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Prediction of Household Carbon Emission During Pandemic Using Machine Learning Model

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ABSTRACT

The pandemic has dramatically altered daily routines worldwide, with increased dependence on electronic gadgets for work, education, and entertainment. Work from home culture increased during the pandemic and persisted even after the pandemic. Though the GHG (Greenhouse Gas) emission is reduced in other sectors, it was predicted that this has increased in housing sectors during the pandemic. Our study aims to investigate the impact of increased electronic gadget usage on household carbon emissions during the pandemic. Through a combination of surveys, energy consumption data analysis, and carbon footprint assessments, we examine changes in electronic device usage patterns and their subsequent environmental consequences. Carbon emissions associated with these changes were quantified, considering factors like the number of device types, number of users, and energy consumption. The proposed study highlights the impact of electronic gadget usage on household carbon emissions during the pandemic. For the prediction of household carbon emissions supervised machine learning technique is used. Supervised machine learning is a digital technology that advances digital systems and processes and is categorized under artificial intelligence. Supervised machine learning is a type of machine learning where the algorithm is trained on a labeled dataset, mapping inputs to outputs by generalizing patterns from the training data and making predictions or decisions based on data. The findings of this research contribute valuable insights into the environmental implications of the widespread use of electronic gadgets during the pandemic. Understanding these impacts is essential for individuals, policymakers, home business makers, and technology developers to formulate strategies that promote sustainable gadget usage, minimize carbon footprints, and contribute to a more environmentally conscious post-pandemic society.

Keywords: Green Computing, Greenhouse Gas (GHG), pandemic, Supervised Machine Learning, Regression Analysis. COVID-19.

1. Introduction

Increasing population and wealth around the world increases demand for housing upgrades in highly urbanized locations. The amount of electricity consumed by each family is also rising because of the improved supply of electricity resulting in an increase in gadget purchases due to rising incomes. By 2050, it is anticipated that the amount of power used nationally by the residential sector will have increased by more than eight times. This impels evaluation of the carbon footprint of the residential sector and its impact on the environment. Moreover, the COVID-19 pandemic forced many organizations to adopt work from home culture which has caused a steep rise in the purchase and usage of electronic devices, resulting in increased energy consumption and greenhouse gas emissions in housing sectors. Considering the green computing factors, optimal usage of all electrical and electronic equipment is necessary to keep the home environment safe and healthy. Moreover, energy costs can be drastically reduced by reducing energy consumption. (Le & Pitts, 2019)

It has been found that research in this field is interdisciplinary and more depth is needed at the city and individual levels. (Zarco-Periñán et al., 2022). Reducing energy consumption can significantly lower energy expenses. Prior knowledge of the sources is essential for implementing strategies to reduce them. As a result, actions can be taken to lower consumption and consequently, carbon emissions.

The proposed study aims to find household carbon emissions from urban housing sectors of Maharashtra state, India. The appliances considered for the study of carbon emission from the housing sector due to the usage of electronic gadgets are air-conditioners, televisions, smartphones, laptops, and network devices. During this study, it was also observed that there is less research done on the reduction of household carbon emissions. To fill in the research gaps in the available data sources on household carbon emission in India, this study will contribute valuable information on carbon emission, appliance ownership, and usage behavior of selected gadgets during the pandemic which will help to supplement the current insufficient data sources on household energy use in India. It will be easier to improve energy efficiency as well as reduce carbon emissions and gain a better understanding of how to make buildings greener, and comfortable to live with the proper knowledge and understanding usage of appliances.

1.1 Literature Review

le Quéré et al., 2020 gathered data on activities and government measures to assess the reduction of CO2 emissions during forced confinements. Though GHG emissions decreased during the pandemic across various sectors, a reverse impact was seen in household sectors. This was observed due to increased activity resulting in increased energy demand in the household sector.

As per the data published by Teehan & Kandlikar, 2013, products manufactured in 2009 or 2010, are significantly lighter in comparison to those manufactured from 2002 to 2004 which is proof that electronic devices are improving over time in terms of material efficiency. According to the authors, modern devices show significantly less material usage for integrated circuits due to higher levels of miniaturization available in modern packaging technologies, as well as reduced numbers of ICs per product. The majority of embedded GHG emissions in most gadgets are caused by circuit boards, particularly ICs. Though the emissions due to product casing are minimal, emissions by laptop casing are higher. According to the findings, there is a direct correlation between product mass and embodied emissions, with heavier or larger products producing more emissions.

