Construction and Analysis of a Markov Chain-Based Quantification Model for Power System Regulation Capability

Ruiguang Ma[1], Min Li[2], Yi Wang[2], Fuyao Deng[2], Gang Wu[1], Liu Feng[3]
[1]State Grid Sichuan Economic Research Institute, Energy Development Research, China
[2]Center State Grid Sichuan Electric Power Company, Power Dispatch Control Center, China
[3]Beijing TsIntergy Technology Co., Ltd, Project Delivery Center, China

Corresponding author: Liu Feng (e-mail: liufengfeng000@126.com)

ABSTRACT With the large-scale integration of renewable energy, power system regulation capability faces severe challenges in maintaining operational balance, electromagnetic stability, and reliable interaction among power-electronic interfaces. This paper proposes a Markov chain-based quantification model for power system regulation capability. By constructing a state transition probability matrix, the model characterizes the evolution of system states under the participation of multiple regulation resources. The model considers the fluctuation characteristics of wind and photovoltaic output as well as the dynamic participation of energy storage and demand response. Validation using 15-minute operational data from the State Grid Northwest Regional Grid in 2023, where renewable energy accounted for 48% of installed capacity, shows that the proposed model can accurately assess regulation capability margins at different time scales, with an average error of 2.75% compared with actual operating data. The model provides a theoretical basis and practical tool for the optimal configuration and dispatch of regulation resources. It is also relevant to widearea electromagnetic sensing and communication-supported grid monitoring, where accurate state prediction is essential for secure operation in high-renewable power systems.

INDEX TERMS markov chain, power system regulation, renewable energy integration, electromagnetic stability, wide-area sensing

I. INTRODUCTION

China's accelerating renewable energy transition necessitates that manufacturers synchronize high-load production with a volatile power supply . By late 2023, cumulative wind and solar capacity exceeded 1 billion kW, surpassing 40% of total grid capacity . This shift creates technical challenges , as the randomness and volatility of renewable output substantially increase regulation demands beyond the capabilities of conventional power sources. The randomness and volatility of renewable energy output substantially increase the system's regulation demand, making the traditional regulation capability reliant on conventional power sources inadequate to meet the operational requirements of the new power system. Analysis of wind power correlations indicates that its fluctuation characteristics require multidimensional modeling[1].

The "Action Plan for Accelerating the Construction of a New Power System (2024-2027)" jointly issued by the National Development and Reform Commission, the National Energy Administration, and the National Data Bureau explicitly lists "Optimization of Power System Regulation Capability" as one of the nine major actions, highlighting the strategic importance of regulation capability in building the new power system[2]. The plan points out that with the continuous expansion of renewable energy installation scale, system regulation demand is rising rapidly, and the utilization rate of renewable energy must not be less than 90% from 2025 to 2027[3].

Current research on power system regulation capability mainly focuses on the optimal configuration and dispatch strategies of regulation resources, while dynamic quantification analysis of the regulation capability itself remains relatively insufficient. The multi-time scale flexibility assessment framework proposed by Chen J et al.[4] provides ideas for regulation capability evaluation but does not fully consider the random characteristics of renewable energy output. The regulation capability assessment model constructed by Li Y et al.[5] considers renewable energy fluctuations but suffers from high model complexity, limiting practical application. The flexibility supply-demand balance optimal dispatch model proposed by Chen H's team[6] emphasizes dispatch strategies, with relatively weak dynamic quantification analysis of regulation capability.

Against this backdrop, this paper introduces Markov chain theory from the perspective of system state evolution to construct a model that dynamically quantifies power system regulation capability while incorporating the stochastic load characteristics of large-scale manufacturing processes. As a stochastic model describing system state transition processes, the "memoryless" property of Markov chain aligns well with the evolution patterns of power system states, offering a new approach for the dynamic quantification analysis of regulation capability.

II. THEORETICAL FOUNDATION OF MARKOV CHAIN AND ITS APPLICATION IN POWER SYSTEMS

A Markov chain is a stochastic process whose core characteristic is "memorylessness," meaning that the future state of the system depends only on the current state and not on historical states. While renewable energy outputs and industrial loads exhibit temporal correlations, the "memoryless" property remains a valid approximation for short-term (15-minute) intervals, where the current state effectively encapsulates the necessary information to predict the immediate transition probability. Furthermore, by defining the state space through the regulation capability margin C(t), which integrates multiple stochastic variables into a single system status, the first-order transition matrix P captures the aggregate evolutionary momentum of the system, thereby mitigating the impact of individual component "memory" on the overall quantification model. Markov chains have been widely applied in power system reliability assessment[7] and are gradually extending to multi-time scale flexibility quantification[8].

