Domestic sector energy demand and prediction models for Punjab Pakistan

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Highlights:

- A unique insight into Punjab domestic energy demand based on 4597 physical surveys
- Average household domestic energy use is 2401kWh/a electricity and 5245 kWh/a gas
- Average per capita domestic energy use is 391 kWh/a electricity and 770 kWh/a gas
- Six well correlated domestic electrical demand prediction models
- Two domestic gas demand prediction models weakly correlated with a total floor area

Abstract:

The domestic sector consumes ~48% of Pakistan's total energy demand, including biofuels. Pakistan is an emerging economy with 210 million people and growing domestic energy demand, facing economic, geographic, geopolitical, and climate change challenges. This paper presents novel insights into the Punjab, Pakistan domestic sector energy demand, which accounts for over 52% of the Pakistan population, along with energy prediction models derived from a statistically significant 4597 responses obtained from a physical questionnaire survey conducted in 2017-18, which aimed at ascertaining the main domestic energy demand drivers. These models will support future government and energy industry policy in this area, especially the transition to a low carbon economy. Currently, 67% of Pakistan's energy demand is met with non-renewable resources. Analysis of the survey data reveals the key drivers of electrical energy demand **per household** are the number of appliances, number of lights, and the number of conditioned rooms. In the **per capita** models, the key drivers are the overall power rating of the appliances, particularly the power rating of the air conditioners for cooling. For annual gas use, weak correlations per household and capita were found only for the floor area. The average annual electricity and gas usages per household are 2401kWh/a and 5245 kWh/a respectively, and per capita are 391 kWh/a and 770 kWh/a. For electricity, the occupancy, floor area, conditioned rooms, appliances, lights and power rating have predictive power. For gas, only floor area is predictive.

Keywords: Pakistan, Punjab, emerging economies, domestic energy survey, energy demand drivers, energy models, domestic energy use

1 Introduction and theoretical approach

The reduction of carbon dioxide (CO_2) emissions as part of the mitigation of potential risk factors contributing to climate change have been a prime concern of policymakers over recent decades [1] [2] A significant reduction in global domestic energy demand related emissions is considered a key policy area to help achieve this goal [2]. However, the growth of the global digital economy, an increasing global population, and a demand for increased living standards generally are leading to increased global energy demand [3] [4] [5].

The Punjab region is the most populous in Pakistan with a growing population [6] of 110M out of a total population of 210M. It contains 17.1M households of Pakistan's 32.2M total [6]. The domestic sector in Pakistan is responsible for 48% of Pakistan's total energy consumption [7]. Approximately 67% of Pakistan's total energy use is from non-renewable resources; therefore addressing this consumption is a key task in the transition to a low carbon economy [6]. It makes it a good Case Study for assessing current and potential energy demands in emerging economies. This study undertakes this assessment by exploring demand drivers via a physical survey and using the findings to produce prediction models for domestic energy consumption.

There are many socioeconomic classes in Punjab society. Prior to this study, domestic energy demand was considered driven by the lifestyle and economic status of the house owners [8] [9] However, the correlations and relative influences of the drivers were not well understood, and there are no domestic energy consumption prediction models available based on a physical survey of the actual demand driver variables, related meta-data, and associated energy bills based on measured consumption. The predominant domestic fuels in Punjab are bio-fuel, electricity and gas.

Pakistan consumed 81.63Mtoe of total energy in 2016, of which 9.9% and 21.2% were provided by electricity and gas respectively [7]. The remaining 69% is provided by oil, coal, and biomass consumption [7]. Punjab's domestic sector respectively consumes 40% and 23% of the total electricity and gas consumed in the country, or around 9% of the total energy consumption [6]. This paper presents a detailed analysis of the domestic energy demand drivers in Punjab, from which energy consumption figures and prediction models are derived.

For reduce in carbon emissions from the domestic sector, it is necessary to understand the interaction of the factors which are responsible for each type of energy demand [10]. The theory behind the data to be collected to achieve this understanding is based on well-established building energy modelling principles [11] [12] which show that a building's services energy demand is mainly determined by fabric, area, location, and control. In contrast, occupant energy demand is considered [13] to be driven mainly by the number of occupants, activities undertaken in the building and economic strength. What is often unknown is how these parameters combine across given communities to create overall energy demand and consumption. This study fills that gap for Punjab. The theory leads to a holistic research approach based on a positivist paradigm for this work. The energy demand and consumption parameters which are addressed in the physical survey underpinning this paper are shown in Figure 1 and explained in 3.4.1

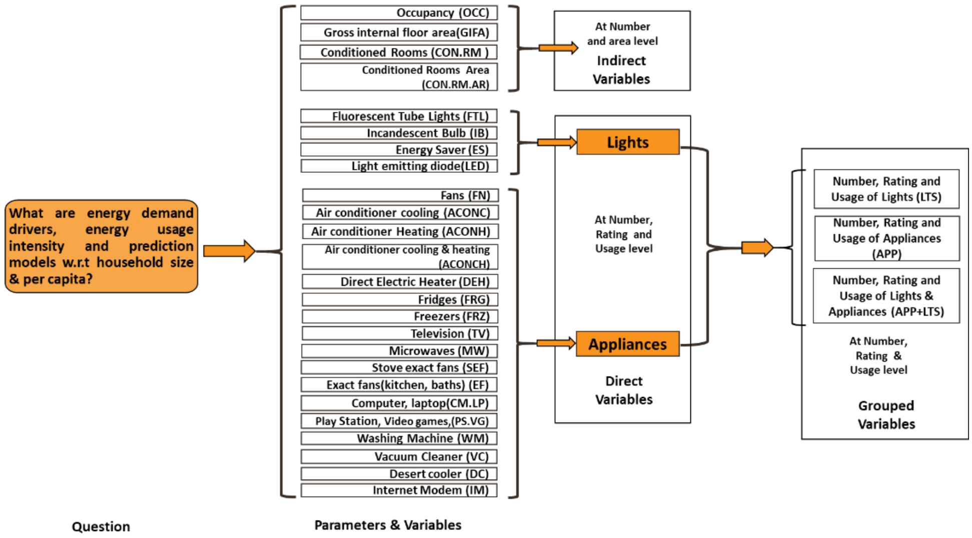

Figure 1 Domestic energy demand parameters plus variables covered in physical survey (and their acronyms, used in the paper)

This paper analyses the data collected from a large-scale survey of these variables and combines them with the recorded monthly and annual energy use at the individual dwelling level to produce models that clarify the drivers for current demand in Punjab. The variables obtained from the survey are further categorised into three groups, i.e. Indirect, direct, and grouped variables. These models enable the prediction of energy consumption based on the availability of data at different levels of granularity. The survey does not address building design or services efficiency, which are also known to have a significant impact on demand. The conclusions presented here relate only to the variables studied.

The survey data collected covered all 36 Districts, arranged in 10 divisions, in Punjab, and a population of 110M out of a total Pakistan population of 210M. While this scale of collection enables statistically significant findings to be produced at the individual division level, this paper only addresses the Punjab Province as a whole. The divisional data sets will be analysed in a forthcoming paper, where the impact on the conclusions from considering the data of individual divisions or districts will be presented. The questionnaire used for the survey is provided in appendix A. Note that the building floor area data are presented in SI. Units of m^2 rather than the more commonly used Pakistan's floor area unit of the Marla (1 Marla = 20.9m^2).

2 Demand factors and prediction modelling from Published work

2.1 Domestic energy demand factors

Identifying the domestic energy demand factors have been the subject of recent research [14] [15] [16]. They broadly fall into three main categories (i) socioeconomic factors, like the number of occupants, family composition, age group, employment status, education, and income level (ii) dwelling factors, like dwelling types and age, number of rooms, number of floors, floor area, HVAC system for cooling and heating, energy-efficient appliances, (iii) appliances factors, like appliances ownership, usage of appliances and power demand of appliances. In one study, four socioeconomic, seven dwelling and nine appliances related factors are identified which have a positive effect on electricity demand [10]. Some authors had reported occupants behaviour with domestic energy use, with a focus on four topics (i) understanding of occupant behaviour with a particular focus on window opening behaviour, lighting control behaviour and space heating/cooling behaviour (ii) methods and techniques for collecting data on behaviour and buildings energy performance (iii) evaluation of energy-saving potential and occupant behaviour (iv) quantitative building energy modelling and occupant behaviour [17] Occupant space conditioning behaviour is identified as a significant factor in cooling electricity energy demand [18], heating demand [19] and both demands [20]. Domestic space heating and consumer electronics are found to be the most influential factors of UK domestic energy demand [14] The literature relating to the impact on energy demand and consumption of the individual variables identified are discussed below:

Occupancy: Many researchers found a positive relationship [[21] [22] [23] [24] [25] [26] between occupancy level in a household and electricity consumption, i.e. increasing numbers of occupants leads to increased electricity usage [27] [28] [13] [29] [30] [31]. One study in Japan found electricity increases by 230kWh/annum for each additional person due to increased use of lighting and appliances [13]. However, research in India [32] found a negative relationship between household area and occupancy w.r.t electricity consumption, suggesting that houses with larger numbers of people had lower electricity consumption. Other research found no significant change in electricity consumption with the number of people living in the house [33] [34]. The conclusions from the literature are that relationships appear to be location-dependent and may vary with time too. It could be due to economic factors, but this has not been assessed in these studies.

Per capita relationship: Researchers have looked at the relationship between the size of household and per capita electricity use. A study in the UK [24] found a negative correlation between per capita electrical energy use and household area, suggesting that electricity use is a mix of demands independent and dependent on occupancy numbers. It means more efficient electricity use per capita in larger households. Similar results are found in the USA [35] and Northern Ireland [28]. The overall conclusion is that larger households may use more electricity in total, but per capita consumption is usually less.

