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International Journal of Performability Engineering

1

Integrated Approaches to Energy Generation, Storage, and Distribution: Utilizing Both Utility and Non-Utility Resources

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***Abstract*— In the evolving landscape of energy management, accurate forecasting of energy consumption plays a critical role in optimizing the operation of smart grids. This research presents a comprehensive approach to energy consumption forecasting by leveraging linear regression models to predict the future consumption of various energy sources, including steam, diesel, gas, hydro, nuclear, and renewable energy sources (RES). Utilizing historical data spanning multiple years, we developed predictive models to forecast the demand for each energy type, alongside the overall energy consumption for upcoming years. The model is trained on key features such as annual consumption data, enabling the prediction of energy trends for smart grids. The methodology employed in this study predicts energy usage for the next fiscal year with a high degree of accuracy, helping grid operators optimize resource allocation and improve energy efficiency. Additionally, the model forecasts the total energy consumption, incorporating both utility and nonutility energy sources, ensuring a holistic view of the energy landscape. This approach allows for better decision-making, particularly in integrating renewable energy into the grid while managing traditional energy sources. The results of this study demonstrate the utility of machine learning in enhancing energy forecasting capabilities, which can serve as a valuable tool for policymakers and energy grid operators in designing future-proof energy systems that meet increasing demands sustainably.**

Keywords*— Energy Consumption, Smart grids, Linear regression, Forecast, Sustainably, Machine Learning, Prediction, Analysis Introduction

I. Introduction

This rapid transformation of global energy systems and increasing demand for sustainable energy has been fuelling the demand for smart grid technologies. Conventional models require testing each customer over every method. However, in the big volume, high velocity environment, it would not be feasible to do it this way [7]. Simply stated, a smart grid is an advanced energy system that facilitates two-way communication between a utility provider and its consumers, which allows for real-time energy management for improved efficiency and integration of renewable energy sources. Smart meters are measuring equipment that perform many functions: Beginning from data collection and data flow management on both ends to controlling with output devices. Smart meters have applications and solutions in oil, water, heating, and electricity industries [9]. This core development is focused on carrying out an accurate prediction of energy consumption. Such good prediction helps the grid operator, balance the supply and demand within minimum wastage of energy and maintains the stability of the grid. With access to large volumes of historical energy data, forecasting of energy consumption has transitioned from traditional statistical methods to advanced machine learning techniques.

This demands that high exactness of short-term and long-term energy forecasting is achieved. It is important not only to run the business operationally efficiently but also for the future-plans on energy infrastructure as well as for including clean energy sources in the grid. The still dominant and inclusive generation methods are steam, diesel, and gas, while hydro, nuclear, and RES represent cleaner alternatives. This will enable policymakers and energy managers to improve carbon footprint reduction by moving towards more sustainable energy solutions. In the following study, we will explore an approach using a machine learning-based linear regression in the forecasting of consumption of different types of energy source, namely conventional and renewable ones. Using historical data, the model shall make predictions of energy consumption trends for future years; this will enable smart grid generation, distribution, and storage.

II. Problem Statement

As energy use worldwide increases, so does the requirement for smart energy management systems that can

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predict with maximum efficiency the energy demand by assuring optimum power distribution and integrating renewable sources of energy. Traditionally conceived energy forecasts are usually inaccurate due to the growing complexities in energy grids, which are now home to diverse sources of energy such as steam, diesel, gas, hydro, nuclear, and renewable energy systems (RES). [1] proposed Grey Wolf Modified Enhanced Differential Evolution Algorithm, a hybrid of Grey Wolf and modified version of the enhanced differential evolution algorithm. It also creates inefficient grid operation, wastage of energy, imbalance between supply and demand, and more operational costs because there is no proper energy consumption forecasting model. Trying to put intermittent sources of renewable energy into the grid presents more significant challenges in terms of what kind of forecasting techniques are needed beyond the kinds being used today. They do not deal with the variability problems concerning any form of energy, nor do holistic models for these forecasts that consider traditional as well as renewable energy sources under one umbrella framework. Failure to get accurate forecasts for electrical energy demand could lead to load shedding, lost revenues on the supply or consumption side, and possibly even the collapse of the grid due to the inherent complexity of the electricity grid [10].

Therefore, there is a desperate need for the correct and detailed energy consumption forecasting model that would predict the upcoming demand over various types of energy sources but with increased contributions by renewable sources. For the operators involved in the grid's management of energy resources, such a model will be helpful to reduce carbon emissions in support of the transition toward sustainable energy systems. Currently, DSM, or Demand Side Management, is one of the key parts of the power grid that sets power requirements, monitors consumption, and controls customer behaviour to bring about power issues within limits, including blackouts, brownouts, and outages [6]. There were some studies that incorporated diesel generators as a backup energy source; however, such an application is not applicable in RES-based microgrids. Some solutions like load shedding may cause user frustration and therefore decrease system welfare and efficiency [11].

III. LITERATURE REVIEW

This is the increasingly fast-changing global energy landscape, due to widespread implementation of renewable energy sources, including solar, wind, and hydropower. Among these types of energy sources, they proved to be relatively more sustainable and cleaner in comparison to traditional fossil fuels, which can particularly help abate greenhouse gases. However, the intermittent nature of renewable energy sources is a significant challenge to the stability of energy grids because renewable energy generation depends greatly on weather conditions and the time of day. This has led to an increased demand for complex forecasting and energy management systems able to effectively predict supply and demand variations.

