Modeling Manual Corrective Actions in Probabilistic Risk Assessment of Cascading Outages

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***Abstract*—Cascading outages in power systems can lead to major power disruptions and blackouts in power systems. By taking Manual Corrective Actions (MCAs), operators could be able to mitigate a cascading outage following an initiating event. However, due to stressful and time-constrained situations, they might not be able to take appropriate corrective actions in time and might even take counter-productive actions. Although numerous approaches have been developed to assess the risk of cascading outages in a probabilistic way, they generally do not consider in a realistic manner MCAs, including their imperfection. This paper aims to address that gap by proposing a Human Reliability Analysis-Optimal Power Flow (HRA-OPF) framework. The developed approach is applied to the New England Test System (NETS) and to the Reliability Test System (RTS). The risks of loss of supplied power are compared for different possibilities: no MCAs, perfect MCAs, and imperfect MCAs.**

***Index Terms*—Cascading outage, power system reliability, power system security, risk analysis, human reliability**

NOMENCLATURE

Indices

- n: node
- l: branch (line or transformer)
- g: generator

Variables

- θ_n: voltage angle at node n
- P_g: active power supplied from generator g
- P_l: power flow through transmission element l
- ΔP_{nd}: load shedding at node n

Parameters

- P_g^{min}/P_g^{max}: minimum/maximum active power generation of generator g
- F_l^{max}: thermal rating of transmission element l
- P_{nd}: active power load at node n
- C_g^+: upward redispatch cost of generator g
- C_g^-: downward redispatch cost of generator g
- B_l: electrical susceptance of transmission element l
- A_{nk}: incidence matrix
- $\mathbb{1}_{ng}$: binary indicator parameter, equal to 1 if generator is g connected to node n, 0 otherwise
- $VoLL$: Value of Lost Load (cost of load shedding)
- λ: Outage rate of a transmission line

I. INTRODUCTION

Large-scale blackouts and other major power disruptions are typically caused by cascading outages. Various cascading mechanisms are behind cascading outages, but one of the major ones relates to thermal overload. Following an initiating event (one contingency or several), the reconfiguration of the power flows increases the thermal stress on remaining active elements, and their related failure probabilities, consequently [1]. Because thermal transients are slow, operators might have the time to take Manual Corrective Actions (MCAs) to alleviate the possible overloads. If they succeed before the failure of these overloaded elements, the cascading outage is avoided. However, they might not succeed because time is limited, stress can be high, and situational awareness can be limited. For instance, on September 28, 2003, the failure of operators to quickly alleviate an overload on a 380-kV line between Switzerland and Italy following an initial outage entailed a complete blackout in Italy [2]. Furthermore, under these stressful conditions, operators might take improper actions to aggravate the overloads instead of alleviating them. For example, on November 4, 2006, following an initial outage, operators in Germany coupled two busbars in a substation, which led to the overload of a line. The subsequent cascading outage entailed power supply disruptions for more than 15 million households across Europe [3].

Given the potentially massive consequences of cascading outages, it is of paramount importance for power system planning and operation to evaluate the risks associated with such events. The aim of a Probabilistic Risk Assessment (PRA) of cascading outages is to identify cascading scenarios and to evaluate their adverse consequences (e.g., loss of supplied power) and their likelihood (probability/frequency). The product of these two quantities gives the risk of the scenario. As operators can play a key role in such cascades, PRA approaches should consider (i) that MCAs can be taken to alleviate overloads, (ii) that operators can fail to take relevant corrective actions on time, and (iii) that incorrect actions can be taken as well. Although numerous approaches have been

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developed for cascading outage PRA, they generally do not integrate all these features entirely. There is thus a need to develop realistic models for the inclusion of MCAs in PRA of cascading outages.

This paper aims to address that gap by proposing a methodology regarding the lack of realistic models of MCAs in PRA of cascading outages. It proposes first a framework that estimates the probability of failure of human operators regarding the estimated parameters of the identified corrective actions. The estimated Human Error Probabilities (HEPs) are then used as branch probabilities to develop the post-contingency progression scenarios during the thermal instability phase.

