

Big Data Analytics for System Stability Evaluation Strategy in the Energy Internet

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Abstract—With the significant improvements in the Energy Internet, we have witnessed the explosion of multisource energy big data, whose characteristics of vast volume, fast velocity, and diverse variety not only formulate an essential infrastructure of the Energy Internet, but also bring threats to the system’s stability. In this paper, we concern with the system-level stability issues in the Energy Internet and study how to maintain a stable and healthy energy network environment. To this end, we propose a system-level stability evaluation model in the Energy Internet based on a critical energy function to explore small disturbance stability region (SDSR), where SDSR can be acquired via estimating the operational data threshold of distributed generations. The threshold is estimated based on energy consumption rather than equilibrium nodes, which applies the energy function theory and reduces the computation complexity. Moreover, in our proposed model, we add the big data approximate analytics algorithm into hyperplane fitting to optimize and analyze the SDSR. Simulation results on SDSR in a single dominant oscillation mode and multiple dominant oscillation mode have demonstrated the advantages and superiority of our proposed method over the prior schemes.

Index Terms—Big data approximate analytics, energy big data, energy function, Energy Internet, hyperplane fitting (HPF) method, small disturbance stability region (SDSR).

I. INTRODUCTION

RECENTLY, researchers have predicted that fossil fuel resources might be exhausted by 2050 [1], arousing great

Manuscript received September 16, 2016; revised December 30, 2016 and February 12, 2017; accepted April 1, 2017. Date of publication April 12, 2017; date of current version August 1, 2017. This work was supported in part by the National Natural Science Foundation of China under Grant 61572262, Grant 51521064, and Grant 51405075, in part by the National Science Foundation of Jiangsu Province under Grant BK20141427, in part by the Natural Science Foundation of Zhejiang Province under Grant LR14E050003, in part by the International Cooperation and Exchange of the National Natural Science Foundation of China under Grant 51561125002, and in part by The Qinlan Project of Jiangsu Province. Paper no. TII-16-1039. (Corresponding authors: Yixiong Feng; Guangdong Tian.)

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Color versions of one or more of the figures in this paper are available online at <http://ieeexplore.ieee.org>.

Digital Object Identifier 10.1109/TII.2017.2692775

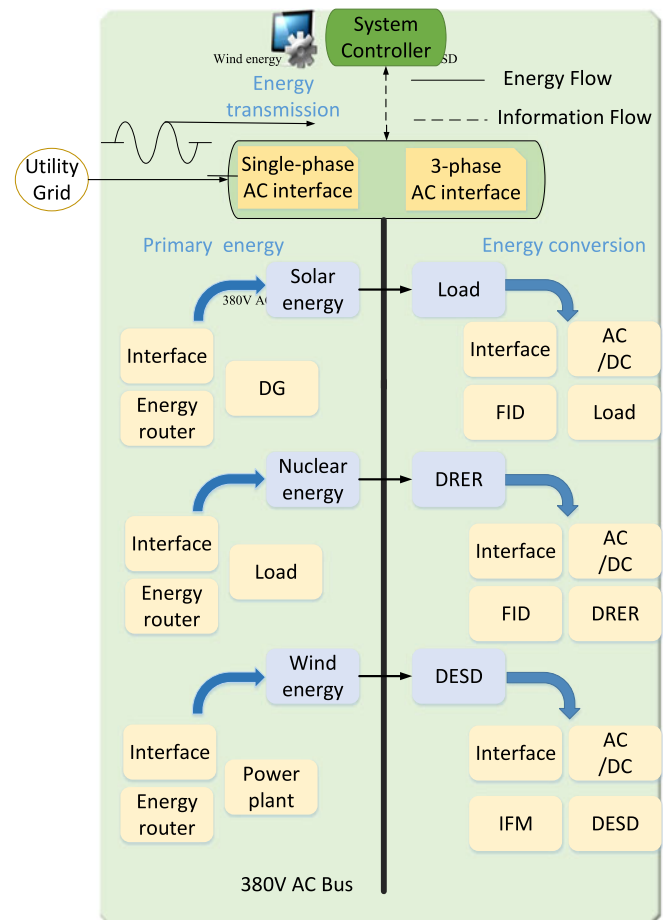


Fig. 1. Structure of the Energy Internet.

concerns from both the academic and the industrial communities. Thus, the concept of the Energy Internet [2] is introduced, which is constructed based on energy routers to enable primary energy conversion, energy transmission, and communication network with plug-and-play functionality, as shown in Fig. 1. Massive amounts of smart energy data emerge during the process of power generation, electricity delivery, energy storage, and intelligent management in the Energy Internet [3], [4]. Since smart energy data are characterized by volume, velocity, variety, and value, which are the key elements of big data, the concept of energy big data is introduced [5].

Energy big data exist anytime and anywhere in the whole energy network, including system monitoring data, operational data, electric transportation data, weather data, business data,

etc., [6]–[8]. Multisource and heterogeneous energy big data evoke various novel data-driven service and promising applications, such as real-time electricity pricing, power consumption measurement, and customer-side management [9], [10]. According to the latest statistics, the size of energy big data grows rapidly and even reaches up to terabytes level. In the foreseeable future, the size of energy big data will continuously expand even larger [11]. We find it a challenging task to handle the ever-growing size of energy big data with limited hardware resources and operating time, which might inevitably result in an unstable environment during the processing and controlling operations in the Energy Internet [12]. System-level power control and stability judgment mechanism shall be taken into consideration in the vast energy big data environment.

