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

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Abstract—**Railway system is 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 to railway loads, maintaining power quality is an imperative challenge for railway power systems (RPS). This paper addresses the economic active power dispatch and coordination problem in RPS considering distributed generation (DG) interconnected via smart inverters. An adaptive energy reserve approach is presented, which routes the surplus energy available to the energy storage system (ESS) to be utilized eventually, considering the constraints on the smart inverter capacity. The power quality problem of maintaining a good voltage profile is formulated as a multi-objective optimization problem. Simulation results from a six-bus system indicate effective reduction in the technical losses and the stress on automatic regulators, and highlight the potential aspects for real-life applications.**

Index Terms--**Automatic voltage control, Distributed power generation, Energy storage, Power generation dispatch, Global optimization**

I. INTRODUCTION

The electrification of RPSs yields convenience and high-efficiency. The demand for railway transportation results in an upward trend for the energy consumption of RPSs [1]. This trend poses a challenge for limited energy generation. It is also affects the power quality (PQ) of RPSs, cost of power generation and efficiency of long distance transmission. Serious power imbalance characteristics and PQ issues due to the railway electrification have been presented in [2] and [3]. Furthermore, because most railroads are built in remote and open areas, lack of instantaneous power supplement and efficient PQ management methods will not ensure the satisfactory power operation between two main power generation substations along the RPS [1]. Voltage fluctuation is one of the issues. Although, some classic solutions, including on-load transformer tap changers and reactive power compensation measures (shunt and series reactors/capacitors) [4]-[6], can be implemented for improving voltage regulation. The problem of technical losses reduction is modeled as an optimization problem and presented in these works [7]-[8]. However, electric locomotive load can cause more intensive voltage fluctuation in a short time period [9]. These classical solutions have limited impacts under this circumstance: the rapid voltage variation cannot be controlled very timely and quickly, thereby maintain PQ. Furthermore, these techniques will not be able to mitigate voltage regulation problems with increased renewable energy penetration.

High penetration of DGs in distribution networks (DNs) has transformed the conventional power systems landscape. 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 [10], impacts of bi-directional power flow on system protection [11], complications in distribution system planning and operation.

According to the amendments for IEEE 1547 interconnection standard [12], DGs are allowed to actively regulate voltage of the system. Thus, we plan to use this strategy to manage PQ in RPS. This work can be seen as a contribution to mathematical-base analytical methodology which utilizes the dynamic power injection capability of smart inverters for real-time PQ management. We envision a multi-agent architecture, in which each DG agent would optimize power losses and improve PQ in RPS. For multi-agent coordination problem, economic power dispatch method is adopted to find the optimal dispatch. 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, the 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 [13] discusses the feasible coordinated control for multi terminal DC grids connected to offshore wind farms. Improved DC load flow algorithm considering active power coordination shows the successful management for power flows. But it ignores the impact of reactive power on voltage regulation. Similarly, the power injection coordination strategy in [14] provides inspiring ideas, it combines both active power and reactive power limitations.

However, it does not consider the cost function analysis for various energy sources, such as power plants and DG's.

The problems related to the voltage regulation on DN's are discussed in [7], where the reactive power of DG's are controlled through a Volt/VAR sensitivity analysis. Although, this work presented interesting results, technical losses were 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 system losses and energy consumption are considered in the optimization problem. However, only one DG is considered on problem formulation. The corresponding control strategy should be adjusted if a multi-agent system exists.

ESS can be utilized to facilitate the interconnection of increased DGs on DNs. In [15] and [16], 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 solutions, Volt/VAR control modes, ESS control strategies and various optimization algorithms, this work presented a multi-agent strategy for real-time PQ 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 because solar energy has numerous advantages like low cost, flexible size, and it produces no noise and pollution [15].

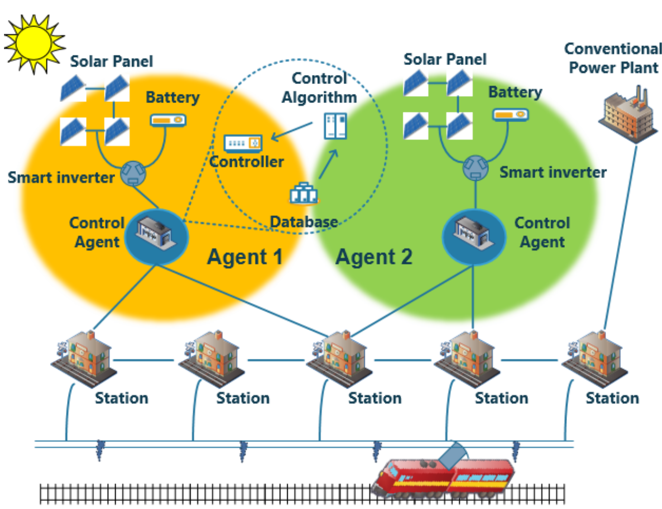

Figure 1. General RPS model with DG interconnection

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 corresponding smart inverter.

