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Research on the relationship between the digital transformation of new energy enterprises in the context of electricity reform

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Abstract

The development of new energy sources such as wind power and photovoltaic power needs to be optimized to improve the sustainability of new energy development. At present, there are digital bottlenecks in the development of new energy, and there is a lack of systematic identification of operating indicators such as current, voltage and power flow, which affects the development of new energy enterprises. In order to expand the development scope of new energy, this paper proposes the Hausmann method to extract data from power generation equipment such as wind power and photovoltaic power, digitize the power index, and verify it with actual cases. Firstly, the power data is mapped, the dataset is constructed, and the fitting of the dataset is realized. Then, we can identify abnormal data values, determine the signal characteristics of power flow, voltage, and current, and optimize them. Finally, the governance results of the power index are output. The results show that the demand for data governance in new energy enterprises is high, and digital transformation can improve the effect of governance, the post-grid connection coefficient of voltage is 0.25, and the variation difference is 0.000, and there is no obvious multicollinearity problem between power indicators, the results of power governance are reliable and high, and the volatility of power indicators is in a controllable range of about 0.42~0.75%. Quantitative results show that digital governance stabilizes key power indices, with grid-connected voltage coefficient reaching 0.25, variation difference approaching 0.000, and power index volatility maintained within 0.42–0.75% for durations below 0.8 seconds. Through further analysis, it is found that there is a correlation between the power indicator and digital transformation, which is within the constraint range, and the fluctuation duration is short, less than 0.8 seconds. Under data governance, the stability of voltage, current and power flow is high, the distribution ratio is reasonable, the distribution ratio is 0.33~0.55, and the power index change after grid connection can be suppressed, and the inhibition rate reaches 10%. Therefore, in the face of external factors such as the policy environment, changes in market demand, and technological innovation, digital transformation can optimize the power generation structure of new energy, improve the control rate of power indicators, maintain the stability of current operation, and improve the sustainability of new energy development.

Keywords: wind power; photovoltaic power; energy governance; power index governance; microgrid operation; digital energy governance; electricity market reform; signal digitization; new energy enterprises

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1. Introduction

Under the condition of continuous deepening of the reform of the power market and companies, the new energy industry, as an important part of the green and low-carbon economic strategy, has gradually become integrated with thermal energy and penetrated into related fields. However, due to the instability of wind and photovoltaic power generation, as well as the expansion of the scope of microgrids, the regulation of current, voltage, and power flow also faces a series of problems that need to be solved urgently [1-2]. Some scholars believe that the low level of wind and photovoltaic operation and maintenance management, the insufficient development of energy form matching, the intensification of microgrid loading, and the increase in equipment data have had a serious impact on corporate governance [3]. The redundancy, complexity and quantification of power data and the instability of power indicators affect the sustainable development of the new energy industry and bring huge survival pressure to the deepening of the new energy structure. Some scholars believe that in the context of the increase in wind and photovoltaic loads, the uneven distribution of power flow will occur, and the failure rate of power generation equipment will increase, which will increase the difficulty of governance of energy enterprises, so the digitalization of governance has become a condition for solving the bottleneck of development [4]. However, the units of power flow, voltage and current signals in new energy are inconsistent, which cannot effectively solve the needs of power flow instability, voltage change, and integration with the main power grid. In addition, the differentiation of power supply and the expansion of the scope of power supply stations will also cause problems such as low efficiency of wind and solar power generation and unreasonable configuration of power generation equipment, inhibit the role of new energy, and even cause energy waste. At the same time, the use of automatic eddy current, sunlight tracking and angle tracking makes it difficult for new energy enterprises to collect data such as current and voltage, and the processing method of online monitoring cannot meet the needs of new energy expansion [5-6]. Therefore, in order to improve the effectiveness of corporate governance of new energy, it is necessary to convert electric energy into digital signals, realize the signal unification of different power indicators, and provide support for the later energy deepening, structural adjustment, and operation and maintenance level improvement. Some scholars believe that the integration of genetic algorithms, Harmansian methods, and clustering methods into new energy sources can standardize data such as voltage and current, simplify the complexity of power generation data, and improve the efficiency of digital transformation [7-8]. The digital governance approach supports national energy reform by enhancing grid stability, optimizing power generation, and reducing resource waste. For enterprises, it drives sustainability by improving operational efficiency and energy management practices. Some scholars believe that there is a lack of a unified way to deal with the digital transformation of electric power, and in the case of frequent anomalies in current and voltage signals, the anomalies cannot be accurately determined, thus wasting wind power resources, so a unified digital transformation method is needed [9-10].

The paper explores sustainable energy optimization through life cycle assessment and digital models in cross-border e-commerce, emphasizing energy governance and digital transformation. It aligns with improving energy systems and supports sustainability goals in new energy enterprises and analyzes the impact of cyberattacks on smart grid protection using real-time co-simulation, highlighting the need for secure digital governance in energy systems [11-12]. Therefore, it is the focus of current research to clarify the relationship between new energy and corporate governance, as well as the specific scope of governance [13]. Jayaprakasam & Hemnath propose a cloud-based solution using LSTM and XGBoost for energy forecasting and anomaly detection. In the proposed work on the digital transformation of new energy enterprises, these techniques will be integrated to improve predictive energy management, scalability, and real-time decision-making. The benefits include enhanced efficiency, cost savings, and better resource management for energy companies navigating electricity reform [14].

