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Modeling and analysis of distribution network with photovoltaic cells based on Markov global sensitivity

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When multiple distributed PV (photovoltaic) systems are integrated into multiple nodes of the distribution network, this will lead to the significant influence of the grid-tied node voltage of the power distribution network resulting from the uncertainty of PV power. Therefore, this aspect needs to be further studied in terms of how to effectively characterize the uncertainty of the voltage influence in a grid-tied multi-PV system distribution network. Focusing on this problem, a modeling and analysis method for distribution networks with PV cells based on Markov global sensitivity is proposed in this paper. Firstly, a global Markov chain is constructed using the Markov chain and the power flow equation to model the uncertainty of PV power. Furthermore, a Markov global sensitivity function is proposed to characterize the influence degree of the voltage on the distribution network nodes while multi-point PV system are grid-tied to system. The case study results show that the uncertainty model of multi-point PV grid-connection can be effectively constructed using the proposed method in this paper, and the uncertainty influence analysis is accurate. This is of great significance for grid connection planning and the optimization control of new energy systems, as well as for the new energy consumption increase.

KEYWORDS

distributed PV, grid connection, Markov chain, sensitivity, uncertainty

1 Introduction

With the development of society, the demand for energy is increasing. Currently, the development of new energy is a dependable way to improve energy supply sustainability. Within new energy developments (Pan al., 2019; Tang et al., 2021; Liang et al., 2023), the PV system is attracting more and more attention.

A small or medium-sized PV cell constructed near load usually called distributed PV system, which is one of the main research directions. The distributed PV system is generally directly connected into the multiple nodes of low-voltage distribution networks.

In this grid-tied mode, on the one hand, the PV power is mostly used by the load of the distribution network, which improves the absorption rate of new energy (Li et al., 2023; Xuan et al., 2020; Reshikeshan et al., 2021; Xing and Mu, 2023); on the other hand, the multi-point integration into the distribution network mode will cause the changing of the node voltage of the distribution network. Further, the PV power is volatile and intermittent, resulting from climate factors, and the large and fluctuant PV power may result in an uncertain power flow and power quality problems in the distribution network, especially at the end of the low-voltage distribution network, which will cause power scheduling difficulties. In addition, the distribution network generally connects the load, which is also uncertain. Therefore, power uncertainty arises in the source side and the load side at the same time, which causes the stability to be challenged in lower voltage distribution networks (Jafari et al., 2022; Liu et al., 2022).

Therefore, the study on the PV power uncertainty is of great significance for distribution networks, in terms of the planning and construction of power systems, the consumption and improvement of new energy, etc.

In traditional research, PV power prediction and load power prediction are attracting more attention and lots of prediction methods have been proposed, which are useful for reducing the power uncertainty of PV cells and the load (Wang et al., 2022; Goh et al., 2023; Zhang et al., 2023; Zhou et al., 2023). Further, the PV power prediction results can be used to analyze its influence on a distribution network connected to PV cells.

In relevant research on the power uncertainty of PV cells connected to power systems, the output power uncertainty probability model of PV or other DG (distributed generation) systems can be modeled (Constante-Flores and Illindala, 2019; Palahalli et al., 2021; Rayati et al., 2022; Reddy et al., 2023), and then the power uncertainty probability model can be used for power flow calculations or power planning calculations. In (Constante-Flores and Illindala, 2019), a non-Gaussian model of DG is developed, namely, its output power uncertainty is represented in the form of a probability. Further, the PV power probability model and the control strategy can be combined together to optimize the control of the system power (Rayati et al., 2022).

On the network side, a probabilistic model of the distribution network's voltage can be established and used. The power flow calculation is probabilistic and the optimal control of the reactive power and voltage can be achieved (Baptista et al., 2019; Chu et al., 2022). Further, focusing on the power uncertainty of DG systems, an ESS (energy storage system) can also be used to restrain the power uncertainty to achieve the optimal control of the system power (Hong and Wu, 2019).

