IEEE TRANSACTIONS ON
POWER SYSTEMS
IEEE POWER & ENERGY SOCIETY

Efficient Estimation of Component Interactions for Cascading Failure Analysis by EM Algorithm

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***Abstract*—Due to a lack of information about the causes of outages, the estimation of the interactions between component failures that capture the general outage propagation patterns is a typical parameter estimation problem with incomplete data. In this paper, we estimate these interactions by the Expectation Maximization (EM) algorithm. The proposed method is validated with simulated cascading failure data from the AC OPA model on the IEEE 118-bus system. The EM algorithm can accurately estimate the interactions and identify the key links and key components only using a small number of the original cascades from a detailed cascading blackout model, which is critical for online cascading failure analysis and decision-making. Compared with AC OPA simulation, the highly probabilistic interaction model simulation based on the proposed interaction estimation method can achieve a speedup of 100.61.**

***Index Terms*—Blackout, cascading failure, efficiency, Expectation Maximization (EM), interaction, mitigation, network, parameter estimation, power transmission reliability, simulation.**

I. Introduction

In real power systems there have been several large-scale blackouts, such as the 1965 northeast U.S. blackout [1], the 1996 western U.S. blackouts [2], the 2003 U.S.-Canadian blackout [3], the 2003 Italy blackout [4], the 2011 Arizona-southern California blackout [5], and the 2012 Indian blackout [6], which have led to many component failures, extensive outage propagations, and significant economic losses and social impacts. It is thus critical to understand why and how cascading failures blackouts can happen and to further propose effective prevention and mitigation measures to greatly reduce the cascading risk and enhance the power grid resilience.

In order to simulate and analyze cascading failures, many models with different levels of details have been developed, such as the Manchester model [7], [8], hidden failure model [9], [10], CASCADE model [11], OPA model [12]–[15], AC OPA model [16], [17], OPA with slow process [18], PRA model [19], dynamic model [20], and sandpile model [21].

Cascading failure simulations based on various models can produce many samples of cascades. The branching process can extract high-level statistical information from these cascades and can quantify the extent of outage propagation by a simple parameter called average propagation [22]–[24]. The interdependencies between different types of outages or different critical infrastructure systems can also be analyzed by the multi-type branching process [25]. However, the branching process cannot be used to study how the outages propagate in the system from one component to another component in detail, because it does not retain any information about the network topology or the power flow.

The recent study on the influence graph [26], [27] and the interaction network [28]–[30] provide another more useful way to extract propagation patterns in the original cascades. In [28] an explicit study of the interactions between components failures obtained from detailed cascading failure simulation helps better understand the mechanisms of cascading failures. In [29] an interaction network is built for an Northeast Power Coordinating Council (NPCC) power system test bed, which represents the northeastern region of the EI system. Then in [30] a multi-layer interaction graph is proposed as an extension of a single-layer interaction network. In this multi-layer graph, each layer focuses on one of several aspects that are critical for the system operators' decision support, such as the number of line outages, the amount of load shedding, and the electrical distance of the outage propagation.

The interactions between component failures may vary under different operating conditions. For online cascading failure mitigation, the interactions should be quantified at least every 15 minutes for the most updated system operating conditions in order to well capture the propagation pattern of cascading failures, which would further require that the simulation of a detailed cascading failure model provide enough original cascades. Therefore, an interaction estimation method that requires a small number of original cascades is critical for the practical implementation of the online application. In this paper, we propose an interaction estimation method based on the Expectation Maximization (EM) algorithm [31], [32]. Compared with the method in [28], the EM algorithm requires a much smaller number of original cascades.

The rest of this paper is organized as follows. Section II introduces the problem of estimating the component interactions and also discusses its major challenges. The EM algorithm is introduced in Section III with a coin-flipping example and is then applied to estimate the interactions between the component failures in Section IV. Section V determines the number of cascades that needs to be simulated. Section VI tests and validates the proposed method by cascading failure simulation data for the IEEE 118-bus system. Finally we draw conclusions in Section VII.

This work was supported by the U.S. Department of Energy, Office of Electricity Delivery and Energy Reliability. Paper no. TPWRS-00741-2017.

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Digital Object Identifier 10.1109/TPWRS.2017.2764041

II. The Problem of Estimating Interactions Between Component Failures

In power systems, the components can be branches such as the transmission lines or transformers. In order to estimate the interaction between the component failures, we need to have a large amount of data that record the processes of cascading failures. These data, which come from utility outage records or cascading failure simulation models, can be grouped into different cascades (one cascade corresponds to one cascading failure process) and generations (one generation corresponds to one stage in a cascade). Assume we have a total of M cascades as

	generation 0	generation 1	generation 2	$\cdots$
cascade 1	$F_0^{(1)}$	$F_1^{(1)}$	$F_2^{(1)}$	$\cdots$
cascade 2	$F_0^{(2)}$	$F_1^{(2)}$	$F_2^{(2)}$	$\cdots$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
cascade M	$F_0^{(M)}$	$F_1^{(M)}$	$F_2^{(M)}$	$\cdots$

where $F_g^{(m)}$ is the set of the failed components in generation g of cascade m.

After obtaining the original cascades, we can estimate the component interactions, which are defined as the *interaction matrix* $\boldsymbol{B} \in \mathbb{R}^{n\times n}$ where n is the number of components in the system. The element of $\boldsymbol{B}$, b_{ij}, is the empirical probability that component i failure causes component j failure.

In order to estimate $\boldsymbol{B}$, we need to obtain another matrix $\boldsymbol{A} \in \mathbb{Z}^{n\times n}$ whose element a_{ij} is the expected number of component j failure caused by component i failure among all of the successive generations of all cascades, because there is

$$b_{ij} = \frac{a_{ij}}{N_i}, \tag{1}$$

where N_i is the number of times that component i fails. The interaction matrix $\boldsymbol{B}$ describes how the components in the system interact with each other. Its nonzero elements are called *links*. For example, for a nonzero element b_{ij}, there is a link $l : i \to j$, representing that the source component i failure causes the destination component j failure with a positive probability. All of the links form a directed *interaction network* $\mathcal{G}(\mathcal{C}, \mathcal{L})$ with the set of vertices $\mathcal{C}$ and the set of links $\mathcal{L}$.