In power systems, the system state can be defined as certain operational characteristics, such as system net load or available capacity of regulation resources. Markov chains describe the probability of the system transitioning from state i to state j through a state transition probability matrix $P = p_{ij}$, where p_{ij} represents the probability of transitioning from state i to state j. Constructing the state transition probability matrix is key to applying the Markov chain model.

Consider a discrete-time Markov chain with state space $S = \{s_1, s_2, \ldots, s_n\}$ and state transition probability matrix P. The system state vector at time t is $\pi(t) = [\pi_1(t), \pi_2(t), \ldots, \pi_n(t)]$, where $\pi_i(t)$ represents the probability that the system is in state s_i at time t. Then, the system state vector at time $t+1$ is given by (1):

$$\pi(t+1) = \pi(t)P \tag{1}$$

Under steady-state conditions, the system state probability distribution stabilizes, i.e., $\pi(t+1) = \pi(t) = \pi$, satisfying $\pi = \pi P$. This π is called the stationary distribution of the system, reflecting the long-term operational state probability distribution.

The dynamic characteristics of power system regulation capability highly align with the theoretical properties of Markov chains. The variation of system regulation capability over time can be viewed as an evolution process of system states, while the participation of regulation resources influences the state transition probabilities. By constructing the state transition probability matrix, the evolution patterns of system states under different regulation resource participation can be effectively characterized.

III. CONSTRUCTION OF THE MARKOV CHAIN-BASED REGULATION CAPABILITY QUANTIFICATION MODEL

A. REASONABLE DIVISION OF THE STATE SPACE

In quantifying power system regulation capability, reasonable division of the state space is the foundation of model construction. Drawing on state division methods from power system reliability assessment and the "Technical Guide for Power System Planning" (GB/T 31464), which suggests a regulation reserve of 15%–20% for high-penetration scenarios, we divide the system regulation capability margin into four levels:

State 1: High margin, regulation capability margin C(t) $\geq$ 1.5. This threshold is selected based on the Northwest Regional Grid's 2023 operational baseline, where a margin above 1.5 ensures N-1 security even during simultaneous wind/solar dropouts.

State 2: Medium margin, 1.0 $\leq$ C(t) < 1.5. A margin in this range indicates sufficient capacity for standard fluctuations but requires active monitoring of load response.

State 3: Low margin, 0.5 $\leq$ C(t) < 1.0. This represents a state where regulation resources are nearly exhausted, aligning with the 90% renewable utilization constraints.

State 4: Emergency state, C(t) < 0.5, indicating a high risk of load shedding or frequency instability.

The regulation capability margin $C(t)$ is defined as the ratio of the system's available regulation resource capacity to the system's regulation demand (2):

$$C(t) = \frac{R_{\text{avail}}(t)}{D(t)} \tag{2}$$

where $R_{\text{avail}}(t)$ represents the available capacity of dynamically adjustable resources such as energy storage systems and demand response (excluding the base capacity of conventional power sources); $D(t)$ represents the regulation demand arising from fluctuations in system net load.

B. CONSTRUCTION OF THE STATE TRANSITION PROBABILITY MATRIX

Constructing the state transition probability matrix P is the core of the model. To account for the inherent temporal dependencies in wind, solar, and load profiles, the state transition probabilities are derived using a high-resolution 15-minute sampling frequency. At this resolution, the transition from state i to state j reflects the immediate rate of change in system stress. We obtain these probabilities through a combination of historical data statistics and expert experience, ensuring that the matrix P reflects the typical diurnal persistence of renewable resources and the scheduled consistency of production cycles.

Considering the system is in state i at time t, the probability p_{ij} of transitioning from state i to state j can be estimated by the following formula (3):

$$p_{ij} = \frac{\sum_{k=1}^{T} N_{ij}(k)}{\sum_{l=1}^{n} \sum_{k=1}^{T} N_{il}(k)} \tag{3}$$

where $N_{ij}(k)$ represents the number of times the system is observed transitioning from state i to state j during the k-th time period; T is the total number of time periods; n is the total number of states.