This study introduces a governance-oriented digital transformation framework that integrates Hausman-based statistical validation to evaluate power index stability in new energy enterprises. It further contributes contextual evidence from electricity market reform settings, demonstrating how regional and environmental factors shape digital governance effectiveness. Existing studies on new energy data collection mainly rely on sensor-based monitoring and real-time acquisition, which often suffer from signal inconsistency, limited anomaly discrimination, and sensitivity to voltage and power flow fluctuations. The Hausman method offers a statistically robust mechanism to test signal consistency, isolate abnormal variations, and enhance data integrity during digital governance. In this study, the Hausman method is incorporated into the digital transformation framework to evaluate the consistency and reliability of digitally transformed power index data. This integration supports governance-oriented data optimization by distinguishing stable signal relationships from irregular variations in new energy enterprise operations. On the basis of the above analysis, this paper collects digital signals such as wind power and photovoltaic power, preliminarily removes abnormal signals, and maps the signals into digital sets to complete the digital transformation. Then, the Hasman processing method is used to identify the characteristics of the data signal, find the abnormal values in wind power and photovoltaic power generation, improve the operation and maintenance management level and fault identification rate, deepen the structure of new energy, and expand its application scope. In addition, the research in this paper can provide a theoretical basis and case support for the digital transformation of the power industry to achieve the national green energy development goals.

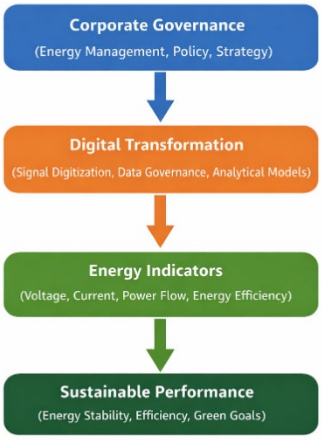

Figure 1. Relationship Between Corporate Governance, Digital Transformation, and Energy Performance

The Figure 1 shows the relationship between corporate governance, digital transformation, and energy indicators in new energy enterprises. It illustrates how governance influences digital transformation through strategies and policies, leading to signal digitization, data governance, and energy indicator management. These elements align to achieve sustainable performance, focusing on energy stability, efficiency, and green energy goals, promoting the sustainability of new energy systems.

This study aims to examine how digital transformation influences power index governance in new energy enterprises under electricity market reform, addressing the lack of empirical clarity on signal stability and governance effectiveness. The research specifically focuses on identifying measurable relationships between digital governance mechanisms and variations in voltage, current, and power flow indicators.

2. Governance and digitization of new energy data such as wind power and photovoltaics

Deeply analyze the relationship between new energy and the corporate governance of small and medium-sized enterprises, judge digital transformation according to the transformation of current, voltage and power flow, as well as trends, and deepen the digital governance of new energy.

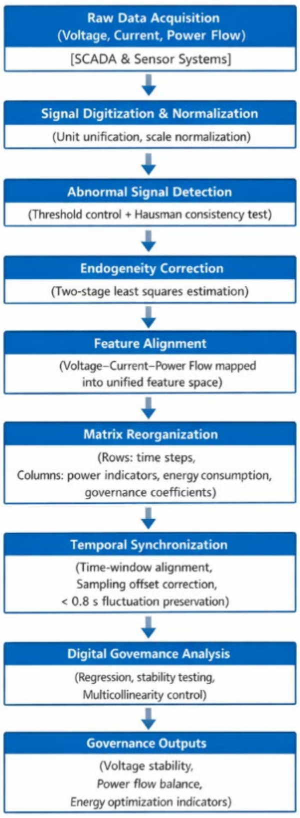

Figure 2. Computational Workflow for Signal Transformation and Data Mapping

The Figure 2 illustrates the complete computational workflow for digital governance of new energy signals, including data acquisition, signal digitization, abnormal detection, endogeneity correction, feature alignment, matrix reorganization, temporal synchronization, and governance output generation, ensuring analytical transparency, methodological consistency, and full reproducibility of results. To ensure reproducibility and transparency of the digital governance process, a standardized computational workflow is implemented. First, raw voltage, current, and power flow signals from wind and photovoltaic systems are collected through SCADA and sensor-based monitoring at uniform sampling intervals. All signals are digitized and normalized to eliminate unit inconsistencies and scale differences. Second, abnormal values are identified using threshold constraints and Hausman-based consistency testing. Signals exceeding predefined fluctuation thresholds are flagged, and two-stage least squares estimation is applied to isolate endogenous deviations and ensure signal independence. Third, feature alignment is performed by mapping voltage, current, and power flow indicators into a unified feature space. Each indicator is standardized and aligned according to power generation type (wind or photovoltaic) to maintain structural comparability across datasets. Fourth, the aligned features are reorganized into matrix form, where rows represent synchronized time steps and columns represent power indicators, energy consumption, and governance coefficients. Separate matrices are constructed for stand-alone microgrid operation and grid-connected states to support comparative analysis. Finally, temporal synchronization is conducted using time-window alignment to correct sampling offsets and preserve short-term fluctuations. This step ensures that transient variations within 0.8 seconds are retained, enabling consistent regression analysis and repeatable governance evaluation.

