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CORRELATING PROBABILISTIC CLIMATE PROJECTIONS WITH COOLING DEMAND IN AN OFFICE BUILDING

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ABSTRACT

Given thousands of probabilistic climate projections available through *UK Climate Projections* (UKCP09), currently it is difficult to quantify the effect of climate change on the energy demand and operation of a building by means of dynamic building software packages such as ESP-r. This study offers a practically efficient technique to correlate these probabilistic climate projections with hourly cooling-demand profiles for a case study – a mechanically cooled office building.

A regression model has been developed and validated to examine, possibility of the cooling plant failing and influence of two simple adaptation techniques in the given building with projected future climate change.

INTRODUCTION

The effect of climate change on energy consumption has recently become an interesting research topic. To provide thermal comfort to occupants many commercial buildings operate some form of cooling system. In office buildings apart from the general lighting and other office machinery, cooling system consumes considerable amount of the electricity energy. Therefore, it is important to understand the effect of climate change on the cooling demand of a building.

Dynamic building simulation software packages such as ESP-r (Clarke, 2007) can simulate a given building to predict hourly profiles of cooling loads for a specified climate information (such as a future climate year of hourly data). However, it is challenging to incorporate probabilistic climate projections (UKCP09) (Murphy *et al.*, 2009) with any dynamic building energy simulators, designed to simulate one climate year in one simulation. Some previous studies exploit advanced computational techniques such as parallel grid computing processes to speed up multiple dynamic building simulations, given UKCP09 probabilistic climate projections (De Wilde, 2011; Tian 2011; De Wilde, 2012). They provide some quantification to the problem, with the amount of computational resources and time required to assess the impact of climate change on the thermal performance of the building found to be considerable. Therefore, it is essential to develop an efficient technique that could conveniently process these thousands of probabilistic climate years to emulate multiple cooling-demand profiles, corresponding to the given climate and building, as predicted by the building simulation software.

The aim of the paper is to present a brief description on the modelling procedure, including an intensive validation exercise, of a simple regression-based tool to predict hourly cooling demand profiles for a case study – a mechanically cooled office building located at a London location. The regression tool is shown to perform a systematic risk analysis of possible failure of the cooling plant in the given building with projected future climate change. Two simple adaptation techniques based on design and occupant behaviour have been examined in relation to this for reducing peak cooling demands and lowering the impact of rising temperature during the periods of occupation.

The results demonstrate the change in the cooling requirements for a future timeline of 2050s (2040 - 2060) in relation to the baseline (1960-1990) climate. The research presented in this article could be used to prepare future guidelines for designing adequately sized cooling plants that could effectively cope with future predicted climate conditions. For cooling plants that are still not oversized even for warmer future summers, there remains the issue of whether the energy consumption (and therefore carbon emissions) of the cooling plant is likely to increase substantially. The use of the regression tool for this type of question will also be discussed.

COOLING DEMAND IN OFFICE BUILDING

This section presents a brief description of the case study building and the processing of probabilistic climate information available from UKCP09 for building energy simulation.

Building Design

The simulation is based on an office building design used in previous projects by the authors (Jenkins *et al.*, 2008; Jenkins, 2009). A summary is given in Table 1, based on a 1980s office design (though more details can be found in the provided references).

Table 1

Summary of simulated office building

PARAMETERS		VALUE
Total height (m)		14.8
Length (m)		40
Breadth (m)		25
Number of occupants		286
Glazing ratio (% external wall)		40
U-values (W/m^2K)	Wall construction U-value	0.65
	Floor construction U-value	0.27
	Roof construction U-value	0.87
Glazing U-value		2.75
Infiltration rate (ac/h)		1
Ventilation rate (I/s/person)		10
Lighting efficacy (lm/W)		70

Due to their importance in producing buildings with high cooling loads, specific hourly internal heat gain profiles are used based on occupant, lighting and equipment schedules; the peak values of these are $5.4W/m^2$, $15.2W/m^2$ and $11.4W/m^2$ respectively, though they vary throughout the day (again, detailed in the aforementioned references).

