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Araştırma Makalesi / Research Article

Development of Trend analysis-based Forecast Models for Türkiye's Fossil Fuel Consumption

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Abstract

In this study, trend analysis-based forecast models were developed for Türkiye using total population (*TP*) and fossil fuel consumption (*FFC*) as independent and dependent variables from 1965 to 2023. The developed models were then verified by various statistical approaches such as determination coefficient (R^2), F – and t tests and predicted vs actual data. Additionally, forecasting accuracies of the developed models were measured using the indicators of mean absolute deviation *(MAD)*, mean square error *(MSE),* root mean square error *(RMSE)*, uncertainty at 95% (U_{95}), relative root mean square error *(RRMSE)*, maximum absolute relative error *(erMAX)* and mean absolute percentage error *(MAPE)*. Moreover, Türkiye's FFC was projected from 2025 to 2035 using the proposed models. The results reveal that the future FFC of Türkiye can be successfully forecasted with one of the proposed models. Furthermore, the forecasting results evidently show that substantial increases are expected in Türkiye's future FFC.

Keywords: Fossil fuel consumption, Trend analysis, Model, Forecast, Türkiye.

Türkiye'nin Fosil Yakıt Tüketimine Yönelik Trend Analizine Dayalı Tahmin Modellerinin Geliştirilmesi

Öz

Bu çalışmada, 1965'ten 2023'e kadar Türkiye için toplam nüfus ve fosil yakıt tüketimini bağımsız ve bağımlı değişkenler olarak kullanan trend analizine dayalı tahmin modelleri geliştirilmiştir. Daha sonra, geliştirilen modellerin determinasyon katsayısı (R^2), F ve t testleri ve tahmin edilen ile gerçek verilerin karşılaştırılması gibi çeşitli istatistiksel yaklaşımlarla doğrulaması yapılmıştır. Ayrıca, geliştirilen modellerin tahmin doğrulukları, ortalama mutlak sapma (*MAD*), ortalama karesel hata (*MSE*), ortalama karekök hata (*RMSE*), %95'te belirsizlik (U_{95}), bağıl ortalama karekök hata (*RRMSE*), maksimum mutlak bağıl hata (*erMAX*) ve ortalama mutlak yüzdelik hata (*MAPE*) göstergeleri kullanılarak ölçülmüştür. Ek olarak, önerilen modeller ile Türkiye'nin fosil yakıt tüketimi 2025'ten 2035'e kadar tahmin edilmiştir. Sonuçlar, Türkiye'nin gelecekteki fosil yakıt tüketiminin önerilen modellerden biri ile başarılı bir şekilde tahmin edilebileceğini ortaya koymuştur. Dahası, tahmin sonuçları Türkiye'nin gelecekteki fosil yakıt tüketiminde önemli artışların beklendiğini açıkça göstermiştir.

Anahtar Kelimeler: Fosil yakıt tüketimi, Trend analizi, Model, Tahmin, Türkiye.

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1. Introduction

Energy is one of the most significant factor in developing and achieving the sustainable economic growth of any country. It can be assessed in many forms and its sources can be classified into three main categories as fossil, renewable and fissile (Gazder, 2016; Wang et al., 2022a). These sources that are either found or stored in nature are referred to as primary energy sources and they can be either used directly as the primary energy and/or converted in industrial utilities into secondary energy sources. In 2023, when the world's primary energy consumption (PEC) reached 620 exajoules, China became the world leader in PEC with its 171 exajoules. This was almost equal to total PECs of the US, India and the Russian Federation which were ranked as second, third, and fourth in PECs respectively in 2023 worldwide. As illustrated in the Figure 1(a), together, more than half of the world's PEC was consumed by these top four countries (EI, 2024). On the other hand; among the primary energy sources, fossil fuels (FFs) are responsible for a significant part of the world's total energy supply. As of 2023, these fuels accounted for almost 82% of the world's PEC in 2023, of which roughly 32% was oil, 24% was natural gas, and 27% was coal, while other types of fuel such as hydropower, renewables and nuclear were used much less as 6%, 8% and 4% respectively (Figure 1b). Even though numerous initiatives and regulations that promote the adoption of sustainable energy resources, the current figures show that the proportion of the FFs in the world's energy mix will keep rising in the coming years (EI, 2024; Ozdemir et al., 2024).

