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RESEARCH ARTICLE

Short-Term Wind Speed Prediction Using a Hybrid Artificial Intelligence Approach Based on Dragonfly Algorithm: A Case Study of the Mediterranean Climate

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ABSTRACT

Wind energy forecasting studies play an important role in the search for sustainable energy solutions. However, wind power generation faces an inherent challenge. It is subject to constant fluctuations caused by meteorological conditions. These fluctuations can lead to inconsistencies in voltage and frequency within power grids, resulting in energy instability. To meet this challenge and ensure a reliable energy supply, measures must be taken to reduce the potential instability caused by changing wind conditions. This includes the development of advanced modeling techniques that take into account time-dependent and non-linear changes in wind speed. This type of modeling is crucial for minimizing energy losses and maintaining grid stability. As a result, the urgent need to meet the increasing energy demand while minimizing the environmental impact has triggered the transition to renewable energy sources. In this study, real short-term wind speed data from Osmaniye region were taken as research object. These data were analyzed in detail and the wind speed was estimated by considering the meteorological conditions. Artificial Neural Network was used in the prediction method, and the artificial intelligence algorithm was hybridized with the Dragonfly Algorithm and the coefficients of the artificial intelligence algorithm were trained with the Dragonfly Algorithm. It was used to compare the performance indexes of the prediction models designed with mean percent error, mean absolute percentage error, root mean square error. The performance analysis of Artificial Neural Network, Adaptive Neuro-Fuzzy Inference System, Fuzzy and Dragonfly-Based Artificial Neural Network are 2,2512,2,0698,1,7458 and 1,5212, respectively, based on mean absolute percentage error. Root mean square error values are 9,4857,8,2945,7,3285 and 6,4711. Finally, mean absolute errors are 8,2310, 7,5269, 6,2385 and 5,9486, respectively.

Index Terms—Artificial intelligence, Dragonfly Algorithm, short-term prediction, wind speed forecast

I. INTRODUCTION

The greenhouse gas emissions have "led to significant climate change issues, such as melting glaciers, shifts in climate zones, droughts, and disruptions in the ecological system. Global and national efforts are being made to address this problem. As time passes, the escalating energy consumption has surpassed the capacity of traditional energy sources to meet the demand. [1]. Fossil fuels are a form of energy that cannot be replenished and their burning can lead to severe environmental contamination [2]. To address the growing need for energy while lessening our carbon footprint, it is suggested that renewable sources of energy be utilized. Renewable energy is considered "clean energy" because it has minimal environmental impact compared to fossil fuels. The European Commission has announced the European Green Deal, a comprehensive plan with the goal of making Europe the first climate-neutral continent by 2050. It encompasses a wide range of initiatives and policies to reduce greenhouse gas emissions, promote energy efficiency, transition to renewable energy sources, and foster a circular economy that minimizes waste and pollution while maximizing resource efficiency. The goal of the circular economy model is to extend the lifespan of resources by utilizing them for as long as possible, extract the utmost value from them during their lifetime, and decrease waste and environmental impact to the lowest possible extent. This approach not only reduces pollution and waste but also contributes to the preservation of biodiversity and the mitigation of climate change. The Paris Climate Agreement, signed by almost all countries around the world, sets the goal of limiting global warming to well below 2°C above pre-industrial levels and pursuing efforts to limit the temperature increase to 1.5°C. The agreement promotes international cooperation to reduce greenhouse gas emissions and

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enhance resilience to the impacts of climate change. The concept of nature-friendly energy has gained significant support globally. Renewable energy sources, such as solar, wind, hydropower, and geothermal energy, are considered nature-friendly as they produce minimal greenhouse gas emissions during operation and have lower environmental impacts compared to fossil fuel-based energy sources. Solar and wind energy are prominent sources in terms of renewable energy production in our country. Wind power has experienced rapid growth as a renewable energy source in recent years, due to its benefits such as being environmentally friendly, emitting no carbon dioxide, having plentiful resources, and being cost-effective [3, 4]. Global electricity generation in 2021 is dominated by renewable energy, which accounts for 38.3% of the total. Among the different sources of renewable energy, wind power comprises 6.7% of the total electricity generated [5]. Globally, the installed wind capacity in 2022 stands at 78 GW, and it is anticipated to increase to 115 GW according to Global Wind Energy Council (GWEC) [6]. Wind energy is becoming widespread throughout the world, especially in order to reduce the problem of foreign dependency and to minimize the shortage of raw materials. In addition, wind energy has gained more importance today due to its advantages such as minimizing the damage to nature and not occupying as much space as solar energy fields. However, wind energy production forecasts need to be made accurately in order to produce, efficiently use, and distribute wind energy effectively. Wind energy forecasts are used to predict future wind conditions and potential energy production. These forecasts are important for ensuring optimum performance of wind farms, planning power generation and managing the distribution network. Accurate forecasts help wind energy investments to be made more effectively and efficiently. Therefore, reliable wind energy forecasting is essential for the planning and management of wind energy projects. Forecasts are made by considering factors such as scientific methods, meteorological data, wind speed, and direction. Thus, optimum use and efficient distribution of wind energy resources can be achieved. Periodic variations in wind speed and direction in wind energy systems can cause energy fluctuations. It is therefore important for the wind energy system to remain in balance and for users and operators. In these systems, where variability is high due to meteorological conditions, short-term energy estimations are more commonly preferred. In recent years, many scientists and researchers have conducted extensive studies on short-term wind power estimation methods in wind energy systems. Wind speed prediction is a critical task when it comes to enhancing the quality of wind power generation. It is an indispensable task that cannot be overlooked [7]. The main purpose of these studies is to optimize wind energy production and to ensure system stability. Models and algorithms are utilized to predict wind speed and power, forming the basis of short-term wind power forecasts. These forecasts are calculated using different data and analysis methods, such as real-time weather data, wind speed and direction measurements, atmospheric models, and statistical methods. Forecasts are usually made on an hourly or daily basis and are used to optimize wind power generation and ensure system stability. These short-term forecasts increase the efficiency of wind power systems, improve energy distribution planning, and allow for adjustments to suit energy demand. The current calculation of the wind generation potential in our country and the use of these estimates contribute to the economy and energy sustainability. As a result, short-term energy forecasts in wind energy systems are an important tool for adapting to high variability natural conditions and optimizing the system. These studies continue to make wind power generation more efficient and stable. The work done in recent years can be summarized as follows;

Main Points

- It is the first time to use Dragonfly Algorithm-based Artificial Neural Network (ANN) to predict wind speed.
- The Dragonfly Algorithm is utilized for training the ANN.
- The proposed algorithm outperforms the results obtained from the literature survey.
- And with this algorithm, the local minimum does not occur in this controller.

