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Topical Review

Mission abort policies in reliability engineering: a review

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Abstract

A mission abort policy (MAP) establishes clear, non-ambiguous criteria that define specific system deterioration conditions for discontinuing a primary mission and initiating a rescue procedure (RP) to survive a valuable system performing the mission. A too-late mission abort can incur low system survivability while a too-early abort may unnecessarily compromise mission success probability (MSP). An optimal MAP should strike a balance between these two performance metrics. Therefore, the optimal design of MAPs plays a crucial role in managing the risk of system losses while ensuring a desired level of MSP for critical systems. This article presents a systematic review of MAP research in reliability engineering, classifying and reflecting on the recent intensive research devoted to the mathematical modeling, analysis and optimization of diverse types of MAPs for both single-attempt and multi-attempt mission systems. Potential directions for advancing the state of the art and the state of practice on MAPs are also outlined.

Keywords: expected mission losses, mission abort policy, mission success probability, multi-attempt, random shock, rescue procedure, system survivability

Acronyms

AI	Artificial intelligence
CAC	Common abort command
ECL	Expected cost of losses
HPP	Homogeneous Poisson process
IoT	Internet of things
MAP	Mission abort policy
MSP	Mission success probability
NHPP	Non-homogeneous Poisson process
PM	Primary mission
RP	Rescue procedure
SS	System survivability
UAV	Unmanned aerial vehicle

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1. Introduction

The research on mission abort can be dated back to 1960s mainly in the aerospace applications [1], where an abort is defined as 'the recognition that an intolerable situation exists and the performance of the activities necessary to terminate the mission and return the crew to earth' [2]. These early research focused on the attainment of the abort capability and planning. In 1974, the mathematical reliability model was put forward to study the impacts of mission abort on the reliability of a

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redundant flight computer system [3], where the mission is aborted when a predetermined number of computer failures have been detected. The studies in [3] revealed that a sound abort strategy should consider not only the number of failed components but also how near the mission is to the completion, laying a foundation for the design and mathematical modeling of diverse MAPs for modern engineering systems in various applications. Another noteworthy study focusing on the mathematical modeling is Myers's work in 2009, where an MAP based on the number of failed components was modeled for a k-out-of-n: G system and the probability of system loss was assessed [4].

As evidenced by nine articles [5–13] published in major reliability journals in 2018, the MAP research has recently received intensive attention from the reliability community. Conducted by several research groups, the MAP research has developed rapidly since 2018 and emerged as a significant topic across various applications (refer to the bibliometric analysis in [14]). For example, a smart healthcare system should revoke treatment and initiate an emergency RP if a threat to the patient's life develops [5]. A multi-engine aircraft may terminate its mission and perform a precautionary emergency landing at a nearby site in the event of a portion of the engines malfunctioning [8].

A too-early mission abort may unnecessarily compromise MSP while a too-late abort can incur low SS. Therefore, it is essential to design an optimal MAP that strikes a balance between these two performance metrics. Achieving such an optimal design requires accurate MAP modeling as well as efficient analysis of MSP and SS. In addition to capturing the complex nature of mission-performing systems, modeling MAPs is challenging because they often introduce extra state and decision parameters into the system mathematical model and further more state transition events that must be considered during the system analysis. This article provides an overview of the MAP developments, addressing these challenges. It covers the evolution of decision parameters for defining MAPs, optimization models and techniques, mathematical modeling and evaluation methods for objective functions (performance metrics), complex mission and system behaviors, and application fields. Some open and challenging issues are also discussed.

The rest of the paper is structured as follows: section 2 summarizes various decision parameters or variables as well as diverse types of MAPs defined using those parameters. Section 3 reviews and classifies optimization problems formulated in the MAP literature, different evaluation methods developed for assessing mission performance metrics or objective functions, and different optimization solution techniques. Section 4 classifies different types of systems studied in the MAP research. Section 5 depicts diverse applications where MAPs have been explored. Section 6 outlines several open research problems.

2. MAP decision parameters

An MAP establishes clear, non-ambiguous criteria for discontinuing a PM and initiating a RP to survive valuable assets. This is achieved through using certain decision parameter(s) whose values can reflect the system deterioration condition. During the mission execution, when the system degrades to a level as defined by the threshold values of decision parameters, the mission abort is triggered [15]. Throughout the years, different parameters have been utilized for defining MAPs as summarized in table 1.

Table 1. MAP decision parameters.

Type	Definition
A	Number of failed or damaged or forced-down components
B	Amount of accomplished or remaining mission work
C	System age or operation time elapsed from the beginning of the mission or an attempt
D	System degradation level
E	Duration of system defective state
F	Number of external shocks survived
G	Early-warning signal of fatal malfunction
H	Number of times entering an unbalanced state
I	System balance degree
J	System predictive reliability
K	Inter-shock interval
L	Number of standby components remaining available
M	Amount of product accumulated in the storage
N	Posterior probability of being in an unhealthy or warning state

Figure 1 showcases single-parameter and multi-parameter MAPs that have been examined in literature. Specifically, back in 1974, the MAP based on Type A parameter was modeled for a redundant flight computer system [3]. The study also suggested that a dual-parameter MAP integrating Type A and Type B or Type C (indicating how near the mission is to completion in mission work or time) would be more effective. In 2009, the Type A MAP was modeled in analyzing the probability of loss of a k-out-of-n: G system [4]. Then only in 2018, the mathematical modeling and optimization of MAP started to receive significant attention. To support future research, some representative research examining different types of MAPs since 2018 are reviewed chronologically in the following subsections.

