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Research Article

Wind Energy Forecasting Based on Grammatical Evolution

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ABSTRACT

The energy generated by wind turbines exhibits a continually fluctuating structure due to the dynamic variations in wind speed. In addition, in the context of seasonal transitions, increasing energy demand, and national/international energy policies, the necessity arises for short and long-term forecasting of wind energy. The use of machine learning algorithms is prevalent in the prediction of energy generated from wind. However, in machine learning algorithms such as deep learning, complex and lengthy equations emerge. In this study, the grammatical evolution algorithm, a type of symbolic regression method, is proposed to obtain equations with fewer parameters instead of complex and lengthy equations. This algorithm has been developed to derive a suitable equation based on data. In the study, through the use of grammatical evolution, it has been possible to obtain a formula that is both simple and capable of easy computation, with a limited number of parameters. The equations obtained as a result of the conducted analyses have achieved a performance value of approximately 0.91 (R^2). The equations obtained have been compared with methods derived using the genetic expression programming approach. In conclusion, it has been ascertained that the grammatical evolution method can be effectively employed in the forecasting of wind energy.

1. INTRODUCTION

The continuously increasing population and expanding industry require the resolution of challenging problems to meet the growing energy demand. The traditional energy sources utilized to meet this energy demand have resulted in significant pollution and caused global warming, which is challenging to reverse, on our planet. Among the developed solution proposals, renewable energy sources are quite promising, leading many governments to make significant investments in them. Wind turbines, holding a significant place among renewable energy sources, are of critical importance for an ecological and sustainable world [1]. However, there are uncertainties in obtaining energy from wind farms, including fluctuations in wind speed, continuously increasing demand and population density, and price instability [2]. To overcome these uncertainties, it is necessary to make short-term and long-term wind speed predictions with high accuracy. Various machine learning algorithms exist for predicting wind speed, but these models possess complex mathematical structures. Moreover, the training of networks containing a large number of layers and neurons can sometimes take days, and the resulting models, having a closed structure, produce equations that are quite challenging to interpret. Conversely, mathematical equations that are simple to compute manually, easy to read, and highly accurate are essential to reduce this complexity. In this study, a grammatical evolution (GE) based algorithm, a significant type of symbolic regression (SR), is proposed for predicting the output energy of wind turbines.

SR is a method where various mathematical models are proposed to understand the relationships among data. SR methods, encompassing various algorithms, typically employ evolutionary algorithms like genetic programming (GP) to find mathematical expressions (formulas) that best fit the datasets. In SR, there is no predetermined model. To find the mathematical model that fits the data, a selection is made from a wide pool of expressions using various operations (such as addition, subtraction, multiplication, division, exponentiation, logarithms, trigonometric functions etc.) [3]. Genetic expression programming (GEP), a type of SR method, is an evolutionary algorithm derived from the foundations of GP. GEP automatically proposes mathematical models to solve complex problems, fundamentally transforming the principles of biological evolution and natural selection into an algorithmic process [4, 5].

GE is a specialized algorithm used for SR and is a type of GP algorithm. GE bases itself on linguistic rules to find mathematical models or expressions that best fit dataset [6, 7].

Dufek et al. [8] proposed a methodology using GE for ensemble wind speed forecasting in northeastern Brazil, developing models that reduced forecasting errors by 7%-56%

compared to existing techniques, including a real-world operational model. Valsaraj et al. developed a new method using SR to estimate high altitude wind speeds from lower altitude data, achieving up to 61.04% reduction in daily RMSE compared to traditional methods, enabling more efficient wind resource assessment [9]. In another study, bayesian SR are used to find new models that better link energy consumption and pollution to socioeconomic factors, challenging existing stochastic impacts by regression on population, affluence, and technology (STIRPAT) assumptions [10].

Rueda et al. proposed using ant colony optimization for straight line programs in SR, comparing it with traditional GP for modeling real energy consumption problems [11]. Hybrid SR with deep multi-layer perceptron model has been proposed for PV power forecasting, achieving higher accuracy and robustness with significant reductions in RMSE and MAE, and improved training efficiency using advanced feature selection techniques [12]. Porras et al. [13] proposed a study for predicting the energy generation of a small wind turbine in a bioclimatic house in northwest Spain, analyzing atmospheric data over a year and exploring regression techniques to accurately forecast short-term power generation levels.

