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Reliability Evaluation of Power System based on Demand Response Program in the Presence of the Electric Vehicles

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ABSTRACT

The use of Demand-Side Management (DSM) to increase the reliability of composite power systems at hierarchical level II (HLII) with Electric Vehicles (EVs) is an important issue that has not been studied so far. Studies that have been conducted assumed that EVs are connected to the power system during the mid-peak load and peak load in two charge levels with uncertainty in influence and three load shifting levels (85%, 90%, and 95%). The reliability indices Loss of Load Expectation (LOLP), Expected Energy Not Supplied (EENS), Expected Health Duration (EHDUR), and Expected Margin Duration (EMDUR) are calculated. The present paper uses Monte Carlo Simulation (MCS) in modeling the uncertainty in the generation and transmission capacity of the power system and the influence of EVs. The modeling was performed on IEEE-RBTS standard system using the MATLAB software. The result indicates that more penetration of EVs will lead to higher load levels, and thereby LOLP and EENS indices will change much more, a trend that increases even more when EVs are charged during peak load. It is possible to increase EHDUR and EMDUR values by increasing load-shifting levels (95% to 90% and 85%).

Nomenclature

U	Random number in range (0, 1)
P_h	Probability of system health
P_m	Probability of system margin
P_r	Probability of system risk
Thi	Duration of the ith healthy states (hours)
Tmi	Duration for the ith marginal states (hours)
Tri	Duration for the ith risk states (hours)
T, Tx	Total simulation time (hours)
m	The length of the program period is based on the year
$F(h)$	Frequency of health (occurrences/year)
$F(m)$	Frequency of marginal (occurrences/year)
$F(r)$	Frequency of risk (occurrences/year)
$n(h)$	Total number of healthy states
$n(m)$	Total number of marginal states
$n(r)$	Total number of risk states
N	Total number of simulated (year)

Subscripts

A	Availability

Greek

λ	Expected failure rate

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μ	Expected repair rate

Abbreviations

FOR	Forced Outage Rate
TTF	Time To Failure
TTR	Time To Repair
LOLP	Loss of Load Probability
EENS	Expected Energy Not Supplied (mwh/year)
EHDUR	Expected Health Duration (hours/occurrences)
EMDUR	Expected Margin Duration

1. Introduction

Global environmental concerns, the decline in fossil fuels, and the consequent rise in fuel prices have led to an ever-increasing demand for electric energy. At the same time, electric power generation and transportation sectors are some but directly linked with 21st-century issues like maximum oil production, climate change, and energy independence. Currently, the facilities to build up transportation and greater electric power generation use more than 60% of the world's primary energies [1]. As a result, there is a growing interest in technologies such as EVs that can replace combustion fuel cars. These technologies help reduce dependence on petroleum products and the emission of greenhouse gases [2]. Electric transportation is considered a good alternative as it can considerably reduce the need for petroleum products and facilitate the use of renewable energies [2]. In recent decades, electric transportation systems such as electric trains have developed significantly and can be considered the primary infrastructure in the field of transportation in the future.

With the growing popularity of EVs, there is a severe challenge to the stability of the power system, as large volumes of mobile consumers across the grid cause imbalances [3]. Increasing the availability of electric machines and lack of proper energy management can lead to instability of the power system [4]. In order to study the reliability and suitability of the grid, it is necessary to recognize the behavior of EVs owners and appropriate management methods for these vehicles. Many researchers and methods have tried to find ways to mitigate these undesirable.

1.1. Background of the Research

In general, various studies and methods have been proposed to reduce the adverse effects of EVs on different loads. For example:

To predict the expected daily power for the uncoordinated charging power demand of an EV, a stochastic process has been utilized in [5]. Different charging time distributions and departure time as another random variable are considered in the model presented to manage the autonomous Demand Response (DR) technique to control the EV charging demand. In

The effect of integration of EVs on DR programs considering classifications types of customers with an emphasis on invaluable services that EVs can provide in smart grid assets is scrutinized in [6].

An optimal power dispatch problem on a 24-hours basis for distribution systems incorporated with directly controlled shiftable loads and renewable energy resources has been introduced. The number of optimization variables has been reduced using the optimization approach presented in [7].

The economic impacts of the vehicle to grid regulation reserves considering the restrictions arising from unpredictable mobility by vehicle users is analyzed through an actual case study in which a dynamic approach reveals a significant improvement compared with static ones is presented in [8].

A stochastic scheduling approach is proposed for many EVs parked in an intelligent parking lot is introduced in [9]. A self-scheduling model for an intelligent parking lot equipped solar systems and distributed generation through which practical constraints, solar radiation uncertainty, spinning reserve requirements, and EVs owner satisfaction are considered.

To coordinate the charging and discharging of EVs considering the frequency deviation signal to deal with the uncertainty of renewable energy generations, a dynamic demand control has been proposed in [10] leads to distinguishing characteristics such as simplicity, efficiency, robustness, and readiness for practical applications.

