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Predicting Electricity Consumption in the Kingdom of Saudi Arabia

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Abstract: Forecasting energy consumption in Saudi Arabia for the period from 2020 until 2030 is investigated using a two-part composite model. The first part is the frontier, and the second part is the autoregressive integrated moving average (ARIMA) model that helps avoid the large disparity in predictions in previous studies, which is what this research seeks to achieve. The sample of the study has a size of 30 observations, which are the actual consumption values in the period from 1990 to 2019. The philosophy of this installation is to reuse the residuals to extract the remaining values. Therefore, it becomes white noise and the extracted values are added to increase prediction accuracy. The residuals were calculated and the ARIMA (0, 1, 0) model with a constant was developed both of the residual sum of squares and the root means square errors, which were compared in both cases. The results demonstrate that prediction accuracy using complex models is better than prediction accuracy using single polynomial models or randomly singular models by an increase in the accuracy of the estimated consumption and an improvement of 18.5% as a result of the synthesizing process, which estimates the value of electricity consumption in 2030 to be 575 TWh, compared to the results of previous studies, which were 365, 442, and 633 TWh.

Keywords: energy consumption; electricity consumption; prediction; Saudi Arabia

Citation: Fahmy, M.S.E.; Ahmed, F.; Durani, F.; Bojnec, Š.; Ghareeb, M.M. Predicting Electricity Consumption in the Kingdom of Saudi Arabia. *Energies* **2023**, *16*, 506. https://doi.org/10.3390/en16010506

Academic Editors: Peter V. Schaeffer and Thanikanti Sudhakar Babu

Received: 27 September 2022
Revised: 29 November 2022
Accepted: 22 December 2022
Published: 2 January 2023

1. Introduction

The Kingdom of Saudi Arabia (KSA) is currently undergoing significant development in all fields, especially in the production of electric energy and electric energy consumption. The government is formulating future plans for the advancement of this sector due to its importance in targeted sustainable development and the mandate to generate electricity through alternative energy sources, as contained in Vision 2030. This is represented in the establishment of a number of economic development projects that pave the way to the goals of the KSA's Vision 2030. This includes goals such as raising the competitiveness of renewable energy and managing carbon emissions in KSA.

KSA is the 14th largest consumer of electricity in the world. Its consumption is similar to that of the most densely populated countries, for example, Mexico, whose population in 2019 reached 127.5 million, compared to 34.2 million for KSA. It is also on par with the most advanced economies, for example, Italy, whose gross domestic product (GDP) for the year 2019 amounted to USD 2151.4 billion, compared to USD 704.0 billion for KSA. The electric energy consumption in KSA is affected by many economic variables, including economic growth, population growth, and income of individuals, and by energy prices, their fluctuations, and their direct and strong connection with the current successive global economic shocks [1,2].

The research problem and its challenges are summed up in the existence of a large variation in the predicted values of consumption in previous studies.

From this point, the importance of predicting electricity consumption until 2030 with greater accuracy using a composite model that helps avoid the large disparity in predictions in previous studies lies in clarifying the predicted electricity consumption for decision makers, in a way that enables them to develop and activate plans to keep pace with increasing energy demand—as proven by the results of this research—by using more renewable energy sources.

1.1. Prior Studies

In this part, we review the most important previous studies from two perspectives. First, the predicted values of electric energy consumption in KSA for the year 2030 are discussed. Second, a number of models used in prediction are reviewed.

1.1.1. The First Perspective: Predicting Consumption Values in 2030

The first study was conducted by Somani and Gracie in 2022 [1] on "Projecting Saudi sectoral electricity demand in 2030 using a computable general equilibrium model". Their study predicted that the value of the total consumption would be 365.4 TWh in 2030. The second study was conducted by Al-Harbi and Shala in 2019 [3] on Saudi Arabia's electricity: Energy supply and demand future challenges, in which they predicted electric energy consumption in KSA for the year 2030 to be 442 TWh. The third study was conducted by Al-Mulla in 2014 [4] on Gulf Cooperation Council (GCC) countries 2040 energy scenario for electricity generation and water desalination, in which he predicted that KSA's electric energy consumption would reach 633.34 TWh in 2030. From the above, it is clear that there is a discrepancy in the estimates of future consumption, which justifies the need for further studies to accurately estimate consumption, especially in light of current global economic challenges.

1.1.2. The Second Perspective: Models Used in Forecasting

Liang and Liang 2017 [5] used a hybrid of the gray model and the logistic model to predict China's electricity consumption from 2016 to 2020. It is noted that these are both distinct models. Muhammed and Podger 2005 [6] used the logistic model after modifying it by making the saturation level a function of population, electricity price, and gross national product (GNP). The modified model was used to predict electricity consumption in New Zealand in the period (2000–2020). Ogungbemi et al. 2017 [7] used the Harvey Model and a first order autoregressive model to predict the industrial electricity consumption in Nigeria from 2015 to 2029. Gharib 2022 [8] used a set of specific and stochastic models to predict the consumption of solar PV energy in China in the period 2019–2030. Al-Samman and Ahmed 2021 [9] used ten polynomial models to predict the consumption of solar PV energy in China in the period (2019–2030).

The research is based on the following hypotheses:

1. *There will be a steady and continuous increase in KSA's electric energy consumption until 2030.*
2. *It is possible to synthesize the polynomial models and the ARIMA models.*
3. *Prediction accuracy using the compound models is better than prediction accuracy using a single polynomial or a single stochastic model.*

The rest of the study structure consists of the following sections: Section 2 presents previous studies. Section 3 develops the general equation of the polynomial models in the following steps: calculating the parameters of the models, comparing models and selecting the best one, testing the significance of the second order polynomial model, prediction using the second order polynomial model in the sample period from 1990 to 2019, modeling residuals using the ARIMA model, calculating residuals of the residuals and making sure that they become white noise, calculating the autocorrelation function (ACF) for residuals of the residuals, testing ACF parameters one by one, synthesizing the second order polynomial outputs with the outputs of the autoregressive integrated moving average (ARIMA) model in the sample period 1990–2019, comparing the polynomial residuals with the compound model residuals in the sample period, and predicting electric energy consumption in KSA in the period from 2020 until the end of 2030. Section 4 explains and discusses the results. The final Section 5 concludes with recommendations.

2. Materials and Methods

The inductive approach, with its descriptive and analytical parts, was used [10,11], where the electric energy consumption in KSA in the period from 1990 to 2019 was described. Then, these data were analyzed, and polynomial models were created to predict consumption. Various models were evaluated and the best of them selected; then, a stochastic model was developed for the residuals of the selected polynomial model, and a compound model was created consisting of a polynomial model and a stochastic model. The significance of the selected polynomial model was tested using the F-statistical test and it passed successfully; the significance of the selected ARIMA model was tested using the Z-statistical test to ensure that its residuals became white noise.

