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STUDY OF ENVIRONMENTAL IMPACTS ON OVERHEAD TRANSMISSION LINES USING GENETIC ALGORITHMS

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Abstract
In our study, we explored the complexities of overhead transmission line (OTL) engineering, specifically focusing on their responses to varying atmospheric conditions (ambient temperature, ambient humidity, solar irradiance, ambient pressure, wind speed, wind direction), and electric current usage. Our goal was to comprehend how these independent variables impact critical responses (dependent variables) such as conductor temperature, conductor sag, tower leg stress, and vibrations – parameters crucial for electric distribution. We modelled the target output variable as a polynomial of a certain degree of the input variables. The precise forms of the polynomial were determined using the genetic algorithms (GA). Developed models are essential for quantifying the influence of each input parameter, enriching our understanding of essential system elements. They provide long-term predictions for assessing transmission line lifespan and structural stability, with particularly high precision in forecasting temperature and sag angle. It is important to note that certain engineering parameters, such as material properties and load considerations, were not included in our research, potentially influencing accuracy.
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Key Words: Overhead Transmission Lines (OTL), Machine Learning, Modelling, Optimization, Genetic Algorithms (GA)

1. INTRODUCTION

Evolutionary algorithms (EAs) have become indispensable tools for modelling and optimizing a diverse array of complex systems in various scientific disciplines [1-5]. Among the EAs, GAs [6, 7] stand out as the most widely applied, especially in scientific and engineering domains, where challenges related to modelling, optimization, and combinatorial complexity are prevalent [8-13]. They are rooted in the principles of evolution and natural selection, GAs initiate with a population of potential solutions to a problem [6]. They then employ genetic operators like selection, crossover, and mutation to iteratively evolve and enhance these solutions across multiple generations.

This paper proposed the genetic algorithm (GA) approach to address issues within the electricity transmission and distribution system, with specific emphasis on the critical components known as support pillars, which play a vital role in sustaining insulators and conductors.

We draw inspiration from various recent research endeavours in the field of electrical transmission systems and modelling. Notably, it aligns with the work of Nguyen and Vu [14], who introduced a novel method combining Differential Evolution (DE) and machine learning to reduce the weight of steel lattice towers. The application of an Adaptive Boosting algorithm in their study demonstrated remarkable efficiency gains, making it 1.5 times faster than the original DE algorithm, with substantial time savings and optimal results.

Du and Hajjar's research on assessing the risk of transmission tower collapse during hurricanes [15] using Incremental Dynamic Analysis (IDA) serves as another relevant reference. Their fragility curves provide valuable insights for regional damage assessment during hurricane events.

Additionally, the optimization of rural electrical distribution networks using GAs, as explored by Fletcher et al. [16], contributes to the practical application of GAs in the power distribution domain.

Another innovative approach is presented by Earp [17], who introduced a methodology for inspecting power transmission towers using high-resolution aerial photographs taken from helicopters, integrating detailed photographic recording with GPS to create a permanent record of tower conditions.

Martinez Ricardo et al. [18] proposed methodology for early fault detection in cable-stayed towers using AI-based predictive maintenance. This study also serves as a valuable reference, demonstrating the versatility of machine learning and finite element models in infrastructure monitoring.

Manninen et al. [19] exploration of supervised classification algorithms and health index determination for overhead transmission lines showcases the potential for enhancing grid reliability through cost-effective methods.

This paper is founded on measurements and experimental data gathered on OTLs. The data encompasses a range of response variables including pillar voltage, vibration, electrical conductor temperature, and conductor sag. These metrics are influenced by a multitude of independent variables such as ambient conditions, conductor current, solar radiation, air pressure, and wind patterns. This dataset serves as the foundation for understanding and quantifying the underlying physical system.

The response values are subject to random variations in input variables. Adverse values in these responses can lead to a reduced lifespan for conductors and their supporting structures. Leveraging GAs, our aim is to discern the relative weight of influence exerted by each input variable on the output parameters. This knowledge empowers us to identify the most critical input variables affecting electrical conductors and their support structures. Ensuring the reliable and uninterrupted flow of electricity depends on the structural integrity, particularly in older transmission lines that were made at different times, which can lead to varying degrees of wear and tear. Harsh weather conditions can also pose threats to power line systems. The purpose of this research is to introduce a method for predicting and assessing the condition of these structures by measuring influencing factors.

