Mathematical modelling of mission-abort policies: a review

Augusto José da Silva Rodrigues
Department of Production Engineering, Federal University of Pernambuco, Recife, Brazil.
E-mail address: a.j.s.rodrigues@random.org.br

Cristiano Alexandre Virgínio Cavalcante*
Department of Production Engineering, Federal University of Pernambuco, Recife, Brazil.
E-mail address: c.a.v.cavalcante@random.org.br

Alexandre Ramalho Alberti
Department of Production Engineering, Federal University of Pernambuco, Recife, Brazil.
E-mail address: a.r.alberti@random.org.br

Phil Scarf
Cardiff Business School, Cardiff University, Cardiff, Wales, UK
E-mail address: scarfp@cardiff.ac.uk

Naif Mohammed Alotaibi
Department of Mathematics and Statistics, Imam Mohammad Ibn Saud Islamic University, Riyadh, Kingdom of Saudi Arabia.
Email address: nmaalotaibi@imamu.edu.sa

**corresponding author*

Abstract: This paper reviews works that consider the mathematical modelling of mission-abort policies. In a mission-abort policy (MAP), a valuable, and perhaps vulnerable system performs a mission with two, sometimes conflicting objectives, mission success and system survival, and the purpose of modelling is to determine conditions under which a mission should be aborted. Such problems are important in defence, and emerging in transportation and health management. We classify models by: the nature of the mission and the system; the nature of the return or rescue; type of deterioration model; and the decision objectives. We show that the majority of works consider a model of a one system, one target mission in which the mission is aborted once the hazard of failure reaches a critical level and the operating environment is the same for the outbound and inbound parts of the mission. Typically, the hazard of failure depends on the number of shocks received so far. Our analysis indicates that there has been little modelling development for multiple systems that can multi-task and dependent systems with common-cause failures, for example. We find no evidence that MAPs are used in practice and no works reviewed develop software demonstrators. We think there is considerable scope for modelling applications in transportation (e.g. dynamic train re-scheduling, last-mile logistics) and medical treatments, and MAPs may be more general than the literature that we have reviewed suggests.

Keywords: mission; reliability; maintenance; shocks; mission-abort; rescue.

1. Introduction

Mathematical modelling of the planning and execution of missions performed by unreliable but valuable systems is a relatively recent development (Levitin and Finkelstein, 2018a). So called “mission-abort policies” (MAPs) are the subject of this inquiry. Mission-abort policies consider a system that is required to perform a mission, for which system survival (to perform other missions in future) and mission success are simultaneous though sometimes conflicting objectives. Typically, system survival has a higher priority than mission success (Levitin *et al*., 2018a). During the mission, the system degrades due to external

"shocks" or internal "wear" or both. Then, three basic outcomes are possible: i) the system fails so that necessarily the mission fails; ii) the mission is aborted so that necessarily the mission fails; iii) the mission succeeds. The key management issue (the decision problem) is: under what conditions should a mission be aborted? Return or rescue of the system can also be considered (and modelled), so that given outcomes ii) or iii) the system may or may not survive, depending on the outcome of the return.

For example, suppose a passenger train operates between *A* and *B* with intermediate calling points at *C*, *D*, … If the train is running late, it might be turned at an intermediate calling point in order to catch-up. This way, the mission (to reach *B*) is aborted, and (the timely execution of) future missions (the return to *A* and so on) are prioritized. In another example, an unmanned aerial vehicle flies from *A* to carry out surveillance between *B* and *C* (Levitin and Finkelstein, 2018a). If the aircraft is attacked enroute, damage incurred may necessitate early return to *A*.

Missions in this framework arise in many areas of industry and human endeavour: in transportation, e.g. transporting people or products by some mode of transport; in communications, e.g. radio communication (Levitin *et al*., 2020a); in defence, e.g. or unmanned aerial vehicle (UAV) operations (Zhu *et al*., 2020); in manufacturing (e.g. urgent production to meet an important order); in agriculture, e.g. growing a crop might be aborted due to bad weather, infestation or disease; in health, e.g. surgery or chemotherapy (Levitin et al., 2020b). The study of mission-abort policies is therefore important. This field is relatively young, and this paper is to our knowledge the first systematic review of it. We think it is important to classify sub-topics that are established, sub-topics that are emerging, and opportunities for new models of real problems.

Mission-abort policies can be broadly classified on the basis of: the type of the mission; the nature of the rescue if any; the system; and the nature of degradation. Thus, in a simple mission, a single system has one attempt to complete one mission with a binary outcome, success or failure. A more complicated mission may have multiple targets, multiple systems, and/or multiple attempts. The simplest rescue process is a perfect rescue in which the system survives with probability 1 if the mission is aborted or the mission succeeds. Imperfect rescue processes are otherwise. The system (single or multi-component) and degradation-model classifications that we describe in this paper concern the models themselves than the MAPs. Notionally, degradation may be due to external or internal factors or both, and these factors may be systematic or random or both (e.g. Levitin and Finkelstein, 2018b). In modelling terms, the models of degradation may be discrete (e.g. countable shocks received) or continuous (e.g. wear of a manufacturing tool) or a combination.

MAPs have much in common with models and policies that are used in maintenance and reliability, particular models with defaulting (e.g. Alotaibi et al., 2020). Although opportunities for preventive maintenance may be rare, using such opportunities is an efficient strategy to mitigate failure risk (Zhao *et al.*, 2021a). Consider, for example, an aerial vehicle (Levitin and Finkelstein, 2018a) or an isolation valve (Alberti and Cavalcante, 2020), for which shocks are responsible for degradation. The extent of degradation may determine whether the mission is aborted, so that the mission-abort decision variable is the critical threshold (to be determined by modelling) for this parameter. A maintenance policy can be configured to restore system performance to a level as good as new, or at least to one better than current (ensuring system survival and mission continuity). In addition, opportunistic inspections can be triggered to detect defective states. Even if the conditions of a mission do not allow the execution of a scheduled inspection (impediment), inspection can be rescheduled and it may still be beneficial (Scarf *et al*., 2019).

Given the importance of MAPs, this paper presents the state-of-the-art on mathematical modelling of them. We survey and describe how the models are being used in artificial and real applications, the main current assumptions and trends, and future prospects. Therefore, our paper contributes to a better understanding of key features that drive the growth of research into MAPs and their use in industry.

The structure of the paper is as follows. Section 2 presents the methodological framework used to select and evaluate the papers we review. Section 3 contains a brief bibliometric analysis of these papers (publication trend, journals, fields, authors and their connections). Section 4 describes a general outline of MAP models, followed by a classification of the models used in the papers reviewed. Section 5 then discusses the content of papers in detail, and consequent identification of gaps and opportunities for further studies. Our findings are briefly reviewed in the conclusions in Section 6.