In [11], DSM of Plug-in Hybrid EVs (PHEVs) will become necessary to reduce peak loads as the penetration of PHEVs becomes greater. Trying to flatten the power-demand curve at transformers will avoid overloading and defer investment.

To control the risk management and participation planning of EVs in the smart grid at high penetration level of renewable energy resources, a stochastic model is introduced from the Independent System Operator's perspective in a away that cover all uncertainties caused by renewables, load patterns, parking patterns, and transmission lines' reliability [12].

In [13] has developed a model to create coordination between various PHEVs charging and discharging to reduce the electricity consumption peak and valley. In addition, the PHEVs owners earn economic profit in the grid through the demand peak and valley reduction. A DR scenario is presented as a corrective action following a contingency to maintain the power system within its limits during the urgent condition.

To quantify the reliability performance under different scenarios considering the influence of information and communication technology as well as automatic control scenarios, Sequential MCS are employed [14].

1.2. Classification of Power Systems for Evaluating Reliability

Modern electric systems are characterized by a vast and complex set of units from generation to individual consumers. Therefore, digital software and hardware are not entirely sufficient for the job of accurate and inclusive reliability evaluation of the grids. The power system parts are classified into three categories of generation, transmission, and transmission, based on their performance and reliability. This classification can be integrated to form hierarchical levels for reliability analysis [15].

The first hierarchical level (HLI) involves the assessment of reliability at the level of generation units and the ability of these generation units to satisfy local loads.

Reliability evaluation of Hierarchical Level II (HLII), includes generation units as well as a transmission network. Reliability evaluation of composite power systems is, in fact, the analysis of the capability to transmit electrical energy to consumers or main load points. Reliability evaluation of the third hierarchical level includes generation, transmission network, and distribution systems, and it considers the system's ability to provide energy for all consumers. Given the compartmentalization of the power system, reliability indices vary at different levels. Therefore, the present study focuses on the reliability indices of HLII.

DSM strategy can be considered a practical solution to increase the reliability of the power system in the presence of EVs [16]. Therefore, DSM can increase the reliability of the power system without expanding it, which helps improve the presence of EVs while maintaining reliability indices.

1.3. DSM plans

The DSM includes two mutually effective plans: Energy efficiency and DR [17]. Energy efficiency or management analyzes daily or seasonal energy consumption and reformats it into an optimal consumption scheme. DR refers to a set of practices that consumers follow in reforming consumption models, enhancing network reliability for greater productivity of facilities, boosting economics of investments, and removing energy limits. These practices help control costs, especially during peak load periods [17]. Various methods of remodeling load in DR are presented in Fig.1. [18].

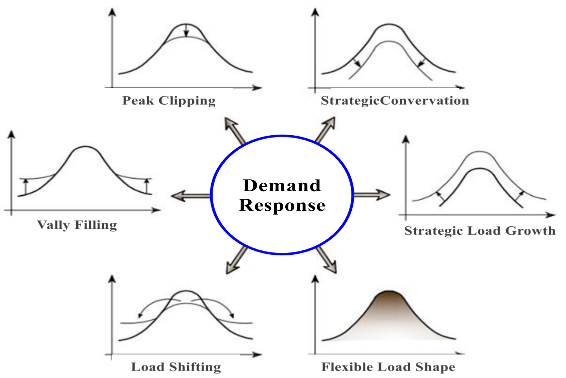

Fig.1. Different methods to change the load curve and shape in the DR program [18].

DR by load shifting technique is a widely used in DSM [19]. The extent DR using the load shifting technique influences reliability indices of the power system is excellent and depends on the shift amount from peak load during low load periods. Therefore, shifting load was performed at different levels, and resulting indices were used to analyze the model [20]. One of these indices is the application of the indices of system well-being criteria incorporating deterministic criteria in the probabilistic framework. These indices can integrate deterministic criteria in probability calculations to determine the system behavior [21]. Well-being analysis can also be considered in establishing the definite or probable criteria for determining the reserve required by power systems [21]. The present paper uses DR (concerning probable state programs for initiatives) at three levels to investigate the impact of the presence of EVs at three levels of 85%, 90%, and 95%, despite the uncertainty. The behavior of the power system in the selected model was evaluated using well-being analysis and indices as basic indices in assessing the reliability of the power system.

1.4. Innovation and Novelty

In general, during the reliability evolution of composite power system, it is necessary to understand calculated indices, which make the problem more complex [22] In this situation, system adequacy assessment is used to evaluate the considered indices. To gain the probability of lacking the system adequacy in the complex power system, each system's power flow analysis is performed considers the load model defined for that network. The load modeling can be done in three different ways: constant current, constant power, and constant impedance loads. load changes over time and each specific amount of load is valid just for an instant. Therefore, the AC power flow analysis is conducted for loads and generators for a short period. As a result, the main purpose of the AC power flow is to determine the steady state condition of bus voltages considering the constant power load model as the worst-case scenario considered in this paper.

