Measurement-Based Formulation for Online Optimal Reactive Power Dispatch Problem

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Received: 16.05.2021 Accepted: 21.06.2021

Abstract- This paper presents a measured data-based formulation to solve the optimal reactive power dispatch problem for real-time applications. The measurements gathered from the phasor measurement units are adopted to estimate sensitivities that present a linear relationship between monitored variables. The optimal reactive power dispatch problem in this paper is formulated in terms of the sensitivities, so that it can be solved by using the measurements only. To minimize overall active power losses while keeping voltages within their limits, the least-square estimation methodology is applied. The formulation enables a new measurement-based strategy that can adjust to changes in the operating point and topology of the system. Simulation results show that the proposed formulation can deal with effectively the reactive power dispatch problem in terms of performance and is much faster in calculation time with other formulation based on load flow calculation, implying that the strategy is ideally suited to real-time applications.

Keywords - Reactive power dispatch; voltage control; phasor measurement units; MVMO algorithm.

1. Introduction

Operation of the power system with proper planning is critical for the country's economic development. The optimal reactive power dispatch (ORPD) is critical for the safe, stable, and efficient operation of the power system. The ORPD is a multi-model, complex, non-linear, non-convex, non-continuous problem with discrete and continuous variables. Due to the non-linearity, the ORPD is generally formulated using the well-known power flow model.

Strategies using the power flow (PF) calculation in addressing the ORPD are model-based ones. There are various model-based optimization methods proposed over years in literature for addressing the ORPD problem. At first, the optimization strategy s such as the gradient-based strategy, interior-point, linear programming, or nonlinear programming, have been adopted to solve the ORPD. However, the complicated infrastructure of power systems, which involves the regulation of a wide range of resources, makes it difficult to discover the optimal solution using these strategies. To cope with the multiple control variables with different types that define the ORPD problem, more advanced strategies must be introduced. In this regard, current research suggests using meta-heuristic algorithms, for example, genetic algorithms [1], the marine predators algorithm [2], improved salp swarm algorithm [3] or the quantum-behaved particle swarm optimization differential mutation algorithm [4], particle swarm optimization algorithm [5], clonal algorithm [6], artificial bee colony, wind driven optimization and gravitational search algorithms [7]. Meta-heuristic algorithms differ from deterministic methods in that they can systematically drive the solution to the nearest possible optimal position during the computation process, avoiding early convergence to local optima. Besides, these strategies usually suffer from the following shortcomings. Firstly, a substantial computation burden is necessary due to repetitive power flow calculation, making real-time implementation challenging. Secondly, algorithm's performance is strongly dependent on the system model's accuracy. For example, in the event of blackout in San Diego in the year of 2011, the lack of an up-to-date system model led to inaccuracy of state estimation process [8].

In order to overcome these problems, in recent years many works [9],[10],[11] proposes a measurement-based strategy that uses only data collected from the phasor measurement units (PMUs), hence being able to adapt to real system topology and operating point variations, removing the requirement for an accurate system model, and being able to withstand delays caused by communication and computation process. This method is proposed to be applied to different cases, for example, it is in [9] implemented to determine active and reactive power set-points of the distributed energy resources (DERs) that minimize bus voltage deviations from their reference values. In [10], the method is used to calculate optimal power flow (OPF) solutions that optimize either reactive power or active power outputs of the DERs. The authors in [11] introduce the method using sparse linear-quadratic-Gaussian control to regulate active power flows in power systems.

In this paper, a novel formulation using sensitivity analysis to characterize the RPD is presented to enable a *measurement-based* strategy in [12] which can adapt to online operation situations when operating points change frequently due to power flow variations or the system topology changes suddenly cause by an interruption of a transmission line, for example. Moreover, the ORPD using the proposed formulation can be solved by using a linear algorithm (the least-square estimation (LSE) chosen in this paper), hence its calculation time is quick enough to be used in real-time applications.