2.1. MAPs in 2018

In 2018, the dual-parameter (Type A + Type B) MAP was modeled and optimized for a heterogeneous nonrepairable 1-out-of-n warm standby system without [8] and [9] with the consideration of component loading. The dual-parameter (Type A + Type C) MAP was addressed for a partially repairable heterogeneous system experiencing non-repairable major failures and repairable minor failures, where the abort is triggered when a pre-defined number of minor failures take place within a pre-defined time [11].

For systems operating in random environments, MAPs using Type F parameter have been studied. Specifically, the single-parameter Type F MAP was designed for systems subject to both internal failures and external shocks, where the

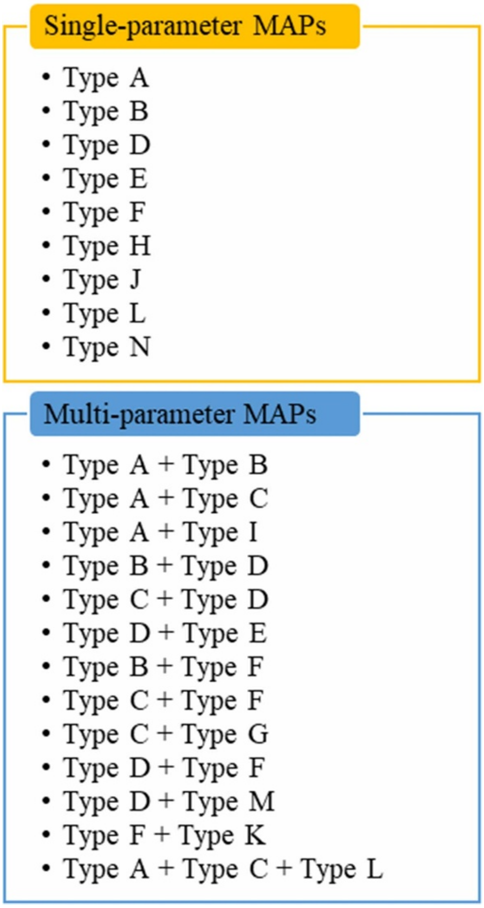

Figure 1. Different types of MAPs.

mission time is divided into adjacent intervals and each interval has a predetermined shock number threshold for triggering the mission abort [7]. The dual-parameter (Type C + Type F) MAP was designed for systems operating in random environment with the same [5] and variable [6, 10] shock processes during PM and RP. The dual-parameter (Type B + Type F) MAP was co-optimized with the routing policy for a team of cooperative UAVs [13].

2.2. MAPs in 2019

In 2019, the MAP research mainly focused on single-parameter policies. Specifically, the Type F MAP was modeled and optimized for a multi-attempt system performing a PM that requires certain time [16]. During each attempt, the abort is triggered when the number of shocks reaches an attempt-dependent and aggregated operation time-dependent threshold, where the Type C parameter was implicitly considered.

The Type A MAP was modeled for a heterogeneous nonrepairable 1-out-of-n warm standby system experiencing propagated failures [17], where the abort is triggered when the number of failed components reaches a threshold depending on the amount of remaining mission work (Type B parameter was implicitly considered).

The Type E MAP was studied for systems subject to a two-stage (normal and defective) degradation process [18]. In [19], two single-parameter MAPs (Type D, Type E) were investigated and compared for such degraded systems.

2.3. MAPs in 2020

In 2020, the Type F MAP was optimized for a series system with common subsystems used in both PM and RP phases during which different shock processes impact the component survivability [20]. The Type F MAP was also designed for a multi-state system operating under an NHPP of shocks [21, 22].

In [23], both fixed and attempt-dependent dual-parameter (Type C + Type F) MAPs were modeled for a homogeneous multi-component multi-attempt system operating under different shock environments during PM and RP. In [24], the component-dependent dual-parameter (Type C + Type F) MAP was co-optimized with the subtask distribution policy for a multi-component system performing a mission with multiple subtasks. In [25], the attempt-independent dual-parameter (Type C + Type F) MAP was studied for a multi-attempt system where successful attempts have cumulative effects on the MSP.

In [26], the dual-parameter (Type D + Type F) MAP was designed for a multi-state system operating under a renewal process of shocks.

In [27], the dual-parameter (Type A + Type C) MAP was addressed for a safety-critical system with self-healing and experiencing competing minor failures (repairable) and catastrophic failures, where the Type A parameter focuses on the minor failures.

In [28], the dual-parameter (Type G + Type C) MAP was examined for UAVs where the abort decision is made based on early-warning signals indicating possible forthcoming fatal malfunction (like over-vibration, overheat, abnormal position) and their acquisition time.

In [29], the dual-parameter (Type B + Type F) MAP was co-optimized with the routing and loading policies for a team of cooperative UAVs executing two types of tasks (visiting and transportation).

In [30], a three-parameter (Type A + Type C + Type L) MAP was optimized for a warm standby system considering the status of standby components in the mission abort decision.