Cooling systems are sized based on typical design guides (CIBSE, 2003). This method produces two 194kW chillers (based on a 12°C flow and 7°C return temperatures) for meeting the simulated cooling loads.

The simulated office building is assumed to remain occupied throughout the year from 9:00 to 19:00 during weekdays.

Dynamic Simulation

To produce hourly cooling loads, and to allow for detailed input variables (such as the internal heat gain profiles), dynamic simulation is a requirement of this work (as opposed to steady-state alternatives). Indeed, it could be argued that any overheating analysis should incorporate dynamic simulation and at a suitable temporal resolution, thus accounting for the thermal response of the building to dynamically changing external (climate) and internal (heat gain) variables. For this exercise, ESP-r, an open source model developed by University of Strathclyde, is used. However, the technique is also being applied to commercial building models.

Two adaptations were also modelled; reduced internal gains (Adaptation 1) and external shading (Adaptation 2 – applied cumulatively to Adaptation 1). These relate to "2030" adaptations that are detailed in the aforementioned publications.

Location and Climate Information (UKCP09)

The building is assumed to be within a city centre location, with London being the default climate (though subsequent work is situating the building in Edinburgh as well). The simulation assumes neighbouring buildings of similar size, which will affect the solar radiation that is incident on the office.

Building simulation software generally requires climate information in the form of a climate year and at an hourly scale. UK climate projections (UKCP09) can be accessed through a "Weather Generator" (WG) (Jones *et al.*, 2009) tool at an hourly temporal resolution. WG provides climate information for seven overlapping future timelines of 30 years ("2020s" denoting 2010 - 2039, "2030s", …, "2080s") covering a period from 2010 – 2099, at three possible carbon emission scenarios, namely "Low", "Medium" and "High". For a specific UK location and a specific future climate scenario (e.g. 2050s at Medium emission scenario) WG produces at least 3000 equally probable hourly climate year files in the form of 100 statistically equivalent time series, each of 30 years in length and equally probable .

It should be noted that these 100 time series are statistically stationary across 30 years, which means that the time series of 30 years of climate data will contain realistic day-to-day and year-to-year weather variability. However, over the longer term, this series will contain little variation in the statistical description of that variability e.g. mean, variance, and autocorrelation. Moreover, WG produces these 100 time-series by sampling 100 different points across the full UKCP09 probabilistic distribution. Thus to explore variation across the entire probability distribution it is essential to consider at least 100 of such time-series in any investigation.

To incorporate this complex climate information in the building simulations process, the first step is to create a representative sample of climate data by means of a random sampling algorithm, developed by "Low Carbon Future" (LCF) project details available elsewhere (Gul, 2012; Jenkins, 2011a; LCF, 2009; Patidar, 2011). This algorithm creates a representative sample of 100 climates years by selecting a climate year randomly from these 100 (30-year long) time series, downloaded from WG for a specified climate scenario. The weather variables generated at hourly scales are: total hourly precipitation (mm), mean hourly temperature (^oC), vapour pressure (hPA), relative humidity (%), sunshine fraction of an hour, downward diffuse radiation and direct radiation (both W/m2).

The random sampling technique is free from selection bias as each of the 30 climate years in each of these 100 time series is equally likely to be selected. Thus, the random sampling algorithm has been designed to generate a well-representative sample where one climate from each of the 100 time series has been included. Furthermore, it has been found that various statistics used to measure building thermal performance for a sample of 100 representative climate years are in good match with those obtained by using the entire suite of 3000 climates years (Patidar, 2011).

For the work presented in this paper a representative sample of 100 climate years have been produced for a baseline and 2050s medium emission scenario.

