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Multi-attempt missions with multiple rescue options

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ABSTRACT

In spite of intensive works on modeling and optimizing diverse mission aborting systems from the reliability community, none of the existing models have considered multiple rescue options. This paper pioneers the study of a multi-attempt mission system with different types of rescue procedures characterized by dissimilar system performance, shock rates, and costs. A new optimization problem is formulated, which determines the aborting rule and rescue option choice for each attempt to minimize the expected mission losses (EML) encompassing the mission failure penalty, system loss cost and rescue cost. A new numerical algorithm is then put forward to assess the EML of the considered multi-attempt mission system under any given mission abort and rescue policy (MARP). The genetic algorithm is further implemented to solve the MARP optimization problem. The proposed model is demonstrated through an unmanned aerial vehicle (UAV) performing a payload delivery mission with four possible rescue options. The UAV case study also investigates the accuracy and efficiency of the proposed numerical EML evaluation algorithm and reveals the impacts of several key parameters (mission failure penalty, system loss cost, the allowed number of attempts, shock resistance deterioration factor) on the EML and the optimal MARP solutions.

1. Introduction

When valuable assets are engaged in carrying out critical missions, the survival of the asset can be equally important to the successful completion of the intended mission. To strike a balance between asset survival and mission success, it may be decided to abort the mission operation before the completion when the risk of asset loss is deemed unacceptable (for example, indicated by the occurrence of a certain deteriorating condition). Following the mission abortion, a rescue procedure is executed to survive the valuable asset.

For instance, a patient care unit should terminate the medical treatment and begin certain emergency rescue procedure when dangers are being developed to jeopardize the life of the patient [1]. Another example is the unmanned aerial vehicle (UAV) or drone employed in diverse military and civil applications [2]. Because of the exposure to electromagnetic interferences from sources like cell phone towers, high voltage power lines, big metal structure, a UAV may deteriorate in its reliability during the mission [3]. After withstanding a certain amount of interferences, it is desirable for the drone to terminate the planned mission and fly back to the base to survive the asset. In addition to healthcare and UAV, mission aborting is a useful practice to effectively manage the system loss risks in many other applications, such as chemical reactor [4,5], transportation [6], aerospace [7], marine [8], and battlefield [9].

A crucial decision problem for mission aborting systems is to design the mission abort policy that defines the specific condition or criterion triggering the mission termination before the completion. On one hand, a too-early or premature abort would unnecessarily lower the mission successful completion probability; on the other hand, a too-late or overdue abort would lower the system survivability. To balance those two mission performance metrics, it is relevant and pivotal to optimize the mission abort policy.

1.1. Literature review

The mission abort research can be traced back to 1970s [10,11], but did not receive significant attention from the reliability community until 2018 [12,13]. Initially, diverse mission abort policies were studied for systems performing single-attempt missions. Below list some major criteria or decision parameters used for defining the aborting rule and the types of systems for which the mission abort has been investigated:

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Acronyms

EML	expected mission losses
MARP	mission abort and rescue policy
OP	operation phase
RP	rescue procedure
UAV	unmanned aerial vehicle

Notation

L	EML
W	amount of work in the OP of any attempt
τ	duration of the OP
T_i	random arrival time of the i th shock
$\varphi(x)$	required amount of work in the RP when the amount of work x was performed in the OP before the RP activation
N	number of RP options
Y	maximum allowed mission time
K	maximum number of attempts during the mission
g_M	system performance during OP
$g(n)$	system performance during RP of type n
$\lambda(n)$	shock rate during RP of type n
Λ	shock rate during OP
m_i	number of shocks after which the OP is aborted in attempt i
ξ_i	time from the beginning of attempt i during which the occurrence of the m_i-th shock triggers the OP abort and RP activation
$r_i(x)$	RP option/type chosen when the OP in attempt i is aborted after performing the amount of work x
$P(t,i,\rho)$	occurrence probability of i shocks in $[0,t)$ given that the shock rate is ρ
$q(i)$	probability that a system survives the i th shock
Γ	survival probability upon the first shock
γ	shock resistance deterioration factor
E_k	random event that the system starts the k-th attempt
Ψ_k	occurrence time of event E_k
Ω_k	RP cost accumulated before time Ψ_k
$e_k(\psi,\omega)$	*pdf* of Ψ_k when $\Omega_k = \omega$.
$s(\boldsymbol{m}, \ \xi)$	probability of OP completion under abort policy $\boldsymbol{m}, \ \xi$
$v(\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{r})$	probability that the OP is aborted and RP is completed under MARP $\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{r}$
$u(\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{r})$	probability of system loss in an attempt under MARP $\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{r}$
$\pi(\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{r})$	expected losses associated with successful RP under MARP $\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{r}$
$c(n)$	cost of losses associated with successful RP of type n (RP cost)
C	cost of system loss
Z	penalty associated with mission failure
ω_{max}	maximum possible cumulated losses associated with RP during the mission
$\lvert\omega_{max}\rvert$	number of different values of cumulated losses associated with RP
$\lfloor x \rfloor$	the greatest integer not exceeding x (i.e., the floor of x)

- The number of failed system components: k-out-of-n:F systems [14], k-out-of-n:F balanced systems [15,16], k-out-of-n:G systems [17], standby sparing systems executing dynamic tasks [18], UAVs [19].
- The number of failed components and system age or operation time: standby sparing systems [20], self-healing systems [21].
- The degradation level: phased-mission systems [22].
- Work accomplished: heterogeneous warm standby systems [12], standby systems with failure propagation [23], standby systems with maintenance [24], standby systems with condition-dependent loading [25].
- The degradation level and work accomplished: multistate systems with storage [26], safety-critical systems [27].
- The degradation level and system age: UAVs [28].
- The number of shocks survived: systems with random rescue time [29], single-component systems [1], multi-state systems with inspections [30], UAV-truck systems [31].
- Early warning signals: mission-based systems like UAVs [32].
- System predictive reliability: multi-component systems with failure interactions [33]

Since 2020, a shift from single-attempt missions to multi-attempt missions has happened for the mission abort research [34]. Two types of research can be distinguished for multi-attempt models:

- Only one functioning unit is available to attempt the mission. Thus, a new attempt cannot begin until the previous attempt is aborted and the unit is successfully maintained or rescued. Examples include the attempt-independent shock-based abort policy for multi-state repairable systems [35], the degradation level-based policy that may vary from attempt to attempt [36,37], task-dependent, shock and operation time-based policy for systems performing multiple independent tasks [3].
- Multiple functioning units are available to attempt the mission either fully or partially in parallel [38,39]. For example, in [40], two groups of units adopting attempt-dependent aborting policies are engaged concurrently during each attempt. To alleviate the high cost of fully concurrent attempts, in [39,41] a consecutive multi-attempt model where functioning units are activated one by one with a prespecified interval was proposed to execute the mission partially concurrently. A common abort command is issued to abort all other ongoing attempts when any attempt succeeds [39] or when any unit is close enough to completing the mission [41]. The consecutive multi-attempt model was extended in [42] for a time-constrained multi-task mission system.

The proposed research focuses on multi-attempt mission systems with one available functioning unit. The mission abort policy of interest is based on the number of shocks survived and the system operation time since the beginning of each attempt.

1.2. Research gap and contributions

The current multi-attempt models assumed that only one rescue option is available for execution following the decision of the mission abort during each attempt. In practice, multiple types of rescue procedures may be available for selection and the choice of the rescue type may affect the mission performance significantly. Consider a UAV performing a payload delivery mission. Different rescue options characterized by different altitudes (affecting the speed/performance of the UAV and the shock rate of the flying environment) and different amounts of payload to save (affecting the rescue cost) can be available. The choice of the rescue option can be made based on the amount of work accomplished before the attempt abort. Refer to Section 5 for a more detailed description of this example. None of the existing models can address such multi-attempt model with multiple different rescue options.

