Spatiotemporal Impact of Electric Vehicles in Mitigating Damages from Destructive Storms

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***Abstract*—The impact of Electric Vehicles (EVs) on the grid and the benefit of utilizing them as a source of energy to increase the grid's reliability and resilience in severe weather conditions are shown in this study. This case study is the winter storm Uri that happened in February 2021 in Texas and impacted a large part of the United States. The studied grid is a realistic 7000-bus electric grid on the Texas footprint to mimic the ERCOT system without revealing confidential data. The results show that using EVs as power sources can help avoid outages and the necessity of load shedding in similar events.**

***Index Terms*—Vehicle-to-grid, winter storms, load shedding, power outages, grid reliability, renewable energy**

I. Introduction

Despite a decrease in overall new car sales in 2020, EV sales increased globally by 39% over the previous year. It is predicted that the sales of EVs will increase up to 30 million cars in 2028 and will include almost 50 percent of new passenger car sales by 2030 [1]. Figure 1 shows the global sale of conventional cars and EVs from 2018 to 2030. According to this Figure, although the global passenger car sale faced several challenges in 2020, EVs have become more popular. It is estimated that the penetration of EVs of Texas in the United States grows to over 3.2 million by 2033 and the total energy capacity of EV energy storage is approximately 208 GWh based on EV type including EV light-duty passenger cars around 60 GWh, EV buses around 28 GWh, and EV Trucks around 120 GWh [2]. Furthermore, according to the kind of vehicle, EVs may store between 20 and 600 kWh of energy in their batteries [2].

One of the main objectives of power system operation and planning is to ensure that electrical power is provided reliably and that the power grid is resilient to severe weather conditions. Several events present various challenges to the power system as they change the expected load and operation situation compared to the usual circumstances. For instance, the Texas winter storm Uri on February 15-17, 2021, damaged hundreds of thousands of customers and caused billions of dollars in damage to the Electric Reliability Council of Texas (ERCOT), which distributes electricity to the majority of Texas. During the winter storm Uri, the unexpectedly low temperatures increased the electrical energy demand for heating. According to the Federal Energy Regulatory Commission report [3], some generator turbines were frozen, and there was a shortage of natural gas reserves that caused a generation shortage compared to the load. Therefore, there was a necessity for load shedding to avoid a complete blackout of the ERCOT grid and keep the optimization problem (power flow) solvable. Figure 2 shows the impact of the winter storm on Feb 15, 2021, in system frequency between 1 am and 2 am, which resulted in the necessity of load shedding. Because of the freezing weather and lack of heating energy, this process affected over 4.5 million households in Texas, causing more than 60 fatalities in over 20 counties of Texas and more than 195,000 million dollars of damage [4]. If more energy storage capacity or EVs with the possibility of injecting power into the grid were available during this event, extreme mitigation measures such as load shedding could be avoided. Reference [5] studies how battery storage could reduce the damage caused by the Power Failure in Texas in February 2021.

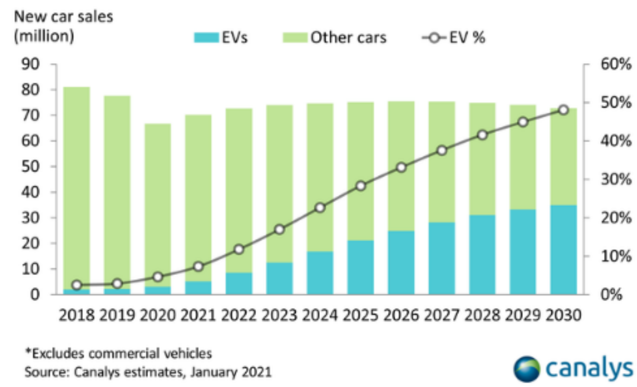

Fig. 1. Global Passenger Car Sales [1]

Overall, with the increase in the penetration of renewable resources and their dependency on the weather, as well as the potential for extreme weather events caused primarily by global warming, there is a tendency toward increased usage of battery storage in the electric grid to help in improving