2. Systematic review methodology

We use an adapted three-step literature review process (see e.g. Zupic and Čater, 2015). The first step is the review design (scope and output). Thus, the scope is articles in peer-reviewed journals on the *mathematical modelling of mission-abort policies* over all time and in leading international journals. The output is: a preliminary descriptive analysis of the articles (article numbers over time, sources, and authors by level of activity, connections between these; keywords; and fields of application); a classification of models, rescue policy, nature of the mission, wear model); a critical analysis of content; and identification of gaps in the literature and opportunities for further research. The second step is the search, and we consider the two most important databases: Scopus (Elsevier) and Web of Science (Clarivate Analytics). Titles, abstracts, and keywords (author keywords and keywords plus) were searched using the term: *"mission abort*"*. This resulted in 161 papers from Scopus and 100 from WoS. These articles were then filtered (see Figure 1). EC1 guarantees papers in the universal language most commonly used among researchers. EC2 was established to ensure quality, as journal papers are rigorously evaluated by experts before publication. Note, there are no books published on MAPs to date. EC3 is self-explanatory. The final cut (EC4) excluded articles that were mostly about human exploration of space, which is not our concern. Our search covered articles available from 1945 to February 2023. Only two articles predate 2018 (Figure 2), strengthening our initial supposition that the research topic is new and of current interest to the academic community. The third step is the development of the output of the review.

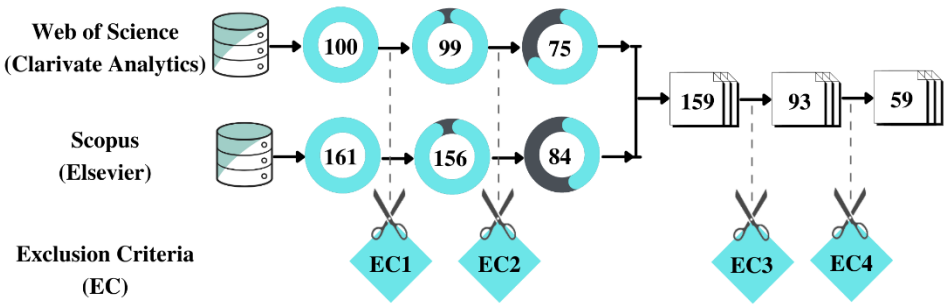

Fig. 1. Search and filter results. EC1: discard non-English-language articles. EC2: discard conference papers and books. EC3: discard duplicate articles. EC4: discard irrelevant articles.

3. Bibliometric analysis

The field is clearly emerging (Figure 2), few authors are working in it, and that some key collaborations are very active (Figure 3). The keyword cloud (Figure 4) shows the 20 most frequent keywords in the 59 articles and their proximity (tendency to be co-listed in a paper). Some authors use different words for the same thing. Thus, we standardise on a single term those words that we judge to be synonyms. For example, the phrases “renewal process of shocks”, “shock process”, and “shocks” were standardized as “shock process”. Of interest in this plot are: MAPs are generally not considered as matters of reliability or

maintenance; mission success probability (MSP) and system survival probability (SSP) are used as standard terms; and UAVs feature quite often (as motivation and/or in applications).

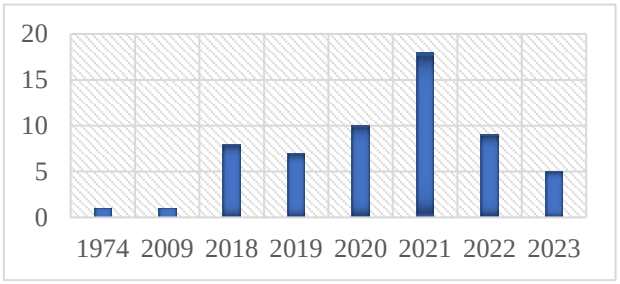

Fig. 2. Number of articles by year.

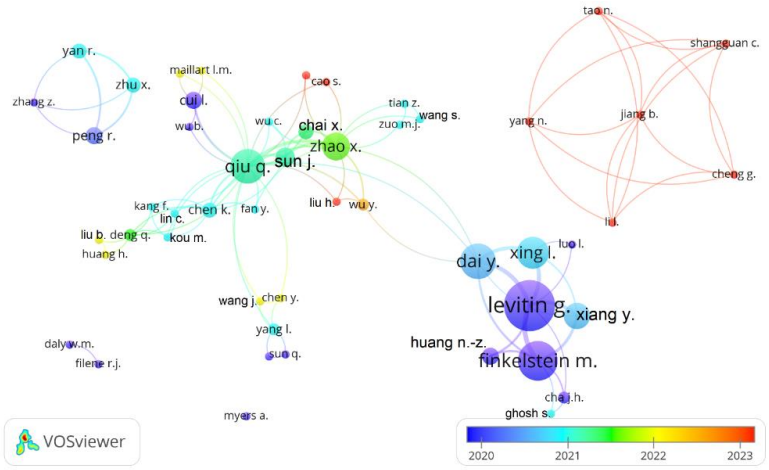

Fig. 3. Co-authorship analysis: size of an author's bubble is proportional to number of articles; arc-width is proportional to strength of link; proximity of bubbles indicates tendency to collaborate.

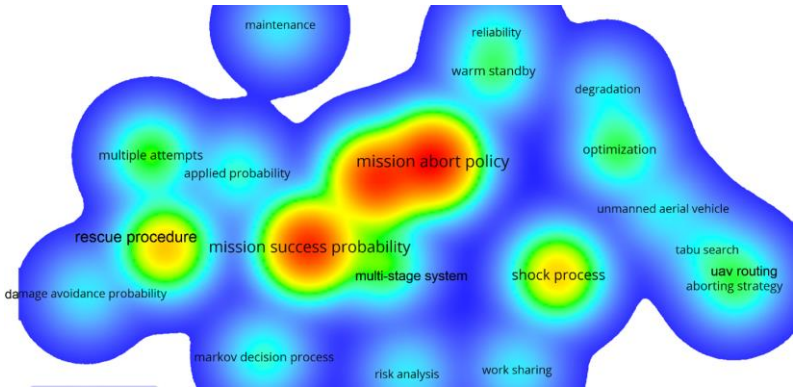

Fig. 4. A cloud plot of the keywords in the reviewed papers.

Reliability Engineering & System Safety is the dominant journal (40 papers) with other journals trailing by some margin: European Journal of Operational Research (4 papers), Risk Analysis (4 papers), IEEE Transactions on Reliability (3 papers) and IEEE Transactions on Industrial Informatics (2 papers). Engineering is the largest field of application, and the UAV is the type of system most frequently studied (Table 1).

Table 1. Percentage of papers by the types of systems covered.

System	%
Unmanned aerial vehicle	42.9
Computer system	19.6
Chemical reactor	16.1
Aircraft	5.4
Electric feeder heating	3.6
Wireless sensor network	1.8
Power generating system	1.8
Autonomous underwater vehicle	1.8
Blowout preventer	1.8
Multiprocessor system	1.8
Trucks carrying drones	1.8
Hydraulic system	1.8

4. Mission-abort policy models

4.1 *Mathematical modelling of mission-abort policies*

Mathematical models of MAPs are varied, and we will classify the models in the reviewed papers in subsection 4.2. Initially, it is helpful to describe the models in general. Thus, mathematical models of MAPs have the following general characteristics. Note, throughout the remainder of the paper when we refer to a mission-abort policy (MAP) we are strictly referring to a mathematical model of a mission-abort policy.

