A Distributed Approach for DG Integration and Power Quality Management in Railway Power Systems

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Abstract—**Currently, railway systems are electrified to meet the rising demand for faster speed, more stable operation and more passenger traffic. Although special electrical traction systems are utilized to provide power for railway load consumption, major power quality challenges are present. This paper addresses the Volt/VAR control problem in railway power systems (RPS) considering distributed generations (DGs) interconnected to the system via smart inverters. An economic Volt/VAR sensitivity analysis approach is developed to obtain ideal reactive power injected from DG units. An adaptive energy reserve method is presented, which routes the surplus energy available to the energy storage system (ESS) to be utilized eventually. The problem of decreasing system losses, and maintaining a good voltage profile is formulated as a multi-objective optimization problem. A six-bus system is used for control architecture validation. Simulation results indicate reduction in the technical losses and the stress on automatic voltage regulators. Easy to implement model, without hard to design parameters and high efficiency, highlights the potential aspects for real-life applications.**

Keywords—Distributed power generation, Railway power systems, Volt/VAR control, Global optimization, Distributed control

I. Introduction

The electrification of RPSs brings with it convenience and high-efficiency. The demand for railway transportation is increasing in recent years [1], which leads to an upward trend for energy consumption on RPSs. This trend poses a challenge for limited energy generation. It also affects the power quality (PQ) of RPS, cost of power generation and efficiency of long distance transmission. RPS has serious power unbalance characteristics and power quality issues due to the railway electrification as discussed in [2] and [3]. Furthermore, because most railway routes are built in remote and open areas, lack of instantaneous power supplement and efficient power management methods will not ensure the satisfactory power operation between two main power generation substations along the RPS [1]. Voltage fluctuation is one of these issues. Several solutions can be implemented for improving voltage regulation in conventional power systems individually. Some of the strategies were proposed to improve the voltage regulation, including by adjusting on-load transformer tap or implementing reactive power compensation measures [4]-[6]. Various objective functions and corresponding optimization algorithms to decrease technical losses were presented in [7]-[8]. However, electric locomotive load can cause more intensive voltage fluctuation in a short time period [9]. Under this circumstance, classical solutions have limited impacts. These solutions are not fast enough to deal with the voltage variation, thereby maintain PQ.

High penetration of DGs in Distribution Networks (DN) has transformed the conventional power systems. There are many economical and technical benefits from renewable energy sources (RES) besides clean energy. However, literature has solely highlighted the technical challenges, such as uncertain power generation, impacts of bi-directional power flow on system protection, distribution system planning and operation.

This work can be seen as a contribution to mathematical-based analytical methodologies which utilizes the dynamic reactive power capability of smart inverters for real-time PQ management. The amendments for IEEE 1547 interconnection standard allow for active voltage regulation [10] and we plan to use this for PQ management in RPS. We envision a multi-agent architecture, in which each DG agent would to optimize power losses and improve PQ in RPS using Volt/VAR sensitivity analysis. The trades-offs between power losses and voltage regulation can be realized by the proposed control approach.

The remaining content of this paper is organized as follows. In section II, problem formulation is discussed. In section III, control strategy is presented. In section IV, case study is presented. Concluding remarks are presented in Section V.

II. Problem Formulation

Previous works such as [7] discuss the voltage regulation problem on DNs, where the reactive power of DG's are controlled through a Volt/VAR sensitivity analysis. Although, these works presented interesting results, technical losses are not considered in problem formulation.

As stated in [4], optimal inverter VAR control strategy on a fast timescale can be used to mitigate fast voltage fluctuations due to high penetration of photovoltaic generation. Both

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system losses and energy consumption are considered in the optimization problem. However, only one DG is considered on problem formulation. If more than one DG would to be connected into the system, the corresponding control strategy should be adjusted.

ESS can be utilized to facilitate the interconnection of increased DGs on DNs. In [11] and [12], an energy storage system is proposed to smooth the output of photovoltaic power generation, which realizes the transition from intermittent renewable energy to controllable energy. This approach, however, does not take into account the actual power demand on systems.

Combining all the aforementioned issues, including voltage regulation, Volt/VAR sensitivity control model, energy storage system and global optimization, this work presents a multi-agent strategy for real-time power quality management and power losses control. In the following section, the proposed distributed control strategy is presented.