2.1. The General Equation of the Polynomial Models Used

The general equation of these models is [12]:

$$y = a_0 + a_1 t + a_2 t^2 + \ldots + a_n t^n \tag{1}$$

where: y is the dependent variable and expresses the value of the electric energy consumption (the unit is terawatt-hours); t is the independent variable and expresses time (the unit is the year); $a_0, a_1, a_2, \ldots$. are the model parameters; n is the order of the polynomial and will be from 1 to 10.

We enter these parameters (a_0, a_1, a_2). into a program called PHP, which calculates the values, and then put the parameter values in Excel to obtain the estimated $\hat{y}$.

2.2. Calculating the Parameters of the Models

The actual electricity consumption data Table A1 will be used [13] in calculating the model parameters by applying the least squares method and using Excel and Hypertext Preprocessor (PHP) programs [14].

The results are shown in the Appendix A, where $\hat{y}$ is the predicted consumption.

In these formulas, numbers in 17 decimal digits are used for accuracy because an important part of this research is related to the study of residuals, which are small quantities.

2.3. Comparing Models

The comparison between the ten models is made on the basis of the coefficient of determination R^2, which is a strong measure of the quality of the model's fit for the sample data. It also expresses the percentage of data interpreted by the model.

The coefficient of determination R^2 is calculated as follows: [15–17]:

$$R^2 = \frac{SSF}{SST} = 1 - \frac{SSR}{SST} \tag{2}$$

where

$$SST = SSR + SSF \tag{3}$$

SST is the sum of the squared deviations of the actual consumption values from their mean. SSR is the sum of the square differences between the actual electricity consumption and estimated electricity consumption. SSF is the sum of the squared deviations of the estimated electricity consumption values from their mean:

$$SST = \sum_{t=1}^{T} (y_t - \overline{y})^2 \tag{4}$$

$$SSR = \sum_{t=1}^{T} (y_t - \hat{y}_t)^2 \quad (5)$$

$$SSF = \sum_{t=1}^{T} (\hat{y}_t - \overline{y})^2 \quad (6)$$

T is the size of the study sample (the number of actual electricity consumption values used in the research).
y_t is the actual electricity consumption.
$\hat{y}_t$ is the estimated electricity consumption.
$\overline{y}$ is the average of the actual electricity consumption values.
$\overline{\hat{y}}$ is the average of the estimated electricity consumption values.

From Figure 1 and Table A2, there is an improvement in the value of the coefficient of determination caused by increasing the polynomial order, which becomes limited after the second order polynomial. Since the lower the polynomial order, the better it is, due to the simplicity of the model, the second order polynomial model was selected.

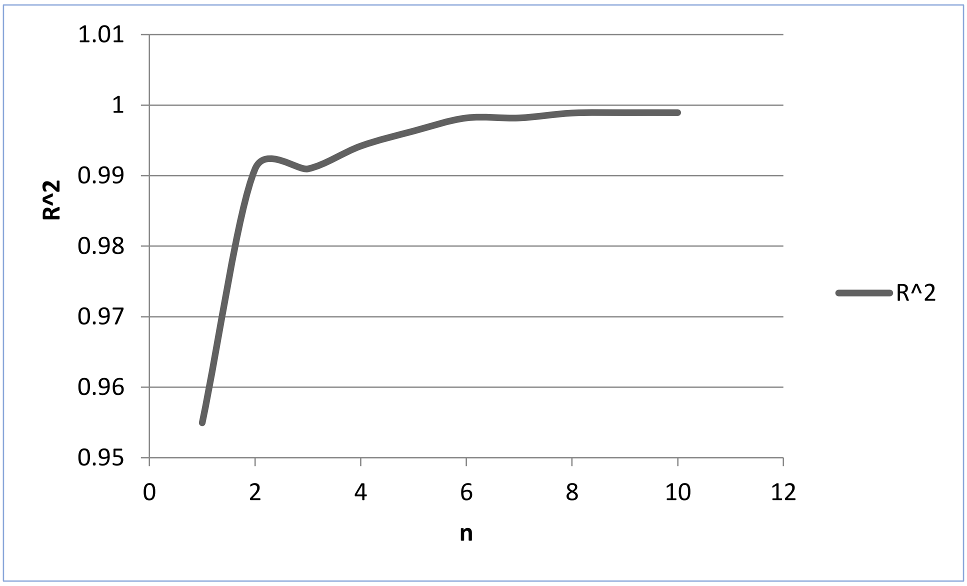

Figure 1. The relationship between the polynomial order (n) and the coefficient of determination R^2 according to the data of Table A2. Source: Authors' calculations.

2.4. Testing the Significance of the Second Order Polynomial Model

In this part, the "F-statistical test" is performed [16,18] to determine the significance of the selected model as a whole.

The general equation of the model is:

$$y_t = a + b\,t + c\,t^2 \quad (7)$$

The test aims to determine if there is a relationship between the dependent variable y_t and a subset of the variables t, t^2.

The hypotheses are the null hypothesis H_0 and the alternative hypothesis H_1, and are as follows:

$$H_0\text{: } a = b = c = 0$$

H_1: at least one of $a, \ldots, c \neq 0$

Rejecting the null hypothesis H_0 results in at least one of the variables t and t^2 contributing significantly to the model.

Test procedures include an analysis of variance (the mean of sum of squared errors) by dividing the sum of the total squared errors (SST) into two parts. The first part is the sum of squared errors resulting from the model (regression process) SSF, and the second is the sum of the squared errors resulting due to the residual SSR, i.e.,

$$SST = SSF + SSR$$

where

$$SSF = \sum_{i=1}^{30} (\hat{y}_i - \overline{\hat{y}})^2 = 241915.7399$$

$$SSR = \sum_{i=1}^{30} (y_i - \hat{y}_i)^2 = 2213.57356$$

The test statistic of the significance of the model is:

$$F_0 = \frac{SSF/k}{SSR/(n-p)}$$

where k is the number of independent variables in the model (it is equal to 2 in the case under study), n is the number of observations (equal to 30 in the case under study), and p is the number of parameters in the model (equal to 3 in the case under study). In the case under study, it will be:

$$F_0 = \frac{241915.7399/2}{2213.57356/(30-3)} = 1475.380149.$$

By comparing the value of F_0 to the value

$$F_{\alpha,k,n-p}$$

taken from the general table of the probability distribution "F" with a level of significance $\alpha = 0.05$ and degrees of freedom for the numerator $k = 2$, and degrees of freedom for the denominator $n - p = 27$, i.e.,

$$F_{0.05,2,27} = 3.35$$

By comparison, it was found that

$$F_0 > F_{0.05,2,27}$$

Thus, the null hypothesis H_0 was rejected with a confidence level of 95% and the alternative hypothesis H_1 was accepted. That is, there is a significant relationship between the dependent variable and a subset of the independent variables; therefore, we accept the model.