2. MATERIALS, METHODS AND EXPERIMENTAL WORK

The research involves comprehensive measurements of L-profile pillars constructed from S270 steel. These measurements capture various stresses arising from factors such as the manufacturing process, load distribution, tensile forces, dead weight, and equipment installations. The "DynaStrain" system equipped with accelerometers and solar panels enables the measurement of stress and vibration, contributing valuable data. An overview of all the measurement systems installed on the pillar is presented in Fig. 1 [20].

Measurements are systematically collected and analysed, considering variables such as stress, pillar vibrations, temperature, and sag in electrical cables. The data provides insights into the long-term impact of different factors, including weather conditions and power usage, on the behaviour of conductors and supporting pillars [20].

We have organized the input and output variables, specifying their respective maximum and minimum values, and presented this information in the upcoming tables. These tables are crucial for providing a clear understanding of the variable intervals that played a pivotal role in generating the prediction models.

Fig. 2 [20] shows how we measured residual stresses in the pillars, followed by the application of adhesive strain gauges in the same location (Fig. 3) [20].

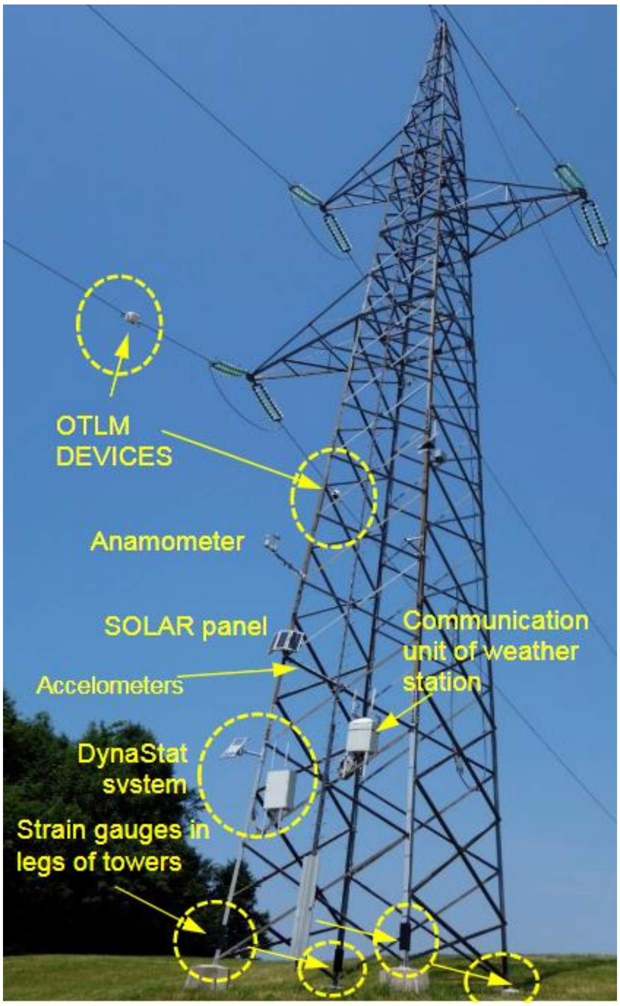

Figure 1: Measuring systems mounted on the pillar [20].

Figure 2: Measurement of residual stresses [20].

Figure 3: Adhesive strain gauges at the location of the measured residual stresses on the L profile [20].

2.1 Input and output variables

The intervals of the independent input variables are presented in Table I, while the intervals of the dependent output variables are shown in Table II.

Table I: Intervals of input variables.

Input variable name	Maximum value	Minimum value
Ambient temperature (K)	284.3	265.3
Ambient humidity (%)	96.16	35.0
Current (A)	111.0	69
Solar irradiance	275.16	0.0
Atmospheric pressure (mbar)	970.98	964.0
Wind speed (m/s)	3.50	0.5
Wind direction (°)	265.0	68.10

Table II: Intervals of output variables.

