PHEVs Contribution to the Self-Healing Process of Distribution Systems

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***Abstract*—Traditionally, distribution system takes a long time to recover after a major outage, due to its top-down operation strategy. As fast response energy resources, Plug-in Hybrid Electric Vehicles (PHEVs) can accelerate the load pickup process by compensating the imbalance between available generation and load in distribution system. In this paper, PHEVs are employed for reliable load pickup and faster self-healing process. The non-homogeneous Markov chain method has been employed for generation of synthetic driving behavior. The optimization problem of finding load pickup sequence to maximize restored energy is formulated as a Mixed Integer Linear Programming (MILP) problem. Simulation results on a 100-feeder test system demonstrate the benefit from PHEVs to restore more energy in a given recovery time. It also provides incentives to deploy a large amount of PHEVs to improve system resiliency.**

***Index Terms*--Distribution system, Markov chain, mixed integer linear programming, plug-in hybrid electric vehicles, self-healing.**

I. INTRODUCTION

Power outages cost billions of dollars every year and jeopardize the lives of hospital patients. Thus, it is critical to restore the system back to normal operating conditions efficiently and quickly. A self-healing smart grid is a sophisticated electrical platform that can keep itself stable during normal condition, automatically isolate its parts that are failing or about to fail, or enable a swift recovery process in the event of a natural disaster or human error [1]. To achieve self-healing functionality, restorative action is required to return the system to its normal state. This process begins with starting blackstart (BS) units, cranking non-blackstart (NBS) units, energizing transmission lines and restoring the loads [2-3]. Traditionally, when a utility company faces a major restoration effort, distribution operators must wait until the bulk transmission grid is fully or partially recovered and electricity is available to pass down to the lower-level system. This top-down restoration strategy prolongs distribution system recovery time. After receiving power from bulk transmission grid, utility operators reconfigure the distribution system and restore load following step-by-step guidelines.

The distribution restoration presents several challenges to system operators, e.g., operators may face simultaneous restorative actions of many distribution circuits in a short period of time. The restoration guidelines prepared offline fall short when system conditions continuously change during the recovery period. To better support operators in the restorative decision-making process, different heuristic optimization techniques have been proposed for distribution system restoration strategies, including, genetic algorithm (GA) [4], particle swarm optimization [5], ant colony optimization [6]. However, none of the mentioned algorithms can guarantee the optimality of the solution they find.

As an important feature in the distribution network, PHEVs provide a perfect solution for a bottom-up restoration. According to International Energy Agency, the penetration of electric vehicles was 0.02% of total vehicle fleet in 2012, and it is predicted that the penetration level will be 2% by 2020 [7]. The increasing number of PHEVs brings the capability of flexible generation and distributed energy storage to distribution system. PHEVs can be utilized as fast response energy resources to buffer energy for grid stabilization, and speed up distribution system recovery as needed. There are many researches focusing on the impact of PHEVs in distribution system [8]-[11]. The role of PHEVs has been investigated in load management [8], demand response [9], power quality [10], and voltage regulation [11]. However, little work has been done on leveraging PHEVs for self-healing distribution networks. Using PHEVs for cold load pick up in the initial stage of a restoration process was proposed in [12]. However, lack of optimization technique and real-world driving pattern are two major drawbacks of this literature.

In this paper we intend to present a distribution system restoration strategy using Mixed Integer Linear Programming (MILP) technique. The MILP formulation provides a globally optimal solution on load restoration and PHEV charging/ discharging sequences. The proposed approach accounts for real-world driving patterns described with a discrete-time Markov chain model. Monte Carlo simulation is performed to derive the estimated value of battery State of Charge (SoC). Charging and discharging efficiency are included and SoC limits are checked to maintain the reliability and lifespan of PHEV batteries.

The organization of this paper is as follows. A coordination strategy for transmission and distribution restoration is introduced in Section II. The overall procedure for the synthesis of real-world driving cycle using Markov chain method is presented in section III. The problem formulation of distribution system restoration is presented in Section IV. Case studies and simulation results are discussed in Section V. Conclusions and future work are summarized in Section VI.

