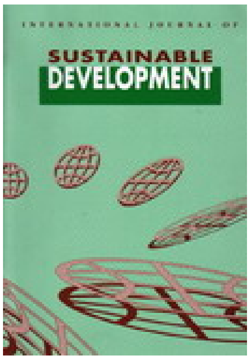

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Environmental resource assessment model design based on fuzzy control algorithm and GIS technology

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Abstract: For the purpose of sustainable development, the nation is progressively promoting the dissemination of wind energy resources. This paper utilises wind power generation as a case study and undertakes the establishment of an assessment model for environmental resources. Firstly, it scrutinises the challenges associated with acquiring wind resource distribution data, followed by the introduction of fuzzy control theory. Finally, the paper conducts wind resource assessment utilising the ArcGISEngine10.1 component, employing the processed data obtained through fuzzy logic techniques. Empirical findings evince that this model begets more precise parameters vis-à-vis alternative resolutions, culminating in a 5.2% augmentation in the efficacy of wind power harnessing via the sagacious instantiation of the fuzzy control algorithm. The wind resource distribution cartography of Minnesota, as ascertained by the system, evinces consonance with the spatial dispersal of extant wind agrarian tracts, with wind energy density oscillating from 562.0021 at diverse sites, attaining a zenith of 673.868.

Keywords: fuzzy control algorithm; wind energy resources; GIS; intelligent control; grid dispatch.

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1 Introduction

In the context of economic development transitioning into the 'new normal' and the promotion of ecological civilisation construction, regions are in dire need of transforming their economic development models and overcoming the limitations imposed by environmental resources on regional progress. Environmental resource efficiency offers a novel research approach to address the interplay between resources, the environment, and regional development. It has emerged as a crucial method for comprehensively evaluating the impact of regional economic activities and represents a cutting-edge subject in academic research, as it accounts for both economic development and environmental resources (Huang et al., 2021).

Nevertheless, the escalating material demands of the population and the process of urbanisation are intensifying the rate of resource consumption, particularly non-renewable energy sources like oil and coal, which are witnessing a twofold increase. The unsustainable exploitation of resources has pushed the world to the brink of energy depletion, leading to countries vying for vital resources and igniting a series of conflicts. Although research into alternatives to non-renewable energy sources is underway, the conditions for large-scale implementation have not yet been achieved. Wind energy, serving as a clean and environmentally friendly renewable energy source, possesses the potential to significantly diminish reliance on fossil fuels (Osman et al., 2023).

In order to realise the sustainable development of wind energy resources, it is necessary to evaluate the distribution and total amount of resources, so as to help practitioners complete the planning of wind energy generation and wind resource utilisation. Existing resource assessment systems lack specific methodologies for reliable statistical analysis of resource distribution parameters. Wind speed prediction research has predominantly focused on deterministic forecasting, paying limited attention to uncertainty prediction, such as interval prediction. However, interval prediction can capture the range of wind speed fluctuations caused by various factors and offer decision-makers valuable uncertainty reference information (Wang et al., 2018; Sweeney et al., 2020). Subsequently, with the advancement of intelligent cybernetics, fuzzy control (Sweeney et al., 2020) has been employed to achieve intelligent system control by emulating human information processing. This approach utilises fuzzy set theory, fuzzy linguistic variables, and fuzzy logical reasoning to reduce manual control and enhance data accuracy (Bouchon-Meunier et al., 2022). Consequently, scholars have developed non-linear, time-varying, and lagged control systems by incorporating fuzzy control algorithms, even in the absence of precise mathematical models for the controlled systems (Liu et al., 2021; Lai et al., 2015). Nevertheless, for environmental resource assessment systems, numerous factors influence the assessment outcomes, necessitating the construction of a multivariate input fuzzy control model with univariate output. Currently, there is a dearth of corresponding fuzzy control algorithms capable of implementing environmental resource assessment.

This paper henceforth examines the potential of wind energy and presents scholarly macro estimations of its overall reserves. In the environmental resource evaluation framework utilising GIS technology, a fuzzy control algorithm is introduced to accomplish the comprehensive aggregation of wind speed time series by means of precise data acquisition, yielding fruitful outcomes in data collection. Consequently, the degree of urban wind energy resource management is effectively attained through the gathered data and wind energy resource assessment, facilitating the prediction of the theoretical wind energy resources within a given region and establishing a foundation for the development of wind energy resources to genuinely achieve sustainable ecological civilisation.

2 Related work

The evaluation of wind energy within the purview of environmental resource assessment employs pertinent observational data to scrutinise the enduring power density of wind and the annual energy density of wind within the designated locale. This comprehensive assessment encapsulates pivotal facets, including the distribution of wind velocity, wind direction, mean power density, and operational hours. The culminating appraisal of wind energy resources ascertains the aggregate wind energy reservoir, the viable quantum amenable to exploitation, and lays the bedrock for the selection of wind farm sites, turbine preferences, strategic deployment, and electricity computation. It bequeaths invaluable guidance for the siting of wind farms, culling fitting wind turbines, conceptualising unit arrangements, and executing electricity computations. Throughout the trajectory of wind energy resource evaluation, cartographic and observational topographical insights are collated in a preliminary maneuver, succeeded by the cartographical delineation of wind energy resources endemic to the analytical demesne (Ahmad Zaman et al., 2019). Subsequently, an overarching stratagem of deployment is formulated, encompassing the simulation of parameters such as discharge volume and power density through computational models. Ultimately, the interrogation of vagaries inherent to the outcomes of wind energy resource evaluation, the assessment of parameters like available operational hours, and the prognostication of potential economic gains are effectuated. Consequently, the exploration of models for resource assessment remains a focal point for numerous research scholars.