Output variable name	Maximum value	Minimum value
Electrical conductor temperature (K)	287.15	266.15
Sag angle (°)	14.36	13.79
Vibration measuring point 1 (Hz)	17.03	7.83
Vibration measuring point 2 (Hz)	16.93	5.86
Stress in pillar 1 measuring point 1 (MPa)	-39.31	-43.37
Stress in pillar 1 measuring point 2 (MPa)	-21.22	-26.96
Stress in pillar 2 measuring point 1 (MPa)	34.32	27.24
Stress in pillar 2 measuring point 2 (MPa)	-3.62	-6.66
Stress in pillar 3 measuring point 1 (MPa)	-53.03	-73.25
Stress in pillar 3 measuring point 2 (MPa)	-52.08	-57.55
Stress in pillar 4 measuring point 1 (MPa)	-12.65	-33.24
Stress in pillar 4 measuring point 2 (MPa)	-11.67	-31.84

2.2 Mathematical model

The preset polynomial mathematical model used in this study is presented in Eq. (1).

$$f_i(x_j) = k_1 + k_2x_1 + k_3x_2 + k_4x_3 + k_5x_4 + k_6x_5 + k_7x_6 + k_8x_7 \quad (1)$$

The $f_i(x_j)$ presents the chosen response f_i ($i = 1, 2, \ldots, 12$) such as conductor temperature, electrical conductor sag, stresses in pillars, and vibrations, dependent on independent input variables x_j ($j = 1, 2, \ldots, 7$). The input variables are:

- x_1 (K) – ambient temperature,
- x_2 (%) – ambient humidity,
- x_3 (A) – current in the conductor at the moment of measurement,
- x_4 (/) – solar irradiance,
- x_5 (mbar) – ambient pressure,
- x_6 (m/s) – wind speed,
- x_7 (°) – wind direction.

The vector of constant k_n ($n = 1, 2, \ldots, 8$) represent an organism undergoing simulated evolution. For each response i, the genetic algorithm is employed to optimize the vector of constants, ensuring that the models effectively capture experimental data.

2.3 Modelling

The computer modelling was performed using the AutoCAD CAD/CAM software. The genetic algorithm system was implemented in the AutoLISP programming language [21, 22]. Key GA-related parameters in this study include population, generation, primary genetic operations (reproduction and crossover), secondary genetic operation (mutation), set of independent input variables, and a set of constants representing multidimensional organisms manipulated by the genetic operations.

2.4 Coding of organism and used genetic operations

Coding of organisms

In our specific case, the population consisted of organisms coded as vector of real numbers. The vector dimension was n = 8. In our specific implementation, the population consisted of 500 organisms, and the maximum number of generations was set to 1000 [23-28].

Reproduction/selection, crossover, and mutation

During the reproduction, a single offspring is generated from an individual parent organism. This operation occurs in two phases. Initially, one of the selection methods is employed [29] to choose the organism based on its fitness. In our study, we adopted the tournament method for selection [29]. By employing the tournament method, we ensured that only individuals with relatively good fitness were permitted to participate in the reproduction process, effectively excluding those with lower fitness [23, 24].

The crossover operation generates two offspring by combining genetic material from two parental organisms [23].

A mutation operation affects one parent organism and one offspring. Its purpose is to introduce random genetic variations into the population of organisms [23].

2.5 Number of constants

The number of constants within our model is determined by the underlying polynomial mathematical model given in subsection 2.2 and is crucial for optimization by the genetic algorithm (GA). In our preliminary study, the range of constants spanned from 8 to 36. However, for the final development of predictive models, we settled on a mathematical model featuring a total of n = 8 constants.

3. RESULTS AND DISCUSSION

The modelling process for each response was a multi-step procedure. In the initial phase, we conducted a series of runs with varying parameters, including population size, maximum number of generations, probabilities for reproduction, crossover and mutation, and tournament size. Our objective was to identify the most suitable settings that would yield satisfactory results without requiring excessive computation time.

Following these preliminary runs, we established a standardized configuration for all responses, which included a population size of 500 organisms, a maximum number of generations 1000, and a tournament size of 7. These parameter values were carefully selected to strike a balance between exploring a broad solution space and achieving computational efficiency.

