Chapter 18
Impediments and Model for Network Centrality Analysis of a Renewable Integrated Electricity Grid

A. B. M. Nasiruzzaman, Most. Nahida Akter and H. R. Pota

Abstract Inclusion of renewable energy changes the power flow direction of the trans- mission grid, resulting in a bidirectional flow model of the power transmission systems. The changing nature of the grid demands for new and improved techniques to analyze the vulnerability of the power grid. In this chapter, a method for identifying critical nodes for smart and bulk power transmission grid environment is presented. A new model based on bidirectional power flow is considered. Three different models of power system based on complex network framework are analyzed. Applicability of these methods in smart grid environment is evaluated. The consequence of removing critical nodes found from the analysis is discussed. Four measures of impact based on topological and electrical characteristics are tested. The efficacy of bidirectional model is studied through rank similarity analysis.

Keywords Closeness centrality · Forward unidirectional graph · Backward unidirectional graph · Bidirectional graph · Path length · Connectivity loss · Load loss · Rank similarity

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18.1 Introduction

Utilities around the world are integrating smart and new technologies towards making the existing electrical power transmission grid much smarter [1]. The scope of smart grid includes various generation options, primarily in the distribution side—near consumers. Engagement of customers with the energy management systems is the most lucrative part of smart grid from the point of view of regulating energy usage. Excess of generation after local use can be transmitted long distance to meet the energy shortage of the destination area.

This introduces a new concept of power flowing from customer end towards the grid. The bidirectional power flow changes the whole power flow pattern of the existing grid [2]. Analytical methods, technical strategies, control system and protecting devices need to be changed along with, to mention a few. Metering and protecting equipments will experience flows coming from the reverse side. Proper operation of the equipments used earlier can be ensured either by changing the instruments themselves or by incorporating new measurement techniques [3].

Recent years have seen several very large scale blackouts initiating from small disturbances. In August 1996, a cascading outage occurred in the Western power grids of North America in USA and Mexico [4]. More than four million people suffered the consequences. Most affected areas were out of electricity for about 4 days. Another large scale blackout which affected around 55 million people happened in August 2003 [5]. Several northeast and mid-western states of USA and some provinces of Canada were affected.

The move towards the smart grid started after the blackouts happened all around the world [6]. From the frequent events of large scale-blackouts it is clear that the existing dynamics security assessment and monitoring system has not been working well [7]. The motivation of complex network framework based analysis approach comes from the necessity of new, alternative and improved methodology to assess the risk involved with cascading events in power system.

Degree centrality, betweenness centrality and closeness centrality measures are commonly used in social network research to find a person with most influence [8]. The person who has most number of links is the most central according to degree centrality. Betweenness centrality measures the importance of a person as an intermediary. The person who comes across a path of communication between two other persons most of the times is considered as central in between centrality. A person is said to be closeness central if he or she is closest to all other persons relative to other persons in the network of interest.

Connectivity of the network is hampered, when nodes with higher degrees are taken out from the system. Removing a node takes out with it many links, which degrades the performance of network. Betweenness central node is important because it has the most ability to control communication between other nodes. The node which has least distance from all other nodes is closeness central. This node is the most independent one since it can communicate with other nodes without the need of intermediate nodes.

Power grid topology has been analyzed by various researchers recently to explore its strength and weakness using complex network framework. The strength of the grid is found to be, from a pure topological analysis of USA power grid, small-world property [9]. This implies that various nodes within the system can be reached easily, which will make the communication that comes along with the smart grid easy and effective. The scale freeness of the topology of the grid is shown to be a weakness of the grid since it makes the system very much vulnerable to targeted attack [10]. This targeted attack can trigger cascading failure which will lead to blackout.

The research on power grid from a system point of view has been triggered after the publications of the preliminary topology based analysis results. Since results from pure topological approach is quite misleading [11], several researchers have a mix of both topological and electrical characteristics based complex network analysis of power system to find reasonably improved results [12, 13].

Motivated by the topological result that found the power grid robust against random failure but vulnerable to targeted attacks [10], critical node and link analysis of power grid have been carried out to explore the criticality of the power grid. If critical components can be spotted out which can initiate cascading effect, special preventive actions could be exercised so that to prevent large scale blackouts from happening.

Network efficiency, a topological measure of performance change after the inclusion or removal of nodes or lines from a grid, is analyzed in [14]. A weighted line betweenness based approach is utilized to find out critical lines responsible for spreading of large scale blackouts from small initial shock [15]. Vulnerable regions of power system are identified employing complex network theory based qualitative simulation in [16]. Transmission line reactance is incorporated to compute a new vulnerability index to identify critical lines [17].

A link is explored between power system reliability and small world effect [18]. Maximum flow based centrality approach is used to find out critical lines which removes the shortcoming of the assumption of power flowing through the shortest paths between source and load nodes [19]. This method has slow convergence but can be useful when used in conjunction of planning issues. A DC power flow model is used and hidden failure of protective equipment is considered to model the structural vulnerability of power grid [20]. Electrical parameters are incorporated extensively to improve the centrality indices for power system [21].