To match these demands, new energy storage systems-batteries and pumped hydro storage-will also emerge as critical parts of the modern energy grids. Load forecasting at the individual level, as opposed to load forecasting at the city level or above system aggregates, is a much more complicated problem owing to the greater stochastic and hence more volatile behaviour of individual household loads [3]. Those storage systems allow for retaining excess energy generated at times of peak renewable generation and can use this stored energy if renewable generation is low, which helps balance the grid to eliminate outages. Energy storage technology is expected to continue and increasingly perform an important role in accelerating the implementation of renewable energies, hence enhancing both reliability and flexibility in energy supply.

Furthermore, the digitalization of energy infrastructure, characterized by the implementation of smart grids, smart meters, and IoT devices, is revolutionizing the methods by which energy is distributed and consumed. Smart grids facilitate real-time monitoring and control of energy flow, thereby enabling operators to optimize the performance of the grid and minimize energy wastage. Through data analytics and machine learning algorithms, such systems can predict consumption patterns, optimize energy use, and ensure there is enough supply available at places and times where it is needed the most. This digital revolution will be very important to address challenges linked with a decentralized and renewable power generation system.

High-performing advanced predictive models and intelligent energy management systems constitute an absolute need for attaining a sustainable, reliable energy future. At the same time, these technologies are capable of assisting not only with the intrinsic difficulties arising with renewable energy but also to promote more resilient and efficient energy structures. As the global demand for energy persists in its upward trajectory, the advancement and implementation of these innovative solutions will be essential in establishing a cleaner, more sustainable energy ecosystem capable of meeting the requirements of future generations.

IV. RELATED WORK

Using Long Short-Term Memory (LSTM) networks for the prediction of energy consumption in smart grids, it is highly accurate in the capture of temporal dependencies within data. The model presents much higher precision in forecasting as compared to ARIMA, thus assisting in achieving demand balancing and optimized energy distribution. The frameworks used in [4] have been condemned due to issues like impotent learning, handcrafted features, inaccurate appraisal, and inadequate guiding significance besides the low capacity of learning. [12] addresses the multi-agent learning in the smart grid system, taking into account both service provider dynamic pricing and customer consumption scheduling methods for the first time ever.

Predictive analytics models, such as gradient boosting machines are used to optimize the management of energy storage by forecasting demand and supply. The approach schedules charging and discharging cycles efficiently to

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minimize the energy losses. This research evidence the cost savings and proper usage of energy. [15] shows two new home energy management systems are introduced here, each with different possibilities for scheduling. The booking of the residential devices is formulated through the multiple knapsack approach. Appliance scheduling at home both serial and parallel-wise wherever applicable via MKSI (Multiple knapsacks with serial implementation) and MKPI (Multiple knapsacks with parallel implementation) are also provided for minimizing the electricity cost besides PAR.

This research uses machine learning models like Random Forests to predict urban transportation patterns and optimize public transit schedules. By analysing mobility data and traffic conditions, it enhances the efficiency of transit systems and reduces energy consumption. The optimized fleet operations lead to reduced emissions and improved commuter experiences. Ensemble learning computes the weight of base predictors and the voting engine selects the appropriate predictor with high accuracy to provide the resultant output [2].

It utilizes machine learning models, such as Random Forests, to predict the patterns of urban transportation and enhances the schedules of public transit. It maximizes efficiency in a transit system by analysing data on mobility and traffic conditions, thereby reducing energy consumption. Optimizing fleet operations leads to a reduction in emissions and enhances commuters' experience. [14] applies Heuristic and Genetic Algorithms for tackling the demand planning problems in intelligent homes, with the goal of either minimizing the overall monetary value of energy consumptions or balancing the seasonality in electric-generating renewable sources, such as wind and solar generators.

This study aims to optimize energy consumption using reinforcement learning, predict peak times for usage, and correct schedules of industrial systems. The AI system automatically makes decisions about energy efficiency, effectively reducing manufacturing plants' operational costs and energy wastes. The demand-side management is applied utilizing an elitist non-dominated sorting genetic algorithm II, taking into account the dynamics of electricity prices over time, priorities to use a piece of equipment, operating cycles, and a battery bank [13].

Ensemble learning techniques, particularly bagging and boosting, are applied to improve the forecast of renewable energy sources, such as wind and solar. Models combined together produce significantly more accurate and reliable predictions compared to those obtained with single algorithms, thereby leading to better energy management for grid operators. Support Vector Machine (SVM) was applied to predict the electric load with three super parameters, i.e., kernel parameter, cost penalty, and incentive loss function parameter. [5]

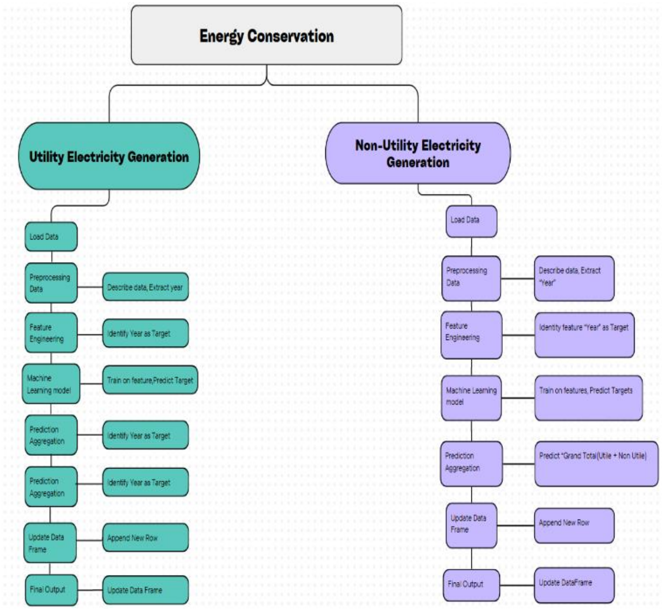
This research manages the distributed energy resources in a device by bringing together IoT sensors and AI-driven optimization algorithms. The system utilizes real-time data for optimizing energy distribution and storage to enhance scalability and efficiency across decentralized energy systems.

