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CLEAN AND GREEN TECHNOLOGY ON CARBON FOOTPRINTING AND PREVENTING THE ENVIRONMENT

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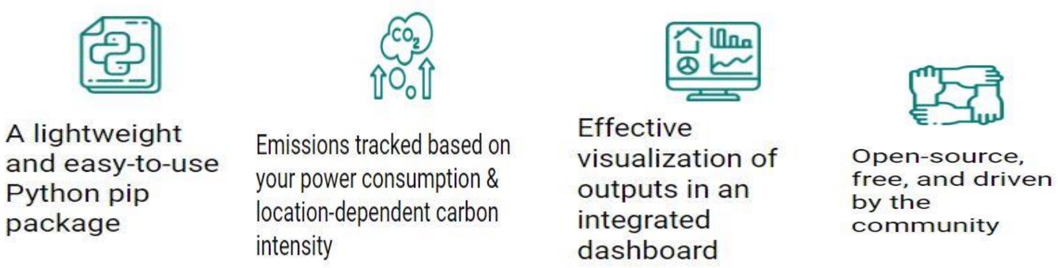
Abstract : Clean And Green Technology on carbon Footprinting is to reduce the carbon capture (CC) and its utilization (CU) and carbon emission is represented as loss of carbon emission (LCE).To improving the clean production level. It is a non-linear mechanism of the transformation of energy consumption. The various values of loss of power supply probability (LSP).It is used to prevent the ecosystem of world. It has become an urgent issue for all countries to ease the sharp conflict between economic growth and ecological conservation. The fundamental way to achieve low-carbon economic growth is to make the energy consumption structure upgrade and develop towards a cleaner direction .The integration of conventional sources with the grid has many challenges, like carbon emission, optimal cost of the system, and power quality issues. All these shortcomings create a non-sustainability in the environment, which is Of great concern. In order to overcome such issues, a hybrid system is designed that is composed of various components or sources like wind energy, solar photovoltaic energy, thermal energy, and battery energy storage with the purpose of providing an environmentally friendly, eco-nomically viable, sustainable, and reliable solution. According to the research results, the paper focuses on adjusting energy resource consumption and improving the clean production level.

Keyword: Irrigated load ,Techno-economic optimization, Environmental assessment ,Sensitivity, analysis Renewable energy, Irrigation system.

I. INTRODUCTION

In recent years, Artificial Intelligence, and more specifically Machine Learning, has become remarkably efficient at performing human-level tasks: recognizing objects and faces in images, driving cars, and playing sophisticated games like chess and Go. In order to achieve these incredible levels of performance, current approaches leverage vast amounts of data to learn underlying patterns and features. Thus, state-of-the-art Machine Learning models leverage significant amounts of computing power, training on advanced processors for weeks or months, consequently consuming enormous amounts of energy. Depending on the energy grid used during this process, this can entail the emission of large amounts of greenhouse gases such as CO_2.



. Figure 1. Simple explanation diagram

LITERATURE SURVEY:

Carbon Intensity of the consumed electricity is calculated as a weighted average of the emissions from the different energy sources that are used to generate electricity, including fossil fuels and renewables. In this toolkit, the fossil fuels coal, petroleum, and natural gas are associated with specific carbon intensities: a known amount of carbon dioxide is emitted for each kilowatt-hour of electricity generated. Renewable or low-carbon fuels include solar power, hydroelectricity, biomass, geothermal, and more. The nearby energy grid contains a mixture of fossil fuels and low-carbon energy sources, called the Energy Mix. Based on the mix of energy sources in the local grid, this package calculates the Carbon Intensity of the electricity consumed