The model is significant with a confidence level of 95%, and it reconciles the data to an excellent degree. The conclusion is that the model can be relied upon in the prediction process.

2.5. Prediction Using the Second Order Polynomial Model in the Sample Period 1990–2019

Table A3 shows estimated electricity consumption by the second order polynomial model (calculating the actual and estimated consumption in the sample period 1990–2019) after concluding that the model as a whole is significant, with a confidence level of 95%, that it reconciles the data to an excellent degree, and that the model can be relied upon in the prediction process. The residuals, which will be inputs to the random model, can be calculated in Table A4.

2.6. Residues of the Second Order Polynomial Model

Table A4 and Figure 2 present the residues of the second order polynomial model by calculating the difference between the actual consumption and estimated consumption $E = y - \hat{y}$ within the period 1999–2019.

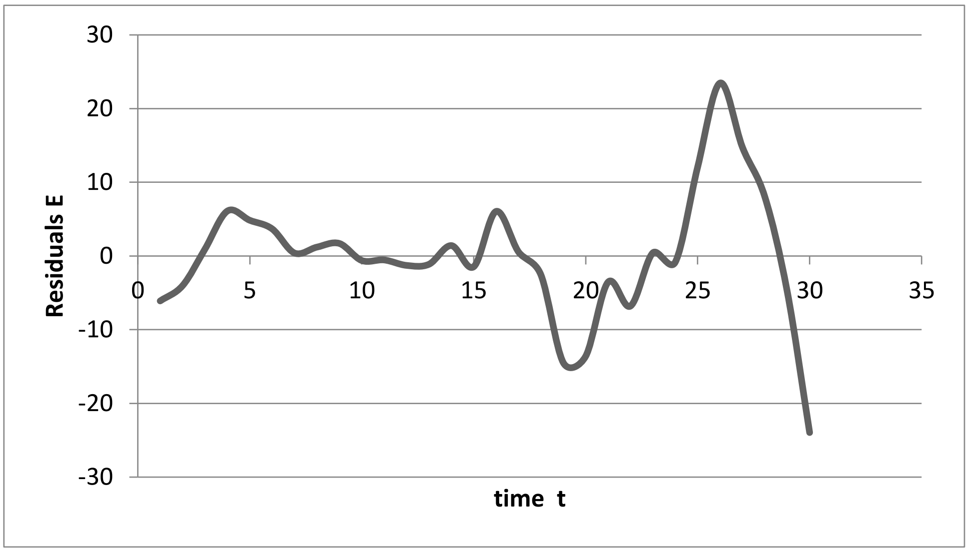

Figure 2. Second order polynomial residuals versus time intervals. Source: Table 1, reference [3], and authors' calculations.

Figure 2 shows that this period (T = 26) (2015) has the biggest difference between actual and estimated consumption.

2.7. Modeling Residuals Using the ARIMA Model

By entering the residuals into the SPSS program and using the EXPERT MODELER, we obtained the optimal model for the residuals, which was ARIMA (0, 1, 0) [15,19,20] with a constant of (−0.616). This is shown in Table A5; by entering the residuals into the SPSS program and using the EXPERT MODELER, we obtained the optimal model for the residuals, which was ARIMA (0, 1, 0) [15,19,20] with a constant of (−0.616). This is a step to calculate the residuals of the residuals.

2.8. Calculating Residuals of the Residuals and Making Sure They Become White Noise

The calculation of residuals of the residuals shown in Table A6 makes sure that it becomes white noise; this is very important for the next step of calculating the autocorrelation function for residuals of the residuals.

2.9. Calculating Autocorrelation Function (ACF) [16,20,21] for Residuals of Residuals

Table A7 shows the calculation of the autocorrelation function. The autocorrelation analysis helps detect patterns and check for randomness. This is especially important when intending to use the (ARIMA) model for forecasting because it helps to determine its parameters.

2.10. Testing ACF Coefficients One by One

If the time series is white noise, then the distribution of the correlation coefficients for the sample follows the normal distribution with a mean of zero and a variance of $1/T$, where T is the number of time periods; in the case under study, T = 30. This can be expressed as follows [19–21]:

$$r_k \sim N\left(0, \frac{1}{T}\right) \quad (8)$$

Thus, the null hypothesis:

$$H_0: \quad r_k = 0$$

and can be tested using the parametric statistical test:

$$Z_0 = \frac{r_k}{\sqrt{\frac{1}{T}}} = r_k\sqrt{T} \tag{9}$$

If it is:

$$|Z_0| < Z_{\frac{\alpha}{2}} \tag{10}$$

where $Z_{\frac{\alpha}{2}}$ is the upper percentage point $\alpha/2$ in the standard normal distribution. This indicates that the coefficients of the ACF are statistically zero. That is, we accept the null hypothesis at the confidence level α = 0.05.

Note that $Z_{\frac{\alpha}{2}} = Z_{0.025} = 1.96$ is from the standard normal distribution table.

From Table A8, it is clear that:

$$|Z_0| < Z_{\frac{\alpha}{2}} \tag{11}$$

This is for all r_k coefficients. Thus, the null hypothesis can be accepted; all coefficients are statistically zero at the level of significance α = 0.05. Therefore, the residual series of the stochastic model is white noise, which means that the model is sufficient and significant with a confidence level of 95%.

2.11. Synthesizing the Second Order Polynomial Outputs with ARIMA Period 1990–2019

Table A9 presents a compound model. It consists of a polynomial model and a stochastic model. It examines the process of superposition between the second order parametric model and the ARIMA model.

2.12. Comparing Polynomial Residuals with Compound Model Residuals (Sample Period 1990–2019)

To show the improvement that occurred in the results due to the synthesizing process of the second order polynomial model and the ARIMA model, the residuals of the compound model were calculated, and we compared the sum of the residuals square and the square root of the mean of residuals of the two models shown in Table A10.

The residual sum of squares of the polynomial model RSS1 = 2213.57356.

The residual sum of squares of the compound model RSS2 = 1471.04359.

The amount of improvement resulting from the synthesizing process = RSS1 − RSS2 = 742.52997.

