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Forecasting Electricity Peak Load: Time-Series Modeling Integrating Economic and Demographic Dynamics—A Case Study From Jordan

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Received: 7 August 2025 | **Revised:** 7 November 2025 | **Accepted:** 3 December 2025

Funding: School of Graduate Studies & Scientific Research at Princess Sumaya University for Technology, Grant/Award Number: 2024/2023-9 (15)

Keywords: economic growth | electricity peak load | linear regression | load forecasting | population growth | time series

ABSTRACT

Factors like pricing, transmission expansion, and capacity planning rely on accurate power demand forecasts. This paper intends to utilize time-series models to forecast the peak electricity demand of Jordan's power grid amidst its energy transition, offering insights into necessary expansion and system adjustments over the next decade It explores the relationship between the country's peak load fluctuations over the last three decades and examining factors including the Gross Domestic Product (GDP) and population growth. Autoregressive Integrated Moving Average (ARIMA), and Autoregressive Integrated Moving Average with Explanatory Variable (ARIMA-X), are employed to forecast yearly peak loads, which are also compared with linear regression, providing an enhanced understanding of power generation and network expansion needs for the coming decade. The results show strong correlations between peak load, population growth, and GDP, with the models proving effective in forecasting future peak loads, albeit with caution regarding ARIMA-X. Projections suggest a potential 41% increase in peak load by 2035, reaching around 5300 MW in 14 years. Assuming consistent growth rates in population and GDP, the projections of the peak load also indicate that the peak load might reach twice its current level in the next 2 to 2.5 decades.

1 | Introduction

The peak electricity load stands as a pivotal parameter for system operators and policymakers, guiding strategic planning for power networks. Accurate forecasting of this load offers vital insights into present and future electricity demands, enabling proactive infrastructure planning. Precise forecasts facilitate a clear understanding of the electricity supply required to meet burgeoning demands. In light of global climate change and resource constraints, dependable, national-scale forecasting is essential for long-term energy planning. Understanding peak load requirements enhances overall electricity system planning, facilitating the integration of new generation units, assessing the feasibility of incorporating new loads such as electric vehicles, implementing storage solutions, and embracing renewable energy technologies more effectively [1, 2]. Moreover, it enables enhancements in cost-efficient planning, maintenance scheduling, and fuel management. The electricity peak load can vary between countries depending on demographic shifts (such as population growth), economic indicators, and climate change. Additionally, factors like weather conditions, oil prices, and tariff fluctuations can influence when peak loads occur, as observed in Jordan, where they may manifest during summer or winter seasons [3].

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It is widely understood that population growth drives up electricity demand, potentially leading to supply shortages. However, peak loads can fluctuate due to various factors, notably changes in electricity consumption patterns influenced by economic conditions. Predicting peak loads enables proactive management to ensure sufficient supply, mitigating potential shortages. Strategies such as integrating additional generation—whether energy comes from renewable sources or conventional fossil fuels—alongside real-time pricing adjustments and optimizing energy consumption policies, can effectively manage fluctuating peak loads and avoid shortages in the supply.

Gross domestic product (GDP), as an economic indicator, often correlate strongly with a country's electricity production and consumption. As the economy expands, so does the reliance on electricity, necessitating careful monitoring and prediction of peak loads to prevent supply-demand disparities. However, depending on a number of variables, such as the energy policies that govern its market, the correlation between peak load and GDP may vary from one country to another. For example, three main policies—security, expansion, and conservation—shape market laws in the energy industry in both developed and emerging nations [4]. The explicit goal of conservation efforts is to cut down on electricity use, which yields savings that contribute to the sustainability of the environment [3, 5]. Expansionary policies, which include investment plans, aim to increase power consumption for two main objectives, in contrast to conservation policies. They first promote the use of clean electric energy in place of conventional energy sources, which are linked to significant greenhouse gas emissions. Second, they help to meet households' expanding needs [5, 6]. Security policies prioritize putting in place the best distribution systems to avoid power interruptions while guaranteeing the sustainability of electricity usage [5, 7]. It is evident from the explanation above that the relationship between the electricity peak load and both GDP and population growth can differ significantly across countries and power systems. These variations stem from factors such as demographics, population growth rates, consumption patterns, and market regulations.

The issue of forecasting power load across short, medium, and long timeframes has received considerable attention. Long-term capacity planning necessitates predicting total consumption based on demographic or economic variables. Utilising time-series analysis to assess overall energy usage is crucial for power consumption forecasts. Analysing annual data from past and present values can prove beneficial for long-term forecasting by estimating future trends [8]. For this purpose, a variety of forecasting models, including multivariate and multiple regression, have been used [9]. Thanks to technological progress and modern computer-assisted calculations, numerous machine-learning algorithms, including artificial neural networks [10, 11], support vector machines [12, 13], and time-series models [8, 14–17], have emerged. Although such algorithms have been extensively studied in the literature as they might achieve satisfactory forecasting accuracy, they have been usually recommended for short-term load forecasting only. Conversely, linear regression and/or multiple regression methods continue to be favoured and proven effective for long-term and even extremely long-term forecasting [14]. Moreover, the suitability of time series models for long-term forecasting has not been thoroughly investigated. Thus, this paper uses the Jordanian system as a case study to assess the effectiveness of time-series models, namely Autoregressive Integrated Moving Average (ARIMA), and Autoregressive Integrated Moving Average with Explanatory Variable (ARIMA-X), in forecasting the yearly electricity peak load over the long term compared to linear regression.

To gain deeper insights into the variables most conducive to predicting load demand, the initial analysis delves into the relationship between the fluctuated GDP and population growth over the years, and the electricity peak load in Jordan. Subsequently, linear regression, ARIMA, and ARIMA-X models are employed to forecast the yearly peak load in Jordan. This endeavour not only sheds light on the future trajectory of peak load but also facilitates a better understanding of forthcoming demand requirements. Accordingly, it enables the formulation of more effective policies and initiatives for the future roadmap of the country's electricity system. The remainder of the paper is structured as follows: Section II provides an overview of the status of the power network in Jordan. Section III offers insights into the country's population growth and GDP. Sections IV and V outline the linear regression and time series models utilised for forecasting, respectively. Section VI presents the results and discussions from the exploratory analysis of the electricity peak load patterns concerning population growth and GDP, alongside forecasts for the next decade. Finally, Section VII summarises the findings and concludes the paper.

2 | Jordan Power Network

2.1 | The Regulatory and Structure Perspective

Jordan has emerged as a frontrunner in the region for renewable energy adoption, marking a substantial increase in the percentage of electricity sourced from renewables, rising from 0.7% in 2014 to a noteworthy 21% in 2020 according to the summary of Jordan energy strategy report revealed by the Ministry of Energy & Mineral Resources [18]. This reflects the country's steadfast dedication to sustainable energy initiatives, notably focusing on solar photovoltaics (PV) and wind expansion The energy transition is led by the energy sector's master plan for 2020–2030, which is supervised by MEMR, the Ministry of Energy and Mineral Resources. It envisions a future characterised by a variety of sustainable energy sources, increased utilisation of domestic energy resources, improved energy security, and lowered electricity expenses. Significantly, the strategy sets ambitious targets aiming for 31% installed capacity from renewable energy and to contribute 14% of the energy mix in 2030. Jordan is a regional leader in sustainable energy initiatives thanks to its proactive promotion of renewable energy. By introducing the first feed-in tariff system in the area specifically designed for renewable energy projects, Jordan's Energy Regulatory Commission (JERC) made an important development in late 2012. This landmark strategy provided crucial regulatory guidance for integrating battery storage across several tiers of the national grid and acted as a springboard for developing a specialized storage code. Coordination at the ministerial level and constant interaction with key players, such as distribution companies and grid operators, were essential to the success of these projects. Renewable energy has since taken a leading role in Jordan's energy transition strategy, reinforced by effective regulations and