In this paper, we study system-level stability issues in the Energy Internet. Unlike traditional microgrid scenarios, the power proportion supplied by distributed generators (DGs) cannot be neglected under the circumstance of the large-scale renewable generation. Thus, the Energy Internet system might cause temporary power failure when the power voltage and frequency exceed the normal threshold, posing threats, and challenges to the system's stability. Our purpose is to discover the potential threats instantly and guarantee a stable and healthy energy network. To this end, we introduce a system-level stability evaluation model, which acts as exploring and analyzing small disturbance stability region (SDSR) [13]. SDSR is a set of steady state, consisting of multiple operating points. To obtain the stability region boundary, we need to acquire operational data threshold of different DGs. Although traditional approaches in studying SDSR for stability evaluation prove to be practicable in power system, there still exist some challenges as follows.

- 1) Operational data threshold of different DGs is predicted according to partial derivative calculation on equilibrium nodes, which has the high computation complexity.
- 2) The relationship between operational data threshold of different DGs is shown to be nonlinear, which increases the difficulty in optimizing computation results in SDSR.

Different from traditional methods in SDSR, we put forward a system-level stability evaluation model based on energy function in the Energy Internet. Specifically, we set up power models of various DGs and the loads for the establishment of power equilibrium equation in the Energy Internet, which can be applied in multiple energy-interconnected scenarios for modeling and analyzing. Since the high proportion of renewable energy power generation access to the Energy Internet, the damping makes greater influence on system's kinetic energy than the generator's movement of inertia. We pay more attention to the improvement of kinetic energy in the construction of energy function for exploring system's critical stability condition and stability decision rules in the Energy Internet. This is different from previous research works on energy function in conventional power system [14]. In addition, we add a hyperplane fitting (HPF) method in dynamic stability region to optimize SDSR and preform stability analysis in our model as well, which involves emerging big data approximate analytics technology [15], [16]. As a result of the large volume and high-speed velocity characteristics of big data, the approximate results using our

proposed method can be acquired dramatically faster than traditional approximation query, which shows superior performance in calculation. The main contributions for our proposed stability evaluation model in the Energy Internet are summarized as follows.

- 1) We estimate the operational data threshold of DGs based on energy consumption, instead of equilibrium nodes, which greatly reduces calculation complexity. The equilibrium nodes are difficult to handle due to their changeable natures, but energy consumption is easy to measure. Our proposed model has stronger theoretical foundation as well as higher practical operability than traditional methods.
- 2) We propose a big data approximate analytics based method to fit the disordered operating points into approximate linear state and carry out a one-dimensional function to formulate the linear relationship. Our proposed method greatly optimizes SDSR and is beneficial for further stability analysis, especially in energy big data environment and heterogeneous data structures.
- 3) We put forward the stability evaluation model based on the Energy Internet background, considering the system's design and operation. This model can support DGs' stable operation as well as enable the seamless connection between different DGs with reduced circulating currents. Extensive simulations are carried out to display the high performance of our proposed stability evaluation model.

The rest of this paper is organized as follows. Section II reviews the related works in energy big data, SDSR, and fitting method. Stability evaluation model for the Energy Internet is presented in Section III. In Section IV, we introduce an energy function to build SDSR and use an HPF method for parameter optimization. Extensive simulations and performance analysis are shown in Section V. Finally, Section VI concludes this paper.

II. RELATED WORK

In this section, we review the related work on energy big data, SDSR, and fitting method.

A. Energy Big Data

Energy big data has been a heated topic in recent years. Jiang *et al.* [5] first gave a comprehensive overview on energy big data covering energy big data's infrastructure, applications, algorithms, and security analysis. Several taxonomies are also presented for illustrating the clear relationship between different components in energy big data. Lee *et al.* [17] set up a prototype of big data management framework to efficiently handle and store massive amounts of energy big data in distributed environment. Using the prototype, they also put forward a power consumption forecast methodology depending on linear regression-based MapReduce model. He *et al.* [18] built an energy big data infrastructure in smart grid, which adds engineering process and mathematical process for energy big data modeling and analysis. A data-driven scheme was used for anomaly detection, and moving split-window method was applied in dynamic data analysis. Ye *et al.* [19] constructed

an information and communication technology architecture and used cloud computing technology to deal with energy big data for energy and electricity price prediction. They also introduced identity-based encryption methodology to guarantee secure energy big data environment.

B. Small Disturbance Stability Region

SDSR has been studied for a long time. SDSR is regarded as a parameter space for maintaining stability under the circumstance of small disturbance, which is also called small-signal stability region (SSSR) [6]. Yu [20] used modified Philips–Heffron model [21] for stability analysis and investigated SDSR’s boundary based on Hopf bifurcation conditions. Jia *et al.* [22] discovered an instability region inside SDSR and were motivated to explore how to explain such phenomenon based on bifurcation analysis. They studied the topological characteristics and drawn a conclusion that a second-order degenerated Hopf bifurcation may be the main reason. Xu *et al.* [23] investigated the stability conditions of a neural network model according to the characteristic equation and found the existence of Hopf bifurcation. Pan *et al.* [24] proposed the concept of robust SSSR based on the traditional theory, in order to perform stability analysis on the power system integrated massive amounts of uncertain wind generation. However, effective calculation methods for the robust SSSR in the power system with large-scale wind farms are not mentioned. Ma *et al.* [25] put forward an improved computation approach based on the guardian map theory, which can be used to calculate the boundary of the stability region in an efficient and accurate way in power system. Yang *et al.* [26] established an analytical expression using a polynomial approximation methodology to calculate the boundaries of SSSR, which can be employed in a high-dimensional space. This method is suitable for energy dispatching in power systems.