2.4. MAPs in 2021

In 2021, both single-parameter and multi-parameter MAPs using Type F continued to receive significant attention for various types of systems operating in random environments. In [31], the attempt-dependent and aggregated operation time-dependent Type F MAP studied in [16] was further modeled for a multi-attempt system performing a PM that requires certain time and the part of mission task completed by previous attempts are additively saved. In [32], the attempt-dependent Type F MAP was optimized for a multistate multi-attempt system performing a mission under a renewal process of shocks by a certain deadline. In [33], the Type F MAP was explored for systems operating in a random shock environment, where two variants of Type F parameter were used including the cumulative number of valid shocks and the number of consecutive valid shocks. In [34], the dual-parameter (Type D + Type F) MAP was examined for inspected multistate systems operating in random environment modeled by a renewal process of shocks. In [35], the dual parameter (Type D + Type F) MAP was also investigated for a heterogenous multi-component system where the abort is triggered when a specified number of shocks takes place or when the system degradation state does not allow continuing the PM execution but allow performing the RP. In [36], the dual-parameter (Type B + Type F) partial and dynamic MAP was investigated for a homogeneous multi-component work-sharing system operating under a renewal process of shocks. Based on the amount of the PM work and the amount of the damage reduction procedure (DPR) work completed, the policy determines the distribution of the remaining available components to performing the PM and the DRP after each shock. In [37], the dual-parameter (Type B + Type F) MAP was jointly optimized with the routing and hitting policies for UAVs executing a target hitting mission. In [38], the attempt-dependent dual-parameter (Type C + Type F) MAP was optimized for a multi-attempt multi-component system where each component may independently complete the mission and re-attempt the mission if being saved during the RP activated the aborted attempt.

In addition to the above mentioned Type F-based MAPs, the Type A MAP was examined for a homogeneous k-out-of-n: F balanced system performing a PM of certain period of time and experiencing both internal component failures and external shocks in [39]. In [40], the Type B MAP was co-optimized with the replacement and maintenance schedule for a dual-unit standby system, where the abort is triggered in the case of one unit failing and the amount of work completed before the unit failure not exceeding a threshold value. In [41], an attempt-dependent Type D MAP was examined for a multi-attempt time-redundant system subject to degradation modelled by Gamma processes. In [42], the Type L MAP was co-optimized with the component switching policy for a multistate 1-out-of-n warm standby system.

Several dual-parameter MAPs were also explored. In [43], an MAP based on two competing criteria of Type A and Type I was studied, where the system balance degree is defined as the maximum state distance among all components and the system is balanced if the balance degree is no greater than a predetermined threshold. In [44], the dual-parameter (Type D + Type E) MAP was optimized for systems subject to a two-stage degradation process with normal and defective stages. In [45], the dual-parameter (Type C + Type D) MAP was optimized for systems subject to continuous degradation and inspections. In [46], the dual-parameter (Type A + Type B) MAP was optimized for a homogeneous multi-component work-sharing system that must perform a specified amount of work during the PM. In [47], this dual-parameter MAP was extended to be a partial policy, that determines the number of components that should continue the PM whereas the rest of the operating units should abort the PM and start the RP when the triggering condition is met.

2.5. MAPs in 2022

In 2022, the single-parameter MAPs optimized include the Type D MAP for a heterogeneous multi-component multi-state systems with different system configurations during PM and RP [48] and the Type E MAP for a system subject to a two-stage degradation process progressing from the normal state to a defective state then to the failure state [49]. In addition, the Type A, Type D, or Type J MAP was co-optimized with other policies. Particularly, the attempt-dependent Type A MAP was co-optimized with the component allocation policy for a multi-attempt k-out-of-n cold standby system under an HPP of shocks [50]. In [51], the type D MAP was co-optimized with the protective device selection policy for a multi-state system under an HPP process of shocks. In [52], the Type J MAP was co-optimized with the inspection policy for a system subject to a Gamma process of degradation.

The dual-parameter MAPs studied include the Type C + Type D MAP for a mission-critical system that executes a continuous mission within a constant period [53] and the Type B + Type F MAP for a truck-UAV collaborative system [54]. In addition, a dual-parameter (Type D + Type M) MAP was optimized in [55] for a unrepairable multistate system with product storage, where the abort is triggered when the production system reaches a certain degradation state and the amount of product accumulated in the storage is below a predefined threshold. In [56], an attempt-dependent dual-parameter (Type C + Type F) MAP was optimized for a multi-attempt system where components are divided into two groups (kamikaze and non-kamikaze) obeying different MAPs depending on the total number of components participating in each attempt.

2.6. MAPs in 2023

In 2023, the single-parameter MAPs optimized include a Type A MAP studied for a k-out-of-n: F balanced system allowing to resume forced-down components to achieve balance [57] and for a multi-component multi-state system operating in a random shock environment [58], and a multi-threshold Type F MAP for systems subject to random rescue time where different time intervals during the mission may have different thresholds for the number of experienced shocks triggering the mission abort [59]. In [60], a Type N MAP was co-optimized with the inspection policy for a safety-critical system performing a mission of fixed duration and subject to degradations modeled by a continuous time Markov process. In [61], an attempt-dependent Type A MAP was co-modeled with the maintenance policy for a multi-attempt UAV mission system operating under a shock environment modeled by a renewal process.

The dual-parameter MAPs studied include a Type C + Type D MAP for a swarm system with multiple units that cooperatively perform tasks to achieve an overall mission objective [62] and several co-optimized with other policies. Specifically, a task-dependent dual-parameter (Type C + Type F) MAP was co-designed with the task execution sequence for a multi-task multi-attempt system with each task being executed under a different environment [63]. The dual-parameter (Type

C + Type F) MAP was also co-optimized with the component activation delay for a multi-component multi-attempt system where multiple components may be activated consecutively with a fixed delay to attempt the same mission task [64]. Two dual-parameter MAPs (Type A + Type B, Type A + Type C) were co-optimized with the system structure for a l-out-of-n: G warm standby system executing dynamic tasks [65]. The dual parameter (Type B + Type D) MAP was co-optimized with the loading policy for systems subject to degradations modeled by a Gamma process [66].

