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Prediction of Temperature Variability on Power Transmission Line Parameters Using Intelligent Approaches

Ashfaq Ahmad[1,2]*, Iqra Javed[3], Changan Zhu[2], Muhammad Babar Rasheed[4], Muhammad Waqar Akram[2,5], Muhammad Wisal Khan[6], Umair Ghazanfar[7], Waseem Nazar[8], Syed Baqar Hussain[3] and Amber Sultan[8]

[1]*Department of Artificial Intelligence, School of Systems and Technology, University of Management and Technology, Lahore, Pakistan*
[2]*Department of Precision Machinery & Instrumentation, University of Science and Technology of China, Hefei, China*
[3]*Department of Computer Science, School of Systems and Technology, University of Management and Technology, Lahore, Pakistan*
[4]*Department of Electronics & Electrical Systems, University of Lahore, Lahore, Pakistan*
[5]*Department of Farm Machinery & Power, University of Agriculture, Faisalabad, Pakistan*
[6]*Department of Intelligent Systems, University of Lahore, Lahore, Pakistan*
[7]*Department of Informatics and Systems, School of Systems and Technology, University of Management and Technology, Lahore, Pakistan*
[8]*Department of Technology, University of Lahore, Lahore, Pakistan*

ABSTRACT

Due to changes in meteorological factors, the instability in the power at the end of the transmission system demands considerable attention. The temperature of the transmission line varies, which has a significant impact on the line parameters. An accurate prediction of line parameters behaviour is necessary to ensure system reliability. The present study is a step towards predicting variations in line parameters with respect to temperature variation. In addition, power loss and voltage drop due to variations in resistance are also predicted. Support Vector Machine (SVM) and ElasticNet, a machine learning algorithm, predict line parameters such as resistance, inductance, capacitance, voltage drop, and power losses. Furthermore, different seasons-based SVM and ElasticNet models for these parameters are considered. Seasons-based models are divided into two types, namely, summer and winter. 220-Kilovolt transmission data and weather

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E-mail addresses:
ashfaqahmad83@hotmail.com (Ashfaq Ahmad)
iqrajaved_07@yahoo.com (Iqra Javed)
electricalengineer9313@gmail.com (Changan Zhu)
babargmeher@gmail.com (Muhammad Babar Rasheed)
mwaqar13@mail.ustc.edu.cn (Muhammad Waqar Akram)
muhammad.wasil@es.uol.edu.pk (Muhammad Wisal Khan)
umair.ghazanfar@umt.edu.pk (Umair Ghazanfar)
waseem.nazar@es.uol.edu.pk (Waseem Nazar)
baqar.hussain@es.uol.edu.pk (Syed Baqar Hussain)
amber.sultan.ahmed@gmail.com (Amber Sultan)
* Corresponding author

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information are used as model inputs. Predicted results of transmission line parameters are described in the form of RMSE and MRE. Moreover, the performance results of SVM and ElasticNet are also compared to show better prediction results. The result shows that the minimum prediction error of line parameters are 0.0511, 0.301, 0.426, 0.913, and 0.1501 in RMSE and 4.212, 0.518, 2.888, 0.097, and 0.615 percentages in MRE. This research work may provide technical guidance to transmission line engineers on enhancing the performance of transmission systems.

Keywords: ElasticNet, line voltage drop, power losses, power transmission line parameters, support vector machine, temperature variation effects

INTRODUCTION

The electrical overhead transmission line is vital to the power system, conveying electricity from the power generating stations to the consumer. During the transmission, they are affected by various environmental conditions, such as temperature, lightning, and wind (Campbell, 2012; Yao et al., 2016). The temperature variation is responsible for variations in transmission line parameters like resistance, inductance, and capacitance, which leads to power losses and voltage drop (Farzaneh et al., 2013). The temperature of a high-voltage transmission line conductor is fixed by its current carrying capacity and meteorological atmosphere conditions (Reddy & Chatterjee, 2016). The variation in line current capacity and meteorological atmosphere conditions cause variations in transmission line temperature (Cecchi et al., 2011). According to a study by IEEE Std 738 – 2006 (2007), environmental factors such as environmental temperature, speed of air and its direction, and solar radiation are responsible for variations in conductor temperature.

Chakrabortty et al. (2009) conducted a study based on voltage control equipment, such as a static var compensator and a synchronous condenser, to investigate the variation of transmission line reactance. Fan (2015) estimated the synchronous generator's parameters based on two estimation methods, least-square error and Kalman-based estimation, using Phasor Measurement Unit (PMU) data. Chavan et al. (2017) conducted a study based on the Phasor Measurement Unit (PMU) to investigate the transmission line inter-area impedances, Thevenin's reactance, rotational inertia, and damping of the aggregated generators. Ahmad et al. (2020) conducted a study to develop a transmission line model to investigate line segments where high tension is generated under symmetrical and unsymmetrical spacing using the finite element method. In another research conducted, Kirschen et al. (1997) found line losses in power transmission lines due to shunt conductance. The conductance between the line-to-line and a line-to-ground occurs due to current leakage and is responsible for losses. In addition, the conductor's resistance is also responsible for power losses and voltage drops in transmission lines (Ajenikoko & Adeleke, 2017). Moreover, the electricity requirement is increasing daily (Nedic et al., 2006). It requires a situational understanding of power transmission lines under varying environmental circumstances (Diao et al., 2010). Particularly, it is important to consider temperature variations in transmission lines to limit the power losses and voltage drop.