2. The RPD Problem's Formulation

In this paper, a formulation of the RPD problem is presented to meet the inequality constraints and to minimize the overall active power losses over the power system. The following are the formulas formulating the objective function selected and its constraints:

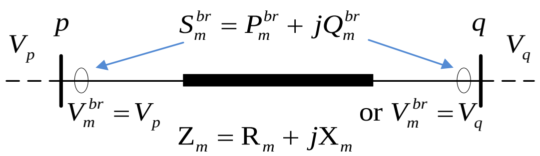

Fig. 1. One-line diagram of a branch *m* in a transmission system

2.1. Objective Function

The losses of the branch *m* can be calculated using active and reactive power (P_m^{br}, Q_m^{br}) flowing in itself and its voltage magnitude V_m^{br} , as shown in Fig. 1, which presents a one-line diagram of the branch *m* between bus *p* and bus *q*.

$$P_m^{loss} = R_m I_m^2 = R_m \frac{P_m^{br2} + Q_m^{br2}}{V_m^{br2}} \qquad (1)$$

Note that the position of the power measurement device on the branch *m* will define $V_m^{br} = V_p$ or $V_m^{br} = V_q$, and the *branch* is denoted by the subscript *br*.

where $\boldsymbol{x}_1 = [Q_1^{br}, ..., Q_m^{br}, ..., Q_{N_{br}}^{br}]^T$ is the branch flow of reactive power with N_{br} being the number of branches, and $\boldsymbol{x}_2 = [V_1^{br}, ..., V_m^{br}, ..., V_{N_{br}}^{br}]^T$ represents the bus voltages of the branches.

The objective function of the RPD problem in this paper is the total losses minimized in the overall power system; as a result,

$$\min P^{loss} = \sum_{m=1}^{N_{br}} P_m^{loss} = \mathbf{R}^T \boldsymbol{I}^2(\boldsymbol{x}_1, \boldsymbol{x}_2) \qquad (2)$$

with $\boldsymbol{I}^2 = [I_1^2, ..., I_m^2, ..., I_{N_{br}}^2]^T$ is a squared vector of electric currents flowing in branches, $\mathbf{R} = [R_1, ..., R_m, ..., R_{N_{br}}]^T$ is a vector of resistance of braches, $\boldsymbol{x}_1 = [Q_1^{br}, ..., Q_m^{br}, ..., Q_{N_{br}}^{br}]^T$ is the branch flow of reactive power, and $\boldsymbol{x}_2 = [V_1^{br}, ..., V_m^{br}, ..., V_{N_{br}}^{br}]^T$ represents the bus voltages of the branches.

The state variables of the system in this case are as follows:

$$\boldsymbol{x} = \left[[\boldsymbol{x}_1]^T, [\boldsymbol{x}_2]^T \right]^T \qquad (3)$$

Assume that the system is working at a specific operating point and that the state variables are defined by $\boldsymbol{x}_1^0 = \boldsymbol{q}^{br,0}, \boldsymbol{x}_2^0 = \boldsymbol{v}^{br,0}$. From (2), optimal adjustments of the variables ($\Delta\boldsymbol{x}_1, \Delta\boldsymbol{x}_2$) to the new operating point must fulfill:

$$\min P^{loss} = \mathbf{R}^T \boldsymbol{I}^2(\boldsymbol{x}_1^0 + \Delta\boldsymbol{x}_1, \boldsymbol{x}_2^0 + \Delta\boldsymbol{x}_2) \qquad (4)$$

Considering $\boldsymbol{I}_D^2$ as the diagonal matrix of $\boldsymbol{I}^2$, and (4) linearized for the chosen operating point $\boldsymbol{x}^0$, (4) is equivalent to (5):

$$\min \Delta P^{loss} \approx \mathbf{R}^T \left[\frac{\partial \boldsymbol{I}_D^2(\boldsymbol{x}_1^0)}{\partial \boldsymbol{x}_1^0} \Delta\boldsymbol{x}_1 + \frac{\partial \boldsymbol{I}_D^2(\boldsymbol{x}_2^0)}{\partial \boldsymbol{x}_2^0} \Delta\boldsymbol{x}_2 \right] \qquad (5)$$

where ΔP^{loss} denoting the loss decreases.