Ahmad *et al*., 2015, studied household microdata from India's 60 largest cities and mapped GHG emissions patterns and their determinants. The key findings of these authors are that income and household size are the most important determinants of household emissions. The characteristics of cities and housing, one's degree of education, and one's gender are only a few of the additional variables that affect emissions.

(Gokarnkar & Sangeetha G, 2023) in this study, a supervised machine learning model called regression analysis is used to predict household power consumption due to the usage of gadgets.. The authors conclude that household operational energy consumption by electronic gadgets during the pandemic depends on various factors rather than the demographic characteristics of households and the number of gadgets respondents own. As per the research (Teehan & Kandlikar, 2013) operating effects of the personal computer (PC) industry are responsible for about 60% of greenhouse gas emissions and the rest 40% by manufacturing.

Researchers (Bahmani & Mosavi, n.d.) investigated that machine learning contributed very well to the advancement of the prediction models used for energy consumption. These models significantly increase the reliability, precision, and generalizability of the traditional time series forecasting methods.

1.2. Objectives

- To understand the impact of owning several gadgets and the usage pattern of consumers on household carbon emission.
- To highlight pointers to reduce household carbon emissions by potentially reducing energy consumption through the adoption of energy-efficient technologies.
- To give recommendations for building architects, policymakers, and consumers on how to reduce household carbon emissions which are contributing to global warming.

Hypothesis H0: Household carbon emission is based on the number of gadgets owned by respondents and their usage patterns during the pandemic.

Hypothesis H1: Household carbon emission is based on various other factors rather than the number of gadgets owned by respondents and their usage patterns during the pandemic.

1.3. Scope

The scope of this study is limited to urban households of Maharashtra State, India. Exploratory data analysis is done by considering highly used gadgets/appliances such as Air-conditioners, Televisions, laptops, Smart mobile phones, Network Devices, etc. during the pandemic.

2. Research Methodology

2.1 Exploratory Data Analysis

Data for analysis is primarily the responses received from the online survey of 101 respondents residing in urban areas of Maharashtra state, India. Secondary data such as the GHG (Carbon) emission of electronic gadgets (or appliances) per hour usage in terms of kg are taken from device data sheets. The total GHG emission of a household is calculated by adding the GHG emission of each device taken into consideration.

The formula applied to find the GHG emission of each device is shown below:

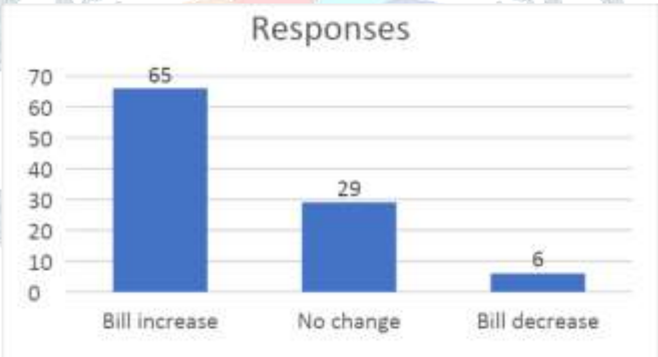
Co_2 Emission of a device (in Kgs) = (Number of such devices × Usage in Hours × Carbon Emission (in Kgs per Hour)

Data analysis is done using machine learning techniques. Regression analysis which is a Supervised Machine Learning technique used to train and test the output variable – Carbon Emission (Total_GHG_Kg).

A supervised Machine Learning Model called Regression analysis is used to train and test the target variable - Total_GHG_Kg. Python and various Python built-in libraries are used such as Pandas, NumPy, Matplotlib, Seaborn, SciPy, SciKit Learn, Min-Max Scaler, etc for data analysis.

