POLİTEKNİK DERGİSİ

JOURNAL of POLYTECHNIC

ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE)

URL: http://dergipark.org.tr/politeknik

Regression model extractions of a t-equivalent circuit modeling for medium-length transmission line based-on the parametric simulation approach

Orta uzunlukta iletim hattı için t-eşdeğer devre modellemesinin parametrik benzetim yaklaşımına dayalı regresyon modeli çıkarımları

Yazar(lar) (Author(s)): *Selami BALCI[1], Mustafa AKKAYA*[2]*

ORCID[1]: 0000-0002-3922-4824

ORCID[2]: 0000-0002-8690-921X

To cite to this article: Balci S. ve Akkaya M. "Regression Model Extractions of a T-Equivalent Circuit Modeling for Medium-Length Transmission Line Based-on the Parametric Simulation Approach", ***Journal of Polytechnic***, 27(4): 1649-1658, (2024).

Bu makaleye şu şekilde atıfta bulunabilirsiniz: Balci S., Akkaya M., "Regression Model Extractions of a T-Equivalent Circuit Modeling for Medium-Length Transmission Line Based-on the Parametric Simulation Approach", ***Politeknik Dergisi***, *27(4): 1649-1658, (2024).*

Erişim linki (To link to this article): http://dergipark.org.tr/politeknik/archive

DOI: 10.2339/politeknik.1456959

Regression Model Extractions of a T-Equivalent Circuit Modeling for Medium-Length Transmission Line Based-on the Parametric Simulation

Highlights

- *Regression Model Extractions of a T-Equivalent Circuit Modeling*
- *Data analysis with the end-of-line voltage value graphs obtained with different line parameters*
- *A data set for different variations by changing the line length and line parameters with certain steps*

Graphical Abstract

The parametric data analysis approach proposed in this study obtained a data set for different variations by changing the line length and line parameters with certain steps.

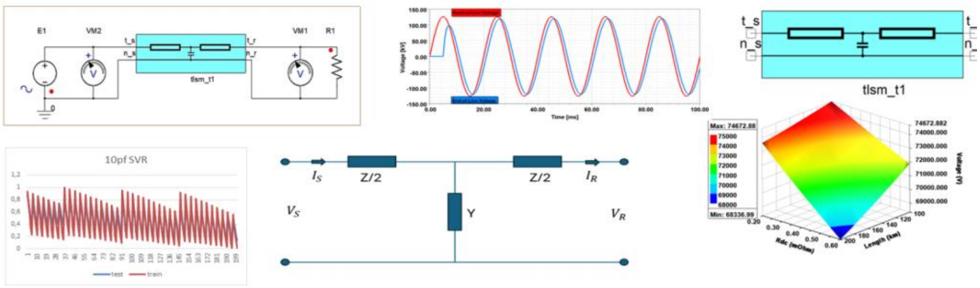

Figure. Regression extractions from the dataset based on parametric simulations

Aim

Modeling of transmission line parameters such as length, resistance, reactance and capacitance of the T equivalent circuit of a medium length 154 kV power transmission line.

Design & Methodology

The simulation circuit used for the T equivalent circuit model and the parameters were changed according to specific line parameter values, and parametric analyses were carried out.

Originality (Özgünlük)

The most important difference of this study is that by changing the line parameters with specific steps, a classification over the data is proposed depending on various variations.

Findings (Bulgular)

The parametric simulation approach can be used to determine the optimum parameter settings of 1-phase and 3-phase overhead transmission lines by considering different bundle conductor combinations for inductor and capacitor.

This study proposes parametric simulation data analysis with T equivalent circuit modeling power transmission line with a voltage value of 154 kV.

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.

Regression Model Extractions of a T-Equivalent Circuit Modeling for Medium-Length Transmission Line Based-on the Parametric Simulation Approach

Araştırma Makalesi / Research Article

Selami BALCI[1], Mustafa AKKAYA*[2]

[1]Mühendislik Fakültesi, Elektrik-Elektronik Müh. Bölümü, Karamanoğlu Mehmetbey Üniversitesi, Türkiye
[2]Hasan Ferdi Turgutlu Teknoloji Fakültesi, Enerji Sistemleri Müh. Bölümü, Manisa Celal Bayar Üniversitesi, Türkiye

(Geliş/Received : 22.03.2024 ; Kabul/Accepted : 20.05.2024 ; Erken Görünüm/Early View : 16.07.2024)

ABSTRACT

In medium-length power transmission line models, the difference between the end-of-line and head-of-line voltage can be calculated with classical mathematical expressions. However, since the line parameters are not linear, these calculations can be approximated according to certain assumptions. The parametric data analysis approach proposed in this study obtained a data set for different variations by changing the line length and line parameters (transmission line-specific parameters such as resistance, inductance, and capacitance) with certain steps. Then, using this data set, a classification is made with machine learning. In addition, data analysis is carried out with the end-of-line voltage value graphs obtained with different line parameters, and the proposed approach is verified by constructing a test simulation circuit of a three-phase 200 km length with a 154 kV line voltage value. Thus, a parametric simulation study has been presented, especially in electrical engineering education. In addition, Support Vector Regression (SVR) and Decision Tree Regression (DTR) models in the field of machine learning were used to measure the consistency of the data set created for 5 pF, 8 pF, and 10 pF capacity values. With the figures and numerical data presented comparatively, it is seen that the Long Short-Term Memory (LSTM) algorithm produces more successful scores in all three categories. In this context, the prediction accuracy was between 97% and 98% with DTR, while the accuracy was between 81% and 85% with SVR. Thus, prediction results in the range of 98% - 99% were obtained in the LSTM model.

Keywords: Transmission line parameters, T-equivalent circuit modeling, parametric simulation, DTR, SVR, LSTM.

