Long-Term Preventive Failure Mitigation Strategy For Transformers Based on Markov Method

Jianzheng Wang [1], Guoqiang Hu [2], and Sungin Cho [3]

[1,2] *Nanyang Technological University, 639798, Singapore*
wang1151@e.ntu.edu.sg
gqhu@ntu.edu.sg

[3] *SP Group, 349277, Singapore*
chosungin@spgroup.com.sg

Abstract

In this paper, we propose a preventive failure mitigation strategy in the power system based on Markov method. Specifically, we consider multiple units in the system, which are of different types and are managed by a single utility company. To characterize the operation, failure mitigation, and deterioration processes of the equipment, a continuous-time Markov model is formulated. By modelling the failure rate of equipment and the reinstallation rate after failures, the steady state of the proposed Markov model is analytically derived. Then to optimize the long-term net revenue of the utility company, the optimal failure mitigation rate is determined by considering the failure mitigation capacity for each equipment type as well as the overall failure mitigation capacity of the company. The performance of the proposed algorithms is demonstrated with three types of transformers in the simulation.

1. Introduction

Power systems can be vulnerable due to the failures of electrical equipment, e.g., transformers, switchgears, and cables, which can in turn lead to power loss, financial loss, and safety issues, etc. To improve the reliability of power systems, failure mitigation has been proven to be a successful solution and is widely implemented around the world. Among the existing failure mitigation strategies, there are two widely discussed topics: corrective failure mitigation and preventive failure mitigation. In the first scenario, the failure mitigation is carried out only when the failure really happens. However, when considering the high cost associated with the system damage, it can be undesirable in the modern society especially when there is a high requirement on the power quality. In contrast, preventive failure mitigation can be implemented before the equipment fails, which can be performed based on the lifetime of equipment, condition information, and criticality index, etc (Wu, Niknam, & Kobza, 2015; Tian & Liao, 2011; Yssaad, Khiat, & Chaker, 2014).

Existing research works on failure mitigation strategies usually consider some optimality criteria, where the objective function of the optimization problems can be long-term revenue, availability of equipment, and life cycle cost, etc. Meanwhile, compared with the optimization problems in single-unit systems (Srinivasan & Parlikad, 2014; Jiang, 2009; Y. Wang & Pham, 2011), we are more interested in multi-unit systems in the sense that the dependency among the units can be a crucial factor in making failure mitigation strategies especially when the system is large and the mitigation capacity of the utility company is limited (Van Oosterom, Peng, & van Houtum, 2017; Rasmekomen & Parlikad, 2013). Therefore, some existing failure mitigation strategies only applicable to single-unit systems may not be applied directly in multi-unit cases (Srinivasan & Parlikad, 2014).

To formulate failure mitigation optimization problems, Markov method is a powerful technique to model the transitions between different states (e.g., operation state, failure mitigation state, and failure state) of equipment. By analyzing the transition rates (e.g., failure rate, failure mitigation rate, and reinstallation rate after failures), it is promising to optimize certain criterion based on the steady state of the Markov model (Ge & Asgarpoor, 2012; Ge, 2010). In such cases, Markov model is usually discussed in long-term failure mitigation optimization problems since some periods of time are required to achieve the steady state. On the other hand, when considering some varying failure rates, the discussion on the failure mitigation optimization becomes more challenging since the steady state of Markov model may be difficult to obtain or even does not exist. Therefore, additional to the fixed failure rate discussed in (Ge & Asgarpoor, 2012; Ge, 2010), it is beneficial to explore how to address varying failure rates in Markov models if some approximated optimal solutions are allowed.

Based on the aforementioned discussions, detailed comparison with the existing research works is summarized as follows.

1. Different from (Zhong & Jin, 2014; R. Wang, 2016), this work takes some financial criteria into account, e.g., the revenue of operation, cost of failure mitigation, and cost of failure. In contrast to single- or double-unit models in (Srinivasan & Parlikad, 2014; Wu et al., 2015; Y. Wang & Pham, 2011; Jiang, 2009; Xiang, Cassady, & Pohl, 2012; Zhang, Fouladirad, & Barros, 2018; Taghipour & Azimpoor, 2018), the failure mitigation strategy with multiple units is discussed by considering the failure mitigation capacity limits of the utility company.
2. Compared with the Markov methods in (Srinivasan & Parlikad, 2014; Wu et al., 2015; Xiang et al., 2012), different equipment types are considered. To adapt to a wider range of practical problems, the failure mitigation strategy with varying failure rates is discussed, which can be viewed as an extension to the conventional Markov method with fixed failure rates (Ge & Asgarpoor, 2012; Ge, 2010; Zhong & Jin, 2014; Y. Wang & Pham, 2011; Van Oosterom et al., 2017), and approximated optimal solutions are provided.

