

Identification of Chains of Events Leading to Catastrophic Failures of Power Systems

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Abstract— Catastrophic failures have been traditionally treated as rare events. However, in view of the manner in which power systems have been evolving over the past decade, and the frequency with which catastrophic failures have occurred in this period, it is imperative that systematic approaches be devised to identify the likely chains of events that lead to these failures, so that appropriate countermeasures—strategic and tactical—may be designed and implemented. This paper discusses the recent body of work on structural issues, such as hidden failures and failure sequences, and identifies the need to further explore how chains conspire to form, and how the transition rates of the dependent events might change as the chain evolves. The paper then proceeds to develop a genetic algorithm based method that searches through the state space to identify likely event trees that connect healthy system states to catastrophic failure states. The method is illustrated via a small test system. The simplicity of the system enables an intuitive understanding of the mechanics of the method.

I. INTRODUCTION

Catastrophic failure states are rare events, and, individually, are encountered very infrequently. However, when several catastrophic failure states, albeit different, are encountered over a relatively short period of time as we have seen in the recent past, one is compelled to reexamine the classical approaches that qualify these events as rare. It is recognized today that while these events, considered in isolation, are indeed rare, they can be reached from valid operational states via chains of events that are, considered as a whole, sufficiently likely that the sequence ceases to be “rare”. In view of the manner in which power systems have been evolving over the past decade, and the frequency with which catastrophic failures have occurred in this period, it is imperative that systematic approaches be devised that will identify the likely chains of events that lead to these failures, so that appropriate countermeasures—strategic and tactical—may be designed and implemented.

There are two challenges. First the recent body of work on structural issues, such as hidden failures and failure sequences, must be abstracted to develop a model of how chains conspire to form. For example, how can we represent an increased possibility of a generator trip as a function of

load and contingency conditions? Secondly, a means must be developed to identify such chains. While work continues on a realistic formulation of the abstraction problem, this paper assumes certain simple relationships and demonstrates the effects of non-stationary transition probabilities that result from such modeling.

This paper presents a genetic algorithm based method that searches through the state space to identify likely event trees that connect healthy system states to catastrophic failure states. The method is illustrated via a test system consisting of 5 buses, 7 lines, 2 generators and 3 load points. The simplicity of the system enables an intuitive understanding of the mechanics of the method.

II. IDENTIFICATION OF EVENT SEQUENCES LEADING TO CATASTROPHIC FAILURES

Much research has already been conducted on the identification of and response to event sequences leading to catastrophic failures. In some efforts [1], [2] event sequences have been recognized as rare, and methods such as importance sampling have been applied to identify them. Some have identified hidden failures as a key contributing cause and modeled their effect in the simulation of cascading outages [3], [4]. Others have researched and constructed models that emulate catastrophic failures, and attempted thereby to understand cascading failures in power systems. For instance, [5] analyzes a symmetrical model where loads are redistributed as components fail, until the system collapses; [6] builds an analogy with self-organized criticality in sandpile models. Yet others have developed strategies for system and operator response to these event sequences as they unfold, thereby mitigating their effect or containing them before they evolve into widespread outages: [7] suggests the use of decision event trees for rapid response, while [8] recommends an information infrastructure for real-time control. There are many other models and methods in the literature, and considerable work is still in progress.

Our approach to the problem is based on the following premise: (1) We contend that if for a given system, a sufficiently large set of event sequences—which may occur as event trees or isolated strands—leading to catastrophic

failures are identified *a priori*, and appropriate strategic and tactical countermeasures are developed to prevent the system from entering these vulnerable modes, then the system security is significantly improved, even if the considered set is not exhaustive. It is also important that the considered set should be well dispersed over the entire space of possible event sequences. (2) We further contend that in the treatment of this problem, inter-state transition probabilities must be considered to be non-stationary. In other words, as the sequence evolves, the inter-state transition probabilities change. For instance, the probability of a system transitioning from one state to the next in a sequence of events leading to a cascading failure will be different from the one-step transition probability between the same pair of states, under other conditions.

Investigation of an approach that models the structural relationships which define the changing probabilities is progress. In a parallel research effort, we have developed a method that identifies likely event sequences leading to catastrophic failure given the non-stationary transition probabilities. In the following sections this method is described, and the consequences of the changing probabilities are demonstrated. The tool used in this method uses a genetic algorithm (GA) [9]. It is appropriate to point out at this stage that there is nothing sacrosanct about the use of GA in this method; it could as well have been implemented using Monte Carlo simulation or any other appropriate tool, ‘intelligent’ or otherwise.