This paper pioneers the modeling and optimization of a multi-attempt mission system with different types of rescue procedures characterized by dissimilar system performance, shock rates, and rescue costs. A new numerical algorithm is suggested to assess the expected

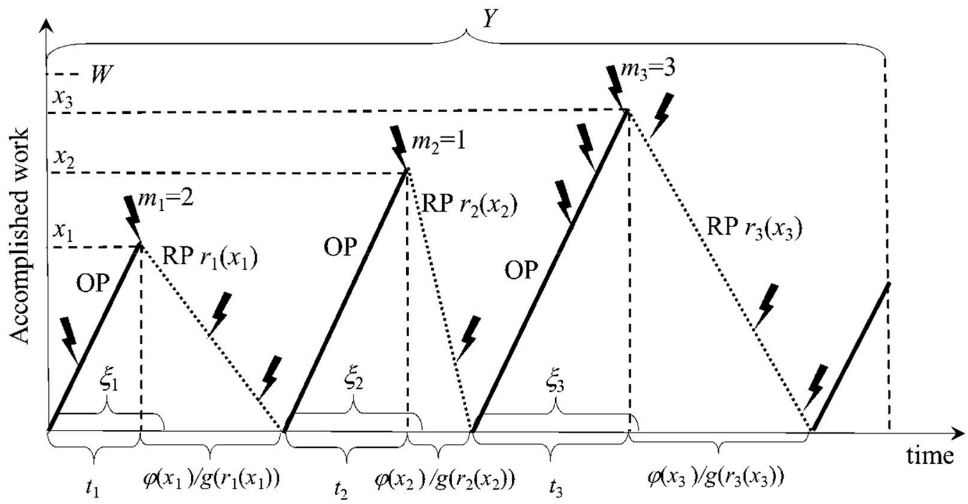

Fig. 1. Example of an unsuccessful mission terminated after three attempts.

mission losses (EML) of the considered system. The EML encompasses the mission failure penalty, system loss cost as well as the rescue cost. As both the mission abort policy and the choice of rescue option may greatly impact the EML, a new optimization problem is formulated and solved, which determines the mission abort and rescue policy (MARP) for each attempt to minimize the EML. A detailed UAV case study is conducted to demonstrate the accuracy and efficiency of the proposed numerical EML evaluation algorithm. We also investigate the impacts of several key parameters including the mission failure penalty, system loss cost, the allowed number of attempts, shock resistance deterioration factor on the EML and the optimal MARP solutions.

As a motivating example, consider a data processing software system that must complete a task operating with sensitive data by the deadline T. The cloud server on which the system operates is exposed to random shocks in the form of hackers' attacks. The attacks aim to corrupt the user's sensitive data. Each attack, even when failing, may provide certain information about the specific server protection codes, which can be used by the hackers in their future attacks. Consequently, as the number of attacks increases, the attack success probability increases. If the number of attacks (shocks) reaches the threshold m within time ξ from the task beginning, the software is deallocated from the server (i.e. its mission is aborted) which presumes encrypting the data and sending it to another server through one of available communication channels. During the data transfer, the communication channels can be also attacked by hackers. Choosing the encryption procedure and the communication channel (RP option), one determines the data transfer speed, cost and hacker attack rate. When the RP is completed, additional attempt to accomplish the task on another server starts if the chance to complete the task in time remains. The optimal task aborting policy must minimize expected losses associated with expensive data transfer procedures, damage caused by the data corruption and the computational mission failure. Another example of the UAV application is provided in Section 5.

The rest of the paper is arranged as follows: Section 2 presents the multi-attempt mission abort system with multiple recue options, formulates the MARP optimization problem, and provides an illustrative example. Section 3 derives the EML. Section 4 depicts the numerical EML evaluation algorithm and analyzes its computational complexity. Section 5 provides the detailed UAV case study. Section 6 gives conclusions and several further research problems.

2. System model and problem formulation

The system aims to accomplish an operation phase (OP) of a mission, which requires performing the amount of work W in a random environment modeled by a homogeneous Poisson process of shocks occurring with rate Λ. The performance (amount of work performed in unit time) of the system during the OP is g_M. To complete the OP, the system must survive all shocks occurring during time $\tau = W/g_M$.

2.1. Mission aborting and rescue

Each shock incurs deterioration to the system and the deterioration increases with the increasing number of shocks, leading to greater risks of system failure and loss [43]. To mitigate such risks, the OP may be aborted before its completion, immediately followed by the activation and execution of a rescue procedure (RP).

After the OP abortion and RP completion, the system can start a new attempt to complete the OP. The total number of attempts cannot exceed K and the total time during which the mission completion remains relevant (mission time) is Y.

Let $T_1 < T_2 < \ldots T_i$ denote random arrival times of shocks from the beginning of the OP in attempt k. If m_k shocks occur during time ξ_k since the beginning of the OP, the system immediately aborts the OP and starts the RP. If fewer than m_k shocks happen during time ξ_k, the system continues operation until the OP completion or system failure.

The work required for a successful RP depends on the amount of OP work performed before the RP activation. Particularly, if the OP is aborted at time t from the beginning of the attempt, the required amount of RP work is $\varphi(g_M t)$. There exist N different options/types of RP. If the RP option n is chosen, the system accomplishes the RP with performance $g(n)$ and is exposed to a homogeneous Poisson process of shocks with rate $\lambda(n)$. The successful completion of the RP of type n is associated with loss $c(n)$. The choice of the RP option can be based on the amount of work performed in the OP before its abortion in attempt k and defined by the integer function $r_k(g_M t) \in \{1, \ldots, N\}$.

If the OP remains uncompleted until either the system failure or the mission time expiration, the mission fails and penalty Z is imposed. If the system fails during the OP or RP accomplishment in any attempt, the cost of the system loss C is imposed.

The following assumptions are made in the model.

- All the shocks are observable.
- The inter-attempt preparation/maintenance time is negligible.
- The operation cost is negligible.
- The system starts each attempt in an as good as new state.

2.2. Problem formulation

The mission abort and rescue policy is determined by the vectors $\boldsymbol{m}=$

$\{m_1,...,m_K\}$, $\boldsymbol{\xi}=\{\xi_1,...,\xi_K\}$ and the set of functions $\boldsymbol{r}(g_M t)=\{r_1(g_M t),...,r_K(g_M t)\}$ that determine the aborting rules and RP option choices for each attempt $1\le k\le K$.

The problem is to find the MARP ***m, ξ, r*** that minimizes the expected mission losses $L(\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{r},)$, which includes the mission failure penalty, system loss cost and the RP cost.

Consider an example of a three-attempt realization of a mission (Fig. 1). In each attempt k, the system experiences m_k-th shock at time $t_k<\xi_k$ from the beginning of attempt (when amount $x_k=g_M t_k$ of OP work is completed) and aborts the OP phase. After the OP aborting, the system starts the RP of type $r_k(g_M t_k)$ which takes time $\varphi(g_M t_k)/g(r_k(g_M t_k))$. In the first two attempts, the system survives all the shocks occurring during the RPs and starts the next attempt. After the third attempt, the system has no time to complete the OP until the mission time expiration, i.e., $\sum_{k=1}^{3}(t_k+\varphi(g_M t_k)/g(r_k(g_M t_k))+W/g_M>Y$. Therefore, it terminates the mission after the third RP completion. In the considered example, the mission fails and the system survives. The total mission losses are $Z+\sum_{k=1}^{3}c(r_k(g_M t_k))$.

3. Deriving the EML

This section derives the system survivability as a function of the number of experienced shocks, the probabilities of different outcomes of an attempt, and further the EML.

