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Cascading Failures Assessment in Renewable Integrated Power Grids Under Multiple Faults Contingencies

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ABSTRACT Cascading overload failures occurred in power systems due to higher penetration of renewable energy resources (RERs), which causes uncertainty in a grid. To overcome these cascading overload failures, proper assessment in the form of load flow balancing and transients stability is required in renewable integrated power grids (RIPGs). This problem becomes more critical in the occurrence of multiple intervals faults in multiple interconnected RIPGs, which causes the tripping of several RERs. Due to which outages occurred in various transmission lines, which lead the power system to cascading overload failures. To tackle this problem, hybrid probabilistic modeling is proposed in this paper for balancing load flow and an assessment of transients stability in multiple interconnected RIPGs. For balancing of load flow, a smart node transmission network topology is utilized along with integrating a unified power flow controller (UPFC), while transients instabilities are assessed through a UPFC alone. Contrary to the previously proposed algorithms, which are only suitable to compensate network instabilities in case of only a single interval fault, this work is supported by probabilistic modeling to compensate network instabilities under the occurrence of not only a single interval fault but also in case of more severe multiple intervals faults in multiple interconnected RIPGs that will lead the network to cascading failure outages. Simulation results verify that our proposed probabilistic algorithm achieved near an optimal performance by outperforming the existing proposed methodologies, which are only confined to mitigate the effect of network instabilities only in case of single interval fault and fails to address these network instabilities under the occurrence of severe multiple interval faults, which leads the network to cascading failure outages. These simulation results are also validated through an industrial case study performed on a western Denmark transmission network to show the superiority of our proposed algorithm.

INDEX TERMS Multiple interconnected renewable integrated power grid, transient stability analysis, cascading overload failures, single and multiple interval faults.

I. INTRODUCTION

To provide electrical energy to the customers in a reliable, efficient, and sustainable environment; the conventional power grid stations are transforming towards a smart grid (SGs), that utilizes state of the art intelligent communication and power network [1]. To provide cheaper electricity and in order to meet unexpected load requirements, SGs relies on clusters of renewable energy resources (RERs), which are interconnected with one another in the form of multiple renewable integrated power grids (RIPGs) [1]–[3]. However, despite cost-effectiveness using RERs, reliability is still a

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growing challenge in these RERs [4]. Due to this reason, structure vulnerabilities and uncertainties occurred in these multiple interconnected (MIRIPGs) infrastructures [5]. For example, considering the phenomena of cascading failures, which is also known as ripple effects, takes place in RIPGs, triggers an unpredictable form of chain reactions [6]–[8]. In 2011, the blackouts in Southern California and Southwest Arizona and the unprecedented blackout in 2012 in India were the most notable examples [9]. These blackouts show that these chain reactions have a devastating impact on RIPGs infrastructures [10]. Considering the phenomena of SGs, load flow balancing, and a proper analysis of transients stability problems [11] for chain reaction compensation in MIRIPGs, is still a challenging task, especially in the case of a multiple interval faults occurrence in power systems, which have severe consequences on RIPGs in the form of cascading failures as compared to single interval fault [1]. Various applications in the power system network may have a single fault that arises in the power system at multiple time intervals, and this phenomenon is commonly known as multiple intervals faults [1].

The proposed work in this research work is to provide stability to the network by compensating load flow balancing and transients stability issues not only in case of single fault contingency but also in case of multiple fault contingencies, which leads the network to cascading failure events. The previously proposed techniques in literature are only suitable to provide stability to a network by compensating load flow balancing and transients stability issues in case of an occurrence of only a single fault contingency in power systems and fails to address these issues in case of multiple faults contingencies that will lead the network to cascading failure outages. The main problem to tackle in this research work is to compensate power system network under severe multiple interval faults that lead the whole network to cascading overload failures. The next section will identify the comparative analysis of our proposed technique with the existing work to validate the novelty of our proposed work.

A. COMPARATIVE ANALYSIS WITH EXISTING WORKS

For cascading overload failures (COFs) analysis, various algorithms have already been proposed in [12]–[16]. These algorithms focus on a set of certain simplified assumptions, which are required to approximate the real power grid infrastructure accurately. However, from a literature point of view, the complex power infrastructure in the form of a MIRIPGs and analysis of COFs due to an occurrence of severe multiple intervals faults in it have not been addressed so far. Therefore, a detailed analysis, which addresses COFs analysis in MIRIPGs under multiple intervals faults, is needed. In this paper, the author proposed a valuable solution to this critical problem by establishing the two models for COFs. The first model is utilized to balance a load flow in MIRIPGs using a UPFC incorporated intelligent network transmission topology. Whereas the second type of model is utilized for the evaluation of transient stability issues in MIRIPGs using a unified power flow controller (UPFC). These hybrid schemes with their proper visualization [17] are regarded as a more suitable choice to compensate cascading failure issues in MIRIPGs under the occurrence of severe multiple intervals faults.

For an accurate estimation of power flow models, steady-state analysis is utilized in the literature. These modeling analyses are used to approximate an accurate power system behavior in the case of COFs in power systems. For example, a power flow model based on stochastic ORNL-PSerc-Alaska was proposed by Dobson *et al.* in [18]. Similarly, for addressing an issue of self-organized criticality, an optimization algorithm based on COFs was suggested in [19]. These algorithms were based on cascade model [20] and an AC power flow Manchester model [21].

In comparison to these suggested models, recent literature in power systems concludes the fact that the power flow model is based on probabilistic analysis [22]–[24] will provide a more valuable solution to compensate for these cascading failures in MIRIPGs. However, these models rely upon power flow parameters, and also, they do not analyze the transient stability issues due to multiple faults [25]. This combination of transients stability model and probabilistic optimum power flow model is considered an optimum choice in terms of power system protection, preventing an unexpected outage, and mitigating COFs in complex power infrastructure in the form of MIRIPGs. While proposed algorithms in this field focused on one parametric model, either on a transients stability model or a probabilistic power model, there are very few methodologies that integrate these two models. These hybrid models are considered a more suitable choice in compensating cascading failures in the power system. This work aims to present a hybrid model, which is utilized to overcome COFs in MIRIPGs under the occurrence of severe multiple intervals faults.

To enhance transients stability in RIPGs, recent power system literature reveals several algorithms based on a control framework, which are integrated within a closed-loop system as given in Fig. 2. For transients stability enhancement, a distributed control algorithm based on a flocking theory approach was proposed in [26]. However, it was concluded from [26] that a controller's operations become slow down as the transients delay increases. Similarly, considering a framework based on a distributed controller using parametric feedback linearization (PFL) technique, Farraj *et al.* in [27] used an energy storage system based on fast ramping to quickly achieved stability in power grids. The flocking theory approach, as suggested in [28] enhances the performance of the PFL controller. It was concluded from the results that for enhancement of transients stability, the PFL controller shows more promising results. The only major drawback in the PFL controller in terms of its comparison to the proposed Kron's reduction method in [29] is that it considers the complete information of angles and voltages of the available generator. To overcome that issue, a robust non-linear controller was suggested in [30] to achieve an enhancement in transients stability within a time limit of 3s when the delay in the form of transients is 400ms. This desired result was also achieved from the PFL controller with the only reduction in transients delay, which was considered 50ms despite 400ms in [30]. These suggested algorithms show promising results for transients stability enhancement in power systems when the delay in terms of transients is just between 50ms and 400ms. A more suitable choice among all of these suggested methodologies is proposed in [30]. However, one of the essential aspects that these controller-based algorithms do not consider is the devastating impact of prolonged power system stability time, due to which an overall network is more vulnerable to cascading failure events, especially in case of multiple faults, which are more severe. This 3.2s delay can make the power grid more vulnerable to cascading overload failures, and this critical problem was highlighted in [31]. Therefore, to overcome certain critical situations, the system should be operated to mitigate the delay due to transients within minimum time durations. To focus on such a critical problem, instead of utilizing a technique based on distributed controller framework to control fast ramping distributed energy storage systems (DESS) in multiple interconnected RIPGs, we utilized the concept of a UPFC.

To stabilize the power grid within a short interval of time, UPFC shows more promising results [32] as compared to other controllers, even if the delay due to transients is prolonged in the power network due to the multiple intervals faults [33]. This concluded that UPFC based algorithms could effectively mitigate COFs outages in severe fault conditions, and this idea was also clearly highlighted in [33]. A power system network based on MIRIPGs is more vulnerable to COFs due to reliability issues and causes unbalanced load flow problems and transients stability issues. Therefore, in such case scenarios, UPFC enabled the smart network to provide an optimal solution of transient stability and unbalanced load flow cases. The importance of load flow balancing algorithm through UPFC integrated smart transmission network topology was already suggested in [1].

The network node breakdown in multiple interconnected RIPGs caused by an extreme overloaded scenario was clearly formulated in [11]. Here in Fig. 1, there is an interconnection between four clusters of multiple interconnected RIPGs, with each cluster represents one power grid station. The breakdown of a network node due to an initial node failure caused by an overloaded condition is shown by red color in cluster 1 as represented in Fig. 1. This is due to the reason of tripping of several RERs in multiple RIPGs stations due to an occurrence of multiple intervals faults in it. This initial node failure will cause the direct failure of other interconnected nodes. Due to which a chain reaction occurred, which causes COFs in MIRIPGs as shown with red spots of clusters 2, 3, and 4 in Fig. 1. To the best of ours knowledge, this is considered to be the first work that formulates the complexity of transient stability effects and load flow balancing in multiple RIPGs stations through stochastically analyzing a hybrid model based on UPFC integrated smart network topology.

