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Research Article

Estimation of the Effect of Electric Vehicles on the Aging of Distribution Transformers Using Fuzzy Logic

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Abstract— **Depending on industrialization and technological advancements worldwide, the demand for electrical energy, recognized as clean and dependable energy, is on the rise. Presently, electric energy consumption has notably increased alongside the rise in Electric Vehicles (EVs). The surge in EVs necessitates a thorough examination of the situation, anticipating the widespread adoption of Electric Vehicle Fast Charging Stations (EVFCS) in the near future and the subsequent escalation of their adverse impact on the grid. To mitigate these negative effects on the grid, proactive measures are essential. EVs function as capacitive loads due to their battery composition, and the harmonics produced during their grid connection detrimentally affect the quality of grid electricity, leading to constraints. Furthermore, the escalating EVFCS loads resulting from the rapid growth in EV numbers distribute the burden on distribution networks, posing a threat to network adequacy and reliability. Therefore, integrating EVFCS with distribution and generation units to minimize overloading, additional losses, and voltage fluctuations in the grid will enhance the efficiency of both systems. In addition, each EVFCS is only connected to the distribution transformer assigned to it or to the distribution transformers considered suitable in the city. Depending on the current drawn by one or more EVFCS linked to the feeder of each transformer, it can lead to overloading in transformers and chemical changes in windings and oils, resulting in the aging of transformers. In this context, a Fuzzy Logic (FL) based estimation is conducted to assess the impact of EVs' charging loads on transformer aging. The FL method utilizes transformer current load, EVFCS load, transformer temperature, and harmonic power quality data. The data utilized are derived from statistical information about a local distribution network and measured values from a feeder, and the aging effects on EVFCS distribution transformers are examined.**

Index Terms— **Distribution network, fuzzy logic, distribution transformers, transformer aging, electric vehicle fast charging station.**

I. INTRODUCTION

IN ORDER to reduce carbon emissions and phase out dependence on oil, conventional engine technologies must be replaced with more efficient and environmentally friendly alternatives [1]. EVs have emerged as a solution to mitigate the negative impacts of traditional cars. EVs undergo fewer energy conversions and experience less energy loss compared to gas-powered vehicles. One of the primary motivations for producing EVs is to curb greenhouse gas emissions and harmful gases that contribute to global warming [2-4]. While the growing adoption of EVs to replace internal combustion engine vehicles decreases carbon dioxide emissions, it also presents challenges. The time needed for full EV charging can be up to 30 hours for home charging, known as Level-1 charging. Home charging typically requires overnight charging, while at regular charging stations it takes 2 to 4 hours; especially for EV fast charging stations designed for long distances, this time is reduced to 30 minutes [5-9]. Furthermore, EVs impact the reliability of the electricity distribution network by introducing uncertain loads on the grid based on battery levels. Charging EVs during peak hours increases the overall energy demand on transformers, potentially leading to transformer overload and degradation of their electromechanical structure and electrical quality [10, 11]. Overloading a transformer leads to an increase in the temperature of its windings and oil. Additionally, the induction flux of the scattered magnetic field rises, causing a surge in eddy currents that heat up and harm the transformer. This scenario is influenced by the current level and temperature, hastening the aging process of the transformer. Moreover, harmonic distortions manifest in the electrical energy system in conjunction with these circumstances [12]. Numerous studies have been conducted to maintain distribution network parameters within specified limits [13, 14]. These studies reveal the application of probabilistic power flow, utilization of various probabilistic models, and execution of stochastic analyses [15-17]. Furthermore, the impact of EVs on distribution networks has been explored; adverse effects such as loading, heating, and aging of transformers have been scrutinized, with assessments made regarding total power loss in the system, the network voltage's adherence to desired levels, voltage instability, and voltage stability [18-24]. The connection of nonlinear loads results in the intake of nonlinear currents into the distribution network, thereby distorting the system's voltage [24, 26]. The primary cause of harmonic distortion in a power distribution system is the increase in power losses, transformer degradation, and potential equipment failure due to temperature elevation [27, 28]. Based on the findings of 130 analyses conducted on a 150 kV power transformer in Indonesia, the aging state of the transformer was compared with its actual age. The determination of the apparent