3.1. System survivability

According to the shock model of [43], the survival probability of a system upon the h-th shock denoted by $q(h)$ ($q(0)\equiv 1$) is evaluated as

$$q(h)=\Gamma\gamma(h)\ \text{for}\ h>0, \tag{1}$$

where Γ is the survival probability upon the first shock and $\gamma(h)$ denotes a shock resistance deterioration factor. To model the decreasing survival probability upon each shock as the number of survived shocks increases, $\gamma(h)$ is defined as a decreasing function of its argument with $\gamma(h)=\gamma^{h-1}$, $0<\gamma<1$. Thus, the probability that the system can survive H shocks can be evaluated as

$$Q(H)=\prod_{h=0}^{H}q(h)=\Gamma^H\gamma^{\frac{H(H-1)}{2}}. \tag{2}$$

3.2. Probabilities of attempt k outcomes

The probability that i shocks occur to the system during time t under the homogeneous Poisson shock process with rate ρ is

$$P(t,i,\rho)=e^{-\rho t}\frac{(\rho t)^i}{i!},\ \text{for}\ i=0,1,2,... \tag{3}$$

The probability that the i-th shock happens in $[t, t+dt)$, where dt is infinitesimal is

$$P(t,i-1,\rho)\rho dt=\rho e^{-\rho t}\frac{(\rho t)^{i-1}}{(i-1)!}dt. \tag{4}$$

The system completes the OP in attempt k if fewer than m_k shocks occur during time ξ_k since the beginning of the attempt and the system survives all the shocks that occur during the time $\tau=W/g_M$. Thus, if $h\in[0, m_k-1]$ shocks occur in time interval $[0,\xi_k]$ and any number j of shocks occur in time interval $[\xi_k, W/g_M]$, then the system survives these shocks and completes the OP with probability $Q(h+j)$. The success probability of the OP in attempt k is

$$s(m_k,\xi_k)=\sum_{h=0}^{m_k-1}P(\xi_k,h,\Lambda)\sum_{j=0}^{\infty}P(W/g_M-\xi_k,j,\Lambda)Q(h+j). \tag{5}$$

The system aborts the OP and starts the RP of type $r_k(g_M t_k)$ if the m_i-th

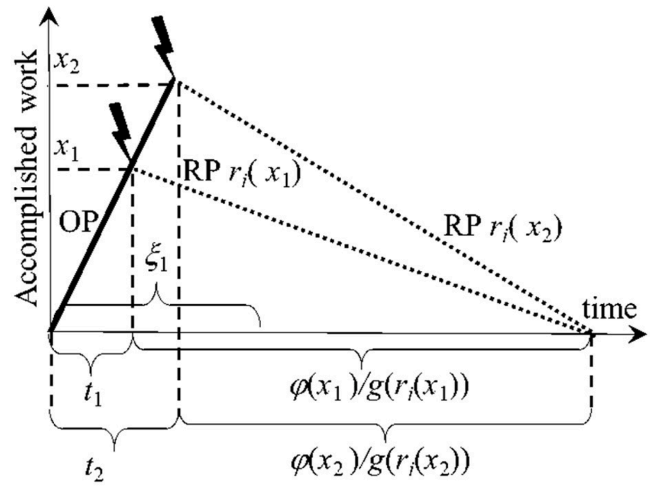

Fig. 2. Example of two RP realizations completed at the same time.

shock occurs at any time $T_{m_k}=t_k$ belonging to interval $[0,\xi_k)$. The time needed to complete the RP is $\varphi(g_M t_k)/g(r_k(g_M t_k))$. The system completes the RP if it survives m_k shocks in the OP during the time interval $[0, t_k)$ and all the shocks in the RP during time $\varphi(g_M t_k)/g(r_k(g_M t_k))$. Thus, the probability that the system following the MARP m_k,ξ_k,r_k completes the RP and survives the k-th attempt, but fails to complete the mission in this attempt is

$$\begin{aligned}v(m_k,\xi_k,r_k)&=\Lambda\int_0^{\xi_k}P(t,m_k-1,\Lambda)\\&\times\sum_{j=0}^{\infty}P(\varphi(g_M t)/g(r_k(g_M t)),j,\lambda(r_k(g_M t)))Q(m_k+j)dt.\end{aligned} \tag{6}$$

The probability that the system is lost during the attempt k is

$$u(m_k,\xi_k,r_k)=1-s(m_k,\xi_k)-v(m_k,\xi_k,r_k). \tag{7}$$

Based on (6), one can evaluate the expected losses associated with the successful RP under the MARP m_k,ξ_k,r_k as

$$\begin{aligned}\pi(m_k,\xi_k,r_k)&=\Lambda\int_0^{\xi_k}c(r_k(g_M t))P(t,m_k-1,\Lambda)\\&\times\sum_{j=0}^{\infty}P(\varphi(g_M t)/g(r_k(g_M t)),j,\lambda(r_k(g_M t)))Q(m_k+j)dt.\end{aligned} \tag{8}$$

3.3. Deriving EML

Let $E_k=\langle\Psi_k,\Omega_k\rangle$ be a random event that the system can start the k-th attempt at time Ψ_k when the RP cost accumulated before time Ψ_k is Ω_k. Let $e_k(\psi,\omega)$ be the *pdf* of Ψ_k when $\Omega_k=\omega$. Observe that there is no unambiguous functional correspondence between Ψ_k and Ω_k because the same RP termination time can correspond to different RP options depending on the OP aborting time (see Fig. 2 for example).

At the beginning of the mission, the system is ready to start the first attempt and the RP cost is zero. Therefore, $e_1(\psi,\omega)=\delta(\psi)$ for $\omega=0$ and $e_1(\psi,\omega)=0$ for $\omega\neq 0$ where $\delta(x)$ is the Dirac delta function.

$e_{k+1}(\psi,\omega)$ can be derived recursively from $e_k(\psi,\omega)$. The event E_{k+1} occurs if after event E_k, the system aborts the OP of attempt k and survives the subsequent RP. If the $(k+1)$-th OP is aborted at time $t_k<\xi_k$, from its beginning, the RP of type $r_k(g_M t_k)$ is chosen, which determines the required amount of RP work $\varphi(g_M t_k)$, the system performance during the RP $g(r_k(g_M t_k))$ and the RP cost $c(r_k(g_M t_k))$. Thus, between the events E_k and E_{k+1} the system spends time t_k in the OP and time $\varphi(g_M t_k)/g(r_k(g_M t_k))$ in the RP. In this case

$$\Psi_{k+1}=\Psi_k+t_k+\varphi(g_M t_k)/g(r_k(g_M t_k)). \tag{9}$$

The RP cost accumulated before time Ψ_{k+1} increases by $c(r_k(g_M t_k))$, i.e.,

$$\Omega_{k+1} = \Omega_k + c(r_k(g_M t_k)). \tag{10}$$

Having the probability (4) that the system aborts the OP in time interval $[t, t+dt)$ and completes the RP, we can obtain the *pdfs* $e_{k+1}(\psi,\omega)$ for $0 \le \psi \le Y$, $0 \le \omega \le \omega_{max}$, where $\omega_{\max} = K \max_{1\le n\le N} c(n)$ is maximum possible cumulated losses associated with RP during the mission

$$e_{k+1}(\psi,\omega) = \Lambda \int_0^{\xi_k} P(t, m_k - 1, \Lambda) \sum_{j=0}^{\infty} P(\varphi(g_M t)/g(r_k(g_M t)), j, \lambda(r_k(g_M t))) Q(m_k + j) \times e_k(\psi - t - \varphi(g_M t)/g(r_k(g_M t)), \omega - c(r_k(g_M t)))dt. \tag{11}$$

The mission can be terminated after event $E_k = \langle \Psi_k, \Omega_k \rangle$ in the following cases.