In a distribution network, the power flow uncertainty caused by the uncertainty of PV power that can be analyzed from the perspective of control and scheduling; for example, economic optimal scheduling can be achieved based on deterministic mixed integer linear programming (L. Meng et al., 2022). And machine learning can also be used to estimate the power flow (A. Demazy et al., 2020). From the perspective of system scheduling, by coordinating the PV power and load, the optimal power flow of the system can be obtained (Widén et al., 2017; Hu et al., 2021).

However, while a large number of PV systems are connected into distribution networks, these DG systems are multi-coupled with distribution networks and loads; each node voltage of the distribution network is related to all the grid-tied PV. This means there is global uncertainty displayed between the photovoltaic and the distribution network, and this uncertainty is enhanced with the increase of PV connected to the network.

In traditional studies, global uncertainty modeling for PV systems and the impact analysis for distribution networks need to be studied further. Therefore, how to develop global uncertainty modeling for PV systems, and how to comprehensively represent the degree of influence on the distribution network tied in with multiple PV cells in a multi-node manner is the key content of this paper. Focusing on the above problems, a modeling and analysis method for a distribution network with multi-PVs based on the Markov global sensitivity for a multi-photovoltaic grid-tied network is proposed, in which a global Markov sensitivity function is established to be associated with the grid-tied PV and the distribution network, to accurately characterize the influence of the distribution network resulting from the PV power uncertainty.

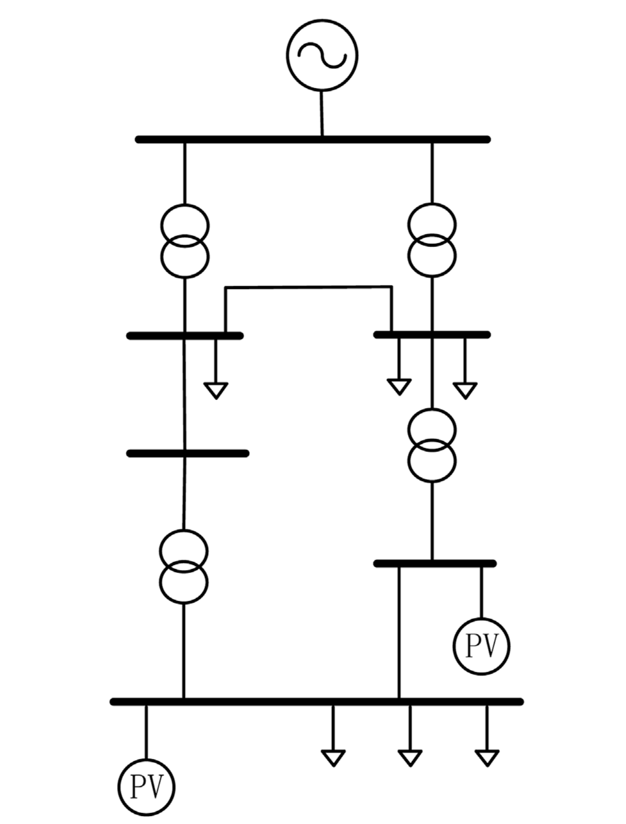

FIGURE 1
Diagram of a distribution network.

This paper is organized as follows. In Section 2, the uncertainty analysis of PV connected into distribution network is carried out. In Section 3, the model based on global Markov sensitivity for multiple grid-tied PV cells is proposed. In Section 4, the case study is developed. Section 5 gives the conclusion of this paper.

2 Uncertainty analysis of PV connected into distribution network

2.1 Principle of distributed multi-node PV grid-tied network

Shown in Figure 1 is a diagram of a distribution network.

As shown in the Figure 1, the network contains multiple buses and nodes. The PV cells and loads are connected into the distribution network in different nodes. The output power of the

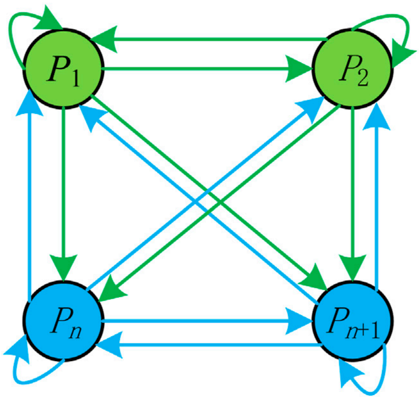

FIGURE 2
Diagram of the state transfer of power sequence.