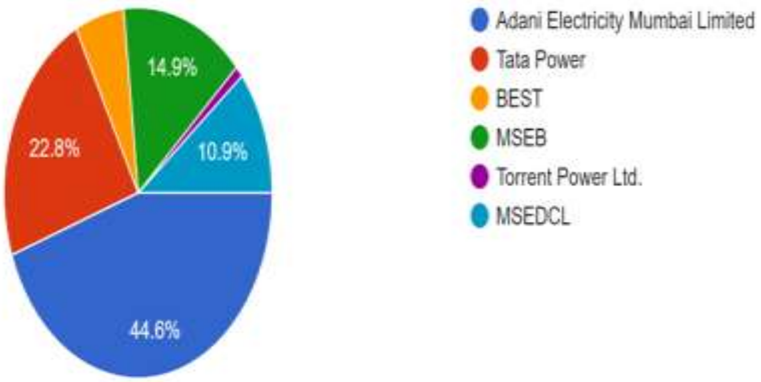
2.2 Demographic Data of Respondents

Figure:1 Responses received for change in Electricity bill during the Pandemic.



65% of people reported that their household electricity bill increased during the pandemic and 6% said that their electricity bill was reduced during the pandemic but 29% responded that there was no change in their electricity bill during the pandemic.

Figure 2: Respondents' electricity service providers in Maharashtra.



Adani Electricity Mumbai Ltd. consumers are more in number. BEST consumers are fewer in number.

Figure 3: Joint plot between Gadgets_owned and Total_GHG_kg.

In the joint plot, the scatter plot and histogram are combined in one visualization. Here the scatter plot shows the relationship between Total GHG emissions in kg and Gadgets owned by people, while the histogram shows the distribution of each variable. According to the plot many households have gadgets between 5 to 10 and there is a linear relationship between Total GHG emissions and Gadgets owned.

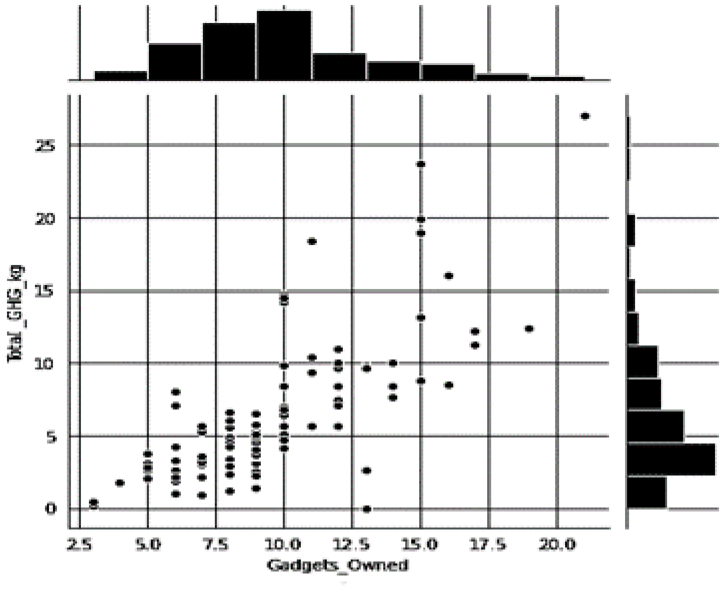


Table 1: Total Number of Electronic Gadgets / Appliances Owned by Respondents

Total No. of Devices owned	AC	Laptop	Smartphone	Network Device	TV
1	39	50	62	50	38
2	48	40	29	27	28
3	18	11	6	12	9
More than 3	0	12	3	9	13
None	0	27	38	31	24

Table 2: Usage Pattern of Electronic Gadgets / Appliances of Respondents

Gadgets / Appliances usage Hours	AC	Laptop	Smartphone	Network Device	TV
Less than 5 Hrs	66	43	23	24	51
5 Hrs to < 8 Hrs	8	21	34	11	32
8 Hrs to < 12 Hrs	5	20	30	20	9
12 Hrs or Greater	1	5	11	39	2

3. Research Findings

It was observed that 65% of people had reported an increase in electricity charges during the pandemic. The rise in electricity bills is predicted due to excess use of gadgets/appliances during forced confinements at home to contain the spread of coronavirus. Regression analysis of machine learning models is used to predict the null hypothesis. This test is carried out by considering Gadets_Owned and Consumption_Hr of gadgets as independent variables and Total_GHG_Kg as dependent (target) variables. The results of the regression are -