2.1 Digitization of power flow, voltage and other signals

In the research, it is necessary to first determine the power flow signals in wind power and photovoltaics, and quantify the digital governance of energy in the process of digital transformation, and at the same time, pay attention to the endogenous problems between power flows and optimize the energy structure. The energy changes between wind power and photovoltaic power cannot reveal the impact of power indicators, so it is necessary to deal with the signal problems in power indicators clearly. In this paper, the Hausman method is introduced to randomly divide the voltage and current indicators, and then calculate the quantification of the stargazing sky between the data, including the energy governance structure, signal digitization, and the transformation of energy forms, as shown in Eq. (1). The following mathematical formulation describes the relationship between digital transformation factors and power index governance outcomes. Each variable represents a governance or energy indicator, while the equation explains their functional interaction in the analytical model.

$$\sum H_i = \frac{(\hat{\beta}_i F_i E_i - \hat{\beta}_j R_j E_j)' \cdot k_i}{[Var(x_i) - Var(y_j)]} + (\Delta F_i \cdot E_i - R_j \Delta E_j) \tag{1}$$

In Eq. (1), $\hat{\beta}_i$ and $\hat{\beta}_j$ represents the power signal parameters, R_j represents the random region of the power signal, $Var(x_i)$ represents the wind power generation, $Var(y_j)$ is photovoltaic power generation, ΔF represents the distribution variance of energy, and ΔE_j represents the variance of energy utilization. The key to the governance of energy data is to identify the energy structure problems in the microgrid and then select the appropriate power indicators for synergy. Through the power framework in the microgrid, the signal data can be clearly transformed, and the transformation of governance and digitalization can be realized, providing an effective tool for the analysis of microgrid grid connection. At the same time, voltage and current data acquisition and preprocessing are mainly to provide high-quality data for governance and deal with potential abnormal signal identification problems. Prior to model input, voltage, current, and power flow signals are normalized to a unified scale and processed using threshold-based denoising and low-pass filtering to suppress measurement noise. These steps ensure waveform consistency and preserve essential signal characteristics for reliable analysis. The effective treatment of abnormal voltage and current signals is important to maintain new energy power generation, especially when the microgrid is connected to the main grid. Based on the correlation of power flow distribution, data mapping and processing methods can be used to reduce the bias of voltage and current signal identification and improve the stability of the microgrid, as shown in Eq. (2).

$$f(X_i) = \sum \alpha_i \cdot \sqrt{Z_i} + \beta_i \cdot X_i + lim\epsilon_i \tag{2}$$

In Eq. (2), X_i is the abnormal change of the microgrid data, Z_i is represented as the fluctuation of the signal, β_i is the mapping of the signal, α_i is the collection weight of the signal, and $f(X_i)$ is the anomaly identification function of the signal, which is estimated by the two-stage least squares method, and the outliers can be found, such as Eq. (3).show.

$$\hat{X}_i = \frac{\gamma_i \cdot Z_i \cdot f(X_i)}{2} \tag{3}$$

Based on equation (3), $\hat{X}_i$ can be seen that for the processed signal data, the voltage and current signals must be detected during data acquisition, γ_i is the abnormal threshold of the signal is set, $lim\epsilon_i$ is the abnormal signal data is collected. In the interplay between digital transformation and governance, there may be a two-way causal relationship between power flow, voltage, and current, so it is important to maintain the independence of signal data. Two-stage least squares estimation is applied to address endogeneity between power governance indicators and operational efficiency. Lagged voltage, current, and power flow variables, along with exogenous wind speed and solar irradiance, are used as instrumental variables. In the first stage, governance indicators are instrumented using these exogenous factors. The predicted values are then used in the second-stage regression to obtain unbiased efficiency estimates. Based on the application environment of wind power and photovoltaic power, the introduction of intervention variables can effectively reduce the abnormal deviation of voltage and current signals, so that the signals are within the threshold range, so as to make the analysis more accurate.

2.2 Correlation and mapping of digital signals such as wind power and photovoltaics

There is a correlation between voltage and current signals, and the identification of outliers is related to the stability of microgrids, which is extremely important for the research of data governance. In this process, the voltage and current signals are constructed into a data collection, and the signal data is mapped and managed. According to the Hausman method, random data were selected for random inspection, and the corresponding analysis of the data was completed. Data governance and signal standardization need to build a continuous mapping, so the correlation of power indicators is shown in equation (4).

$$y(P_i) = \sum_{P_n \in R} \big(w_i(P_n) \cdot x(P_i + P_n)\big) \tag{4}$$

In equation (4), $y(P_i)$ represents the power generation effect of new energy, P_i is the governance effect, and P_n is the relationship between energy and corporate governance, x is the wind power generation volume, w_i represents the degree of governance. In the process of corporate governance, it is necessary to quantify signals such as power and voltage, and establish the necessary connections by mapping data signals to two-dimensional space. In the process of power signal and voltage identification, it is necessary to fully consider the power generation capacity and effect to form a stable power generation closed loop. Moreover, external factors such as power generation process, power generation time and power load should be taken into account during the analysis process. Combined with the above factors, the connection between corporate governance and power generation indicators is used to find the deviation of the circuit and current signal in time, and the deviation range is determined to make it within a controllable range. Therefore, the accumulation of deviation reduction is the basis for corporate governance and power digitalization, and the focus of power equilibrium is realized, as shown in Eq. (5).