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age and aging condition of the transformer was performed using the Health Index Method [29]. Furthermore, a novel intelligent charging algorithm that controls the PEV through the Monte Carlo method was also investigated to assess the impact of plug-in electric vehicle (PEV) charging on the overhead load under various scenarios aimed at mitigating distribution transformer overloading. The influence of ambient temperatures on the distribution transformer was examined, revealing that PEVs can significantly decrease the thermal aging of the transformer through the implementation of intelligent charging strategies [30]. Another study concluded that electrical and thermal aging in transformers not only leads to rapid transformer failures but also results in degradation of transformer oil. Research has been conducted on the recycling of transformer oil [31-34].

In this study, unlike other studies, using transformer data from an existing real HV/LV distribution network, the changes in power, harmonics, load, and temperature values of distribution transformers in a newly modelled network [25] created by the default EVFCS are analyzed with fuzzy logic (FL). When EVFCS is connected to the normal network, the changes in the transformer are compared. The aging rate of the transformer is investigated.

II. MATERIAL AND METHOD

A. Model distribution network

Istanbul Province has 4 units of 1600 kVA HV/LV transformers connected to Kavacik and Umraniye step-down transformers at various HV levels. These are situated on the lower feeders of the 380/34.5 kV and 125 MVA transformer, supplying the distribution network. Additionally, there are units of 1600 kVA HV/LV transformers on the lower feeders of the 154/34.5 kV and 125 MVA transformer. The technical details of the transformers and default EVFCS load data of a semi-ring network with 3 HV/LV transformer feeders of 1000 kVA and 1 HV/LV transformer feeder of 1600 kVA at the 34.5/0.4 kV level through a coupling breaker were employed. Figure 1 depicts a single-line diagram of the existing network [25].

B. Distribution network data

Existing urban distribution networks are heavily loaded based on consumer density. Furthermore, the integration of EVFCS leads to an increase in the network's loading rate on the

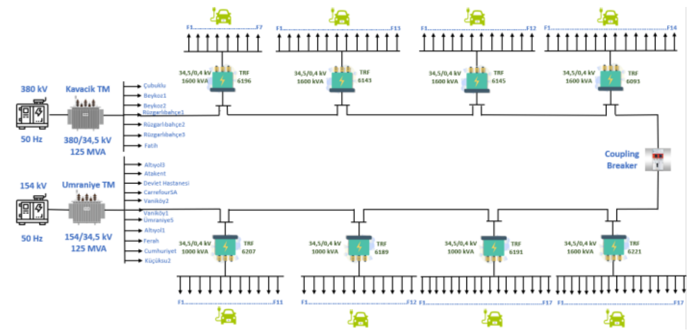


Fig.1. Single line diagram of the selected distribution network

transformer, distributed according to the Electric Vehicle's battery charge. Figure 2.a illustrates the grid's loading status with the connection of EVFCS. Moreover, with the growing number of EVFCS, overloading occurs beyond a certain power threshold, resulting in phase imbalances. Analyzing the battery capacities of EVs reveals the impact of harmonics on the system as sinusoidal disturbances, which vary quadratically due to other influencing factors. Since EVs from different manufacturers have varying capacities, the harmonic effects they generate differ. Figure 2.b demonstrates the shift in the network's harmonic state as the number of EVFCS increases, nearly doubling the fluctuations in the standard network. These increased fluctuations further impact the transformer. In