1. The system terminates the mission because no time remains to complete the next attempt OP, i.e., $\Psi_k + \tau > Y$. In this case, the system survives, but the mission fails. The cost of the mission losses after the event $E_k = \langle \Psi_k, \Omega_k \rangle$ is $Z + \Omega_k$. The EML corresponding to this case are

$$l_1(k) = \sum_{\omega=0}^{\omega_{max}} (Z+\omega) \int_{Y-\tau}^{\infty} e_k(\psi,\omega) d\psi. \tag{12}$$

2. The system fails in the attempt $k+1$. In this case, the system is lost and the mission fails. The cost of the mission losses after the event E_k is $C + Z + \Omega_k$. The EML corresponding to this case are

$$l_2(k) = u(m_{k+1}, \xi_{k+1}, r_{k+1}) \sum_{\omega=0}^{\omega_{max}} (C + Z + \omega) \int_0^{Y-\tau} e_k(\psi,\omega) d\psi. \tag{13}$$

3. The system completes the OP in the next attempt. In this case, the system survives, and the mission succeeds. The cost of the mission losses after the event E_k is Ω_k. The EML corresponding to this case are

$$l_3(k) = s(m_{k+1}, \xi_{k+1}) \sum_{\omega=0}^{\omega_{max}} \omega \int_0^{Y-\tau} e_k(\psi,\omega) d\psi. \tag{14}$$

4. The survived system terminates the mission after K failed attempts. The cost of the mission losses after the event $E_{K+1} = \langle \Psi_{K+1}, \Omega_{K+1} \rangle$ is $Z + \Omega_{K+1}$ because no further attempt is allowed. The EML corresponding to this case are

$$l_4 = \sum_{\omega=0}^{\omega_{max}} (Z+\omega) \int_0^{Y} e_{K+1}(\psi,\omega) d\psi. \tag{15}$$

The four cases considered above are mutually exclusive. Therefore, the overall EML can be obtained as

$$L(\boldsymbol{m}, \boldsymbol{\xi}, \boldsymbol{r}) = \sum_{k=1}^{K} (l_1(k) + l_2(k) + l_3(k)) + l_4. \tag{16}$$

4. Numerical procedures for the EML evaluation

To realize the EML derivation in a numerical procedure, we define a discrete time interval $d\psi$ to replace the infinitesimal values in (6), (10)-(13) and replace the functions $e_k(\psi,\omega)d\psi$ with a vectors of probabilities $\Pi_k(\psi,\omega) = \Pr(\psi \le \Psi_k < \psi + d\psi, \Omega_k = \omega)$ for any discrete realizations ω of Ω_k. Instead of the backward Eq. (10), we use a forward procedure that updates the values of $\Pi_{k+1}(\psi + t + \varphi(g_M t)/g(r_k(g_M t_k)), \omega + c(r_k(g_M t)))$ for any realization t of the time to OP aborting under a predetermined MARP in attempt $k+1$. As repeated updating of variables cannot be presented in the form of equations, the pseudo-code of the numerical algorithm is given below. It determines the EML for any given MARP $\boldsymbol{m}$, $\boldsymbol{\xi}$, $\boldsymbol{r}$.

1	For $k = 1,\ldots,K$: For $\psi = 0, d\psi, \ldots, Y$: For $\omega = 0, \ldots, \omega_{max}$: Set $\Pi_k(\psi,\omega) = 0$;
2	Set $\Pi_1(0,0) = 1$;
3	For $k = 1,\ldots,K$:
4	Obtain $s(m_k, \xi_k)$, $v(m_k, \xi_k, r_k)$ and $u(m_k, \xi_k, r_k)$;
5	For $\omega = 0,\ldots,\omega_{max}$: For $\psi = 0, d\psi, \ldots, Y$:
6	If $\psi > Y - \tau$ then $L = L + \Pi_k(\psi,\omega)(Z+\omega)$;
7	If $\psi \le Y - \tau$ then
8	$L = L + \Pi_k(\psi,\omega) \{u(m_k, \xi_k, r_k)(C + Z + \omega) + s(m_k, \xi_k)\omega\}$;
9	For $t = 0, d\psi, \ldots, \xi_k$
10	$x = g_M t$; $n = r_k(g_M t)$; $w = \varphi(x)/g(n)$; $q = \min(Y, \psi + t + w)$;
11	$\Pi_{k+1}(q, \omega + c(n)) = \Pi_{k+1}(q, \omega + c(n)) + \Lambda \Pi_k(\psi,\omega) P(t, m_k - 1, \Lambda) \sum_{j=0}^{\infty} P(w, j, \lambda(n)) Q(m_k + j)$;
12	For $\omega = 0,\ldots,\omega_{max}$: For $\psi = 0, d\psi, \ldots, Y$: $L = L + \Pi_{K+1}(\psi,\omega)(Z+\omega)$;

Steps 1 and 2 of the algorithm initiate the values of vectors $\Pi_k(\psi,\omega)$. Step 4 obtains $s(m_k, \xi_k)$, $v(m_k, \xi_k, r_k)$ and $u(m_k, \xi_k, r_k)$ using (5),(6), (7). Observe that $\prod_{j=0}^{J} q(j)$ is a decreasing function of J. Therefore, in practice the infinite sum in (5), and (6) can be replaced by the sum in which j varies from 0 to J, where $\prod_{j=0}^{J} q(j)$ is negligible. The computational aspects of obtaining the infinite sums in (5) – (7) and an example of determining the value of J are presented in [43]. The computational complexity of Step 4 is $O(JY/d\psi)$ [43]. Steps 6 and 8 update the value of the EML according to (12)-(14). Step 12 updates the value of the EML according to (15). Steps 9–11 update the vector $\Pi_{k+1}(\psi,\omega)$ in accordance with (11).

As it can be seen from the pseudo code above, the computational complexity of Steps 3–11 of the algorithm is $O(K|\omega_{\max}|(Y/d\psi)^2)$, where $|\omega_{max}|$ is the number of possible realizations of the total RP cost in the mission.

5. UAV case study

5.1. System description

Consider a UAV that must accomplish a mission of delivering a payload consisting of three containers to a destination position located at a distance $W = 120$ km from the UAV base. During the flight, the UAV is exposed to electromagnetic interference from high voltage power lines, cell phone towers, large metal structures and other sources [2,3], which usually causes deteriorating or damaging the UAV or its key components [44,45]. The electromagnetic impulses arrive at random times with specific rates depending on the AV altitude. The interference filter that detects the electromagnetic impulses (shocks) and protects the UAV deteriorates as the number of experienced shocks increases due to overheating, leading to the decrease of its resistance to shocks. Such deterioration is considered using (2) with $\Gamma = 0.97$, $\gamma = 0.93$.

During the flight to the destination point (OP), the UAV keeps speed

Table 1
Parameters of different RP types.

n	$c(n)$	$g(n)$	$\lambda(n)$
1	0	80	5.0
2	6	110	3.0
3	12	120	1.8
4	18	125	1.2

g_M=80 km/h and remains at an altitude which allows carrying the payload. The OP flight duration is $\tau=W/g_M$=1.5 h. The number of shocks arrivals during the OP flight obeys the homogeneous Poisson process with rate Λ=5 h^{-1}. The total mission duration (time during which the payload delivery remains relevant) is $Y = 2.5$ h.

To alleviate the risk of the UAV loss, the OP can be aborted if the m_k-th shock occurs during time ξ_k since its beginning. If the OP is aborted at time $t_k \le \xi_k$ from its beginning, the UAV starts the RP by flying back to the base. The distance of the rescue flight is equal to the distance covered by the UAV by the moment of the OP abort, i.e., $\varphi(x)=x$. There are four possible options of the RP. Option 1 presumes flying on the same altitude and with the same speed $g(1)=g_M$ as in the OP (being exposed to the same shock process with rate $\lambda(1) = \Lambda$). The cost associated with this RP option is $c(1)$=0. Any option $2 \le n \le 4$ presumes dropping n-1 containers, which allows the UAV to rise to a greater altitude where the shock rate is $\lambda(n)$ and increase its speed to $g(n)$. The loss of n-1 container is associated with cost $c(n)$. The parameters of different RP options are presented in Table 1.

The failure of the delivery mission is associated with penalty of $Z = 500$. The cost of the lost UAV with all three containers is $C = 130$.