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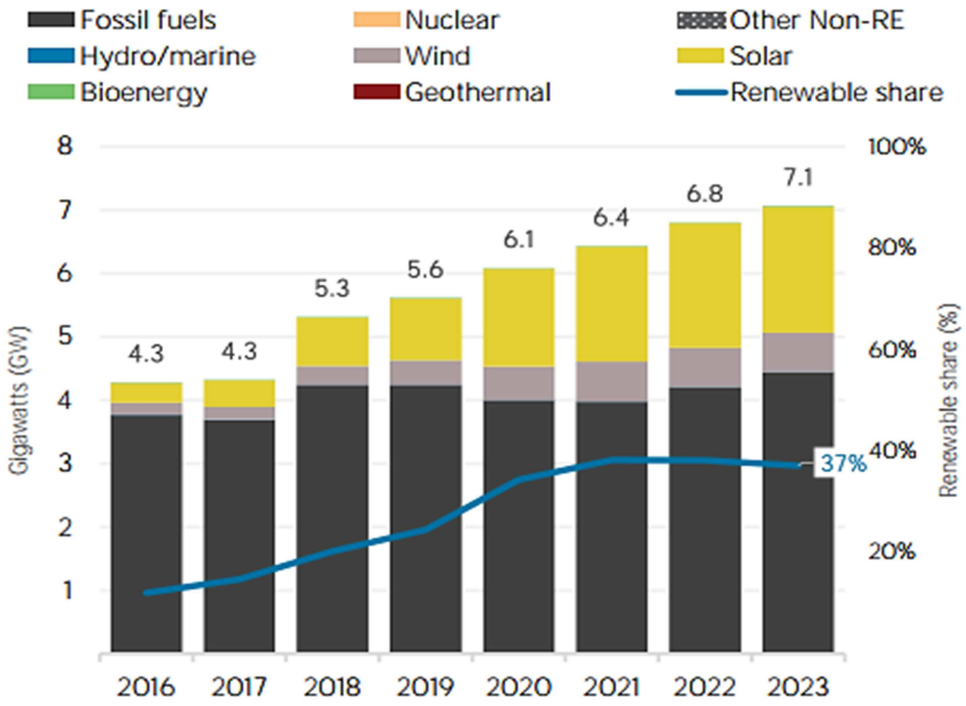

FIGURE 1 | Installed capacity trend in the power sector, by source (2016–2023) [19].

policy frameworks. Dramatic declines in the cost of solar PV and wind technologies have enhanced the competitiveness of renewables against traditional sources, contributing to the achievement of 13% electricity generation from renewables in 2019. Jordan's clean energy landscape is primarily shaped by statutory provisions, particularly Electricity Law No. 64 of 2002, which regulates production, transmission, and distribution activities. This legal base is supported by various secondary instruments, including directives, bylaws, and implementation guidelines. Figure 1 displays the progression and the trend of installed electricity capacity from 2016 to 2023 [19].

Nevertheless, current electricity suppliers and distribution companies have difficulties when switching to renewable energy sources. Industrial and Commercial consumers are increasingly relying on the grid infrastructure while reducing the dependence on conventional power resources. In response to such shift, the government has taken active measures to encourage natural gas integration into domestic industries while adhering to the necessary contractual, technical, and regulatory aspects of this shift. These initiatives align with Jordan's overarching energy objectives, geared towards enhancing industrial competitiveness and reducing production costs [20, 21].

2.2 | Energy Generation and Consumption

Jordan's MEMR EIS website now provides easy access to historical energy statistics, offering statistics dating back to 2005, which is quite useful for decision-making and energy planning. NEPCO anticipates a growth rate of 4%–5%, whereas 13%–14% of grid losses occur during the transmission and distribution of electricity. Traditional generation units, including natural gas combustion, have historically fuelled Jordan's electricity production. However, there is a global alteration towards eco-friendly alternatives, emphasising intermittent renewables and efficient energy storage solutions. Jordan embarked on many renewable energy projects between 2015 and 2018, with momentum that persisted from 2019 to 2021, accounting for 14% of the overall power production. A main generating station, a high-voltage transmission grid with operational voltages of 132 and 400 kV, and connections with adjacent countries comprise Jordan's power capacity. The population is reliably covered by distribution networks. As of 2016, Jordan's net electricity generation capacity was 4,266 MW, supported by a transmission grid extending approximately 4,531 km. Major substations collectively had an installed capacity of 12,865 MVA. In 2017, total electricity generated and imported reached 20,811 GWh, showing a 4.1% annual increase. Domestic production accounted for 20,760 GWh, reflecting a 5.6% rise, while imported electricity dropped sharply by 84.6%, down to 51.3 GWh. Generation capacity rose slightly to 4,300 MW in 2017, up 0.74% from 4,269 MW in 2016. Figure 2 shows how Jordan's demand for electricity has increased during the period between 2010 and 2022.

Electricity usage increased by 4.8% annually from 16,700.2 GWh in 2016 to 17,503.8 GWh in 2017. Due to variables such residential expansion, the average per capita usage increased 1.7% from 1,712 kWh the year before to 1,741 kWh. The demand for electricity in Jordan is dispersed across several industries, making it difficult to keep up with growing demands. These industries include public illumination, commercial, industrial, residential, and agricultural [22]. Figure 3 illustrates the breakdown of total electricity consumption by sector for the year 2018.

3 | Population Growth and Economic Indicators

3.1 | Growth in the Population

Jordan grapples with challenges stemming from the rapid increase in population, standing at 11.44 million in 2023, which places strain on its economy. To mitigate these challenges, it's

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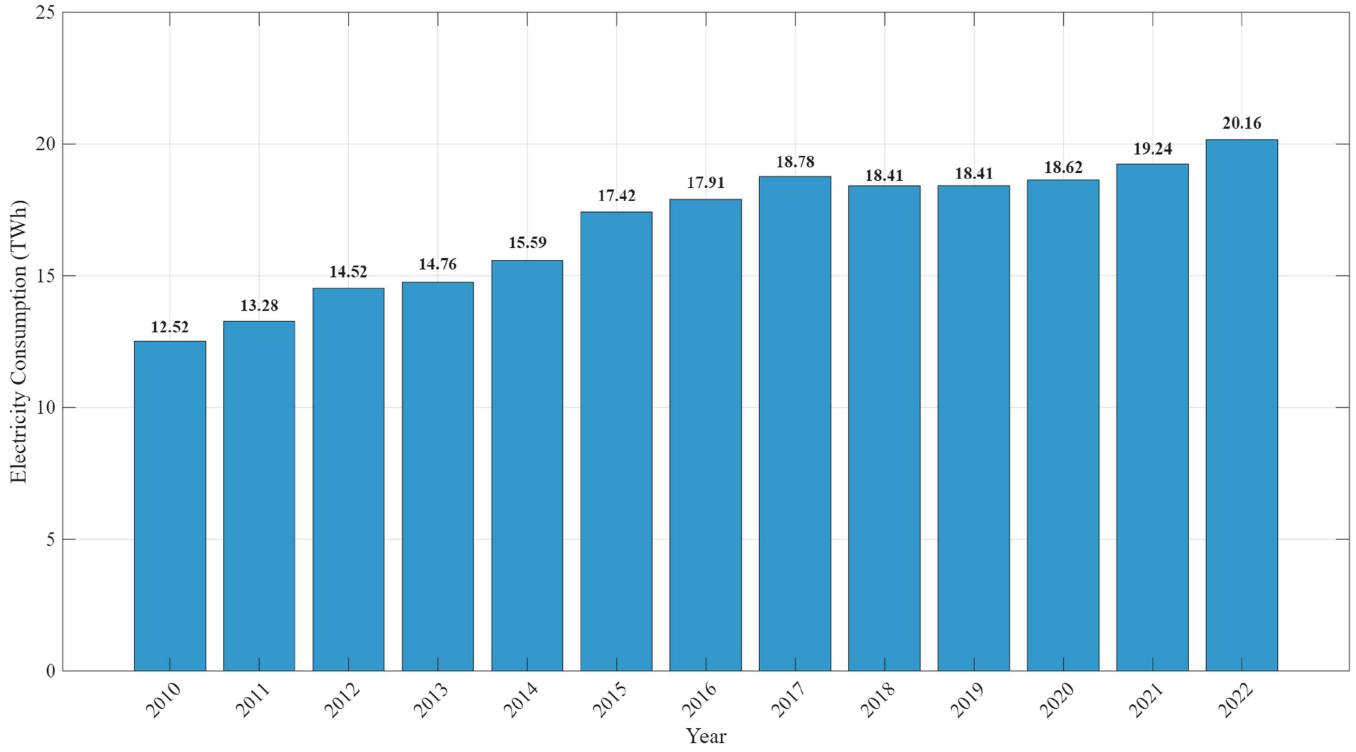

FIGURE 2 | The electricity demand in Jordan from 2010 to 2022.