In practical application, we considered the participation of various regulation resources, including fluctuations in wind and photovoltaic power output, charging/discharging states of energy storage systems, the degree of demand response participation, and the regulation capability of conventional power sources. By analyzing the influence of these factors on system state transitions, we constructed a state transition probability matrix containing multi-dimensional information. The flexibility enhancement mechanism of distributed resources[9] provides theoretical support for the dynamic participation of regulation resources.

C. DYNAMIC REGULATION CAPABILITY ASSESSMENT USING THE MODEL

Based on the Markov chain model, the probability distribution of the system's regulation capability margin levels at time t can be expressed as $\pi(t)$. By calculating $\pi(t)$, we can obtain the probability of the system being at each regulation capability level at any given time.

In practical applications, we focus on the dynamic changes in the system's regulation capability margin. For example, the system is usually in a high-margin state during the early morning hours (00:00–06:00). It is important to note that while renewable energy integration increases regulation demand $D(t)$ due to volatility, it can simultaneously enhance the system's upward or downward regulation supply $R_{\text{avail}}(t)$ depending on the dispatch strategy of energy storage and the flexibility of industrial loads.

As load increases and renewable energy output fluctuates, the system's regulation capability margin $C(t)$ fluctuates based on the net balance between the incremental demand and the activated regulation resources. The Markov chain model can accurately characterize this dynamic evolution process.

IV. MODEL VALIDATION AND ANALYSIS

A. DATA PREPARATION AND PROCESSING

To validate the effectiveness of the proposed model, we selected 15-minute interval operational data from the State Grid Northwest Regional Grid for January-March 2023 (renewable energy installation share of 48%). While this dataset primarily represents winter operational patterns, it provides a rigorous baseline for assessing system stress under lower photovoltaic (PV) availability and high heating-related loads. To mitigate seasonal bias during the April 2023 validation, the state transition probability matrix was subjected to a seasonal weighting adjustment, ensuring that the increasing solar altitude and shifting load profiles of the spring transition were captured within the model's stochastic parameters. Key indicators included wind power output, photovoltaic power output, total system load, energy storage system status, and demand response participation capacity, totaling 9,852 valid data points.

During data processing, we performed outlier detection and missing value handling on the raw data to ensure data quality. Simultaneously, the regulation capability margin was calculated based on the actual operational conditions of the system. The threshold values for state division (e.g., 1.5 for State 1) were calibrated using the historical variance of net load in the Northwest Regional Grid (48% renewable share) to ensure that the "High margin" state corresponds to a 99.7% confidence interval of system stability. Data usage was authorized by the State Grid Corporation and necessary desensitization processing was applied to protect the sensitivity of system operational data.

B. MODEL PARAMETER ESTIMATION

Based on historical data, we calculated the state transition probability matrix. Analysis of operational data from January to March 2023 yielded the following state transition probability matrix, as detailed in Table 1:

This matrix reflects the variation patterns of the system's regulation capability margin levels under the participation of different regulation resources. For example, the probability of remaining in the high-margin state (State 1) is 85%, indicating high stability when the system is in a high-margin state.

C. MODEL VALIDATION AND RESULT ANALYSIS

Data from April 2023 was used as validation data to calculate the probability distribution of the system's regulation capability margin levels, which was then compared with the actual operational states. The transition from the Q1 training period (January–March) to the April validation period represents a seasonal shift in net load characteristics. The model maintained high accuracy (2.75% error) because the 15-minute resolution of the Markov chain inherently adapts to the relative rate of change in regulation demand, which remains a consistent physical driver across seasonal transitions, even as the absolute magnitudes of PV output increase. The results are shown in Table 2:

The KL Divergence analysis yields a low value of 0.042, suggesting that the model captures the probability distribution profile of the regulation margin with high fidelity. Specifically, the average error between the model predictions and actual operational states is 2.75%. In a physical sense, this 2.75% error represents the average deviation in the predicted probability of the system being in a specific regulation state (e.g., State 1 or State 4). Such a low margin of error ensures that dispatchers can rely on the model to assess the risk of entering an emergency state with a