Floor area: A positive correlation has been found between electricity consumption and the floor area of a dwelling. Research conducted in the UK found that the dwelling floor area has a significant correlation with electricity consumption [9]. Similarly, a proportional increase in electricity consumption with an increase in floor area is found in China [26] and India [32] with different percentages of increase in electricity demand. Per unit floor area consumption was also found to remain constant as the number of occupants increased [32]. A positive association was also found between floor area and energy consumption, but it becomes non-linear beyond a floor size of $100m^2$ in the UK [36].

Other research also found a reasonable correlation between floor area and electricity consumption in different countries, including Portugal [22], Netherlands [23], China [25] [37], UK [30] [38] [36] and Sweden [33]. These researchers also concluded that larger floor areas were linked to increasing electrical use for heating and cooling in line with the seasonal requirements in different parts of the world. It was also observed that this increased demand is more evident in those dwellings where the electricity is the main source of space conditioning. No effect of floor area on the energy demand is observed by Merve [21]. However, some research also found income [39] and weather & location [35] along with floor area, were strong predictors of energy consumption. In conclusion, the floor area is usually found to have a positive correlation with electricity consumption. Demand also changes with location and if electricity is being used as the main fuel for space conditioning.

Power rating for appliances: It is found that appliances with lower power ratings had a smaller effect on the overall electrical Power demand [35]. However, the higher efficiency of an appliance often results in increased use, hence overall energy consumption is increased, known as the 'rebound effect' [40]. A similarly high potential for more significant energy usage is found in Ireland [41] in homes having more energy-saving features. The power rating of appliances seems to have a positive effect on decreasing the electricity demand, but it also enables appliances owners to use them more as their affordability increases.

Total number of appliances: The number of electrical appliances has a positive correlation with electricity consumption [26] depending on the number [42] , type, power rating, and the number of hours each appliance is used [21] on average per day. The effect of a higher number of electrical appliances is reported to be the cause of increased domestic electricity consumption from a study in Japan which concluded that electricity consumption increased by 62kWh/year per unit increase in the number of appliances [13]. Further [21], the number of appliances explained 21% of the variance in electricity consumption in the Netherlands, with a similar trend reported in Portugal [23]. Besides, it is concluded [43] Certain types of appliances use a more significant portion of electricity than others in the USA. We conclude that increasing the number of appliances, and certain types increase electricity demand.

2.2 Energy prediction Modelling

Simple and multiple regression models have been extensively used to examine and predict the energy demand in different energy-using sectors. Previous research using regression models to forecast domestic energy demand is presented here to show the applicability of this technique for forecasting future Punjab demand.

A structured questionnaire-based energy data study was used for forecasting energy demand using different models, including the regression model, in China. This work predicted future demand for the year 2025 [44]. Regression analysis for predicting residential energy consumption found the outdoor temperature and solar radiation variables offered the best coefficients of determination in the USA. [45]. Linear regression analysis showed that household area was the main determining factor of electrical energy demand in Oahu, USA [46].

A multiple linear regression model applied to four parameters of electricity demand in Ireland found that space heating and cooling, along with the number of appliances and their usage patterns, were the independent variables best correlated with electricity consumption [47]. Regression models using historical electricity consumption data, GDP(Gross Domestic Product), GDP per capita, and population significantly estimated the elasticities of domestic and non-domestic electricity consumption in Italy [48]. The influence of economic and demographic variables on electricity demand consumption in New Zealand was modelled using multiple linear regression, and it was found that both variables have positive explanatory power [49]. Variables like population, GDP per capita, inflation percentage, and average seasonal temperatures were used as domestic electric energy predictor variables in Turkey, concluding that population and GDP per capita were key determinants of electrical energy use [50]. Utilising the LEAP model in Iran found that appliances usage time, per capita income and geographical location are predictor variables of electricity demand in the domestic sector [51] [52].

A multivariate linear regression model was used in Jordan to simulate residential electricity and fuel consumption. It predicted 100% and 23% increases, respectively, in the next ten years' [15]. Another regression model is used to determine the heating energy demand in the residential sector in Palestine; 60.6 % of the variance is explained by the model [53]. In a study of four different predictive models of variables, the model based on appliance ownership and use showed the highest (34%) variability of electricity consumed in the UK [16] [54]. Finally, residential energy use was found to be the second-largest consumer of final energy demand in China, consuming 24.5% in 2012 [55]. The occupant modelling methodologies are categorised into three groups (a) adaptive behaviour models, includes occupants action is taken to regain the comfort conditions like blind closing, light switch-on, (b) non-adaptive behavioural models, includes actions driven by contextual factors rather than physical discomfort like plug-in appliances switches, turning off lights when leaving, (c) occupancy models, includes occupancy patterns and durations [56] [57].

In the context of Pakistan, most of the research related to domestic demand drivers focus on household income, GDP growth, and the price of electricity. Surveys considering household income and expenditure show that household occupancy and income of householders have positive correlations with the electricity demand. While the short and long-term prices of electricity are not very significant factors in its consumption, suggesting it is a necessary commodity at its current consumption levels [58] [59] whereas the price of electricity and income both are found significant in other research [60]. The Pakistan finding may be influenced by frequent power cuts meaning that power is consumed when it is available. A greater supply of reliable electricity in Pakistan may start to exhibit different correlations. In a recent study, 17 different end uses of electrical energy consumption are identified using 523 survey responses; most of these are individual types of appliances, causing electricity demand [61]. Overall, Pakistan's domestic energy demand drivers and specific demand intensity as per household characteristics or per capita are not well understood. This paper goes on to explore these in detail.

3 Research methodology

The problem to be solved is how to predict energy demand from the drivers of energy demand. This type of problem requires the use of regression techniques which allow the correlation of independent variables with dependent variables. This approach is an established method found in the wider research when undertaking energy prediction and estimate analyses. A quantitative field research methodology [62] [63] [64] is appropriate based on the positivist research paradigm adopted for this research. The methodology and analysis approach are detailed in this section. The domestic sector of the Punjab province is studied through a survey methodology designed to yield statistically significant results. Figure 2 shows the assessment is based on actual billed consumption data, household floor area, occupancy level, number of conditioned rooms and their area, appliances ownership, appliances ratings, and usage hours/day data, for the year 2017-18 obtained from individual household questionnaires collected via physical surveys. '**Households**' are taken as our survey population. The questionnaire is provided in appendix A. The Data is analysed using correlation coefficients to understand demand drivers. The energy consumption prediction models are produced using regression. The survey data produced three electrical and one gas energy prediction models, all at per household and per capita level. These analyses were used to determine energy consumption data for the survey year and produce prediction models of consumption based on variable changes.

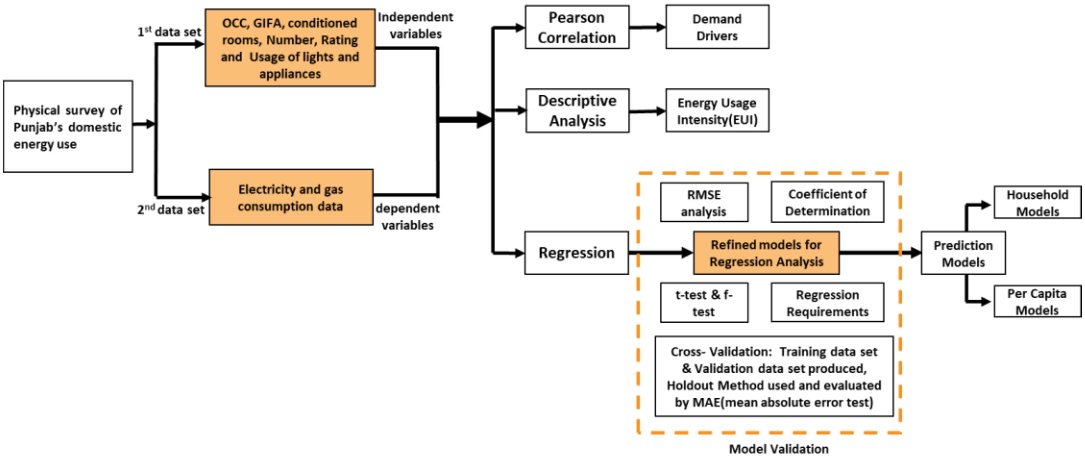

Figure 2 Method flowchart

Descriptive statistical techniques [65] [66] [67] combined with a quantitative methodology are used to interpret the numerical results [68] [69] [70]. These include univariate and multivariate measures, Using these techniques, investigation of the goodness-to-fit correlation between dependent and independent variables is analysed [71] [72] [73]. In addition, an inferential statistical technique can be used for future estimation, enabling us to generalise to the whole population from our sample with a given error, utilising the prediction models produced in this paper [74] [75].

3.1 Data type & Survey sample

The data set consists of primary data collected by the researchers in 2017-18 through conducting a physical domestic field survey covering the whole Punjab. Using a probabilistic clustered sampling method [76] [77] [78] and random sampling principles, a confidence level of 95% and a confidence interval of 1.45% was achieved from gathering 4597 valid samples from the whole Punjab for electricity demand. We define a valid sample as one which contained all the information needed to address each of the objectives set in this research. For gas demand, 2901 valid samples were obtained, achieving 95% confidence level and 1.8% confidence interval (Table 1), our sample covered all house sizes ranges available (21-418m^2) and presents the proportionate samples of each house size, and included all ten divisions of Punjab. The survey questionnaire [79] [80] was developed as per the objectives of the research. We needed to ask a couple of questions to answer one objective. For example, to find out the demand drivers, we needed to know 'how much energy is being consumed' in relation to type, number, and usages of different appliances and lights in any households. A pilot study was carried out to ensure the questions are correctly understood as per the objectives of the research. The questionnaire was also checked for errors and ambiguities by relevant experts before starting the survey.

3.2 Tools and methods used to collect data

The questionnaire was designed using 'online survey' software (provided by Cardiff University, UK) [81] [82]. The data presented here was then collected from the field using this questionnaire. It was distributed in 3 ways (a) online (b) door-to-door physical survey (field staff, with hard copies of forms) and (c) approaching university students in entire Punjab (hard copies of survey forms were distributed). Along with the questionnaire, the energy bills of respondents were collected, either in the form of photocopies or using mobile phone pictures. Each bill was coded with the name and a unique number for each respondent, to ensure minimum errors in the data entry process, for use as the validated consumed energy for each dwelling. In Pakistan, these bills are accurately read, and provided each month, so consumptions are known to be correct to the accuracy of each meter.