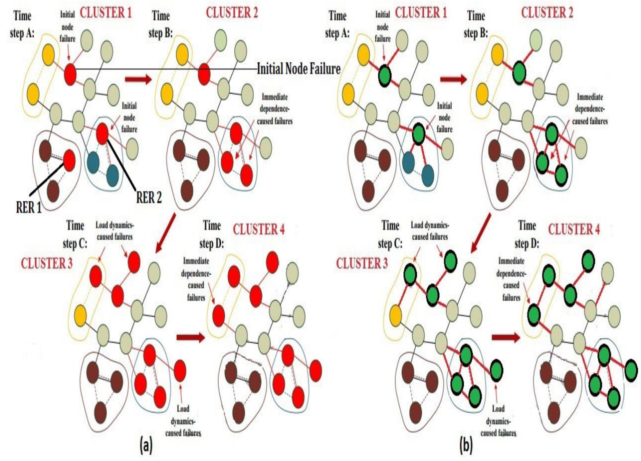

FIGURE 1. Modelling of Cascading failure events in multiple power grid stations [11].

Through this probabilistic analysis, future contingencies in the form of COFs due to severe multiple interval faults in the power system can be easily compensated.

The major contributions of this research work are as follows:

1) Compensating the effect of multiple intervals faults in multiple interconnected RIPGs stations that lead to cascading overload failures using UPFC incorporated smart network transmission,
2) leveraging the synchronization in case of larger variations in load due to an occurrence of multiple intervals faults by tuning optimally the UPFC incorporated smart network transmission,
3) and formulating the complexity of randomness of load flow and transients stability through probabilistic modeling of an integrated UPFC smart transmission network.

The rest of the paper is organized as follows: Section II gives a detailed methodology overview. Section III provides a comparative overview of the proposed methodology with the existing model of load flow balancing and cascading failures through simulation results. Finally, section IV concluded the paper having future directions as well.

II. METHODOLOGY

The suggested methodology in this paper is mainly divided into two sections. In the first part, the vulnerability of the power system is found out in the form of cascading overload failures, which occurred in the power system due to multiple intervals three-phase (L-L-L) faults (TPF) [11]. The load flow randomness in case of overloaded conditions due to the tripping of RERs and addressing an issue of transients due to an occurrence of multiple interval TPFs are also considered. For this purpose, we considered a MIRIPGs network that are vulnerable to COFs, as suggested in [11]. Algorithm 1 shows a step-by-step response to compensate COFs in MIRIPGs in case of multiple faults. This can be done through UPFC

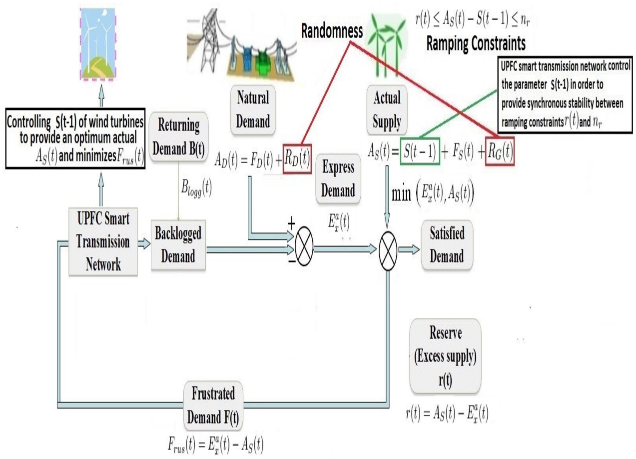

FIGURE 2. **Probabilistic modeling of demand response based cascading failure event in multiple RIPG.**

incorporated intelligent network transmission topology, which provides a reliable and efficient power flow and transients stability improvement. Through this scenario, we can reduce the probability of events that leads the system to COFs. To verify such scenario through simulation results, we considered four clusters in MIRIPGs with each cluster have three RERs, i.e., (RERs 1, 2 and 3) in cluster-1, (RERs-4, 5 and 6) in cluster-2, (RERs-7, 8 and 9) in cluster-3 and (RERs-10, 11 and 12) in cluster-4 and are interconnected through UPFC incorporated smart network transmission topology, as shown in Fig. 3. Considering a vulnerability issue in the form of COFs [11], a network node breakdown occurred in power system network due to an occurrence of multiple intervals TPF in cluster-1 near an RERs-1, as shown in Fig. 1. This will cause RER-1 tripping in cluster-1, i.e., initial node failure. Due to this reason, the power drop (n_{c1RER1} - $p_{c1(wtt1)}$) occurred in cluster-1. If the power drop issue in cluster-1 is not compensated, it will create an overloading scenario in cluster-1. As a result, a chain reaction occurred in MIRIPGs in the form of COFs, which will further cause the tripping mechanism of RERs-2 and 3 in cluster-1, as shown in Fig. 3. An operation in the form of shifting of active power is performed from RERs-2 and 3 to RER-1 to mitigate COFs. The cascading failure events due to an arising of multiple intervals faults in cluster-1 are easily mitigated through this scenario. This is the scenario when RERs-2 and 3 active power is sufficient to accommodate RER-1 receiving side load of cluster-1. If this condition is not satisfied, then a COFs will occur in cluster-1. This will lead to RERs-1, 2, and 3 trippings in cluster 1, respectively, as shown in Fig. 3. Due to this reason, a further power drop of (n_{c1RER1} - $p_{c1(wtt1)}$), (n_{c1RER2} - $p_{c1(wtt2)}$) and (n_{c1RER3} - $p_{c1(wtt3)}$) occurred in cluster-1. IF not taken remedial action in the meantime, then these cascading failure events in cluster-1 will cause COFs in cluster-1, 2, 3, and 4. For the compensation of these chain reactions, we utilized the probabilistic model of relay and circuit breaker operation as suggested in Sec. B of methodology. Through such a probabilistic model, we can easily sense the cluster-1 overloading conditions, which can be compensated by optimally operating cluster-2, 3, and 4 RERs that are connected with cluster-1 in the form of UPFC incorporated smart network transmission. If there are further random deviations occurred in a load pattern of cluster-1 connected load and the generation response from RERs of cluster-2, 3, and 4 are not sufficient to accommodate cluster-1 connected loads, then the power network is at risk again. To compensate for these random fluctuations in demand profile patterns, an integrated UPFC in smart network transmission should be further tuned optimally. A UPFC incorporated smart network transmission has a strong capability to compensate mentioned COFs events and correspondingly reduce its occurrence probability in MIRIPGs, especially in case of severe multiple intervals faults conditions.

Moreover, a UPFC incorporated smart network transmission provides a balanced load flow in the power system network to mitigate COFs and countermeasure the transients due to faults in the network. A UPFC incorporated smart network transmission schematic can be visualized from Fig. 2, which can be utilized to provide a balanced load flow and transients stability improvement in MIRIPGs. Through Fig. 2, the power system operators regularly monitor the network. This will further reduce the chances of COFs events to be occurred in the power system due to multiple intervals of faults in it. The terminologies utilized in Fig. 2 are discussed in the upcoming section.

A. WIND TURBINES PROBABILISTIC MODELLING CONSIDERING RISK INDEX FACTOR (P_r)

The probabilistic model of wind turbines tripping considering risk index factor P_r in case of an occurrence of any kind of power quality disturbances was clearly formulated in [34]. In [34], the power loss expectation due to tripping of wind turbines is defined in terms of probabilistic risk, which is found out as the collective sum of product of tripping wind turbines active power and probabilistic contingency in all states, as modelled in (2),

$$P_{Risk} = \sum_i \left[P_r(C_i \mid S) Cri(C_i, S) \right], \tag{1}$$

$$P_{Risk} = \sum_i^{S_C} \left[P_r(C_i \mid S) \left(\sum_i^{N_T} \left[P_{trip-off,T}(C_i \mid S) \right] \right) \right]. \tag{2}$$

1) The power system current state is represented by S,
2) the i_{th} interval contingency is represented with C_i,
3) the contingency probability under operating condition S is represented with $Pr(C_i \mid S)$,
4) the i_{th} contingency critical impact under an operating condition S is represented with $Cri(C_i, S)$. It shows the critical impact in terms of a collective sum of active power losses due to wind turbines tripping under S state operating condition,