PV is affected by a variety of climate factors, as shown below (Wang and Yang, 2017):

$$U_{OC} = \frac{A_0 KT}{q} \ln\left(\frac{I_{sc}}{I_{DO}} + 1\right) \tag{1}$$

where A_0 is a constant; μ is the Boltzmann constant; q is the electronic charge; I_{SC} is the short circuit current varied with irradiation intensity; I_{DO} is the equivalent saturation current of the diode; T is the environment temperature.

It can be seen from the above formula that the climate factors are the main factors to result in the strong uncertainty of PV power.

The PV system can be equivalent to a PQ node if the PV system is connected into a power system. With the fluctuation of grid-connected power, the power quality problem may be generated, such as voltage fluctuations, flicker, and other problems.

2.2 Principle of uncertainty modeling for grid-tied PV

Uncertainty modeling is helpful to quantitatively understand the uncertainty of PV power. In this paper, a Markov chain is used to model the power state of PV cells.

The Markov chain is one of the typical algorithms used to describe the uncertainty of a random variable process, in which the present state can be used to describe the future state of the variable; the state of the variable at different times can present the variable development uncertainty. For a discrete power sequence $\{p_1, p_2 \ldots \ldots p_t, p_{t+1}\}$, the state in t+1 can be described by the following probabilities (He, 2008; Tabone and Callaway, 2015; Zhang et al., 2021):

$$\begin{aligned} &P\left[x_{t+1} = p_{t+1} \middle| x_t = p_t, x_{t-1} = p_{t-1}, \cdots x_1 = p_1\right] \\ &= P\left[x_{t+1} = p_{t+1} \middle| x_t = p_t\right] \end{aligned} \tag{2}$$

where p is the probability of each state.

Figure 2 shows the process transfer between various random states:

As can be seen from Figure 2, each power state can be transferred to its own initial state or other states, and the transition uncertainty can be described by the transition probability. All the state transition processes can be represented as a state transition matrix:

$$A = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ A_{m1} & A_{m2} & \cdots & A_{mn} \end{bmatrix} \tag{3}$$

where A_{mn} is the transition probability. Namely, in the state transition matrix, each element corresponds to the transition probability of a variable state.

When modeling the power uncertainty of a PV cell, the historic data of the PV cell's power are classified first to obtain different states. And then, the transfer probability matrix of the Markov chain is trained to obtain the uncertain Markov chain model for the target PV system.

However, in the case where multiple PV systems are connected into the distribution network in different nodes, the impact on the network from the PV cells is global and comprehensive, in other words, the node voltage of the distribution network is affected by all the grid-connected PV cells, to present the mutual coupling, which increases the difficulty of the relational analysis.

Therefore, how to intuitively and accurately characterize the effect caused by the grid-connected PV is one of the key aspects addressed in this paper.

3 Proposed model and analysis based on global Markov sensitivity for multiple grid-tied PV cells

Focusing on the mutual coupling of the node voltage and the multiple grid-tied PV, an uncertainty modeling and analysis method based on the Markov global sensitivity is proposed, in which the Markov chain is used to describe the uncertainty of PV power firstly, and then the Markov chain is combined with the node voltage distributed, to present the uncertainty between the PV power and the node voltage. Further, a sensitivity function is developed to quantitatively characterize the effect of the node voltage resulting from the multiple grid-tied PV cells.

3.1 Modeling of node voltage of distribution network

The power flow of a traditional distribution network is in the form of a feeder line; the voltage of node i is related to the power and the line impedance, as in the following (Demazy et al., 2020; Wan, 2022; Yang et al., 2023):

$$U_i \approx U_{i-1} - \frac{PR - QX}{U_i} \tag{4}$$

where P is the active power; Q is the reactive power; R and X are the equivalent line impedance of the node i-1 and node i, respectively.