Hur [8] focuses on a wind power estimation scheme that consists of two stages. In the first stage of the estimation scheme, modeling is performed using a three dimensional (3D) wind field model and an extended Kalman filter. The 3D wind field model helps in capturing the complex nature of wind patterns and variations in different directions and heights. The extended Kalman filter, designed based on the nonlinear rotor model, aids in improving the accuracy of wind power estimation. In the ongoing estimation phase, extrapolation and machine learning methods are employed. Extrapolation techniques are used to extend the available data beyond the observed period, enabling predictions of wind power in the future. Algorithms and models are utilized by machine learning methods to learn patterns from past data, which are then used to make predictions. The integrated wind power forecast chart developed in the study is tested using data from an aeroelastic model.

Jiang et al [9] focuses on proposing a combined estimation system for wind speed forecasting. The study presents experimental results that prove the effectiveness of the proposed forecasting system. This system is capable of providing both point and range forecasts for wind speed. It is shown to outperform other benchmark models, indicating its usefulness for the programming and management of electrical power systems.

Four distinct models of Recurrent Neural Networks (RNNs) were utilized to estimate wind energy production in a study [10]. The objective of the research was to predict short-term wind speed using data from a wind station located in Yalova, Türkiye. The forecasts were designed to predict 1 hour ahead, so as to facilitate sudden failure and maintenance planning. The data obtained from the station were initially examined in detail, and data analyses were carried out. Subsequently, new datasets were created from existing data and were made suitable for the models. Four different TSA models were then employed to predict wind speed. The findings suggest that wind speed estimation can be effectively carried out using TSA techniques. The performance results of the models fall within the acceptable range, and it was found that they provide better results than traditional time series methods. The study demonstrates that TSA methods are an effective tool for wind power generation by estimating wind speed.

Neshat et al [11] focus on short-term wind speed estimation using the bidirectional Long Short-Term Memory (LSTM) method. The research employed an optimization algorithm for the estimation of parameters. Machine learning models often use optimization algorithms to adjust their parameters and enhance their performance. The goal of the optimization process is to identify the optimal parameter values that lead to the lowest possible error or loss function and the highest possible predictive accuracy. It analyzed the spatial and temporal changes in the wind energy field. The results indicated significant seasonal differences and regional characteristics in the wind energy resources within the study area. Furthermore, the study found that wind energy resources have been gradually increasing since 2010. The reason for this increase was attributed to changes in large-scale ocean and atmosphere circulation patterns, particularly influenced by global warming.

Wickramasinghe et al [12] Using statistical techniques and machine learning, a new wind energy prediction model was developed and tested for a specific wind farm. In order to develop the model, wind speed and ambient temperature were selected as input variables, while daily wind energy production was chosen as the output variable. The Pearson and Spearman correlation coefficients were used to investigate the correlation between wind energy and each weather index. The study tried several statistical prediction models, including Multiple Linear Regression, Power Regression (PR), Support Vector Regression (SVR), Gaussian Process Regression, Feedforward Backpropagation Neural Network (FFBPNN), Cascade Forward Backpropagation Neural Network, and Recurrent Neural Network (RNN) using machine learning techniques. The accuracy of the prediction models was evaluated based on the determination coefficient, root mean square error (RMSE), and Nash–Sutcliffe Efficiency (NSE). Based on the performance evaluation, the study concluded that all models achieved high accuracy, with the FFBPNN-based model exhibiting exceptional performance and very low error.

Yang et al [13] aimed to assess the impact of climate uncertainties on predicting future renewable energy potential across five climate regions in Europe. The study focused on quantifying the effects of uncertainty arising from global climate models (GCMs) on renewable energy project planning. The results indicated that the uncertainty associated with GCMs had the most significant impact on the design of renewable energy production. The study identified differences in solar photovoltaic (PV) and wind energy potential resulting from climate change uncertainties. Furthermore, the research presented how the climate change signal in solar radiation affected different scenarios and changed over time. It also explored the impact rates on wind generation through case studies.

Zhang and Chen [14] propose a signal processing method that combines Singular Value Decomposition (SVD) with two adaptive noise reduction techniques: Complete Ensemble Empirical Mode Decomposition with Adaptive Noise and Full Ensemble Empirical Mode Decomposition. Elman neural networks have been used in the study, and they have been optimized with the Particle Swarm Optimization algorithm. Additionally, the Autoregressive Integrated Moving Average model has also been utilized for the purpose of predicting Intrinsic Mode Functions (IMFs). These IMFs are obtained through the decomposition of the wind speed data using the proposed signal processing method. The results of the study indicate that the proposed model improves the accuracy of wind speed estimation and reduces estimation errors. This has significant implications for the stable operation of wind farms and the grid connection of power plants relying on wind energy. By incorporating advanced signal processing techniques and machine learning models, the proposed approach enhances the effectiveness of wind speed estimation. This, in turn, contributes to the efficient utilization of wind energy resources and the optimization of wind power generation.

Yildirim et al [15] focused on estimating 1-hour-ahead solar radiation using different methods based on neural networks. The study utilized solar PV data collected from the Tarsus region in Türkiye in 2023. Neural networks are a type of machine learning model that can learn patterns and make predictions based on input data. In this study, neural networks were used to estimate solar radiation, which is a crucial factor in solar energy generation. At the end of the study, numerical and graphical comparisons were made to evaluate the performance of different methods for 1-hour forward solar radiation estimation. The results indicated that the LSTM method was the most successful among the methods examined.

Bounoua and Mechaqrane [16] focused on estimating Global Horizontal Solar Irradiation (GHI) using the LSTM method. The research used real data from the city of Erfoud in Morocco. The main objective of the study was to estimate GHI at both hourly and sub-hourly intervals using only historical data without relying on external factors. Two scenarios were considered: a yearly scenario that accounted for all climatic conditions and a seasonal scenario that considered the specific climatic conditions of each season. In the study, the LSTM method was compared with other methods such as Neural Networks (NN) and Random Forest (RF). Despite the high variability of GHI, the LSTM network was found to be the most robust method for estimation. It exhibited good performance and high stability compared to the ANN models. Long Short-Term Memory is a type of RNN that is particularly effective in capturing long-term dependencies and modeling sequences of data. Its ability to handle sequential information makes it suitable for time series forecasting tasks, such as solar irradiation estimation. The study's findings suggest that the LSTM method outperformed other methods, including ANN models, in estimating GHI. The robustness, performance, and stability of LSTM make it a promising choice for accurate and reliable solar irradiation predictions.

