Online Voltage Optimization of the Power Distribution System

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***Abstract*—The power distribution is facing increasing voltage control problems due to the increasing penetration of intermittent distributed energy sources. This study describes a method for voltage optimization of a power distribution system that faces this challenge. The study depends on the digital twin concept to create a continually updated optimizer that uses the current load measurements to provide optimum reactive power injection set points to the smart inverters operating on the active nodes. This method can be applied to control a distribution system in an unknown and dynamic environment. The results for a basic network show that system voltage can be significantly optimized by using the proposed method.**

***Index Terms*—Neural Networks, Optimization Voltage Control, Particle Swarm Optimization, Power Distribution System.**

I. Introduction

The amount of Distributed Energy Resources (DERs) connected to the distribution system are expected to rise at a increasing rate [1] resulting in increasing level of fast voltage fluctuations. Unfortunately, the underlying distribution infrastructure is not expected to change at a pace fast enough to cope with this increase in generation, and help from the base infrastructure to counter the expected power quality degradation is expected to be minimal.

Both current experiences as well as the results from simulations for future scenarios [2] show that a significant amount of DERs will have to be curtailed if the system is operated using the current state of the art technology, which is defined in IEEE 1547 standard [3].

Even a small distribution grid of a few MVA capacity can have hundreds of nodes with fast varying loads. Additionally, if the DERs are Photovoltaics (PV) based, then there will be significant changes in the system loading occurring in a second time scale. Due to the large number of nodes and the fast paced changes it is practically impossible to apply traditional static optimization techniques to control the voltage of the power distribution system. On the other hand, the local volt var control (VVC), which is the state of the art, cannot provide control over the system. In some scenarios VVC could even cause degradation of the system voltage.

Whereas the voltage could potentially degrade with increasing penetration of DER, the voltage quality required to reliably operate the loads are increasing, as a result of the increasing penetration of power electronics in the demand side. Therefore, decreasing voltage quality in the distribution system can have severe ramifications.

It is crucial to find a solution that can modulate the voltage to achieve a high voltage quality in a system which has increasing DER penetration [4], [5], [6], [7]. There are solutions presented in literature that solve this problem both in centralized as well as distributed fashion. However, the models used for the analysis are balanced, decoupled and linearized models, that do not reflect the unbalanced and fast changing nature of the distribution system.

The method presented in this paper is data-driven, which means that a physics based model is not required. Additionally, it has online optimization capability that helps to operate the same voltage controls even when the system undergoes significant structural changes. Therefore, it provides a robust and efficient framework to solve the voltage control problem in the distribution grid.

II. State of the Art

The current state of the art of voltage control in the distribution grid is detailed in the IEEE 1547 standard. It is a local voltage control method [8] where the reactive power injection is used to control the local voltage to a given bandwidth of control provided to the controller (as a Q-V curve as shown in Fig. 1). Field performance has shown that this is a very effective method when there is significant impedance between the two active nodes. It is also more reliable since it does not rely on external controllers or depend on communication channels. However, the future distribution grid is bound to have an abundance of local generation in nodes that are electrically close to each other. Additionally, it was proven in [9] that this method is not the optimum solution. According to [9], for optimum voltage control, communication is a necessary requirement.

In the bulk grid voltage control is carried in real time by leveraging the inherent reactive power control capabilities of

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the PV buses. The voltage compliance and system security is ensured by carrying out feed forward optimization based on forecasted system load and generation. However, due to the large number of nodes associated with the distribution grid, coupled with the difficulty to forecast distribution system loads at scale makes this approach infeasible to be applied to the distribution system.

The other option for voltage control is to use communication. Many research studies in the past have looked at this problem and used communication to improve voltage control in the distribution system [9], [10]. However, most of these studies use models that are balanced and use a decoupled linearized power flow approach. Physics based models require three phase unbalanced modeling supported by many parameters that are not realistic to be approximated or calculated. Therefore, using a physics based model and applying traditional optimization techniques is not a practical solution to the voltage control in the distribution grid. This is the reason as to why we propose a data driven optimization and control technique for voltage control in the distribution grid.