In his pursuit of assessing environmental resources, Putnam initially estimated the global reserves of wind energy in 1948 (Putnam, 1948). His findings indicated that the total energy present in the atmosphere amounted to approximately 10^{14} MW. This value was acknowledged by the World Meteorological Organisation (WMO) and was later referenced in the WMO report titled ‘Energy from the Wind,’ No. 4, published in 1954. The report posited that one ten-millionth of this total energy was accessible for human utilisation, equating to 10^7 MW, which surpassed the available hydroelectric power on Earth by a factor of ten. Following this, a comprehensive survey of wind resources in Africa was conducted, utilising a grid system with 25 km × 25 km points offshore. Furthermore, nearly 2000 additional wind measurements were specifically conducted for this purpose, resulting in the creation of a wind resource map (Olaofe, 2018). The wind speeds were extrapolated to a height of 50 m above the towers, using data from 570 towers ranging in heights of 20 m and 25 m, which had been established since 1987. This effort culminated in the development of a wind resource map for India at a height of 50 m (Boopathi et al., 2021).

All of the aforementioned processes rely on meticulous statistical analysis of site-specific data to obtain the final wind resource distribution map. In contrast, in recent years, advancements in numerical simulations (Luo et al., 2022; Liu et al., 2022) have significantly enhanced the efficiency of data analysis. Consequently, numerous sophisticated wind resource assessment models have been developed, leveraging these numerical simulation techniques. One such model, described in the literature (Kamdar et al., 2021), utilises numerical simulation to design a resource analysis tool called WindAtlas analysis and application program (WASP) specifically for micro-siting of wind farms. Building upon this work, the literature Roga et al. (2022) has constructed a wind energy resource assessment system that incorporates unique features and has been implemented in over 20 countries and regions for wind energy resource assessment. Additionally, Japan has employed the US atmospheric boundary layer model RAMS to conduct high-resolution numerical simulations of wind energy resources (Hu et al., 2015). To facilitate the visualisation of the final wind resource assessment, scholars have developed various systems. The internet-based wind navigator system, provided by associated weather services, offers a dynamic and interactive platform for wind resource assessment (da Silva et al., 2021). Similarly, the first look system, provided by 3TIER (Yuan et al., 2011), serves as an interactive tool for wind resource assessment. Furthermore, the literature Repetto et al. (2018) utilises the MapServer open-source GIS component (Chen et al., 2022; Mahdi et al., 2022), along with JavaScript and PHP/MapScript languages on the client side, to develop a decision support visualisation system for wind farm planning. The Tuscany region of Italy serves as an exemplar in this study.

Despite the abundant wind energy resources and the ongoing exploration of wind energy resource estimation models, several challenges persist, impeding further development. The intermittent and unstable nature of wind speed poses a challenge to the stability of the power system once wind power is connected to the grid (Shi et al., 2014; Mokeke and Thamae, 2021). There are two approaches to addressing this issue: firstly, increasing the installed capacity of wind power and the rotating reserve capacity of conventional units (Wang et al., 2022) can mitigate the impact of wind power integration into the grid. However, this approach leads to an increase in the system’s operating costs.

The second method involves the accurate and effective collection and prediction of wind speed (Wang et al., 2021). This enables timely grid dispatch, enhancing the economic viability of wind power. Wind speed forecasting is crucial for mitigating the impacts of large-scale grid integration and facilitating timely adjustments to grid operation plans. Accurate and effective wind resource assessment, along with precise wind speed prediction, are therefore vital for wind farm selection and the safe and stable operation of power systems.

In 1985, Maiers introduced fuzzy set theory (Maiers and Sherif, 1985) to address the limitations of data collection under manual control. Since then, fuzzy set theory has gained significant development and has been widely employed in various domains of life. Bui et al. (2022) proposed the use of fuzzy linguistic variables to represent the control state of relevant control variables, thereby achieving effective control of these variables. This marked the formal introduction of fuzzy control and its related theory. The introduction of fuzzy control concepts provided a research direction for the accurate collection of certain data in environmental resource assessment. Subsequently, researchers began utilising fuzzy control algorithms to establish assessment models for environmental resources, including electricity and water resources (Tayfur, 2014; Yaseen et al., 2019). However, due to the complexity arising from multiple variables involved in wind energy, there has been a lack of ground breaking research on the utilisation of fuzzy control algorithms for wind energy resource assessment.

3 Model design

An accurate and macroscopic estimation of the total reserves of wind energy is crucial in assessing the viability and potential of utilising wind energy. Simultaneously, in the development of smart cities, the collection of data pertaining to wind energy resources is carried out in an automated and intelligent manner. However, the data obtained from sensors may be subject to inaccuracies caused by natural environmental influences. Therefore, it becomes necessary to employ fuzzy control algorithms to enable intelligent and precise data collection of the parameters used in wind energy resource assessment.