The flow chart in Fig. 2 presents the overall data flow of the proposed strategy. In this control model, final power output is determined by the global optimization problems. Before implementing this step, economic active power dispatch analysis is performed to compute optimal power dispatch of each energy source. The available solar power is routed to appropriate output power by adaptive energy reserve approach. The impact of the power handling capacity of the smart inverter is considered in this voltage regulation problem to maintain a good voltage profile. As stated in this flow chart, appropriate size of the smart inverters is selected for practical situation according to the ideal apparent power amount. In this work, ideal power means the power required to maintain voltage profile within an acceptable range without considering other system objectives.

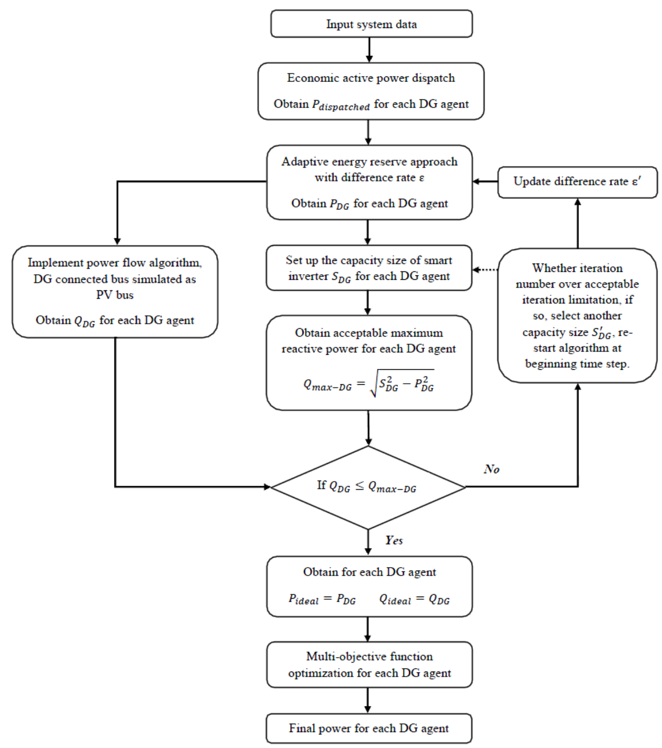

Figure 2. Control algorithm flow chart

B. *Economic Active Power Dispatch*

In this multi-agent control architecture, both DG agents and the conventional power plants are responsible for supplying power to systems. Various types of power injection plants have different input-output characteristics, consequently, have different marginal costs. Although each DG agent has its own control region, reliable power dispatch can provide reasonable power injection basis both technically and economically.

To accurately estimate corresponding dispatched power for each control agent, Lagrange Multiplier method [17] is utilized to realize the coordination among each agent. Also, network losses is considered into the algorithm to produce more precise calculation results. The economic dispatch problem is formulated as following:

$$Min \qquad F_T = \sum_{i=1}^{N_{gen}} F_i(P_i) + \sum_{j=1}^{N_{DG}} F_j(P_j) \tag{1}$$

$$\text{s.t} \quad \phi = 0 = P_{load} + P_{loss} - \sum_{i=1}^{Ngen} P_i - \sum_{j}^{N_{DG}} P_j \tag{2}$$

The F_T is equal to the total cost for supplying the indicated power, N_{gen} is the total number of generators in systems, N_{DG} is the total number of DG agent in systems, P_{load} is the load demand on systems and P_{loss} is the technical losses existing in power transmission process.

The coordination equation or Lagrange function is organized as following:

$$£ = F_T + \lambda \cdot \phi \tag{3}$$

$$\frac{\partial £}{\partial P_i} = \frac{\partial F_i}{\partial P_i} - \lambda \cdot \left(1 - \frac{\partial P_{loss}}{\partial P_i}\right) \tag{4}$$

Where λ is the Lagrange multiplier, it keeps updating with the algorithm operation until the objective function is satisfied.