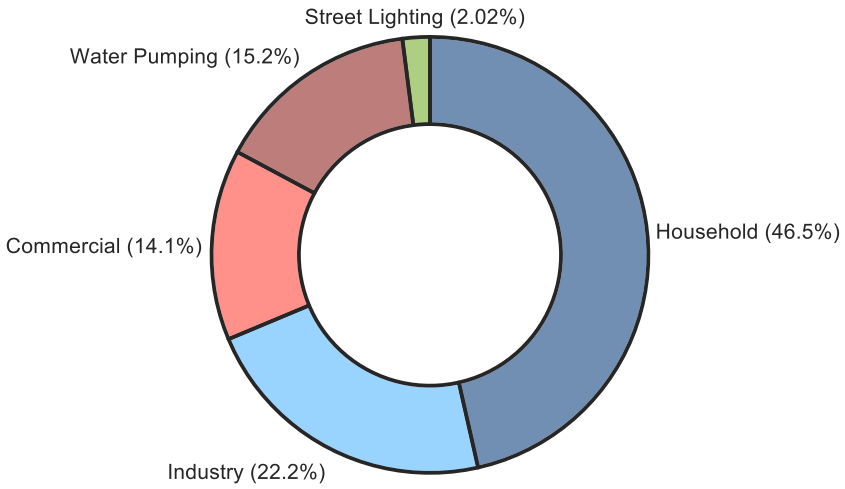

FIGURE 3 | The breakdown of total electricity consumption by sector for the year 2018 [20].

imperative to identify new avenues for economic development to ensure long-lasting benefits. Factors impacting energy projections and policies include comprise consumer preferences, trade interactions, financial performance, demographic growth, and technological developments. The surge in population, propelled by both natural growth as well as the influx of refugees, exacerbates the strain placed on Jordan's electrical infrastructure. A total of 16.84 TWh of electricity was consumed in 2016, accounting for 85.4% of total generation. The distribution stage is mostly responsible for energy losses. Electricity demand has nearly doubled by 2020 and is expected to quadruple by 2030 due to rising population numbers and the refugee crisis, demanding proactive measures to meet this growing energy demand [3, 18]. Figure 4 displays Jordan's population density [1, 23].

3.2 | Economic Indicators

GDP serves as a comprehensive metric reflecting the entire market or monetary worth of all completed products and services produced inside a country's boundaries over a specified time frame, thereby offering an overarching assessment of economic well-being. Typically computed annually, GDP calculations are occasionally conducted quarterly. In the United States, for instance, Every fiscal quarter and every year, the government releases annualized GDP estimates. In 2022, at $47.45 billion, Jordan's GDP represented a 5.18% rise over the previous year. Over the last 15 years, Jordan has continuously had to deal with energy costs that exceed 10% of its yearly gross domestic product. This problem became more serious in 2011 when natural gas import disruptions led to a spike in the

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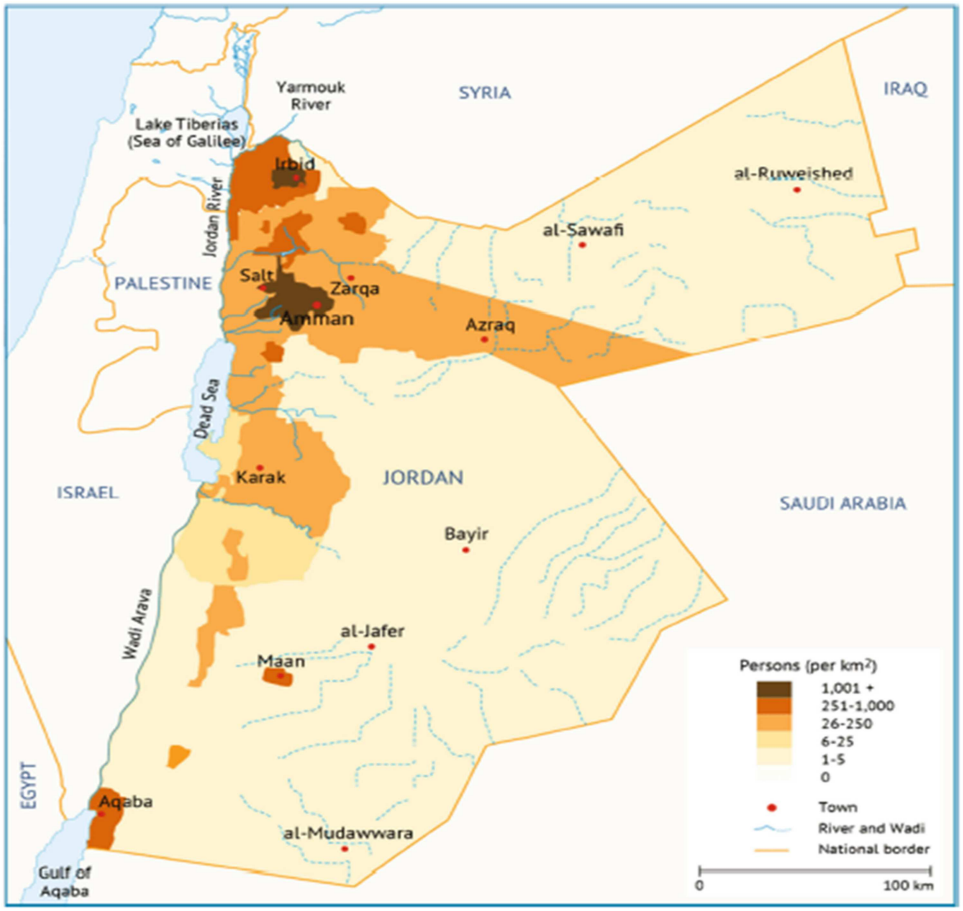

FIGURE 4 | Jordan's population density [1].

nation's energy bill, which reached almost $4.8 billion, or almost 20% of GDP. Jordan has been under tremendous economic and financial strain due to the lack of domestic fossil fuel resources, which has forced it to rely heavily on imported energy. Jordan imports 96% of its energy needs approximately, with gas and oil alone contributing close to a fifth of the country's GDP. The country's high rate of energy imports demonstrates how vulnerable the country is to shifts in the external market. As of December 2022, Jordan's GDP has increased from 44.885 billion dollars in 2021 to 46.946 billion. Long-term data may show significant fluctuations; the GNP surged in 2022 and then dropped to its lowest recorded amount of $575.960 million in 1968 [24, 25].

4 | Methodology

This study's methodology attempts to forecast future electricity peak load and thoroughly analyses the factors influencing it. The methodology includes data collection, preprocessing, analysis, model selection, and validation; this methodology aims to provide meaningful insights for stakeholders and policymakers involved in planning for electricity provision and the shift to sustainable energy sources. Hence, a variety of statistical techniques and forecasting models are utilised in an attempt to clarify the intricate relationships between changes in electricity peak load patterns considering economic and demographic factors. The methodology starts with data collection and reprocessing, where pertinent data sources about Jordan's electricity peak load, economic indicators such as GDP, demographical population trends, and electricity peak load consumption have been identified and collected. The information collected then undergoes a thorough cleaning procedure to remove errors, missing values, outliers, and inconsistencies that could affect the accuracy of subsequent analyses.