REGRESSION MODEL FOR COOLING LOADS

This section describes the model development procedure for emulating hourly cooling loads, as simulated by ESP-r. The proposed model is based on the idea of capturing dynamic behaviour of the cooling system installed in the building in relation to the outdoor climate conditions. To formulate a linear relationship between the hourly cooling profiles and corresponding hourly climate information we adopted multiple regression technique. The regression model has been fitted by "R" software environment (R, 2010). The steps involved in calibrating the tool for generating hourly cooling load profiles are summarized in the next subsection.

Modelling Procedure

To fit the regression model for estimating cooling load profiles, the first step is to select a single climate randomly from the sample of 100 representative years. The one used here is from the sample of London 2030s medium emission scenario. Following the methodology developed by the LCF project, the regression tool attempts to identify any possible relationship between the hourly ESP-r estimated cooling loads and climate information available at that time and for up to 72 hours previously. Including climatic information at previous hours allows the regression model to account for thermal mass and heat retention effects of the building. It should be noted that, each climate file provides hourly information for 7 different climate variables and thus to estimate the cooling load at any time (*t*), the potential regression model needs to include $7 \times 72 = 504$ input variables.

To reduce this large amount of input information the LCF methodology uses Principal Component Analysis (PCA) (described in next subsection) (Jolliffe, 1982). PCA applied to climatic data significantly reduces the number of hourly climate input variables from 504 to 33. Furthermore, it has been shown in previous studies (Jenkins *et al.*, 2011b) for modelling internal temperatures that, including information on hourly internal heat gain profiles for up to 7 previous hours can significantly enhance the efficiency of the regression model in estimating ESP-r outputs. In this specific case study of an office building, internal heat gains could have a substantial influence on internal temperatures and subsequently in cooling requirements. Therefore, for the proposed regression model we decided to include these 8 internal heat gain variables at time (*t*) and at 7 previous hours.

Finally, a multiple regression model has been fitted in three steps, as part of segmented modelling, to the hourly cooling load and a corresponding simplified set of these 33 climate variables plus 8 internal heat gain variables. The usage of a cooling system will vary significantly across different seasons and therefore segmented modelling has been preferred in this case. Three segments used to calibrate the regression model are January – April; May – August; and September – December. Notably, the regression model needs to be re-calibrated with updated cooling load profiles when any adaptations applied to the building.

Climate Data Processing with PCA

Models that require a large amount of input information are not convenient in application and are statistically less significant if input variables are correlated (Naes, 2001). PCA is a proven data processing technique and deemed suitable for this study. PCA transforms a number of possibly correlated variables into a smaller number of uncorrelated variables (or components), such that a smaller set of selected components can describe most of the variation in the original dataset.

We applied PCA to the given climate data in two simple steps:

1) Firstly, PCA is applied to 72 hours of dataset corresponding to each climate variable such that selected components corresponding to each variable retains at least 95% of total variation of the original data. This step reduces 504 total input variables into 148 total components, by exploiting the correlation within the 72 hours of dataset of each climate variable.
2) In the next step, keeping the external temperature variable apart, the rest of the climate variables are grouped into two categories reflecting moisture and solar aspects of climate. The first climate category includes precipitation, vapour pressure and relative humidity, whereas sunlight fraction, downward radiation and diffused radiation form the other category. PCA applied to these two groups further reduces these 148 components, such that 99% of the total variation in these 148 components can be described by a selection of only 33 sub-components (Patidar *et al.*, 2011). This extra step of PCA is possible due to the correlation among different climate variables.

REGRESSION MODEL VALIDATION

This section describes the validation exercise carried out for the regression model, calibrated separately for "No Adaptation", "Adaptation 1", and "Adaptation 2", by following the above specified procedure. For an effective validation of the proposed regression models, hourly cooling load profiles generated by ESP-r and the regression tool have been compared for all 100 climates years corresponding to London baseline and 2050s medium emission scenario. Thus, in total, the validation exercise includes 600 ESP-r simulations of the case study building.

