Two-Stage Dynamic Voltage/Var Control in Distribution Network Considering Uncertain Distributed Generations

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Abstract. After integrating distributed generators (DGs), the voltage/var control in distribution networks requires addressing multiple objectives, including power loss reduction, lifetime saving of mechanical switching voltage control devices and uncertain power output of DGs. Therefore, this paper proposes a two-stage voltage/var control method for distribution networks with uncertain power generation from DGs. A dynamic voltage/var optimisation model is formulated in the primary optimisation stage. It dispatches all the voltage/var controllers to minimise the action times of mechanical switching devices and the total active power loss over the day. The second stage consists of a stochastical optimisation model in which probabilistic scenarios replace the deterministic parameters of DGs and loads. The Monte Carlo approach and K-mean clustering technic are utilised to generate the scenarios to be used in the second stage. The DGs' setpoints are recursively calculated to address the uncertainties. The proposed method is tested on a modified IEEE 33-node distribution network. The effectiveness of the method is demonstrated through the simulation results.

Keywords: voltage/var control · dynamic optimisation · stochastical modelling

1 Introduction

The distribution network is being evolved from a traditionally radial system to a multiterminal grid with high penetration of distributed generators (DGs). This evolved system imposes a challenge in achieving voltage control objectives. With the increasing integration of DGs, reversed power flow makes traditional voltage/var control (VVC) schemes invalid because the downstream power injections are unpredictable to traditional voltage control devices. The supply reliability and system stability can severely deteriorate if the voltage deviates from

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the safety limit. Thus, extensive research has been proposed to achieve reduced active power loss and optimised node voltage quality by considering DGs' participation [1,2].

A distributed coordinated voltage control scheme was proposed in [3]. The gradient projection method and model predictive control were utilised to formulate the controllers for on-load tap changers (OLTCs), static synchronous compensators and DGs in the system. The voltage violation caused by distributed photovoltaic (PV) generation was addressed in [4]. A two-stage coordinated control was utilised to achieve the VVC objectives by considering multiple operation modes of PV inverters. The local voltage control method proposed in [5] aimed at mitigating the overvoltage caused by DGs. It utilised enhanced power factor voltage control methods that adjust active and reactive power with PI controllers to regulate the voltage. The voltage control scheme in [6] have considered different control time scales of traditional switching equipment and distributed power supply when establishing the voltage/var optimisation model. It achieved voltage control objectives through coordinated control under multiple time scales. The dynamic VVC optimisation model in [7] limited the total action numbers of switching voltage regulating equipment which effectively reduces the operating loss of mechanical controllers. Furthermore, the dynamic optimisation was also established in [8]. The second-order cone relaxation technic was utilised to reduce the complexity of solving the dynamic optimisation model. In [9], the power electronic soft switch was considered. The system voltage was further optimised by utilising the characteristics of the soft switch that can quickly control the active and reactive power flow. In [10], the dynamic voltage control was established. The fast control characteristics of power electronic devices were utilised to improve the dynamic voltage quality in the time segment after adjustment of the traditional reactive power compensation devices. A combined centralised and decentralised voltage control scheme was proposed in [11]. It combined the local control of DGs with a centralised optimisation model to achieve system-level dynamic voltage/var coordination. Literature [12] proposed a data-driven coordinated voltage control scheme. Based on real-time measurements, it realised a coordinated and optimised control for multiple voltage regulating devices under different time scales. In [13], a two-layer VVC model was proposed that integrates the optimal operation model of the microgrid into the distribution network voltage control. The model was established based on Stackelberg game theory and described the game relationship between microgrid and distribution network. A quantification method of voltage control contribution for the grid-tied microgrids was proposed in [14] where the fair resource allocation theory was utilised. A multi-objective VVC model was established to maximises the voltage control contribution of grid-connected microgrids in the distribution network.

The above-reviewed VVC schemes improve the system voltage quality for the distribution network with DGs. Most of these schemes prioritised the objective of active power loss reduction. However, only a few of them address the wear and tear of mechanical voltage controllers such as OLTC and shunt capacitors (SCs).