Improvement percentage = (RSS1 − RSS2)/RSS1 × 100 = 33.5444%.

Root-mean-square of residuals of the polynomial model RMSE1 = 8.58987.

Root-mean-square of residuals of the compound model RMSE2 = 7.00248.

Difference = RMSE1-RMSE2 = 1.58739.

Improvement percentage = (RMSE1 − RMSE2)/RMSE1 × 100 = 18.47979%.

As shown above, the synthesizing process of the two models led to a significant improvement in the accuracy of the results.

Figure 3 shows the synthesizing process of the two models that led to a significant improvement in the accuracy of the results in line y-(yhat + Ehat) compared to line E.

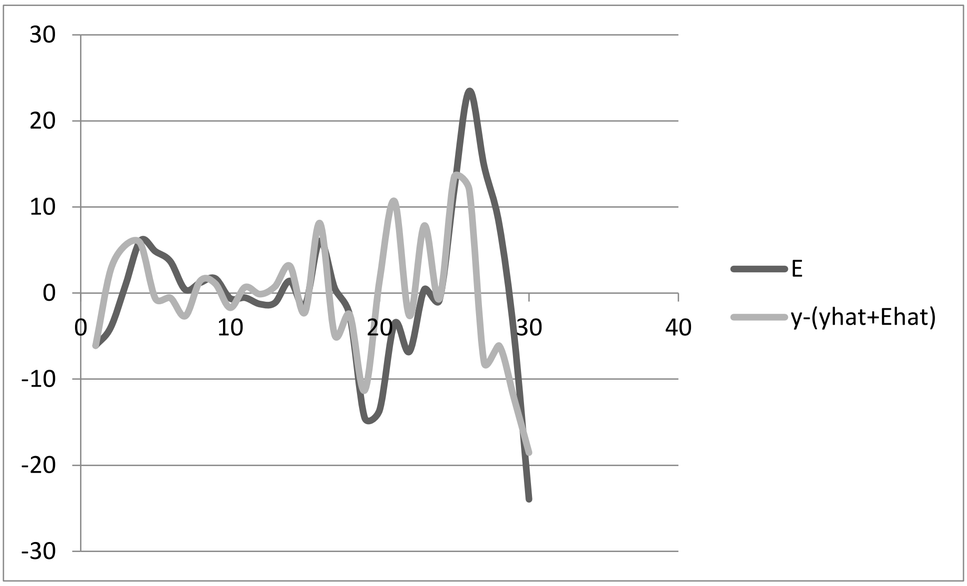

Figure 3. Comparing the residuals of the polynomial model E with the residuals of the compound model y-(yhat + Ehat). Source: Authors' calculations.

2.13. Predicting Electricity Consumption in KSA from 2020 to 2030 Using Compound Model

Table 1 shows the last step in predicting the electricity consumption values for the period 2020–2030 by using the compound model.

Table 1. Electricity consumption prediction values for the period 2020–2030.

T	Year	Estimated Consumption by the Second Order Polynomial	Residuals Estimated by the ARIMA Model	Estimated Consumption by the Compound Model
31	2020	399.2145	−24.5705	374.64405
32	2021	417.586	−25.1862	392.39983
33	2022	436.4692	−25.8019	410.6673
34	2023	455.864	−26.4176	429.44637
35	2024	475.7705	−27.0334	448.73714
36	2025	496.1887	−27.6491	468.53961
37	2026	517.1186	−28.2648	488.85378
38	2027	538.5601	−28.8806	509.67955
39	2028	560.5133	−29.4963	531.01702
40	2029	582.9782	−30.112	552.8662
41	2030	605.9548	−30.7277	575.22707

Source: Authors' calculations.

3. Explanation of the Results

The polynomials of the first order to the tenth order were experimented, where their parameters were calculated by entering the actual electricity consumption data, available in the study sample, into the PHP program on the Internet based on the method of least squares. The coefficient of determination R^2 was calculated for each polynomial.

The coefficient of determination is a measure of how well the model fits the sample data; that is, the extent of convergence between the estimated electricity consumption and actual electricity consumption in the sample period. It also expresses the percentage of the data explained by the model from the total data in the sample.

By comparing the values of the coefficient of determination of the polynomials, it was found that the improvement in the value of the coefficient of determination was little for the polynomials from the third order to the tenth order. Considering that the simpler the model, the better, the second order polynomial was selected as a model for the sample data.

A graph was made showing the relationship between the polynomial and the value of determining factor. From the graph, it was found that the improvement in accuracy became imperceptible after the second order polynomial; this compendium could reduce the number of selected orders, but this was not possible before this experiment.

The significance of the model was tested using the F-statistical test at the level of significance $\alpha = 0.05$, where the test was successfully passed. The residuals of the model were calculated, showing the difference between the actual electricity consumption and estimated electricity consumption in the sample period.

The ARIMA model was developed for these residuals by entering them into the SPSS statistical program and using the Expert Modeler available in the software. The ARIMA (0, 1, 0) model was produced with a constant, which is the best model for expressing residuals. The estimated residuals were calculated in the sample period using the ARIMA model, and then the residuals of the residuals were calculated, revealing the difference between the estimated residuals and the actual residuals. To make sure that the residuals of residuals became white noise, i.e., that they became statistically zero, the coefficients of the ACF were calculated and the Z-test was applied at the level of significance $\alpha = 0.05$; the test was passed successfully. This means that the residuals estimated by the ARIMA model are all the remaining meaningful values in the actual residuals, and they can then be added to the electricity consumption estimated by the second order polynomial model in order to increase its accuracy.

In order to obtain the outputs of the compound model, the outputs of the ARIMA model were added to the outputs of the second order polynomial model. In order to find out the extent of improvement in the results obtained from the synthesizing process, the sum of the root-mean-square error in the sample period was calculated for each of the second order polynomial model and the compound model; a decrease of 33.5% was found, the root mean square deviation was calculated in both cases, and a decrease of 18.5% was found. All this means an improvement in the prediction accuracy using the compound model. The compound model was used in calculating the prediction for the period 2020–2030, where the value of the predicted electricity consumption in the year 2030 was 575 TWh. This result can be compared with the results of previous studies, mentioned in the current study, which were 365, 442, and 633 TWh. It should be noted that the actual electricity consumption for the year 2020 was 341 TWh, while the estimated electricity consumption in the compound model was 375 TWh, with an increase of about 10% from the actual. This can be understood as a result of the impact of the COVID-19 pandemic on actual electricity consumption in that year. As for the year 2021, the actual electricity consumption value had not yet been published at the time of preparation of this research.