$$lim L_S = dif(L_i + L_d + L_c)|Z_i \quad (5)$$

In Eq. (5), L_S represents the digitalization of electricity, L_i is wind power and photovoltaic energy, L_d is power grid flow, L_c is mapping features, and Z_i is constraints. The deviation of the power signal reflects the overall operation of the power grid, which is the main identifying indicator of digital transformation and corporate governance. To capture uncertainty and volatility in power signals, a stochastic variance design is incorporated by modeling time-varying fluctuations of voltage, current, and power flow as conditional variances. This approach enables probabilistic interpretation of grid performance and dynamic representation of short-term volatility patterns. At the same time, the power deviation reflects the deviation of voltage, current, and power flow signals, and is the indirect embodiment of the stability of the microgrid.

2.3 The impact of digital transformation and corporate governance on the new energy structure

The key content of digital transformation is the energy return rate, which reflects the relationship between the power system function and energy consumption, and is also the power system to identify fault points, as well as the proportion of wind and photovoltaic power generation. Corporate governance parameters are quantified using indicators of digital governance intensity, data governance effectiveness, and operational control capability, which are empirically linked to voltage stability, power flow balance, and energy efficiency metrics to assess managerial impact. In the process of digital transformation of power signals, the relationship between power and energy plays a guiding role, which can reveal the energy balance and abnormal energy output, which is the key to digital transformation. Therefore, mining its energy structure has become the main research direction, as shown in Eq. (6).

$$ROA_i = 2f_i \rightarrow q_i \, ln\left(\frac{S_i S_j R_i}{q_i}\right) \quad (6)$$

In equation (6), ROA_i is the energy structure of power generation S_i represents the dissipation of energy, S_j isthe stability of the power index, the R_i relationship between the power index and dissipation, q_i is the degree of governance, and f_i is the degree of digitalization of the company. Through the mining of energy structure and digital transformation, the power generation energy consumption is judged, the relationship between power generation energy consumption and output is balanced, and guiding suggestions are provided for operation and maintenance management. In addition, in the process of voltage and current signal identification, it is necessary to conduct an in-depth analysis of its optimization structure and governance structure, comprehensively consider the power index, and complete the energy consumption allocation of new energy, as shown in equation (7).

$$y_{ij} = G_i(x_i, x_j) \cdot A_i + B_i x_i + C_j x_j + D_i \quad (7)$$

In Eq. (7), y_{ij} represents the distribution results of energy consumption in the digital transformation of new energy, including instantaneous energy consumption, continuous energy consumption, and energy consumption row and column measurement standards; A_i represents the constant term, which is the basic energy consumption of the transmission network, $G_i(x_i, x_j)$ is the energy usage rate of the energy consumption adjustment process, C_j is the energy consumption loss under the company value, x_i is the basic energy consumption, x_j is the optimized energy consumption, B_i is the data governance coefficient, C_j is the digitization coefficient, and D_i is the energy consumption deviation. In the process of dynamic adjustment of energy consumption, the signal changes of current and voltage, as well as the power flow changes after grid connection, are analyzed in depth, and the level of operation and maintenance management is judged. Analyze the problem based on the comprehensive power index, combine the wind power and photovoltaic power generation technology, and make a comprehensive judgment on the power generation effect, and identify the level of energy consumption. In addition, it provides feedback for the company's energy consumption governance, forms a long-term digital transformation system, establishes a long-term identification relationship in the energy consumption, governance and digital transformation chain, and forms a dynamic power generation cooperation relationship, as shown in Eq. (8).

$$\mu_i(x) = exp\left(-\frac{(x_i - c_i)^2}{\delta^2}\right) \quad (8)$$

In equation (8), $\mu_i(x)$ represents the level of energy consumption relationship, c_i is the improvement process of energy consumption, and δ is the relationship between energy consumption and power index. In the process of micro-power structure adjustment, wind power and photovoltaic power generation at the same time will cause multicollinearity, resulting in a significant increase in power flow and voltage. At the same time, the instability of wind and photovoltaic power is also amplified in this process, so it is necessary to optimize the synergy of photovoltaic and wind power, so that the power generation structure tends to be reasonable, and a stable power generation set is formed. At present, the main method of stabilizing the power generation structure is to introduce the expansion factor, as shown in Eq. (9).

$$VIF_j = \left[\frac{n}{1-\lim_{ls} R_j^n}\right] |Q_i \tag{9}$$

In Eq. (9), VIF_j represents the variance expansion factor of the jth variable in the adjustment of power generation structure, $\lim_{ls} R_j^n$ represents the relationship mining of power index, and Q_i represents the constraint of the application of the expansion factor. The application of power generation expansion factor can suppress the superposition of fluctuations in the process of wind power and photovoltaic power generation, and ensure the stability of photovoltaic power generation output. However, the adjustment of the expansion factor, as well as the process of parameter analysis, can also lead to fluctuations in wind power and photovoltaic power generation. In order to improve the constraints of the regulation factor, the power signal values in it should be identified, and the signal quantification will be established. By suppressing the small fluctuation of the power signal, the power structure adjustment is completed, which is more concrete, and can also improve the accuracy of signal recognition and optimize the existing power structure. At the same time, in the process of optimizing the power signal, the power structure and advantages of the entire power grid are maintained, and the overall energy structure adjustment is shown in Eq. (10).