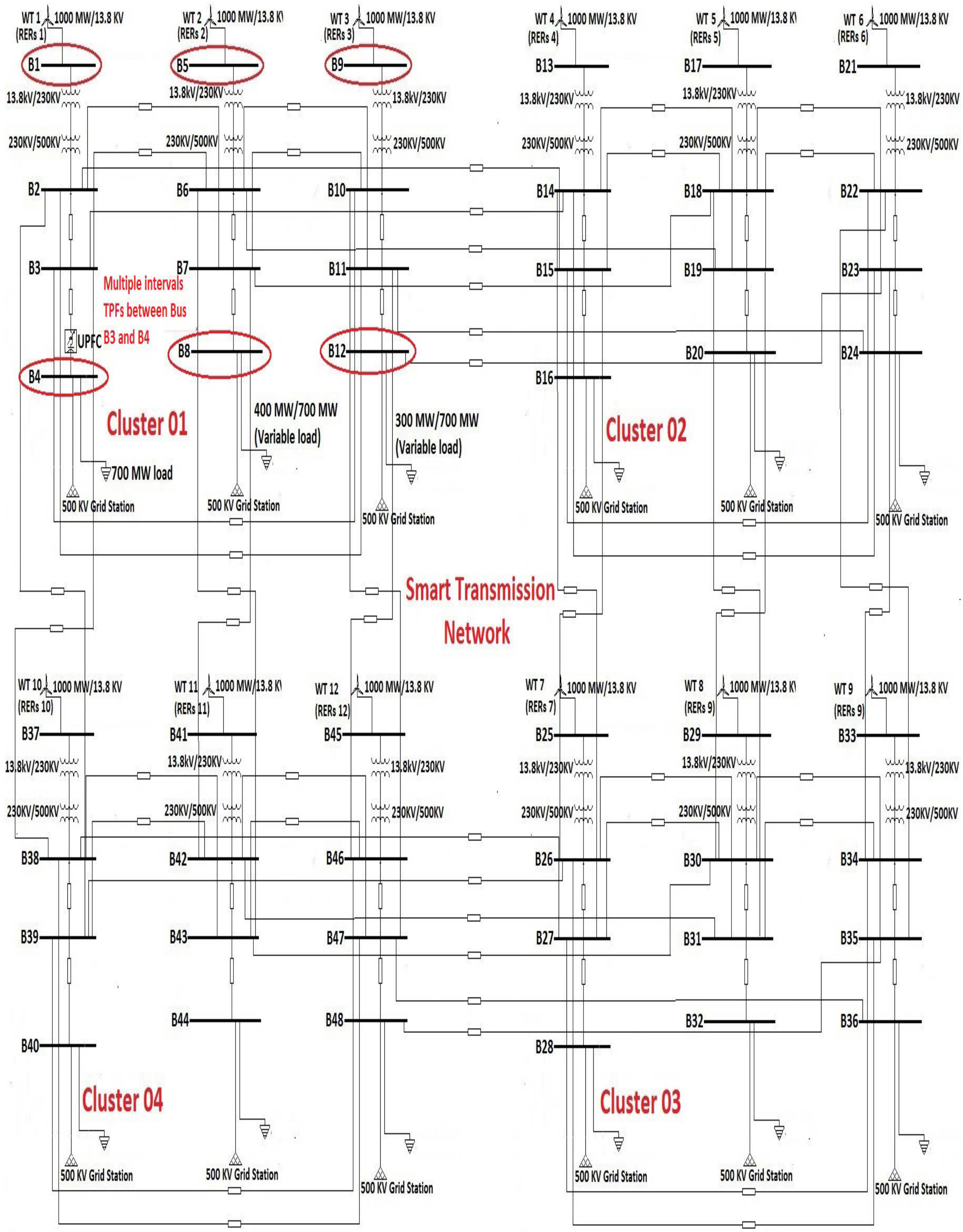

FIGURE 3. Cascading failure model in multiple RIPGs.

Algorithm 1:

Input : Clusters 1 interconnected three RERs are operating in their normal states, i.e., (n_{c1RER1}), (n_{c1RER2}), (n_{c1RER3}), tripping of wind turbines (wtt_1) of RER 1 in cluster 1 due to occurrence of multiple intervals TPFs (f_{c1} and f_{c2}) leads a power outage (p_{c1}) and transients delay (d_{e1}) in cluster 1

Output: To compensate (d_{e1}) and (p_{c1}), a set of next transition state for cluster 1 $(t_{c_j} \rightarrow t_{c_{j+1}})$

while $\left((f_{c_1})\&\&(f_{c_2})\right)$ **do**

proceed to next transition state $(t_{c_j} \rightarrow t_{c_{j+1}})$

if *Cluster 1* $\rightarrow$ *Power Drop* $= n_{c1RER1} - p_{c1(wtt_1)}$ **then**

$t_{c_{j+1}} \rightarrow$ UPFC smart transmission network

else if *Cluster 1* $\rightarrow$ *Still in Overloading phase* $\rightarrow$ *Power Drop* $\rightarrow n_{c1RER1} - p_{c1(wtt_1)} \rightarrow n_{c1RER2} - p_{c1(wtt_2)} \rightarrow n_{c1RER3} - p_{c1(wtt_3)}$ **then**

$t_{c_{j+1}} \rightarrow$ UPFC smart transmission network

else if *Further load variations occurred* $\rightarrow$ *leads to power drop issues in* $\rightarrow$ *Cluster 1* $\rightarrow$ *Cluster 2* $\rightarrow$ *Cluster 3* $\rightarrow$ *Cluster 4* $\rightarrow$ *An arising of an overloading conditions in all Clusters along with a transients delay in cluster 1* $\rightarrow d_{e_1} = d_{e_1} + d_{e_{1+0.1s}}$ **then**

$t_{c_{j+1}} \rightarrow$ UPFC smart transmission network

else

the proceeded next transition state should be, $t_{c_{j+1}} \rightarrow n_{c1RER1} \rightarrow n_{c1RER2} \rightarrow n_{c1RER3}$

end

Send transition state $t_{c_{j+1}}$ as an input to Algorithm 1

end

5) the tripping wind turbines active power is represented with $P_{trip-off,T}$, i.e., $T = 3$ in our case scenario, i.e., the active power of tripping RERs 1, 2, and 3 in cluster 1 due to an occurrence of CFEs in case of an arsing of multiple intervals TPFs in multiple interconnected RIPGs,
6) the size contingency is represented with S_C,
7) in our case scenario, the tripping of wind turbines in cluster 1 is represented with N_T, i.e., tripping of RERs-1, 2, and 3 due to an arising of cascading overload failure in case of occurrence of multiple intervals TPFs in MIRIPGs.

B. CASCADING OVERLOAD FAILURE MODEL BASED ON RELAY AND CIRCUIT BREAKER MODELLING

The main cause of COFs is the tripping of generator sources due to any disturbances [25], [35]. Therefore, an RERs tripping each time in MIRIPGs is represented with a cascading failure event (CFE). The CFEs makes the generation buses overloaded G_l when it occurs individual time. The generalized equation including power flow P_{G_l}, thermal rating power T_{G_l} an generation branch overloading G_l as provided in [25] and [35] can be given as,

$$O_{ver}(G_l, t) = \int_{t_o}^{t} [P_{G_l}(t) - T_{G_l}]dt \quad P_{G_l}(t) > T_{G_l}, \tag{3}$$

where, at a time t power system network overloading is represented with $O_{ver}(G_l, t)$ and is combined from t_0 to t. It can also be represented at the time intervals during power system network overloading while preserving the steady-state condition. Then, the RERs reliability and load demand curtailments related issues are considered, especially in the case of the CFEs event occurrence in power networks, random deviations in power flow behavior were observed P_{G_l}, that alters the overloaded duration time accordingly, i.e., t_0 to t. Hence, the power system network is no longer able to maintain the steady-state condition. Therefore, as the state changes, the function $O_{ver}(G_l, t)$ immediately attains unsafe threshold limit, i.e., $O_{verlimit}(P_{G_l})$ at a time $T_f(l)$. Hence, to minimize the function $O_{verlimit}(G_l)$, relay operation is carried out to trip-off the overloading generation branch G_l automatically.

Now, as previously discussed that if the occurred CFE in cluster-1 is not being properly compensated, then it will lead to CFEs in cluster-2, 3, and 4. Therefore to accommodate cluster-1 through ramping constraints, a UPFC based smart transmission network scheme is utilized. It will solve the problem of CFEs occurring in MIRIPGs under severe multiple TPFs conditions. In this case scenario, we make a supposition that a shifted active power from cluster-2, 3, and 4 RERs are sufficient enough to minimize the random deviations between demand and response through achieving a desired ramping rate r, so to accommodate cluster-1 receiving connected side loads. To verify this, let us consider a case scenario in which an occurrence of CFEs in cluster-2, 3, and 4 interrupts the ramping process r. In this case, the time interval in which the network operator achieved the desired generation ramping rate r using UPFC incorporated smart network transmission topology in case of an occurrence of two CFEs in cluster-1, 2, 3, and 4 is represented with T_{ramp} and it can be expressed through below equation,

$$T_{ramp} = \min_{I \epsilon L}[T_f(l)], \tag{4}$$

where, $T_f(l)$ represents the time at which a critical overloading $O_{verlimit}(G_l)$ occurred in multiple interconnected RIPGs as aforementioned. To minimize $O_{verlimit}(G_l)$, the concept of relay modelling is utilized in cluster 1, 2, 3 and 4, which senses these overloading states $O_{verlimit}(G_l)$ at time $T_f(l)$ in cluster 1 and correspondingly operates the RERs from cluster 2, 3 and 4. Through this scenario, an optimum power flow is achieved between all clusters, i.e., 1, 2, 3 and 4 of multiple interconnected RIPGs, which minimizes the probabilistic risk assessments of an occurrence of CFEs due to multiple intervals TPFs in multiple interconnected RIPGs and it can be expressed as,

$$O_{over}(limit, t) = \int_{t_o}^{t_o+T_{ramp}} [P_{G_l}(t) - T_{G_l}]dt \quad P_{G_l}(t) > T_{G_l}. \tag{5}$$

The ramping period is expressed through the above equation, through which a balanced power flow between demand and response is achieved through relay operations by mitigating a generation deficit in cluster 1. However, if the optimum load flow balancing is not achieved between demand and response through UPFC integrated smart transmission system, then a feedback control signal is generated from relays towards a UPFC, which is already integrated with the smart transmission network. This will improvise the system network in the form of an additional ramping to mitigate CFEs to occur in multiple interconnected RIPGs.

C. PROBABILISTIC MODELING OF UPFC INCORPORATED SMART NETWORK TRANSMISSION

Considering contingencies issues in the state of CFEs due to multiple intervals TPFs, the UPFC integrated smart transmission network probabilistic modeling aims at finding out the optimal generation from RERs in multiple interconnected RIPGs. To verify this scenario, we performed probabilistic modeling to analyze the effect of power quality disturbances in terms of load flow balancing in an interconnected power network of four clusters, with each having three RERs. In this modeling, we can minimize the frustrated demand $F_{rus}(t)$ as shown in Fig. 2 by equalizing the forecast demand $F_D(t)$ according to forecast supply $F_S(t)$.