In traditional distribution networks, most of time, the load R_L is connected into a node. However, with the development of new energy, more and more DGs are connected into distribution networks. The connected node is usually called PCC (point of common coupling). The modeling for the PCC voltage can be shown as the following:

$$U_{PCC} = U_{i-1} - \frac{(P_{PV} - P_L)R - (Q_{PV} - Q_C)X}{U_{PCC}} \tag{5}$$

where P_{PV} and Q_{PV} are the active power and reactive power of the PV system into the PCC, respectively; Q_C is the reactive power of the local compensation.

It is assumed that the reactive power demand in PV systems and the load can be compensated completely by the local compensation device. Thus, the above formula can be simplified as the following:

$$U_{PCC} = U_{i-1} - \frac{(P_{PV} - P_L)R_{(i-1)PCC} - QX_{(i-1)PCC}}{U_{PCC}} \tag{6}$$

where Q is the reactive power flow in the bus.

For the next node i+1, its active power can be obtained as the following:

$$P_{PCC(i+1)} = p_{(i-1)PCC} - P_{LPCC} + P_{PVPCC} \tag{7}$$

The above discussion is about a distribution network connected a single PV. In cases where multiple PVs are connected into the distribution network, the modeling for node voltage is as follows:

$$U_1 = U_N - U_{e01} = U_N - \frac{P_{01}R_{01} - Q_{01}X_{01}}{U_1} \tag{8}$$

where P_{01} and Q_{01} are the active power and reactive power of the initial node and its successive node, respectively; R_{01} and X_{01} are the equivalent line impedance between the initial node and its successive node, respectively.

Similarly, the voltage of node two and node three of the system is as follows:

$$\begin{aligned} U_2 &= U_1 - U_{e12} = U_1 - \frac{P_{12}R_{12} - Q_{12}X_{12}}{U_2} \\ &= U_N - \frac{P_{01}R_{01} - Q_{01}X_{01}}{U_1} - \frac{P_{12}R_{12} - Q_{12}X_{12}}{U_2} \end{aligned} \tag{9}$$

$$U_3 = U_2 - U_{e23} = U_2 - \frac{P_{23}R_{23} - Q_{23}X_{23}}{U_3} = U_N - U_{e01} - U_{e12} - U_{e23} \tag{10}$$

And then, the voltage of node j can be obtained as the following:

$$U_j = U_N - \sum U_{eij} = U_N - \frac{P_{ij}R_{ij} - Q_{ij}X_{ij}}{U_j} \tag{11}$$

If there are multiple PV cells connected into the node of a distribution network, the power between the node i and node j is as follows:

$$P_{ij} = p_{(i-1)i} - P_{Li} + P_{PVi} = P_{01} - \sum P_{Li} + \sum P_{PVi} \tag{12}$$

$$Q_{ij} = Q_{(i-1)i} - (Q_{Li} - Q_{PVi} - Q_{Ci}) \tag{13}$$

where $P_{(i-1)i}$ is the active power; $Q_{(i-1)i}$ is the reactive power; P_{Li}, Q_{Li}, and Q_{Ci} are the real power, reactive power, and the compensation reactive power of node i, respectively. P_{PVi} is the real power of the PV cells in node i. Assuming that the reactive power of the node can be compensated completely and locally, the above, Formula (13), can be simplified as follows:

$$Q_{ij} \approx Q_{01} \tag{14}$$

Taking Formula (14) and Formula (12) into Formula (11), the voltage model for node j is as follows:

$$U_j = U_N - \sum \frac{(P_{01} - \sum P_{Li} + \sum P_{PVi})R_{ij} - Q_{01}X_{ij}}{U_j} \tag{15}$$

3.2 Modeling for multiple grid-tied PV based on Markov chain

As mentioned above, the output power of a PV can be seen as a discrete process. Therefore, the Markov chain can be used to describe the uncertainty in power transition. For the PV system in node i of a network, the PV power can be presented as a time series:

$$P_{PVj} = [P_{PV}^0, P_{PV}^1, P_{PV}^2, \cdots, P_{PV}^n] \tag{16}$$

where n is the time number; P_{PVj} is the output power in each time.