Orta Uzunlukta İletim Hattı İçin T-Eşdeğer Devre Modellemesinin Parametrik Benzetim Yaklaşımına Dayalı Regresyon Modeli Çıkarımları

ÖZ

Orta uzunlukta enerji nakil hattı modellerinde hat sonu ve hat başı gerilimi arasındaki fark klasik matematiksel ifadelerle hesaplanabilmektedir. Ancak hat parametreleri doğrusal olmadığından bu hesaplamalara belirli varsayımlara göre yaklaşılabilir. Bu çalışmada önerilen parametrik veri analizi yaklaşımı, hat uzunluğunu ve hat parametrelerini (direnç, endüktans, kapasitans gibi iletim hattına özgü parametreler) belirli adımlarla değiştirerek farklı varyasyonlar için bir veri seti elde etmiştir. Daha sonra bu veri seti kullanılarak makine öğrenmesi ile bir sınıflandırma yapılmıştır. Ayrıca farklı hat parametreleri ile elde edilen hat sonu gerilim değeri grafikleri ile veri analizi yapılmış ve önerilen yaklaşım, 200 km uzunluğunda, 154 kV hat gerilim değerine sahip üç fazlı bir test benzetim devresi kurularak doğrulanmıştır. Böylece, elektrik mühendisliği eğitiminde parametrik bir simülasyon çalışması ortaya konmuştur. Ayrıca, makine öğrenimi alanında Destek Vektör Regresyonu (SVR) ve Karar Ağacı Regresyonu (DTR) modelleri kullanılarak 5 pF, 8 pF ve 10 pF kapasite değerleri için oluşturulan veri setinin tutarlılığı ölçülmüştür. Karşılaştırmalı olarak sunulan rakamlar ve sayısal verilerle Uzun Kısa Süreli Bellek (LSTM) algoritmasının her üç kategoride de daha başarılı değerler ürettiği açıkça görülmektedir. Bu bağlamda, DTR ile tahmin doğruluğu %97 ile %98 arasında, SVR ile doğruluk %81 ile %85 arasında gerçekleşmiştir. Böylece, LSTM modelinde %98 - %99 aralığında tahmin sonuçları elde edilmiştir.

Anahtar Kelimeler: İletim hattı parametreleri, T-eşdeğer devre modellemesi, DTR, SVR, LSTM.

1. INTRODUCTION

Transmission line impedance parameters were traditionally calculated using the geometry of transmission line conductors. It is known that the materials from which the conductors were made, their placement forms, and other geometric calculations were made based on assumptions. Besides the inaccuracy introduced into the calculations by approximating the sag and the chain effect, the impedance (R-L) parameters change with ambient temperature and load conditions. In power systems in general, there is potential to make transmission line impedance parameters more accurate by measuring parameters directly using synchronous phasor measurements. However, since all calculations were made during the establishment of power system transmission lines, many parameters based on

*Corresponding Author
e-posta : mustafa.akkaya@cbu.edu.tr

assumptions can cause difficulties in realizing this potential. In this context, four methods that can be used to estimate impedance parameters in transmission lines are the single measurement method, dual measurement method, multiple measurement methods using linear regression, multiple measurement methods using nonlinear regression, and the last two of these methods are new approaches in the past literature [1,2,3,4]. It is essential to make fault detections based on parameter estimates in transmission lines. Fault detections were made with models developed in different line types. Mercy and Jyosthna carried out a study to detect the defective phase using the Adaptive Neuro-Fuzzy Inference System (ANFIS). In this study, the authors propose Discrete Wavelet Transform (DWT). They were conducted studies on fault detection, fault classification, and identification of faulty phase using ANFIS techniques [5]. Kammel and Hassan were used the exciting ANFIS for fault classification in transmission lines. In the study, based on the fact that fuzzy logic concepts were embedded in the network structure, they have integrated the ANFIS system numerically. The proposed algorithm modeled phase to earth, phase to phase, and dual phase to earth to classify the fault type. After the Fourier transform of the input data was performed, the primary data of the voltage-current values were obtained [6]. Azriyenni and Wazir have realized distance protection for the transmission line with ANFIS application using hybrid intelligent techniques. The authors were determined how long the distance relay would maintain the channel spacing in transmission lines. The authors stated that they developed an alternative algorithm to protect the system on the transmission line by using the Matlab package program. They were used the ANFIS system as an integration by using a fuzzy inference system and neural network, unlike other applications. To improve the performance of transmission lines, they have implemented one of the intelligent alternative techniques [7].