According to the discussion and analysis of related work, it can be seen that by combining MISO fuzzy controller and data acquisition based on fuzzy control algorithm, a model can be built to evaluate wind energy resources. This model can use multiple input variables to predict the wind energy generation, and control the output by fuzzy control algorithm, which makes the model more accurate and reliable. Here is a basic step:

1 First, we analyse the characteristics of the wind resource assessment system and build a multi-paste controller. According to the multi-input characteristics of wind resource evaluation system, considering the relationship between multiple input variables (such as wind speed distribution, wind direction, average wind power density) and one output variable (wind speed), we define fuzzy rule base and realise the control of output through fuzzy reasoning.

2 Next, we obtain the input of MISO fuzzy controller based on fuzzy control algorithm. These data were pre-processed in the experiment, such as data cleaning, outlier removal, data interpolation and normalisation, to ensure the accuracy and consistency of the data.

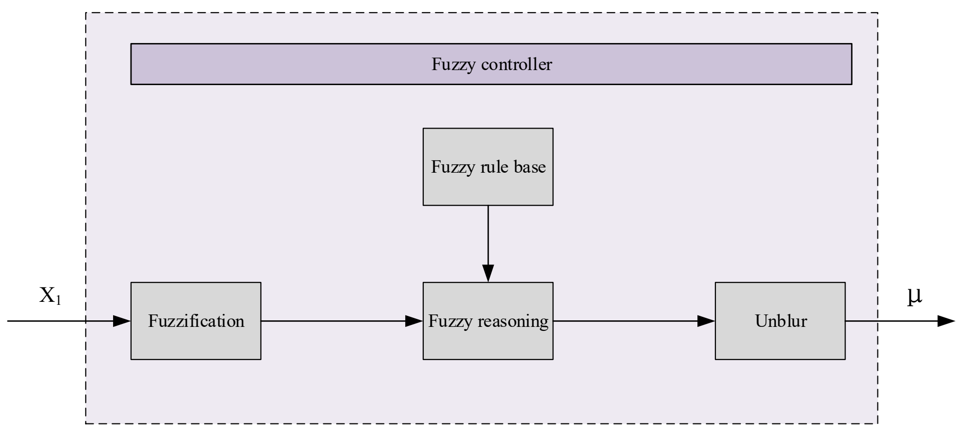
4 Finally, we build the model and optimise the parameters

Using the obtained wind energy resource data and the corresponding wind energy generation data, a wind energy resource evaluation model is established.

4.1 Multi-input and single-output fuzzy controller

The central component of the fuzzy control algorithm is the fuzzy controller, depicted in Figure 1. It operates by taking the pre-identified numeric variable X1 as input and transforming it into a linguistic variable or fuzzy quantity through the process of fuzzification. The fuzzy quantity is then passed into the fuzzy inference engine, where it is reasoned based on the corresponding fuzzy rules stored in the fuzzy rule base. The defuzzification module subsequently converts the fuzzy set into a digital quantity μ, which serves as the output control signal. This control signal is then transmitted to the lower level to accomplish the fuzzy control of the target under consideration.

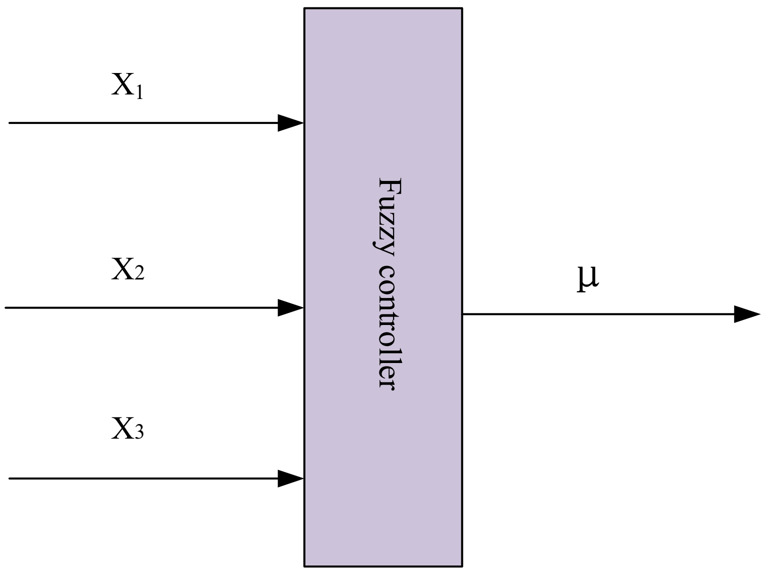
Figure 1 Fuzzy controller structure framework (see online version for colours)



Over the course of several decades, fuzzy control has garnered significant attention from researchers due to its ability to function without relying on a mathematical model and its capability for nonlinear intelligent control (Wang et al., 2002). As a result, fuzzy control has become an area of increased scholarly exploration. It has developed a comprehensive theoretical framework and is increasingly applied in various domains, demonstrating its growing popularity and systematic theoretical foundation.