Overall, in the present study, the applicability of DSM for enhancing the productivity of the facilities and enhancing the reliability of a hybrid power system, including generation, transmission lines, and loads in the presence of EVs, is evaluated using the MCS method and in correspondence to their uncertainty. It is assumed:

The probabilistic situations created by MCS for load, generation, and transmission lines for 1000 years of the study (due to the enormity of the calculations) are equal to 36 matrices representing 36 different modes of penetration of EVs. Each matrix includes the number of hours (8736000 rows) and 25 columns (the symbols of probabilistic loads, generation, transmission lines).

That EVs are connected to the power system during the critical and influential mid-peak load and peak load in two charging levels with uncertainty in influence and three load shifting levels (85%, 90%, and 95%).

Considering the voltage of busbars as a critical criterion to determine the level of a load shift. (A voltage range of 0.97-1.05V is chosen for the present study. In case voltages fall outside this range after the power flow, reactive power can be injected to put voltages within the predetermined limits. Thus, these cases in the evaluation of the variables can be considered as non-problematic situations.)

Employing well-being for the reliability evolution of the power system.

An AC power flow is selected to better evaluate the research variables, including LOLP, EENS, EHDUR, and EMDUR, so that the effects of the transmission lines on the precise evaluation of variables can be analyzed.

This is the case because when the loading level of power transmission lines is considered the loading criteria, the DC power flow is enough. But, while the busbar voltage value is also considered, the AC power flow should be used [23].

Because the AC power flow helps determine the effects of transmission lines on the provision of load and thus a better evaluation of the variables.

DR programs are generally divided into two types (i.e., price-based DR and incentive-based DR). In this paper, DR is considered motivational which is determined by companies and governments.

2. Proposed Methods

2.1. Simulation Flowchart

In this paper, MCS was applied to simulate different states of power system with uncertainty in generation capacity and in transmission and also well-being model was applied to evaluate different states of operation of the system in HLII level with penetration of EVs (shown in Fig.4. MCS is a probabilistic method with approximate results which vary a little in various runs [24]. Thus, these results can be minimized and negligible when the method is applied carefully. The present study, therefore, conducted 1000 samples (equal to 1000 years).

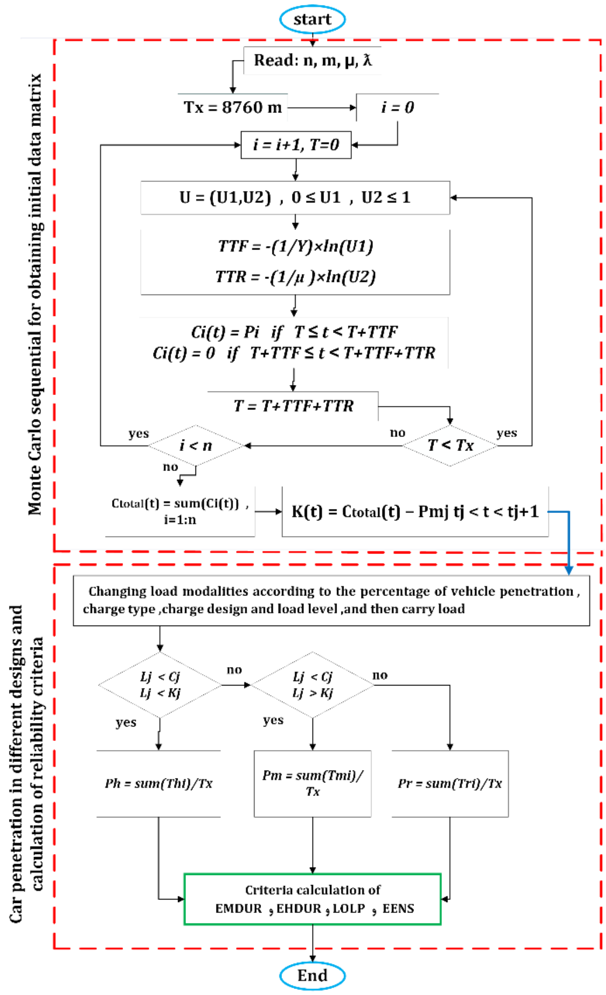

Fig. 2. Proposed simulation flowchart

3. Formulating the Problem

3.1. Well-being analysis Models

Health state refers to a condition when a power system can provide the required load and secure a desirable reserve. When the system fails to provide the necessary load, it is in a risk state. Any condition that falls between these two states is known as marginal: the system can only provide its required load [25], [26].

Since the actual load is continually fluctuating, the uncertainty in predicting short-term load and possible errors create particular problems. A sufficient reserve load must be thought out to adequately feed the required load [26]. MCS can track working/failed generation units and, thus, can be used to evaluate the operation of the power system. Accordingly, the reserve is calculated when the most significant unit is subtracted from the available capacity at any given reserve level. Then heath, risk, and marginal states are determined by assuming the following periods:

The risk is linked to those levels with loads more abundant than available capacity and is calculated by the following equation [26].

$$P_r = \frac{\sum Tri}{T} \tag{1}$$

Health defines the condition when the system provides its load and has a desirable reserve. In other words.