C. Fitting Method

Various fitting methods have been taken into consideration for optimization and analysis. Wang and Cassidy [27] proposed a nonlinear least-square fitting method to measure and analyze the gain in semiconductor lasers. This nonlinear fitting method can directly infer the gain from the lasers and need no extra processing, which also shows less noise sensitive characteristic compared with other indirect approaches. Deniz *et al.* [28] used reduction strategies based on stability boundary locus (SBL) fitting to design and analyze proportional-integration differentiation controller. Different from other studies of SBL analysis in controller’s stability, the high-order system can be converted into the second-order model by applying SBL fitting methods. Negro and Vieira [29] carried out the local fit methodology to enable overcurrent relays’ coordination and protection, which shows outstanding performance. The local fit methodology collects the characteristics and operating parameters of relays and applies linear weighted logarithmic integral algorithm to make analysis.

Abimbola *et al.* [30] proposed to use bow-tie models to make risk assessments in bottom-hole pressure drilling technology, which are mapped into Bayesian networks. They analyze the

Bayesian networks to assess key safety elements and safe operating pressure regime. Xuan *et al.* [31] developed a Bayesian network-based risk assessment model to assess the transportation risks on the Middle Route of the South-to North Water Transfer Project. They first chose several parameters from different impact factors as accidents’ quintessential risk factors. Then, the Bayesian network-based risk assessment model is used to forecast the probability of accidents, where bidirectional inference is also taken into consideration for ranking the significance of the effects of these risk factors and making analysis. However, these research works aiming to study risk assessments in a certain system by learning Bayes networks might not be suitable to apply in the Energy Internet for its complexity. Thus, our proposed stability evaluation model in the Energy Internet is set up based on the energy function theory. In our model, we can obtain SDSR’s boundary by investigating injected active power of DGs, instead of traditional point by point method. Compared with traditional fitting methods, we conduct big data approximate analytic based HPF method to optimize SDSR in different dominant oscillation modes, which effectively reduces fitting error and provides fast computation time. We are motivated to employ this model in the Energy Internet, in order to evaluate stability in loads, distributed renewable energy resource (DRER), and distributed energy storage device (DESD) [32].

III. SYSTEM MODEL AND ASSUMPTIONS

In the Energy Internet, we add energy routers in intelligent fault management (IFM) and fault isolation device (FID) to control the stability in communication network [2]. We also employ multiple power controlling networks to ensure the stability in energy conversion according to different output requests of inverters.

In our proposed stability evaluation model, DGs employ biaxial model. Excitation system is built based on the IEEE-DC1 excitation model, and all the loads use constant impedance model [21]. Fig. 2 illustrates the stability evaluation model employed in the Energy Internet. It utilizes information flow to monitor every node’s energy, in order to realize real-time control and management by control center. Multiport dc–dc converter is an important part in our proposed model in the Energy Internet, which acts as transforming the primary energy into ac circuit for production through the operations in an integrated circuit and an inverter circuit [33].

The whole system model contains complex power transmission lines, and most of them are in weak links and overload in a long distance. Generally, system’s transient instability is often caused by low-frequency oscillation [34], [35]. When the system lacks damping, the corresponding rotators of generators will relatively swing. This means power fluctuations may occur in electricity transmission lines and result in the transient instability of system. Inappropriate coordination between DGs could lead to transient instability, and such instability case will cause new disturbance during transmission. Therefore, the instability cases are often associated with each other in the Energy Internet.

In this paper, we investigate the active power relationships between DGs in the Energy Internet, and explore the SDSR

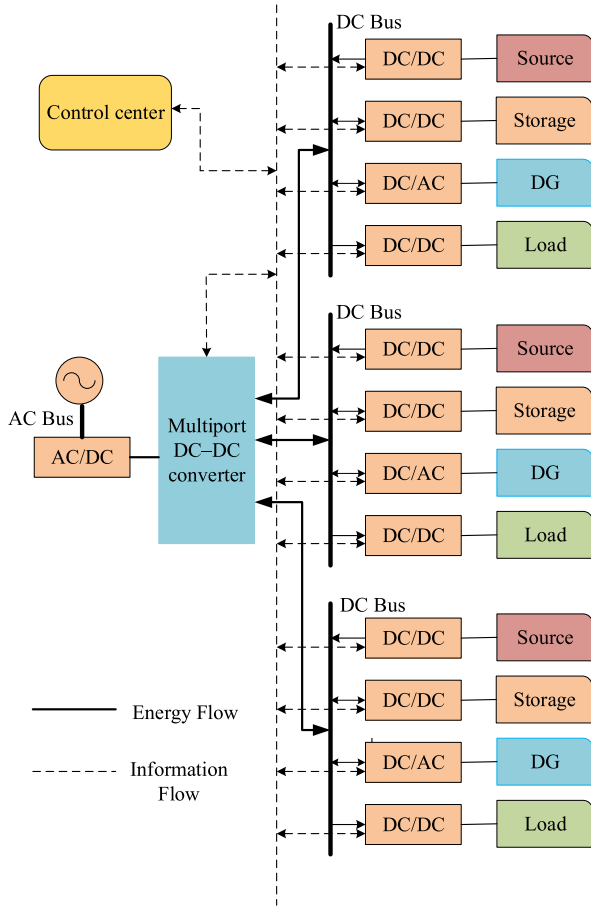


Fig. 2. Stability evaluation model in the Energy Internet.

to evaluate system's stability. The state equation in the Energy Internet can be written as

$$F(x, y, p) = \dot{x} \quad (1)$$

$$G(x, y, p) = 0 \quad (2)$$

where $x \in \mathbb{R}^n$ and $y \in \mathbb{R}^m$ are the state variable and algebraic variable of the system, respectively. $p \in \mathbb{R}^p$ is control variable including injected active power control parameter of generator node and load node, and \dot{x} is differential value of system's state variable.

