# Prediction of Static Voltage Stability in a Power System with Large-Scale Electric Vehicles

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## ABSTRACT

This paper takes a classic 3-machine 11-bus system integrated with scaled and disorderly electric vehicles (EVs) as an example, and uses the power system analysis toolbox PSAT to analyze the static voltage stability of the system which appears limit-induced bifurcation (LIB) phenomenon before the saddle-node bifurcation (SNB). Large-scale disorderly charging of EVs will make the load parameter $\lambda_{LIB}$ at the LIB point become smaller, and discharging of large-scale EVs can increase the $\lambda_{LIB}$. Local compensation capacitor groups dispersedly at the low voltage buses and various types of photovoltaic power plants installed on load region can, in some extent, increase the $\lambda_{LIB}$, and reduce the adverse effects caused by EVs charging. The support vector machine (SVM) algorithm is used to predict the LIB point in the 3-machine 11-bus system with scaled and disorderly EVs. After training, the SVM optimal model can fleetly and accurately predict the LIB point and is convenient for computing the system's load margin index according to real-time charging power of EVs. The prediction method based on SVM is beneficial to improve the system static voltage stability, and suitable for on-line application.

*Keywords: Electric vehicles (EVs); static voltage stability; limit-induced bifurcation (LIB); saddle-node bifurcation (SNB); load margin index*

## 1. INTRODUCTION

As the two-carbon target advances, the impact of electric vehicle (EV) integration into the power grid has attracted widespread attention. EVs can be classified into pure electric vehicles (PEV), plug-in hybrid electric vehicles (PHEV), and fuel cell electric vehicles (FCEV) [1,2]. Among them, PEVs are the main development direction in the future. With the development of large-capacity battery technology and the reduction of manufacturing costs, the number of PEVs will increase on a large scale. The EVs discussed in this paper refer to PEVs. From the perspective of power systems, EVs can be regarded as loads or distributed power sources. When used as a charging load, they have the characteristics of mobility, randomness, and intermittency. When connected to the urban distribution network for charging, they will have an impact on load balance and power supply capacity, aggregated charging and local overloading, power quality and harmonic pollution, load curves and peak-on-peak, power grid environment and energy conservation and emission reduction, and the life of distribution transformers [3]. Large-scale disorderly charging of EVs is bound to impact the stable operation of the distribution network [4,5]. In the early development stage of EV industry, disordered charging mode was basically adopted, and users can charge at any time according to their needs. In the EV charging and swapping station, the replaced batteries will be charged immediately, that is, "charged immediately after replacement". With the large-scale development of EVs, this disordered charging state will inevitably have an adverse impact on the static voltage stability of the power grid.
Literature [6] proposed a voltage control method considering EV charging and the system's voltage instability. Literature [7] analyzed the voltage stability mechanism in a distribution network with large-scale EVs. Literature [8] proposed a static voltage stability assessment scheme considering EV charging state and load fluctuation limit. Literature [9] presented the charging load curve of a typical day in a Beijing Olympic EV charging station. It can be seen that the charging power gradually increases throughout the morning, reaches a peak at around 12 noon, and reaches a second peak at around 10 pm. After the large-scale development of EVs, this charging power curve superimposed on the power grid load curve will put great pressure on the system to maintain the static voltage stability. Literature [10] analyzed the impact of EV charging on the static voltage stability margin of the distribution network when disordered charging methods and peak-valley time-of-use electricity price-regulated charging methods are adopted. Literature [11] proposed three control methods for EV charging equipment that can improve the system load margin, and through simulation verification, it is found that the droop control method has the most significant effect and can effectively improve the static voltage stability. Literature [12]

proposed a distributed voltage stability monitoring method that makes full use of the chargeable and dischargeable characteristics of EVs, preferentially reducing the load of EVs to reduce the load reduction of traditional power grid loads, and verified the accuracy and feasibility of this method through simulation. Literature [13] applied the MLP neural network algorithm to predict the voltage stability L index of a classic system with EVs integration to evaluate the static voltage stability and obtains good prediction results. Literature [14] found through research that the clustered EV fast charging stations can significantly reduce the static voltage stability. Literature [15] proposed a preventive control strategy for improving the system's static voltage stability based on an efficient power plant EV model under the vehicle-to-grid (V2G) mode. Literature [16] studied EVs' impact on the steady-state stability of power systems, and established the corresponding research framework. Literature [17] developed a scheme to evaluate the power supply based on voltage stability considering the large-scale EVs charging scenario.