In a MAP, there exists a system, a mission, a return (or rescue), and an agent (the decision-maker) who may decide to abort the mission. The system degrades while it is operating. The system operates from the start of the mission (at time $t = 0$, say) until the end of the return or until it fails, if that occurs sooner. While the system is not failed and the mission is not completed, the decision-maker can abort the mission. A mission that is aborted is not completed. The return (or rescue) commences at the instant the mission is aborted or the mission is completed. The system survives if and only if the return is successful.

The decision framework is probabilistic and there are events: M (mission success); A (mission aborted); S (system survival). At any time *t*, provided the system is not failed, the mission is not complete, and the return has not started, the decision-maker has two choices: abort (A) or continue (notA). Then, a MAP model determines the best choice between these two alternatives by trading-off the mission success probability (MSP), $\Pr(\mathrm{M})$, and the system survival probability (SSP), $\Pr(\mathrm{S})$. More precisely one can maximise $\Pr(\mathrm{M})$ subject to $\Pr(\mathrm{S})>q$, or specify rewards r_{M} and r_{S} for mission success and system survival respectively, and maximise $r_{\mathrm{M}} \Pr(\mathrm{M})+r_{\mathrm{S}}P(\mathrm{S})$. The important point to note here is that, provided degradation is regular, as time passes mission success becomes more likely and system survival less likely.

To determine MSP and SSP, the system and the degradation model must be specified. There are many ways to specify these, so that we use type of system and type of degradation model as classifiers. Perhaps the simplest mission is one of known duration undertaken by a system with *n* identical components in parallel subject to shocks that occur at random at a known rate. In this model, initially component 1 operates and the remaining components are on cold-standby (neither operating or degrading). When the first shock occurs, component 1 fails and component 2 begins operating at the same instant. The system fails once all components have failed (at the *n*-th shock). Then, naturally, shocks are decision epochs; that is, it is only necessary to model the abort decision at the instant of a shock, or strictly, once the next component begins operating. This is because there is no degradation in the interval between shocks. Typically, it is assumed

that shocks occur according to Poisson process with rate λ, or a nonhomogeneous Poisson process with rate $\lambda(t)$. Then, at a decision epoch, at the *m*-th shock at time T_m, say, the number of surviving components is known ($n-m$), and the expected numbers of shocks that will occur during the remainder of the mission and during the return are known, in both cases, A (abort) or notA. Then, MSP and SSP can be calculated, and the best action D* chosen from (A, notA). D* will depend on T_m: if the *m*-th shock occurs early in the mission, then one would be inclined to abort, while if it occurs late in the mission (close to the target), one would be likely to continue. Alternatively, a model may specify a one-component system with a hazard rate function that depends on the number of shocks received so far. While the calculations are different, the principles are the same. On the other hand, if wear (degradation) is continuous, so that the system fails once the wear reaches a critical level *L*, say, then the abort decision must be continuously updated. At a decision epoch at time *t*, D* will depend on the current wear, on *t* itself (if there is a return), and the time remaining to complete the mission.

The nature of the return (or rescue procedure) will impact on SSP only. The return can be specified in many ways, so we use type of return as a classifier. Most simply, the return is null, that is, the system survives if the mission is completed or the mission is aborted. In this case, there is no sense that the system travels from home to a target and then returns to home. Instead, the system is made safe (survives) at the instant the mission is completed or aborted, viz, a degrading manufacturing system that aims to complete tasks by a deadline. A simple return is one in which the phases, "out" and "back", are probabilistically identical. On the other hand, the phases may be different if the system is "faster" on return (lower payload or closer point of safety, say).

In some MAPs, components may have three (or more) states, good, defective (but operating), and failed. Then, at a decision epoch, D* depends on the state of the system. In the simplest model, the only decision point is the time at which the system enters the defective state. Then, since system-life in the defective state is very limited, if the system becomes defective early in the mission then the mission should be aborted, and vice versa. More complicated models arise when there are inspections to determine system state—these themselves might be chosen—or when there are multiple components.

Modelling extensions can be envisaged: standby components may be warm or hot; system configurations may be generalised; shocks may multi-factorial, that is, different types of shock may act on a system in different ways; the rewards may be non-binary, that is, system survival reward may depend on the system state at the end of the mission; the system may be unobserved (hidden) but stochastically related to an observed condition-indicator (additional uncertainty); system state may be partially observed by (costly) inspection, so that the inspection frequency influences MSP and SSP; system parameters may be unknown or environment severity may be unknown, or both; there may be multiple systems in which, say, the mission is completed if *k* of *n* systems reach the target, or *n* system share *k* targets, and so on.

Note, time is typically clock-time, but it could be operational cycles.

4.2. *Classification of MAPs*

Now we describe the classifiers we use to summarise the models in the reviewed papers (Table 2).

The first classifier is mission type. The classes are: simple (one target, one system); single system many targets; many systems single target; many systems many targets. We might have put the last three classes in a single "non-simple" class, although we think it is informative to describe the mission more finely because the review then indicates where there are and are not gaps in the literature.

The second classifier is binary, so we only show one class (in Table 2). This classifier is mission-related and broadly corresponds to whether the mission is one "journey" or perhaps multiple journeys (attempts).

Table 2. Summary of the attributes of the model used in each reviewed paper. Papers listed by year and alphabetically within year. Objective 1: max MSP s.t. SSP>q). Objective 2: min total cost.