The survey initially aimed to obtain 10000 responses to achieve a 1% confidence interval. In practice, approximately 5800 surveys were completed, from which, after checking for completeness, 4597 valid samples were obtained. Of the valid responses, 14 were obtained from the online survey, 2610 from the door-to-door survey, and 1973 from university students. It must be noted that the online surveys were not a successful means to obtain information in the context of Punjab.

In the final sample, 40% of responses were from public sector university students who come from any sector or class of society in Pakistan, as public sector universities operate on open merit policy. Student can compete and get admission [83](based on the admission criteria [84]); further, the responses we received, along with their home addresses confirmed the inclusion of all classes of the society. 60% of samples were from randomly selected addresses by surveyors physically calling from door-to-door, representing all three classes of society, consisting of proportionate samples of lower(21%), middle(71%) and upper(8%) classes of Punjab's society [6] [85]. The survey was designed to collect information from all ten divisions of Punjab; within all divisions in all social sectors. Neighbourhoods from lower to upper classes were all included in the physical surveys. The physical presence of surveyors was also observed to help data accuracy and survey completeness. In the survey, 'households' were the survey population, not individual people, for different divisions of Punjab. We, therefore, also collected proportionate data from all house size ranges of households available in the whole Punjab.

3.3 Data preparation, cleaning, and processing for analysis

The field data collected was either in the form of hard copies or entered online in 'Bristol online software' [86] [87]. The data in the form of a hard copy was manually entered, by Punjab district, to the same software online by the lead author and the field surveyors. Pictures were taken and archived of the hard copies. In this way, the data-set was divided into manageable numbers, and this approach helped avoid data entry error.

Incomplete or invalid questionnaires were discarded at this stage, i.e. any response missing energy bills, house size, occupancy, types, the number of appliances and usage hours, were not included in the final data set. The lead author assessed random samples entered by other surveyors to provide confidence in the accuracy of the data-set. Divisional level data files were then prepared in Excel format by combining respective district files for each division.

Each divisional file was filtered using statistical methods to detect outliers. Only 15 outliers (0.003%) with extreme values were validated for use in the final calculations, and these made no difference to the accuracy of the models produced. Boxplots were used for visual analysis of the data. Final data cleaning involving removing or correcting irrelevant responses, wrongly entered values, blank spaces, converting text data to numeric, duplicate removal, wrong units, inappropriate unit conversions, was undertaken by the lead author.

Approximately 1200 questionnaires, or 20% of responses, were rejected during the editing and cleaning process, because of either being incomplete or having incorrect responses.

3.4 Analysis Procedures

Standard statistical software's are used for data analysis. Single attributes at a time were checked. Further 'aggregated' variables such as total annual energy demand, total power rating (kW) of appliances and lights(APP+LTS), average usage of appliances (kWh) and lights, the total number and types of appliances and lights, were also created where appropriate from the variables. These aggregated variables were used to assess whether they could be successfully used in regression models to represent the individual variables they contained. Correlation and multiple regression procedures were undertaken on the sample variables shown in Table 1.

3.4.1 Variables Groupings

(a) Indirect Variables – 4 (OCC, GIFA, CON.RMS, CON.RM.AR). These variables do not directly consume energy
(b) Grouped Variables – 9 (number of appliances, lights and the combined number of appliances +lights, Rating of the appliances, lights and combined rating of appliances, usage of the appliance, lights, and the combined number of appliances +lights). Groupings of direct variables to help simplify physical surveys
(c) Direct variables-63 (the list is in the questionnaire, 21 individual appliances and lights variables at three levels, i.e. number, rating, and Usage) Table 1. These variables directly consume energy.

Table 1 Survey variables and their confidence level and confidence interval achieved, for correlation and regression analysis

<table>
<tr><th>Survey Questions or Variables(as per questionnaire)</th><th>Acronym</th><th colspan="3">Responses Received</th><th colspan="3">Confidence level=95%, with Confidence intervals, CI</th></tr>
<tr><td colspan="8">Indirect Variables</td></tr>
<tr><td>How many people are usually living in the house? (also include house worker(s)/servant(s) who live(s) in the same house?</td><td>OCC</td><td colspan="3">4597</td><td colspan="3">1.45</td></tr>
<tr><td>What is the total covered area of your house? (Gross internal floor area)</td><td>GIFA</td><td colspan="3">4597</td><td colspan="3">1.45</td></tr>
<tr><td>What is the total number of conditioned rooms (rooms which are heated and/or cooled) in your house?</td><td>CON.RM</td><td colspan="3">4388</td><td colspan="3">1.48</td></tr>
<tr><td>What is the total combined area of conditioned rooms?</td><td>CON.RM.AR</td><td colspan="3">2515</td><td colspan="3">1.95</td></tr>
<tr><td>How much electricity do you use per month(kWh) or per year?</td><td>kWh/year/Electric</td><td colspan="3">4597</td><td colspan="3">1.45</td></tr>
<tr><td>How much gas do you use per month(kWh) or per year?</td><td>kWh/year/gas</td><td colspan="3">2901</td><td colspan="3">1.8</td></tr>
<tr><td colspan="8">Grouped Variables</td></tr>
<tr><td rowspan="2"></td><td rowspan="2">Acronym</td><td>Number (Owned)</td><td>Rating (kW)</td><td>Use (kWh) /day</td><td>Number (Owned)</td><td>Rating (kW)</td><td>Use (kWh) /day</td></tr>
<tr><td colspan="3">Responses Received</td><td colspan="3">Confidence level=95%, with Confidence intervals, CI</td></tr>
</table>

Number of appliances, Rating (Appliances) & Usage (Appliances)	APP, APP (kW), APP (kWh)	4479	4479	4287	1.46	1.46	1.50
Number of Lights, Rating (Lights) & Usage(Lights)	LTS, LTS (kW), LTS (kWh)	4473	4491	4265	1.46	1.46	1.51
Number of appliances and lights, Rating (Appliances +Lights) & Usage(Appliance + Lights)	APP.+ LTS, APP+LTS (kW), APP+LTS (kWh)	4519	4519	4348	1.46	1.46	1.48
Direct Variables							
# of Fluorescent tube lights, their wattage(W), and their average seasonal use per day(kWh)?	FTL, FTL (kW), FTL (kWh)	1921	1921	1784	2.24	2.24	2.32
# of Incandescent Bulbs, their wattage(W), and their average seasonal use per day(kWh)?	IB, IB (kW), IB (kWh)	566	566	513	4.12	4.12	4.33
# of Compact Fluorescent bulbs, their wattage(W), and their average seasonal use per day(kWh)?	ES, ES (kW), ES (kWh)	4071	4071	3853	1.54	1.54	1.58
# of LED & SMD, their wattage(W), and their average seasonal use per day(kWh)?	LED, LED (kW), LED (kWh)	1202	1202	1069	2.83	2.83	2.99
# of Fan(s) (bracket, ceiling, Pedestal, etc.), their wattage(W), and their average seasonal use per day(kWh)?	FN, FN (kW), FN (kWh)	4455	4455	4227	1.47	1.47	1.51
# of the Air conditioner(s) (cooling only), their wattage(W), and their average seasonal use per day(kWh)?	ACONC, ACONC (kW), ACONC (kWh)	1807	1807	1694	2.30	2.30	2.38
	Acronym	**Number (Owned)**	**Rating (kW)**	**Use (kWh) /day**	**Number (Owned)**	**Rating (kW)**	**Use (kWh) /day**
		Responses Received			**Confidence level=95%, with Confidence intervals, CI**		
# of the Air conditioner(s) (heating only), their wattage(W), and their average seasonal use per day(kWh)?	ACONH, ACONH (kW), ACONH (kWh)	65	65	55	12.2	12.2	13.3
# of the Air conditioner(s) (both cooling & heating), their wattage(W), and their average seasonal use per day(kWh)?	ACONCH, ACONCH (kW), ACONCH (kWh)	59	59	40	12.8	12.8	15.5
# of Direct electric heater (bar, fan heaters), their wattage(W), and their average seasonal use per day(kWh)?	DEH, DEH (kW), DEH (kWh)	349	349	328	5.25	5.25	5.41
# of Fridge(s), their wattage(W), and their average seasonal use per day(kWh)?	FRG, FRG (kW), FRG (kWh)	3906	3906	3712	1.57	1.57	1.61
# of Freezer(s), their wattage(W), and their average seasonal use per day(kWh)?	FRZ, FRZ (kW), FRZ (kWh)	408	408	358	4.85	4.85	5.21
# of Television(s), their wattage(W), and their average seasonal use per day(kWh)?	TV, TV (kW), TV (kWh)	3756	3756	3547	1.60	1.60	1.65
# of Computer(s) & Laptop(s), their wattage(W), and their average seasonal use per day(kWh)?	CM.LP, CM.LP (kW), CM.LP (kWh)	1396	1396	1212	2.62	2.62	2.81
# of Microwave(s), their wattage(W), and their average seasonal use per day(kWh)?	MW, MW (kW), MW (kWh)	1153	1153	1007	2.88	2.88	3.10
# of Play Station/video games, their wattage(W), and their average seasonal use per day(kWh)?	PS.VG, PS.VG (kW), PS.VG (kWh)	85	85	70	10.63	10.63	11.72
# of Cooker extract fan, their wattage(W), and their average seasonal use per day(kWh)?	SEF, SEF (kW), SEF (kWh)	302	302	240	5.63	5.63	6.33

# of Extract fan (kitchen, bathrooms), their wattage(W), and their average seasonal use per day(kWh)?	EF, EF (kW), EF (kWh)	1317	1317	1268	2.70	2.70	2.75
# of Internet Modem/router/hub, their wattage(W), and their average seasonal use per day(kWh)?	IM, IM (kW), IM (kWh)	728	728	455	3.63	3.63	4.59
# of washing machines(s) their wattage(W), and their average seasonal use per day(kWh)?	WM, WM (kW), WM (kWh)	3261	3261	2984	1.72	1.72	1.79
# of the vacuum cleaner(s), their wattage(W), and their average seasonal use per day(kWh)?	VC, VC (kW), VC (kWh)	206	206	131	6.83	6.83	8.60
# of water cooler/Desert cooler(s) their wattage(W), and their average seasonal use per day(kWh)?	DC, DC (kW), DC (kWh)	411	411	281	4.85	4.85	5.84

3.5 Data accuracy and quality of regression models

Quantitative data obtained from surveys of this type have differing accuracies associated with the data for each variable. The energy consumption values are considered accurate within +/- 2 percent. Published accuracies for most electricity fiscal meters are better than 2% for many meter manufacturers [88] [89] [90] [91] as they are taken from official electricity and gas bills. In Pakistan, energy bills are sent to the users' homes as hard copies. We have similar confidence in the gross internal floor area (GIFA) values. The occupancy of the house is considered accurate. For data on appliances and lights, the general accuracy is likely to be slightly less but could not be quantified. The physical presence of field surveyor during the questionnaire completion was known to have improved the accuracy with which values were reported.