When the UAV successfully returns to the base, its interference filter

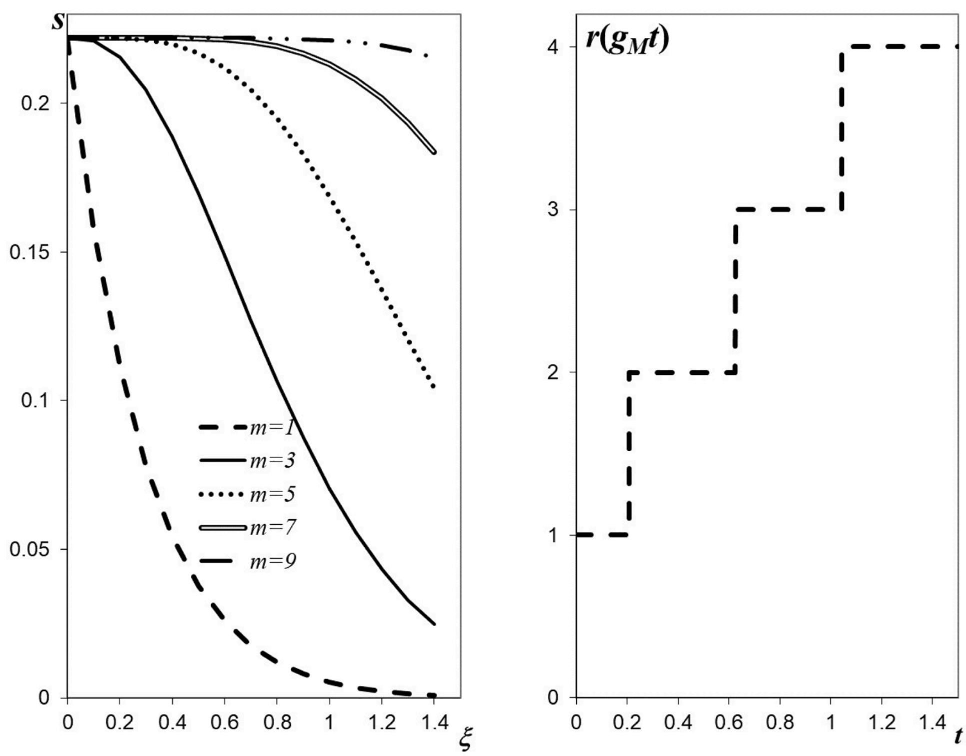

Fig. 3. Probability of attempt success $s(m, \xi)$ and example of the RP type choice function $r(x) = r(g_M t)$.

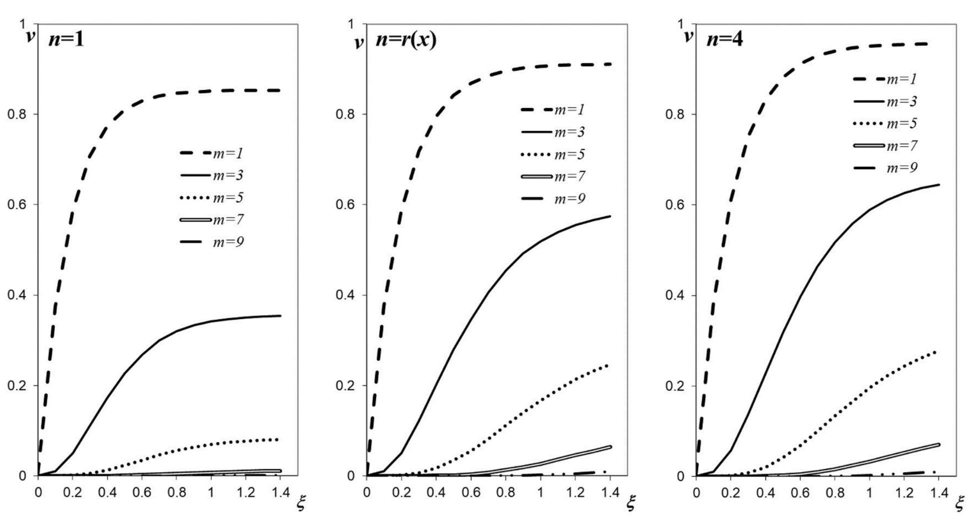

Fig. 4. Probability of attempt abort and RP success $v(m, \xi, r)$ for three different RP type choice functions $r(x)\equiv1$, $r(x)\equiv4$ and $r(x)$ presented in Fig. 3.

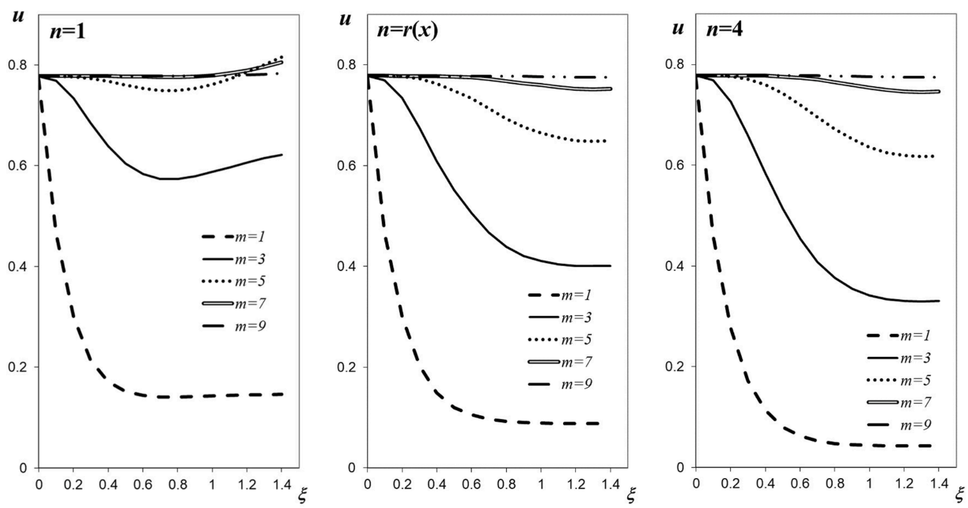

Fig. 5. Probability of system loss in an attempt $u(m, \xi, r)$ for three different RP type choice functions $r(x)\equiv1$, $r(x)\equiv4$ and $r(x)$ presented in Fig. 3.

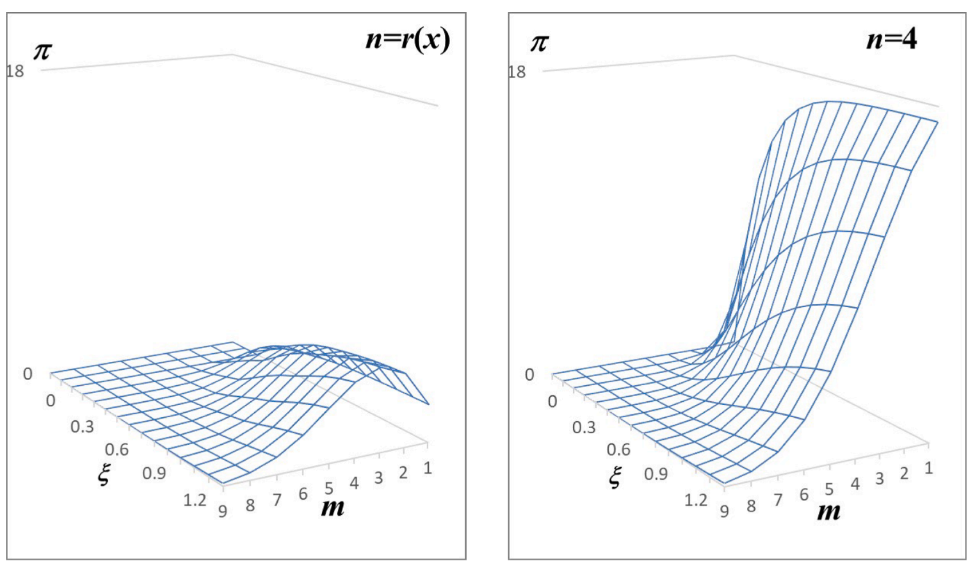

Fig. 6. Expected losses associated with successful RP for $r(x)\equiv4$ and $r(x)$ presented in Fig. 3.

is replaced and missing containers are replenished. Then the UAV starts a new attempt if the remaining mission time is not less than τ. The number K of available interference filters in the base determines the number of attempts.