II. PHEVS PARTICIPATION IN DISTRIBUTION NETWORK RESTORATION

In the bottom-up restoration strategy, the coordination between transmission and distribution restoration is critical for an efficient restoration process. First, transmission restoration determines the generator startup sequence and transmission line energization sequence to provide the generation capability curve, i.e. the maximum available generation that can be used to pick up load. Then, Load Serving Entities (LSEs) receive the information of available generation and real/reactive power limits, and determine the load pickup sequence. The restored load from each LSE cannot exceed the assigned load from the upper level transmission restoration procedure. This feedback is sent back to transmission restoration to update the generation output curve. Fig. 1 illustrates the coordination strategy between transmission and distribution systems in the presence of PHEVs. In this model, first, transmission restoration determines the upper limit of available generation that can be delivered to the distribution system. Then distribution restoration optimizes the picked up load within this limit. An optimization problem with the objective function of maximizing total served energy is solved at the distribution level to determine the restorative actions. If there is available generation from PHEVs, this information is sent back to update the generation limit.

During system restoration, PHEVs can be utilized as either generation source or load. PHEVs parked in garages or parking lots can be used to supply the feeder containing prioritized loads immediately after an outage or blackout. In case of distributed generation connected to different feeders, PHEVs can also serve as BS sources to crank NBS generators. Considering generation availability and different feeder characteristics, the charging/discharging sequence of battery storage system in PHEVs can be determined. If the available generation exceeds the maximum amount of load that can be restored, PHEVs can be operated in the charging mode. Otherwise, if there is no enough generation to restore the feeder load, instead of waiting for extra generation from on-line units, PHEVs can be operated in the discharging mode. Therefore, the aggregated PHEVs can be regarded as one generation or load in distribution system.

PHEVs traveling data can be derived from the National Transportation Survey and used as the input for the proposed model shown in Fig. 1. Having determined PHEVs mobility, the required probability data to build Markov chain transition matrix can be calculated. Markov chain model is employed to generate synthesized driving cycle. Monte Carlo type simulation method is used to estimate the mean value of PHEV parameters at each specific time of a day. The result of the Monte Carlo simulation is then used to predict the impact of PHEVs on the distribution system restoration.

In real-world scenario, aggregator acts as an interface between the grid and a group of plug-in hybrid electric vehicles. As shown in Fig. 2, it collects PHEV parameters, communicate with upper-level operators, and decide the charging or discharging mode of each PHEV [13]. The prerequisite for PHEV owners to participate in restoration process is the SoC of vehicles that must be at satisfactory level by the time they arrive at one of the charging stations. Then, the aggregator will report the amount of power that can be provided to the power grid and finally will establish a contract. Once this contract is established, it propagates the pricing signals which may vary with the time of restoration. It is because that at initial phase of restoration, there is a limited number of generation units available compared with the amount of load. Therefore, PHEVs can actively contribute to the restoration process to pick up the critical loads which reduces the recovery time.

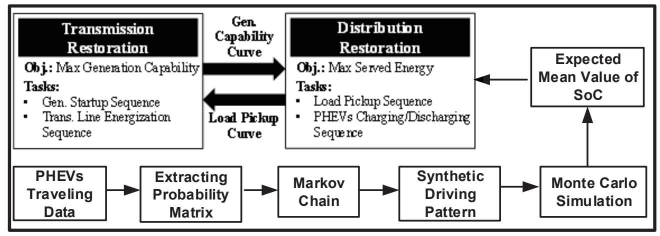

Fig.1. Proposed model for coordination between transmission and distribution systems with PHEVs participation in distribution system restoration.

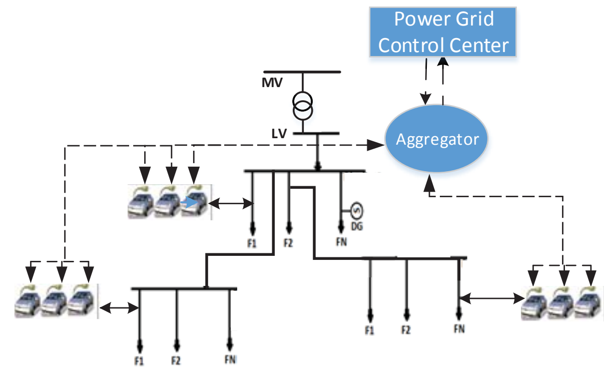

Fig. 2. Illustration of connections between vehicles, aggregator, and upper-level operator.