Marinho et al [17] were conducted on short-term solar irradiance estimation. The research focused on comparing three different estimation methods and evaluating their performance. It was observed that the Convolutional Neural Network (CNN-1D) and LSTM methods performed better in predicting short-term solar irradiance, according to the results and analysis of various error criteria. The researchers aimed to estimate short-term solar irradiance using the LSTM network approach through time series prediction in this study. Wind power has become increasingly popular as one of the most rapidly growing sources of renewable energy around the globe. The use of this technology has been on the rise, largely due to its eco-friendliness and the vital part it can play in tackling the obstacles associated with climate change. Wind energy is considered a priority because it offers several benefits, including being a clean and sustainable alternative to fossil fuels. Among the various types of wind energy technologies, horizontal axis wind turbines (HAWTs) have emerged as the predominant choice for large-scale wind energy generation. The rotor shaft and blades of these turbines are positioned horizontally and they rotate around an axis that is also horizontal. This axis is perpendicular to the direction of the wind. Horizontal axis wind turbines are commonly seen in wind farms and are known for their efficiency and capacity to generate substantial amounts of electricity. Horizontal axis wind turbines are also used in this study. Within the scope of the research, 10 000 real data were processed. Seventy percent of the data were used for training and 30% for testing in Artificial Neural Network (ANN). In the study, wind speed estimation was made. The speed, wind power, blade angle, air temperature, and time input of the HAWTs were taken as inputs and the system modeling was carried out.

A TCM system [18] that involves the Walsh–Hadamard transform for signal processing is suggested. Deep Convolutional Generative Adversarial Network (DCGAN) aims to tackle the challenge of limited experimental dataset availability. Additionally, three machine learning models, namely SVR, gradient boosting regression, and RNN, are explored for tool wear prediction. The mean absolute error, mean square error, and RMSE are used to assess the prediction errors of the three machine learning models. In order to choose relevant features, three metaheuristic optimization feature selection algorithms_Dragonfly, Harris hawk, and Genetic algorithms—are tested, and the prediction outcomes are compared.

A novel approach [19], called stochastic distributed cooperative control, is presented for island microgrids (MGs). The suggested approach for achieving efficient active power sharing is to use a proportional resonant (PR) controller and virtual impedance droop control in stationary reference frames, combined with distributed averaging secondary control optimized by the Dragonfly Algorithm (DA). This technique enables mean-square synchronization for the voltage and frequency restoration of distributed generators (DGs). A sparse communication network is employed to reduce the need for extensive communication and information exchange, as well as to avoid data congestion. The proposed system offers a balance between voltage regulation and reactive power sharing, making it intuitive. To assess performance and compare results, a conventional centralized secondary control with PR droop control has been simulated. Empirical evidence is presented to demonstrate the MG's ability to confront communication failure and work reliably during plug-and-play operations.

Tittu George et al [20] proposed that renewable solar–wind power generation can be implemented on unutilized rooftop spaces and underutilized potential locations of educational institutions, in addition to conventional grid power solutions, in order to achieve effective and cost-optimal power solutions. A mathematical modeling technique called Modified DA was utilized to reduce the net present value of the power systems over their lifespan. The model was designed to consider various scenarios and found that the best case to improve economic reliability significantly is a hybrid renewable energy system with grid interaction.

In recent years, the DA has been increasingly utilized due to its low parameter count, adaptability to various problems, and comprehensible algorithmic steps during operation. Simultaneously, the DA can identify the optimal local outcome, while also determining the global best result. The DA tends to cluster around each optimal outcome, allowing it to find the best possible result with the shortest iteration number.

II. METHODS

A. Wind Speed Prediction Models

There are several factors that have contributed to the rise in energy production costs. These include changes in regulations, disruptions in the supply chain, fluctuations in fuel prices, and the adoption of renewable energy sources. Unlicensed solar power plant (SPP) and renewable energy sources (RES) regulations likely refer to the challenges posed by decentralized energy production from small power plants and renewable sources, which can affect the overall energy market dynamics and pricing. Forecasting studies are essential to navigate these complex challenges. Stakeholders in the energy sector can make informed decisions regarding resource allocation, investment, and regulatory adjustments by anticipating energy consumption and production trends across various time frames such as short-term, medium-term, and long-term. When examining estimation studies in the literature related to various fields, including energy production, economics, and beyond, it is common to find that forecasts are categorized into short-, medium-, and long-term estimations. After analyzing the research, it is clear that the commonly used models are the ANN and hybrid models. The dragon-based hybridized ANN technique was implemented in this study for the first time in the literature.

B. Artificial Neural Networks

Artificial Neural Networks are a critical part of deep learning, which is a branch of artificial intelligence and machine learning. Artificial Neural Networks are designed to model the behavior of biological neural networks by mimicking their structure and function. They are utilized for tasks such as recognizing patterns in data, processing information, and making decisions. Due to their hierarchical structure, ANNs are particularly effective in handling complex and non-linear relationships within data. Unlike traditional linear models, ANNs can process and learn from data with non-linear patterns, making them suitable for a wide range of applications.

An ANN typically comprises three distinct types of layers. The first layer, known as the input layer, is responsible for receiving the initial input data, which could be in the form of numerical values, images, text, or any other type of data. Each input node in the input layer represents a feature or attribute of the data. The second type of layer are the hidden layer(s), which are located between the input and output layers. These layers perform intermediate computations by processing and transforming the input data through a series of interconnected nodes, also known as neurons. Each neuron takes

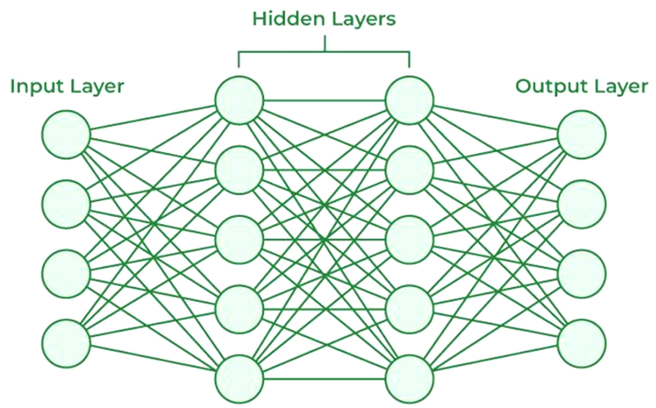

Fig. 1. ANN structure.