2.7. MAPs in 2024 and beyond

The MAP research has continued to grow in 2024 for both single-parameter and multi-parameter policies. Among the single-parameter MAPs, the Type A MAP was co-optimized with the task allocation policy for a k-out-of-n: F multi-state system with identical components in [67]. In [68], two Type A MAPs were optimized for a generalized k-out-of-n: F system, where the abort is triggered when the number of consecutive failed components reaches a predetermined value or the total number of failed components exceeds a predetermined value. In [69], the Type D MAP was co-designed with the sampling policy for a partially observable safety-critical system, where the underlying system health state can only be revealed by sampling. In [70], the Type D MAP was modeled for a system that degrades due to random shocks, whose degradation level as well as the number of experienced shocks are revealed by condition monitoring. In [71], the Type D MAP was modeled for the reliability analysis of a deep-water human-occupied scientific submersible. In [72], the Type H MAP was first modeled for assessing the MSP and SS of a balanced system with two subsystems, where the system balance is achieved when the state distance between the two subsystems is below a specified threshold. In [73], the Type J MAP was co-designed with the inspection policy for a multi-component system with failure interactions, where the abort is triggered when the system predictive reliability updated based on the system degradation and age information is below a threshold.

Among the dual-parameter MAPs, the dual parameter MAP (Type C + Type F) has been mainly examined for different types of multi-attempt systems, except that in [74] this MAP was co-optimized with the performance policy for a single-attempt mission with constrained system resource. For multi-attempt systems, the dual parameter MAP (Type C + Type F) may be the same or different for different attempts. In [75], an attempt-independent dual parameter MAP (Type C + Type F) was co-optimized with the issue policy of a CAC and the component activation policy for a system performing missions with multiple consecutive attempts executed by identical components activated one by one with a fixed time interval. In [76], the joint optimization problem of [75] was extended by considering dissimilar intervals and CAC dependent on the cumulative effect of attempts. In [77], the component/attempt-dependent dual-parameter (Type C + Type F) MAP was co-designed with the component activation policy for a heterogenous multi-component, multi-attempt system where multiple attempts performed by different components may be activated according to a pre-defined schedule that allows overlaps, and the CAC is issued upon the mission completion by any attempt/component. In [78], an attempt-dependent dual parameter MAP (Type C + Type F) was co-optimized with the loading policy for a multi-attempt system that must accomplish a specified amount of work within a certain number of sequentially executed attempts in random shock environment modeled by an HPP. In [79], the attempt-dependent dual-parameter (Type C + Type F) MAP was co-designed with the rescue option choice for a multi-attempt mission system with different types of RPs characterized by dissimilar system performance, shock rates, and costs. In [80], the task-dependent dual-parameter (Type C + Type F) MAP was co-optimized with the task execution sequencing policy for a time constrained multi-task multi-attempt mission system, where each task may be attempted multiple times.

For systems operating in random shock environment, MAPs using Type F parameter are popular, which presume the PM abort when a predefined number of shocks take place during a certain time interval since the beginning of the mission or attempt. Research on single and multi-parameter MAPs based on Type F has been supported by rich efforts from the reliability community since 2018, as discussed above in this subsection and in the previous subsections. However, those MAPs become ineffective when the shock rate is uncertain as they cannot adapt themselves to the changing shock rates. In 2024, a self-adaptive MAP based on Type K (i.e. inter-shock interval) and Type F was modeled for systems operating in uncertain random shock environment [81]. This dual-parameter MAP determines the inter-shock interval within which the PM should be aborted upon the next shock based on the previous inter-shock interval, which outperforms the shock number-based MAPs in MSP, as shown by the empirical study in [81].

Other dual-parameter MAPs include the Type B + Type D MAP that was co-optimized with the loading and rescue site selection policies for a k-out-of-n: F system [82], and the Type C + Type D MAP for systems with adaptive performance control [83], and for multi-component transportation systems with dependence between components [84].

2.8. Summary

Figure 2 shows the evolution of different types of MAPs investigated since 2018 when MAP research started to gain significant attention from the reliability community. Both single-parameter and multi-parameter MAPs have gained intensive attentions and MAPs based on parameter A, B, C, D, or F have been more commonly investigated than MAPs based on other decision parameters.

It is also worth noting that while the existing shock-based models mostly assumed that each system component experiences independent shocks, in recent work [85] common shocks simultaneously affecting all operating components were considered for a homogeneous multi-component