At equilibrium point (x_0, y_0) , we linearize (1) and (2) and eliminate the algebraic variables. Then, the deformation equation can be obtained as

$$\Delta \dot{x} = [A(p) - B(p)D^{-1}(p)C(p)] \times \Delta x = J(p) \times \Delta x \quad (3)$$

where $J(p)$ represents Jacobian matrix, Δx represents the increment of state variable, and $A(p) = \partial F / \partial x$, $B(p) = \partial F / \partial y$, $C(p) = \partial G / \partial x$, $D(p) = \partial G / \partial y$.

In (3), we know that the real parts of matrix eigenvalues are all negative when the system is in stable operation state. As the parameter p changes, Hopf bifurcation phenomenon will occur in the system under the circumstances that a pair of conjugate complex eigenvalues goes across the imaginary axis. In this paper, we mainly study the stability region's boundary consisting

of Hopf bifurcation nodes in active power parameter space, and evaluate system-level stability in energy transmission in the Energy Internet.

IV. EXPLORATION AND ANALYTICS FOR STABILITY REGION

In this section, we employ stability evaluation model in the Energy Internet. We need to ensure a stable and healthy system during the controlling operation.

A. SDSR Construction

SDSR is a controlling parameter space containing equilibrium nodes, which can maintain stability under the circumstance of small disturbance. SDSR's boundary consists of bifurcation points, classified as saddle node bifurcation, Hopf bifurcation, and singularity induced bifurcation [36]. In this paper, we only consider the SDSR's boundary based on Hopf bifurcation.

Traditionally, we use point by point method to explore SDSR's boundary. This method can be briefly described as: When the parameter of injected power is continuously changing, we need to investigate every operating point's stability under small disturbance. The boundary nodes of SDSR can be obtained under the circumstances that the variation amplitude of the parameter is small enough.

Based on the traditional point by point method, we summarize the approach for investigating SDSR as follows.

Step1: Select a parameter subspace to construct a stability region and suppose that other parameters do not change.

Step2: Investigate a stable equilibrium point under small disturbance in parameter space. If it operates normally, such point can be regarded as an initial point for exploring the boundary of SDSR.

Step3: Change the parameter variable in a quasi-static manner from the initial point along a certain ray direction. Then, we can obtain a series of new equilibrium points and calculate eigenvalues of Jacobi matrix on every equilibrium point.

Step4: Judge whether the system is running to a critical point based on the eigenvalues. When there exists a pair of conjugate pure virtual eigenvalues and the rest of eigenvalues have negative real parts, Hopf bifurcation will occur in the system and such critical point can be regarded as the SDSR's boundary node. We record the parameter's value at this time.

Step5: Change the ray direction for exploring the boundary, repeat *Step3* and *Step4* so as to obtain the boundary nodes in a new direction.

However, many uncertainties exist in the point by point method, such as low calculation speed. This method is carried out based on the traditional power system. Therefore, we propose a new stability evaluation model based on the energy function, which can be greatly employed in the Energy Internet. Generally, SDSR's boundary nodes are equilibrium points in essence, which means we need to calculate the active power of these equilibrium points correspondingly. In order to investigate boundary nodes, a parameter space on injected active power is needed. We assume that there are two generators $G1$ and $G2$ in

such parameter space. $P1$ and $P2$ represent the injected power of the two DGs. The equations of active power and reactive power are shown as

$$\begin{aligned}\alpha_{ij} &= 90^\circ - tg^{-1} \frac{X_{ij}}{R_{ij}} \\ P_{Li} &= p \times P_{0i} \left(\frac{V}{V_{0i}} \right) \\ Q_{Li} &= p \times Q_{0i} \left(\frac{V}{V_{0i}} \right) \\ P_{Gi} &= \frac{V_{G1}^2}{|Z_{ii}|} \sin \alpha_{ii} + \sum_{j=1, j \neq i}^n \frac{V_{Gi} V_{Gj}}{|Z_{ij}|} \sin(\delta_{ij} - \alpha_{ij}) \\ Q_{Gi} &= \frac{V_{G1}^2}{|Z_{ii}|} \cos \alpha_{ii} - \sum_{j=1, j \neq i}^n \frac{V_{Gi} V_{Gj}}{|Z_{ij}|} \cos(\delta_{ij} - \alpha_{ij})\end{aligned}\quad (4)$$

where δ_{ij} is the angular difference between the i th and the j th node, Z_{ii} is the input impedance, Z_{ij} is the transfer impedance between the i th and the j th node, X_{ij} is the reactance between the i th and the j th node, and R_{ij} is the resistance between the i th and the j th node. P_{Gi} , Q_{Gi} , and V_{Gi} represent DG's active power, reactive power, and voltage, respectively. P_{Li} and Q_{Li} represent active power and reactive power used by loads, respectively.