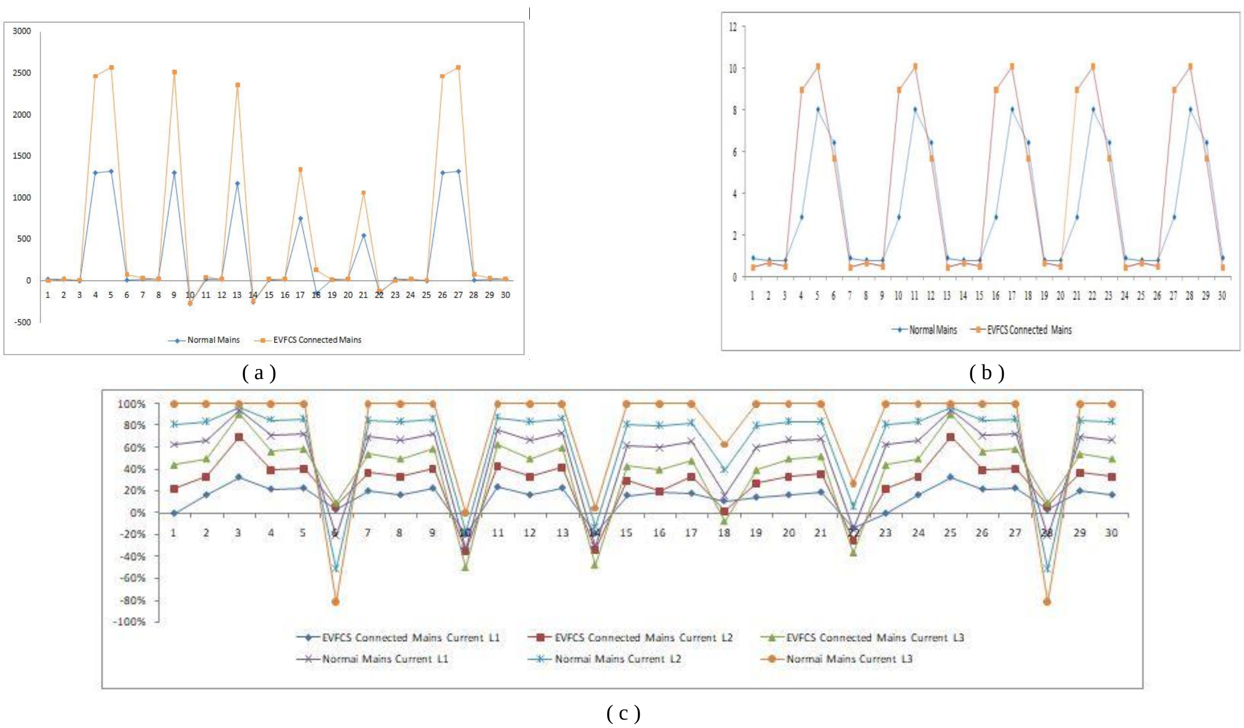


Figure 2. a) Load variation in the network, b) Harmonic variation in the network, c) Graph illustrating the percentage change in network phases when EVFCS is connected to the standard network

addition, when EVs are connected to the charging station, the harmonic loads they generate in the grid result in power losses, leading to adverse effects on charging infrastructure and restricting the number of EVs that can be charged simultaneously. Figure 2.c illustrates the phase variations based on the fluctuation of current drawn from the grid. The imbalance among the phases results in an excessive current draw and subsequent overheating. This rise in temperature will impact the transformer oil and windings, accelerating insulation deterioration, which in turn increases the risk of insulation damage and the likelihood of dielectric failure. Consequently, the transformer experiences wear and aging, making it challenging to manage and minimize losses in aging transformers. Moreover, the phase imbalance caused by the load compels the transformer to consume reactive power, imposing a burden on both the transformer and the network. With the increase in reactive power, the efficiency of both the transformer and the network decreases [25].