Furthermore, the impact of DGs' uncertain generations on the voltage control objectives is inadequately discussed. Since the fluctuated power generations of DGs could lead to decreased life duration of mechanical devices and node voltage violation, it is required to simultaneously consider various factors, including the active power loss, the lifetime of OLTC and SCs and uncertain generation of DGs. Therefore, this paper proposes a two-stage voltage/var control model that addresses multiple factors. The primary optimisation stage calculates the setpoints of OLTC, SCs and DGs. These devices are coordinately controlled in the first stage optimisation to minimise the action times of OLTC and SCs and active power loss in the system. The secondary optimisation stage address the uncertainty of DGs' active power forecasts. The setpoints of OLTC and SCs determined in the first stage are treated as input, while the DGs' reactive power can be recursively adjusted. The Monte Carlo sampling approach and K-means technic are utilised to generate the scenarios for secondary stage optimisation.

The rest of the paper is organised as follows: Sect. 2 formulates the coordinated voltage/var dispatch model and presents the two-stage voltage optimisation strategy. Section 3 introduces the simulation system and presents the results and discussions. Section 4 concludes the paper.

2 Two-Stage Voltage/Var Optimisation Strategy

The proposed VVC method aims to address cost reduction and parameter uncertainty simultaneously. Thus, a new two-stage voltage optimisation strategy is utilised in this paper. In the primary stage, all the DGs' forecasted generations and loads are assumed as deterministic parameters. VVC controllers such as OLTC, SCs and DGs are coordinately controlled to achieve the optimisation objectives. In the secondary stage, a stochastic dispatch model is formulated by introducing probabilistic scenarios. The OLTC and SCs remain in the first-stage positions while the setpoints of DGs are recursively calculated to address the newly introduced uncertainties.

2.1 Primary Stage Optimisation

In the primary stage, a VVC optimisation model is formulated based on the DistPF [15]. The objective function (1) consists of three terms. The first term minimises the aggregated active power loss along the distribution lines. The second and third terms minimise the action times of OLTC and SCs over the whole period. Three weights α_1, α_2 and α_3 scale the objectives. In this paper, α_1 takes the largest value among the three weights because the power loss reduction is considered the primary objective. The weight α_2 takes a large value while the weight α_3 is the smallest because the operation cost of OLTC is usually higher than SCs. The control variable set u consists of OLTC's setpoint tap, SC's setpoint k and DG's reactive power Q^{DG}. The set s includes all the state variables such as bus voltage and power flow in the system. It is worth noting that using the second and third objectives constitutes a dynamic optimisation model, which increases the computation complexity. Still, it is economically necessary as the minimised action times of OLTC and SCs will significantly contribute to their life duration.

$$\begin{aligned} \min f(u,x) &= \alpha_1 P_{loss} + \alpha_2 C_{OLTC} + \alpha_3 C_{SC} \\ P_{Loss} &= \sum_{h=1}^{H}\sum_{i=1}^{L} R_i \frac{P_i^2(h)+Q_i^2(h)}{V_S^2} \\ C_{OLTC} &= \sum_{h=1}^{H-1}\sum_{i=1}^{O} |tap_i(h+1) - tap_i(h)| \\ C_{SC} &= \sum_{h=1}^{H-1}\sum_{i=1}^{J} |k_i(h+1) - k_i(h)| \end{aligned} \tag{1}$$

The objective function is applied by following certain constraints, which are categorised into (2) and (3). The set (2) includes all the equality constraints representing each distribution bus's voltage and power balance.

$$\begin{cases} V_{i+1}(h) = V_i(h) - \dfrac{P_i(h)R_i + Q_i(h)X_i}{V_S} \\ V_1(h) = V_N + tap(h)\Delta V_{tap} \\ P_{i+1}(h) = P_i(h) - P_{i+1}^{Load}(h) + P_{i+1}^{DG}(h) \\ Q_{i+1}(h) = Q_i(h) - Q_{i+1}^{Load}(h) + Q_{i+1}^{DG}(h) + k_i(h)\Delta Q_i \end{cases} \tag{2}$$

The set (3) consists of the constraints for bus voltage, the adjustment range of OLTC and SCs and the control capacity of DGs. Note that the DGs' reactive power can be regulated in four-quadrant as they interface to the system via converters. Table 1 defines the variables in the formulated model.

$$\begin{cases} V^{min} \le V_i(h) \le V^{max} \\ 0 \le k_i(h) \le k_i^{max} \\ tap^{min} \le tap(h) \le tap^{max} \\ |Q_i^{DG}(h)| \le \sqrt{(S_i^{DG})^2 - (P_i^{DG}(h))^2} \end{cases} \tag{3}$$

In this stage, the forecasted loads and active power from DGs are assumed as accurate. Therefore, there are no uncertain variables in the optimisation model. The control variables in this stage include the action sequences of OLTC and SCs and the reactive power of DGs.