Rueda et al. suggested using SR with single and multi-objective algorithms to develop a generalized model for forecasting energy consumption time series, learning shared properties across different series [14]. Ramon et al. explored using neural networks and symbolization techniques for electric demand prediction, testing various architectures and methods on Spanish electric data. Their symbolization approach yielded slightly lower accuracy but was trained much faster [15].

Kochueva et al. proposed novel predictive models using SR and genetic algorithms for CO and NOx emissions from gas turbines, enhancing interpretability and transparency, and introduced a new classification model based on fuzzy inference systems [16]. Li et al. used SR and Tapio decoupling analysis to identify key factors influencing rural energy consumption in Henan, China, revealing significant elements and various decoupling statuses affecting energy usage patterns from 2000 to 2015 [17]. Kefer et al. proposed an energy management system optimized through GEP based SR, outperforming existing systems in minimizing energy costs, supporting grid stability, and prolonging battery life in residential buildings [18].

There are studies where GE algorithms have been used in the context of wind energy. Rodriguez et al. developed a grammatical swarm algorithm to forecast a country's total energy demand using macroeconomic variables, successfully testing it in Spain and France for one-year predictions [19]. Colmenar et al. introduced a novel hybrid approach using GE and differential evolution (DE) to generate and optimize models for predicting a country's total energy demand from macro-economic variables, demonstrating high accuracy in Spain and France [20]. Aditya et al. used GE algorithm to predict the daily load of a power plant from Indonesia's 2019 Jamali region electricity system data, outperforming the autoregressive integrated moving average model with a lower mean average percentage error (MAPE) of 1.77% [21]. Jamil et al. proposed a novel approach combining GE and DE for one-year-ahead energy demand estimation in Turkey, achieving high accuracy and outperforming previous models with a low RMSE [22]. Lourenço et al. developed a structured GE algorithm, hybridized with DE, to create accurate models for predicting annual energy demand in Spain based on macro-economic indicators [23].

The GE algorithm has also been employed for various other purposes. Lujan et al. developed an AI-based method using GE and DE to predict poly-crystalline silicon PV module temperature, significantly reducing error rates compared to the traditional sandia model under varying weather conditions [24]. In another study, the authors have proposed a multi-layered LSTM model for wind speed prediction [33]. Jeschke et al. developed a parameterized model predictive control (PMPC) for urban traffic using GE, reducing the computational complexity of real-time implementations while maintaining high performance efficiency [25]. In another study, Christou et al. designed a GE based method for automatic feature selection in radial basis function networks, achieving the highest classification accuracy (90.07%) for distinguishing hemiplegia types in patients using accelerometer sensor data [26].

In summary, in this article:

1- A GE based algorithm is proposed, deriving an equation with a minimal number of parameters. This results in a straightforward, easily readable, and writable equation for predicting wind energy.

2- Statistical analyses have been conducted on a dataset from an actual wind turbine.

3- For comparative purposes, GEP, a significant method in SR, has been utilized.

4- Performance comparisons have been made for the considered SR methods.

5- Various mathematical functions were employed in the equation generation phase, and the one yielding the best performance results is presented.

The article is organized into four sections. Section 1 provides an introduction and a summary of the literature. In section 2, explanations of the GE algorithm and its pseudocode are presented. The fundamentals of GEP are discussed, and the statistical metrics used are explained. In section 3, the equations and performance metrics obtained using the proposed GE based algorithm are presented, along with comparisons to GEP methods. Finally, section 4 presents the conclusions of the study.

2-MATERIALS VE METHODS

2.1 Wind Energy

The energy that can be harnessed from wind is directly proportional to the kinetic energy of the wind, as shown in Eq. 1. According to Betz's law, the maximum power a wind turbine can extract from wind is defined as approximately 59.3% of the theoretical limit [27].

$$P_w = \frac{1}{2}.\rho.A.C_p(\lambda,\beta)V^3 \tag{1}$$

A represents the turbine blade area (m²), C_p the performance coefficient, P_w the turbine power, V the wind speed (m/s), ρ the air density (1.225 kg/m³), β the blade angle (°), and λ the blade speed ratio. The blade area can be represented as shown in Eq. 2.