Capacity of the total load < (Available Capacity largest unit)

Equation 2 shows the probability of system health [26].

$$P_h = \frac{\sum Thi}{T} \tag{2}$$

A risk state refers to a state when the system can provide its load but cannot maintain a reserve load [18].

$$P_m = \frac{\sum Tmi}{T} \tag{3}$$

Where:

$$P_h + P_m + P_r = 1 \tag{4}$$

A better and more detailed description of these states is given in Fig.3.

3.2. *Reliability*

The primary task of a power system is to provide electric energy for consumers economically and reliably [27]. There are many parameters in a power system that affect reliability [28]: load demand, generation units' specifications, associated systems, consuming available resources, and load control and management. In HLII or composite system, the Loss of Load Expectation (LOLP) and Expected Energy Not Served (EENS) are essential factors which are calculated by (٥) and (٦). Other reliability indices are health and marginal duration, which are represented in (7) and (8), respectively [26].

3.3. *Monte Carlo Simulation (MCS)*

According to references [29], there are two ways to determine the reliability indices: deterministic or analytical method and probabilistic or accidental simulation. The analytical methods usually employ mathematical models that include simplification. Here, reliability indices are achieved through solving the mathematical problems directly. However, in simulation methods, these indices are determined along the actual process and according to system behavior.

MCS is a widely used method for determining reliability indices [27]. The term MCS is generally applied to any technique that estimates quantitative variables through simulation. Finally, it is fair to say that MCS can be used to simulate the power system and penetration of EVs [30].

$$LOLP = \frac{\sum_{i=1}^{n(r)} t(r)_i}{N \times 8760} \tag{5}$$

$$EENS = \frac{\sum_{i=1}^{n(r)} e_i}{N \times 8760} \tag{6}$$

$$EHDUR = \frac{\sum_{i=1}^{n(H)} t(H)i}{n(H)} \tag{7}$$

$$EMDUR = \frac{\sum_{i=1}^{n(M)} t(M)i}{n(M)} \tag{8}$$

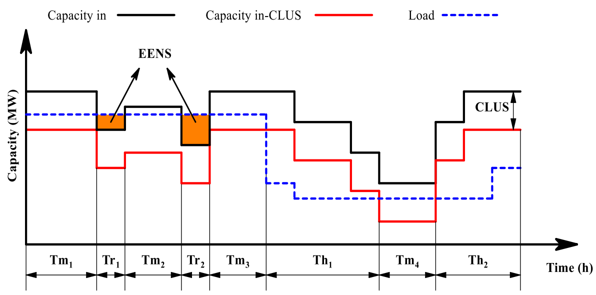

Fig.3. Three modes of health, margin, and risk in power systems according to load profile and generation capacity

3.4. *States of Generating Units*

The trial IEEE-RBTS system under study is characterized by 11 generating units with 240MW capacity. These units can be coupled in discreet and mutually incompatible pairs. Therefore, the case where working and failed units are displayed as available and unavailable in a bimodal demonstration (Forced Outage Rate). The probability of other occurrences demands the introduction of a highly complex arrangement in mode space. The probability of the bimodal availability and unavailability is computed by using the following equations in the analytical method [27], [32]:

$$A = \frac{\mu}{\mu + \lambda} \quad \text{Available Status} \tag{9}$$

$$FOR = \frac{\lambda}{\mu + \lambda} \quad \text{Unavailable Status} \tag{10}$$

In the present paper, the MCS of units in the bimodal unit is possible by using a random value between (0 - 1).

3.5. *The Duration of States*

The random value must be transferred to the time domain to determine the duration of the state. The bimodal generating units are described by the model presented in Fig.4.

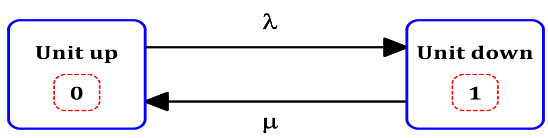

Fig.4. Dual-mode generation unit [14], and [19].

The random values for time to failure (TTF) and time to repair (TTR) for a bimodal model of the generating units (Fig.4.) are computed as follows [17], [32]:

$$TTF = -\frac{1}{\lambda} Ln\, U_1 \tag{11}$$

$$TTR = -\frac{1}{\mu} Ln\, U_2 \tag{12}$$

Where U1 and U2 represent two random values between 0 and 1.

The sequential sampling of the functioning, failure, and usage-repair can be realized by a chronological sampling of the values for TTF, TTR, and TTF.

