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Evaluating the effect of electric vehicle charging stations on power grids in Sivas province

Sivas ilindeki elektrikli araç şarj istasyonlarının elektrik şebekelerine etkisinin değerlendirilmesi

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Highlights

- *Electric vehicles*
- *Energy distribution*
- *Power capacity*
- *Power network*
- *Time series analysis*
- *Energy consumption*

Graphical Abstract

It is accepted that the rate of increase will be slow at the beginning of the determined period, higher than the middle of the period, and slow again at the end of the period.

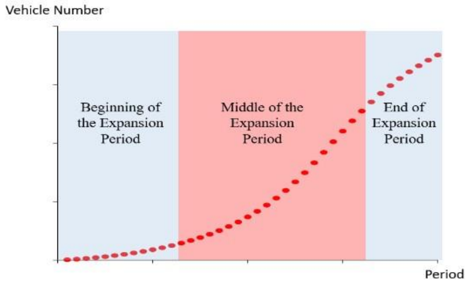

Figure. Exchange model of EVs with conventional vehicles

Aim

Modeling of the load capacity that will occur in electricity transmission lines with the increase in the use of electric vehicles in Sivas.

Design & Methodology

In this study time series analysis were used.

Originality

According to scenario comparisons over the 30-year planning, the J value on the grid will exceed the current value between 2029 and 2030, R-value will fall below the current value between 2031 and 2032 in the best case. It is necessary to invest in electricity distribution lines in 2029-2030 and transformer capacities in 2031-2032.

Findings

The results showed the developed method could be used to determine the line and transformer capacities due to the prevalence of electric vehicles.

Conclusion

Electricity distribution companies allow EVs to become widespread in their investment plans. In this study, with the widespread use of EVs, the value of J, which shows the distributed power value in the network, and R, the ratio of transformer capacity to consumption, are analyzed in the Sivas province case. The study is innovative in analyzing the loads on the network, which is one of the critical problems in the spread of EVs within the scope of the study, a new mathematical equation has been proposed for EVs to replace conventional vehicles.

Declaration of Ethical Standards

The author(s) of this article declares that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Evaluating the Effect of Electric Vehicle Charging Stations on Power Grids in Sivas Province

Araştırma Makalesi / Research Article

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ABSTRACT

Due to the damage of fossil fuels to the environment, fossil fuels will finish soon, the interest in electric vehicles has increased. Determining the trend of electric/classic vehicle replacement and additional load on the transformer is vital importance for the investment plans of energy distribution companies. It presents a comprehensive method for including electric vehicle replacements in the investment planning of electric distribution companies. A new model is proposed, used to replace classical vehicles by becoming widespread of electric vehicles. The power density and transformer capacity ratio were examined using the proposed model for scenarios. Electricity consumption, line length, transformer installed power capacity, population, and the number of vehicles data for the last ten years were obtained from ÇEDAŞ and Turkish Statistical Institute. According to scenario comparisons over the 30-year planning, the J value on the grid will exceed the current value between 2029 and 2030, R-value will fall below the current value between 2031 and 2032 in the best case. It is necessary to invest in electricity distribution lines in 2029-2030 and transformer capacities in 2031-2032. The results showed the developed method could be used to determine the line and transformer capacities due to the prevalence of electric vehicles.

Keywords: Electric vehicles (EVs), energy distribution, power capacity, power network, time series analysis, energy consumption.

Sivas İlindeki Elektrikli Araç Şarj İstasyonlarının Elektrik Şebekelerine Etkisinin Değerlendirilmesi

ÖZ

Fosil yakıtların çevreye verdiği zararlar nedeniyle, elektrikli araçlara ilgi sürekli artmaktadır. Elektrikli/klasik araç değişimi ve trafoya ek yük trendinin belirlenmesi, enerji dağıtım şirketlerinin yatırım planları için hayati önem taşımaktadır. Bu çalışmada elektrik dağıtım şirketlerinin yatırım planlamasına elektrikli araç ikamelerini dahil etmek için kapsamlı bir yöntem sunulmaktadır. Elektrikli araçların yaygınlaşmasıyla klasik araçların yerini alacak yeni bir model önerilmektedir. Farklı senaryolar için önerilen modeller kullanılarak güç yoğunluğu ve trafo kapasite oranı incelenmiştir. Son on yıllık elektrik tüketimi, hat uzunluğu, trafo kurulu gücü, nüfus ve araç sayısı verileri ÇEDAŞ ve Türkiye İstatistik Kurumu'ndan alınmıştır. 30 yıllık planlama üzerinden senaryo karşılaştırmalarına göre, en iyi ihtimalle 2029-2030 yılları arasında şebekedeki J değeri mevcut değeri aşacak, R-değeri ise 2031-2032 yılları arasında mevcut değerin altına düşecektir. 2029-2030 yıllarında elektrik dağıtım hatlarına, 2031-2032 yıllarında ise trafo kapasitelerine yatırım yapılması gerekmektedir. Elde edilen sonuçlar, geliştirilen yöntemin elektrikli araçların yaygınlaşması nedeniyle hat ve trafo kapasitelerinin belirlenmesinde kullanılabileceğini göstermiştir.

Anahtar Kelimeler: Elektrikli araçlar, enerji dağılımı, güç kapasitesi, güç ağı, zaman serileri analizi, enerji tüketimi

1. INTRODUCTION

With advances in technology new era has started in car manufacturing as well. Fossil fuel-powered cars cause air pollution by high carbon emissions. Air pollution is hazardous for human health and nature[1, 2]. Scientists and engineers seek more clean technology to hand down a sustainable world to new generations. Electric-powered cars are one outcome of hard and dedicated work.

Electric vehicles offer a cleaner technology by reducing noise and air pollution and economical solutions. EVs reduce carbon emissions [3], are also considered a promising solution to air pollution, and would eliminate the disadvantages caused by fossil-powered cars [4, 5]. People tend to have more environmentally friendly cars instead of conventional fossil fuel-powered cars. Therefore, EVs are spreading worldwide[6, 7].

The unexpected fast rise in the number of EVs in the streets can cause insufficient charging stations or too many charging stations with random locations. The second case causes considerable differences in electricity supply and demand, creating voltage imbalance and power losses in the network [7-12]. Governments and electricity distribution companies should consider these electricity supply and demand differences during the maturation period to revise their future investment plan in the network and distribution lines according to this situation. Some modeling tools should be employed to improve the location distribution of the charging stations

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to have maximum profits from EVs and minimize the drawbacks on the power networks[13].

The main motivation behind this study is to propose a new model to determine the prevalence of electric vehicles and determine the effect of the prevalence of electric vehicles on the grid by using the proposed model. Thus, it is to develop a technique that allows energy distribution companies to consider the proliferation of EVs in their investments in fields such as transformer and line additions. This study consists of five sections. Related works and previous studies are presented in the second section. The third section included the prediction method, comparison criteria, proposed spreading model, and analysis method. Data and satistical analysis predicted values, and a numerical example for calculating the spreading of EVs and comparison of Spreading of EVs scenario were included in the fourth section. Evaluation of findings and future work were presented in the fifth section.

2. RELATED WORKS

Numerous researches have been proposed to eliminate the disadvantages of the EV charging station effects on power networks in literature. Scientists worldwide are concerned about grid stress caused by charging many EVs; some optimization tools have been employed to optimize charging infrastructure.

Martins et al.[6] have employed time series analysis to determine charging infrastructure location for minimizing drawbacks on power distribution systems. Metaheuristic techniques were applied in this study to lessen power losses caused by the EV charging station. Zhu et al. [14] proposed time series analysis to investigate the charging station location and its effects on power networks. Lubos Buzna et al.[7] The literature rarely studied EV load estimation and proposed time series and machine learning approaches to provide a qualified study.

Sajjad Ahmadi et al.[15] claimed that uncontrolled charging of too many EV batteries damages the power network. A hybrid technique of Monte Carlo probabilistic model with JAYA meta-heuristic algorithm was developed to predict uncertain variables plus battery capacity, a period for EV in charging station, and how often EV needs recharging. Successfully implementing EVs charging and discharging plays a vital role in decreasing negative effect in most busy times.

Kang Miao Tan et al. [16] conducted research to minimize power network load changes by using a genetic algorithm. Charging EV cars formed interaction between power networks and EV. This led to innovative grid technology, valuable EV fleets, and power networks.

Genetic algorithms were used to design charging station locations by Susana Alegre et al. [17]. Due to this, installation costs decreased, and charging station location distribution was improved to serve better. A case study [18] for long-term charging stations for EV in the California urban area demonstrated that charging station location was very important for decreasing range anxiety. Jamal Abushnaf et al. [19] employed a genetic algorithm to optimize the component size and capacity. The genetic algorithm was the tool to develop a model to determine the station's location. Deterioration effect on the power network system caused by improper setup of the charging stations is the main obstacle for EV Metaheuristic algorithms used for locating the charging station's strategy [20].