input from the previous layer and applies an activation function to produce an output. Finally, the output layer provides the final results or predictions based on the computations performed in the hidden layers. The number of nodes in the output layer varies depending on the specific task, such as classification (multiple nodes representing different classes) or regression (a single node representing a continuous value). The structures and operations of human neurons serve as the basis for ANNs. It is also known as neural networks or neural nets. The input layer of an ANN is the first layer, and it receives input from external sources and releases it to the hidden layer, which is the second layer. In the hidden layer, each neuron receives input from the previous layer neurons, computes the weighted sum, and sends it to the neurons in the next layer. These connections are weighted means effects of the inputs from the previous layer are optimized more or less by assigning different–different weights to each input and it is adjusted during the training process by optimizing these weights for improved model performance in Fig. 1. Inn ANN; Input values and weight for each input values w_0 are available. The entered value and the weights w_0 are multiplied (W_nX_n) all together with the multiplication value addition function and is summed to obtain the net input value of the system. Net after adding bias (b) to the input value is passed to the activation function and an output value (Y) is obtained.

In this study, Short with Neural Network periodical wind speed estimation was made. Analysis has been carried out using the MATLAB 2023-A Program. The network structures have five inputs and an output. Input parameters are wind power, turbine speed, blade angle, air temperature, and time. The wind speed is the output parameter. The ANN method requires the determination of the number of neurons, including input and output layers. For this study, only one layer was used for the output parameter, while five different parameters were used as input parameters, each requiring its own input layer. The model architecture included a hidden layer consisting of ten neurons. With these configurations, it is aimed to determine the best method based on the results of experiments and the margin of error. For both methods, 10 000 total data were processed. In the ANN technique, 70% of the data were allocated for testing and 30% for training. The real dataset used in Osmaniye's wind turbine power plant consists of 10 minutes of data for July 2022.

C. The Dragonfly Algorithm

The DA is an optimization algorithm inspired by nature, specifically the swarming behavior of dragonflies. The algorithm takes inspiration from the hunting behavior of dragonflies, which involves both individual exploration and collective cooperation. Dragonflies exhibit efficient foraging and hunting strategies, making them an interesting model for optimization algorithms.

The DA consists of three main components:

1) Swarm Movement

Dragonflies search for food by moving in a synchronized manner. In a similar way, an algorithm employs a group of solutions, known as dragonflies, to explore the search space. Each dragonfly corresponds to a prospective solution to the optimization problem.

2) Prey Location and Capture

Dragonflies locate and capture their prey based on visual perception and movement prediction. In the algorithm, this behavior is simulated by considering the fitness value of each solution and the distances between them. The objective of the algorithm is to discover the optimal solution. This is achieved by applying certain rules to adjust the positions of dragonflies. Information exchange: Dragonflies communicate with each other by exchanging information about prey locations. In the algorithm, this is modeled through a mechanism called information sharing, where dragonflies update their positions based on the knowledge gained from their neighbors.

The DA is particularly suited for solving optimization problems in continuous domains. Various optimization tasks, such as function optimization, parameter tuning, and data clustering, have been targeted by it. The DA's three basic operators are separation, alignment, and cohesion (rapport).

3) Separation Operator

The separation operator in the DA is responsible for preventing collisions and overcrowding among individual dragonflies in the swarm. It ensures that dragonflies maintain a certain minimum distance from each other to prevent them from converging to the same solutions and getting stuck in local optima.

4) Alignment Operator

The alignment operator helps dragonflies in the swarm to maintain a certain level of coherence and synchronization. It ensures that each dragonfly's movement direction and speed are influenced by the average direction and speed of its neighboring dragonflies. This alignment allows the swarm to explore the search space in a coordinated manner.

5) Cohesion (Rapport) Operator

The cohesion, also known as the rapport operator, is responsible for maintaining the cohesion of the swarm by moving each dragonfly toward the center of mass of its neighboring dragonflies. This helps in keeping the swarm together and avoiding fragmentation.

The pseudo code of the Dragonfly Algorithm is below:

```
{
Generate the dragonfly population Ti (i=1,2……..n)
Generate step vector Δ Ti(i=1,2……..n)
While (continue until the termination condition is fulfilled)
        Calculate fitness value of all dragonflies
Update food source and enemy
Update weight values (s, a, c, f, e and w)
Calculate S, A, C, F and E
Update neighborhood Radius
If (there is at least one neighbour)
        Update step vector
        Update position vector
   else
        Update position vector
   end if
   Keep dragonflies within optimization limits
end while
}
```

The equations (1), (2), and (3) are below that related to the DA;

$$S_0 = \sum_{J=1}^{N} \left(T - T_j\right) \tag{1}$$

$$A_0 = \frac{\sum_{i=1}^{N} \left(K_i\right)}{N} \tag{2}$$

$$C_0 = \frac{\sum_{i=1}^{N} \left(T_j\right)}{N} - T \tag{3}$$

The orientation to food operator F_i denotes orientation to the global best solution. The evasion operator *Ei* stands for moving away from the worst solution. In these transactions, they are given as (4) and (5), respectively.

$$F_i = T^{+} - T \tag{4}$$

$$E_i = T^{-} + T \tag{5}$$

As seen in the program flow, after the completion of these five operations, if there is a neighbor in the neighborhood radius, each dragonfly's position is updated using equations (6) and (7), respectively.

$$\Delta T_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta T_t \tag{6}$$

$$T_{t+1} = T_t + \Delta T_t \tag{7}$$

If there are no neighbors in the neighborhood radius, the relations given by (8), (9), and (10) are used to improve the position update randomness. Here, σ Levy represents the flight distribution.

$$T_{t+1} = T_t + Levy(d)T_t \tag{8}$$

$$Levy\left(x\right) = 0.01 \times \frac{r_1 \times \sigma}{\left|r_2\right|^{\frac{1}{\beta}}} \tag{9}$$

$$\sigma = \left[\frac{\Gamma\left(1+\beta\right) x \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) x\beta x 2^{\left(\frac{\beta-1}{2}\right)}} \right]^{-\beta} \tag{10}$$

The study aims to minimize the sum of the square error given by (11) as the objective function.

$$E = \sum_{K_i=1}^{n} \left(f_{observation}(K_i) f_{prediction}\left(K_i\right) \right)^2 \tag{11}$$

n is the number of histogram rate intervals, $f_{prediction}$ (K_i) shows the frequencies set by the calculated parameters, and $f_{observation}$(K_i) shows the frequencies formed from the observations in the histogram.