Viahinic et al. pointed out that transmission line parameters vary depending on the environment and operating conditions, and statistically analyzed the uncertainties associated with the estimation of line parameters based on the equivalent pi model valid for short and medium-length transmission lines. Also, the actual data from synchrophasor measurements on two short high-voltage transmission lines were analyzed and compared with test data. According to the observed correlation values, the voltage and current magnitudes were taken at the highest value, which significantly affected the results [8]. In addition to modeling the short-line parameters, it is also imperative to detect the faults that may occur in the transmission line. Algorithms and simulations developed for fault detection in the literature [9, 10, 11, 12]. For example, Akmaz et al. proposed a new approach for detecting an uncertain fault location in transmission lines. According to this approach, they used to travel wave frequencies and an Extreme Learning Machine (ELM) to determine the location of the fault. The authors were used the Alternative Transitions Program/Electromagnetic Transients Program (ATP/EMTP) to model the J.Marti frequency-dependent line model and the MATLAB package program to perform the fault detection algorithms. This improved fault location method has many short circuits such as fault resistance, fault type, and source inductance. Remarkably, it is not affected by the fault parameter. The simulation results were used; they were reported that the traveling wave frequency and the ELM could accurately predict the fault location between 0-400 km [13]. Fei et al. were proposed a new high-voltage transmission line fault model based on the application of Support Vector Regression (SVR). The authors have investigated faults at different locations with different fault impedances and various fault initiation angles in a 400 kV-300 km high voltage transmission line power system. Unlike other simulations, it has been reported that the model in this study requires less information and a shorter time data window. Thus, it was concluded that this scheme could find faults in different impedances accurately and quickly [14]. Bendjabeur et al. have developed a model for boundary conditions using synchronized data recorded from sending and receiving terminals. They have developed a distribution model with distributed parameters given as Partial Differential Equations (PDE). The system algorithm created through the results was suitable for effectively solving the problem [15]. Ghaedi et al. were proposed an integrated method to identify fault location, fault line separation, fault type, and faulty phases in transmission lines. The proposed method was created by utilizing the capabilities of the state prediction formulation and the Weighted Least Squares (WLS) solution algorithm. For each of the error cases, the inherent errors of the measured parameters are taken into account according to the proposed error model. They were showed that for all functions, the error percentage of the fault location algorithm is much less than 0.5% [16]. Nowadays, studies on machine learning and deep learning are becoming widespread. In their study, Özer and Türkmen emphasized a Histogram Equalization (HE) based preprocessing technique to develop an artificial intelligence model. They made a detailed comparative analysis of the performance metrics of the developed models [17]. Sebastian et al. developed several methods to detect theft or anomalies in smart meter readings using machine learning techniques in their proposed work based on past and future energy consumption data forecasts on the consumer side [18]. Ganguly et al. developed a machine learning technique that can help classify the risk of cervical cancer by analyzing patient datasets and identifying important factors that predict the likelihood of cervical cancer occurrence [19]. In general, when the operating capacity of the line is not sufficient in power systems, a new parallel transmission line must be established between two substations due to the load increase. On the other hand, parameter estimation becomes essential when an underground cable replaces it within the scope of updating an overhead line, or when it is desired to determine the electrical parameters of parallel-connected transmission lines. In the process of estimating transmission line parameters from voltage, current, and power measurements at both ends of the transmission line, the Newton-Raphson method, i.e. Deterministic, is used to solve nonlinear equations regarding the equivalent pi or T equivalent circuit parameters of the transmission line (resistance/m, inductance/m and capacitance/m). It can be obtained from real-time measurements at the line ends using the parameter estimation method. Conductivity parameters can also be added to these parameters [20]. Apart from this, the longtime sequential EMTP-ATP simulations required by the application of the Monte Carlo method, which is one of the different estimation methods in the previous literature, encourages researchers to use different methods [21]. It is natural to have systematic errors in voltage and current measurements for real-time estimation of power line impedance parameters. Therefore, a simulated transmission line case study and optimization method are proposed to determine the correction constants for the phasors to obtain accurate estimates of potentially variable impedance parameters [22]. Power system analysis results are based on a generally known system model but may still contain errors. In this context, model errors can affect the accuracy of results and it is important to use data collected over a period when estimating transmission line parameters. Results can be compared for both simulated and real data. Thus, the fact that the estimation based on real measurement data includes difficulties not encountered in simulation affects the accuracy of estimation processes [23]. Transmission line parameters are affected by factors such as mutual inductance effects of phase conductors, internal resistance, and capacitance. Based on the simulation results, transmission line parameters can be accurately predicted [24, 25, 26]. The simulation study and field test results indicate that the proposed technique could be a useful addition to the energy management systems of utilities. Transmission line parameters, i.e. series impedance and shunt acceptance of a line, are fundamental data for reliable evaluation and estimation of power system responses. Data is traditionally acquired using line-fixed programs under default conditions [27, 28]. Transmission line parameters are inputs to various power system analysis algorithms, and the precision of these parameters is therefore important in ensuring analysis accuracy [29, 30]. In this context, many of the studies in the past literature are about artificial intelligence or fuzzy neural networks, which are based on real measurements of error classification and estimation of errors. Thus, the most important contribution of this study to the literature is that it is extremely useful and scientifically original with the dataset analysis obtained from parametric simulations. In this study, transmission line parameters such as length, resistance, reactance, and capacitance of the T equivalent circuit of a medium-length 154 kV power transmission line were modeled with specific steps. Parametric simulations were performed in the simulation ANSYS-Electronics Twin Builder software. As a result of these analyses, several data sets were obtained for the end-of-line voltage values, and classifications were made for the line's efficiency. Thus, the difficulties in classical calculations are eliminated by modeling a power transmission line, and an approach based on parametric simulation studies was proposed. The outlines of this study are as follows; in the first section, T-equivalent circuit modeling and previous literature are given in detail. In the second section, materials and methodology are given. In the third section, the estimation methods are presented comparatively with graphic and numerical data. Finally, in the conclusion section, the results obtained, originality and future work are given.

2. T-EQUIVALENT CIRCUIT MODEL

The unit length of the conductors forming the transmission line has resistance (R) and inductance (L). In addition, there is a capacitance (Cp) between parallel and insulated line conductors and small conductance (G) due to the imperfection of the insulator. These parameters are calculated according to the physical properties, dimensions, and construction of the material of the line; it changes with frequency and environmental conditions such as atmospheric conditions, the need to replace a section on the line with a new conductor due to maintenance, added lines, change of the line's route due to terrain conditions, etc. [2, 3]. The vital issue in the establishment and operation of energy transmission lines is the correct determination of the electrical characteristics of the line and the calculation of other electrical information. When the current and voltage at any point of the line are known, the current and voltage or powers at other points can be calculated. The equations designed to find the current and voltage at other points based on the known current and voltage at specific points of the lines are called line equations [2]. Line parameters were used while creating line equations. For lines longer than 80 km, the simple series impedance representation gives erroneous results when the parallel admittance is completely ignored. Several currents flow due to the capacities of the conductors relative to each other, to the protective conductor, and the ground. As the line length increases, these currents become too large to be ignored. For modeling medium-length lines (between 80 and 240 km in length), nominal π or T circuits were used, considering parallel admittance [4]. The nominal T-equivalent circuit is arranged as in Eq. 1, with a series impedance on both sides of the total parallel admittance given in Figure 1. Constants A, B, C, D for the nominal T circuit [4];

$$A = 1 + \left(\frac{ZY}{2}\right) \qquad B = Z + \left(\frac{Z^2Y}{4}\right)$$

$$C=Y \qquad D = 1 + \left(\frac{ZY}{2}\right) \tag{1}$$

In balanced transmission lines, operations should be done for a single phase. However, in unbalanced transmission lines, each phase should be considered separately. If the system was considered balanced, the line equations for the single-phase are expressed in matrix form as Eq. 2. Here, the variables given with the subscript S symbolize the current and voltage at the beginning of the line, and the variables with the subscript R symbolize the current and voltage at the end of the line [4].

$$\begin{bmatrix} V_S \\ I_S \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} V_R \\ I_R \end{bmatrix} \tag{2}$$

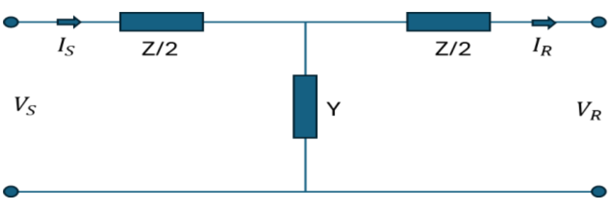

Fig. 1. T-equivalent circuit modeling of the transmission line

3. MATERIAL AND METHOD

In this section, T-equivalent circuit modeling and data set creation studies are explained with the parametric simulation approach. The definitions of parametric simulation setup settings run according to T-equivalent circuit parameters are also discussed.