Residuals for Hourly Cooling Loads

To see how well the regression model for cooling load emulates hourly ESP-r outputs, we plotted discrete probability distribution and cumulative distribution plots of residuals – i.e. the difference between ESP-r and the regression tool estimations of hourly cooling loads [Figure 1]. The case study building remains occupied for 2849 hours in a year. Therefore, with each climate scenario represented by 100 climate years, 284,900 data points have been used to calculate these probabilities. Specifically, validation has been carried out for six sets of 284,900 hourly residual values, corresponding to two climate scenarios (baseline and 2050s medium emission scenario) and three adaptation choices.

Figure 1 shows the regression model estimating more than 95% of the hourly cooling loads with residuals within the range of 20 kW when compared to ESP-r. Furthermore, 75% of estimated values of cooling loads are found to have residuals of less than 10 kW. Another interesting thing to notice is the trends of the residual distribution plots. These distribution plots for residuals appear to follow a similar kind of trend across all six different scenarios, though a systematic transitional variation in the probabilities can be noted for the baseline and the 2050s scenario. The model appears to perform a little better for the baseline climate than for the 2050s. Moreover, it is interesting to notice that the performance of the regression model for adaptations 1 and 2 are similar, performing slightly better in comparison to the model without any adaptation.

Next section presents an analysis of the distribution of residuals across different ranges of cooling loads.

Residuals for Specified Range of Cooling Loads

To investigate distribution of residuals in relation to the specified range of estimated values of cooling loads, hourly residual values of 100 climate years were analyzed corresponding to London baseline and no adaption scenarios. Cooling loads were divided into four ranges, [0 to -50kW], [-50 to -100kW], [-100 to -150kW] and (over -150kW). As is often the convention, cooling loads are denoted with a minus sign (to distinguish them from heating loads). 58.2% of the entire dataset of estimated cooling load lies in the range of [0 to -50kW], 24.4% in the range of [-50 to -100kW], 15.7% in the range of [-100, -150kW] and 1.7% in the range of (over -150). Thus, more than 80% of hourly cooling loads never exceed -100 kW in set of 100 representative climates years.

Discrete cumulative probabilities for the residuals were then compared, corresponding to the four different ranges of cooling loads [Figure 2]. These graphs demonstrated a reasonable performance of the regression model. Cumulative probabilities for residuals are consistently large for higher cooling load ranges, except for [0 to -50kW], which means that the model is estimating high values of cooling loads with more accuracy. One possible reason to this is the use of the segmented modelling approach, which fits regression model separately to three parts of the data: segment 1 to (January - April), segment 2 to (May - August), and segment 3 to (September - December). In UK cooling systems are mainly used in the summer periods and therefore most of the observed higher values of cooling loads are within segment 2. It is possible that the accuracy of the regression model is slightly biased towards this period of data, as there are longer periods of cooling and therefore more data to calibrate the regression equation.

Beside this, in Figure 2, it can be noted that, for residuals of value less than 5 kW cumulative probabilities associated with [0 to -50 kW] range of cooling loads are highest than all other cooling load. This could possibly due to a large number of zero values in the range [0 to -50 kW]. For these zero values of cooling loads, the regression model could be estimating some small non-zero values of cooling load, and thus slightly biasing the resultant values of the cumulative probabilities for these smaller values of residuals. It should be noted that this is just a mere observation and to make any specific claims values around zero cooling load should be carefully analyzed.

However, the intensive validation procedure presented here clearly justifies the potential of the regression model in estimating a wide range of cooling loads with reasonable efficiency, including the values in extreme ranges. Thus, for this particular building, it is justifiable to adopt the proposed regression model as an alternative to multiple building energy simulator.

