DER-Integrated Grid Operations Under Extreme Weather Events Incorporating DWPT System

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***Abstract*—Due to environmental concerns, electric vehicles (EVs) have become increasingly popular in recent decades. While EVs offer several benefits, they also present challenges such as prolonged charging times and range anxiety. To address these issues and enhance EV market participation, dynamic wireless power transfer (DWPT) is gaining a great attention in electrified-transportation sector, leading to an emergence of DWPT for EVs. DWPT offers advantages like charging while in-motion. However, DWPT roadways also impose additional demands on the power system, potentially increasing operational costs. The main objective of this paper is to manage effectively the additional load caused by DWPT roadways, and this paper presents the utilization of distributed energy resources (DERs), such as photovoltaic (PV) systems and battery storage system (BSS), to minimize the system costs. The importance of our proposed load management strategy becomes even more critical during extreme events. Therefore, this paper further examines two scenarios, i.e., normal operations and under extreme conditions considering line outages, to compare the costs associated with DWPT systems. The efficiency of the proposed method is validated using IEEE 33-bus distribution systems through a mixed integer linear programming (MILP) optimization problem. Test results demonstrate that integrating DWPT system increases the system costs under both normal and extreme conditions, however, the DER-based mechanism is capable of mitigating these costs optimally.**

***Index Terms*—Distributed energy resources, distribution networks, dynamic wireless power transfer, electric vehicles, optimization.**

NOMENCLATURE

Indices

i	Index of generators
j	Index of loads
l, k	Indices of buses
t	Index of time

Parameters

P^{BSS}_{cont}	Continuous charging/discharging power of BSS
$P^D(j,t)$	Conventional active load
P^{EV}_t	EV in-motion load
$\overline{P}^G_{i,t}$	Upper limit of active generation of DGs
$\underline{P}^G_{i,t}$	lower limit of active generation of DGs
$\overline{P}^{m,buy}_t$	Upper limit of buying power from upstream network
$\overline{P}^{m,sell}_t$	Upper limit of selling power to upstream network
$Q^D(j,t)$	Conventional reactive load
$\overline{Q}^G_{i,t}$	Upper limit of reactive generation of DGs
$\underline{Q}^G_{i,t}$	lower limit of reactive power of DGs
r_{lk}, x_{lk}	Resistance/Reactance of branch $l{-}k$
$VOLL_t$	Load shedding cost
λ^G_i	Marginal cost of DG
λ^G_i	Market price of energy selling/buying

Variables

$LS_{j,t}$	Load-shedding of demand j
P^E_t	Excess power of PV
$P^E_{ch,t}$	Charging power of battery
$P^E_{dis,t}$	Discharging power of battery to supply EV in-motion load
$P^F_{lk,t}$	Active power flow of branch $l{-}k$
$P^G_{i,t}$	Power produced by the *i*th generation unit
$P^{m,buy}_t$	Power bought from upstream network
$P^{m,sell}_t$	Power sold to upstream network
P^m_t	Power bought (or sold) from (or to) the upstream network
$P^N_{dis,t}$	Discharging power of battery to supply conventional load
P^{PV}_t	Total PV power
$P^{PV,E}_t$	PV power to supply EV in-motion load
$P^{PV,N}_t$	Excess PV power to supply conventional load
$P_{dis,t}$	Total discharging power of battery
$Q^F_{lk,t}$	Reactive power flow of branch $l{-}k$
SOC_t	State of charge of BSS
$V_{l,t}$, $V_{k,t}$	Voltage magnitude of buses
x_t, y_t	Binary variable for BSS charging/discharging state
$\delta_{l,t}$, $\delta k, t$	Voltage angles of buses
ϵ_t	Binary variable for buying/selling power

I. INTRODUCTION

TO improve the environmental conditions and reduce the dependency on fuel, the adoption of electric vehicles (EVs) is growing significantly [1], and it is also predicted that

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EVs will constitute 24% of the light vehicle fleet and 64% of light vehicle sales in the United States [2]. Despite the rapid growth of the EV market, challenges such as charging time, battery capacity, and range anxiety still persist. These issues have hampered the widespread use of EVs in both private and public transportation sectors [3]. Dynamic wireless power transfer (DWPT) technology, which allows EVs to charge while in-motion, has been recognized as a potential technology to cope with these challenges. Besides addressing range limitations, this technology enables the use of smaller onboard battery packs, which could result in cost savings [4].