In this work, F_i is simulated as quadratic equation with the corresponding injection power serving as the variable for power plants. We propose a different model for DG's. The mathematics expression of power losses is simplified as sum of the multiple quadratic equation [17]. It is a function of the power output of each of the units.

$$P_{loss} = \sum_{i}^{N_{gen}} C_i \cdot P_i^2 + \sum_{j}^{N_{DG}} C_i \cdot P_j^2 \tag{5}$$

Where the C_i is the weight constant for each output power, it depends on the power injection capacity of each unit.

We propose a capital cost recovery model for the solar plants. The marginal cost function is computed by taking the time to recover the invested capital cost into consideration. The marginal cost of the solar plant is more when the plant is operating at its partial capacity to a full capacity. The amount of power injected into the DG's is computed by the adaptive energy reserve approach. The marginal cost of all the energy sources is then computed using the energy obtained by optimal dispatch. Fig. 3 shows one example for marginal cost change pattern against its injection power for solar plants with different capacity.

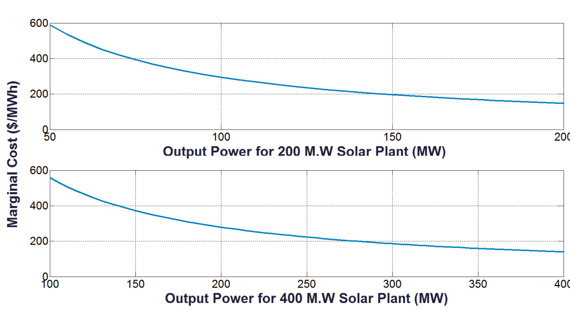

Figure 3. The marginal cost examples of solar plants with different power injection capacity

C. Adaptive Energy Reserve Approach

The adaptive energy reserve approach in this work takes into consideration dynamics in available solar energy and dispatched power for each DG agent. Fig. 4 shows the complete energy reserve data flow chart.

By comparing these two different power patterns, the battery status (SOC) is determined. If SOC is positive, the battery is in charging state; if SOC is negative, the battery is in discharging state. Then P_{DG} is calculated according to the iteration number. The total charging or discharging coefficient will vary for every iteration. Relatively, the energy inside the battery is calculated according to different SOC.

Difference rate ε and Δε will define the acceptable variation range for P_{DG}, which makes P_{DG} pattern extremely close to the $P_{dispatched}$ pattern. These constants can be pre-set by experiment, or empirical data.

$$P_{DG} = n \cdot \omega \cdot P_{solar} \cdot \frac{(1+SOC)}{2} + \left(n \cdot \omega \cdot P_{battery} + P_{solar}\right) \cdot \frac{(1-SOC)}{2} \tag{6}$$

$$P_{battery} = n \cdot \omega \cdot P_{solar} \cdot \frac{(1+SOC)}{2} + \left(n \cdot \omega \cdot P_{battery} + P_{solar}\right) \cdot \frac{(1-SOC)}{2} \tag{7}$$

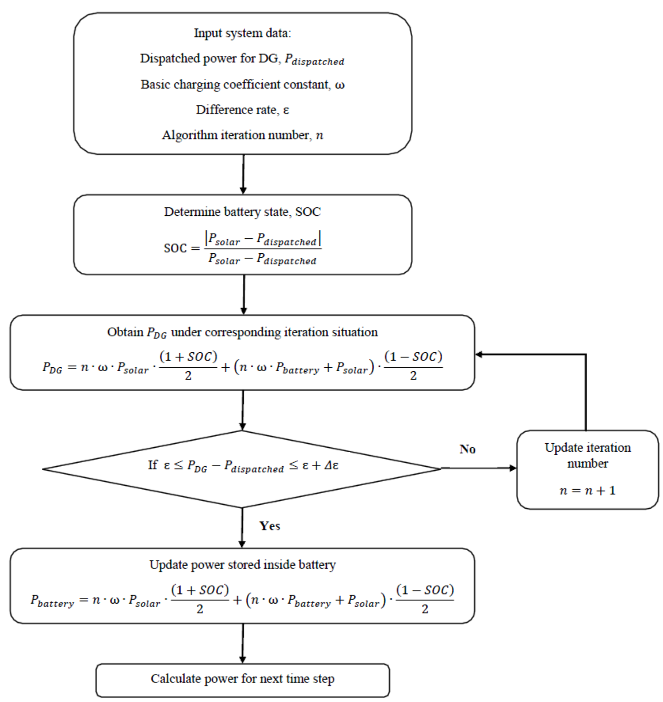

Figure 4. Adaptive energy reserve approach flow chart

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 [18]. 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 [19].