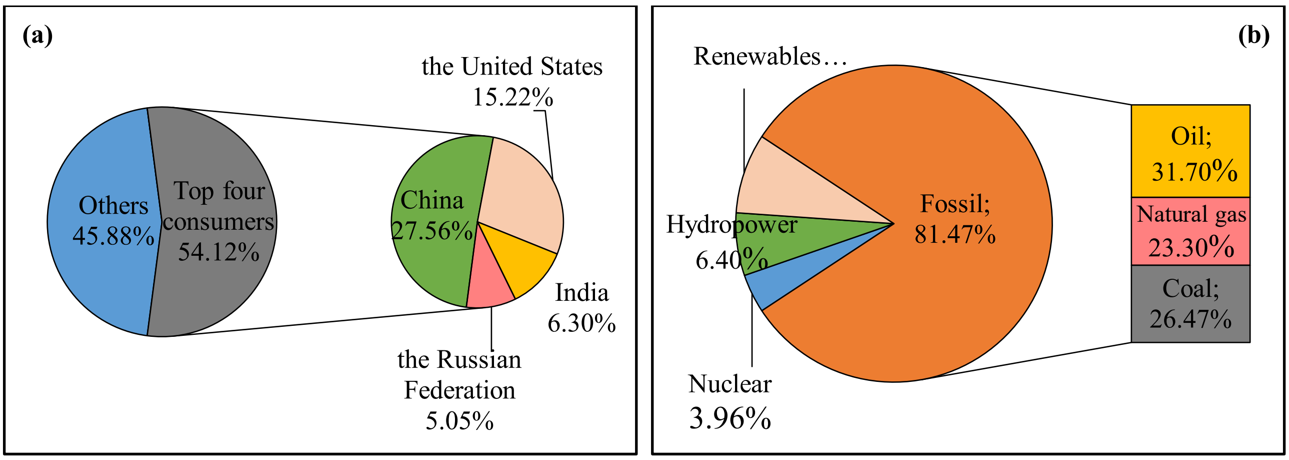

Figure 1. a) Top four primary energy consumers in the world, b) fuel types' share in the world PEC (EI, 2024)

Owing to the significance of energy (especially FFs) for both domestic and global economic growth, and the rise in energy demand in recent years, there have been numerous debates among all relevant parties over how to meet this demand. Therefore, almost all stakeholders such as policy makers, energy investors and scholars are stepping up their efforts to ensure that the development of the energy sector is more secure, more affordable and more sustainable. In order to achieve these goals, future projections need to be much more effective. This will enable countries to rigorously plan their energy projections. A significant contribution can be made to overcome the aforementioned problem by deriving sound, reliable and consistent predictive models on a regional or national scale. Therefore, the current study aimed at developing models to forecast the fossil fuel consumption (FFC) of Türkiye employing trend analysis (TA). In the study, the forecasting models were derived using the data of total population (TP) and FFC spanning from 1965 to 2023 for Türkiye. Actually, the current study's main objective is based on two-fold as to derive predictive models and forecast the future FFC of Türkiye. In this regard, the following summarizes the importance of our study and what distinguishes it from earlier studies in terms of methodology and scope.

i. It is fact that the majority of artificial intelligence-based computing techniques have the benefits of precisely representing long-term trends phenomenon. However, they have certain drawbacks (e.g. black box in it) in the development of the models and applied in real-world scenarios due to their complex structures. Simpler and less accurate modeling strategies may be, therefore, more suitable to overcome the relevant challenges. This is precisely the goal of the chosen methodology of the current study.
ii. The TA is less complex than other methods that require more parameters and are significantly more complex. It puts out the notion that readers may predict what's going to occur in the future by examining prior events that have already occurred. In other words; the TA is a branch of study that uses historical data to attempt to forecast future movements. The primary focus is on identifying and quantifying patterns that can be represented by lines or surfaces (Kone and Buke, 2010; Celiker et al., 2021). Hence, the predictive models in the current study were derived using the TA.
iii. As far as the authors are aware, there isn't a published study addressing the TA's ability to model FFC of Türkiye. Thus, the current study is the first study that applies the TA for testing its ability to model Türkiye's FFC.

2. Socio-Economic and Energy Profile of Türkiye

Located in a strategically advantageous geographic location between Asia and Europe, Türkiye has continued to maintain her status as a rising star in the region. She has over 85 million populations, representing 1.05% of the world total. As of the latest data from WBI (2025), her gross domestic product exceeded 1.1 trillion US dollars, with an annual growth rate of 5.11%, which was above the world's average annual growth rate of 2.83% in 2023. On the other hand, one can infer from Table 1 that there are substantial coal reserves in Türkiye among the non-renewable resources or FFs. In addition, she has significant amount of renewables such as wind, hydropower and geothermal-biomass as well. Moreover, Türkiye consumed 7 exajoule primary energy, constituting 1.1% of the world's total PEC in 2023. The FFs dominated the PEC of Türkiye, with 81.30%, followed by the renewables and hydropower with 10.17% and 8.53% respectively in the same year. As it can be understood that the renewables were the second largest energy resources for Türkiye's PEC. These indicators demonstrate evidently that Türkiye is continuing to be popular as a growing country worldwide.