4. Simulation results of the proposed method

One of the main parts of simulation is the matrix arrangement of the data about the system that are the input for MCS. The simulation is considered for 1000 years to get better accurate results. Therefore, the matrixes include 25 columns and 8736 rows, and therefore the entire matrix has 8736000 rows. Given the probability function of MCS about integrating loads, generation, and transmission lines, there are some states that have no generation or transmission lines. This means that some buses display drop or decrease in load (in this study, the min and max voltages are 0.97 and 1.05, respectively). To correct the voltage profile and identify buses, AC loads are distributed to any rows from the matrix and buses with a drop in voltage are corrected through adding reactive power to both buses no. 4 and 6 up to 10MVar in 0.01 steps. If after this addition, the voltage of buses remains still beyond the desirable range, the load is interrupted in steps of 0.1MW to correct the voltage profile. In case that voltage drop is still not corrected, it is considered a defective state and will be removed from the matrix and analytical calculations of the power system. In the power system under study, 165000 rows are removed from the matrix. As such, 25 columns and 8571000 rows are considered.

After removing defective states, 36 penetration states are applied to the matrix. As a result, 36 matrixes with 25 columns and 8571000 rows are under study. Distribution is conducted for each row of these 36 matrixes, and those EVs whose voltage profiles are not corrected at this point are removed from the matrix and then the reliability indices are computed.

4.1. The System under Study

This research studies a 6-bus IEEE-RBTS system for which a Single-Line Diagram (SLD) is used in this article [31]. This system consists of 6 buses, and buses no. 1 and 2 represent generation units. On the whole, there are 11 generating units. Transmission lines operate with 230KV the total capacity is 240MW, and the peak load is 185MW. The network also includes two distribution systems installed in buses no. 2 and 4. These systems are comprehensive and contain main reforms and factors [30]. This research studies a 6-bus IEEE-RBTS system for which a Single-Line Diagram is presented in Fig. 5.

4.2. Simulating Parameters

4.2.1. *Load Simulation*

There are two main ways to display variations in the load employed in MCS: temporal and non-temporal [24].

- The temporal method extends the load levels in the order or chronological format of their actual or possible occurrences. This can be annually or in

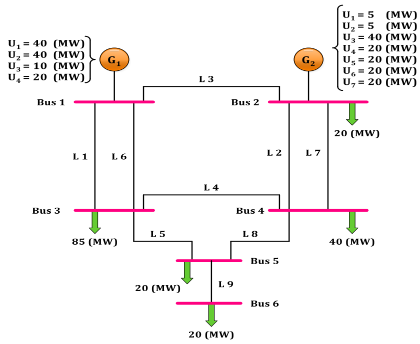

Fig.5. SLD of the IEEE-RBTS network.

  other time frames. In the simulation, in 365 days, the maximum demands are specified, while it can also be displayed on an hourly basis, i.e., 8760 hours.
- The non-temporal method displays the load levels in decreasing order and form of cumulative values.

The present paper uses an hourly temporal method to display the variations.

4.2.2. Estimating the number of Consumers

The trial IEEE-RBTS system includes six buses with two distribution systems in buses no. 2 and 4. Buses 2 and 4 feed 1850 and 4700 household consumers, respectively [28]. Moreover, every consumer has an average share of 3.981KW (Table I). The total number of household consumers was computed by dividing the total household load by the mean share of each consumer.

The average consumption of household loads is equal to 62.9 MW, with the number of consumers equal to 15800 people; the same amount of EVs can be added to the power system.

4.2.3. The Penetration Schemes for EVs

Introducing EVs into the system means an extra load for the system. The load curve changes according to the number, speed, and charge time of these EVs. Load simulation shows days with the maximum load if a year is assumed to have 365 days. The present paper analyzes various scenarios and different states along with penetration percentage, time, charge amount and length of the plug-in are as follow:

4.2.3.1. Penetration percentage

Adding EVs happens at different levels. This research considers three levels (Table II): 10%, 20%, and 30% [31].

4.2.3.2. Speed and duration of the charge

Today, there are different models of EVs, and these models will develop in performance and range. According to references [32], this study considers three models of EVs (Table III). A single type of battery (24.1KW) is assumed here in this study, while the equation (16) is held to be true for all EVs and shows the average size battery [33].

$$\text{EVs}'\text{composition } (\%) \times \text{Battery Capacity } (\text{kWh}) = (0.37 \times 35) + (0.1 \times 16) + (0.53 \times 18) = 24.1\ (kwh) \quad (16)$$

Table I. Residential Consumer Specifications for IEEE-RBTS Distribution Systems

Bus	Number of residential customers	Total residential load in the bus MW	Average load per consumer KW
2	1580	7.25	3.919
4	4700	19	4.043
Average			3.981

Table II. EV penetration percentage

State of	% Penetration	Number of EV
1	10	1580
2	20	3160
3	30	4740

Table III. Electrical vehicle info

EV's Parameter	EV type	Value
EVs′composition (%)	BEV	37
	City-BEV	10
	PHEV90	53
Battery Capacity (kWh)	BEV	35
	City-BEV	16
	PHEV90	18
Average battery capacity (kWh)		24.1

Two modes are considered for charging EVs (Table IV) that vary according to the hours of charge and the power received from the network [34].