A few studies have investigated the effect of temperature on transmission line parameters. Bockarjova and Andersson (2007) have developed a two-stage state estimation algorithm to study the variations in the behaviour of a transmission line resistance due to temperature changes and utilised estimated current for resistance correction. Fu et al. (2011) have proposed a dynamic line rating method to measure peak current flow within the steady-state temperature limit. However, the dynamic line rating method did not consider the unsteady-state temperature. Indulkar and Ramalingam (2008) conducted a study to assess the transmission line parameters at starting and receiving ends using the power, voltage, and current magnitude. Du and Liao (2012) employed line voltage and current phasors to assess the positive phase sequence transmission line parameters. However, these studies have considered the single-temperature profile impact on transmission line conductors and have not considered the impact of the multi-temperature profile. Duta et al. (2020) conducted a study using Variance-based re-weighted nonlinear least squares to estimate the three-phase untransposed scheme-based distribution lines parameter and obtained RMS of 10% and 30.7%. Morteza et al. (2023) conducted a study for dynamic line rating (DLR) forecasting, which reliably predicted the overall current carrying potential of overhead transmission lines using support vector machines (SVM), random forest (RF), and multi-layer perceptron (MLP) and achieved an average prediction accuracy of 6.7%, 9.4% and 3.4%. Wei and Goa (2021) developed a model to predict the transmission line galloping using machine learning algorithms GA-BP, SVM and GA-BP-SVM. Their research achieved a combined model accuracy of 95.5% and an F1 score of 0.938. Ghiasi et al. (2019) proposed a study to identify transmission line parameters by considering measured data from one side of the transmission line using the least squares estimation method. They achieved relative error (RE) of 0.054%, 1.078%, 0.209% and 1.121%. In Bendjabeur et al. (2020), the authors conducted a study based on the Galerkin method using Synchronised time-domain data to identify the transmission line parameters. They obtained absolute relative errors of 7.55%–2.45%, 8.36%–0.25% and 3.35%–0.02%. However, in the studies mentioned above, the percentage error of the model could still be improved.

The effect of temperature variation on power transmission line parameters is very important for the effective influence of power transmission line operation. High variation in the temperature causes high variation in transmission line parameters, resulting in less precision on parameter values, which affects the output power at the receiving station. The literature review shows that different machine-learning approaches have been applied for transmission line parameters estimation and classification and are successfully used in other power systems fields. Moreover, various numerical methods have also been applied to analyse the effects of temperature on the power system and some of the line parameters. Based on the successful application of machine learning algorithms in other fields, it is presumed that a machine learning method can also be used to accurately predict the effects of temperature on transmission line parameters. In this regard, a study using intelligent machine learning approaches is needed to predict the effect of temperature variation on power transmission line parameters such as resistance, inductance, and shunt capacitance. In addition, power loss and voltage drop due to variations in resistance also need to be predicted.

In this context, the present study aims to efficiently predict the temperature variation effect on transmission line parameters that affect the transmission system output power. Based on the aim, the objectives of the present study are: First, to efficiently predict the variation of transmission line parameters like resistance, inductance, capacitance, power losses, and voltage drop due to temperature by considering the effect of the polynomial kernel and radial-based kernels of Support Vector Machine and ElasticNet. Second, to predict transmission line parameters using a multi-temperature profile (-10°C to 50°C). Third, the seasonal SVM and ElasticNet models should be considered to predict the transmission line parameters and, in the end, to compare the obtained results with the Poly kernel, RBF kernels, and ElasticNet.

METHODOLOGY

Basic Theory of Transmission Line Current-temperature Relationship and Machine Learning

Transmission Line Current Relationship with Temperature

The carrying capacity of the transmission current and environmental weather conditions affect the transmission line temperature. The main factors affecting the temperature of the transmission line include the heat created due to the current that passes from the transmission line and the heat absorbed by solar rays. The line temperature is determined by equating the total input heat to the total output heat (House & Tuttle, 1958). As there is a difference in the ambient temperature and the conductor temperature, the transmission conductor output heat is in the form of convection heat and radiant heat. The power transmission line heat balance equation is presented in Equation 1, as indicated in Yan et al. (2017).

$$q_1 + q_s = q_c + q_r \qquad [1]$$

In Equation 2, $q_1 = I^2 R$ then, the Equation 2 becomes:

$$I^2 R + Q_{Solar} = Q_{Convection} + Q_{Radiation} \qquad [2]$$

In Equation 2, the heat gain is I^2R because of the current flowing in the conductor of the transmission line, and R is transmission line resistance and is a function of temperature; heat gain is Q_{Solar} due to solar radiation received on the transmission line, heat loss is $Q_{Convection}$, which is due to the ambient temperature, transmission line conductor temperature and wind speed and heat radiation is $Q_{Radiation}$, which is due to the temperature difference. Then, the current capacity of the high-voltage transmission line conductor can be calculated, as shown in Equation 3.

$$I = \sqrt{\frac{Q_{Convection} + Q_{Radiation} - Q_{Solar}}{R}} \quad [3]$$

Basic Theory of Machine Learning

SVM Theory. SVM is the most popular, powerful, and versatile tool for machine learning. The SVM algorithm is used to solve linear or nonlinear classification and regression problems. SVMs are particularly fit for small or medium-sized complex datasets. It gives low false positives under small or medium datasets (Géron, 2017). A high-dimensional feature space is used in SVM for nonlinear mapping of the input vectors. Finding the minimum validation error is the key feature of the SVM, and for this purpose, the margin parameter γ is used (Brownlee, 2016; Chang & Lin, 2011).

SVR Theory. The key concept of prediction with SVR is expressed as suppose that the training data set is $(x_i, y_i)(i = 1, 2, \dots \dots \dots n)$, whereby the input vector with n-dimensions is $x_i \in R^n$; $y_i \in R$ pertained to the required output data of (Bhavsar & Ganatra, 2012; Vapnik, 1999). In Support Vector Regression, it aims to finds a function $f(x)$ that is commonly divergent ε from abs. y_i targets are achieved for all the data sets used for training. The Support Vector Regression algorithm defines function $f(x)$, as shown in Equation 4 (Chang & Lin, 2002; Scholkopf et al., 2000).

$$f(x) = < w, x > + b \qquad \text{with } w \in x, b \in \Re \quad [4]$$

Whereas "comma (,)" implies the dot product in x and from the x_i input space x as a nonlinear feature mapped, the vector weight is w, and to ensure function flatness, f, b is a constant. The normal weight shall be reduced as in Equation 5.

$$Minimise\ \frac{1}{2}\|w^2\|$$

$$Subject\ to \begin{cases} y_i - < w, x_i > - b \le \varepsilon \\ < w, x_i > + b - y_i \le \varepsilon \end{cases} \quad [5]$$

Setup of ξ_i, ξ_i^* is presented in Equations 6 and 7.

$$Minimize\ \frac{1}{2}\|w^2\| + C\sum_{i=1}^{l}(\xi_i\,.+.\,\xi_i^*) \qquad [6]$$

$$Subject\ to \begin{cases} y_i -.< w, x_i >.-b \leq \varepsilon + \xi_i \\ .< w, x_i >.+b.-y_i\ l \leq .\varepsilon + .\xi_i^* \\ \xi_{i.},.\xi_i^* \geq 0 \end{cases} \qquad [7]$$