An extended topological approach proposed in [22] takes into consideration traditional topological metrics as well as operational behavior of power grids like real power flow allocation and line flow limits. Power Transfer Distribution Factor (PTDF) is used to simulate cascading event in an attempt to identify correlated lines [23].

All these analysis are carried out for electric grids where power flow is directed from generating nodes to load nodes. But since with the inclusion of distributed generations the power flow pattern is going to change, new methodologies have to be proposed which takes into account bidirectional power flow. Since communication is an important factor in smart grid, identifying those nodes in the system would be very much useful which are important for communication.

In this chapter, a method based on complex network theory has been proposed to identify critical components in smart grid. This method is a modification of closeness centrality which takes into account power flow distribution among various power lines during steady state. This is a reasonable extension of previous work carried out by researchers since it captures the power flow in smart grid environment. Rank similarity analysis result is carried out to verify that proposed index is useful although there is a slight change in network. The impact of removing critical components is identified using well known impact metrics like path length, connectivity loss and load loss.

The organization of the rest of the chapter is as follows. Sect. 18.2 provides a model for the analysis of smart power grid under complex network framework. A new model based on bidirectional power flow is considered and a method is discussed to find critical nodes in the power grid. The critical node identification procedure is illustrated in Sect. 18.3. The effect of removal of critical nodes on various topological and electrical measures is addressed in Sect. 18.4. Effect on the rank of critical nodes for different models, when the network is changed slightly is observed in Sect. 18.5. Conclusion is drawn and future research direction is provided in Sect. 18.6.

18.2 System Model and Methodology

The first step of analyzing power grid under complex network framework is to model the system as a directed graph [7]. Vertices in the graph represent generating stations, substations, loads etc. Edges of links represent transmission lines that connect various generating stations, substations and load points. In this model, only transmission system is considered. The overall distribution system is regarded as a lumped load at the distribution substation terminal.

Power flow analysis is conducted for the given test system during nominal condition. Newton–Raphson method is used to solve the simultaneous nonlinear algebraic power flow equations [24]. The direction of real power flowing through the lines is taken as the direction of edges in the modeled graph. From this point this graph will be known as forward unidirectional flow graph, which can be defined as:

Definition 18.1 (*Forward Unidirectional Graph*) A nominal unidirectional graph model of a power system can be obtained from the normal operating states of the system. It can be represented by $\Gamma = (\varsigma, \mathrm{E}, \Omega)$ comprising of a set ς, whose elements are called vertices or nodes, a set $\mathcal{E}$ of ordered pairs of vertices, called edges or lines and a set Ω, whose elements are weights of edge set elements. There exists a one-to-one correspondence between set E and set Ω. An element $e = (x, y)$ of the edge set E, is considered to be directed from x to y, where y is called the head and x

is called the tail of the edge. In this model, transmission line impedances in pu is considered as weights of the edges between nodes. There exists a one-to-one correspondence between set E and set Ω.

In order to consider the bidirectional flow in smart grid, a backward unidirectional flow graph is also modeled, which is presented in a formal definition as follows:

Definition 18.2 (*Backward Unidirectional Graph*) A backward unidirectional graph model of a power system can be obtained from the reversed operating states of the system. It can be represented by $\mathrm{G} = (\mathrm{V}, \mathrm{E}, \mathrm{W})$ comprising of a set V, whose elements are called vertices or nodes, a set E of ordered pairs of vertices, called edges or lines and a set W, whose elements are weights of edge set elements. There exists a one-to-one correspondence between set E and set W. An element $e = (x, y)$ of the edge set E, is considered to be directed from x to y, where y is called the head and x is called the tail of the edge. In this model, transmission line impedances in pu is considered as weights of the edges between nodes. There exists a one-to-one correspondence between set E and set W.

As we can find out from the definition, the direction of edges in the backward unidirectional flow graph is exactly opposite to the nominal unidirectional flow graph. Now, the combination of the forward and backward unidirectional graph is considered to be the bidirectional graph, which is used to model the power flow pattern of the future smart power grid. The bidirectional graph can be defined as:

Definition 18.3 (*Bidirectional Graph*) A bidirectional graph model of a power system can be obtained from the superposition of nominal unidirectional and backward unidirectional graph models. It can be represented by G = (V,E,W) comprising of a set V, whose elements are called vertices or nodes, a set E of ordered pairs of vertices, called edges or lines and a set W, whose elements are weights of edge set elements. There exists a one-to-one correspondence between set E and set W. An element $e = (x, y)$ of the edge set E, is considered to be directed from x to y , where y is called the head and x is called the tail of the edge. In this model, transmission line impedances in pu is considered as weights of the edges between nodes. There exists a one-to-one correspondence between set E and set W.