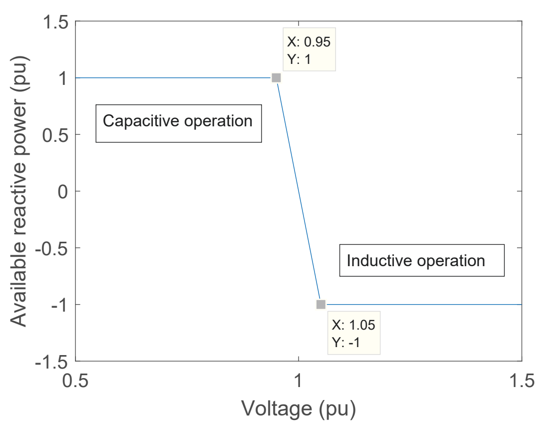

Fig. 1. State of the art for local voltage control [11].

III. Problem Statement

Consider the below system g that models the power flow manifold, $\mathcal{M}$, in the power distribution system.

$$x(k) = g(x(k), y(k), u(k)) \quad (1)$$

Where, x is the state vector described by (2), y is the independent variable vector described by (3), n is the number of nodes, and u is the control vector described by (4).

$$x := \begin{bmatrix} |V| \\ \delta \end{bmatrix} \in \mathbb{R}^{2n} \quad (2)$$

$$y := \begin{bmatrix} P \\ Q \end{bmatrix} \in \mathbb{R}^{2n} \quad (3)$$

$$u := \begin{bmatrix} Q_{Inverter} \end{bmatrix} \in \mathbb{R}^{m} \quad (4)$$

The function to be optimized, the utility function, U, is the sum of mean squared voltages of the system nodes and is shown below in (5).

$$U(x) = \sum_{i=1}^{n} 0.5(|V_i| - |V_0|)^2 \quad (5)$$

The objective is to find the reactive power injections, u, such that U is minimized under the constraints $\mathcal{C}$.

$$\begin{aligned} \underset{x \in \mathcal{M}}{\text{minimize}} \quad & U \\ \text{subject to} \quad & x \in \mathcal{C} \end{aligned} \quad (6)$$

We assume that the future distribution grid is populated by either actual or virtual passive nodes that have a reasonable internet connection (10Mbps), a voltage and load measurement that can measure and transmit voltage and load measurements at at least 1 Hz (could be a Micro PMU [12]). A typical distribution node can include a combination of storage, reactive power loads, active power loads and generation. The most common generation source is Photovoltaics (PV). As shown in [13] PV response time is, at maximum 100 ms and if we estimate another 100 ms for measurement, communication and computation, then the total time lag from measurement to actuation is in the range of 200 ms. This is very fast when compared to the fastest process in the distribution system, which is the change in PV generation. All these assumptions are reasonable for a residential neighborhood. An example active node, H_1, that shows the component level structure is given in Fig. 2.

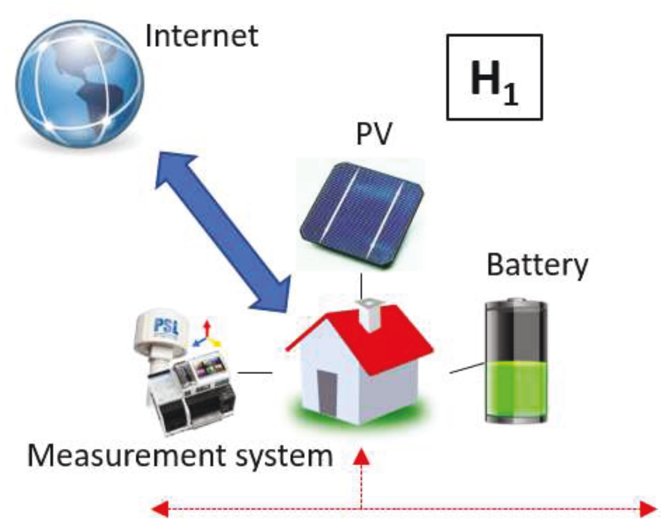

Fig. 2. A complete active node of the system.

IV. Methodology

In this section the proposed method for voltage control with its constraints and requirements are explained in detail. In this preliminary stage an OpenDSS [14] model of a system is used to represent the actual system. Therefore, data captured by the simulator is assumed to be an accurate representation of the response and performance of the system in real world.