The fundamental constituents of a fuzzy controller encompass fuzzy quantitative input, the formulation of a fuzzy rule corpus, fuzzy inference, and defuzzification (Dong et al., 2022; Belman-Flores et al., 2022). In the paradigm of wind energy resource evaluation, the orchestration of input variables for the astute controller is predicated upon the quartet of cardinal constituents intrinsic to the fuzzy controller: the dissemination of prevailing wind velocity, wind orientation, and mean wind energy density. Upon assimilating the aforestated data, the astute controller, via the prism of fuzzy inference, begets the corresponding wind velocity. The operational modality is delineated as follows: The astute controller, in response to signals transmitted by sensors gauging wind velocity, detects the exigency for grid allocation, thus amplifying the economic efficacy of wind power generation. Determinations regarding grid allocation are rendered grounded in system-identified data facets, like wind velocity and energy reserves. By means of fuzzy control, these variables metamorphose into directives of control, subsequently deployed to effectuate commensurate adjustments to grid-generated power. Manifestly, the core linchpin of the astute wind energy control apparatus resides in the astute controller, whereby the fuzzy control algorithm assumes the mantle of chief algorithmic agent. Extraneous peripherals are harnessed for signal amalgamation and the transmission of pertinent data to the microprocessor.

Figure 2 Multi-input and single-output fuzzy controller (see online version for colours)



Upon analysing the input variables of the model, namely the current wind speed distribution, wind direction, and average wind power density, it is evident that these variables are not singular but rather relatively independent of each other. Existing fuzzy controller constructions typically involve a single input variable, differing only in the number of components of the input variables. However, such univariate fuzzy controllers are not suitable for the subject matter discussed in this paper.

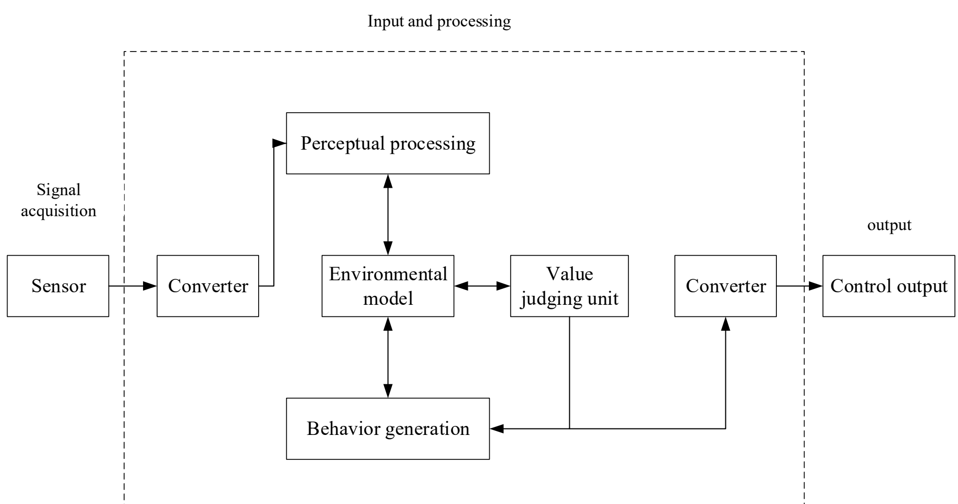
To address this issue, a multiple input and single output fuzzy controller is constructed, allowing for the utilisation of multiple independent input variables within the controller. This is a system that is capable of dealing with multiple input variables and one output variable. MISO fuzzy controller considers the information of multiple input variables simultaneously, thus providing better control performance. In addition, MISO fuzzy controller has a strong ability to model and control complex nonlinear systems. It can use fuzzy rules to describe the dynamic characteristics and nonlinear behaviour of the system, so as to achieve effective control. Compared with other linear control algorithms, MISO fuzzy controller can adapt more flexibly to the changes and nonlinear characteristics of complex wind resources. In order to simplify the structure, the study did not consider the rate of change of the input variables. As a result, a one-dimensional fuzzy controller with multiple inputs and a single output, as depicted in Figure 2, was ultimately chosen for the purpose of fuzzy control.

4.2 Resource assessment model

4.2.1 Data acquisition

Fuzzy control algorithm can deal with system parameter uncertainty and external disturbance. In wind power system, the change of wind speed and the fluctuation of wind power will affect the performance of the system, and fuzzy control can adjust the fuzzy rules of the controller to adapt to these changes and maintain the stability and efficiency of the system. In addition, the wind power system has nonlinear characteristics, and the traditional linear control method is often difficult to meet the control requirements of the system. Fuzzy control theory can deal with nonlinear system effectively. By constructing fuzzy rule base and fuzzy inference, the nonlinear system can be controlled and optimised. So we use fuzzy control algorithm to acquire and process the data.

Figure 3 Intelligent controller processing flow



In order to meet the parameter requirements of the wind energy resource assessment model, we have developed an intelligent data acquisition module, which follows the processing flow illustrated in Figure 3. The intelligent controller consists of a signal acquisition module, a signal input/processing module, and an intelligent controller with a signal output/display module.