3.1. Parametric Simulation Studies

The simulation circuit diagram used for the T equivalent circuit model of a medium-length power transmission line is shown in Figure 2. In this line modeling, the voltage value per line is 154 kV, the parameters were changed according to specific line parameter values, and parametric analyses were carried out.

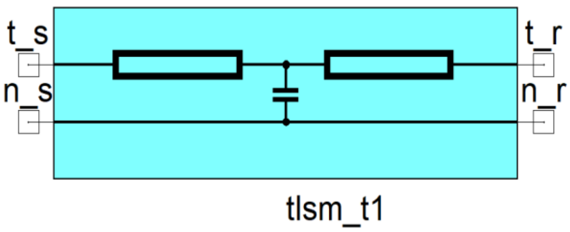

Fig. 2. Single-phase equivalent T circuit topology of the power transmission line

In this equivalent circuit, parameters such as the length of the line (l), the resistance of the line (r), the inductance value of the line (L), and the capacitance (C) value of the line were given in Table 1 as well as simulation studies based on various variations with parametric steps in the value ranges.

Table 1. Line variables and parametric analysis setup

Parameters	Value Range	Linear Step Int.
Line Length (*l*)	100-200 km	10 km
Resistance Value (r)	0.2-0.6 mΩ	0.1 mΩ
Reactance Value (L)	1-2 µH	0.1 µH
Capacitance Value (Cp)	5-10 pF	0.5pF

Transmission line simulation was made with existing data using ANSYS Electronics Twin Builder software. The simulation circuit used to obtain parametric data is given in Figure 3. This circuit was created in the ANSYS Electronics Twin Builder software, and for a medium-length transmission line (200 km), the line length (length), conductor resistance value (Rdc), inductance (Ls), and capacitance (Cp) are calculated for the end-of-line voltage value according to the input parameters. Data analysis was carried out.

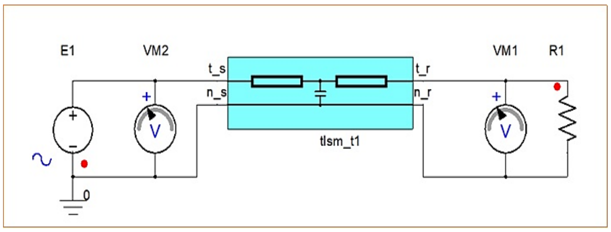

Fig. 3. Line parametric analysis simulation circuit

A scenario was created for different variations of these parameters, and a parametric setup was set for the data set with specific linear steps. The length of the line is from 100 km to 200 km with 10 km steps; line ohmic resistance value from 0.2mΩ to 0.6 mΩ in 0.1 mΩ steps; line inductance value from 1µH to 2 µH in 0.1 µH steps and finally line capacitance value from 5pF to 10 pF Parametric simulation was run with 0.5pF steps. The parametric setup window of the software, as shown in Figure 4 provides valuable data.

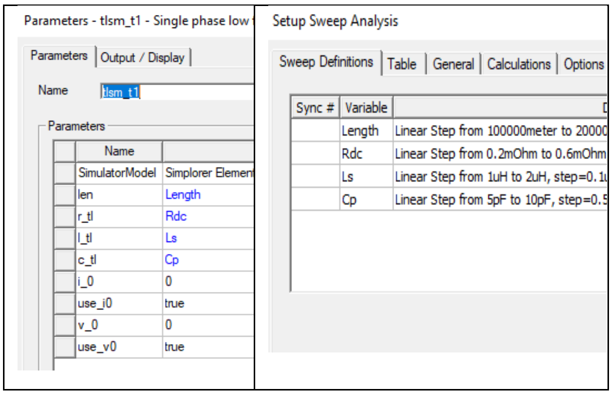

Fig. 4. Parametric analysis setup window

When L:1uH and Cp:5pF are fixed, the 3D graph seen in Figure 5 can be given for the end-of-line phase voltage depending on the length of the line and the resistance value. Thus, when the two parameters were kept constant, it can be easily determined how much the end-of-line voltage value was affected by the change in the length of the line and the resistance value, and it can facilitate the determination of the conductor type and cross-section.

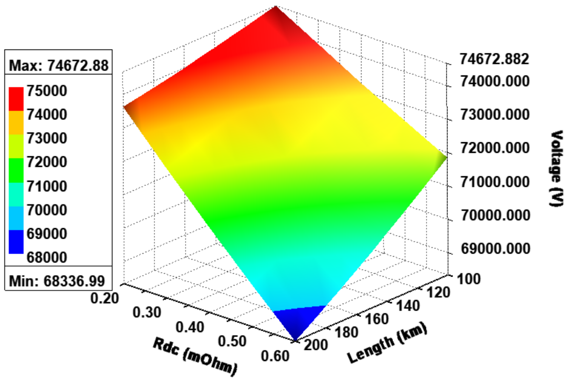

Fig. 5. End of line phase voltage change while L:1uH and Cp:5pF are constant

In the same graph, when the line inductance value was doubled (L:2uH), while the capacitance of T-equivalent circuit is at a constant value (Cp:5pF), the end-of-line voltage value is highly affected can be seen in Figure 6. In this context, line inductance, which varies according to the geometric distance and placement between the conductors, increases the voltage drops on the line in a transmission line, and this increase is not a linear increase. Thus, it is imperative to provide a data set with parametric analyses for classical calculations' nonlinear behaviors.

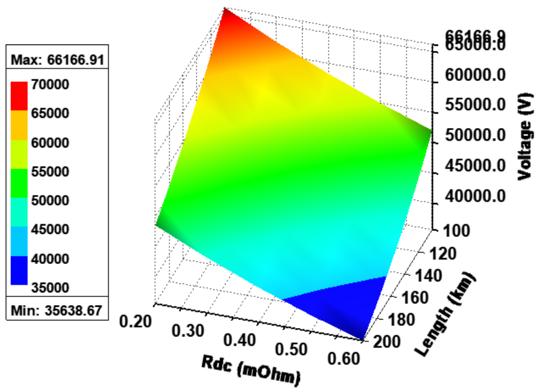

Fig. 6. End of line phase voltage change when L:2uH and Cp:5pF are constant

When the line length, which is another parameter, is 100 km and the line capacitance is kept constant at 5pF, the change in the end-of-line voltage depending on the resistance value and inductance values can be seen in the 3D graph given in Figure 7. Thus, the correct conductor selection and the placement of the conductors significantly affect the inductance and resistance values that affect the end-of-line voltage value.