Bifurcation theory is an effective tool for studying the voltage stability of power grids containing random and intermittent new energy generation [18], and it is still very practical when studying the integration of large-scale EVs into the power grid. This paper will take the disordered integration of large-scale EVs into the classic 3-machine 11-bus system as an example, and study the static voltage stability critical bifurcation points by analyzing the bifurcation phenomena of the system. The SVM algorithm will be used to conduct the static bifurcation points' prediction.

## 2. INTRODUCTION TO STATIC BIFURCATION ANALYSIS OF POWER SYSTEMS

There are two methods for analyzing the voltage stability of power systems using bifurcation theory: static bifurcation analysis and dynamic bifurcation analysis. The static bifurcation analysis method does not consider the dynamic characteristics of components such as generators and loads and automatic control devices or systems. It searches for bifurcation points based on the power flow equations of the system. The bifurcation phenomena related to static voltage stability generally include the saddle-node bifurcation (SNB) and the limit-induced bifurcation (LIB) [19]. In contrast, dynamic bifurcation analysis must take into account the dynamic characteristics of components and control systems and solve the system of ordinary differential equations (ODEs) to search for bifurcation points [20]. Currently, the continuation power flow (CPF) method is the most commonly used method for static bifurcation analysis. It has good robustness, but it has a large amount of calculation, the step size is difficult to control, and the calculation time is long, so it is not suitable for online application. More realistically, CPF is difficult to truly reflect the impact of large-scale grid-connection new energy on the voltage stability of the system [21].

In the static bifurcation analysis of power system voltage stability, SNB is the most basic type of bifurcation. At the bifurcation point, the Jacobian matrix of the power flow equations is singular. LIB is caused by one or more constraint variables reaching their boundary values, resulting in system voltage instability. In particular, when the reactive power output of a generator reaches its limit, the operating state of the generator changes from a PV node type to a PQ node type, and the system voltage suddenly collapses. At this time, the system Jacobian matrix does not become singular. Generally, LIB occurs before SNB, so it poses a greater threat to the system's voltage stability [22,23]. The LIB point that can induce system voltage collapse can be regarded as the critical point of system static voltage stability, and the load margin index $\mu$ can be redefined:

$$\mu = 1 - \frac{P}{P_{\mathrm{LIB}}} = 1 - \frac{\lambda}{\lambda_{\mathrm{LIB}}} \tag{1}$$

where, $P_{\mathrm{LIB}}$ and $\lambda_{\mathrm{LIB}}$ represent the active power of the system load and the load parameter at the LIB point, respectively; $P$ and $\lambda$ represent the current active power of the system load and the load parameter ($\lambda = P/P_0$, where $P_0$ is the active power of the system base load).

The value of the load margin index $\mu$ is between 0 and 1. The closer it is to 0, the more unstable the voltage is; the closer it is to 1, the more stable the voltage is.

## 3. ELECTRIC VEHICLE INTEGRATION SYSTEM MODEL AND STATIC BIFURCATION ANALYSIS

The system shown in Fig. 1 is modified from the 3-machine 11-bus system in Literature [24]. This system includes a large system Gen 1 with a limited capacity and a generator Gen 2 that supplies power to the load area through five parallel transmission lines with a length of 200 km, as well as a local generator Gen 3 that supplies power to the load area. The 11-bus system has been used to analyze the voltage stability under large disturbances and other related issues of voltage stability. Now, by adding two distribution transformers T7 and T8 with a voltage level of 13.8 kV/0.4 kV and two 0.4 kV buses Bus d1 and Bus d2, as well as EV charging loads EV1 and EV2 (connected in a disordered cluster) to the original system, the static voltage stability of the EV grid-connected system can be studied. At present, most EVs use lithium batteries and exhibit constant power characteristics in about the first half of the charging time from the start of charging. Therefore, EV1 and EV2 in Fig. 1 are simulated by a constant power load model.