Several studies have explored the potential of DWPT for EVs. Machura *et al.* [5] presented the driving range of EVs that were charged by wireless power transfer (WPT) systems. Their results showed that utilizing dynamic and quasi-dynamic wireless charging at medium power levels is sufficient to achieve unlimited range compared to high power requirements for standalone charging. Fathollahi *et al.* [6] proposed a long-term stochastic model to allocate and size dynamic wireless charging (DWC) while considering power distribution losses, transportation network traffic, and EV location routing. An optimal placement strategy of power tracker based on city traffic information and EV energy demand was investigated by Zhang and Yu [7]. Further, EVs were considered as ancillary services as they can be operated in vehicle-to-grid (V2G) mode. Since the DWPT system puts an additional load on the distribution networks (DN), it is imperative to carry out optimal management/scheduling of DN when the grid infrastructure is designed utilizing DWPT. The sustainability and impact of varying densities of EVs on the DN were explored in [8] where they reported that an increase in DWPT infrastructure length led to reduced demand fluctuations. Additionally, Newbolt *et al.* [9] introduced a priority load control method aimed at mitigating the load impact on the DN caused by EVs in-motion. Efficient energy management for wireless charging roads equipped with energy storage was described in [10] where their simulation results showed that effective control of energy storage not only reduced the cost associated with wireless charging road systems but also alleviated the stress on the power system caused by the wireless charging load. Moreover, the optimal deployment of DWC facilities for electric bus routes was presented in [11] where they considered the uncertainty of travel times through stochastic optimization, aiming to minimize the cost of purchasing power transmitters and inverters.

Recently, research on DWPT systems within electrical power systems is receiving a significant amount of attention with an aim to integrate EVs in-motion into DN to enhance driver comfort and reduce anxiety. However, a balance between comfort and cost is essential. To the best knowledge of authors, no studies have thoroughly examined the economic impact of DWPT on DN under both normal and extreme events, specifically how the integration of DWPT system impacts the system costs and the additional power needed from the main grid, thus making this paper novel. That being so, this paper addresses these gaps by integrating distributed energy resources (DERs), primarily, photovoltaic (PV) system and battery storage system (BSS), to mitigate the system load create by DWPT and compare costs with and without the integration of DERs. The major contributions of this paper are following: (1) Load modeling of an EV in-motion utilizing the real traffic data and integration of PV and BSS to support the DWPT infrastructure; (2) New optimization strategy to manage DN in the presence of DWPT system with a goal to minimize the cost; (3) Investigating the impact of EV in-motion load on the electric distribution grid under extreme events from an economic perspective; and (4) New research direction to the emerging sector of electrified-transportation.

The remainder of this paper is organized as follows. In Section II, the theoretical explanation of several steps of the proposed method is discussed. Results and discussions are presented and discussed in Section III, and the major findings of the papers including future work are presented Section IV.

II. Proposed Approach for EV In-Motion Load Management

This section presents the proposed approach to manage the DN in the presence of DWPT system for EV in-motion load management. This section further provides a formulation of optimization problem for DER-integrated DN incorporating DWPT. Our proposed load modeling as well as optimization (and scheduling) strategies are illustrated in Fig. 1.

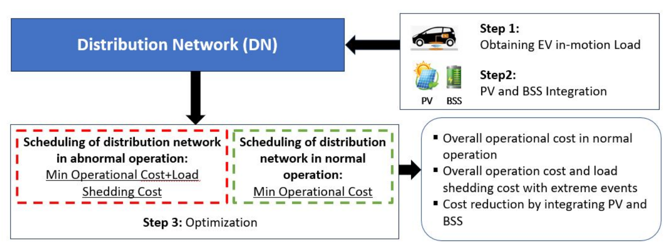

Fig. 1. Overall flow of the proposed approach for optimizing the distribution network by integrating DWPT system, PV, and BSS illustrating three major steps: (1) EV in-motion load modeling; (2) Integration of PV and BSS; and (3) Optimal scheduling of DN.