A flowchart of the DA process is given in Fig. 2, and the steps included in this process are:

- Assign random locations to the dragonflies and find the fitness. Assign values to food and enemy.
- Decide the stopping criterion and start iterations.
- Update the weights based on iteration number and randomness.
- In the presence of a neighbor, calculate (1), (2), and (3) for each fly. Update the position by adding the current position.
- In the absence of a neighbor, assign a new position to the dragonfly using a random walk.
- Perform the third step and then the fourth or fifth step depending on the neighbor's presence after updating food and enemy.
- Repeat the above step till termination is reached.
- Note down the food position.

D. Adaptive Neuro-Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System (ANFIS) utilizes a training process for neural networks to modify the membership function and its parameters associated with it to attain the desired data sets. Compared to the mean square error criteria, it produces more precise results by leveraging expert recommendations. The hybrid ANFIS learning algorithm integrates the back-propagation learning algorithm and the least squares method. To simplify the process, a

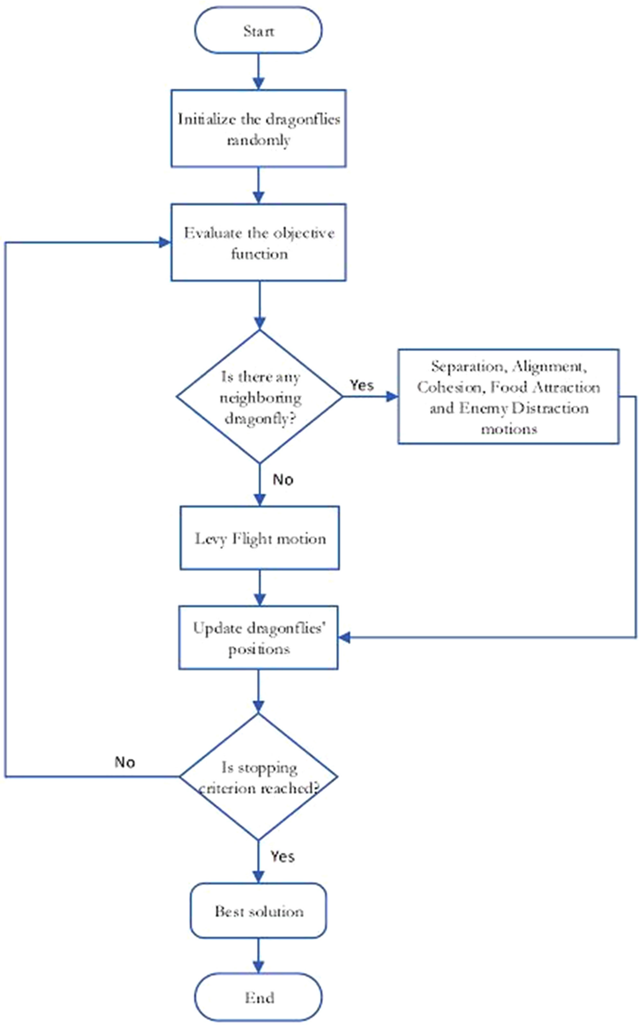

Fig. 2. Dragonfly Algorithm Structure

scenario is considered with two inputs and one output. The ANFIS structure in Fig. 3 comprises five levels, and each layer's functions are summarized as follows:

Layer 1: The first layer generates output based on the membership values obtained from input samples and membership functions.

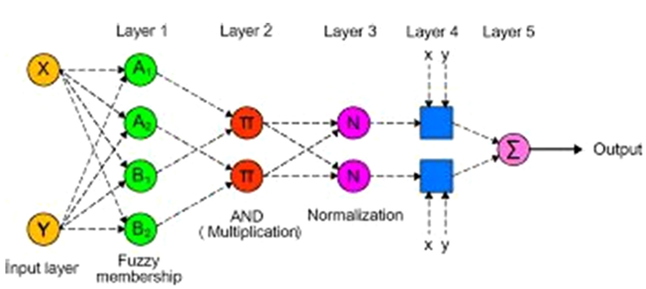

Fig. 3. ANFIS structure.

The output values are expressed as follows, assuming that the input nodes are x and y, and the linguistic labels are A and B, with µAi and µBi representing the membership functions (12).

$$O_i^1 = \mu_{Ai}(x) \qquad i=1,2$$

for (12)

$$O_{i+2}^1 = \mu_{Bi}(x) \qquad i=3,4$$

The common belief is that µAi and µBi membership functions have a distribution shaped like a bell, with a maximum of 1 and a minimum of 0. Mi represents the midpoint of the bell-shaped membership function, while σ represents the standard deviation. Equation (13) can be used to calculate µ (x), which is the value of the membership function at a given point x.

$$\mu(x)= \frac{1}{1\{+\frac{x-c_i}{o_i}\}^{2b_i}} \tag{13}$$

The determination of the strength of each rule's activation takes place in layer 2, by using mathematical multiplication in (14).

$$O_i^2 = \omega_i = \mu_{Ai}(x).\mu_{Bi}(y) \quad \text{for } i=1,2 \tag{14}$$

The normalization of firing strengths occurs in layer 3. In this layer, each node computes the ratio of the firing strength of the rule it represents to the total firing strength of all other rules. The ith node determines this ratio for the ith rule in (15).

$$O_i^3 = \omega_i = \varpi_i = \frac{\omega_i}{\omega_1+\omega_2} \quad \text{for } i=1,2 \tag{15}$$

The output for each node in layer 4 is calculated by adding the normalized firing strength to a first-order polynomial. The outputs specified in 16 correspond to the fuzzy if-then rules, which are marked by "and."

o Rule 1: if x is A_1 and y is B_1 then $f_1 = p_1x+q_1y + r_1$

o Rule 2: if x is A_2 and y is B_1 then $f_2 = p_2x+q_2y + r_2$

$$O_i^4 = \varpi_i f_i = \varpi_i\,(p_1 \; x + q_i y + r_i) \tag{16}$$

Linear p, q, and r are the parameters that are known as consequent parameters. This node adds the total incoming signals from the 4th layer to calculate the ANFIS's overall output in layer 5 by using 17.