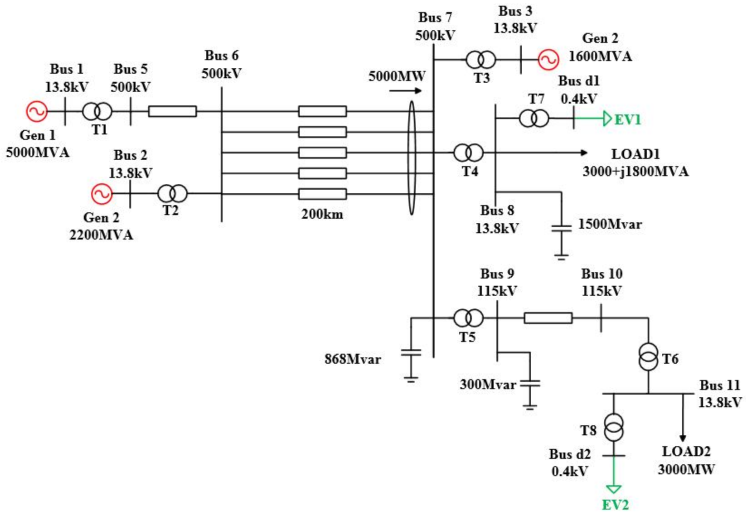


**Fig.1. The 11-bus system with large-scale EVs**

Generator parameters: Gen 1: slack bus, 5000 MVA, voltage 0.98 p.u., phase angle 0°; Gen 2: PV bus, 2200 MVA, voltage 0.964 p.u., active power output 0.6818 p.u.; Gen 3: PV bus, 1600 MVA, voltage 0.972 p.u., active power output 0.68375 p.u. Loads: LOAD1: 3000 + j1800 MVA, LOAD2: 3000 MW, both are assumed to be at peak values. Initial charging power of EV1 and EV2: the active power is set to 0.8 p.u., and the power factor is 0.98 and remains unchanged. The parameters of each line, transformer, etc. can be found in Literature [24]. The base capacity for calculating the per-unit value is 100 MVA.

The continuation power flow (CPF) calculation module provided by the power system analysis toolbox PSAT based on MATLAB is used to calculate and analyze the static voltage stability bifurcation of the system shown in Fig. 1. Figs. 2 and 3 show the *λ-V* curves of four load buses (Bus8, Bus11, Bus d1, Bus d2), where $\lambda$ is the load parameter.
Fig. 2 shows the *λ-V* curve obtained without considering the reactive power output limit of the generator. The system undergoes SNB, and the $\lambda_{SNB}$ at the bifurcation point is 1.2262 p.u. Fig. 3 shows the *λ-V* curve obtained considering the reactive power output limit of the generator. The system undergoes LIB and can lead to voltage collapse, and the $\lambda_{LIB}$ at the bifurcation point is 1.1484 p.u. Since $\lambda_{LIB} < \lambda_{SNB}$, the LIB point should be taken as the voltage collapse critical point in this system.



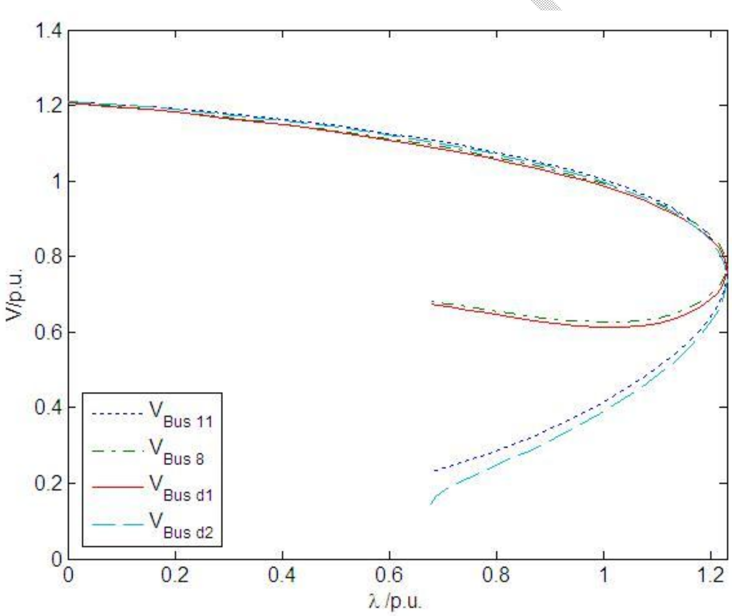


**Fig.2. *λ-V* curve (SNB)**

When the EV charging is not connected to the system shown in Fig. 1, it can be calculated that $\lambda_{SNB}$ = 1.2645 p.u. and $\lambda_{LIB}$ = 1.1799 p.u., both of which are greater than those when connected. Obviously, the large-scale disorderly charging of EVs reduces the static voltage stability of the system to a certain extent.