The overall contribution of this paper is summarized as follows.

1. The optimal failure mitigation strategy for transformers with different types is discussed based on Markov method. Specifically, three types of transformers are discussed and three states (operation state, failure mitigation state, and failure state) are considered.
2. By analyzing the failure rate of the equipment, the steady state of the Markov model is analytically derived. Then the optimal failure mitigation strategy is obtained by optimizing the net revenue of the system with the failure mitigation capacity limits for each equipment type as well as the overall failure mitigation capacity limits. To be more practical, the Markov model with varying failure rates is also discussed, and approximated optimal strategy is provided.

2. System Modelling And Analysis

2.1. Markov model

In this work, we consider three states of the transformers, namely operation state, failure mitigation state, and failure state, which are explained as follows.

- At the operation state, the equipment is in an in-operation mode and works normally.
- At the failure mitigation state, the equipment is under preventive failure mitigation before it fails. After the failure mitigation, the equipment can be as good as new.
- At the failure state, the equipment is out-of-operation, and repair (or replacement depending on the specific requirement) is needed. After the repair (or replacement), the equipment can be as good as new.

Based on the above discussion, a continuous-time Markov diagram of equipment $i \in \mathcal{N}$ (i is the index of equipment, and $\mathcal{N} = \{1, 2, ..., N\}$ is the set of all equipment) is shown in Fig. 1. The practical meaning of the transition rates is given as follows.

- a_i^{12}: Failure mitigation rate.
- a_i^{21}: Reinstallation rate after failure mitigation.
- a_i^{13}: Failure rate.
- a_i^{31}: Reinstallation rate after the repair (or replacement) of failures.

In this model, the reinstallation rate after failure mitigation or repair/replacement can be obtained based on the practice of the utility company. In addition, the failure rate can be obtained by certain mature prediction technique if adequate data about the equipment is available.

Remark 1 *Note that for different equipment types, the Markov diagrams can be different. For example, it is possible that there is a transition from states 2 to 3 (i.e., failures occur during failure mitigation process). However, we do not consider such a diagram in this work since we didn't identify the transition from states 2 to 3 in the actual data (the failure data of transformers investigated in Singapore's power system).*

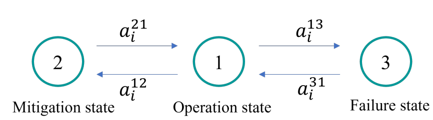

Figure 1. Markov diagram of equipment i.

Then, the steady state of the Markov model can be analytically derived by solving the following equations (P_i^1, P_i^2, and P_i^3 are the probabilities of staying at states 1, 2, and 3, respectively).

$$\begin{bmatrix} -a_i^{12} - a_i^{13} & a_i^{21} & a_i^{31} \\ a_i^{12} & -a_i^{21} & 0 \\ a_i^{13} & 0 & -a_i^{31} \end{bmatrix} \begin{bmatrix} P_i^1 \\ P_i^2 \\ P_i^3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \quad (1)$$

$$P_i^1 + P_i^2 + P_i^3 = 1, \quad (2)$$

which gives

$$P_i^1 = \frac{a_i^{21} a_i^{31}}{a_i^{13} a_i^{21} + a_i^{12} a_i^{31} + a_i^{21} a_i^{31}}, \quad (3)$$

$$P_i^2 = \frac{a_i^{12} a_i^{31}}{a_i^{13} a_i^{21} + a_i^{12} a_i^{31} + a_i^{21} a_i^{31}}, \quad (4)$$

$$P_i^3 = \frac{a_i^{13} a_i^{21}}{a_i^{13} a_i^{21} + a_i^{12} a_i^{31} + a_i^{21} a_i^{31}}. \quad (5)$$

2.2. Mitigation Capacity

We consider some constraints of the failure mitigation capacity of the utility company, which can characterize the maximum number of failure mitigations in progress during certain period of time. In particular, the constraint of the failure mitigation capacity for equipment i is given by

$$a_i^{12} \in [\underline{a}_i^{12}, \overline{a}_i^{12}], \quad \forall i \in \mathcal{N}. \quad (6)$$

In addition, we consider an overall failure mitigation capacity constraint of the utility company, which is

$$\sum_{i \in \mathcal{N}} a_i^{12} \in [\underline{a}, \overline{a}]. \quad (7)$$

Here, $\underline{a}_i^{12}$, $\overline{a}_i^{12}$, $\underline{a}$, and $\overline{a}$ are some constants.