$$A = \pi R^2/4 \tag{2}$$

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The performance coefficient changes depending on the blade speed ratio λ, wind speed V, the blades' angular rotation speed ω, and the blade radius R. Eq. 3 provides the blade speed ratio.

$$\lambda = \frac{R\omega}{V} \tag{3}$$

2.2. Grammatical Evolution (GE)

GE [7], rooted in GP, leverages a grammar-oriented approach. This method integrates a context-free grammar (CFG) with a rule-selection system executed through a genetic algorithm, facilitating the mapping procedure. CFG defines the structural rules of the language and allows GE to create various expressions. These algorithms reach solutions by utilizing the fundamental principles of genetic algorithms (selection, crossover, and mutation). Chromosomes generated by the genetic algorithm are transformed into a program or expression using CFG rules, thereby automatically determining mathematical expressions suitable for the problem. CFG defines the solution space of GEP and the structures it can generate.

CFG is a concept used in linguistics and comprises rules and symbol sets that express the structure of a language. In CFG, T (terminal symbol), N (non-terminal symbols), S (start symbol), and R are defined as production rules. CFGs are often expressed in Backus-Naur form (BNF) [28]. An example template for BNF is given between Eq. 4-7. In these equations, it is possible to generate production rules using non-terminal symbols $N = \{expr, op, coef, var\}$ and terminal symbols $T = \{+, -, x, \div, v_1, v_2, c_1, c_2, (,)\}$.

$$< expr > ≔ (< expr >) < op > (< expr >) \tag{4}$$

$$< op > ≔ +| - |x| \div \tag{5}$$

$$< coef > ≔ c_1|c_2 \tag{6}$$

$$< var > ≔ v_1|v_2 \tag{7}$$

Figure 1 shows the flow of the algorithm related to GE. In this algorithm, an initial population of solutions is created, and a context-free grammar is defined. Each iteration involves generating a program for each individual using CFG and evaluating its effectiveness via a fitness function. A new population is then formed by selecting the best individuals and applying genetic operations like crossover and mutation. The current population is replaced with this new one. The process repeats until a termination criterion, such as a maximum number of iterations or a desired fitness level, is met. Upon meeting this criterion, the best solution found is returned.

Figure 2 illustrates an example tree structure generated by GE and GEP. Although these two algorithms have different working structures, the structures of the generated trees resemble each other. However, there are some differences in terms of certain fundamental mathematical functions in the constructed structural tree.

```
Initialize:
      Create initial population
      Define CFG
Each iteration:
    For each individual:
        Generate program using CFG
        Evaluate program (fitness function)
        Create new population:
        Select best individuals
        Apply crossover and mutation
    Replace old population
    If met, termination criteria:
        If met, return best solution
    Else, continue iterations
```

Figure 1. GE Pseudocode

2.3. Genetic Expression Programming (GEP)

GEP is used to obtain equations based on data, similar to what GE does [5]. In the GEP method, chromosomes are represented as mathematical operations. The GEP method consists of five main components: a function set, a terminal set, control parameters, fitness functions, and termination conditions [29]. The function set represents mathematical operations, while the terminal set includes the algorithm's input variables. Control parameters define the population size, and the fitness function serves as a measure of the solution's effectiveness. The termination criterion determines when the iterative process will end [30].

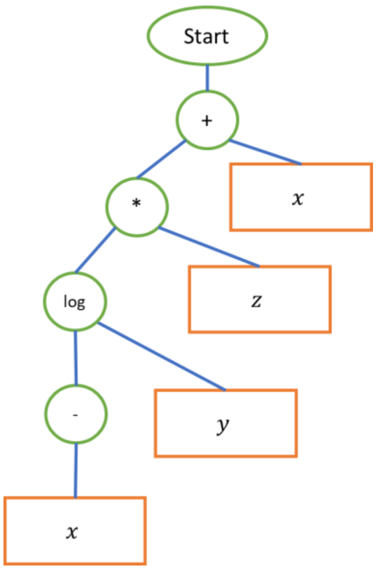

Figure 2. An example of a grammatical and genetic expression tree

In the genetic expression tree shown in Figure 2, the expression $(\log(y) - x) * z + x$ can be readily obtained. The orange-colored rectangular boxes represent terminals (x, y, z), while the circular green nodes represent mathematical operations $(+, -, *, log)$.