III. Discrete Time Markov Chain Model to Synthesize Driving Behaviors

Markov chain model is an effective way to generate representative driving pattern in a statistical way, which has been applied in the former literature [14], [15]. The Markov property says that when time proceeds from t to $t+1$, the next state of the process depends only on the present state and not on the previous states. A discrete-time Markov chain is a sequence of random variables X_1, X_2, X_3, ... with the Markov property that can be expressed as:

$$\mathbb{P}(X_{t+1}=k \mid X_0=x_0,\ldots,X_t=x_t)=\mathbb{P}\left(X_{t+1}=k \mid X_t=x_t\right) \quad \forall t\geq 0,\{k,x_0,\ldots,x_t\}\in S \tag{1}$$

In this paper, it is assumed that each PHEV can be in three different parking states: parked in industrial area (P_I), parked in commercial area (P_C), or parked in residential area (P_R). We also defined three driving states D_A, D_B, and D_C representing different type-of-trips performed by PHEVs between the different parking locations. Therefore, our model comprises three parking and driving states as shown in Fig. 3. Let's assume that vehicle m occupied parking state P_I at time step t. The probability of vehicle m remaining at the same state at time $t+1$ is $P^t_{P_I\to P_I}$. Whereas, the probability of transition from parking state I to driving states D_A, is $P^t_{P_I\to D_A}$. Here, it is assumed that a vehicle in driving state D_A can only park in parking state P_I, due to the type of trip. We made the same assumption for vehicles in driving states D_b and D_c that can only park in parking states P_C and P_R, respectively. Since the transition probabilities depend on t, the process is known as an inhomogeneous Markov chain. For a given time t, this leads to formation of a transition probability matrix T^t on the following form:

$$T^t = \begin{bmatrix} P^t_{P_I \to P_I} & 0 & 0 & P^t_{P_I \to D_A} & P^t_{P_I \to D_B} & P^t_{P_I \to D_C} \\ 0 & P^t_{P_C \to P_C} & 0 & P^t_{P_c \to D_A} & P^t_{P_C \to D_B} & P^t_{P_C \to D_C} \\ 0 & 0 & P^t_{P_R \to P_R} & P^t_{P_R \to D_A} & P^t_{P_R \to D_B} & P^t_{P_R \to D_C} \\ P^t_{D_A \to P_I} & 0 & 0 & P^t_{D_A \to D_A} & 0 & 0 \\ 0 & P^t_{D_B \to P_C} & 0 & 0 & P^t_{D_B \to D_B} & 0 \\ 0 & 0 & P^t_{D_C \to P_R} & 0 & 0 & P^t_{D_C \to D_C} \end{bmatrix} \quad (2)$$

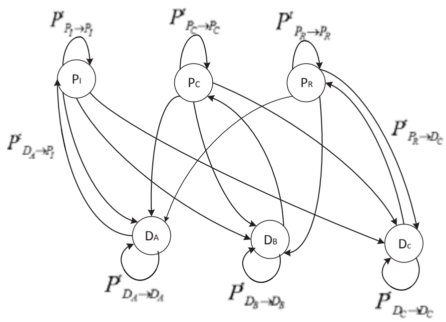

Fig. 3. Discrete-time Markov chain states representation.

Note that changing from a driving state to another driving state requires that the PHEV first occupies a parking state. Thus, several elements of transition matrix are zero. The sum of the probabilities in each row of the transition matrix (2) equals to one. Markov chain transition matrix is cyclostationary and can be calculated for a period of one week. Having defined the initial state probabilities and state transition matrix, Markov chain model can be fully characterized and will be periodically repeated for weekly cycles.

IV. Distribution System Restoration Problem Formulation

A. Objective Function

The objective is to maximize the total restored energy in the loads and PHEV batteries during the restoration period. The total restored energy of load is defined as the area under the load pickup curve [16]. The objective function of distribution restoration with PHEVs can be written as:

Maximize

$$\left\{ \sum_{l \in L} w_l \times \left(T - t_l^p\right) \times P_l^{Load} + \sum_{t \in T} \sum_{b \in B} w_b \times N_b \times SoC_b^t \times \left(\frac{E_b}{1000}\right) \right\} \quad (3)$$

where, T is the pre-set maximum restoration time. The notation t_l^p represents the pickup time of load L, P_l^{Load} is the MW of load l, L is the set of all loads, SoC_b^t denotes the state of charge of battery b belongs to set B, E_b shows the battery size in KWh, and N_b denotes the number of vehicles participating in restoration process. w_l and w_b show the priority of loads and PHEV batteries respectively. B is the set of PHEV batteries.