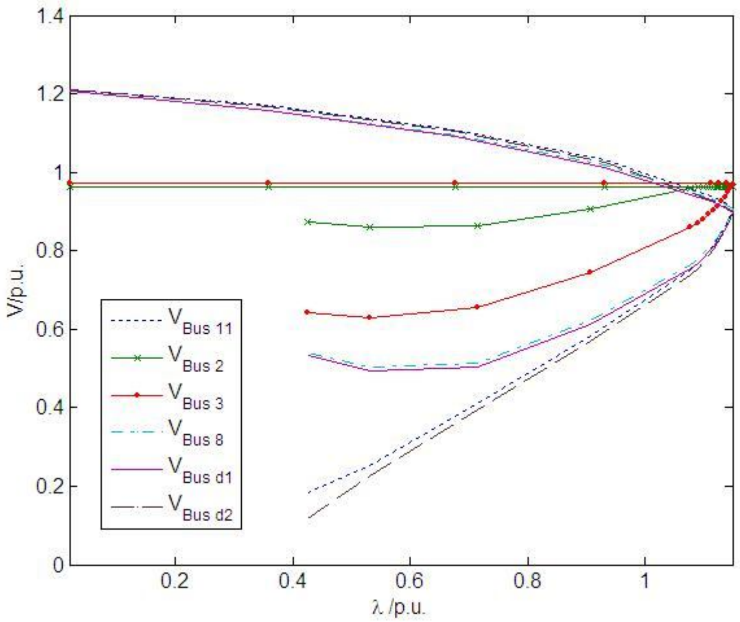


**Fig.3. *λ*-*V* curve (LIB)**

If the EVs adopt the V2G mode and EV1 and EV2 are connected to the system as power sources (simulated by a PQ generator model with a constant power output, and the initial active power is still 0.8 p.u.), $\lambda_{SNB}$ = 1.2909 p.u. and $\lambda_{LIB}$ = 1.2054 p.u., respectively. It can be seen that when the EVs discharge to the power grid, the occurrence of SNB and LIB can be effectively delayed, and the static voltage stability of the system can be improved.

## 4. LIB BIFURCATION CONTROL

The goal of bifurcation control is to take certain control measures for bifurcation phenomena to delay or eliminate bifurcation and improve the voltage stability of the system. To improve the static voltage stability of the system after EV integration, the following bifurcation control methods can be used to increase the load parameter value at the LIB point.

### 4.1 LOCAL PARALLEL CAPACITOR BANKS

The method of parallel static capacitor banks for local compensation can be used to achieve the delay control of the system LIB. From Figs. 2 and 3, it can be seen that on the upper branch of the *λ*-*V* curve, among the four load buses, the voltage of Bus d1 drops the most with the increase of the load, that is, it has the worst ability to withstand the load growth. Therefore, it can be qualitatively judged that Bus d1 is the load bus with the weakest voltage stability, and capacitor banks should be preferentially compensated locally at this bus. In practice, low-voltage capacitor cabinets should be decentralized and connected to each distribution station.
Table 1 shows the load parameter values at the LIB point of the system when 0.4 kV low-voltage capacitor banks C1 and C2 are connected in parallel at Bus d1 and Bus d2, respectively. It can be seen that as the total capacity of the parallel capacitor banks increases, the occurrence of LIB will be gradually delayed, but the increase in $\lambda_{LIB}$ is relatively small.

**Table 1. $\lambda_{LIB}$ values at LIB point**

| $Q_{C1}$ /p.u. | $Q_{C2}$ /p.u. | $\lambda_{LIB}$ /p.u. |
|---|---|---|
| 0 | 0 | 1.1484 |
| 0.1 | 0 | 1.1498 |
| 0.2 | 0 | 1.1503 |
| 0.3 | 0 | 1.1508 |
| 0.4 | 0 | 1.1513 |
| 0.5 | 0 | 1.1522 |
| 0.1 | 0.1 | 1.1504 |

| | | |
|---|---|---|
| 0.2 | 0.2 | 1.1515 |
| 0.3 | 0.3 | 1.1535 |
| 0.4 | 0.4 | 1.1563 |
| 0.5 | 0.5 | 1.1592 |

### 4.2 CONNECTING PHOTOVOLTAIC POWER SOURCES IN THE LOAD AREA

Considering that the integration of EVs can promote the consumption of new energy such as wind power and photovoltaic power [25], photovoltaic power sources can be connected to delay the LIB of the system. Now, a 3.8 MW distributed photovoltaic power station is connected to Bus 8 with a voltage level of 13.8 kV, and a 20 MW relatively large-scale photovoltaic power station is connected to Bus 10 with a voltage level of 115 kV. The photovoltaic power stations are simulated by the PQ generator model. After continuous power flow calculation, the $\lambda_{LIB}$ of the system is 1.1521 p.u. (approximately equivalent to the effect of connecting a 50 Mvar capacitor bank), which can delay the occurrence of LIB to a certain extent. If a 100 MW large-scale photovoltaic power station is connected to Bus 10, then $\lambda_{LIB}$ = 1.2379 p.u., which can significantly increase the static voltage stability region of the system. With the increasing integration of photovoltaic power sources into the power grid, they will play an increasingly important role in delaying the inherent static bifurcation and improving the system's static voltage stability.