V. SYSTEM ARCHITECTURE

The Non-Utility Pipeline processes data from the data.csv file, which contains historical metrics on electricity generation from non-utility sources. This pipeline is intended to clean, preprocess, and analyse data pertaining to non-utility energy sectors such as renewable energy, private generators, and other decentralized sources. The processed data is then used to train models that may forecast future energy generation trends from these sources, providing significant insights into their function in the energy ecosystem.

The Utility Pipeline processes data from the data2 - Sheet1.csv file, which offers comparable indicators for power generation in the utility industry. This pipeline ensures that utility-specific data is properly cleaned, processed, and integrated for forecasting. This pipeline, which focuses on large-scale, centralized power generation plants, provides crucial inputs for optimizing smart grid operation and planning.

Both pipelines are critical components of the entire design, functioning together to provide a full picture of energy generation trends from utility and non-utility sources. The



outputs of these pipelines feed into predictive models, allowing for comprehensive energy forecasting and smart grid decision-making.

Fig 1. Architecture Diagram

The data preprocessing procedure starts with loading the datasets into Pandas for both utility and non-utility processes. The 'year' is taken from the 'date' column and used as a crucial feature for temporal analysis. Each pipeline requires certain column changes. The 'total' column is removed from non-utility data in order to focus on particular energy indicators. In the utility dataset, descriptive statistics are used for

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exploratory research, revealing trends and patterns in the data. Load data with Pandas.

Characteristic engineering indicates 'year' as the major characteristic for predicting energy usage. Targets for prediction are determined by the dataset type. The non-utility pipeline's aims include ['steam', 'diesel', 'gas', 'hydro', 'RES'], whereas the utility pipeline targets ['steam', 'diesel', 'gas', 'hydro', 'nuclear', 'RES']. These properties distinguish between contributions from different energy sources and allow for exact forecasts. To anticipate energy usage, the primary machine learning strategy is to use a linear regression model. The model is trained using historical data to maximize its simplicity and efficiency for continuous prediction jobs across several energy sources. The approach entails fitting the linear regression model to preprocessed historical data and making predictions.

The trained model predicts the goal values for the future year, providing detailed information on energy consumption trends for each source. Individual energy sources are predicted, allowing for more detailed study. The aggregate target values are then calculated to provide an overall picture of energy use. The non-utility pipeline computes the grand total (GrandTotal(Ut+NonUt)), whereas the utility pipeline calculates the total energy (Total). The anticipated row, which includes all energy indicators and aggregated totals, is added to the corresponding dataset. This connectivity enables ongoing trend analysis and monitoring, allowing for more informed decisions about smart grid optimization.

VI. Key Components of Pipeline

The first input in the Non-Utility Electricity Generation pipeline is historical data from data.csv. Steam, diesel, gas, hydro, and renewable energy sources (RES) are the five energy sources for which this data includes metrics. After processing this data, the pipeline forecasts the specific energy consumption goals for every source. In order to provide a thorough prediction, it also computes the overall energy consumption, which is represented as GrandTotal(Ut+NonUt) and incorporates utility and non-utility contributions.

The Utility Electricity Generation pipeline uses historical data from data2 - Sheet1.csv as its input. This data includes six target energy sources: steam, diesel, gas, hydro, nuclear, and RES. The pipeline generates forecasts for each energy source individually and computes the aggregated energy consumption total, referred to as Total, providing insights specific to the utility sector.

These two pipelines collectively form the backbone of the energy forecasting framework, ensuring accurate predictions for smart grid optimization and energy planning.

VII. Comparison Analysis

To effectively manage the flow of energy in a utility, especially with regard to the electricity generation process, a clear use of forecast limited by perfect reliability has immediately to be adopted [8]. The datasets from 2012 to 2023 offer an in-depth look at energy production trends across various methods. This analysis highlights the key patterns, including increases in renewable energy, steady steam and hydropower growth, and declines in diesel usage, reflecting shifts toward cleaner, more sustainable energy sources.

A. Steam Power Generation

The growth in steam power generation has been steady and incrementing from 2012 through 2023 for both utility and nonutility sources. Utility sources of steam production have increased over these years from 112,022 GWh in 2012 to 236,049 GWh in 2023. This steady growth highlights steam's long history as a source of energy that it has merely fed continuously into consumption, mainly driven by fossil-fueled thermal power plants.

In the non-utility sector, the production of steam increased from 22,615 GWh in 2012 to 55,137 GWh in 2023. Though renewable energy has now become everybody's priority worldwide, steam is bound to always be a part of that infrastructure. Still, the more environmental issues escalate, the more challenging its future will be because of coal and other non-renewable sources on which it depends.

B. Diesel Power Generation

Diesel power generation has declined precipitously. This is indicative of a drift away from expensive and polluting fuel sources. In the utility sector, diesel generation was down to 354 GWh in 2023 from 1,200 GWh in 2012. It is consistent with the broader global swing toward cleaner alternatives like gas and renewables.

The non-utility sector forms a different pattern. Diesel generation was still low but did increase from 9,955 GWh in 2012 to 17,526 GWh in 2023. Diesel is, thus, less preferred due to high costs and emissions, but some utilization does remain in certain areas, especially in very remote regions where options for other power sources may not be possible.