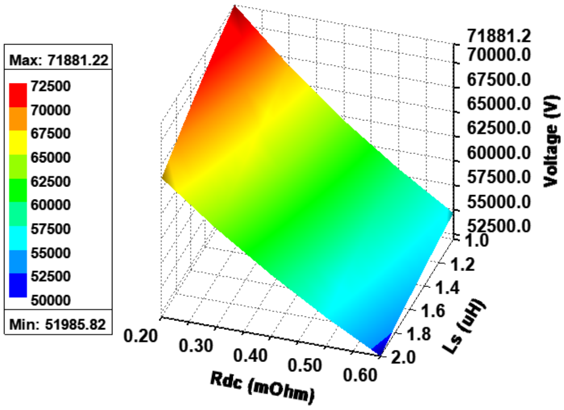

Fig. 7. Line end phase voltage change when line length is 100 km and Cp:5pF was fixed

If the capacitance value is kept constant at 5pF in a medium-length transmission line when the line length was doubled, the decrease in the end-of-line voltage value according to the resistance and inductance values was given in Figure 8. In this context, both the conductor resistance value and the inductance value must be changed depending on the length of the line.

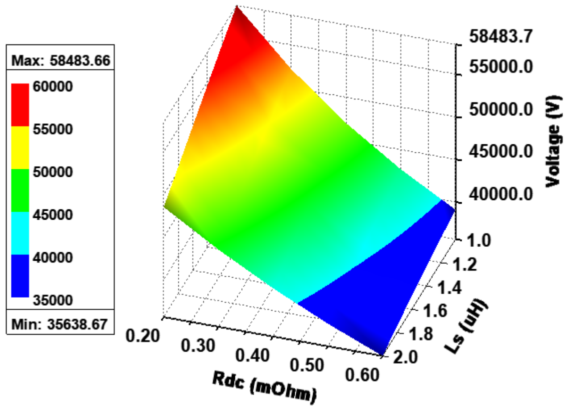

Fig. 8. Line end phase voltage change when line length is 200 km and Cp:5pF was fixed

In order to compare the end-of-line voltage value depending on the capacitance and inductance values, when the line length is 100 km, and the resistance value is kept constant as 0.2mohm, the graph given in Figure 9 can be determined as a nonlinear behavior where the inductance value tends to decrease the voltage. In contrast, the capacitance value tends to increase the voltage on the contrary.

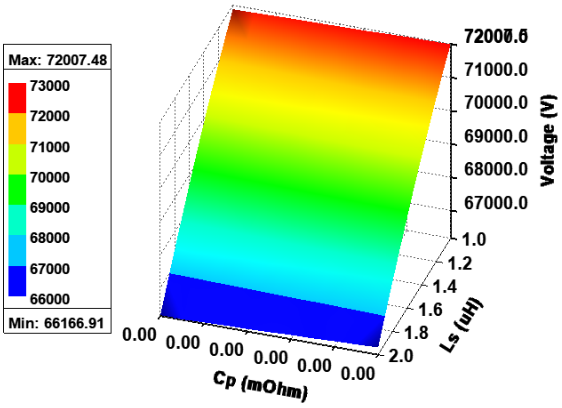

Fig. 9. Line length 100 km and Rdc: 0.2mohm constant, end-of-line phase voltage change

If the line length and the resistance value double, the end-of-line voltage value also decreases too much as seen in Figure 10. Line length increases both inductance and capacitance values.

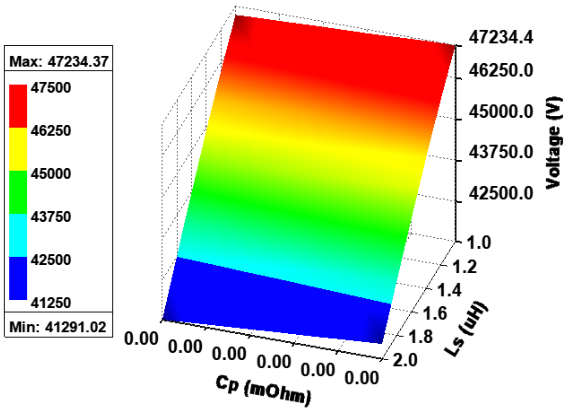

Fig. 10. Line length 200 km and Rdc: 0.4 mΩ constant, end-of-line phase voltage change

In order to verify the proposed parameter data analysis, the test circuit given in Figure 11 has been run with T equivalent circuit modeling for a 200 km long power transmission line of 154 kV. The line parameters of this equivalent circuit are Rdc=0.1 mΩ, L=1 uH and Cp=8 pF.

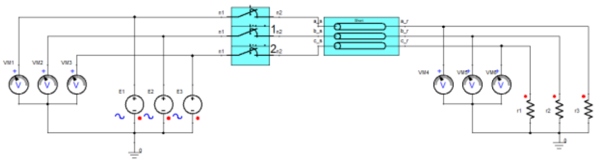

Fig. 11. T equivalent test circuit for a 200 km long power transmission line of 154 kV [31]

Thus, the difference between the end-of-line voltage and the head-of-line voltage values is as seen in the test circuit given in Figure 12. The difference voltage value gives the voltage value falling on the 200 km long power transmission line. As a result, an energy transmission line can be modeled with a simulation test circuit instead of the difficulties in classical calculations on this circuit.

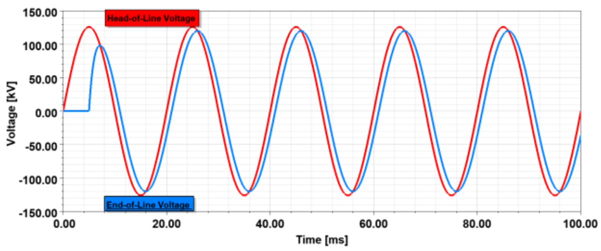

Fig. 12. The difference between the head-of-line voltage (red line) and the end-of-line voltage (blue line) for a 200 km long power transmission line of 154 kV

4.RESULTS AND DISCUSSION

In this section, different regression modeling and estimation studies were carried out using the dataset obtained from parametric simulation studies. Thus, the results obtained with both prediction models are presented comparatively.