Table IV. Battery charge time

Charge type	Charging time (hrs)	Consuming EV at the time of recharging (kW)
Slowly	6	3.7
Fast	2	11

Table V. Available states of 10% and 20% of EV penetration, with Taking load levels

State of	1 to 18						19 to 36					
Charging speed	Fast						Slowly					
Scheme type	1			2			1			2		
Load level %	85	90	95	85	90	95	85	90	95	85	90	95

4.2.3.3. Hours of connection to the network

Previous studies usually assume that EVs are charged during low load periods [34]. This study assumes that some EVs are also charged during mid-peak and peak load. For this purpose, two charge schemes are considered:

- Scheme 1: 70% of the vehicles are charged during low load periods and 30% during mid-peak hours.
- Scheme 2: 60% are charged during low load hours, 30% during mid-peak load, and 10% during peak load hours.

There are three penetration levels (10%, 20%, and 30%), two charge modes, two penetration schemes, and three load shifting levels. Therefore, 36 states are considered for EVs under this study (Table V).

4.3. Well-Being Model

According to section 3.3.5. EVs were added to the power system under study while applying DSM. As a result, the load curve changed, and consequently, the values for the probability of health, risk, and marginal states underwent changes since the primary factor for evaluation of penetration of EVs, analysis of DSM, and comparison of different states is the analysis of the probability of risk mode in the system.

It is necessary to determine the reliability indices at default conditions to evaluate the penetration of EVs and evaluate the effect of DSM on the reliability of the power system in the presence of EVs. Therefore, a table shows the definite capacity of generating units before adding EVs. Then, the probability values in each health, risk and marginal states are computed according to the load curve. The probability values of each state at default phase are computed using values for Th, Tm, Tr as well as total time period of applying the management (Table VI).

Table VI. Results for the simulated power system at the base state.

PR	Pm	Ph
0.00229	0.01794	0.97852

As indicated in section 4.2.3, penetration schemes for EVs are as follow:

- Penetration percentage (10%, 20% and 30 %.)
- Speed and duration of the charge
- Hours of connection to the network (Scheme 1 and Scheme 2)
- DR, according to Fig. 6.
- A simulation of 36 different penetration states for EVs is presented in Table 7.

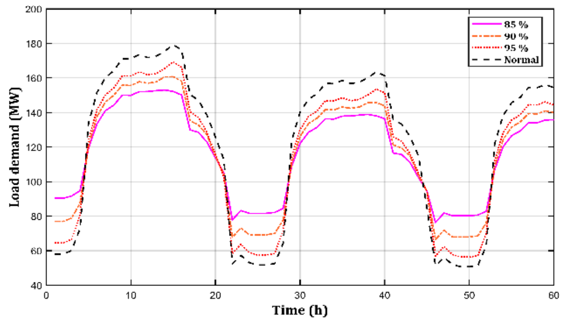

Fig.6. Small Portion of the DR curve in the load shifting approach for three levels, including 85%, 90%, and 95%.

As shown in Table VII, it is possible to conclude that the probability of a health state is 85% greater than the default conditions since in low load levels, fewer portions of peak load are in a risk state and vice versa. For instance, the probability of risk mode for penetration of EVs at three penetration levels and at three load shifting levels, and in 2 penetration schemes at a fast charge is given in Figs. 7 and 8.

As shown in Figs. 7 and 8, the probability of risk mode increases with the penetration of EVs and an increase in load shifting levels. According to Fig.8, the probability of risk mode in scheme 2 is higher than in scheme one since 10% of EVs are charged during peak load. Also, the probability of risk mode for the system has decreased by 85% of response in proportion to default conditions. This shows the importance of demand-side management.

Table VII. Simulation results for various DR considering EVs penetration

Penetration level			% 10		% 20		% 30	
			Slow	Fast	Slow	Slow	Slow	Slow
Ph	1	%85	0.97829	0.97827	0.97806	0.97790	0.97775	0.97755
		%90	0.97687	0.97687	0.97664	0.97647	0.97637	0.97612
		%95	0.97388	0.97405	0.97388	0.97373	0.97368	0.97337
	2	%85	0.97816	0.97817	0.97775	0.97776	0.97740	0.97741
		%90	0.97665	0.97666	0.97620	0.97621	0.97569	0.97571
		%95	0.97385	0.97385	0.97336	0.97336	0.97285	0.97289
Pm	1	%85	0.01965	0.01967	0.01986	0.02002	0.02015	0.02036
		%90	0.02021	0.02029	0.02036	0.02063	0.02055	0.02095
		%95	0.01944	0.01965	0.01958	0.01996	0.01971	0.02031
	2	%85	0.01977	0.01977	0.02015	0.02014	0.02048	0.02047
		%90	0.02023	0.02023	0.02039	0.02039	0.02057	0.02057
		%95	0.01937	0.01937	0.01938	0.01938	0.01957	0.01957
Pr	1	%85	0.00081	0.00081	0.00083	0.00082	0.00086	0.00084
		%90	0.00167	0.00163	0.00175	0.00165	0.00184	0.02095
		%95	0.00544	0.00505	0.00529	0.00506	0.00536	0.00507
	3	%85	0.00082	0.00082	0.00085	0.00085	0.00087	0.00087
		%90	0.00187	0.00187	0.00216	0.00215	0.00249	0.00247
		%95	0.00553	0.00553	0.00600	0.00600	0.00632	0.00629