$$O_i^5 = \sum_i \varpi\, f_i = \frac{\sum_i \omega_{fi}}{\sum_i \omega_i} \tag{17}$$

The following output represents the conclusive outcome of the adaptive neuro-fuzzy inference system in (18).

$$f_{out}=\varpi_1 f_i+\varpi_2 f_i=\frac{\omega_1}{\omega_1+\omega_2}f_1+\frac{\omega_2}{\omega_1+\omega_2}f_2=(\varpi_1 x)p_1+(\varpi_1 y)q_1+(\varpi_1)r_1+(\varpi_2 x)p_2+(\varpi_2 y)q_2+(\varpi_2)r_2 \quad (18)$$

E. Fuzzy Expert System

A computational model is combined with a fuzzy model based on the Mamdani inference system to predict the probability of newborn death. A fuzzy linguistic model is a rule-based system that uses fuzzy set theory to solve problems. It comprises four primary parts:

- The role of a fuzzifier is to transform precise input or traditional numbers into fuzzy values.
- An inference engine is utilized to produce a fuzzy output using a fuzzy reasoning mechanism for Mamdani inference.
- A knowledge base comprises a collection of fuzzy rules and membership functions that represent the fuzzy sets of linguistic variables.
- A defuzzifier, which converts the fuzzy output to sharp values.

The inference engine utilizes the rule base values to make decisions. Fuzzy rules define the relationship between the fuzzy input and fuzzy output. A fuzzy rule has an antecedent and consequent, with fuzzy operators representing the antecedent and an expression providing the output variable's fuzzy values as the consequent. The inference process evaluates each rule in the rule base, aggregates the weighted consequences of all relevant rules into a single output fuzzy set (the Mamdani model), and produces a "crisp" output value using a defuzzification process to replace the fuzzy output set.

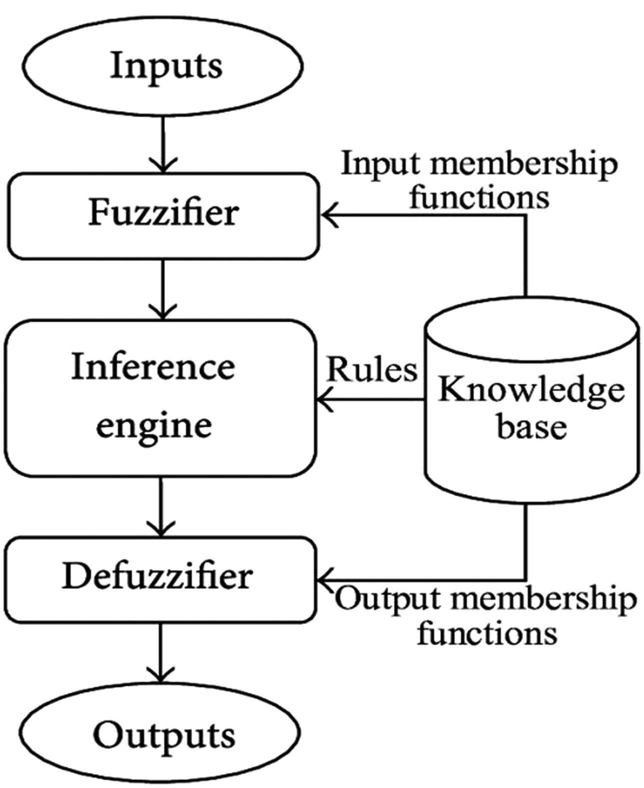

Fig. 4. Fuzzy expert system structure.

Fuzzy expert systems, which work based on the fuzzy-logic approach, can model the rules obtained from fuzzy preferences of experts and can provide outputs by using these rules. The main elements of a fuzzy expert system are fuzzy logic, fuzzy base rule, fuzzy inference, and learning method in Fig. 4.

F. The Properties of Data Set

In this study, Short with Neural Network periodical wind speed estimation was made. Analysis has been carried out using the MATLAB 2023-A Program. The network structures have five inputs and an output. Input parameters are wind power, turbine speed, blade angle, air temperature, and time. The output parameter is the wind speed. In the use of the ANN method, the number of neurons which includes input and output layers is determined. In the study, there is one layer used for the output parameter. In addition, five different parameters were used as input parameters. An input layer has been determined for each. The hidden layer in the model architecture is designed to have ten neurons. With these configurations, it is aimed to determine the best method based on the results of experiments and the margin of error. For both methods, 10 000 total data were processed. In the ANN method, 70%–30% of testing and training data were taken respectively. Located in Osmaniye of the wind turbine power plant, which contains 10 minutes of data for July 2022, the real dataset is used.

III. RESULTS AND DISCUSSION

In this section, the created systems are examined according to the modeling architectures. It was aimed to determine the best method based on the results of the margin of error obtained by conducting the experiments, and the results of these studies were presented. Mean Percentage Error MPE and Mean Absolute Percentage Error (MAPE) calculations are the most powerful methods used for accuracy comparisons of a method. In the literature, models with a MAPE below 10% are "very good," models with a MAPE between 10% and 20% are "good," models with a margin of error between 20% and 50% are "acceptable," and MAPE greater than 50% are models with a value of "wrong and erroneous." The MAPE, RMSE, and MAE values of four different models established within the framework of the

TABLE I.
THE MAPE-RMSE-MAE VALUES OF CONVENTIONAL ANN, ANIFS, FUZZY, AND DA-BASED ANN METHOD

METHODS	MAPE	RMSE	MAE
ANN	2.2512	9.4857	8.2310
ANFIS	2.0698	8.2945	7.5269
FUZZY	1.7458	7.3285	6.2385
DA-based ANN	1.5212	6.4711	5.9486

ANN, Artificial Neural Network; ANFIS, Adaptive Neuro-Fuzzy Inference System; DA, Dragonfly Algorithm; MAPE, mean absolute percentage error; RMSE, root mean square error.

article are shown in Table I. In the evaluation of the MAPE values obtained, it is clearly seen that the DA-based ANN model has the best accuracy.

A single hidden layer neural network has been selected with five neurons and an output layer. The parameters for training the network are shown below:

- There are ten weights between the input-hidden layer.
- At the hidden layer, there are five bias values assigned to neurons.
- There are five weights that connect the hidden-output layer.
- At the output layer of the neural network, a lone bias value is allocated to the neuron.