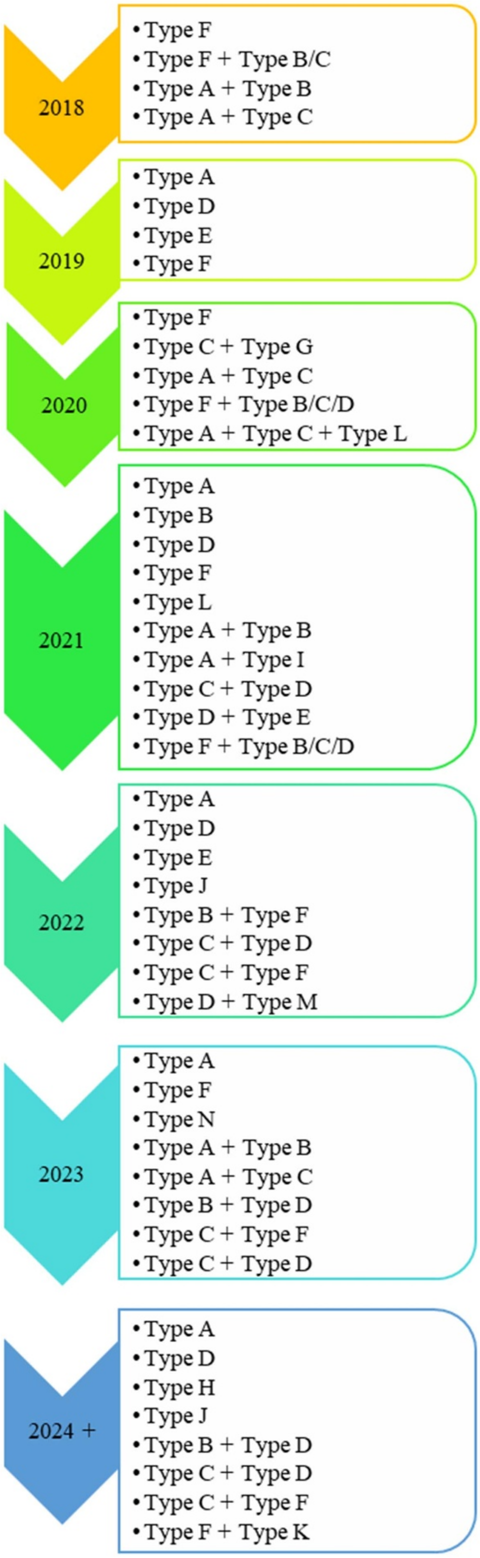

Figure 2. Evolution of MAPs.

system with CAC being issued upon mission completion by any attempt/component. Considering common shocks is a new direction in designing various MAPs for different types of multi-component systems.

3. Optimization models and solution techniques

MAP research has been driven by systems that are valuable, implying that their survival could be equally important or even have a higher priority than achieving mission success. Therefore, the MAP optimization problems are mainly concerned with MSP and SS and achieving a balance between these two performance metrics. As the MAP research develops, different forms of optimization models have been formulated and solved. This section summarizes these models, different methods for evaluating performance metrics used in the objective functions, and different techniques used for solving the MAP optimization problems.

3.1. Optimization models

The MAP optimization models encompass unconstrained and constrained problems. With the exception of the case in [32] where an unconstrained optimization problem was formulated to maximize MSP, all other unconstrained models aim to minimize the ECL, achieving a balance between MSP and SS using the following cost models:

(1) Cost associated with system losses, component losses and mission failures [5, 6, 18, 19, 22–24, 26–28, 30, 33, 39, 41–44, 49–53, 56–58, 60, 63–65, 68, 75–78, 80].
(2) Cost associated with system destructions/losses and uncompleted mission works [10, 13, 29, 36, 37, 46, 47, 54].
(3) Cost caused by system and component losses, mission failures, and inspections [34, 70, 73] or sampling [69].
(4) Cost caused by system losses, mission failures, and rescue cost [79].

While some models cover costs related to activities like inspection and rescue, all the cost models encompass costs incurred by system losses and mission failures so the MSP and SS can be balanced when the expected total cost is minimized.

The constrained optimization models can be classified based on three objectives: maximizing MSP, maximizing SS, and minimizing expected cost. The constraints used in the three types of models are summarized below.

(1) Maximize MSP *subject to* a desired level of
- SS [5, 6, 8, 9, 11, 17, 20–22, 26, 33, 35, 39, 40, 43, 48, 57, 59, 74]
- SS and expected total cost [61]
- system loss probability [16, 25, 31]
- expected number of lost units [38]
- damage avoidance probability [55].

(2) Maximize SS *subject to* a desired level of
- MSP and expected total cost [61]
- expected total cost [82].

(3) Minimize expected cost *subject to* a desired level of
- MSP and SS [61]
- SS [82].

There are also joint optimization models where different types of MAPs are co-designed with other policies that affect MSP, SS and/or ECL, including but not limited to

- Standby component activation sequencing policy [8, 17]
- Routing policy [13]
- Routing and loading policies [29]
- Component loading policy [9, 66, 78]
- Component switching policy [42]
- Task distribution policy [24, 67]
- Replacement and maintenance scheduling policy [40, 61]
- Component allocation policy [50]
- Protective device selection policy [51]
- Inspection policy [52, 60, 73]
- Task execution sequencing policy [63, 80]
- Component activation policy [64, 77]
- CAC issue and component activation policies [75, 76]
- System structure [65]
- Sampling policy [69]
- Component performance policy [74]
- Rescue option choice [79]
- Loading and rescue site selection policies [82].

3.2. Performance metrics evaluation methods

As discussed in section 3.1, the objective functions of MAP optimization models involve three major performance metrics: MSP, SS, ECL, and the ECL is assessed based on MSP and SS. The following methods have been developed for evaluating those metrics in the MAP literature.

- Markov process-based methods [21, 22, 26, 33, 39, 42, 43, 51, 57, 58, 66–69, 72].
- Probabilistic modeling approaches [5, 6, 10, 11, 16, 19, 20, 23–25, 27, 28, 31, 32, 38, 40, 44, 45, 48, 52, 56, 59, 73, 74, 81].
- Simulations [18, 29, 41, 65, 84].
- Probabilistic model-based numerical algorithms [8, 9, 17, 30, 34–36, 46, 47, 50, 55, 61, 63, 64, 75–80, 82].