A. Voltage Control Framework

The proposed framework shown in Fig. 3 consists of two main components, a digital twin of the system and an optimizer. The digital twin uses a feedforward neural network (Multi Layer Perceptron (MLP)) as its computational engine. Data captured from the measuring systems encompassing a reasonable period of time is used to tune the digital twin. A tuned twin can accurately estimate the system voltages based on the power injections from across the distribution system. Based on infrastructure limitations as well as regulatory limitations, application of this type of method could be constrained to a limited area; for example, a neighborhood of around 100 houses is a reasonable and realistic scenario. Note that the presented framework uses the resources that already exist in the active nodes to operate optimally across the distribution network.

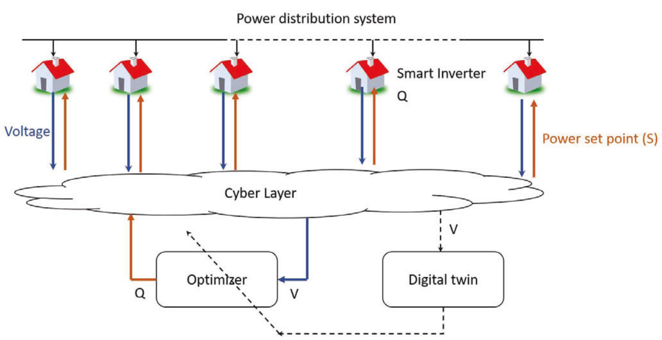

Fig. 3. The proposed framework for voltage control.

B. Development of Digital Twin of the Distribution System

The development of digital twin of the distribution system (DTDS) is shown in Fig. 4. It uses the gathered data from the measurements over a time period of minimum 24 hours to train the neural network. The digital twin estimates node voltages, V_{est}, based on load measurements at each node, S_{meas}, and reactive power injection, Q_{inj} by the smart inverters at the n active nodes in the system. The DTDS is tuned to ensure that the difference between estimated and measured voltages (ΔV) is minimized. When the DTDS is tuned the algorithm leads to a new tuning cycle of the optimizer.

1) Tuning: When implementing in a real system the digital twin will be created based on historical data captured from the measurement system. However, since we use a simulator of the distribution system to generate the data, we initialize and train the digital twin by applying random values for the independent variables, within the given upper and lower limits and use that to generate a dataset that emulates the system response. This dataset is then used to train the digital twin. The final output of the trained model estimator is shown in Fig. 4. Here $\underset{\sim}{S} = P + Qj$ and $\underset{\sim}{V} = |V|\angle\delta$. This is a $3 \times 36 \times 6$ MLP network that has 3 inputs, 6 outputs and 36 neurons in the hidden layer.

C. Voltage Control in Operation

The normal operation, which is an online optimization is shown in the Online Optimizer block in Fig. 4. The optimizer uses the measured power of the system nodes to generate reactive power injection values at active nodes.

D. Re-tuning Online Optimizer

When the voltage estimate by the digital twin of the system shows significant deviation from the measured voltage, the optimization system is re-trained based on the process flow shown in the Development of DTDS block in Fig. 4. This necessitates retraining of the optimizer shown in the Development of DTO block of Fig. 4.

In this process Particle Swarm Optimization (PSO) algorithm generates a swarm of possible optimum reactive power injections, $Q_{swarm,i}$, which is moved through the solution space iterating till convergence. For each iteration, PSO generates a better swarm of solutions ,$Q_{swarm,i}$. The measured apparent power and $Q_{swarm,i}$ is used to find the swarm of system voltage vectors, $V_{swarm,i}$. This is used by the Fitness function (U) to evaluate the fitness of the swarm. The swarm of fitness values are then used by the PSO algorithm to generate a new set of solutions.

In the next stage the Q_{inj} is compared against Q_{best} and the resulting different ΔQ is used to update the weights of the digital twin of the optimizer (DTO). The DTO uses S_{meas} and Q_{inj} to tune its weights. The Optimizer is then updated by replacing its existing weights with the new tuned weights, W_{new}. This brings the system back to optimal operation.