(5) becomes as follows for clarity:

$$\min \Delta P^{loss} \approx \boldsymbol{w}^T \Delta\boldsymbol{x} \qquad (6)$$

where $\boldsymbol{w} = \left[\mathbf{R}^T \frac{\partial \boldsymbol{I}_D^2(\boldsymbol{x}_1^0)}{\partial \boldsymbol{x}_1^0}, \mathbf{R}^T \frac{\partial \boldsymbol{I}_D^2(\boldsymbol{x}_2^0)}{\partial \boldsymbol{x}_2^0} \right]^T$ is a weighting matrix

Linear programming can be used to address the problem (6). In this paper, however, the LSE algorithm is used to address the RPD problem. It was mentioned in [13] that both methods' parameter estimation and objective function value are roughly identical, so their outputs are similar.

From the physical viewpoint, there are two strategies to address the objective function:

Firstly, all branches should ideally have zero reactive power flows, $\boldsymbol{Q}^{br}=0$. As a result, the optimal changes $\Delta\boldsymbol{Q}^{br,opt}$ should be:

$$\Delta\boldsymbol{x}_1^{opt}=\left[-Q_1^0,\ldots,-Q_m^0,\ldots,-Q_{br}^0\right]^T \tag{7}$$

Secondly, the bus voltages $\boldsymbol{x}_2^0+\Delta\boldsymbol{x}_2$ should be at their upper limit $V^{br,\max}$, as a result:

$$\Delta\boldsymbol{x}_2^{opt}=\boldsymbol{V}^{br,\max}-\boldsymbol{x}_2^0 \tag{8}$$

These create an optimal collection of state variables' variations $\Delta\boldsymbol{x}^{opt}=\left[\left[\Delta\boldsymbol{x}_1^{opt}\right]^T,\left[\Delta\boldsymbol{x}_2^{opt}\right]^T\right]^T$. Therefore, problem (6) can be rewritten as follows:

$$\boldsymbol{w}_D^T\Delta\boldsymbol{x}^{opt}=\boldsymbol{w}_D^T\Delta\boldsymbol{x} \tag{9}$$

where $\boldsymbol{w}_D^T$ is diagonal matric of $\boldsymbol{w}^T$.

Besides, reactive power injected into buses is in this paper adopted as a control variable $\boldsymbol{u}=\left[Q_1,\ldots,Q_{N_{bus}}\right]^T$ to obtain optimal state variables.

$$\Delta\boldsymbol{x}_1\approx\boldsymbol{S}_{\boldsymbol{u}}^{\boldsymbol{x}_1}\Delta\boldsymbol{u} \tag{10}$$

where $\boldsymbol{S}_{\boldsymbol{u}}^{x_1}=\left[\boldsymbol{S}_{\boldsymbol{u}}^{\boldsymbol{x}_{1,1}},\ldots,\boldsymbol{S}_{\boldsymbol{u}}^{\boldsymbol{x}_{1,N_{br}}}\right]^T$ is a sensitivity matrix between $\boldsymbol{x}_1$ and the variables $\boldsymbol{u}$, and its elements $\boldsymbol{S}_{\boldsymbol{u}}^{\boldsymbol{x}_{1,m}}=\left[\partial Q_m^{br}/\partial Q_1,\ldots,\partial Q_m^{br}/\partial Q_{N_{bus}}\right]^T$, are the sensitivities between branches' reactive power flows and buses' reactive power injection.

In the same way, state variables $\boldsymbol{x}_2$ and control variables $\boldsymbol{u}$ have the following relationship:

$$\Delta\boldsymbol{x}_2\approx\boldsymbol{S}_{\boldsymbol{u}}^{x_2}\Delta\boldsymbol{u} \tag{11}$$

As a result, the equation (10) and (11) is rewritten:

$$\Delta\boldsymbol{x}\approx\boldsymbol{S}_{\boldsymbol{u}}^{\boldsymbol{x}}\Delta\boldsymbol{u} \tag{12}$$

where $\boldsymbol{S}_{\boldsymbol{u}}^{\boldsymbol{x}}=\left[\left[\boldsymbol{S}_{\boldsymbol{u}}^{x_1}\right]^T,\left[\boldsymbol{S}_{\boldsymbol{u}}^{x_2}\right]^T\right]^T$ is a sensitivity matrix between the state variables and the control variables.