Where the constant is C, which has a value above zero, that decides the compromise between *'f'* flatness and the quantity by which deviations are greater than *ε*. It accepts that with an *ε*–unresponsive loss function $|\xi|_\varepsilon$ is presented in Equation 8.

$$|\xi|_\varepsilon : \begin{cases} 0 \quad if \quad |\xi| \leq \varepsilon \\ |\xi| - \varepsilon \quad otherwise \end{cases} \qquad [8]$$

The main concept is to create a Lagrange function with the objective function. Equation 9 illustrates the problem of twofold optimisation.

$$Maximize \begin{cases} -\frac{1}{2}\sum_{i.j=1}^{l}.(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*).k.(x_i, x_j) \\ -\varepsilon\sum_{i=1}^{l}.(\alpha_i + \alpha_i^*).+\sum y_i.(\alpha_i - \alpha_i^*). \end{cases}$$

$$subject\ to \sum_{i=1}^{l}(\alpha_i - \alpha_i^*) = 0\ \ and\ \ \alpha_i, \alpha_i^* \epsilon[0, C] \qquad [9]$$

The weights of the models are determined by Equation 10.

$$w = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)x_i \qquad [10]$$

Finally, the model can be written as Equation 11:

$$f(x) = \sum_{i-1}^{l} y_i(\alpha_i - \alpha_i^*)k(x_i, x) + b \qquad [11]$$

Where the linear relationship of x_i training samples can be represented by w and by considering the conditions of Karush Kuhn Tucker (KKT), the parameter b can be evaluated (Steidl et al., 2005). The kernel function is represented with k; the kernel functions which are commonly used for SVM are described as Equation 12:

$$Linear: k.(x, x').= x, x'$$
$$Polynomial: .(x, x').=.(\gamma x, x' + c)^d.$$
$$Sigmoidal: k.(x, x').=.\tanh(\gamma x, x' + c).$$
$$RBF: k(x, x') = \exp\left(\frac{-\left\|x, x'\right\|^2}{2\sigma^2}\right) \quad [12]$$

Where γ, c and d are kernel parameters

ElasticNet Theory. Elastic net is a popular machine learning algorithm used to solve regression problems. ElasticNet regression is a regularisation regression algorithm combining the power of ridge regression and lasso regression into a single algorithm. It implies that the ElasticNet algorithm can control the mix ratio x. When $x = 0$, the ElasticNet algorithm is equivalent to the ridge regression, and when $x = 1$, the ElasticNet algorithm is equivalent to the lasso regression. The elastic net algorithm is best for reducing the regression model's complexity, magnitude, and number of regression coefficients. It uses the L2-norm (sum squared coefficient values) and the L1-norm (sum absolute coefficient values). The elastic net algorithm is very suitable for conditions where the dimensional data is greater than the number of samples. The key features of the elastic net algorithm are groupings and variable selection. The cost function of the ElasticNet algorithm is presented in Equation 13.

$$f(\emptyset) = MSE(\emptyset) + x\alpha \sum_{i=1}^{n} |\emptyset_i| + \frac{1-x}{2}\alpha \sum_{i=1}^{n} \emptyset_i^2 \quad [13]$$

Season-based Prediction Model of Transmission Line Parameters

This research paper uses a Support Vector Machine for transmission line model prediction. Following transmission line parameters such as resistance ($R_{(T)}$), inductance ($L_{(T)}$), capacitance ($C_{(T)}$), voltage drop ($V.D_{(T)}$), and power losses ($P.L_{(T)}$) are considered for prediction. There are various factors which affect the parameters of the transmission line. It is hard to figure out the relationship of the transmission line model with a single weather. The transmission line parameter models have been divided into two weather-based groups, summer and winter, according to the weather variability and the factors influencing the line parameters.

Line Parameters Relationship with Temperature

A transmission line usually has three components: resistance (R), inductance (L), and capacitance (C). They are distributed uniformly over the line length and affect the transmission power from the sending to the receiving end. The resistance and inductance of transmission line conductors are the series components, and capacitance is the shunt component (Mellit & Pavan, 2010). The transmission resistance is the most significant cause of power loss in a transmission line. The electric, magnetic and material characteristics of the conductors mainly determine these parameters. Temperature-based relationships of transmission line parameters are shown in the equations below (Rashid et al., 2005).

The resistance as a function of temperature can be calculated using Equation 14.

$$R_{(T)} = R_{(T_0)} * [1 + TC_1 * (T - T_0) + TC_2 * (T - T_0)^2] \quad [14]$$

The inductance as a temperature and current dependence function can be calculated using Equation [15].

$$L_{(T)} = L_{(T_0)} * (1 + IL_1 * I + IL_2 * I^2) * [1 + TC_1 * (T - T_0) + TC_2 * (T - T_0)^2] \quad [15]$$

The capacitance as a function of temperature and voltage-dependent can be calculated using Equation [16].

$$C_{(T)} = C_{(T_0)} * (1 + VC_1 * V + VC_2 * V^2) * [1 + TC_1 * (T - T_0) + TC_2 * (T - T_0)^2] \quad [16]$$

where $R_{(T_0)}$, $L_{(T_0)}$, and $C_{(T_0)}$ are the reference temperature parameters, T, T_0 is the reference and actual conductor temperature, I, V is the voltage and current, TC_1, TC_2 IL_1, IL_2, and VC_1, VC_2 are linear and quadratic temperature, current and voltage coefficients.

Support Vector Machine Implementation

In defining the procedure for training the SVM algorithm, first, a transmission line and weather dataset are available with several instances categorised by several features. The data is saved to the machine using Comma Separated Values (CSV) in a specified readable format. The following steps are used in the initial procedure to train the SVR and ElasticNet algorithms.

Step 1: In this step, the CSV format transmission line and weather dataset are loaded into the machine.

Step 2: In this step, the dataset is divided into input and output features.

Step 3: This step involves splitting our dataset into training data and test data.

Step 4: Finally, the SVR and ElasticNet models were applied for prediction.