The output power P_{PVj} can be converted to the power state as follows:

$$M_{PVj} = \left[M_{PV}^0, M_{PV}^1, M_{PV}^2, \cdots, M_{PV}^k\right] \tag{17}$$

where k is the number of state; M_{PVj} is the power state.

In this case, a T function can be defined to achieve the conversion between the PV power and the power state:

$$\left[M_{PVj}^k\right] = T\left[P_{PVj}^{n-1}\right] \tag{18}$$

As mentioned above, the state transition processes of the PV power state can be represented as a state transition matrix $\boldsymbol{A}$ in Formula (3). Therefore, the PV power state conversion can be presented as follows:

$$\left[M_{PVj}^r\right] = \left[M_{PVj}^k\right]A \tag{19}$$

And the PV power in the nth time can be obtained by the inverse transformation, as follows:

$$\left[P_{PVj}^n\right] = T^{-1}\left[M_{PVj}^r\right] + \sigma \tag{20}$$

where σ is the correction factor. In the above process, the power error may be appear, therefore this correction factor is used to correct the PV power. While the Markov chain is constructed for a PV system, the transition error distribution can be extracted and it is used to generate the correction factor, namely, the correction factor can be obtained using the historical error statistics.

As can be seen from the above formulas, the Markov chain is used to describe the PV power uncertainty transfer process; the power uncertainty is represented as a probability function.

Taking Formula (20) into Formula (15), the voltage of node j can be obtained as follows:

$$U_j = U_N - \sum U_{eij} \tag{21}$$

The voltage error is as follows:

$$U_{eij} = \sum \frac{\left(P_{01} - \sum P_{Li} + \sum (T^{-1}((T\left[P_{PVj}^{n-1}\right])A) + \sigma)\right)R_{ij} - Q_{01}X_{ij}}{U_j} \tag{22}$$

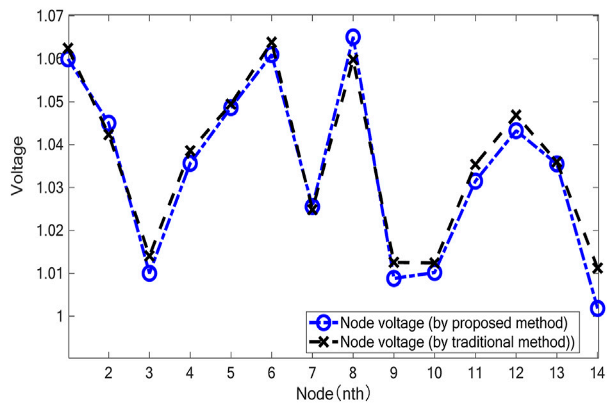

FIGURE 3
Voltage distribution.

As can be seen from the above formulas, the PV power uncertainty is represented by the Markov chain, and then, Formula (22) shows the global voltage effect of the distribution network resulting from the PV power uncertainty.

Generally, In this paper, the Markov chain is used to present the uncertainty of PV power, in which the PV power in time t+1 can be obtained by the PV power in time t. Furthermore, the Markov model is combined with the above mentioned voltage model of distribution network, to describe influence of the voltage on the distribution network nodes resulted from the uncertainty of PV power.

3.3 Development of Markov global sensitivity function

A sensitivity function is usually used to describe the relationship among the variables quantificationally, as in the following (Xiong et al., 2021; Zhou and Zhang, 2021):

$$S = \frac{dy}{dx} \tag{23}$$

where y is dependent variable; x is the independent variable.