Replacing equation (12) into (9), the objective function is rewritten:

$$\boldsymbol{w}_D^T\Delta\boldsymbol{x}^{opt}=\boldsymbol{w}_D^T\boldsymbol{S}_{\boldsymbol{u}}^{\boldsymbol{x}}\Delta\boldsymbol{u} \tag{13}$$

In order to specify the control variables $\Delta\boldsymbol{u}$ in equation (13), the LSE algorithm can be used:

$$\min\boldsymbol{e}^T\boldsymbol{e} \tag{14}$$

where $\boldsymbol{e}=\boldsymbol{w}_D^T\Delta\boldsymbol{x}^{opt}-\boldsymbol{w}_D^T\boldsymbol{S}_{\boldsymbol{u}}^{x}\Delta\boldsymbol{u}$

2.2. Constraints

$$\Delta\boldsymbol{u}^{\min}\le\Delta\boldsymbol{u}\le\Delta\boldsymbol{u}^{\max} \tag{15}$$

$$\boldsymbol{V}^{\min}\le\boldsymbol{V}\le\boldsymbol{V}^{\max} \tag{16}$$

where $\left[V_1,\ldots,V_j,\ldots,V_{N_{bus}}\right]^T$: a bus voltage vector

$$\boldsymbol{V}=\boldsymbol{V}^0+\Delta\boldsymbol{V}=\boldsymbol{V}^0+\boldsymbol{S}_{\boldsymbol{u}}^{\boldsymbol{V}}\Delta\boldsymbol{u} \tag{17}$$

where $\boldsymbol{V}^0$ is a voltage profile at the current operating point, $\boldsymbol{S}_{\boldsymbol{u}}^{\boldsymbol{V}}=\left[\boldsymbol{S}_{\boldsymbol{u}}^{V_1},\ldots,\boldsymbol{S}_{\boldsymbol{u}}^{V_j},\ldots,\boldsymbol{S}_{\boldsymbol{u}}^{V_{N_{bus}}}\right]^T$ presents the sensitivity matrix between the bus voltages and the control variables $\boldsymbol{u}$, and its elements $\boldsymbol{S}_{\boldsymbol{u}}^{V_j}=\left[\partial V_j/\partial Q_1,\ldots,\partial V_j/\partial Q_{N_{bus}}\right]^T$ are the sensitivities between the bus voltage and reactive power injection at buses.

3. Sensitivities Estimation Methodology

The sensitivities $\boldsymbol{S}_{\boldsymbol{u}}^{x_1}$ between reactive power flow in branches and reactive power injection at buses must be available in (10). At the branch *m*, $\boldsymbol{S}_{\boldsymbol{u}}^{x_{1,m}}=\left[\partial Q_m^{br}/\partial Q_1,\ldots,\partial Q_m^{br}/\partial Q_i,\ldots,\partial Q_m^{br}/\partial Q_{N_{bus}}\right]^T$ can be calculated as follows.

At time t, $N_{meas}+1$ strings of PMU's measured data are stored in advance.

$$\begin{cases}\boldsymbol{x}_{meas}\left((k+1).\Delta t\right), & k=1,\ldots,\mathrm{N}_{meas}\\ \boldsymbol{u}_{meas}\left((k+1).\Delta t\right), & k=1,\ldots,\mathrm{N}_{meas}\\ \boldsymbol{V}_{meas}\left((k+1).\Delta t\right), & k=1,\ldots,\mathrm{N}_{meas}\end{cases} \tag{18}$$

The effect of active power injection on reactive power flow and voltage is negligible in the transmission system due to its high X/R ratio. As a result, the equation (10) turns into:

$$\Delta\boldsymbol{x}_{1,meas}=\boldsymbol{S}_{\boldsymbol{u}}^{\boldsymbol{x}_1}.\Delta\boldsymbol{u}_{meas} \tag{19}$$

where $\Delta\boldsymbol{x}_{1,meas}=\left[\Delta\boldsymbol{x}_{1,meas}(1),\ldots,\Delta\boldsymbol{x}_{1,meas}(N_{meas})\right]$, and $\Delta\boldsymbol{x}_{1,meas}(k)=\Delta\boldsymbol{x}_{1,meas}((k+1).\Delta t)-\Delta\boldsymbol{x}_{1,meas}(k.\Delta t)$,