The model parameters are optimised to achieve the best performance of the SVR and ElasticNet model. During the parameter's optimisation procedure, the following steps are used: SVR parameter's optimisation step:

Step 1: In the parameter optimisation step, we first select the kernel in our study: a polynomial or RBF kernel.

Step 2: In this step, the procedure of step 1 is repeated by varying the kernel function parameter ε to find the lowest selected error, i.e. RMSE, MRE for selected iterations.

Step 3: In this step, steps 1 and 2 are repeated by varying the capacity parameter C to find the lowest selected error, i.e. RMSE and MRE for selected iterations.

Step 4: In the final step, the above procedures are repeated by varying the kernel parameter γ to find the lowest selected error, i.e. RMSE, MRE for selected iterations.

The following steps are used for the training algorithm, the prediction from data, and the evaluation of the algorithm. ElasticNet parameter's optimisation step:

Step 1: The elastic net tuning parameters alpha and l1_ratio are selected in the parameter's optimisation step.

Step 2: In this step, the procedure is repeated by varying the elastic net tuning parameters alpha to find the lowest selected error, i.e., RMSE and MRE for selected iterations.

Step 3: In the final step, the above procedures are repeated by varying the elastic net tuning parameters $l_1\text{−}ratio$ to find the lowest selected error, i.e., RMSE and MRE for selected iterations.

The following steps are used for the training algorithm, the prediction from data, and the algorithm's evaluation.

Step 1: After selecting the best optimisation parameters, the fit command of SVR and ElasticNet is separately called to train the algorithm on the training data, which is passed as a parameter to the fit method.

Step 2: After algorithm training, the SVR and ElasticNet predict command is used for prediction.

Step 3: Once the prediction is done, the last step of the learning algorithm is to make evaluations. In our study, RMSE and MRE are considered for evaluation. Finally, the findings are presented graphically for every parameter.

All steps are repeated in the development of each model. The pseudocode of the prediction algorithm is shown below.

Algorithm Prediction of Temperature Variation in Transmission Line Parameters

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Start

1: Require:

2: Datafile: [Loaded input and output features in CSV format]

3: Labels: [Loaded all parameter labels]

4: Dataset = Read all instances and features with a label from steps 1 and 2 using [read_csv (Datafile, Labels = Labels)]

5: Data = Load numerical values without labels [Dataset.values]

6: Input: Feature of any line parameter such as R_T from Dataset [[=data [:, 0:F_T], $X_{i,}$ … X_n]

7: Output: Feature of any line parameter such as R_T from Dataset [y_{out}=data [:, F_T], $Y_{i,}$ … Y_n]

Data splitting into training data and test data

8: Input: 90% input data for training [x_train= x_{in} [0: l_{T90},:]]

9: Test Input: 10% input data for test [x_test= x_{in} [l_{T90}: l_{T90},:]]

10: Output: 90% output data for training [y_train= Y_{out} [0:l_{T90}]]

11: Test Output: 10% output data for test [y_test= Y_{out} [l_{T90}:l_T,:]]

12: Processing: StandardScaler function used for data pre-processing [sc=StandardScaler ()]

13: Model: SVR and ElasticNet models are applied for prediction [reg = svm. SVR (, , ,…,)]and [reg = ElasticNet (, , ,…,)]

Selection of Kernel, C, gamma, and epsilon parameters

14: Kernel: In the present study, polynomial / BRF kernel was considered [reg=svm. SVR (kernel='poly')]

15: SVR Parameters Selection: for parameter selection grid search function used [gs=GridSearchCV (cv=10, estimator=reg, param_grid= ["C": C, "gamma": gamma, "epsilon": epsilon], scoring=scoring)]

15: ElasticNet Parameters Selection: for parameter selection grid search function used [gs=GridSearchCV (cv=10, estimator=reg, param_grid= ["alpha": alpha, "l1_ratio": l1_ratio], scoring=scoring)]

Training, prediction, and evaluation of model

16: Training: fit command is used to train the model reg.fit(x training instances, y training instances)

17: Prediction: y_pre is the predicted result of test instances x, for prediction the predict command is used [y_pre=reg.predict(x test instances)]

18: Evaluation: Results are presented in the form of the RMSE and MRE [final= (rmse (y_pre, test output))]

Graphical Representation of Model

19: Finally, line parameters predicted error results are presented graphically.

20: End

Data Description and Machine Learning Models

In order to predict the temperature effect on line parameters, 220-Kv transmission line data and weather data are used as model input. The transmission line data used in our study are described below: Line length is 675.9 km (420 miles), type of transmission conductor is

Falcon with delta configuration. The following of the characteristics of transmission line conductor at a standard temperature of 20°C and a frequency of 60 Hz; $r(T_o)$ is 0.0985 ohm per kilometre (0.0612 ohms per mile), $X_L(T_o)$ is 0.9786 ohms per kilometre (0.6081 ohms per miles), $X_C(T_o)$ is 0.2290 mega ohm per kilometre (0.1423 mega ohms per miles), the resistance temperature coefficient, α_1 is 0.003(1/°C). The reactance temperature coefficient, α_2, is 0.005(1/°C). On the other hand, the meteorological temperature data for the summer and winter seasons and a conductor temperature based on the relationship of current and meteorological circumstances around the line are considered.

The time interval between data is 30 minutes. In the present work, 4368 sample datasets are used, which is further distributed into two subsets: for the training of the model, 3931 samples are used, and for validation of the model, 437 samples are utilised. Moreover, the 3931 training samples are further split into two subsets according to the selected weather: 1987 samples are utilised in the summer transmission line model, and in the winter transmission line model, 1944 samples are used. The validation data sample set 437 is divided into two transmission line models. Two hundred twenty-one samples are utilised in the transmission summer model, and for the transmission line winter model, 216 samples are used.

Furthermore, to achieve the most proficient model, the dataset was pre-processed. As indicated in Rashid et al. (2005), the relationship of pre-processing is provided in Equation [17].

$$x_i^{/} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad [17]$$

Where $x_i^{/}$ and x_i are the processed and original input data values, x_{min} and x_{max} are the minimum and maximum data values.

The present study uses Python libraries such as Python sklearn, pandas, and NumPy to develop the transmission line parameters' summer and winter models. Figure 1 shows the steps involved in the development of these models. Individual hyperparameters have been chosen to develop these models.