B. Constraints

Let u_l^t denote the status of load l at time t, the pickup time of each load l can be represented as (4). The total generation could be from distributed generators in distribution system, PHEVs, or determined by transmission system restoration. PHEV can be operated as either generation or load depended on the imbalance between available generation and load. A general form of generation-load balance is presented in (5). where, P_i^t is the MW output of generator i at time t, I is the set of all generator numbers, P_b^t is the power input/output of vehicle b at time t, B is the set of all PHEV batteries, and T is the set of time. In constraint (6), δ_b^t and η_b^t are binary variables determining charging and discharging cycles respectively, and Pch_k denotes the maximum power that can be provided by charging station k.

$$t_l^P = \sum_{t \in T} (1 - u_l^t) + 1 \quad \forall l \in L, u \in \{0,1\} \quad (4)$$

$$\sum_{i \in I} P_i^t \geq \sum_{l \in L} u_l^t P_l^{Load} + \sum_{b \in B} P_b^t \quad \forall t \in T \quad (5)$$

$$P_b^t = \delta_b^t Pch_k - \eta_b^t Pch_k \quad \forall b \in B, \forall k \in K, \forall t \in T \quad (6)$$

During the restoration process, once load l is picked up, it should remain online at all times to prevent load shedding. This constraint can be expressed as:

$$u_l^t \geq u_l^{t-1} \quad \forall l \in L, \forall t \in T \quad (7)$$

Constraints (8) states that a block of load can be picked up after its respective bus is energized. Let $P_l^{Load,\max}$ denote the maximum load available at load bus l.

$$u_l^t P_l^{load,\max} \leq P_l^{load} \leq u_l^t P_l^{load,\max} \quad \forall l \in L, \forall t \in T \quad (8)$$

In order to operate batteries at high efficiency and also maintain the cycle life of batteries, battery SoC should be within certain limits, as given by:

$$SoC_{min} \leq SoC_b^t \leq SoC_{max} \quad \forall b \in B, \forall t \in T \quad (9)$$

where, SoC_{min} and SoC_{max} are the lower and upper limits of SoC. The relationship between functions of SoC and the battery charging/discharging power can be achieved as follows.

$$SoC_b^t = \begin{cases} SoC_b^{t-1} + (1/\eta_d) \times P_b^t \Delta t, & \text{discharging} \\ SoC_b^{t-1} + \eta_c \times P_b^t \Delta t, & \text{charging} \quad \forall b \in B, \forall t \in T \\ SoC_b^{t-1}, & \text{else} \end{cases} \quad (10)$$

where, η_c and η_d are the efficiency of charging and discharging, respectively. The power loss and the battery temperature limit are simplified as charging/discharging efficiency.

V. Simulation Results

A. Test System Data

The developed restoration strategy is tested in a 100-feeder system to validate the proposed model. The load profile and load priority are presented in Fig. 4. Two BS units and two NBS units are considered in the transmission system and generator characteristics are derived from [3]. Transmission restoration first determines the upper limit of available generation that can be delivered to the distribution system. Distribution restoration optimizes the picked load within this limit. It is assumed that there are total 750 MW of generation, whereas, the total load is 679 MW. In this study, all PHEV batteries have the lowest priority ($w_b = 0.5$). It is also assumed that load pickup actions are performed every 10 minutes (as 1 per unit time) which requires for preparation and frequency stabilization. A total blackout is assumed in distribution system. Given the total load of test system (679 MW), the total number of vehicles is calculated based on the data from U.S. Energy Information Administration. The daily demand of each household is approximately 30 kWh [17]. It is assumed that each household has two vehicles and 50% of the total demand in our test system is consumed by residential sector. Using PHEV penetration level 2%, the total number of PHEVs can be calculated as approximately 10,800.