Different goal functions in optimization problem may have various magnitude ranges. To tackle this, a weighted goal programming is proposed. The basic principle is that the weight coefficient is added to each part to achieve the magnitude uniformity for whole function [19]. The optimization model is proposes as the following equation:

$$Min \quad F_{DG}(x) = w_l \cdot P_{loss-k} + \gamma \cdot \left(\frac{\Delta V_k}{\Delta \mathrm{V}}\right)^2$$

$$+w_p \cdot \left(P_{DG}^{ideal} - P_{DG}^{final}\right)^2 + w_Q \cdot \left(Q_{DG}^{ideal} - Q_{DG}^{final}\right)^2 \quad (8)$$

$$k \in DG\ region$$

Subject to:

$$V_{min} \le V_k \le V_{max} \quad (9)$$

$$P_{final}^2 + Q_{final}^2 \le S_{DG}^2 \quad (10)$$

Where:

$$\Delta V_k = \begin{cases} V_k - V_{max} & if\ V_k > V_{max} \\ 0 & if\ V_{min} < V_k < V_{max} \\ V_{min} - V_k & if\ V_k < V_{min} \end{cases} \quad (11)$$

$$\Delta \mathrm{V} = V_{max} - V_{min} \quad (12)$$

$$P_{loss} = \sum_i^k \sum_j^k G_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j cos(\theta_i - \theta_j)\right) \quad (13)$$

$$P_{DG}^{final} = V_{DG} \sum_{j=1}^{k} V_{DG}\left(G_{DG-j} cos(\theta_{DG} - \theta_j) + B_{DG-j} sin(\theta_{DG} - \theta_j)\right) \quad (14)$$

$$Q_{DG}^{final} = V_{DG} \sum_{j=1}^{k} V_j\left(G_{DG-j} sin(\theta_{DG} - \theta_j) - B_{DG-j} cos(\theta_{DG} - \theta_j)\right) \quad (15)$$

Where γ is the penalty factor if the voltage index is out of expected range. DG represents the number of control agent.

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

$$\omega_l = \frac{1}{\max(P_{loss}) - \min(P_{loss})} \quad (16)$$

$$\omega_{pi} = \frac{1}{\max\left(\left(P_{DG}^{ideal} - P_{DG}^{final}\right)^2\right) - \min\left(\left(P_i^{ideal} - P_{DG}^{final}\right)^2\right)} \quad (17)$$

$$\omega_{Qi} = \frac{1}{\max\left(\left(Q_i^{ideal} - Q_{DG}^{final}\right)^2\right) - \min\left(\left(Q_i^{ideal} - Q_{DG}^{final}\right)^2\right)} \quad (18)$$

IV. Case Study

A. Test System and Data

A six-bus system model is chosen for method validation, the system is presented in Fig. 5.

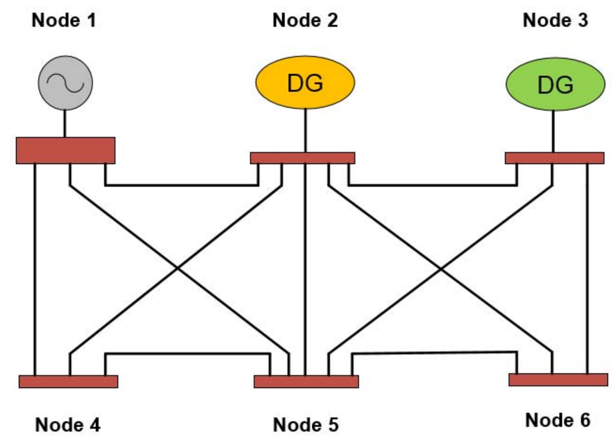

Figure 5. Six-bus test system

The model data can be found in [17], some modifications have been made to introduce DG into the system. Node-1 is considered as the slack bus connected to the 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 directly supply electricity to load.

In this paper, recorded measurements of solar insolation from National Radiation Data Base (NREL) are used to simulate the solar energy pattern. The measured data from DB Fernverkehr AG Company has been used to simulate the load power consumption [20]. These data patterns are shown in the Fig. 6.