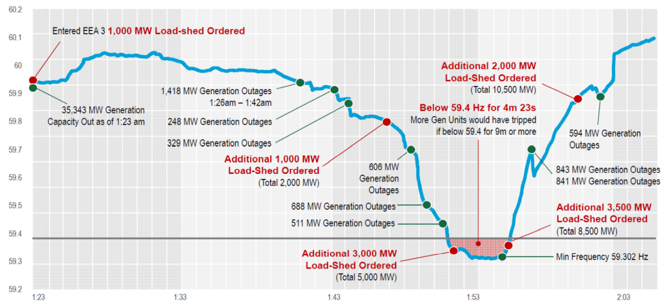

Fig. 2. Winter Storm - February 2021 [4]

the grid's reliability and resilience [6]. On the other hand, as energy storage is a little expensive power source, it is encouraging to use the capacity of EVs in times of emergency. Bidirectional EVs usage will reduce the need for costly stationary distributed energy storage. Vehicle-to-Grid (V2G) technology has been proposed as an area of research over several years to use the capacity of EVs as the power source. It can be beneficial for saving the power generated by renewable energy resources in EV batteries and supplying electricity to the grid in an emergency [7]. References such as [8] and [9] discuss the advantages and disadvantages of the V2G system. The technical difficulties in bidirectional charging are discussed in reference [10]. Reference [11] reviews the role of EVs as portable energy storage devices for power system resilience enhancement. Reference [12] shows that both utilities and EV owners can benefit from V2G because when its power transactions are performed, EV owners will be compensated for using the energy stored in their cars while in idle mode. According to [13], which examines the effects of V2G on electric grid frequency management, transient stability has also received interest in V2G technology and demonstrated that EVs might be able to offer efficient frequency control.

Studies like [14] believe that companies are reluctant to implement this technology due to the battery life reduction and increased anxiety of drivers of depleting the required charging. However, as EV batteries continue to improve, this will be a less concerning issue. Ford company is one of the pioneers that implemented bidirectional EV chargers [15]. In addition, Electric Power Research Institute (EPRI) launched a research to assess the viability of integrating V2G technology with mainstream car manufacturers, such as Fiat Chrysler Automobiles and Honda Motor, who offered cars with bidirectional power conversion systems [9].

In this paper, the impact of Electric Vehicles (EVs) on the grid and the benefit of utilizing them as a source of energy to increase the grid's reliability and resilience in severe weather conditions are shown. This case study is the winter storm Uri that happened in February 2021 in Texas and impacted a large part of the United States. The studied grid is a realistic 7000-bus grid on the Texas territory to emulate the ERCOT system without releasing sensitive data.

II. Modelling EVs in the Grid

A. EV Modeling Strategy

1) EV Charging Model: The linkage between transportation and the power system is the spatiotemporal charging demand. Considering the critical importance of a realistic charging pattern, we constructed a realistic charging demand strategy considering the original travel model for trip origins and destinations, a vehicle's dynamic model for EV energy consumption, and used surveys on travel and charging behaviors. The estimated Travel Demand Model (TDM) and travel studies run the EV charging simulation from [16]. TDMs consist of both the start-travel node (departure location) and the end-travel node (arrival location). In addition, they contain information such as total distances, operating time, and fuel consumption throughout a day in the regional transportation network. The network was created by urban traffic simulation [17] and the traffic dynamics are generated by a simulator called Mobiliti [18].

To predict the in-transit power usage of EVs, the model creates travel paths that it produces as output after taking the transportation system and traveling needs as inputs. A subset of travel itineraries is selected randomly to become EV traveling utilizing a predetermined EV market share. It is necessary to employ an activity-based EV model to analyze how distinct transportation-related characteristics affect energy consumption [19]. The next step is to estimate EV power usage depending on the circumstances of in-transit operation using a parametric simulation inferences technique [20]. A Bayesian Network statistic modeling (BNSM) that accepts the industry experience beforehand and can be improved to utilize an information method is employed to describe the automobile powertrain. The specifics of its modeling and verification are described in [20].

For a list of trips in the region, we simulated a specific percentage for the penetration of different types of EVs and the model considering whether it is a 100, 200, or 300-mile range EV. The range from each allocated EV in the network is picked according to the anticipated EV market penetration from EV sales figures [21]. EVs having distances of 100, 200, and 300 miles each made up 25%, 13%, and 52% of the overall EV fleet. The state of charge is then simulated for each travel at the beginning of a trip to evaluate if it needs to charge considering the available energy depending on the energy usage patterns for EVs with various distances. It also estimates if this trip is the last trip of the day, based on model outputs, and assigns home demand charging accordingly. The road linkage driving length and velocity discovered from the automobile itineraries were used to fit the energy usage rates per mile produced from the EV models to each driving. Using the recharging needs modeling, the overall drive in road usage transformed into recharging demands. Finally, a Monte Carlo strategy was implemented to consider the uncertainties of the model.