## 5. LIB POINT PREDICTION BASED ON SVM ALGORITHM

To prevent voltage instability or collapse of the system caused by the disorderly charging of large-scale EVs when they are integrated into the power grid, it is of great significance to conduct online monitoring of the static voltage stability of the system when they are integrated. The SVM algorithm is simple, has good robustness and generalization ability, and can effectively solve the pattern recognition problems in high-dimensional, nonlinear and limited sample situations. At present, it has been applied to a certain extent in the daily load prediction of EVs, static voltage stability assessment and online monitoring. Literature [26] used SVM to conduct prediction research on the daily load of a pure electric bus charging and swapping station. The prediction time of SVM is much faster than that of the CPF method. Considering that this algorithm is suitable for online applications, SVM is used to predict the LIB of the large-scale EVs grid-connected system shown in Fig. 1. The prediction process is shown in Fig. 4.

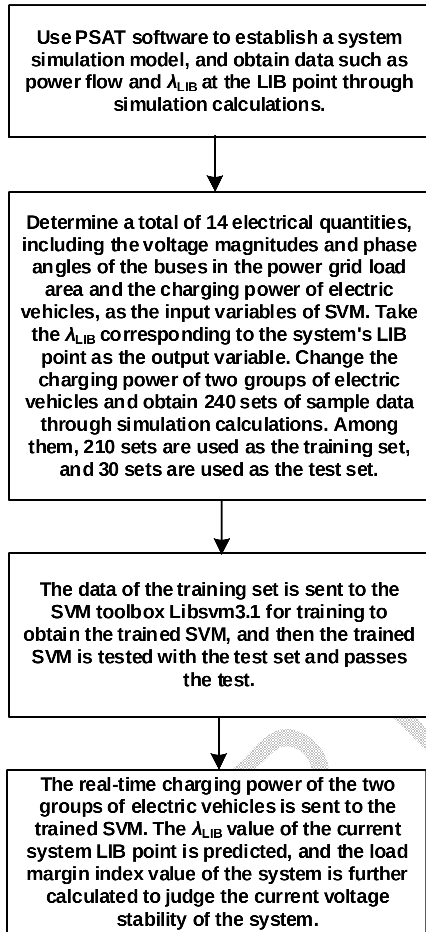


**Fig.4 Prediction process of LIB using SVM**

The input variables of SVM take the voltage magnitudes and phase angles of Bus 8, Bus 9, Bus 10, Bus 11, Bus d1, and Bus d2 in the load area, as well as the active powers of EV1 and EV2, with a total of 14 variables. Since the peak periods of the disordered charging load curves of EVs generally occur in the morning and evening, when collecting the training sample data, the powers of LOAD1 and LOAD2 are kept at their peak values. The output variable takes the corresponding $\lambda_{LIB}$ at the LIB point of the system.

Based on the system simulation model established in PSAT software, the charging power values of the two groups of EVs EV1 and EV2 are changed (traversing through various combinations from small to large). Through power flow calculations, the voltage magnitudes and phase angles of the six buses in the load area are obtained. Then, under the new base state, the CPF calculation is used to obtain the corresponding $\lambda_{LIB}$ values of the system. Eventually, 210 sets of data are obtained as the training set, and 30 sets of data are obtained as the test set.

The Radial Basis Function (RBF) is adopted as the kernel function of the SVM. The training set is randomly divided into five parts, and a 5-fold cross-validation is carried out. The Libsvm3.1 software package for SVM based on MATLAB is used for SVM regression prediction to generate the optimal model. Through calculations, the optimal model parameter combination is obtained as follows: the error penalty coefficient $C$ = 18.985, the insensitive loss parameter $\varepsilon$ = 0.01, and the RBF kernel function parameter $\gamma$ = 0.37098, all of which are within the set ranges.