This is followed by an examination of patterns of peak load variation, where the underlying features, patterns, and seasonality of peak load change during the previous 20 years are explored and descriptively analyzed. The relationship between variations in peak load and demographic and economic (such as GDP) indicators is then examined using correlation analysis. Furthermore, trend analysis is performed to investigate long-term patterns in electricity peak load and assess the impact of external variables like population expansion and economic development on patterns of energy consumption. The outcome of the analyses aided in picking the most correlated variables, such as population growth and GDP, to be fed to the forecasting models. Then, the models that are employed for forecasting are selected and calibrated as three distinct models are developed in this stage to estimate the demand for peak loads. These are based on linear regression, ARIMA, and ARIMA-X. To forecast the electricity peak load, the linear regression model makes use of certain independent variables like GDP variations and the population increases over the years. This is followed by the model of ARIMA, which is employed to understand the time series nature of peak load data and forecast future demand trends. Additional explanatory variables like GDP fluctuations and population increase are added to the ARIMA-X model to improve forecasting accuracy.

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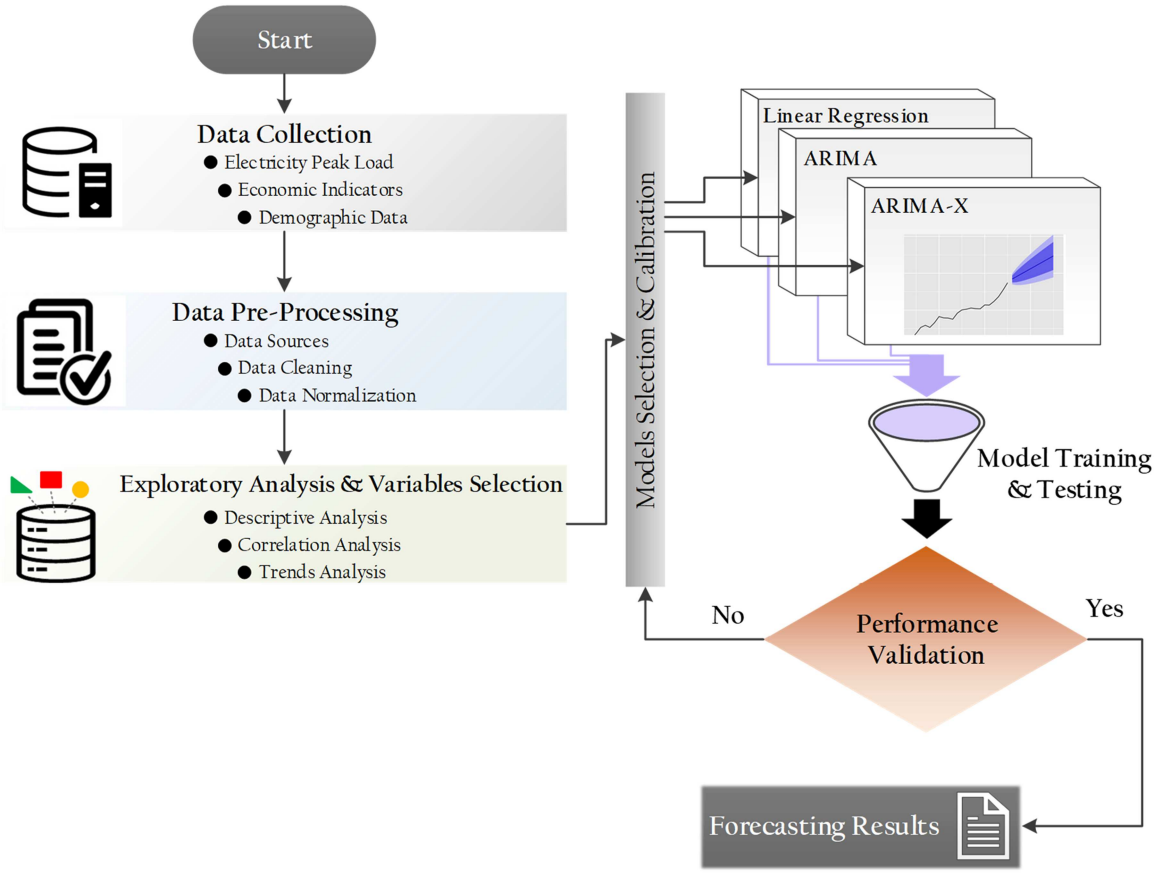

FIGURE 5 | Data forecasting methodology used in this work.

All these models are then evaluated and validated in such a way as to guarantee an accepted level of accuracy in forecasting. In this regard, the dataset is divided into sets for training and then testing phase in order to evaluate how well the constructed models perform. The performance metric, the root mean squared error (RMSE) has been computed to assess the models' accuracy and suitability. At the forecasting stage, these validated models have been employed to investigate the possible future trajectories of electricity peak load. The future electricity peak load is then projected using the chosen forecasting models throughout a period of 10 years. Finally, the forecasting models' results are examined, and the implications of the expected electricity peak load for Jordan's electrical grid and energy transition initiatives are examined. The flow chart shown in Figure 5 summarizes the methodology followed in this paper.

5 | Linear Regression

There are numerous technical and financial advantages to predicting the peak load. Generation planners have long employed regression models to estimate peak load [26]. The linear relationship between two or more variables can be predicted using both simple and multiple linear regression models [27]. Assuming a linearity pattern of peak load change, the linear regression model can be used to predict peak electricity load because it is fairly simple to execute and comprehend. The Linear Regression model is used to construct the forecasts, which fit a linear equation to the historical data (in this case study, the years and corresponding peak load). The model then forecasts peak load amounts for upcoming years using this equation. A mathematical representation of such a model is given as described in (1) [28]:

$$L(t) = Ln(t) + \sum a_i x(t)_i + e(t) \quad (1)$$

Where n is the number of observations, $x(t)_i$ are the independent influencing factors like weather influence, $e(t)$ is a white noise component, and the normal load at time t is represented by $Ln(t)$, is the normal or standard load at time t, and a_i is the predicted slowly varying coefficients.

6 | Time Series Models

When there is non-linearity in the load series, linear regression may not be able identify it [29]. As a result, time-series models such as ARIMA and ARIMA-X have been widely suggested for power systems load forecasting [30–32]. Time series analysis encompasses methodologies for analyzing time series data to extract crucial statistics and additional insights from the dataset. Time series forecasting involves utilizing a model to predict future values based on past observations. Time series data differs from other datasets primarily in the continuity of a single entity over a defined period. Consequently, variables exhibiting time dependency are forecasted using time-series models like ARIMA and ARIMA-X. The goal is to find the most suitable model which reduces disparities between the anticipated values and actual observations.

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6.1 | ARIMA

ARIMA is the most popular time-series approach in load forecasting as it simply requires past load data to forecast the load; no further presumptions need to be taken into account [33]. The fact that a time-series tracks a single entity over a predetermined period of time is the main way that it differs from other datasets. Thus, time-series models such as ARIMA would be used to forecast a time-dependent variable. It is worth observing that ARIMA model is decomposed into the following components: the first component, known as autoregressive (AR), depicts the correlation between the current observation and its historical values. Integrated (I), which differentiating the time series to make it stationary (constant mean and variance), and Moving Average (MA) component, which simulates the correlation between the current observation and a moving average model's residual error. These models capture trends, seasonal patterns, and other intrinsic structures in time-series data. When there is proof of autocorrelation, which shows a connection between past and future values, they are especially useful. Three parameters determine a nonseasonal ARIMA model, "ARIMA(p,d,q): p is the number of autoregressive (AR) terms; d is the number of nonseasonal differences required to attain stationarity; and q is the number of lagged forecast error terms that are part of the model's moving average (MA) component. The designation ARIMA(p, d, q) is as follows [34]:

$$\varphi_p(B)\nabla^d x_t = \alpha + \Theta_q(B)e_t \tag{2}$$

where x_t is the value of the signal at time t. e_t is the error representing a white noise. The term d represents the degree of differencing. The operator $\varphi_p(B)$ is the autoregressive of order p, while the operator $\Theta_q(B)$ is the moving average of order q. These operators are also defined as follows:

$$\varphi_p(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots - \varphi_P B^P \tag{3}$$

$$\Theta_q(B) = 1 - \Theta_1 B - \Theta_2 B^2 - \ldots - \Theta_q B^q \tag{4}$$

More detailed information on the mathematical expressions and the equations defining ARIMA models, can be found in [30, 34, 35].