A. Load Modeling of EV In-Motion

This paper considers the traffic data acquired from the the Texas Department of Transportation [12] in order to calculate the load for EV in-motion. The dataset also involves an hourly data of density of vehicles (over a period of 24 hours) passing through the I-10 highway for August 1, 2022.

This paper focuses on DN management incorporating DWPT system at a small-scale, i.e., only 10% of the vehicles in-motion are considered. Accordingly, the simulation is carried out by utilizing the IEEE 33-bus system with DWPT injected only at bus-10. This involves the consideration of Nissan Leaf having a battery capacity of 40 kWh as a major case study vehicle. However, the algorithm developed in this paper is scalable to other EV models as well. Based on the speed data available in [12], the random speed for each EV is generated within the range of 50 mph−60 mph. The state-of-charge (SOC) for batteries is randomly generated, varying from 30%−60%. The length of DWPT road is considered to be 10 miles and it is assumed that an EV will continue to charge while on the DWPT road until it reaches 80%. Based on these data, the total EV load for each hour is obtained.

B. Photovoltaic and Battery Storage System Integration

To support the EV load over a 24-hour period, integration of PV and BSS into DN are utilized in this paper. Initially, the solar irradiance for each hour is obtained from [13] and this irradiance data is then converted into solar power using the method described in [14], which is given by

$$P^{PV} = si \times \eta \times A \tag{1}$$

where P^{PV} represents the output power (W) of solar panel, si is solar irradiance (W/m^2), η is the efficiency of solar panel, and A is the area of the solar panel (m^2).

Based on the EV load information available (described in previous sub-section III.A), the number of solar panels required to support the EV load will be determined. In hours when solar power generation is insufficient or non-existent (e.g., during dark hours), BSS is employed to provide continuous support to meet the load over 24 hours. The BSS is designed to store excess PV power generated during peak sunlight hours and discharge it during the periods of low or non-sunny hours. It is important to note that the battery is charged exclusively with surplus power from the PV system. Additionally, when the EV load is fully satisfied, any remaining discharge capacity can be utilized to assist the DN in supplying conventional loads. The mathematical formulation of integrating PV and BSS into the DN is described below.

$$SOC_t = SOC_{t-1} + \eta \cdot P_{ch,t} - \frac{P_{dis,t}}{\eta}, \tag{2}$$

$$P_t^E = P_t^{PV} - P_t^{EV}, \tag{3}$$

$$P_{ch,t} = P_{cont}^{BSS} \cdot x_t, \tag{4}$$

$$P_{dis,t} = P_{cont}^{BSS} \cdot y_t, \tag{5}$$

$$x_t + y_t \leq 1, \tag{6}$$

$$y_t = \begin{cases} 0 & \text{if } P_t^E \geq 0 \\ 1 & \text{if } P_t^E < 0 \end{cases}, \tag{7}$$

where (2) presents the battery SOC at each time. The excess power is shown in (3); The charging and discharging power of battery is shown in (4) and (5), respectively. The limitation requiring the battery to be in only one operational mode—either charging or discharging—is specified in (6). Finally, the condition mandating battery discharge when the EV load exceeds the PV output is described in (7).

C. Optimization Problem and Formulation

Based on the initial steps, the optimization problem is formulated to schedule the units for supplying loads and performing economic load dispatch in DN to minimize the cost. The cost includes operational costs during normal operation; and in the case of operations during extreme events (e.g., impacting on the line outages), additional costs associated with load shedding are considered. The DN is considered to be connected to the upstream network, allowing for the buying (or selling) of power to (or from) the upstream network when local generation is insufficient. The linearized AC power flow model used in this optimization is adopted from [15]. The objective function and constraints of the proposed model are presented below.