After this introduction, this paper is structured as follows. Section II gives an overview of the literature regarding the consideration of operator actions in risk assessment of cascading outages. Section III then develops the proposed approach. Section IV applies the framework to two case studies, the New England Test System (NETS) and the IEEE three-area Reliability Test System (RTS), and compares the risks of loss of supplied power for three different possibilities: (1) No MCAs, (2) Perfect MCAs (failure-free grid operators), and (3) Imperfect MCAs. Section V concludes.

II. STATE OF THE ART

PRA of cascading outages is typically based on probabilistic simulations: cascading events are sequentially triggered to the considered power system and electrical variables are recomputed after each event. Typically, overloaded electrical elements are identified in each round of cascading simulation based on the results of power distribution in the network, and removed consequently. It naturally opens the door to the integration of MCAs following each event. There are three approaches to do that.

First, MCAs can be modeled in a heuristic way to address specific problems. For example, in the Manchester model, the load is shed heuristically when the numerical solution of the power flow equations is not convergent [4]. These heuristics fail to be universal and to integrate possible failures of operators.

Second, MCAs can be modeled through an Optimal Power Flow (OPF) problem. For example, [5] integrates optimization-based emergency control in a dynamic cascading outage simulator. Such approaches are based on the abundant literature related to OPF problems, able to provide a list of possible corrective actions that could be taken within a given period after the occurrence of the contingency. Considering both the possibility and efficiency of the actions, it has been emphasized that the subset list of control actions must be limited in size to include only the most effective actions [6]. A 3-step methodology, as proposed by Capitanescu et al. in [7] and completed in [8] identifies and suppresses the ineffective control actions in the solution list of OPF and Security-Constrained OPF problems, at the price of a pre-agreed percentage of cost increase. The time needed to implement the control actions is also mentioned as an alternative optimization criterion, considering the presence of both extremely fast or quasi-instantaneous controls, and comparatively slower controls, such as load curtailment and generation re-dispatch, respectively [9]. However, this second approach relies implicitly on a set of failure-free human interventions to make critical decisions (diagnosis) and take manual reactions (action) for the restoration of the secure operation of power grids. In other words, pre-destined success, with zero probability of failure or degree of imperfectness, is expected for the entire set of corrective actions. Past blackouts demonstrate that such an assumption is unrealistic [2], [3].

Third and finally, several works tried to model in a more explicit manner operators, including their imperfectness based on Human Reliability Assessment (HRA). Before that, HRA had been receiving a significant concern in the reliability assessment of catastrophic man-made accidents in key industries for several years [10]–[12]. Indeed, the historical data of various industries including power systems indicate that several factors may shape the performance of human operators in both the diagnosis and action phases of critical situations. They are called Performance Shaping Factors (PSFs). Examples of such PSFs are: levels of stress of the operators at the time of the event, fatigue, experience level, the amount of time available to respond to a situation, etc. [13], [14]. Human failure is mentioned as a significant challenge to the safe operation of the power grid [15], as well. Nonetheless, only a few works make use of HRA for power systems [16]. [17] defines the operator success rate based on the seriousness of the situation the operator is faced with after an overload-inducing incident, i.e. the nature and the number of overloads. A 4-state Markov modeling is proposed by [18] to investigate the effect of insufficient Situation Awareness (SA) on preserving the power system security. The proposed modeling assumed that SA enables the operators to make effective and timely decisions and react to an incident. However, neither it discusses nor evaluates the success (failure) of operator actions probabilistically in different states of the system. The influence of the average response time of the operators, i.e., the time necessary to decide regarding the existing variables, on the reliability indices of the cyber-physical power systems, is identified via the development of a stochastic model of human operator's performance, in [19]. The HRA model in [20] uses the Standardized Plant Analysis Risk Human Reliability analysis (SPAR-H) methodological framework to estimate the probability of human failure under various circumstances during and due to the progression of cascades. Related PSFs are identified in [14] based on the combination of both the observation from the historical data and the information from the interviews with the power system operators of New England and Southeast about the emergencies that happened during their shifts.

According to this literature review, either MCAs are considered, in an exhaustive manner, through an OPF but neglecting the unreliability of human grid operators, and their failure probability, or the unreliability of human grid operators is considered but a restricted number of corrective actions is considered. No approach currently combines both. Inspired by the existing SPAR-H framework from the risk and human reliability assessment methodologies of nuclear and aerospace safety studies, this paper develops in the next section an HRA-OPF framework to address that gap. This framework considers the HEP in the identification of the solution to the OPF problems.