III. WORMS

In classical reliability analysis we describe the system by a state vector X . For the system in Figure 1, we might define X as a vector of nine binary elements, each corresponding to the status of a component (generator or line). $X_i = 1$ implies component i is in service, and $X_i = 0$ implies that the component has failed. The transition from state X^M to state X^N is an *event*. Each event can be assigned a probability based on the states of the components describing that event. An event occurs at a specific point in time—if the event involves multiple component outages, all components are assumed to fail or trip simultaneously. This is where we will depart from classical modeling. The view we want corresponds to the event evolving in time with a corresponding evolution of the underlying failure mechanisms in the system.

Consider the following example. The outage of both generators, or the outage of generator 1, line 2 and line 6 causes a complete loss of load. These events are readily identified in conventional analysis.

However consider the following sequence of events:

- Generator 1 trips, some load is lost, and short-term overloads occur on lines 2 and 6. Overload relays have picked up *thereby increasing the likelihood that additional line failures will cause these lines to trip*.
- Line 1 trips increasing the overload on lines 2 and 6, eventually causing a trip on line 2, followed by an instantaneous trip on line 6.

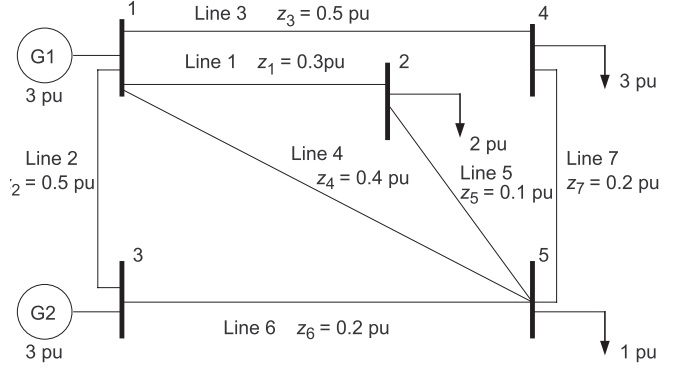


Figure 1. Test System.

In effect, the event is a fourth order contingency that will never be considered in conventional analyses. Further, from an operational standpoint line, Line 1 is unlikely to be flagged as a critical line. Practically, a simultaneous trip is an *impossible* event. As an evolving event, it is very likely one. We will call such an event a “worm”.

Definition: A *worm* is sequence of state transitions $W = \{X^{P1} X^{Q2} X^{R3} \dots X^{TN}\}$ corresponding to time instants $1, 2, 3, \dots, N$, that leads to a significant loss of load in state X^{TN} , i.e., state X^T at time N . The “probability of occurrence” of the worm W is greater than the “raw probability” of the event X^N .

We assume that the manner (probability, possibility, likelihood, ...) of transition from X^{P1} to X^{TN} is a known function of the sequence.

The *worm* in our example can be written as:

$$W = \{[111111111][111111101][011111101][001110101]\}$$

The increased likelihood of a *worm* is due to the fact that:

$$P[X^{Q2} | X^{P1}] \gg P[X^{Q2}]$$

IV. FINDING WORMS — A GA APPROACH

We suggest an approach based on Genetic Algorithms. As illustrated in Figure 2, let each time slice i , $i = 1, 2, \dots, N$ be represented by a layer.

- Each layer contains a population of states, X^{kN} , $k=1, 2, \dots, M$, where M is the population size.
- Layer zero is restricted to a single state, namely, the known starting state.
- Our goal is to create a population of states in the last or lowest layer that are “catastrophic”. A catastrophe may be measured by the amount of load lost.
- Intermediate layers contain states that have
 - A large likelihood of originating from the state(s) in the previous layer, AND
 - A large likelihood of terminating in a loss of load state(s) in the subsequent layer
- Intermediate layer states may be loss of load states.
- The state transition $X^{ki} \rightarrow X^{j(i+1)}$ is a function of the origin state X^{ki} , the power system conditions at time i .