$$RGR_i = \frac{R_i - R_j}{R_n} \times 100\% \tag{10}$$

In Eq. (10), R_i is the current total energy, R_j represents the adjustment of the energy structure, RGR_i is the optimization of energy consumption. The change of energy consumption should be combined with external interference factors and the energy consumption demand of the microgrid, and the balance of energy consumption should be ensured. Through the change of overall energy consumption, the energy consumption can be suppressed and expanded, and the energy consumption of the entire microgrid can be effectively ensured. Energy consumption adjustment can reflect the effect of corporate governance and digital transformation, while stagnant and negative growth energy consumption reflects the negative effect of microgrid integration, so it is extremely important to improve the power generation potential by adjusting the energy structure.

2.4 Scope of digital governance of new energy signals

The digital governance of new energy signals is the governance of the results after digital transformation, including signal relevance, signal independence, digital directionality, digital governance mapping, etc. The proposed framework does not integrate a blockchain-based transaction validation layer. Instead, data integrity and operational consensus are ensured through statistically grounded digital governance mechanisms, including signal independence constraints, anomaly threshold control, and two-stage least squares–based consistency verification. The digital control system stabilizes voltage and power flow through real-time signal monitoring and adaptive feedback regulation, dynamically adjusting control parameters based on detected fluctuations. Algorithmic feedback loops continuously tune control gains to maintain grid equilibrium during microgrid and main-grid interaction. The purpose of digital governance is to apply the results of digital governance to a comprehensive analysis, and provide a basis for the identification of voltage, current, and power flow signals of the microgrid, as well as the operation level of the microgrid the specific governance constraints are shown in Eq. (11).

$$k_i = argmax_j \left(a(i,j) + r(i,j)\right) \tag{11}$$

In Eq. (11), k_i represents the structure of digital governance and $a(i,j)$ represents the mapping dimensions of digital governance, including i representing power flow, j representing energy consumption, $r(i,j)$ representing digital relevance, $i,j = 1$ representing relevance, and $i,j = 2$ representing independence. Combined with voltage and current signals, the comprehensive constraints of digital governance can be realized, and the dual optimization of governance and digitalization can be completed. In the governance constraints of microgrids, it is necessary to maintain the stability of microgrids, identify their power flow and voltage, connect the microgrid with the main grid, and constrain the microgrid independently, as shown in equation (12)

$$S_i(t) = \sqrt{f_i[D_i(t), \theta_i]} \tag{12}$$

In equation (12), $S_i(t)$ represents the state of the microgrid at time t, including signals such as power flow, voltage, and current, and f_i represents the grid-connected decision-making function, which is the real-time monitoring of the power parameter changes of the microgrid after it is connected to the grid, and θ_i is the state when the microgrid is independent.

3. Results and Discussion

3.1 Cases of New Energy, Corporate Governance, and Digital Transformation

Taking area, A as the study area, the wind power and photovoltaic power generation enterprises were investigated, and the research content included the stability of power generation, the degree of data of voltage and current, the rational distribution of power flow, and the grid connection of the main power grid and the microgrid. Regional characteristics, study duration, and environmental conditions such as wind variability and solar irradiance influence power index behavior by shaping operational stability and signal fluctuation patterns. Considering these contextual factors improves the interpretability and transferability of governance-related findings across different new energy deployment settings. Model evaluation in this study focuses on digital signal governance performance, assessed through statistical stability, fluctuation suppression latency, and consistency of voltage, current, and power flow indicators. Cryptographic transaction validation mechanisms, such as RSA-based blockchain operations, are considered outside the analytical scope of the present evaluation framework. Among them, the indicators of power are real-time test data, voltage and current fluctuations, grid connection time, and the rationality of the distribution of power flow. Measurement accuracy is verified by cross-validating power signal data obtained from SCADA systems with high-resolution PMU measurements. This comparison ensures temporal precision, improves event detection accuracy, and reduces uncertainty in identifying short-term grid fluctuations. For the digital identification of power index signals, classification identification, quantitative identification, and taking the 35KV main power grid as an example, the 10KV microgrid as a reference, the test area is 3 administrative districts, 2 urban areas, the new energy power generation conditions are good sunlight, rich wind resources, the research time is 6 months, and the geographical situation of the test area is shown in Figure 3.

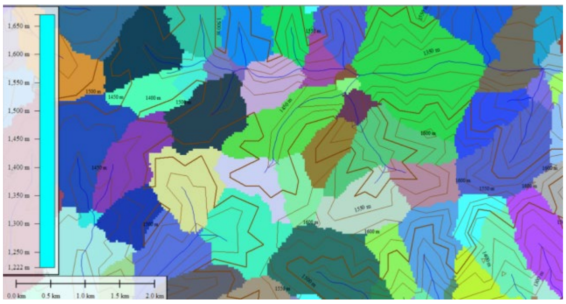

Figure 3. Geography of the test area

The analysis of the data in Figure 3 shows that the terrain of the test area is very complex, with not only plains, but also mountains and hills, as well as lakes, making it an ideal location for new energy research. To contextualize system reliability, the study region is characterized by complex terrain, mid-latitude continental climate conditions, variable wind speed, stable solar irradiance, and a dual-layer grid structure consisting of a 35 kV main grid and a 10 kV microgrid.