Table 1. Energy sources of Türkiye (EI, 2024; MEN, 2025)

Resources	**Amount**	**Share (%)**
Oil (Billion tonnes)	-	-
Natural gas (Billion m^3)	544	0.29
Coal (Million tonnes)	11525	1.1
Nuclear (TWh)	-	-
Hydropower (TWh)	63.9	1.5
Wind (TWh)	34.1	1.5
Solar (TWh)	20.5	1.2
Other renewables* (TWh)	19.5	2.5

* Geothermal and biomass; TWh: Terawatt-hours

3. An Overview of Existing Literature

Enormous researches can be found in the existing literature, studying and utilizing different modeling and forecasting techniques. Various studies have also tested these techniques for energy production/consumption using a variety of data sets from various countries or regions over various time periods. Some recent examples of these studies concentrating on the PEC are as follows. Gazder (2016) presented comparison on Saudi Arabia and Pakistan regarding their PECs and the variables influencing them and proposed predictive models to forecast their PECs till 2040 using regression analysis. The link between economic growth and the PEC was explored by Pedroni cointegration test, the second-generation panel cointegration test, Westerlund and Edgerton test and FMOLS test for BRICS-T countries (Yıldırım et al., 2019). On the basis of data from the G-7 and the N-11 countries for the period from 1990 to 2016, Zafar et al. (2019) probed the relationship between carbon emissions and disaggregated financial development and REC using second generation unit roots testing. Analyzing the links between economic growth, fossil fuel use, CO_2 emissions and oil prices in 54 African countries according to a PMG panel ARDL methodology was carried out by Mensah et al. (2019). The nexus between PEC and economic growth in Tanzania was empirically analyzed on the basis of Engel and Granger tests (Simba and Oztek, 2020). Karakurt (2020) proposed regression models, derived from the social and economic variables of BRICS-T countries to forecast the PECs in the related countries. In another study, BRICS-T countries' oil consumption was modelled and forecasted through proposed predictive models (Karakurt, 2021). Khan and Osinska (2021) proposed predictive models for forecasting the PECs in BRICS utilizing the annual time series data set from 1992 to 2019 as the foundation for a novel FGM with various order parameters, both at the aggregate and disaggregate levels. Konuk et al. (2021) investigated how the next eleven countries' economies (except for Vietnam) and BEC correlated employing the annual data covering the years 1970–2017 were used to perform panel data analysis. Ehigiamusoe and Dogan (2022) used empirical estimations to examine the effects of real income, renewable energy, and their interaction effect on carbon emissions in low-income countries. Zeeshan et al. (2022) compared the nexus among CO_2 emissions, PEC, trade liberalization and economic growth in Latin American and Southeast Asian nations using structural equation modeling technique. Chang and Fang (2022) investigated empirically the effect of REC on the growth of the economies of the N-11 and BRICS using MMQR and AMG methods. The role of PEC, environmental deterioration in the top five carbon emitting countries from fossil, nuclear and renewable energy sources was empirically investigated through multivariate adaptive regression splines (Kartal, 2022). Evidence from Autoregressive distributed lagged in error correction approach was presented for the determinants of REC in Nigeria (Samoye et al., 2022). An innovative time-delay grey model employing mixed-frequency data to predict China's PEC was applied by Wang et al. (2022a). Fareed and Pata (2022) employed recently developed Fourier panel cointegration and causality tests to examine the effects of renewable and non-REC on economic growth in the top ten countries that consume renewable energy between 1970 and 2019. Lorente et al. (2022) verified the EKC and PH hypotheses in order to examine the relationship between BRICS countries' economic growth, urbanization, PEC, and carbon emissions between 1990 and 2014. Wang et al. (2022b) developed a conceptual framework using the Dumitrescue-Hurlin test to look at the causal relationship between variables and the Driscolle-Kraay test to estimate the long-term coefficient in order to investigate the moderating role of financial development in the REC-CO_2 emissions linkage for the Next 11 countries from 1990 to 2015. The relationship between foreign direct investment, BEC and air pollution was analyzed by means of a panel data analysis for the BRICS countries from 1992 to 2017 (Tuzemen and Tuzemen, 2022). PEC in Türkiye was analyzed using ANN method and PEC forecast for 2021–2025 was made (Demircioglu and Esiyok, 2022).

4. Modelling Approach

4.1. Data and Methodology

This study used the data of FFC and TP of Türkiye over 1965 – 2023, which were collected from the officially and freely available on-line sources (EI, 2024; WBI, 2025). For variable selection, the researches of Kavaklioglu et al. (2009) and Kankal et al. (2011) were mainly followed since they indicated that an increasing number of people means that there is a greater need for energy resources because of various human activities. Additionally, the TP and energy requirements have a strong correlation, and their time series are readily accessible in a variety of statistical databases. Thus, the TP was used as an independent variable in the current study. A historical trend of both variables is depicted in Figure 2. As it can be followed, both variables have been trending increasing despite a small decrease in 2020 due to the extremely likely coronavirus pandemic-COVID-19 for the FFC.