C. Gas Power Generation

Trends in gas-based power generation fluctuate. In the utility sector, it begins at 18381 GWh in 2012 and increases to 27008 GWh during the year 2023. In the non-utility sector, the generation of gas is relatively smaller in amounts but increased from 5885 GWh in 2012 to 8311 GWh in 2023.

Fluctuation in gas production could have resulted from price fluctuations and changes in the availability of natural gas. However, the increase overall is towards a cleaner fossil fuel in that gas is viewed by many as less dangerous than coal and diesel.

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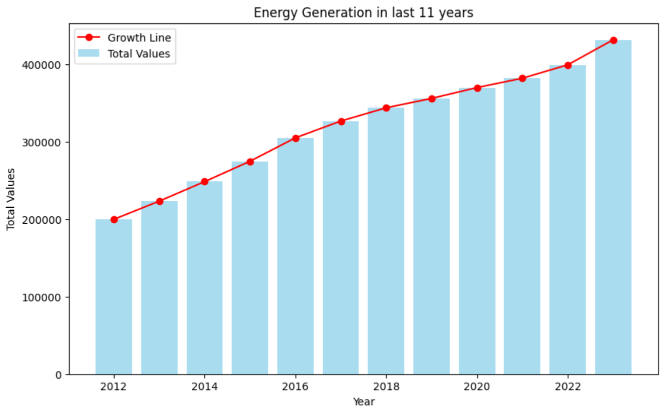

D. Hydropower Generation

Hydropower is the most reliable source of renewable energy, with steady growth from 2012 to 2023. Utility-scale hydropower improved from 38,990 GWh in 2012 to 48,359 GWh in 2023. Hydropower growth reflects its value as clean, dependable energy that is not subject to fuel price volatility.

The non-utility contributions are slightly higher, forecast to reach 135 GWh in Q1, up from 48 GWh in 2012. Given their lower costs of production and rather fractional environmental impacts, hydropower will increasingly continue to factor into any energy strategies pursued by countries with abundant hydrological resources.

E. Generation via Nuclear Power

The contributions to nuclear energy from the utility sector vary on the downside from one year to the next, by 4780-7525 GWh. For the non-utility sector, there's almost no contribution in nuclear generation. This isn't especially shocking given that nuclear plants are, for the most part, big government-owned institutions. Nuclear offers one of the more dependable electric power generation sectors.

F. RES (Renewable Energy Sources)

The index has gone for renewable sources-the highest growth rate from 24,503 GWh in 2012 to a whopping 112,528 GWh in 2023. Also, an overall consistent growth pattern in wind, solar, and biomass-based generation embedded in broader shifts towards green and sustainable paths because of technological breakthroughs along valuing policies which made renewable energy sources more practical or favorable for developing energy policies.

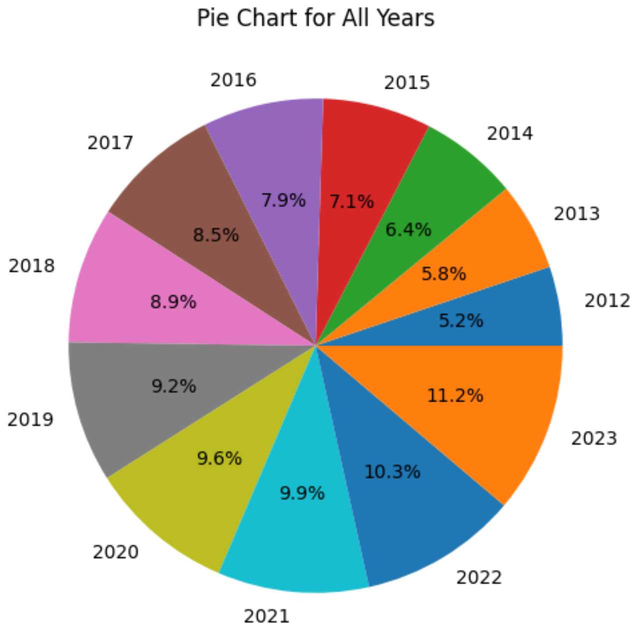

Fig 2 - Comparision between all the years from 2012 – 2023

Fig 3 - Energy Generation in the past 11 years from 2012 to 2023.

The non-utility sector story was even more dramatic, rising from 872 GWh in 2012 to climb up-to an incredible never seen level of over nearly almost a six-fold increase with the total offshore win

Kindly refer to below images and table below for a better understanding of the data.

	date	steam	diesel	gas	hydro	RES	Total	GrandTotal(Ut+NonUt)	year
0	2012-03-31	22615.000000	9955.000000	5885.0	48.000000	872.000000	39375.000000	239252.000000	2012
1	2013-03-31	23890.000000	11148.000000	4498.0	67.000000	1124.000000	40726.000000	264070.000000	2013
2	2014-03-31	24752.000000	11432.000000	4751.0	64.000000	1259.000000	42258.000000	290812.000000	2014
3	2015-03-31	26089.000000	12009.000000	5193.0	65.000000	1301.000000	44657.000000	319561.000000	2015
4	2016-03-31	28688.000000	12347.000000	5819.0	59.000000	1368.000000	48279.000000	353442.000000	2016
5	2017-03-31	30572.000000	13350.000000	6109.0	65.000000	1433.000000	51529.000000	378362.000000	2017
6	2018-03-31	32854.000000	13145.000000	7156.0	51.000000	1726.000000	54933.000000	398935.000000	2018
7	2019-03-31	47679.000000	15571.000000	8787.0	103.000000	3067.000000	75207.000000	431307.000000	2019
8	2020-03-31	51543.000000	12775.000000	7316.0	131.000000	4475.000000	76239.000000	446346.000000	2020
9	2021-03-31	47760.000000	17563.000000	7361.0	131.000000	5694.000000	78508.000000	460659.000000	2021
10	2022-03-31	51000.000000	17700.000000	7400.0	135.000000	6500.000000	82735.000000	482232.000000	2022
11	2023-03-31	55137.854545	17526.963636	8311.2	135.909091	5890.345455	87002.272727	517968.939609	2023