In this modeling, the deviations in the pattern of demand response due to RER-1 tripping of cluster-1, which causes CFEs in cluster 1, forcing RERs-2 and 3 to trip. Moreover, the effect of transients in multiple inter-connected RIPGs due to the occurrence of multiple intervals TPFs are also analyzed. For the analysis of these two future unexpected contingencies, $F_S(t)$ and $F_D(t)$ are incorporated in the closed-loop operating system. To provide a balanced load flow in four clusters of multiple interconnected RIPGs having various RERs to compensate CFEs of cluster-1, an optimum load flow balancing is required between generation and demand. For this purpose, there must be a equate the stability between $F_S(t)$ and $F_D(t)$, i.e.,

$$F_S(t) = F_D(t) + n_r, \tag{6}$$

where, n_r is the nominal reserve, which can adjust an optimal supply from UPFC integrated smart transmission network to achieved stability between $F_S(t)$ and $F_D(t)$.

To validate the above circumstances through modeling, we analyzed the effect of contingency issues in the form of the occurrence of multiple interval TPFs in multiple interconnected RIPGs. For this purpose, we consider λ as a delay time slot, i.e., average delay (A_{delay}). The expression for the model of (A_{delay}) due to occurrence of TPFs that occurs in multiple time instant in MIRIPGs can be expressed as,

$$A_{delay} = \lambda_1 + \lambda_2. \tag{7}$$

The average delay model in (7) represents the occurrence of multiple intervals TPFs upto two intervals, i.e., first interval (λ_1) and second interval (λ_2).

$$A_d = \frac{1}{n_1} \sum_{i_1=i_2=1}^{n_1} \left(\lambda_{i_1} + \lambda_{i_2}\right), \tag{8}$$

where the delays which arise due to TPFs in the form of multiple intervals are represented with λ_{i_1} and λ_{i_2} for each closed-loop iteration. Where the effect of multiple intervals TPFs in the form of CFEs in multiple interconnected RIPGs having four clusters with each having three RERs is represented with n_1, i.e., ($n_1 = 12$), as there are 12 RERs in four clusters of multiple interconnected RIPGs.

Similarly, actual demand $A_D(t)$ expression can be formulated as,

$$A_D(t) = F_D(t) + R_D(t). \tag{9}$$

where $R_D(t)$ represents the randomness in a power system network.

After A_{delay} model incorporation in (9), it can be expressed as,

$$A_D(t) = \left\{ \left[F_D(t) \times \frac{1}{n_1} \sum_{i_1=i_2=1}^{n_1} \left(\lambda_{i_1} + \lambda_{i_2}\right), \right] + R_D(t) \right\}. \tag{10}$$

Similarly, the changes occurred in $A_D(t)$ suggested risk index and COFs modeling as expressed in (2) and (5), so (10) can be represented as,

$$A_D(t) = \left\{ \left[F_D(t) \times \frac{1}{n_1} \sum_{i_1=i_2=1}^{n_1} \left(\lambda_{i_1} + \lambda_{i_2}\right) \right] \times \left[O_{ver}(limit, t) \times P_{Risk} \right] + R_D(t) \right\}. \tag{11}$$

By transforming (10) in terms of a closed loop equation will be as,

$$A_D(t) = \left\{ \left[F_{D_i}(t) \times \frac{1}{n_1} \sum_{i_1=i_2=1}^{n_1} \left(\lambda_{i_1} + \lambda_{i_2}\right) \right] \times \left[O_{ver_i}(limit, t) \times P_{Risk_i} \right] + R_{D_i}(t) \right\}. \tag{12}$$

where, $R_D(t)$ is the random deviation between $A_D(t)$ and $F_D(t)$ and can be represented as,

$$R_D(t) = E[A_D(t) F_D(t)], \tag{13}$$

when, $A_D(t)$ approaches $F_D(t)$, $R_D(t)$ approaches to zero. Through this, a balanced load flow is achieved between demand and supply, i.e,

$$F_S(t) = F_D(t). \tag{14}$$

Similarly, actual supply $A_S(t)$ expression can be formulated as,

$$A_S(t) = S(t-1) + F_S(t) + R_G(t), \tag{15}$$

In this case, the stability between $A_S(t)$ and $F_S(t)$ is maintained by controlling the previous supply $S(t-1)$.

Now, by incorporating the probabilistic model of risk index and cascading overload failure model and expressing (15) in terms of an average delay model (A_{delay}) and generalized form, it can be represented as,

$$\begin{aligned} A_S(t) = \sum_{i=1}^{n} \Bigg\{ & \left[S_i(t-1) \times \frac{1}{n_1} \sum_{i_1=i_2=1}^{n_1} \left(\lambda_{i_1} + \lambda_{i_2} \right), \right] \\ & + \left[F_{S_i}(t) \times \frac{1}{n_1} \sum_{i_1=i_2=1}^{n_1} \left(\lambda_{i_1} + \lambda_{i_2} \right), \right] \\ & \times \left[O_{ver_i}(limit, t) \times P_{Risk_i} \right] + R_{G_i}(t) \Bigg\}, \end{aligned} \tag{16}$$

whereas, the optimal value of $R_G(t)$ in probabilistic model can be expressed in (17),

$$R_G(t) = E[A_S(t)F_S(t)]. \tag{17}$$

Similarly, when $A_S(t)$ approaches to $F_S(t)$, $R_G(t)$ approaches to zero. Through this, a load flow balancing is accomplished in MIRIPGs by minimizing the variation between $F_S(t)$ and $F_D(t)$.

To make $R_G(t)$ approaching zero forcefully, a tuning of control parameter $S(t-1)$ using UPFC incorporated smart network transmission can be performed optimally.

The power deficiency due to occurrence of multiple intervals TPFs in MIRIPGs can be given as frustrated demand $F_{rus}(t)$ in terms of the equation,

$$F_{rus}(t) = E_x^a(t) - A_S(t), \tag{18}$$

where, $E_x^a(t)$ is the expressed demand. The system network will be in $F_{rus}(t)$ state, when

$$E_x^a(t) > A_S(t), \tag{19}$$

After incorporation of A_d model in (18), it can be re-expressed as,

$$F_{rus}(t) = \left[\left(E_x^a(t) - A_S(t) \right) \times \frac{1}{n_1} \sum_{i_1=i_2=1}^{n_1} \left(\lambda_{i_1} + \lambda_{i_2} \right), \right]. \tag{20}$$

In a generalized form and in terms of probabilistic risk index and cascading failure modeling, (20) can be represented as,

$$\begin{aligned} F_{rus}(t) = \sum_{i=1}^{n} \Bigg\{ & \left[\left(E_{x_i}^a(t) - A_{S_i}(t) \right) \right. \\ & \left. \times \frac{1}{n_1} \sum_{i_1=i_2=1}^{n_1} \left(\lambda_{i_1} + \lambda_{i_2} \right) \right] \\ & \times \left[O_{ver_i}(limit, t) \times P_{Risk_i} \right] \Bigg\}. \end{aligned} \tag{21}$$

This $F_{rus}(t)$ when not satisfied produces backlog demand $B_{logg}(t)$ along with an association of closed loop delay λ_{c_1} is expressed as,

$$B_{logg}(t) = \sum_{c_1=1}^{n_1} \left(\frac{1}{\lambda_{c_1}} \right) \times \left(E_x^a(t) - A_S(t) \right). \tag{22}$$

Now, (22) can be rewritten as,

$$\begin{aligned} B_{logg}(t) = \sum_{c_1=1}^{n_1} \left(\frac{1}{\lambda_{c_1}} \right) \times \sum_{i=1}^{n} \Bigg\{ & \left[\left(\frac{E_{x_i}^a(t) - A_{S_i}(t)}{n} \right) \right. \\ & \left. \frac{1}{n_1} \sum_{i_1=i_2=1}^{n_1} \left(\lambda_{i_1} + \lambda_{i_2} \right), \right] \\ & \times \left[O_{ver_i}(limit, t) \times P_{Risk_i} \right] \Bigg\}. \end{aligned} \tag{23}$$

The expression for the reserve r(t) should be,

$$r(t) = A_S(t) - E_x^a(t). \tag{24}$$

There must be reserve required for power system network, when,

$$A_S(t) > E_x^a(t). \tag{25}$$

Equation (24) can be rewritten as,

$$\begin{aligned} r(t) = \sum_{i=1}^{n} \Bigg\{ & \left[\left(A_{S_i}(t) - E_{x_i}^a(t) \right) \right. \\ & \left. \times \frac{1}{n_1} \sum_{i_1=i_2=1}^{n_1} \left(\lambda_{i_1} + \lambda_{i_2} \right) \right] \\ & \times \left[O_{ver_i}(limit, t) \times P_{Risk_i} \right] \Bigg\}. \end{aligned} \tag{26}$$

The threshold policy for reserve $r(t)$ requirements is, if

$$r(t) < n_r. \tag{27}$$

$$r(t) > n_r, \tag{28}$$

where equation 27 an d28 are ramping constraints and can be expressed as,

$$r(t) \leq A_S(t) - S(t-1) \leq n_r. \tag{29}$$

From (15), $A_S(t) - S(t-1)$ will be as,

$$r(t) \leq F_S(t) + R_G(t) \leq n_r. \tag{30}$$

The critical issue is to make $B_{logg}(t)$ stabilized in every state. This can be done through keeping $R_G(t)$ in control using UPFC incorporated smart network transmission, considering the ramping constraints from (27) and (28).

$$r(t) \leq F_S(t) \leq n_r, \tag{31}$$

From (6), the balanced load flow response is achieved between $F_S(t)$ and $F_D(t)$, i.e.,

$$r(t) \leq F_D(t) \leq n_r. \tag{32}$$

Here, UPFC also performed power buffer operation to mitigate the inconstancy of RERs, i.e., compensating an RERs transient stability problems when multiple intervals

TPFs occur in MIRIPGs. Through this, the power system network operators reduces the probabilistic events in the form of COFs in MIRIPGs. To verify this scenario, we considered F_t^D as a demand to be forecasted during transients and U_t^f as the supply forecast using UPFC to mitigate it. This can be done by setting the parameters of $P_t^f(t+f)$ equals to $(F_t^D(t+f) - U_t^f(t+f) + n_r)$, where, an n_r can be positive or negative, depending upon the scenarios. Therefore, $P_t^f(t+f)$ final equation can be given as,

$$\sum_{i=1}^{n}\left\{\left[P_{t_i}^{f_i}(t_i+f_i)\right]\right.$$
$$=\sum_{i=1}^{n}\left[\left(F_{t_i}^{D_i}(t_i+f_i)\right)\right.$$
$$\left.\left.-\left(U_{t_i}^{f_i}(t_i+f_i)\right)\right]\times\left[O_{ver_i}(limit,t)\times P_{Risk_i}\right]\right\}. \quad (33)$$

where the UPFC optimal supply is represented with $U_t^f(t+f)$, which can mitigate the effects of transients and power outages in multiple interconnected RIPGs.