When δ_{ij} becomes 90° , active power will reach up to the maximum value $P_{Gi_{max}}$, but it is not the maximum active power to ensure the stability of the Energy Internet. We need to calculate the partial derivative on equilibrium nodes to acquire the maximum active power for stable operation. However, it is difficult to perform complex computation on equilibrium nodes due to their changeable features. Our proposed energy function theory can be applied to reduce computation complexity.

In the Energy Internet, the energy function consists of two parts: kinetic energy and potential energy, and the critical energy function [37] in theoretical can be written as

$$\begin{aligned}E_c &= E_K(-w_{0i}^s) + E_P(\pi - \delta_{0i}^s, V_{0i}^s) \\ &= \sum_{i=1}^l (P_{Mi} - P_{Li}) (\pi - \delta_{0i}^s) \\ &\quad - \sum_{i=1}^l \frac{(V_0^s)^2}{2(R_{0i}^2 + X_{0i}^2)} \left(1 + \frac{R_{0i}^2}{X_{0i}^2} \right) \\ &\quad \times [R_{0i}(\cos^2 \delta_{0i} + \cos \delta_{0i})] \zeta \left(\delta_{0i}^{\pi - \delta_{0i}^s} \right) \\ &\quad - \sum_{i=1}^l \frac{(V_0^s)^2}{2(R_{0i}^2 + X_{0i}^2)} \left(1 + \frac{R_{0i}^2}{X_{0i}^2} \right) \\ &\quad \times [X_{0i}(\sin \delta_{0i} \cos \delta_{0i} - \sin \delta_{0i})] \zeta \left(\delta_{0i}^{\pi - \delta_{0i}^s} \right) \\ &\quad + \sum_{i=1}^l [(T_i w_{0i}^s)^2 + 5D_i t (w_{0i}^s)^2 - (t_s + 2\kappa t^2) D_i w_{0i}^s]\end{aligned}\quad (5)$$

where t_s and t represent recovery time and normal time, respectively; w_{0i}^s represents the angular frequency difference; δ_{0i}^s represents after-failure stable angular; V_{0i}^s represents the input voltage difference; P_{Mi} is the mechanical active power; D_i is the damping matrix; T_i is the moment of inertia; and E_c , E_P , and E_K are the critical energy, potential energy, and kinetic energy theoretically, respectively.

The energy function theory provides the theoretical foundation for evaluating the stability of the system. Zero energy means that the system remains stable. With the increase of energy, the system's stable structure becomes weaker and weaker. The system will display a critical stable state at the time the injected power reaches up to a certain threshold. When energy exceeds this threshold, the system becomes disordered. Therefore, the stability evaluation criteria in the Energy Internet can be summarized as follows:

$$\begin{aligned}E_{SUM} &= 0, \quad \text{stable} \\ E_{SUM} &< E_c, \quad \text{oscillation} \\ E_{SUM} &= E_c, \quad \text{critical stable} \\ E_{SUM} &> E_c, \quad \text{disordered}\end{aligned}\quad (6)$$

where E_{SUM} includes both E_K and E_P .

Generally, SDSR can describe the stability region between two DGs. We can explore multiple SDSRs to obtain the Energy Internet's stability region. The approach to acquiring two DGs' SDSR is carried out as follows. For two DGs, the potential energy E'_P and kinetic energy E'_K in practical operations can be formulated as

$$\begin{aligned}E'_P &= \sum_{i=1}^2 [(P_{Mi} - P_{Li}) \delta_{0i} + (Q_{Gi} - Q_{Li}) \log V_{0i}/V_{0i}^s \\ &\quad - P_{Gi}(\delta_{0i}^s - \delta_{0i}) - Q_{Gi} \log V_{0i}/V_{0i}^s]\end{aligned}\quad (7)$$

$$E'_K = \sum_{i=1}^2 [2T_i(\omega_{0i}/2)^2 + D_i t \omega_{0i}^2 + D_i \kappa t^2 (\omega_{0i}^s - \omega_{0i})]\quad (8)$$

where κ represents angular frequency changing rate, δ_{0i} represents the angular difference between the grid and the i th node, w_{0i} represents angular frequency difference between the grid and the i th node, and P_{G1} can be measured in practical operations.

Combining (7) and (8), the critical energy E'_c in practical operations for two generators can be obtained as

$$\begin{aligned}E'_c &= E'_K(-w_{0i}^s) + E'_P(\pi - \delta_{0i}^s, V_{0i}^s) \\ &= \sum_{i=1}^2 (P_{Mi} - P_{Li}) (\pi - \delta_{0i}^s) - \sum_{i=1}^2 \pi P_{Gi} \\ &\quad + \sum_{i=1}^2 [2(T_i w_{0i}^s)^2 + 4D_i t (\omega_{0i}^s)^2 + \kappa D_i t^2 \omega_{0i}^s].\end{aligned}\quad (9)$$

Then, E_w is introduced to denote potential energy injected by primary generators and used by loads. It can be written as

$$E_w = E'_c - \sum_{i=1}^2 (2T_i \omega_{0i}^s)^2 - \sum_{i=1, j=1}^2 \int_{\delta_i^s + \delta_j^s}^{\delta_i + \delta_j} B_{ij} V_i V_j \cos \delta_{ij} d(\delta_i + \delta_j) + \sum_{i=1}^2 \int_{E_i}^{E_i^s} (Q_{Gi} - Q_{Li}) / V_i dV_i \quad (10)$$

where B_{ij} represents the control matrix between the i th node and the j th node.