		Mission				Rescue			System		Failure model				
	Objective	Simple	Many systems, single target	Many systems, many targets	Multiple attempts	Null return	Simple return (rescue)	Non-simple return (rescue)	One component	Multi-component	Indirect-shock model	Direct-shock model	Multi-state model	Continuous wear model	Time remaining is decisive
Filene and Daly (1974)	1	Y					Y			Y		Y			
Myers (2009)	1	Y					Y			Y				Y	
Cha, Finkelstein and Levitin (2018)	1	Y						Y	Y		Y				Y
Levitin and Finkelstein (2018a)	1,2	Y						Y	Y		Y				Y
Levitin and Finkelstein (2018b)	1,2	Y					Y		Y		Y				Y
Levitin and Finkelstein (2018c)	1	Y					Y		Y		Y				
Levitin, Xing and Dai (2018a)	1	Y						Y		Y				Y	Y
Levitin, Xing and Dai (2018b)	1	Y						Y		Y				Y	Y
Levitin, Finkelstein and Dai (2018c)	1,2	Y						Y	Y		Y				Y
Peng (2018)	2			Y			Y		Y		Y				Y
Levitin, Xing and Luo (2019a)	1	Y					Y			Y				Y	Y
Levitin, Finkelstein and Huang (2019b)	1,2	Y			Y			Y	Y		Y				Y
Levitin, Finkelstein and Huang (2019c)	1	Y						Y	Y				Y		
Levitin, Finkelstein and Huang (2019d)	1	Y						Y		Y		Y			
Qiu and Cui (2019a)	2	Y					Y		Y				Y		Y
Qiu and Cui (2019b)	2	Y					Y		Y				Y		Y
Yang, Sun and Ye (2019)	2	Y					Y		Y				Y		Y
Levitin, Finkelstein and Dai (2020a)	1	Y					Y			Y		Y			
Levitin, Finkelstein and Xiang (2020b)	1	Y			Y		Y		Y		Y				Y
Levitin, Finkelstein and Xiang (2020c)	1,2	Y			Y			Y		Y		Y			Y
Levitin, Finkelstein and Dai (2020d)	1,2	Y					Y		Y				Y		
Levitin, Finkelstein and Dai (2020e)	1	Y					Y		Y				Y		
Levitin, Finkelstein and Huang (2020f)	1,2	Y					Y		Y				Y		
Levitin, Xing and Dai (2020g)	1,2	Y					Y			Y				Y	
Levitin, Finkelstein and Xiang (2020h)	2			Y				Y	Y			Y			Y
Qiu, Cui e Wu (2020)	2	Y					Y		Y		Y				
Zhu, Yan, Peng and Zhang (2020)	2			Y			Y		Y			Y			
Finkelstein, Cha and Ghosh (2021)	2	Y				Y			Y					Y	
Levitin, Finkelstein and Xiang (2021a)	1	Y			Y			Y	Y				Y		
Levitin, Finkelstein and Xiang (2021b)	1	Y			Y			Y		Y	Y				Y
Levitin, Finkelstein and Xiang (2021c)	1	Y			Y			Y	Y		Y				
Levitin, Finkelstein and Xiang (2021d)	1	Y						Y		Y			Y		
Levitin, Xing and Dai (2021e)	1	Y						Y		Y	Y				
Levitin, Xing, Xiang and Day (2021f)	1,2	Y						Y		Y	Y				
Levitin, Xing and Xiang (2021g)	1,2	Y						Y		Y				Y	
Levitin, Xing and Dai (2021h)	1,2	Y					Y			Y		Y			
Levitin, Xing and Dai (2021i)	1,2	Y						Y		Y				Y	
Qiu, Kou, Chen, Deng, Kang and Lin (2021)	1,2	Y			Y			Y	Y					Y	Y
Wang, Zhao, Tian and Zuo (2021)	1,2	Y					Y			Y			Y		Y
Wu, Zhao, Qiu and Sun (2021)	1,2	Y						Y		Y		Y			Y
Zhao, Fan, Qiu and Chen (2021a)	2	Y						Y	Y				Y		Y

Table 2 (continued). Summary of the attributes of the model used in each reviewed paper. Papers listed by year and alphabetically within year. Objective 1: max MSP s.t. SSP>q). Objective 2: min total cost.

		Mission				Rescue			System		Failure model				
	Objective	Simple	Many systems, single target	Many systems, many targets	Multiple attempts	Null return	Simple return (rescue)	Non-simple return (rescue)	One component	Multi-component	Indirect-shock model	Direct-shock model	Multi-state model	Continuous wear model	Time remaining is decisive
Zhao, Sun, Qiu and Chen (2021b)	2	Y					Y		Y					Y	
Zhao, Chai, Sun and Qiu (2021c)	1,2	Y						Y	Y		Y				Y
Zhao, Chai, Sun and Qiu (2021d)	1,2	Y						Y		Y			Y		Y
Zhu, Zhu, Yan and Peng (2021)	2			Y				Y	Y			Y			Y
Levitin, Xing and Dai (2022a)	1	Y						Y		Y			Y		
Levitin, Xing and Dai (2022b)	1	Y						Y		Y			Y		
Levitin, Xing and Dai (2022c)	1,2	Y			Y			Y		Y		Y			
Liu, Huang and Deng (2022)	2	Y				Y			Y					Y	
Qiu, Maillart, Prokopyev and Cui (2022)	2	Y				Y			Y				Y		
Yan, Zhu, Zhu and Peng (2022)	2			Y		Y			Y			Y			
Yang, Chen, Qiu and Wang (2022)	1,2	Y						Y	Y					Y	Y
Zhao, Dai, Qiu and Wu (2022a)	1,2	Y			Y			Y		Y		Y			
Zhao, Chai, Sung and Qiu (2022b)	2	Y						Y	Y				Y		Y
Cheng, Li, Shangguan, Yang, Jiang, and Tao (2023)	2	Y				Y			Y				Y		
Levitin, Xing and Dai (2023)	1	Y						Y	Y		Y				Y
Zhao, Li, Cao and Qiu (2023a)	2	Y					Y		Y		Y				Y
Zhao, Liu, Wu and Qiu (2023b)	2	Y						Y		Y				Y	Y
Zhao, Lv, Qiu and Wu (2023c)	1,2	Y			Y			Y		Y		Y			

The third classifier is the return or rescue procedure. The classes are: null (no return), in which mission completion or mission-abort guarantee system survival; simple; or non-simple. A simple return is one in which conditions on the "out-" and "back-" phases are identical, the back-phase commencing at the instant the mission is aborted or completed.

The fourth classifier the type of system: one-component system; multi-component system. We show both classes in Table 2 because we are interested to pick out the connection with the fifth classifier, the type of degradation model: indirect-shock model, in which the hazard rate is modified by the accumulation of shocks and the system is either operating or failed; direct-shock model, in which the system fails if number of shocks > n; multi-state model including the delay-time model, in which the system is good, defective, or failed, and operates in the good and defective states; continuous-wear model, e.g. the system degrades according to a gamma process.

The final classifier indicates whether the decision depends on the time remaining to complete the mission. The class is binary, so we only show one class. Note, it may appear strange that the abort decision might not be time-dependent, but in a simple model it might not be so.

Assigning papers to classes is not always straightforward. Careful reading is required. For example, Liu et al. (2022) state "…if the task is terminated…then a rescue is initiated immediately… rescue duration is negligible compared with the task duration". Thus, superficial reading suggests their model has a non-null return (rescue procedure). However, as the duration is zero, the return is null (no rescue). Cheng et al.

(2023) is similar. Furthermore, identifying a non-simple return is not trivial. Some authors make it easier and state "...the environment for the rescue operation differs from that for the primary mission..." (e.g., Levitin et al., 2019d). However, sometimes (e.g., in Levitin et al., 2021a), it is necessary to look more deeply to identify, for example, that the frequency of shocks (and therefore degradation) is different between "out" and "back".

Also, we describe the nature of the objective function in the models reviewed. Objective 1 (maximise MSP subject to SSP>q) and objective 2 (minimise total cost of mission failure and system loss) are discussed above in subsection 4.1. One or other or both of these criteria feature in all papers. Some few papers discuss other criteria, such as the "expected fraction of the completed PM work" (Levitin et al., 2021h), which appears to be unrelated to the mission, and others that are synonymous with system survival: "rescue procedure success probability" and "damage avoidance probability" (Levitin et al., 2021i).