Interested readers may refer to the corresponding references for details of those evaluation methods.

3.3. Optimization solution methods

The solution to the MAP optimization models aims to determine the optimal threshold values of the involved decision variables, maximizing or minimizing the objective functions. The methods implemented for solving the MAP optimization problems include, for example,

- The brute force or exhaustive search method for decision variables with small or limited ranges of values [8, 32, 35, 43, 59, 61, 66, 67, 74, 76].
- Mixed technique integrating the brute force on one variable (e.g. Type F [6, 10], Type A [11]) and the golden section search algorithm [86] on the other variable (Type C).
- Tabu search [13, 29, 37].
- Genetic algorithm [9, 16, 23, 24, 30, 31, 34, 36, 40, 41, 46–48, 55, 56, 63, 77–80].
- Stochastic dynamic programming [27, 49].
- Markov decision process solved using deep reinforcement learning [45, 60, 62, 69, 70, 83, 84].
- Adaptive large neighborhood search [54].

4. Mission and system types

Mathematical modeling and optimization of MAPs have been conducted for single-attempt and multi-attempt mission systems [87]. A mission attempt refers to any initiated effort to carry out the PM task, during which the system or a system component begins its operation with the intention of accomplishing a predefined objective, but may be aborted or terminated before achieving the objective. Diverse structure and function characteristics have been addressed for systems performing single-attempt or multi-attempt missions, as discussed in the following subsections.

4.1. Single-attempt systems

Considering operating environment, MAPs have been modeled for systems performing single-attempt missions under non-shock (e.g. [4, 8, 9],) and random shock environments (e.g. [5, 6, 10, 81],). In a non-shock environment, internal failures are considered for modeling MSP and SS while in a shock environment both internal failures and external shocks may cause the deterioration and failure of the system. Internal failures or degradations are typically modeled by time-to-failure distributions (exponential [4, 39] or arbitrary [8, 9, 17, 30]) or stochastic processes like Gamma [19, 45, 52, 66] and Markov [60, 67]. Stochastical processes used for modeling random shock environments include the HPP [6, 10, 35, 39, 74, 81, 82], NHPP [5, 21], and renewal process [22, 26, 34]. Some works assume the same random environment during PM and RP [5] while others assume different shock processes during these two phases [6, 10].

Considering system complexity, single-component [6, 10, 18, 19, 44, 49] and multi-component [4, 8, 9, 17, 30] systems have been modeled for designing MAPs. Depending on whether system components are stochastically identical or not, homogeneous [4, 36, 42, 43, 46, 47, 67, 68] and heterogenous [8, 9, 11, 17, 30, 35, 40, 48] multi-component systems are differentiated. Depending on the system configuration, multi-component systems structured in the series [20], parallel with work sharing [36, 46, 47], and standby sparing using the hot [4] or warm [8, 9, 17, 30, 42, 65] mode have been investigated. Several works on multi-component systems also consider the balance feature, where the system is balanced if the state distance among all components [43] or subsystems [72] is below a pre-specified threshold or for systems with multiple k-out-of-n: F sectors/subsystems, if the number of working components in any sector is the same [39, 57]. In addition, MAPs were optimized for heterogeneous systems with arbitrary structure, including, for example, the sliding window system and the linear consecutively connected system [35].

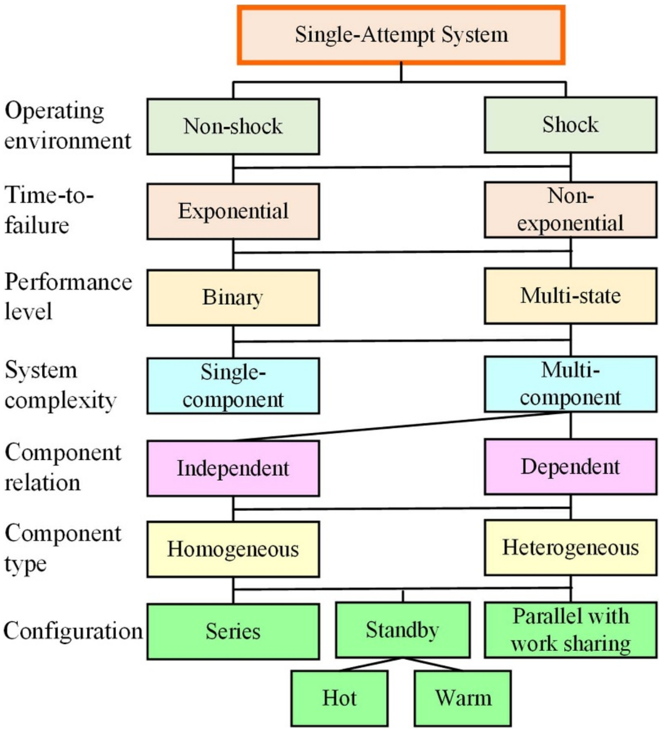

Figure 3. Different types of single-attempt systems.

Depending on the number of states or performance levels, MAPs have been designed for binary [4, 8, 9, 17, 30, 39] and multi-state [21, 22, 26, 34, 42, 43, 48, 51, 55, 67, 82] systems. Other features like loading [9], propagated failures [17], self-healing [27], inspections [34, 66], storage function [55], dynamic task [65], failure interactions [73] have also been addressed for the design of single-attempt MAPs.