This estimation of the $\boldsymbol{B}$ matrix (the graphical model) is very challenging mainly due to the following reasons.

1) If we know matrix $\boldsymbol{A}$, then matrix $\boldsymbol{B}$ can be very easily estimated by (1).
2) If the interaction matrix $\boldsymbol{B}$ is known, for two consecutive generations in each cascade we can infer how probable one component failure causes another component failure, based on which we can get the matrix $\boldsymbol{A}$. For the very simple example shown in Fig. 1, if $b_{AC} \approx 1$ while $b_{BC} \approx 0$, it is much more probable that the failure of component C is caused by component A failure. In these two consecutive generations, the probability that component A failure causes component C failure is approximately 1 while that for component B failure causing component C failure is around 0. More general and detailed discussion about how to make the inference can be found in Section IV.

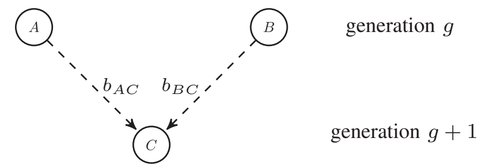

Fig. 1. Illustration for finding the cause of a component failure.

3) However, neither $\boldsymbol{A}$ or $\boldsymbol{B}$ is initially known. Therefore, the estimation of the interactions between component failures is actually a typical parameter estimation problem with incomplete data.

In [28], the interaction matrix $\boldsymbol{B}$ is directly estimated from an approximated matrix $\boldsymbol{A}$ that is not statistically inferred from $\boldsymbol{B}$ but is only estimated based on a simple assumption that the component j failure in generation $g+1$ is caused only by the component in generation g that is in the previous generation of component j for the largest number of times. This assumption will inevitably ignore some interactions and thus can only get approximated estimations of $\boldsymbol{A}$ and $\boldsymbol{B}$. In the next section, we will apply the EM algorithm to effectively deal with incomplete data and more accurately estimate the interaction matrix.

III. Expectation Maximization Algorithm

Here the EM algorithm [31], [32] is introduced by a coin-flipping example. It is a simple yet effective method for performing maximum likelihood estimation of parameters when there are incomplete data.

A. A Coin-Flipping Example

We adapt the coin-flipping experiment in [32] to illustrate how the EM algorithm works. Assume there are n coins denoted by $c_1, \cdots, c_n$, and coin c_i lands on heads and tails with probability θ_i and $1-\theta_i$, respectively. We perform the following experiments for m times and based on the results of these experiments we want to estimate $\boldsymbol{\theta} = (\theta_1, \cdots, \theta_n)$.

1) Exactly one coin is selected from the n coins and each coin is selected by the same probability;
2) A total of K tosses are independently performed for the chosen coin.

During the experiments we record $\boldsymbol{x} = [x_1, \cdots, x_m]$ where $x_j = i$ if c_i is chosen in the jth set of tosses and $\boldsymbol{y} = \left[\boldsymbol{y}_1^\top, \cdots, \boldsymbol{y}_m^\top\right]^\top$ where $\boldsymbol{y}_j = [y_{j1}, \cdots, y_{jK}]$ and $y_{jk} = 1$ if the selected coin in the jth set of tosses lands on heads for the kth toss and $y_{jk} = 0$ otherwise.

Note that in this parameter estimation problem there are *complete data*. This is because both the type of the coin used for each toss and the result of each coin toss are known. The parameters $\boldsymbol{\theta}$ can be estimated by the maximum likelihood estimation as

$$\hat{\theta}_i = \frac{\sum\limits_{j|x_j=i} \sum\limits_{k=1}^{K} y_{jk}}{K \sum\limits_{j=1}^{m} I(x_j = i)}, \tag{2}$$

where $j|x_j = i$ indicates the set of tosses with coin c_i and I equals to one if $x_j = 1$ and to zero otherwise. The estimated parameters $\hat{\boldsymbol{\theta}} = (\hat{\theta}_1, \cdots, \hat{\theta}_n)$ from (2) maximize $\log P(\boldsymbol{x}, \boldsymbol{y}; \boldsymbol{\theta})$, which is the logarithm of the joint probability of having the coin types $\boldsymbol{x}$ and the observed result $\boldsymbol{y}$.

Then we change the problem settings by only recording the result of the coin-flipping $\boldsymbol{y}$ but not the types of the coins $\boldsymbol{x}$. We refer to $\boldsymbol{x}$ as hidden variables. Because we do not have the data for the types of the coins, in this parameter estimation problem there are *incomplete data*.

The EM algorithm can perform parameter estimation under this new setting. Specifically, starting from some initial parameters $\hat{\boldsymbol{\theta}}^{(0)} = (\hat{\theta}_1^{(0)}, \cdots, \hat{\theta}_n^{(0)})$, the EM algorithm uses the parameters in this iteration to calculate the probabilities for each possible case of the incomplete data. Then the classic maximum likelihood estimation method is modified to be able to consider these probabilities, based on which the updated parameter estimates $\hat{\boldsymbol{\theta}}^{(t+1)}$ can be obtained. The EM algorithm iterates between the E-step and M-step as follows until convergence:

1) **E-step:** Estimate a probability distribution of the incomplete data based on the parameter in this iteration;
2) **M-step:** Estimate the parameters using the completions obtained in the E-step.