5. Detailed content analysis

5.1. *Description of reviewed papers*

The first paper to describe a mission-abort policy was written 50 years ago (Filene and Daly, 1974). Their policy, although they use the term *strategy*, aborted a manned flight once the number of detected computer failures passed a critical threshold (multicomponent, direct failure model). In the model, the mission time-remaining had no impact on the decision, and the authors clearly indicate this drawback of their model. Nonetheless, it was 35 years before the next paper appeared (Myers, 2009), wherein rescue commenced upon failure of the k-th subsystem among n identical, hot-standby subsystems, with independent exponential lifetimes (multicomponent, direct failure model). This paper uses the term *mission abort policy* for the first time, and appears to be unaware of the earlier work of Filene and Daly. Thus, interest in the mathematical modelling of MAPs was very slow to develop. Then, in 2018, papers began to appear in a rush and the direction of their development becomes blurred, although order can be inferred from citation linkages (Figure 3). Thus, Levitin *et al.* (2018a) extended the model in Myers (2009) to non-identical components on warm standby with non-exponential lifetimes, and modelled decisions about the sequence of activation of components and mission-abort. Levitin and Finkelstein (2018a) proposed the indirect-shock model, and the mission of fixed length τ is aborted, and return commences, if the m-th shock occurs before a critical time ξ, with m and ξ as decision variables. The shock-rate is allowed to depend the phase (mission or return). Shock-modelling generalizations followed. In Levitin and Finkelstein (2018b), the mission interval is sub-divided and an abort-threshold is determined for each interval. In Levitin and Finkelstein (2018c), external damage (due to shocks) and internal wear accumulate, and the mission is reviewed at each shock and aborted if the damage exceeds a threshold. The majority of these works were motivated by missions undertaken by military systems (e.g. submarines, aircraft, UAVs).

Thereafter, work progressed in a number of directions. Levitin et al. (2018b) allowed components to be loaded differently. The loading-failure model has received much attention, especially in production systems (e.g. Gajpal and Nourelfath, 2015). The novelty of Levitin et al. (2018b) was to formulate it as a MAP. Fractional mission completion is modelled in Levitin et al. (2018c) by rewarding partial. Vehicle routing (see e.g. Rodrigues and Lima, 2021; Kundu et al., 2022) is integrated with MAPs by Peng (2018), in which multiple UAVs perform missions in a random environment, and extended to variable loading (Zhu *et al.*, 2020) and variable capability (Zhu *et al.*, 2021). Minor and major failures are modelled in Cha *et al.* (2018) and in Qiu *et al.* (2020). Levitin et al. (2019a) modelled failure propagation in 1-out-of-n warm standby systems. Again, failure propagation has been studied by many (see e.g. Levitin and Zing, 2010; Xing *et al.*, 2013) but in a MAP context the work was new. Another group of papers models a mission that can be attempted more than once (Levitin *et al.* 2019b; 2020b; 2020c; 2021a; 2021b; 2021c; 2022c; Qiu *et al.*,

2021; Zhao *et al.*, 2022a). This idea is pioneered by Levitin *et al.* (2019b) considering the assumption that the mission success does not depend on the results of previous attempts. Levitin *et al.* (2020b) show that an additional attempt can increase the mission success probability (MSP) substantially. Qiu et al. (2021) uses a continuous wear model.

In multi-component models, successive components are assigned to successive attempts (Levitin *et al.*, 2020c), or successive components are assigned to what remains of a mission (Levitin et al., 2021c), or the number of components that can fail is limited (Levitin *et al.* (2021b). In Levitin *et al.* (2021a), multi-state systems are considered. In Zhao *et al.* (2022a), dynamic allocation of a fixed number of standby components are discussed for *k*-out-of-(*n*+*m*):F system (subject to extreme shocks), in which the optimal number of failed components to be replaced after each rescue procedure is also determined.

Inspections are introduced to models by Finkelstein *et al.* (2021), Levitin *et al*. (2019c, 2021d), and Zhao *et al.* (2021b). In Levitin *et al.* (2019c) inspections are scheduled to identify the defective state and abort the mission prior to failure. False positives and negatives, in the manner of Berrade *et al.* (2013), can also occur. In Levitin *et al.* (2021d), the decision to abort is dependent on the number of shocks so far and the state of the system., and Zhao *et al*. (2021b) and Finkelstein *et al*. (2021) consider a Gamma degradation process rather than a shock process, the latter allowing the system can operate at full or reduced load if the system is degraded and the mission is not aborted. On the other hand, Zhao *et al*. (2021b) use a Markov decision process to dynamically optimize mission-abort. A two-stage Gamma process for the normal and defective states is considered by Qiu and Cui (2019a). They propose two models: one with a continuous wear model in which the mission is aborted when the degradation level crosses a threshold; and the other with a delay-time model (three states) in which the mission is aborted if the sojourn in the defective state exceeds a threshold. Qiu and Cui (2019b) model shocks that increase the virtual age of the system. Notably, Zhao *et al.* (2021a), extending Zhao *et al.* (2021b), use a multi-criteria approach, wherein the abort decision depends not only on the degradation state but also on the time in mission, and degradation is modelled by a Wiener process (continuous wear model). Yang *et al.* (2022) proposes a MAP with a bivariate wear model based on degradation of the monitored health features and system age. Abort policies for continuous monitoring are trending, as many industries are deploying sensors in their equipment and processes.

The assumption that mission time is constant has been relaxed (Yang *et al.*, 2019). Random mission duration was treated by Qiu *et al.* (2022), for a continuously monitored two-phase system. They examine a joint optimization problem in which the optimal MAP and the degree of deterioration delay are determined simultaneously.

Other works have generalized the shock process: as a bivariate process (external shocks and internal degradation) (Levitin et al., 2020d); as a non-homogeneous Poisson process (Levitin et al., 2020e); as a renewal process (Levitin *et al.*, 2020f); as a mixed shock process (number and size) (Zhao *et al.*, 2021c). In Levitin *et al.* (2020g), the abort decision depends on the numbers of failed online components and available standby components. Other works have also considered systems with standby components. Zhao *et al*. (2021d) allows switching of warm-standby components. Levitin et al. (2021e) consider non-identical components in which offline components are maintained. Levitin et al. (2023) consider the multi-threshold MAP, where different numbers of shocks are acceptable in different time intervals.

Regarding joint issues, Levitin *et al.* (2020h) studied the joint optimization problem of subtask distribution among components to balance the risk of component losses and mission failure. This was the first work to divide a mission into subtasks. In Levitin *et al.* (2019d), the failure of a subset of components in series terminates the mission, while another subset rescues the system. In Levitin *et al.* (2020a), the mission is aborted preventively if the number of shocks exceeds a threshold. Levitin *et al.* (2021f) discusses MAP for systems with arbitrary series-parallel structure. Balanced *k-out-of-n:F* systems have been considered by Wu *et al.* (2021) and Wang *et al.* (2021), the latter considering the balance degree of the

system as the mission-abort condition. In Levitin *et al.* (2021g) partial-abort is allowed but the load distribution of components is fixed throughout the mission. In Levitin *et al.* (2021h), multiple units try to complete the mission and the mission-load is dynamically redistributed. Further work on partial mission-abort for multi-component load-sharing systems is extant. Sharing systems were also modelled by Levitin *et al.* (2021i), in which system performance changes at random during the mission or rescue. Levitin *et al.* (2022a) were the first to model a MAP for a multistate system with product storage, whereby excess performance of one unit can compensate for the inefficiency of another. In Levitin *et al.* (2022b), the rescue procedure depends on the state of the mission and state of the system, simultaneously. Zhao *et. al* (2022b) develop a condition-based policy for multi-state systems with protective device subject to external shocks, evaluating the probabilities of mission success and system survival using the Markov process imbedding method. Subsequently, they propose a joint optimization model to find the optimal protective device selection policy and optimal MAP. Zhao et al. (2023a), design joint loading and mission-abort policies are for safety-critical systems in dynamic environments. A structure for the *l-out-of-n:G* warm standby system, with a dynamic arrival of tasks and random amount of work was considered by Zhao et al. (2023b). Finally, Zhao et al. (2023c) introduced the idea of two-level rescue depot location policies.