In this paper, in order to describe the relationship between the node voltage and the grid-tied PV power, the sensitivity function is developed as follows:

$$S^{U_e}_{eP_{PVj}} = \frac{\partial U_{eij}}{\partial P_{PVj}} = \frac{\partial \sum \frac{\left(P_{01} - \sum P_{Li} + \sum \left(T^{-1}\left(\left(T\left[P^{n-1}_{PVj}\right]\right)A\right) + \sigma\right)\right) R_{ij} - Q_{01} X_{ij}}{U_j}}{\partial P_{PVj}} \tag{24}$$

The above function is called the Markov global sensitivity, in which the power uncertainty of all the PV systems in a distribution network can be represented by the Markov chain.

As seen from the above mentioned, the proposed model is combined with the Markov chain, the voltage model of distribution network, and the sensitively function. By using the proposed model, the influence of the distribution network resulting from the PV power uncertainty can be characterized.

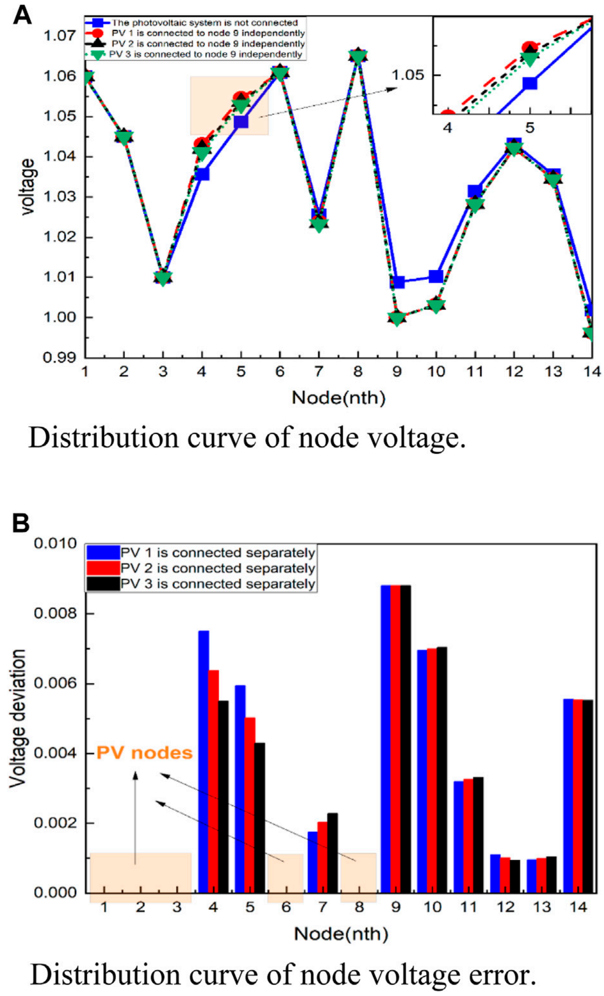

FIGURE 4
Voltage distribution for PV cell connected to a single node in distribution network. **(A)** Distribution curve of node voltage. **(B)** Distribution curve of node voltage error.

4 Example verification

In order to verify the effectiveness of the proposed modeling method, an example is developed based on the IEEE 14-node model, in which three PV systems are grid-tied into the system, as 3 MW, 5 MW, and 10 MW. Several test cases are carried out as follows.

4.1 Testing between the proposed method and the traditional method

In order to test the feasibility of the proposed method, the voltage distribution of network is calculated by the proposed method and the traditional method, as shown in Figure 3.

It can be seen that the voltage distribution is basically consistent by using the proposed method and the traditional method, this verify the feasibility of the proposed method. Further, comparing with the traditional method, the proposed method combines the uncertainly analysis and the sensitivity analysis in the following test expediently.