2.2 Secondary Stage Optimisation with Stochastical Modelling

In the secondary stage, uncertain parameters are introduced to formulate a stochastical optimisation model. The forecasted parameters for DGs and loads are replaced by their probabilistic scenarios. Considering that the reduced wear and tear of OLTC and SCs are expected to save their lifetime, their setpoints

Table 1. Nomenclature for variables in the dispatch model.

Name	Definition
h	Time interval
H, L	Time horizon and distribution line set
O, J	Device set of OLTCs and SCs
V_i	The voltage of bus i
P_i,Q_i	Active and reactive power flow
R_i,X_i	Resistance and reactance
V_S	Nominal voltage
tap	Tap position of OLTC
ΔV_{tap}	Tap step of OLTC
k_i	Position of the shunt capacitor i
ΔQ_i	Step size of shunt capacitor i
P_i^*,Q_i^*	Active and reactive power of component *
S_i^*	Capacity of DG i
$(\star)^{min}$	Minimal value of variable *
$(\star)^{max}$	Maximal value of variable *

calculated in the primary stage are treated as input in the secondary stage optimisation. However, the setpoints of DGs are recursively calculated as frequent adjustment of electronically interfaced DGs is more economical to address the newly introduced uncertainties. Therefore, the optimisation objective in this stage is formulated in (4). The control variable set $u^{'}$ includes all the DGs' setpoints, and s is the scenario index.

$$\min\ f(u^{'}, x, s) = \sum_{h=1}^{H} \sum_{i=1}^{L} R_i \frac{P_i^2(h,s) + Q_i^2(h,s)}{V_S^2} \tag{4}$$

The probabilistic scenarios of loads and DGs are generated by (5). The terms $\widehat{P}_i^{Load}(h,s)$, $\widehat{Q}_i^{Load}(h,s)$ and $\widehat{P}_i^{RG}(h,s)$ are utilised to model the possible deviation of parameters. The Monte-Carlo sampling method is utilised to generate the probabilistic deviation terms. The probability for each of them follows a normal distribution. The original deterministic parameters are chosen as the mean values, and the standard deviations for loads and DGs are 3% and 5%, respectively. Therefore, for each scenario s, the parameters $P_i^{Load}(h,s)$, $P_i^{Load}(h,s)$ and $P_i^{Load}(h,s)$ will deviate from their deterministic values according to the probabilistic deviations.

$$\begin{cases} P_i^{Load}(h,s) = P_i^{Load}(h) + \widehat{P}_i^{Load}(h,s) \\ Q_i^{Load}(h,s) = Q_i^{Load}(h) + \widehat{Q}_i^{Load}(h,s) \\ P_i^{RG}(h,s) = P_i^{RG}(h) + \widehat{P}_i^{RG}(h,s) \end{cases} \tag{5}$$

A large number of scenarios will be produced after Monte-Carlo sampling. To select representative scenarios, the K-means clustering approach is utilised. It is an iterative data-partitioning algorithm that assigns N parameters to exactly one of K clusters defined by centroids, where K is chosen before starting the algorithm. Initially, the approach chooses k centroids by K-means++ algorithm [16]. Then the following steps repeat until cluster assignments do not change: First, assign each parameter to the cluster with the closest centroid using the squared Euclidean distance between parameters to each cluster centroid, or individually assign each parameter to a different centroid if doing so decreases the sum-of-squares point-to-cluster-centroid distances; Then, update K centroids by calculating the average of the parameters in each cluster.