3. Failure Mitigation Strategy Optimization With Fixed Failure Rates

In this section, we will optimize the failure mitigation strategy based on the steady state of Markov process with fixed failure rates. The objective function of the optimization problem can be formulated in different forms depending on the requirement of the utility company. Here, we are interested in the total net revenue harvested from all the equipment during certain time horizon. To this end, we investigate two failure mitigation modes: online mitigation and offline mitigation.

For online failure mitigation, we consider that the function of the system can still be maintained during the failure mitigation procedure without the interruption of power supply. In this case, objective function is defined as

$$R^{on} = \sum_{i \in \mathcal{N}} R_i^{on}, \quad (8)$$

where R_i^{on} is the revenue from equipment i:

$$R_i^{on} = A_i P_i^1 L + A_i P_i^2 L - B_i P_i^2 a_i^{12} L - C_i P_i^3 a_i^{31} L.$$

The parameters involved are explained as follows.

- Term $A_i P_i^1 L + A_i P_i^2 L$ represents the average revenue of operation harvested from equipment i over time horizon L. A_i is the revenue coefficient at operation and failure mitigation states (note that the system is normal at failure mitigation state in online mitigation mode). In practice, A_i can be obtained by considering the total revenue harvested from the system and the weighting factor of the contribution of equipment i. For example, for a total revenue A, if the weighting factor of equipment i is $w_i \in [0, 1]$, then $A_i = w_i A$.
- Term $B_i P_i^2 a_i^{12} L$ is the average failure mitigation cost over time horizon L. B_i is the cost coefficient of failure mitigation activity for equipment i, which includes all the related costs during the failure mitigation process, e.g., cost of consumable and transport charge.
- Term $C_i P_i^3 a_i^{31} L$ is the average failure cost over time horizon L. C_i is the cost coefficient of failure for equipment i, which can be defined based on all the effects caused by the failure. For example, for non-repairable equipment, C_i can include the unit price of equipment i, transport charge, and reputation loss, etc.

Alternatively, in the offline mitigation mode, the power supply is interrupted during the failure mitigation process, and therefore no revenue can be harvested from the equipment. In this case, the total net revenue function can be given by

$$R^{off} = \sum_{i \in \mathcal{N}} R_i^{off}, \quad (9)$$

where R_i^{off} is the revenue from equipment i:

$$R_i^{off} = A_i P_i^1 L - B_i P_i^2 a_i^{12} L - C_i P_i^3 a_i^{31} L.$$

Compared with online mitigation, the difference of offline mitigation is that the revenue during failure mitigation process $A_i P_i^2 L$ is not involved.

Then the online failure mitigation rate optimization problem can be formulated as follows.

$$\text{(P1)} \max_{a_i^{12}, \forall i \in \mathcal{N}} \quad R^{on} \quad \text{subject to} \quad (6), (7).$$

Similarly, the offline failure mitigation rate optimization problem can be formulated as follows.

$$\text{(P2)} \max_{a_i^{12}, \forall i \in \mathcal{N}} \quad R^{off} \quad \text{subject to} \quad (6), (7).$$

By solving the optimal failure mitigation rate a_i^{12}, the utility company can choose averagely $\sum_{i \in \mathcal{N}} a_i^{12} P_i^1$ units out of the in-operation units for the failure mitigation process.