To illustrate uni- and bi-directional graph models in a power system, a simple example of 14 bus system [25] is used in this chapter. Figure 18.1 depicts the system with 14 bus bars, and 20 links connecting them, while Figs. 18.2 and 18.3 represent the forward and backward unidirectional graph model of Fig. 18.1. We can model the system as a graph which contains 14 nodes/vertices which correspond to the slack, voltage-controlled, and load bus bars of the original system. The transmission lines can be represented by the 20 links/edges which connects various nodes. The system data is given in Table 18.1.

Assume that, k represent the intermediate bus within the shortest path originating from bus s and ends at bus t. Let, P_{st} represents the maximum power

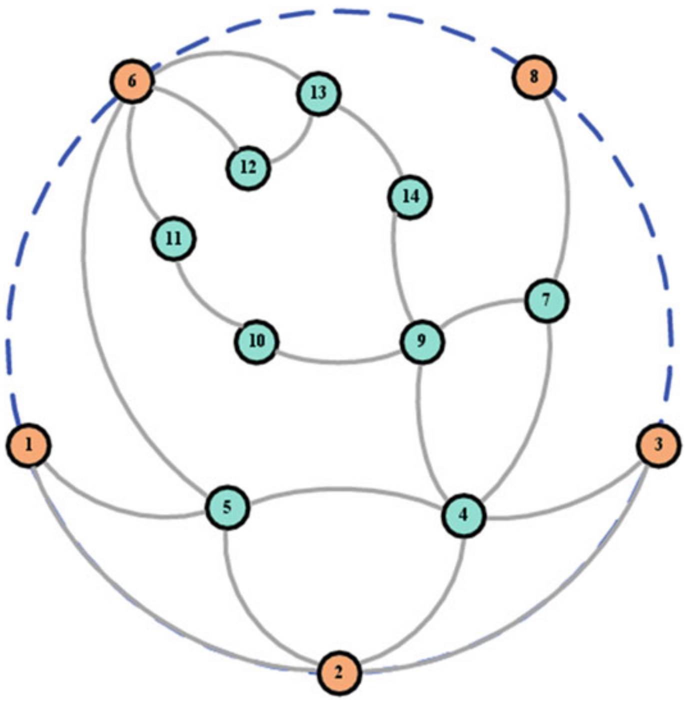


Fig. 18.1 Topology of the IEEE 14 bus test system

flowing in the shortest electrical path between buses s and t, and $P_{st}(k)$ is the maximum of inflow and outflow at bus k within the shortest electrical path between buses s and t. Then, let their fraction is represented by $r_{st}(k)$ as in:

$$r_{st}(k) = \frac{P_{st}(k)}{P_{st}} \tag{18.1}$$

where, the ratio $r_{st}(k)$ is an index of the degree to which buses s and t need bus k to transmit power between them along the shortest electrical path. If a double sum is taken of (18.1) over all intermediate buses k and all destination buses t for the source buses s,

$$C_C^E(s) = \sum_{k=1}^{n}\sum_{t=1}^{n}\frac{P_{st}(k)}{P_{st}}, s \neq t \neq k \in V \tag{18.2}$$

a centrality measure for bus s within the grid is obtained. This measure (18.2) adds up the real power of the lines originating at bus s and terminating at all other buses. This quantity takes high values if the difference between numerator and denominator term is low. This fact represents that very few amount of power is lost in the shortest path. Such buses might have more direct influence on other buses since very few amount of power is lost.

