African Journal of Advanced Pure and Applied Sciences (AJAPAS)
Online ISSN: 2957-644X
Volume 4, Issue 3, 2025
Page No: 188-204
Website: https://aaasjournals.com/index.php/ajapas/index
ISI 2025: 1.126 SJIFactor 2024: 6.752 معامل التأثير العربي: 1.62

A Hybrid Forecasting Methodology: Statistical-Neural Fusion for Electricity Demand Prediction

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منهجية التنبؤ الهجينة: الاندماج الإحصائي-العصبي لتوقع الطلب على الكهرباء

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Received: June 14, 2025	Accepted: August 05, 2025	Published: August 16, 2025

Abstract:
Accurate electricity demand forecasting is crucial for efficient planning and operation of electrical systems, necessitating the integration of diverse demographic, economic, statistical, and engineering data through advanced methodologies to mitigate risks of under or over-investment , this imperative is recognized as a multifaceted problem requiring diverse techniques , this study addresses the complex, non-linear nature of long-term electrical energy loads by designing and developing an advanced hybrid forecasting methodology termed "Statistical-Neural Fusion," which aligns with the need for robust deep learning frameworks, this hierarchical approach utilizes a Level 0 "Statistical Expert" (Multiple Linear Regression model) to capture initial linear relationships and generate a "Smart Feature" forecast based on historical data including Year, Population, and Gross Domestic Product (GDP), considering demand determinants. Subsequently, a Level 1 "Mastermind" (Integrated Neural Network, specifically an MLP) refines and corrects this initial forecast by learning complex, non-linear patterns from an enhanced dataset comprising both original inputs and the "Smart Feature," aligning with the understanding of demand forecasting over various time scales , this method was applied to forecast energy production and maximum load for the national electricity grid up to 2034, relying on a comprehensive database of historical operational, demographic, and economic data.

Keywords: Electricity Demand, Load Forecasting, Hybrid Model, Neural Network, Statistical Fusion.

الملخص

يُعد التنبؤ الدقيق بالطلب على الكهرباء أمرًا حيويًا للتخطيط الفعال وتشغيل الأنظمة الكهربائية، مما يستلزم دمج بيانات ديموغرافية واقتصادية وإحصائية وهندسية متنوعة من خلال منهجيات متقدمة لتقليل مخاطر الاستثمار الزائد أو الناقص. يُعترف بهذا الأمر كمشكلة متعددة الجوانب تتطلب تقنيات متنوعة. تتناول هذه الدراسة الطبيعة المعقدة وغير الخطية للأحمال الكهربائية طويلة الأمد من خلال تصميم وتطوير منهجية تنبؤ هجينة متقدمة تُسمى "الاندماج الإحصائي-العصبي"، والتي تتوافق مع الحاجة إلى أُطر تعلم عميق قوية. يستخدم هذا النهج الهرمي مستوى 0 "خبير إحصائي" (نموذج الانحدار الخطي المتعدد) لالتقاط العلاقات الخطية الأولية وتوليد تنبؤ "خاص ذكي" بناءً على البيانات التاريخية التي تشمل السنة، السكان،

والناتج المحلي الإجمالي(GDP) ، مع الأخذ في الاعتبار محددات الطلب. بعد ذلك، يقوم مستوى 1 "العقل المدبر) "شبكة عصبية متكاملة، وتحديدًا (MLP بتحسين وتصحيح هذا التنبؤ الأولي من خلال تعلم الأنماط المعقدة وغير الخطية من مجموعة بيانات محسنة تضم كل من المدخلات الأصلية و"الخاص الذكي"، بما يتماشى مع فهم التنبؤ بالطلب عبر مقاييس زمنية مختلفة. تم تطبيق هذه الطريقة لتوقع إنتاج الطاقة والحمولة القصوى للشبكة الكهربائية الوطنية حتى عام 2034، بالاعتماد على قاعدة بيانات شاملة من البيانات التشغيلية والتاريخية والديموغرافية والاقتصادية .

الكلمات المفتاحية: الطلب على الكهرباء، تنبؤ الأحمال، نموذج هجين، شبكة عصبية، الاندماج الإحصائي.

Introduction

Accurate and reliable electricity demand forecasting stands as a fundamental prerequisite for sustainable energy planning and efficient grid management on both national and global scales, this inherently complex process is shaped by an intricate interplay of demographic shifts, economic fluctuations, technological advancements, and evolving consumer behavior, as highlighted in comprehensive overviews of forecasting techniques [1], its paramount importance to all electricity companies and institutions stems from its role as the foundational step in the strategic design and planning of electrical systems, this encompasses the precise formulation of future expansion plans for new generation units, the development and reinforcement of transmission and distribution networks, and the meticulous preparation of institutional, financial, and economic studies vital for ensuring long-term viability and sustainability [2].

Inaccurate forecasting carries significant inherent risks, an underestimation of actual demand can precipitate critical shortages in funding and infrastructure, leading to a palpable deficit in the required energy production and consequent restrictions in its distribution to consumers, this, in turn, can severely impede economic activity and incur substantial financial losses, emphasizing the need for robust deep learning frameworks in forecasting [3]. Conversely, an exaggerated overestimation of demand results in the misallocation of immense capital resources into projects that may yield negligible economic returns, compounded by difficulties in securing necessary funding, thereby hindering overall development [4,5], both scenarios are highly undesirable for the electricity industry and the broader economy, underscoring the critical imperative for conducting highly accurate demand studies. Such precision necessitates the rigorous application of the latest mathematical and statistical methodologies, extensive utilization of advanced computational tools, and the provision of comprehensive and precise actual information to enhance the reliability of the forecasting process [6].

Demand forecasting requirements vary significantly across different time horizons. Short-term forecasting studies, spanning from an hour to a week, are indispensable for daily station operations, load distribution management, and the regulation of operating reserves and safety margins within the grid [7]. Medium-term forecasts, typically ranging from a week to a year, are crucial for organizing maintenance schedules and optimizing fuel supply [8]. Long-term forecasting studies, extending over decades, form the strategic bedrock for planning and constructing new power stations and expanding transmission and distribution networks [9], within the scope of this particular study, electricity grid demand forecasts for the forthcoming seventeen years were meticulously prepared using two distinct approaches, assuming two specific scenarios, the underlying data for these forecasts was comprehensively gathered from multiple sources, including statistics from the National Electricity Company pertaining to generated, sold, and lost energy, as well as historical national economic and population data, whose determinants are crucial for demand forecasting [10], obtained from the Department of Statistics, the Central Bank, and the Ministry of Planning.

Literature Review

The domain of electricity demand forecasting has undergone significant evolution over recent decades, largely driven by advancements in mathematical, statistical, and economic sciences, the consensus among researchers is that accurate electricity demand forecasting presents an intricate problem that inherently requires the interplay of diverse techniques, as highlighted by contemporary studies on ensemble methods [7].

Historically, simpler approaches such as the trend method have offered a straightforward means of projection for medium and long-term horizons, this methodology fundamentally assumes a consistent relationship between electricity consumption and time across the future forecasting period, relying heavily on historical data pertaining to past demand growth rates, its principal advantages lie in its simplicity, speed, ease of application, and low implementation cost, proving particularly useful when comprehensive data is scarce or when time and financial resources are limited. However, a significant limitation of the trend method is its inability to explicitly incorporate and represent fundamental variables that directly influence demand, such as economic or demographic factors. Consequently, it yields only a single projected demand outcome, which offers little insight into the underlying reasons for demand behavior, thus hindering deeper analytical understanding [8].

A more sophisticated approach involves the economic method, which systematically integrates established economic theories with rigorous statistical techniques to forecast electricity demand[9], the core premise of this method is to utilize robust historical data with minimal simplifying assumptions to derive mathematical equations that elucidate the intricate relationship between electricity demand (the dependent variable) and various independent variables, including macroeconomic indicators like Gross Domestic Product (GDP), population dynamics, income levels, and electricity prices[11], this methodology commonly employs a range of techniques, such as time series analysis, single or multiple regression models, and the least squares method, often seen in mid-term forecasting using improved models [12], the economic method offers substantial advantages, providing detailed insights into demand levels, the causal factors behind increases or decreases in demand, and the precise extent to which demand is influenced by diverse factors. Furthermore, it enables separate load forecasts for distinct sectors—residential, commercial, industrial—and its economic models are inherently flexible, facilitating the analysis of load growth under different scenarios [13]. Despite these strengths, the method demands highly accurate historical data, which can restrict its applicability for long-term forecasting where data quality might degrade, another inherent disadvantage is its reliance on the assumption that factors affecting demand remain constant as they were historically, often termed "constant elasticity," an assumption that can be challenging to justify, particularly when significant fluctuations in electricity prices occur [14].