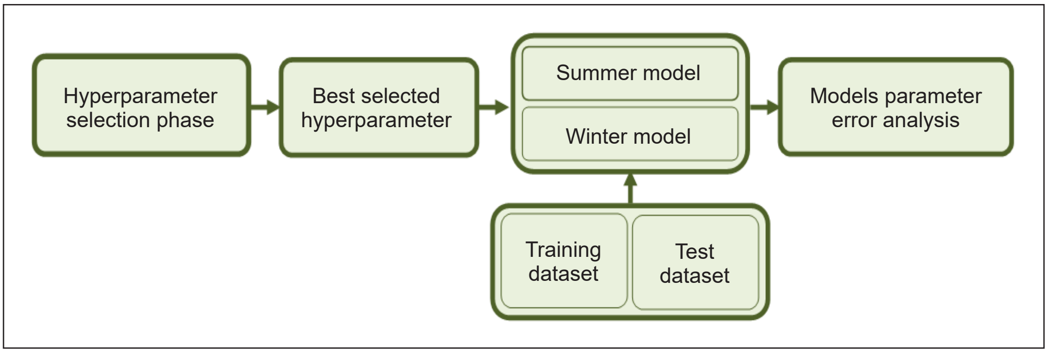


Figure 1. Flow chart of power transmission line parameter prediction

Parameters Selection. In machine learning, hyperparameters affect the precision of the model. Every machine learning algorithm has its hyperparameters, which are used to optimise the model's performance. In the present study, two machine learning algorithms, such as SVM and ElasticNet, are considered for prediction. The commonly used SVM kernel parameters are gamma (γ), the insensitive loss (ε) and the upper bound (C). On the other hand, the ElasticNet algorithm hyperparameters are alpha and l1_ratio. Hence, a suitable range for these hyperparameters is necessary. The setting of this hyperparameter is based on the real training set of data. Furthermore, two SVM kernel functions, poly, radial-based function (RBF), and ElasticNet algorithm, are examined in the present work. Both kernel functions are classical and perform well in many cases (Changsong et al., 2009). According to Huang et al. (2006), when the data is normally distributed, it is suggested that the Radial Based Function (RBF) or the Polynomial (Poly) kernel be used. Finally, the findings are compared with these two kernels' functions and ElasticNet. As previously mentioned, various combinations of SVM parameters C, d, ε and γ and ElasticNet parameters such as (alpha, l1_ratio) are chosen to optimise the seasonal transmission line models for both kernel functions such as poly, RBF and ElasticNet. The description of optimisation parameters is illustrated in Table 1 (Ali & Smith, 2003).

Table 1
Hyperparameters of season-based models of transmission line with poly, RBF kernel and ElasticNet

Models	**Parameters of Poly kernels Model**				**Parameters of RBF kernels Model**				**Parameters ElasticNet Model**	
	C	d	ε	γ	C	d	ε	γ	alpha	l1_ratio
					$R_{(T)}$					
Summer	1000	3	0.10	0.1	1000	3	0.1	10	1.5	0.09
Winter	1000	3	0.10	2.5	1000	3	0.1	9	1.6	0.09
					$L_{(T)}$					
Summer	1000	3	0.10	0.9	1000	3	1.5	5	0.05	0.09
Winter	1000	3	0.5	1.5	1000	3	0.5	10	0.001	0.38
					$C_{(T)}$					
Summer	1000	3	0.8	0.9	1000	3	0.5	0.8	1.5	0.009
Winter	1000	3	0.9	0.9	1000	3	0.9	1.5	1.8	0.009
					$V.D_{(T)}$					
Summer	1000	3	0.25	0.1	1000	3	0.05	2	0.55	0.9
Winter	1000	3	0.1	0.4	1000	3	0.06	2.5	0.555	0.99
					$P.L_{(T)}$					
Summer	1000	2.9	0.05	9	4000	3	0.05	6	1.3	0.33
Winter	1000	2.9	0.05	17	5000	3	0.05	0.2	2.5	0.22

Evaluation Criteria. Mean Relative Error (MRE) and Root Mean Square Error (RMSE) have been used to assess the accuracy of the transmission line model prediction. The relationships of these errors are given in Equations 18 and 19, respectively.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - a_i)^2}{n}} \quad [18]$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{P_i - a_i}{a_T}\right) * 100 \quad [19]$$

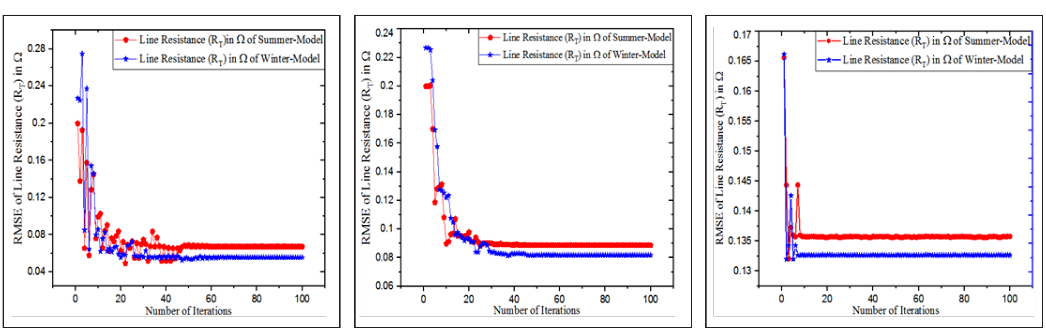
Where the predicted value is P_i, the actual value is a_i, the total parameter measured value is a_T, and the total sample is n.

RESULTS AND DISCUSSION

This discussion presents the prediction error results of transmission line parameter models, such as resistance ($R_{(T)}$), inductance ($L_{(T)}$), capacitance ($C_{(T)}$), voltage drop ($V.D_{(T)}$), and power losses ($P.L_{(T)}$). The prediction models are trained for each transmission line parameter to attain the best prediction result. The input data in these SVM and ElasticNet models includes weather and transmission line parameter data.

Transmission Line Resistance Model (R_T)

Figure 2 shows the retrieved prediction results of the summer and winter models for the transmission line resistance. The value of optimisation parameters is selected for both SVM kernels and ElasticNet. The line resistance models are trained for 100 different iterations. It is concluded that the MRE was reduced to approximately 4.2115% for the SVM poly kernel after 48 iterations. In contrast, the MRE reduced to 6.734% for the SVM RBF kernel after 30 iterations, while for the ElasticNet, it reduced to 9.254% after 32 iterations.