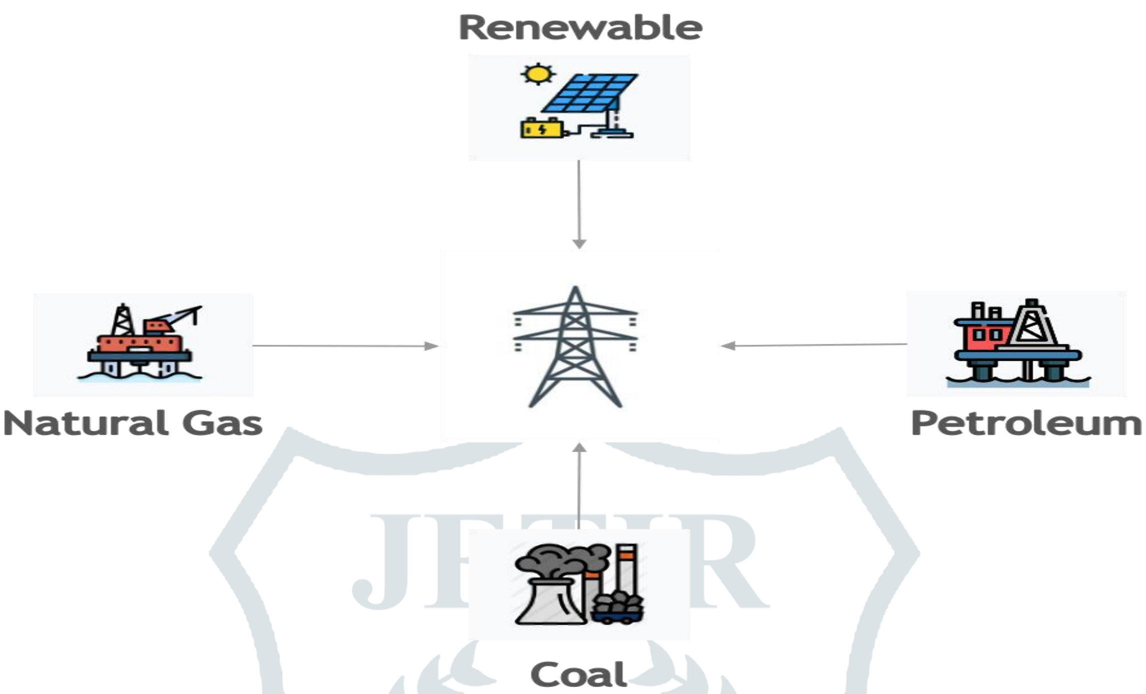


Figure 2. Carbon Intensity of the electricity consumed.

Carbon Intensity Across Energy Sources

Energy Source	Carbon Intensity (kg/MWh)
Coal	995
Petroleum	816
Natural Gas	743
Geothermal	38
Hydroelectricity	26
Nuclear	29
Solar	48
Wind	26

Figure 3. carbon intensity across energy sources

Power Usage

Power supply to the underlying hardware is tracked at frequent time intervals. This is a configurable parameter measure_power_secs, with default value 15 seconds, that can be passed when instantiating the emissions' tracker

. Currently, the package supports the following hardware infrastructure.

GPU

Tracks Nvidia GPUs energy consumption using pynvml library (installed with the package).

RAM

Code Carbon uses a 3 Watts for 8 GB ratio source . This measure is not satisfying and if ever you have an idea how to enhance it please do not hesitate to contribute.

CPU

• On Windows or Mac (Intel)
Tracks Intel processors energy consumption using the Intel Power Gadget. You need to install it yourself from this source .

FIGURES AND TABLES:

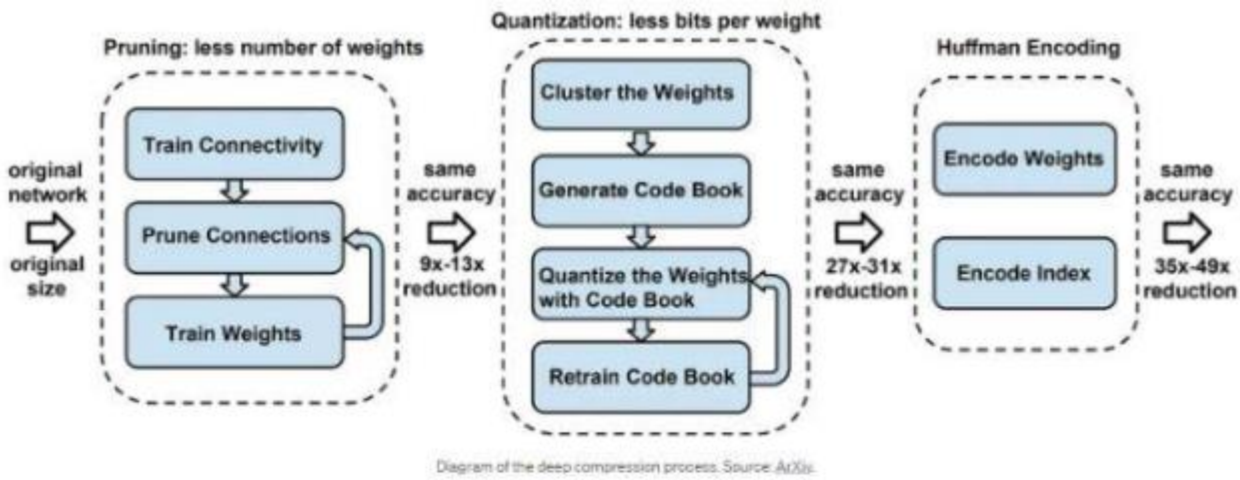


Figure 4.Decompression Process

RESEARCH METHODOLOGY:

The current technology claims that the researchers have figured out how to lower the amount of heat and carbon that is there. In the form of carbon 0. Using machine language, it is suggested that we compute the frequency of carbon emissions and lessen our carbon footprint using the same methodology. To use the software in order to.The applover program, which uses Python 3.10, has been used to calculate carbon footprinting and the frequency of carbon emissions. SPEG has been updated and used at the testing level.The program's output displays the carbon emission.

There are 3 major factors that drive the environmental impact of AI, and data scientists can have a direct impact on the rate of CO_2 emissions by making informed choices on each of these factors:.

1. Grid Energy Mix: Electricity from the grid that the hardware infrastructure is connected to may be generated by a combination of different energy sources (coal, petroleum, natural gas, low-carbon fuels). The combination used can result in significant variation in the average emissions in a single region, ranging from between 20g CO_2eq/kWh in Quebec, Canada to 736.6g CO_2eq/kWh in Iowa, USA [3]. The choice of cloud server region where you run your algorithms is the single most important choice to limit the environmental impact.

2. Compute Time: Training a powerful machine-learning algorithm can require running multiple compute machines for days, if not weeks. For example, the fine-tuning required to improve an algorithm by searching through different neural network parameters can be especially computationally intensive, since all possible combinations of parameters are usually tested via grid search. For recent state-of-the-art architectures like VGG, BERT and GPT-3, which have millions of parameters and are trained on multiple GPUs (graphic processing units) for several weeks, this can correspond to a difference of hundreds of kilograms of CO_2eq.

3. Choice of Hardware: Instead of using traditional chips, data scientists can reduce their environmental impact by turning to newer generations of computing hardware such as GPUs and tensor processing units (TPUs). These have been specifically designed for the parallel computations involved in training neural networks. Using this hardware can improve the efficiency of training ML models, reduce training time and energy and, therefore, reduce climate impact.

Using the Emissions Tracker:

To track the carbon emissions of training AI/ML models, our team has built a tool called CodeCarbon. It comes as a light-weight pip package that seamlessly integrates into a Python codebase. As such, developers around the world who use Python can add this tool to their code and, with just a few more lines of code, start tracking CO_2 emissions from the execution of the codebase.

The tracker logs the estimated CO_2eq produced by each experiment then stores the emissions across projects that can be aggregated at an organizational level. This gives developers greater visibility into the amount of emissions generated from training their models and makes the amount of emissions tangible by showing equivalents in the number of automobile miles driven, the hours of TV watched, and the daily energy consumed by an average US household [5].

- **Installing CodeCarbon**
- **Installing Tensorflow**
- **Create an EmissionTrackerℑ**
- **Track emission**
- **Output**

COMPARISON OF DAILY USAGE:

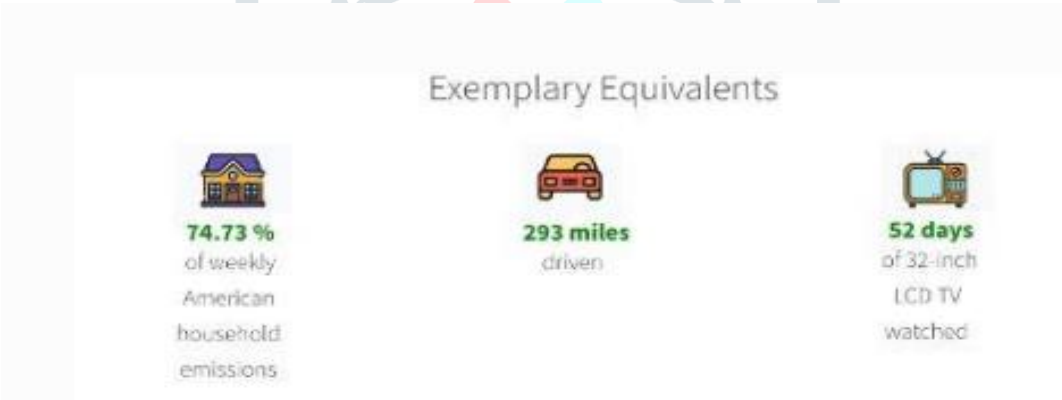


Figure 5. Maximum Carbon Emission

ENERGY CONSUMPTION ACCURACY:

GPU	Training Time (H)	Consumption (kWh)
4 V100	6	3.1
8 V100	36	37.3
256 A100	192	13 812.4
1 P40	0.3	0.02
1 P40	0.3	0.03
1 P40	0.4	0.04
1 V100	19	1.7
1 V100	19	2.2
1 V100	21	4.7
4 V100	90	93.3

Figure 6. Carbon Emission Accuracy Value Table

RESULT:

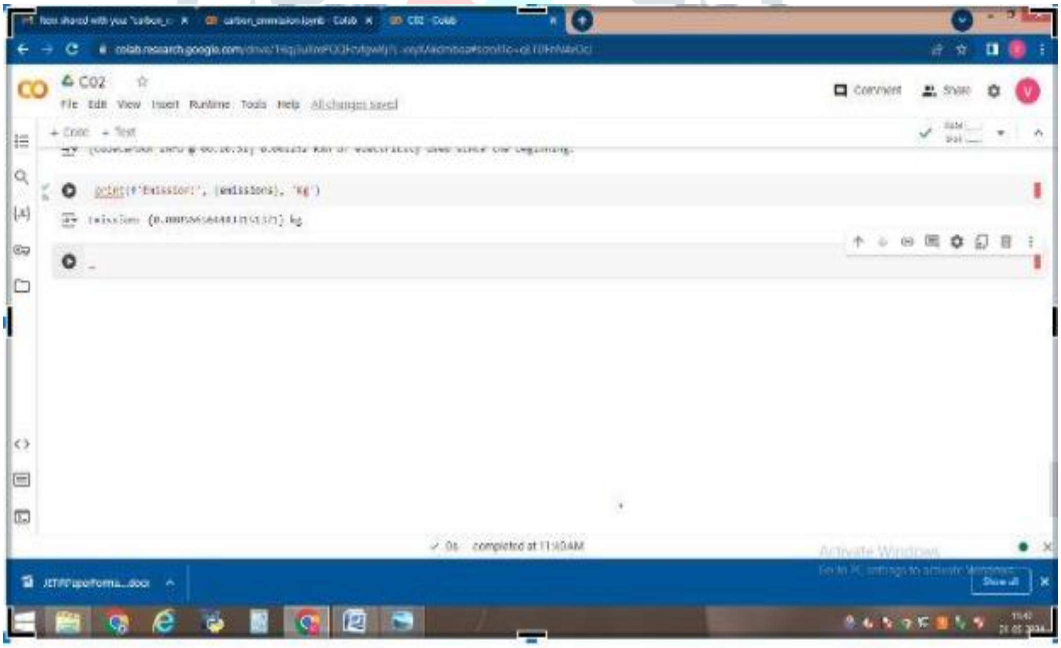


Figure 7. Final Output For Your Program

CONCLUSION:

The integration of renewable energy sources with the conventional grid. The carbon emissions generated from conventional sources do not match the gap between source and demand, which is one of the major challenges. The renewable energy sources or components, like solar, wind, and BESS, are integrated with the conventional grid to meet load demand because they contribute very little in carbon emissions. All such outputs generated from hybrid methods ensure sustainability in the environment. The challenges associated with environmental concerns and sustainability can also be improved by other intelligent techniques. Still, there is a little scope for improvement in the performance parameters related to carbon emissions, distortion level,cost, and size of components of the hybrid integrated system. It could be expected that a slight change in performance parameters could address the environmental challenges.