The optimizer uses the digital twin to find the optimum reactive power set points across the full range of passive nodes by applying the particle swarm optimization algorithm as shown in the 'Development of DTO' block of Fig. 4. The generated Q_{gbest}) dataset will consist of measured loads and corresponding optimum reactive power injection calculated by PSO for a dataset that spans at least one day of system operation.

This dataset is then used to train the optimizer, which is also another feed forward neural network structured as a Multi Layer Perceptron. The first step is to tune the digital twin to reflect the new input output relationship of the system. The second step is to replace the old digital twin in the PSO loop in the optimizer with the new digital twin of the system. Then the optimizer re-tuning is triggered. In this step PSO runs to generate a data set of load apparent power and corresponding optimum reactive power injection. Next, this generated dataset is used to retrain the optimizer. Finally, the retrained optimizer replaces the old optimizer and the system returns back to optimal operation.

The estimator also requires to be re-tuned when the estimator changes, since the optimization uses the digital twin to generate the training data-set for the optimizer.

In normal operation, the framework relaxes to the set up shown in Fig. 3.

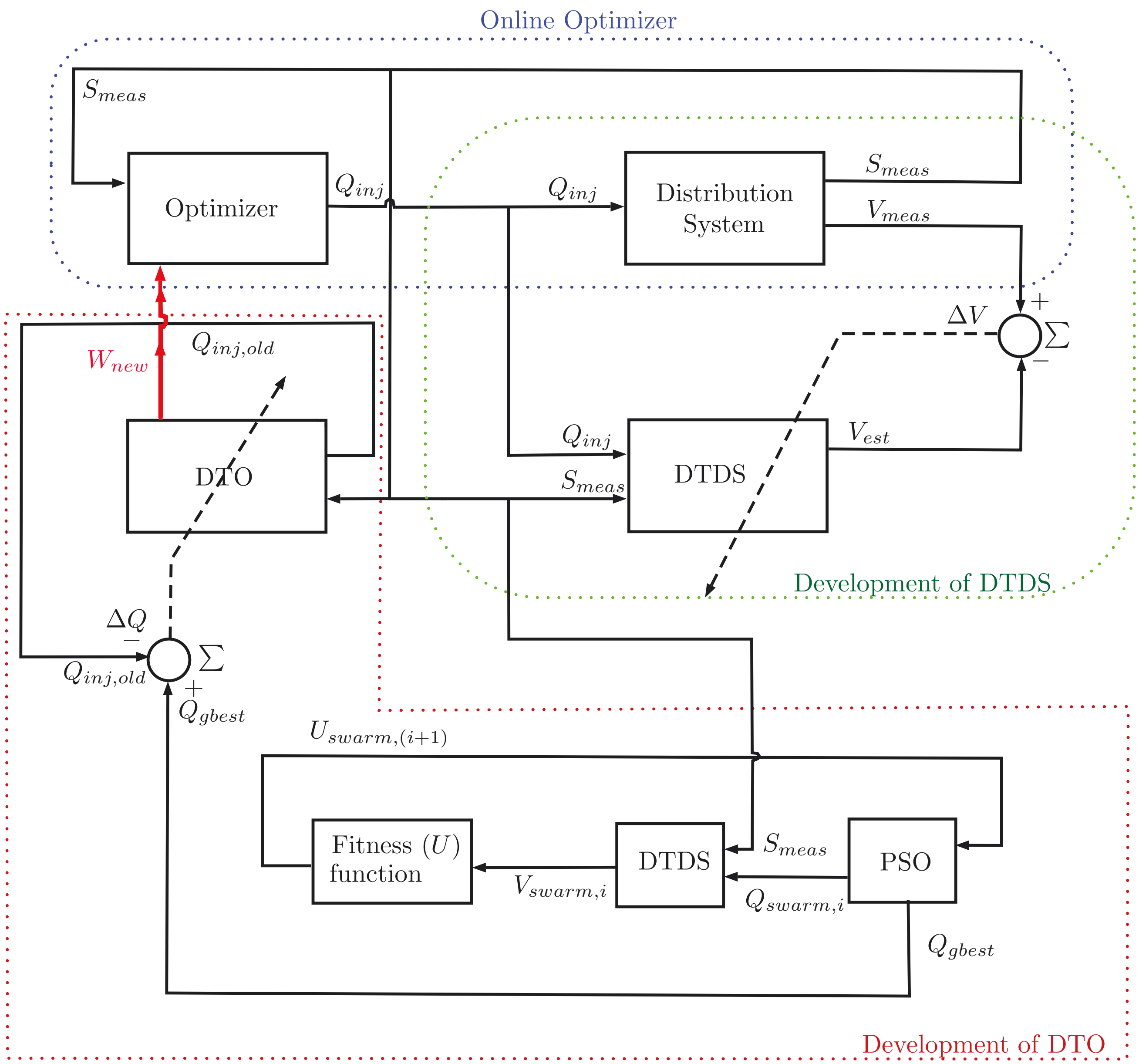

Fig. 4. System process flow and overview diagram. The three subsystems required for this method, Development of DTO, Development of DTDS, and Online Optimizer, are shown inside red, green and blue dotted frames.

V. Results

A. Case Study

The framework is tested on the IEEE 4 bus test system [15] shown in Fig. 5. Here, the load at bus 4 is changing randomly and the reactive power injections at buses 3 and 4 are operating to control the system voltage.

B. Utility Function

The utility function for optimization for this case study is the sum of the mean squared error of the node voltage (based on $V_0 = 1pu$).

$$U = 0.5[(|V_3| - |V_0|)^2 + (|V_4| - |V_0|)^2] \tag{7}$$

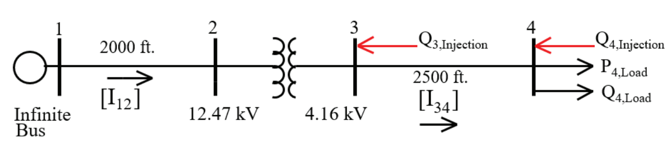

Fig. 5. System under study.

C. Digital Twin of the Distribution System (DTDS)

The performance of the DTDS is at a high level since the estimated voltage at bus 4 closely matches the values that were obtained from the OpenDSS simulator, as shown in Fig. 6. The maximum Mean Absolute Percentage Error (MAPE) that is observed is less than 0.6%.

D. Digital Twin of the Optimizer (DTO)