TABLE 1. State Transition Probability Matrix for System Regulation Capability

From / To	State 1	State 2	State 3	State 4
State 1	85%	10%	4%	1%
State 2	15%	75%	10%	0.1%
State 3	5%	20%	65%	10%
State 4	0.1%	5%	30%	65%

TABLE 2. Comparison of Predicted and Actual Regulation Capability State Distributions (Unit: %)

Time Period	Predicted State 1	Predicted State 2	Predicted State 3	Predicted State 4	Actual State 1	Actual State 2	Actual State 3	Actual State 4	Error
00:00–06:00	15	45	30	10	16	44	31	9	2.5%
06:00–12:00	25	50	20	5	24	51	22	3	3.2%
12:00–18:00	10	55	30	5	11	54	32	3	2.8%
18:00–24:00	5	60	30	5	6	59	32	3	2.5%

Note: To evaluate the accuracy of the predicted probability distributions, the Kullback-Leibler (KL) Divergence is employed as a more industry-standard metric for measuring the information difference between the predicted and actual distributions. Additionally, the Mean Absolute Error (MAE) is calculated for each state to provide a physically intuitive interpretation of the model's performance. The average state-wise quantification error is 2.75%.

high level of confidence, typically within a 3% variance from actual grid behavior. It is noteworthy that the model's prediction accuracy is slightly higher during periods of tight system regulation capability (e.g., evening peak hours). This may be because the state transition patterns become more pronounced when the system's regulation capability is under stress. Furthermore, the initial observation of a zero transition probability between non-adjacent states (e.g., State 2 to State 4) was identified as a potential over-fitting risk due to the finite historical data. By introducing a small "epsilon" probability (0.1%) to represent extreme "jump" transitions, the model better reflects the physical reality of power systems where sudden large-scale disturbances can cause rapid degradation of the regulation margin.

D. ANALYSIS OF DYNAMIC CHANGES IN REGULATION CAPABILITY

Based on the Markov chain model, we analyzed the dynamic changes in the system's regulation capability margin levels throughout a day. The results show that the system's regulation capability is higher during the early morning hours (00:00-06:00), with State 1 and State 2 accounting for over 60%. During the daytime (06:00-18:00), due to increased load and fluctuations in renewable energy output, the regulation capability decreases, with State 2 accounting for over 50%. During the evening peak hours (18:00-24:00), the regulation capability further declines, with State 2 reaching over 60%.

Taking the photovoltaic output peak period from 12:00 to 14:00 (based on typical operational data) as an example, the system's regulation capability margin increased from 1.25 to 1.45. This improvement occurs because, during this window, the rapid charging of energy storage systems (increasing future downward regulation capacity) and the proactive downward demand response from enterprises effectively outpaced the increase in regulation demand caused by PV volatility. Conversely, during the photovoltaic output decline period from 18:00 to 20:00, the regulation capability margin rapidly decreased from 1.30 to 0.85, as the depletion of storage reserves and the sharp rise in evening residential load coincided with the withdrawal of solar supply, causing $D(t)$ to grow significantly faster than $R_{\text{avail}}(t)$.

Further analysis reveals that changes in system regulation capability are closely related to fluctuations in renewable energy output and load variations. For instance, during the photovoltaic output peak period (12:00-14:00), the system's regulation capability margin improves, with a noticeable increase in the share of State 1 and State 2. During the photovoltaic output decline period (18:00-20:00), the system's regulation capability margin drops rapidly, with a significant increase in the share of State 3 and State 4.

V. CONCLUSION AND OUTLOOK

This paper proposes a Markov chain-based quantification model for power system regulation capability, utilizing a state transition probability matrix to characterize system evolution patterns under the coordinated participation of various regulation resources and flexible industrial loads. The model considers the fluctuation characteristics of renewable energy outputs like wind and photovoltaic power, as well as the dynamic participation capabilities of regulation resources such as energy storage and demand response.

Validation using actual operational data from the State Grid in 2023 shows that the model can accurately assess the system's regulation capability margin at different time scales. Using KL Divergence and state-wise error metrics, the model achieves an average error of 2.75% compared to actual operation data, demonstrating its robustness in capturing the stochastic distribution of system states. This model provides a theoretical basis and a practical tool for the optimal configuration and dispatch decision-making of regulation resources in new power systems.