3. RESULTS AND DISCUSSION

3.1 Preliminary Analysis

Scada systems [34] in wind turbines measure and record data such as wind speed, direction, and generated power at 10-minute intervals, as exemplified by this file from a functioning wind turbine in Turkey. The dataset (50530) was recorded at 10-minute intervals between January 01, 2018, and December 31, 2018. The acquisition of the GEP tree and performance analyses were conducted using the HeuristicLab program developed by the Heuristic and Evolutionary Algorithms Laboratory [31]. The dataset was divided into three subsets: 15% for testing, 15% for validation, and 70% for training. This resulted in the use of 35371 data points for training, 7580 for validation, and 7580 for testing. In order to improve the performance during the testing phase, the data was randomly shuffled. The operation and function sets used in the construction of the GE algorithm are presented in Table 1. This table contains information about the function set, maximum generation count, population size, and depth used.

TABLE I

Parameter settings for the GE algorithm

Definitions	Parameters
Function Set	$+,-,*,/,\sqrt{},\sqrt[3]{},log,x^2,$
Number of Max. Generations	100
Population Size	1000
GE Depth	5-7

The operation and function sets used in the generation of genetic expression trees are presented in Table 2. Studies were conducted using the parameters in Table 2 to achieve the best performance of the genetic tree.

TABLE II

Parameter settings for the GEP

Definitions	Parameters
Function Set	$+,-,*,/,\sqrt{},\sqrt[3]{},log,x^2,$ $x^3,sin,cos,tan,tanh$
Number of Generations	200
Population Number	1000
GEP Depth	5
GEP Symbol Number	80
Mutation Probability	0.15

The sets of operations and functions used in the creation of the genetic expression tree are presented in Table 2. These parameters were determined as the most suitable through the research conducted. Table 3 displays the statistical values for the data collected from the wind turbine. Figure 3 displays the density distribution of four variables, including wind speed, direction, and generated power, measured during the operation of a wind turbine in Turkey.

TABLE III

Pre-descriptive statistics analysis

	Active Power (kW)	Wind Speed (m/s)	Theoretical Power (kWh)	Wind Direction (°)
count	50530	50530	50530	50530
mean	1307,684	7,557952	1492,175	123,6876
std	1312,459	4,227166	1368,018	93,44374
min	-2,47141	0	0	0
25%	50,67789	4,201395	161,3282	49,31544
50%	825,8381	7,104594	1063,776	73,71298
75%	2482,508	10,30002	2964,972	201,6967
max	3618,733	25,20601	3600	359,9976

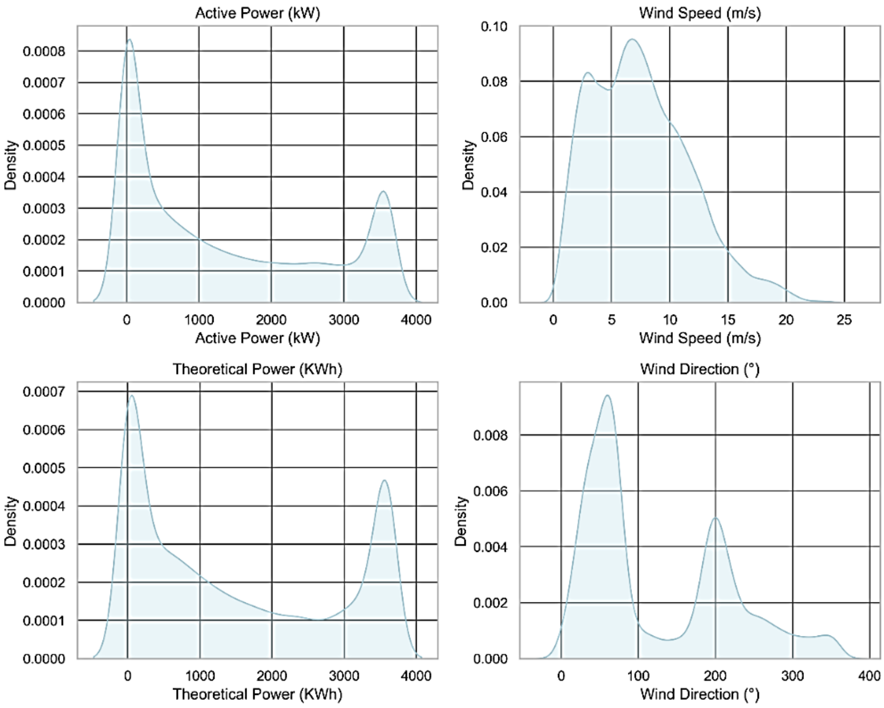

Figure 3. Density of active power, wind speed, theoretical power and wind direction