The end-use method represents a more recent and highly accurate advancement in demand forecasting, its fundamental principle is to directly estimate consumed energy by leveraging comprehensive information about the specific end-uses of electrical energy, such as lighting, cooling, air conditioning, and heating, as well as detailed data on the end-users themselves across residential, industrial, agricultural, and commercial sectors[15], while requiring less historical aggregate data, this method necessitates a substantial volume of highly granular microeconomic data concerning customers and their specific devices, including details like household size, individual and family income levels, types of end-use devices, and usage patterns, this method, by focusing on fine-grained consumption, aligns with studies on forecasting at distribution and household levels [16]. Despite its capacity for precise definition of energy-consuming sectors and the potential for energy conservation, a key disadvantage is that most end-use models presuppose a constant relationship between demand and end-use, which may hold true for a few years but is unlikely to remain constant over longer periods due to evolving energy conservation technologies and changing energy prices [17]. Additionally, it demands comprehensive data on energy consumed for a multitude of uses within buildings and various instruments, data that is often limited or unavailable [9].

For short-term forecasting, which is critical for daily operational management, various methods are employed, the daily electricity consumption rate is heavily influenced by the actual equipment in use and by weather factors such as temperature, humidity, and wind speed, which significantly impact load fluctuations [18], economic factors also play a crucial role in these short-term predictions. Short-term forecasting methods are generally categorized based on the data utilized: one segment relies on weather data combined with historical demand data, while another solely uses historical data [20].

Table 1 Comparison of Engineering Methodologies for Electricity Demand Forecasting.

Methodology Category	Key Approach/Technique	Time Scale Focus	Key Contribution/Insight	References
Deep Learning Frameworks	Utilizes deep learning to extract complex patterns from historical data for demand forecasting.	General: Framework capable of handling various time scales.	Highlights deep learning's capacity to extract complex patterns from historical data, fundamentally correcting initial estimates and preventing "perpetual linear growth" traps.	[15]
Hybrid (Statistical-ML Fusion)	Combines classical statistical models with machine learning algorithms, often in a hierarchical "stacking" architecture.	General/Applied: Demonstrated in a case study for long-term forecasting in Ukraine, showing the success of hybrid models.	Achieves more accurate and reliable forecasts by fusing statistical clarity (linear relationships) with ML flexibility (non-linear patterns), indicating significant correction capabilities over simplistic models.	[16]
Ensemble Time Series	Develops novel time series ensemble techniques to combine forecasts from multiple models.	General: Applicable to various time scales based on the nature of time series modeling.	Proves that combining forecasts from multiple models (an ensemble approach) leads to results that significantly outperform any single model, reinforcing the strength of hybrid methodologies.	[17]
Advanced Deep Learning (CNN-Bi-GRU)	Employs a CNN-Bi-GRU model, which is a specialized deep learning architecture.	Short and Long-Term: Specifically designed for both short and long-term renewable electricity demand forecasting.	Showcases advanced deep learning capabilities for precise forecasting across different time horizons, particularly for renewable energy demand, indicating complex pattern learning.	[18]
Explainable Graph Neural Networks	Utilizes explainable causal graph neural networks to forecast electricity demand at granular levels.	Distribution and Household Levels: Focuses on specific granularities, implying applicability from short to medium-term analysis.	Introduces a unique approach to forecasting at granular levels (distribution and household), emphasizing explainability in understanding demand drivers and patterns.	[19]
Hybrid (PSO-Enhanced SVR)	Combines improved multi-mode reconstruction with Particle Swarm Optimization (PSO)-enhanced Support Vector Regression (SVR).	Mid-Term: Explicitly applied for mid-term electricity demand forecasting.	Demonstrates an enhanced machine learning approach for mid-term forecasting, showing how optimization techniques can improve the performance of regression models in complex energy demand scenarios.	[20]

Table 1 systematically compares advanced engineering methodologies for electricity demand forecasting, illustrating their evolution from traditional statistical methods to sophisticated computational and machine learning approaches crucial for tackling complex, non-linear energy demand. Deep Learning Frameworks [15] excel at extracting intricate patterns from historical data, fundamentally correcting initial estimates and preventing forecasting fallacies that lead to mis investments, building on this, the Hybrid (Statistical-ML Fusion) methodology [16] strategically combines statistical clarity with machine learning's robust pattern recognition, effectively refining forecasts and boosting accuracy, as demonstrated in complex energy systems. Further enhancing prediction, Ensemble Time Series techniques [17] leverage multiple models for superior performance, showcasing the robustness of collective intelligence in forecasting. Advanced Deep Learning models like CNN-Bi-GRU [18] represent specialized neural network architectures designed to capture complex temporal dependencies for precise short and long-term renewable electricity demand forecasting. For granular insights, Explainable Graph Neural Networks [19] offer a cutting-edge approach to forecasting at distribution and household levels, emphasizing both accuracy and interpretability of demand drivers. Lastly, the Hybrid (PSO-Enhanced SVR) methodology [20] exemplifies an advanced machine learning technique for mid-term forecasting, utilizing optimization to significantly enhance traditional model accuracy in complex scenarios, in essence, Table 1 reflects a clear trend towards integrated, intelligent, and specialized models that harness advanced computational power to overcome conventional limitations, yielding greater accuracy and deeper insights into dynamic energy consumption patterns.

Methodology

The process of forecasting electricity demand and load analysis is a fundamental pillar in the strategic planning of the energy sector, as it enables relevant authorities to ensure the efficient and effective fulfillment of future needs, this forecasting requires the adoption of precise scientific methodologies based on reliable historical data and in-depth analysis of influencing factors, whether demographic, economic, or environmental.

3.1. Linear Regression Methodology for Long-Term Forecasting

The applicability of long-term forecasting methodologies is fundamentally determined by the nature of available databases, which guided the selection of the prevailing trend method for preparing energy demand and electrical load forecasts for the 2009-2025 master plan, this method, chosen for its ease of use and the availability of historical data, assumes a constant relationship between electrical energy consumption and time over the future forecast period, it leverages a linear regression equation model to predict specific variable values by analyzing their relationships, using both internal data (total energy produced) from the General Electricity Company and external demographic and economic data (population and GDP), in this model, a linear relationship between the two variables is essential, allowing the estimation of future values of one variable given the other, effectively applying a straight line to a scatter plot of the variables (X, Y), the core equation for this straight line is $Yi = a + bXi$ (1), where Yi represents the dependent variable targeted for prediction, and Xi is the independent variable, the coefficients 'a' and 'b' are crucial to this relationship, and their values are derived from historical data using the equations:

$$b = \frac{(\Sigma XY - n\bar{X}\bar{Y})}{(\Sigma X^2 - n\bar{X}^2)} \quad (2)$$

$$a = \bar{Y} - b\bar{X} \ (3).$$

Here, $\bar{X}$ denotes the arithmetic mean of the independent variable, $\bar{Y}$ is the arithmetic mean of the dependent variable, and 'n' signifies the number of years, to ensure the derived formula accurately reflects the real-world relationship, the correlation coefficient (R) must be calculated using the formula:

$$R = \frac{(\Sigma XY - n\bar{X}\bar{Y})}{\sqrt{[(\Sigma X^2 - n\bar{X}^2)(\Sigma Y^2 - n\bar{Y}^2)]}} \ (4).$$

For an accurate result, the value of R must fall between 0.9 and 1, indicating a very strong relationship; conversely, if R is less than 0.9, the variable in question should be excluded from the energy calculation, as specified in reference [11].