4. Failure Mitigation Strategy Optimization With Varying Failure Rates

In practice, the failure rate may be varying due to the complicated degradation process of the equipment. In this case, the steady state of the conventional Markov model may not be obtained easily or even does not exist. However, it is possible to provide some approximated optimal strategies by following the analysis procedure in Section 3. In this work, we derive the steady state of the Markov model based on (3)-(5) by viewing the failure mitigation rate $a_{i,t}^{12}$ and failure rate $a_{i,t}^{13}$ as varying (in this work, the varying nature of parameters is reflected by time index $t \in \mathcal{T}$), which gives

$$P_{i,t}^1 = \frac{a_i^{21} a_i^{31}}{a_{i,t}^{13} a_i^{21} + a_{i,t}^{12} a_i^{31} + a_i^{21} a_i^{31}}, \quad (10)$$

$$P_{i,t}^2 = \frac{a_{i,t}^{12} a_i^{31}}{a_{i,t}^{13} a_i^{21} + a_{i,t}^{12} a_i^{31} + a_i^{21} a_i^{31}}, \quad (11)$$

$$P_{i,t}^3 = \frac{a_{i,t}^{13} a_i^{21}}{a_{i,t}^{13} a_i^{21} + a_{i,t}^{12} a_i^{31} + a_i^{21} a_i^{31}}. \quad (12)$$

Remark 2 *(10) to (12) can be viewed as the approximation of the steady state (if exist) of the Markov model with varying failure rates. The approximation error can be lower when the failure rate varies slowly compared with the failure mitigation/repair/replacement activities. As a consequence, the proposed failure mitigation strategies (as discussed later) can provide an approximated optimal solution to the varying Markov model.*

Then by following (8), the total net revenue in online mitigation mode can be given by

$$R_t^{on} = \sum_{i \in \mathcal{N}} R_{i,t}^{on},$$

where

$$R_{i,t}^{on} = A_i P_{i,t}^1 L + A_i P_{i,t}^2 L - B_i P_{i,t}^2 a_{i,t}^{12} L - C_i P_{i,t}^3 a_i^{31} L.$$

By following (9), the total net revenue in offline mitigation mode can be given by

$$R_t^{off} = \sum_{i \in \mathcal{N}} R_{i,t}^{off},$$

where

$$R_{i,t}^{off} = A_i P_{i,t}^1 L - B_i P_{i,t}^2 a_{i,t}^{12} L - C_i P_{i,t}^3 a_i^{31} L.$$

Similar to Section 3, the constraints of failure mitigation capacity are considered as

$$a_{i,t}^{12} \in [\underline{a}_i^{12}, \overline{a}_i^{12}], \quad \forall i \in \mathcal{N}, t \in \mathcal{T}, \quad (13)$$

$$\sum_{i \in \mathcal{N}} a_{i,t}^{12} \in [\underline{a}, \overline{a}], \quad \forall t \in \mathcal{T}. \quad (14)$$

Then, the failure mitigation rate optimization problems in online and offline mitigation modes can be given by

$$\text{(P3)} \max_{a_{i,t}^{12}, \forall i \in \mathcal{N}} \quad R_t^{on} \quad \text{subject to} \quad (13), (14),$$

and

$$\text{(P4)} \max_{a_{i,t}^{12}, \forall i \in \mathcal{N}} \quad R_t^{off} \quad \text{subject to} \quad (13), (14).$$

Table 1. Data of transformers

Equipment type	A	B	C
Failure rate	0.0008	0.0002	0.0005
Number of units	582	9315	8920

Table 2. Financial parameters of revenue functions (unit: S$)

Equipment type	A	B	C
Operation revenue	800	1000	500
Failure cost	1000000	250000	500000
Mitigation cost	5000	10000	500

5. SIMULATION

In this section, we will show the performance of the proposed failure mitigation strategies. In particular, we consider three types of transformers, whose data is set in Table 1. In practice, the failure rate of each equipment type can be obtained by modelling the failures based on certain distribution (e.g., Weibull distribution). Some financial parameters of revenue functions are set in Table 2. In addition, let $\underline{a}_i^{12} = 0.01$, $\overline{a}_i^{12} = 0.5$, and $a_i^{21} = a_i^{31} = 0.01, \forall i \in \mathcal{N}$.

5.1. Simulation With Fixed Failure Rates

To demonstrate the performance of the proposed failure mitigation strategy with fixed failure rates, we directly use the failure rates in Table 1 without any modification. In addition, to show the influence of the overall failure mitigation capacity of the utility company on the optimal failure mitigation rate, we let $\underline{a} = \sum_{i \in \mathcal{N}} \underline{a}_i^{12}$ and conduct the simulation with different $\overline{a}$.