4.1.Machine Learning and Estimation Methodology

In the study, data sets were created that allow monitoring the changes in rms AC voltage [V] value depending on three different parameters (Line Length, Rdc and Ls). These data are kept in 3 different capacity categories as 5pf, 8pf and 10pf. Regression models used in Machine Learning and Deep Learning fields were used to measure the consistency of the generated data. While selecting the Regression models to be used in the study; Algorithms that produce successful results with both linear and non-linear data have been investigated. When similar studies in the literature are examined, it has been observed that Support Vector Regression (SVR), Decision Tree Regression (DTR) and Long Short-Term Memory (LSTM) models are frequently used and produce successful predictions [32-38]. For this reason, in the present study, prediction values were taken from three algorithms and compared. In addition, in order to detect the dependencies between the parameters, the noisy (stray) records in the data set were determined and the existing regression models were used in the data normalization phase.

4.2.Support Vector Regression

The Support Vector Machine (SVM) algorithm, developed for the solution of classification problems, is a popular algorithm that produces very successful results in data science. The customized version of this algorithm developed by Vapnik et al. is used as SVR to generate predictions for nonlinear data and to be used in regression models [39]. This algorithm, assuming that nonlinear data is located on a hyperplane, aims to determine the most successful representation lines covering this data. Unlike most of the other regression models; the focus is on minimizing the threshold on the representation lines rather than reducing the difference between actual and predicted values. Thanks to its usability in both linear and non-linear data, the SVR model was used in the experiments in the current study. In order to compare the experimental results for the two models used, success was calculated with the RMSE as given in Eq.3 [40], and R2 (R Squared) metrics. In addition, data normalization was performed by scaling the data to the 0-1 range for both models.

$$RMSE = \frac{1}{N}\sqrt{\sum_{i=1}^{N}(P_i - O_i)^2} \tag{3}$$

4.3.Decision Tree Regression

Decision trees have an architecture that divides the arguments into intervals according to the information inputs. This structure provides a successful prediction model that can be used for solving both classification and regression problems. It differs from other algorithms with its discrete rather than continuous working structure for the solution of regression problems. It is considered an important disadvantage of this algorithm that it gives the same results for predictions coming in a certain interval [41]. However, it has been clarified by the studies in the literature that this method produces very successful estimations of data with sensitive intervals and is compatible with linear or non-linear data types. It has been seen that the data used in the study provides the appropriate conditions to benefit from the DTR model since it has a sensitivity of over a thousand slices.

4.4.Long Short-Term Memory

The long-short-term memory model is frequently used in problems involving sequential data or time series problems with a memory-passing architecture by learning the data dependency that is often seen in traditional neural networks. With each step in this architecture, the probability of producing an outcome prediction that becomes increasingly successful thanks to the results obtained from the previous prediction and the patterns kept in memory increases. With this aspect, learning skills increase in expanding networks and it becomes possible to detect hidden patterns. For the data set used in the study, the predictive value produced at each step does not directly affect the next prediction value. However, the LSTM model is used in addition to Machine Learning models, as it will facilitate the determination of noisy records that will cause deviation in these data and the detection of unusual situations specific to these records.

Table 2. Results obtained for different regression models

	Decision Tree Regression (DTR)		Support Vector Regression (SVR)		Long Short-Term Memory (LSTM)	
	RMSE	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**
5pf	3.519	0.979	10.549	0.821	3.014	0.988
8pf	3.514	0.978	10.603	0.819	3.077	0.983
10pf	3.521	0.980	9.405	0.859	2.996	0.991

It is seen that the LSTM algorithm produces more successful scores in all three categories. While the prediction accuracy was between 97% and 98% with DTR, the accuracy was between 81% and 85% with SVR. In the LSTM model, estimation results in the range of 98% - 99% were obtained. The fact that the existing data was obtained with very sensitive intervals and the sensitivity increased with the 0-1 scaling process makes the DTR model more prominent. The results for SVR, DTR, and LSTM are given in Figure 13, Figure 14, and Figure 15, respectively.

Fig. 13. Results obtained with the Support Vector Machine (SVR) algorithm

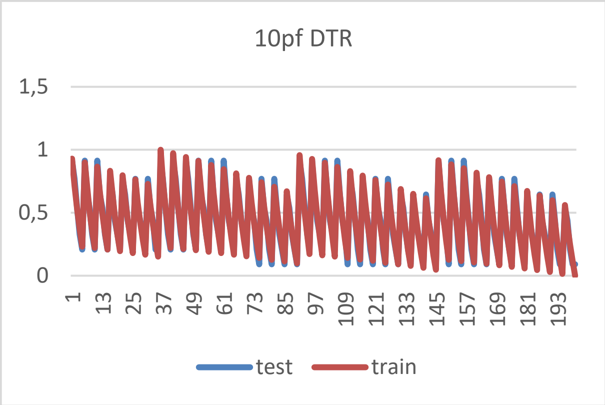

Fig. 14. Results obtained with the Decision Tree Regression (DTR) algorithm

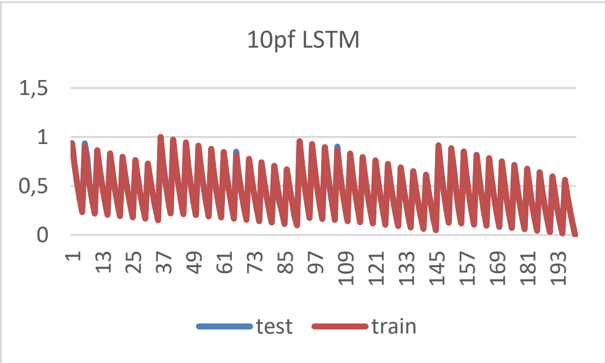

Fig. 15. Results obtained with the Long Short-Term Memory (LSTM) algorithm

Thus, the parametric simulation approach, which is similar to the previous literature, can be used to determine the optimum parameter settings of 1-phase and 3-phase overhead transmission lines by considering different bundle conductor combinations for inductor and capacitor. In this context, metaheuristic parameter estimations are stochastic in nature, but implying that they will show performance variation in different parametric simulations while providing primarily optimum solutions [42].