During the optimization process, a total of 21 parameters of the neural network are trained. The network structure decides three important parameters required for wind power. The neural network is being trained using data, with 20 dragonflies being utilized for over 300 steps. Once training is complete, the testing phase begins. Swarm-based methods in the study commence with a population that is randomly dispersed, and then they are relocated based on an objective function that identifies the convenience value for each particle in the search space. An algorithm related to the equations of the particle is used to update particle information, creating a new generation. These procedures are repeated until the termination criterion is reached. Following the completion of testing, the optimal values obtained by the best particle are utilized to create the ANN. Each dataset is executed independently 25 times, and the neural network consists of the best parameters obtained at the end of the 25 runs and used in the test phase.

The wind farm's current wind speed is displayed in blue on Fig. 5, representing actual system data. Based on the current wind speed, the wind speed forecast was generated using the traditional ANN method, and is shown in yellow on the graph. When the data in the graph and table are examined, the MAPE value of the traditional ANN is 2.2512, the RMSE value is 9.4857, and the MAE value is 8.2310. These values are within the estimation acceptance limits and are recorded as systemic performance. Looking at the system performance with the dragonfly-hybridized ANN proposed in the article, as can be seen from Fig. 6 and the table, the orange waveform represents the hybridized ANN and the blue waveform represents the real wind speed. When the MAPE, RMSE, and MAE values are observed, respectively, it is seen that they are 1.5212, 6.4711, and 5.9486. Considering the performance of the system with the two proposed algorithms, it is clearly seen that the hybridized ANN performance is quite high, not being stuck to the local minimum, the learning is completed quickly and effectively, and directly affects the performance positively.

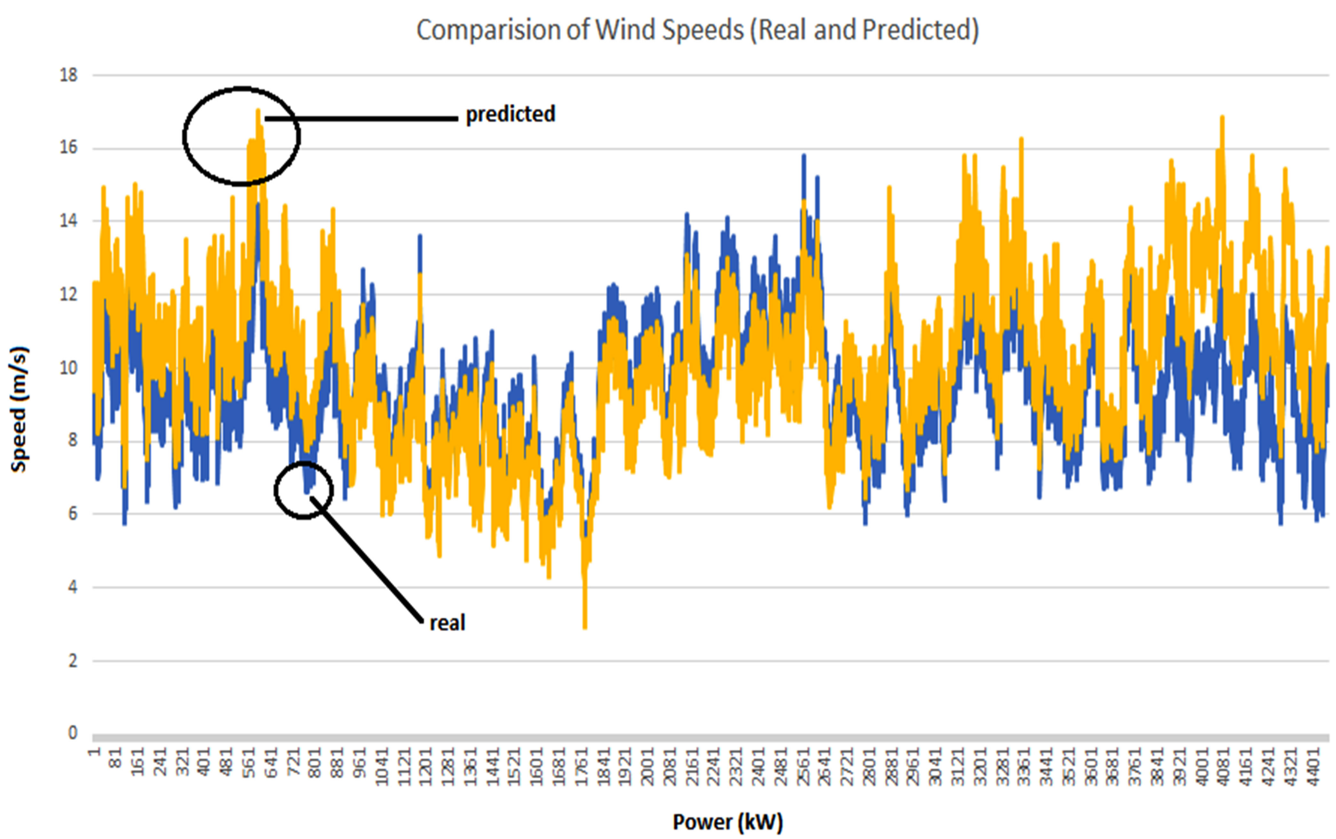

Fig. 5. Conventional ANN method for prediction wind speeds (real and predicted).