There will be a steady and continuous increase in the KSA's electricity consumption until 2030. It is also possible to make a synthesis of the polynomial models and the ARIMA models.

Prediction accuracy using compound models solves the research problem of a large discrepancy in the predicted values of consumption in previous studies. It also proves the validity of the research hypotheses, which are:

- There will be a steady and continuous increase in the KSA's electric energy consumption until 2030.
- It is possible to synthesize the polynomial models and the ARIMA models.
- Prediction accuracy using the compound models is better than prediction accuracy using a single polynomial or a single stochastic model.

4. Discussion

Energy is the mainstay of comprehensive and sustainable development in all societies and the artery of development in various economic and social fields, in addition to being one of the most important pillars of national security. Comprehensive sustainable development plans are linked to the state's ability to provide the energy resources needed for these plans during trade-offs between state regulation, and deregulation and liberalization of energy markets [22,23].

In the case of KSA's economy, the Ministry of Energy is working on diversifying the energy mix used in the production of electricity by increasing the share of gas and renewable energy sources in it in a more efficient and less costly manner. This is done by replacing liquid fuels with natural gas in addition to renewable energy sources. This makes the process of predicting electric energy consumption a very important component of the future planning of any economy, especially in light of current challenges and external shocks in the global economy from the impact of the COVID-19 pandemic and the Russia–Ukraine war. Therefore, the importance of this research is to achieve accurate forecasting of electric energy consumption by making an overlay between polynomial models and ARIMA models, and to confirm that the accuracy of the prediction using complex models is better than prediction accuracy using single polynomial or singular stochastic models. From this point of view, the current research provides an accurate vision of what will be the level of energy consumption in KSA up to 2030, contrary to what has been presented by previous studies, which gives a clearer picture for decision makers to make the best decision regarding the generation of electrical energy through a variety of renewable energy sources. This is in line with the sustainable development goals in KSA's 2030 vision.

KSA's goal of increasing and diversifying the use of renewable energy sources in generating electric energy by nearly 50% in 2030 on the one hand, and the existence of a large discrepancy in the predicted values in most of the studies conducted on this subject on the other, prompted the researchers to perform this study in order to predict KSA's electric energy consumption for the period from 2020 to 2030. The current study was based on a sample size of 30 observations representing KSA's actual electric energy consumption in the period from 1990 to 2019 [13]. A composite model was constructed consisting of two parts. The first part is parametric and the second part is the ARIMA model. The limits were tested from the first degree to the tenth degree, where their parameters were calculated by entering the actual consumption data, available in the study sample, into the PHP program, which is based on the method of least squares. An ARIMA model was built for these residuals by entering them into the SPSS statistical program, and with the help of the Expert Modeler available in the program, the ARIMA (0, 1, 0) model was produced with a fixed term, which is the best model for expressing the residuals.

In order to obtain the outputs of the composite model, the outputs of the ARIMA model were added to the outputs of the parametric model of the second degree. In order to find out the extent of improvement in the results resulting from the fitting process, the sum of the squared errors RSS was calculated in the sample period for each of the parametric models of the second degree and the composite model, and a decrease of 33.5% was found. All of this means an improvement in prediction accuracy using the composite model.

The composite model was used to calculate the forecast for the period 2020–2030, where the predicted consumption value in the year 2030 is 575 terawatt-hours (TWh). This result can be compared to the results of previous studies that were mentioned in this study, where they were 365, 442, and 633 TWh. It should be noted that the actual consumption for the year 2020 was 341 TWh, while the estimated consumption in the composite model was 375 TWh, an increase of about 10% from the actual. This can be understood as a result of the impact of the COVID-19 pandemic on the actual consumption in that year [24–26]. As for the year 2021, the actual consumption value had not yet been published by the date of preparation of this research.

Although the actual electricity consumption value for the year 2020, which was 341 TWh [27], was available, it was not used in creating the prediction models and was left to compare with the predicted values.

Therefore, the research problem is presented in the presence of a large discrepancy in the predicted values of electricity consumption in previous studies, taking these values as an indicator for sustainable development plans in the generation of electric energy and comparing them with the target for 2030. This is done in order for decision makers to be able to do what is required to keep pace with the increase in electric energy consumption by generating it through a variety of renewable energy sources and reducing carbon emissions in line with the goals of sustainable development and KSA's vision 2030. One of the potential sources can be solar energy [28], as well as more efficient use of energy in sustainable economic development [29].

The aim of the present research is to shed light on polynomial predictive models, indicate the degree of confidence in their outputs using appropriate statistical methods, predict the electric energy consumption values using the compound model representing the period from 2020 until the end of 2030, and create a synthesis of the selected best 'polynomial' and its ARIMA model in order to increase prediction accuracy. It also aims to draw a future picture of electric energy consumption in KSA.

Finally, it is useful to mention that in the literature, several other forecasting approaches have been developed, such as those based on statistical and artificial neural network models, projections based on artificial intelligence [30–33], machine learning models [34–36], and those using novel hybrid models [37–40]. These are challenging issues for KSA, as well as other countries in the Middle East and Asian region, and are thus among the issues deserving of research in future.

5. Conclusions

The research problem was represented in forecasting the consumption of electricity consumption in the KSA in the period of the years 2020 to 2030, depending on a sample size of 30 observations, representing the actual consumption of electrical energy by Saudi Arabia in the period from 1990 to 2019. Although the actual consumption value for the year 2020 was available, which was 341 Twh, it was not used in building forecast models and was left to compare with the forecast values. The motivation for this research came from the presence of a large discrepancy in the estimated values presented in previous research.

The importance of the current research pertains to KSA's goal of increasing and diversifying the use of renewable energy sources in generating electric energy by nearly 50% by 2030 on the one hand, and the presence of a large discrepancy in the predicted values in most of the studies conducted on this subject, on the other hand. This prompted the researchers to perform this study to predict KSA's electric energy consumption for the period from 2020 to 2030, based on a sample size of 30 observations representing the actual electric energy consumption by KSA in the period from 1990 to 2019. Accordingly, a two-part compound model was developed. The first part is the polynomial model and the second part is the ARIMA model. Polynomials have the advantage that they can be used to express a wide range of mathematical models.

An improvement in the prediction accuracy was observed using the compound model. The compound model was used in calculating the prediction for the period 2020–2030, where the value of the predicted electricity consumption in the year 2030 was 575 TWh. This result can be compared with the results of previous studies that were mentioned in this study, where they were 365, 442, and 633 TWh. It should be noted that the actual electricity consumption for the year 2020 was 341 TWh, while the estimated electricity consumption in the compound model was 375 TWh, with an increase of about 10% from the actual.