To identify a *worm* we apply a GA at each level, to converge to a layer-by-layer population that is dominated by states that have characteristics defined above. The population evaluation at each layer is performed as usual through selection, crossover and mutation [9]. In this work, tournament selection has been employed. Each GA iteration will perform a forward sweep through the layers and a backwards sweep. The forward sweep is expected to emphasize the transition likelihood requirement from the original state. The backward sweep is anticipated to emphasize the loss of load of the terminal, loss of load, state.

The fitness function of state j in layer K is defined as

$$F(X^{jK}) = C^{jK} \times \left(\sum_{r=1}^M P(X^{r(K-1)}, X^{jK}) C^{r(K-1)} \right) \times \left(\sum_{r=1}^M P(X^{jK}, X^{r(K+1)}) C^{r(K+1)} \right)$$

where $P(X^{r(K-1)}, X^{jK})$ is the transition probability from state $X^{r(K-1)}$ to state X^{jK} , $P(X^{jK}, X^{r(K+1)})$ is the transition probability from state X^{jK} to state $X^{r(K+1)}$, and C^{jK} is the load curtailment in state X^{jK} .

In the example to follow we assume a dc load flow model and use a Linear Programming approach to calculate curtailment for a given state. The example uses the 5-bus test system shown in Figure 1. Even with such a small system, the computational effort required was considerable. We are currently working on developing a parallelized implementation to test on the 24-bus IEEE Reliability Test System. This implementation will include a more rational representation of the non-stationary transition probabilities. Results of this work will be reported in due course.

V. EXAMPLE

The GA approach was applied to the system in Figure 1. The one step transition probabilities of components from up to down states (down states being reached by failure or tripping) of the different components were assigned as follows: generators: 0.01; lines: between 0.01 and 0.05 for the different lines. The non-stationarity of transition probabilities was modeled by a simple rule: *If, in layer k , line 1 is failed in state j , then the probability of line 6 failing is 0.5 and that of line 2 failing is 0.2.*

At each layer the GA used a population of 50 chromosomes. The GA was run for 2000 generations. In order to visualize the results Figure 3 was constructed from the populations at end of 2000 generations. At each layer the ten most fit chromosomes are displayed. The decimal number corresponding to the binary state representation is shown. The size of the ellipse surrounding the state indicates the level of curtailment. For the largest ellipses, for example, all load must be curtailed. For each state the three most likely transitions from states in the previous layer, and the three most likely transitions to states in the subsequent layer, are shown by connecting lines. The thickness of the lines is

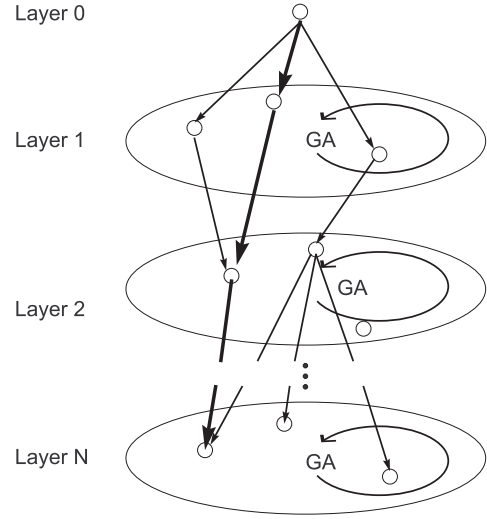


Figure 2. Layered GA Search.

proportional to the probability of transition from one state to the other.

Layer 0 has only one state, with all components in service. States in layer 1 are failure states with a moderate level (0.5–3 pu) of load curtailment. Many of these states involve triple-contingencies and thus their probability of occurrence is low, as indicated by the narrow lines. States 247, 253, 255, 509, 381, 501 and 505 have higher probabilities and involve single or double contingencies. At the other extreme, in layer 4, most of the states are ones with a complete loss of load.

High probability transitions from the original state to complete loss of load states, or worms, are indicated by relatively high probability transitions. An example of such a sequence is 511-255-253-125-117. The sequence 511-253-125-117 is another worm. In both, the components which fail are Line 1, Generator 1, Line 2 and finally Line 6. This sequence, of course corresponds to our model of changing failure probabilities. The rule makes the failure of Lines 2 and 6 more likely when Line 1 fails.

Another, lower probability worm consists of the sequence 511-125-93-349-341. This worm involves the failure of one additional line—Line 4.