For the above coin-flipping example, when we consider the incomplete data case the EM algorithm can be formulated as

1) **E-step:** For the jth set of tosses, the number of heads is $n_j^{\text{head}} = \sum_{k=1}^{K} y_{jk}$ and that for tails is $n_j^{\text{tail}} = K - n_j^{\text{head}}$. Then the probability distribution of x_j is

$$P(x_j = i) = \frac{\left(\hat{\theta}_i^{(t)}\right)^{n_j^{\text{head}}} \left(1 - \hat{\theta}_i^{(t)}\right)^{n_j^{\text{tail}}}}{\sum_{l=1}^{n} \left(\hat{\theta}_l^{(t)}\right)^{n_j^{\text{head}}} \left(1 - \hat{\theta}_l^{(t)}\right)^{n_j^{\text{tail}}}}, \tag{3}$$

and the corresponding expected number of heads for coin c_i is $E_i^{\text{head}} = n_j^{\text{head}} P(x_j = i)$.

2) **M-step:** The parameters can be updated as

$$\hat{\theta}_i^{(t+1)} = \frac{\sum_{j=1}^{m} n_j^{\text{head}} P(x_j = i)}{K \sum_{j=1}^{m} P(x_j = i)}. \tag{4}$$

For example, we assume there are two coins, c_1 and c_2, with $\theta_1 = 0.7$, $\theta_2 = 0.4$. We set $m = 5$, $K = 10$ and get the following data

$$\boldsymbol{x} = [1 \quad 0 \quad 0 \quad 1 \quad 1],$$

$$\boldsymbol{y} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 & 1 & 1 & 0 & 1 & 1 & 1 \\ 1 & 1 & 1 & 0 & 1 & 1 & 0 & 1 & 1 & 0 \end{bmatrix}.$$

For the EM algorithm, the initial parameter is assumed to be $\hat{\boldsymbol{\theta}}^{(0)} = (0.6, 0.5)$. Then in E-step the number of heads, the probability that a specific coin is chosen, and the expected numbers of heads for each coin in each set of the tosses are listed in Table I. In M-step we update the parameters as $\hat{\theta}_1^{(1)} = 0.596$ and $\hat{\theta}_2^{(1)} = 0.453$. After 9 iterations we get $\hat{\theta}_1 = 0.702$ and $\hat{\theta}_2 = 0.383$, both of which are very close to the real parameters.

TABLE I
QUANTITIES IN E-STEP

j	n_j^{head}	$P(x_j = 1)$	$P(x_j = 0)$	E_1^{head}	E_2^{head}
1	3	0.266	0.734	0.798	2.202
2	4	0.352	0.648	1.409	2.591
3	4	0.352	0.648	1.409	2.591
4	8	0.733	0.267	5.868	2.132
5	7	0.647	0.353	4.531	2.470
total	-	-	-	14.014	11.987

B. Mathematical Foundation

With complete data, the objective function of the maximum likelihood estimation ($\log P(\boldsymbol{x}, \boldsymbol{y}; \boldsymbol{\theta})$) usually only has one global optimum, which can often be obtained in closed form, such as by (2) in the coin-flipping example [32]. However, with incomplete data, the modified maximum likelihood estimation has to find $\hat{\boldsymbol{\theta}}$ that maximizes $\log P(\boldsymbol{y}; \boldsymbol{\theta})$, which usually has multiple local optima. If there are several local optima, there might be only one global optimum.

In order to solve this problem, the EM algorithm converts the one single optimization problem of $\log P(\boldsymbol{y}; \boldsymbol{\theta})$ into a series of subproblems, each of which has an objective function with a unique global optimum. In the E-step, it chooses a function g_t that lower bounds $\log P(\boldsymbol{y}; \boldsymbol{\theta})$ and satisfies $g_t\left(\hat{\boldsymbol{\theta}}^{(t)}\right) = \log P\left(\boldsymbol{y}; \hat{\boldsymbol{\theta}}^{(t)}\right)$. In the M-step, it determines the updated parameter $\hat{\boldsymbol{\theta}}^{(t+1)}$ that maximizes g_t. Since g_t matches $\log P(\boldsymbol{y}; \boldsymbol{\theta})$ at $\hat{\boldsymbol{\theta}}^{(t)}$, there is $\log P\left(\boldsymbol{y}; \hat{\boldsymbol{\theta}}^{(t)}\right) = g_t\left(\hat{\boldsymbol{\theta}}^{(t)}\right) \leq g_t\left(\hat{\boldsymbol{\theta}}^{(t+1)}\right) = \log P\left(\boldsymbol{y}; \hat{\boldsymbol{\theta}}^{(t+1)}\right)$, meaning that the objective function monotonically increases during each iteration [32], as illustrated in Fig. 2.

The estimated parameter increases the likelihood function after each iteration until a local maximum is achieved. There is no guarantee that the EM algorithm will converge to a global maximum, which is similar to most optimization methods for non-convex functions. Starting from different initial parameters may get different solutions. Running the algorithm for multiple times by using different initial parameters may help to get the solution with global optimum. Although other numerical optimization methods, such as gradient descent or Newton's method [33], can in theory be used to solve the optimization problem, the EM algorithm provides a simple, robust, and easy-to-implement tool for parameter estimation in models with incomplete data [32].

IV. ESTIMATING THE INTERACTIONS BETWEEN COMPONENT FAILURES BY EM ALGORITHM

Assume $M_{\text{u}} \leq M$ original cascades are utilized to estimate the interactions between component failures. Here we discuss how to estimate the interaction matrix by applying the EM algorithm introduced in Section III. The corresponding

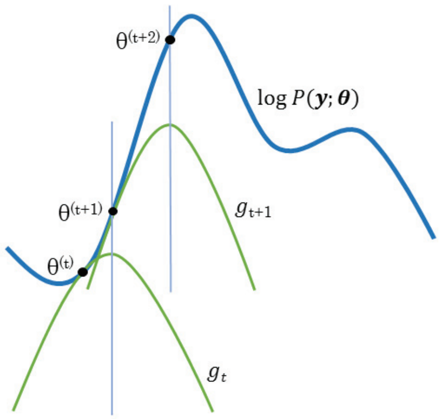

Fig. 2. Illustration of the convergence of EM algorithm [32].

maximum likelihood estimation problem is to estimate the parameters $\boldsymbol{B}$ in order to maximize $\log P(\boldsymbol{A}, \boldsymbol{y}; \boldsymbol{B})$, which is the logarithm of the joint probability of having the specific interactions between components in any two successive generations among all used cascades that are represented in $\boldsymbol{A}$ and the observed result $\boldsymbol{y}$ as the M_{u} original cascades. Specifically, the EM algorithm can be implemented in the following four steps.