To overcome possible translation/explanation errors, (as the questionnaire was in English with translation in the local language, i.e. Urdu), the field surveyors were given training before conducting the survey, and any possible ambiguity was cleared prior to starting the survey. The surveyors selected for the field were well educated (all above 12 standards or A-Level equivalent education), they were able to understand the questionnaire fully and were able to convey it clearly to the respondents, in the local language, if required. Moreover, the questionnaires were filled in by surveyors themselves, so chances of errors due to lack of understanding are minimised. Similar confidence is given to the samples received from the universities students as all are well educated and can easily understand the questions, and they are fluent in English and Urdu. English is the medium of study in the universities of Pakistan. Overall, the data on which this analysis is undertaken is considered consistent, accurate, and high quality.

The quality of the regression models produced was confirmed by checking if the following criteria are met:

- The dependent and independent variables are continuous, the level of measurement is the scale, and there is a linear relationship ideally greater than 0.3 and less than 0.7 (Pearson Correlation).
- The values of residuals are independent, Durbin Walton's criteria values should be less than 2
- The variance of residuals is constant. Homoscedasticity is observed in the models, meaning the same variance is central to the linear regression model.

- Data must not show multicollinearity, i.e. independent variables are not highly or perfectly correlated. Highly correlated variables, showing multicollinearity ($r>.65$), or singularity ($r=1$), were removed.
- The unique contribution of each independent variable is checked for significance before use in the regression equations.
- The residuals (errors) are approximately normally distributed in a normal P-P plot.
- **Cronbach's alpha:** Cronbach's alpha is the measure of internal consistency. The higher the value of alpha (α) between 0 and 1, the better it is. A value above 0.7 is considered acceptable. We checked Cronbach's alpha and found its value as 0.77, which shows the data is reliable.

3.6 Validation and Diagnostic criteria

The results presented were validated using a number of tests, and only the strongest models are finally shown. The tests used are:

Coefficient of Determination: The coefficient of determination is used to show the percentage of the variation in the dependent variable explained by the independent variables. It is given as $R^2 = \frac{SST}{SSR}$, where: SST= sum of squares total, SSR= sum of squares regression.

f- Test & t-test: To check the goodness of fit and significance ($p<0.001$) of the models and independent variables, f-test, and t-test checks were used. In all final model cases, they were significant. For the **f-test**, the null hypothesis is $H_0 = 0$, (all coefficients are 0), i.e. it cannot predict the dependent variable from the Mean. It means the model has no explanatory power, and none of the independent variables helps to predict the dependent variable. If $Ha \neq 0$ (at least one coefficient is different from 0) then the model has explanatory power.

For the **t-test**, the null hypothesis is $H_0 = 0$, (all coefficients are 0), i.e. the true population value of the coefficient is equal to 0. It means independent variables do not help to predict dependent variables. If $H_a \neq 0$ (at least one coefficient is different from 0) then independent variables do help to predict dependent variables. In all model cases, the null hypotheses were rejected. The f-test and t-test are valid when the diagnostic or residual assumptions are adequately met.

Root Mean Square Error (RMSE): The square root of the sum of the square of differences between the predicted and observed value divided by the number of observations. It can be expressed mathematically [64] as;

$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Et - \hat{E}t\right)^2}$, where Et = observed energy consumption and $\hat{E}t$ = predicted energy consumption.

Cross-Validation: In order to check the validity of the models that are produced from the full data sample**,** we also performed a cross-validation procedure to check the models produced are not over-fitted. To do so, we randomly separated the data into two halves (training data set and validation data set) and produced Models. We then re-ran the analysis to see if the models are similar and tested the model predictions against a sample of the validation data-set to prove applicability. The cross-validation is done using the Holdout method, and the predictions are made for the validation data set using models produced from the training data set. The errors found are aggregated to give the **mean absolute test error**, which is used to evaluate the model. The MAE (Mean Absolute Error) analysis shows similar results to our predicted models, and so validates the models.

4 Results

The house sizes covered in the survey range from 20.9m² to 418m²˒ which covers the dominant house sizes in Punjab. The average house size is 109m²˒ and the house size of 104.5m² is the most surveyed house in the data set shown in Table 2. The average size available per capita is 17m². The minimum and maximum values of m² per capita are 2.9m² and 146.3m²˒ respectively (Table 2). These variations show that the data set covers the full range of Punjab society and provides further confidence in the general application of the findings.

Table 2. House area and per capita area of the sample houses

Values	House size (m²)	Capita(m²)
Mean	109	17
Median	104.5	14.9
Mode	104.5	20.9
Standard Dev	70.5	10.2
Minimum	20.9	2.9
25th percentile	62.7	11.9
75th percentile	125.4	20.9
Maximum	418	146.3

The results are presented in three parts. In the first part, the current Punjab energy demand drivers in the domestic sector are shown (4.1, Figure 3, Figure 4). In the second part, energy usage intensity (EUI) is presented using descriptive statistics (4.2), and in the third part, energy consumption prediction models are presented, utilising simple & multiple regression procedures (4.3).

4.1 Domestic Demand Drivers

Pearson's correlations for the dependent variable, annual electricity consumption per household (kWh/year), and the independent variables defined in Table 1 are shown in Table 3. A correlation > 0.3 is used to show the variables have a relationship with the dependent variable per household. This table also shows the correlations of annual electricity consumption per capita with these variables.

The results of modelling the **direct and indirect** variables **per household** show CON.RMS (r=0.604), CON.RM.AR (r=0.554), ACONC(kW) (r=0.553), ACONC (r=0.543) and ACONC(kWh) (r=0.504) have a good correlation with the dependent variable. The result of modelling **indirect and grouped** variables per household show APP+LTS (r=0.636), APP(kW)+LTS(kW) (r=0.629), APP (r=0.617), APP(kW) (r=0.616) and CON.RMS (r=0.604) have a good correlation with the dependent variable.

The results of modelling the **direct and indirect** variables **per capita** show ACONC (kW) (r=0.569), ACONC (r=0.558), CON.RMS (r=0.550), CON.RM.AR (r=0.538) and ACONC (kWh) (r=0.524) have a good correlation with the dependent variable. The result of modelling **indirect and grouped** variables per capita show APP(kW) (r=0.655), APP(kW)+LTS(kW) (r=0.654), APP (r=0.637), APP+LTS (r=0.626) and APP(kWh)+LTS(kWh) (r=0.580) also have good correlations with the dependent variable.

The hierarchical relationship of drivers of electricity demand for **direct and indirect** variables are presented in Figure 3 and Table 3, which shows the strongest correlation is with the total number of CON.RMS (r=0.604), for the per household model, and with an installed electrical capacity of the appliances ACONC (kW) (r=0.569), for the per capita model. The hierarchical relationship of drivers of electricity demand for general and grouped variables derived from the modelling are presented in Figure 4 and Table 3, shows the number of appliances and lights(APP+LTS) and power rating of appliances has the strongest correlation for per household and per capita models respectively.

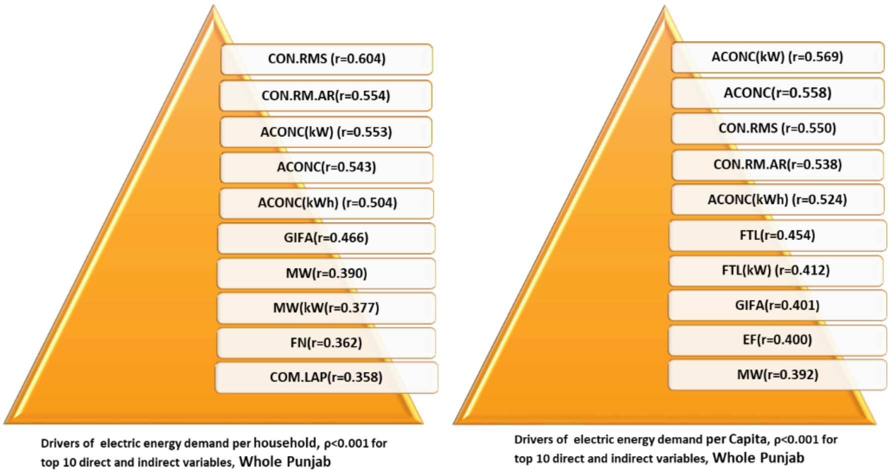

Figure 3 Hierarchical presentation of electricity demand drivers per household and per capita in Punjab, Pakistan for direct and indirect Variables

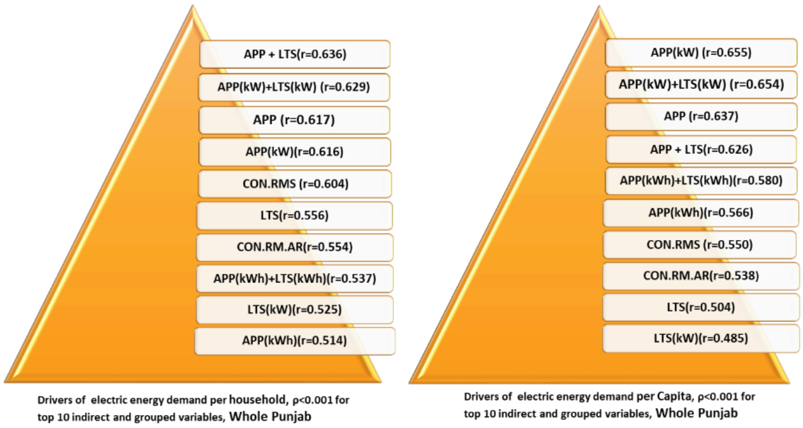

Figure 4 Hierarchical presentation of electricity demand drivers per household and per capita in Punjab, Pakistan for indirect and Grouped Variables

The variables having correlations of r ≥ 0.30, confidence levels of > 95% and confidence interval 5% or better, are shown in Table 3 below in descending order for both models (i.e. per household and capita), including all types of variables. All variables not meeting these criteria are discarded. The highest correlation we found from all variables is with the number of appliance and light (APP+LTS, r=0.636) and power rating of the appliances (APP(kW), r=0.655) for per household and per capita models respectively Table 3.