C. The FL Method

In this study, transformer aging is analyzed using 4 different input values and 1 output value in the network. The Mamdani fuzzy inference model, a commonly preferred fuzzy model in FL, is utilized. The 4 input values are defined as EVFCS power, network harmonic values, ambient temperature values, and the current load of the distribution network. The desired output value is the aging rate of the transformer, calculated as a percentage. The proposed FL output is illustrated in Figure 3.

For various EVFCSs, EV power (kW), temperature (°C), and grid power load (kW) in each of them are considered inputs to estimate the aging in a given network. The study aims to determine the network output using the input values. Membership functions were established for the input and output

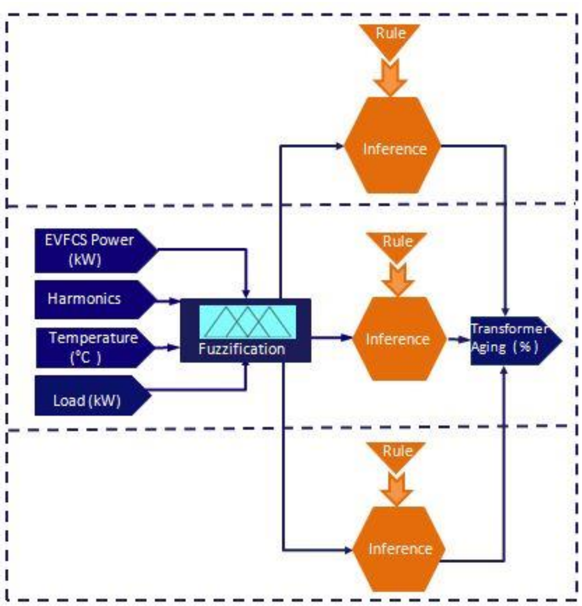


Fig.3. General flow diagram of FL

parameters identified in the FL application. The minimum and maximum values of the membership functions are depicted in Figure 4.a–e.