1) **Initialization:** We set the initial interaction matrix as $\boldsymbol{B}^{(0)}$. In order to avoid ignoring any useful information, we assume that any failed components in generation g is the cause of the component failures in generation $g+1$. Then the initial matrix $\boldsymbol{A}^{(0)} \in \mathbb{Z}^{n\times n}$ can be obtained from all original cascades and $\boldsymbol{B}^{(0)}$ can be calculated from $\boldsymbol{A}^{(0)}$ by using (1).
Note that the assumption here tends to overestimate the component interactions. This is because a component that fails before the failure of another component may not be the cause of that particular failure. However, it is appropriate to use $\boldsymbol{A}^{(0)}$ to get the initial guess for $\boldsymbol{B}$ since in this way we will not miss any interaction between component failures. As mentioned in Section III-B, running the algorithm for multiple times by using different initial parameters may help to get the solution with global optimum. However, in this paper we do not need to do so, because the chosen $\boldsymbol{A}^{(0)}$ has a clear physical meaning and is a good initial parameter. This will be validated by the test results in Section VI.
2) **E-step:** Estimate $\boldsymbol{A}^{(k+1)}$ based on $\boldsymbol{B}^{(k)}$.
For any two successive nonzero generations $g, g+1$ of any cascade m, under the condition that component j has failed, the component j failure in generation $g+1$ is caused by component $i \in F_g^{(m)}$ in generation g by probability

$$p_{ij}^{(k+1)m,g} = \frac{b_{ij}^{(k)}}{1 - \prod\limits_{l\in F_g^{(m)}} \left(1 - b_{lj}^{(k)}\right)}. \tag{5}$$

If $i \notin F_g^{(m)}$, $p_{ij}^{(k+1)m,g} = 0$. For example, for the two consecutive generations shown in Fig. 3, there is

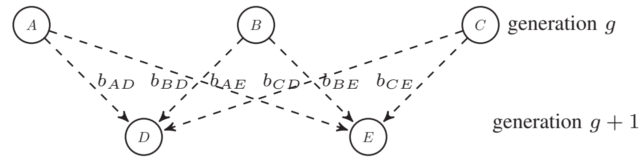

Fig. 3. Illustration for inferring the probability of one component failure in generation $g+1$ caused by a specific component failure in generation g.

$$p_{AD} = \frac{b_{AD}}{1-(1-b_{AD})(1-b_{BD})(1-b_{CD})}, \tag{6}$$

and p_{AE}, p_{BD}, p_{BE}, p_{CD}, and p_{CE} can also be written in a similar manner.
The updated entry of $\boldsymbol{A}^{(k+1)}$ can be obtained as the summation over all consecutive nonzero generations for all cascades

$$a_{ij}^{(k+1)} = \sum_{m=1}^{M_{\mathrm{u}}} \sum_{g=0}^{G^m-2} p_{ij}^{(k+1)m,g}, \tag{7}$$

where G^m is the number of generations with nonzero number of outages in cascade m.
3) **M-step:** Estimate $\boldsymbol{B}^{(k+1)}$ based on $\boldsymbol{A}^{(k+1)}$.
After $\boldsymbol{A}^{(k+1)}$ is obtained, the updated interaction matrix $\boldsymbol{B}^{(k+1)}$ can be calculated by using (1).
4) **End:** Iterate the E-step and M-step until

$$\frac{\left|\left|\boldsymbol{B}_{ij}^{(k+1)} - \boldsymbol{B}_{ij}^{(k)}\right|\right|_{\mathrm{F}}}{\sqrt{N_{\mathrm{nonzero}}}} < \epsilon, \tag{8}$$

where $||\boldsymbol{X}||_{\mathrm{F}}$ is the Frobenius norm of a $u \times v$ matrix $\boldsymbol{X}$ defined as

$$||\boldsymbol{X}||_{\mathrm{F}} = \sqrt{\sum_{i=1}^{u}\sum_{j=1}^{v} |X_{ij}|^2}, \tag{9}$$

N_{nonzero} is the number of nonzero elements in $\boldsymbol{B}_{ij}^{(k+1)} - \boldsymbol{B}_{ij}^{(k)}$, ϵ is the tolerance, and the $\boldsymbol{B}_{ij}^{(k+1)}$ that satisfies (8) will be the estimated interaction matrix.

V. Determining the Number of Cascades Needed

In this section we discuss how to determine the minimum number of cascades that is needed to guarantee that 1) we almost do not lose any interaction and 2) we get all of the dominant interactions that can produce cascades with similar statistics to the original cascades. They are the lower bounds of M and M_{u} and are denoted by $M^{\min}$ and $M_{\mathrm{u}}^{\min}$, respectively.