Minimize OF

$$= \sum_{t \in T} \left(\sum_{i \in I} P_{i,t}^G \lambda_i^G + P_t^m \lambda_t^m + \sum_{j \in J} LS_{j,t} VOLL_t \right) \tag{8}$$

s.t.

$$(2) - (7) \tag{9}$$

$$P_t^m + P_{i,t}^G = P_{j,t}^D - P_{dis,t}^N + P_t^{PV,N} + \sum_{l,k} P_{lk,t}^F \tag{10}$$

$$P_t^{PV,E} + P_{dis,t}^E - P_{ch,t}^E = P_t^{EV} \tag{11}$$

$$Q_t^m - Q_{i,t}^G = Q_{j,t}^D + \sum_{lk} Q_{lk,t}^F \tag{12}$$

$$P_t^{PV,N} + P_t^{PV,E} = P_t^{PV} \tag{13}$$

$$P_{dis,t}^N + P_{dis,t}^E = P_{dis,t} \tag{14}$$

$$P_t^m = P_t^{m,buy} - P_t^{m,sell} \tag{15}$$

$$0 \leq P_t^{m,buy} \leq \overline{P}_t^{m,buy} \cdot \varepsilon_t \tag{16}$$

$$0 \leq P_t^{m,sell} \leq \overline{P}_t^{m,sell} \cdot (1 - \varepsilon_t) \tag{17}$$

$$\underline{P}_{i,t}^G \leq P_{i,t}^G \leq \overline{P}_{i,t}^G \tag{18}$$

$$\underline{Q}_{i,t}^G \leq Q_{i,t}^G \leq \overline{Q}_{i,t}^G \tag{19}$$

$$LS_{j,t} \leq r P_{j,t}^D \tag{20}$$

$$P_{lk,t}^F = \frac{h_{lk,2}}{x_{lk}}(\delta_{l,t} - \delta_{k,t}) + \frac{h_{lk,1}}{x_{lk}}(V_{l,t} - V_{k,t}) \tag{21}$$

$$Q_{lk,t}^F = -\frac{h_{lk,1}}{x_{lk}}(\delta_{l,t} - \delta_{k,t}) + \frac{h_{lk,2}}{x_{lk}}(V_{l,t} - V_{k,t}) \tag{22}$$

$$h_{lk,1} = \frac{r_{lk} x_{lk}}{r_{lk}^2 + x_{lk}^2} \tag{23}$$

$$h_{lk,2} = \frac{x_{lk}^2}{r_{lk}^2 + x_{lk}^2} \tag{24}$$

where (8) represents the objective function of the optimization problem. The first term in (8) reflects the cost of generation; the second term indicates the cost associated with buying (or selling) power from (or to) the upstream network; and the final term accounts for the costs related to load shedding. Active and reactive power balance equations are indicated in (10)−(12). PV power and discharging power are divided into the parts involved in DN and EV as shown in (13) and (14), respectively. Net power purchased from the upstream network is represented by (15). The limitation for buying power, selling power, active diesel generator (DG) power, reactive DG power, and load shedding are represented by (16)−(20); Moreover, the linearized AC active and reactive power flow are explained in (21)−(24).

III. Simulation Results and Discussion

This paper proposed a method for optimal scheduling of DN with and without EV in-motion loads, i.e., utilizing the DWPT infrastructure. It is crucial for power system operators to manage the load (generated by DWPT system and others) efficiently while minimizing the costs. To address the additional demand from EVs in-motion, we integrated PV systems and BSS as DERs using the IEEE 33−bus test system, where the EV load, PV, and BSS are strategically placed at bus-10, which has the minimum conventional load. The configuration of the modified distribution network (33−bus) is illustrated in Fig. 2. The data associated with DGs is presented in Table I and network data is extracted from [16]. Load profiles and market prices are collected from NYISO [17] for August 1, 2022. The resultant mixed integer linear programming (MILP) optimization problem is solved using Gurobi solver.

Moreover, under extreme events due to hurricanes impacting the line outages, the proposed strategy aims to minimize load shedding, thus preventing cost escalations. Two case studies are presented to demonstrate the effectiveness of the proposed approach. In the first case, the amount of EV in-motion load is obtained (Step 1 in Fig. 1), and then the sizing of the PV and BSS (Step 2 in Fig. 1) is performed to support EV load. The optimization problem (Step 3 in Fig. 1) is carried out to determine how EV load can affect the cost with and without PV and BSS integration. Moreover, in the second case study, the system under extreme events is considered and the cost of scheduling with and without DWPT system (i.e., EV in-motion) is compared.