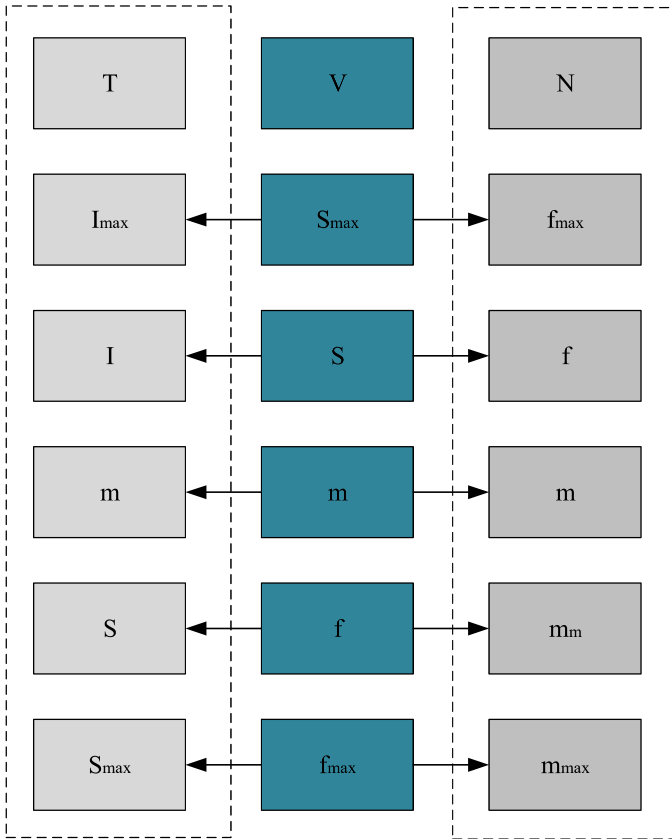
Given that the wind speed measured by the sensor is not a unique value, we employ the variables v (wind speed), d (wind direction), and s (distribution) obtained through sensor processing as the inputs to be fuzzified by the fuzzy control algorithm in the intelligent control system. The fuzzy domains for v, d, and s are denoted as V, D, and S, respectively.

For wind speed v, it is divided into five fuzzy subsets within the range [0, n], and the resulting fuzzy subset obtained after fuzzification is represented by V.

$$[s_{max}, s, m, f, f_{max}] \tag{1}$$

The determination of the number of fuzzy subsets is conducted through careful analysis. If too many fuzzy subsets are defined, the fuzzification process becomes challenging and the computational workload increases significantly. Conversely, if too few fuzzy subsets are utilised, the reliability of the modal processing results decreases, thereby impacting the effectiveness of control (Dumitrescu et al., 2021; Yao et al., 2023). Similarly, the variables *D* (wind direction) and *S* (distribution) are both divided into five fuzzy subsets for the purpose of the fuzzy control algorithm.

Figure 4 V corresponding fuzzy control rules (see online version for colours)



The process of establishing fuzzy control rules is introduced using *v* as an example. When the intelligent street light energy saving control system detects that the fuzzy subset corresponding to the speed is S_{max}, it says that the wind speed is very slow at this time and the power network should be adjusted upwards for conversion efficiency. When *v* corresponds to the fuzzy subset f_{max}. The number of fuzzy subsets for wind speed determines how the speed is classified, such as very slow, slow, moderate, fast, or very fast. Each fuzzy subset represents a different range of wind speeds and corresponds to different characteristics of wind energy resources.

By defining the fuzzy subsets for wind speed, we can establish fuzzy control rules that govern the behaviour of the system. These rules determine how the system responds based on the input variables. All the fuzzy control rules corresponding to wind speed can be depicted in Figure 4, outlining the relationships between different fuzzy subsets of wind speed and the corresponding actions or behaviours of the system.

For a fuzzy controller with a single input variable, each fuzzy control rule is associated with a relative fuzzy implication relation, denoted as R_i (where $i = 1, 2, \ldots, n$). When these fuzzy implication relations are combined, they form a total fuzzy implication relation within the fuzzy controller. In the case of a single input variable fuzzy controller, the expression for the fuzzy inference rule, considering all fuzzy control rules and their relative fuzzy implication relations, can be described as follows:

$$O = (EoR_1) \vee (EoR_2) \vee \ldots \vee (EoR_i) \tag{2}$$

Let E represent the input to the fuzzy controller, R denote the relative fuzzy entailment relation of the fuzzy control rule, and O represent the fuzzy output. In accordance with equation (3), the expressions for fuzzy inference rules associated with the fuzzy subset T of wind speed and the fuzzy subset N of the number of variables can be derived as follows, respectively:

$$T = (VoR_1) \vee (VoR_2) \vee \ldots \vee (VoR_5) \tag{3}$$

$$N = (VoR_1) \vee (VoR_2) \vee \ldots \vee (VoR_i) \tag{4}$$

A fuzzy inference rule for a fuzzy controller with a number of input variables of 2 can be synthesised according to different fuzzy control rules with their corresponding fuzzy implication relations as

$$O = ((E \wedge F)oR_1) \vee ((E \wedge F)oR_2) \vee \ldots \vee ((E \wedge F)oR_i) \tag{5}$$

In comparison to equation (2), where E represents the first input variable to the fuzzy controller and F denotes the second input variable to the fuzzy controller, the expressions for the fuzzy inference rules pertaining to the wind direction D and the distribution S can be derived from equation (5) as follows:

$$O = ((D \wedge S)oR_1) \vee ((D \wedge S)oR_2) \vee \ldots \vee ((D \wedge S)oR_i) \tag{6}$$

The fuzzy output results obtained from the fuzzy inference rules are in the form of fuzzy subsets. However, the intelligent control system requires digital quantities as control signals. Therefore, it is necessary to transform the obtained fuzzy subsets into digital quantities through a process called defuzzification. In the defuzzification process, priority should be given to the subset of T output results along with the subset of N output results, in accordance with the system requirements. The maximum subordinate mean method is employed for defuzzification, which helps obtain accurate wind speed, distribution, and other data essential for environmental resource assessment.