The simulation result for online mitigation mode is shown in Figs. 2(a) to 2(c). In particular, the optimal failure mitigation rate with different overall mitigation capacities is given in Fig. 2(a). The probability of failure state with different overall mitigation capacities is given in Fig. 2(b). To determine the number of failure mitigation times (i.e., the number of units under failure mitigation) for each equipment type, one can first set a targeted failure number on the curve of "expected failure number" in Fig. 2(c). Then the number of failure mitigation times is determined by drawing a vertical line through the point of the targeted failure number and finding the intersections on the curves of "mitigation times". For example, to achieve an average 2.1 failures, the number of failure mitigation times of the three types of transformers are around 64, 61, and 58, respectively. That means one needs to choose around 64 Type A transformers randomly in the in-operation Type A transformers. The simulation result for offline mitigation mode is shown in Figs. 3(a) to 3(c), which can be understood in a similar way as the online mitigation counterpart.

5.2. Simulation With Varying Failure Rates

To show the performance of the proposed failure mitigation strategies in Section 4, the varying failure rate of different equipment types is designed as $a^{13}_{i,t+1} = a^{13}_{i,t} + \delta_i$, where

$$\delta_i = \begin{cases} 0.00005 \text{ if } i \text{ is an index of Type A transformers,} \\ 0.0001 \text{ if } i \text{ is an index of Type B transformers,} \\ 0.0002 \text{ if } i \text{ is an index of Type C transformers.} \end{cases}$$

For online mitigation strategy, the simulation result is shown in Figs. 4(a) to 4(c). Figs. 4(a) and 4(b) provide the optimal failure mitigation rate and the number of failure mitigation times in each year, respectively. To verify the benefit of varying failure mitigation rate, we simulate the total net revenue with a fixed failure mitigation rate during the next 50 years, which is chosen as the optimal mitigation rate in Year 1. Fig. 4(c) shows that the varying failure mitigation rate can produce more revenue than the fixed rate counterpart. The simulation result in offline mitigation mode is given in Figs. 5(a) to 5(c), which can be understood in a similar way as the online failure mitigation counterpart. The negative net revenue in some years is due to the high failure rates in those years.

6. Conclusion

In this paper, we discussed several optimization problems for failure mitigation strategies based on Markov method. Specifically, we optimized the total net revenue by considering the failure mitigation capacity of the utility company as well as different mitigation modes (i.e., online and offline mitigations). It shows that the optimal mitigation strategy can be settled by setting a targeted expected failure number. Then to adapt to a wider range of practical problems, the failure mitigation strategies with varying failure rates were also discussed.

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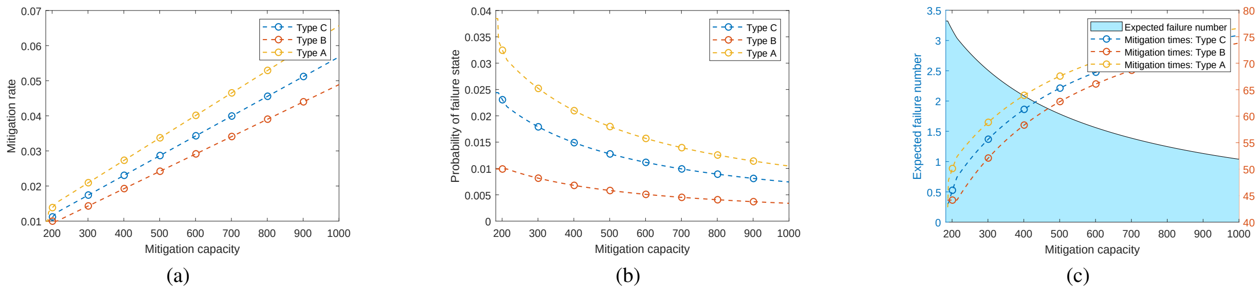

Figure 2. Simulation with fixed failure rates (online failure mitigation). (a) Optimal failure mitigation rate with different overall mitigation capacities. (b) Probability of failure state with different overall mitigation capacities. (c) Determination of optimal mitigation times based on expected failure numbers.