III. METHODOLOGY

The overall methodology is presented in this section through a step-by-step approach. First, Subsection III-A presents an initial probabilistic simulation model of cascading outages neglecting MCAs. Then, Subsection III-B integrates perfect MCAs. Finally, Subsection III-C introduces imperfectness in the modeling of these actions based on an HRA-OPF framework.

A. No manual corrective actions

Probabilistic simulation models of cascading outages can be classified according to the computation of the electrical variables after each cascading event: static computation (Quasi-Steady-State (QSS) methodologies), dynamic computation (dynamic methodologies), or a combination of both (hybrid methodologies) [21]. Dynamic computations are especially crucial for the second phase of typical development of a cascading outage, the fast cascade [1]. However, this second phase is too fast to allow operators to take MCAs. The modeling of MCAs is thus especially relevant for the first phase, the slow cascade, for which static computations are sufficient. Therefore, a QSS methodology is used in the paper [21].

Many different QSS methodologies have been developed over the past decades, following a common canvas although each one has its specificity [21]. To select one methodology amongst all for this work, the following criteria are applied: (i) it must be open-source such that it can be enhanced in the next steps with MCAs, (ii) it must correspond to the state-of-the-art knowledge by integrating a large number of features relevant for the slow cascade, and (iii) it must be well recognized such that it can be used as a solid foundation. The AC Cascading Failure Model (ACCFM) [22] meets these requirements. ACCFM is a typical QSS methodology that checks for violations (including frequency, voltage, and loading of branches) upon outages and performs corrective actions till solving them entirely. However, ACCFM trips any post-contingency overloaded branches immediately without considering any remedial actions.

In this work, considered initiating events are all single and double contingencies (N-1 and N-2 events). An occurrence frequency is associated with each initiating event, regarding the outage rate of the transmission lines, and assuming their independent occurrence. As the subsequent events are considered in a deterministic manner, each initiating event results in a unique cascading scenario. The risk of each scenario is defined as the product of the scenario frequency by the amount of loss of supplied power resulting from it. The total risk is then calculated by summing over the values for all scenarios.

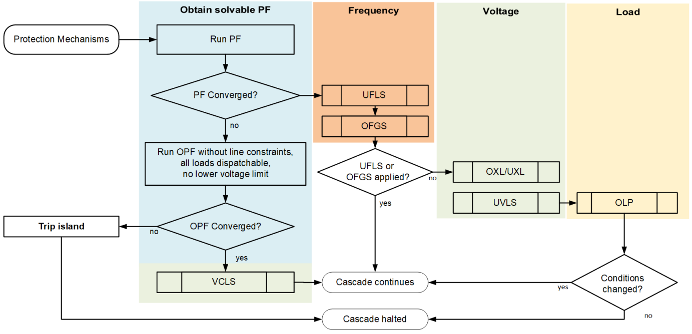

Fig. 1. Flowchart illustrating the implementation and succession of protection mechanisms in ACCFM [22]

B. Perfect MCAs

Following one or several contingencies, violations of operational constraints, such as overloads of branches, can occur. In order to mitigate the cascading outage, operators must implement corrective actions as quickly as possible. Corrective actions can consist in redispatching the generation, changing the grid topology, changing the tap ratio of transformers, shedding load (as a last resort), etc. As explained in Section II, finding MCAs required to alleviate the violation of operational constraints can be achieved through an OPF problem. This work focuses on thermal overloads and considers two mechanisms to alleviate them: redispatch and load shedding. Therefore, finding the optimal set of optimal actions can be achieved by solving the following DC OPF problem:

$$\min \sum_{g} \left[C_g^+ \Delta P_g^+ + C_g^- \Delta P_g^- \right] + VoLL \sum_{n} \Delta P_{nd}, \quad (1)$$

such that

$$\Delta P_g^+, \Delta P_g^- \geq 0, \forall g, \quad (2)$$

$$P_{nd} \geq \Delta P_{nd} \geq 0, \forall n, \quad (3)$$

$$P_g = P_g^0 + \Delta P_g^+ - \Delta P_g^-, \forall g, \quad (4)$$

$$\sum_{g} \mathbb{1}_{ng} P_g + \sum_{l} A_{nl} P_l = P_{nd} - \Delta P_{nd}, \forall n, \quad (5)$$