B. PHEV Owners' Driving Patterns

PHEV owners' daily driving patterns need to be determined by using the Markov chain method described in Section III. Driving is assumed to be related to three different velocities sampled from normal distributions with 20% standard deviation of mean 50 (km/h). Maximum and minimum battery size are assumed to be uniformly distributed in the intervals [16, 20] and [4, 6] kWh, respectively. Fast, medium, and slow charging power for three stations P_I, P_C, and P_R are set to 5.5, 3.7, 2.3 kW, respectively. Initial SoC is assumed to be 50% of maximum battery size. The lower bound of SoC is 20%, and the upper bound of SoC is 90%. Travel behavior data was extracted from [18], by which the state transition matrix (2) can be calculated.

Fig. 5 shows the transition states for three vehicles starting their trips from parking states P_I, P_C, and P_R. From Fig. 5 one can observe that a sample vehicle occupying parking state P_I starts driving state D_A at 6:00 am before returning to its initial state (P_I) at 6:30 am. Whereas, another vehicle occupying initial state P_C will leave its current state at 8:00 am by starting type of trip D_A. One thousand random samples were generated to model the driving behavior of vehicles in different states by using state transition matrix (2). Monte Carlo simulation method is employed to estimate the mean value of PHEV parameters at time t. Fig. 6 shows the estimated mean SoC profile at different time of the day. In order to ensure that the number of samples needed for Monte Carlo simulation is sufficient, the convergence test was performed. Fig. 7 shows how the estimate of mean SoC converges at 6:00 am and 6:00 pm for 1000 samples.

C. Case Studies

We study three cases, in case 1, PHEVs will not participate in the restoration process, whereas, PHEVs will feed power into the grid in cases 2 and 3. It is assumed that once an outage occurs, PHEVs occupying one of the parking states will receive incentive signal to stay at their current parking lots up to end of restoration time to aid restoration process. The time of outage is assumed to be at 6:00 am in case 2 and 6:00 pm in case 3. The restoration optimization problem (3) is run for 100-feeder test system considering PHEVs driving patterns. Fig. 8 shows the number of energized feeders at each restoration time. It can be observed that in case 2 and at initial phase of restoration 10 feeders have been energized, whereas, in case 1 and 3, this value decreased to 8 and 9 feeders, respectively. As restoration process proceeds, case 2 takes the priority over the other cases in terms of the number of energized feeders. However, at the final stage (after 18 restoration time) all feeders are energized and their corresponding loads are picked up. This arises from the fact that in case 2, the number of PHEVs and the estimated mean SoC level are significantly greater than case 3. With this in mind, PHEVs in case 2 can help to improve load pick up capability of system by discharging the energy stored in their batteries. In particular, at initial phase of restoration when most of conventional NBS units have not been started. Table I compares the total served energy throughout the restoration period in different cases. Case 2 is the best case and case 1 is the worst case in terms of total served energy.

Fig. 9 shows the charging/discharging sequence of PHEV batteries. As stated earlier, the charging process of PHEVs may occur when the available generation exceeds the maximum amount of load that can be restored. Note that in this study the lowest priority has been assigned to the PHEV loads. Therefore, in case 2, after 17 restoration time the charging process of PHEV batteries will be started with the target of charging all PHEVs to their Soc_{max} level. However, in case 3, we see the first recharging cycle started at t = 8. This is due to the fact that in case 2 and after 6 restoration time, the SoC level of PHEVs are not enough to pick up a block of load. Instead, generation-load mismatch can charge PHEVs at $t = 7$. Similar to case 2, the final charging cycle commenced after full restoration of all loads at $t = 17$.

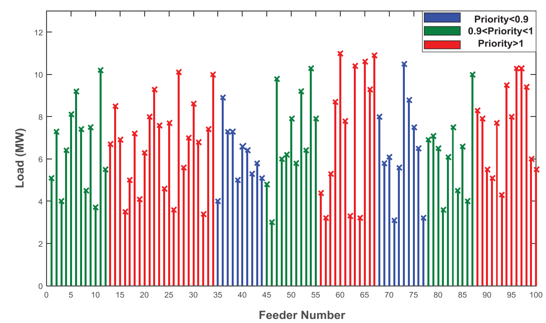

Fig. 4. 100-feeder load data (colors represent different load priorities).