$\Delta\boldsymbol{u}_{meas}=\left[\Delta\boldsymbol{u}_{meas}(1),\ldots,\Delta\boldsymbol{u}_{meas}(N_{meas})\right]$, and $\Delta\boldsymbol{u}_{meas}(k)=\Delta\boldsymbol{u}_{meas}((k+1).\Delta t)-\Delta\boldsymbol{u}_{meas}(k.\Delta t)$.

It should be emphasized that $\boldsymbol{S}_{\boldsymbol{u}}^{x_2}$ is a sub-matrix of $\boldsymbol{S}_{\boldsymbol{u}}^{V}$, which may be derived as follows from (17):

$$\Delta \boldsymbol{V}_{meas} = \boldsymbol{S}_{\boldsymbol{u}}^{V}.\Delta \boldsymbol{u}_{meas} \quad (20)$$

where $\Delta \boldsymbol{V}_{meas}(k) = \Delta \boldsymbol{V}_{meas}((k+1).\Delta t) - \Delta \boldsymbol{V}_{meas}(k.\Delta t)$, and $\Delta \boldsymbol{V}_{meas} = \left[\Delta \boldsymbol{V}_{meas}(1),\ldots,\Delta \boldsymbol{V}_{meas}(N_{meas})\right]$.

Lastly, $\boldsymbol{S}_{\boldsymbol{u}}^{x_1}$ and $\boldsymbol{S}_{\boldsymbol{u}}^{V}$ in (19) and (20) can, in turn, be obtained by addressing the following LSE problems in (14) with $\boldsymbol{e} = \Delta \boldsymbol{x}_{1,meas} - \boldsymbol{S}_{\boldsymbol{u}}^{x_1}.\Delta \boldsymbol{u}_{meas}$ and $\boldsymbol{e} = \Delta \boldsymbol{V}_{meas} - \boldsymbol{S}_{\boldsymbol{u}}^{V}.\Delta \boldsymbol{u}_{meas}$, respectively.

4. Test System and Simulation Results

4.1. Test System

The proposed strategy is tested with the Western Electricity Coordinating Council's (WECC) 3-machine 9-bus system, as shown in Fig. 2. Bus #1 is a slack bus, while buses #2 and #3 are powered by generators, making them PQ buses. The reactive power injection by these two generators is the control variable.

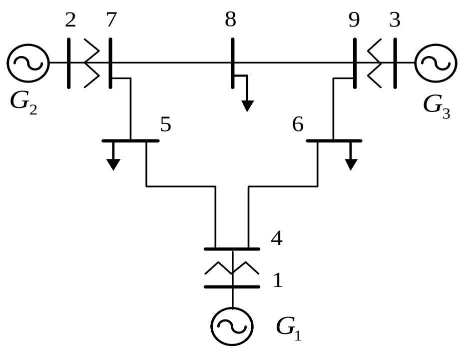

Fig. 2. Single-line diagram of the 3-machine 9-bus WECC system

4.2. Simulation Process

The simulation process is carried out as shown in Fig. 3. To begin with, a new operating point is generated that corresponds to a sampling step. Based on this operating point, a sequence of 800 data points for active and reactive power at all busses are created to imitate PMU measurements that are supposed to be available right now.

The power injection, for example, (P_i, Q_i) at bus *i* is calculated from nominal active and reactive power values of bus *i* denoted by ($P_i^0(k)$ and $Q_i^0(k)$) as follows:

$$\begin{aligned} P_i(k) &= P_i^0(k) + \sigma_1^P P_i^0(k)\gamma_1^P + \sigma_2^P \gamma_2^P \\ Q_i(k) &= Q_i^0(k) + \sigma_1^Q Q_i^0(k)\gamma_1^Q + \sigma_2^Q \gamma_2^Q \end{aligned} \quad (21)$$

where γ_1 and γ_2 are pseudorandom values obtained from standard normal distributions with a mean of zero and standard deviation $\sigma_1 = 0.02$ and $\sigma_2 = 0.02$, respectively. The first element of variance, $\sigma_1^P P_i^0(k)\gamma_1^P$ and $\sigma_1^Q Q_i^0(k)\gamma_1^Q$ represents a generation and load inherent variations, while the second element, $\sigma_2\gamma_2$, shows noise measurement at random.