$$P_{lc} = \mathbb{1}_l B_l \sum_{n} A_{nl} \theta_n, \forall l, \quad (6)$$

$$P_g^{min} \leq P_g \leq P_g^{max}, \forall g, \quad (7)$$

$$-F_l^{max} \leq P_l \leq F_l^{max}, \forall l. \quad (8)$$

The objective function corresponds to Eq. 1. It minimizes the aggregate cost of the corrective actions, including both generation re-dispatch and load-shedding. Eq. (5) balances the powers at each node, and Eq. (6) enforces power flows in the branches, while taking into account possible failures. Equation (7) limits the active power outputs to physical capabilities. Equation (8) enforces the line flows to be less or equal to the thermal rating in all states.

The simulation model considering perfect MCAs solves this optimization problem following any contingency (or set of contingencies) and implements the solution instantaneously and perfectly (i.e., without failure) in the ACCFM described above[1]. Any cascading outage is thus assumed to be directly stopped by MCAs.

C. Imperfect manual corrective actions

As explained in Section II, assuming that failure-free MCAs can be taken instantly is unrealistic. This subsection enhances the model of the previous subsection by considering imperfectness. In a nutshell, the OPF problem previously described identifies first after each contingency the list of credible corrective actions that enable the restoration of the secure state of the power system from a post-contingency emergency condition. The SPAR-H technique is then used to evaluate failure probabilities for overload-relieving MCAs. Hereafter, the SPAR-H technique is first described, and its application to cascading outages is then detailed.

1) The SPAR-H technique: The central role of the entire HRA technique is to estimate the HEPs for manual tasks. SPAR-H, as one of the most practiced and relatively straightforward methods for the U.S. Nuclear Regulatory Commission (NRC) [12]. SPAR-H produces the best-estimate HEPs via the following two-fold steps:

- Decomposing each identified Human Failure Event (HFE) into contributions from the failure of diagnosis and/or action tasks

- Assignment of a Nominal HEP (NHEP) to each task and adjusting them by using relevant PSFs.

Diagnosis is a cognitive process to understand the ongoing post-accident conditions. It aims at the determination of the appropriate course of action, which is then implemented via the action tasks. According to the existing SPAR-H guidelines, 1E-02 and 1E-03 are assigned to the NHEP for the tasks of diagnosis and actions, respectively, and 1.1E-02 for the entire tasks involving both [12]. Then, eight SPAR-H PSFs specify salient performance drivers on human performance, either with beneficial or detrimental influence. The final HEP is calculated via:

$$HEP = NHEP \times \prod_{i=1}^{8} PSF_i. \tag{9}$$

This study intends to consider time-related PSF in the evaluation of HEPs. The time available and time required to perform an action are two time-related factors that affect the decision-making process and human error probability during an incident. The Time Margin Ratio (TMR) is defined as the ratio of the available time to the required time. To estimate HEPs, the levels of related PSFs are identified regarding the TMR, according to which time-related multipliers are extracted from I.

TABLE I
TIME-RELATED MULTIPLIERS FOR THE DIAGNOSIS AND ACTION PORTION OF THE MANUAL TASK

PSF Level	Multipliers
Inadequate time	$P_{Failure} \simeq 1$
Barely adequate time ($TMR \leq \frac{2}{3}$)	10
nominal time ($TMR \simeq 1$)	1
Extra time ($1 \leq TMR \leq 2$)	0.1
Expansive time ($TMR \geq 2$)	0.01

2) Application to the PRA of cascading outages: In the context of corrective actions in electrical power systems, available time (AvailTime) represents the maximum duration until the overloaded branch(es) endures its abnormal overloading conditions. It denotes the time point after when the implemented overload-relieving operator action is no longer effective. According to the deterministic industrial practice and standard documents, a branch must not remain overloaded for longer than its thermal time constant so that the thermal instability be avoided [23]. However, the non-identical difference between pre- and post-contingency loads on the remaining branches affects the triggering onset of (a) thermal-induced event(s) and the magnitude of available time, as a result. Therefore, the available time should be addressed and evaluated based on the simulation results. Should a one-to-one correspondence be assumed between the initial and final loading steady-state currents (I_i and I_f, respectively) and the corresponding temperatures of a transmission line, the following equation gives a good estimation of the available time for given weather conditions [23]:

$$t_{avail} = \tau \times ln \frac{I_f - I_i}{I_f - I_c}, \tag{10}$$

where τ represents the thermal time constant, and I_c represents the critical current tolerable by the branch for a temporary emergency period so that any excessive damage or line sag and the consequential contact of it to the underneath vegetation is avoided. We will consider τ as equal to 15 minutes, which is the value for a step change of current in a Drake ACSR conductor from 800A to 1200A, in the emergency state [12], and I_c being equal to 105 % of the normal rating.

On the other hand, the required time equals the summation of three timing terms needed for diagnosis, implementation, and realization of the intended effect(s) after the implementation. More concretely, the operator takes a diagnosis time for interpretation of the post-contingency power flows in the power system to derive a corrective plan based on the diagnosed situation. Thereafter, he/she implements the planned action(s) by the end of the action time. The desired effect(s), finally, emerge(s) by the accomplishment time. Related time intervals and terms for the HRA-OPF framework are indicated in Fig. 2.

The required time varies for various corrective actions in the solution list of OPF problems for the restoration of post-contingency states. In this study, we assume that an average power system operator spends 15 minutes to complete both

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[1] In case the optimization problem is infeasible. In case it is infeasible, no action is taken.

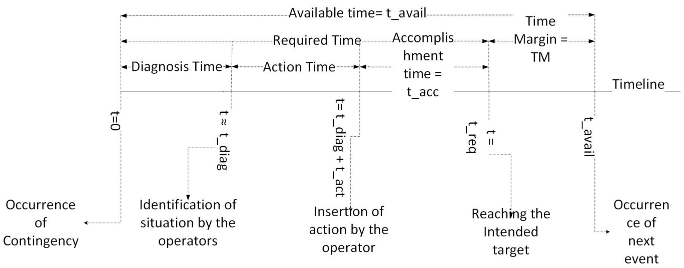

Fig. 2. Schematic for the timeline of HRA after each transition

the diagnosis and action phases. Furthermore, accomplishment time is calculated as the maximum time required by the requested generators in the dispatch list to reach the intended target after implementation. The time required to implement load-shedding is neglected in our study.

Since both required time and available time vary amongst the post-contingency scenarios, their ratio (TMR) and the resultant HEP vary, consequently. Per each post-contingency scenario, HRA-OPF estimates the corresponding TMR of each corrective post-contingency manual action in the solution space of a developed DC OPF problem. Related HEP is estimated based on the calculated TMR.

IV. NUMERICAL RESULTS

In this section, the methodology presented in Section III is implemented on two test systems: the NETS [24] and the IEEE three-area RTS [25]. Risk values are estimated for the cases with No, Perfect, and Imperfect MCAs. Sensitivity cases are also added with the base NHEP multiplied by either 50 or 1/50. The optimization problems are defined and solved using the *OPTIMPROB* package in *MATLAB R2023/b*, and the grid data are obtained from the data m-files of case studies in *MATPOWER* [26]. Table II represents the value of used parameters in the analysis.

TABLE II
MODEL PARAMETERS FOR THE BASE CASE ESTIMATION

Parameter	Value
$RR(MW/hr)$	$0.4 \times P_{Max}$
$I_c(\%)$	105
$C_g^+, C_g^-(\$/MWh)$	10
$VoLL(\$/MWh)$	100
$\lambda(1/(km.yr))$	0.0055

A. NETS

The individual and total values of risk estimated for the N-1 contingencies are given in Table III for three cases. All MCAs are obtained through the maximization of TMR. The total risk of the case with imperfect MCAs is less than that with the absence of manual grid operators. It keeps true for the risk of individual contingencies that have lower probabilities of operator failure ($PSF \leq 1$). In contrast, for those contingencies with shorter time margins and resultant higher failure probabilities of MCAs (i.e. $PSF \geq 10$), the imperfection of grid operators results in a significant relative increase in risk. Furthermore, considering the imperfection of manual grid operators modifies the order of the riskiest N-1 contingencies.