3.2 The degree of digitalization of wind power and photovoltaic power generation indicators

Taking the power flow, signal and current signal of power as an example, this paper conducts an in-depth analysis of its digital governance, and judges the current indicators of grid connection, digital transformation changes and microgrid changes, and analyzes the power index governance effect, and the specific results are shown in Table 1.

Table 1. Comparison of corporate governance and digitalization of new energy enterprises [unit: %]

Index	Grid connection changes (%)	Digital transformation changes (%)	Microgrid changes (%)	Governance rate of power indicators (%)	Sample size (N)	Data source	Environmental conditions
Voltage	3.2	4.5	0.15	12	Continuous 6-month records	On-site monitoring system	Variable wind speed, solar irradiance
Tidal current	4.1	5.0	0.18	15	Continuous 6-month records	SCADA power logs	Wind fluctuation, grid-connection events
Current	2.9	3.8	0.10	10	Continuous 6-month records	Sensor-based acquisition	Load variation, ambient temperature

As can be seen from Table 1, the change rate of power flow is 4.1% after grid connection, followed by 3.2% of voltage, and the above reasons are mainly due to the angle of interference factors in the process of wind power and photovoltaic power generation, such as nature, light, etc. Additional information on sample size, data sources, and environmental conditions was incorporated to enhance data transparency and provide clearer contextual understanding of the empirical analysis. Therefore, voltage and power flow are the focus of digital transformation and corporate governance. At the same time, the voltage, power flow and current signals do not change greatly within the scope of the microgrid, which proves that the operation of wind power and photovoltaic power generation is relatively stable, and the change values of voltage, power flow and current are small, and the constraints on their amplitude changes should be strengthened. Therefore, new energy companies should strengthen the suppression of power indicators for grid-connected changes, and also find the stability effect of digital transformation and corporate governance on voltage and tilographic power generation, which can reduce the amplitude of their changes and ensure the balance of power flow between microgrids and main grids, as shown in Figure 4.

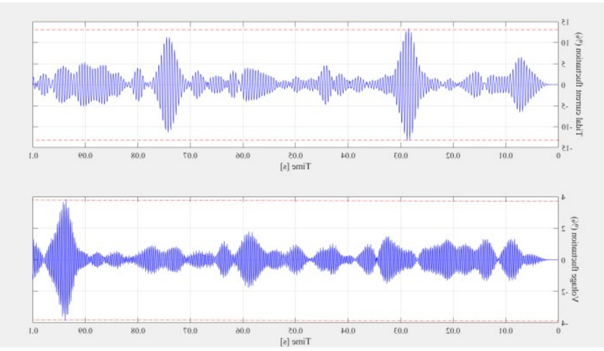

Figure 4. Amplitude changes in power flow and voltage

From the analysis in Figure 4, it can be seen that in the early stage, the amplitude of the voltage changed greatly, but the change value was relatively stable. In the later stage, there is a large change, and the change rate is 3%, indicating that the voltage fluctuates greatly after grid connection. Power flow and voltage fluctuations are continuously tracked through digitally mapped signals using the Hausman-based governance framework, while data integrity is maintained via anomaly threshold control and two-stage least squares–based outlier identification. At the same time, the power flow fluctuates greatly in the early stage and tends to stabilize in the later stage, indicating that digital transformation and corporate governance can balance the difference between power flow and voltage changes, achieve dislocation fluctuations, and avoid the accumulation of fluctuations, which will cause a serious burden on the microgrid, affect the operation and maintenance stability of the microgrid, or burn down wind and photovoltaic power generation devices. Through the regression analysis of the power flow voltage, it can be found that the power flow and voltage, as well as the changes in energy consumption, are stable, as shown in Table 2. Toward certify independent contribution of explanatory variables, correlation analysis and Variance Inflation Factor (VIF) testing are conducted. All VIF values remain below conventional thresholds, indicating no significant multicollinearity and strong statistical robustness. The R-squared value represents the proportion of variance in power index fluctuations explained by the digital governance model, indicating the explanatory strength of signal mapping and regression-based governance efficiency. Prediction accuracy is assessed using RMSE, R^2, and MAPE to quantify forecasting errors and explanatory power. These indicators provide objective validation of model accuracy and reliability under different operating conditions.

Table 2. Voltage, power flow, and energy consumption changes [in %]

variable	After grid connection,it will be unified	Grid connection amplitude	Stand-alone microgrids	Variability
voltage	0.25	0.05	5.00	0.000
current	0.18	0.04	4.50	0.000
tidal current	0.10	0.03	3.33	0.002
Energy consumption	0.12	0.04	3.00	0.005

As can be seen from Table 2, the coefficient of voltage after grid connection is 0.25, and the difference of change is 0.000, indicating that the power index table is stable after grid connection, and the current is 0.18 after grid connection, and the difference of change is 0.000. The empirical results align with the theoretical framework by demonstrating that digital governance mechanisms strengthen corporate performance through improved power index stability and governance consistency. This linkage confirms that governance-driven digital transformation supports operational stability across diverse energy market environments. The R-squared value measures the proportion of variance in power index fluctuations explained by the regression model, indicating how well voltage, current, and power flow changes are captured under digital governance. A higher R-squared confirms that the model reliably reflects the effectiveness of digital transformation in stabilizing power indicators. It shows that digital transformation and corporate governance can play a role in promoting the balance of energy and the uniform distribution of power flow, which has a significant positive impact on the optimization of new energy and promotes the sustainable development of new energy enterprises.