4.2.2 Model optimisation and reorganisation

After obtaining the wind speed, distribution status and other data, we divide the observed area into N km grid cells in GIS R_i, the wind resource of the km grid geographical cell R_i is P_i, under the influence of the variables of wind speed v_i, wind direction d_i and distribution s_i of each network cell, each P_i will be different, and the final total wind resource is $\sum_{i=1}^{N} P_i = P$, At this stage, we allocate the values within the specified range to the grid cells, representing their wind resource information. The wind resource of each kilometre grid cell is determined by factors such as its internal wind speed, wind direction, and other attributes and quantities. Based on this, we construct the wind resource assessment model for each kilometre grid cell.

Since accurately assessing the wind energy density within a specific location can be challenging, we have selected the wind distribution (s) as the influencing factor for the wind energy density in the grid cell. This is expressed as a linear combination of various variable attributes within the kilometre grid cell, where the coefficients are determined based on specific considerations and calculations.

$$D_i = \sqrt{v_i^2 + d_i^2 + s_i^2} \tag{7}$$

For the obtained wind distribution simulation values:

$$s_i^{'} = D_i s_i + \tfrac{1}{2} D_i v_i \tag{8}$$

We utilised statistical analysis calculations to optimise the structure of the wind resource distribution assessment model for kilometre grid cells. This optimisation was performed based on the number of site datasets collected at each specific location. Through statistical analysis, we determined the most effective and accurate approach to assess the wind resource distribution within the kilometre grid cells.

$$RS = \left[\frac{1}{N} \sum_{i=1}^{N} (s_i^{'})^2 \right]^{\frac{1}{2}} \tag{9}$$

5 Experimental results and analysis

ArcGISEngine 10.1 is a set of development components for building geographic information system (GIS) applications. It provides a wealth of features and tools for data analysis, map making, spatial query, and visualisation. In this paper, we mainly use the map making and visualisation tools of ArcGISEngine 10.1 to draw the distribution map of wind energy resources, wind rose chart, heat map, etc.

In order to carry out wind energy resource assessment using the ArcGISEngine 10.1 component, it is important to address the challenges posed by the irregular and incomplete data collected from various site sensors. The sampling frequency of the data varies among different sites, ranging from hourly recordings to measurements taken every 20, 10, or 5 minutes. Furthermore, some sites have irregular recording patterns, with recording durations ranging from 7 to 19 hours. Additionally, there are instances where certain stations are unavailable for unknown reasons, resulting in missing data for key parameters. To overcome these challenges, we follow certain definitions and procedures. The positive wind speed is defined as the average wind speed recorded within the first 10 minutes of a given time interval. If there is no available data for the first 10 minutes, the last 10 minutes are considered. If data is still missing, the first 20 minutes or the last 20 minutes are used as substitutes, and so on. By applying these definitions and procedures, we can effectively handle the irregularities and missing data in the wind speed recordings, which enables us to proceed with the wind energy resource assessment using the ArcGISEngine 10.1 component.

5.1 Analysis of simulation results

The algorithm simulation was conducted utilising the fuzzy logic tool integrated within the MATLAB software. To facilitate the creation of the algorithm, we employed the graphical interface visualisation tool provided by MATLAB software. The generation of the power intelligent control curve during the simulation operation was based on the aforementioned design and an actual wind power conversion simulation. This facilitated a subsequent comparison with actual parameters, enabling an evaluation of the simulation operation and the resultant energy-saving effect. In accordance with the settings outlined in Section 3.2, we established the variables, employing wind speed (v), wind direction, and distribution as inputs for the fuzzy control algorithm. Following the implementation of intelligent control, we plotted wind speed (v) against grid efficiency for Minnesota in 2020. The outcomes of this analysis are depicted in Figure 6.

Figure 6 Grid dispatching relationship diagram (see online version for colours)