For the lower bounds $M^{\min}$, the method proposed in [28] can be directly applied. Here we only discuss how to determine $M_{\mathrm{u}}^{\min}$. Similar to [28], we define the propagation capacity of the obtained interaction network $\mathcal{G}(\mathcal{C},\mathcal{L})$, $\mathrm{PC}^{\mathcal{G}}$, and that of the original cascades, $\mathrm{PC}^{\mathrm{ori}}$, as

$$\mathrm{PC}^{\mathrm{ori}}(M_{\mathrm{u}})=\frac{\sum\limits_{m=1}^{M_{\mathrm{u}}}\sum\limits_{g=1}^{\infty}\mathrm{card}\Big(F_g^{(m)}\Big)}{M_{\mathrm{u}}} \tag{10}$$

$$\mathrm{PC}^{\mathcal{G}}(M_{\mathrm{u}})=\frac{\sum\limits_{l\in\mathcal{L}}I_l'(M_{\mathrm{u}})}{M_{\mathrm{u}}}, \tag{11}$$

where I_l is an index defined in [28] for the link $l:i\to j$, which is the expected value of the number of failures propagated through the link.

The selected $M_{\mathrm{u}}^{\min}$ should make sure the mismatch between $\mathrm{PC}^{\mathrm{ori}}(M_{\mathrm{u}})$ and $\mathrm{PC}^{\mathcal{G}}(M_{\mathrm{u}})$ is acceptably small and at the same time the $\mathrm{PC}^{\mathrm{ori}}(M_{\mathrm{u}})$ has almost stabilized. Therefore, we want to find the $M_{\mathrm{u}}^{\min}$ satisfying the following two conditions

$$|\Delta_{\mathrm{PC}}(M_{\mathrm{u}})|\leq\epsilon_1\mathrm{PC}^{\mathrm{ori}}(M_{\mathrm{u}})$$
$$|\mathrm{PC}^{\mathrm{ori}}(M_{\mathrm{u}})-\mathrm{PC}^{\mathrm{ori}}(M_{\mathrm{u}}-\Delta M)|\leq\epsilon_2\mathrm{PC}^{\mathrm{ori}}(M_{\mathrm{u}}-\Delta M),$$

where $\Delta_{\mathrm{PC}}(M_{\mathrm{u}})=\mathrm{PC}^{\mathcal{G}}(M_{\mathrm{u}})-\mathrm{PC}^{\mathrm{ori}}(M_{\mathrm{u}})$, and ϵ_1 and ϵ_2 are the acceptable tolerance. We start from a very small value for M_{u}, such as $M_{\mathrm{u}}^0=100$, and then increase it by ΔM at each step until the conditions listed here are satisfied.

VI. Results

All tests are performed on a desktop computer with 3.2 GHz Intel(R) Core(TM) i7-4790S. In order to test the proposed interaction estimation method, a total of $M=50,000$ cascades are obtained by open-loop AC OPA simulation [16], [17] on the IEEE 118-bus system [22], [23], [28].

A. AC OPA Simulations

AC OPA is a variant of the basic OPA [12]–[15]. Different from the basic OPA that uses DC OPF, AC OPA uses AC OPF and thus can consider reactive power and voltage. Specifically, one AC OPA simulation is implemented in the following steps.

- Step 1: The loads are varied around their mean values by multiplying a factor uniformly distributed in $[2-\gamma,\gamma]$. Here γ is chosen as 1.67, which is the same as [22], [23]. Initial line outages are generated by assuming that each line can fail independently with probability $p_0=0.0001$.
- Step 2: Calculate the following AC OPF problem:

$$\begin{aligned}
&\min\sum_{i\in\mathcal{S}_{\mathrm{G}}}P_{\mathrm{g}i}-\sum_{j\in\mathcal{S}_{\mathrm{L}}}P_{\mathrm{d}j}\\
&\text{s.t. } P_i=V_i\sum_{j\in i}V_j(G_{ij}\cos\theta_{ij}+B_{ij}\sin\theta_{ij}),\ i\in\mathcal{S}_{\mathrm{B}}\\
&\quad Q_i=V_i\sum_{j\in i}V_j(G_{ij}\sin\theta_{ij}-B_{ij}\cos\theta_{ij}),\ i\in\mathcal{S}_{\mathrm{B}}\\
&\quad P_{\mathrm{g}i}^{\min}\leq P_{\mathrm{g}i}\leq P_{\mathrm{g}i}^{\max},\ i\in\mathcal{S}_{\mathrm{G}}\\
&\quad Q_{\mathrm{g}i}^{\min}\leq Q_{\mathrm{g}i}\leq Q_{\mathrm{g}i}^{\max},\ i\in\mathcal{S}_{\mathrm{G}}\\
&\quad V_i^{\min}\leq V_i\leq V_i^{\max},\ i\in\mathcal{S}_{\mathrm{B}}\\
&\quad -F_l^{\max}\leq F_l\leq F_l^{\max},\ l\in\mathcal{S}_{\mathrm{Line}},
\end{aligned}$$

  where $P_{\mathrm{g}i}$ and $Q_{\mathrm{g}i}$ are the active and reactive power outputs of generator i, $P_{\mathrm{g}i}^{\min}$ and $P_{\mathrm{g}i}^{\max}$ are the lower and upper limits of the active power outputs of generator i, $Q_{\mathrm{g}i}^{\min}$ and $Q_{\mathrm{g}i}^{\max}$ are the lower and upper limits of the reactive power outputs of generator i, V_i is the voltage magnitude of bus i, $V_i^{\min}$ and $V_i^{\max}$ are the lower and upper limits of the voltage magnitude, $\theta_{ij}=\theta_i-\theta_j$ is the phase angel difference between bus i and bus j, $j\in i$ denotes the buses that are connected to bus i including bus i itself, F_l is the power flow of line l, $F_l^{\max}$ is the line flow limits and is determined by the same method in [23], [28], G_{ij} and B_{ij} are the real and imaginary elements of the admittance matrix, and $\mathcal{S}_{\mathrm{G}}$, $\mathcal{S}_{\mathrm{L}}$, $\mathcal{S}_{\mathrm{B}}$, $\mathcal{S}_{\mathrm{Line}}$ are the sets of generators, loads, buses, and lines.