TABLE III
COMPARISON OF RISKS AMONGST N-1 CONTINGENCIES (**LS(%)/YEAR**)

Cont.	No Manual	Perfect Manual	Imperfect Manual
L4-14	12.68	0.00	0.05
L6-11	7.04	0.00	0.01
L10-11	3.52	0.00	0.01
L10-13	4.28	0.00	0.01
L13-14	10.08	0.00	32.12
L16-21	17.10	0.72	3.43
L21-22	23.14	1.56	53.69
L23-24	47.67	0.72	8.89
L26-27	0.00	0.38	0.12
TOTAL	125.51	3.37	98.32

Fig. 3 depicts the Complementary Cumulative Density Function (CCDF) of the percentage curtailed load. Triple curves for both cases of perfect and imperfect manual action are obtained by solving related OPF problems with three objectives: minimization of the cost, minimization of the number of actions, and, maximization of the time margin of corrective moves. Only a single curve is presented for the case with no manual action since the optimization objective does not affect the results.

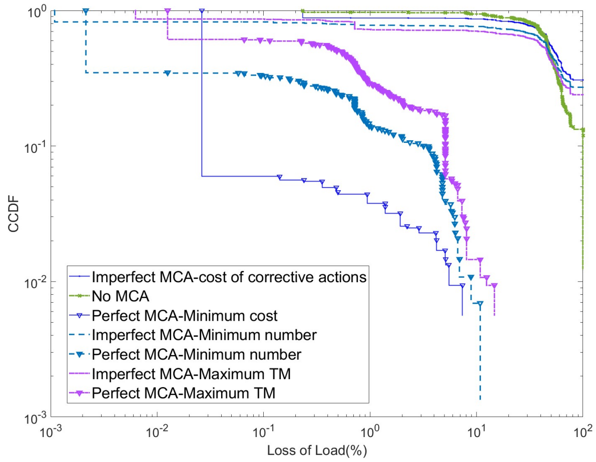

Fig. 3. CCDF of loss of power supply (NETS grid)

Optimization of cost or number of corrective moves instead of the TMR reduces the total risk if the MCAs are perfect. Such a decrease has been expected due to the avoidance of costlier moves in the solution list of the formers. However, the selection of corrective actions at a lower cost or a smaller number of moves increases the value of the total risk of cascades where imperfection is considered. The mentioned increase is meaningfully higher in the right tail of the curves with the bigger loss of loads. It highlights the need to compromise between minimization of the cost or number of actions, and HEP as the optimization objectives, where the failure probability of operators to perform the identified corrective actions is a determinant variable.

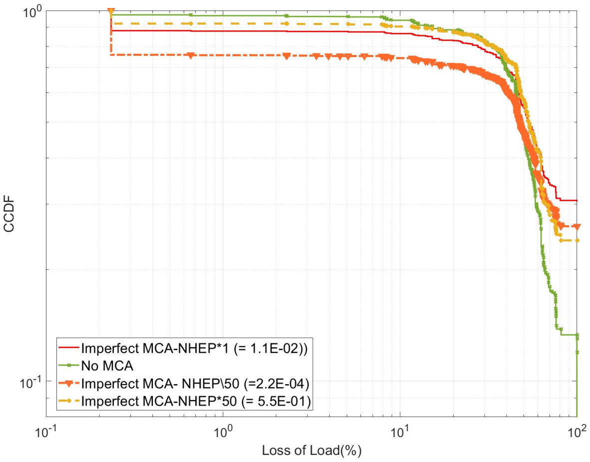

Fig. 4. CCDF of loss of power supply (NETS grid)

Comparison of the total risks of three cases of No, Perfect, and Imperfect MCA signifies the importance of taking the failure probability of MCAs into account in the evaluation of the risk of cascades, despite the objective. Neglecting such improperness culminates in a meaningful underestimation of the risk value. Nevertheless, for the smaller loss of loads, the risk value for the case with no MCAs is still higher than the imperfect manual one (left and central parts of Fig. 4). It shows that manual corrective actions by ordinary grade grid operators are on average more effective than no action at all. On the contrary, for those bigger cascade scenarios with the heavier loss of loads, the risk of imperfection in MCAs exceeds the risk in the absence of it (Fig. 4). It implies that for bigger-size cascades, MCAs must be avoided even though their decent reliability is guaranteed. In other words, If the grid operators choose to observe the cascading outage process instead of aggravating the situation by taking highly probable failure actions, fewer supplies will be lost. Bearing in mind that in large-size cascades, the post-contingency operating conditions may shorten the time margin and increase the failure probability of operators to one, which equals total operator absence. According to the CCDF of loss of power supply upon increase/decrease in the NHEP, any aggravation in the reliability of manual operators has an outstanding worsening effect on the risk of cascades with lighter loss of load. On the contrary, extra investment in improving the reliability of ordinary operators does not have a meaningful ameliorating effect on the CCDF.