6.2 | ARIMA-X

The Autoregressive Integrated Moving Average with Exogenous Variables is referred to as (ARIMA-X). The main difference between an ARIMA model and an ARIMA-X is that the latter also contains relevant independent variables which are referred to as exogenous variables [8, 36]. In addition to the previous equations representing ARIMA model, once exogenous inputs are added, the ARIMA-X model will be produced and (2) could be expressed as:

$$\varphi_p(B)\nabla^d x_t = \Gamma I_t + \alpha + \Theta_q(B)e_t \tag{5}$$

Where ΓI_t, is the linear term representing the exogenous input I.

7 | Results and Discussions

This section endeavors to forecast the peak load for the Jordanian electricity system over the forthcoming decade, employing linear regression, ARIMA, and ARIMA-X models. Prior to the forecasting process, it conducts an analysis of the peak load variation patterns, considering variables that potentially influence the country's electricity consumption across the past three decades. Special attention is given to both demographic factors, represented by population trends, and economic indicators, particularly GDP fluctuations. By examining the historical trends and correlations between peak load, population growth, and GDP performance, this analysis is aimed at providing insightful information on the underlying dynamics shaping Jordan's electricity consumption landscape. Subsequently, these insights will inform the selection and calibration of appropriate forecasting models to accurately predict the future trajectory of electricity peak load in the Jordanian electricity system.

7.1 | The Correlation Heatmap

The correlation coefficients are obtained by developing the heat map shown in Figure 6. The heatmap shows the correlation coefficients of several variables that affected the population demography, for instance, the number of refugees who are given asylum and population growth, in addition to several economic indicators, including the GDP, the GNP, and the inflation rate. Notably, a perfect positive linear relationship is represented by a correlation value of 1, which varies from −1 to 1. On the other hand, −1 representing a perfect negative linear relationship, and 0 indicating no linear association between the variables.

Population growth and electricity peak load have a strong positive linear relationship, according to the correlation heatmap, as indicated by the observed correlation coefficient of 0.97. Likewise, a 0.98 correlation coefficient has been found between the number of refugees granted asylum and the peak load. Hence, both indicators could be employed to serve as a good fit for forecasting the peak load. On the other hand, not all economic indicators have shown a strong correlation with the peak load. For instance, while both the GDP and the GNP have a strong correlation of 0.99 for each, the inflation rate has only shown a poor correlation of −0.13, as shown in Figure 6. Hence, the population and the GDP provide indicative variables of both population and economic indicators and therefore will be utilized for forecasting the yearly peak load to enable a deeper understanding of the demands for the upcoming 10 years.

7.2 | Peak Load and Population Growth

Over the years, Jordan's population has grown significantly, expanding from 4.075 million in 1993 to 11.44 million in 2023, representing a remarkable increase of 280.7%. This growth corresponds to an average yearly growth rate of approximately 9.35%. At the same time, the peak load of electricity has also experienced a notable increase, increasing from 717 MW in 1993 to over 3700 MW in 2021 [1], as illustrated in Figure 7. With an average yearly growth rate of 18.77%, this substantial increase translates into an approximate growth of 525.8%. An intriguing observation is that for every 1% increase in population, there is an associated 1.92% increase in electricity peak load, suggesting a robust relationship between population

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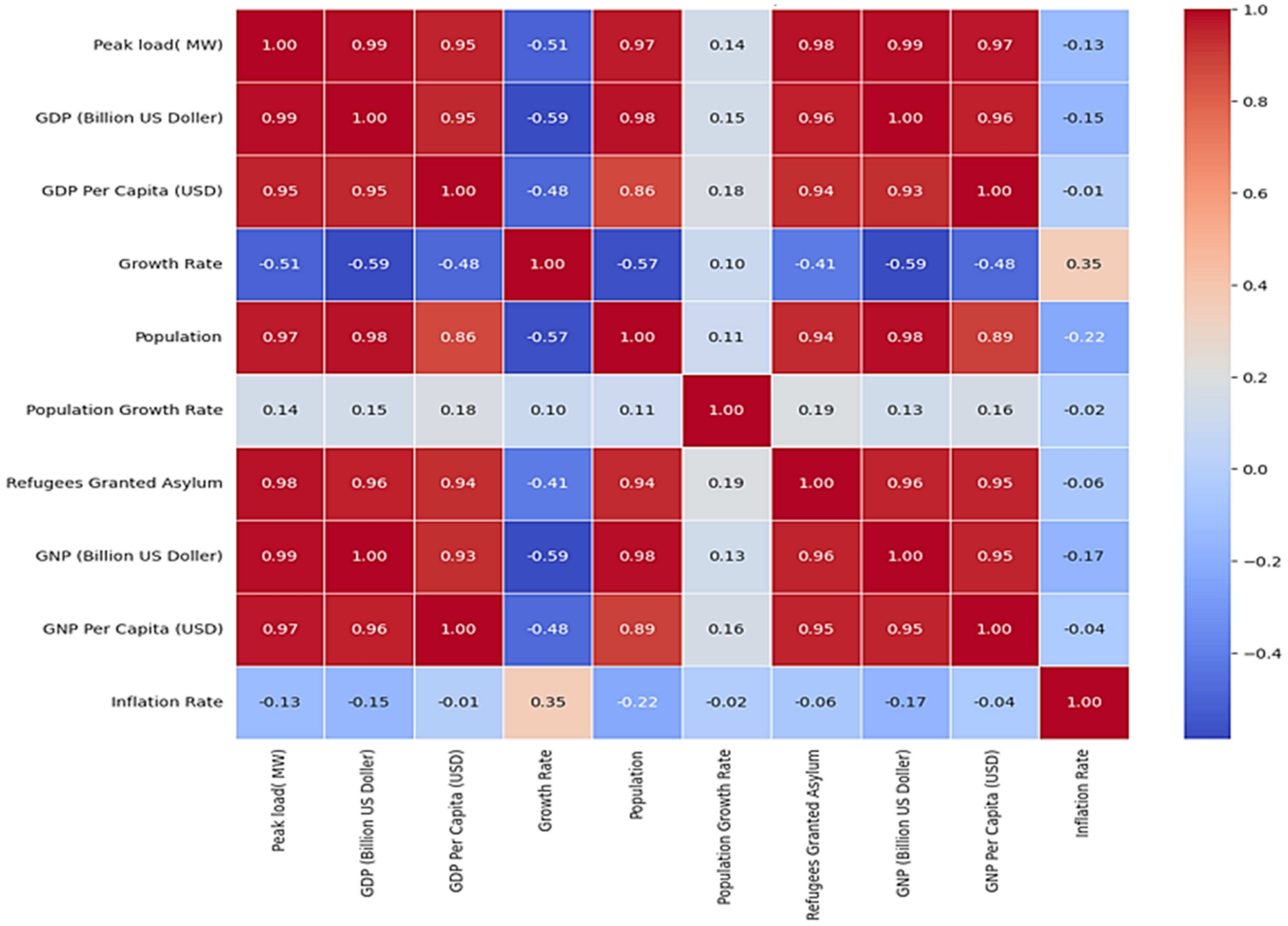

FIGURE 6 | Correlation Heatmap of the considered variables.