(a) (b) (c)

Figure 2. Prediction of R_T with SVM and ElasticNet: (a) SVM poly kernel; (b) SVM RBF kernel; and (c) ElasticNet

Table 2 compares the results of the $R_{(T)}$ transmission line resistance model for SVM poly, RBF kernel, and ElasticNet. Mean Relative and Root Mean Square Error have been chosen for the model evaluations. The polynomial kernel models perform better than ElasticNet and RBF kernel models.

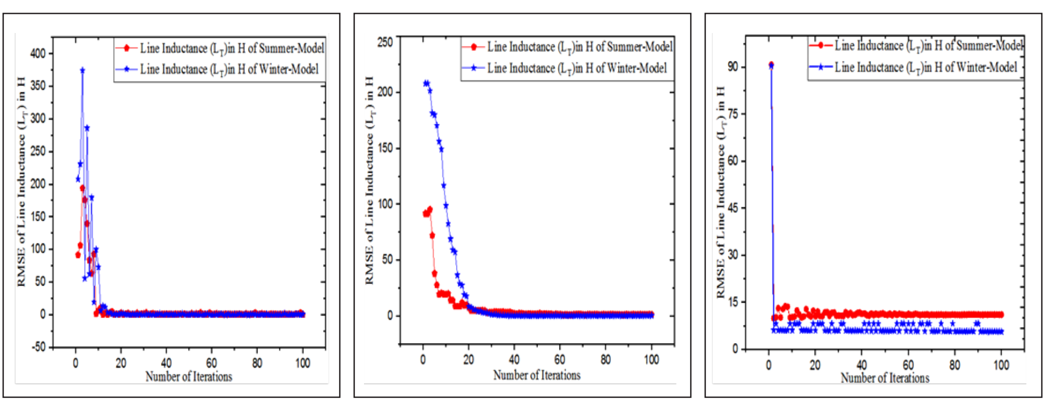
Table 2
Comparison of transmission line resistance (R_T) poly SVM model, RBF SVM model and Elastic Net model (accuracy measurement with RMSE and MRE)

Support Vector Machine and ElasticNet Models	Samples Tested	RMSE and MRE of Line Inductance (R_T)					
		Kernel (poly)		Kernel (RBF)		Elastic Net	
		RMSE (Ω)	MRE (%)	RMSE (Ω)	MRE (%)	RMSE (Ω)	MRE (%)
Model-1 (Summer)	2208	0.0494	7.659	0.0884	12.12	0.1321	9.136
Model-2 (Winter)	2160	0.0527	0.764	0.0815	1.351	0.1645	9.372
Average Value	4368	0.0511	4.212	0.0850	6.734	0.1483	9.254

Transmission Line Inductance Model (L_T)

The extracted prediction results of the developed seasons-based models for the transmission line inductance are shown in Figure 3. The value of optimisation parameters is selected for both SVM kernels and ElasticNet. The line inductance models are trained for 100 different iterations. It is concluded that the MRE reduced to 0.5195% for the SVM poly kernel approximately after 15 iterations. In contrast, the MRE reduced to 0.609% for the SVM RBF kernel after 28 iterations, while for the ElasticNet, it reduced to 3.266% after 60 iterations of the summer model and 90 iterations of the winter model.

Table 3 compares the results of the transmission line inductance $L_{(T)}$ model for SVM poly, RBF kernel and ElasticNet. MRE and RMSE were selected for the model evaluations. The poly kernel models perform much better than RBF kernel models and ElasticNet.



(a) (b) (c)

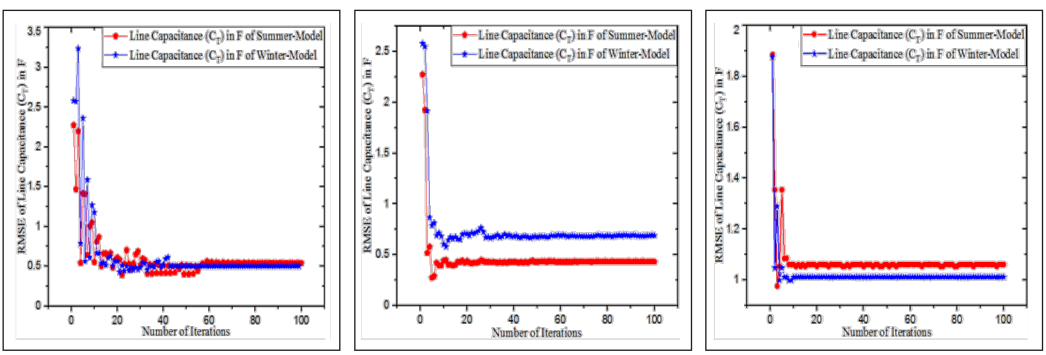
Figure 3. Prediction of transmission line inductance L_T with SVM and ElasticNet: (a) SVM poly kernel; (b) SVM RBF kernel; and (c) ElasticNet

Table 3
Comparison of transmission line inductance (L_T) poly SVM model, RBF SVM model and ElasticNet model (accuracy measurement with RMSE and MRE)

Support Vector Machine and ElasticNet Models	Samples Tested	RMSE and MRE of Line Inductance (L_T)					
		Kernel (poly)		Kernel (RBF)		Elastic Net	
		RMSE (H)	MRE (%)	RMSE (H)	MRE (%)	RMSE (H)	MRE (%)
Model-1 (Summer)	2208	0.369	0.364	1.412	0.810	10.04	0.964
Model-2 (Winter)	2160	0.232	0.675	0.480	0.387	12.85	5.569
Average Value	4368	0.301	0.518	0.946	0.609	11.45	3.266

Transmission Line Capacitance Model (C_T)

The retrieved prediction results of the summer and winter models for the transmission line capacitance are shown in Figure 4. The value of optimisation parameters is selected for both SVM kernels and ElasticNet. The line capacitance models are trained for 100 different iterations. It is concluded that the MRE reduced to 3.021% for the SVM poly kernel approximately after 60 iterations. In contrast, the MRE was reduced to 2.888% for the SVM RBF kernel after 32 iterations. For ElasticNet, it was reduced to 6.088% after 60 iterations of the summer model and 12 iterations of the winter model.