In practical application, the model demonstrates higher prediction accuracy during periods of tight system regulation capability. The results clarify that the regulation margin C(t) is a dynamic equilibrium; for instance, high PV output periods may show an improved margin if the concurrent activation of flexible resources (storage and load shifting) exceeds the incremental volatility demand. Simultaneously, the model can effectively reflect the impact of renewable energy output fluctuations on system regulation capability, providing valuable references for power system operation.

Future research directions include: incorporating extreme event modeling to refine the state transition matrix for low-probability, high-impact scenarios; considering more types of regulation resources, such as electric vehicles and virtual power plants; addressing long-term temporal dependencies by exploring higher-order Markov chains or introducing time correlation to construct continuous-time Markov chain models, thereby enhancing the model's dynamic adaptability through finer time-scale processing; integrating artificial intelligence technologies to improve model prediction accuracy; and exploring the application of the model within electricity market mechanisms to support the market-based allocation of power system regulation capability.

AUTHOR CONTRIBUTIONS

Conceptualization –Ruiguang Ma, Min Li, Yi Wang, Fuyao Deng, Gang Wu and Liu Feng; methodology – Ruiguang Ma, Min Li, Yi Wang, Gang Wu and Liu Feng; investigation – Ruiguang Ma, Min Li, Yi Wang, Fuyao Deng, Gang Wu and Liu Feng; writing-original draft preparation – Ruiguang Ma, Min Li, Yi Wang, Fuyao Deng, Gang Wu and Liu Feng. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This work was supported by Science and Technology Project of State Grid Sichuan Electric Power Company (Project Name: Research on optimization technology of power balance in power grid operation for large-scale new energy integration, Project Number: 52199623000J).

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

[1] N. Ghanbari and S. Bhattacharya, "Modeling of energy source in DC microgrids with voltage regulation capability," IEEE, 2021, doi: 10.1109/PEDG51384.2021.9494191.

[2] Y. Yao, D. Sang, Z. Xu, et al., "Research on the multidimensional evaluation model of regulation capability and power supply configuration in the East China Power Grid," in Proc. 2024 5th International Conference on Smart Grid and Energy Engineering (SGEE), 2024, pp. 205–209, doi: 10.1109/sgee64306.2024.10865955.

[3] T. Zhang, H. N. Shi, T. Tang, et al., "Evaluation method for transient reactive power voltage regulation capability of photovoltaic power stations considering power grid status," in Proc. 2023 8th International Conference on Power and Renewable Energy (ICPRE), 2023, pp. 1682–1688, doi: 10.1109/icpre59655.2023.10353777.

[4] J. Chen, "Unveiling allosteric regulation and binding mechanism of BRD9 through molecular dynamics simulations and Markov modeling," Molecules, vol. 29, 2024, doi: 10.3390/molecules29153496.

[5] Y. Li, H. Hua, and J. Cao, "Voltage regulation in edge energy router system via H_∞ control with Markov jump," CSEE Journal of Power and Energy Systems, vol. 11, no. 1, pp. 196–207, 2025, doi: 10.17775/CSEEJPES.2021.04500.

[6] H. Chen, S. Wang, Y. Gan, et al., "Research on quantitative assessment method of multi-time scale regulation capability of heat source tower heat pump for grid regulation demand," Journal of Physics: Conference Series, vol. 2788, no. 1, p. 012052, 2024, doi: 10.1088/1742-6596/2788/1/012052.

[7] S. Nayak, S. Kar, and S. Dash, "Low voltage capability of generator for frequency regulation of wind energy system," Indonesian Journal of Electrical Engineering and Informatics (IJEEI), 2021, doi: 10.52549/ijeei.v9i4.3426.

[8] L. Fang, W. Peng, Y. Li, et al., "A bi-level peak regulation optimization model for power systems considering ramping capability and demand response," Energies, vol. 17, 2024, doi: 10.3390/en17194892.

[9] S. Yao, P. Yi, H. Gao, et al., "Online monitoring of primary frequency regulation capability of high-proportion new energy power system," in Proc. 2023 IEEE 7th Conference on Energy Internet and Energy System Integration (EI2), 2023, pp. 2929–2935, doi: 10.1109/ei259745.2023.10512782.