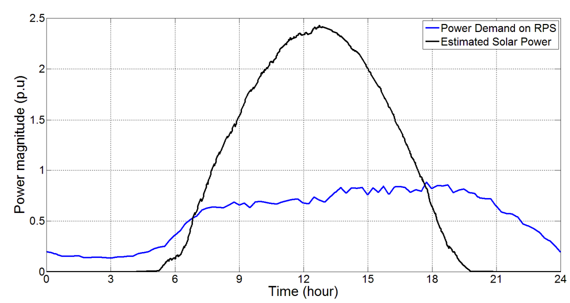

Figure 6. Comparison: Solar power pattern and load power consumption pattern per unit

Through experiment, a 16,000 square meters is selected as the base size of solar plant for each DG station, and 8.5 MW power is determined as the base value for power calculation. 11.9 MW is determined as the capacity size of smart inverters.

B. Simulation from Energy Reserve Approach

By applying the proposed adaptive energy reserve approach, the stored energy pattern in each ESS is presented in Fig. 7.

From the simulation, even if the same initial battery energy is pre-set for two ESS's, the result shows the different energy change pattern due to the various power dispatched from the coordination method.

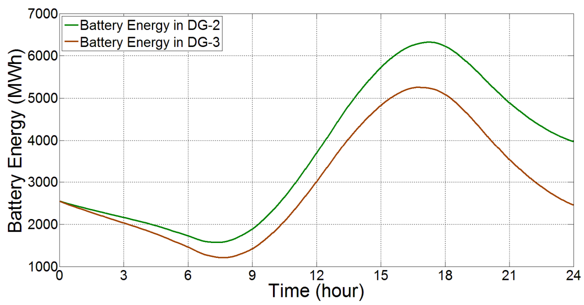

Figure 7. Battery energy pattern in each DG agent

In Fig. 8 and Fig. 9, the comparison of the ideal power and dispatched power is presented for each ESS. The difference between ideal power and dispatched power is determined by the difference rate ε and the acceptable rate change range Δε.

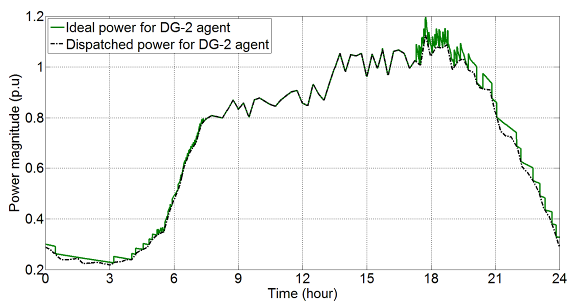

Figure 8. Comparison: Ideal power pattern and dispatched power pattern for DG-2 agent with difference rate $\varepsilon = 0$ and $\Delta\varepsilon = 0.2$

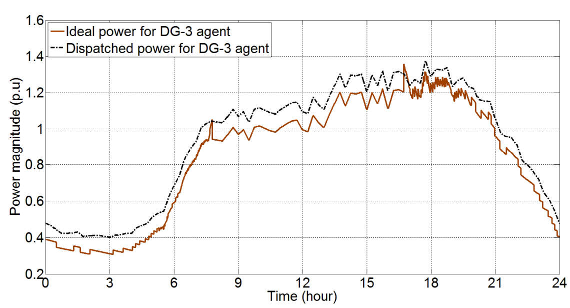

Figure 9. Comparison: Ideal power pattern and dispatched power pattern for DG-3 agent with difference rate $\varepsilon = -0.1$ and $\Delta\varepsilon = 0.2$

From this simulation result, intermittent solar power pattern is transformed to the power pattern that is extremely close to the dispatched power, with maintaining the enough battery energy for further utilization simultaneously, which is illustrated in Fig. 7.

C. Voltage Profile Comparison

Fig. 10 and Fig. 11 illustrates the comparison with voltage profile for load buses over 24 hours before DG connection and after optimization.

From the simulation results, the proposed control approach can effectively improve voltage profiles and maintain them inside pre-set acceptable range. The final voltage pattern is related to the final power output pattern, which is obtained from the global optimization.