Mean Absolute Error MAE: 0.1040960215465015

Mean Squared Error MSE: 0.017641445860781504

Root Mean Square Error RMSE: 0.1328211047265513

Values obtained for MAE, MSE, and RMSE are very low and are not within acceptable limits. Further T-test is conducted for Total_GHG_Kg (target variable) to check the null hypothesis. The statistic and p-value of the T-test are as follows:

Ttest_indResult (statistic= array ([4.20017491]). P Value = array([5.15127824e-05])

As the p-value is also less than the significance level of 0.05, the null hypothesis H0 - Household carbon emission is based on the number of gadgets owned by respondents, and their usage pattern during the pandemic is disproved. Hence alternate hypothesis H1: Household carbon emission is based on various other factors rather than the number of gadgets owned by respondents and their usage pattern during the pandemic is predicted correctly.

Table 3: Details Of Number of Electronic Gadgets / Appliances Purchased by Respondents During Pandemic:

VALUES (Quantity)	No. of people purchased AC	No. of people purchased TV	No. of people purchased Laptops	No. of people purchased Network Devices	No. of people purchased Smartphones
01	10	13	29	22	37
02	2	2	4	6	11
03 or more	0	0	0	0	7
No purchase Done	89	86	68	73	46

Interestingly, our findings indicate a notable rise in the purchase rate of gadgets and appliances, such as smartphones and laptops, among consumers compelled to work from home, despite the closure of traditional office spaces. Though many researchers predicted the carbon emission from the housing sector increased during the pandemic, our analysis predicted that total household carbon emission is dependent upon various other factors such as income level, lifestyle, surrounding environment, climatic conditions, education level, area of the house, gadgets usage habits, etc. However, it is essential to note that this research does not encompass the collection of data on these parameters. Consequently, further research is warranted to comprehensively identify the factors contributing to the heightened greenhouse gas emissions from the housing sector during the pandemic.

Figure 4: Heat map of independent and dependent variables

Correlation between independent (Gadgets_Owned, Consumption_Hr) and dependent (Total_GHG_Kg) variables. The heat map is a two-dimensional graphical representation of data used to analyse large data sets. Colours are used to signify values in this context. Total_GHG_Kg is found to be more associated with Gadgets_Owned.

4. Suggestions

1. One of the ways that electronic gadgets contribute to GHG emissions is through their use. Many electronic gadgets require electricity to operate, and the generation of electricity is a major source of GHG emissions. The usage of electronic gadgets, therefore, contributes to GHG emissions impacting global warming and climate change.

2. People purchased gadgets to fulfill their job/study requirements during the pandemic. More gadgets mean more e-waste. The ecosystem will get unhealthy if e-waste is not disposed of appropriately. The chemicals released from e-waste will gradually deteriorate the physical and mental health of humans. Hence, once products reach the end of the life cycle they must be recycled through a certified recycler.

3. Environmentally responsible citizens must buy the device only when it is needed. One must look into the refurbished section before buying brand-new equipment.

4. If the equipment is truly broken and cannot be repaired, recycling it responsibly is another option for ensuring that the device is disposed of sustainably.

5. In terms of other environmental impacts like global warming, acidification, eutrophication, summer haze, and land usage, household carbon footprint may have unanticipated and unintended harmful implications that would negatively impact human health and shorten life spans. The government must thus seriously consider this element and start active campaigns to raise public knowledge.

6. Country can also plan for negative carbon emission by making carbon absorption and removal more than carbon emission. Though carbon removal technology is very expensive, carbon absorption can be done by creating carbon sinks such as green forests.

7. Mumbai ranks first in generating e-waste in India followed by Delhi, Bengaluru, Chennai, and Kolkata. According to the latest data released by the Ministry of Environment, Forest and Climate Change, e-waste generated during the financial year 2021-2022 is 16,01,155.36 Tonnes, hence e-waste recycling in an environmentally sound manner is the primary issue to be addressed to reduce Carbon emission.

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