Jing Dong et al. [21] studied the effect of the EV charger location and the impact of the infrastructure on the range of the EV. The genetic algorithm was used to model to find optimum locations for EV charging infrastructure.

3. METHOD

Today, technology development has become widespread using the tools available to a limited number of people at the beginning of the 20th century. The number of vehicle use has caused to increase energy consumption. Fossil fuels must be widely used in vehicles physically transported to relatively high-cost consumption points. EV use is becoming widespread for low energy costs, not harmful to the environment, and relatively easy transportation. With the introduction of the jet engine in 1941, the transformation of the aviation industry is undergoing today in motor vehicles. This technology change brings opportunities and problems with it. Problems with EV have been extensively researched in the literature. However, a detailed examination of the model and parameters to determine the impact of EVs grid load has not been made.

In this research, a new model to be used to determine the load that the rise in the number of EVs will bring to the power grid is proposed, and the model's parameters are determined. The data regarding the number of consumers, line length, and transformer installed power between 2013 and 2020 and provided by Çamlıbel Elektrik Dağıtım Corp. were used. The notation used in the study is presented in Table.1.

Table 1. Notation

Independent Variables		Dependent variables
Population (person)	$\hat{Y}_1$	Distributed Energy Dwelling (GW)
Line length (km)	$\hat{Y}_2$	Distributed Energy Industry (GW)
Residential Subscribers (Number)	$\hat{Y}_3$	Distributed Energy Business (GW)
Industry Subscribers (Number)	$\hat{Y}_4$	Distributed Energy Agricultural Irrigation (GW)
Business Subscribers (Number)		
Agricultural Irrigation Subscribers (Number)	$\hat{Y}_5$	Total Incoming Energy

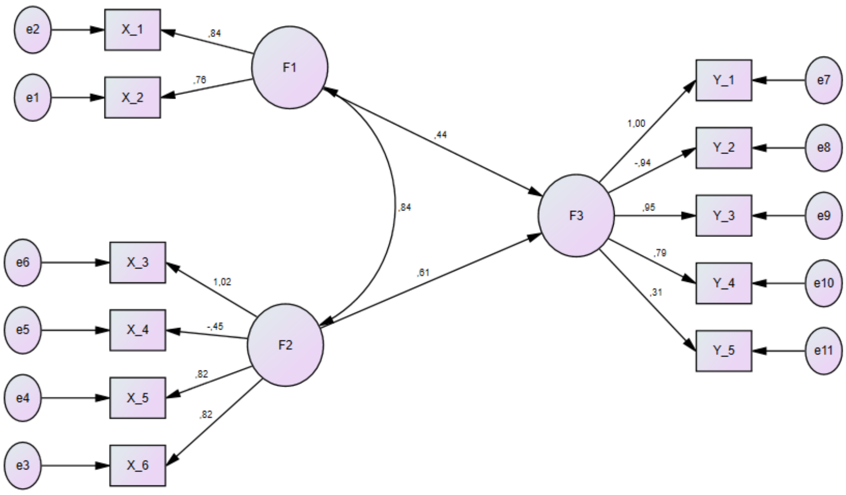

Figure 1. The model of dependent and independent variables

Structural equation models are used for demonstrating the relationship between more than one dependent and independent variable in the analyzed data. The dependent and independent variables are presented in Table.1, the model is presented in Figure.1 The validity of the proposed model was tested at a 95% ($p < 0.05$) confidence level by Using the data between 2013 and 2020 from Çamlıbel Elektrik Dağıtım Corporation. The data were analyzed using SPSS 25 program with a 95% confidence level. For the sake of scales' validity, exploratory and confirmatory factor analyses were performed, and their reliability was calculated. Kurtosis/skewness value for scale scores was accepted between +3 and -3 [22-25]. The minimum discrepancy (CMIN/DF) is equal to 3.896.

3.1 Prediction Method

Time series is a widely used method in prediction. Simple exponential smoothing (SES) and double exponential smoothing (DES) methods [26-30] were employed as the time series-based methods for predictions in this research. In this study, the single exponential technique, double exponential technique, and Holt-Winters technique were used to predict electric vehicle increase amount and load on the grid. Simple exponential smoothing results can be computed from an equation given Eq 1. Y_i is the prediction value at the sample i. X_i is the input and the α is the weight factor where α is more significant than zero and less than one. If α is close to 1, high priority is in recent changes in the input value; if α close to 0, the previous forecast value are the key in the calculations [31, 32]

$$Y_i = \alpha X_i + (1-\alpha)Y_i - 1 \quad (1)$$

For any time period t, the smoothed value S_t is found by computing Eq 2.

$$S_t = \alpha y_{t-1} + (1-\alpha)S_{(t-1)} \qquad 0 < \alpha \leq 1 \qquad t \geq 3 \quad (2)$$

The basic equation for the single exponential technique can be written as Eq 3.

$$S_t = \alpha \sum_{i=1}^{t-2} (1-\alpha)^{i-1} y_{t-i} + (1-\alpha)^{t-2} S_2, t \geq 2 \quad (3)$$

Eq 4 can be written using the geometric series properties with $\alpha(1-\alpha)^t$ decreasing geometric weight features.

$$\alpha \sum_{i=1}^{t-1} (1-\alpha)^{i-1} = \alpha\left[\frac{1-(1-\alpha)^t}{1-(1-\alpha)}\right] = 1-(1-\alpha)^t \quad (4)$$

Double Exponential Smoothing is an advanced form of SES; it is also known as Exponential Moving Average. DES has been used to forecast the future data in time series analysis, where a trend is present. The Holt-Winters technique is a modified version of a simple exponential smoothing model. The equation of m-steps prediction is given in Eq 5. [33-35]

$$F_t + m = S_t + mbt \quad (5)$$

3.2 Comparison criteria

In the formation of cities, houses, apartments, small industrial sites, parks, market places, etc., occupies an important place. The power values of these consumers can be used in calculations by finding them as bulk loads, but this is not practical. Instead, the electricity consumption in the LV network is found by determining the distributed load values. The power values (J) that are assumed to be spread over each meter of the lines extending along the streets and streets are called distributed load.

The population of the network to be designed, the accepted power value per population, and the lengths of the conductors are used to determine power densities. After the distribution and bulk load detection, and power density determination, the load estimation of the region to be fed should be made. The load estimation will enable the demand power to emerge. While estimating the load, natural population growth, feeding zones that may occur due to zoning plans, and measurements on the existing grid are considered. After the demand power emerges, the practical power values of the distribution transformers suitable for the region are determined.

The power density was used to determine the effect of EV on the grid and calculated with power density J (MWh/km) Eq 6 with population P, per capita consumption unit Q, total grid length L.

$$J = \frac{PxQx1.1}{L} \tag{6}$$

In this study, electricity consumption in period t is TC_t The number of EV in traffic is EVN_t and total electricity consumption in period t is calculated using ETC_t Eq 7. Consumption amount per capita was calculated by using Eq 8. If the power density in the period is J_t (see Eq 9) is used. The loss and leakage rate (coefficient 1.1) are neglected.

$$ETC_t = \frac{3.7x6xEVN_t}{24x1000} + TC_t \tag{7}$$

$$Q_t = \frac{ETC_t}{P_t} \tag{8}$$

$$J = \frac{P_t x Q_t}{L} \tag{9}$$

Another effect of electric tools on the system is the transformer capacity. Transformer capacities are selected by estimating the consumption in the settlement. This study determined the total consumed energy contribution of the daily charging need, which emerged with the widespread use of EV in the market. The electricity consumption in the period t is calculated by using the consumed energy transformer capacity ratio R (see Eq 10), with ETC_t being the installed transformer power capacity TCa_t.

$$R = \frac{ETC_t}{TCa_t} \tag{10}$$

3.3 The Spreading Model

It has been accepted that the prevalence of EVs in the market will increase gradually depending on time. It is accepted that the rate of increase will be slow at the beginning of the determined period, higher than the middle of the period, and slow again at the end of the period. The graphical representation of the model is presented in Figure 2. The number of EVs for the forecast period t is calculated using EVN_t (see Eq 11), with forecast period length d, forecast period t, the estimated number of conventional vehicles CVN_t at the end of the period.

$$EVN_t = CVN_t \frac{\sin\left(3\left(\frac{t}{d}+\frac{\pi}{2}\right)+1\right)}{2} \tag{11}$$

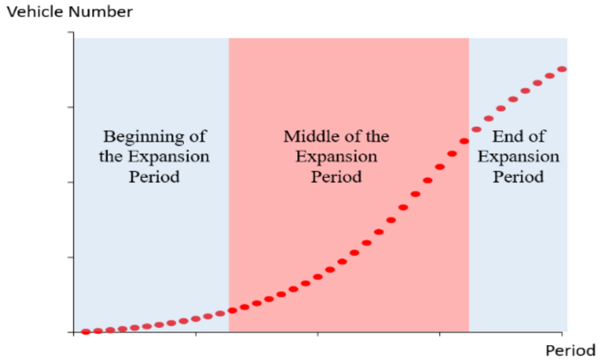

Figure 2. Exchange model of EVs with conventional vehicles

The change in CVN_p in the forecast, the model should be considered when calculating the number of EVs the estimated numbers of EVs vary depending on the CVN values of the lower, medium, and upper points of the conventional vehicles in the T_1 and T_2 periods. Depending on these changes, S_1, S_2, S_3 scenarios for T_1 period and S_4, S_5, S_6 scenarios for T_2 the period is created. $S_1, S_2, S_3, S_4, S_5, S_6$ scenarios CVN change graph is presented in Figure 3. S_1 scenario T_1 (15) period.