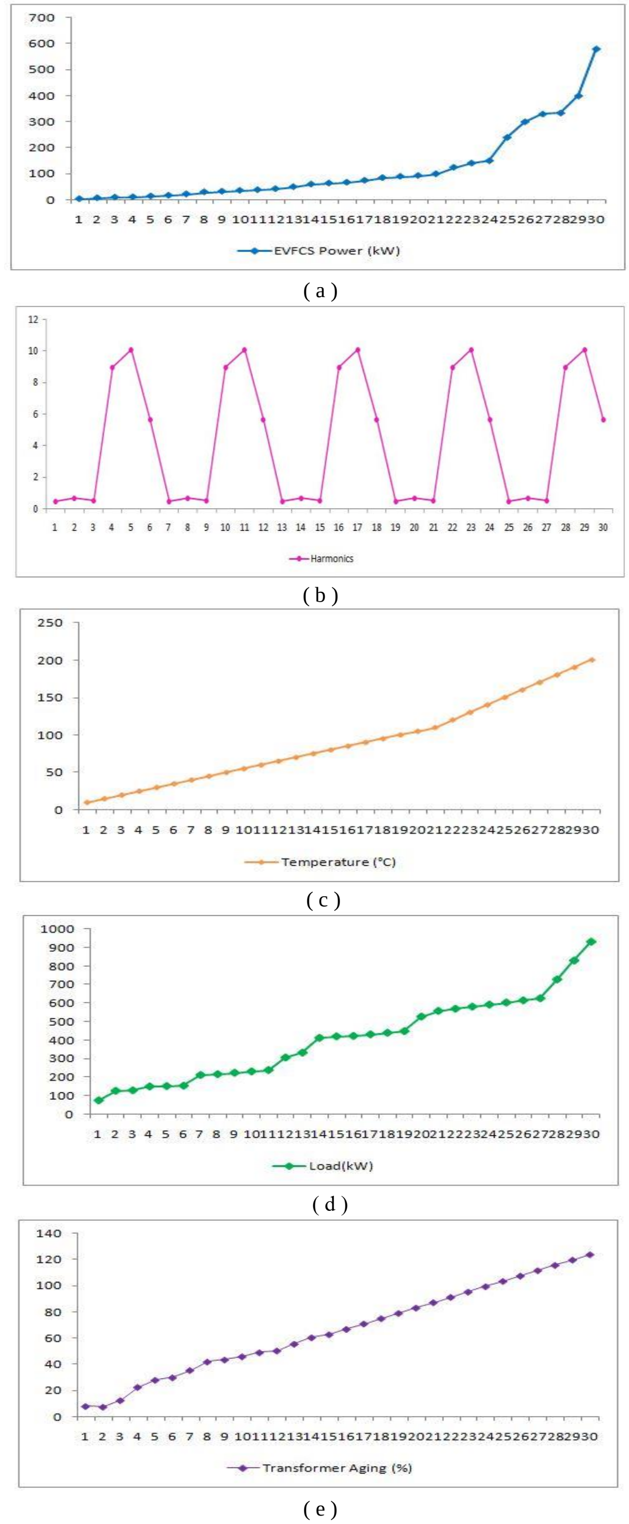


Fig.4. a) EVFCS power (kW), b) Harmonic, c) Temperature (°C), d) Load (kW), e) Graphical representation of membership function values for transformer aging (%)

While creating the membership functions in the parameters used, the membership functions commonly used in the electricity demand forecasting model in the literature were preferred. The membership functions shown in Figures 5–9 define the fuzzy sets Ai and Bi. The triangular membership function in equation (1)-(2) is used for the input and output variables. The clusters defined in the figures are validated with the membership functions in equation (1)-(2) [35, 36].

$$\mu_A = \mu_A(x; a, b, c) = \begin{Bmatrix} \dfrac{(x-a)}{(a-b)} & if & a \le x < b \\ \dfrac{(c-x)}{(c-b)} & if & b \le x \le c \\ 0 & if & x > c \quad or \quad x < a \end{Bmatrix} \quad (1)$$

$$A = \sum_{i}^{n} \mu_{A\frac{(x_i)}{X_i}} \Rightarrow \{(x, \mu_A(x))\}\ x \quad (2)$$

EVFCS power, harmonic, current grid load status inputs, and transformer aging rate output are determined using triangular membership functions, each comprising 7 categories: Very Very Small (VVS), Very Small (VS), Small (S), Normal (N), Big (B), Very Big (VB), and Very Very Big (VVB). Graphical representations of the maximum and minimum values of these membership functions can be found in Figs. 5–7.

The triangular membership function of the temperature parameter consists of 7 groups: Very Very Low (VVL), Very Low (VL), Low (L), Normal (N), High (H), Very High (VH), Very Very High (VVH). The graph showing the values of the

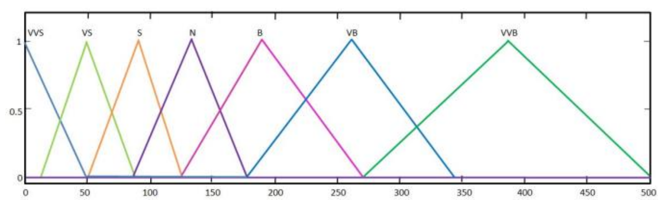


Fig.5. Membership function for the EVFCS power parameter

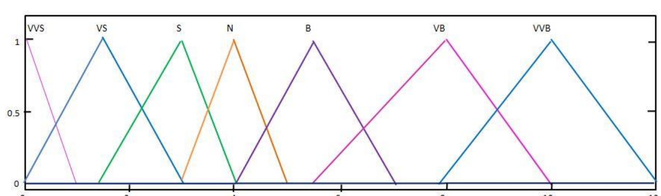


Fig.6. Membership function for the harmonic parameter

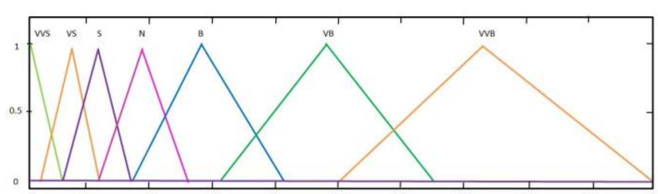


Fig.7. Membership function for the load parameter

membership function for the temperature parameter is shown in Figure 8.