5.2. *Gaps in the literature*

Table 2 indicates some gaps: MAPs in general have objective functions restricted to reducing costs and increasing the survival probability of the system. Despite the importance of these, this is a limitation and new objective functions can be addressed in the future e.g. relating to damage to the system and degree of success of the mission. Also, multiple systems have been explored in a limited way. Furthermore, several studies can be extended to consider the assumption of multiple attempts, an approach rarely studied, and there has been little modelling of non-binary missions.

The gap between theory and application is unexplored, and whether models developed to date are used in practice is unknown. Consequently, the modelling work to date may not be having an impact beyond academia. This is an important issue for the field, but not confined to this field (Scarf, 1997).

The majority of applications are in Engineering and a minority in Computer Science. Therefore, there may be more opportunities for development of MAP models for health management. Only Levitin et al. (2020b) mention a potential health application, in which an infection (shock) can interrupt (abort) cancer chemotherapy (mission) to prevent the patient's condition deteriorating.

5.3. *Future directions*

Research that explores the gap between theory and application would be welcome. However, this gap may be difficult to study because many MAP models are motivated by military applications. Applications in health may be slower to develop, and so the field may not be ready for a study of the use of MAP models. There may be scope for looking at application in manufacturing, however, arguably, MAPs are less interesting in this field than in military, health, and transportation applications, because rescue procedures are not relevant.

The theory-practice gap might be filled to some extent by developing downloadable code for simple decision support systems. Modelling is useful for laying the groundwork, and to illustrate the potential of mathematical analysis of models that are motivated by real problems. Nonetheless, application and impact upon management will likely come closer with the development of demonstrators and digital twins (e.g. Ranasinghe, 2022).

As a consequence, whether industry would benefit from more generalisations of existing models is a moot point. Nonetheless, our review suggests that models might be developed for multiple systems that can

multi-task, so that a system that has completed its mission can finish an incomplete mission of another system. Not less important, shock models might be generalized so that shocks act simultaneously on multiple systems (common cause failures). Maintenance policies in MAP models might be extended to include: imperfect repairs; opportunities for repair or replacement; life extension; and the issue of spare-parts and resource limitations more generally. Degradation of a system may impact both its survivability and its performance, and low performance may also motivate mission-abort. One can envisage applications in transportation, such as dynamic train re-scheduling or last-mile logistics (Demir et al., 2022), manufacturing (re-tooling), and energy (overhaul might be modelled as a mission-abort policy). In this way, MAPs are perhaps more general than the literature that we have reviewed suggests.

Multicriteria MAPs can be expanded to include multiple attempts and to multi-stage degradation processes. Further, multi-criteria approaches can be supported by studies of decision-makers' preferences for mission completion and system survival.

There are sources of uncertainty that are yet to be analysed in models. While system state evolves stochastically in models, system resilience (the extent to which a system can withstand shocks and damage) is assumed fixed. Random resilience would introduce much more uncertainty into the decision problem, so that abort decisions might become more conservative. This is an open problem. Environment may also be more heterogeneous, and hence more uncertain, that many models assume.

Finally, the further modelling of non-binary missions may be worthwhile. Thus, suppose there are three types of mission: binary, discrete, continuous. A binary mission either fails or succeeds (e.g. delivery of a parcel). A discrete mission has n binary sub-missions, some of which may fail (e.g. a train service). A continuous mission is such that a proportion p of the mission may succeed ($p \in [0,1]$) (e.g. surveillance). Furthermore, mission failures themselves may be strict (e.g. when an order is lost if a product is not supplied by a hard deadline) or cumulative (e.g. when lateness incurs an increasing penalty). Thus, mission success and mission failure can be expressed in non-simple ways and consequent models developed.

6. Final considerations

This paper is the first to review the mathematical modelling of mission-abort policies. In a mission-abort policy (MAP), system survival and mission success are simultaneous objectives, and these objectives typically conflict. MAP modelling is an important field because MAPs arise in many areas of industry and human endeavour. We critically analyse papers in this field, highlighting trends and identifying opportunities for future research.

The field is very new—only a handful of papers predate 2018—despite the frequent discussion of "mission abort" in space missions. Few authors are contributing to this field and most published papers are limited to one journal. Unmanned aerial vehicles as the main application context (43%), although applications are illustrative rather than case study oriented. There is a scarcity of studies in the field of health, despite the relevance of MAPs to medical treatments, and transportation and logistics. Models are increasing in their sophistication, with consideration of multiple systems undertaking multiple missions and subject to internal and external deterioration processes, although optimisation methods are mostly unsophisticated—direct search for optima is the most common (60%).

There is scope for the development of new models of: multiple systems that can multi-task, completing missions left incomplete by other systems (dependent mission): multiple systems with common-cause failures (dependent systems); and multi-level systems (e.g. drones and drone tnasporters). There is also considerable scope for bridging the gap between academia and industry, between theory and application. There has been little by way of reporting of the development of demonstrators for MAP decision making. Impact upon management practice we think requires the development of demonstrators and digital twins.

There is a natural overlap between maintenance modelling and modelling of MAPs, and in future work there is scope for modelling the repair of systems, both within and between missions, so that models are closer to reality. The principal opportunity for future research, in our view, is the modelling of health treatment using MAPs.

Data statement: No data were used in the work described in this paper.

Acknowledgements: The authors extend their appreciation to the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) for funding and supporting this work through Research Partnership Program no. RP-21-09-05. The work of Phil Scarf was carried out in part with funding for a research project by the Coordinator for the Coordination for the Improvement of Higher Education Personnel in Brazil (CAPES), within the scope of the Capes - PrInt Program. The work of Augusto, Cristiano and Alexandre has been supported by CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico), FACEPE (Fundação de Amparo à Ciência e Tecnologia do Estado de Pernambuco) and CAPES.

References

ALBERTI, A.R. & CAVALCANTE, C.A.V. (2020) A two-scale maintenance policy for protection systems subject to shocks when meeting demands. *Reliab. Eng. Syst. Saf.*, **204**, 107118.

ALOTAIBI, N.M., CAVALCANTE, C.A.V., LOPES, R.S., & SCARF, P.A. (2020). Preventive replacement with defaulting. *IMA J. Manag. Math.*, **31**, 491-504.

BERRADE, M.D., SCARF, P.A., CAVALCANTE, C.A.V., & DWIGHT, R.A. (2013) Imperfect inspection and replacement of a system with a defective state: A cost and reliability analysis. *Reliab. Eng. Syst. Saf.*, **120**, 80–87.

CHA, J.H., FINKELSTEIN, M., & LEVITIN, G. (2018) Optimal mission abort policy for partially repairable heterogeneous systems. *Eur. J. Oper. Res.*, **271**, 818–825.