3.2. Forecasting Steps and Data Collection

Electricity load forecasting involves a structured process beginning with collecting, reviewing, auditing, classifying, and characterizing historical data, followed by its analysis to identify influencing economic, demographic, and climatic factors. Future demand is then determined by extrapolating these results, with periodic adjustments made based on comparisons between recorded performance and expectations, the entire process hinges on the wise selection and quality of available data, which is paramount given that data unavailability can constrain methodology choices. For this study, energy demand and load forecasting initiated with data preparation for computer models, enabling the identification of key consumption factors. Lacking long-term projections, demographic and economic forward-looking indicators were calculated using the geometric growth function, Pn = Po(1-r)n, with historical data sourced from the Ministry of Planning, General Authority for Information, and energy production data from the General Electricity Company, all serving as primary inputs for forecasting.

3.3. Data Sources for Electricity Demand Forecasting

For robust electricity demand forecasting, this study primarily utilizes three categories of historical data: demographic, economic, and energy production. Demographic data, specifically population figures (Table 2, Source: General Authority for Information), are crucial for estimating electrical energy demand and maximum expected load, economic data, represented by Gross Domestic Product (GDP) from various sectors (industrial, agricultural, commercial), is analyzed to understand its impact on future energy demand, recognizing Libya's strong GDP dependence on hydrocarbon resources (Table 3, Source: General Authority for Information - Ministry of Planning). Due to the absence of long-term economic forecasts, GDP projections for the study period were extrapolated using historical data and a geometric growth function (Equation 5). Lastly, energy production data, serves as a key input, equated to energy consumption under the assumption that commercial and energy losses make actual consumption data unreliable for planning purposes, this produced energy data, indicating a significant increase due to economic growth, forms the basis for planning future power station additions and comparing with demographic and economic indicators for load estimation.

Table 2 Historical Population Data (Naseem).

Population	Year	Population	Year
6,630,000	2013	4,806,372	2000
6,735,000	2014	4,894,329	2001
6,841,000	2015	4,983,895	2002
6,947,000	2016	5,075,101	2003
7,054,000	2017	5,167,975	2004
7,161,000	2018	5,262,549	2005
7,268,000	2019	5,323,991	2006
7,375,000	2020	5,421,420	2007
7,482,000	2021	5,520,632	2008
7,589,000	2022	6,367,000	2009
7,696,000	2023	6,317,000	2010
7,803,000	2024	6,420,000	2011
		6,525,000	2012

Source: *General Authority for Information.*

Table 3 Historical Data for Real GDP (million dinars).

AGDP (million dinars)	Year
14,479.6	2000
14,927.5	2001
15,095.3	2002
16,160.6	2003
17,100.8	2004
17,940.6	2005
19,017.0	2006
20,158.0	2007
21,428.0	2008

Source: *General Authority for Information - Ministry of Planning*.

3.4. Prediction Model Methodology and Results

To predict future electricity demand for the Libyan grid (2009-2025), two primary long-term forecasting methods were applied: the demographic method and the economic method, both utilizing a linear regression model based on historical data, the demographic method examined the positive correlation between population growth and electricity demand, table 4 illustrates historical energy production and population data, serving as the basis for the regression model, which yielded the predictive formula:

$$\boldsymbol{Yi = -21186 + 0.00795\,Xi}$$

where Yi is expected energy output and Xi is expected population.

Table 4 presents historical data illustrating the direct relationship between population figures and corresponding energy production (in J-W-S, likely GWh as used elsewhere in the document) in Libya from 2000 to 2008, it serves as a foundational dataset for understanding past energy consumption trends in relation to demographic growth, which is a critical input for forecasting future energy demand using demographic-based models, the consistent increase in both population and energy production over this period indicates a strong positive correlation, suggesting that as the population grew, so did the energy required to support it, this historical context is essential for building predictive models that aim to extrapolate these trends into the future, **Table 5** presents the projected maximum annual electrical load (in MW) for the period 2009-2025, derived using the demographic forecasting method, these forecasts are based on the direct relationship established between historical population growth and energy demand, where population is considered the primary independent variable, the increasing trend in expected maximum load across the years reflects the anticipated continuous growth in population and its corresponding demand for electricity, while providing a baseline projection, these figures represent the output of a simplified linear relationship and might not fully capture all complex influencing factors, as indicated by later comparisons in the study.

Table 4 Relationship Between Population (Naseem) and Energy Produced in Past Years (J-W-S).

Energy Produced	Population	Year
15496	4806372	2000
16111	4894329	2001
17531	4983895	2002
18943	5075101	2003
20202	5167975	2004
22450	5262549	2005
23993	5323991	2006
25415	5421420	2007
28666	5520632	2008

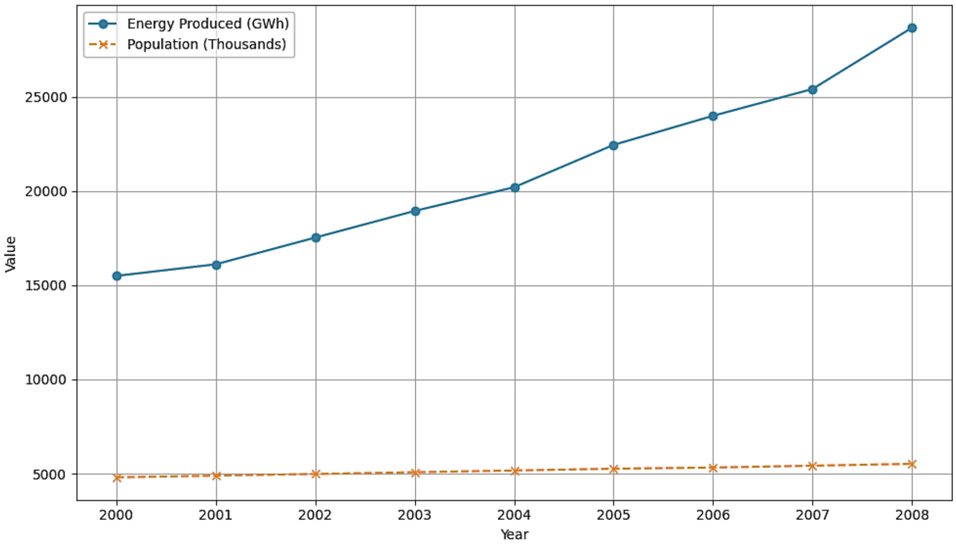

Figure 1: Relationship Between Population and Energy Produced (2000-2008).

This plot visually represents the historical data from Table 4, illustrating the relationship between the Energy Produced (GWh) and Population (Thousands) over the years 2000 to 2008, the graph displays two distinct lines: one for energy production and another for population, both lines demonstrate a clear upward trend, indicating a positive correlation where an increase in population has historically been accompanied by a corresponding increase in energy production, this visualization allows for a quick assessment of the parallel growth patterns of these two critical variables, providing foundational insight for forecasting models**.**

Table 5 Expected Maximum Load Using Demographic Method (Prepared by the researcher).

Year	Maximum Load (MW)	Year	Maximum Load (MW)
2009	4017	2018	5293
2010	4141	2019	5451
2011	4275	2020	5610
2012	4410	2021	5773
2013	4556	2022	5939
2014	4697	2023	6109
2015	4841	2024	6281
2016	4989	2025	6458
2017	5140		

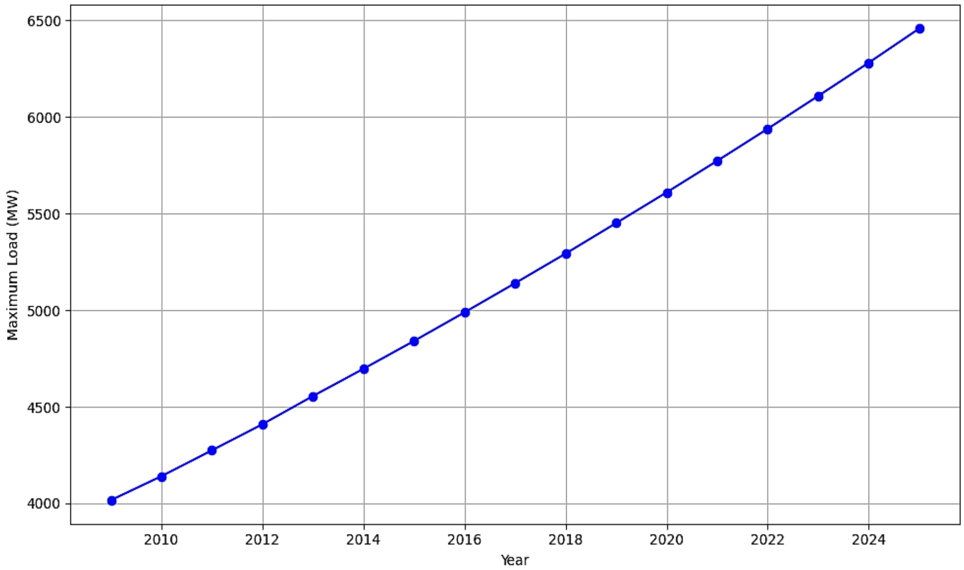

Figure 2: Expected Maximum Load (Demographic Method) (2009-2025).