We gradually increase the injected power of one generator $G1$, which formulates various sampling points. Then, we calculate the maximum injected power of the other generator $G2$ under every sample point. Based on the above derivation, $P_{G2_{max}}$ can be given as

$$P_{G2_{max}} = E_w / \delta_1 + P_{L1} + P_{L2} - P_{G1}. \quad (11)$$

Finally, these two generators' SDSR can be acquired, and we can further derive SDSR of multiple DGs in the Energy Internet as well. As long as the operating parameters are within SDSR, the whole system will remain stable.

Generally, SDSR can be drawn in images, which is intuitive and clear. In order to better investigate and analyze SDSR, we propose an HPF method to optimize SDSR, where the stability's boundary can be written as an analytic expression directly in the next part.

B. Big Data Approximate Analytics Based HPF Method

SDSR construction is a vast big data work, and dynamic system becomes more complex because of real-time data processing. Thus, emerging big data approximate analytics technology can be efficient to investigate SDSR's boundary. We need to set up an approximate analytical model based on mathematical expressions and perform rational analysis in order to conveniently build approximate relationship between variables. Our proposed big data approximate analytics based HPF method is shown in Algorithm 1, which can approximately fit the disordered operating points into linear state. The approximate analytical results based on various sampling points for optimizing and analyzing SDSR can reduce the computation time and solve the computation resources constraints issues, which are suitable for massive datasets.

The SDSR boundary is defined as

$$\alpha_1 S_1 + \alpha_2 S_2 + \dots + \alpha_n S_n = 1 \quad (12)$$

where $S_i (i = 1, 2, \dots, n)$ represents the active power of each DG's sampling node, $\alpha_i (i = 1, 2, \dots, n)$ is the coefficient of an HPF function, and n is the number of sampling nodes.

We first substitute the active power of calculated boundary sampling nodes into (12). Then, we use the least-square fitting method to calculate the least-square estimated value of HPF function's coefficient. The estimated coefficient is also

Algorithm 1: Big data approximate analytics based HPF algorithm.

Input: (x_i, y_j, p_k) , $x_i \in \mathbb{R}^n$, $y_j \in \mathbb{R}^m$, $p_k \in \mathbb{R}^p$

Output: $S(x_i, y_j, p_k) = 0$

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1 choose any feasible equilibrium point  $(x_i, y_j, p_k)$ ;
2 define  $SDO$  mode = 1,  $MDO$  mode = 2;
3 set  $P_{G1} = 0$ ; set  $i = 0$ ;
4 repeat
5   increase  $P_{G1}$ , sample multiple equilibrium points;
6   if mode = 1 then
7     select the same data set;
8     linearize active power function  $S(x_i, y_j, p_k)$ ;
9   else
10    group into multiple data sets  $(x_{1i}, y_{1j}, p_{1k}), \dots,$ 
11      $(x_{ni}, y_{nj}, p_{nk})$ ;
12    linearize every active power function  $S_1, \dots, S_n$ ;
13  end
14  calculate SDSR boundary
15   $\alpha_1 S_1 + \alpha_2 S_2 + \dots + \alpha_n S_n = 1$  between  $P_{G1}$  and  $P_{G2}$ ;
16  evaluate fitting error  $E_r$ ;
17   $i = i + 1$ ;
18 until  $P_{G2} = P_{G2_{max}} = E_w / \delta_1 + P_{L1} + P_{L2} - P_{G1}$ ;

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substituted into (12) for obtaining approximate boundary expression of hyperplane. In order to measure the accuracy of the approximate value, we need to estimate every sampling node's fitting error. For the whole SDSR's boundary sampling nodes, we define the HPF error as

$$E_r = \frac{d}{\sqrt{\sum_{i=1}^n S_i^2}} \quad (13)$$

where $d = |\sum_{i=1}^n \alpha_i S_i - 1| / \sqrt{\sum_{i=1}^n \alpha_i^2}$ is the distance from boundary nodes to origin of coordinates in hyperplane.

For the SDSR's boundary of two DGs in the Energy Internet, there are two kinds of oscillation modes: single dominant oscillation (SDO) mode and multiple dominant oscillation (MDO) mode. In SDO mode, the stability region's boundary is smooth, which is close to the real stability domain boundaries by fitting methods. In MDO mode, the stability region is divided into two parts. Due to the existence of two low-frequency signals, the geometry may suffer mutation in the conversion between two parts, which could affect system's stability. However, the stability region's boundary still shows the smoothness feature in each dominant oscillation mode, regardless of suffering mutation phenomenon.

V. PERFORMANCE SIMULATION

To study the performance of our proposed stability evaluation model, we conduct some simulations in this section.

A. Simulation Setup

Based on New England energy system with 39 nodes and 10 machines [21], we choose any two generators to construct a parameter space on injected active power for studying SDSR. All the simulations are conducted using MATLAB in a Sony

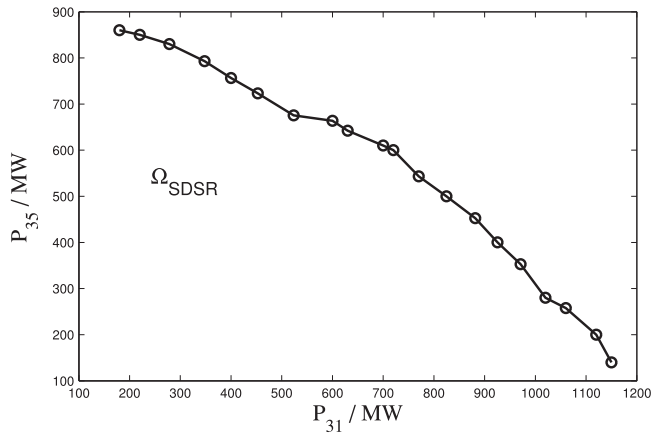


Fig. 3. Stability region in SDO mode.