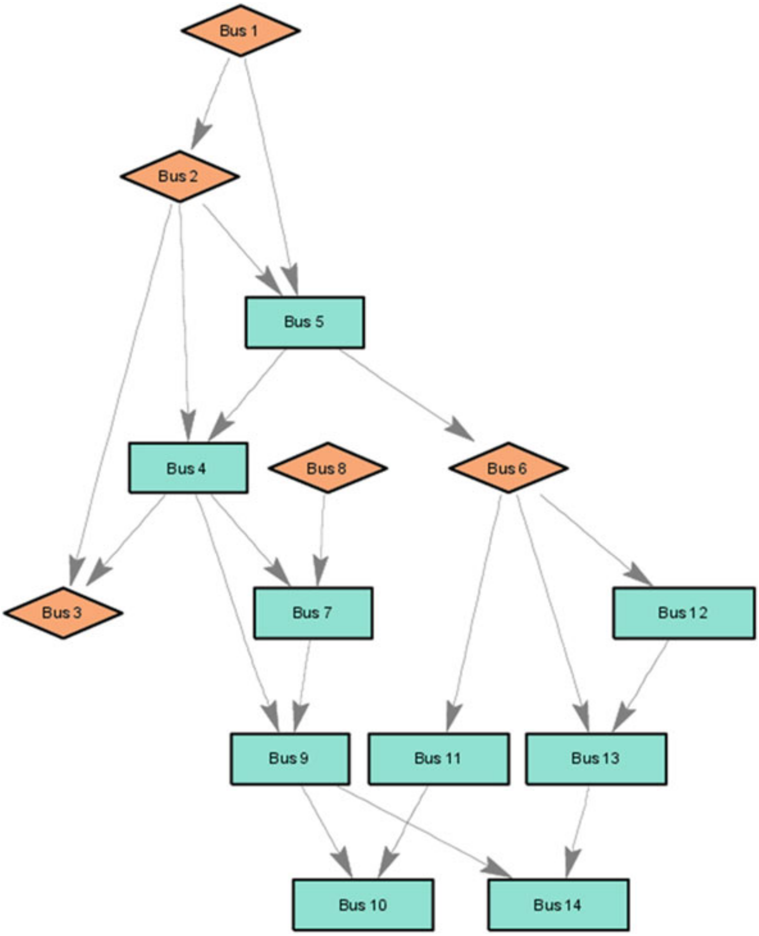


Fig. 18.2 Forward unidirectional graph model of the IEEE 14 bus test system

Table 18.2 lists top ten critical nodes in IEEE 30 bus test system [24, 25] found from nominal and backward unidirectional as well as bidirectional model.

18.3 Measure of Pair Dependence of Various Buses

The concept of pair dependence of various buses is presented in [26], which is described here to maintain the flow of this chapter.

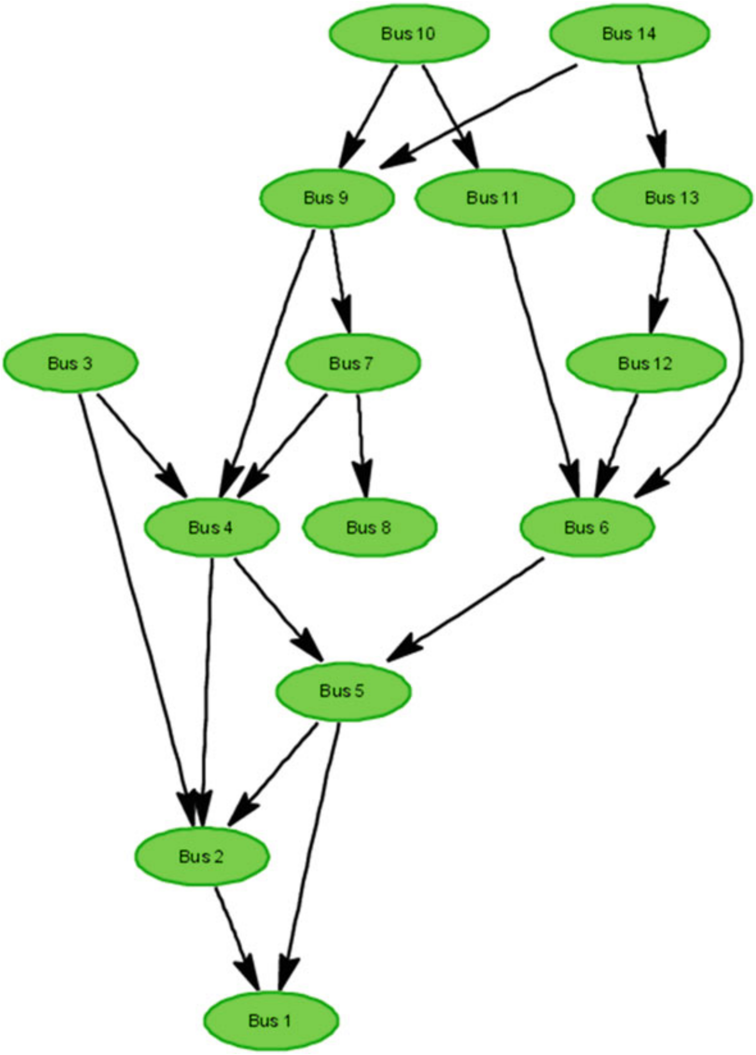


Fig. 18.3 Backward unidirectional graph model of the IEEE 14 bus test system

18.3.1 Shortest Path

The concept of shortest path is used by the researchers of power system who use complex network framework for network vulnerability analysis [17]. In order to assess the vulnerability of a power grid researchers used dynamic power system model where the concept of network flow is introduced [20]. The flow between two nodes s and t takes on shortest path between them. If there are two or more

Table 18.1 System data for network in Fig. 18.1

Branch number	From bus	To bus	From bus P_{inj} (MW)	To bus P_{inj} (MW)	Loss P (MW)
1	1	2	156.88	−152.59	4.30
2	1	5	75.51	−72.75	2.76
3	2	3	73.24	−70.91	2.32
4	2	4	56.13	−54.45	1.68
5	2	5	41.52	−40.61	0.90
6	3	4	−23.29	23.66	0.37
7	4	5	−61.16	61.67	0.51
8	4	7	28.07	−28.07	0.00
9	4	9	16.08	−16.08	0.00
10	5	6	44.09	−44.09	0.00
11	6	11	7.35	−7.30	0.06
12	6	12	7.79	−7.71	0.07
13	6	13	17.75	−17.54	0.21
14	7	8	0.00	0.00	0.00
15	7	9	28.07	−28.07	0.00
16	9	10	5.23	−5.21	0.01
17	9	14	9.43	−9.31	0.12
18	10	11	−3.79	3.80	0.01
19	12	13	1.61	−1.61	0.01
20	13	14	5.64	−5.59	0.05