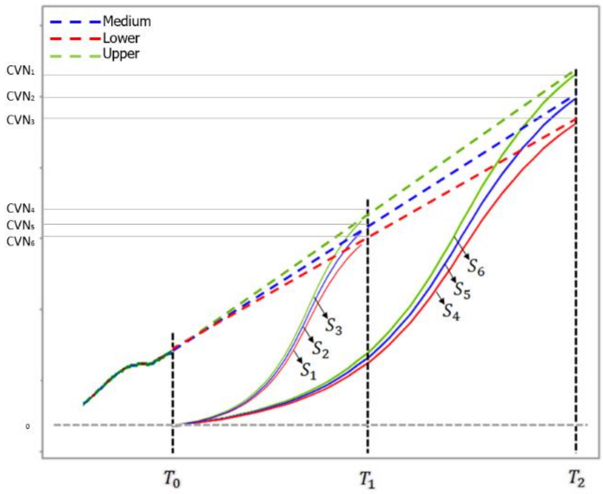

Figure 3. $S_1, S_2, S_3, S_4, S_5, S_6$ scenarios CVN change graph

3.4 Analysis Method

With the widespread use of EVs by end-users, the power density of distribution lines and the ability to exist transformer capacities to meet the increasing demand have been examined.

In this context, electricity consumption amount, line length, and transformer installed power capacity data for the last ten years were obtained from ÇEDAŞ, which carries out electricity distribution operations in Sivas. The reliability of the data was tested by performing the distribution test and analysis of variance on the data. Data on population and number of vehicles were obtained from the Turkish Statistical Institute (TUIK, 2021).

Using time series, the population of Sivas province, the number of vehicles in traffic, the increase in transformer capacity, and total electrical energy consumption were estimated in the coming years. Analyzes were made using Minitab 17 program. The Holt-Winters time series estimates the consumption amount, transformer capacity, and line length when electrical energy consumption includes seasonality. The Holt-Winters method was used because the number of vehicles in traffic is seasonal. In the population estimation, a double exponential time series was employed.

It is necessary to forecast the number of EVs in use in the coming years to determine the load on the electrical system of EVs. It has been accepted that EVs will replace conventional vehicles in time, and a new model has been proposed for this transformation. In the proposed model, the increase in conventional vehicles is considered. While determining the load that the electric vehicle will bring on the grid in the charging process, it is assumed that a full charge will be made in 6 hours with an average value of 3.7 kVA charger. The selected average charge value is sufficient for Renault Fluence or Tesla Model S [36, 37]. The estimated number of EVs for the relevant period and the amount of energy required for a full charge are added up with the amount of energy consumption determined for the relevant period. The total energy consumption amount is determined after the widespread use of EVs.

The number of traditional vehicles was used to determine the number of uses in the spread of EVs regression analysis was made from the total number of vehicles in traffic between 2012 and 2021 in Sivas. Using the Winters' method, the total number of vehicles in Sivas between the years 2022-2052 was estimated. In the Winters' method, the average and upper limit of the number of vehicles in traffic were estimated.

Six different scenarios have been created to spread EVs in two different periods, fifteen and thirty years. Three scenarios were prepared for the lower bound estimate, median estimate, and upper estimate value in the fifteen-year planning horizon. The other three were prepared for the thirty-year planning horizon's lower bound, median, and upper estimate value. The effect of electric vehicle conversion estimated for each scenario on total electricity consumption has been calculated. The load distribution (J) for the grid and the total consumption transformer capacity ratio were calculated based on the new consumption amounts calculated.

4. RESULTS AND DISCUSSION

In this section, data and statistical analysis were performed first. Six different scenarios were prepared for the different cases of the number of conventional vehicles, transformer capacity, distribution line length, and electrical energy consumption between 2022 and 2052. The population of Sivas, the number of conventional vehicles, transformer capacity, distribution line length, and electrical energy consumption between 2022 and 2052 were predicted as the second step. The spreading of EVs was determined using the spreading model (see section 3.3) and the conventional vehicle number.

4.1 Data and Statistical Analysis

The data used in this study are between 2000 and 2020. Regarding electricity consumption, Lighting Consumption (L.C.), Residence Consumption (R.C.), Agricultural Watering Consumption (AWC), Commercial Consumption (CC), Total Consumption (T.C.) were obtained from ÇEDAŞ. The kurtosis and skewness values are used for the normality distribution of data containing qualitative and seasonal information [1-3]. It was determined that L.C., R.C., AWC, CC, and T.C. did not have a normal distribution. Descriptive Statistics for the data received from ÇEDAŞ are presented in Table 2.

Table 1. Spearman's rho results of Data

			L.C.	RC	AWC	CC	TC
Spearman's rho	LC	Correlation Coefficient	1	0,168	**-,410****	**,387****	-0,087
		Sig. (2-tailed)	.	0,2	0,001	0,002	0,506
		N	60	60	60	60	60
	RC	Correlation Coefficient	0,168	1	0,163	0,25	**,438****
		Sig. (2-tailed)	0,2	.	0,214	0,054	0
		N	60	60	60	60	60
	AWC	Correlation Coefficient	**-,410****	0,163	1	**-,256***	**,455****
		Sig. (2-tailed)	0,001	0,214	.	0,048	0
		N	60	60	60	60	60
	CC	Correlation Coefficient	**,387****	0,25	**-,256***	1	**,421****
		Sig. (2-tailed)	0,002	0,054	0,048	.	0,001
		N	60	60	60	60	60
	TC	Correlation Coefficient	-0,087	**,438****	**,455****	**,421****	1
		Sig. (2-tailed)	0,506	0	0	0,001	.
		N	60	60	60	60	60

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 2. Descriptive Statistic of Data

	Mean	Variance	Std. Deviation	Skewness	Kurtosis
LC	5752	70416841	8391	7,28	55,092
RC	29209	275885781	16610	6,946	51,326
AWC	9559	2472427454	49724	7,657	59,061
CC	27694	78000042	8832	6,419	46,555
TC	115714	6650627527	81551	7,384	56,226

Two-way Spearman's rho test was performed to determine the relationship between the data. As a result of the analysis, there is a significant level of 0.001 between T.C. and R.C. (r=0.438), AWC (r=0.455) and CC(r=0.421), between L.C. and AWC(r=-0.410) and CC (r=0.387), AWC and CC (r=-0,256), there is a correlation of 0.05 significance level. Spearman's rho results of Data are presented in Table 3.

4.2 Prediction

Within the scope of the study, Double Exponential Smoothing was used with the data between 2007-2021 while estimating the population of Sivas. The population increase level was calculated as α=0.584 and γ=0.232 in the train. Population estimation data of Sivas province between 2022 and 2051 are presented in Table 4. Mean absolute deviation (MAD) is one of the concepts used to make sense of the amount of error. The extreme values are relatively more minor on the MAD. Therefore, the MAD values of the estimated data were calculated. The MAD value of the population estimation of Sivas province was calculated as 6656. Population Double Exponential Smoothing graph of Sivas province is presented in Figure 4.