Table 3 Hierarchal Pearson's correlations statistics of electric energy Models for direct, indirect and grouped Variables

Hierarchal Correlations of all variables		
	Model	**Model**

Sr. No	Electric kWh/year per household		Electric kWh/year per capita	
	Acronym	Pearson coefficient(r)	Acronym	Pearson coefficient(r)
1	APP+LTS	0.636	APP (kW)	0.655
2	APP (kW)+LTS (kW)	0.629	APP (kW)+LTS (kW)	0.654
3	APP	0.617	APP	0.637
4	APP (kW)	0.616	APP+LTS	0.626
5	CON.RMS	0.604	APP(kWh)+LTS(kWh)	0.580
6	LTS	0.556	ACONC (kW)	0.569
7	CON.RM.AR	0.554	ACONC	0.558
8	ACONC (kW)	0.553	APP (kWh)	0.566
9	ACONC	0.543	CON.RMS	0.550
10	APP (kWh)+LTS(kWh)	0.537	CON.RM.AR	0.538
11	LTS (kW)	0.525	ACONC (kWh)	0.524
12	APP (kWh)	0.514	LTS	0.504
13	ACONC (kWh)	0.504	LTS (kW)	0.485
14	GIFA	0.466	FTL	0.454
15	LTS (kWh)	0.437	FTL (kW)	0.412
16	MW	0.390	GIFA	0.401
17	MW (kW)	0.377	EF	0.400
18	FN	0.362	MW	0.392
19	COM.LAP	0.358	FTL (kWh)	0.388
20	FTL	0.350	LTS (kWh)	0.384
21	FTL (kW)	0.350	WM	0.370
22	MW (kWh)	0.343	MW (kW)	0.355
23	FTL (kWh)	0.333	FRG	0.350
24	OCC	0.332	TV	0.348
25	FRG	0.330	EF (kW)	0.344
26	TV	0.329	FRG (kWh)	0.346
27	FN (kWh)	0.325	FN	0.326
28	LED/SMD	0.318	FRG (kW)	0.325
29	ES	0.315	FN (kWh)	0.324
30	EF	0.311	MW (kWh)	0.319
31	COM.LAP (kW)	0.300	TV (kWh)	0.317
32	-	-	DEH	0.314
33	-	-	DEH (kW)	0.309

Acceptable gas correlations were found only with the size of the house (GIFA), where r= 0.228 & 0.280 for the per household and capita models, respectively. The other variable we used to try and predict the gas demand is the occupancy of the house, which showed little or no correlation so was discarded.

4.2 Energy usage intensity (EUI)

Analysis of the average annual Energy Usage Intensity (EUI) reveals the following (Table 4):

- Average **annual energy use per household** is 2401 kWh for electric and 5245 kWh for gas.
- Average **annual energy use per capita** is 391 kWh for electric and 770 kWh for gas.
- Average **annual energy use/m² per household** is 26 kWh/m² for electric and 55 kWh/m² for gas.
- Average **annual energy use/m² per capita** is 5 kWh for electric and 8.3 kWh for gas.
- The predicted ranges of electric and gas demand are large in both per household and per capita models.

Table 4 Energy usage Intensity

Survey findings (to 3 significant figures)						
Utility	**Sample size (N)**	**Average**	**SD.**	**Median**	**Min.**	**Max.**
kWh/household/annum						
Electric	4597	2401	1570	2100	3.0	12700
Gas	2901	5245	4760	4190	40.6	31400
kWh/capita/annum						
Electric	4597	391	248	340	0.65	2970
Gas	2901	770	743	594	5.8	8150
kWh/ m²/household/annum						
Electric	4597	26	18.6	22	0.05	288
Gas	2901	55	61.4	34.2	0.32	643
kWh/ m²/capita/annum						
Electric	4597	5	3.9	3.54	0.01	52.7
Gas	2901	8.3	10.4	5	0.05	204

The metered consumption data collected also allows us to consider these figures monthly. The average EUI for electric and gas use per household per month can be seen in Figure 5 and Figure 6. Over a year, the average EUI/month ranges from 114kWh to 303kWh for electricity use. For gas use, the monthly average range is from 269 kWh to 673 kWh. Along with the correlations already observed, they reinforce the impact on the annual energy use of the electrical use in Summer (driven by cooling loads) and the gas used in Winter (driven by heating loads). Reductions in these demands should, therefore, focus on these uses first.

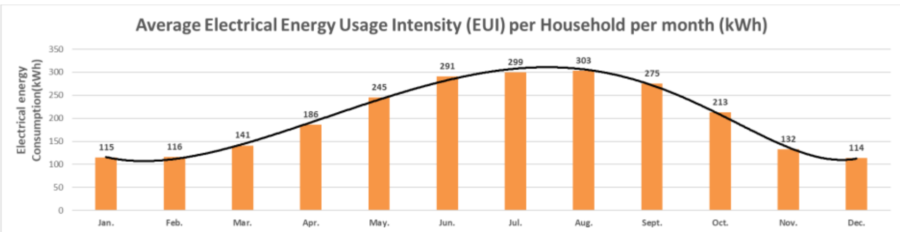

Figure 5 Metered average electrical energy Intensity (EUI) per household per month

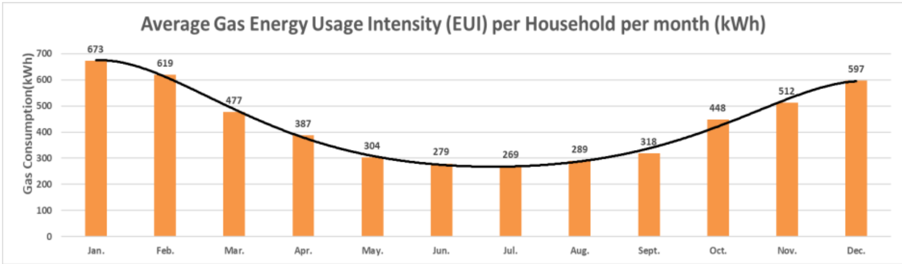

Figure 6 Metered average gas energy Intensity (EUI) per household per month

4.3 Energy consumption prediction models

Eight energy consumption prediction models are produced, six for electricity, and two for gas.

The electricity models are differentiated into:

- Detailed models (direct + indirect variables)
- Grouped Models (indirect + grouped variables)
- Combined Models (detailed+ grouped models, OR direct, indirect and grouped variables)

For both electricity and gas, all models are produced 'per household' and 'per capita'. For gas, as we have only one predictive variable, i.e. GIFA, the models are named simply as 'per household' and 'per capita'. The six different electricity models were produced to enable their use with different data availability. There is not a significant difference between their accuracies, so all should give similar results.

4.3.1 Descriptive statistics for models' final predictive variables

For Gas, GIFA is the only predictor variable in the data set for both gas models. The dependent variable (kWh/year) and independent variable (GIFA) are related by 0.228 & 0.280 (Pearson's correlation) for per household and per capita gas models, respectively. Only simple prediction regression models can be produced for gas consumption.

Table 5 presents the means and standard deviations of the dependent (criterion) and independent (predictor) variables for all the models produced in this paper. The correlations of the electrical models' variables with the dependent variable (electricity consumption kWh) were shown in Table 3.