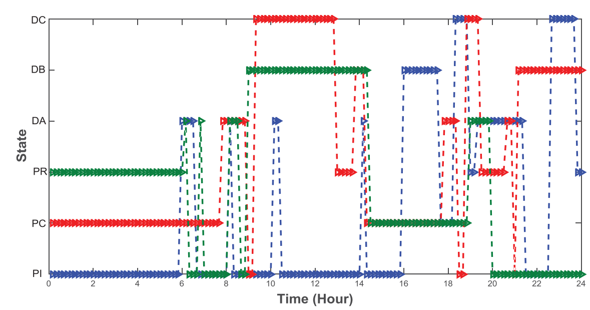

Fig. 5. Synthetic driving patterns for a sample vehicle in various parking states.

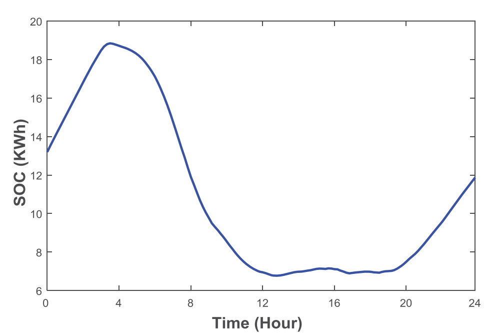

Fig. 6. Estimated mean SoC profile for a weekday.

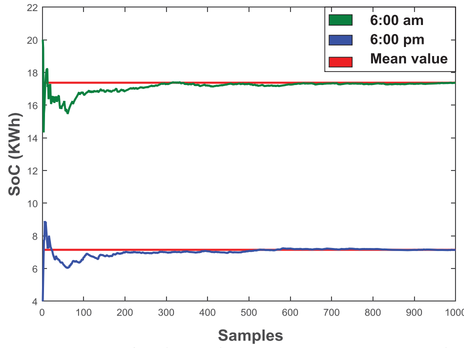

Fig. 7. Convergence of estimated mean SoC at 6:00 am and 6:00 pm.

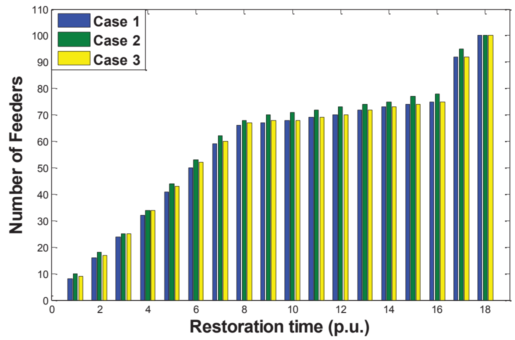

Fig. 8. Number of energized feeders in different case studies.

TABLE I
TOTAL ENERGY SERVED IN DIFFERENT CASES

Case	*Case 1*	*Case 2*	*Case 3*
Served Energy (GWh)	1.174	1.219	1.192

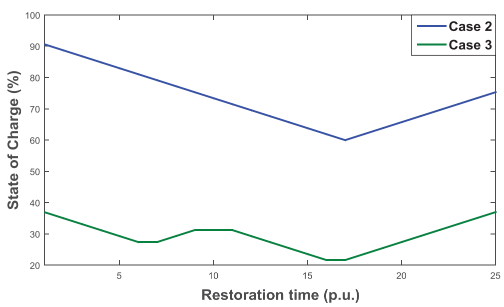

Fig. 9. State of charge of PHEV batteries in different case studies.

VI. CONCLUSIONS

The increased PHEV penetration provides a promising solution to faster distribution restoration. This paper proposed an efficient MILP-based load restoration strategy using PHEVs that can determine globally optimal sequence for PHEV charging and discharging as well load pickup. Our model is built based on the assumption that incentives will be provided by the utilities with the aim of encouraging PHEV owners to participate in self-healing process. Simulation results demonstrated that PHEVs can contribute to pick up more loads, and the contribution is significantly affected by the charging level of PHEVs, which depends on the driving behavior. The developed optimal management strategy of PHEVs in service restoration can facilitate system operators to achieve efficient system restoration plans. It also provides incentives to deploy a large amount of PHEVs to improve system reliability and resiliency. This strategy can be integrated into future distributed Energy Managements Systems for the self-healing smart distribution system.

For the future work we plan to improve our model by adding new constraints such as three-phase unbalanced load flow, voltage profile, battery dynamics, and allocating PHEV loads to different buses. After incorporating new constraints, power system restoration problem can be re-solved accounting for the objective function presented in this paper.

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