B. Three-area RTS

CCDF of loss of supply for the cascade scenarios upon N-2 contingencies in IEEE three-area grid are sketched in Fig. 5. Unlike the NETS grid, risk due to the imperfection of MCA exceeds the risk in the absence of MCAs even for the small loss of loads. The reason behind that must be the insufficient time margin. Both initial grid status and contingency-related specifications can extend time margin by either lengthening the available time or shortening the required time (or both). To realize the former, the critical ratings of the branches or their thermal time constant might be increased, and to provide the latter, more agile power plants are required to expedite the implemented corrective re-dispatch.

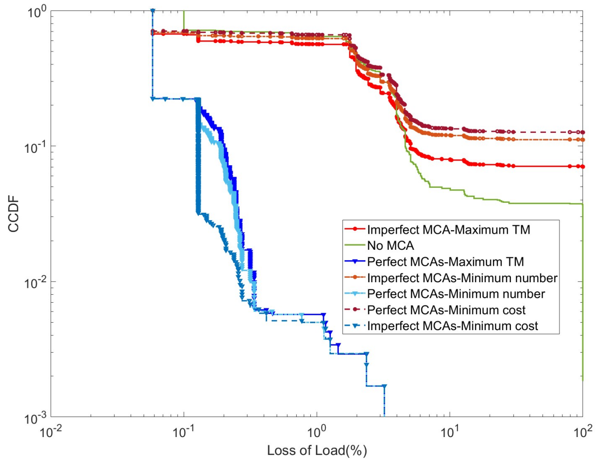

Fig. 5. CCDF of loss of power supply (three-area RTS)

Any improvement in the reliability of grid operators, which lowers the HEPs for MCAs, decreases the risk of cascading outages with a small loss of supply. The effect of decreasing HEPs on the risk of cascading outages with a higher loss of supply is not similar. Corrective actions in those areas may lead to a total blackout due to the voltage-related non-convergence of DC-OPF.

V. CONCLUSIONS

This paper attempts to consider the effect of the imperfection of MCAs in the estimation of the risk of cascading outages which is generally neglected in most related studies. For this, an HRA-OPF framework has been developed to evaluate the risk of cascading outages for three cases of No, Perfect, and, Imperfect MCAs. The proposed framework has been applied to two test systems, the NETS, and the IEEE three-area RTS. Results show that disregarding the imperfection of operators in the corrective actions leads to a significant underestimation of the risk of cascading outages.

Results on the NETS grid show that, for a smaller loss of load, the existence of even imperfect MCAs still lowers the risks of cascading outages in comparison to their absence. In this regard, benefiting from more skillful operators, and using supervisory policies to correct the probable initial errors in manual actions during the cascading outages with small loss of load will improve the reliability of MCAs. In addition, lengthening the available time and/or shortening the required time will extend the time margin. The former can be achieved by increasing the critical ratings of the branches or their thermal time constant, and the availability of more agile power plants to expedite the corrective re-dispatch can provide the latter. Such an ameliorating effect does not keep true for cascading outages with a higher loss of supply. In other words, the imperfection of MCAs exacerbates the cascading outages instead of mitigating them.

However, according to the results of the three-area RTS, the risk due to the imperfection of grid operators exceeds that in the absence of them, even for the cascading outages with a smaller loss of supply. The justification behind that can be the short time margins for the implementation of MCAs in cascading outages with a larger loss of power supply. Both initial grid parameters and contingency-related characteristics can affect the related TM. Furthermore, it sheds light on using DC-OPF as a limitation of the current study. It can lead to a voltage collapse after implementing some corrective actions which is not feasible if AC-OPF is used. This aspect must be included in further research to obtain more precise results by avoiding total blackouts upon such MCAs.

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