With the program settings configured to anticipate reasonably accurate models, we executed 10 runs for each response. Afterward, we thoroughly examined and showcased the top-performing model for each response in this study.

The results are presented through predictive model equations, detailing the influence of input variables on the output responses. The findings highlight the significant impact of factors like ambient temperature, wind speed, and wind direction on various aspects of electrical conductors and supporting structures. Each coefficient represents the contribution of an individual independent variable to the change in the dependent variable, assuming that all other independent variables are constant.

3.1 Predictive models

In this subsection, the obtained models using the genetic algorithm system are presented. The responses from Eq. (1) have the following meanings:

- Y_1 (K) – conductor temperature,
- Y_2 (°) – electrical conductor sag,
- Y_3 (MPa) – stress in pillar 1 measuring point 1,
- Y_4 (MPa) – stress in pillar 1 measuring point 2,
- Y_5 (MPa) – stress in pillar 2 measuring point 1,
- Y_6 (MPa) – stress in pillar 2 measuring point 2,
- Y_7 (MPa) – stress in pillar 3 measuring point 1,
- Y_8 (MPa) – stress in pillar 3 measuring point 2,
- Y_9 (MPa) – stress in pillar 4 measuring point 1,
- Y_{10} (MPa) – stress in pillar 4 measuring point 2,
- Y_{11} (Hz) – vibration at accelerometer 1,
- Y_{12} (Hz) – vibration at accelerometer 2.

$$Y_1 = 6.90907 + 1{,}02695x_1 + 0.00954072x_2 + 0.00839891x_3 + 0.0116645x_4 - 0.0155549x_5 - 0.0881284x_6 + 0.00033537x_7 \quad (2)$$

$$Y_2 = -1.0159 + 0.0302691x_1 - 0.003389x_2 - 0.0012134x_3 - 8.4061\mathrm{e}^{-5}x_4 + 0.00746533x_5 + 0.0537743x_6 - 0.00097334x_7 \quad (3)$$

$$Y_3 = 0.203574 + 0.32509x_1 + 0.04662x_2 + 0.0204123x_3 - 5.227\mathrm{e}^{-5}x_4 - 0.089383x_5 + 0.507477x_6 - 0.00031282x_7 \quad (4)$$

$$Y_4 = 1.17944 + 0.269083x_1 + 0.02737x_2 + 0.0104x_3 + 0.00692x_4 - 0.07568x_5 - 0.05875x_6 - 0.00022185x_7 \quad (5)$$

$$Y_5 = 1.95414 + 0.21259x_1 + 0.02520x_2 - 0.00203x_3 + 0.01398x_4 - 0.03389x_5 - 0.22411x_6 + 0.00119x_7 \quad (6)$$

$$Y_6 = -0.20441 + 0.12280x_1 - 0.002777x_2 - 7.18\mathrm{e}^{-5}x_3 - 1.693\mathrm{e}^{-5}x_4 - 0.028858x_5 + 0.44050x_6 - 0.008312x_7 \quad (7)$$

$$Y_7 = -3.4336 + 1.03683x_1 + 0.07327x_2 + 0.005162x_3 + 0.02999x_4 - 0.2839x_5 + 0.6672x_6 - 0.00160x_7 \quad (8)$$

$$Y_8 = 1.38056 + 0.02904x_1 - 0.00301x_2 + 0.00252x_3 + 0.02034x_4 - 0.00963x_5 + 0.72312x_6 + 0.01262x_7 \quad (9)$$

$$Y_9 = 1.1925 + 1.1194x_1 + 0.0834x_2 - 0.04123x_3 + 0.01941x_4 - 0.3060x_5 + 0.3810x_6 - 0.00182x_7 \quad (10)$$

$$Y_{10} = -0.78588 + 0.86590x_1 + 0.08331x_2 + 0.04667x_3 + 0.033926x_4 - 0.24013x_5 - 0.22906x_6 - 0.00224x_7 \quad (11)$$

$$Y_{11} = -0.68216 - 0.76730x_1 - 0.23476x_2 - 0.03150x_3 - 0.02242x_4 + 0.26423x_5 - 0.17072x_6 - 0.044816x_7 \quad (12)$$

$$Y_{12} = 0.9739 + 0.1526x_1 + 0.001294x_2 + 0.001294x_3 - 0.03421x_4 - 0.01235x_5 - 1.34822x_6 - 0.05441x_7 \quad (13)$$

3.2 Weighted influence of independent input variables on responses

The percentage of influence exerted by each independent input variable on the dependent output variables (responses) are presented in Table III. In the following subsections, we have provided a brief discussion on the qualitative impact of input variables on the system response.