Alternatively, the K-means clustering can be represented by objective function (6) and (7) [17]. It applies (6) to minimise the closeness to cluster centroids while utilises (6) to seek the minimised sum-of-squares point-to-cluster-centroid distances. ξ is the parameter that needs to be clustered, and pi_x is the uniform weight of the parameter. k is the cluster index and m_k represents the centroid in cluster C_k. $dist(*)$ is represented as the squared Euclidean distance. n_k represents the number of feature sets n_k.

$$\min \sum_{k \in K} \sum_{\xi \in C_k} \pi_\xi dist(\xi, m_k) \tag{6}$$

$$\min \sum_{k \in K} \frac{1}{2n_k} \sum_{\xi_i, \xi_j \in C_k} ||\xi_i - \xi_j||^2 \tag{7}$$

3 Numerial Simulation

3.1 Simulation System

The proposed VVC was tested on a modified IEEE 33-bus distribution network as shown in Fig. 1. The raw data of the system is obtained from [15]. The modifications include an OLTC, three SCs and four DGs. The DGs on bus 14 and 30 are small wind turbine generators, while the DGs on bus 25 and 8 are photovoltaic generators. Their maximum generations are 2 MVA, 3 MVA, 1.5 MVA and 1MVA, respectively. The OLTC has 20 steps and 0.05 pu step size. The SC at bus 2 has 5 steps, while both the SCs at bus 25 and 30 have 3 steps. The step size of all the SCs is 0.1 MVAr. Moreover, the original loads are timed by 4 to accommodate the augmented power generation. The timed loads and the maximum generations of DGs are treated as base data. The base data is multiplied by the coefficients obtained from [13] to produce the DGs' generations and loads over the next 24 h. Figure 2 shows the produced DGs' generations.

3.2 Results and Discussions

Primary Voltage Optimisation Results: The total active power loss is 18.52 MW and the average node voltage deviation is 2.06 pu in the original system.

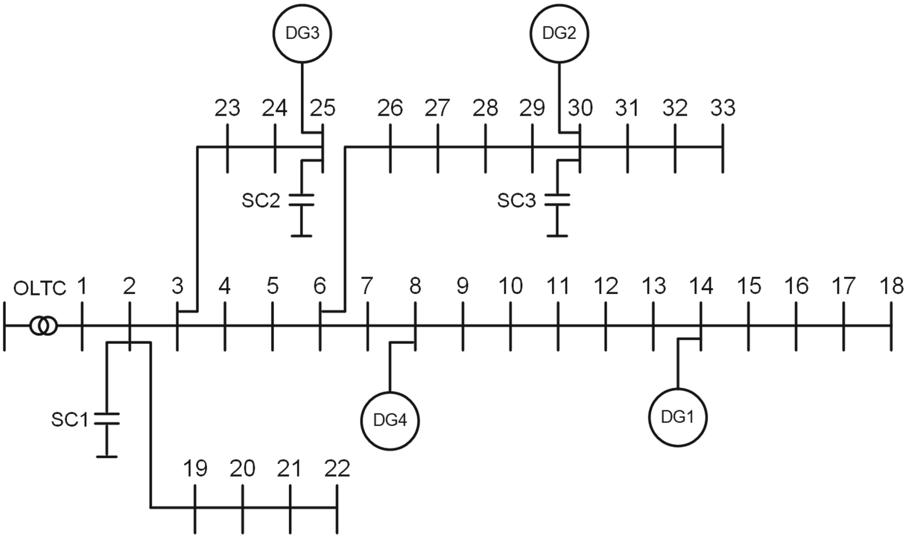

Fig. 1. Modified IEEE 33-bus distribution network.