III. SIMULATION RESULTS

We have used MATLAB as a simulation toolbox to validate the proposed analysis. Through an optimal and reliable load flow balancing scenario using UPFC incorporated smart network transmission, this paper provides an extension for the proposed methodology in [11], which provides valuable information regarding power system network vulnerability in the form of occurrence of CFEs due to severe types of faults in multiple interconnected RIPGs. In this paper, we have addressed the problem highlighted in [31], i.e., an arising of transient dynamics due to severe fault conditions increasing the vulnerability of the network to COFs. This can be achieved by outperforming the idea suggested in [30] by comparing it with our suggested methodology devised for the proper transients stability analysis problem in [31].

A. LOAD FLOW BALANCING THROUGH UPFC BASED INTELLIGENT TRANSMISSION NETWORK

For the verification of our suggested methodology in the form of balancing load flow to mitigate CFEs in MIRIPGs due to severe multiple TPFs, we adopted two different case scenarios. Case-A: A forecast demand requirements of three AC power grid stations of cluster-1 are $F_{D_1}(t) = 700\ MW$, $F_{D_2}(t) = 400\ MW$ and $F_{D_3}(t) = 300\ MW$ as evident from Fig. 3. Case-B: The forecast demand requirements of an RERs-2 and 3 receiving side connected loads for an AC power stations 2 and 3 rises to $F_{D_2}(t) = 700\ MW$ and $F_{D_3}(t) = 700\ MW$. This means that to overcome the cluster-1 critical overloading condition, which leads to the CFEs in MIRIPGs due to multiple TPFs, the load requirements for the three AC power grid stations in cluster-1 as suggested in case-A and case-B must be fulfilled at any cost. The verification of the proposed methodology to provide optimum balance for load flows, which reduces the probability of CFEs in

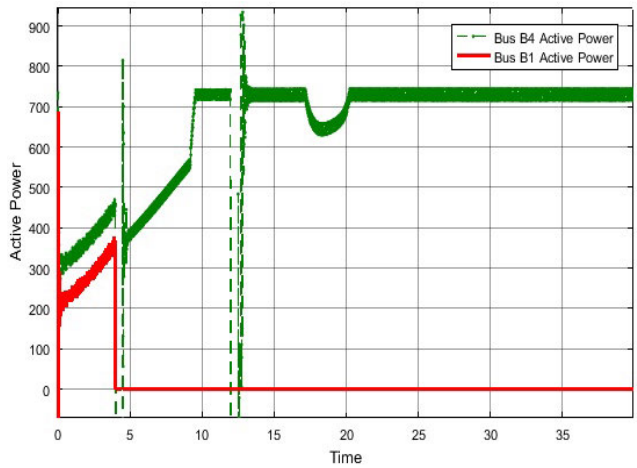

FIGURE 4. Active power graph of Buses B1 and B4.

MIRIPGs due to multiple TPFs using UPFC incorporated smart network transmission, is verified from the simulation results of these two cases.

1) CASE A

Considering RERs vulnerability and reliability issues as suggested in [11], we considered that an unexpected multiple intervals TPFs is occurred in multiple interconnected RIPGs at a time period of (4s-4.5s) and (12s-12.5s) near the electric station 1 of cluster-01, which is clearly shown in Fig. 3. Due to this, RER-01 tripping occurs at $t = 4s$. This is also clearly verified through Fig. 4, which shows that RER-01 get tripped, i.e., Bus B1. Now, due to an RER-01 tripping, it's actual supply becomes $A_{S_1}(t)$ =0 MW, whereas, the requirement in terms of forecasted demand is $F_{D_1}(t) = 700\ MW$. Therefore, if proper compensation has not been done in cluster-01, then it will cause severe overloading states in cluster-01, which will result in the form of RERs-02 and 03 trippings in cluster-01 or, in other words, CFEs occurred in cluster-01. To overcome this, we must provide a synchronous stability between the actual supply and forecast supply requirements, i.e., $A_{S_1}(t) = F_{S_1}(t)$. Through this, the power network operators meet the desired forecast demand requirements of power station 1 of cluster-01, i.e., $F_{D_1}(t) = 700\ MW$. This will provide an effective load flow balancing between generation and demand response pattern of power station 1 of cluster-01, i.e., between $F_{S_1}(t)$ and $F_{D_1}(t)$. Due to this, the problem of a serious overloading state in cluster-01 is easily resolved. This can be done by using UPFC incorporated intelligent/smart network transmission topology as evident from Fig. 3. Here, UPFC enabled smart transmission network represents an optimal transmission network topology that intelligently interconnects various electric-power stations in such a way that it will easily accommodate the desired forecast demand requirements of an RER 01 tripping of an electric-power station 1 of cluster-01. Through UPFC incorporated intelligent/smart network transmission, the extra amount of active power is shifted from RERs-02/Bus B5 and RER 03/Bus

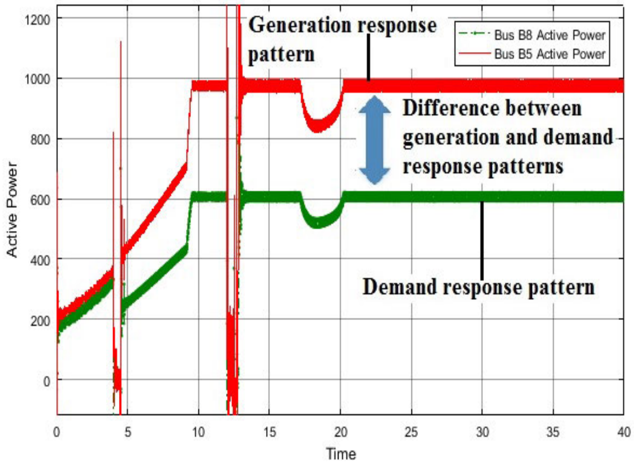

FIGURE 5. Active power graph of Buses B5 and B8.

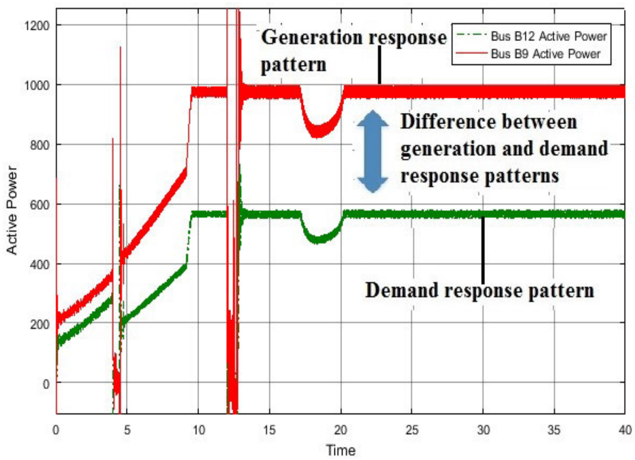

FIGURE 6. Active power graph of Buses B9 and B12.

B9 of an electric-power stations 2/Bus B8 and 3/Bus B12 of cluster-01 to the receiving side of a tripping RER-01 to serve their connected loads. In this case scenario, the actual supplies at RER-02/ Bus B5 and RER-03/Bus B9 are $A_{S_2}(t) = 979.5MW$ and $A_{S_3}(t) = 979.5MW$, while it's forecast demand requirements are $F_{D_2}(t) = 400MW$ and $F_{D_3}(t) = 300MW$. Therefore, an RERs 2 and 3 surplus active power, i.e., $(A_{S_2}(t) - F_{D_2}(t))$ and $(A_{S_3}(t) - F_{D_3}(t))$ are shifted to meet the desired demand response forecast requirements of receiving side connected loads of a tripped RER 1. This phenomenon is also verified from Figs. 4, 5 and 6. The deviation patterns between demand and response as shown in Figs. 5, 6 clarified that the surplus active power of RERs-02/Bus B5 and 3/Bus B9 is shifted to compensate the receiving connected loads of an electric-power station 1/Bus B4 of cluster-01, whose RER-01 is tripped due to the occurrence of multiple intervals TPFs in it. This will minimize the chances of CFEs occurring in cluster-1 of MIRIPGs.

The forecast reserve $r(t)$ requirements, i.e., $F_{D_1}(t)$, $F_{D_2}(t)$ and $F_{D_3}(t)$ of an electric-power stations 1, 2 and 3 in cluster 01 are $r_1(t) = 700\ MW$, $r_2(t) = 400\ MW$ and $r_3(t) = 300\ MW$. Similarly, for the compensation of an $r(t)$,

TABLE 1. Active power on different buses.