  If the OPF converges, go to Step 3; otherwise, shed load until the OPF converges and then go to Step 3.
- Step 3: If there are lines that violate their line limits, go to Step 4; otherwise, stop the simulation.
- Step 4: The overloaded lines in Step 3 are independently tripped with probability $\beta=0.999$. If there are line outages, go to Step 5; otherwise, stop the simulation.
- Step 5: If the system is separated into islands, balance the generation and load in each island by shedding load or adjusting the generators' outputs and go to Step 2; otherwise, directly go to Step 2.

B. Number of Cascades Needed

Here we choose the ϵ in (8) as 0.01. The number of links, $\mathrm{card}\big(\mathcal{L}(M_i)\big)$, obtained by using M_i's from 100 to $50,000$ is shown in Fig. 4. The results for both the proposed method in this paper and that in [28] are shown. When M is small, the number of links increases with the increase of M, indicating that more cascades can provide more information about the cascading outage propagation. However, when M reaches a threshold, the number of links will not grow anymore. In addition, although the number of links for the two methods are different, they very consistently saturate at $M_i=41,000$, which is chosen as $M^{\min}$.

The numbers of identified links under $M^{\min}$ are 419 and 715, respectively for the method in [28] and the proposed method. Note that the number of identified links by the proposed method in this paper is much greater than that by the method in [28]. This is mainly because for the latter method the component j failure in generation $g+1$ is only considered to be caused by the component failure in generation g that has caused the component j for the largest number of times among all cascades. If the numbers of times for two components in generation g are very close, ignoring the slightly smaller one will inevitably ignore important interactions.

For determining $M_{\mathrm{u}}^{\min}$, we set M_{u}^0, ϵ_1, ϵ_2, and ΔM in Section V as 100, 0.05, 0.05, and 100. After four ΔM iterations $M_{\mathrm{u}}^{\min}$ is determined as 400, which only accounts for 0.98% of $M^{\min}$. By contrast, for the interaction estimation method in [28], $M_{\mathrm{u}}^{\min}$ is determined as $3,700$, which is almost one order of magnitude more, indicating the greatly improved efficiency of the proposed method in this paper.

In Fig. 5 we present the propagation capacity calculated from the original cascades and the interaction network for different M_{u}'s. It is seen that the mismatch is always small

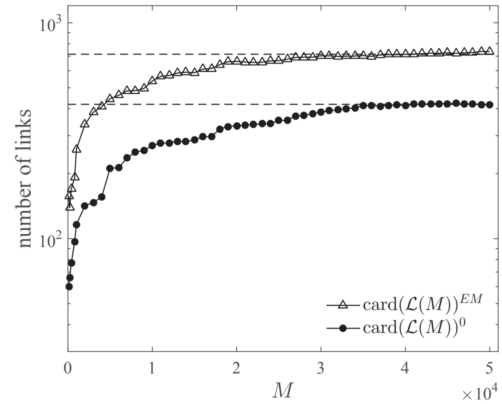

Fig. 4. Number of links for different M. Triangles denote the number of links obtained by EM algorithm and Dots denote that by the method in [28].

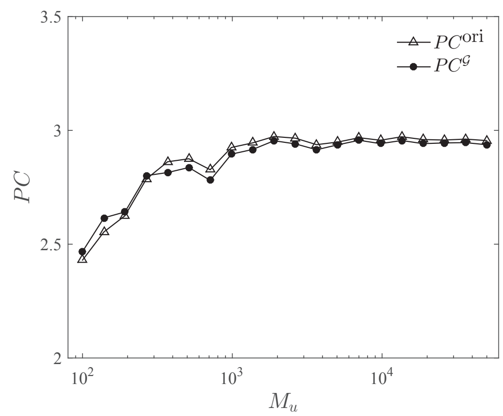

Fig. 5. Propagation capacity for different M_{u}.

even when the number of cascade is very small and the propagation capacity of the original cascades can stabilize around $M_{\mathrm{u}} = 400$.

C. Interaction Matrix and Interaction Network

The component interactions (links) are estimated by the proposed method in this paper and the method in [28] based on M_{u} cascades. For the proposed method, the EM algorithm converges after 5 iterations. In Table II we present the number of identified links ($\mathrm{card}(\mathcal{L})$). The ratio of nonzero elements in the interaction matrix $\boldsymbol{B}$ is defined as $r = \mathrm{card}(\mathcal{L})/n^2$ where n is the number of components. The very small value of r suggests that $\boldsymbol{B}$ is a sparse matrix and only a very small number of components have interactions in terms of cascading outage propagation.

TABLE II
NUMBER OF ESTIMATED LINKS

Method	M_{u}	n	$\mathrm{card}(\mathcal{L})$	r
Proposed method	41000	186	715	0.0207
Proposed method	400	186	170	0.0049
Method in [28]	400	186	77	0.0022

Based on the interaction matrix obtained by using different estimation methods based on different number of original cascades, the interaction networks can also be constructed, which provide a graphical representation of the interactions between the components. Based on the interaction network, the key links and key components that play important roles in failure propagation can also be identified, which will be discussed in detail in the following section.

D. Identifying Key Links and Key Components

Key links and key components that are most critical for cascading outage propagations are identified by the method in Section III of [28], in which I_l (the expected value of the number of failures propagated through the link) is defined for a link l to indicate its importance. The ϵ_l in [28] is set to be 0.15 to make sure that all of the key links have their I_l in the same order of magnitude.

In Table III we list the identified key links and their I_l. Note that I_l corresponds to the links obtained from the interaction estimation method in this paper and I_l^* for the method in [28]. The numbers highlighted in bold font correspond to the identified key links and the numbers in the parentheses are the ranking of the links. When $41,000$ cascades are used, 15 links are identified as key links. Although the key links only account for 2.1% of all links, their total I_l is 79.9% of the total I_l of all links. In Table III we can seen that the identified key links by using the EM algorithm based only on 400 cascades (denoted by a set $\mathcal{L}_1$) are almost the same as those from $41,000$ cascades. By contrast, when also using the same 400 cascades, the identified key links from the method in [28] (denoted by a set $\mathcal{L}_2$) are very different.