B. Mapping EV Charging Demand to the Electric Grid

The results of transportation studies and the transportation simulation are the location and time series of EV charging.

The geographic coordinates of the grid's substations and buses, along with their latitudes and longitudes, are used to apply the recharging needs to the power network simulations to include this information in the power system simulation. The methodology to map the EV charging demand to electric grid substations is explained in more detail in [22].

C. Load Time Series

The method described in [23] and [24] generates the 24-hour time series load data for each bus for one year. Considering load data of the time step, each bus's physical locations are employed to specify a distinctive power usage profile for that region. After that, an iterative aggregation method is used to combine freely accessible building-level and facility-level load time data to the buses. This method generates bus-level load data by merging location prototype building and facility load data every time with the concentration of resident, business, and industry loads at each node in the system. The synthetic load data each time are confirmed by applying the time series of an authentic power system in [24].

Once the load from each EV charging station is mapped to its substation within the transmission system, the EV load time series from Section II-A is represented as a load at the bus level within its assigned substation. The synthetic load data at the bus level is also updated to include this load.

D. Vehicles to Grid Modeling

The possibility of connecting EVs to the grid is modeled as batteries at the end-of-trip locations of EV fleets where the vehicles are in parking and idle mode. The geographical coordinates of the start and end travel nodes are from TDMs, and if the travel distance is shorter than 40 miles it is assumed that EVs are not depleted and can be used as a source of power. For integrating this information into the electric grid, the parking locations of EV fleets must be mapped to electric grid models with transmission-level substations by using a Voronoi diagram. The EV battery stations that EVs are parked and they are in idle mode are allocated to the substation connected to the location of end-travel nodes of EV fleets. The EV battery stations are connected to the electric grid model as generators such as battery storage.

III. Time Step Simulation

A. AC Optimal Power Flow (OPF)

To calculate the steady-state outcomes in a power system that minimizes the generation cost from Eq. 1, the ac OPF [25] is employed. Coefficients (a, b, and c) that represent quadratic cost curve elements of generators specify $\mathcal{F}_c(P_G)$:

$$\min_{P_G} \mathcal{F}_c(P_G) = \sum_{g=1}^{|\mathcal{G}|} [a_g + b_g P_G, g + c_g P_G^2, g] \tag{1}$$

The power balancing equations (2, 3) have to be satisfied. In addition, additional operational constraints from (Eq. 4) to (Eq. 7) should be considered [25].

$$P_{G,(g \in g(i))} - P_{D,i} = |V_i| \sum_{k=1}^{|N|} |V_k| (G_{ik}^Y cos\theta_{ik} + B_{ik}^Y sin\theta_{ik}) \tag{2}$$

$$Q_{G,(g \in g(i))} - Q_{D,i} = |V_i| \sum_{k=1}^{|N|} |V_k| (G_{ik}^Y sin\theta_{ik} - B_{ik}^Y cos\theta_{ik}) \tag{3}$$

$$P_{min,g} \leq P_{G,g} \leq P_{max,g} \qquad \forall g \in \mathcal{G} \tag{4}$$

$$Q_{min,g} \leq Q_{G,g} \leq Q_{max,g} \qquad \forall g \in \mathcal{G} \tag{5}$$

$$V_{min,i} \leq |V_i| \leq V_{max,i} \qquad \forall i \in \mathcal{N} \tag{6}$$

$$P_e^2 + Q_e^2 \leq S_{max,e}^2 \qquad \forall e \in \mathcal{E} \tag{7}$$

In the equations, the variables $|Vi|$ and $|\theta_i|$ stand in for the size and degree of the voltage at the i-th bus, respectively. The θ_{ik} is the gap between the voltage degrees from the i-th bus to the k-th bus. The system's representation of the fleet of buses is N, and the actual and reactive power demands at the i-th bus are $P_{D,i}$ and $Q_{D,i}$, respectively. Similarly, $P_{G,g}$ indicate the g-th generator's actual power, and $Q_{G,g}$ reflect the g-th generator's reactive power.