5. CONCLUSION

Line power losses in the transmission of electrical energy are of great importance in terms of efficient energy efficiency. Generally, in electrical engineering, approximate calculations based on certain assumptions are made with classical calculation methods. This study proposes parametric simulation data analysis with T equivalent circuit modeling of a medium-length power transmission line with a voltage value of 154 kV using ANSYS-Twin Builder software. In the past literature, studies have been carried out on the classification of faults in energy transmission lines, generally with artificial intelligence techniques. The most important difference of this study is that by changing the line parameters with specific steps, a classification over the data is proposed depending on various variations. Then, to verify the proposed approach, the test simulation circuit was run when the resistance value of a 200 km long transmission line was Rdc=0.1 mΩ, L=1 uH, and Cp=8 pF, and the results were given. Thus, the difference between the voltage at the beginning of the line and the voltage at the end of the line was made more understandable, and parametric 3D graphics supported this approach. Thus, it is thought that this proposed approach based on parametric data set analysis can be used as a virtual laboratory environment in electrical engineering education. With the figures and numerical data presented comparatively, it is clearly seen that the LSTM algorithm produces more successful scores in all three categories. In this context, the prediction accuracy was between 97% and 98% with DTR, while the accuracy was between 81% and 85% with SVR. Thus, prediction results in the range of 98% - 99% were obtained in the LSTM model. As a result, the fact that the available data is obtained with very sensitive intervals and the sensitivity of the 0-1 scaling process increases, makes the DTR model even more prominent. Comparative analysis can be made in transmission line modeling according to different parameters and equivalent circuits in future studies. Moreover, a dataset can be created for other modeling approaches in electrical power transmission lines in the future and parameter estimations can be made with the proposed methods.

NOMENCLATURE

Cp	Line capacitance (F)
G	Line conductance (Siemens)
Ir	Current at the end of the line (A)
Is	Current at the beginning of the line (A)
I	Line length (km)
L	Line inductance (H)
N	Total number of samples
Oi	Value of observed variable
Pi	Value of predicted variable
R	Line resistance (Ohms)
r	Conductor resistivity (Ohms)
Rdc	DC resistance (Ohms)
Vr	Voltage at the end of the line (V)
Vs	Voltage at the beginning of the line (V)
Y	Line admittance (Siemens)
Z	Line impedance (Ohms)

ABBREVIATIONS

ANFIS	Adaptive Neuro-Fuzzy Inference System
ATP	Alternative Transitions Program
DTR	Decision Tree Regression
DWT	Discrete Wavelet Transform
DC	Direct Current
AC	Alternative Current
LSTM	Long Short-Term Memory
PDE	Partial Differential Equations
SVM	Support Vector Machine
SVR	Support Vector Regression
WLS	Weighted Least Squares

DECLARATION OF ETHICAL STANDARDS

The author(s) of this article declare that the partial materials and methods do not require ethics committee approval and/or legal-specific permission.

AUTHORS’ CONTRIBUTIONS

Selami BALCI: Conducted theoretical analysis and interpreted the results. Simulation, validation.

Mustafa AKKAYA: Analyses the results and write the manuscript. Original draf, validation.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

REFERENCES

[1] Karaer E., “An Examination of Power Transmission Line Parameters Estimation”, *Thesis (M.Sc.)* ***İstanbul Technical University, Institute of Science and Technology*****, Turkiye,** (2005).

[2] Gönen T., “Electric Power Transmission System Engineering, Analysis and Design”, **J. *Wiley***, New York, USA, (1988).

[3] Atalay H., “Transmission Technique, *Karadeniz Technical University”,* ***Mechanical-Electric Faculty Publications*****.** 5, Turkiye, (1977).

[4] Chen Y., Hu Z., Zhang C., “A Study of Parameters Live Measurement of Transmission Lines with Mutual-inductance Based on GPS”, ***IEEE Power Engineering Society Winter Meeting***, 4: 2658-2663, (2000).

[5] Mercy, E. L., & Jyosthna, G., “Fault detection and classification in transmission line using DWT and ANFIS techniques”, ***Advanced Research in Electrical and Electronic Engineering***, 2(2): 123-129, (2014).

[6] Hassan, T. S. K. M. M. “Adaptive neuro fuzzy inference system (ANFIS) for fault classification in the transmission lines”, ***Online J. Electron. Electr. Eng.(OJEEE),*** 2: 2551-2555, (2010).

[7] Azriyenni, A., & Mustafa, M. W., "Application of ANFIS for Distance Relay Protection in Transmission Line", ***International Journal of Electrical and Computer Engineering***, *5*(6): (2015).

[8] Vlahinić, S., Franković, D., Đurović, M. Ž., & Stojković, N., "Measurement Uncertainty Evaluation of Transmission Line Parameters", ***IEEE Transactions on Instrumentation and Measurement***, 70: 1-7, (2021).

[9] Li, X., Li, F., Liu, P., Cai, W., & Cai, Z. "Modeling Approach for Short-Transmission Lines on the same Tower with Different Wire Parameters and Tower Structure", ***IEEE International Conference on Power System Technology (POWERCON),*** 376-383, (2018).

[10] Pal, S., Sikdar, B., & Chow, J. H., "Classification and detection of PMU data manipulation attacks using transmission line parameters", ***IEEE Transactions on Smart Grid***, *9*(5): 5057-5066, (2017).

[11] Huang, N., Qi, J., Li, F., Yang, D., Cai, G., Huang, G., and Li, Z., "Short-circuit fault detection and classification using empirical wavelet transform and local energy for electric transmission line". ***Sensors,*** *17*(9): 2133, (2017).

[12] Coban, M., & Tezcan, S. S., "Detection and classification of short circuit faults on transmission line using current signal", ***Bulletin of the Polish Academy of Sciences: Technical Sciences***, e137630-e137630, (2021).

[13] Akmaz, D., Mamiş, M. S., Arkan, M., and Tağluk, M. E. "Transmission line fault location using traveling wave frequencies and extreme learning machine", ***Electric Power Systems Research***, *155*: 1-7, (2018).

[14] Fei, C., Qi, G., and Li, C. "Fault location on high voltage transmission line by applying support vector regression with fault signal amplitudes", ***Electric Power Systems Research***, *160*: 173-179, (2018).

[15] Bendjabeur, A., Kouadri, A., and Mekhilef, S. "Transmission line fault location by solving line differential equations**".** ***Electric Power Systems Research***, 192: 106912, (2021).

[16] Ghaedi, A., Golshan, M. E. H., and Sanaye-Pasand, M., "Transmission line fault location based on three-phase state estimation framework considering measurement chain error model". ***Electric Power Systems Research***, 178: 106048, (2020).