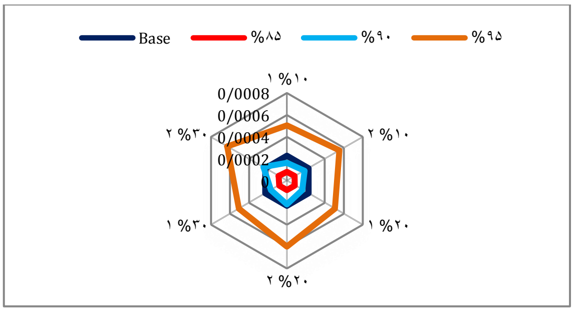

Fig.7. The probability of risk mode for EVs penetration scenarios with 10, 20, and 30% at three load movement levels, two penetration schemes, and EVs fast recharge.

4.4. EHDUR and EMDUR criteria

The duration of heath and marginal states is another reliability index useful for evaluating the reliability of generating the energy required by the consumers. The portion of time when the system remained in health and marginal states is computed using equations no. 7 and 8. The values for EHDUR and EMDUR are shown in Tables VIII and IX: they are based on simulation results for the default state and other states.

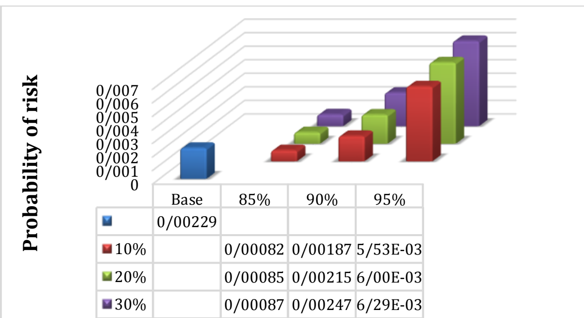

Fig.8. The probability of risk mode for EVs penetration scenarios with 10, 20, and 30% at three load movement levels, second scheme, and EVs fast recharge.

According to results presented in Tables VIII and IX, it can be said that more extensive penetration of EVs and the consequent elevation of load shifting levels (90% and 95% instead of 85%) lead to shorter duration of health and marginal states. It is possible to hold that duration of health and marginal states are in a reverse relationship with the penetration percentage of EVs and load shifting level. Duration of health and marginal states is maximum in case of 85% response. For instance, the duration of the health state in 85% and 90% response to load is better than the default state, which a fact that confirms the necessity of demand-side management. In scheme 2, health durations and marginal conditions have been reduced more than in scheme 1.

Table VIII. Durability index for modes of health and margin in the base state (in percentages)

EHDUR	EMDUR
0.0380	6.00782

Table IX. Frequency index in modes of health, margin, and risk for various load levels (in percentages).

Load	Penetration level		10%		20%		30%	
	Type of Scheme	Load	Slow	Fast	Slow	Fast	Slow	Fast
EHDUR	1	%85	496.51834	496.94421	495.36586	477.91435	493.49100	466.67067
		%90	451.08798	451.30899	450.17465	445.44184	448.41521	435.03752
		%95	376.85885	381.71031	368.45478	380.81724	365.35846	377.64950
	2	%85	495.53324	495.53550	494.35177	494.41310	492.37771	492.38036
		%90	441.97182	442.36246	434.60940	434.63420	426.53329	426.62569
		%95	376.83047	376.88077	369.44418	369.44431	366.40120	365.67198
EMDUR	1	%85	9.66733	9.69004	9.74640	9.50499	9.85555	9.45225
		%90	7.87525	7.91312	7.92634	7.96325	7.96451	7.93532
		%95	5.32436	5.52758	5.12961	5.61060	5.09155	5.68124
	2	%85	9.70058	9.69839	9.87512	9.87313	9.99659	9.99413
		%90	7.53177	7.55008	7.34443	7.34498	7.13702	7.13650
		%95	5.32461	5.32506	5.14466	5.14460	5.14753	365.67198

4.5. LOLP and EENS criteria

LOLP and EENS, other useful reliability indices, are computed by equations 5 and 6. The values for LOLP and EENS are shown in Tables X and XI: they are based on simulation results for the default state other states.
Furthermore, LOLP and EENS in the event of EV penetration for 10%, 20%, and 30% at three load shifting levels and according to 2 penetration schemes at fast charge mode are presented in figs. 9 and10.
According to results presented in Tables X and XI as well as figs. 9 and 10, it can be said that more extensive penetration of EVs and the consequent elevation of load levels lead to more significant variations in LOLP and EENS that can bring about a higher probability of risk state. Since 10% of the EVs are charged during peak load in scheme 2, the variations in LOLP and EENS are higher than in scheme 2.