TABLE I
Technical data of DGs

DG_n	P_n^G [MW]	$\dot{P}_n^G$ [MW]	Q_n^G [MVar]	Q_n^G [MVar]	λ_n^S [$/MWh]
1	3	0.21	2.1	-2.1	90
2	2	0.19	1.9	-1.9	90
3	2	0.19	1.9	-1.9	90
4	3	0.22	2.2	-2.2	90
5	3	0.22	2.2	-2.2	90

A. Normal Operation of Distribution Network

This section considers the DN operating under normal conditions with no extreme events affecting the system. The conventional loads as well as EV in-motion loads along with the price data are illustrated in Fig. 3. As previously explained, an EV load is recognized within the system when an EV is on DWPT road and its SOC is below 80%.

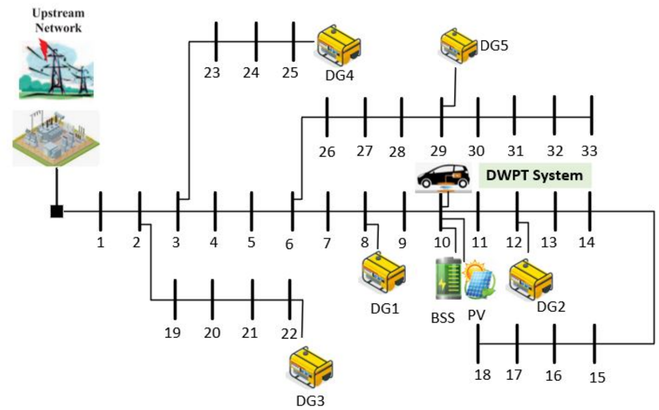

Fig. 2. Modified IEEE 33−bus for optimal scheduling of DN incorporating DERs. In this figure, DG1−5, EV, PV, and BSS represent diesel generator, electric vehicle on DWPT roadway, photovoltaic, and battery storage system, respectively. The normal condition considers operation without any outage, and extreme event conditions considers the operation of the system with the outage of lines 3-4, 6-7, and 6-26

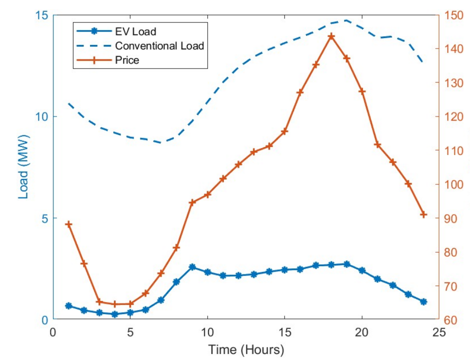

Fig. 3. Load (conventional and EV in-motion) and price data in distribution system.

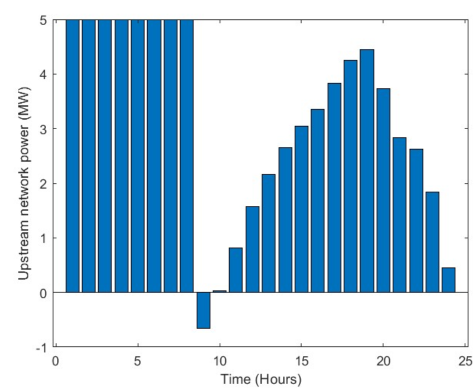

Fig. 4. Power bought (or sold) from (or to) upstream network without PV and BSS integration.

Fig. 3 depicts that the peak EV load occurs at hour-19 (2.74 MW), which aligns with the overall peak hour for the system load. Managing this additional load at hour-19 is crucial for alleviating the stress on the system. The proposed optimization model based on (8)−(24), generated the operational costs amounting to $29.7k. The capacity for power transmission to the upstream network is capped at 5 MW. Fig. 4 displays these power transactions, highlighting how power is bought (or sold) from (or to) the upstream network to meet demand. During the early morning hours, when electricity costs are lower than the generation costs, power is predominantly purchased from the upstream network. At hour-9, when the electricity price surpasses the cost of generation, there is a sharp decrease in power procurement, dropping to -0.66 MW. Subsequently, the power transaction increases, reaching 4.44 MW at hour-19 to accommodate the peak load.

