skea, "Industry, Energy and Transportation: Impacts and Adaption", in *Climate Change 1995: Impacts, Adaptations and Mitigation of Climate Change: Scientific-Technical Analysis*, R. T. Watson, M. C. Zinyowera and R. H. Moss, Eds., New York: Cambridge University Press, 1996.

[13] EGAT, Power Development Plan 2004. Bangkok: Electricity Generating Authority of Thailand, 2004.

[14] H. M. Al-Hamadi and S. A. Soliman, "Long-term/mid-term electric load forecasting based on short-term correlation and annual growth", *Electric Power Systems Research*, vol. 74, no. 3, pp. 353-361, June 2005.

[15] C.-L. Hor, S. J. Watson and S. Majithia, "Analyzing the impact of weather variables on monthly electricity demand", *IEEE Trans. Power Syst*., vol. 20, no. 4, 2078 – 2085, Nov. 2005.

[16] X. Li and D.J. Sailor, "Electricity use sensitivity to climate and climate change", *Energy Planning and Policy*, vol. 7, no. 3, pp. 334-346, 1995.

[17] E. Valor, V. Meneu and V. Caselles, "Daily air temperature and electricity load in Spain", *J. Applied Meteorology*, vol. 40, no. 8, pp. 1413–1421, Aug. 2001.

[18] N. Nakicenovic, and R. Swart, Eds., *Special Report on Emissions Scenarios: A Special Report of Working Group III of the Intergovernmental Panel on Climate Change*, Cambridge, UK: Cambridge University Press, 2000.

[19] IPCC Data Distribution Centre, website at http://www.ipcc-data.org/. Accessed on 15/01/2007.

[20] S. E. Belcher, J. N. Hacker, D. S. Powell, "Constructing design weather data for future climates", *Building Services Engineering Research and Technology*, vol. 26, no. 1, pp. 49-61, Jan. 2005.

[21] Z. Mohamed, P. Bodger, "Forecasting electricity consumption in New Zealand using economic and demographic variables", *Energy*, vol. 30, no. 10, pp. 1833-1843, 2005.

[22] T. Morita, Y. Matsuoka, I. Penna, and M. Kainuma, *Global Carbon Dioxide Emission Scenarios and Their Basic Assumptions: 1994 Survey*, CGER-1011-94, Tsukuba, Japan: Center for Global Environmental Research, National Institute for Environmental Studies, 1994.

[23] C. Gordon, C. Cooper, C.A. Senior, H. Banks, J.M. Gregory, T.C. Johns, J.F.B. Mitchell and R.A. Wood, "The simulation of SST, sea ice extents and ocean heat transports in a version of the Hadley Centre coupled model without flux adjustments", *Climate Dynamics*, vol. 16, no. 2/3, pp. 147-168, 2000.

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