III. ANALYTICAL METHOD

A. Control System Formation

With the advent of several smart grid technologies and RES high level penetration, we advocate a multi-agent strategy for DNs PQ management and losses optimization. In this work, solar energy is the DER of interest. Solar energy has numerous advantages like low cost, flexible size, and it produces no noise and pollution [11].

Proposed multi-agent strategy is illustrated in Fig. 1. Each agent is composed by a control agent, a smart inverter, the solar panels, and battery. The control agent consists of a database center, a control algorithm implementer, and the signal controller. The function of the control agent is to actuate on the smart inverter.

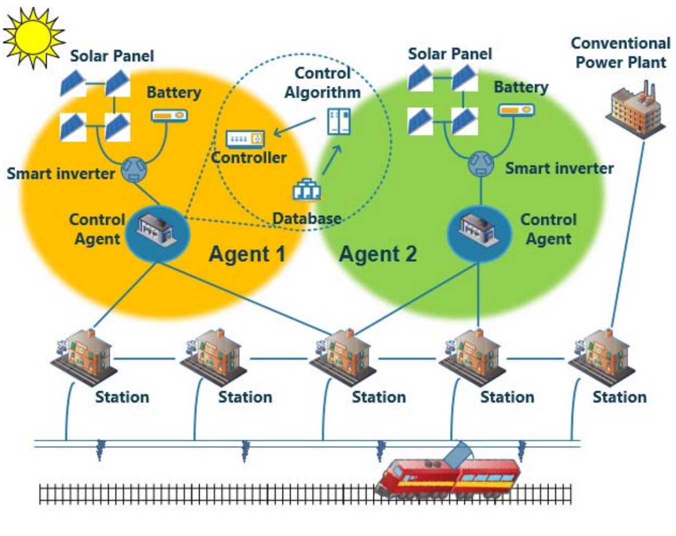

Fig. 1. General RPS model with DG connection

The flow chart in Fig. 2 presents the overall data flow of the proposed strategy. In this control model, final solution is determined by the global optimization problem. Before implementing this step, economic Volt/VAR sensitivity analysis is proposed to estimate ideal reactive power for each DG unit. The available solar power is transformed to appropriate output by adaptive energy reserve approach. Then, the ideal power is derived from these prerequisites. In this work, ideal power means power that can help maintain voltage profile within an acceptable range without considering other system objectives. The rating of inverter at the interconnection point of DG is assumed to be greater than the maximum energy available from DER.

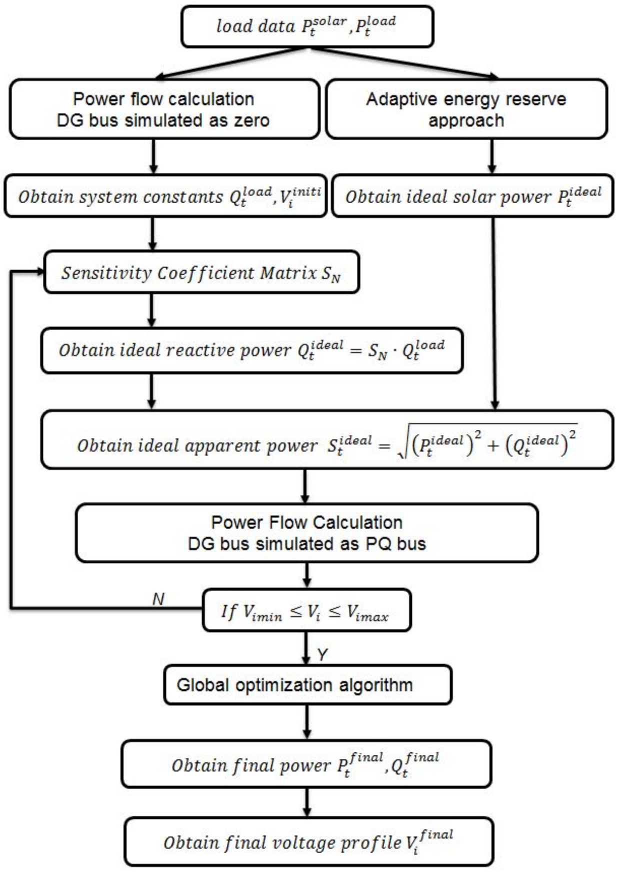

Fig. 2. Control algorithm flow chart

B. Economic Volt/VAR sensitivity control

In this work, Volt/VAR sensitivity is defined as the impact level of reactive power generated from various stations on voltage magnitude of load buses. Specific sensitivity relationship is obtained from Jacobian matrix in the power flow equations [13]-[14], as shown in the following:

$$J \cdot \begin{bmatrix} \Delta\theta_1 \\ \vdots \\ \Delta\theta_n \\ \Delta V_1 \\ \vdots \\ \Delta V_n \end{bmatrix} = \begin{bmatrix} \Delta P_1 \\ \vdots \\ \Delta P_n \\ \Delta Q_1 \\ \vdots \\ \Delta Q_n \end{bmatrix} \tag{1}$$

Where $\Delta\theta_n$ is the phase angle variations at bus n. ΔV_n is the nodal voltage variations and J is the Jacobian matrix, which is formulated by calculating derivation of power to state variables.

$$J = \begin{bmatrix} J_{P\theta} & J_{PV} \\ J_{Q\theta} & J_{QV} \end{bmatrix} \quad (2)$$

However, compared to reactive power, active power has less impact on system voltage profile. Thus initial Volt/VAR sensitivity matrix can be obtained by assuming ΔP_n equals to zero.

$$J'_N = J_{QV} - J_{Q\theta} \cdot inv(J_{P\theta}) \cdot J_{PV} \quad (3)$$

Furthermore, associated cost for different power generation modes, including the conventional power plants existing in the system, should be considered into the sensitivity matrix. In this work we propose to assign weights to output power for each station and improve power dispatch efficiency, both technically and economically. Thus, the financial condition represents the corresponding weight factor, which is given by the following equations:

$$W_i = \frac{\sum_i^{ng} COST_i}{COST_i} \quad (4)$$

Where $COST_i$ is the levelized cost of energy on each power generation station and ng represents the total number of power generation buses in the system. From this equation, higher economic weight means lower price investment, which translates in higher tendency to use.

Thus initial economic sensitivity matrix is adjusted from Equation (3) to the following matrix:

$$J'_N = \begin{bmatrix} W_i \frac{\partial Q_i}{\partial V_j} & \cdots & W_i \frac{\partial Q_i}{\partial V_{nl}} \\ \vdots & \ddots & \vdots \\ W_{ng} \frac{\partial Q_{ng}}{\partial V_j} & \cdots & W_{ng} \frac{\partial Q_{ng}}{\partial V_{nl}} \end{bmatrix} \quad (5)$$

Where nl represents the total number of buses in the system.

And the sum of each column of the above matrix is the base value for calculating the sensitivity coefficient for each load bus j. The corresponding equation is given by:

$$Sum_j = \sum_i^{ng} \left| W_i \frac{\partial Q_i}{\partial V_j} \right| \quad (6)$$

The final economic sensitivity coefficient matrix S_N is thus derived, as presented in the following:

$$S_N = \begin{bmatrix} \frac{\left| W_i \cdot \frac{\partial Q_i}{\partial V_j} \right|}{Sum_j} & \cdots & \frac{\left| W_i \cdot \frac{\partial Q_i}{\partial V_{nl}} \right|}{Sum_{nl}} \\ \vdots & \ddots & \vdots \\ \frac{\left| W_{ng} \cdot \frac{\partial Q_{ng}}{\partial V_j} \right|}{Sum_j} & \cdots & \frac{\left| W_{ng} \cdot \frac{\partial Q_{ng}}{\partial V_{nl}} \right|}{Sum_{nl}} \end{bmatrix} \quad (7)$$

Because the voltage profile of each load bus is impacted by its power consumption, we can infer that the ideal reactive power of each power generation station is directly proportional to the reactive power demanded on load buses. So the ideal reactive power of each power generation bus is derived by:

$$\begin{bmatrix} Q_{ideal-i} \\ \vdots \\ Q_{ideal-ng} \end{bmatrix} = S_N \cdot \begin{bmatrix} Q_j \\ \vdots \\ Q_{nl} \end{bmatrix} \quad (8)$$

C. Adaptive Energy Reserve Approach

The adaptive energy reserve approach in this method takes into consideration dynamics in available solar energy and load consumption. Fig. 3 shows the complete energy reserve data flow chart.