REFERENCES:

- [1]An Effective Optimal Economic Sustainable Clean Energy Solution With Reduced Carbon Capturing/Carbon Utilization/ Carbon Footprint for Grid Integrated Hybrid System - 29 March 2023-Abhinav Saxena ,Sampath Kumar V, J. P. Pandey

- [2]Energy Consumption Transformation, Cleaner Production, and Regional Carbon Productivity in China: Evidence Based on a Panel Threshold Model-January 13, 2021-ZHENG LI, YINGYING DING , DONGRI HAN

- [3]S. Zhang, Y. Mishra, and M. Shahidehpour, “Fuzzy-logic based frequency controller for wind farms augmented with energy storage systems,” IEEE trans. Power Syst., vol. 31, no. 2, pp. 1595–1603, Mar. 2016.

- [4]T. R. Ayodele, A. A. Jimoh, J. L. Munda, and J. T. Agee, “Challenges of grid integration of wind power on power system grid integrity: A review,” Int. J. Renewable Energy Res., vol. 2, no. 4, pp. 618–626, 2012.

- [5]M. Z. Abid, M. Yousif, S. Ullah, and M. Hassan, “Design, sizing and economic feasibility of a hybrid PV/diesel/battery based water pumping system for farmland,” Int. J. Green Energy,”

- [6]M. Pourakbari-Kasmaei, M. Lehtonen, J. Contreras, and J. R. S. Mantovani, “Carbon footprint management: A pathway toward smart emission abatement,” IEEE Trans. Ind. Inform., vol. 16, no. 2, pp. 935–948 Feb. 2020,

- [7]G. Liu, J. Liu, J. Zhao, F. Wen, and Y. Xue, “A real-time estimation framework of carbon emissions in steel plants based on load identification,” in Proc. Int. Conf. Smart Grids Energy Syst., 2020, pp. 988– 993.

- [8]N. Zhu and Y. F. Zhang, ‘‘Mechanism of carbon emissions intensity response to industrial evolvement and energy consumption structur echange in Shaanxi Province,’’ Arid Land Geography, vol. 38, no. 4,pp. 843–850, 2015.

- [9]B. E. Hansen, ‘‘Threshold effects in non-dynamic panels: Estimation, testing, and inference,’’ J. Econometrics, vol. 93, no. 2, pp. 345–368,Dec. 1999.
- [10]B. Xu, Y. F. Chen, and X. B. Shen, ‘‘Clean energy development, carbon dioxide emission reduction and regional economic growth,’’ Econ. Res. J.vol. 54, no. 7, pp. 188–202, 2019.

- [11]M. A. Destek and A. Aslan, ‘‘Renewable and non-renewable energy consumption and economic growth in emerging economies: Evidence from bootstrap panel causality,’’ Renew. Energy, vol. 111, pp. 757–763,Oct. 2017.

- [12]S. O. Susam and B. Hudaverdi Ucer, ‘‘Modeling the dependence structure of CO2 emissions and energy consumption based on the Archimedeancopula approach: The case of the united states,’’ Energy Sources, B, Econ.Planning, Policy, vol. 14, no. 6, pp. 274–289, Jun. 2019.

- [13]J. Chen, C. Zhou, S. Wang, and S. Li, ‘‘Impacts of energy consumption structure, energy intensity, economic growth, urbanization on PM2.5 concentrations in countries globally,’’ Appl. Energy, vol. 230, pp. 94–105,Nov. 2018.

- [14]J. R. Liang, Y. J. Shi, and X. J. Xi, ‘‘Clean production technology innovation, abatement technology innovation and environmental regulation,’China Econ. Stud., no. 6, pp. 76–85, Dec. 2018.

- [15]H. Q. Wang, ‘‘Study on threshold effects of environmental regulation on economic growth from the perspective of human capital,’’ China Soft Sci.vol. 6, pp. 52–61, Jun. 2016.