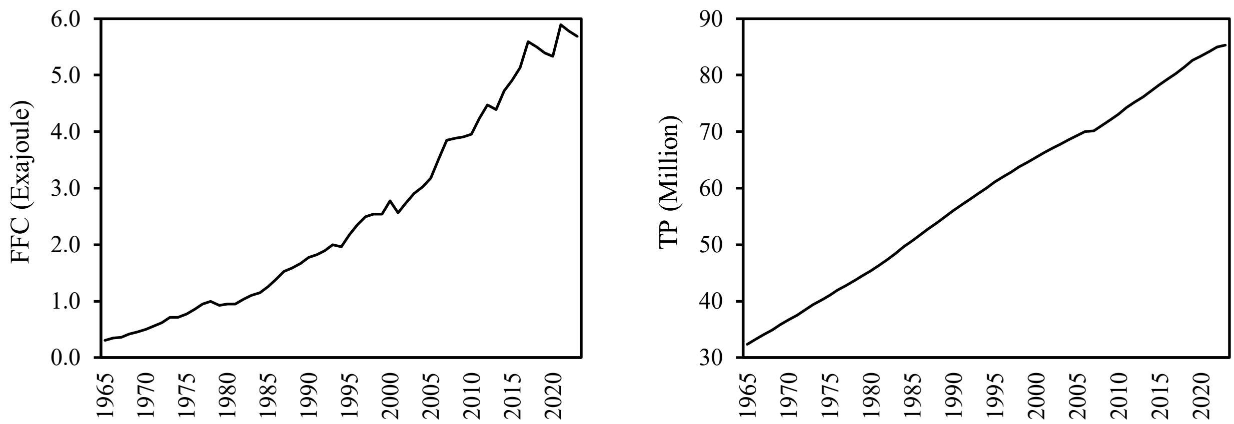

Figure 2. Historical trend of the FFC (left) and TP (right) of Türkiye from 1965 to 2023

Additionally, Table 2 records the results of descriptive statistic, which was performed on raw data which are FFC and TP. Table 2 descriptively reveals that the FFC (exajoule) and TP (million) on average are 2.49 and 59.068, with the standard deviation of 1.754 and 15.946 respectively. On the other hand; for an observed series to be considered symmetric or normally distributed, the normal values for kurtosis and skewness must be zero (the ideal one). Nonetheless, some academics contend that the observed series is also comparable to a normal distribution if both values fall within ±1.5 (Tabachnick and Fidell, 2013; Erba and Beydogan, 2017).

Table 2. Descriptive statistics of the variables

	Data number	Max	Min	Mean	Standard Deviation	Skewness	Kurtosis
FFC	59	5.89	0.30	2.49	1.754	0.557	-0.990
TP		85.330	32.350	59.068	15.946	-0.036	-1.214

Based on the skewness and kurtosis in Table 2, the results suggest that every observed series has a normal distribution. In particular, values based on skewness indicate that the FFC variable is positively skewed, which means that the variables are biased to the right, whereas the variable TP is skewed negatively. Additionally, based on the kurtosis results, every variable has a kurtosis value that is lower than the normal value (≤3) giving evidence that this distribution's kurtosis curve is platykurtic. That is, data are dispersed over a larger area and have a slightly flatter distribution than normal. Conclusively, the results of skewness and kurtosis affirm that every variable follows a normal distribution.

As aforementioned, we utilized trend TA to derive and/or propose predictive models and forecast the FFC for Türkiye. This technique makes use of the past correlation between a dependent and independent variable to propose predictive models for forecasting the dependent variable's future values. In the analysis, the assumption is that future FFC and TP will be in line with historical trends. This approach's primary benefit is its simplicity, and projections are made using whatever data is available (Aydin et al., 2015a; Aydin, 2015; Kok and Benli, 2017). The mathematical equations for the TA, used in the study are given in Table 3.

Table 3. Mathematical expressions of the trend analysis-based models

Model function	**Equation**
Linear	$y = a + b.(t)$
Logarithmic	$y = (a) + \ln(t)$
Power	$y = (a).(t)^b$
Exponential	$y = (a).e^{b(t)}$
Inverse	$y = (a) + (b).\left(\frac{1}{t}\right)$
Growth	$y = e^{[(a)+(b).(t)]}$
S	$y = e^{\left[(a)+(b).\left(\frac{1}{t}\right)\right]}$

where; y is the FFC (exajoule), *a* is the intercept or the constant, *b* is the slope, and *t* is the TP.