The integration of PV systems and BSS offers significant cost benefits in managing EV in-motion loads for efficient management of DN incorporating DWPT. When only the PV system is considered, cost decreased to \$24.6k representing a reduction of about 17% in system cost. However, by adding BSS, the surplus PV power can be stored during low demand periods and released when needed. This further contributes to lowering the costs to \$23.7k, which is around 20% reduction in cost compared to scenarios without any PV and BSS integration. Thus, our proposed optimization strategy demonstrates the financial effectiveness of combining PV and BSS for efficient energy management systems. During this

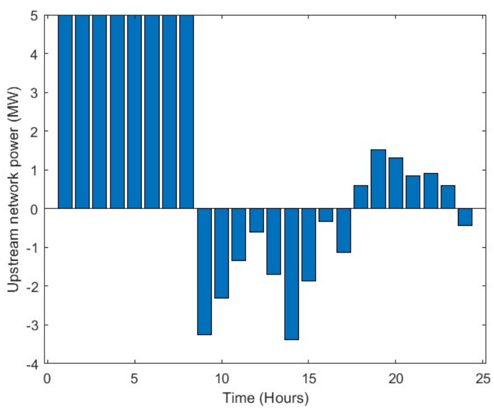

Fig. 5. Power bought (or sold) from (or to) upstream network with PV and BSS integration.

scenario, the BSS is active in such a way that it discharges the needed power to meet the EV load when the PV power is not sufficient. It is to be noted our optimization strategy is also designed in such a way that the BSS, after fulfilling the EV load, can still supply the remained surplus power to meet the conventional load, partially. This mechanism can affect the power transmitted from the upstream network, as shown in Fig. 5 where we can observe that the power bought from network is less than the previous case (without PV and BSS), and also during peak hours, the DN can sell the power to the upstream network to gain profit. Therefore, test results demonstrate the effect of managing the EV in-motion load in the distribution grid as well as its impact on the system cost. Note that the cost of PV and battery installation is ignored in this paper. The cost can be considered and optimal placement can further be determined, however, this is out of scope of this paper.

B. *Operation of Distribution Network Under Extreme Events*

Ensuring the load in the system can be met under both normal and extreme conditions is crucial for system operators. Since the goal in this section is to investigate the effect of EV in-motion load on the cost under extreme events (due to hurricane), we considered three line outage scenarios involving the outage of lines $3-4$, $6-7$, and $6-26$ due to the hurricane. These scenarios are chosen based on the most load shedding cost when the optimization solution is feasible. The load shedding for each line outage with and without DWPT integration is depicted in Fig. 6. The maximum allowable limit for load shedding at each bus is set at 50% of the load for that particular bus.

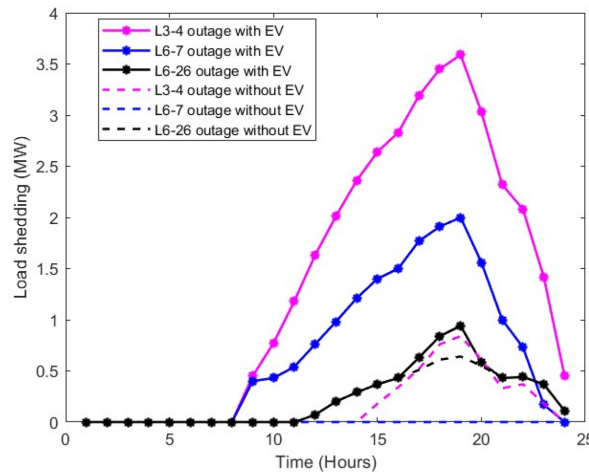

Fig. 6. Total load shedding in each hour.