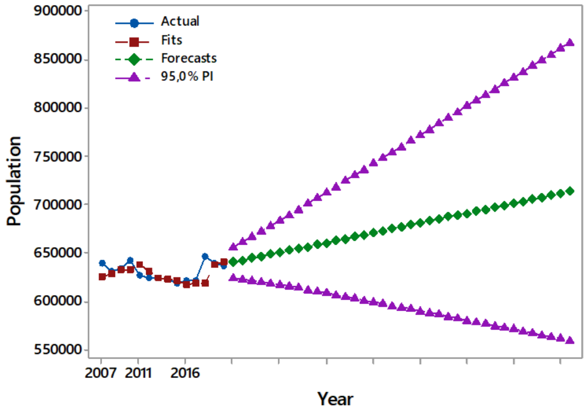

Figure 4. Sivas Province Population Double Exponential Smoothing Graph

While estimating the number of vehicles in Sivas, the monthly vehicle number data between 2013-2021 and The Holt-Winters method were used. It was assumed that the level of vehicle increases, trend, and seasonality coefficient was equal ($\alpha = \gamma = \delta = 0.02$). Population estimation data of Sivas province between 2022 and 2051 are presented in Table 5. Mean absolute deviation (MAD) is one of the concepts used to make sense of the amount of error. The extreme values are relatively more minor on the MAD. Vehicle estimated MAD value of Sivas province was calculated as 396. The population estimation graph of Sivas province is presented in Figure 5.

Table 3. Population estimation data for Sivas province between 2022-2051

Year	Forecast	Lower	Upper	Year	Forecast	Lower	Upper
2022	642124	622827	661421	2037	672645	597105	748185
2023	644159	621575	666742	2038	674680	595238	754122
2024	646193	620140	672247	2039	676715	593367	760062
2025	648228	618585	677871	2040	678750	591493	766007
2026	650263	616950	683576	2041	680784	589615	771954
2027	652298	615258	689337	2042	682819	587734	777904
2028	654332	613525	695140	2043	684854	585851	783856
2029	656367	611761	700973	2044	686889	583966	789811
2030	658402	609974	706830	2045	688923	582079	795768
2031	660437	608168	712705	2046	690958	580190	801726
2032	662471	606348	718595	2047	692993	578300	807685
2033	664506	604516	724497	2048	695028	576409	813647
2034	666541	602674	730408	2049	697062	574516	819609
2035	668576	600824	736328	2050	699097	572622	825572
2036	670611	598967	742254	2051	701132	570727	831537

Table 4. Forecast data for the number of vehicles in Sivas province for the years 2022-2051

Year	Lower	Medium	Upper	Year	Lower	Medium	Upper
2022	173497	174578	175659	2037	254876	263205	271535
2023	179053	180487	181920	2038	260276	269114	277952
2024	184534	186395	188257	2039	265675	275022	284369
2025	189980	192304	194628	2040	271075	280931	290786
2026	195409	198212	201016	2041	276474	286839	297204
2027	200828	204121	207413	2042	281874	292747	303621
2028	206242	210029	213817	2043	287273	298656	310039
2029	211652	215938	220224	2044	292671	304564	316457
2030	217059	221846	226633	2045	298070	310473	322875
2031	222464	227754	233045	2046	303469	316381	329294
2032	227868	233663	239458	2047	308868	322290	335712
2033	233271	239571	245872	2048	314266	328198	342131
2034	238673	245480	252287	2049	319664	334107	348549
2035	244074	251388	258702	2050	325063	340015	354968
2036	249475	257297	265118	2051	330461	345924	361386

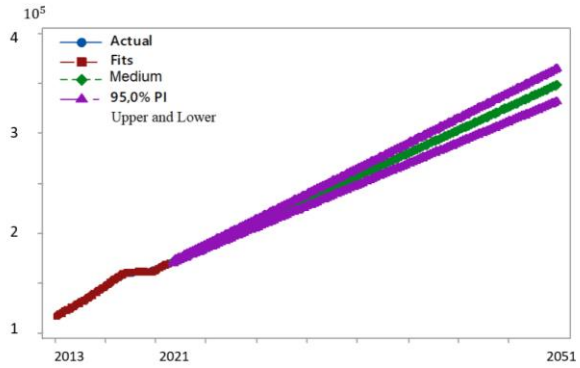

Figure 5. Sivas province vehicle increase forecast graph

While estimating the transformer capacity of Sivas, The Holt-Winters method was used with the data between 2013-2021. The transformer capacity increase level was calculated as α=1.25753 and the trend as γ=0.15565. The transformer capacity MAD value of Sivas province was calculated as 65.33. The transformer capacity increase estimation data for Sivas province between 2022-2051 are presented in Table 6, and its graph is presented in Figure 6

Table 5. Transformer capacity forecast data (MWh) for Sivas province between 2022-2051

Year	Lower	Medium	Upper	Year	Lower	Medium	Upper
2022	2588	2879	3171	2037	2610	4940	7271
2023	2591	3017	3442	2038	2612	5078	7544
2024	2594	3154	3715	2039	2613	5215	7818
2025	2595	3292	3988	2040	2614	5353	8092
2026	2597	3429	4261	2041	2615	5490	8365
2027	2598	3566	4535	2042	2616	5628	8639
2028	2600	3704	4808	2043	2617	5765	8913
2029	2601	3841	5082	2044	2618	5902	9186
2030	2602	3979	5355	2045	2619	6040	9460
2031	2603	4116	5629	2046	2621	6177	9734
2032	2605	4253	5902	2047	2622	6315	10007
2033	2606	4391	6176	2048	2623	6452	10281
2034	2607	4528	6450	2049	2624	6589	10555
2035	2608	4666	6723	2050	2625	6727	10828
2036	2609	4803	6997	2051	2626	6864	11102

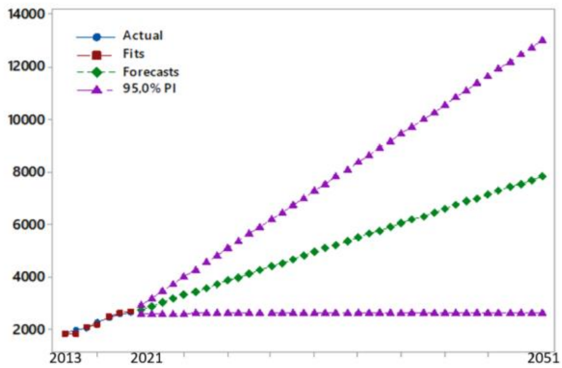

Figure 6. The forecast graph of Sivas province transformer capacity

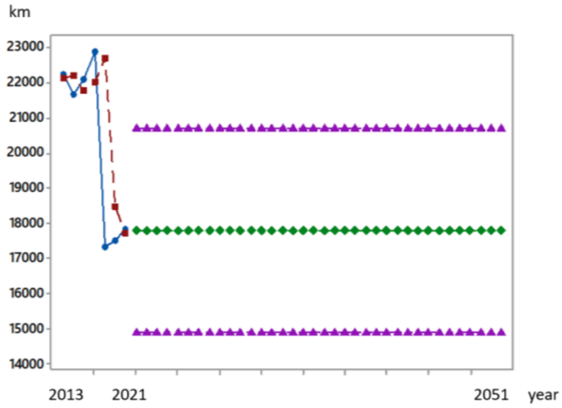

Figure 7. The forecast graph Sivas distribution line length

While estimating the distribution line length of Sivas, the single exponential method was used with the data between 2013-2021. The effect of the increase in vertical construction in the last ten years on distribution lines has been added to the estimation model. The distribution line length increase level was calculated as α=0.785. Sivas province distribution line length MAD value was calculated as 1187. In Sivas province, between 2022-2051, fixed limit values have been determined as 14900 km for distribution line length lower and 20716 km for 17808 uppers for medium. Sivas province distribution line forecast graph is presented in Figure 7.

While estimating the electrical energy consumption of Sivas, the Holt-Winters method was used with the data between 2013-2021. The increase in electrical energy consumption was calculated as α=0.290 and the trend as γ=0.1. The MAD value was calculated as 5.268. The seasonality ratio varied between 0.9 and 1.2. The increased electrical energy consumption amount (T.C.) in Sivas province between 2022-2051 is presented in Table 7 and its graph in Figure 8.