The data were split into two sets: one set was used to train the model from 1965 and 2014 (85% of the whole data), and the other set was used to test it between 2015 and 2023 (15% of the whole data). The SPSS statistical software, providing an option for regression, was utilized for building the predictive models. Following model development, a variety of statistical tests were used to confirm the generality, plausibility and statistical significance of the estimated variables such as R^2, assessing how well a model fits actual data points, or a metric that indicates the model's degree of prediction, F – and t tests to confirm that the independent and dependent variables having meaningful relationships and to evaluate the strength of each model coefficient individually, and examining the predicted versus actual trends respectively. The R^2 serves as a benchmark for gauging the model's accuracy, in addition to providing the percentage of one variable's variance that can be predicted from another. Higher R^2 values suggest a more trustworthy model. In other words; since it fluctuates between 0 and 1, the latter of which indicates that the data and the fitted curve points have a perfect linear functional connection, but, the first indicates the opposite as noted by Despotovic et al. (2015) and Aydin (2014). The F – and t – tests play crucial roles, directly affecting the significance and confidence ranges of models in statistical inference and coefficients and finally, the conclusions drawn from testing the hypotheses. When the computed F- and t-values surpass the tabulated F- and t-values, the model's validation is verified (Uma et al., 2011). It implies, in other words, that every independent variable in the model is significant and that there is a substantial link between the dependent and independent variables. Moreover; robustness and/or accuracies of the derived models was measured in order to choose the most effective forecasting model, following the verification of the derived models. The statistical indices that were used to assess the robustness of the derived models, are presented in Table 4 with their mathematical forms. Regardless of performance criteria, generally, the lower the criteria's value, the more closely the fitted curve resembles the actual data (Paiva et al., 2021).

Table 4. Mathematical forms of the error indicators for assessing the models' accuracy

Mean absolute deviation	$MAD = \left(\frac{1}{n}\sum_{i=}^{n}\lvert X_i - Y_i\rvert\right)$
Mean square error	$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2$
Root mean square error	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2}$
Relative root mean square error	$RRMSE = \frac{RMSE}{\bar{O}}.100$
Maximum absolute relative error	$erMAX = max\left(\left\lvert\frac{X_i - Y_i}{Y_i}\right\rvert\right)$
Mean absolute percentage error (%)	$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\lvert X_i - Y_{i)}\rvert}{Y_i}\right).100$
Uncertainty at 95%	$U_{95} = (1.96)\sqrt{SD^2 + RMSE^2}$

where; n is the total number of data, X_i is the predicted FFC, Y_i is the actual FFC, $\bar{O}$ is the mean value of observed data

Stated differently, the forecasting model's accuracy increases with decreasing values of the statistical indices. On the other hands; a pair of measures of the average magnitude of absolute projected errors are the MAD and MSE (Bianco et al., 2014), whereas the RMSE measures the change of estimated values around the measured data and offers information on the performance over the short period. Calculated by dividing the RMSE with average value of measured data, the RRMSE serves as a gauge for a model's general relative correctness. Additionally, the U_{95} shows more information about the model deviation as well Despotovic et al. (2015). Furthermore, the research flowchart can be seen in Figure 3.

5. Results and Discussion

5.1. Derived Models and Statistical Verification

Derived models, which were based on the TP are provided in Table 5. Models in all equation forms (see Table 4) were firstly derived and then, the models in Table 5 were selected, based on their acceptable MAPE and RRMSE values. As it can be followed from Table 5, the derived models for Türkiye's FFC are explained as power, linear and S functions.