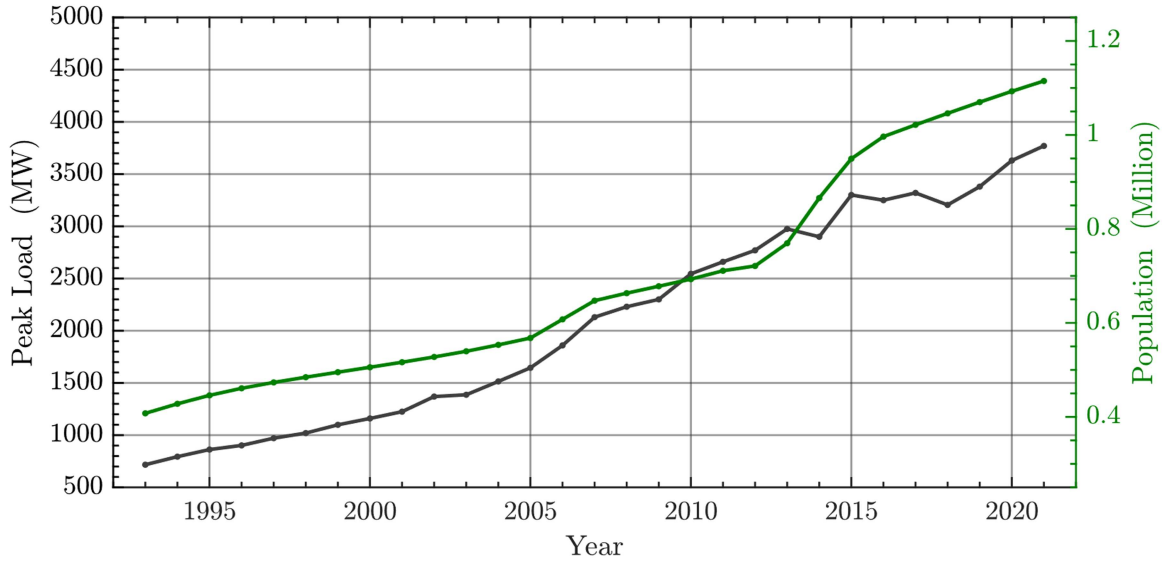

FIGURE 7 | The electricity peak load and population in Jordan between 1993 and 2021.

expansion and peak load demand, a relationship further validated by a correlation heatmap analysis, revealing a correlation coefficient of 0.97, signifying a highly strong positive linear correlation between population growth and peak load demand. This correlation underlines the evolving consumption patterns of the populace, influenced significantly by advancements across various sectors that necessitate increased electricity consumption.

On the contrary, the pattern of load variation from 1993 to 2021 exhibits three distinct trends, as illustrated in Figure 7. The peak load gradually increased from 717 Megawatts to 1225

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Megawatts between 1993 and 2001, growing at a moderate average yearly rate of 2.13%. Subsequently, from 2002 to 2016, a notable surge in peak load occurred, characterized by a yearly growth rate of 17.7%, surpassing the corresponding population growth rate. This trend could be attributed to anomalous electricity consumption behaviors influenced by waves of immigration from bordering countries. The other trend of peak load raise unfolded between 2017 and 2021, witnessing a decline in the growth rate compared to the previous period. During this timeframe, the peak load exhibited irregular fluctuations; Between 2016 and 2018, the peak load decreased from 3,250 MW to 3,205 MW. In 2019, 2020, and 2021, it increased once more to reach 3,380 MW, 3,630 MW, and 3,770 MW, respectively.

7.3 | Peak Load and GDP

In the past three decades, the country's GDP has displayed a consistent upward trajectory. Beginning at 5.61 billion US dollars in 1993, it reached 45.12 billion US dollars in 2021 and further rose to 47.45 billion US dollars in 2022 [1]. Analyzing the relationship between GDP and the electricity peak load reveals a 0.99 correlation coefficient, as illustrated in Figure 6. This correlation is unsurprising, considering that GDP is a clear indicator of economic expansion, which is propelled by developments across sectors which rely on electricity. Remarkably, there is a clear and strong relationship between the rise of the peak load of electricity and the GDP growth rate, as depicted in Figure 8.

Despite the strong correlation observed over the last three decades, particularly from 1993 to 2013, fluctuating variations were seen in the rate of peak load growth between 2013 and 2022. Specifically, in the period between 2016 and 2019, where the peak load experienced a decline despite an increase in the GDP growth rate. This suggests that the GDP growth rate may not always accurately reflect the peak load growth rate, indicating the influence of other critical economic factors like the rate of inflation, industrial activity, and the cost of electricity.

As a developing nation, Jordan's electricity peak load pattern is significantly influenced by economic growth across various sectors. This relationship typically follows a linear trend, wherein GDP growth corresponds to an increase in peak load. However, to comprehensively understand periods where this relationship deviates from linearity, such as the period from 2016 to 2019, more detailed investigations are warranted. This could entail analyzing energy consumption patterns, taking into account the needs of business and industry, urbanization and building projects, infrastructural development, and technological breakthroughs. Additionally, examining the impact of government-set electricity pricing policies over the years would provide valuable insights into the dynamics influencing peak load variations during these periods.

7.4 | The Peak Load Forecasting for the Upcoming Decade

This part uses Python programming to anticipate Jordan's peak demand over the next 10 years using linear regression, ARIMA, and ARIMA-X models. From 2022 to 2035, the variable "predictions" includes the anticipated peak load values for each year. First, it should be noted that "predictions" is a NumPy array (numpy. ndarray), where each member is the expected peak demand (in MW) for a given year. This array encapsulates the forecasted peak load values, providing insights into the anticipated electricity demand trends for Jordan in the forthcoming years.

7.4.1 | Forecasted Peak Load Using Linear Regression

By fitting a line to past data, the linear regression model was utilized to predict future peak loads. A strong linear link between year and peak load is indicated by the correlation coefficient, which is approximately 0.989. With an RMSE of 0.0383, the model demonstrated high accuracy. The blue line in Figure 9 represents predictions that the peak load will increase by 41%, from 3,770 MW in 2021 to around 5,353 MW in 2034, with an annual growth rate of about 3.4%. This pattern suggests that the peak demand for energy could double in the next 25 years, assuming comparable rates of GDP and population growth.

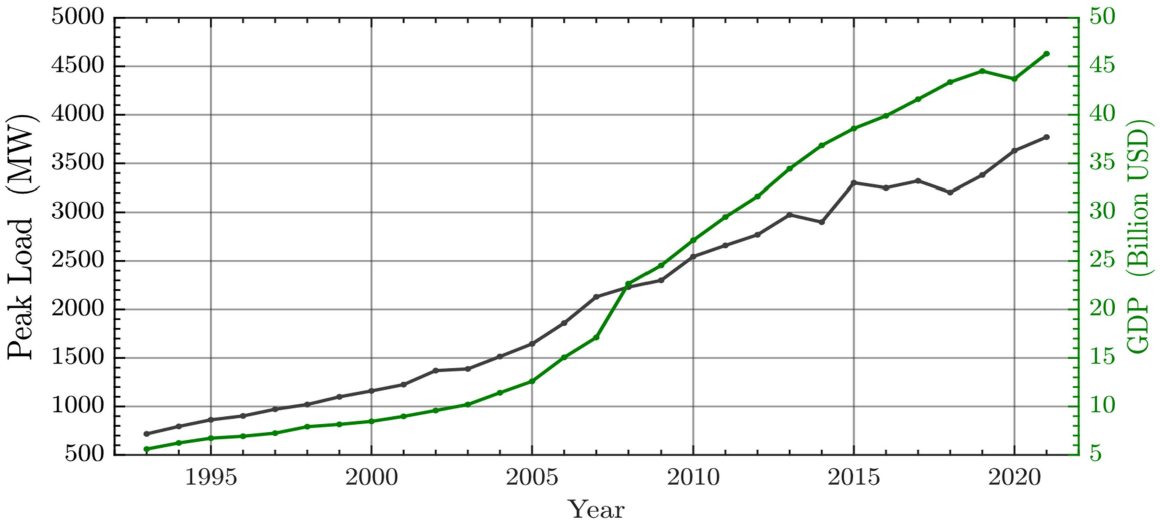

FIGURE 8 | The electricity peak load and GDP in Jordan between 1993 and 2021.

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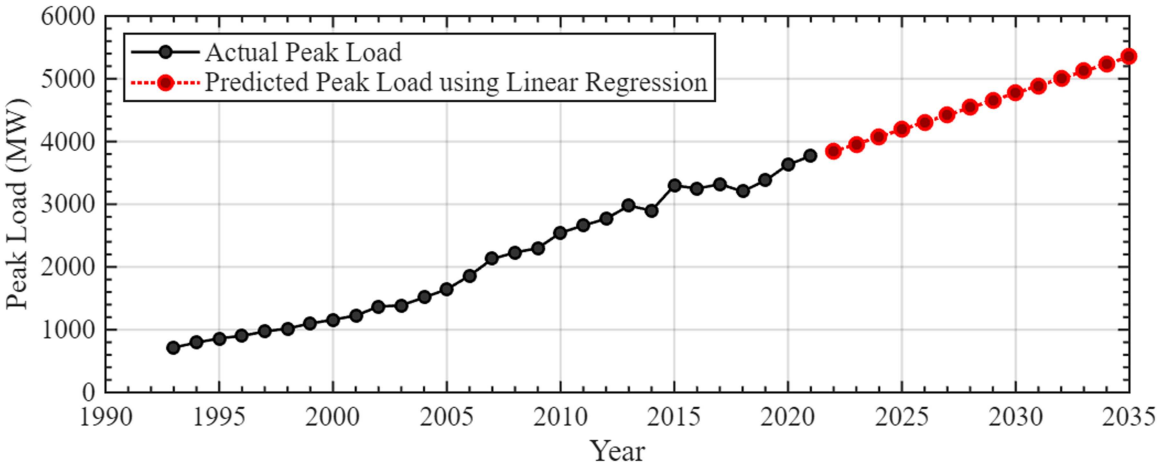

FIGURE 9 | Forecasted peak load using linear regression.