Transformer aging is represented by triangular membership functions, each comprising 7 distinct groups: Very Very Little Aging (VVLA), Very Little Aging (VLA), Little Aging (LA), Normal Aging (NA), Large Aging (LA), Very Large Aging

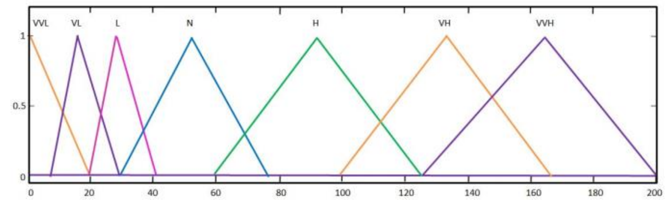


Fig.8. Membership function for the temperature parameter

(VLA), and Very Very Large Aging (VVLA). These categories are visually depicted in Figure 9.

The membership function table defined according to EVFCS, harmonic, current transformer load, and temperature is as defined in Table I.

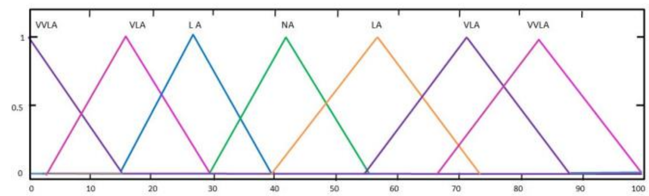


Fig.9. Membership function for the transformer aging parameter

III. FINDINGS AND DISCUSSION

TABLE. I
TABLE OF RULES SHOWING THE EFFECT OF INPUT VALUES ON OUTPUT VALUES

EVFCS Power,Harmonic,Load / Temperature	VVS	VS	S	N	B	VB	VVB
VVL	VVSA	VSA	SA	NA	VBA	VBA	VVBA
VL	VSA	VVSA	VSA	VSA	BA	VBA	VVBA
L	VVSA	VSA	VSA	NA	BA	VBA	VVBA
N	VVSA	VSA	SA	NA	BA	BA	VBA
H	BA	BA	BA	BA	VBA	VVBA	VBBA
VH	VBA	BA	VBA	VBA	VVBA	VBBA	VBBA
VVH	VVBA	VVBA	VVBA	VVBA	VVBA	VVBA	VVBA

In the FL method utilized in this research, rules are established based on the membership functions of the input parameters. The input data ranges from 0 to 1000 as numerical values. However, the adjustment to the range of 0 to 1 is determined through rule-based fuzzification. A total of 196 rules were defined for membership functions based on these 4 inputs and 1 output. Following the definition of these rules in the program, the percentage change in transformer aging was analyzed in relation to the input values of harmonic, temperature (°C), EVFCS power (kW), and grid load (kW).

The 3D graph illustrating aging predictions in the transformer system is displayed in Figure 10. This graph depicts the relationship between input values and output values. The steepness of the blue section indicates that transformer aging