Table X. The probability of loss of load index and expected unsupplied energy at various load levels (in percentages)

Penetration level			% 10		% 20		% 30	
			Slow	Fast	Slow	Fast	Slow	Fast
LOLP	1	%85	0.00081	0.00081	0.00083	0.00082	0.00086	0.00084
		%90	0.00167	0.00163	0.00175	0.00165	0.00184	0.00168
		%95	0.00544	0.00505	0.00529	0.00506	0.00536	0.00507
	2	%85	0.00082	0.00082	0.00085	0.00085	0.00087	0.00087
		%90	0.00187	0.00187	0.00216	0.00215	0.00249	0.00247
		%95	0.00553	0.00553	0.00600	0.00600	0.00632	0.00629
EENS	1	%85	158.34029	157.36419	162.41795	160.46481	167.03972	164.10974
		%90	205.94852	204.29843	209.08356	205.56381	213.09863	207.43705
		%95	396.71956	375.93725	390.37591	377.02637	398.96287	378.25962
	2	%85	160.88077	160.80423	167.35078	167.18895	174.18564	173.93146
		%90	213.26638	213.09636	224.88555	224.48871	238.21935	237.53162
		%95	404.96918	404.48007	437.82488	436.75410	472.96213	471.31908

Table XI. The probability of loss of load index and expected unsupplied energy for the base power system (in percentages)

LOLP	EENS
0.00023	310.31593

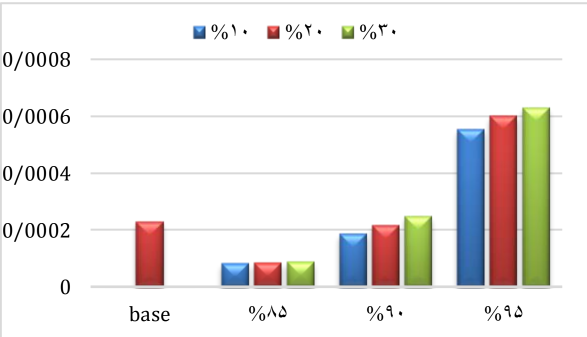

Fig.9. LOLP index for EVs penetration scenarios with 10, 20, and 30% at three load movement levels, second schemes, and EVs fast recharge.

5. Analysis of results

- Since the present study assumed the 10%, 20%, and 30% penetration levels for EVs at three load shifting levels (85%, 90%, and 95%), the following results can be expressed:
- EVs reduce the probability of a health state and increase the probability of marginal and risk states. With more significant penetration percentages or more EVs added to the system, the probability of risk mode increases while the reliability of the power system decreases. In other words, the following relationship holds in this study according to the assumed penetration levels:

The probability of risk mode at 30% penetration level > Probability of risk mode at 20% penetration level > Probability of risk mode at 10% penetration level

- According to the results, charging EVs during peak load reduces reliability much more than during mid-peak load and low load. This leads to an increased probability of the risk state. Therefore, it is better to charge EVs during low and mid-peak loads.
- Reduction or addition of load during peak loads has the most significant impact on the risk probability. In other words, charging the EVs during peak load can negatively affect system reliability.

Probability of Risk in Scheme 2 > Probability of Risk in Scheme 1

When the number of EVs charged at different times is determined, the speed of charging can have a different impact on system risk. The results show that the probability of risk for the system in slow charging mode is higher than in fast charging mode.

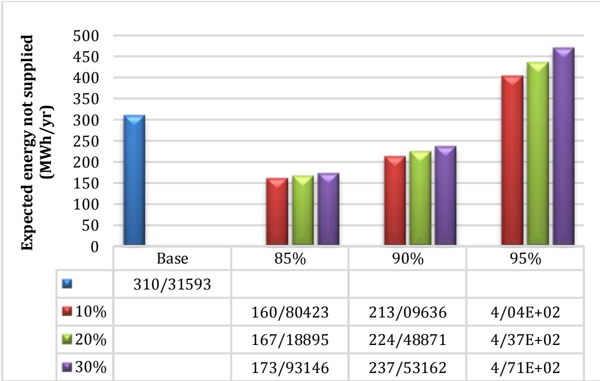

Fig.10. EENS index for EVs penetration scenarios with 10, 20, and 30% at three load movement levels, second scenario s, and EVs fast recharge.

6. Conclusion

This paper investigates the effects of EVs in power systems regarding penetration percentage, charging speed, time of charging speed, and various penetration schemes. The analyses show that adding EVs into HLII as new loads lead to an increase in the risk state in the power system. Therefore, demand-side management can be applied as an effective and inexpensive way to reduce the probability of risk mode without expanding facilities of the grid or transmission lines. The application of demand-side management with load shifting technique in HLII showed that this method could maintain the penetration level of EVs and enhance the reliability level of the power system.

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