Table 5. Calculated values from the physical survey for selected predictive variables

Descriptive Statistics					
PER HOUSEHOLD			**PER CAPITA**		
Electricity use per household of Detailed model			**Electricity use per capita of Detailed model**		
Variable	**Mean-unit**	**Std. Deviation**	**Variable**	**Mean-unit**	**Std. Deviation**
kWh/year	2401 kWh	1568.1	kWh/year /capita	391 kWh	248.1
OCC	6.44	2.4	GIFA/capita	17.5	10.2
GIFA	109.3 m^2	70.5	FN/capita	0.59 m^2	0.35
FN	3.73	2.22	DEH/capita	0.015	0.06
FRG	0.92	0.47	FRG/capita	0.16	0.11
TV	1.1	0.73	MW/capita	0.043	0.08
ES	5.3	4.2	ACONC (kW) /capita	0.11	0.16
LED/SMD	1.3	3.1	TV (kWh) /capita	0.16	0.15
MW	0.26	0.47	CON.RM.AR/capita	0.99	1.39
FTL	1.3	1.99	FTL/capita	0.24	0.35
CON.RMS	1.6	1.1	-		
Electricity use per household of Grouped model			**Electricity use per capita of Grouped model**		
Variable	**Mean**	**Std. Deviation**	**Variable**	**Mean**	**Std. Deviation**
kWh/year	2401 kWh	1568.1	kWh/year/capita	391 kWh	248.1
OCC	6.44	2.4	GIFA/capita	17.5 m^2	10.2
GIFA	109.3	70.5	APP (kW)+LTS (kW)/capita	0.36 kW	0.31
APP+LTS	17.3	9.76	CON.RM.AR/capita	0.99 m^2	1.4
CON.RMS	1.63	1.1	-		
Electricity use per household Combined model			**Electricity use per capita Combined model**		
Variable	**Mean**	**Std. Deviation**	**Variable**	**Mean**	**Std. Deviation**
kWh/year	2401 kWh	1568.1	kWh/year /capita	391 kWh	248.1
OCC	6.44	2.4	GIFA/capita	17.5 m^2	10.2
GIFA	109.3 m^2	70.5	FN/capita	0.6	0.36
FN	3.73	2.21	DEH/capita	0.02	0.06
FRG	0.92	0.47	FRG/capita	0.16	0.11
LED/SMD	1.26	3.06	TV (kWh) /capita	0.16 kWh	0.16
FTL	1.32	1.99	CON.RM.AR/capita	0.98 m^2	1.39
CON.RMS	1.63	1.03	FTL/capita	0.24	0.35
APP (kW)	1.96 kW	1.75	APP (kW)+LTS (kW)/capita	0.36 kW	0.31
ES	5.31	4.15	-		
Gas use per household model			**Gas use per capita model**		
Variable	**Mean**	**Std. Deviation**	**Variable**	**Mean**	**Std. Deviation**
kWh/year	5245 kWh	4764	kWh/year/capita	769.5 kWh	743
GIFA	121.57 m^2	77.1	GIFA /capita	17.45 m^2	11.63

4.3.2 Strength of models

Two methods of deciding which variables were included or removed from the models were adopted. These were the 'stepwise' and 'forward' methods. In both methods, variables with $p<0.05$ and independent variables with the smallest partial correlations, which have no significance, were removed until the best-fit models were obtained. The final method chosen was 'enter'. Table 6 shows the strengths of the various models produced.

The final models selected for use were those with the following characteristics:

- the lowest RMSE,
- the highest coefficient of determination R^2,
- satisfying predictive strengths (f-test) of models,
- individual variables with unique values (t-test) at sig. $p<0.001$, and
- meeting the required regression assumptions (as presented in section 3.5)

Table 6 Strength of the electricity and gas use per household and capita models

Models Summary				
R	**R Square**	**Adjusted R Square**	**Std. Error of the Estimate**	**Durbin-Watson**
Electricity use per household of Detailed model				
0.723	0.523	0.522	1084.6	1.65
Electricity use per household of Grouped model				
0.719	0.517	0.517	1090.3	1.62
Electricity use per household of Combined model				
0.729	0.531	0.53	1075.1	1.65
Electricity use per Capita of Detailed model				
0.698	0.487	0.486	177.8	1.60
Electricity use per Capita of Grouped model				
0.727	0.528	0.527	170.6	1.66
Electricity use per Capita of Combined model				
0.729	0.532	0.531	169.9	1.66
Gas per household area model				
0.228	0.056	0.052	4054.9	0.78
Gas per capita model				
0.280	0.078	0.078	713.46	0.87

4.3.3 Analysis of model coefficients

The higher the beta value of the independent variables, the higher the strength it has to explain the dependent variable (

Table 7). For example, in the electricity use per household (detailed) model shown in

Table 7, the number of conditioned rooms (CON.RMS) is clearly the most influential variable on the electricity demand.

All variables with little or no predictive power, i.e. variable coefficient (**β** =Beta) is equal or near zero, have been removed to provide clarity.

Table 7 Predictive Coefficients for final annual electric and gas use per household and capita models.

Coefficients															
Electricity use per household of Detailed model								**Electricity use per Capita of Detailed model**							
Variables	**B**	**Beta**	**t**	**Sig.**	**Correlations part**	**Tolerance**	**VIF**	**Variables**	**B**	**Beta**	**t**	**Sig.**	**Correlations part**	**Tolerance**	**VIF**
Constant	-206.3							Constant	103.4						
OCC	56.8	0.09	6.7	0.000	0.099	0.64	1.6	GIFA/capita	2.13	0.09	7.5	.000	0.11	0.74	1.4
GIFA	1.62	0.07	5.5	0.000	0.081	0.59	1.7	FN/capita	136.9	0.2	18.1	.000	0.26	0.88	1.2
FN	77.33	0.11	7.8	0.000	0.12	0.53	1.9	DEH/capita	661.9	0.15	14.2	.000	0.21	0.88	1.1
FRG	191.1	0.06	4.9	0.000	0.072	0.77	1.3	FRG/capita	215.2	0.09	7.6	.000	0.11	0.72	1.4
TV	120.6	0.06	4.8	0.000	0.070	0.76	1.3	MW/capita	228.1	0.08	6.3	.000	0.09	0.75	1.3
ES	47.94	0.13	9.4	0.000	0.138	0.57	1.8	ACONC (kW)/capita	299.8	0.2	13.9	.000	0.20	0.51	1.9
LED/SMD	62.1	0.12	10.5	0.000	0.153	0.78	1.3	TV (kWh)/capita	121.2	0.08	6.5	.000	0.10	0.76	1.3
MW	219.44	0.07	5.5	0.000	0.080	0.73	1.4	CON.RM.AR/ capita	45.9	0.26	19.4	.000	0.28	0.58	1.7
FTL	117.62	0.15	12.4	0.000	0.180	0.71	1.4	FTL/capita	71.1	0.10	8.2	.000	0.12	0.68	1.5
CON.RMS	566.96	0.37	28.6	0.000	0.389	0.62	1.6	-							
Electricity use per household of Grouped model								**Electricity use per Capita of Grouped model**							
Constant	-55.41							Constant	165.3						
OCC	53.27	0.08	6.8	0.000	0.099	0.74	1.4	GIFA/capita	2.48	0.102	8.5	0.000	0.13	0.77	1.3
GIFA	1.39	0.06	4.8	0.000	0.070	0.61	1.6	APP (kW)+LTS (kW)/capita	404.33	0.501	37.9	0.000	0.49	0.64	1.6
APP+LTS	61.73	0.39	28.8	0.000	0.391	0.59	1.7	CON.RM.AR/ capita	37.45	0.211	15.9	0.000	0.23	0.64	1.6
CON.RMS	548.68	0.36	28.2	0.000	0.383	0.64	1.6	-							
Electricity use per household of Combined model								**Electricity use per Capita of Combined model**							

Constant	-89.28							Constant	101.8						
OCC	67.14	0.10	8.1	0.000	0.118	0.64	1.6	GIFA/capita	1.9	0.08	6.6	0.000	0.097	0.74	1.4
GIFA	1.45	0.07	4.9	0.000	0.073	0.59	1.7	FN/capita	112.1	0.16	14.6	0.000	0.210	0.84	1.2
FN	70.1	0.1	7.2	0.000	0.105	0.54	1.9	DEH/capita	415.8	0.096	8.3	0.000	0.121	0.75	1.3
FRG	135.1	0.04	3.5	0.000	0.051	0.77	1.3	FRG/capita	124.4	0.053	4.3	0.000	0.063	0.67	1.5
LED/SMD	58.51	0.11	9.9	0.000	0.146	0.78	1.3	TV (kWh)/capita	97.9	0.061	5.3	0.000	0.077	0.76	1.3
FTL	97.15	0.12	10.1	0.000	0.147	0.68	1.5	CON.RM.AR/ capita	45.7	0.257	19.8	0.000	0.280	0.61	1.7
CON.RMS	445	0.29	19.2	0.000	0.273	0.45	2.3	FTL/capita	62.32	0.089	7.2	0.000	0.105	0.67	1.5
APP (kW)	178.3	0.19	11.8	0.000	0.171	0.36	2.8	APP (kW)+LTS (kW)/capita	245.7	0.305	18.2	0.000	0.260	0.37	2.7
ES	44.84	0.19	8.9	0.000	0.130	0.57	1.8	-							
Gas use per household model								**Gas use per capita model**							
Constant	3532.2							Constant	458.1						
GIFA	14.1	.228	12.6	.000	.228	1.0	1.0	GIFA/CAPITA	17.85	0.280	15.68	0.000	0.280	1.0	1.0

4.3.4 Analyses of the annual electricity consumption prediction per household model

Multiple regression analysis was undertaken to refine the models that were now capable of being produced. It helped clarify the predictive strengths of each variable shown to have an acceptable correlation within each model. It is explained in more detail for the following models:

Detailed Model:

The ten independent variables, OCC, GIFA, FN, FRG, TV, ES, LED/SMD, MW, FTL and CON.RMS, were tested to see if they significantly predicted annual electricity use (kWh/year) **per household**. The results showed that they explained 52.2% of the variance (R^2=0.522, F (10,4587) =502.6, p<0.001). It was further found that CON.RMS, FTL and ES were the most significant predictors of the ten variables (**β**=0.371, p<0.001), (**β**=0.149, p<0.001) and (**β**=0.127, p=0.001) respectively (Table 6 &Table 7).

Grouped Model:

If the independent variables OCC, GIFA, APP+LTS and CON.RMS significantly predicted annual electricity use (kWh/year) **per household**. The results showed that they explained 51.7% of the variance (R^2=0.517, F (4,4593) =1229.8, p<0.001). It was, further, found that APP+LTS and CON.RMS were the most significant predictors of the four variables (**β**=0.384 & 0.359, p<0.001). GIFA (**β**=0.062, p<0.001) and OCC (**β**=0.081, p=0.001) were shown to only weakly predict annual energy use per household (Table 6 &Table 7).

Combined Model:

Whether independent variables OCC, GIFA, FN, FRG, LED/SMD, FTL, CON.RMS, APP (kW) and ES significantly predicted the annual electricity use (kWh/year) **per household**. The results showed that they explained 53.0% of the variance (R^2=0.530, F (9,4588) =576.9, p<0.001). It was found that CON.RMS, FTL and APP (kW) were the most significant predictors (**β**=0.292, p<0.001), (**β**=0.123, p<0.001) and (**β**=0.199, p=0.001) (Table 6 &Table 7).