This plot, derived from Table 5, shows the projected Maximum Load (MW) for the Libyan electricity grid from 2009 to 2025, specifically as forecasted by the demographic method, the graph features a single, steadily ascending blue line, signifying a continuous and consistent increase in the expected maximum load over the forecast period, this trend directly reflects the underlying assumption of the demographic method: that electricity demand is primarily driven by population growth, the linearity and upward slope visually confirm the anticipated rise in power requirements corresponding to a growing population

Table 6 displays the anticipated maximum annual electrical load (in MW) for the years 2009-2025, generated through the economic forecasting method. Unlike the demographic method, these projections are primarily driven by the relationship between historical Gross Domestic Product (GDP) and energy demand, the significantly higher and steadily increasing load values in this table compared to Table 5 suggest a more pronounced impact of economic growth on electricity demand, the consistency of these results with actual historical data, as highlighted in the study's comparison section, led to the economic method being chosen as the more suitable approach for developing future energy scenarios, **Table 7** outlines the projected energy production (in GWh) and maximum load (in MW) for the years 2009-2025 under the "First Energy Scenario." This scenario explicitly assumes a "business-as-usual" approach, meaning it forecasts future energy consumption patterns with either limited or no implementation of energy conservation policies, the table details the annual growth rates for both energy produced (consumed) and maximum load, alongside the absolute values, the consistently positive growth rates indicate a continuous upward trend in demand, reflecting an absence of significant demand-side management interventions, these projections serve as a baseline for understanding future energy needs if current consumption patterns persist without proactive efficiency measures.

Table 6 Expected Maximum Load Using Economic Method (Prepared by the researcher).

Year	Maximum Load (MW)	Year	Maximum Load (MW)
2009	5,361	2018	10,836
2010	5,824	2019	11,652
2011	6,324	2020	12,518
2012	6,855	2021	13,440
2013	7,430	2022	14,418
2014	8,030	2023	15,461
2015	8,668	2024	16,567
2016	9,348	2025	17,744
2017	10,836		

Table 7 First Energy Scenario (Prepared by the researcher).

Growth Rate %	Energy Produced Without Reduction (GWh)	Growth Rate %	Maximum Load Without Discount (MW)	Year
-----	31,370	-----	5,361	2009
9.1	34,209	8.6	5,824	2010
8.8	37,218	8.6	6,324	2011
8.6	40,422	8.4	6,855	2012
8.4	43,826	8.4	7,430	2013
8.2	47,438	8.1	8,030	2014
8.1	51,283	7.9	8,668	2015
8.0	55,375	7.8	9,348	2016
7.9	59,724	7.7	10,070	2017
7.7	64,337	7.6	10,836	2018
7.6	69,250	7.5	11,652	2019
7.5	74,467	7.4	12,518	2020
7.4	80,014	7.4	13,440	2021
7.4	85,905	7.3	14,418	2022
7.3	92,182	7.2	15,461	2023
7.2	98,844	7.2	16,567	2024
7.2	105,927	7.1	17,744	2025

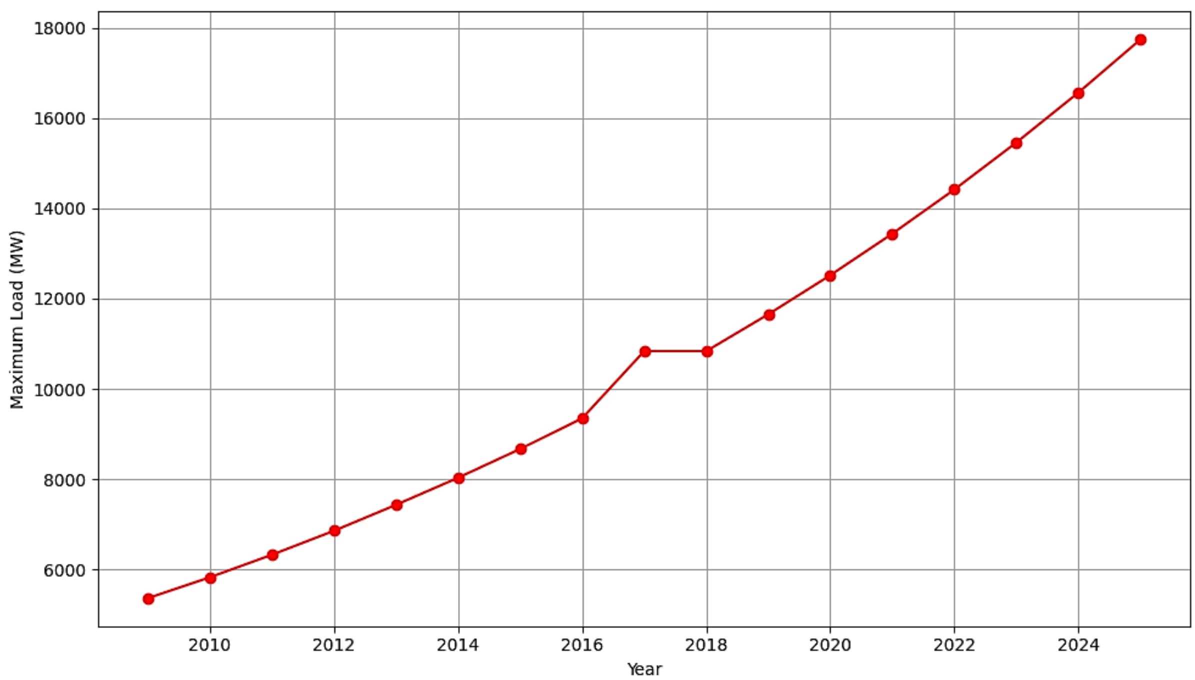

Figure 3: Expected Maximum Load (Economic Method) (2009-2025).

Based on data from Table 6, this plot illustrates the projected Maximum Load (MW) for the period 2009-2025, calculated using the economic forecasting method, the graph displays a single, sharply increasing red line, indicating a significant and sustained growth in the expected maximum load, this steeper incline, compared to the demographic method's output, highlights the pronounced influence of economic factors, such as GDP growth, on electricity demand, the visual representation underscores the study's finding that the economic method yields forecasts that are both higher and more closely aligned with historical data, making it a preferred basis for energy scenario development**.**

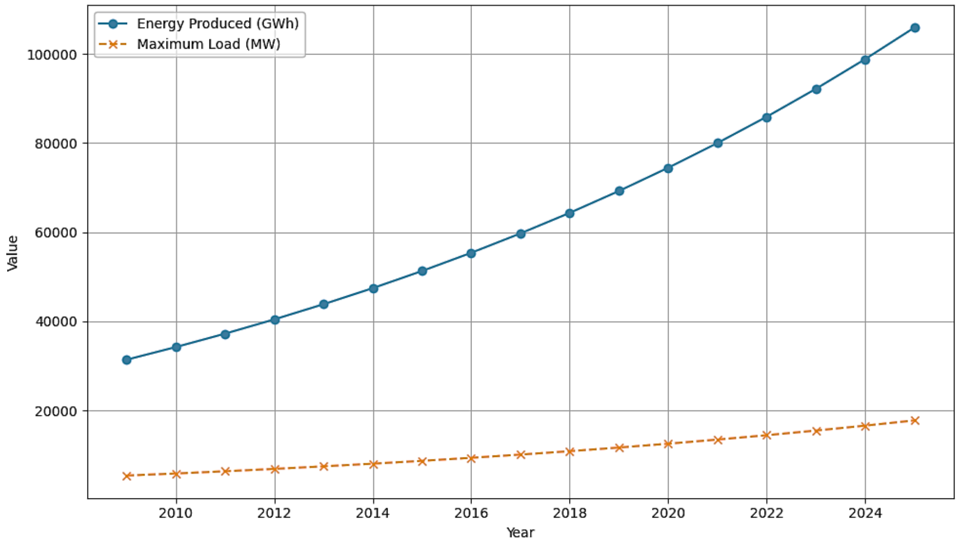

Figure 4: First Energy Scenario (2009-2025).