The choice of the RP option is determined by the stepwise linear function defined by two parameters a_k and b_k as

$$r_k(x) = 1 + \max(\min(3, \lfloor a_k + 0.01 b_k x \rfloor), 0). \tag{17}$$

Thus, the MARP is defined by the set of K quadruplets $\{m_1, \xi_1, a_1, b_1, \ldots, m_K, \xi_K, a_K, b_K\}$.

5.2. Single attempt outcome parameters

Figs. 3-6 present the outcome probabilities of a single attempt and expected losses associated with the RP as functions of abort parameters m, ξ for three different RP type choice functions: fixed $r(x)\equiv1$, fixed $r(x)\equiv4$ and variable $r(x)$ presented in Fig. 3. It can be seen that the probability of attempt success $s(m, \xi)$ decreases with increasing ξ and increases with increasing m because as ξ decreases and m increases, the attempt aborting can be performed during a shorter time and after a greater number of shocks, which gives the system greater chances to complete the mission. On the contrary, the probability that the UAV aborts the OP and survives the attempt $v(m, \xi, r)$ increases with increasing ξ and decreases with increasing m because with more cautious MARP (smaller m and greater ξ), the system aborts the attempt earlier and has greater chances to survive. With an increase of the function $r(x)$, which corresponds to a safer RP option, the probability $v(m, \xi, r)$ increases.

When $r(x)\equiv1$, i.e., the return flight conditions are the same as in the OP flight, the system loss probability $u(m, \xi, r) = 1 - v(m, \xi, r) - s(m, \xi)$ behaves non-monotonically. On one hand, an early attempt aborting increases the system's chance to survive the attempt. On the other hand, the mission aborting on the late OP stages requires covering return distance exceeding the distance remaining to the destination point. Therefore, for the values of ξ approaching τ=1.5, the attempt aborting can result in a greater system loss probability than for ξ=0 (no aborting). For the fixed $r(x)\equiv4$ and dynamic $r(x)$ presented in Fig. 3, the return flight conditions are better than those during the OP flight (greater speed and lower shock rate). Therefore, the more cautious aborting policy does not cause the increase of the system loss probability and $u(m, \xi, r)$ monotonically decreases when m decreases and ξ increases. However, the decrease in $u(m, \xi, r)$ is achieved by the price of the

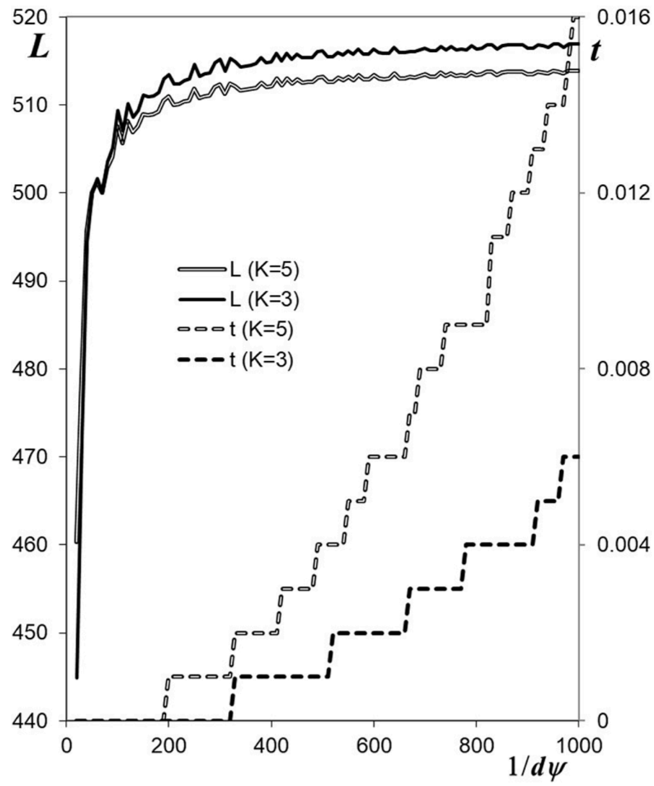

Fig. 7. EML and running time as functions of $1/d\psi$ for $Z = 500$ and MARP $r(x)\equiv 1$, $m = 1$, ξ=0.4.

increased expected cost associated with a successful RP $\pi(m, \xi, r)$.

As it can be seen from Fig. 6, for $r(x)\equiv 4$, $\pi(m, \xi, r)$ monotonically increases with increasing ξ and decreases with increasing m (i.e., increases when the aborting policy becomes more cautious and the attempt abort probability increases). For variable $r(x)$ presented in Fig. 3, $\pi(m, \xi, r)$ for ξ<0.2 remains zero because $r(x)$=$r(g_M t)$=1 for $t \le 0.2$ and $c(1)$=0, i.e., only a costless RP option can be used. With an increase of m, the probability of attempt aborting at a later time increases, which causes the choice of costlier RP options according to the $r(g_M t)$ function. Therefore, the expected cost $\pi(m, \xi, r)$ increases as m increases. However, a further increase of m considerably reduces the overall attempt abort probability (the probability that a greater number of shocks occur in [0, ξ]), which causes a decrease of $\pi(m, \xi, r)$ and explains its non-monotonic behavior. For $r(x)\equiv 1$, only the costless RP option 1 can be used, which causes $\pi(m, \xi, r) = 0$.

5.3. Influence of the discretization parameter dψ

To evaluate the influence of the discretization factor $d\psi$ on the solution accuracy, we obtain the EML L as a function of $d\psi$ for $r(x)\equiv 1$, $m = 1$, ξ=0.4 and two values of allowed number of attempts ($K = 3$ and $K = 5$). Fig. 7 presents the EML and running time of the C language realization of the numerical algorithm (Section 4) on 3.2 GHz PC as a function of $1/d\psi$. It can be seen that the running time is a quadratic function of $1/d\psi$.

The obtained values of the EML quickly converge with a decrease in $d\psi$. The related discrepancy between the values of L for $d\psi = 0.01$ and $d\psi = 0.001$ is 1.46 % for $K = 5$ and 1.23 % for $K = 3$. The related discrepancy between the values of L for $d\psi = 0.005$ and $d\psi = 0.001$ is 0.67 % for $K = 5$ and 0.58 % for $K = 3$. The value of $d\psi = 0.005$ is chosen in the optimization problems presented further.

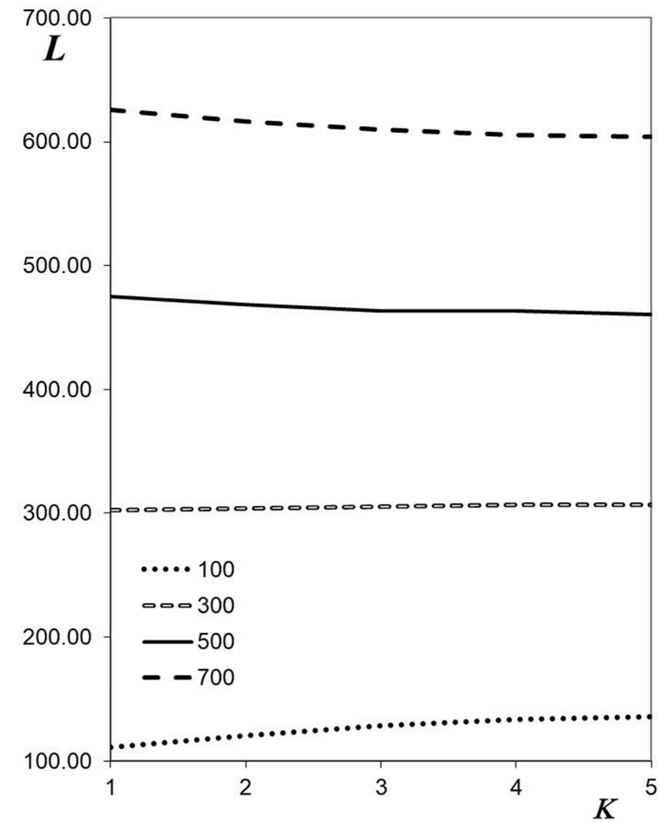

Fig. 8. Best obtained values of the EML as functions of mission failure penalty Z and allowed number of attempts.