4.3.5 Analyses of the annual electricity consumption prediction per capita model

The same analysis was undertaken as for the 'per household' models.

Detailed Model:

For the **per capita** model, the analysis showed that nine per capita predictors GIFA, FN, DEH, FRG, MW, ACONC(kW), TV(kWh), CON.RM.AR and FTL explained 52.7% of the variance (R^2=0.527, F(9,4588) =570.6, p<0.001). Of these, the most significant predictors were CON.RM.AR/capita (**β**=0.258, p<0.001), FN/capita (**β**=0.196, p<0.001), and ACONC(kW)/capita (**β**=0.196, p<0.001) (Table 6 &Table 7).

Grouped Model:

For the **per capita** model, the analysis showed that three predictors, GIFA/capita, APP(kW)+LTS(kW)/capita and CON.RM.AR/capita, explained 48.6% of the variance (R^2=0.486, F (3,4594) =1452.1, p<0.001). APP(kW)+LTS(kW)/capita significantly predicted annual electricity use (kWh/year/capita) (**β**=0.501, p<0.001), as did CON.RM.AR/capita (**β**=0.211, p<0.001), and GIFA/capita (**β**=0.102, p<0.001) (Table 6 &Table 7).

Combined Model:

For the **per capita** model, the analysis showed that eight per capita predictors GIFA, FN, DEH, FRG, TV(kWh), CON.RM.AR, FTL & APP(kW)+LTS(kW) explained 53.1% of the variance (R^2=0.531, F(8,4589) =651.5, p<0.001). Of these, the most significant predictors were APP(kW)+LTS(kW))/capita (**β**=0.305, p<0.001), CON.RM.AR/capita (**β**=0.257, p<0.001) and FN/capita (**β**=0.160, p<0.001), (Table 6 &Table 7).

In all three models for per household, we found that number of conditioned rooms and number of appliances & lights are the variables with higher predictive strengths. However, in per capita models, the area of conditioned rooms and the power rating of appliances & lights are better predictors of electrical energy consumption.

4.3.6 Analyses of the annual gas consumption prediction per household & capita models

Simple regression analysis tested whether the independent variable (GIFA) significantly predicted the annual gas use (kWh/year) **per household**. The result showed that the predictor explained 5.6% of the variance (R^2=0.056, F(1,2900)=159.1, p<0.001). GIFA therefore, very weakly predicts annual gas use (kWh/year) (**β**=0.228, p<0.001). For the **per capita** model, the analysis showed that the predictor GIFA explained 7.8% of the variance (R^2=0.078, F(1,2800)=245.8, p<0.001). GIFA therefore, weakly predicts annual gas use per person (kWh/year/capita) (**β**=0.280, p<0.001) (Table 6 &Table 7).

Table 7 and Equations 1 to 8 below present the independent variables regression coefficients from the study for all the models. If all independent variables are known, we can predict the dependent variable $\overline{Y}$.

4.3.7 Final energy prediction models

Having demonstrated which independent variables can be used for modelling, we are able to derive models for predicting the electrical and gas consumption in the domestic sector of Punjab for both 'per household' and 'per capita'. For the electrical demand prediction models, there is no practical difference in the accuracies found in any of the three models, so we would recommend using whichever model it is easiest to obtain the required data for.

4.3.7.1 Annual electricity consumption in kWh per household models

The following three models have been produced. They are all similar in their accuracy, so the choice of which one to use will depend on the information available.

Detailed Model: Where OCC, GIFA, FN, FRG, TV, MW, ES, LED/SMD, FTL and CON.RMS are known, then the following equation is valid to an accuracy of **R^2=0.522**, RMSE=1084.6

$$\overline{Y} = -206.33 + 56.8*(OCC) + 1.62*(GIFA) + 77.33*(FN) + 191.1(FRG) + 120.6(TV) + 47.94(ES) + 62.1(LED/SMD) + 219.44(MW) + 117.62(FTL) + 566.96*(CON.RMS) \quad (1)$$

Grouped Model: Where OCC, GIFA, APP+LTS and CON.RMS are known then the following equation is valid to an accuracy of $\mathbf{R^2 = 0.517}$ and RMSE= 1090.3:

$$\bar{Y} = -55.41 + 53.27*(OCC) + 1.39*(GIFA) + 61.73*(APP+LTS) + 548.68*(CON.RMS) \quad (2)$$

Combined Model: Where OCC, GIFA, FN, FRG, ES, LED/SMD, FTL, CON.RMS and APP(kW) are known then the following equation is valid to an accuracy of $\mathbf{R^2=0.530}$, RMSE=1075.3:

$$\bar{Y} = -89.28 + 67.14*(OCC) + 1.45*(GIFA) + 70.1*(FN) + 135.1*(FRG) + 44.84*(ES) + 58.51*(LED/SMD) + 97.15*(FTL) + 445*(CON.RMS) + 178.3*(APP_{(kW)}) \quad (3)$$

4.3.7.2 Annual electricity consumption in kWh per capita models

The following 3 models have been produced. The same comments apply to accuracy as for the 'per household' models:

Detailed Model: Where GIFA/capita, FN/capita, DEH/capita, FRG/capita, TV/capita, MW/capita, ACONC(kW)/capita, FTL/capita and CON.RM.AR/capita are known than the following equation is valid to an accuracy of $\mathbf{R^2 = 0.527}$, RMSE= 170.6

$$\bar{Y} = 103.38 + 2.14*(GIFA/capita) + 136.9*(FN/capita) + 661.9*(DEH/capita) + 215.21*(FRG/capita) + 121.52*(TV_{(kW)}/capita) + 228.1*(MW/capita) + 299.8*(ACONC_{(kW)}/capita) + 71.1*(FTL) + 45.9*(CON.RM.AR/capita) \quad (4)$$

Grouped Model: Where GIFA/capita, APP+LTS/capita and CON.RM.AR/capita are known then the following equation is valid to an accuracy of $\mathbf{R^2 = 0.486}$, RMSE= 177.8:

$$\bar{Y} = 165.33 + 2.48*(GIFA/Capita) + 404.3*(APP_{(kW)}+LTS_{(kW)}/Capita) + 37.45*(CON.RM.AR/Capita) \quad (5)$$

Combined Model: Where GIFA/capita, FN/capita, DEH/capita, FRG/capita, TV/capita, FTL/capita, CON.RM.AR/capita and APP(kW)+LTS(kW)/capita are known then the following equation is valid to an accuracy of $\mathbf{R^2 = 0.531}$, RMSE= 170:

$$\bar{Y} = 101.77 + 1.9*(GIFA/capita) + 112*(FN/capita) + 415.82*(DEH/capita) + 124.37*(FRG/capita) + 97.87*(TV_{(kW)}/capita) + 62.32*(FTL) + 45.74*(CON.RM.AR/capita) + 245.64*(APP_{(kW)}+LTS_{(kW)}/Capita) \quad (6)$$

4.3.7.3 Annual gas consumption in kWh per household model

The equation for the prediction of annual gas consumption per household in kWh is: (R^2= 0.056, RMSE= 4050.9)

$$\bar{Y} = 3532.13 + 14.1*(GIFA) \quad (7)$$

4.3.7.4 Annual gas consumption in kWh per capita model

The equation for the prediction of annual gas consumption per capita in kWh/capita is: (R^2= 0.078, RMSE= 713.5)

$$\bar{Y} = 458.1 + 17.85*(GIFA/capita) \quad (8)$$

5 Discussion

The models produced now allow various energy consumption scenarios to be modelled. In absolute energy terms, we are now able to identify statistically the range of electrical energy impact each variable has when present in a dwelling. The table below shows the ranges of annual electricity consumption per household that models have shown can be expected due to the presence of each instance of the following variables:

Table 8 Ranges of electrical energy consumption(kWh) per instance of a variable

Variable	Annual Energy Consumption Range per instance (kWh)
Per air-conditioned room (CON.RMS)	445 – 567
Per Microwave (MW)	219
Per Fridge (FRG)	135 – 191
Per TV (TV)	120
Per fluorescent tube (FTL)	97 – 117
Per ceiling fan (FN)	77 – 97
Per LED light/SMD (LED/SMD)	58 – 62
Per occupant (OCC)	53 – 67
Per Energy Saving CFL or halogen bulb (ES)	45 – 48
Per m^2 of gross internal floor area (GIFA)	1.4 – 1.6

These findings are generally in line with section 4.1. The main implications for future energy policy are that they show the potential impact that a warming climate could have on domestic energy demand as the number of rooms needing cooling will increase plus fridges and fans must work harder. With a current average electricity demand of 2401 kWh/year per household, every additional room cooled would increase the average household's annual electrical energy demand by around 18 - 23%. The additional energy increase per person as shown in table 8 is only 57-63 kWh/annum, showing that larger households are more energy efficient on a per capita basis due to the sharing of background electrical loads across more people.

The models presented in section 4.3.7 do not vary much in their accuracies, so the choice of which ones to use will be dictated by the format of data available and user choice. We have cross-validated the models produced (section 3.6), which gives us the confidence to recommend them for general application in the whole of Punjab. The values predicted by using these models should be seen in combination with the error of estimates given against each model, for better utilisation of these models.

As the drivers identified with the highest correlation (section 4.1, Table 3), the numbers of appliances and lights, their installed power and space conditioning for cooling are the main drivers of electrical energy demand in the

Punjab domestic sector. Addressing these drivers is, therefore, key to reducing or reversing the growth in carbon emissions in Punjab domestic sector. A mitigation strategy would, therefore, be expected to involve:

- Increasing the energy efficiency of installed appliances and lights, especially air conditioners for cooling; and it is an important policy to enact to maximise the positive impact of any growth in the Pakistan energy supply and to improve the current electricity crisis in the country
- Reducing the demand for cooling in conditioned rooms

Other controls available to address the demand drivers require either reduced floor areas per household or reduced ownership of appliances.