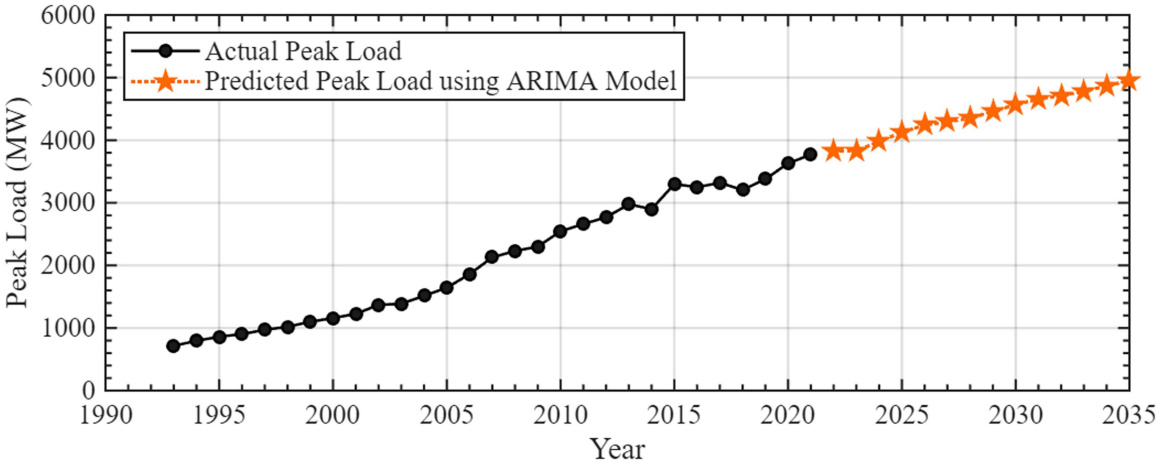

FIGURE 10 | Forecasted peak load using ARIMA.

7.4.2 | *Forecasted Peak Load Using ARIMA*

The Electricity peak load projections were produced using the ARIMA model during the same time period, and Figure 10 displays a similar pattern of rise. On the other hand, ARIMA's results are marginally worse than linear regressions. As illustrated in Figure 10, forecasts suggest that the peak load will increase by 29%, or almost 2.4% each year, from 3,770 MW in 2021 to approximately 4,951 MW in 2035. The model's RMSE of 0.369 was larger than that of linear regression, suggesting that the latter may be more accurate in light of the previously noted linear trend. However, more research using bigger datasets and seasonal load fluctuations may increase the models' validity.

7.4.3 | *Peak Load Using ARIMA-X*

In order to account for both the population and the GDP as exogenous variables, the ARIMA-X model was developed, and the population and GDP variables are considered one at a time. The obtained results of the forecasted peak load are shown in Figures 11 and 12, respectively.

Both models have demonstrated low RMSE values of 0.255 and 0.317, respectively. It can be noticed that both models showed an improved performance when compared to the ARIMA model, where an RMSE of 0.369 was observed. However, neither ARIMA nor ARIMA-X models have shown more accurate performance when compared to the linear regression model, where the RMSE was 0.0383. Observe Figure 11, where ARIMA-X results with population as an exogenous variable are shown. With the peak load rising from 3,770 MW in 2021 to a maximum of 3,978 MW by 2035, the predicted values are lower at a roughly 0.5% yearly pace, representing a 6% rise only. It can be noticed that the results of ARIMA-X, when taking population growth into account, are not indicative even though the RMSE is small and lower than the one previously obtained using the ARIMA model. Observe the slight increase in the peak load throughout the expected 12-year period as shown in Figure 11. On the other hand, the predictions obtained using ARIMA-X with the GDP as an exogenous variable have displayed more realistic values since the peak load is expected to increase from 3770 MW in 2021 to a maximum of 4700 MW by 2035. This amounts to an increase of 25% at an expected annual rate of 2.5%. Hence, it can be concluded that both ARIMA and ARIMA-X with GDP are more indicatives, and they converge to

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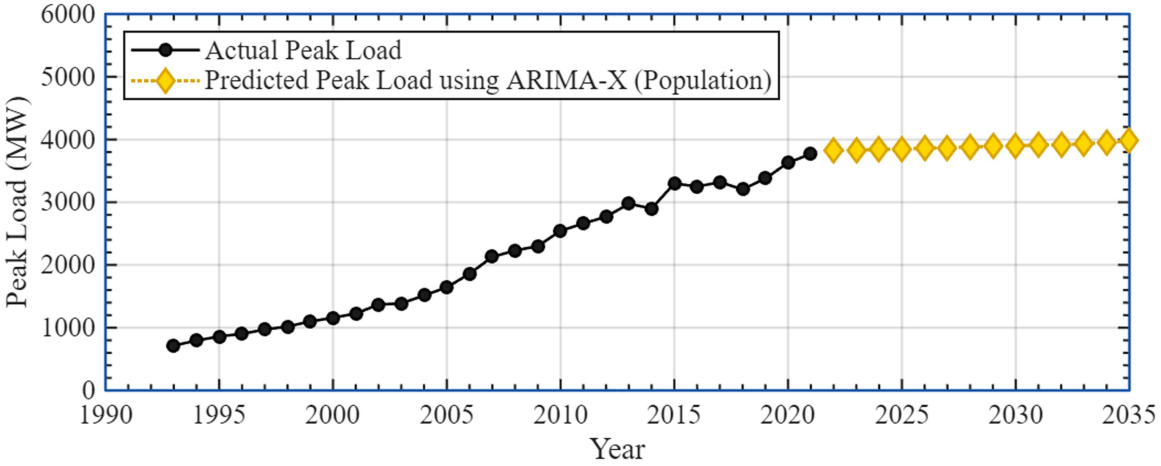

FIGURE 11 | Forecasted peak load using ARIMA-X with population as an exogenous variable.

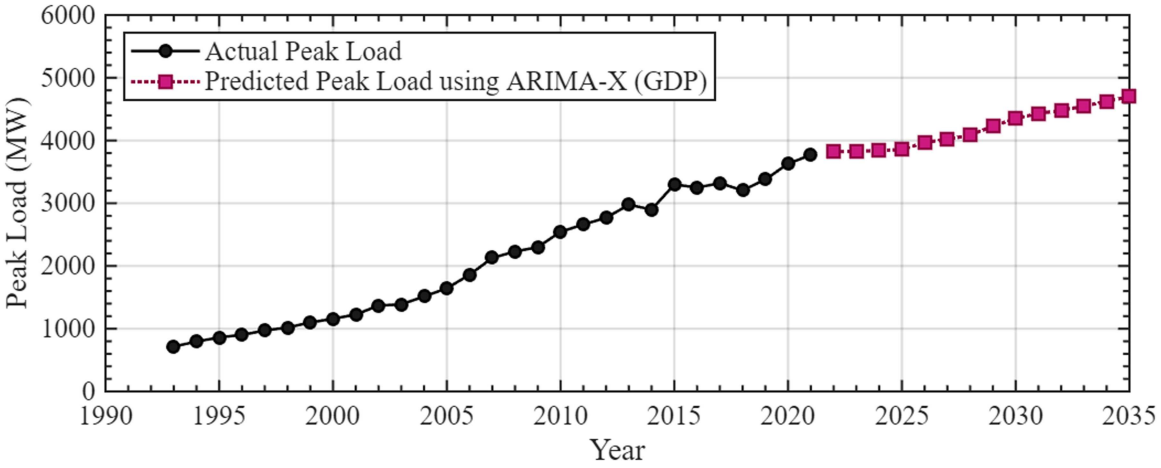

FIGURE 12 | Forecasted peak load using ARIMA-X with GDP as an exogenous variable.

almost the same results that have been obtained from the linear regression model.