Figure 3 summarizes the main types of single-attempt systems studied in MAP research, which are classified according to operating environment, time-to-failure distributions, the number of states or performance levels, system complexity, and several component complexity factors for multi-component systems.

4.2. Multi-attempt systems

In real-world settings where accomplishing a mission is important and the cost-related and time-wise restrictions are not severe, a mission may be reattempted to enhance the MSP. Multiple attempts may be carried out sequentially by the same component/system after being properly maintained in or after a successful RP [16, 31, 32, 41, 61, 78–80]. In the case of sufficient resources (operating components) available, multiple attempts may be carried out by different components concurrently [23, 56, 88] or consecutively (one by one) with prespecified activation delays [64, 75–77], which may be constant [64] or dissimilar [76, 77]. Thus, depending on the execution mode of multiple attempts, sequential, concurrent and consecutive multi-attempt systems may be differentiated. Under the consecutive mode, MAPs have been co-designed with a CAC, which may be issued upon a successful attempt [64, 77], when any component is close enough to completing the mission [75], or when a certain number of components complete the operation phase successfully [76].

Depending on whether the work completed in different attempts can be counted or not, additive (considering partial [50] or no [16, 31, 78] losses), cumulative [25, 38, 76], and non-cumulative [32] multi-attempt systems have been studied. While being additive means that the part of mission task accomplished in earlier attempts can be saved additively to be counted towards the mission goal of accomplishing a specified total amount of work, being cumulative is more general meaning that the probability of achieving a mission goal is a function of the number of successfully completed attempts.

Similar to single-attempt systems, MAPs have been modeled for multi-attempt systems operating in non-shock [41] and random shock environments [16, 23, 32, 50, 76, 78, 79] though majority of them considered effects of external shocks. Depending on the number of states or performance levels, multi-attempt MAPs have also been designed for binary [64, 75, 76] and multi-state [32] systems. Depending on the type of the system components, homogeneous [23, 38] and heterogenous [24, 77] multi-component systems have been considered in multi-attempt MAP research. Depending on the system configuration, multiple components may work in parallel [24, 38, 56] or standby sparing using the cold mode [50].

Both attempt-independent and attempt-dependent MAPs have been explored. For example, for sequential multi-attempt systems, the same MAP is adopted in [16, 32] while different MAPs are adopted in [31].

While most of MAP research focused on single-task missions, several recent works modeled multi-task missions [24, 63, 80]. Particularly, in [63, 80], MAPs were optimized for systems performing multiple tasks according to a predefined sequence and each task may be attempted multiple times sequentially. In [24], different tasks can be executed by different subsets of operating units in parallel. In addition, the single-rescue option modeled in most of MAP research has recently been extended to multiple rescue options that may be chosen based on the amount of work accomplished before the abort [79].

Figure 4 summarizes the main types of multi-attempt systems studied in MAP research, which are classified according to operating environment, system configuration, the number of states or performance levels, the dependence of MAPs on attempts, task and system complexity, as well as component types and execution modes.

5. Applications

As revealed in [14], the largest field of applications where MAP research has been explored is diverse engineering systems with UAVs being the most frequently studied type [89]. The following summarizes the various applications used in MAP case studies. Figure 5 showcases the major application areas of MAP research.

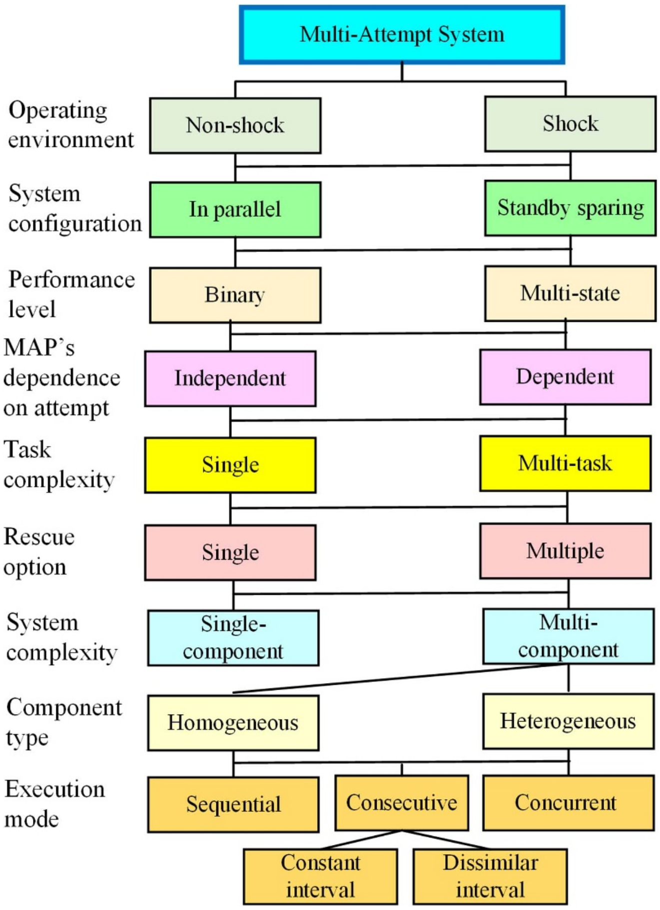

Figure 4. Different types of multi-attempt systems.