[17] Özer, T., & Türkmen, Ö., "An approach based on deep learning methods to detect the condition of solar panels in solar power plants". ***Computers and Electrical Engineering,*** 116: 109143, (2024).

[18] Sebastian, P. K., Deepa, K., Neelima, N., Paul, R., & Özer, T., A comparative analysis of deep neural network models in IoT-based smart systems for energy prediction and theft detection. ***IET Renewable Power Generation***, *18*(3): 398-411, 2024.

[19] Ganguly, T., Pati, P. B., Deepa, K., Singh, T., & Özer, T., "Machine learning based comparative analysis of cervical cancer risk classifications algorithms", **In *2023 international conference on advances in computing, communication and applied informatics (ACCAI)*** (pp. 1-7). IEEE, (2023).

[20] Indulkar, C. S., Ramalingam, K., "Estimation of transmission line parameters from measurements", ***International Journal of Electrical Power & Energy Systems***, 30(5): 337-342, (2008).

[21] Sarajcev, P., "Monte Carlo method for estimating backflashover rates on high voltage transmission lines", ***Electric Power Systems Research***, 119: 247-257, (2015).

[22] Ritzmann, D., Wright, P. S., Holderbaum W., and Potter, B., "A Method for Accurate Transmission Line Impedance Parameter Estimation," ***in IEEE Transactions on Instrumentation and Measurement***, 65(10): 2204-2213, Oct. ,doi: 10.1109/TIM.2016.2556920, (2016).

[23] Davis, K. R., Dutta, S., Overbye, T. J., and Gronquist, J., "Estimation of Transmission Line Parameters from Historical Data," ***46th Hawaii International Conference on System Sciences, Wailea***, HI, USA, 2151-2160, doi: 10.1109/HICSS.2013.206, (2013).

[24] Asprou, M., and Kyriakides, E., "Estimation of transmission line parameters using PMU measurements," ***IEEE Power & Energy Society General Meeting,*** Denver, CO, USA, 1-5, doi: 10.1109/PESGM.2015.7285847, (2015).

[25] Costa, E.C.M. and Kurokawa, S. "Estimation of transmission line parameters using multiple methods", ***IET Gener. Transm. Distrib***., 9(16): 2617–2624, (2015).

[26] Felipe P. Albuquerque, Eduardo C. Marques Costa, Luísa H. B. Liboni, Ronaldo F. Ribeiro Pereira, and Maurício C. de Oliveira, "Estimation of transmission line parameters by using two least-squares methods", ***IET Gener. Transm. Distrib.*** ;15:568–575, (2021).

[27] Wang, Y., Xu, W., and Shen, J., "Online Tracking of Transmission-Line Parameters Using SCADA Data," ***in IEEE Transactions on Power Delivery***, 31(2): 674-682, April 2016, doi: 10.1109/TPWRD.2015.2474699, (2016).

[28] Liao, Y., "Power transmission line parameter estimation and optimal meter placement," ***Proceedings of the IEEE SoutheastCon*** *2010 (SoutheastCon)*, Concord, NC, USA, 2010, 250-254, doi: 10.1109/SECON.2010.5453876, (2010).

[29] Liao, Y., "Some algorithms for transmission line parameter estimation," ***IEEE 41st Southeastern Symposium on System Theory, Tullahoma***, TN,

USA,, 127-132, doi: 10.1109/SSST.2009.4806781, (2009).

[30] Sivanagaraju, G., Chakrabarti, S, and Srivastava, S. C., "Uncertainty in Transmission Line Parameters: Estimation and Impact on Line Current Differential Protection," ***in IEEE Transactions on Instrumentation and Measurement***, 63(6): 1496-1504, doi: 10.1109/TIM.2013.2292276, (2014).

[31] Ansys Electronics 2024R1 Desktop, Academic Version, Twin Builder Examples, Transmission Line Modeling Help Datasheet.

[32] Khodapanah, M., Zobaa, A. F., & Abbod, "Estimating power factor of induction motors at any loading conditions using support vector regression (SVR)", ***Electrical Engineering***, 100(4): 2579-2588, (2018).

[33] Chen, Y., Xu, P., Chu, Y., Li, W., Wu, Y., Ni, L., and Wang, K. "Short-term electrical load forecasting using the Support Vector Regression (SVR) model to calculate the demand response baseline for office buildings", ***Applied Energy***, 195: 659-670, (2017).

[34] Ahmad, M. W., Mourshed, M., and Rezgui, Y. "Tree-based ensemble methods for predicting PV power generation and their comparison with support vector regression". ***Energy***, 164: 465-474, (2018).

[35] Ahmad, M. W., Reynolds, J., and Rezgui, Y. "Predictive modelling for solar thermal energy systems: A comparison of support vector regression, random forest, extra trees and regression trees", ***Journal of cleaner production***, 203, 2018, 810-821, (2018).

[36] Wang, J., Li, P., Ran, R., Che, Y., and Zhou, Y.. A "Short-term photovoltaic power prediction model based on the gradient boost decision tree", ***Applied Sciences***, 8(5): 689, (2018).

[37] Persson, C., Bacher, P., Shiga, T., and Madsen, H. "Multi-site solar power forecasting using gradient boosted regression trees", ***Solar Energy***, 150: 423-436, (2017).

[38] Zahid, M., Ahmed, F., Javaid, N., Abbasi, R. A., Zainab Kazmi, H. S., Javaid, A., and Ilahi, M. "Electricity price and load forecasting using enhanced convolutional neural network and enhanced support vector regression in smart grids", ***Electronics,*** 8(2): 122, (2019).

[39] Smola, A. J. and Schölkopf, B. ,"A tutorial on support vector regression", ***Statistics and computing,*** 14(3): 199-222, (2004).

[40] Sarkar, A., Maity, P. P., Ray, M., Chakraborty, D., Das, B., and Bhatia, A. "Inclusion of fractal dimension in four machine learning algorithms improves the prediction accuracy of mean weight diameter of soil", ***Ecological Informatics,*** 74: 101959, (2023).

[41] Tso, G. K. and Yau, K. K. "Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks". ***Energy***, 32(9): 1761-1768, (2007).

[42] Shaikh, M.S., Raj, C.H.S., Kumar, S., Hassan, M., Ansari, M.M., and Jatoi, M.A., "Optimal parameter estimation of 1-phase and 3-phase transmission line for various bundle conductor's using modified whale optimization algorithm", ***International Journal of Electrical Power & Energy Systems,*** 138: 107893, (2022).