Figure 4. Correlation matrix

The correlation matrix is employed to examine the influence of variables on each other. If values are close to -1, there is a strong inverse relationship, if close to 1, there is a strong linear relationship between the data. If close to 0, there is no linear relationship between the data [32]. The correlation matrix presented in Figure 4 reveals a strong relationship (0.95) between active power and theoretical power. Additionally, as evident from the equations, there are robust relationships between wind and power (both theoretical and active).

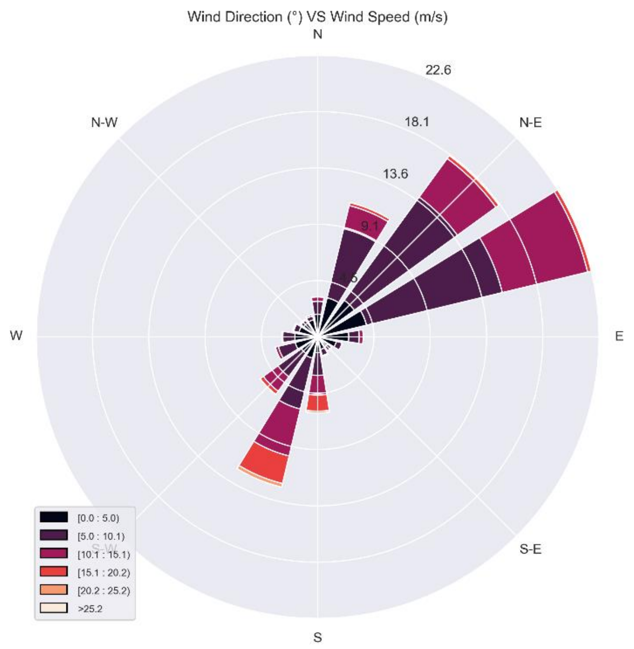

Figure 5. Relationship between wind speed and direction

Figure 5 illustrates the relationship between wind speed and wind direction. The figure demonstrates how wind direction varies with wind speed. The distribution of wind direction has been normalized based on wind speed. In this chart, the highest wind speeds (22.6 m/s) are observed in the easterly directions (NE and E). Particularly, in the east, wind speeds exceeding 20.2 m/s indicate that the wind is considerably strong. Conversely, in the northern and western directions, the wind appears to be relatively less frequent and predominantly registers speeds below 5.0 m/s.

3.2. Results of the Grammatical Evolution Analysis

The tree structure depicted in the graph integrates the values of theoretical power (T_p) and wind direction (W_d) within a complex equation to yield a result. Each node within this structure represents a mathematical operation, including addition, multiplication, and square rooting. The constants (-5.921, 1.823, and 3.69) are utilized to fine tune the dynamics of the equation, while average functions moderate the impact of input variables with a mean value. This model facilitates the analysis of the interactions between T_p and W_d, offering an output that is applicable in areas such as wind energy forecasting. For the proposed initial mathematical equation based on GE, the performance has achieved an R^2 value of 0.904 during the training phase and 0.902 (R^2) in the testing phase.

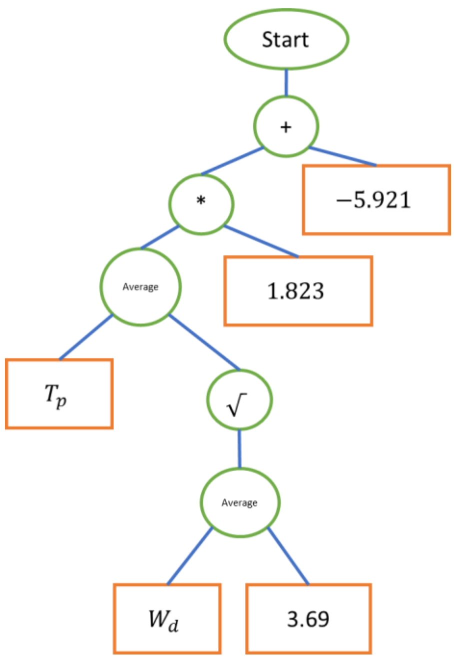

Figure 6. Proposed GE tree 1

The equation obtained using the tree depicted in Figure 6 is presented in Eq. 8. In this equation, P_A represents active power (kWh), P_T represents theoretical power (kWh), W_D denotes wind direction (°) and wind speed ($w_s - m/s$). Eq. 9 represents the second equation derived using GE. This equation has achieved a performance value of 0.9103 in the training phase and 0.909 in the testing phase.