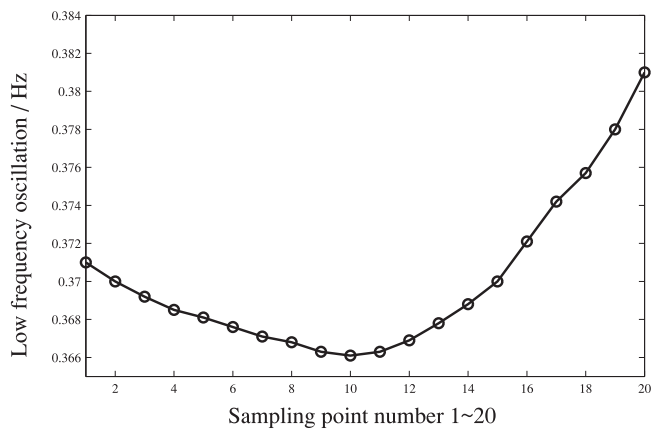


Fig. 4. Frequency oscillation curve in SDO mode.

server equipped with 4-core CPU, 16 GB memory, and Mango DB. We use (11) to calculate the stability region's boundary. The loads consist of constant resistance static load model and constant current static load model. The proportion of active power and reactive power on the two static load models is the same. In this section, we first simulate the stability region's boundary under SDO mode and MDO mode. Then, we use big data approximate analytics based hyperplane method for fitting nonlinear sampling points and exploring approximate mathematical expressions.

B. Simulation Results

Fig. 3 presents the system's SDSR based on 20 boundary sampling points. We change the active power parameters P_{31} and P_{35} of generators G_{31} and G_{35} , and keep other injected power parameters unchanged in the space. The SDSR's boundary shown in Fig. 3 is smooth and there is no mutation phenomenon occurring on every sampling point. Fig. 4 illustrates the variation curve of oscillation frequency on every boundary sampling point under SDO mode. We can find that low-frequency oscillation around 0.37 Hz may affect system's small disturbance stability. From the simulation results, we see that

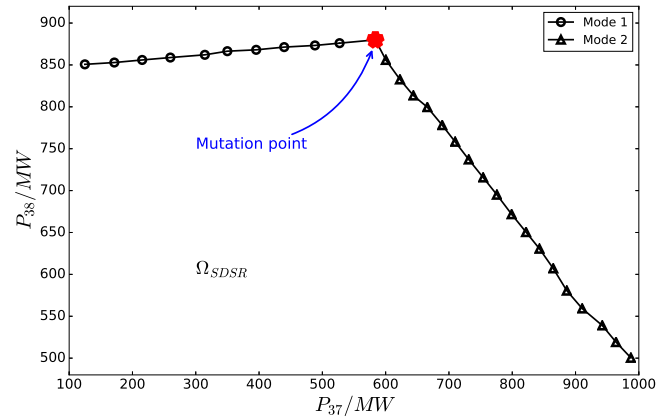


Fig. 5. Stability region in MDO mode.

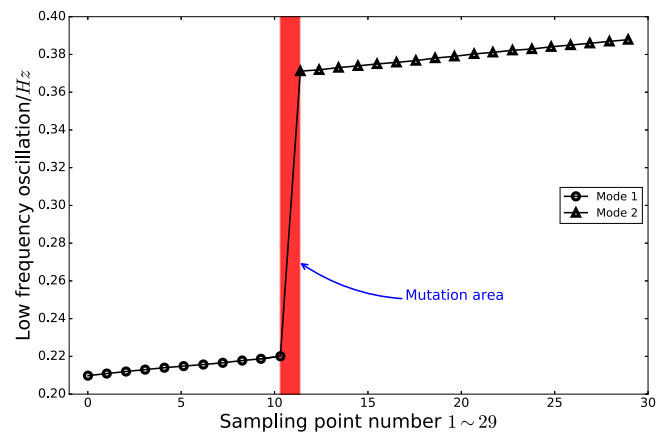


Fig. 6. Frequency oscillation curve in MDO mode.

stability region's boundary is smooth under SDO mode so that we can use the HPF method to explore more authentic boundary.

Having simulated the SDSR's boundary under SDO mode, we are motivated to investigate the boundary under MDO mode. Fig. 5 shows SDSR in a space consisting of injected active power of generators G_{37} and G_{38} . The stability region's boundary shape suffers mutation between sampling point 11 and point 12 under MDO mode. Fig. 6 describes 29 points' oscillation frequency variation curve which are sampled from the boundary. There are 0.21 Hz frequency oscillation mode and 0.38 Hz frequency oscillation mode. Inevitably, mutation phenomenon will occur in the conversion between the two modes. In the same mode, stability region's boundary still remain smooth. Thus, the HPF method is still suitable for obtaining the estimated value of boundary within allowable error range, which can greatly reduce the computation complexity. Compared with the traditional point by point method, our proposed method can save at least 30% time and 20% computation resource.