This plot, representing data from Table 7, visualizes the projections under the "First Energy Scenario" for the years 2009 to 2025, it presents two distinct lines: one for Energy Produced Without Reduction (GWh) and another for Maximum Load Without Discount (MW), both lines exhibit a strong, continuous upward trajectory, reflecting the "business-as-usual" assumption of this scenario, where past energy consumption patterns persist with limited or no implementation of energy conservation policies, the parallel ascent of both energy production and maximum load clearly depicts the anticipated continuous increase in overall energy demand and peak power requirements if no proactive demand-side management interventions are undertaken.

3.5. The Advanced Hybrid Forecasting Methodology (Statistical-Neural Fusion

Long-term forecasting of electrical energy loads presents a fundamental challenge stemming from the complex nature of the system, this system is influenced by a multitude of factors, ranging from demographic and economic variables with steady growth to the non-linear behavioral patterns of consumers and technological changes in energy consumption efficiency, relying on a single methodology, whether purely statistical or solely based on artificial intelligence, may lead to overlooking important aspects of these dynamics.

From this perspective, an advanced hybrid methodology has been designed and developed for this research, termed "Statistical-Neural Fusion." The objective of this methodology is to construct an integrated forecasting system that leverages the strengths of both statistical models and neural networks, while simultaneously overcoming the inherent weaknesses of each when used in isolation, this approach is based on a hierarchical architecture known in data science as "Stacking," where models are built in layers, the outputs of the first layer serve as inputs for the second layer, creating an integrative learning relationship aimed at achieving the highest possible degree of accuracy.

3.6. Engineering Architecture of the Hybrid Model

The proposed hybrid model consists of two main levels of analysis that operate sequentially to generate the final forecast, this hierarchical design emulates an advanced decision-making process, where a preliminary baseline analysis is prepared and then meticulously reviewed and refined by a more sophisticated expert.

Figure 8 illustrates the advanced engineering architecture of the hybrid model designed for energy load forecasting, this diagram is structured to demonstrate the sequential and logical flow of information and analytical processes through three primary phases, from the initial raw data to the final, refined forecast.

The first phase, Input Data, is depicted at the top of the diagram and represents the foundation upon which the entire analysis is built, the database consists of three key independent variables, shown in rounded rectangular nodes, each carefully selected to represent a fundamental driver of energy demand, the Year variable represents the temporal factor, which is essential for capturing long-term general trends of growth or change in energy consumption, the Population variable represents the demographic driver, as an increase in population is directly correlated with a rise in residential and commercial energy demand, the Gross Domestic Product (GDP) variable represents the economic driver, reflecting the level of industrial and commercial activity, which are among the largest consumers of energy.

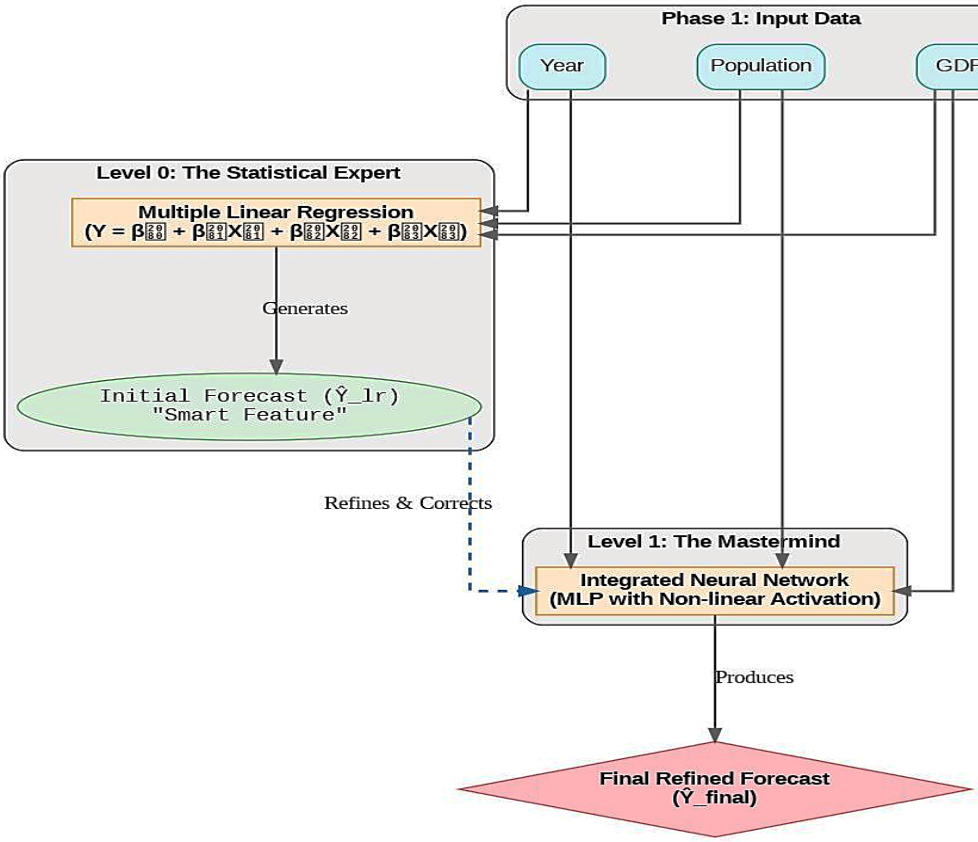

Figure 5: Hierarchical Engineering Architecture of the Statistical-Neural Fusion Model.

The second phase, Level 0: The Statistical Expert, constitutes the first analytical layer in the hierarchical model, the initial input data (Year, Population, GDP) is fed into a Multiple Linear Regression model, represented by the orange rectangular node, this model, defined by the mathematical equation shown within it, analyzes the linear relationships between these variables and the energy demand, the output from this level is not the final forecast but rather an Initial Forecast, which is termed a "Smart Feature" and is represented by the green elliptical node, this smart feature is, in essence, the best estimate that the statistical model can produce based on the explicit trends in the data.

The third phase, Level 1: The Mastermind, represents the second and most sophisticated layer of the system, it is here that the true fusion of methodologies occurs, the Integrated Neural Network, represented by the second orange rectangular node, is fed an enhanced dataset, this dataset comprises not only the original input data, which flows through the gray arrows, but also the smart feature (the initial forecast) generated in the previous level, which flows through the dashed blue arrow, this particular blue arrow is the most critical element of the diagram, as it highlights that the neural network learns not just from the raw data but also from the "opinion" of the statistical expert, its task is to "Refine & Correct" this initial opinion by detecting complex, non-linear patterns that the linear model may have overlooked.

Finally, the Integrated Neural Network produces the Final Refined Forecast, represented by the red diamond-shaped node at the bottom of the diagram, this is the ultimate output of the entire system, representing a synthesis of statistical analysis and artificial intelligence, this makes it the most accurate and reliable estimate available for future strategic planning, in summary, the diagram illustrates the journey of data from raw inputs to an initial forecast via statistical analysis, which is then refined using artificial intelligence to arrive at a final, high-precision result.