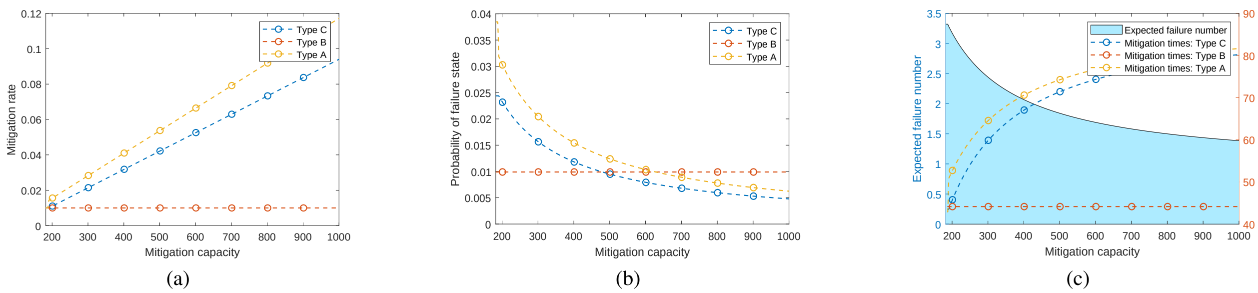

Figure 3. Simulation with fixed failure rates (offline failure mitigation). (a) Optimal failure mitigation rate with different overall mitigation capacities. (b) Probability of failure state with different overall mitigation capacities. (c) Determination of optimal mitigation times based on expected failure numbers.

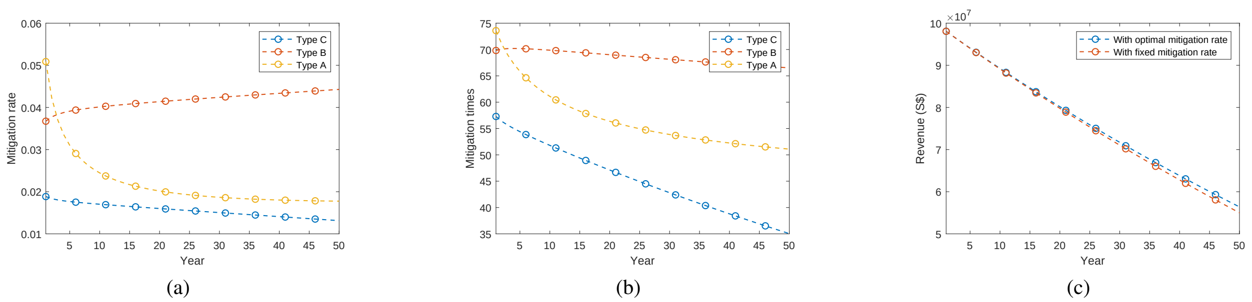

Figure 4. Simulation with varying failure rates (online failure mitigation). (a) Optimal failure mitigation rate in different years. (b) Number of failure mitigation times in different years. (c) Net revenues with and without varying failure mitigation rate.

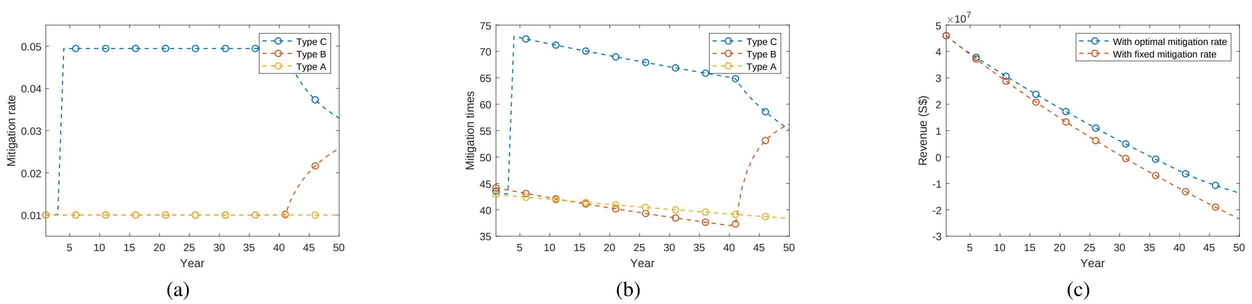

Figure 5. Simulation with varying failure rates (offline failure mitigation). (a) Optimal failure mitigation rate in different years. (b) Number of failure mitigation times in different years. (c) Net revenues with and without varying failure mitigation rate.