Table III: Influence of independent input variables on responses in percentages.

Input variable name / Output variable name	Ambient temperature x_1 (%)	Ambient humidity x_2 (%)	Current (A) x_3 (%)	Solar irradiance x_4 (%)	Atmospheric pressure x_5 (%)	Wind speed x_6 (%)	Wind direction x_7 (%)
Y_1	88.49	0.82	0.72	1.01	1.34	7.59	0.03
Y_2	31.15	3.49	1.25	0.09	7.68	55.34	1.00
Y_3	32.86	4.71	2.06	0.00	9.03	51.29	0.03
Y_4	60.01	6.10	2.32	1.54	16.88	13.11	0.05
Y_5	41.44	4.91	0.40	2.73	6.61	43.69	0.23
Y_6	20.35	0.46	0.01	0.00	4.78	73.01	1.38
Y_7	49.42	3.49	0.25	1.43	13.53	31.80	0.08
Y_8	3.63	0.38	0.31	2.54	1.20	90.36	1.58
Y_9	57.34	4.27	2.11	0.99	15.67	19.52	0.09
Y_{10}	57.68	5.55	3.11	2.26	16.00	15.26	0.15
Y_{11}	49.96	15.29	2.05	1.46	17.21	11.12	2.92
Y_{12}	9.51	0.08	0.08	2.13	0.77	84.03	3.39

3.3 Electrical conductor temperature

The model reveals that ambient temperature significantly influences power line temperature, while wind direction has a minimal impact. It effectively follows the temperature trend, with an average deviation of 0.135 K from measured values, Eq. (2).

3.4 Electrical conductor sag

The model highlights the predominant effect of wind speed on electrical conductor sag, with solar irradiance and wind direction playing minor roles. It accurately tracks sag trends, with an average absolute difference of 0.02° compared to measurements, Eq. (3).

3.5 Stresses in high-voltage electricity pillars

We developed eight models to predict stresses in the electricity pillars, Eqs. (4) to (11). Created models reveal consistent trends:

- Solar irradiance, wind direction, and conductor current have minimal impact on pillar stresses.
- Ambient temperature and wind speed exert the most significant influence on pillar stresses.

Model Y_5, Eq. (6) achieved the smallest mean difference of 0.1 MPa. Interestingly, this model weighed the influence of ambient temperature and wind speed practically on a par.

3.6 Vibration in the pillar

Accelerometer 1

Vibrations measured at accelerometer 1 are primarily influenced by ambient temperature and minimally affected by solar irradiance. The model's average absolute vibration difference from measurements is 1.10 Hz. Refer to Eq. (12).

Accelerometer 2

Vibrations measured at accelerometer 2 are most influenced by wind speed, with minimal impact from ambient humidity and conductor current. The model reasonably predicts values for these measurements, with an average absolute difference of 0.58 Hz, Eq. (13).

4. CONCLUSION

This survey focused on the modelling and generation of predictive models using genetic algorithms to predict the behaviour of electrical conductors on overhead transmission lines and their supporting structures. These models aim to predict various responses, including power line temperature, line sag and stresses, and vibrations in pillars. The primary objective was to determine the influence of individual input variables on these responses. The study successfully created predictive models for these responses, and the results aligned well with measurements. It is important to acknowledge that limitations arise from overlooking material properties of the supporting OTL structure and equipment weight in our current approach. To enhance accuracy, future models should incorporate these factors and expand their knowledge base by drawing from a larger and more diverse database. This expansion will significantly broaden their prediction capabilities. In the context of our research, we primarily concentrated on the utilization of polynomial fittings for system modelling. Our focus on specific polynomial shapes was a deliberate choice in alignment with the study's defined scope and scale.

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