(a) (b) (c)

Figure 4. Prediction of transmission line capacitance C_T with SVM and ElasticNet: (a) SVM poly kernel; (b) SVM RBF kernel; and (c) ElasticNet

Table 4
Comparison of transmission line capacitance (C_T) poly SVM model, RBF SVM model and ElasticNet model (accuracy measurement with RMSE and MRE)

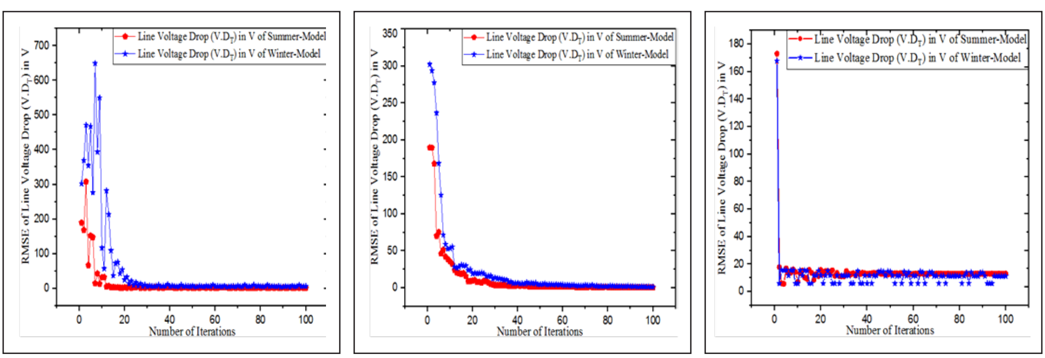
Support Vector Machine and ElasticNet Models	Samples Tested	RMSE and MRE of Line Capacitance (C_T)					
		Kernel (poly)		Kernel (RBF)		Elastic Net	
		RMSE (F)	MRE (%)	RMSE (F)	MRE (%)	RMSE (F)	MRE (%)
Model-1 (Summer)	2208	0.390	5.4	0.273	5.075	0.977	5.578
Model-2 (Winter)	2160	0.428	0.642	0.579	0.701	1.262	6.597
Average Value	4368	0.409	3.021	0.426	2.888	1.119	6.088

Table 4 compares the results of the transmission line capacitance $C_{(T)}$ model for SVM Poly, RBF kernels and ElasticNet. MRE and RMSE were chosen for the model evaluations. The efficiency of SVM models is different for both summer and winter models. The RBF kernel performs better for the summer model, whereas the Poly kernel performs better for the winter model.

Transmission Line Voltage Drop Model ($V.D_T$)

The extracted prediction results of transmission line voltage drop developed seasons-based models are shown in Figure 5. The value of optimisation parameters is selected for both SVM kernels and ElasticNet. The line voltage drop models of SVM and ElasticNet are trained for 100 different iterations. It is concluded that the MRE reduced to 0.798% for the SVM poly kernel approximately after 30 iterations. In contrast, the MRE was reduced to 0.097% for the SVM RBF kernel after 40 iterations and errors of ElasticNet models were reduced to 3.247% after 35 iterations of the summer model and 90 iterations of the winter model.

Table 5 compares the transmission line voltage drop $V.D_{(T)}$ model's results for SVM poly, RBF kernel and ElasticNet. MRE and RMSE were chosen for the model's evaluation.



(a) (b) (c)

Figure 5. Prediction of transmission line voltage drop V.D with SVM and ElasticNet : (a) SVM poly kernel; (b) SVM RBF kernel; and (c) ElasticNet

Table 5
Comparison of transmission line voltage drop ($V.D_T$) poly SVM model and RBF SVM model (accuracy measurement with RMSE and MRE)

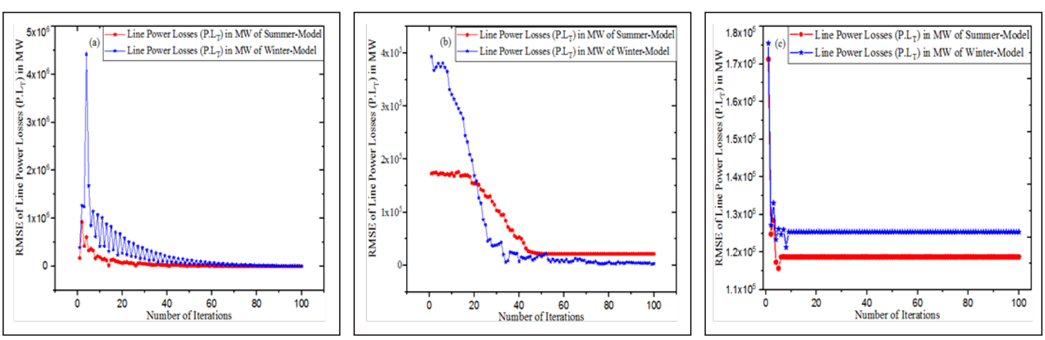
Support Vector Machine and ElasticNet Models	Samples Tested	RMSE and MRE of Line Voltage Drop ($V.D_T$)					
		Kernel (poly)		Kernel (RBF)		Elastic Net	
		RMSE (V)	MRE (%)	RMSE (V)	MRE (%)	RMSE (V)	MRE (%)
Model-1 (Summer)	2208	0.840	0.408	0.548	0.070	5.639	0.531
Model-2 (Winter)	2160	3.818	1.188	1.277	0.124	5.056	5.962
Average Value	4368	2.329	0.798	0.913	0.097	5.347	3.247

The errors from RBF kernel models are much less than those from Poly kernel and ElasticNet models.

Transmission Line Power Losses Model ($P.L_T$)

The extracted prediction results of transmission line power losses developed seasons-based models are shown in Figure 6. The value of optimisation parameters is selected for both SVM kernels and ElasticNet. The line power loss models of SVM and ElasticNet are trained for 100 different iterations. It is concluded that the MRE reduced to 1.1765% for the SVM poly kernel, approximately after 30 iterations of the summer model and 60 iterations of the winter model. In contrast, the MRE was reduced to 0.6156% for the SVM RBF kernel after 45 iterations for the summer model and 75 iterations for the winter model. In contrast, the ElasticNet reduces to 8.448% after 7 iterations of the summer model and 15 iterations of the winter model.