For better investigation and analytics for SDSR, the HPF method is often used. We approximately fit critical equilibrium nodes of boundary under SDO mode, the hyperplane analytic expression can be obtained as:

$$P_{G35} = -0.7186P_{G31} + 1060 \quad (14)$$

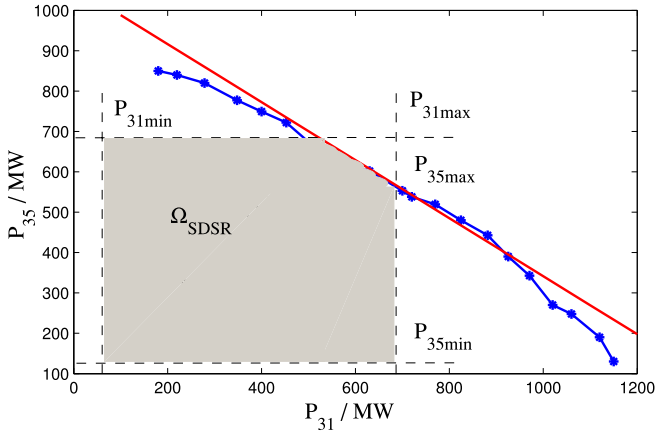


Fig. 7. HPF in SDO mode.

where the fitting error on every sampling point is controlled under 0.59%. The shaded area in Fig. 7 illustrates stability region under SDO mode. Dotted lines represent the upper limit and lower limit of the injected active power. These upper and lower limits form stability region's boundary together with linearized critical equilibrium nodes. For generators G_{31} and G_{35} , the SDSR in practical applications under SDO mode can be written as

$$\begin{aligned} P_{G_{35_{\max}}} &= 710, & P_{G_{35_{\min}}} &= 120 \\ P_{G_{31_{\min}}} &= 140, & P_{G_{31_{\max}}} &= 700 \\ P_{G_{35}} &= -0.7186P_{G_{31}} + 1060. \end{aligned} \quad (15)$$

In order to avoid large fitting error in mode conversion process, we first analyze the characteristics of acquired sampling points. Then, we divide the sampling points into different sets according to the dominant oscillation modes. Finally, we apply the HPF method to fit critical equilibrium nodes in every set and obtain approximate linear expression in corresponding boundary domain. The hyperplane analytic expressions under 0.21 Hz oscillation mode 1 and 0.38 Hz oscillation mode 2 can be obtained as:

$$\begin{aligned} \text{Mode1 : } P_{G_{38}} &= 0.0654P_{G_{37}} + 852 \\ \text{Mode2 : } P_{G_{38}} &= -P_{G_{37}} + 1475 \end{aligned} \quad (16)$$

where the maximum fitting error in mode1 is 0.25%, and the maximum fitting error in mode2 is 0.13%. The intersection of approximate fitting boundary under different oscillation modes constitutes a stability region in the active power injection space, as shown in Fig. 8. For generators G_{37} and G_{38} , the SDSR under MDO mode can be written as

$$\begin{aligned} P_{G_{37_{\max}}} &= 900, & P_{G_{37_{\min}}} &= 350 \\ P_{G_{38_{\min}}} &= 430, & P_{G_{38_{\max}}} &= 880 \\ P_{G_{38}} &= 0.0654P_{G_{37}} + 852 \\ P_{G_{38}} &= -P_{G_{37}} + 1475. \end{aligned} \quad (17)$$

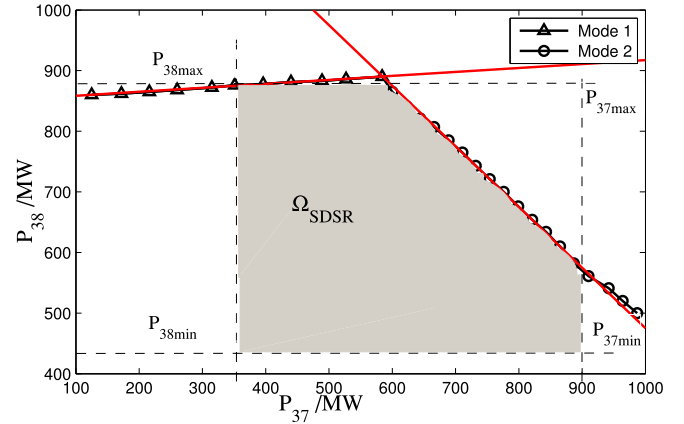


Fig. 8. HPF in MDO mode.

From the simulation results, we find that the HPF method provides high accuracy for analytics of SDSR under different modes.

VI. CONCLUSION

The Energy Internet is constructed to realize all-round energy dispatching and sharing between generators and the loads, where multisource and heterogeneous energy big data are produced in the energy network operation. However, potential threats might be bought inevitably along with the ever-growing size of energy big data, which could lead to an unstable Energy Internet environment. To this end, we put forward a reliable energy function-based stability evaluation model, which avoids computation complexity. Different from other traditional methods, in our model, the operational data threshold of DGs can be estimated according to energy consumption rather than equilibrium nodes so as to acquire SDSR's boundary. Moreover, we use big data approximate analytics based HPF method to optimize and analyze the SDSR, which acts as fitting the nonlinear operating points into approximate linear state and deducing a one-dimensional function. Finally, simulation results in SDO mode and MDO mode show the superiority of stability evaluation via our proposed model.

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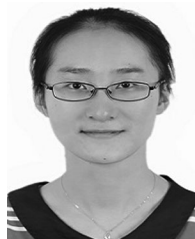
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