In the system, the fleet of all generators is denoted by $\mathcal{G}$. The real and reactive value of the Y bus matrix is denoted by its real component as G_{ik}^Y and B_{ik}^Y. $(P_{min,g}, P_{max,g})$ as real power and $(Q_{min,g}, Q_{max,g})$ as reactive power show the generator operating limits by minimum and maximum. Bus voltage operating limits are constrained by $(V_{min,i}, V_{max,i})$. The thermal limit, $S_{max,e}$, constrains the flow of power to each bus of e, and it is connected to the flow of real and reactive power in (Eq. 7). The power flow on each bus is provided by the power equations (Eq. 8) and (Eq. 9).

$$P_e = |V_i|^2 G_{ik}^Y - |V_i||V_k| (G_{ik}^Y cos\theta_{ik} + B_{ik}^Y sin\theta_{ik}) \tag{8}$$

$$Q_e = -|V_i|^2 B_{ik}^Y - |V_i||V_k| (B_{ik}^Y cos\theta_{ik} - G_{ik}^Y sin\theta_{ik}) \tag{9}$$

B. Direct Inclusion of Weather Data in OPF

We have proposed a strategy in our previous work [26], to map weather stations with electric grid generators, input time-dependent weather measurements such as wind speed, cloud coverage percentage, and temperatures directly into OPF modeling, and output the actual time-dependent capacities of generators especially renewable generators based on the weather. The renewable generators' models are extracted from [27]. These models and input data are then used in a time-step simulation to update the actual capacities of generators and find the output generation of renewable resources based on the availability of renewable resources [26].

TABLE I
TEXAS SYNTHETIC GRID STATISTICS

Parameter	Numerical Value
Buses	6,717
Generators	731
Loads	5,095
Switched Shunts	634
Substations	4,894
Transmission lines	7,173
Maximum load (MW)	74,667
Maximum generation (MW)	104,914

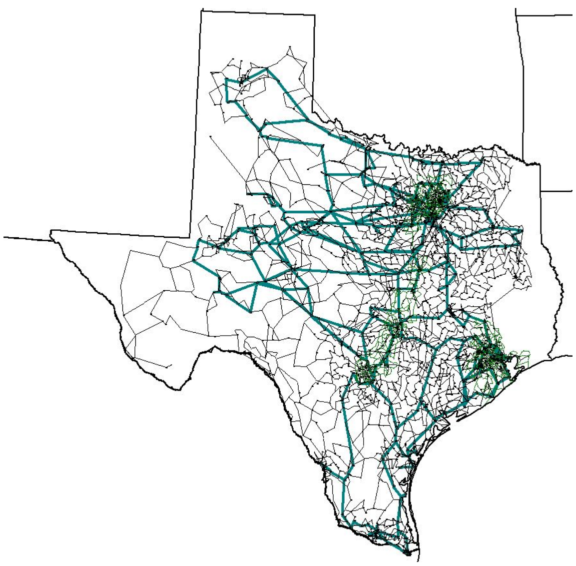

Fig. 3. The one-line diagram of transmission lines of the studied grid over Texas footprint. This grid is synthetic grid and is not real one.

IV. CASE STUDY

A. Grid Model

The grid, in this study, is a synthetic but realistic grid that covers the territory of Texas in the U.S. without disclosing any Critical Energy/Electric Infrastructure Information (CEII). This grid was developed using publicly accessible data, including U.S. Census statistics [28] and information on generators from online in the Energy Information Administration (EIA) [29]. The detailed strategy to create this grid is explained in [30] including assignment of substations, transmission lines and reactive power control devices. All the planning for substations, transmission lines, and reactive power fall under the same procedure. Grids are created and verified using validation metrics, which are essential characteristics of real grids [31], [32] to offer data sets that are realistic. The availability of geographical data for system components is a crucial component of these synthetic grids. This grid can be available in [33]. The 7000-bus synthetic grid, seen in Fig. 3, includes the ERCOT [34] geographical territory. Bolded green lines show 345 kV transmission lines, 138 kV lines are shown in black, and 69 kV lines with light green.