The seven components with the largest out-strengths are identified as key components. The tripping of these lines could produce extensive outage propagations in the system and should be avoided as much as possible. These key components, the corresponding branches, and their out-strengths are presented in Table IV. Note that s_i^{out} is the out-strength obtained from the proposed interaction estimation method and $s_i^{\mathrm{out}*}$ for the method in [28]. The numbers highlighted in bold font correspond to the identified key components and the numbers in the parentheses represent the ranking of the components in terms of the out-strength.

When $41,000$ cascades are used, the number of key components are 3.76% of all of the components and the summation of their out-strengths accounts for 83.41% of the total out-strengths of the components. It is clearly seen from Table IV that by using the proposed interaction method we can identify the same key components based on only 400 cascades as those using $41,000$ cascades. By contrast, when only using 400 cascades, the interaction estimation method in [28] identifies very different key components and several important components cannot be identified.

E. Validating the Estimated Interactions

Here, we validate the estimated interactions between component failures by the proposed interaction estimation method

TABLE III
IDENTIFIED KEY LINKS

$i \to j$	Line pairs	$I_l(41,000)$	$I_l(400)$	$I_l^*(400)$
$74 \to 73$	(53, 54) $\to$ (52, 53)	**12490**	**122 (2)**	**123 (3)**
$74 \to 72$	(53, 54) $\to$ (51, 52)	**12436**	**126 (1)**	**127 (2)**
$40 \to 34$	(29, 31) $\to$ (27, 28)	**11187**	**109 (4)**	**112 (5)**
$74 \to 82$	(53, 54) $\to$ (56, 58)	**11125**	**111 (3)**	**110 (7)**
$40 \to 35$	(29, 31) $\to$ (28, 29)	**10864**	**98 (5)**	**100 (8)**
$62 \to 68$	(45, 46) $\to$ (45, 49)	**9922**	**91 (6)**	**92.6 (10)**
$121 \to 122$	(77, 78) $\to$ (78, 79)	**9581**	**90 (7)**	**90 (14)**
$121 \to 125$	(77, 78) $\to$ (79, 80)	**9579**	**90 (8)**	**90 (15)**
$40 \to 182$	(29, 31) $\to$ (114, 115)	**7396**	**85 (9)**	**80 (16)**
$12 \to 18$	(11, 12) $\to$ (13, 15)	**5307**	**41 (10)**	**42 (20)**
$68 \to 59$	(45, 49) $\to$ (43, 44)	**3682**	**32 (12)**	**33 (21)**
$182 \to 43$	(114, 115) $\to$ (27, 32)	**3317**	**27 (13)**	10 (39)
$46 \to 47$	(35, 36) $\to$ (35, 37)	**2167**	17 (17)	**47 (18)**
$40 \to 43$	(29, 31) $\to$ (27, 32)	**2154**	**34 (11)**	**48 (17)**
$82 \to 74$	(56, 58) $\to$ (53, 54)	**2085**	**21.1 (15)**	21 (26)
$182 \to 40$	(114, 115) $\to$ (29, 31)	1458 (19)	**23 (14)**	26 (25)
$155 \to 151$	(94, 100) $\to$ (80, 97)	918 (22)	**20.9 (16)**	21 (29)
$102 \to 82$	(65, 66) $\to$ (56, 58)	164 (52)	0.51 (74)	**127.2 (1)**
$102 \to 73$	(65, 66) $\to$ (52, 53)	134 (57)	0.49 (77)	**123 (4)**
$102 \to 34$	(65, 66) $\to$ (27, 28)	395 (29)	1.38 (48)	**112 (6)**
$102 \to 35$	(65, 66) $\to$ (28, 29)	382 (30)	1.24 (52)	**100 (9)**

TABLE IV
IDENTIFIED KEY COMPONENTS

Key component	Line	$s_i^{\text{out}}(41,000)$	$s_i^{\text{out}}(400)$	$s_i^{\text{out}*}(400)$
74	(53, 54)	**38230**	**384 (1)**	**380 (2)**
40	(29, 31)	**32317**	**328 (2)**	**342 (3)**
121	(77, 78)	**19805**	**185 (3)**	**181 (4)**
62	(45, 46)	**10300**	**92 (4)**	**93 (6)**
12	(11, 12)	**6561**	**50 (7)**	42 (8)
68	(45, 49)	**6250**	**59 (5)**	**61 (7)**
182	(114, 115)	**4831**	**52 (6)**	39 (9)
102	(65, 66)	4221 (9)	22 (11)	**908 (1)**
46	(35, 36)	4751 (8)	27 (9)	**137 (5)**

based on EM algorithm. In Fig. 6 we show the probability distributions of the line outages for the $41,000$ original cascades and the $41,000$ cascades obtained by the interaction model in [28] based on the interactions estimated from the method in [28] and the proposed method in this paper. Note that the interaction model uses the distribution of the initial outages and the interactions obtained from 400 original cascades to generate $41,000$ cascades.

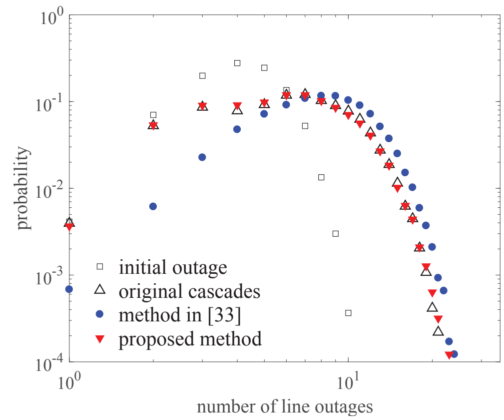

Fig. 6. Probability distributions of the line outages. "□" and "△" denote initial outages and total outages of the original cascades; "●" and "▼" denote total outages of the simulated cascades using 400 cascades, respectively for the method in [28] and the proposed method in this paper.