Table 2
Best obtained attempt dependent MARP solutions for $Z = 100$ and different values of allowed number of attempts K.

K	L	i	m_i	ξ_i/τ	a_i	b_i
1	110.90	1	1	0.5	0	5
2	120.65	1	1	0.5	0	4
		2	1	0.5	0	5
		1	1	0.5	0	4
3	128.26	2	1	0.5	0	4
		3	1	0.5	0	5
		1	1	0.5	0	4
4	133.30	2	1	0.5	0	4
		3	1	0.5	0	4
		4	1	0.5	0	5
		1	1	0.5	0	4
		2	1	0.5	0	4
5	136.07	3	1	0.5	0	4
		4	1	0.5	0	4
		5	1	0.5	0	5

5.4. EML minimization

Finding the optimal MARP minimizing the EML $L(m, \xi, r)$ is multidimensional optimization problem, in which 4 K parameters {m_1,ξ_1,a_1, b_1, …, m_K,ξ_K,a_K,b_K} should be obtained. To solve this problem, the genetic algorithm (GA) is applied in this work, which is one of the most applied techniques for solving optimization problems in the reliability engineering field [46,47].

The GA requires solutions to be represented in strings. The solution encoding for the EML minimization problem is as follows. The string consists of 4K integer numbers ζ_{11},…, ζ_{14},…,ζ_{K1},…,ζ_{K4} ranging from 0 to 100. The MARP parameters are obtained as m_i=1 + 0.1ζ_{i1}, ξ_i=0.01$\tau\zeta_{i2}$, a_i=mod$_4\zeta_{i3}$, b_i=0.2ζ_{i4}–10. Such encoding provides variation of the

Table 3
Best obtained attempt dependent MARP solutions for $Z = 700$ and different values of allowed number of attempts K.

K	L	i	m_i	ξ_i/τ	a_i	b_i
1	625.58	1	1	0.0	–	–
2	616.45	1	1	0.2	0	5
		2	–	0.0	–	–
		1	1	0.2	0	5
3	609.75	2	1	0.2	0	5
		3	–	0.0	–	–
		1	1	0.2	0	5
4	605.60	2	1	0.2	0	5
		3	1	0.1	0	0
		4	–	0.0	–	–
		1	1	0.2	0	5
		2	1	0.2	0	5
5	603.89	3	1	0.1	0	0
		4	1	0.1	0	0
		5	–	0.0	–	–

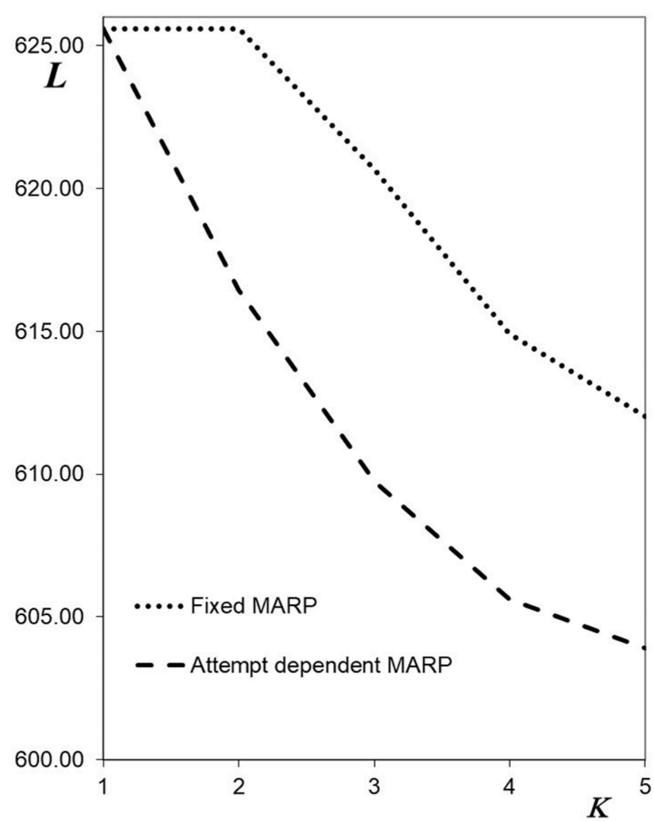

Fig. 9. Comparison of EML for fixed and attempt dependent MARP for $Z = 700$.

parameters in the ranges $m_i \in [1,11]$, $\xi_i/\tau \in [0,1]$, $a_i \in [0,3]$, $b_i \in [-10,10]$. With parameters a_i and b_i, the RP option is determined using (17).

With the proposed string solution representation, the standard mutation, crossover, and selection operations involved in the GA optimization process [46,47] are implemented to solve the proposed MARP optimization problem. The GA running on 3.2 GHz PC solves a single optimization problem $L(m,\xi,r) \rightarrow \min$ in around 2.5 min.

Fig. 8 presents the best obtained values of the EML as functions of the mission failure penalty Z and allowed number of attempts. Tables 2 and 3 present examples of the best obtained MARP solutions for different values of K when $Z = 100$ and $Z = 500$. It can be seen that when Z is low, the increase in K causes an increase in the EML because the system loss probability and the RP costs increase as K increases, which is not compensated by the decrease in the mission failure probability. When

Table 4
Best obtained fixed MARP solutions for $Z = 700$ and different values of allowed number of attempts K.

K	L	m	ξ/τ	a	b
1	625.58	–	0.0	–	–
2	625.58	-	0.0	-	-
3	620.66	1	0.1	0	0
4	614.91	1	0.1	0	0
5	612.02	1	0.1	0	0

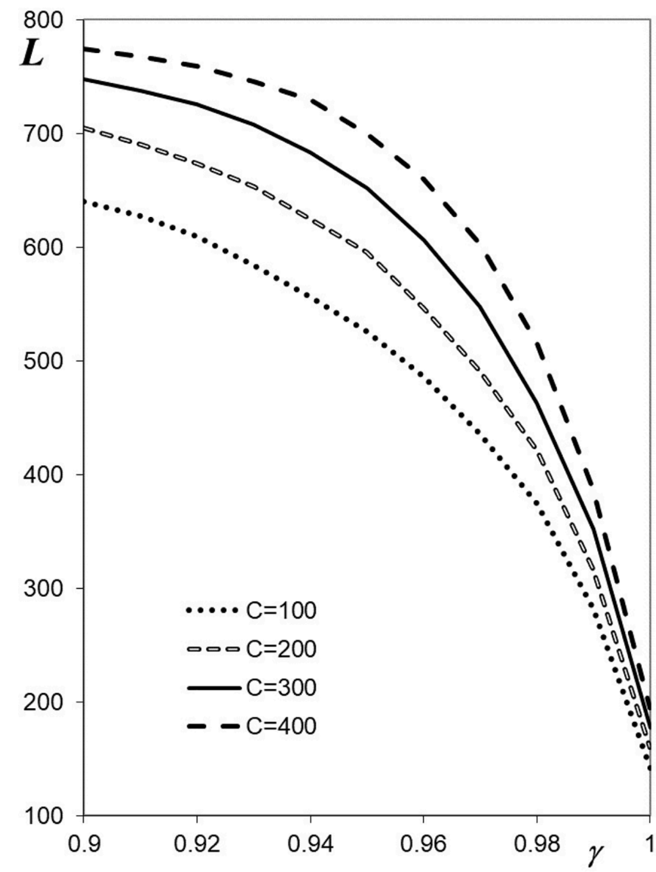

Fig. 10. Best obtained EML as function of shock resistance deterioration factor γ and cost of system loss C for $Z = 700$.

the mission failure cost increases, reducing the mission failure probability becomes more important and it should be achieved by the price of increasing the number of attempts and expected cost of RP and system loss probability. Therefore, the EML decreases with increasing K when Z is high.