Table 6. Forecast data of electrical energy consumption in Sivas province for the years 2022-2051 (MWh)

Year	TC	Year	TC	Year	TC
2022	126.32	2032	138.42	2042	150.52
2023	127.53	2033	139.63	2043	151.73
2024	128.74	2034	140.84	2044	152.94
2025	129.95	2035	142.05	2045	154.15
2026	131.16	2036	143.26	2046	155.36
2027	132.37	2037	144.47	2047	156.57
2028	133.58	2038	145.68	2048	157.77
2029	134.79	2039	146.89	2049	158.98
2030	136.00	2040	148.10	2050	160.19
2031	137.21	2041	149.31	2051	161.40

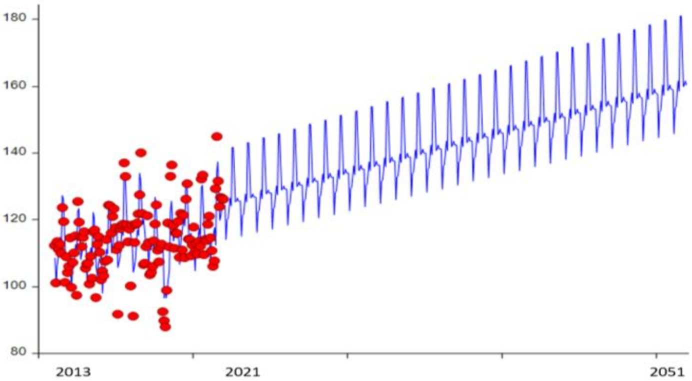

Figure 8. Sivas electrical energy consumption forecast graph

4.3 The Spreading of EVs

The regression equations presented in Eq.12, 13, and 14 were determined for lower, medium, and upper, respectively, using the Holt Winter method to increase the number of EVs and replace conventional vehicles. Equations give the number of conventional vehicles in t period (month).

$$CVN_t = 171376 + 448.468t \quad (12)$$

$$CVN_t = 171376 + 492.316t \quad (13)$$

$$CVN_t = 171376 + 536.164t \quad (14)$$

For each scenario created, Conventional Motor Vehicles and EVs Forecast data are presented in Table 8.

Table 7. Conventional Motor Vehicles and EVs Forecast data (annual average)

	Conventional Motor Vehicles			Electric Vehicles					
Year	PCVN-L	PCVN-M	PCVN-U	S1	S2	S3	S4	S5	S6
2022	173497	174578	175659	933	964	995	296	311	326
2023	179053	180487	181920	6178	6384	6589	2010	2110	2211
2024	184534	186395	188257	16307	16849	17392	5391	5660	5929
2025	189980	192304	194628	30915	31944	32972	10404	10924	11444
2026	195409	198212	201016	49421	51065	52710	17001	17850	18699
2027	200828	204121	207413	71086	73451	75816	25114	26369	27624
2028	206242	210029	213817	95047	98209	101372	34664	36395	38127
2029	211652	215938	220224	120349	124353	128357	45553	47829	50105
2030	217059	221846	226633	145982	150839	155697	57675	60556	63438
2031	222464	227754	233045	170926	176613	182300	70907	74450	77992
2032	227868	233663	239458	194185	200646	207107	85118	89370	93623
2033	233271	239571	245872	214832	221980	229128	100165	105169	110173
2034	238673	245480	252287	232045	239765	247486	115897	121688	127478
2035	244074	251388	258702	245136	253292	261449	132159	138762	145365
2036	249475	257297	265118	253585	262022	270459	148787	156221	163654
2037	254876	263205	271535				165616	173890	182164
2038	260276	269114	277952				182476	191593	200709
2039	265675	275022	284369				199200	209152	219104
2040	271075	280931	290786				215621	226393	237165
2041	276474	286839	297204				231574	243143	254712
2042	281874	292747	303621				246899	259235	271570
2043	287273	298656	310039				261445	274507	287569
2044	292671	304564	316457				275066	288808	302550
2045	298070	310473	322875				287625	301994	316364
2046	303469	316381	329294				298997	313934	328872
2047	308868	322290	335712				309068	324509	339950
2048	314266	328198	342131				317738	333612	349486
2049	319664	334107	348549				324920	341153	357386
2050	325063	340015	354968				330543	347056	363570
2051	330461	345924	361386				334549	351263	367977

4.4 Numerical Example

Let's assume that the analysis is made for fifteen years. Prediction period will be d=180. If it is desired to determine the number of EVs for the last month of the tenth year, t = 120. Let CVN_L, CVN_M ve CVN_U be the number of conventional means in period t for lower, medium, and upper bounds.

$CVN_L = 171376 + 448.468$x120=225192

$CVN_M = 171376 + 492.316$x120=230453

$CVN_U = 171376 + 536.164$x120=235715

Let the number of EVs in the target period be EVN_L, EVN_M and EVN_U for the lower, medium and upper bounds.

$$EVN_L = 235715\frac{\sin\left(3\left(\frac{120}{180}+\frac{\pi}{2}\right)+1\right)}{2} = 159207$$

$$EVN_m = 230453\frac{\sin\left(3\left(\frac{120}{180}+\frac{\pi}{2}\right)+1\right)}{2} = 162927$$

$$EVN_u = 235715\frac{\sin\left(3\left(\frac{120}{180}+\frac{\pi}{2}\right)+1\right)}{2} = 166647$$

Electricity consumption in period t is TC_t, the number of EVs in traffic is EVN_t and total electricity consumption in period t is calculated using ETC_t Eq.14.

$$ETC_t = \frac{3.7\text{x}6\text{x}EVN_t}{24x1000} + TC_t \quad (14)$$

Let the order of consumption amounts be ETC_L, ETC_M ve ETC_U for the lower, medium, and upper bound after the charge load of EVs is included in the system, with the total electricity consumption amount in the period ($t = 120$) being 137.5499 MWh.

$$ETC_L = \frac{3.7\text{x}6\text{x}159207}{24x1000} + 137.549 = 284.8$$

$$ETC_M = \frac{3.7\text{x}6\text{x}162927}{24x1000} + 137.549 = 288.2$$

$$ETC_M = \frac{3.7\text{x}6\text{x}166647}{24x1000} + 137.549 = 291.6$$

The total population in the period ($t = 120$) $P\_L = 606348$, $P\_M = 662471$ and $P\_U = 718595$, per capita electricity consumption amount for lower, medium, and upper bound Q_L, Q_M and Q_U are calculated as follows.

$Q_L = 284.8/606348 = 19\, x10^{-3}$

$Q_M = 288.2/662471 = 44x10^{-5}$

$Q_U = 291.6/718595 = 41x10^{-5}$

With line length L_L=14900, L_M=17808 and L_U=20716, the distributed load distribution for lower, medium, and upper bound J_L, J_M and J_U is calculated as follows.

$$J_L = \frac{606348x47x10^{-5}}{14900} = 19\, x10^{-3} \text{ MWh/km}$$

$$J_M = \frac{662471x44x10^{-5}}{17808}x1000 = 16\, x10^{-3} \text{ MWh/km}$$

$$J_U = \frac{718595x41x10^{-5}}{20716}\, x1000 = 14x10^{-3} \text{ MWh/km}$$

The installed transformer capacity in the period (t=120) $\text{TCa}_L = 2605$, $\text{TCa}_M = 4253$ and $\text{TCa}_U = 5902$ for lower, medium and upper bound are calculated as below for R_L, R_M and R_U for lower, medium and upper bound.

$$R_L = \frac{\text{ETC}_L}{\text{TCa}_L} = \frac{284.8}{2605} = 10x10^{-2} \text{ MWh/MWA}$$

$$R_M = \frac{\text{ETC}_M}{\text{TCa}_M} = \frac{288.2}{4253} = 6x10^{-2} \text{ MWh/MWA}$$

$$R_U = \frac{\text{ETC}_U}{\text{TCa}_U} = \frac{291.6}{5902} = 4x10^{-2} \text{ MWh/MWA}$$

Installed transformer capacity (TCa), totally consumed energy (ETC) for lower, medium, and upper bound, and transformer capacity ratio (R) are calculated as follows.

4.5 Comparison of Scenario

When comparing scenarios according to J value, $-L$ suffix represents the lower bound, $-M$ suffix represents medium bound, and $-U$ suffix represents the upper bound. The NCJ prefix represents the grid J value under normal conditions where EVs do not have a charging load. Scenarios starting with S are the scenarios where the system load of EVs is taken into account. $NCJ - L$ represents the lower bound of the network J value under normal conditions, $NCJ - M$ represents the medium bound of the network J value under normal conditions, and N$CJ - U$ represents the upper bound of the network J value under normal conditions. The generating scenarios are presented in Table 9 for CVN and line length.