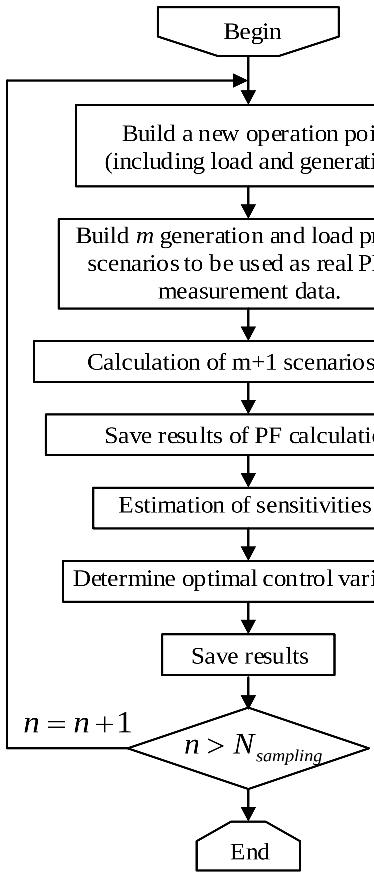

Fig. 3. Flowchart of simulation process

Following that, $N_{meas} = 801$ cases of power flows, voltages and bus power injection are computed and saved. Then, by using equations (19) and (20), the sensitivities are estimated to address the problem in (14). The Monte Carlo simulation with the number of iterations equal to these sampling steps is used in this analysis to demonstrate the efficiency of the proposed strategy.

In this study, the number of iterations for the Monte Carlo simulation is selected to be equal to $N_{sampling} = 100$, to show the efficiency of the proposed strategy.

In addition, a base case for comparison is created and we consider this case to be the best performance. In this case, a heuristic optimization algorithm, namely Mean-Variance Mapping Optimization presented in [14], is employed to identify optimal control variables by using repetitive power flow calculations. Therefore, this case is considered as the model-based strategy for comparison.

4.3. Simulation Results

a) Performance of the proposed strategy *vs. a model-based* strategy *with an accurate system model:*