Substituting the 30 sets of data in the test set into the trained optimal SVM model, the predicted values of $\lambda_{LIB}$ of the system can be calculated. Table 2 shows the predicted values of $\lambda_{LIB}$ and the actual values of $\lambda_{LIB}$ calculated by PSAT. It can be seen that the relative errors between the predicted values and the actual values are all less than 1%, which can meet the actual engineering requirements.

Table 2. Predicted values and actual values of $\lambda_{LIB}$

| $P_{EV1}$ /p.u | $P_{EV2}$ /p.u | The actual value of $\lambda_{LIB}$ /p.u | the predicted values of $\lambda_{LIB}$ /p.u | relative error |
|---|---|---|---|---|
| 0.8*0.1 | 0.8*0.1 | 1.1749 | 1.165934 | -0.007631034 |
| 0.8*0.1 | 0.8*0.2 | 1.1731 | 1.165790 | -0.006231522 |
| 0.8*0.1 | 0.8*0.4 | 1.1696 | 1.164699 | -0.004190691 |
| 0.8*0.1 | 0.8*0.5 | 1.1678 | 1.163711 | -0.003501448 |
| 0.8*0.1 | 0.8*0.6 | 1.1661 | 1.162506 | -0.003082277 |
| 0.8*0.1 | 0.8*0.9 | 1.1608 | 1.157847 | -0.002544067 |
| 0.8*0.1 | 0.8*1.0 | 1.159 | 1.156054 | -0.002541795 |
| 0.8*0.3 | 0.8*0.1 | 1.1725 | 1.166425 | -0.005180946 |
| 0.8*0.5 | 0.8*0.1 | 1.1700 | 1.165843 | -0.003553082 |
| 0.8*0.7 | 0.8*0.1 | 1.1676 | 1.164299 | -0.002826776 |
| 0.8*0.95 | 0.8*0.98 | 1.1494 | 1.149533 | 0.000115604 |
| 0.8*0.96 | 0.8*1.03 | 1.1484 | 1.148389 | -9.23989E-06 |
| 0.8*0.98 | 0.8*0.97 | 1.1492 | 1.149301 | 8.78212E-05 |
| 0.8*0.99 | 0.8*0.98 | 1.1489 | 1.148958 | 5.08486E-05 |
| 0.8*1.0 | 0.8*1.05 | 1.1475 | 1.147415 | -7.37552E-05 |
| 0.8*1.02 | 0.8*1.0 | 1.1482 | 1.148127 | -6.36052E-05 |
| 0.8*1.03 | 0.8*1.02 | 1.1477 | 1.147583 | -0.000101624 |
| 0.8*1.05 | 0.8*0.94 | 1.1489 | 1.148880 | -1.77459E-05 |
| 0.8*1.06 | 0.8*0.99 | 1.1479 | 1.147746 | -0.000133873 |
| 0.8*1.07 | 0.8*1.04 | 1.1469 | 1.146607 | -0.000255519 |
| 0.8*2.0 | 0.8*2.0 | 1.1152 | 1.124629 | 0.008455015 |
| 0.8*2.0 | 0.8*1.6 | 1.1223 | 1.127398 | 0.004542532 |
| 0.8*2.0 | 0.8*1.3 | 1.1275 | 1.131641 | 0.003672628 |
| 0.8*2.0 | 0.8*1.1 | 1.1309 | 1.135114 | 0.003726083 |
| 0.8*2.0 | 0.8*1.0 | 1.1327 | 1.136935 | 0.003738537 |
| 0.8*1.0 | 0.8*2.0 | 1.1274 | 1.130530 | 0.002775921 |
| 0.8*1.2 | 0.8*2.0 | 1.1251 | 1.127987 | 0.002565708 |
| 0.8*1.4 | 0.8*2.0 | 1.1227 | 1.125888 | 0.002839739 |
| 0.8*1.6 | 0.8*2.0 | 1.1202 | 1.124524 | 0.003860449 |
| 0.8*1.8 | 0.8*2.0 | 1.1178 | 1.124088 | 0.005625156 |

According to the real-time charging power of EVs EV1 and EV2, the $\lambda_{LIB}$ value can be input into the SVM for prediction, and then the load margin index of the current operating point can be calculated (the current operating point is the load parameter $\lambda$ = 1 p.u. in the base state). The voltage stability degree of the current system can be judged to determine whether more EVs are allowed to be connected to the power grid for charging. For example, when the charging powers of EVs EV1 and EV2 connected to the system are 0.8 p.u. and 0.8 * 1.05 p.u., respectively, the $\lambda_{LIB}$ predicted by the SVM is 1.147415 p.u. Substituting it into Equation (1), the margin index $\mu$ of the current operating point can be calculated as $\mu$ = 1 - 1/1.147415 = 0.12848. If it is assumed that the voltage stability load margin index of the system during normal operation is not less than 10 - 15%, the system has a certain load margin at this time, and it is allowed to continue to connect EVs for charging. Once the calculated load margin index value is lower than the specified lower limit, no more EVs are allowed to be connected to the power grid for charging, thus ensuring the static voltage stability of the system.