The PSO output is shown in Fig. 7. These results show that PSO can find the control vector to optimize voltages at both bus 3 and 4, successfully satisfying the optimization objective defined in (7).

The system performance when operated with a tuned DTO is given in Fig. 8. The results are for a 1000 second dataset in which the loads have large variations across their full operating range. This shows that both buses have significant improvement in voltage quality and that smart inverters at both bus 3 and 4 contribute in a coordinated manner to improve system voltage in varying operating conditions. The voltage quality improvement can be clearly observed by comparing the utility before and after this method was applied.

E. Discussion

The results of this study show that system performance can be enhanced by using the proposed voltage control framework. If local voltage control is applied there will be degradement of performance because the two injections will be adversely affecting each other. That is because the largest impact on the U (which is a function of V_3 and V_4) is by the remote end voltage, which is the weakest bus in the system. This provides the basis for why a coordinated voltage control scheme will be of greater value to ensure better overall voltage control. The voltage at each bus is still maintained between the required limits, but using coordinated control the voltage at Bus 4 is brought from over-limit to within the standard of +/-3% . It is clear that without this strategy (by only using local control) the overall system voltage quality is deficient.

We assume zero delay between measurement, computation and action. For a system with above solar irradiation based variation, simulations show that even a 1 second (1 step) delay, does not impact the system operation. This is because the changes observed in the independent variable (Solar Irradiation) changes in a slow and smooth way when measured in a second basis.

VI. Conclusion

The framework proposed in this study can successfully optimize in a non real-time simulation environment for a small power system. The next stage of this study will look at a real time simulation, since a big challenge in this domain is the requirement to ensure that the computation time required for the control method stays within reasonable bounds. This will assist to generate and implement control actions before the system operating state changes significantly. Additionally, the case study will need to be expanded to reflect a more realistic power distribution system with respect to size and topology as well as load and generation dynamics.