This study recommends using the composite model as a tool that has proven its effectiveness and accuracy through the findings of this research, in order to provide accurate data and results for decision makers in KSA to determine the current and future consumption of electricity in line with the goals of sustainable development and KSA's Vision 2030 to achieve economic benefit for KSA.

Author Contributions: Conceptualization, M.S.E.F., F.A. and Š.B.; methodology, F.D. and M.M.G.; software, F.A.; validation, M.S.E.F., F.A. and Š.B.; formal analysis, F.D. and M.M.G.; investigation, M.S.E.F. and F.A.; resources, F.A. and Š.B.; data curation, F.D. and M.M.G.; writing—original draft preparation, M.S.E.F., F.A. and F.D.; writing—review and editing, F.A. and Š.B.; visualization, M.S.E.F. and M.M.G.; supervision, F.A. and Š.B.; project administration, M.S.E.F. and M.M.G.; funding acquisition, Š.B. All authors have read and agreed to the published version of the manuscript.

Funding: This study has not received any external funding.

Data Availability Statement: Data can be provided on request.

Acknowledgments: Authors would like to thank the AGM Institute of Research & Development (AGM-IRD) Pakistan and Development Policy Practice and Research Center (DPPRC) Pakistan for their technical support in completing this study.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Contains all the tables and formulas that were used in the model, including: Calculating the Parameters of the Models a; The relationship between the polynomial order and the coefficient of determination; Modeling residuals using the ARIMA model; Calculating residuals of the residuals and making sure they become white noise; Calculating autocorrelation function; Calculation of the significance test parameter of the stochastic model of the second order polynomial residuals; and a table presenting the compound model, which was created by combining a polynomial model and a stochastic model.

Table A1. Electricity Consumption Time Series (Research Sample).

Year	Period T	Actual Consumption TWh	Year	Period T	Actual Consumption TWh	Year	Period T	Actual Consumption TWh
1990	1	79.9	2000	11	138.7	2010	21	240.1
1991	2	85	2001	12	146.1	2011	22	250.1
1992	3	93.5	2002	13	154.9	2012	23	271.1
1993	4	102.7	2003	14	166.6	2013	24	284.1
1994	5	106	2004	15	173.4	2014	25	311.8
1995	6	109.9	2005	16	191.1	2015	26	338.5
1996	7	112.2	2006	17	196.3	2016	26	345.6
1997	8	119.1	2007	18	204.4	2017	28	355.2
1998	9	126.2	2008	19	204.2	2018	29	359.2
1999	10	131	2009	20	217.3	2019	30	357.4

Data source: reference [3].

Table A1 will be used [3] in calculating the model parameters by applying the least squares method and using Excel and Hypertext Preprocessor (PHP) programs [15].

Table A2. The relationship between the polynomial order and the coefficient of determination.

Polynomial Order, n	Coefficient of Determination, R^2
1	0.954939
2	0.990933
3	0.990954
4	0.994186
5	0.996316
6	0.998177
7	0.998177
8	0.998873
9	0.998929
10	0.998929

Source: Authors' calculations.

Table A3. Estimated electricity consumption by the second order polynomial.

Period T	Actual Consumption Y	Estimated Consumption y Hat	Period T	Actual Consumption Y	Estimated Consumption y Hat	Period T	Actual Consumption Y	Estimated Consumption y Hat
1	79.9	85.99859	11	138.7	139.2364	21	240.1	243.6417
2	85	89.01984	12	146.1	147.3744	22	250.1	256.8965
3	93.5	92.55276	13	154.9	156.0241	23	271.1	270.6629
4	102.7	96.59736	14	166.6	165.1854	24	284.1	284.941
5	106	101.1536	15	173.4	174.8585	25	311.8	299.7308
6	109.9	106.2216	16	191.1	185.0432	26	338.5	315.0322
7	112.2	111.8012	17	196.3	195.7395	27	345.6	330.8453
8	119.1	117.8925	18	204.4	206.9476	28	355.2	347.1701
9	126.2	124.4955	19	204.2	218.6673	29	359.2	364.0066
10	131	131.6101	20	217.3	230.8987	30	357.4	381.3547

Source: Table 1, reference [3], and authors' calculations.

Table A4. Residues of the second order polynomial model.

Period T	Actual Consumption Y	Estimated Consumption by Second Order Polynomial $\hat{y}$	Residuals $E = y - \hat{y}$	Period T	Actual Consumption Y	Estimated Consumption Second Order Polynomial $\hat{y}$	Residuals $E = y - \hat{y}$
1	79.9	85.99858871	−6.09858871	16	191.1	185.0431591	6.05684093
2	85	89.01983732	−4.01983732	17	196.3	195.7395278	0.56047215
3	93.5	92.55276061	0.94723939	18	204.4	206.9475713	−2.54757131
4	102.7	96.59735857	6.10264143	19	204.2	218.6672894	−14.4672894
5	106	101.1536312	4.84636878	20	217.3	230.8986823	−13.5986823
6	109.9	106.2215785	3.67842146	21	240.1	243.6417498	−3.54174976
7	112.2	111.8012005	0.39879946	22	250.1	256.8964919	−6.79649194
8	119.1	117.8924972	1.20750278	23	271.1	270.6629088	0.43709121
9	126.2	124.4954686	1.70453142	24	284.1	284.9410003	−0.84100032
10	131	131.6101146	−0.61011461	25	311.8	299.7307665	12.0692335
11	138.7	139.2364353	−0.53643532	26	338.5	315.0322074	23.4677926
12	146.1	147.3744307	−1.27443072	27	345.6	330.845323	14.754677

Table A4. *Cont.*

Period T	Actual Consumption Y	Estimated Consumption by Second Order Polynomial $\hat{y}$	Residuals E = y − $\hat{y}$	Period T	Actual Consumption Y	Estimated Consumption Second Order Polynomial $\hat{y}$	Residuals E = y − $\hat{y}$
13	154.9	156.0241008	−1.12410079	28	355.2	347.1701132	8.02988678
14	166.6	165.1854455	1.41455447	29	359.2	364.0065781	−4.80657814
15	173.4	174.858465	−1.45846496	30	357.4	381.3547177	−23.9547177

Source: Table 1, reference [3], and authors' calculations.

Table A5. The estimated residuals using the ARIMA model in the sample period 1990–2019.