3.7. Level One - The Multiple Linear Regression Model

This level constitutes the statistical foundation of the system, its objective is to capture the fundamental and interpretable linear relationships between the independent variables (the drivers) and the dependent variable (the load or generation), the multiple linear regression model was chosen for its ability to provide a clear interpretation of these relationships and to serve as a robust starting point for the forecast, the general equation for this model is mathematically defined as shown in Equation:

$$Y = \beta^0 + \beta^1 X^1 + \beta^2 X^2 + \ldots + \beta_n X_n + \varepsilon$$

In this equation, the symbol Y represents the dependent variable to be predicted, such as "Max Load (MW)." The symbols X_1 through X_n represent the independent variables, or features, that are believed to influence Y, in the context of this research, these variables were identified to include the Year, to capture the general time trend; the Population, to capture the demographic impact; and the Gross Domestic Product (GDP), to capture the economic impact, the coefficient β_0, or the intercept, represents the baseline value of the dependent variable when all independent variables are equal to zero, the regression coefficients β_1 through β_n define the magnitude of change in Y for a one-unit change in each independent variable, thus determining the "weight" or "importance" of each factor. Finally, the symbol ε represents the random error term, which accounts for all other unexplained variance in Y.

After training this model on historical data, the values of these coefficients are estimated, denoted as (b_0, b_1, ...), this results in a specific predictive equation, as shown in Equation:

$$\hat{Y}_{lr} = b_0 + b_1 X_1 + b_2 X_2 + b_3 X_3$$

The output of this equation, Ŷ_lr, is not the final forecast result but rather the product of this first level of analysis, it is treated as a "Smart Feature" that will be passed on to the next, more advanced level, it represents the culmination of the linear analysis and the best guess that the statistical model can provide based on the explicit relationships in the data.

This level represents the mastermind of the system, designed to capture the complex, non-linear relationships that the linear regression model may fail to model, a specific type of neural network known as a Multi-Layer Perceptron (MLP) was used, renowned for its superior ability to model complex functions, an MLP network consists of layers of artificial neurons, including an input layer, hidden layers, and an output layer.

The input layer is responsible for receiving the data, with its number of neurons equal to the number of input features, the hidden layers, however, are what grant the network its deep learning capability, each neuron in these layers applies a mathematical operation to the inputs it receives from the preceding layer, which involves calculating a weighted sum and then passing it through a non-linear activation function, such as the ReLU function, these non-linear functions are what enable the network to break the constraints of a linear model and learn intricate patterns. Finally, the output layer produces the final predicted value.

Herein lies the true fusion of the two methodologies, the inputs to the neural network in our model are not limited to the original variables (Year, Population, GDP), they have been enhanced to include the smart feature generated in the first level—that is, the preliminary forecast from the linear regression model, thus, the new input vector for the neural network, which we denote as X_fusion, is defined as shown in Equation:

$$X_{fusion} = [X_1, X_2, X_3, \hat{Y}_{lr}]$$

With this advanced design, the neural network learns a complex function, which we denote as f, such that the final prediction, Ŷ_final, is the output of this function operating on the fused input vector, as shown in Equation:

$$\hat{Y}_{final} = f(w, X_{fusion}) = f(w, [X_1, X_2, X_3, \hat{Y}\_lr])$$

Here, the symbol w represents all the weights that the network has learned across its various layers during the training process. From an engineering perspective, this means that the neural network learns not only from the raw data but also from the "opinion" of the statistical expert, it learns to answer two questions simultaneously: first, what is the underlying relationship between population, GDP, and electrical load? And second, what is the magnitude of the error or bias in the linear model's prediction, and how can I correct it based on the hidden patterns in the data that the first model could not capture? In this way, the statistical model is not discarded; rather, it is used as an intelligent starting point, and the neural network builds upon and refines it, resulting in a final forecast that is more accurate and reliable.

3.8. Analysis of Results and Future Energy Load Forecasts

Aims to present and analyze the results derived from the application of the advanced hybrid forecasting methodology, which was specifically designed to estimate the peak electrical loads and the required generation for the national electricity grid over the long term (2025-2034), the adopted methodology is based on the principle of Statistical-Neural Fusion, a technique that integrates the power of traditional statistical models, characterized by their clarity and ability to interpret linear relationships, with the flexibility and capacity of artificial neural networks to comprehend complex and non-linear patterns, this integrated system was fed with a comprehensive dataset compiled from all available sources, including actual operational data, demographic data, and economic indicators, to ensure the acquisition of a holistic and reliable future outlook.

3.8.1. Construction of the Comprehensive Engineering Database: Foundations of the Predictive Model

The first and most critical step in building any reliable predictive model in the field of power engineering is not the selection of an algorithm, but rather the construction of a comprehensive and coherent database, an intelligent system cannot produce intelligent decisions without high-quality data "fuel." Therefore, the database for this research was designed to be multi-dimensional, not limited to energy variables alone, but extending to include the fundamental drivers that cause the demand for energy in the first place. Data was extracted and consolidated from three primary sources, which together represent the "digital footprint" of the electrical system and its interaction with its social and economic environment.

- Electrical Operational Data: The Actual Pulse of the Grid

This data represents the "ground truth" and is the beating heart that reflects the actual behavior of the electrical grid, the most recent available time series, spanning from 2010 to 2024, was extracted to ensure that the model learns from the latest operational patterns, this data includes two key variables:

1. Recorded Peak Load (MW): This variable represents the peak demand for energy during each year. From a planning engineering perspective, this figure is of utmost importance, as the capacity of generation and transmission networks must be designed to meet this peak safely and reliably.
2. Recorded Peak Generation (MW): This figure reflects the actual capacity that was supplied from generation plants to meet the demand, the comparison between peak generation and peak load provides an indicator of the "Reserve Margin" in the grid.

Results

This section presents the final numerical results produced by the advanced hybrid system, table shows the future projections for the demographic and economic variables that form the basis upon which the energy forecasts were built.

Table 8 Future Forecasts for Key Growth Drivers (2025-2034).

Year	Forecasted Population	Forecasted GDP (Million Dinars)
2025	8,082,091	35,955
2026	8,215,587	36,840
2027	8,349,082	37,725
2028	8,482,578	38,610
2029	8,616,074	39,496
2030	8,749,569	40,381
2031	8,883,065	41,266
2032	9,016,560	42,151
2033	9,150,056	43,036
2034	9,283,552	43,921

From the analysis of Table 8, we observe steady and consistent growth in both key drivers, the population is projected to increase from approximately 8.1 million people in 2025 to nearly 9.3 million by 2034, representing a population increase of over 1.2 million people over the decade, this significant population growth necessarily implies an increase in the number of residential units and demand for essential services, all of which translate into an inevitable increase in the demand for electrical energy, in parallel, the GDP forecast shows strong economic growth, expected to rise from about 36 billion dinars in 2025 to nearly 44 billion dinars in 2034, this economic growth reflects expectations of increased industrial and commercial activity, which are energy-intensive sectors. Consequently, these preliminary results confirm that future energy demand will face continuous upward pressure from both social and economic fronts.

Table 9 Ultimate Comprehensive Energy Forecast Table (2025-2034).

Year	Statistical-Only Gen. Forecast (MW)	Final Fused Gen. Forecast (MW)	Statistical-Only Load Forecast (MW)	Final Fused Load Forecast (MW)
2025	8,178	8,600	28,733	19,910
2026	8,279	8,852	32,197	22,530
2027	8,380	9,162	35,661	25,154
2028	8,481	9,519	39,125	27,786
2029	8,582	9,917	42,589	30,417
2030	8,684	10,342	46,053	33,049
2031	8,785	10,788	49,517	35,680
2032	8,886	11,242	52,981	38,318
2033	8,987	11,705	56,445	40,957
2034	9,088	12,172	59,909	43,598