Table 6 compares transmission line power losses $P.L_{(T)}$ model results for SVM poly, RBF kernel and ElasticNet. MRE and RMSE have been used to evaluate the models. The performance of SVM models is different for both summer and winter models. The Poly kernel performs better for the summer model, whereas the RBF kernel performs better for the winter model.



(a) (b) (c)

Figure 6. Prediction of transmission line power losses $P.L_T$ with SVM and ElasticNet: (a) SVM poly kernel; (b) SVM RBF kernel; and (c) ElasticNet

Table 6
Comparison of transmission line power losses ($P.L_T$) poly SVM model and RBF-SVM model (accuracy measurement with RMSE and MRE)

Support Vector Machine and ElasticNet Models	Samples Tested	RMSE and MRE of Line Power Losses ($P.L_T$)					
		Kernel (poly)		Kernel (RBF)		Elastic Net	
		RMSE (MW)	MRE (%)	RMSE (MW)	MRE (%)	RMSE (MW)	MRE (%)
Model-1 (Summer)	2208	0.4128	0.201	0.0215	1.087	0.1257	9.345
Model-2 (Winter)	2160	0.3817	2.152	0.2786	0.144	0.1904	7.551
Average Value	4368	0.3972	1.177	0.1501	0.615	0.1581	8.448

Comparison

The comparison of the resulting error is shown in Table 7. Bockarjova and Andersson (2007) used a state estimation accuracy tool to estimate the power losses by considering the effect of temperature on line resistance. They divided the model into correct line resistance and uncorrected line resistance, and estimated power losses were inaccurate in the case of the uncorrected line resistance model. They obtained the best results using Monte Carlo Simulations and achieved the best relative error of 20%. The total value for the whole system is approaching 15%, respectively. The power loss error determined zero in the case of correct line resistance. Another study Wang et al. (2018) used time-space variation for power flow analysis in transmission systems to investigate the power losses based on the relationship between temperature and transmission line parameters. For that, they have considered five cases in case 1 and case 2, where temperatures are 70°C and -10°C, respectively. In case 3, the average temperature is considered -20°C; in case 4, the weight average temperatures -28°C and -34°C are taken. In case 5, the temperature threshold of 6°C is taken. They concluded that in case 1 and base case, the power loss was 26.14%, and in case 1 and case 2, the power loss was 14.09%. In case 3, case 4, and case 5, the difference in power losses is 19.71%. The existing studies worked on power losses. However, our study predicts all transmission line parameters, power losses and voltage

Table 7
Comparison of proposed study prediction results with poly-SVM, RBF-SVM and ElasticNet

Studies	Prediction-Method	Predicted Parameters	Error
Bockarjova & Andersson, 2007	State Estimation Accuracy	$P.L_{(T)}$ (Uncorrected model)	20 % and for the whole system 15 % (RE)
		$P.L_{(T)}$ (Correct model)	Zero (error)
Wang et al., 2018	Time–Space Variation	$P.L_{(T)}$ (Case 1 and base case)	26.14 %
		$P.L_{(T)}$ (Case 1 and Case 2)	14.09 %
		$P.L_{(T)}$ (Case 3, 4 and 5)	19.71 %
Our Study	ElasticNet	$R_{(T)}$	0.1483 (RMSE), 9.254 (% MRE)
		$L_{(T)}$	11.451 (RMSE), 3.266 (% MRE)
		$C_{(T)}$	1.119 (RMSE), 6.088 (% MRE)
		$V_{(T)}$	5.347 (RMSE), 3.247 (% MRE)
		$P.L_{(T)}$	0.1581 (RMSE), 8.448 (% MRE)
	Support Vector Regression Poly and RBF Kernel	$P.L_{(T)}$	0.0511, 0.0850 (RMSE), 4.212, 6.734 (% MRE)
		$L_{(T)}$	0.301, 0.946 (RMSE), 0.518, 0.609 (% MRE)
		$C_{(T)}$	0.409, 0.426 (RMSE), 3.021, 2.888 (% MRE)
		$V.D_{(T)}$	2.329, 0.913 (RMSE), 0.798, 0.097 (% MRE)
		$P.L_{(T)}$	0.3972, 0.1501 (RMSE), 1.177, 0.615(% MRE)

drop based on the relationship between temperature and line parameters. It can be clearly observed that our SVM models show less error.

CONCLUSION AND FUTURE WORK

Transmission lines are a pillar of electrical power transmission systems that need to be protected on a priority basis. The impact of changes in transmission line parameters due to temperature variations cannot be neglected. This research developed the prediction models for transmission line parameters using Support Vector Machines and the ElasticNet modelling approach. For each line parameter, two seasons-based models were established. The transmission line's parameters and weather data were used as model inputs. The polynomial, RBF kernel and ElasticNet results have also been compared to express the predicted results' better performance.

The predicted results showed that in transmission line resistance and inductance models, the poly-SVM kernel performed better than the RBF-SVM kernel for both season models. The average minimum prediction errors in line resistance and inductance were 0.0511Ω, 0.301 H in RMSE and 4.212, 0.518% in MRE, respectively. Furthermore, the predicted results of the transmission line capacitance model showed that the performance of the polynomial kernel was better than RBF for a winter model. Meanwhile, the summer-model RBF-SVM kernel performed better than the poly-SVM. The average minimum prediction error in line capacitance with RBF kernel was 0.426 F in RMSE and 2.888% in MRE. Moreover, the performance of transmission line voltage drops ($V.D_T$) and power losses ($P.L_T$) were better with the RBF kernel than the polynomial kernel for both seasonal models. The average prediction error of voltage drop was 0.913 V in RMSE and 0.097% in MRE, while the average prediction error in power losses was 0.1501 MW in RMSE and 0.6156% in MRE. On the other hand, the average prediction errors in the line resistance, inductance, capacitance, voltage drop and power losses with ElasticNet algorithm are 0.1483Ω, 11.451 H, 1.119 F, 5.347 V, 0.1581 MW in RMSE and 9.254, 3.266, 6.088, 3.247, 8.448% in MRE, respectively.

In the future, the seasons-based predicted models of transmission line parameters can be further divided into four seasons based on the availability of large training data. In addition, the hybrid algorithm machine learning approach can also be used to achieve good performance for predicting transmission line parameters and losses. That can be used to improve the transmission line output without affecting the secure operation of the transmission line.

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