Period T	Actual Consumption Y	Estimated Consumption $\hat{y}$	Actual Residuals E	Estimated Residuals $\hat{E}$
1	79.9	85.99859	−6.09859	
2	85	89.01984	−4.01984	−6.71432
3	93.5	92.55276	0.94724	−4.63557
4	102.7	96.59736	6.10264	0.33151
5	106	101.1536	4.84637	5.48691
6	109.9	106.2216	3.67842	4.23064
7	112.2	111.8012	0.39880	3.06269
8	119.1	117.8925	1.20750	−0.21693
9	126.2	124.4955	1.70453	0.59177
10	131	131.6101	−0.61011	1.08880
11	138.7	139.2364	−0.53644	−1.22584
12	146.1	147.3744	−1.27443	−1.15216
13	154.9	156.0241	−1.12410	−1.89016
14	166.6	165.1854	1.41455	−1.73983
15	173.4	174.8585	−1.45846	0.79883
16	191.1	185.0432	6.05684	−2.07419
17	196.3	195.7395	0.56047	5.44111
18	204.4	206.9476	−2.54757	−0.05526
19	204.2	218.6673	−14.46729	−3.16330
20	217.3	230.8987	−13.59868	−15.08302
21	240.1	243.6417	−3.54175	−14.21441
22	250.1	256.8965	−6.79649	−4.15748
23	271.1	270.6629	0.43709	−7.41222
24	284.1	284.941	−0.84100	−0.17864
25	311.8	299.7308	12.06923	−1.45673
26	338.5	315.0322	23.46779	11.45350
27	345.6	330.8453	14.75468	22.85206
28	355.2	347.1701	8.02989	14.13895
29	359.2	364.0066	−4.80658	7.41416
30	357.4	381.3547	−23.95472	−5.42231

Source: Table 1, reference [3], and authors' calculations.

Table A6. Calculation of the residuals of residuals in the sample period 1990–2019.

Time T	Actual Error E	Estimated Error Ê	Difference between Actual Error and Estimated Error E − Ê the Residuals of Residuals
1	−6.09859		
2	−4.01984	−6.71432	2.69448
3	0.94724	−4.63557	5.58281
4	6.10264	0.33151	5.77113
5	4.84637	5.48691	−0.64054
6	3.67842	4.23064	−0.55222
7	0.39880	3.06269	−2.66389
8	1.20750	−0.21693	1.42443
9	1.70453	0.59177	1.11276
10	−0.61011	1.08880	−1.69892
11	−0.53644	−1.22584	0.68941
12	−1.27443	−1.15216	−0.12227
13	−1.12410	−1.89016	0.76606
14	1.41455	−1.73983	3.15438
15	−1.45846	0.79883	−2.25729
16	6.05684	−2.07419	8.13103
17	0.56047	5.44111	−4.88064
18	−2.54757	−0.05526	−2.49231
19	−14.46729	−3.16330	−11.30399
20	−13.59868	−15.08302	1.48434
21	−3.54175	−14.21441	10.67266
22	−6.79649	−4.15748	−2.63901
23	0.43709	−7.41222	7.84931
24	−0.84100	−0.17864	−0.66236
25	12.06923	−1.45673	13.52596
26	23.46779	11.45350	12.01429
27	14.75468	22.85206	−8.09739
28	8.02989	14.13895	−6.10906
29	−4.80658	7.41416	−12.22074
30	−23.95472	−5.42231	−18.53241

Source: Authors' calculations.

Table A7. Coefficients of the two autocorrelation functions.

Lag	Coefficients of the Autocorrelation Function ACF	La	Coefficients of the Autocorrelation Function ACF
1	0.258	13	0.000
2	0.112	14	−0.123
3	−0.088	15	−0.067
4	−0.322	16	−0.116
5	−0.036	17	0.047
6	−0.274	18	0.014
7	−0.174	19	0.007
8	−0.079	20	0.034
9	−0.041	21	0.049
10	0.180	22	0.110
11	0.136	23	0.081
12	0.156	24	−0.021

Source: Authors' calculations.

Table A8. Second order polynomial residuals.

Lag	r_k	$Z_0 = r_k$ Ö30	$\mid Z_0 \mid$
1	0.258	1.413	1.413
2	0.112	0.613	0.613
3	−0.088	−0.482	0.482
4	−0.322	−1.764	1.764
5	−0.036	−0.197	0.197
6	−0.274	−1.501	1.501
7	−0.174	−0.953	0.953
8	−0.079	−0.433	0.433
9	−0.041	−0.225	0.225
10	0.180	0.986	0.986
11	0.136	0.745	0.745
12	0.156	0.854	0.854
13	0.000	0.000	0.000
14	−0.123	−0.674	0.674
15	−0.067	−0.367	0.367
16	−0.116	−0.635	0.635
17	0.047	0.257	0.257
18	0.014	0.077	0.077
19	0.007	0.038	0.038
20	0.034	0.186	0.186
21	0.049	0.268	0.268
22	0.110	0.602	0.602
23	0.081	0.444	0.444
24	−0.021	−0.115	0.115

Source: Authors' calculations.

Table A9. Synthesis of the second order polynomial outputs with the ARIMA model outputs.

T	Y	Second Order Polynomial Outputs $\hat{y}$	E	ARIMA Model Outputs $\hat{E}$	Compound Model Outputs $\hat{y}+\hat{E}$
1	79.9	85.99859	−6.09859		85.99859
2	85	89.01984	−4.01984	−6.71432	82.30552
3	93.5	92.55276	0.94724	−4.63557	87.91719
4	102.7	96.59736	6.10264	0.33151	96.92887
5	106	101.1536	4.84637	5.48691	106.64051
6	109.9	106.2216	3.67842	4.23064	110.45224
7	112.2	111.8012	0.3988	3.06269	114.86389
8	119.1	117.8925	1.2075	−0.21693	117.67557
9	126.2	124.4955	1.70453	0.59177	125.08727
10	131	131.6101	−0.61011	1.0888	132.6989
11	138.7	139.2364	−0.53644	−1.22584	138.01056
12	146.1	147.3744	−1.27443	−1.15216	146.22224
13	154.9	156.0241	−1.1241	−1.89016	154.13394
14	166.6	165.1854	1.41455	−1.73983	163.44557
15	173.4	174.8585	−1.45846	0.79883	175.65733
16	191.1	185.0432	6.05684	−2.07419	182.96901
17	196.3	195.7395	0.56047	5.44111	201.18061
18	204.4	206.9476	−2.54757	−0.05526	206.89234
19	204.2	218.6673	−14.4673	−3.1633	215.504
20	217.3	230.8987	−13.5987	−15.083	215.81568
21	240.1	243.6417	−3.54175	−14.2144	229.42729
22	250.1	256.8965	−6.79649	−4.15748	252.73902
23	271.1	270.6629	0.43709	−7.41222	263.25068
24	284.1	284.941	−0.841	−0.17864	284.76236
25	311.8	299.7308	12.06923	−1.45673	298.27407
26	338.5	315.0322	23.46779	11.4535	326.4857
27	345.6	330.8453	14.75468	22.85206	353.69736
28	355.2	347.1701	8.02989	14.13895	361.30905
29	359.2	364.0066	−4.80658	7.41416	371.42076
30	357.4	381.3547	−23.9547	−5.42231	375.93239

Source: Table 1, reference [3], and authors' calculations.