REGRESSION MODEL FOR RISK ANALSIS: COOLING PLANT FAILURE

This section presents an application of the regression model in performing a risk analysis of the cooling plant failure in the case study building for future (2050s), in relation to the baseline, climate. The regression model for adaptation 1 and 2 has been used to examine the effectiveness of proposed adaptation techniques in reducing peak cooling demands.

Summary Statistics for Cooling Loads

In statistics, it is common to use a collection of five summary statistics to describe a large amount of information in a simple and efficient way. These five summary statistics are comprised of Minimum, 1st Quartile, Median, 3rd Quartile and Maximum. For estimated cooling loads, we measured five summary statistics for each climate year in a representative sample set of 100 climates years corresponding to the two climate scenarios (baseline and 2050s medium emission) and the three adaptation choices. In this way, we get a set of 100 possible values for each summary statistic, which are then averaged for ease of presentation [Figure 3].

Figure 3 illustrates the variation in these five averaged summary statistics of estimated cooling loads in future 2050s medium emission scenario, in comparison to the baseline climate. This graph shows a substantial rise in cooling demand in 2050s; this rise in cooling demand can be reduced considerably by incorporating specified adaptation techniques in building designs and occupant behaviour. Peak cooling load (i.e. Maximum) could cross over 200 kW in 2050s, however, how frequently this could happen can be easily calculated and analysed for a specific threshold-based study. For example, if the size of chiller is known, the designer could check how often the required cooling load might exceed a safe limit (e.g. 90% of the rated size).

This type of information, estimating the size of cooling loads in different quartiles, could be related to the size of a cooling plant of an actual building. Even if the projected cooling loads are not expected to exceed the size of a plant, it would be of interest to a building services engineer if that plant has to meet higher cooling loads more frequently for a future climate scenario. This would be indicated by comparing the value of the upper quartile (i.e. loads above 75% of the maximum projected cooling load) of the baseline climate with the future climate. Further guidance could then be used to judge whether this projected change will be a problem for that cooling plant. The application of suggested adaptation techniques would therefore reduce the risk of failure of a cooling system and this could be quantified by the proposed regression tool.

CONCLUSION

This paper presents a systematic procedure for calibrating a simple and elegant regression model to effectively predict hourly cooling load profiles for a office case-study building, with probabilistic climate projections. Proposed regression model has been thoroughly validated at hourly scale for its potential in emulating multiple cooling demand profiles in match with one obtained by the application of ESP-r. The validation procedure uses hourly outputs of 600 ESP-r simulations to examine the suitability of the proposed regression tool as an alternative to dynamic building simulation software.

The regression model, formulated with a single run of ESP-r simulation, can simulate 1000s of climates in minutes, and therefore can be easily adopted for risk analyses of cooling systems failing, or in to investigate a rise in cooling demand for a given building in a future climate. Following the methodology, regression models for two adaptations techniques have been developed and analysed, however a range of adaptation behaviour can be modelled and examined in this way.

In summary, this work presents a simple application of LCF's regression tool (in this case emulating cooling loads), which aims to serve as a viable decision support tool for building design professionals. LCF's regression tool can perform a quick and reliable risk analysis of possible overheating or HVAC system failure for a given building design in future probabilistic climates. The tool has been designed to flexibly incorporate a range of adaptation models to examine any user-specified criteria of overheating or HVAC system.