Active power of generation and receiving side (MW)					
B1	B4 (n_{r_1})	B5	B8 (n_{r_2})	B9	B12 (n_{r_3})
-1.016	733.4	979.5	609.7	979.5	568.3
Case B					
B1	B4 (n_{r_1})	B5	B8 (n_{r_2})	B9	B12 (n_{r_3})
-2.942	700.1	-2.942	700.1	-2.942	700.1

the nominal reserve n_r, which is available on the spot are $n_{r_1} = 733.4\ MW$, $n_{r_2} = 609.7\ MW$ and $n_{r_3} = 568.3\ MW$ as evident in Table 1. Due to this deviations between $r_1(t)$ and n_{r_1}, $r_2(t)$ and n_{r_2} and $r_3(t)$ and n_{r_3}, there is still certain randomness $R_G(t)$ occurred between the generation and demand response of three AC power grid stations in cluster 1, i.e., between $F_{S_1}(t)$ and $F_{D_1}(t)$, $F_{S_2}(t)$ and $F_{D_2}(t)$ and $F_{S_3}(t)$ and $F_{D_3}(t)$. This randomness can be expressed as, i.e., $R_{G_1}(t) = n_{r_1} - r_1(t) = 733.4 - 700 = 33.4\ MW$, $R_{G_2}(t) = n_{r_2} - r_2(t) = 609.7 - 400 = 209.7\ MW$ and $R_{G_3}(t) = n_{r_3} - r_3(t) = 568.3 - 300 = 268.3\ MW$.

2) CASE B

It is different scenario from the case A in a way when there occurs a sudden enhancement in the forecast demand of receiving stations 2 and 3 of cluster 1, i.e., from $F_{D_2}(t) = 400\ MW$ to $F_{D_2}(t) = 700\ MW$ and from $F_{D_3}(t) = 300\ MW$ to $F_{D_3}(t) = 700\ MW$. Now, in this case scenario, if a multiple intervals TPFs occurred in MIRIPGs, as mentioned in Case-A:, causes the tripping of an RER 01 in cluster-01. Now, due to an enhancement of forecast demands of receiving stations 2 and 3, a serious overloading state occurred in cluster-01, which suddenly started an RERs-02 and 03 tripping of an electric-power stations-2 and 3 in cluster-01 as shown in in Fig. 3. This is also clarified through Fig. 7, which shows an RER-1/Bus B1, RER-2/Bus B5 and RER-3/Bus B9 tripping of an AC electric power grid stations 1, 2 and 3 of cluster-01. This shows that a CFEs occurred in cluster 1. Now, if proper compensation has not been done in this situation, then this CFEs will cause a devastating impact on other clusters and therefore lead the whole power network connected in the form of MIRIPGs to cascading failure outages. Hence, to mitigate the forecast demands requirements of 300 MW and 400 MW for an electric-power stations 2 and 3 in order to compensate the serious overloading state occurred in cluster-01, an UPFC incorporated smart network transmission is utilized, which provides a balanced flow through an integration of various RERs of corresponding four clusters in an optimal way. Here, in this case scenario, using UPFC incorporated smart network transmission, an excess of active energy of an RERs-04, 05 and 06 of cluster-02, RERs-07, 08 and 09 of cluster-03 and RERs-010, 011 ans 012 of cluster-04 is transfered to compensate the enhanced forecast demand requirements of 300 MW and 400 MW of corresponding AC power grid

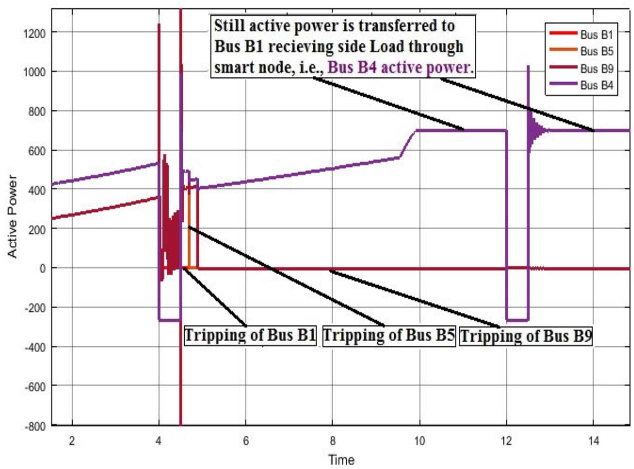

FIGURE 7. Buses B1, B5, B9, and B4 active power graph.

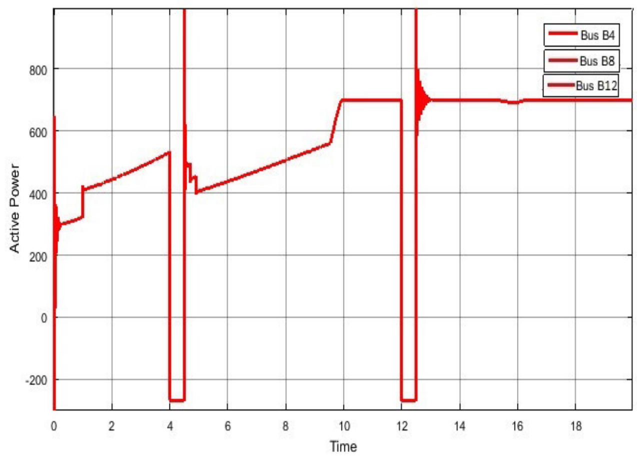

FIGURE 8. Bus B4, B8, and B12 active power graph.

stations-2 and 3 of cluster-01, as evident from Figs. 7 and 8. Now, in this case scenario, inspite of the cascading failure outages in cluster-01 in the form of an RER-01/Bus B1, RER-2/Bus B5 and RER-3/Bus B9 tripping as shown in Fig. 7, it's connected load on the receiving side, i.e., 700 MW forecast demand requirements for an electric-power station 1/Bus B4, 2/Bus B9 and 3/Bus B12 of cluster-1 is accommodated in an optimal way as shown in Fig. 8. This will provide a synchronous stability between $F_{S_1}(t)$ and $F_{D_1}(t)$, $F_{S_2}(t)$ and $F_{D_2}(t)$ and $F_{S_3}(t)$ and $F_{D_3}(t)$, which will return the multiple interconnected RIPGs back to it's normal demand conditions. Here, in case-B, we have $r_1(t) = 700\ MW$, $r_2(t) = 700\ MW$ and $r_3(t) = 700\ MW$ and $n_{r_1} = 700.1\ MW$, $n_{r_2} = 700.1\ MW$ and $n_{r_3} = 700.1\ MW$ as evident in Table 1. Therefore, an $R_G(t)$ in cluster 1 will now becomes, i.e., $R_{G_1}(t) = n_{r_1} - r_1(t) = 700.1 - 700 = 0.1\ MW$ (first AC power grid station), $R_{G_2}(t) = n_{r_2} - r_2(t) = 700.1 - 700 = 0.1\ MW$ (second AC power grid station) and $R_{G_3}(t) = n_{r_3} - r_3(t) = 700.1 - 700 = 0.1\ MW$ (third AC power grid station). This shows that when there is a sudden enhancement occurred in the forecast demand requirements, i.e., from 400 MW and

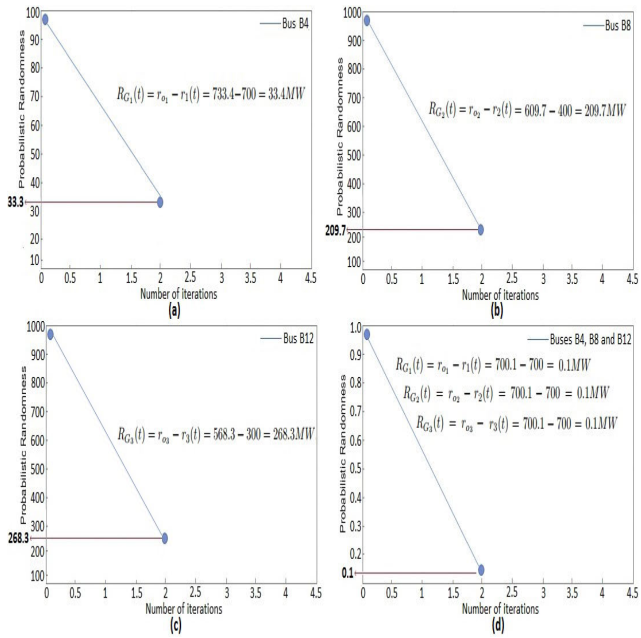

FIGURE 9. Load flow analysis (a) Case-A: B4 Bus (b) Case-A: B8 Bus (c) Case-A: B12 Bus (d) Case-B: B4 bus, B8 bus and B12 bus.

300 MW to 700 MW of an electric-power stations 02 and 03, n_{r_1}, n_{r_2} and n_{r_3} approach to $r_1(t)$, $r_2(t)$ and $r_3(t)$, thereby minimizing $R_G(t)$. This concludes a very unique result that UPFC incorporated smart network transmission provides an optimal platform to balanced the deviations between demand and generation response patterns and therefore reducing the chances of CFEs to be arises in MIRIPGs in case of severe multiple TPFs. Simulation results show that the proposed algorithm converges faster in case if a larger deviation in the forecasted demand occurs. In a normal situation, the system converged to its stable state just after two iterations, as shown in Fig. 9. Fig. 9a, 9b and 9c shows the analysis of Buses B4, B8 and B12 against case-A. Where the load flow analysis of Buses B4, B8, and B12 for case-B is given in Fig. 9d. It shows that larger fluctuation case causes the network to converge quickly by minimizing the probabilistic randomness $R_G(t)$, i.e., $R_{G_1}(t)$, $R_{G_2}(t)$ and $R_{G_3}(t)$ to 0.1 MW as illustrated in Fig. 9d. Also, $G^f(t)$ and $D^f(t)$ get synchronized.