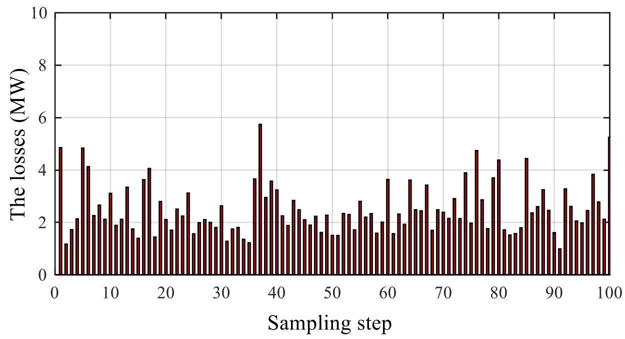

Fig. 4. The losses without optimization

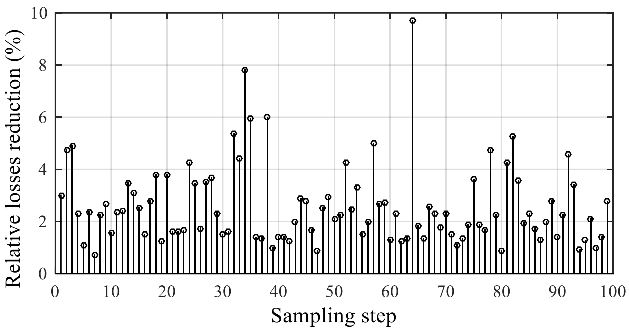

Fig. 5. Model-based optimization implementation

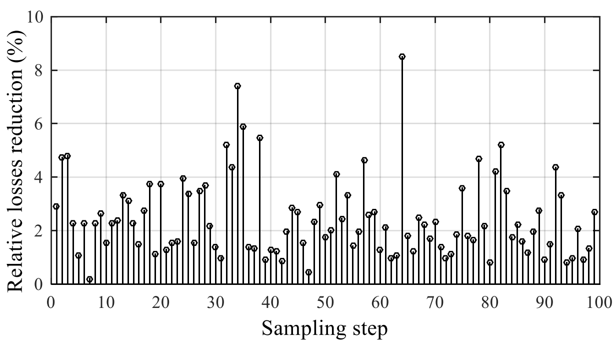

Fig. 6. Measurement-based optimization implementation

The losses associated with the generated operating points without the optimization are shown in Fig. 4. The decrease in the relative loss of the model-based strategy is presented in Fig. 5, whereas the relative loss decrease of the measurement-based strategy is shown in Fig. 6.

The average relative decrease is adopted for statistical analysis. The average relative loss decrease for the entire system is calculated as follows:

$$e^{loss}(\%) = \frac{100}{\mathrm{N}_{sampling}} \sum_{n} \left| \frac{\hat{P}^{loss}(n) - P^{loss}(n)}{P^{loss}(n)} \right| \quad (22)$$

where $\hat{P}^{loss}$ and P^{loss} are the losses with and without optimization, respectively, and $N_{sampling}$ denotes the number of sample steps.

Table 1 shows that the measurement-based strategy performs similarly to the model-based strategy in terms of loss decrease.

Table 1. Average decrease in the relative losses

Model based strategy (%)	Measurement based strategy (%)
2.567	2.429

The measurement-based strategy, as shown in Fig. 7, will adjust to changes in operating points by fulfilling the voltage constraint of (5% of nominal value).

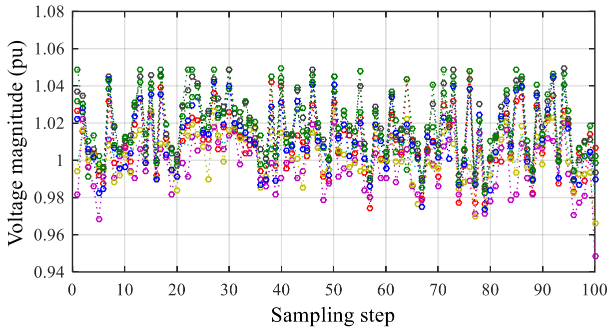

Fig. 7. Busses' voltage (except the slack bus)

b) Performance of the measurement-based strategy vs. the model-based strategy with an inaccurate system model:

This section investigates the ability of the proposed methodology to adapt to changes in system topology. The assumption is that the line connecting bus #6 to bus #9 is a double-line and that one of them has an outage that is not identified by the operators.

As seen in Fig. 8, the model-based strategy causes voltage violations at some intervals, as shown by the blue circles. On the other hand, the voltages in Fig.9 remain within their limits, because the unknown changes in topology can be accommodated using a measurement-based strategy.

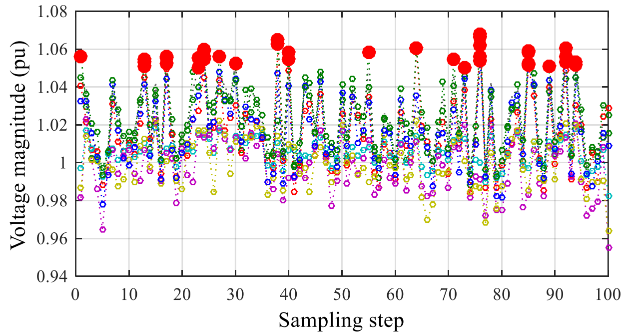

Fig. 8. All busses' voltage (except the slack bus) using the model-based strategy