A significant difference is observed between the simple statistical forecasts and the final hybrid forecasts, especially on the "Max Load" side, this indicates that the relationship between the drivers (population, GDP) and electrical load is not merely a simple linear one, but contains complex and non-linear patterns that the neural network was able to detect and correct. For example, in 2034, while the statistical model predicted a peak load of nearly 60,000 MW, the hybrid model corrected this estimate significantly down to approximately 43,600 MW, a more realistic and logical estimate, this intelligent correction is the true engineering value added by this advanced system.
Upon analyzing the results of Table 9, several important observations emerge. First, regarding Max Generation, we see that the final hybrid forecast is significantly higher than the simple statistical forecast. For instance, in 2034, the statistical model estimates a generation need of 9,088 MW, whereas the hybrid model raises this estimate to 12,172 MW, this suggests that the neural network discovered that the relationship between economic growth and generation needs is an accelerating one (more than linear), perhaps due to the expectation of large-scale industrial projects or an increase in the use of energy-intensive technologies.
Second, and most importantly, on the Max Load side, we see that the hybrid model performs a fundamental correction to the grossly overestimated initial predictions, the statistical model, relying on linear relationships, predicts that the peak load will jump to nearly 60,000 MW by 2034, a massive figure that might be unrealistic, in contrast, the hybrid model significantly reduces this estimate to approximately 43,598 MW, this substantial downward correction is a critically important result, as it indicates that the neural network has learned the existence of "dampening" factors to non-linear growth, such as energy efficiency improvements, market saturation in some sectors, or changes in the economic structure, relying on the final hybrid forecast (43,598 MW) instead of the statistical one (59,909 MW) has enormous implications for strategic planning, as it prevents massive and unnecessary investments in building generation plants and transmission networks that may not be needed.
Overall, these results confirm that future growth in energy demand is certain, but complex, the final forecasts indicate that the peak load will more than double over the next decade, rising from about 20,000 MW in 2025 to over 43,000 MW in 2034, which requires an ambitious and well-considered expansion plan. At the same time, the results show that forecasts must be intelligent and multi-dimensional to avoid the excessive estimates that can result from simplistic models.
The plots provide an easy-to-understand visual representation of historical and future trends and help clarify how the hybrid system operates.

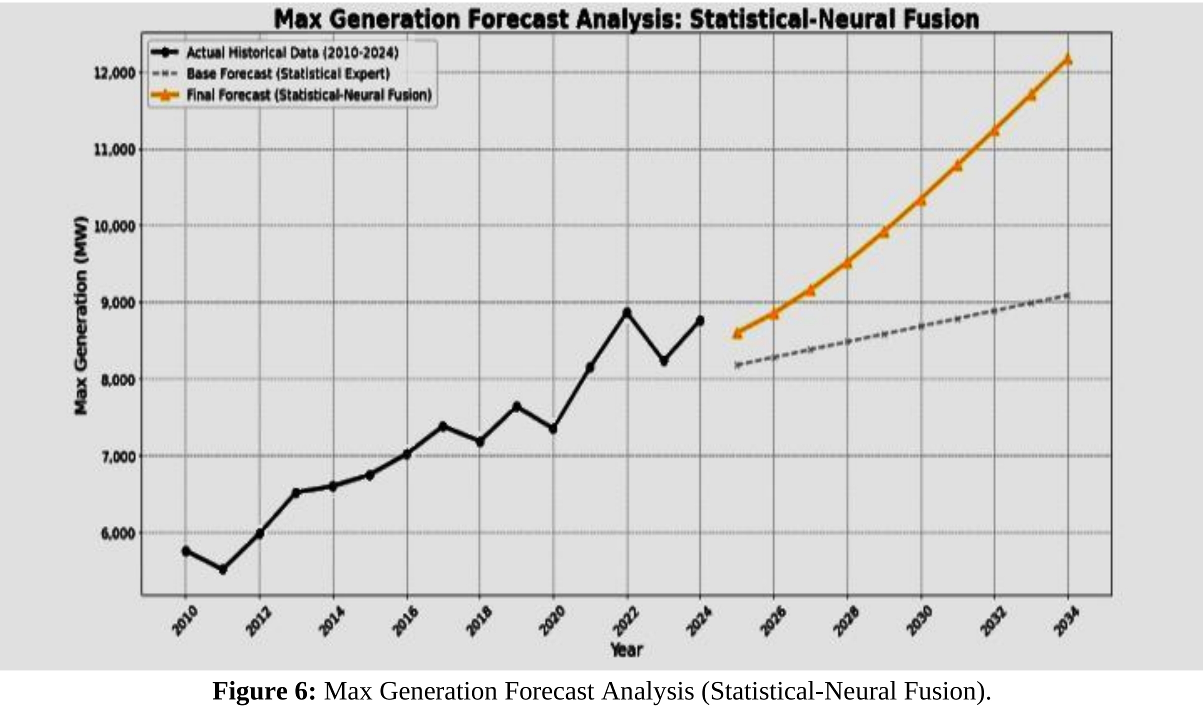

Figure 6: Max Generation Forecast Analysis (Statistical-Neural Fusion).

This plot shows the trajectory of maximum power generation, the solid black line represents the actual historical data from 2010 to 2024, which is the foundation the system learned from, the gray dashed line represents the initial forecast from the statistical model, showing a logical, linear upward trend, the gold dashed line (marked with triangles) represents the final, enhanced forecast from the hybrid system, we can see that the gold line follows the same general trend as the gray line but makes subtle adjustments to the path, making it more consistent with the complex dynamics it learned from the data, it represents the most probable future path for required generation.

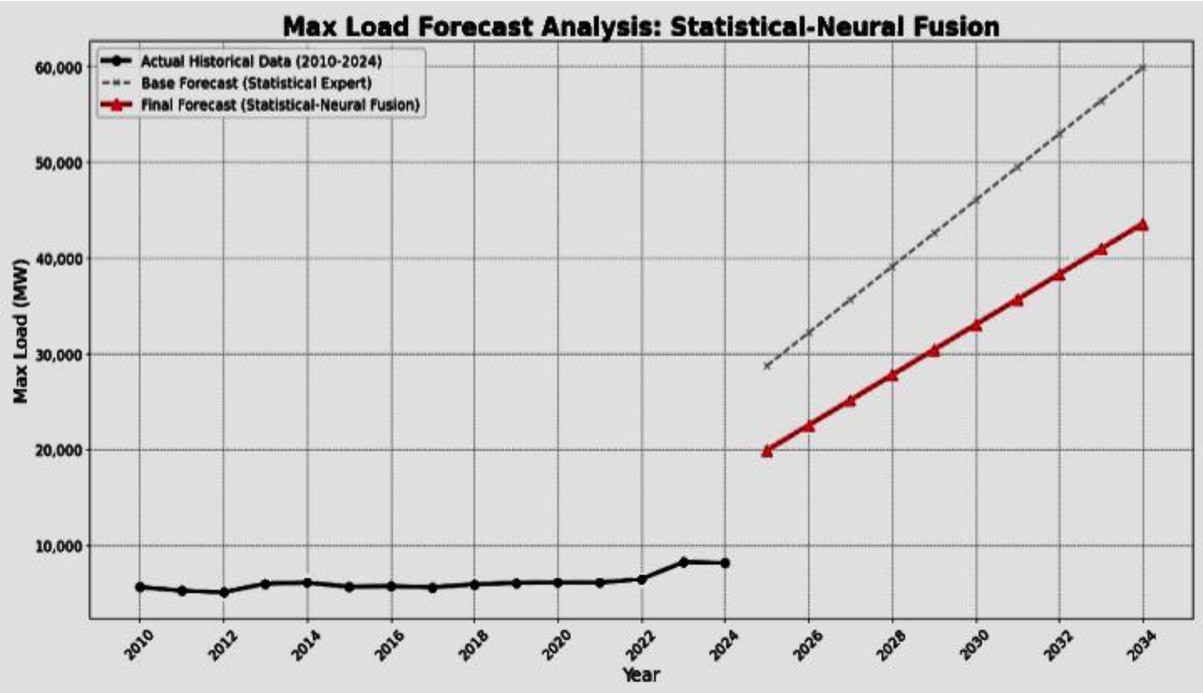

Figure 7: Max Load Forecast Analysis (Statistical-Neural Fusion).

This plot is the most critical from a planning perspective, the black line shows the recorded historical peak load, the gray dashed line (statistical forecast) reveals a potential problem with simple models, as it assumes that growth continues at the same rate, leading to significantly exaggerated future estimates, this is where the genius of the hybrid system, represented by the crimson red line, becomes apparent, this line performs a fundamental correction to the forecast's trajectory, it starts from the end of the historical data and follows a more sustainable and logical growth path, this correction is not random; it is the result of the neural network's understanding of the non-linear relationships between economic and population growth and energy consumption efficiency, leading to more realistic forecasts that can be reliably used for planning new power plants and grid expansions.