Table 18.2 Top ten nodes of IEEE 30 bus test system in unidirectional & bidirectional power flow models

Unidirectional nominal	Unidirectional backward	Bidirectional nominal
1	24	1
3	19	3
2	26	2
4	18	4
6	23	6
13	21	24
12	25	19
9	29	13
14	30	12
28	17	14

paths between two buses then the path that has less weight is regarded as the shortest path between those two buses.

Only the physical connection is considered in traditional modeling approach by complex network researchers. The weight of the line between nodes reflects simply the topology of the network. If there is a connection between node s and node t then the weight of the corresponding line is taken as 1, otherwise it is 0 in traditional approach [20]. In case of a power system the main parameter of a

Table 18.3 Various possible connections between buses 1 and 4 of the system of Fig. 18.1

Connection	Weight (pu)
1–2–4	1.21
1–2–3–4	2.01
1–2–5–4	1.04
1–3–4	0.72
1–3–2–4	1.50
1–3–2–5–4	1.33

transmission line which has significant effect in the power flow in the line between buses is its impedance which is not considered in this model.

Several researchers have considered the reactance of the line [15], neglecting the line resistance which is very small for transmission systems. But, in order to generalize the model for both the transmission and the distribution system, the impedance, (i.e., both the reactance and resistance) needs to be taken into consideration [17].

In this chapter, we have used absolute measure of impedance,$|Z|$, as weight of the line. If we want to find shortest electrical path between buses 1 and 4, several paths are possible as given in Table 18.3. We can clearly see that the shortest path between buses 1 and 4 is $1-3-4$ whose weight is 0.72 pu.

Finding the shortest path set for a network is a problem of graph theory and several efficient algorithms are available.

18.3.2 Bus Dependency Matrix

In the context of complex network theory, when a pair of buses in the power system is connected via a transmission line without any other buses in between (intermediaries), they are said to be adjacent. A bus s adjacent to bus k, another bus t adjacent to bus k, creates a transmission path between buses s and t via bus k. The shortest electrical path linking a pair of buses is called a geodesic.

Let, P_{st} is the maximum power flowing in the shortest electrical path between buses s and t, and $P_{st}(k)$ is the maximum of inflow and outflow at bus k within the shortest electrical path between buses s and t. Then, let their fraction is represented by $r_{st}(k)$ as in:

$$r_{st}(k) = \frac{P_{st}(k)}{P_{st}} \tag{18.3}$$

where, the ratio $r_{st}(k)$ is an index of the degree to which buses s and t needs bus k to transmit power between them along the shortest electrical path.

The pair dependency of nodes in a network is defined in [27]. The concept of pair dependency in [27] is used here in case of electrical power grid. The dependency of bus pairs can be regarded as the degree to which a bus s must depend upon another bus k to transmit its power along the shortest electrical path or geodesic to and from all other reachable buses t's in the network. For a power grid with n number of buses the dependency of bus s upon bus k to transmit power on any other buses in the network can be represented as follows:

$$d_{sk} = \sum_{t=1s\neq t\neq k\in V}^{n} r_{st}(k) = \sum_{t=1s\neq t\neq k\in V}^{n} \frac{P_{st}(k)}{P_{st}} \tag{18.4}$$

The dependency of bus pairs for the whole system can be calculated and the result can be summarized in a matrix $\mathbf{D}$ as follows:

$$\mathbf{D} = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \cdots & d_{nn} \end{bmatrix} \tag{18.5}$$

Each element of $\mathbf{D}$ is an index of degree to which a bus designated by row number must depend upon another bus designated by column number to transmit its power along the shortest electrical path or geodesic to and from all other reachable buses in the network. Thus this matrix captures the information of importance of a bus as an intermediary with respect to other buses in the network. So we can call the matrix $\mathbf{D}$ as bus dependency matrix.

18.3.3 Steps to Find Bus Dependency Matrix from System Data

The procedural steps to find bus dependency matrix from the system data is as follows:

1. Model the system as a graph.
2. Find a shortest path set for the graph using Johnson's algorithm [28].
3. Find flow in various lines of the system solving load flow problem.
4. Find the maximum power flowing in the shortest electrical path between buses s and t, P_{st}, for the shortest path set.
5. Find$P_{st}(k)$, the maximum of inflow and outflow at bus k within the shortest electrical path between buses s and t.
6. Evaluate bus dependency matrix $\mathbf{D}$ from P_{st} and $P_{st}(k)$.