## 6. Conclusions

In this paper, a classic 3-machine 11-bus system with large-scale disorderly integrated EVs is taken as an example. The PSAT software is used to analyze the static voltage stability of the system, and the SVM algorithm is used to conduct prediction research on LIB. The following conclusions:

a. In the system with disordered clustering access of EVs, there not only exists the SNB phenomenon but also the LIB phenomenon which can induce the system voltage collapse. However, this LIB phenomenon is not caused by the access of EVs but is an inherent bifurcation phenomenon of the system itself. The LIB point should be regarded as the voltage collapse critical point of the system.

b. When EVs charge in the system with disordered clustering access, it will cause the load parameter $\lambda_{LIB}$ at the LIB point to become smaller, thus reducing the load margin of the current operating point. Conversely, if a large number of EVs discharge to the power grid, $\lambda_{LIB}$ will increase, delaying the occurrence of LIB.

c. Installing shunt capacitor banks for decentralized compensation on the low-voltage bus side can delay the occurrence of the system LIB to a certain extent, but the effect of bifurcation control is limited.

d. Connecting distributed photovoltaic power stations and large-scale or very large-scale photovoltaic power stations in the load area can effectively increase $\lambda_{LIB}$ (especially the effect of very large-scale photovoltaic power stations is quite remarkable), thereby improving the static voltage stability of the system with EVs accessing, and also facilitating the absorption of new energy power generation.

e. The designed LIB prediction method for the system with EVs accessing based on the SVM algorithm can accurately predict the LIB point and quickly calculate the load margin index. It can quickly judge the voltage stability degree of the current operating point according to the real-time charging power of EVs connected to the distribution network and determine whether more EVs are allowed to access the power grid for charging. The prediction method based on SVM is convenient for online application and is beneficial to improving the static voltage stability of the system.

## COMPETING INTERESTS

Authors have declared that no competing interests exist.

**COMPETING INTERESTS DISCLAIMER:**

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

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Option 1:

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

## REFERENCES


1. WANG, X., SHAO, C., WANG, X., DU, C. (2013). Survey of Electric Vehicle Charging Load and Dispatch Control Strategies. Proceedings of the CSEE, 33(1), 1-10.
2. YAN, Y., XIE, S., WU, Q., ZHANG, Y., ZHENG, L. (2024). An Energy Station Hydrogen Pricing Model and Its Solution Method to Guide User Behaviors of Hydrogen Energy Vehicles. Proceedings of the CSEE, https://link.cnki.net/urlid/11.2107.tm.20240929.1813.006
3. Samuel Dias Vasconcelos, José Filho da Costa Castro, Felipe Gouveia, Antonio Venancio de Moura Lacerda Filho, Ricardo Fonseca Buzo, Luiz Henrique Alves de Medeiros. (2024). Assessment of Electric Vehicles Charging Grid Impact via Predictive Indicator. IEEE Access, 12, 163307-163323.
4. CHEN, H., TANG, J., WU, H., SONG, J., DONG, H., LI, H. (2024). Optimal Scheduling of Distribution Network Considering Electric Vehicle Demand Response and Carbon Quota Revenue. Power System Technology, https://doi.org/10.13335/j.1000-3673.pst.2024.1365
5. YUAN, Q., TANG, Y. (2024). Multi-time Scale Decarbonization Coordination Strategy of Electric Vehicle Fleets Considering Transportation and Electricity Coupling. Power System Technology, 48(12), 4969-4979.
6. Yang, X., Du, X, Lei, J, Zou, C., Zhang, H., Li, B. (2023). A Voltage Control Method for Electric Vehicle Charging in the New Power System. 2023 5th International Conference on Electrical Engineering and Control Technologies (CEECT), 15-17 December, 2023, Chengdu, China.
7. Zhang, Y., Song, X., Gao, F., Li, J. (2016). Research of Voltage Stability Analysis Method in Distribution Power System with Plug-in Electric Vehicle. 2016 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), 25-28 October, 2016, Xi'an, China.
8. ZHANG, Q., TANG, F., LIU, D., ZHOU, S., GUAN, B., YANG, J. (2017). A Static Voltage Stability Assessment Scheme of Electric Power Systems Considering Charging State of Plug-in Electric Vehicles and Load Fluctuation Limits. Power System Technology, 41(6), 1888-1894.
9. HE, J., XIE, Y, YE, H., WANG, X., LI, Z. (2015). Influence of Electric Vehicles Charging Modes on Active Network Distribution. Electric Power Construction, 36(1), 97-102.