$$P_A = 0.5 * \left(P_T + \sqrt{0.5 * W_D + 3.69}\right) * 1.823 - 59.21 \tag{8}$$

$$P_A = \left(P_T * log\left(3.82 + \frac{W_S}{\sqrt{3.69 * W_D}}\right)\right) * 0.321 + 2.817 \tag{9}$$

Figure 7 depicts the histogram of the number of elements in the tree when the tree depth is set to 5. The small number of symbols indicates that the structure of the predicted mathematical equation is simple. Figure 8 displays a tree structure created using the GE algorithm. Each node of the tree represents a mathematical operation or function. Basic arithmetic operations such as multiplication, division, and root

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extraction, as well as the logarithm function, are included in this structure. Constants and variables (theoretical power, wind speed, wind direction) are combined with these operations to formulate an equation.

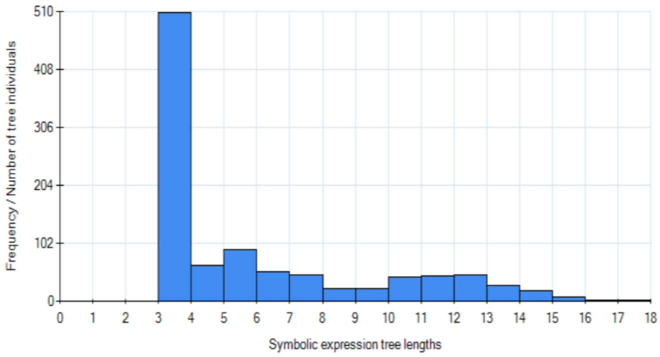

Figure 7. Proposed GE tree-1 histogram

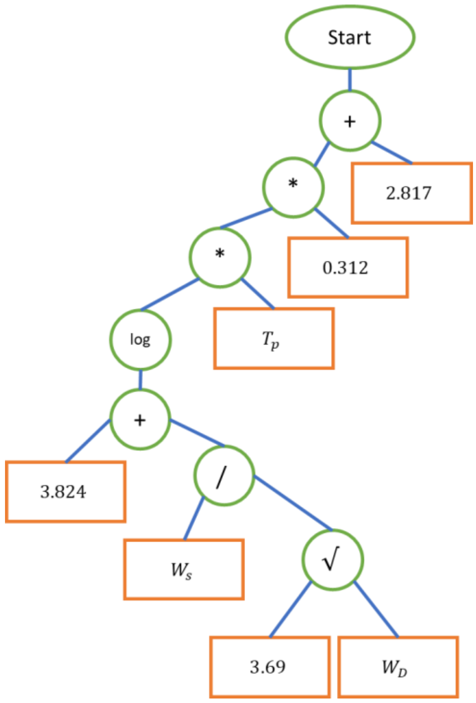

Figure 8. Proposed GE tree 2

Figure 8 presents the proposed GE tree, which consists of 14 symbols. Figure 9 shows the histogram of the number of tree elements when the tree depth is set to 7.

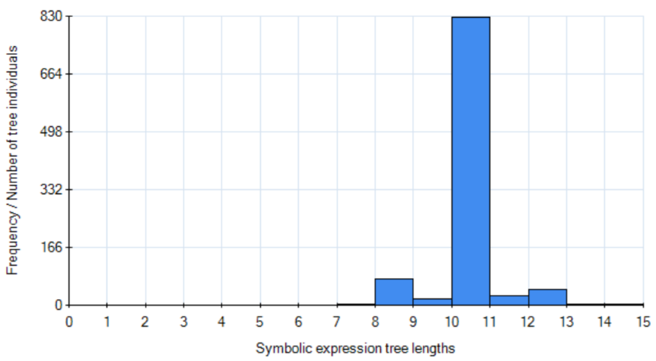

Figure 9. Proposed GE tree 2 histogram

3.3. Results of Genetic Expression Programming Analysis

Figure 10 displays the tree generated by the GEP algorithm. The tree is composed of operations such as logarithm, multiplication, and addition. Despite the simplicity of the resulting equation, it has attained a value of 0.906 during the training phase and 0.903 in the testing phase. Figure 11 illustrates how the tree depth varied in the attempts of the GEP algorithm to find Eq. 10.