Table 8. CVN and Line Length for scenarios

Scenario	CVN	Line Length	Scenario	CVN	Line Length
S1J-L	170918	14900	S4J-L	332931	14900
S1J-M	171877	14900	S4J-M	348628	14900
S1J-U	172836	14900	S4J-U	364324	14900
S2J-L	170918	17808	S5J-L	332931	17808
S2J-M	171877	17808	S5J-M	348628	17808

Table 10 (continue)

Scenario	CVN	Line Length	Scenario	CVN	Line Length
S2J-U	172836	17808	S5J-U	364324	17808
S3J-L	170918	20716	S6J-L	332931	20716
S3J-M	171877	20716	S6J-M	348628	20716
S3J-U	172836	20716	S6J-U	364324	20716

The J values calculated based on the scenarios created for the 15-year planning period are presented in Appendix-1. The comparative graph of the network J value under normal conditions and the scenario-based J values for the 15-year planning period is presented in Figure 9. Annual average data of J values for the 15-year planning period are presented in Table 10. $S3J-U$ scenario J value exceeded $NCJ-M$ value at I_1 the intersection between 2024-2025 and NCJ-L value at I_3 the intersection between 2026-2027. $S3J-M$, $S2J-M$ and $S1J-M$ scenarios J value exceeded $NCJ-L$ value at I_2 the intersection between 2024-2025.

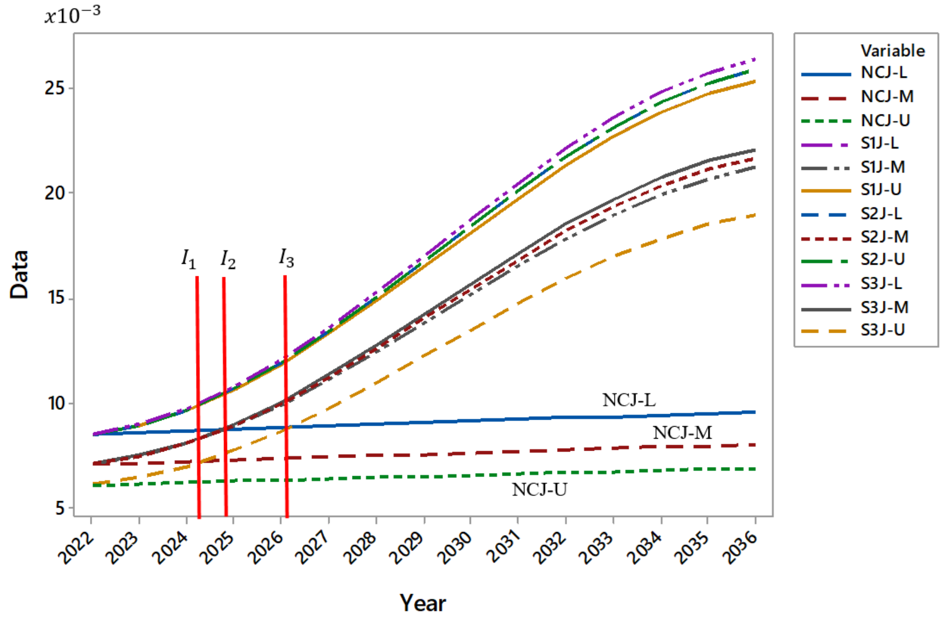

Figure 9. S_1, S_2, S_3 scenarios NCJ comparison chart for 15-year planning period

Table 9. J value for 15 in year (annual average)

Year	NCJ-L	NCJ-M	NCJ-U	S1J-L	S1J-M	S1J-U	S2J-L	S2J-M	S2J-U	S3J-L	S3J-M	S3J-U
2022	8.5	7.1	6.1	8.5	7.1	6.1	8.5	7.1	8.5	8.5	7.1	8.5
2023	8.6	7.2	6.2	8.6	7.2	6.2	8.9	7.5	8.9	9.0	7.5	9.0
2024	8.6	7.2	6.2	8.6	7.2	6.2	9.7	8.1	9.7	9.7	8.1	9.7
2025	8.7	7.3	6.3	8.7	7.3	6.3	10.6	8.9	10.6	10.7	9.0	10.7
2026	8.8	7.4	6.3	8.8	7.4	6.3	11.9	9.9	11.9	12.0	10.0	12.0
2027	8.9	7.4	6.4	8.9	7.4	6.4	13.3	11.1	13.3	13.4	11.2	13.4
2028	9.0	7.5	6.4	9.0	7.5	6.4	14.9	12.4	14.9	15.1	12.6	15.1
2029	9.0	7.6	6.5	9.0	7.6	6.5	16.5	13.8	16.5	16.8	14.0	16.8
2030	9.1	7.6	6.6	9.1	7.6	6.6	18.2	15.2	18.2	18.5	15.5	18.5
2031	9.2	7.7	6.6	9.2	7.7	6.6	19.8	16.6	19.8	20.2	16.9	20.2

Table 12 (continue).

Year	NCJ-L	NCJ-M	NCJ-U	S1J-L	S1J-M	S1J-U	S2J-L	S2J-M	S2J-U	S3J-L	S3J-M	S3J-U
2032	9.3	7.8	6.7	9.3	7.8	6.7	21.3	17.9	21.3	21.7	18.2	21.7
2033	9.4	7.8	6.7	9.4	7.8	6.7	22.7	19.0	22.7	23.2	19.4	23.2
2034	9.5	7.9	6.8	9.5	7.9	6.8	23.9	20.0	23.9	24.3	20.4	24.3
2035	9.5	8.0	6.9	9.5	8.0	6.9	24.8	20.7	24.8	25.3	21.1	25.3
2036	9.6	8.0	6.9	9.6	8.0	6.9	25.4	21.2	25.4	25.9	21.7	25.9

The J values calculated based on the scenarios created for the 30-year planning period are presented in Annex-2. The comparative graph of the network J value under normal conditions and the scenario-based J values for the 30-year planning period is presented in Figure 10. Annual average data of J values for the 30-year planning period are presented in Table 11. Upper scenarios J value exceeded NCJ-M value at I_4 the intersection between 2025-2026 and NCJ-L value at I_6 the intersection between 2029-2030. Medium scenarios exceeded NCJ-L at I_5 the intersection between 2026-2027.

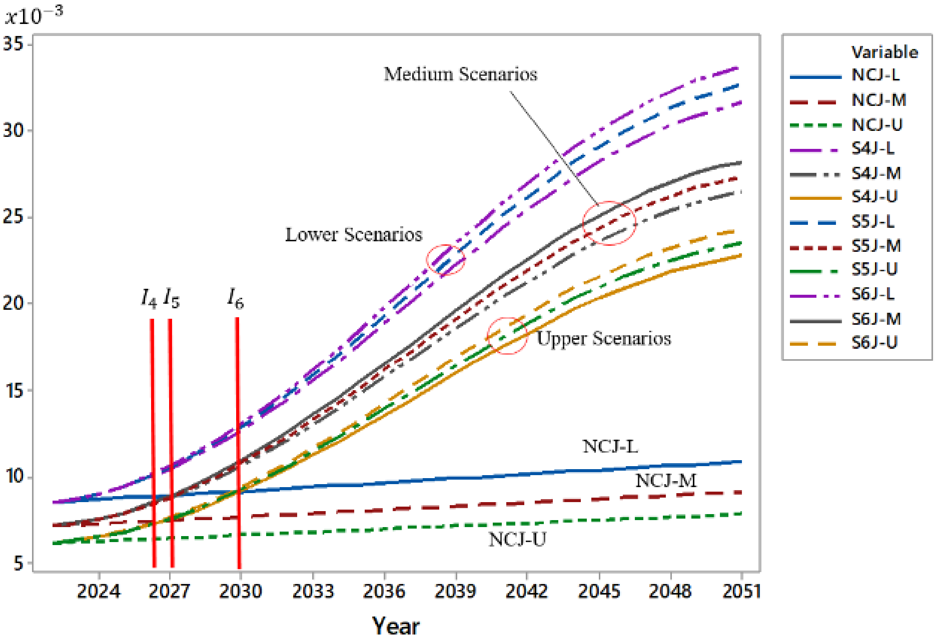

Figure 10. S_4, S_5, S_6 scenarios NCJ comparison chart for the 30-year planning period

Table 11. *J* value for spreading in 30 year

Year	NCJ-L	NCJ-M	NCJ-U	S4J-L	S4J-M	S4J-U	S5J-L	S5J-M	S5J-U	S6J-L	S6J-M	S6J-U
2022	8.5	7.1	6.1	8.5	7.1	6.1	8.5	7.1	6.1	8.5	7.1	6.1
2023	8.6	7.2	6.2	8.7	7.3	6.2	8.7	7.3	6.3	8.7	7.3	6.3
2024	8.6	7.2	6.2	9.0	7.5	6.5	9.0	7.5	6.5	9.0	7.5	6.5
2025	8.7	7.3	6.3	9.4	7.8	6.7	9.4	7.9	6.8	9.4	7.9	6.8
2026	8.8	7.4	6.3	9.9	8.2	7.1	9.9	8.3	7.1	10.0	8.3	7.2
2027	8.9	7.4	6.4	10.4	8.7	7.5	10.5	8.8	7.6	10.6	8.9	7.6
2028	9.0	7.5	6.4	11.1	9.3	8.0	11.2	9.4	8.1	11.3	9.5	8.2

Table 13(continue).