18.3.4 Several Observations About Bus Dependency Matrix

Several observations about the bus dependency matrix are enumerated as follows:

- The (s,t)-th element of the matrix represents the dependency of bus s on bus t.
- Diagonal elements of the bus dependency matrix are zero.

- This matrix is non-symmetric.
- The row sum of the matrix could be used as an electrical closeness centrality measure.
- The column sum of the matrix is electrical betweenness centrality measure.

18.4 Measures of Impact

At first, the nominal network is solved and nodes are removed from the system one by one in the descending order of centrality measure. In order to measure the impact of removing critical nodes from the system various measures are being used. In this chapter, four measures are considered. The first two of them, path length and connectivity loss are purely topological. The last two measures are percentage of load lost due to the removal of critical nodes and number of overloaded lines.

18.4.1 Path Length

The path length is used by researchers as a measure of network connectedness. It is the average length of the shortest paths between any two nodes in the network [29]. It is found that if a node is removed from a system, it generally increases the distance between other nodes. So, the increase in network characteristic path length is considered as a measure of impact analysis of removing critical nodes from the system.

A simple IEEE 30 bus test system is used to simulate the consequence of node removal on path length and the result is depicted in Fig. 18.4. It is seen that, if node with high centrality is removed found from nominal unidirectional graph model, the path length increases slightly. A mix result of increase and decrease in path length is found if backward unidirectional flow model is used. In case of bidirectional flow model the maximum impact is found.

18.4.2 Connectivity Loss

This is a purely topological measure of impact a power grid encounters when some nodes are removed from the system. In this measure we calculate how much connectivity is lost in terms of how many generators a transmission or distribution node can access due to effect of removing a node from the system. The less is the number of generators a node is connected with, the less is the redundancy and the more is the vulnerability of the node. It is given as (18.6) originally proposed in [30].

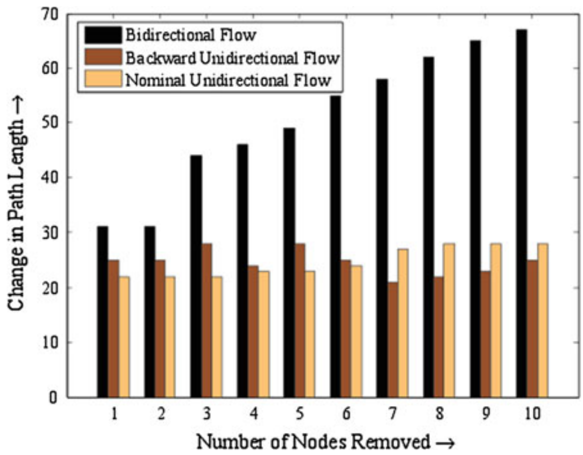


Fig. 18.4 Change in path length in IEEE 30 bus test system for removal of critical nodes based on three different measures

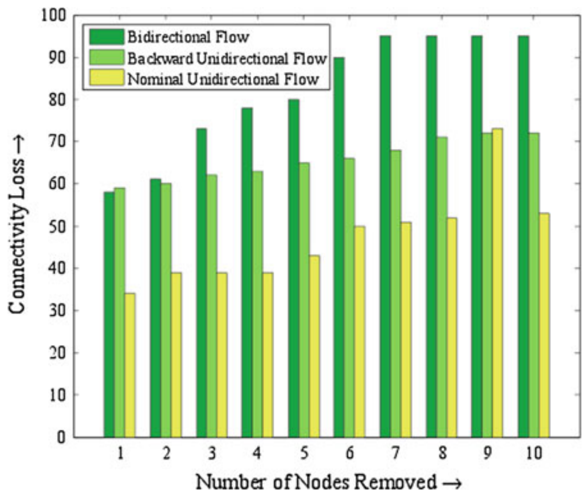


Fig. 18.5 Connectivity loss of IEEE 30 bus test system as a function of removal of critical nodes from three different points of view

$$C = 1 - < \frac{N_g^i}{N_g} >_i \tag{18.6}$$

where, the averaging is done over each intermediate node, i.e., substations. N_g is the total number of generators and N_g^i is the number of generators that a node i can reach. Impact on connectivity loss for three different models is presented in Fig. 18.5.

It is found that connectivity is lost to a great extent in all three cases, although the effect is highest in case of bidirectional flow model. Initially nominal and bidirectional method had similar impact, but the impact becomes more prominent in case of bidirectional flow model after removal of three nodes only.

18.4.3 Load Loss and Number of Overloaded Lines

Last two measures of impact are found from a simple model of cascading failure that is presented here. Since it is not possible to exactly model the blackout, various approximate measures have been taken by several researchers to mimic the situation [11, 31–33].

Power system is a very much complex interconnected system whose exact modeling would require consideration of dynamics of rotating machines and devices within the system, discrete dynamics of switchgear elements, non-linear algebraic equations that govern line flows and social dynamics of governing and operating bodies.