Table A10. Residues of the Compound Model.

T	Y	$\hat{y}$	Boundary Residuals $E = y - \hat{y}$	$\hat{E}$	$\hat{y}+\hat{E}$	Residuals of the Compound Model $y-(\hat{y}+\hat{E})$
1	79.9	85.99859	−6.09859		85.99859	−6.09859
2	85	89.01984	−4.01984	−6.71432	82.30552	2.69448
3	93.5	92.55276	0.94724	−4.63557	87.91719	5.58281

Table A10. *Cont.*

T	Y	$\hat{y}$	Boundary Residuals $E = y - \hat{y}$	$\hat{E}$	$\hat{y} + \hat{E}$	Residuals of the Compound Model $y - (\hat{y} + \hat{E})$
4	102.7	96.59736	6.10264	0.33151	96.92887	5.77113
5	106	101.1536	4.84637	5.48691	106.64051	−0.64051
6	109.9	106.2216	3.67842	4.23064	110.45224	−0.55224
7	112.2	111.8012	0.3988	3.06269	114.86389	−2.66389
8	119.1	117.8925	1.2075	−0.21693	117.67557	1.42443
9	126.2	124.4955	1.70453	0.59177	125.08727	1.11273
10	131	131.6101	−0.61011	1.0888	132.6989	−1.6989
11	138.7	139.2364	−0.53644	−1.22584	138.01056	0.68944
12	146.1	147.3744	−1.27443	−1.15216	146.22224	−0.12224
13	154.9	156.0241	−1.1241	−1.89016	154.13394	0.76606
14	166.6	165.1854	1.41455	−1.73983	163.44557	3.15443
15	173.4	174.8585	−1.45846	0.79883	175.65733	−2.25733
16	191.1	185.0432	6.05684	−2.07419	182.96901	8.13099
17	196.3	195.7395	0.56047	5.44111	201.18061	−4.88061
18	204.4	206.9476	−2.54757	−0.05526	206.89234	−2.49234
19	204.2	218.6673	−14.46729	−3.1633	215.504	−11.304
20	217.3	230.8987	−13.59868	−15.083	215.81568	1.48432
21	240.1	243.6417	−3.54175	−14.2144	229.42729	10.67271
22	250.1	256.8965	−6.79649	−4.15748	252.73902	−2.63902
23	271.1	270.6629	0.43709	−7.41222	263.25068	7.84932
24	284.1	284.941	−0.841	−0.17864	284.76236	−0.66236
25	311.8	299.7308	12.06923	−1.45673	298.27407	13.52593
26	338.5	315.0322	23.46779	11.4535	326.4857	12.0143
27	345.6	330.8453	14.75468	22.85206	353.69736	−8.09736
28	355.2	347.1701	8.02989	14.13895	361.30905	−6.10905
29	359.2	364.0066	−4.80658	7.41416	371.42076	−12.22076
30	357.4	381.3547	−23.95472	−5.42231	375.93239	−18.53239

Source: Table 1, reference [3], and authors' calculations.

Calculating the Parameters of the Models

The first order polynomial model:

$$\hat{y} = 41.19057471264368 + 10.184694104560624t \quad \text{(A1)}$$

The second order polynomial model:

$$\hat{y} = 83.48901477832513 + 2.253736592245352t + 0.25583733910694423t^2 \quad \text{(A2)}$$

The third order polynomial model:

$$\hat{y} = 84.83395730706076 + 1.7721439626681563t + 0.2940459336732974t^2 - 0.0008216902057280256t^3 \quad \text{(A3)}$$

The fourth order polynomial model:

$$\hat{y} = 63.33479221927498 + 13.867819507823924t - 1.395524075804146t^2 + 0.08300972446366839t^3 - 0.0013521195914418776t^4 \quad \text{(A4)}$$

The fifth order polynomial model:

$$\hat{y} = 86.16489832007073 - 4.099943959460825t + 2.400591494097555t^2 - 0.23516904422015494t^3 + 0.010093454991176316t^4 - 0.00014768483332410572t^5 \quad \text{(A5)}$$

The sixth order polynomial model:

$$\hat{y} = 57.75731211317419 + 24.83996800501148t - 6.041637787034118t^2 + 0.8068538789773372t^3 - 0.051680440105507985t^4 + 0.0015929760862161242t^5 - 0.00001871678408107774t^6 \quad \text{(A6)}$$

The seventh order polynomial model:

$$\hat{y} = 57.643512858955226 + 24.9819845514518t - 6.095377306021259t^2 + 0.815862184315436t^3 - 0.05245280907224429t^4 + 0.0016282585012546156t^5 - 0.00001953344097961959t^6 + 0.00000000752679169163t^7 \quad \text{(A7)}$$

The eighth order polynomial model:

$$\hat{y} = 90.76698650674774 - 23.644465498609527t + 16.69659216991278t^2 - 4.0949632466064285t^3 + 0.5120294538898259t^4 - 0.035190806450623516t^5 + 0.0013459517043590157t^6 - 0.00002680117056660032t^7 + 0.00000021619917224429t^8 \quad \text{(A8)}$$

The ninth order polynomial model:

$$\hat{y} = 77.18611694154131 - 0.8930437908518888t + 3.950515271184289t^2 - 0.7057407804364993t^3 + 0.015718240582896285t^4 + 0.007782396358829107t^5 - 0.0009080646201480251t^6 + 0.00004348308707838665t^7 - 0.00000098162131905363t^8 + 0.00000000858652681934t^9 \quad \text{(A9)}$$

The tenth order polynomial model:

$$\hat{y} = 77.67766416789804 - 1.8113357174773226t + 4.54824364199519t^2 - 0.8957648439793898t^3 + 0.04986512462338578t^4 + 0.004043738455536497t^5 - 0.0006497488448332843t^6 + 0.00003217491257888407t^7 - 0.00000067763036404404t^8 + 0.00000000401026876840t^9 - 0.00000000002952424549t^{10} \quad \text{(A10)}$$

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