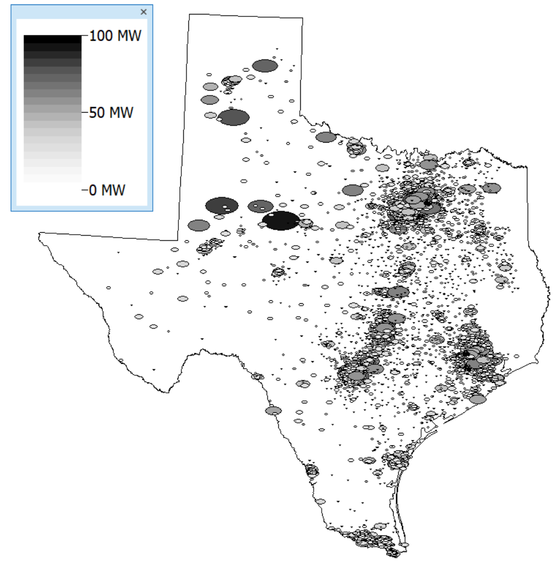

Fig. 4. Geographical Data View of Load Substations in Peak Loads in the Texas Case Study

Figure 4 shows a geographical data view (GDV) of the load substations based on the strategy presented in [35], [36]. The main parameters of the case and the maximum load are shown in Table I. The oval's size is related to the dimensions of the power stations.

B. Scenarios

The studied scenarios in this paper include weather and load data in February 15, 2021. The hourly load data at the bus level created in Section II-C is then scaled based on [3]. Weather models of generators in this paper are based on [26]. In Texas weather stations, hourly measurements such as temperatures, wind speed, wind direction, cloud coverage percentage, and dew points are gathered from [37] and directly included in optimal power flow models to update the output and actual capacities of generators, primarily renewable generators.

Two scenarios that are studied in this paper include:

- The Base case: Texas load on February 15, 2021
- The V2G case: base case Texas load with the addition of the required EV charging demand a with 15% EV penetration with V2G capability

Figure 5 shows that Dallas, Austin, and Houston are the three major cities with the most EV registration in Texas. In addition, from Fig. 4 the highest electricity demand is in these cities as both are related to the population distribution in Texas. As a result, if EVs in big cities are used as energy resources to the grid when an emergency case such as a Texas winter storm Uri, they are very close to the electrical loads.

V. RESULTS

Simulations are run by PowerWorld [39], Python and MATLAB installed on an Intel(R) Xeon(R) CPU E5-1650 v4 @ 3.60GHz and RAM 64GB. After time step simulation is

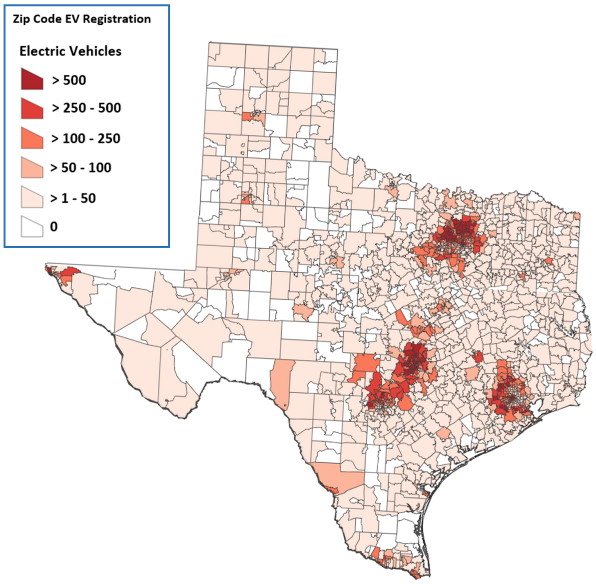

Fig. 5. Texas Electric Vehicle Registration Mapping [38]