3.3 Sustainability and stability of wind power and photovoltaic power generation

Sustainability and stability are the main evaluation indicators of wind power generation, and they are also the main direction for new energy enterprises to carry out corporate governance and digital optimization. However, there are certain stage differences in the sustainability of wind power and photovoltaic strip orders, and whether the voltage and current signals are stable needs to be further verified, as shown in Table 3.

Table 3 Continuity and stability of voltage, current, and energy consumption

variable		Amplitude (%)	Volatility (%)	Duration (seconds)	Signal Digital Utilization (%)	Ratio of wind power/photovoltaic power generation (none)
Microgrids	voltage	0.23	0.75	0.40	0.45	0.55
	current	0.75	0.42	0.50	0.60	0.58
	tidal current	0.40	0.50	0.75	0.80	0.35
	Energy consumption	0.45	0.60	0.80	0.62	0.42
Microgrids → mainnets		0.55	0.58	0.35	0.42	0.33

As can be seen from Table 3, taking the microgrid → main grid as a reference, the amplitude rate of voltage, current, and energy consumption of the microgrid is relatively high, mainly because the above-mentioned power indicators are the main content of corporate governance, and are affected by factors such as light and wind speed, as well as frequent grid connection, which will cause its amplitude to change. At present, the volatility of wind power and photovoltaic power generation is in a controllable range of about 0.42~0.75%, indicating that the fluctuation rate of current, voltage and power flow is relatively stable and within the constraint range, and the fluctuation duration is short, less than 0.8 seconds. In addition, the digital utilization rate of signals and the proportion of wind/photovoltaic power generation tend to be reasonable, so corporate governance and digital transformation can improve the new energy structure and optimize the power index, as shown in Figure 5.

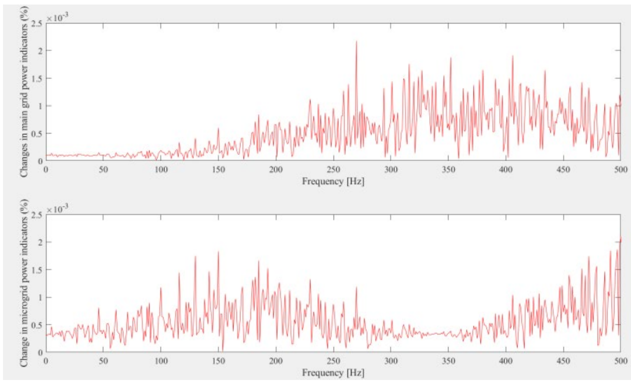

Figure 5. Comparison of power indicators

From the analysis of Figure 5, it can be seen that the changes of microgrid indicators show a steady change, and the change trend is consistent. In the process of microgrid change, the frequency of microgrid changes fluctuated, and there were ups and downs, indicating that wind power and photovoltaic power generation were unstable. Through the treatment of corporate governance and digital transformation, the power index can be stabilized, and the effectiveness of corporate governance and digital transformation can be further verified, which will have an impact on the stability of wind power and photovoltaic power generation.

Table 4 Comparison of Key Findings between Studies on Digital Transformation and Energy Governance

Study	Focus	Key Findings	Comparison with Your Study
Digital Transformation in New Energy (proposed work)	Digital transformation in new energy enterprises.	Focuses on how governance and digital transformation improve energy efficiency and sustainability.	Emphasizes energy indicators and governance in digital transformation.
Digital Transformation and Firm Performance [15]	Impact of digital transformation on firm performance.	Digital transformation improves firm performance in the energy industry.	Your study focuses more on energy indicators and sustainability.
Governance and Energy Efficiency [16]	Corporate governance and energy efficiency in new energy enterprises.	Governance mechanisms improve energy efficiency and company performance.	Your study adds a technical layer with data governance and signal digitization.

The Table 4 compares the key findings from your study and two related studies, [15-16]. It highlights the focus, key conclusions, and how each study approaches digital transformation, governance, and energy efficiency. The comparison emphasizes your study's detailed analysis of energy indicators, data governance, and technical methodologies like signal digitization, which distinguishes it from the broader focus on firm performance and governance in the other studies.