CHENG, G., LI, L., SHANGGUAN, C., YANG, N., JIANG, B., & TAO, N. (2023) Optimal joint inspection and mission abort policy for a partially observable system. *Reliab. Eng. Syst. Saf.*, **229**, 108870.

DEMIR, E., SYNTETOS, A., & VAN WOENSEL, T. (2022) Last mile logistics: Research trends and needs. *IMA J. Manag. Math.*, **33**, 549-561.

FILENE, R.J. & DALY, W.M. (1974) The reliability impact of mission abort strategies on redundant flight computer systems. *IEEE Trans. Comput.*, **C–23**, 739–743.

FINKELSTEIN, M., CHA, J.H., & GHOSH, S. (2021) Optimal inspection for missions with a possibility of abortion or switching to a lighter regime. *TOP*, **29**, 722-740.

GAJPAL, Y. & NOURELFATH, M. (2015) Two efficient heuristics to solve the integrated load distribution and production planning problem. *Reliab. Eng. Syst. Saf.*, **144**, 204–214.

KUNDU, A., ESCOBAR, R.G. & MATIS, T.I. (2022) An efficient routing heuristic for a drone-assisted delivery problem. *IMA J. Manag. Math.*, **33**, 583-601.

LEVITIN, G. & FINKELSTEIN, M. (2018a) Optimal mission abort policy for systems in a random environment with variable shock rate. *Reliab. Eng. Syst. Saf.*, **169**, 11–17.

LEVITIN, G. & FINKELSTEIN, M. (2018b) Optimal Mission Abort Policy for Systems Operating in a Random Environment. *Risk Anal.*, **38**, 795–803.

LEVITIN, G. & FINKELSTEIN, M. (2018c) Optimal mission abort policy with multiple shock number thresholds. *Proc. Inst. Mech. Eng. Part O J. Risk Reliab.*, **232**, 607–615.

LEVITIN, G., & XING, L. (2010). Reliability and performance of multi-state systems with propagated failures having selective effect. *Reliab. Eng. Syst. Saf.*, **95**, 655-661.

LEVITIN, G., FINKELSTEIN, M., & DAI, Y. (2018c) Mission abort policy balancing the uncompleted mission penalty and system loss risk. *Reliab. Eng. Syst. Saf.*, **176**, 194–201.

LEVITIN, G., FINKELSTEIN, M., & DAI, Y. (2020a) Mission abort policy optimization for series systems with overlapping primary and rescue subsystems operating in a random environment. *Reliab. Eng. Syst. Saf.*, **193**, 106590.

LEVITIN, G., FINKELSTEIN, M., & DAI, Y. (2020d) State-based mission abort policies for multistate systems. *Reliab. Eng. Syst. Saf.*, **204**, 107122.
LEVITIN, G., FINKELSTEIN, M., & DAI, Y. (2020e) Mission abort and rescue for multistate systems operating under the Poisson process of shocks. *Reliab. Eng. Syst. Saf.*, **202**, 107027.
LEVITIN, G., FINKELSTEIN, M., & HUANG, H.-Z. (2019b) Optimal abort rules for multiattempt missions. *Risk Anal.*, **39**, 2732–2743.
LEVITIN, G., FINKELSTEIN, M., & HUANG, H.-Z. (2019c) Scheduling of imperfect inspections for reliability critical systems with shock-driven defects and delayed failures. *Reliab. Eng. Syst. Saf.*, **189**, 89–98.
LEVITIN, G., FINKELSTEIN, M., & HUANG, H.-Z. (2019d) Analysis and optimal design of systems operating in a random environment and having a rescue option. *Int. J. Gen. Syst.*, **48**, 170–185.
LEVITIN, G., FINKELSTEIN, M., & HUANG, H.-Z. (2020f) Optimal mission abort policies for multistate systems. *Reliab. Eng. Syst. Saf.*, **193**, 106671.
LEVITIN, G., FINKELSTEIN, M., & XIANG, Y. (2020b) Optimal multi-attempt missions with cumulative effect. *Reliab. Eng. Syst. Saf.*, **203**, 107091.
LEVITIN, G., FINKELSTEIN, M., & XIANG, Y. (2020c) Optimal aborting rule in multi-attempt missions performed by multicomponent systems. *Eur. J. Oper. Res.*, **283**, 244–252.
LEVITIN, G., FINKELSTEIN, M., & XIANG, Y. (2020h) Optimal abort rules and subtask distribution in missions performed by multiple independent heterogeneous units. *Reliab. Eng. Syst. Saf.*, **199**, 106920.
LEVITIN, G., FINKELSTEIN, M., & XIANG, Y. (2021a) Optimal mission abort policies for repairable multistate systems performing multi-attempt mission. *Reliab. Eng. Syst. Saf.*, **209**, 107497.
LEVITIN, G., FINKELSTEIN, M., & XIANG, Y. (2021b) Optimal aborting strategy for three-phase missions performed by multiple units. *Reliab. Eng. Syst. Saf.*, **208**, 107408.
LEVITIN, G., FINKELSTEIN, M., & XIANG, Y. (2021c) Optimal abort rules for additive multi-attempt missions. *Reliab. Eng. Syst. Saf.*, **205**, 107245.
LEVITIN, G., FINKELSTEIN, M., & XIANG, Y. (2021d) Optimal inspections and mission abort policies for multistate systems. *Reliab. Eng. Syst. Saf.*, **214**, 107700.
LEVITIN, G., XING, L., & DAI, Y. (2018a) Mission abort policy in heterogeneous nonrepairable 1-out-of-n warm standby systems. *IEEE Trans. Reliab.*, **67**, 342–354.
LEVITIN, G., XING, L., & DAI, Y. (2018b) Co-optimization of state dependent loading and mission abort policy in heterogeneous warm standby systems. *Reliab. Eng. Syst. Saf.*, **172**, 151–158.
LEVITIN, G., XING, L., & DAI, Y. (2020g) mission abort policy for systems with observable states of standby components. *Risk Anal.*, **40**, 1900–1912.
LEVITIN, G., XING, L., & DAI, Y. (2021e) Joint optimal mission aborting and replacement and maintenance scheduling in dual-unit standby systems. *Reliab. Eng. Syst. Saf.*, **216**, 107921.
LEVITIN, G., XING, L., & DAI, Y. (2021h) Dynamic task distribution balancing primary mission work and damage reduction work in parallel systems exposed to shocks. *Reliab. Eng. Syst. Saf.*, **215**, 107907.
LEVITIN, G., XING, L., & DAI, Y. (2021i) Mission aborting in n-unit systems with work sharing. *IEEE Trans. Syst. Man, Cybern. Syst.*, **52**, 4875 - 4886.
LEVITIN, G., XING, L., & DAI, Y. (2022a) Optimal mission aborting in multistate systems with storage. *Reliab. Eng. Syst. Saf.*, **218**, 108086.
LEVITIN, G., XING, L., & DAI, Y. (2022b) Mission aborting and system rescue for multi-state systems with arbitrary structure. *Reliab. Eng. Syst. Saf.*, **219**, 108225.
LEVITIN, G., XING, L., & DAI, Y. (2022c) Using kamikaze components in multi-attempt missions with abort option. *Reliab. Eng. Syst. Saf.*, **227**, 108745.
LEVITIN, G., XING, L., & DAI, Y. (2023) Optimal aborting policy for shock exposed missions with random rescue time. *Reliab. Eng. Syst. Saf.*, **233**, 109094.
LEVITIN, G., XING, L., & LUO, L. (2019a) Influence of failure propagation on mission abort policy in heterogeneous warm standby systems. *Reliab. Eng. Syst. Saf.*, **183**, 29–38.
LEVITIN, G., XING, L., & XIANG, Y. (2021g) Partial mission aborting in work sharing systems. *Reliab. Eng. Syst. Saf.*, **214**, 107716.
LEVITIN, G., XING, L., XIANG, Y., & DAI, Y. (2021f) Mixed failure-driven and shock-driven mission aborts in heterogeneous systems with arbitrary structure. *Reliab. Eng. Syst. Saf.*, **212**, 107581.
LIU, B., HUANG, H., & DENG, Q. (2022) On optimal condition based task termination policy for phased task systems. *Reliab. Eng. Syst. Saf.*, **221**, p. 108338.
MYERS, A. (2009) Probability of loss assessment of critical k-Out-of-n:G systems having a mission abort policy. *IEEE Trans. Reliab.*, **58**, 694–701.