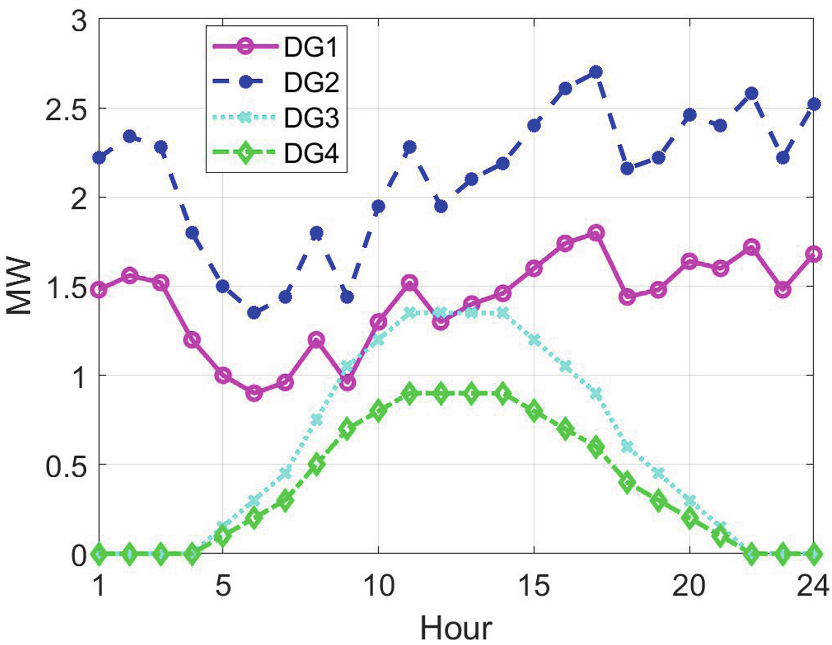

Fig. 2. Day-ahead DGs' generations for numerical simulation.

After applying the primary stage optimisation, the power loss reduces to 3.85 MW and the average voltage deviation decreases to 0.551 pu. The enhanced VVC performance is due to the fact that all the devices are coordinately dispatched in the proposed model. Figure 3 shows the coordinated pattern in the setpoints of OLTC, SCs and DGs. The OLTC only adjusts two times, and three SCs remain at the original position throughout the day. However, all the DGs actively change their reactive power in responding to the load variations. Figure 4 shows the bus voltages over 24 h. It can be seen that the voltage of each bus secures in the safety range from 0.95 pu to 1.05 pu.

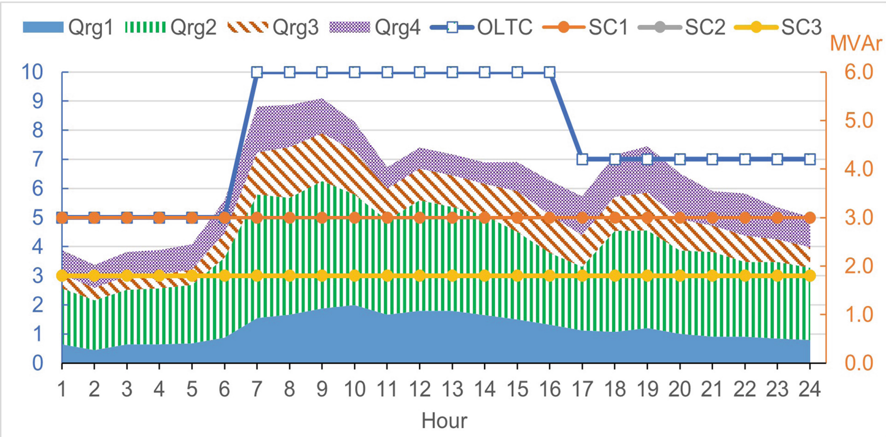

Fig. 3. Setpoints of OLTC, SCs and DGs in the primary stage.

Scenarios Production and Reduction: In the secondary optimisation stage, probabilistic scenarios are produced to replace the deterministic data of loads and DGs. By using the Monte-Carlo sampling method, 3000 scenarios are constructed, and their probability follows the normal distribution as stated in Sect. 2.2. Then, five representative clusters are calculated by the K-means clustering approach. Finally, the five cluster centroids are selected as the representative scenarios. The probability of each scenario depends on the number of points in the corresponding cluster.

To illustrate the clustering approach, the clustered data of DG1 is selected to be shown here. Figure 5(a) shows the five clusters and centroids for DG1's generation at hour 1. Figure 5(b) shows the generation of DG1 in five scenarios. The probabilities of DG1s' active power generation at the first hour in the five representative scenarios are listed in Table 2. Due to the page limit, the probabilities of other DGs and loads are not shown here. The secondary optimisation model is solved for all the scenarios. The expected value of parameters and objective function are obtained by Eq. (8) and (9). $X_i(s)$ represent the i_{th} parameter in scenario s, such as $P_i^{DG}(s)$ and $P_i^{Load}(s)$. S is the scenario set, and I is the parameter set.