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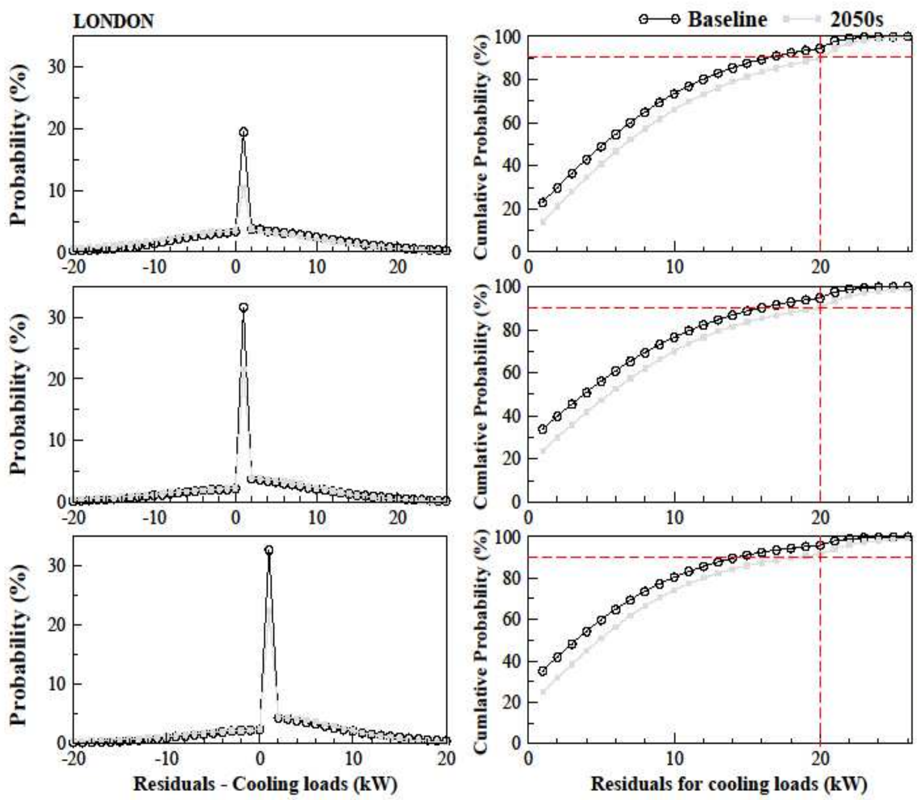

Figure 1 Probability density distribution and cumulative density distribution plots of residuals (difference of ESP-r and regression tool estimated cooling loads) for hourly data of 100 climate years corresponding to London baseline and 2050s (medium emission) climate scenario.

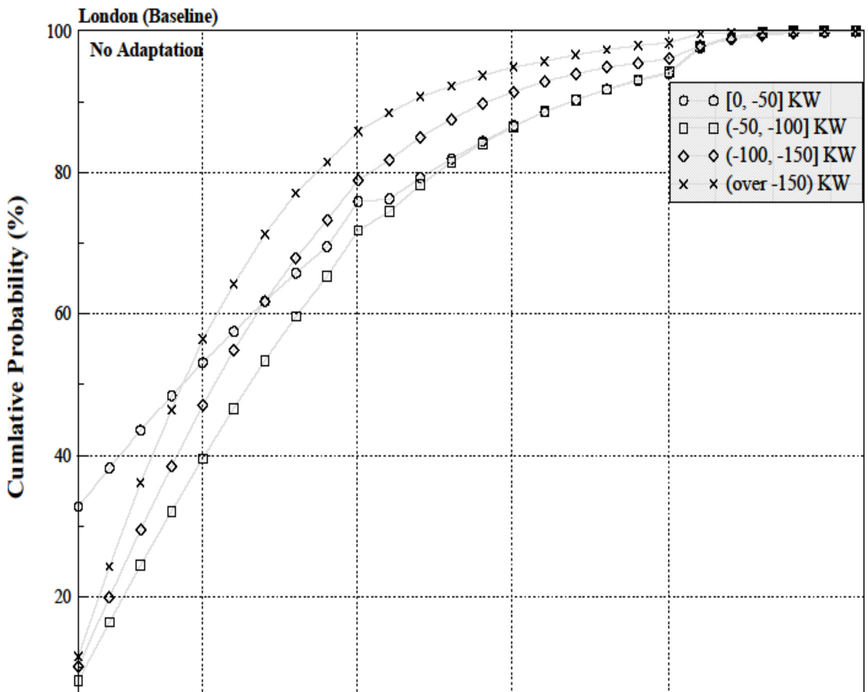

Figure 2 Cumulative density distribution plots of residuals (difference of ESP-r and regression tool estimated cooling loads) corresponding to <u>four specified ranges of cooling load</u> for London baseline climate.