- Aircraft [33]
- Hydraulic system of helicopter [51]
- Single UAV
    - target destruction [25]
    - surveillance [5, 6, 10, 16, 20, 21, 43, 59, 63, 72, 80]
    - payload delivery [78, 79, 81, 82]
    - photographing [31]
    - power-grid inspection [28, 44, 53, 70, 83]
    - reconnaissance [58, 74]
- A team of UAVs
    - visiting and transportation [29]
    - surveillance mission [23, 24, 56]
    - target visit [13, 37]
    - target destruction [38, 76]
    - reconnaissance [64, 75]
- Truck-UAV combined system [54]
- Autonomous underwater vehicle [50]
- Chemical reactor [9, 11, 17, 18, 27, 30, 40, 41, 45, 46, 52, 69]
- Multiprocessor system [8, 36, 47, 65]
- Cloud computing system [34, 42]
- Distributed computer system [67]
- Online data processing system [22, 26, 32, 77]
- Wireless sensor network [35]
- Electric heating system [35, 48].
- Power generating system [55]

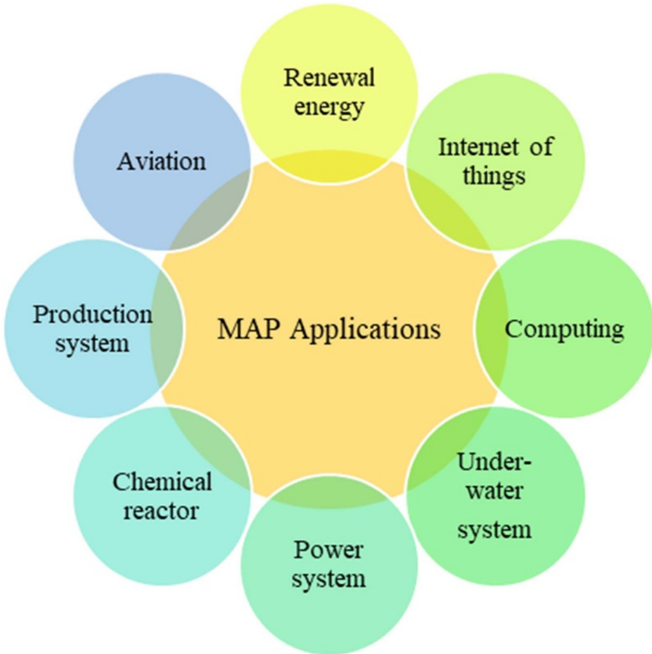

Figure 5. Major application areas of MAP research.

- Autonomous marine systems [90]
- Deep-water human-occupied submersible [71]
- Subsea oil production system [66]
- Offshore wind turbines [73]
- Solar lighting system [68].

6. Open problems

The overview and classification of representative MAP research in this paper aim to offer insights for managing system and mission failure risks of safety-critical systems. It is also hoped to stimulate more researchers and practitioners to explore and contribute to MAP research, addressing new challenges that may arise from increasing complexity and scale of modern technological systems, especially those integrating IoT [15, 91] and AI technologies [92, 93]. For example, new mathematical MAP models are needed for systems performing multi-phase PM and/or multi-phase RP where decisions about mission task and/or RP task reduction should be optimized.

Moving forward, MAP research could also be advanced in the following directions, both in theory and in application.

(1) AI-enabled MAPs: Several current works like [62] and [84] made efforts to use AI techniques like deep reinforcement learning to solve the formulated MAP optimization problems. AI-guided MAPs could be explored to improve the effectiveness in balancing MSP and SS.

(2) Real-time adaptive MAPs: Related to the first direction, with advancements in both AI and IoT technologies, there is significant potential to develop real-time MAPs that can adapt to changes in system conditions and configurations over time, enabling on-the-fly MAP design. It is crucial to

develop an online learning and adaptive AI system that can continuously learn from new data and dynamically adjust MAP decision parameters based on changing system states and real-time feedback.

(3) Cascading failure mitigation: Due to interactions and dependencies between various IoT devices, cascading failures become a major threat to IoT systems [94]. In particular, when one device fails, a cascade of undesired state changes of other IoT devices may be triggered due to the dependencies, introducing or accelerating catastrophic cascading failures. MAPs may be explored as a during-hazard in-process mitigation technique to stop the spread of cascading faults, preventing extensive damages. As cascading failures often evolve quickly, it is crucial to detect them early and in real-time. Techniques like machine learning and predictive analytics could be leveraged to spot early signs of cascading failures.

(4) Incorporating uncertainty: Recent work [81] made attempts to address uncertain shock environments. Such efforts should continue to capture other uncertainties encountered in real-world systems likes those related to component time-to-failure parameters or degradation processes, shock resistance capabilities, system configurations, and abort decision parameters. These uncertainties in the MAP models introduce additional challenges in MAP implementation, particularly in reliable fault detection and prediction, as well as robust and adaptive decision making.

(5) Bridging theory and practice: Despite the rich research efforts devoted to mathematical modeling and designs of MAPs, their impacts beyond academia are still unclear. Implementing MAPs in real systems through, for example, developing accessible and autonomous MAP embedded software could be pursued to bridge the gap between MAP theory and practice. Challenges such as fast and accurate fault detection, real-time autonomous decision-making under uncertainty, and the seamless integration of MAP-related hardware and software with the core mission-performing system must be effectively addressed. Additionally, maintaining compliance with industry-specific safety and regulatory standards is crucial for implementing MAPs across different sectors.

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