TABLE I. DESCRIPTION OF SELECTED STATES IN FIGURE 3

State	Failed Components
509	Generator 1
255	Line 1
253	Line 1, Generator 1
125	Line 1, Line 2, Generator 1
117	Line 1, Line 2, Line 6, Generator 1 (Total loss of load)
113	Line 1, Line 2, Line 6, Line 7, Generator 1 (Total loss of load)

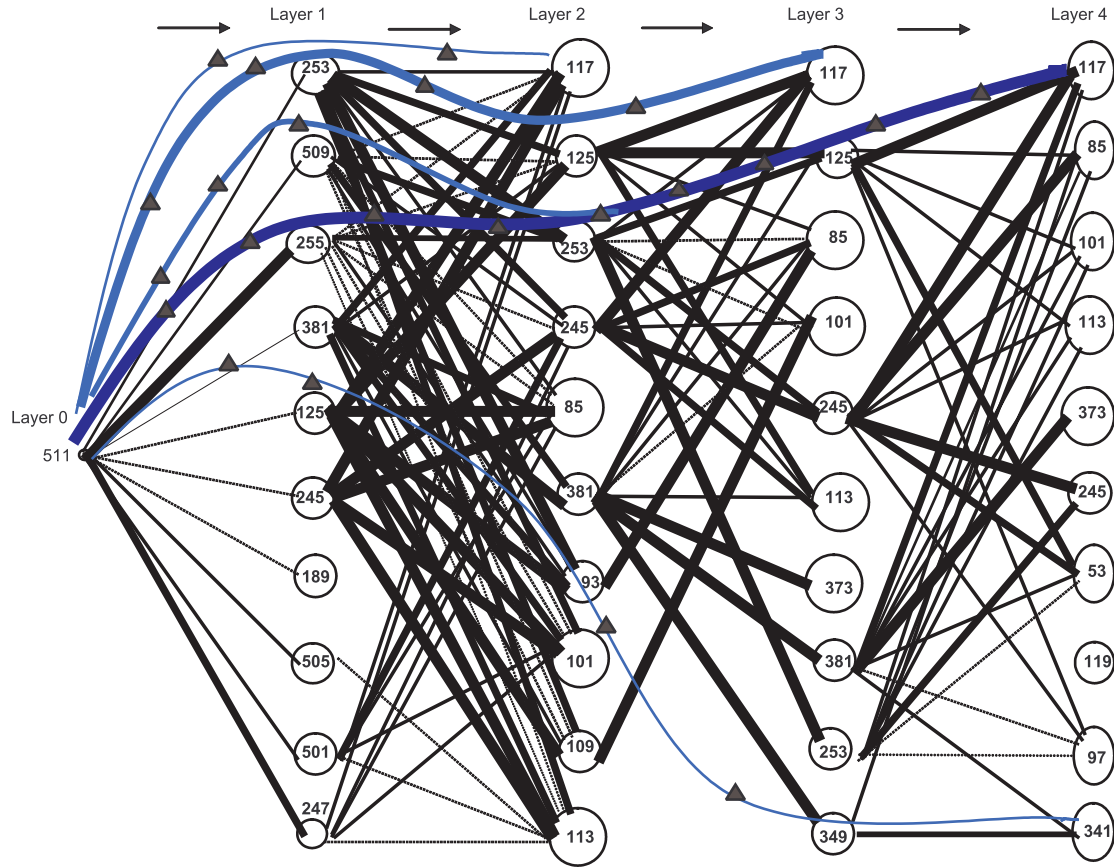


Figure 3. Worms for the System in Figure 1.

VI. DISCUSSION AND CONCLUSIONS

We have demonstrated that once the various factors are modeled that contribute to the non-stationarity of transition probabilities amongst system states, it is possible to identify an arbitrarily large set of event trees that lead to catastrophic failures, and such identification can enable the development of preventive measures, both at the planning and operation levels, to strengthen a system against inherent vulnerabilities. The contributing factors are numerous and complex—structural relationships, hidden failures, operator action (or inaction), and system stability are only some of the major considerations. The level of detail to which these need to be modeled is another concern that must be explored.

We are currently engaged in research to model some of the above factors. However, this work represents a first step in the direction of establishing the need to develop a methodology to abstract the important factors contributing to changing transition probabilities and in demonstrating the viability of constructing a possibility space that enables system immunization strategies.

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