In this chapter, a fairly simple model of cascading failure of the power grid is proposed by incorporating important electrical features ignoring those which are too complicated but have little effects. The detail of the model is described here.

At first AC power flow is used to calculate the steady state condition of the network. Real and reactive power of transmission lines are found from numerical solution of line flow equations given in (18.7) and (18.8)

$$P_i = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \tag{18.7}$$

$$Q_i = -\sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) \tag{18.8}$$

where, the symbols have their usual meanings as found in power system literature.

During the analysis, generator and load dynamics are not included. Although the limitation of not using dynamics of generators and loads are well understood but it is at least useful for modeling one mechanism of cascading failure that is cascading overload. Also, Generation Shift Factors (GSF) and Line Outage Distribution Factors (LODF) [34] are used to recalculate flows in lines after disturbance. This helps achieving fast results without using actual load flow after each disturbance. The speed and accuracy of the result and comparison with actual load flow is out of the scope of this chapter and will be addressed in another research article in future.

The transmission lines are removed if overloaded. The number of lines tripped is taken as a measure of impact which is demonstrated in Fig. 18.6. It is clear that, the number of overloaded lines in nominal and backward unidirectional flow methods is almost same. The bidirectional flow model gives highest impact and a large number of lines are overloaded for removing only seven nodes.

Also, time delayed over current relays are used in every line so if there is a lot of overload it trips fast and if there is a little bit of overload it trips slowly. Another thing that is added to the model is ramping up of generators. As the system separates into sub grids, generators are allowed to ramp up or ramp down to rebalance a little bit.

Fig. 18.6 Number of overloaded lines increases drastically in bidirectional flow based algorithm

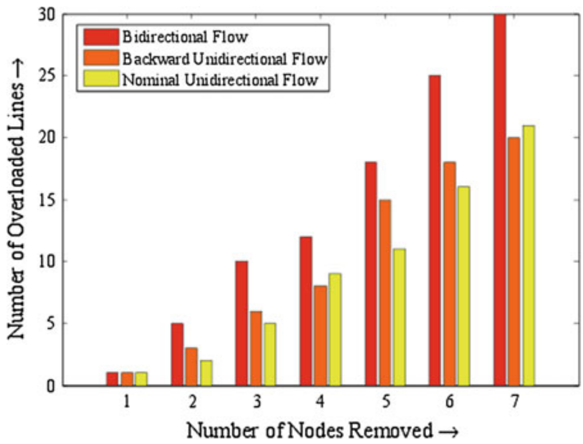
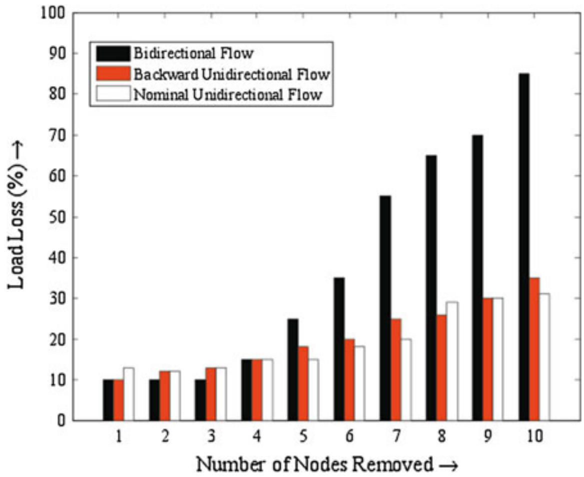


Fig. 18.7 Three different effects on load loss due to loss of functionality of important nodes in IEEE 30 bus system



So, if a component failure disturbs the supply–demand balance, through generator set-point adjustment this balance is achieved. But if there is not enough ramping ability, then the ultimate choice is to trip lowest possible system load. The total amount of load lost during the successive removal of nodes is used as a measure of impact.

Figure 18.7 shows load loss as a percentage of total system loads. Up to six node removal the load loss is nearly equal and does not increase much for both unidirectional models. After five node removal, more than 50 % load of the system need to be shedded to ensure secure and reliable operation of the remaining system.

This introduces a new concept of power flowing from customer end towards the grid. The bidirectional power flow changes the whole power flow pattern of the

Table 18.4 Top ten critical nodes in bidirectional power flow model for IEEE 30 bus system under various changed topological conditions

Nominal case	Line 24–25	Line 29–27	Line 6–2	Line 17–10	Line 4–3	Line 10–6	Line 18–15	Line 30–29	Line 15–14
1	1	1	1	1	1	1	1	1	1
3	3	3	2	3	2	2	3	3	3
2	2	2	3	2	4	4	2	2	2
4	4	4	6	4	6	6	4	4	4
6	24	24	4	13	24	24	6	6	6
24	13	6	24	12	19	19	24	24	24
19	6	19	19	24	13	13	19	19	19
13	12	29	13	6	12	12	18	13	9
12	19	13	12	16	14	14	9	12	26
14	14	12	14	19	9	9	26	14	13
9	9	14	9	17	26	26	23	9	18

existing grid [18]. Analytical methods, technical strategies, control system and protecting devices need to be changed along with, to mention a few. Metering and protecting equipments will experience flows coming from the reverse side. Proper operation of the equipments used earlier can be ensured either by changing the instruments themselves or by incorporating new measurement techniques [27].