The forecast demand requirements on the receiving end of electric-power stations 1, 2 and 3, i.e., $F_{D_1}(t) = 700MW$, $F_{D_2}(t) = 400MW$, $F_{D_3}(t) = 300MW$ in case-A and $F_{D_1}(t) = 700MW$, $F_{D_2}(t) = 700MW$, $F_{D_3}(t) = 700MW$ in case-B is properly fulfilled through UPFC incorporated smart network topology. This is also verified through Table-1, where the receiving side connected loads of an electric-power station 1/Bus B04, 2/Bus B8 and 3/Bus B12 is served in an optimal way.

IV. UPFC BASED TRANSIENT STABILITY ASSESSMENT

To validate the usefulness of a UPFC for transients stability enhancement in smart power network in case of multiple TPFs occurrences, we make a supposition that there is an

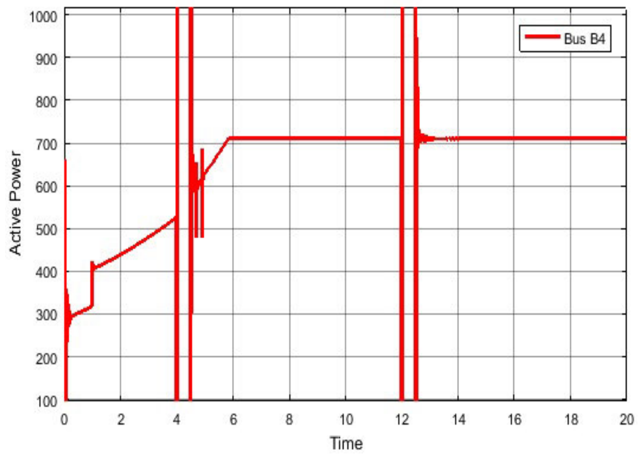

FIGURE 10. Bus B4 active power graph.

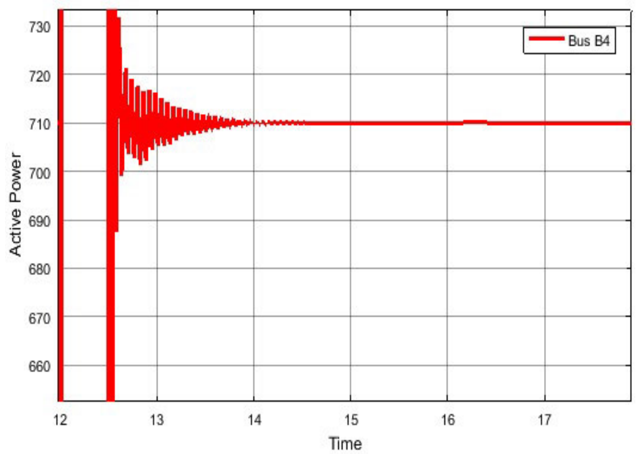

FIGURE 11. Bus B4 active power graph.

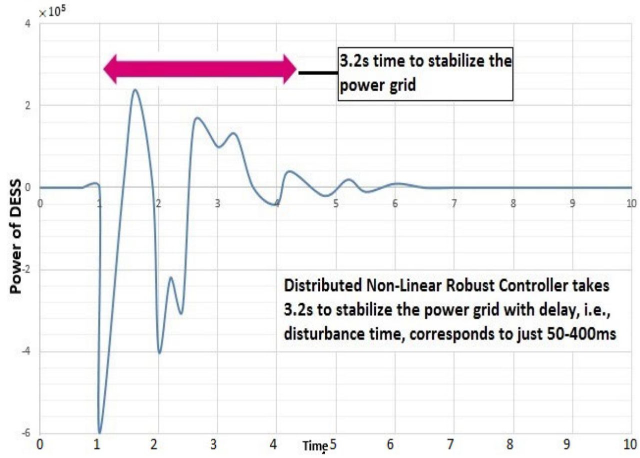

FIGURE 12. Transient stability improvisation in power system using distributed non-linear robust controller technique [30].

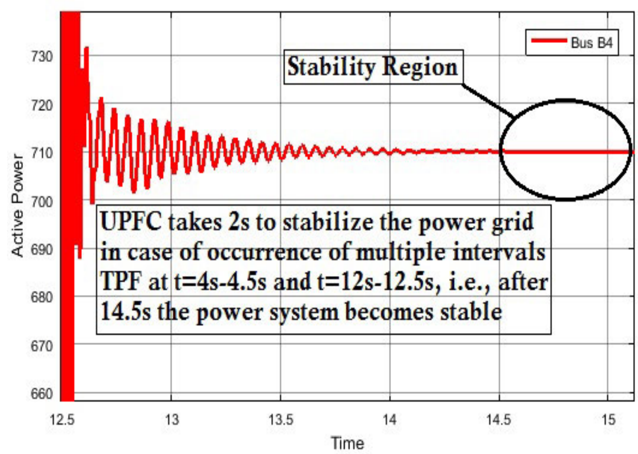

FIGURE 13. Transient stability improvisation in power system using UPFC.

enhancement occurred in an active power from 700 MW to 710 MW on an electric-power station 1 of cluster 01. Now, if proper compensation has not been done in this situation, then this immediate enhancement of 10 MW will lead towards a serious overloading scenario in cluster 1, which will lead the whole cluster of MIRIPGs towards cascade failure outages. To overcome this situation, a cascading overload failure model, as suggested in Sec. B of the methodology is utilized to sense this deviation of 10 MW in demand response and give a feedback signal to an already incorporated UPFC in intelligent/smart transmission network for switching purposes. This will mitigate the outage of 10 MW on power network station 1/Bus B4. The simulation results in Fig. 10 verifies this impression. A better representation of Fig. 10 is shown in Fig. 11. It is evident from Fig. 11 that by using UPFC in the intelligent network, a sudden increase of 10 MW power is easily achieved, i.e., from 700-MW to 710 MW. Therefore, reducing the probability of CFEs occurrence in MIRIPGs due to multiple interval TPFs events in it and therefore restore the power system network to its normal conditions. To verify this scenario, we compared our proposed methodology with the algorithm suggested in [30]. Furthermore, to provide an optimal compensation to reduce the vulnerability of power system network to CFEs, the network operators should choose an optimum path in which an enhancement in transients stability occurred within a short period, even with the high fault latency rate due to a severe fault condition, as in our scenario (a TPF arising time of 0.5s for both fault intervals). This is also clarified through simulation results Fig. 13. From Fig. 13, it is evident that for the stabilization of power grids in case of occurrence of multiple intervals TPFs with a high latency rate of 0.5s for both fault intervals, UPFC just takes a period of 2s. Figs. 12 and 13 comparison clearly verified that UPFC provides an optimal compensation as compared to distributed non-linear robust controller to improve transients stability issues in multiple interconnected RIPGs. The network node breakdown issue is critical in MIRIPGs due to multiple intervals TPFs events. It is solved with the help of these two strategic techniques, i.e., balancing of load flow using and transient stability analysis using UPFC enabled transmission network. This will further reduce the CFEs probability in the power system network. Through utilizing these two approaches, the overloaded vulnerable red spots as

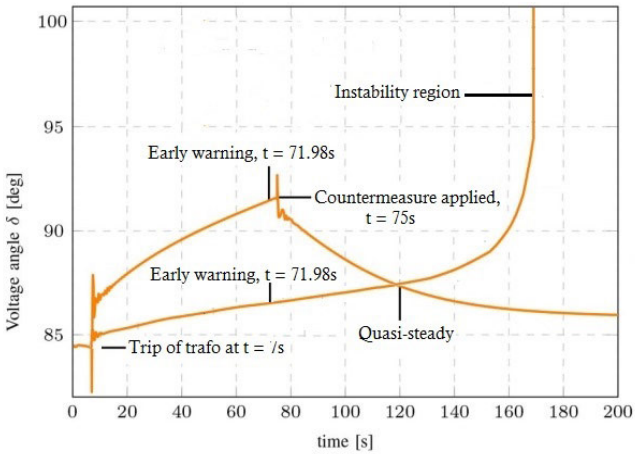

FIGURE 14. Generator voltage angle [36].

evident in Fig. 1a get eliminated, i.e., Fig. 1a transforms into Fig. 1b, which solves the spreading problem in the form of chain reactions (CFEs) in MIRIPGs. This concludes the fact that by utilizing UPFC enabled smart transmission network hybrid model; the network operators can restore the power system back to it's normal demand conditions, even after an occurrence of CFEs in MIRIPGs due to severe multiple TPFs.

V. INDUSTRIAL CASE STUDY

The proposed work in this manuscript is to provide stability to the network not only in case of single fault contingency but also in case of multiple fault contingencies, which leads the network to cascading failure events. The previously proposed techniques in literature are only suitable to provide stability to the network in case of an occurrence of only a single fault contingency in power systems and fail to address the issues of multiple fault contingencies that will lead the network to cascading failure outages. To validate this idea and also that our proposed methodology fits according to the industrial needs, I compare my proposed methodology with the one suggested in [36].