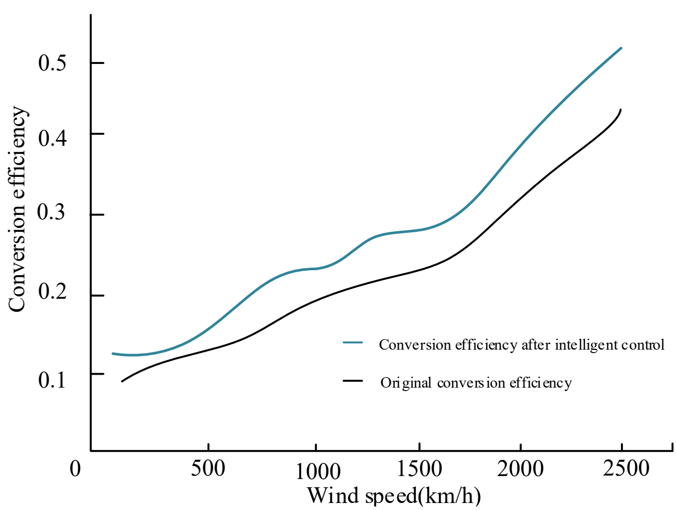
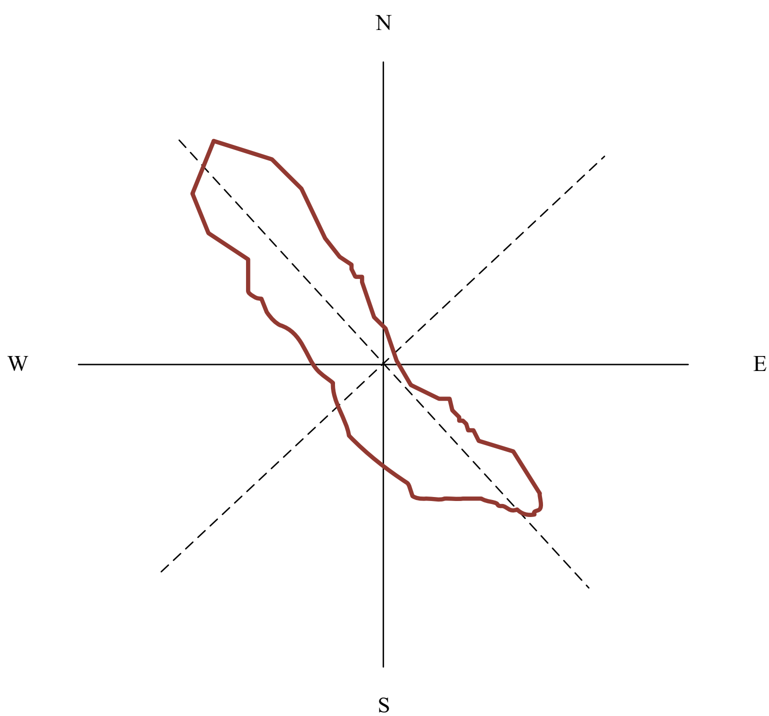


Figure 6 illustrates the positive association between wind velocity (v) and wind power conversion efficiency. As the wind speed increases, the availability of wind resources amplifies. This phenomenon arises primarily due to the insufficiency of wind resources when wind speed is low, as the conversion rate is contingent upon the magnitude of available wind resources. Consequently, a positive correlation between these two variables emerges. Additionally, within this framework, we achieve the realisation of intelligent wind energy control, enabling adjustments to power distribution at sites during periods of reduced wind speed. This adaptation ensures the fulfillment of power conversion demands. Through the implementation of intelligent power regulation, our model effectively enhances wind power conversion efficacy by 5.2% in comparison to non-intelligent power regulation.

5.2 Resource assessment

The wind energy evaluation module is constructed to facilitate the subsequent processing of meteorological data following pre-processing by the fuzzy control algorithm. By utilising Minnesota as an exemplar, we conduct wind direction statistics and wind energy assessment. The outcome of the fuzzy control algorithm's processing of weather data includes the compilation of wind direction statistics into individual XML files for each site and the respective month. Furthermore, we employ the mean wind speed and its standard deviation to estimate the shape and scale parameters for resource assessment, and the resulting values are recorded in the database. Ultimately, to assess the stability of wind direction at each site, a wind direction rose diagram is generated for the study area, encompassing each site and month (or year). Drawing upon data collected from 8603 stations, the analysis reveals that the average frequency of wind direction in Minnesota over the course of a year is 0.085, while the average frequency of static wind stands at 0.07. Additionally, the prevailing wind direction throughout the year is 320 degrees. Based on these acquired data, we present a wind direction rose map exclusively for Minnesota.

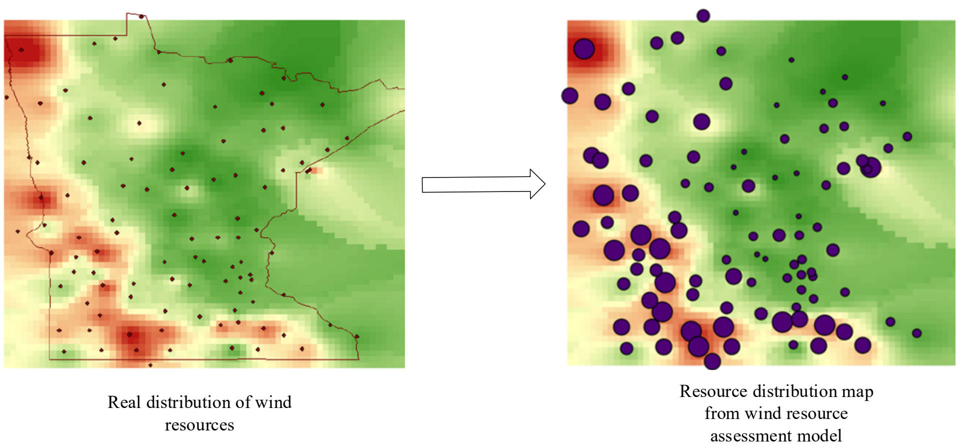
Figure 7 Wind rose chart (see online version for colours)



To generate the wind rose map, we begin by calculating the average wind energy density using statistical wind speed data from each station. We then adjust the wind energy density to a standardised height based on the elevation of each meteorological station. The calculated wind energy density is subsequently recorded in the relevant field within the station data. Additionally, we incorporate the influence of topographic relief on wind energy density. This entails constructing weights based on distance and height differences and performing interpolation to obtain a comprehensive wind energy density map for the entire study area. The calculated results are stored in TIF format. Figure 7 showcases the resulting wind rose map specifically for Minnesota.