Fig 4. Prediction for Non-Utility Sector

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Fig 5. Prediction for Utility Sector

VIII. Result Analysis

The data analysis and visualizations provide an in-depth discussion of trends in generating energy over the years through various sources: steam, diesel, gas, hydro, nuclear, and renewable energy sources (RES). Breaking the data allows for insights into energy shifts and trends and, therefore, a better appreciation of the changes that have occurred in the different sources between 2012 and 2023.

A. 2-D Distribution Analysis:

The 2-D distribution plots are essential in understanding the relationships between different energy sources. By comparing two types of energy in each scatter plot, we can identify possible correlations, patterns, or outliers. Here are some key findings from the plots:

1. Steam vs. Diesel: The comparison between steam and diesel energy generation shows a moderate positive correlation over the years. Both sources, while distinct in their operations, tend to increase in tandem during certain periods, particularly between 2012 and 2018. However, after 2018, diesel starts to show signs of decline, while steam continues its steady rise. This divergence can be attributed to the increasing global shift away from diesel due to its environmental impact, while steam-based energy, being a more traditional form of power generation, remains consistent in many regions. Despite this, steam’s environmental sustainability is under scrutiny, and future trends may show a decline like diesel as cleaner technologies continue to advance.

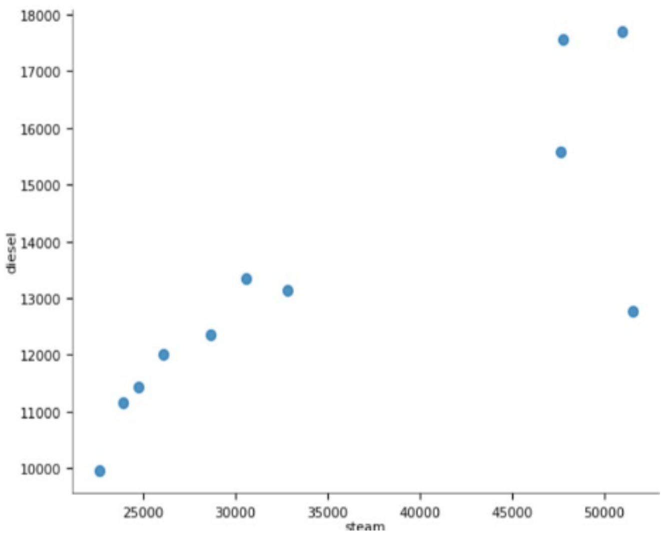
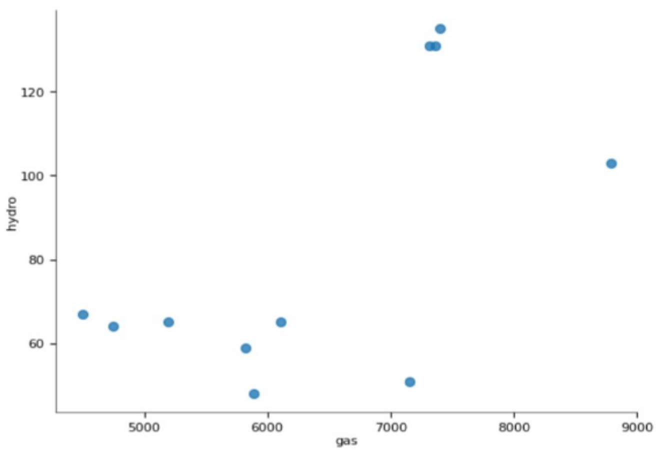


Fig 6. Comparison between Steam and Diesel

2. Diesel vs Gas:The comparison between gas and diesel shows an interesting contrast. While diesel energy generation declines over time, gas experiences fluctuations but maintains an overall upward trend. Gas, being a cleaner alternative to diesel, becomes a preferred option as the global energy landscape shifts toward reducing carbon emissions. From 2012 to 2022, the declining trend of diesel is mirrored by gas's growing significance. The role of gas as a transition fuel, cleaner than both coal and diesel, is evident, and it is increasingly being used in regions where diesel was once dominant. The inverse relationship becomes clearer in the later years of the dataset, reinforcing the global move towards greener energy solutions.