Removing inefficient appliances and lights from the market would bring Punjab (Pakistan) in line with more developed economies [92] [93]. However, with current Punjab (Pakistan) per capita and household energy demands still very low relative to industrialised and advanced economies [7], as shown in Figure 7, it appears that increased appliance energy efficiency standards will only help reduce demand growth, not prevent it. Figure 7 shows an expected per capita value of 230kWh/annum for Pakistan as a whole, and we have used this figure as an initial starting point that we might have expected for Punjab, in relation to the other countries noted. However, from our study, the per capita consumption within Punjab is almost 70% higher than this figure at 391kWh/annum, which means that either the rest of Pakistan uses very little electricity per capita in relation to Punjab to balance this out or, more likely, Pakistan's consumption per capita has substantially increased compared to the previous figures produced by the IEA in figure 7 [7]. Per capita consumption of electrical energy value thus needs to be updated to closer to that found in the survey.

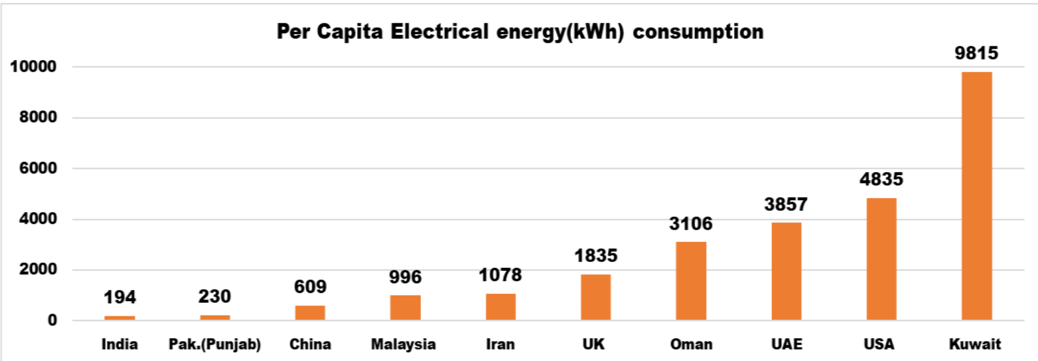

Figure 7 electrical energy consumption(kWh) per capita, source [7]

The average demand models produced in this paper per household and per capita, along with the per-instance demand ranges shown, can be used by policymakers to assess the likely impact of changes in the drivers of energy demand as they consider future energy policy and power supply options. This paper also identifies that the monthly EUI's for electricity and gas have predictable variations throughout the year per household. Electricity demand is highest in summer, whereas gas demand is highest in the Winter. The summer peaking electricity demand is helpful as it coincides with peak renewable energy output from PV systems, which could help meet the demand over this period.

For gas demand, the gross internal floor area (GIFA) is the only predictive variable in both gas models (4.5.3 & 4.5.4) showing that the internal gains from occupancy, appliances, and lighting do not significantly impact heating demands. It suggests the houses are probably poorly designed from a thermal efficiency viewpoint.

Statistically, there is no significant relationship between the number of people and gas usage, despite its predominant use for space heating, cooling, and water heating. The reasons for this could be gas cost, system efficiencies and/or personal habits. These parameters require further research to understand how they influence gas use in regions where heating is not a major consumer of energy. Separating the use of gas for space/water heating and cooking would enable an understanding of the potential for renewable sources to offset some of this still important demand. Statistically, the domestic energy consumption prediction models can be used for the whole population if all these variables are known.

6 Conclusions

This study aimed to understand the domestic demand drivers and energy usage intensity (EUI) of the Punjab, Pakistan. Eight energy prediction models have been produced, based on information gathered in 2017-18 on 76 different independent variables and associated measured annual energy consumption data in 4597 Punjab households. Pearson coefficient analysis (r) was used to identify demand drivers, descriptive statistics like average values were used to understand EUI (energy usage intensity), and regression analysis was conducted to develop the prediction models. All these results are presented at two levels, i.e. per household and capita.

The results show that the annual demand for electricity use per household and capita can be significantly predicted from knowledge of the numbers and types of appliances and lights, their installed power ratings, the number of conditioned rooms, and their area (especially for cooling). Gross internal floor area and occupancy are not very significant factors in predicting electrical consumption. The gross internal floor area is the only demand driver variable available for gas demand in both models. Annual energy usage intensity (EUI) of gas is greater than electricity for both cases, i.e. per household and capita.

This paper's findings suggest that increasing the efficiency of appliances (especially air conditioners for cooling) and lights would help significantly in reducing the current electrical energy consumption of the domestic sector of Punjab and in achieving low carbon economy goals. It is suggested this efficiency improvement should happen as quickly as possible to both ease the current impact of daily electrical supply interruptions and to prepare the country for managed growth in increasing energy use. Comparison of the per capita electricity use in Punjab with the average electricity use per capita internationally suggests there is a large potential for domestic electricity growth which will exacerbate existing power shortages in Pakistan. Identifying the variables of domestic energy demand will be of value to the energy supply and policy-making authorities when formulating policies to address supply capacity issues and carbon emissions. The research helps the policymakers broadly in two ways; (a) to understand what causes the energy demand in the domestic sector of Punjab so that policies can be put in place to mitigate the demands. (b) the prediction models help the policymakers to predict future energy demand based on predicted population growth, enabling effective measures to be implemented to meet this likely future demand down to the level of individual buildings. The findings are also of use to Engineers and Architects looking to design or renovate domestic properties to meet Zero Carbon or Positive Energy Housing standards. Further analysis will be undertaken on the sample data-set at monthly, Division and District levels to see if the whole of Punjab findings is replicated at different scales, and to assess the impact of occupant indicated desires for growth.

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Appendix A:

Survey Form

<u>Survey form</u>

How do we move towards a low carbon and resilient energy future for Punjab, Pakistan?

This academic research project is being conducted to understand and feed into the debate on how Punjab's energy supply will need to evolve to meet future demands.

This is your opportunity to ensure your voice is heard in the discussions concerning how we achieve the energy and power needs we have as a society, as we try to improve standards of living and our economy.

The study is considering everything from energy supply through to end-use energy demand. For this part of the study we are looking to understand:

1. How much energy (power & gas) is being used in relation to household size and the number of occupants?
2. Potential future increases in energy demand. For example, if more energy is made available, how much is demand likely to increase?
3. What produces this energy demand in a typical household?
4. When is this energy being used?

All information provided is confidential and will only be used for this study.

This study is being undertaken by Usman Awan, University of Engineering and Technology, Lahore Pakistan in conjunction with the Welsh School of Architecture, Cardiff University, U.K.

Your consent to keep information for this and later studies (like research papers): **Yes** **No**

Q1. Name/Roll Number

Q2. Address

Q3. How many people are usually living in the house? (also include house worker(s)/servant(s) who live(s) in the same house?

Total Adults- children- servants-

Q4. What is the total covered area of your house? (Including each floor covered area of the ground floor, first-floor basement, etc., and excluding outer spaces?

A.4

Q5. What is the total number of conditioned rooms (rooms which are heated and/or cooled) in your house?

A5.

Q6. What is the total combined area of conditioned rooms? (sq. Ft, sq.M, Dimensions)

A6.

Q7. How many rooms would you like to condition in total if you could afford it? (heating or cooling)

A7.

Q8. What would the new total combined area of conditioned rooms then be? (sq.ft,or sq.m)

A8.

Q9. How much electricity do you use per month(kWh)? And power cut, hours per day in each month?

A9. January - / , Feb- / Mar- / ,April / ,May / ,June /
July / ,Aug / ,Sep. / ,oct. / ,Nov. / ,Dec. /

Q10. How much Gas do you use per month(hm3)? AND Gas cut ,hours per day in each month?

A9. January - / , Feb- / Mar- / ,April / ,May / ,June /
July / ,Aug / ,Sep. / ,oct. / ,Nov. / ,Dec. /

Q11. Are you aware of the use of solar cell (PV) to help supplement the electrical energy you purchase from the national grid?

A11. 1-NO, 2-Yes(have heard but never seen it used),
3-Yes(have heard and seen it used), 4-Yes (Already used it by myself

Q12. If you answered 'Yes' to the last question, what is the size (generation capacity) of your Solar cells(PV)? (KW)

A12.

Q13. In which direction your solar cells are installed?

A13.

Q14. What is the angle of installation?

A14.

Q15. Would you be willing to install Solar cells (PV)? (or if it will not reduce the rooftop area for other activities)?

A15. 1-No, 2-Yes (self-financed) 3-Yes (if given some subsidy by the government)

Q16. How large is your rooftop area?

A16.

Q17. Please list all the lights in your house by type, wattage and average usage per day, And additional required if you can afford it?

Sr. No	Type	No.	Wattage /size (W)	Summer Usage hrs	Winter Usage hrs	additional required no.	addition usage hr
1	Fluorescent tube lights						
2	Incandescent Bulbs						
3	Energy Saver (C.F.L)						
4	LED, SMD						
5	Others						

Q18 Please list all the electrical appliances in your house by type, wattage and average usage per day, And additional required if you can afford?

Sr. No	Type	No.	Wattage /size (W)	Summer Usage hrs	Winter Usage hrs	Spring Usage hrs	Autumn Usage hrs	additional required no.	additional usage hrs
1	Fan(s)(bracket, ceiling, Pedestal, etc.)								
2	Air conditioner(s) (cooling only)								
3	Air conditioner(s) (heating only)								
4	Air conditioner(s) (both cooling & heating)								
5	Direct electric heater (rod, fan heaters, etc.)								
6	Fridge(s)								
7	Freezer(s)								
8	Television(s)								
9	Computer(s), Laptop(s)								
10	Microwave(s)								
11	Playstation/video games etc								
12	Stove exhaust fan								
13	Exhaust fan(kitchen, bathrooms, etc)								
14	Internet Modem/router/hub etc								
15	washing machine								
16	vacuum cleaner								
17	water cooler/Desert cooler								
18	central heating or cooling system								

Your Signature as respondent: ___________________________

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