PENG, R. (2018) Joint routing and aborting optimization of cooperative unmanned aerial vehicles. *Reliab. Eng. Syst. Saf*., **177**, 131–137.
QIU, Q. & CUI, L. (2019a) Gamma process based optimal mission abort policy. *Reliab. Eng. Syst. Saf*., **190**, 106496.
QIU, Q. & CUI, L. (2019b) Optimal mission abort policy for systems subject to random shocks based on virtual age process. *Reliab. Eng. Syst. Saf*., **189**, 11–20.
QIU, Q., CUI, L., & WU, B. (2020) Dynamic mission abort policy for systems operating in a controllable environment with self-healing mechanism. *Reliab. Eng. Syst. Saf*., **203**, 107069.
QIU, Q., KOU, M., CHEN, K., DENG, Q., KANG, F., & LIN, C. (2021) Optimal stopping problems for mission oriented systems considering time redundancy. *Reliab. Eng. Syst. Saf*., **205**, 107226.
QIU, Q., MAILLART, L. M., PROKOPYEV, O. A., & CUI, L. (2022) Optimal condition-based mission abort decisions. *IEEE Trans. Reliab.*, **72**, 408–425.
RANASINGHE, K., SABATINI, R., GARDI, A., BIJJAHALLI, S., KAPOOR, R., FAHEY, T., & THANGAVEL, K. (2022). Advances in Integrated System Health Management for mission-essential and safety-critical aerospace applications. *Progress in Aerospace Sciences*, **128**, 100758.
RODRIGUES, A. J. S., & LIMA, G. L. (2021) A metaheuristic to support the distribution of COVID-19 vaccines. *Production*, **31**, e20210031.
SCARF, P. A. (1997) On the application of mathematical models in maintenance. *Eur. J. Oper. Res*., **99**, 493-506.
SCARF, P.A., CAVALCANTE, C.A.V., & LOPES, R.S. (2019) Delay-time modelling of a critical system subject to random inspections. *Eur. J. Oper. Res.*, **278**, 772–782.
WANG, S., ZHAO, X., TIAN, Z., & ZUO, M.J. (2021) Optimal mission abort policy with multiple abort criteria for a balanced system with multi-state components. *Comput. Ind. Eng*., **160**, 107544.
WU, C., ZHAO, X., QIU, Q., & SUN, J. (2021) Optimal mission abort policy for k-out-of-n: F balanced systems. *Reliab. Eng. Syst. Saf*., **208**, 107398.
XING, L., LEVITIN, G., WANG, C., & DAI, Y. (2013) Reliability of systems subject to failures with dependent propagation effect. *IEEE Trans. Syst. Man, Cybern. Part ASystems Humans*, **43**, 277–290.
YAN, R., ZHU, X., ZHU, X., & PENG, R. (2022) Optimal routes and aborting strategies of trucks and drones under random attacks. *Reliab. Eng. Syst. Saf*., **222**, 108457.
YANG, L., CHEN, Y., QIU, Q., & WANG, J. (2022) Risk control of mission-critical systems: abort decision-makings integrating health and age conditions. *IEEE Trans. Industr. Inform*., **18**, 6887–6894.
YANG, L., SUN, Q., & YE, Z.-S. (2019) Designing mission abort strategies based on early-warning information: Application to UAV. *IEEE Trans. Ind. Informatics*, **16**, 277–287.
ZHAO, X., CHAI, X., SUN, J., & QIU, Q. (2021c) Optimal bivariate mission abort policy for systems operate in random shock environment. *Reliab. Eng. Syst. Saf.*, **205**, 107244.
ZHAO, X., CHAI, X., SUN, J., & QIU, Q. (2021d) Joint optimization of mission abort and component switching policies for multistate warm standby systems. *Reliab. Eng. Syst. Saf*., **212**, 107641.
ZHAO, X., CHAI, X., SUN, J., & QIU, Q. (2022b) Joint optimization of mission abort and protective device selection policies for multistate systems. *Risk Anal.*, **42**, 2823–2834.
ZHAO, X., DAI, Y., QIU, Q., & WU, Y. (2022a) Joint optimization of mission aborts and allocation of standby components considering mission loss. *Reliab. Eng. Syst. Saf*., **225**, 108612.
ZHAO, X., FAN, Y., QIU, Q., & CHEN, K. (2021a) Multi-criteria mission abort policy for systems subject to two-stage degradation process. *Eur. J. Oper. Res*., **295**, 233–245.
ZHAO, X., LI, R., CAO, S., & QIU, Q. (2023a) Joint modeling of loading and mission abort policies for systems operating in dynamic environments. *Reliab. Eng. Syst. Saf*., **230**, 108948.
ZHAO, X., LIU, H., WU, Y., & QIU, Q. (2023b) Joint optimization of mission abort and system structure considering dynamic tasks. *Reliab. Eng. Syst. Saf*., **234**, 109128.
ZHAO, X., LV, Z., QIU, Q., & WU, Y. (2023c) Designing two-level rescue depot location and dynamic rescue policies for unmanned vehicles. *Reliab. Eng. Syst. Saf*., **233**, 109119.
ZHAO, X., SUN, J., QIU, Q., & CHEN, K. (2021b) Optimal inspection and mission abort policies for systems subject to degradation. *Eur. J. Oper. Res*., **292**, 610–621.
ZHU, X., YAN, R., PENG, R., & ZHANG, Z. (2020) Optimal routing, loading and aborting of UAVs executing both visiting tasks and transportation tasks. *Reliab. Eng. Syst. Saf*., **204**, 107132.
ZHU, X., ZHU, X., YAN, R., & PENG, R. (2021) Optimal routing, aborting and hitting strategies of UAVs executing hitting the targets considering the defense range of targets. *Reliab. Eng. Syst. Saf*., **215**, 107811.
ZUPIC, I. & ČATER, T. (2015) Bibliometric methods in management and organization. *Organ. Res. Methods*, **18**, 429–472.