7.4.4 | *Comparative Analysis*

The results obtained from all the four utilized models show noticeable variations in the peak demand estimates and different trends can be observed too. To help visualise the differences in prediction generated by the different models, Figure 13 depicts the forecasted peak load in MW generated by each of the models. The numerical results of the load forecasts and the RMSE are also listed in Table 1. Assuming consistent growth based on historical data, linear regression projects a steady rising trend, reaching its peak value of 5353 MW by 2035. ARIMA, on the other hand, exhibits a slower, steadier growth that takes into account previous variations and possible saturation. Both ARIMA-X models show the flattest growth, suggesting that socioeconomic considerations play a significant role in regulating demand. Observe the noticeable differences after the year 2025; by 2035, the difference between ARIMA and Linear Regression is more than 400 MW, and ARIMA-X is more than 650 MW. While ARIMA and ARIMA-X may offer more reliable, accurate projections, Linear Regression may overestimate future demand, as these divergent trends demonstrate. Generally, the results have shown that the lower RMSE does not necessarily mean more accurate results of peak load forecasting. Hence, when the linear correlation is observed, the linear regression model would serve as extra guidance on validating the models in such cases. In other words, we can rely on not only one variable in the case of ARIMA-X for peak load forecasting but also linear regression, and ARIMA models would provide an extra evaluation tool for ARIMA-X.

8 | Conclusions

This study has forecasted the Jordan peak electricity load using different models based on linear regression and time-series. At first, it examined the pattern of the future electricity peak load in the power grid in Jordan. It has provided an exploratory analysis for the connections among many variables represented by the population demography, such as population growth, and economic indicators, like GDP and the annual electricity peak load, through the last three decades. The study then forecasted the peak demand for electricity over the next ten years using linear regression, which is followed by time series models including ARIMA and ARIMA-X. The findings show that the peak load, GDP, and population growth are strongly correlated (coefficients of 0.97 and 0.99). Peak load is estimated to increase by 41% at an annual rate of 3.4%, from 3,770 MW in 2021 to around 5,300 MW by 2035, if existing growth rates hold true.

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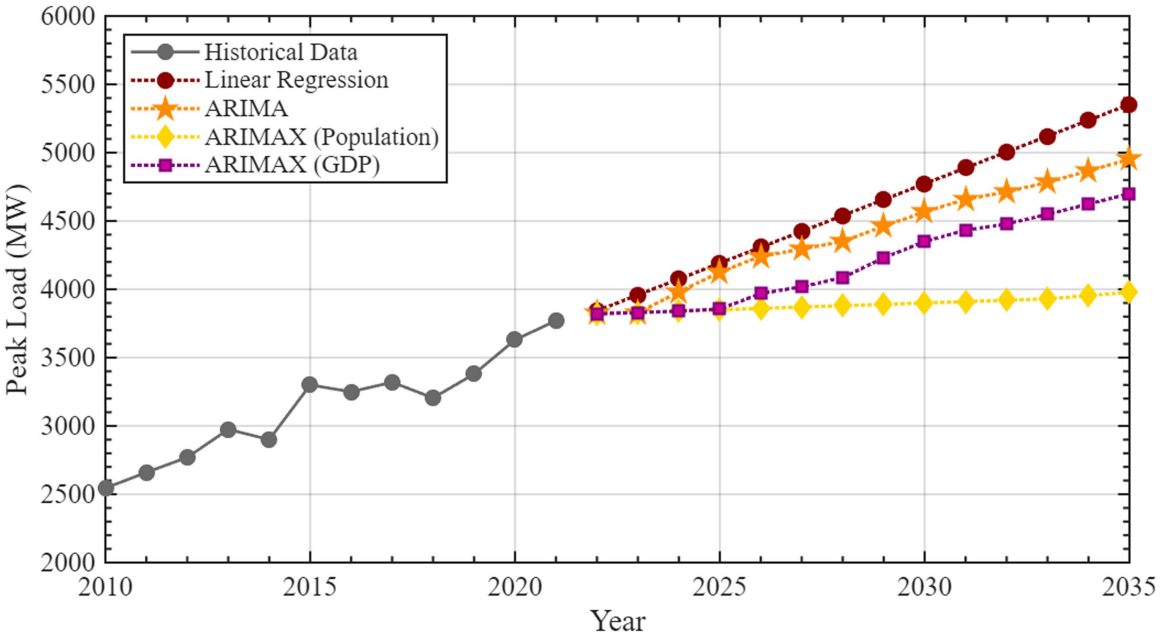

FIGURE 13 | Forecasted peak load using different models.

TABLE 1 | Results of the peak load forecast using the different models.

	Model			
Year	**Linear regression**	**ARIMA**	**ARIMA-X (POPULATION)**	**ARIMA-X (GDP)**
2022	3842.6	3827.1	3820	3820
2023	3958.8	3830.2	3830	3830
2024	4075	3980.2	3840	3840
2025	4191.2	4125.2	3850	3855.3
2026	4307.4	4241.8	3860	3969.1
2027	4423.6	4294.3	3870	4018.1
2028	4539.8	4350.6	3880	4085.9
2029	4656	4461.6	3890	4230.1
2030	4772.1	4566.7	3900	4349.5
2031	4888.3	4657.9	3910	4432.7
2032	5004.5	4713.6	3920	4477.7
2033	5120.7	4782.4	3930	4548.5
2034	5236.9	4867.1	3954.3	4624.1
2035	5353.1	4951.8	3978.6	4699.7
RMSE	**0.0383**	**0.369**	**0.255**	**0.317**

Furthermore, projections suggest that demand could double in the next 25 years. The results obtained from all the four utilized models show noticeable variations in the peak demand estimates and different trends can be observed too. While ARIMA shows moderate and relatively slow growth, Linear Regression tend to provide the fastest and largest growth. ARIMA-X exceed Linear Regression by more than 650 MW and ARIMA by more than 400 MW by 2035. On the other hand, while ARIMA-based models may provide more realistic estimates, it can be concluded that Linear Regression may overstate future demand. To improve the forecasting accuracy and to capture nonlinear demand patterns, future research may be still required by incorporating weather and other vital socioeconomic variables, or combined statistical and artificial intelligence techniques might be considered altogether.

However, taking into account the technical difficulties involved, these results are enough to emphasize the urgent need for capacity increase through grid upgrades, infrastructure development, and integration of renewable energy. To avoid supply and demand imbalances in the future, strategic planning is also essential. The findings have also shown that both ARIMA and ARIMA-X, with GDP as an exogenous variable, show similar patterns and produce results that are close to those obtained from linear regression modelling. Interestingly, the results show

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that enhanced peak load forecasting accuracy does not always correlate with a lower RMSE. As a result, the linear regression model is added as further validation in cases where linear association is apparent. This emphasises the need to use both linear regression and ARIMA models as supplementary assessment tools to increase the predictive power of ARIMA-X rather than relying only on one variable for peak load forecasting.

Author Contributions

Rafat Aljarrah: conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing – original draft, writing – review and editing. **Qusay Salem:** investigation, methodology, visualization, writing – review and editing. **Anas Abuzayed:** funding acquisition, resources, validation, visualization, writing – review and editing. **Mazaher Karimi:** conceptualization, methodology, validation, visualization, writing – review and editing. **Ibrahim Abuishmais:** investigation, methodology, resources, visualization, writing – review and editing. **Hamzeh Jaber:** methodology, resources, validation, visualization, writing – review and editing.

Acknowledgments

This work was supported by the King Abdullah I School of Graduate Studies & Scientific Research at Princess Sumaya University for Technology under grant number 2024/2023-9 (15). Open Access funding enabled and organized by Projekt DEAL.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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