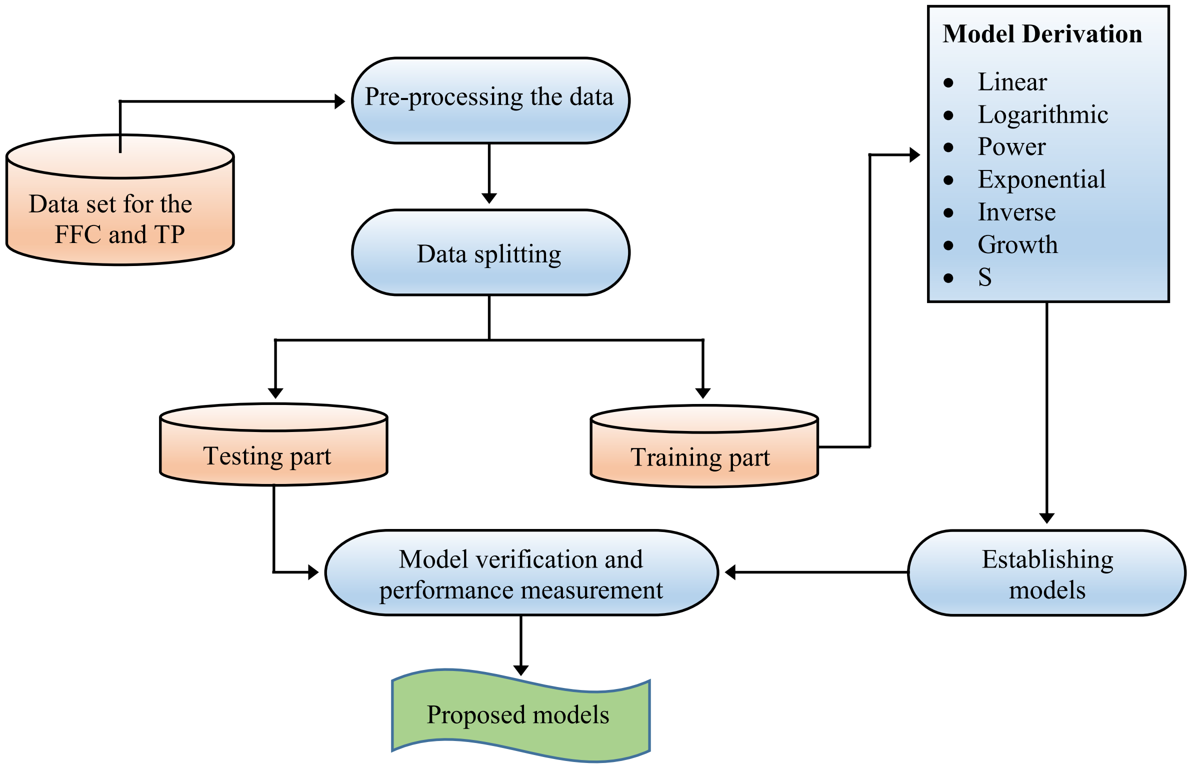

Figure 3. Flow chart of the study

Table 5. Derived models

Model function	Derived models
Power	$y = [(12).(10^{-5}).(TP)^{(2.955)}]$
Linear	$y = (-3.104)+(0.092).(TP)$
S	$y = e^{(3.256) - [(146.063) / (TP)]}$

On the other hand, Table 6 displays the statistically verified results of the derived models using the R^2 and F – and t tests. It can be seen that all of the proposed models have R^2 values greater than 0.93, indicating a robust correlation between TP and FFC. Of course, fitting a model based on R^2 alone is insufficient to complete the regression analysis; neither is it sufficient to offer confidence intervals or run tests. These steps just offer the statistical inferences, which tell us half of the story. Thus, additional tests are required for robust verification. For this reason, the F – and t values are listed in Table 6. At the 95% confidence level, the computed F – and t values for each model are both larger than the tabular values, confirming the accuracy of the equations and the model's coefficients, respectively. Additionally, when looking at predicted versus actual trends as indicated in Figure 4, it may be concluded that the predicted and actual FFCs have a strong correlation for the power model, demonstrating the ability of the derived model to provide accurate FFC forecasts for the study's conditions. Despite statistically verified, the actual vs predicted data achieved by the linear and S models have acceptable correlations. Overall, it may be deduced that these verification results approve the statistical significance of the derived models.

Table 6. Statistical results of the derived models indicating the verification

Model function	Variable	$t_{computed}$	t_{table}	$F_{computed}$	F_{table}	R^2
Growth	Constant	-39.262	1.690	2181.293	4.125	0.98
	TP	46.704				
Linear	Constant	-16.079	1.690	728.042	4.125	0.94
	TP	26.982				
S	Constant	56.767	1.690	2627.147	4.125	0.98
	TP	-51.255				

5.2. Forecasting Accuracy of the Derived Models

In this part, the robustness of the derived models has been highlighted. Among the several performance criteria which were tested in the current study, the MAPE is the most useful tool when estimating relative error since raw data, preprocessed data, and input data used to estimate the model have distinct scales (Azadeh et al., 2011). Kim and Kim (2016) identify the MAPE as one of the most popular statistical metrics for assessing forecast accuracy owing to its benefits of interpretability and scale independence. The MAPE is well-liked by industry practitioners due to its scale independence and ease of interpretation (Byrne, 2012). Because it presents the error as a percentage, this measure is simple to interpret. The usage of absolute percentage errors also solves the issue of positive and negative errors canceling each other out. Furthermore, while in the same tendencies with other indices, value of the RRMSE was also selected for the conclusive index on the robustness of the models that were derived in this study together with the MAPE values as recommended by other forecasting studies (Bianco et al., 2010; Azadeh et al., 2011; Bianco et al., 2014; Li et al., 2013; Kim and Kim, 2016). The classification table of the MAPE and RRMSE levels and the outcomes of the calculated models' performance metrics are provided in Table 7 and Table 8 respectively. Based on the MAPE values, it is obviously noticed that the power model shows *excellent* forecasting accuracy, while others have *good* forecasting accuracies.