It is seen that the simulated cascades by using the interactions obtained from 400 original cascades with the proposed estimation method have very similar statistical features to the original $41,000$ cascades. By contrast, the distribution of the simulated $41,000$ cascades based on the interactions obtained from the same number of cascades using the estimation method in [28] is very different from the original cascades, indicating that the proposed estimation method can more accurately estimate the interactions of component failures.

F. Cascading Failure Mitigation

Similar to [28], removing some key links can mitigate the cascading outage propagations. In power systems this can be realized by blocking the operation of zone 3 relays [34]. In order to test the identified key links in Section VI-D, we first obtain the distributions of initial outages and the interaction matrix $\boldsymbol{B}$ by using $41,000$ original cascades and then remove the top 10 key links in $\mathcal{L}_1$ or $\mathcal{L}_2$ by setting the corresponding elements in $\boldsymbol{B}$ to be zero. By doing this we get $\boldsymbol{B}_{\text{int}}^1$ and $\boldsymbol{B}_{\text{int}}^2$, which are further used to simulate $41,000$ cascades by using the interaction model [28], [29].

By comparing the probability distribution of the total number of line outages of the $41,000$ original cascades and those of the $41,000$ simulated cascades with the key-link based mitigation, we will be able to figure out 1) if the key-link based mitigation is effective in reducing the cascading failure risk, and 2) if the key links in $\mathcal{L}_1$ identified based on the proposed interaction estimation method are better than those in $\mathcal{L}_2$ from the simple interaction estimation method in [28].

Fig. 7 shows the comparison of the probability distributions of total line outages before and after mitigation. We can see

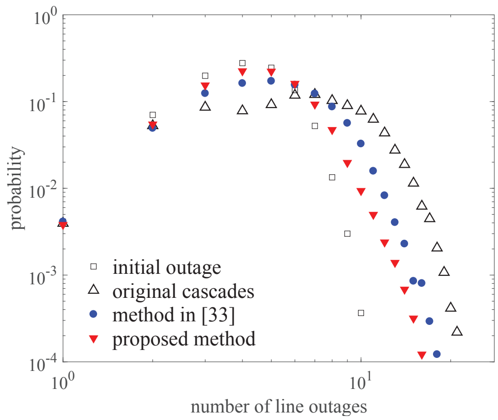

Fig. 7. Probability distributions of the line outages under key-link based mitigations. "□" and "△" denote initial outages and total outages of the original cascades; "•" and "▼" denote total outages of the simulated cascades with mitigation based on $\boldsymbol{B}_{\text{int}}^1$ and $\boldsymbol{B}_{\text{int}}^2$.

that the probability of having a cascading blackout with a large number of line outages is greatly reduced by removing only 10 key links and removing the same number of key links in $\mathcal{L}_1$ can better mitigate the cascading risks than removing those in $\mathcal{L}_2$. The estimated average propagation of the branching process [22]–[25] for the original cascades before mitigation is 0.40, which can be reduced to 0.23 and 0.12, respectively, after mitigation based on $\mathcal{L}_1$ key links and $\mathcal{L}_2$ key links, indicating that the proposed interaction estimation method can more accurately identify the key links.

G. Efficiency Improvement

As in Section VI-B, the $M_{\text{u}}^{\text{min}}$ for the proposed interaction estimation method and that for the method in [28] are, respectively, 400 and 3,700. We list the time used to simulate $M_{\text{u}}^{\text{min}}$ cascades by AC OPA (T_1) and that used to estimate the interactions (T) for both methods in Table V. Compared with the interaction estimation method in [28], for getting reliable interactions the proposed method can achieve a speedup of $(18,518 + 5.07)/(2,002 + 8.59) \approx 9.21$.

In Table V, we also list T_2 which is the time for simulating 41,000 cascades by using the interaction model. Compared with purely relying on the AC OPA simulation, the interaction model simulation based on the proposed interaction estimation method can achieve a speedup of $205,200/(2,002 + 8.59 + 29) \approx 100.61$. The time efficiency can be significantly improved by first estimating the component interactions using $M_{\text{u}}^{\text{min}} \ll M^{\text{min}}$ original cascades and then conducting highly probabilistic interaction model simulation.

It is seen in Table V that when using the proposed estimation method and the interaction model to perform simulation, the majority of the time is for simulating the original cascades by detailed simulation models such as AC OPA, although the number of required original cascades has been significantly reduced by the proposed estimation method. Therefore, in order to further reduce the total simulation time and finally make possible the online application, it is also needed to improve the computational efficiency of the detailed cascading

TABLE V
EFFICIENCY IMPROVEMENT

Model	Method	M_{u}	T_1 (second)	T (second)	T_2 (second)
AC OPA	–	–	205,200	0	0
Interaction	Proposed method	400	2,002	8.59	29
Interaction	Method in [28]	3700	18,518	5.07	29

failure simulation, such as by parallel computation or other high performance computing techniques.

VII. Conclusion

The estimation of component interactions is a parameter estimation problem with incomplete data. In this paper, we apply the EM algorithm to perform an effective estimation. The proposed method is tested and validated by cascading failure data produced by the AC OPA simulations on the IEEE 118-bus system. The identified key links and key components based on the estimated interactions from 400 original cascades are very similar to those that are directly from 41,000 original cascades, and the removal of a few key links can effectively mitigate cascading outage propagations. The interaction model simulations based on the interactions estimated from the proposed method can generate cascades with very similar statistical features to the original cascades, while being able to achieve a speedup of 100.61 compared with purely relying on AC OPA simulation.

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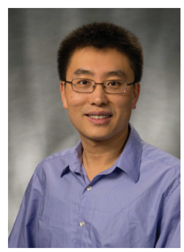

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