	date	steam	diesel	gas	hydro	nuclear	RES	Total	year
0	2012-03-31	112022.000000	1200.000000	18381.000000	38990.000000	4780.000000	24503.000000	199877.000000	2012
1	2013-03-31	130221.000000	1200.000000	20110.000000	39491.000000	4780.000000	27542.000000	223344.000000	2013
2	2014-03-31	145273.000000	1200.000000	21782.000000	40531.000000	4780.000000	34988.000000	248554.000000	2014
3	2015-03-31	164636.000000	1200.000000	23062.000000	41267.000000	5780.000000	38959.000000	274904.000000	2015
4	2016-03-31	185173.000000	994.000000	24509.000000	42783.000000	5780.000000	45924.000000	305162.000000	2016
5	2017-03-31	192163.000000	838.000000	25329.000000	44478.000000	6780.000000	57244.000000	326833.000000	2017
6	2018-03-31	197172.000000	838.000000	24897.000000	45293.000000	6780.000000	69022.000000	344002.000000	2018
7	2019-03-31	200705.000000	638.000000	24937.000000	45399.000000	6780.000000	77642.000000	356100.000000	2019
8	2020-03-31	205135.000000	510.000000	24955.000000	45699.000000	6780.000000	87028.000000	370106.000000	2020
9	2021-03-31	209295.000000	510.000000	24924.000000	46209.000000	6780.000000	94434.000000	382151.000000	2021
10	2022-03-31	210700.000000	510.000000	24900.000000	46723.000000	6780.000000	109885.000000	399497.000000	2022
11	2023-03-31	236049.127273	354.727273	27008.254545	48359.272727	7525.454545	112528.018182	431823.596047	2023



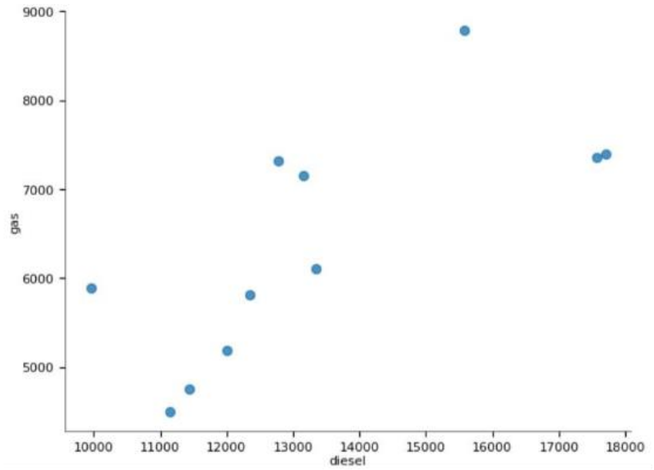


Fig 7. Comparison between Diesel and Gas

3. Gas vs. Hydropower: There is a limited correlation between gas and hydropower generation, which might suggest that regions rich in natural hydro resources do not rely as heavily on gas energy. It could also indicate that investments in hydropower infrastructure are being made in areas where gas is less accessible or cost prohibitive. Hydropower is highly dependent on geographic factors, while gas can be imported, leading to different regional preferences for energy sources.

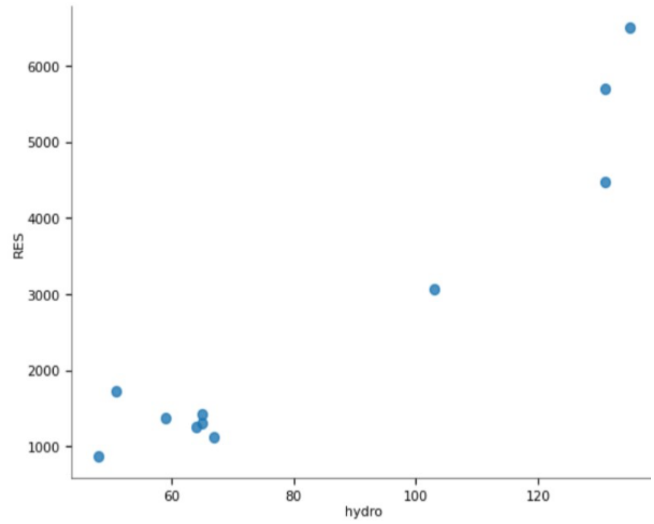
Fig 8. Comparison between Gas and Hydropower

4. Hydro vs. RES (Renewable Energy Sources): The relationship between hydropower and RES (primarily wind and solar) shows an interesting trend. While both are renewable energy sources, hydro has a slower, steady growth compared to the rapid rise of other renewables like wind and solar. This trend becomes particularly evident from 2016 onwards when RES begins to experience exponential growth. Hydropower remains a stable and reliable contributor to the energy mix, while newer renewables gain traction due to advances in technology and decreasing costs. The distinction here underscores the diversification within the renewable energy sector, with RES seeing significant global investments and policy support, leading to its rapid expansion.

Fig 9. Comparison between Hydro and RES

B. Time Series Analysis:

The time series analysis plots give us a visual sense of how the growth of each source evolved. The upward trend with renewable energy sources stands out the most and provides evidence that renewables are the fastest-growing form of energy in the dataset. Diesel shows a steady decrease along the same trend as the rest of the world switches away



from fossil fuel-like energy sources.

1. Steam: The production trend for steam power is a steady year-by-year improvement. This trend reveals that despite its older age, steam power is still highly important to the energy infrastructure, with a high recourse environment and low-cost fossil fuels. However, over the long term, it remains questionable due to environmental impact.