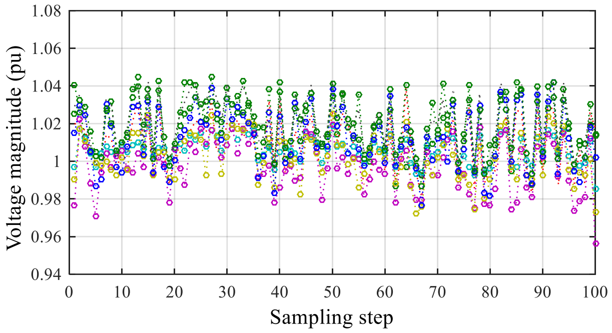

Fig. 9. All busses' voltage (except the slack bus) using the measurement-based strategy

c) Computation time:

On a Dell Laptop 3350 (Intel® CoreTM i7 processor, and 8GB of RAM), numerical tests were conducted. To calculate power flow, MATPOWER, a simulation tool, is adopted.

Table 2. An average amount of time of the CPU for calculating an operating point.

Model-based strategy (s)	Measurement-based strategy (s)
3.37	0.053

Table 2 shows that in the proposed strategy using the measurement, calculating optimal control variables is much quicker than in the model-based strategy. It is noted that the model-based strategy in this simulation uses 500 normal power flow calculations (s) to calculate the control variables.

5. Discussions

Requirements on a PMU and relevant communication protocols for the phasor data exchange are introduced in the IEEE C37.118 and discussed in [15]. The PMUs provide the precise time synchronized measurements of magnitude and phase of voltage and current. These aspects represent a substantial improvement in the concept of AC quantity measurement and provide power system operators many useful applications [16].

This study focuses on the mathematical formulation of the RDP to enable the optimization strategies using only measurements from the PMUs. Then, the measurement-based strategy using the LSE algorithm as an optimization tool is proposed to theoretically and numerically demonstrate the strategy's performance in real operational conditions as compared to the model-based strategy. Other uncertainties (e.g., generator or transmission line outages, measurement noise, etc.) that can occur unpredictably during system operation, however, have a negative impact on the proposed strategy's success in the real world.

Data with large margins of variation (resulting from the data collection during both pre-and post-disturbances) can be gathered, because the measurement-based strategy collects a sequence of data points over time intervals in an estimating window.

This could result in inaccurate sensitivity calculation due to insufficient tracking of the operating points. Implementing the weighted least squares (WLS) estimate, which gives higher weight to just lately measurements and lower to previous ones, may be a solution to this problem.

Furthermore, a bad sub-dataset may occur in a large dataset as a result of measurement and communication devices. After an approximation has been computed, bad data is usually detected and identified by utilizing techniques such as χ^2 -test and hypothesis testing, respectively, in [17] to analyze the measurement residuals. Moreover, by using a suitable forgetting factor and replacing LSE with recursive LSE as suggested in [18], the bad data can be diminished or eliminated.

On the other hand, the authors in [19] demonstrated that the reduced row echelon form-based greedy method could accurately find the sparsest attack vector against the non-linear state estimation, which could evade the bad data detection more efficiently. In [20], a method to deal with PMU's measurement noise is proposed and it is implemented for the state estimation using Parallel Kalman Filter for bilinear model systems. Moreover, the authors in [21] propose an approach for interpolation of PMU data in case of missing data points by optimal filtering of phasor data along with event detection. It is shown that optimal filters can be estimated on the basis of non-linear recursive search optimization on real-time PMU data and these filters can be used to generate forecasts in case of missing PMU measurements.

6. Conclusions

In this paper, a novel formulation of the RDP is presented to enable the measurement-based strategies. An optimal strategy using the LSE algorithm is investigated to demonstrate the effectiveness of the formulation in solving the ORDP by relying just on PMU measurements and having no prior knowledge of the system topology. In ideal operational conditions, the performance of the proposed methodology was shown to be comparable to that of conventional model-based strategies, indicating that the system model is well comprehended. Nonetheless, the proposed strategy outperformed the model-based strategy significantly in case of the unknown changes in the system topology or the out-of-date model. Moreover, the formulation using the sensitivity analysis to characterize the RPD; therefore, the problem can be solved using linear optimization algorithms effectively. As a result, the calculation time is much faster, implying that the strategy is ideally suited to real-time applications.

Acknowledgements

This work was fully supported by the research funding of Tra Vinh University under the contract No. 208/HD.HDKH-DHTV.

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