$$X_e = \sum_{s=1}^{S} Prob_i(s) \times X_i(s) \tag{8}$$

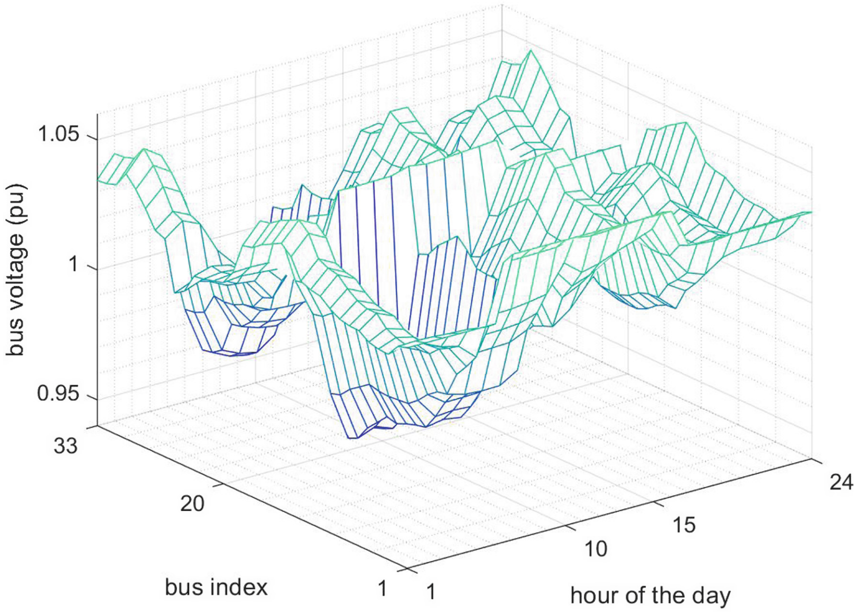

Fig. 4. Bus voltage after primary stage optmisation.

$$f_e^{'} = \sum_{s=1}^{S} Prob(s) \times f^{'}(s) = \sum_{s=1}^{S} [\prod_{i=1}^{I} Prob_i(s)] \times f^{'}(s) \tag{9}$$

Table 2. Probablity for DG1's generation at hour 1 in scenarios.

Index of scenari	DG1's generation (MW)	Probability
1	1.609	24%
2	1.424	18%
3	1.481	17%
4	1.350	21%
5	1.538	19%

Secondary Voltage Optimisation Results: In the secondary stage, all the representative scenarios are solved. The expected results are calculated by (8) and (9). Compared to the results of the primary stage, the power loss slightly increases to 4.07 MW while the voltage deviation decreases to 0.549 pu. The deterministic and expected values for DGs' reactive power are compared in Fig. 6.

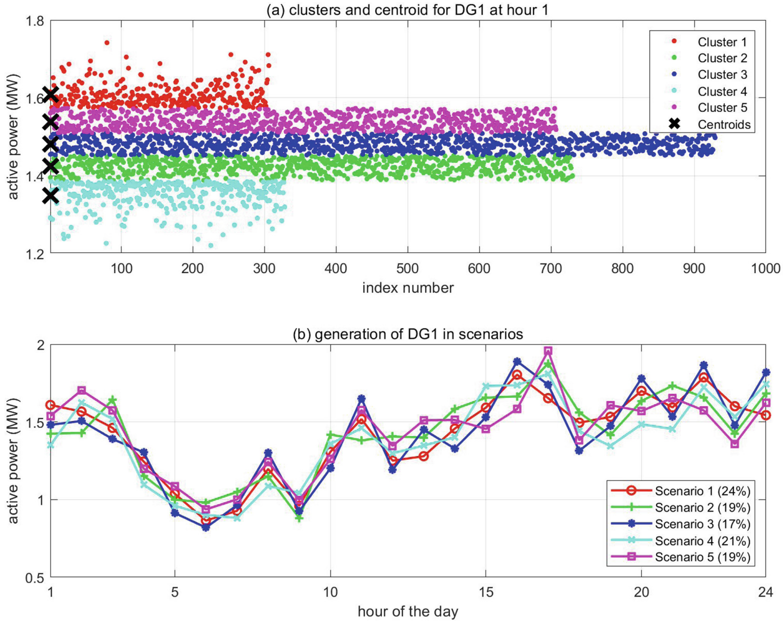

Fig. 5. DG1's parameters in scenarios.