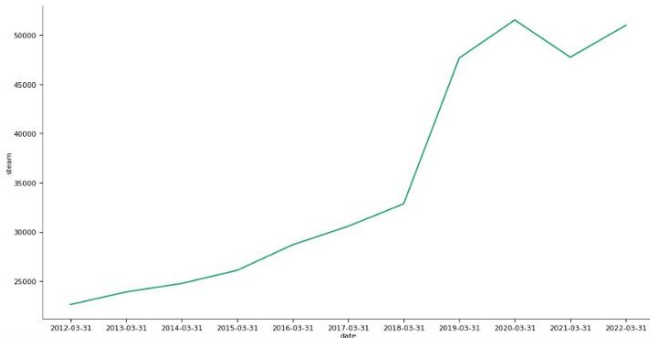
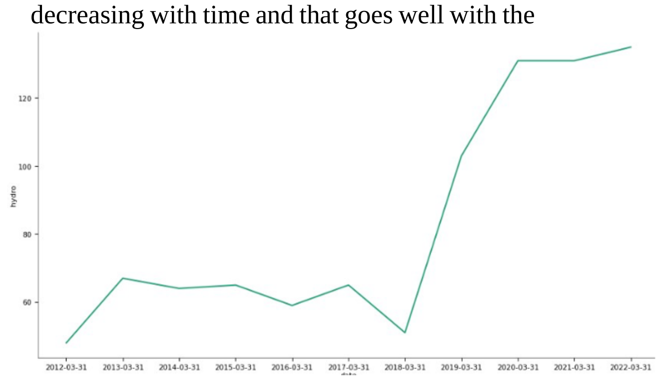


Fig 10. Time Series Anlysis of Steam

2. Diesel: Diesel power generation is gradually decreasing with time and that goes well with the



general trend in the world of moving away from dirty fuel. Diesel has been employed in the past only in those places where quick or mobile

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power generation was required but as cleaner technologies are becoming more readily available and inexpensive, that is less often to be seen. The decline reflects a desire to be free of dependency on this expensive and damage-causing fuel source.

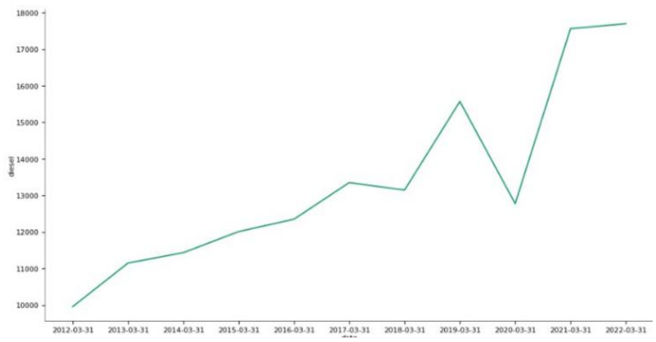

Fig 11. Time Series Analysis of Diesel

3. Gas: This power generation fluctuates a little from year to year, yet it is generally going upwards. Natural gas has become a vital constituent of the mix of energies because it serves as a less polluting alternative to coal and oil, giving less CO_2 per unit of energy generated. Rising importance of gas, it is also due to the role of gas in being a transition fuel in the global energy shift towards renewables.

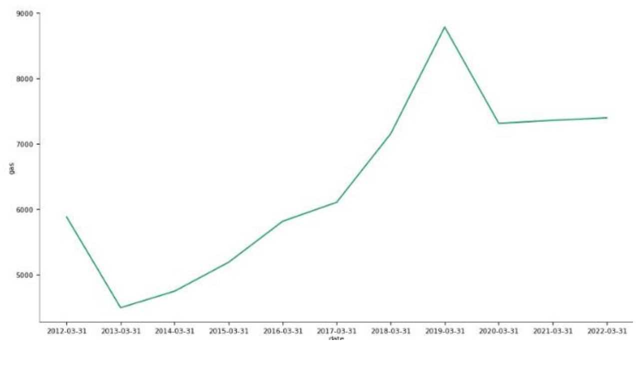

Fig 12. Time Series Analysis of Gas

4. Hydro: Hydropower remains in steady growth and is reflected in terms of reliability and importance as a source of renewable energy. Investments in dam infrastructure and water management will bring steady growth in hydropower generation. Hydropower remains one of the most reliable sources of renewable energy, and hence, going forward, it will continue to lead the pack in the energy play.

Fig 13. Time Series Analysis of Hydro

5. Nuclear: Nuclear energy production is relatively flat over the period, having grown at minimal growth rates. While nuclear power is considered one of the electricity sources with a lower rate of emission, it was high capital investment, long lead times on new plant building, and safety concerns that have curtailed its expansion. However, nuclear is still a reliable source of energy in countries where this technology has been invested in.

6. RES: Renewable energy sources, mainly wind and solar, are marked by the highest growth of all energy types. From 2016 onwards, renewable energy generation steeply increases and reflects the final impetus toward low carbon. This is exemplified through technological advances and government incentives across declining costs associated with renewables, making this a steeper upward trend that is already sounding a strong indicator that renewables will be the significant shapers of future energy.

C. Total Energy and Grand Total Analysis

1. Utility Sector: The total energy produced by the utility sector increased from 199,877 GWh in 2012 to 431,823 GWh in 2023, doubling the energy production over the decade. This reflects the increased energy demands both in developing and developed countries and extra infrastructural investments.
2. Non-Utility Sector: Generation by the non-utility sector has also surged and reached around 87,002 GWh in 2023 from 39,375 GWh in 2012. The rising level of private and decentralized energy production, such as small-scale renewable projects or industrial self-generation, manifests that this sector is assuming a more massive role.
3. Grand Total: While combining utility and non-utility data, the total energy produced under the Grand Total column nearly doubled from 239,252 GWh in 2012 to 517,968 GWh in 2023. This increase in more than a decade has virtually doubled. What made this significant growth possible was when RES increased rapidly while steam and gas power maintained its steady contributions. This is important not only for meeting the increasing energy needs of modern economies but also for supporting sustainable development.
4. Values Insights : The "Values" section, written as a series of line graphs, shows the trend of each energy source over time. These graphics allow us to easily visualize which energy sources are growing and which are in decline:

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a. Steam: Steam energy continues to grow steadily, and this trend reflects the fact of its well-established position in the global energy mix. At least environmentally unfriendly, steam is a robust way of energy production at scale.