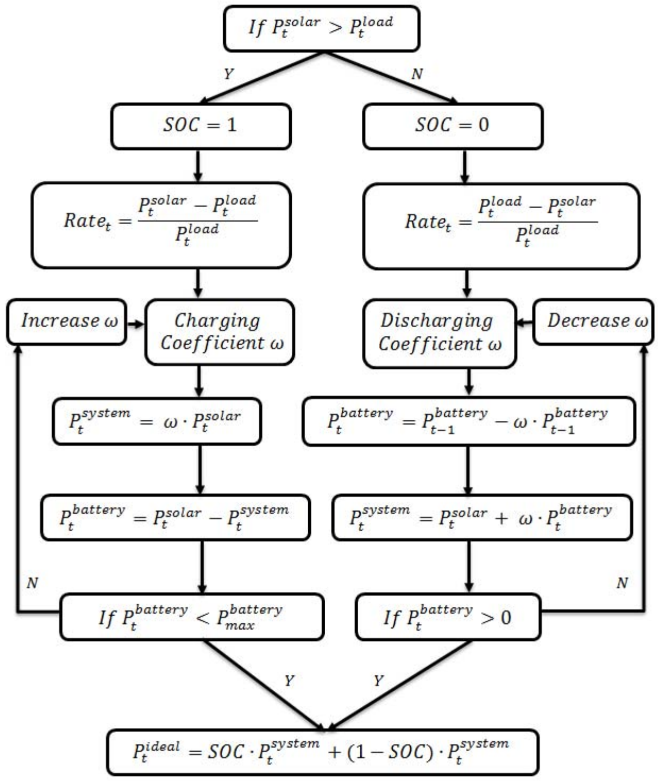

Fig. 3. Adaptive energy reserve approach flow chart

Where P_t^{solar} is the initial solar power profile and P_t^{load} is the power consumption of RPS.

$$Rate_t = \frac{\left| P_t^{solar} - P_t^{load} \right|}{P_t^{load}} \quad (9)$$

By comparing these two different power profiles, the status of charging or discharging (SOC) for battery is determined, and the corresponding charging or discharging coefficient could be selected by the difference rate, which is presented in equation (9) under each branch. Charging or discharging coefficient ω determines state of operation of ESS (charge or discharge). The benefit of comparing these two energy profiles is to utilize distributed energy resources, to the fullest decrease resources waste, and to provide more reasonable power, and to meet the power demand of the system.

D. Multi-objective optimization

Goal programming is a multi-objective optimization technique based on the concept of trying to achieve a specific set of goals that are at the nearest possible distance from the optimal solution [15]. Because of the non-linear characteristic of this multi-objective function, it may be hard to find the optimal solution. Thus the nearest solution will be seen as the best solution, which is constrained in the small distance range from optimal solutions [18].

Different goal functions in multi-objective optimization problems may have various magnitude ranges. To tackle this, a weighted goal programming approach is proposed. The basic principle is that the weight coefficient is added to each part to achieve the magnitude uniformity for whole function [18]. The optimization model is proposed as the following equation and gradient descent algorithm [14] is used to search final solutions in MATLAB.

$$Min \quad F(x) = w_l \cdot P_{loss} + w_v \cdot \gamma \cdot \left(\frac{\Delta V_i}{\Delta V}\right)^2 + \sum_i^{np} w_{pi} \cdot \left(P_i^{ideal} - P_i\right)^2 + \sum_i^{np} w_{Qi} \cdot \left(Q_i^{ideal} - Q_i\right)^2 \quad (10)$$