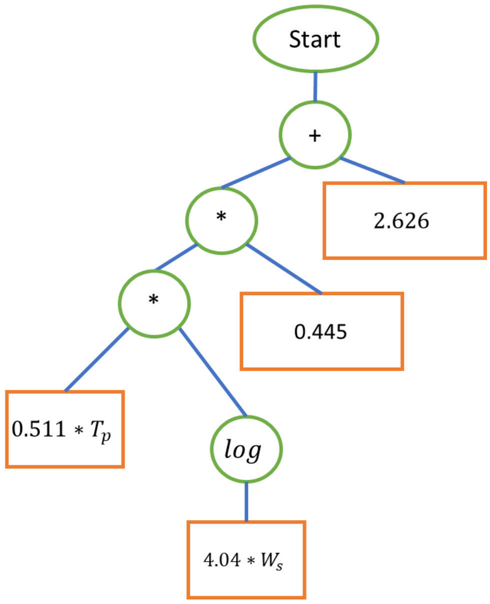

Figure 10. Proposed GEP tree

Eq. 10 represents the equation of the tree created in Figure 10. This equation expresses active power as dependent on theoretical power and wind direction. However, it should not be forgotten that the theoretical power is largely dependent on wind speed.

$$P_A = (0.445 * (0.511 * T_p * \log(4.04 * W_s))) + 2.626 \qquad (10)$$

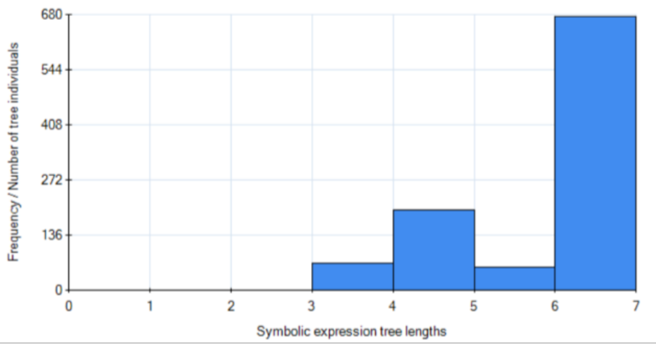

Figure 11. Proposed GEP tree-1 histogram

The three different equations proposed based on GE and GEP have been expressed with much simpler functions compared to the complex equations and time-consuming solutions of machine learning algorithms. Moreover, their overall performances possess values higher than 0.9, indicating that these R^2 performance values demonstrate the comprehensibility of the values in the dataset and the ease of generating equations. The Eq. 9, predicted using the GE algorithm, not only exhibits superior performance (0.91) compared to other equations but can also be represented with just 14 symbols. Using 14 symbols demonstrates that the equations created are quite concise. Both GEP and GE have been able to generate highly successful results in producing equations.

4. CONCLUSION

Wind turbines hold a significant position among renewable energy sources and their usage is increasingly growing. However, the dynamic changes in wind speed, seasonal variations, increasing user demand, and the need to meet national policies make the prediction of wind energy essential. To make these predictions, numerous machine learning-based methods have been proposed in the literature. However, the training of these methods can be lengthy, and the resulting equations can be quite complex. This study utilizes wind speed, wind variation, and theoretical power information as inputs for predicting active power output from wind turbines and attempts to derive mathematical models. For this purpose, data collected via SCADA from a wind turbine in Turkey has been used. A Grammatical evolution-based algorithm has been proposed to derive equations dependent on this data. Through this algorithm, it is possible to generate equations containing a limited number of parameters and coefficients, thereby facilitating the creation of equations that are easily readable and writable. For comparison purposes, the grammatical expression programming method, one of the common symbolic regression techniques, has been proposed. The results indicate that the grammatical evolution algorithm has achieved a highly successful performance (0.91) in wind power prediction.

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