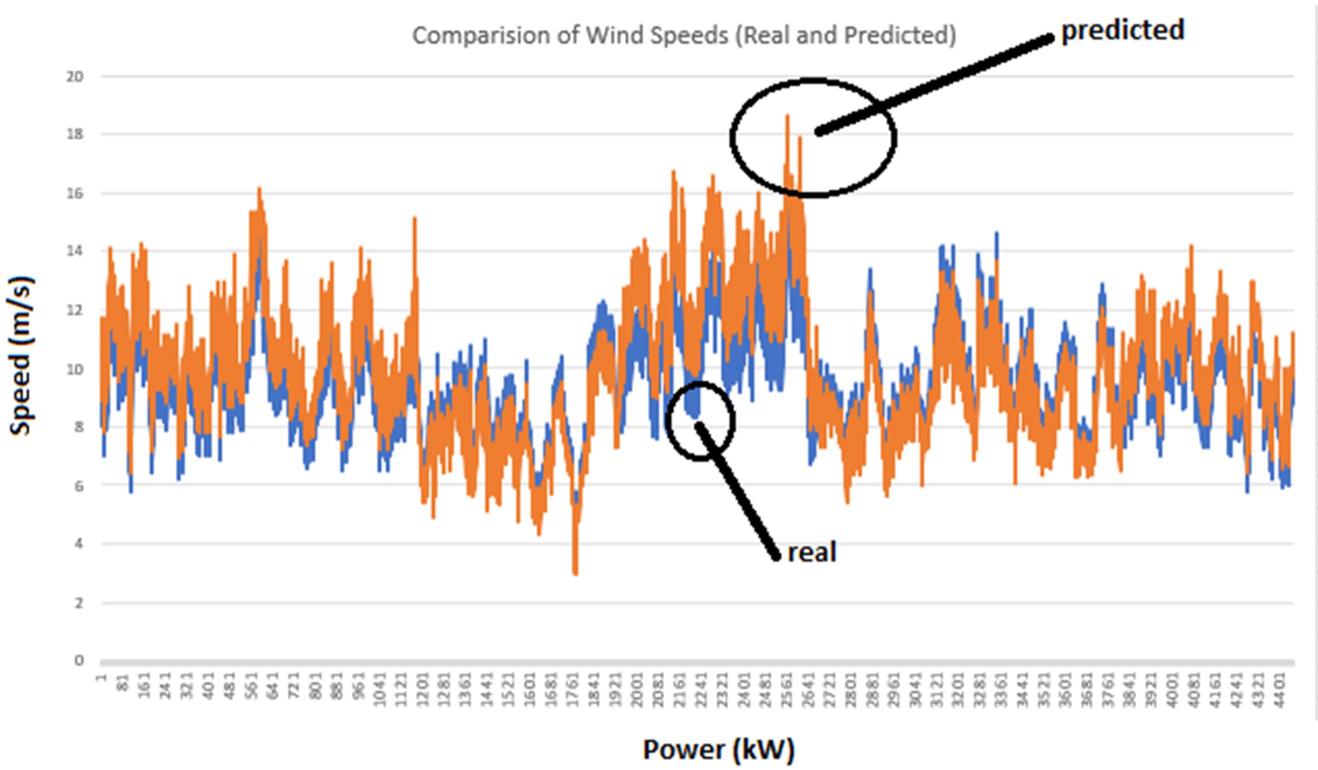

Fig. 6. Dragonfly algorithm-based ANN method for prediction wind speeds (real and predicted).

Compared with the literature works, recent articles are used with ANN-based optimization method for fast response and not limited to local minimum for prediction to real values. Dragonfly Optimization Algorithm has faster response in other swarm-based algorithms that are preferred in literature mostly. The performance database is examined in detail, and it is obviously a fact that the performance is nearly 15% higher than the conventional ANN with swarm-based optimization such as firefly, butterfly, and shark.

The artificial intelligence-based wind speed prediction articles have been observed in recent literature within 5 years. When these articles are examined, it is seen that artificial intelligence is no longer used alone, but is integrated with optimization methods, which are hybrid methods. It is seen that optimization methods are preferred day by day in a way that does not get stuck in local minima. With this algorithm, which has emerged in recent years, we have solved the local minimum problem and hybridized the algorithm with the highest accuracy and accuracy detection speed with artificial intelligence methods. It is seen that MAPE and RMSE values are well below acceptable levels, as seen in the table. The method will also be used in long-term wind forecasts in the future.

IV. CONCLUSION

The management of wind power plants, power generation, and the stability of electricity grids is heavily reliant on accurate short-term wind speed forecasting. For wind power plants to operate efficiently and reliably, the wind speed must be accurately predicted. In addition, wind speed forecasts are important for the planning and management of electricity generation. Renewable energy sources such as wind power play a critical role in supporting the goals of the Green Deal. These energy sources produce less greenhouse gas emissions compared to fossil fuels and have less environmental impact. However, accurate forecasts and management strategies are required for the efficient use of these resources. In Osmaniye, ANN and ANN-based DA models were estimated by using hourly time series consisting of data such as wind power, turbine speed, and blade angle. The most efficient model of the study was found by comparing the results with each other and with the actual wind speed values. The study was conducted using a wind speed dataset consisting of 10.000 data points obtained from the wind farm in Osmaniye. Input parameters are wind power, turbine speed, blade angle, air temperature, and time. The output parameter is the wind speed. This study focused on the estimation of wind turbine output velocity and compared the performance of two different models with real wind turbine performances. The study aims to determine the wind turbine exit speed and to assess the forecast models' performance by comparing the predicted exit speeds with the actual ones. Forecast results, regression, and error when evaluated within the framework of the analysis, it is seen that the best estimation results are obtained with the "ANN-based Dragon Algorithm" method. In conclusion, dragon-based hybridized ANN method was used for the first time in the literature.

V. ACKNOWLEDGMENT

The sample of data set is shown in Table II.

TABLE II.
THE 30 DAYS OF DATA SET

Day	Wind Speed	Atm. Temperature	Rotational Speed	Wind Power	Blade Angle
1	14.06	16.95	16.30	1946.27	157.619
2	16.61	18.80	16.30	1958.09	156.025
3	17.36	16.81	16.30	1985.12	150,29
4	18.70	16.64	16.17	1976.83	155.717
5	7.76	13.83	14.25	621.05	158.095
6	9.32	11.41	16.19	993.31	161,34
7	10.56	12.44	16.30	1359.49	163.662
8	10.33	14.22	16.26	1283.49	166.656
9	11.05	16.22	16.28	1436.36	168.922
10	13.32	15.66	16.30	1906.71	168.922
11	10.98	14.29	15.55	1403.07	173.566
12	7.04	13.72	14.18	424.67	173.818
13	7.51	11.42	14.59	568.04	173.818
14	8.14	11.73	14.47	677.22	173.818
15	6.74	12.15	13.45	427.51	173.818
16	10.82	13.44	16.14	1383.16	182.462
17	16.10	14.56	16.30	1988.96	185.148
18	13.03	13.65	16.16	1769.99	188.393
19	8.74	14.04	13.72	917.73	193.205
20	5.68	13.65	10.18	371.68	188.561
21	11.78	13.85	16.01	1587.02	187.274
22	8.72	11.70	14.73	974.74	187.274
23	6.80	12.08	12.65	578.60	193.094
24	5.56	10.88	11.41	241.12	191.947
25	7.88	10.15	14.22	691.10	189,82
26	7.87	6.47	14.68	652.56	189,82
27	11.78	4.00	16.28	1628.39	186.239
28	17.36	4.15	16.30	1991.23	186.211
29	14.56	4.88	16.30	1985.53	188.925
30	18.09	7.96	13.29	1603.22	192,31

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