As illustrated in Fig. 6, during the line outages L$3-4$ and L$6-7$, the regions equipped with EVs become isolated from those connected to the upstream network, leading to significantly increased load shedding compared to scenarios without EV integration. Specifically, for L$3-4$ outage, total load shedding escalates dramatically from 4.12 MW in the non-EV scenario to 33.38 MW when EVs are integrated. For L$6-7$ outage, load shedding rises from 0 MW without EVs to 16.35 MW with EVs. Meanwhile, for L$6-26$ outage, the increase is more modest, from 5 MW to 5.69 MW.

TABLE II
COMPARISON OF COST WITH AND WITHOUT MITIGATION OF DWPT GENERATED LOAD DEMANDS BY PV AND BSS INTEGRATION

Outages	With mitigation (k\$)	Without mitigation (k\$)	Improvement
L$3-4$	25.8	32.6	26%
L$6-7$	25.5	31	21%
L$6-26$	25.6	30.2	18%

Moreover, to assess the impact of DWPT system on the system costs, a comparison is presented in Table II showing the costs with and without EV integration. The costs analyzed include operational costs and load shedding costs. The price for load shedding is fixed at all times and is set at \$200 /MWh. This fixed rate allows for a straightforward comparison of the financial implications of integrating EVs into the system. As shown in Table II, for line outages L3-4, L6-7, and L6-26 the costs increased by about 26%, 21%, and 18%, respectively. The cost values as seen in Table II highlight the effectiveness of the method explained in Section II to mitigate the EV in-motion load in the system through the integration of DERs (i.e., PV and BSS). Although the PV and BSS in this paper are primarily utilized to serve the EV load, they also have the potential to assist in meeting the system's overall load demands whenever there is excess power available.

This paper contributes to solve an important problem of EV in-motion integration into DN in which the authors have proposed DERs integration to overcome the stress that EV imposes on the system and to manage the increase in operational cost. The EV in-motion load is calculated using the real traffic data, and then the PV and BSS are introduced to support this load. Test results show that the cost associated with the DN is found to be significantly increased under both normal and extreme events conditions when EVs are considered. However, incorporating DERs helps to mitigate the load and makes the solution economically attractive.

IV. Conclusion

This paper presented an interesting and evolving problem created by DWPT roadway, in particular, we investigated the impact of EV load on the operational costs associated with the efficient management of DN. Real traffic data was utilized with 10% of vehicles designated as EVs to calculate the EV load. Subsequently, the necessary sizing for PV systems and BSS was determined to support the EV load throughout a day. An MILP optimization problem was formulated to minimize the system costs, and two case studies were conducted to assess the effectiveness of the proposed optimization framework.

In this paper, the first case (under normal condition) involved the system that was operating under normal conditions incorporating PV and BSS to mitigate the EV load, and test results demonstrated that the operating cost of DN while incorporating PV and BSS was found to be lower ($23.7k) than the DN without PV and BSS ($29.7k). In other words, this represents a significant contribution of DERs to reduce the system cost by about 20%. The second case (under extreme event condition) involved operating the system by considering the line outages caused by a hurricane. The inclusion of the DWPT system introduced additional challenges to the DN operations. Notably, these challenges intensified when an outage occurred on a line that isolated the zone containing the DWPT system from the area connected to the upstream network. In the most severe scenarios, load shedding increased dramatically from 4.12 MW to 33.38 MW, underscoring the significant impact on the system costs. This analysis highlighted the critical need for the strategic integration of PV and BSS to enhance system efficiency with respect to economic aspect.

Since the EVs on DWPT roads are vehicles in-motion, the uncertainty of speed can introduce errors in calculating the EV load, and this will be an interesting future work. This paper considered only one DWPT system at bus-10 of the DN. Additionally, the potential future work would be to consider DN management incorporating DWPT system at a large-scale with high (%) EV in-motion penetration. Furthermore, to provide a comprehensive analysis of the economic aspects, the impact of EVs on the locational marginal price will be another future work as this analysis will aid the power system planners for optimal decision making process with respect to the placement of DWPT roads with a goal to ensure that electrified-transportation infrastructure development aligns well with both economic efficiency and system reliability.

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