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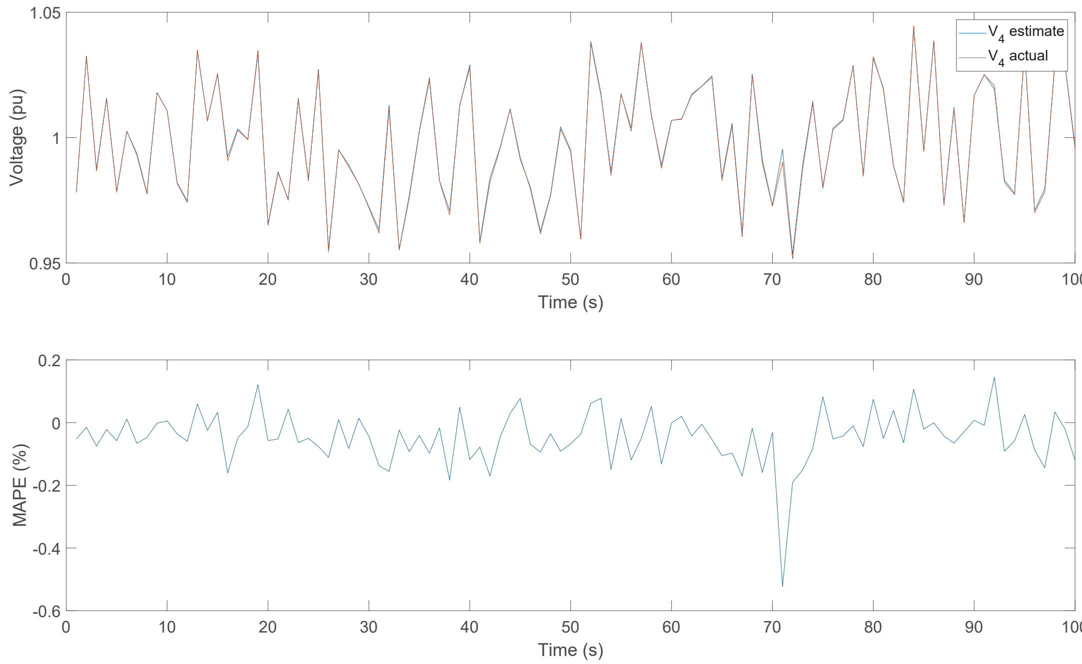

Fig. 6. DTDS Validation: The top plot compares voltage estimation from the digital twin with the actual values for bus 4 over a period of 100 seconds. The bottom figure shows the MAPE values for the same dataset.