Subject to:

$$V_{imin} \le V_i \le V_{imax} \quad (11)$$

Where:

$$\Delta V_i = \begin{cases} V_i - V_{imax} & if\ V_i > V_{imax} \\ 0 & if\ V_{imin} < V_i < V_{imax} \\ V_{imin} - V_i & if\ V_i < V_{imin} \end{cases} \quad (12)$$

$$\Delta V = V_{imax} - V_{imin} \quad (13)$$

$$P_{loss} = \sum_i^n \sum_j^n G_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j cos(\theta_i - \theta_j)\right) \quad (14)$$

$$P_i = V_i \sum_{j=1}^n V_j\left(G_{ij} cos(\theta_i - \theta_j) + B_{ij} sin(\theta_i - \theta_j)\right) \quad (15)$$

$$Q_i = V_i \sum_{j=1}^n V_j\left(G_{ij} sin(\theta_i - \theta_j) - B_{ij} cos(\theta_i - \theta_j)\right) \quad (16)$$

γ is the penalty factor if the voltage index is out of expected range.

And each weight coefficient for multi-objective function is given by the following equation by order.

$$\omega_l = \frac{1}{\max(P_{loss}) - \min(P_{loss})} \quad (17)$$

$$\omega_v = \frac{1}{\max\left(\gamma \cdot \left(\frac{\Delta V_i}{\Delta V}\right)^2\right) - \min\left(\gamma \cdot \left(\frac{\Delta V_i}{\Delta V}\right)^2\right)} \quad (18)$$

$$\omega_{pi} = \frac{1}{\max\left(\left(P_i^{ideal} - P_i\right)^2\right) - \min\left(\left(P_i^{ideal} - P_i\right)^2\right)} \quad (19)$$

$$\omega_{Qi} = \frac{1}{\max\left(\left(Q_i^{ideal} - Q_i\right)^2\right) - \min\left(\left(Q_i^{ideal} - Q_i\right)^2\right)} \quad (20)$$

IV. CASE STUDY

A. Test System

A six-bus system model is chosen for method validation. The model data can be found in [16], with some modifications to introduce DG, which are described in the following.

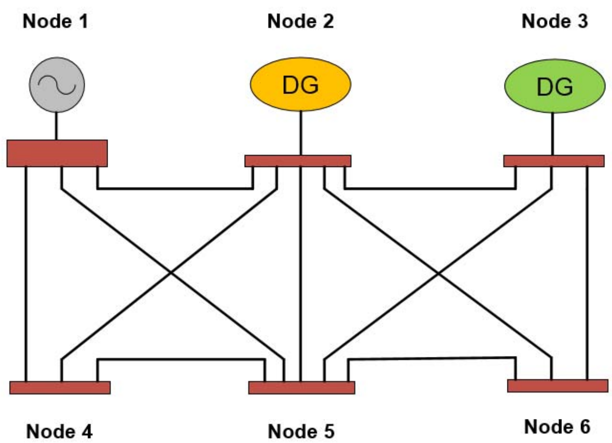

Fig. 4. Six-bus test system

Node-1 is considered as the slack bus connected to conventional distribution substations. Two DGs are connected at node-2 and node-3. All other buses will be simulated as traction substations, which is connected to each nearby substation and labeled as node-4, node-5 and node-6. These traction substations will provide power to load directly.

In this paper, recorded measurements of solar insolation from National Radiation Data Base (NERL) are used to simulate solar energy pattern. The simulation result is shown in Fig. 5.

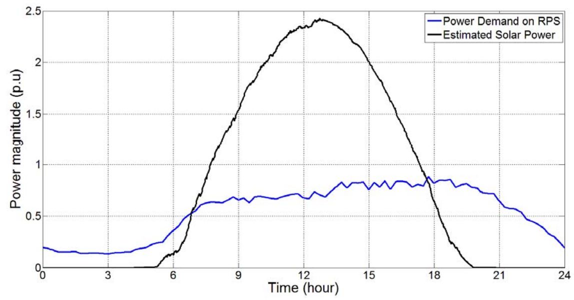

Fig. 5. Comparison: forecast solar power and load power consumption per unit

From [17], the measured data from DB Fernverkehr AG Company has been used to simulate load power consumption on the RPS, which is given by equation:

$$E_{total-t} = N_{timetable-t} \cdot P_t \cdot E_{speed} \quad (21)$$

Where $E_{total-t}$ represents the total energy consumption or power demanding for railroad system at time t. And P_t

describes the punctuality by comparing number of actual running trains in the system and that from the pre-configured timetable. E_{speed} stands for the energy consumption for each vehicle under the target speed [17]. The simulation result is also shown in the Fig. 5.