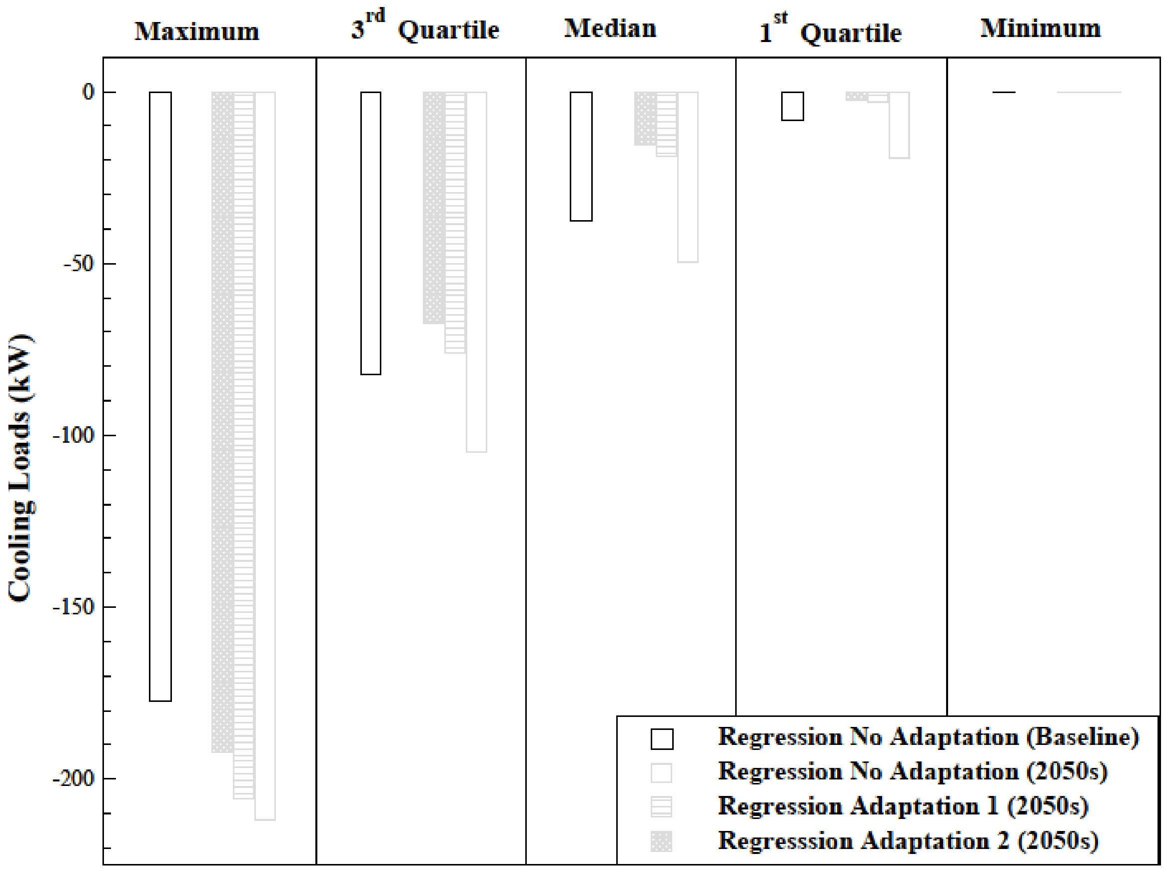

Figure 3 Comparing five summary statistics (averaged over 100 climate) as estimated by ESP-r and regression model for "no adaptation", "adaptation 1", and "adaptation 2", London baseline and 2050s (medium emission) climate scenario.