18.5 Rank Similarity of Critical Nodes

From the results of Sect. 18.4 it is clear that, the nodes found from bidirectional flow model has much more impact than nominal and backward unidirectional models. In order to analyze the effect of system change on ranks of critical nodes a rank similarity analysis is performed. A structural change like change in the direction of power flow is incorporated in the model and critical nodes are found out for the modified system. This change in network corresponds to a situation when there is a pushback of power from low voltage network via transmission system to meet energy needs in other area.

Table 18.4 compares the changes in top ten critical nodes in IEEE 30 bus test system. This analysis is carried out for bidirectional power flow model. Top row of Table 18.4 corresponds to the topological state of the system. The first column gives the top ten critical nodes from the bidirectional model. The rest of the columns list change in critical nodes for changed topology. As for example, the third column represents the top ten critical nodes when the nominal direction of flow is changed through line 29–27. It is clear that; changed topology does not affect much the node criticality.

On the other hand, slightly more change is observed in criticality for the unidirectional model as shown in Fig. 18.8. When power flow pattern through the grid is unidirectional, nominal unidirectional method is effective. But, in order to model

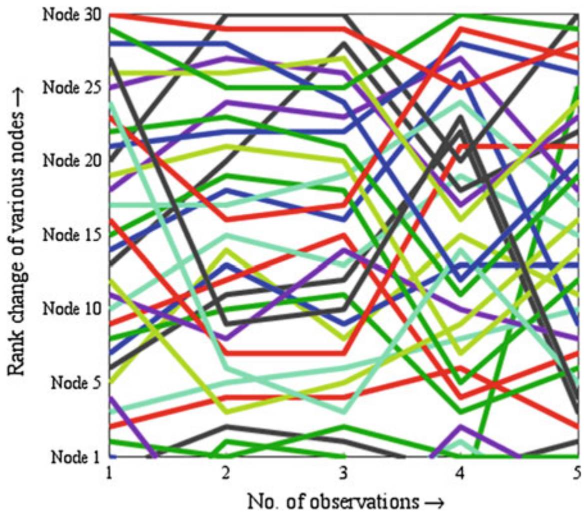


Fig. 18.8 Variation of ranks of nodes in unidirectional model of IEEE 30 bus test system when the network is modified slightly

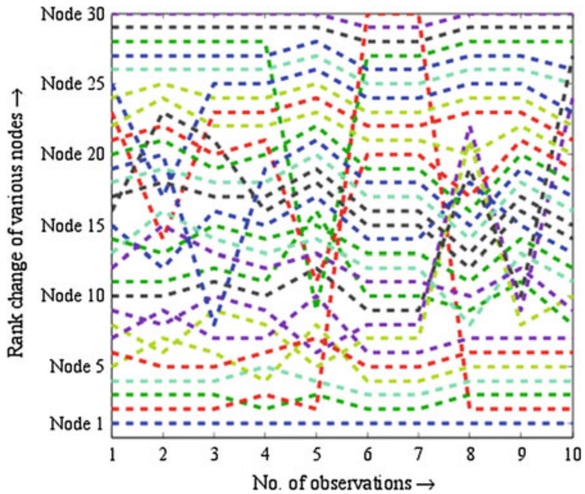


Fig. 18.9 Rank similarity of nodes in bidirectional power flow model is better than that of unidirectional one

the situation in the future smart grid, bidirectional model gives better result in terms of rank similarity as given in Fig. 18.9.

This introduces a new concept of power flowing from customer end towards the grid. The bidirectional power flow changes the whole power flow pattern of the existing grid [18]. Analytical methods, technical strategies, control system and protecting devices need to be changed along with, to mention a few. Metering and protecting equipments will experience flows coming from the reverse side. Proper operation of the equipments used earlier can be ensured either by changing the instruments themselves or by incorporating new measurement techniques [27].

18.6 Conclusions

The prospect of complex network theory based research in analyzing the critical components in smart grid environment is analyzed here with Monte-Carlo simulation techniques on various standard test systems. A bidirectional flow graph is constructed from the superposition of forward and backward unidirectional flow graphs. The bidirectional flow graph captures the true power flow scenario of the future smart electricity grid. Electrical centrality measure, motivated by closeness centrality measure of power system, is used to find critical components. Four different measures of impacts are analyzed to quantify the effect of removing critical nodes from the grid. The results found from different measures show that, bidirectional power flow based model is more effective in smart grid environment than unidirectional ones. Rank similarity analysis shows that, critical nodes of bidirectional models do not change much with system topology change as a result of reverse power flow through transmission network in smart grid environment.

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