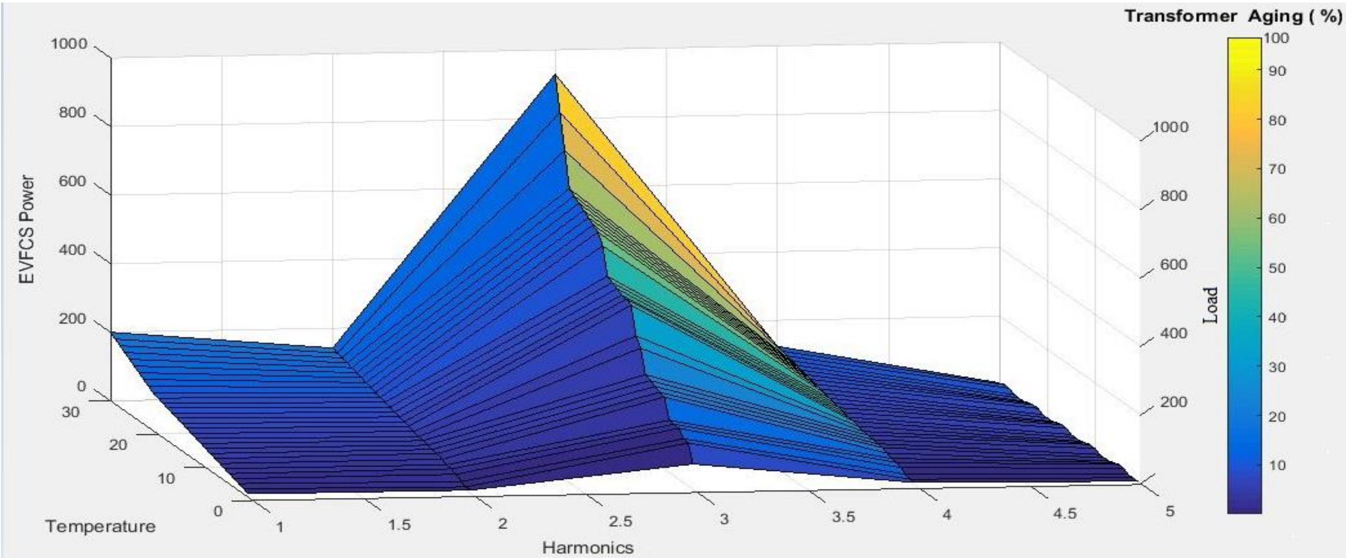
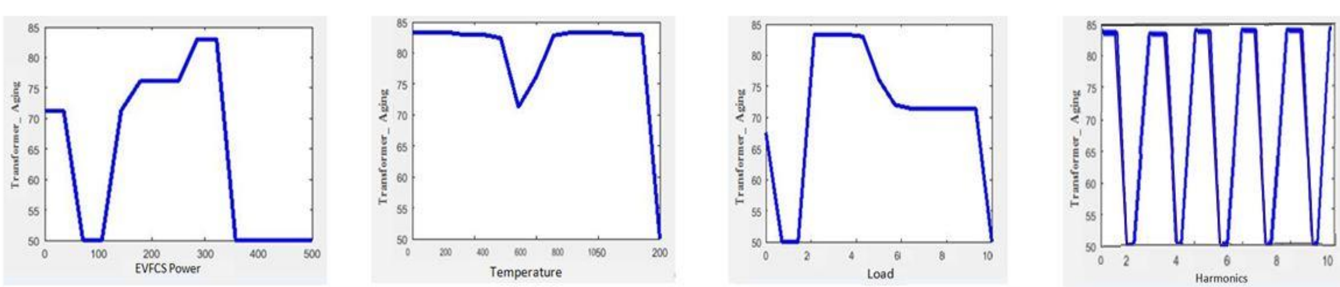


Fig.10. 3D graph of the output obtained according to the input values used in transformer aging

escalates with rising temperatures. Moreover, the heightened intensity of the yellow section suggests that aging in the transformer is influenced by EVFCS power variations. The distortions in the 3D graph, along with the increased yellow intensity, highlight the impact of adding EVFCS power to the load on transformer aging. The presence of distortions in the 3D graphics intensifies with the aging rate of the transformer.