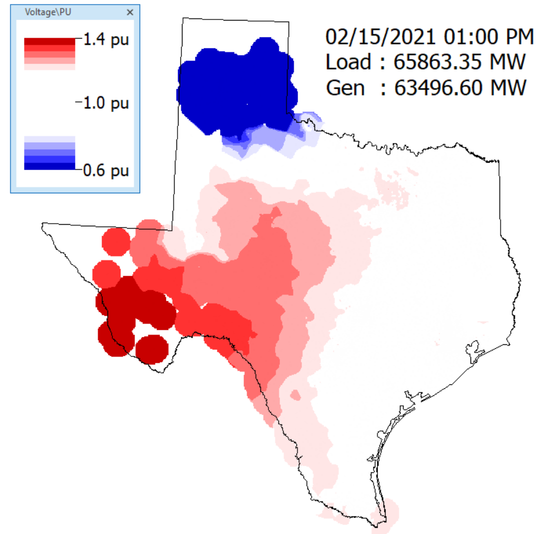

Fig. 6. Voltage magnitude on February 15, 2021 with the base case

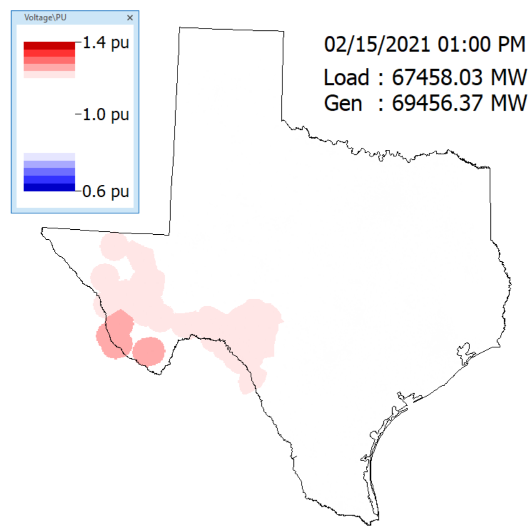

Fig. 7. Voltage magnitude on February 15, 2021 with EV15%

applied in the base case with the impact of load and weather but without including any EVs to solve AC OPF, there was a convergence issue because of the voltage collapse at 1 pm on February 15, 2021. The North of Texas had low voltage issues below 0.9 per unit (p.u) in 165 buses as well as The West of Texas resulted in high voltage problems above 1.1 p.u in 1747 buses. Overall 1912 buses had severe voltage violation problems in this case because of a shortage in generation compared to the load. In general, if generation is lower than load in the real power grid, it would be a blackout as the simulation shows the voltage collapse and the slack bus provides a very large real and reactive power. In this situation, ERCOT enforced load shedding several times to avoid a general blackout all over this state.

Figure 6 shows a voltage contour of p.u voltage levels of buses of this case based on the strategy mentioned in [40]. It should be noted that the generation, in this case, is lower than the load and therefore this case goes to a blackout. After implementing the impact of EVs with the capability of energy storage is mapped to the grid, although the overall demand is increased by around 1.5 GW due to the EV charging demand, the available generation from EV batteries is also increased by around 6 GW, so the AC OPF is solved and there is no major voltage convergence issue in the system. Figure 7 depicts the voltage contour of buses inside the Texas network following the application of the effect of EVs with V2G capabilities. Please note that in this case, it is assumed that only 15% of the overall cars are EVs with V2G capability.

VI. Conclusion and Future Work

The hourly required demand to charge EVs in specific locations and times of the day is calculated based on travel patterns and then added to the hourly load of the studied grid over the Texas footprint. Then the possibility of taking advantage of EVs as the power source in severe weather events is researched. The V2G capability is added to the grid at times that EVs are parked and in an idle mode based on end-of-travel geographic coordinates and if the duration of their previous travel is rather short. The same charging capacity of EV fleets mapped to the grid assumes that 15% of light-duty cars in two cities of Texas are EVs with V2G capability. The main weather measurements, such as wind speed, cloud coverage, and temperatures of a winter storm called Uri in February 2021 in Texas, are added as the input, and the capacities of generators and outputs of renewable generators are updated as output based on specific generator models. Then, for a scenario with bidirectional EVs, an ac OPF is solved. The outcomes compared to the basic simulations with no EVs.

The simulation outcomes demonstrate that although the basic scenario has a convergence issue and voltage collapse due to high load and less available generation, the base case adding 15% EVs with V2G capabilities overcomes this issue. This result indicates the advantage of using EVs as energy resources to increase the grid's stability and resilience in the case of some emergencies and the potential to save losses in millions of dollars.

ACKNOWLEDGMENT

The research was partly supported by funding provided by the U.S. National Science Foundation (NSF) in Award 1916142, the U.S. Department of Energy (DOE) under Award DE-OE0000895, the US ARPA-E Grant No. DE-AR0001366, and the Power Systems Engineering Research Center (PSERC).

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