Year	NCJ-L	NCJ-M	NCJ-U	S4J-L	S4J-M	S4J-U	S5J-L	S5J-M	S5J-U	S6J-L	S6J-M	S6J-U
2029	9.0	7.6	6.5	11.9	9.9	8.5	12.0	10.1	8.6	12.2	10.2	8.7
2030	9.1	7.6	6.6	12.7	10.6	9.1	12.9	10.8	9.3	13.1	10.9	9.4
2031	9.2	7.7	6.6	13.6	11.4	9.8	13.8	11.6	9.9	14.1	11.8	10.1
2032	9.3	7.8	6.7	14.6	12.2	10.5	14.8	12.4	10.7	15.1	12.6	10.9
2033	9.4	7.8	6.7	15.6	13.0	11.2	15.9	13.3	11.4	16.2	13.6	11.7
2034	9.5	7.9	6.8	16.6	13.9	12.0	17.0	14.2	12.2	17.4	14.5	12.5
2035	9.5	8.0	6.9	17.7	14.8	12.8	18.1	15.2	13.1	18.6	15.5	13.3
2036	9.6	8.0	6.9	18.9	15.8	13.6	19.3	16.2	13.9	19.8	16.5	14.2
2037	9.7	8.1	7.0	20.0	16.7	14.4	20.5	17.1	14.7	21.0	17.6	15.1
2038	9.8	8.2	7.0	21.1	17.7	15.2	21.7	18.1	15.6	22.2	18.6	16.0
2039	9.9	8.2	7.1	22.2	18.6	16.0	22.8	19.1	16.4	23.5	19.6	16.9
2040	9.9	8.3	7.1	23.3	19.5	16.8	24.0	20.1	17.3	24.7	20.6	17.7
2041	10.0	8.4	7.2	24.4	20.4	17.5	25.1	21.0	18.1	25.8	21.6	18.6
2042	10.1	8.5	7.3	25.4	21.3	18.3	26.2	21.9	18.8	27.0	22.6	19.4
2043	10.2	8.5	7.3	26.4	22.1	19.0	27.2	22.8	19.6	28.0	23.5	20.2
2044	10.3	8.6	7.4	27.3	22.9	19.7	28.2	23.6	20.3	29.0	24.3	20.9
2045	10.3	8.7	7.4	28.2	23.6	20.3	29.1	24.3	20.9	30.0	25.1	21.6
2046	10.4	8.7	7.5	29.0	24.3	20.8	29.9	25.0	21.5	30.8	25.8	22.2
2047	10.5	8.8	7.6	29.7	24.8	21.4	30.7	25.6	22.0	31.6	26.4	22.7
2048	10.6	8.9	7.6	30.3	25.4	21.8	31.3	26.2	22.5	32.3	27.0	23.2
2049	10.7	8.9	7.7	30.8	25.8	22.2	31.8	26.6	22.9	32.9	27.5	23.6
2050	10.8	9.0	7.7	31.3	26.2	22.5	32.3	27.0	23.2	33.3	27.9	24.0
2051	10.8	9.1	7.8	31.6	26.4	22.7	32.6	27.3	23.5	33.7	28.2	24.2

The R values calculated based on the scenarios created for the 15-year planning period are presented in Annex-3. The comparative graph of the R value under normal conditions and the R values on a scenario basis for the 15-year planning period is presented in Figure 11. Annual average data of R values for the 15-year planning period are presented in Table 12. Upper scenarios R value decreased below the $NCR-M$ value at the I_7 the intersection between 2024-2025 and below the $NCR-L$ value at the I_9 the intersection between 2031-2032. Medium scenarios fell below the $NCR-L$ value at the I_8 the intersection between 2025 and 2026.

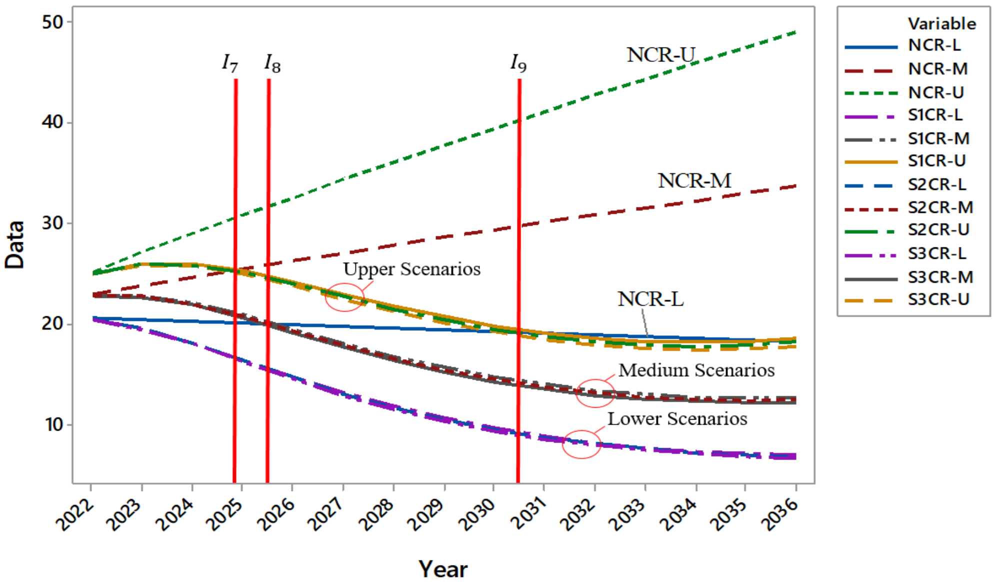

Figure 11. S_1, S_2, S_3 scenarios NCR comparison chart for the 15-year planning period

Table 14. Ratio to transformer capacity (R) to total conception for spreading in 15 year

Year	NCR-L	NCR-M	NCR-U	S1CR-L	S1CR-M	S1CR-U	S2CR-L	S2CR-M	S2CR-U	S3CR-L	S3CR-M	S3CR-U
2022	20.56	22.88	25.19	20.43	22.72	25.02	20.42	22.72	25.02	20.42	22.71	25.01
2023	20.39	23.74	27.09	19.53	22.74	25.94	19.50	22.70	25.91	19.48	22.67	25.87
2024	20.22	24.59	28.96	18.11	22.03	25.94	18.05	21.95	25.85	17.99	21.88	25.77
2025	20.04	25.42	30.80	16.44	20.85	25.26	16.34	20.73	25.11	16.25	20.61	24.97
2026	19.87	26.24	32.60	14.74	19.47	24.19	14.62	19.30	23.98	14.49	19.14	23.78
2027	19.70	27.04	34.38	13.16	18.07	22.97	13.02	17.87	22.72	12.88	17.68	22.48
2028	19.53	27.83	36.12	11.77	16.77	21.78	11.62	16.56	21.49	11.47	16.34	21.22
2029	19.36	28.60	37.83	10.60	15.65	20.70	10.44	15.42	20.40	10.29	15.19	20.10
2030	19.20	29.36	39.52	9.62	14.71	19.80	9.46	14.47	19.48	9.31	14.24	19.17
2031	19.04	30.10	41.17	8.83	13.96	19.09	8.68	13.72	18.76	8.53	13.48	18.44
2032	18.88	30.84	42.79	8.20	13.39	18.59	8.05	13.15	18.24	7.90	12.91	17.91
2033	18.73	31.56	44.39	7.71	12.99	18.27	7.56	12.74	17.92	7.42	12.50	17.59
2034	18.58	32.27	45.96	7.34	12.75	18.16	7.20	12.50	17.80	7.06	12.26	17.46
2035	18.43	32.96	47.50	7.08	12.66	18.24	6.94	12.41	17.88	6.80	12.16	17.53
2036	18.28	33.65	49.02	6.91	12.72	18.53	6.77	12.46	18.16	6.64	12.22	17.79

The R values calculated based on the scenarios created for the 30-year planning period are presented in Annex-3. The comparative graph of the R value under normal conditions and the R values on a scenario basis for the 30-year planning period is presented in Figure 12. Annual average data of R values for the 30-year planning period are presented in Table 13. Upper scenarios R value fell below the $NCR-M$ value at the $I_{10} the$ intersection between 2028-2030. Medium scenarios fell below the $NCR-L$ value at the I_{10} the intersection between 2032 and 2033.