When Z is low, the conservative MARP is accepted, which allows the attempt aborts during 50 % of the OP. This allows the UAV survival during the mission with a high probability. The number/index of the chosen RP option increases with the time of the attempt abort ($b > 0$ provides an increasing function $r(x)$), which allows the UAV to cover a greater distance during its flight back to the base with a greater speed reducing the time of its exposure to the shocks. For example, for $K = 2$, in the first attempt, the RP option $r = 1$ is chosen if the OP is aborted during first 21 % of the OP, $r = 2$ is chosen if the OP is aborted when from 21 % to 42 % of the OP is performed, and $r = 3$ is chosen if the OP is aborted when from 42 % to 50 % of the OP is performed. In the second attempt, the RP option $r = 1$ is chosen if the OP is aborted during first 16.7 % of the OP, $r = 2$ is chosen if the OP is aborted when from 16.7 % to 33.3 % of the OP is performed, and $r = 3$ is chosen if the OP is aborted when from 33.3 % to 50 % of the OP is performed.

Table 5
Best obtained MARP solutions for $C = 100$, $Z = 700$, $K = 5$ and different values of shock resistance deterioration factor γ.

γ	L	i	m_i	ξ_i/τ	a_i	b_i
		1	1	0.2	0	5
		2	1	0.2	0	5
0.9	640.23	3	1	0.2	0	5
		4	–	0.0	–	–
		1	1	0.2	0	5
		2	1	0.2	0	5
0.93	583.92	3	1	0.1	0	5
		4	–	0.0	–	–
		1	1	0.2	0	5
0.97	435.96	2	1	0.1	0	5
		3	1	0.1	0	1
		4	–	0.0	–	–
1.0	141.80	1	–	0.0	–	–

Table 6
Best obtained MARP solutions for $C = 400$, $Z = 700$, $K = 5$ and different values of shock resistance deterioration factor γ.

γ	L	i	m_i	ξ_i/τ	a_i	b_i
		1	1	0.4	1	5
		2	1	0.4	1	5
0.9	774.61	3	1	0.4	1	5
		4	1	0.4	1	5
		5	1	0.4	1	5
		1	1	0.3	1	4
		2	1	0.3	1	5
0.93	745.60	3	1	0.3	1	5
		4	1	0.3	1	5
		5	1	0.3	1	5
		1	1	0.2	0	5
0.97	602.43	2	1	0.1	0	5
		3	–	0.0	–	–
1.0	194.98	1	–	0.0	–	–

Table 7
Comparison of the best obtained MARP for one and four RP options when $C = 400$, $Z = 700$, $K = 5$.

	Four RP options						One RP option		
γ	L	i	m_i	ξ_i/τ	a_i	b_i	L	m_i	ξ_i/τ
		1	1	0.4	1	5		1	0.3
		2	1	0.4	1	5		1	0.3
0.9	774.61	3	1	0.4	1	5	832.75	1	0.3
		4	1	0.4	1	5		1	0.3
		5	1	0.4	1	5		1	0.3
		1	1	0.3	1	5		1	0.2
		2	1	0.3	1	5		1	0.2
0.92	759.28	3	1	0.4	1	5	799.69	1	0.3
		4	1	0.4	1	5		1	0.3
		5	1	0.4	1	5		1	0.3
		1	1	0.3	1	4		1	0.2
		2	1	0.3	1	4		1	0.2
0.94	729.42	3	1	0.3	1	4	748.25	1	0.2
		4	1	0.3	1	4		1	0.2
		5	1	0.4	1	4		1	0.2
		1	1	0.2	1	4		1	0.2
		2	1	0.2	1	3		1	0.1
0.96	660.29	3	1	0.2	1	3	670.06	1	0.1
		4	1	0.2	1	3		1	0.1
		5	1	0.1	0	5		1	0.1

When Z is high, the MARP becomes riskier, allowing attempt aborting during a shorter part of the OP. In the last K-th attempt, the OP abort is not allowed and the UAV either completes the attempt or is lost. As in the case of $Z = 100$, the number of the chosen RP option increases with the time of the attempt abort. For example, for $K = 2$, in the first attempt, the RP option $r = 1$ is chosen if the OP is aborted during the first 16.7 % of the OP, $r = 2$ is chosen if the OP is aborted when from 16.7 % to 20 % of the OP is performed. In the second attempt, no aborts are allowed.

Fig. 9 presents the best obtained values of the EML for $Z = 700$ and different values of allowed number of attempts. Two type of MARP are compared: fixed MARP which is identical for any attempt and variable attempt dependent MARP. Table 4 presents the best obtained fixed MARP and the corresponding values of the EML. When $K < 3$ the minimum EML for the fixed MARP is achieved when no attempt aborts are allowed. When $3 \le K \le 5$ the fixed MARP that attempt OP aborting upon the first shock occurring during the first 10 % of the OP and RP option $r = 1$ remains the same. The variable attempt dependent MARP provides lower EML than the fixed one.

Fig. 10 presents the best obtained EML as a function of the shock resistance deterioration factor γ and the cost of system loss C for $Z = 700$ when no more than $K = 5$ attempts are allowed. Tables 5 and 6 present some MARP solutions for $C = 100$ and $C = 400$. As γ increases, the UAV becomes more shock-tolerant and can use a riskier MARP allowing attempt abortion during a shorter time and using riskier and cheaper RP options. For γ=1, no attempt abort is allowed. When C increases and saving the UAV becomes more important, the MARP become more cautious allowing aborts during a longer time of the OP. More expensive, but safer RP options are used.

When $C = 100$, all five allowed attempts are never used as the MARP presumes no abort in attempt 4 for $\gamma<1$, which increases the mission success probability by the price of increasing the probability of the UAV loss. For $C = 400$ and $\gamma \le 0.93$, the more cautious MARP allows aborting in all five attempts.

Intuitively, the EML increases when the UAV cost increases and the shock resistance deterioration factor γ decreases making the UAV more vulnerable.

Table 7 presents comparisons of the best obtained MARP solutions in situations where all four RP options are available and when the UAV is unable to drop containers upon attempt abortion (Single RP option 1 remains). It can be seen that in the situation where the only one riskiest RP option exists because the UAV cannot increase its speed and amplitude, the OP aborting becomes less beneficial and the optimal time during which the OP abort is allowed decreases compared to the case where all the RP options are available. The lowest achieved EML for the case of the single RP option is greater than that for the case of four available RP options.

6. Conclusion and future research directions

This paper contributes to the body of knowledge on the mission aborting research by modeling and optimizing a multi-attempt mission system with different RP options that are characterized by dissimilar system performance, shock rates, and rescue costs. We formulate a new MARP optimization problem, which finds the aborting rule as well as the rescue option choice for each attempt minimizing the EML. The solution encompasses a new numerical EML evaluation algorithm and the implementation of the genetic algorithm based on the suggested string representation of the MARP. As revealed from the detailed analysis of a UAV system performing a payload delivery mission with four types of RPs, the major findings are: 1) as the mission failure penalty increases, the MARP becomes riskier allowing attempt aborting during a shorter time; 2) the variable attempt-dependent MARP can provide lower EML than the fixed, attempt-independent MARP; 3) as the shock resistance deterioration factor increases, the system becomes more shock-tolerant, it becomes beneficial to adopt a riskier MARP allowing attempt abortion during a shorter time and a riskier and cheaper RP option; 4) as the system loss cost increases, the EML increases, more cautious MARP and more expensive but safer RP options should be adopted.

Observe that, though, for the sake of presentation clarity and simplicity, it is assumed that the operation and inter-attempt maintenance costs are negligible in this work, the model can easily include these costs by adding corresponding constants in (12)-(15) without affecting the presented algorithm.

A single task is assumed in the proposed model. One further research problem is to extend the model for missions engaging multiple tasks [3]. Task-dependent MARPs may be investigated. Another direction is to relax the assumption that the system starts each attempt in an as good as new state by considering imperfect rescue or maintenance.

CRediT authorship contribution statement

Gregory Levitin: Conceptualization, Software, Writing – original draft. **Liudong Xing:** Formal analysis, Writing – original draft, Writing – review & editing. **Yuanshun Dai:** Data curation, Visualization.

Declaration of competing interest

There is no conflict of interests associated with this paper.

Data availability

No data was used for the research described in the article.

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