A 16,000 square meters is selected as the base size of solar panel for each DG station, and 8.5 MW power is determined as the base value for power. By applying proposed adaptive energy reserve energy, the stored energy change in the battery is presented in Fig. 6.

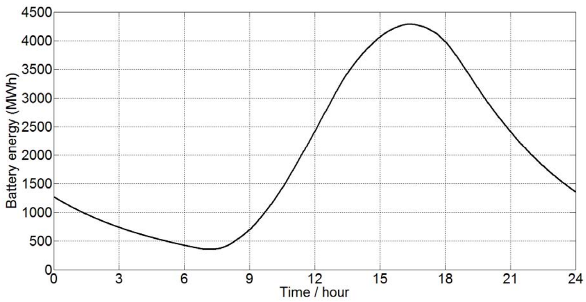

Fig. 6. Stored energy in battery from adaptive energy reserve approach.

B. Voltage Profile Comparison

Fig. 7 and Fig. 8 illustrates the comparison with voltage profile for all connection buses over 24 hours before DG connection and after overall control strategy.

Because the problem is defined as of global optimization, the voltage profile of each DG station is the control goal as well. Fig. 9 presents the voltage profile for two DGs.

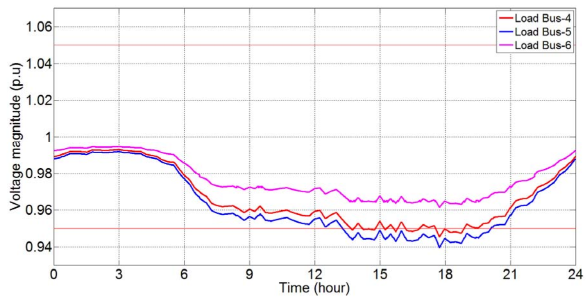

Fig. 7. Initial voltage profile for load bus without DG connection

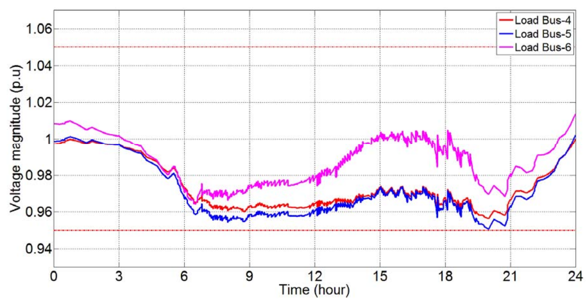

Fig. 8. Final voltage profile for load bus after overall control process

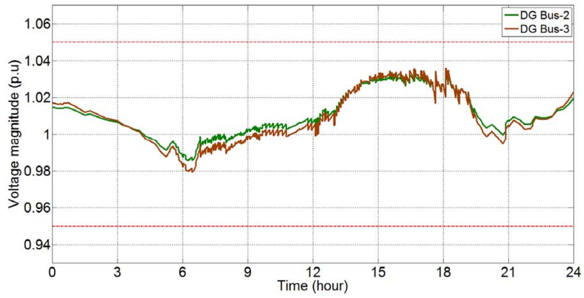

Fig. 9. Final voltage profile for DG connection bus

C. Ideal Power for DG stations

Fig. 10 and Fig. 11 presents the ideal active power and the ideal reactive power pattern for each DG agent.