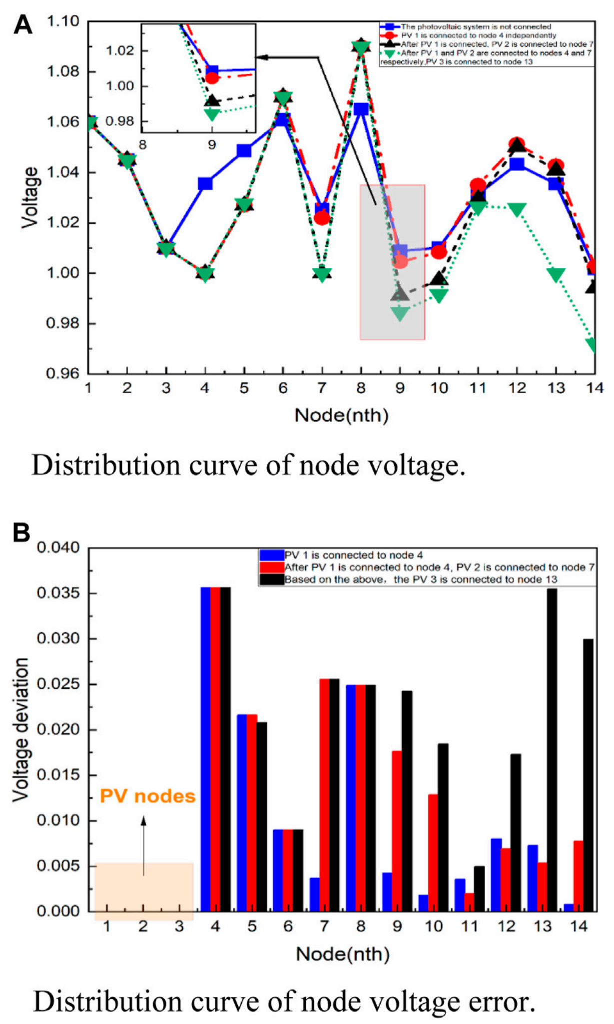

FIGURE 5
Voltage distribution for PV cells connected to multiple nodes in distribution network.

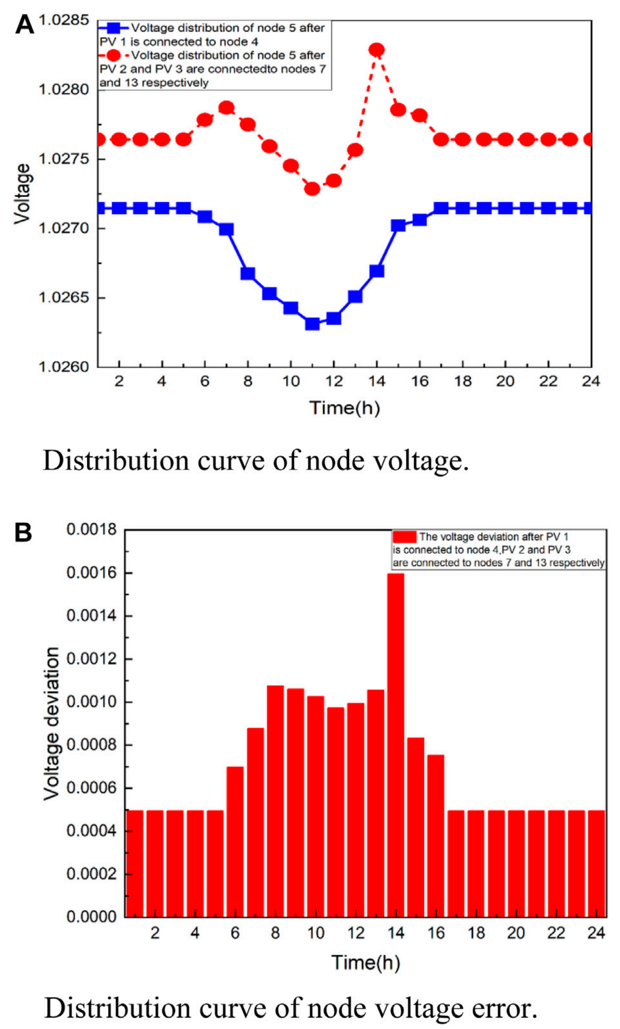

FIGURE 6
Voltage distribution of fifth node while PV cells are connected to multiple nodes in the distribution network.