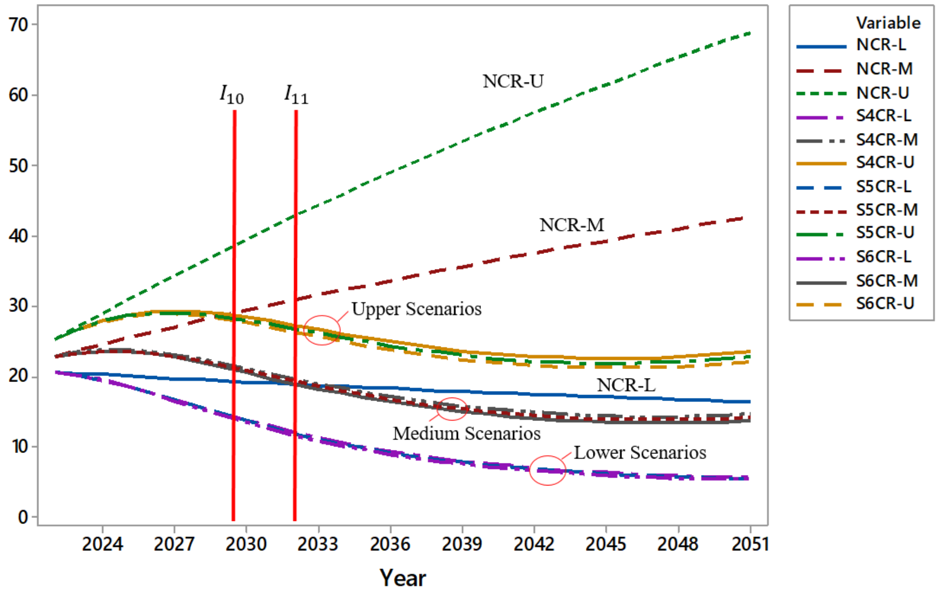

Figure 12. S_4, S_5, S_6 scenarios NCR comparison chart for 30-year planning period

Table 15. Ratio to transformer capacity to total conception for spreading in 30 year

Year	NCR-L	NCR-M	NCR-U	S4CR-L	S4CR-M	S4CR-U	S5CR-L	S5CR-M	S5CR-U	S6CR-L	S6CR-M	S6CR-U
2022	20.56	22.88	25.19	20.52	22.83	25.13	20.52	22.82	25.13	20.52	22.82	25.13
2023	20.39	23.74	27.09	20.10	23.40	26.70	20.09	23.39	26.68	20.07	23.37	26.66
2024	20.22	24.59	28.96	19.47	23.68	27.88	19.43	23.63	27.83	19.40	23.59	27.78
2025	20.04	25.42	30.80	18.66	23.67	28.68	18.60	23.59	28.58	18.54	23.51	28.48
2026	19.87	26.24	32.60	17.74	23.43	29.12	17.65	23.31	28.96	17.56	23.18	28.81
2027	19.70	27.04	34.38	16.76	23.00	29.24	16.63	22.83	29.03	16.51	22.66	28.81
2028	19.53	27.83	36.12	15.74	22.43	29.12	15.59	22.22	28.84	15.45	22.01	28.57
2029	19.36	28.60	37.83	14.74	21.78	28.81	14.57	21.52	28.47	14.40	21.27	28.14
2030	19.20	29.36	39.52	13.78	21.07	28.36	13.59	20.78	27.97	13.40	20.49	27.58
2031	19.04	30.10	41.17	12.87	20.35	27.83	12.67	20.02	27.38	12.47	19.71	26.96
2032	18.88	30.84	42.79	12.02	19.63	27.25	11.81	19.28	26.76	11.60	18.95	26.29
2033	18.73	31.56	44.39	11.24	18.94	26.65	11.02	18.57	26.12	10.81	18.22	25.62
2034	18.58	32.27	45.96	10.53	18.29	26.05	10.31	17.90	25.50	10.09	17.53	24.97
2035	18.43	32.96	47.50	9.89	17.68	25.48	9.66	17.28	24.91	9.45	16.90	24.36
2036	18.28	33.65	49.02	9.30	17.13	24.95	9.08	16.72	24.35	8.87	16.33	23.78
2037	18.13	34.32	50.51	8.78	16.62	24.46	8.56	16.20	23.85	8.35	15.81	23.26
2038	17.99	34.98	51.97	8.32	16.17	24.02	8.10	15.75	23.39	7.89	15.34	22.80
2039	17.85	35.63	53.41	7.90	15.77	23.64	7.69	15.34	23.00	7.48	14.94	22.39
2040	17.71	36.27	54.83	7.53	15.42	23.31	7.32	14.99	22.66	7.12	14.58	22.04
2041	17.58	36.90	56.23	7.20	15.12	23.03	6.99	14.68	22.38	6.80	14.28	21.75
2042	17.44	37.52	57.60	6.91	14.87	22.82	6.71	14.43	22.15	6.52	14.02	21.52
2043	17.31	38.13	58.95	6.66	14.66	22.66	6.46	14.22	21.99	6.27	13.81	21.35
2044	17.18	38.73	60.28	6.43	14.50	22.57	6.24	14.06	21.88	6.05	13.65	21.24
2045	17.05	39.32	61.59	6.24	14.38	22.53	6.05	13.94	21.84	5.87	13.53	21.19
2046	16.93	39.90	62.88	6.07	14.31	22.55	5.88	13.87	21.85	5.71	13.45	21.19
2047	16.80	40.47	64.15	5.93	14.28	22.63	5.74	13.83	21.92	5.57	13.41	21.26
2048	16.68	41.04	65.39	5.81	14.29	22.77	5.63	13.84	22.06	5.46	13.42	21.38
2049	16.56	41.59	66.62	5.71	14.35	22.98	5.53	13.89	22.25	5.36	13.47	21.57
2050	16.45	42.14	67.84	5.64	14.44	23.25	5.46	13.98	22.51	5.29	13.55	21.82
2051	16.33	42.68	69.03	5.58	14.58	23.59	5.40	14.12	22.84	5.24	13.69	22.13

5. CONCLUSION AND FUTURE WORKS

With advances in technology new era has started in car manufacturing. People tend to have more environmentally friendly cars instead of conventional cars. EVs offer a cleaner technology by reducing noise and air pollution. The unexpected rapid increase in EVs causes considerable differences in electricity supply and demand, creating voltage imbalance and power losses on the grid.

In this study, a new model to be used to determine the load that the increase in the number of EVs will bring to the power grid is proposed, and the model's parameters are inspected. The data regarding the number of consumers, line length, and transformer installed power between 2013 and 2020 and provided by Çamlıbel Elektrik Dağıtım Corp. were recruited to determine the parameter coefficients. The population of Sivas, the number of conventional vehicles, transformer capacity, distribution line length, and electrical energy consumption between 2022 and 2052 were predicted. The spreading of EVs was determined using the spreading model (see section 3.3) and the conventional vehicle number. Six different scenarios were prepared for the different cases of the number of conventional vehicles, transformer capacity, distribution line length, and electrical energy consumption between 2022 and 2052

With the spread of EVs in line with the proposed model in the 15-year planning horizon, the J value on the grid will exceed the current value between 2024 and 2025 in the best case. This means that the electrical power transmitted with the existing lines will increase. With the spread of EVs in line with the proposed model in the 30-year planning horizon, the J value on the grid will exceed the current value between 2029 and 2030 in the best case. This means that the electrical load transmitted by existing lines will increase between 2029 and 2030. As the *R* value used for evaluating the transformer capacity becomes widespread in line with the proposed model in the 15-year planning horizon, the *R* value will fall below the current value between 2031 and 2032 in the best case. This means that the current transformer capacity will be insufficient between 2031 and 2032 in the best scenario. With the spread of EVs in line with the proposed model in the 30-year planning horizon, the *R* value will fall below the current value between 2032 and 2033 in the best case. This means that the current transformer capacity will be insufficient between 2032 and 2033 in the best scenario.

Electricity distribution companies allow EVs to become widespread in their investment plans. In this study, with the widespread use of EVs, the value of J, which shows the distributed power value in the network, and *R*, the ratio of transformer capacity to consumption, are analyzed in the Sivas province case. The study is innovative in analyzing the loads on the network, which is one of the critical problems in the spread of EVs within the scope of the study, a new mathematical equation has been proposed for EVs to replace conventional vehicles.

Future studies can be expanded by using data on electricity consumption, the number of vehicles, and transformer capacity across the country. In addition, changes in agricultural irrigation and industrial consumption that affect electricity consumption can be considered in future studies. In estimation, techniques such as artificial neural networks can be used instead of time series.

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

M. Tarık ÇAKIR: Collected data from relevant institutions and performed statistical analysis. Wrote the manuscript.

Musa Faruk ÇAKIR: Performed the experiments and analyse the results. Wrote the manuscript and check the analysis.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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