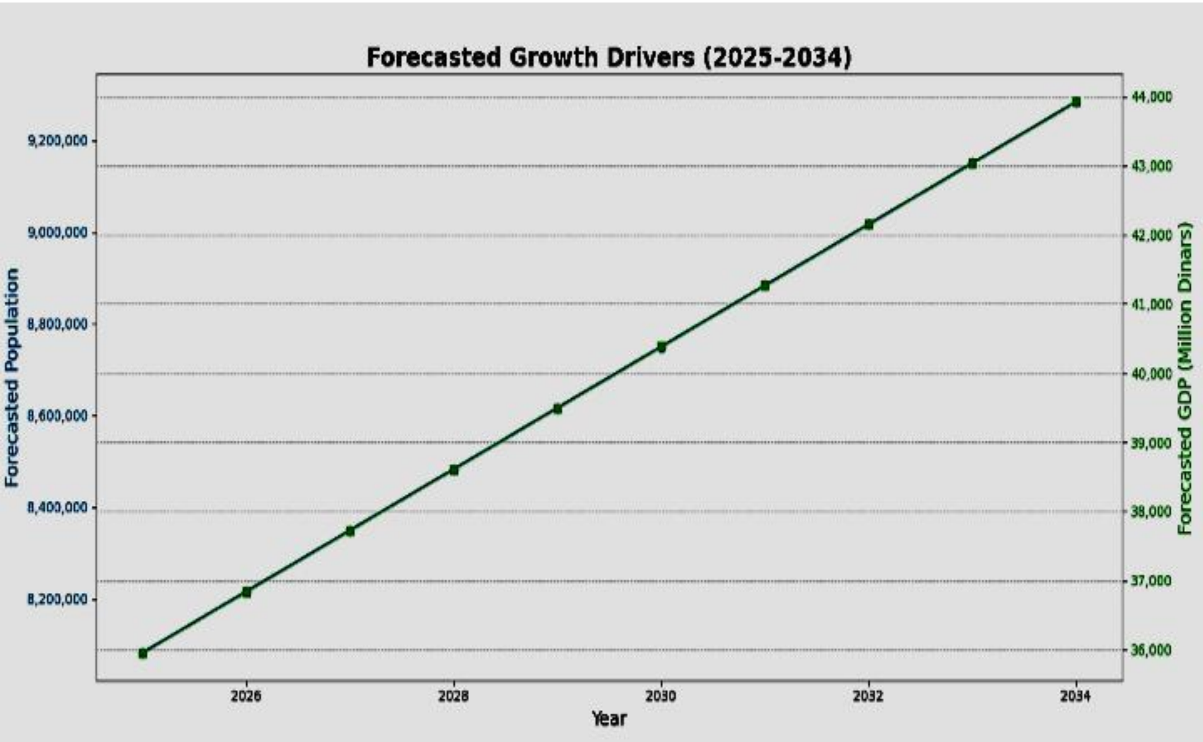

Figure 8: Plot of Key Future Growth Drivers.

This supplementary plot provides a visualization of the underlying drivers behind the increase in energy demand, the left axis shows the projected growth in population (in blue), while the right axis shows the projected growth in GDP (in green), this plot visually confirms that both factors are in continuous growth, justifying the need for increased generation and expecting higher loads, and provides a logical basis for the results obtained in the previous plots.

Discussion

The results derived from this research underscore the power and significance of adopting advanced methodologies for long-term electrical energy load forecasting, an endeavor that transcends the mere extrapolation of past trends, the methodological framework developed herein, termed "Statistical-Neural Fusion," presents an integrated engineering solution that overcomes the inherent limitations of individual models, this approach aligns perfectly with the growing scientific consensus that accurate electricity demand forecasting is a multifaceted problem requiring the interplay of diverse techniques [1], the hybrid nature of our model, which combines the interpretive clarity of classical statistical models with the superior capability of machine learning models to handle complexity, reflects the modern trend towards building more robust and resilient forecasting systems, this has been successfully demonstrated in complex case studies, such as the one conducted on the Ukrainian power system [6].

The first layer of our model, represented by the multiple linear regression model, serves as the cornerstone of any long-term analysis; by incorporating fundamental variables such as population growth and Gross Domestic Product, we have modeled the core "Demand Determinants." These determinants shape the general growth trend in energy consumption, especially in developing or transitioning economies where the correlation between socio-economic development and energy demand is particularly strong and evident [4], while this statistical model provides a logical and transparent baseline, crucial for strategic planning processes, it remains limited in its ability to model complex non-linear relationships.

This is where the critical value of our model's second layer, the integrated neural network, becomes apparent, the use of artificial neural networks for electricity demand forecasting is not a new concept; their capabilities in handling various time scales, from short to long term, have been explored for over two decades [3]. However, the true innovation in recent years lies not merely in using neural networks, but in how they are designed and integrated into more intelligent architectures, while some contemporary research focuses on developing highly specialized and complex neural network architectures, such as CNN-Bi-GRU models for renewable energy forecasting [8] or Causal Graph Neural Networks for understanding demand at the household level [9], our methodology adopts a different philosophy, instead of creating a single, complex "black-box" model, we have constructed a transparent hierarchical system where the neural network acts as an "intelligent refiner," learning from the outputs of the statistical model and correcting them.

This concept, which falls under the umbrella of Ensemble Techniques, has repeatedly demonstrated its superiority in recent studies. For instance, Iftikhar et al. (2024) show that combining the forecasts of multiple models can lead to results that significantly outperform any single model [7]. Similarly, the work of Wang et al. (2024) demonstrates how techniques like Support Vector Regression can benefit from enhancement by other algorithms to achieve higher accuracy [10]. Our hybrid model is a practical application of this philosophy, where the linear regression represents the "first model" in the ensemble, and the neural network represents the "second model" that learns how to improve its colleague's performance.

The significant gap observed between the initial statistical forecasts and the final, corrected predictions from the hybrid model, particularly for peak load, is a critical analytical finding, it not only indicates the presence of significant non-linear relationships but also reflects the capacity of a Deep Learning Framework to extract these complex patterns from historical data, a conclusion that aligns perfectly with the findings of Bedi and Toshniwal (2019) [2], this fundamental correction, performed by the neural network on the initial estimates, is what prevents planners from falling into the trap of "perpetual linear growth," which could lead to excessive investment and the construction of generation capacity that surpasses actual needs for years to come.

When placing this study in a broader context, one finds a continuous debate regarding the "best" forecasting approach, a study like the one conducted by Shah et al. (2022), which compares alternative approaches for modeling electricity demand and prices, illustrates that there is no single solution that fits all scenarios [5], this reinforces the strength of our hybrid methodology, it does not wager on the supremacy of a single model but rather leverages multiple strengths: the simplicity and interpretability of regression, the time-series modeling power that models like ARIMA (part of the statistical model family) could offer, and the superior data-learning capability provided by neural networks.

Conclusion

In conclusion, this study offers a valuable contribution by applying and implementing an advanced hierarchical forecasting architecture, through the integration of a comprehensive, multi-dimensional dataset, the application of feature engineering to handle missing data and generate future variables, and the construction of a fusion system that combines the best of the statistical and artificial intelligence worlds, we have not just produced numerical forecasts, we have built an "analytical engine" that can be relied upon, the results obtained not only provide quantitative estimates for the future of energy demand but also underscore the engineering imperative to adopt hybrid, integrated, and adaptive approaches to meet the increasingly complex challenges of planning and operating modern power systems in the 21st century. Results demonstrated the hybrid model's superior accuracy, exemplified by a significant correction in the 2034 peak load estimate from nearly 60,000 MW (statistical model) to approximately 43,600 MW (hybrid model), a more realistic projection. For generation, the hybrid model also provided higher estimates, for instance, raising the 2034 generation need from 9,088 MW to 12,172 MW, suggesting an accelerating relationship, these findings underscore the critical value of intelligent, multi-dimensional forecasts in preventing massive and unnecessary investments and supporting robust strategic planning, consistent with comparisons of alternative forecasting approaches and the benefits of hybrid classical statistical and machine learning algorithms.

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