4.2 Test case with single PV is grid-tied to the distribution network

The PV systems are connected into node nine of the distribution network. In this case, the power flow of the network will change, resulting in changing of the voltage distribution of the nodes; the voltage distribution and the voltage deviation are shown in Figure 4.

It can be seen that the effect on the voltage is finite because the capacity of a single PV system is not large compared with the distribution network. It can be seen that though the voltage of the grid-tied node is mainly affected, the voltage of the other nodes are also effected by a grid-tied PV system.

4.3 Test case with multiple PV are grid-tied to the distribution network

In this case, the three PVs are connected into the distribution network in node 4, node 7, and node 13, respectively. The voltage distribution of the nodes and the voltage deviation is shown in Figure 5.

It can be seen that, in terms of the connection of the PV system, the power flow of system is changed, leading the voltage distribution changing. And the effect of the node voltage is increasing, especially for the nodes which are grid-tied in the PV system.

From the sensitivity analysis of the node voltage, it can be seen that the node voltage will be affected by the all grid-tied PV system; the degree of influence can be estimated by the proposed Markov global sensitivity in this paper. For example, the voltage of node five is effected by the grid-tied PV cells, though it is not a node that is connected to a PV.

In order to analyze the voltage of node 5, in the experiment, the grid-tied node of the PV cell is changed to observe the voltage change, as shown in Figure 6.

As can be seen from the figures, the voltage distributed of node is different as the PV system are connected into the system. The changing trend of the node voltage is different, which can be described by the voltage sensitivity by using the proposed Markov global sensitivity, as shown in Figure 7 from the sensitivity analysis, it can be seen that the node voltage will

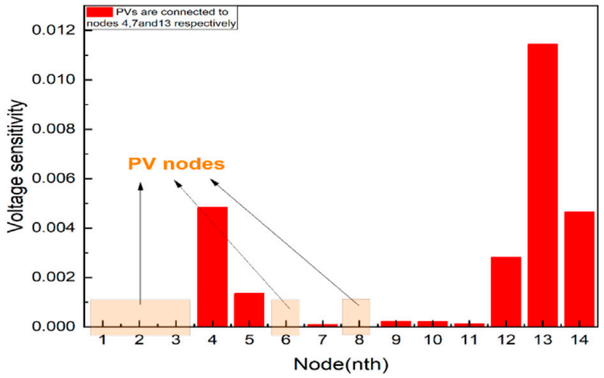

FIGURE 7
Voltage sensitivity analysis distribution network.

effected by all the grid-tied PV cells, and the degree of influence is different.

5 Conclusion

A modeling and analysis method for a distribution network with PV cells based on Markov global sensitivity is proposed in this paper. Comparing with the traditional method, the Markov chain and voltage modeling of the distribution network are combined to obtain the Markov global sensitivity function to describe the degree of the influence of the node voltage resulting from the grid-tied PV cells. The example has verified the effectiveness and plausibility of the proposed method. And the example results show that the node voltage is effected by all the grid-tied PV cells, and the degree of influence is different, due to the different grid-tied nodes. The analysis results can be used in the design and planning of distribution networks, the grid-tied node evaluation of PV cells, and the optimization control of distribution networks. The modeling method can be used to developed corresponding model for meshed network in the future work.

Data availability statement

The raw data supporting the conclusion of this article will be made available by the authors, without undue reservation.

Author contributions

TH: Data curation, Investigation, Methodology, Validation, Writing–original draft, Writing–review and editing. BZ: Data curation, Formal Analysis, Software, Validation, Writing–review and editing, Writing–original draft. PL: Software, Validation, Writing–review and editing. XC: Data curation, Writing–review and editing.

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Conflict of interest

Authors TH and PL were employed by State Grid Ningxia Electric Power Company Marketing Service Center. Author XC was employed by Ningxia Longji Ningguang Instrument Co., Ltd.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fenrg.2024.1374467/full#supplementary-material

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