In FL, besides the established membership rules, different output values were obtained through testing with various input values in addition to the defined rules in the image. Figures 11.a–d depict the prediction output graphs of the values utilized as parameters for transformer aging prediction. When diverse input values were tested, a high level of agreement was noted between the prediction outcome and the data acquired in response to the test values. Figure 11.a illustrates the variation in transformer aging based on the EVFCS power commissioned. In Figure 11.b, the transformer maintains a constant temperature. However, with the current drawn from the network, the transformer experiences heating. There is a specific decrease observed. Nevertheless, once the current drawn from the network decreases, the temperature stabilizes after reaching a certain point. Yet, if the temperature surpasses a specific threshold, the aging rate of the transformer escalates, leading to insulation deterioration. If this situation persists, the aging of the transformer will increase, leading to operational failure and necessitating replacement. This is unfavourable due to the associated costs. Figure 11.c illustrates the variation in the transformer's aging rate based on the load. The aging rate of the transformer adjusts according to the load increment. Figure 11.d shows the aging of the transformer due to harmonics. The connection of EVs to the charging station introduces harmonic loads to the grid, resulting in adverse effects. The continuous escalation of harmonic imbalances accelerates the aging process of the transformer, rendering it inoperable. Following numerous tests, the accuracy rate of FL estimation was determined to be 96.973%, in line with the specified criteria. The test verification rate was established at 95.321%. Statistical analysis of the prediction results revealed an error rate of 1.652%. A high degree of similarity was observed between the expected and actual outcomes. The 85th trial yielded results closest to the predictions.

As can be seen from the figures examined, as the number of EVFCS connected to the network increases, the load on the transformer also increases proportionally. Additionally, factors



(a) (b) (c) (d)

Figure 11. Prediction output graphs of the values used for the transformer aging prediction parameter
a)Transformer _Aging- EVFCS, b)Transformer _Aging- Temperature, c) Transformer _Aging- Load d) Transformer _Aging- Harmonics

such as load and temperature contribute to the deterioration of transformer insulation, leading to the drawing of reactive power due to phase imbalances. Overloading results in up to 70% wear and tear on the transformer. The 100 kVA transformers in rural areas are insufficient to support EVFCS connections, necessitating an increase in transformer capacity to prevent overloads. In urban networks, overloads occur when both the network experiences a heavy load and EVFCS are introduced, causing premature aging and rendering the transformers inoperable. The increase in harmonics directly correlates with the accelerated wear and tear on the transformer. This continuous deterioration leads to the aging of the transformer over time, increasing the likelihood of replacement, which is a costly process.

However, with the increase in the rate of EVs used, the income level for EV purchase varies according to location, and although it is necessary in terms of efficiency and environmental impacts, it emerges as an additional burden on the network. Load conditions on the grid vary depending on the synchronization, charging power, and duration of the vehicles. Companies operating the distribution system should consider these situations while planning. It has been known that high and unbalanced currents occur in the phases to which single-phase EVFCS are connected. This situation adversely affects the cable heating, losses, and devices connected to the network due to the unbalanced loading of the lines. This situation is not seen very often in the phases to which the three-phase EVFCS is connected. In addition, if fast charging is used, it will bring much more additional load to the grid, that is, the existing transformer, compared to the normal charging situation, so appropriate studies should be carried out and precautions should be taken.

VI. CONCLUSION

In this study, when the results obtained in the estimation with FL were tested with the given approximate values, it was observed that it was achieved at a rate of 95.321%. 1,652% of the errors were obtained based on the defined rules. As a result of the predictions made by classifying the numerical data according to qualitative characteristics in FL, the accuracy rate in prediction with FL was found to be 96.973%. Thanks to the accurate estimation, the aging rate in the transformer can be reduced by determining the rate of aging in the transformer as a percentage. The study has provided the opportunity to determine the aging rate in transformers as a percentage and offers new suggestions to mitigate the factors influencing aging. One suggestion is that smart grids, where instantaneous grid power flow and the physical condition of transformers can be monitored, should be preferred over existing distribution networks to eliminate the negative effects of EVFCS on the grid. It is believed that this study will make a significant contribution to the literature.

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