4. Conclusion

In order to improve its stability, in-depth analysis can be carried out through corporate governance and digital transformation, and a number of indicators such as voltage and current can be observed to judge its change trend, and the role of corporate governance and digital transformation has been verified. Digital governance frameworks optimize power generation, stabilize grid connections, and minimize resource waste, supporting national energy reforms. For enterprises, it enhances sustainability by improving energy management and operational efficiency. The results of this paper show that the grid-connected coefficient of voltage is 0.25, and the difference is 0.000, and there is no obvious multicollinearity problem between the power indexes, and the fluctuation rate of the power index is in a controllable range of about 0.42~0.75%. Moreover, it is within the constraint range, and the duration of the fluctuation is short, less than 0.8 seconds. Therefore, under data governance, the stability of voltage, current and power flow is high, the distribution ratio is reasonable, and the distribution ratio is 0.33~0.55, and the change of power indicators after grid connection can be suppressed. At the same time, digital transformation can weaken the impact of changes in the policy environment and market demand, optimize the power generation structure of new energy, improve the control rate of power indicators, maintain the stability of current operation, and improve the sustainability of new energy development. There are also some shortcomings in this research, mainly because the amount of data for corporate governance and digital transformation is large, and data simplification functions will be added to analyze it in depth in the future.

Declarations

Data Availability

The datasets generated and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author Contribution

Chunxi Wang conceived and designed the research framework, performed data analysis, and drafted the manuscript. Tong Shi contributed to methodology refinement, data interpretation, and critical revisions of the manuscript. Both authors read and approved the final version of the manuscript.

References

[1] S. Feng, Y. Mao, G. Li, and J. Bai, "Enterprise digital transformation, biased technological progress and carbon total factor productivity," Journal of Environmental Planning and Management, vol. 68, no. 1, pp. 154–184, 2025. https://doi.org/10.1080/09640568.2023.2239493.

[2] K. Jia and L. Li, "The moderate level of digital transformation: from the perspective of green total factor productivity," Mathematical Biosciences and Engineering (MBE), vol. 21, no. 2, pp. 2254–2281, 2024. https://doi.org/10.3934/mbe.2024099.

[3] H. Li, J. Liu, Y. Liu, G. Yang, L. Zhang, and X. Yang, "Can digital transformation drive green innovation in China's construction industry under a dual-carbon vision?," Sustainability, vol. 16, no. 18, 2024. https://doi.org/10.3390/su16188042.

[4] M. Li, G. Cao, H. Li, Z. Hao, and L. Zhang, "How government subsidies affect technology innovation in the context of Industry 4.0: evidence from Chinese new-energy enterprises," Kybernetes, vol. 53, no. 11, pp. 4149–4171, 2024. https://doi.org/10.1108/k-08-2022-1098.

[5] W. Li and N. Li, "Green innovation, digital transformation and energy-intensive enterprises' carbon-emission reduction performance," Journal of Industrial Engineering and Engineering Management, vol. 37, no. 6, pp. 66–76, 2023.

[6] B. Lin and Q. Zhang, "New energy products going global: the impact of digital transformation amid trade frictions," Sustainable Energy Technologies and Assessments, vol. 71, 2024. https://doi.org/10.1016/j.seta.2024.104009.

[7] W. Liu, Z. Wang, Q. Shi, and S. Bao, "Impact of the digital transformation of Chinese new-energy vehicle enterprises on innovation performance," Humanities & Social Sciences Communications, vol. 11, no. 1, 2024. https://doi.org/10.1057/s41599-024-03109-y.

[8] Y. Liu and P. Song, "Digital transformation and green innovation of energy enterprises," Sustainability, vol. 15, no. 9, 2023. https://doi.org/10.3390/su15097703.

[9] Q. Sun and Y. Shi, "Will digital disclosure affect corporate stocks? Based on stakeholders' cognition," Inzinerine Ekonomika-Engineering Economics, vol. 34, no. 2, pp. 223–229, 2023. https://doi.org/10.5755/j01.ee.34.2.31514.

[10] Y. Tao, H. Lu, Y. Ye, and H. Wu, "Does firms' digital transformation drive environmental innovation in China?" Sustainable Development, vol. 32, no. 3, pp. 2139–2152, 2024. https://doi.org/10.1002/sd.2769.

[11] H. Liu & R. Cui, "Life cycle assessment and model optimization for sustainable energy cross-border e-commerce," *EAI Endorsed Transactions on Energy Web*, vol. 11, 2024. https://doi.org/10.4108/ew.5493

[12] N. Boumkheld, G. Deconinck, & R. Loenders, "Real-time co-simulation for the analysis of cyber-attacks impact on distance relay backup protection," *EAI Endorsed Transactions on Energy Web*, 2024. https://doi.org/10.4108/ew.4862

[13] L. Yang and K. Yan, "Impact of digital transformation on pollution emissions of manufacturing enterprises in China: a micro-level analysis based on three-dimensional panel data," Resources Science, vol. 45, no. 8, pp. 1481–1496, 2023.

[14] B. S. Jayaprakasam & R. Hemnath, "Optimized microgrid energy management with cloud-based data analytics and predictive modelling," *International Journal of Mechanical Engineering and Computer Applications*, vol. 6, no. 3, pp. 79–94, 2018.

[15] Y. Zhang, J. Liu, Y. Wang, & Z. Zhou, "Impact of digital transformation on firm performance in the energy industry: Evidence from China," *Energy Economics*, vol. 96, p. 105181, 2021. https://doi.org/10.1016/j.eneco.2021.105181.

[16] X. Liu, E. Wang, & D. Cai, "Electricity market reform, corporate governance, and energy efficiency: Empirical evidence from new energy enterprises," *Energy Policy*, vol. 162, p. 112791, 2022. https://doi.org/10.1016/j.enpol.2022.112791.