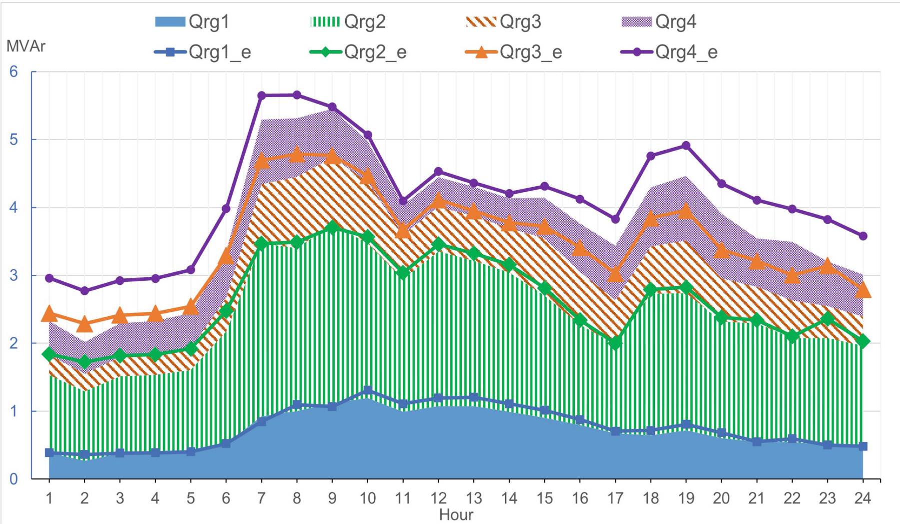

Fig. 6. Comparative results of reactive power of DGs.

The difference between deterministic and expected values indicates that the optimisation results are sensitive to the uncertainties constructed in Subsect. 3.2. Due to the change of DGs' setpoints, the voltage for each node correspondently

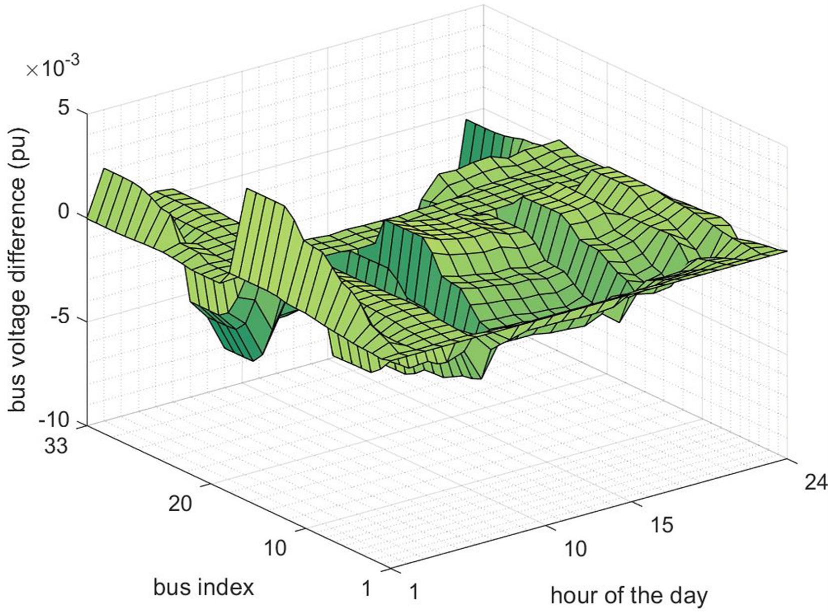

Fig. 7. Bus voltage difference between primary and secondary stage.

varies. Figure 7 shows the difference between the voltage in the primary and secondary stages. All the bus voltages are slightly changed while they are still secured in a safety range between 1.05 pu and 1.05 pu.

4 Conclusion

This paper has proposed a two-stage voltage/var optimisation strategy. In the primary stage optimisation, minimised action times of OLTC and SCs and active power loss reduction are achieved by coordinating all the controllable VVC controllers. In the secondary optimisation stage, uncertain generations of DGs and loads are introduced via a stochastic approach. The stochastical scenarios were generated by the Monte-Carlo technic and reduced by the k-means clustering method.

The two-stage voltage optimisation strategy has been tested on a modified IEEE 33-bus distribution network. The results after the first stage optimisation show a significant improvement both in loss reduction and node voltage quality in comparison with the original system. The second stage optimisation was performed by applying probabilistic scenarios. The setpoints of DGs' reactive power are adjusted in response to the uncertainties, and the expected values of active power loss and node voltage deviation vary. The results demonstrate that the optimisation results are sensitive to uncertainties. To further improve the voltage control performance under uncertain distributed generations, the impact of uncertain parameters on the optimisation results should be studied in detail in future works.

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