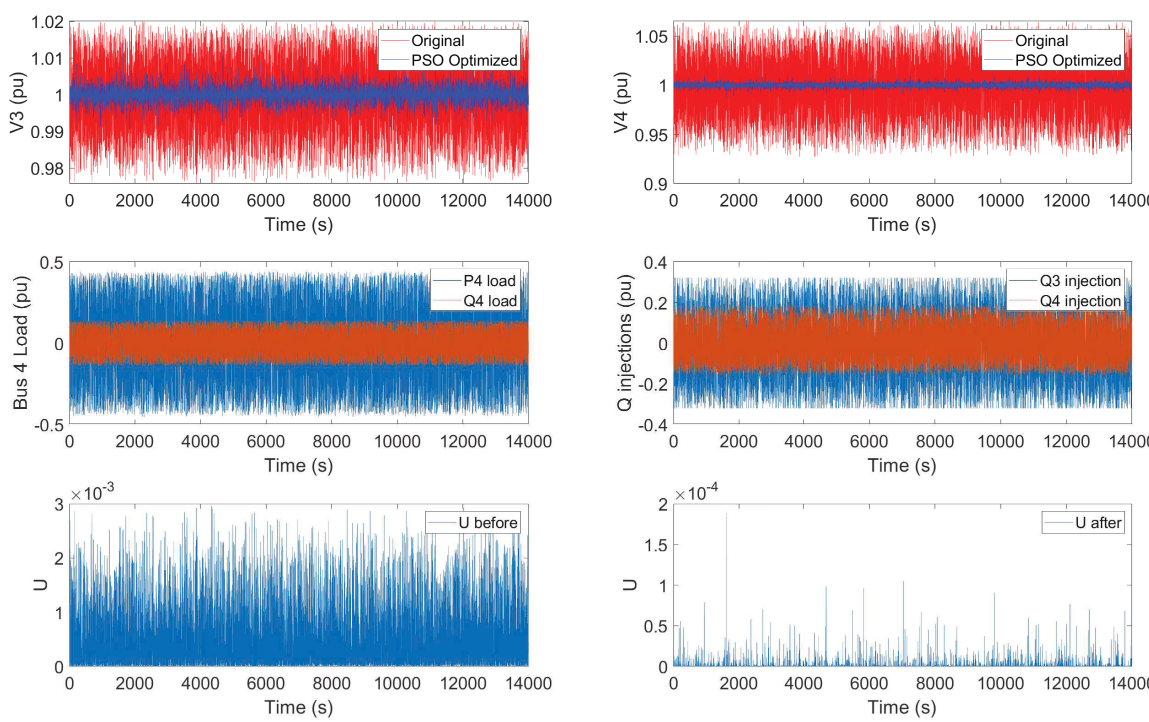

Fig. 7. PSO results [16]: The top 4 plots compare the system performance with and without optimization. The bottom plots compare the Utility before and after applying the optimization.

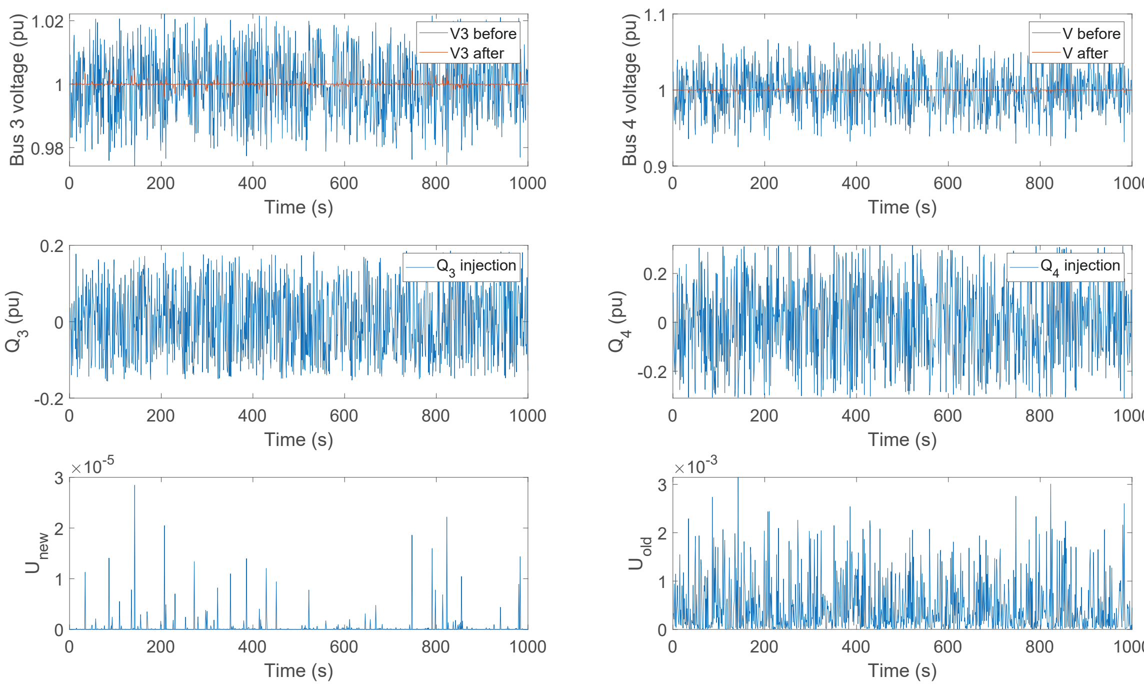

Fig. 8. Optimization results operating under proposed method: The top 2 plots compare the voltage performance of bus 3 and 4, before and after optimization. The middle 2 plots show the variation of reactive power injection of bus 3 and 4 when participating in voltage control. The bottom plots compare the utility and function after and before applying voltage optimization over a period of 1000 seconds.