A. APERIODIC SMALL DISTURBANCE ROTOR ANGLE INSTABILITY

A methodology is proposed in [36], considering small disturbances in the power system network based on rotor angle instability. The model was developed considering the western Denmark transmission system (WDTS), as given in Fig. 15. Fig. 15 shows that synchronization of the generator gets disturbed due to inexperienced manual excitation of a generator. This causes transformer tripping at $t = 7s$ and initiates a warning at $t = 71.98s$, where instability arises at $150s$. To mitigate such issue, a self-propagation graph-based scheme is presented [36]. The sensitivities for each of the nodes are calculated, and it is founded that node AP-160 is the most critical node. That is why the countermeasure is applied at that node to make the system stable by disconnecting the 60 MVAR load. This phenomenon can be verified in Fig. 14,

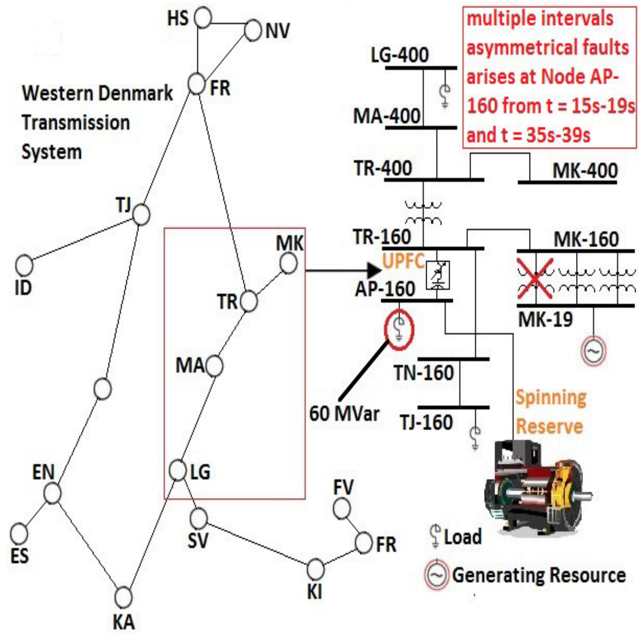

FIGURE 15. Single line diagram showing the transmission system of Western Denmark. A comprehensive overview of a specific area is incorporated under the applications of contingencies and countermeasure implementation.

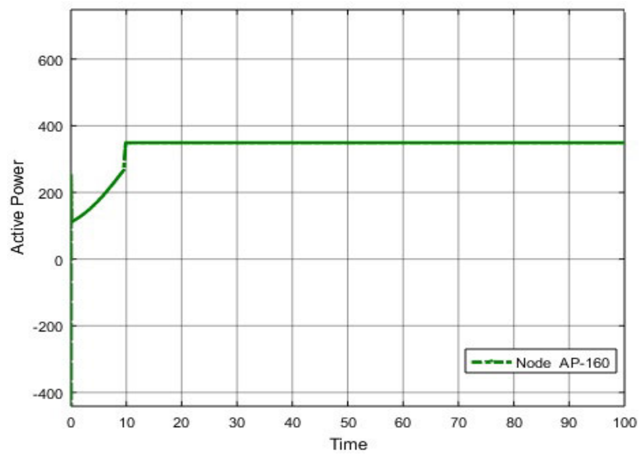

FIGURE 16. Node AP-160: active power under normal operational mode.

which shows that by applying a countermeasure, the stability in the power system is achieved at $t = 75s$.

B. TPFs BASED ON MULTIPLE INTERVALS

The same set of parameters are used as in [36], according to multiple intervals TPFs, the power system response is quite worse, even after applying the countermeasure. To verify this, active power graph is simulate at critical Node `AP-160`, which is already identified through proposed work in [36], results are provided in Fig. 15. Figs. 16, 17, and 18 showing the operation in normal, faulty and countermeasure mode respectively. Fig. 17 shows the unstable condition of power system network at $t = 50s$, i.e. leading to cascading overload failures, after the event of multiple intervals TPFs at Node `AP-160` during intervals $t = 15s - 19s$ and $t = 35s - 39s$ as

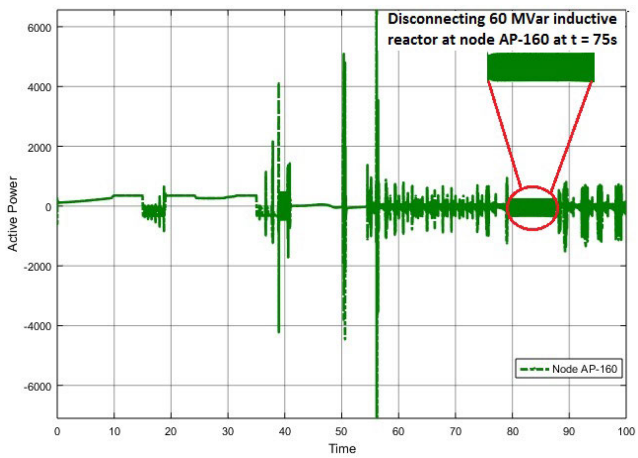

FIGURE 17. Node AP-160: active power under multiple intervals asymmetrical faults mode.

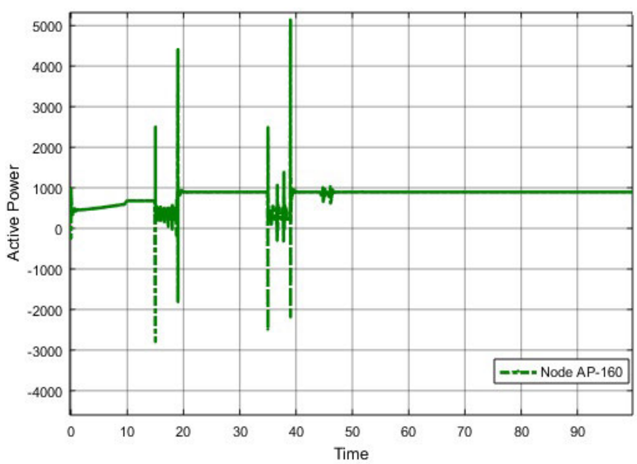

FIGURE 18. Node AP-160: active power under countermeasure implementation (UPFC + spinning reserves).

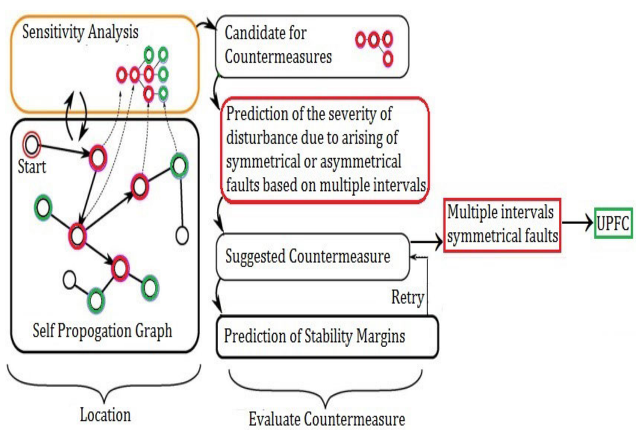

FIGURE 19. Self-propagation graph to identify the optimal location for UPFC.

given in Fig. 15. The same approach is suggested in [36], i.e. at $t = 75s$, disconnecting the 60 `MVar` load at Node `AP-160`, the magnitude of transients decreases as given in Fig. 17 during interval $t = 75s - 86s$. Nevertheless, the network remains in unstable condition as given in Fig. 17, i.e., power system network subjected to cascading failure event. This issue is tackled via utilization of a UPFC based smart transmission network scheme. It is evident from Fig. 15 that by operating a UPFC between Node `TR-160` and Node `AP-160`, the network operators can easily bring the power system back to it's normal mode of operation as given in Fig. 18.

For the placement of UPFC at an optimal location to mitigate the effect of multiple fault contingencies, we utilized the concept of self-propagation graph, as proposed in [15]. A self-propagation graph is a well-known technique through which the network operators can easily identify the critical nodes in the power system network at the earliest stages, as shown in Fig. 19. After identifying the critical nodes, the placement of UPFC at an optimal location can be easily identified.

VI. CONCLUSION

The occurrence of cascading overload failures in different geographical parts of the world results in the form of network node breakdown, which leads to an occurrence of major blackouts in power systems. To overcome these CFEs to have occurred, proper assessment in the form of protection for a power system network is required. However, the severe impact on the power system network due to the occurrence of such catastrophic events is not always predictable. There is a lot of skepticism presents in the literature that there would be enough time for the power network operators to apply a suitable countermeasure against such catastrophic events. Moreover, the critical impact of these suitable countermeasures against such catastrophic events cannot be deemed accurate unless the power system network operators tried and tested it in a different unpredictable event, i.e., under different types of severe faults that will lead the network to cascading failure outages. Considering this scenario, and in order to validate the novelty of this proposed study with the existing work, the point-by-point findings of this research work are as follow:

1) probabilistic modeling is utilized in this paper to mitigate CFEs in multiple interconnected RIPGs under the critical assessment in the form of load flow balancing and transients stability both in case of occurrence of single interval fault and more severe multiple interval faults,
2) contrary to the previous proposed studies in literature, which are only confined to mitigate the effect of network instabilities in case of occurrence of only a single interval fault, the suggested methodology in this paper is backed by hybrid probabilistic modeling and detailed empirical evidence to mitigate network instabilities in power systems both in case of single interval and more sever multiple interval faults that lead the network to cascading failure outages,
3) simulation results verified that our proposed probabilistic algorithm achieved near an optimal performance by outperforming the existing proposed methodologies,

which was only confined to provide stability to the network only in case of single interval fault and fails to address issues of severe multiple interval faults in power system network that leads the network to cascading overload failures,
4) these simulation results were also validated through an industrial case study, which was performed on a western Denmark transmission power system network to show the novelty of our proposed algorithm.

VII. FUTURE DIRECTIONS

1) To enhance system reliability and protection of power system network, an upgrade in power system monitoring and control must be further required. For this purpose, the wide-area measurement systems (WAMS) is considered to be one of the most promising solutions in this case.
2) Demand side management program for mitigating overloading conditions, that leads to cascading failures must be trained in such a way that customers must be encouraged to participate in these demand-side management programs. The two way flow of information between utility and customers will increase the reliability of the complete power system network.
3) The power system network must be operated in such a way that its reserve requirement must be improvised at any time to reduce the risk of catastrophic events in the form of cascading failure outages in power systems. This can be done by using advanced optimization techniques in power system networks.
4) Pre-disturbance systems analysis could be done, which includes the possibility of an arising of catastrophic events in a power system network. Also, UPFC optimum placement techniques must be improvised so that they can quickly respond to accommodate loads in such catastrophic events.

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