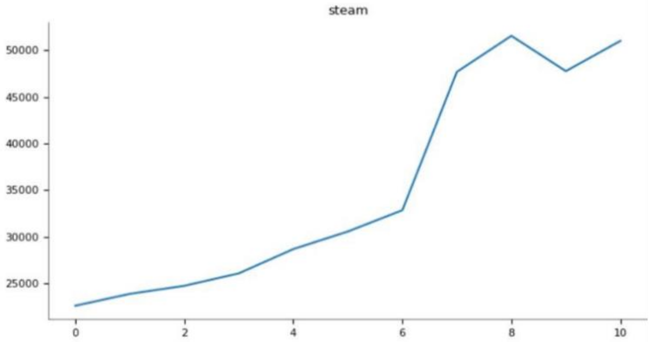

Fig 14. Insights on Steam

b. Diesel: Diesel power has an overall steep decline, but after 2018, as it's being gradually phased out due to growing cleaner sources. The variability over its earlier years may also be partly due to its having once been more frequently used for emergency or peak power situations, but long-term decline indicates a permanent shift away from diesel.

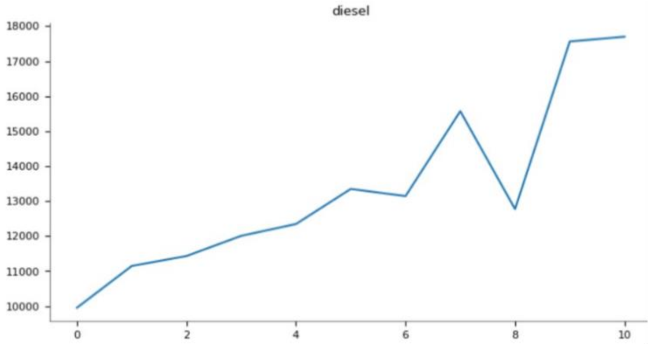

Fig 15. Insights on Diesel

c. Gas: Gas overall is an upward curve, mainly based on market availability and prices. If there is a cleaner alternative to coal, gas will always be part of the energy landscape.

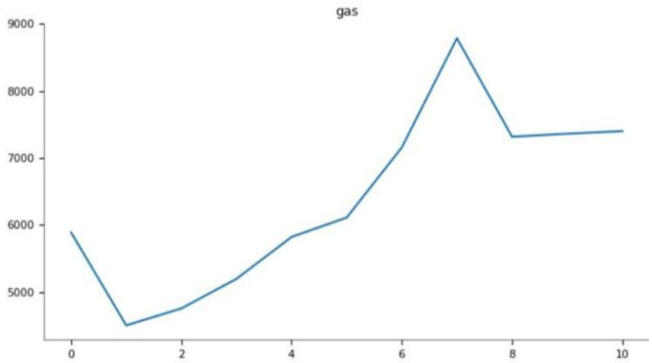

Fig 16. Insights on Gas

d. Hydropower: Hydropower remains firm on its growth path and reinforces its position as one of the stalwarts of renewable energy. It is predictability and reliability that are making it a leading component in many nations' renewable energy policy mix.

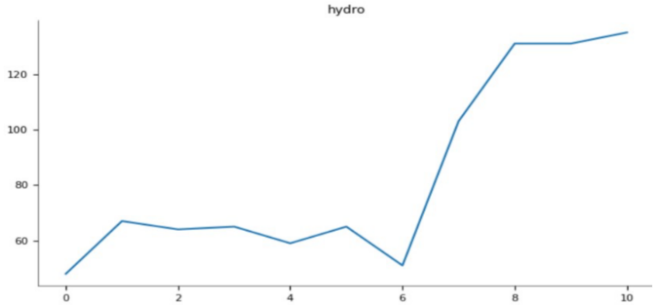

Fig 17. Insights on Hydropower

e. RES: The sheer amount of renewable energy sources parallels the fight against climate change worldwide. Renewables like wind and solar are taking over a fair amount of market share, even faster than traditional energy sources, so the growth in recent years and the past decade is going sharply upward, tracing a pathway toward clean or green energy.

These values also reflect the continuation of energy transitions, with the biggest leap being that of renewables followed by gas as a relatively clean alternative to coal and diesel. Base-load steam and nuclear provide energy stability in supply.

IX. Conclusion

Visualizations and data analysis show a world energy system undergoing significant change. Technology, environmental concerns, and a growing global emphasis on sustainability have all contributed to the remarkable expansion of renewables, and particularly RES. In contrast, steam and gas have been relatively steady in the overall energy mix, whereas fossil-based energy generation methods like diesel have been dropping overall. The steady growth of hydropower further outlines the potential for using that clean and dependable energy source to generate electricity. Although nuclear power has not grown significantly, it is a significant base-load source that maintains energy stability in many areas. All things considered, the trend is obvious: the energy industry will move toward more sustainable, eco-friendly supply sources, and renewables will soon take center stage in this new paradigm.

With the increasing number of investments in solar, wind, and other clean technologies, energy will likely move considerably more firmly toward renewables in the near future. As countries aim to meet ambitious climate targets

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while pursuing decarbonization, fossil fuels—especially diesel—will become less and less essential. With a focus on current trends and a foundation for understanding the future trajectory of energy production—when renewables are likely to dominate and traditional fossil fuel-based methods will likely remain at the periphery—this integrated analysis, which spans the years 2012 to 2023, thus offers pertinent insights into the evolution of the global energy landscape.

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