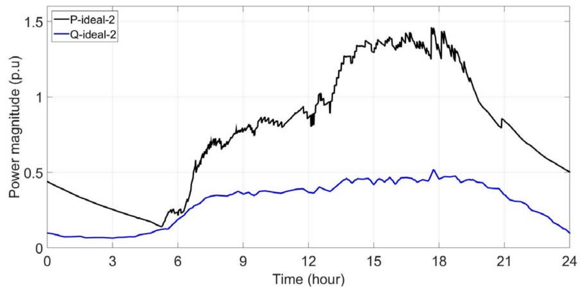

Fig. 10. Ideal active power and reactive power for DG-bus-2

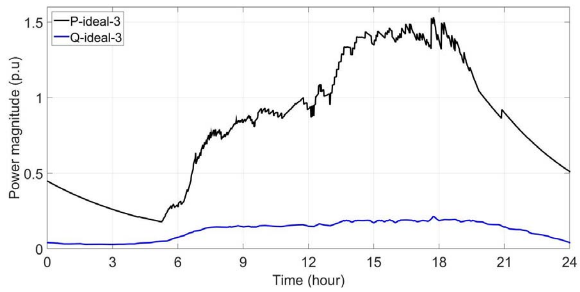

Fig. 11. Ideal active power and reactive power for DG-bus-3

D. Optimization Results

Fig. 12 presents the reduction of the value of objective function before and after optimization, including power losses reduction. It shows the viability of proposed control strategy

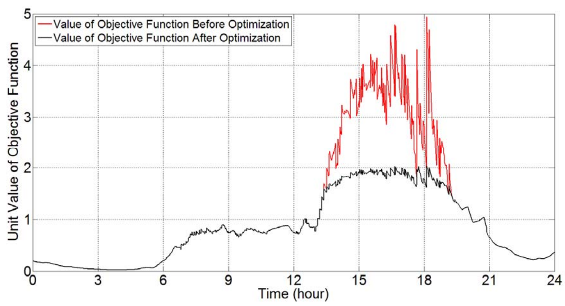

Fig. 12. Comparison with the value of objective function before and after optimization

E. Appendix data

The difference rate with its corresponding charging and discharging coefficient for proposed control approach validation is presented in Table. I. The line data of six-bus test system is presented in Table. II.

TABLE I. DIFFERENCE RATE WITH CORRESPONDING CHARGING AND DISCHARGING COEFFICIENT LIST

Absolute value of difference rate	SOC=1	SOC=0	
		before 12:00 a.m	***after 12:00 a.m***
0.0~0.1	1	0.0035	0.0014
0.1~0.2	0.95	0.00345	0.0015
0.2~0.3	0.90	0.0034	0.0016
0.3~0.4	0.85	0.00335	0.0020
0.4~0.5	0.80	0.0033	0.0022
0.5~0.6	0.75	0.00325	0.0023
0.6~0.7	0.70	0.0032	0.0025
0.7~0.8	0.65	0.00315	0.0027
0.8~0.9	0.60	0.0031	0.0029
0.9~1.0	0.58	0.00305	0.0030
1.0~1.1	0.56	0.003	0.0032
1.1~1.2	0.54	---	---
1.2~1.3	0.52	---	---
1.3~1.4	0.50	---	---
1.4~1.5	0.48	---	---
1.5~1.6	0.46	---	---
1.6~1.7	0.44	---	---
1.7~1.8	0.42	---	---
1.8~1.9	0.40	---	---
1.9~2.0	0.38	---	---
2.0~2.1	0.36	---	---
2.1~2.2	0.34	---	---
2.2~2.3	0.32	---	---
2.3~2.4	0.30	---	---
2.4~2.5	0.28	---	---

TABLE II. LIST OF LINE PARAMETERS OF SIX-BUS SYSTEM

From Bus-i	To Bus-j	Resistance (p.u)	Reactance (p.u)	Bus Shunt (p.u)
1	2	0.10	0.20	0.02
1	4	0.05	0.20	0.02
1	5	0.08	0.30	0.03
2	3	0.05	0.25	0.03
2	4	0.05	0.10	0.01
2	5	0.10	0.30	0.02
2	6	0.07	0.20	0.025
3	5	0.12	0.26	0.025
3	6	0.02	0.10	0.01
4	5	0.20	0.40	0.04
5	6	0.10	0.30	0.03

V. CONSLUSIONS

In this work, a multi-agent strategy considering DG integration for power quality management of RPS is presented. An adaptive energy reserve approach utilizing both the available solar energy and ESS, taking the power demand into the account, is presented. Furthermore, economic sensitivity analysis leverages financial cost condition for power generation and power dispatch based on system structure. A goal programming model is proposed for the multi-objective optimization problem.

From the perspective of simulation results, the proposed approach can improve voltage profiles and decrease power losses simultaneously. Thus, we conclude that the success of this control model can present great benefits for DNs operation and general case for DERs use for real-time PQ management.

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