10. Zheng, Y., SUN, J., ZHANG, C., Lin, X. (2014). Study of Voltage Stability Margin for the Distribution Network with Electric Vehicle Integration. Transactions of China Electrotechnical Society, 29(8), 20-26.
11. XIAO, Y., ZHANG, M., ZHANG, Y., GUO, Q., ZHAO, W. (2015). Study of Electric Vehicle Charging Equipment Local Control Method Considering the System Static Voltage Stability. Power System Protection and Control, 43(13), 30-37.
12. WANG, X., GUO, Q., SUN, H., GE, H., XIN, S. (2015). Distributed Voltage Stability Assessment and Control Considering Electric Vehicle Charging and Discharging Load. (2015). Power System Protection and Control, 43(16), 43-49.
13. Makasa, K.J., Venayagamoorthy, G.K. (2010). Estimation of Voltage Stability Index in a Power System with Plug-in Electric Vehicles. Bulk Power System Dynamics and Control-VIII (IREP), 2010 IREP Symposium, Buzios, RJ, Brazil.
14. Dharmakeerthi, C.H., Mithulananthan, N., Saha, T.K. (2014). Impact of Electric Vehicle Fast Charging on Power System Voltage Stability. International Journal of Electrical Power and Energy Systems, 57(5), 241-249.
15. Wang, M., Mu, Y., Jia, H., Wu, J., Yao, X., Yu, X., Ekanayake J. (2015). A Preventive Control Strategy for Static Voltage Stability Based on an Efficient Power Plant Model of Electric Vehicles. Journal of Modern Power Systems and Clean Energy, 3(1), 103-113.
16. Zhou, B., Littler, T., Meegahapola, L., Zhang, H. (2016). Power System Steady-Sate Analysis with Large-Scale Electric Vehicle Integration. Energy, 115, 289-302.
17. Lyu, L., Yang, X., Xiang, Y., Liu, J, Jawad, S., Deng, R. (2020). Exploring High-Penetration Electric Vehicles Impact on Urban Power Grid based on Voltage Stability Analysis. Energy, 198,117301.
18. Li, S., Zhang, C., Zuo, J. (2023). Long-Term Voltage Stability Bifurcation Analysis and Control Considering OLTC Adjustment and Photovoltaic Power Station. Energies, 16(17), 6383.
19. ZHAO, X., ZHANG, X., SU X. (2008). Voltage Stability Studies and Bifurcation Theory in Power Systems. Transactions of China Electrotechnical Society, 23(2), 87-95.
20. Li, S., Duan, C., Gao,Y., Cai, Y. (2023). Classification Study of New Power System Stability Considering Stochastic Disturbance Factors. Sustainability, 15(24), 16614.
21. LI, X.，LIU, Y.，JIANG, T.，LI, G. (2024). Static Voltage Stability Region of Hybrid Multi-Terminal AC/DC Power Systems Utilizing Holomorphic Embedding Forming Method. Electric Power Automation Equipment, https://doi.org/10.16081/j.epae.202411017
22. ZHONG, H., YAO, D. (2014). Quick Tracking of Limit-induced Bifurcation Point of Voltage Stability. Electric Power Automation Equipment, 34(12), 65-69.
23. LIU, D., QI, Y., LI, S., BAO, M., GUO, Y., LI, J. (2024). Static Voltage Stability Region Considering Limit Induced Bifurcation. Electric Power. 57(4): 118-129.
24. KUNDUR, P. (1994). Power System Stability and Control. New York: McGraw-Hill.
25. Ma, M., Ren, Z., Liu, L., Liu, X. (2024). Orderly Charging Control Strategy for Electric Vehicles Considering New Energy Accommodation. Acta Energiae Solaris Sinica, 45(8), 94-103.
26. LIU, W., XU, X., ZHOU, Xi. (2014). Daily Load Forecasting Based on SVM for Electric Bus Charging Station. Electric Power Automation Equipment, 34(11), 41-47.