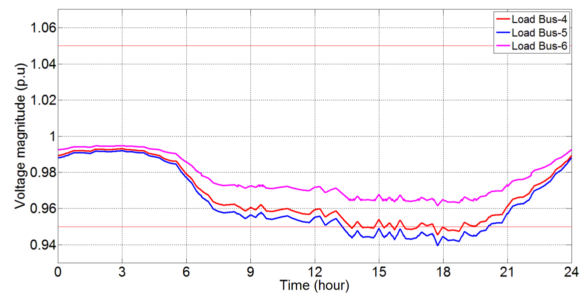

Figure 10. Initial voltage profile for load bus without DG connection

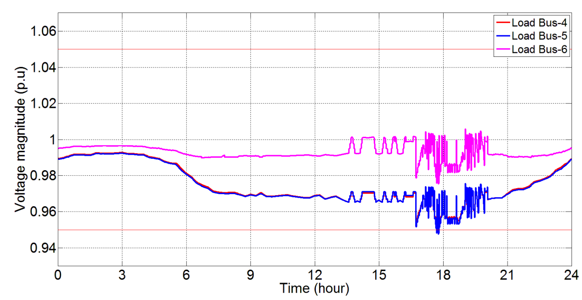

Figure 11. Final voltage profile for load bus after global optimization

D. Multi-objective Optimization Results

Fig. 12 and Fig. 13 presents the reduction of the value of objective function in each DG agent before and after optimization, including the power losses, the distance between final power pattern and ideal power pattern. In this work, the Gradient Descent method [21] is used to realize optimization.

For system global optimization, the reduction of value of objective function indicates the reduction of power technical losses, and the difference between the ideal output power and the final output power.

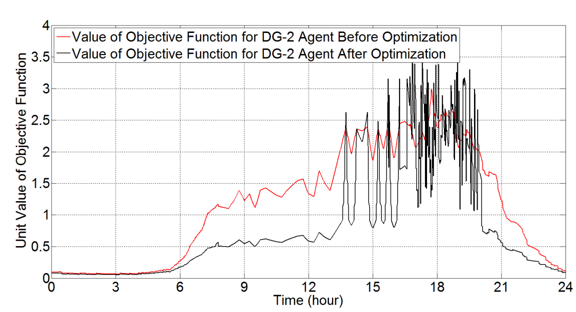

Figure 12. Comparison: The value of objective function DG-2 agent

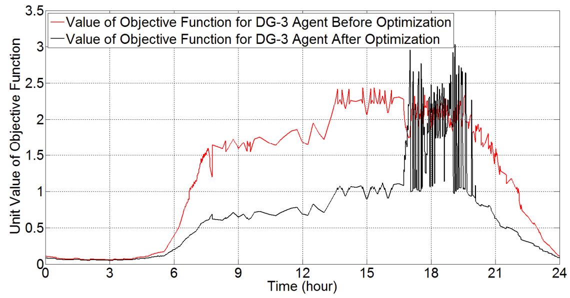

Figure 13. Comparison: The value of objective function for DG-3 agent

Fig. 14 and Fig. 15 present the final output power pattern.

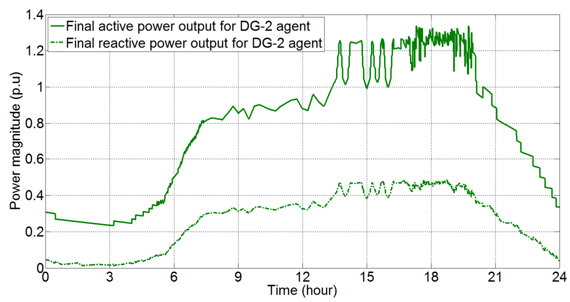

Figure 14. Final output active power and reactive power for DG-2 agent

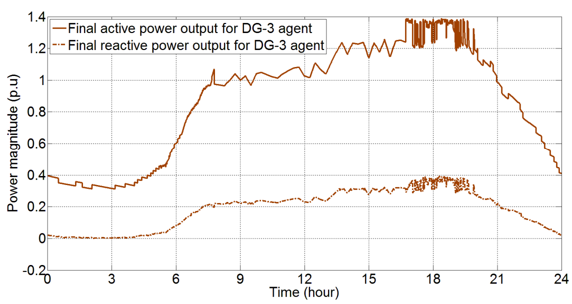

Figure 15. Final output active power and reactive power for DG-3 agent

However, due to the limitation of power injection capacity of smart inverters, the results for final output power are not so encouraging, especially when the power demand is huge.

E. Appendix data

The line data of six-bus test system is presented in Table. I.

TABLE I. LIST OF LINE PARAMETERS FOR 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	0.04

V. CONCLUSIONS

In this work, a multi-agent strategy considering DGs integration for power quality management of RPS is presented. Economic active power coordination method leverages the financial cost condition for power generation and demanded power dispatch based on the system structure. A weighted goal programming model is proposed for the multi-objective optimization problem, considering the system power technical losses, voltage profile maintaining and PQ management inside each DG control agent.

We can 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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