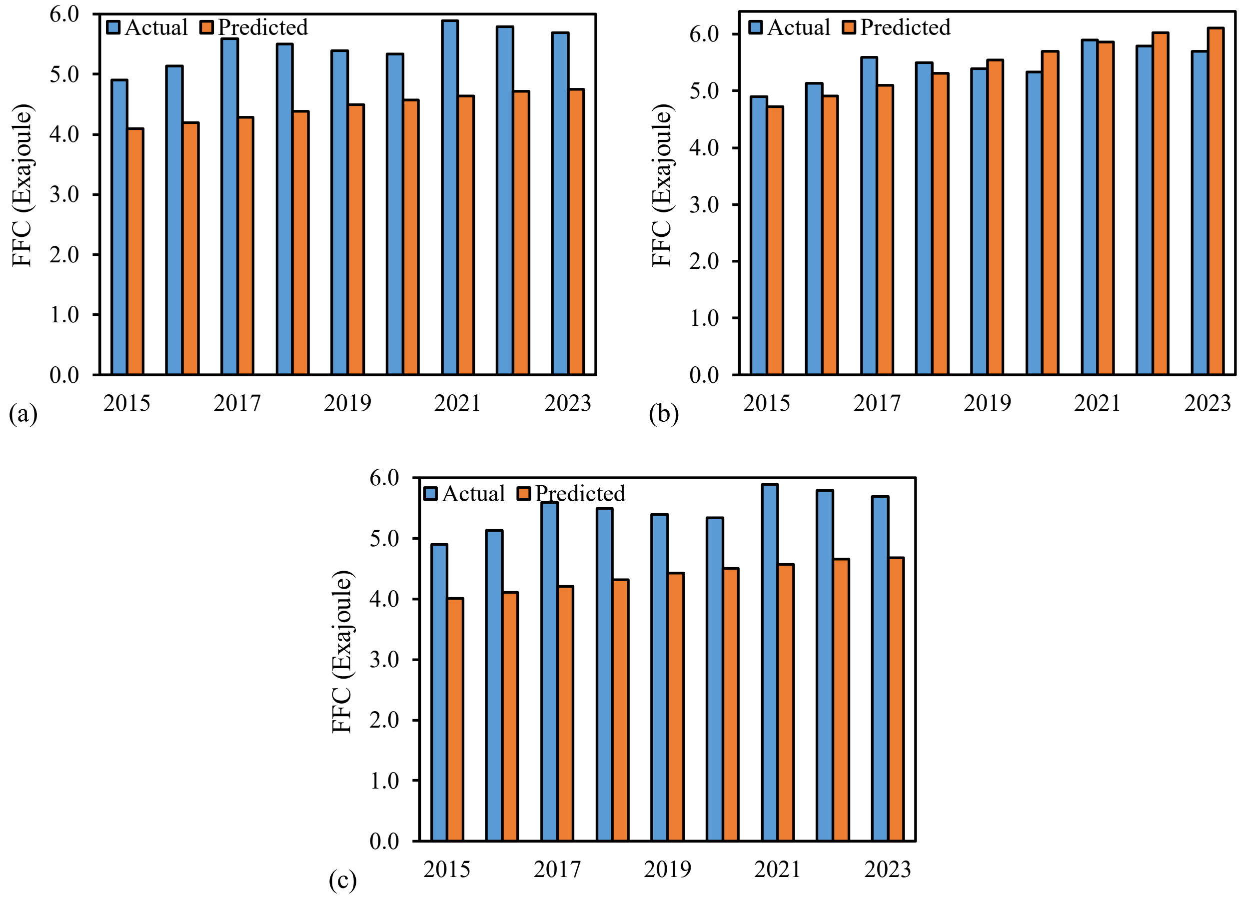

Figure 4. Predicted vs actual values of the FFCs; **a)** Linear model, **b)** Power model, **c)** S model

Table 7. Reference table of the MAPE and RRMSE for the model accuracies (Lewis, 1982; Li et al., 2013)

MAPE (%)	RRMSE (%)	Forecasting ability
MAPE ≤ 10	RRMSE < 10	Excellent
11 ≤ MAPE ≤ 20	10 < RRMSE < 20	Good
21 ≤ MAPE ≤ 51	20 < RRMSE < 30	Qualified
MAPE > 51	RRMSE ≥ 30	Unqualified

In contrast to the MAPE values, it can be clearly seen that the all proposed models indicate the excellent forecasting abilities in terms of the RRMSE values. Additionally, the proposed models indicate high robustness according to other statistical indices as well since their values are close to zero confirming the high forecasting capabilities of the proposed models.

5.3. Forecasting the FFC of Türkiye from 2025 to 2035

Since the statistical verifications and forecasting accuracies were proven, the FFC of Türkiye was estimated from 2025 to 2035 by the proposed models. For this purpose, the TP estimations data of the United Nations (2018) was utilized and the results are exhibited in Figure 5 together with the historical trend starting from 1965. One can infer from Figure 5, total FFC of Türkiye is projected to rise from 5.69 exajoule in 2023 to 7.33 exajoule in 2035 with total increasing rate of almost 30%, indicating an increasing rate of 2% annually when power model was employed. In contrast to the forecasting results of power model, the linear and S models showed a decreasing trend for the FFC of Türkiye towards 2035. In other words, the FFC of Türkiye was forecasted to decrease from 5.69 exajoule in 2023 to 5.26 exajoule and 5.20 exajoule in 2035 when linear and S models were employed respectively. That means, a total decrease of 7.61% and 8.60% or an annual decrease of 0.77% and 0.78%is expected in the FFC of Türkiye by 2035 for these both models.