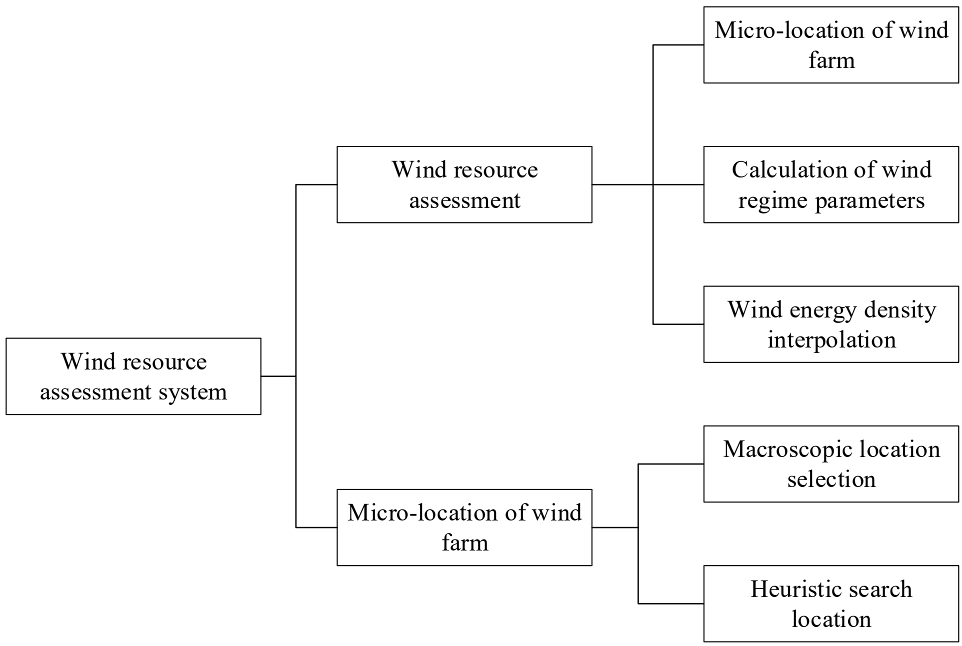
By examining Figure 7, it becomes evident that the prevailing wind directions at the Minnesota site are northwest and southeast, with a relatively low frequency of static wind. The wind conditions indicate the site's suitability for wind farm establishment. Subsequently, after conducting further calculations, we generate the wind energy density map for Minnesota at a height of 70 metres, as depicted in Figure 8. The figure reveals that Minnesota possesses considerable wind energy resources, with an average wind energy density of 562.0021. Notably, the northwest to southwest region of Minnesota exhibits a gradual increase in wind resource distribution density, with the southwest region boasting an exceptionally rich wind energy resource concentration, reaching a peak wind energy density of 673.868.

Figure 8 Wind energy density map (see online version for colours)



The rapid progress of economic and social advancement has resulted in the excessive consumption of resources and the escalating issue of environmental pollution. Consequently, finding effective measures to protect the ecological environment and achieve sustainable development of environmental resources has become an urgent global task. In the aforementioned study, a comprehensive analysis was conducted on the distribution of wind resources, wind speed, and wind direction data. Based on various factors such as wind patterns, meteorological conditions, transportation accessibility, and economic considerations, the study successfully identified the most valuable locations for wind farm placement. By employing this information, wind farms can be strategically sited to maximise power generation and promote the overall development of wind energy. Furthermore, the correct siting of wind farms contributes to the realisation of economic benefits for the entire wind farm industry. Figure 9 showcases the wind resource assessment system.

Figure 9 Wind resource assessment system



6 Conclusions

This paper employs conventional GIS-based components for wind energy resource assessment analysis, processing, and modelling to develop a GIS-based wind energy resource assessment system. Recognising the inherent instability and uncontrollability of data collected from the sites, a fuzzy control algorithm is introduced to achieve intelligent data control. Through fuzzy processing operations, the algorithm transforms the data into operational instructions for grid regulation, thereby enabling effective control over wind resources. The fuzzy control algorithm is simulated using MATLAB software, and the experimental results align with the calculated results of the algorithm. Meanwhile, our 5.2% increase in wind energy efficiency will allow more wind energy to be converted into electricity. This can reduce energy waste, reduce unit power production costs, improve the economic competitiveness of the wind power industry, and effectively help China reduce its dependence on non-renewable energy sources. By reducing the need for energy imports, it improves the country's energy security. Furthermore, the wind resource distribution map of Minnesota is utilised as an example for resource assessment, and the final outcomes align with the existing spatial distribution of wind farms, reflecting the system's real-world applicability.

Presently, the accuracy and reliability of the wind energy resource assessment model depend on the quality and precision of the input data. However, the data used for wind resource assessment (such as wind speed and direction) often have uncertainty and locality problems, and the fuzzy control algorithm has certain limitations on the processing of uncertainty. Therefore, how to deal with and optimise the uncertainty and accuracy of input data is an important direction of future research. Meanwhile, the fuzzy control rules in the algorithm are manually entered based on experience. However, future research aims to enhance the self-learning capability of the fuzzy control algorithm. This would enable the system to autonomously improve its rules based on collected data and continuously enhance the effectiveness of the model's control. Additionally, incorporating other environmental factors into the control algorithm is anticipated to improve the model's adaptability and stability.

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