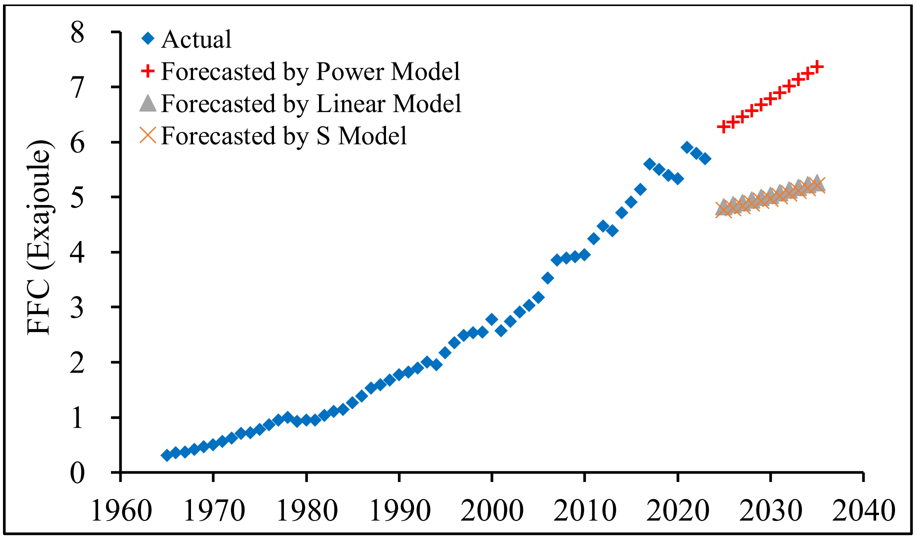

Figure 5. Historical and forecasted trends of the FFC for Türkiye by the proposed models

Table 8. Results for the error indicators of the proposed models

Model Function	MAPE	MAD	MSE	RMSE	U_{95}	RRMSE	erMAX
Linear	18.44	1.01	0.19	0.44	0.93	7.99	0.23
Power	4.65	0.25	0.01	0.12	0.37	2.24	0.09
S	19.75	1.08	0.22	0.47	0.99	8.54	0.25

The forecasting results of the current study, achieved by the power model appear to be in line with the claims found in the energy literature that the TP significantly affects countries' PECs. In other words; the current results have been confirmed by the results of researches in the body of current literature showing the population density and energy use are positively correlated (Ohlan, 2015; Kunvitaya and Dhakal, 2017; Otsuka, 2018; Rahman, 2020; Rahman and Vu, 2021). Additionally, Türkiye has relied on imports to meet more than half of its energy needs. Türkiye's economy and population are currently growing, and it appears that in the foreseeable future, the PEC will rise in tandem with economic growth as indicated by Terzi and Pata (2016) and Ozturk and Ozturk (2018). Thus, it is possible to say that these growths may lead to an increase in the country's energy needs.

6. Concluding Remarks and Recommendations

This study intends to derive and propose trend analysis-based forecast models for projecting the FFC of Türkiye. Basic conclusions are as follows. Firstly, it was discovered that the derived models are explained by power, linear and S functions respectively based on their statistical verifications. Secondly, although three of model functions have been statistically verified and forecasting accuracies were proven, the power model has shown the best results in terms of the aligning with the prospects on the energy requirements of Türkiye. Thirdly, the statistical verification and robustness tests have showed that the power model has the potential to be useful in projecting the future FFC of Türkiye, confirming that the TA is one of the effective and simple tools for modelling and forecasting purposes. Fourthly, the forecasting results demonstrated evidently that there will be a substantial increase for the FFC of Türkiye in coming years.

Türkiye was adopted as the case for the current study. Therefore, it should be noted that there may be limitations for the results obtained from the perspective of followed methodology. In order to generalization the results in future, studies can be conducted for other developed and emerging/developing countries as well with the same methodology. Similarly, the current research has only considered the population as the independent variable. Other relevant variables that may affect the FFCs such as urban population and gross domestic products, may be adopted and forecasting models can be derived by the proposed approach. Additionally, unforeseen occurrences such as the COVID-19 pandemic, the war between the Russian Federation and Ukraine could pose serious obstacles to precisely projecting the FFCs. This could result in several missing data points and poor data quality in the FFC databases, which would make accurate prediction difficult. Therefore, such events will require a further study, reassessed and re-scenarised. Conclusively, it is strongly suggested that the improvements in the FFCs forecasts method should be carefully pursued for the indispensable contribution to the related countries' growths.

Authors' Contributions

Izzet Karakurt contributed to the study conception and design. Preparation, data collection and analysis were mainly performed by **Nokta Nurani Bektaş**. The initial draft of the manuscript was written by **Izzet Karakurt** and **Gokhan Aydin**. All authors commented on the manuscript. All authors read and approved the final manuscript.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The author declares that this study complies with Research and Publication Ethics.

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