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Optimal system loading and aborting in additive multi-attempt missions

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A R T I C L E I N F O

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A B S T R A C T

Despite considerable research efforts devoted to the mission aborting policies for diverse systems, little work considered the effects of loading and the existing models assumed single-attempt missions only. In practice, loading may affect mission work progress and system loss risk. This paper contributes by modeling and optimizing the mission aborting and loading policy (MALP) for a mission system that must accomplish a specified amount of work through multiple attempts. A successful attempt includes an operation phase (OP) that completes a portion of required work dependent on the loading level, followed by a return phase (RP). The OP in an attempt may also be aborted followed by a rescue action (RA) to survive the system. The system undergoes different, loading-dependent shock processes during OP, RP, and RA. A new numerical method is proposed to evaluate the expected mission losses (EML), encompassing costs associated with uncompleted work and system losses. The optimal MALP problem is then solved to minimize the EML. The case study of an aerial vehicle performing a goods delivery mission is conducted to illustrate the proposed model. Managerial insights are also derived through investigating impacts of different model parameters on the EML and optimal MALP solutions.

1. Introduction

Managing the risk of system losses is a great challenge for safety-critical applications (e.g., chemical reactor [1,2], aerospace [3], battlefield [4], healthcare [5], marine [6]). As an effective method to control such a risk, a mission operation may be aborted before the completion in the event of a certain deterioration condition occurring, followed by a rescue action (RA) to survive the system [7,8]. The condition triggering the mission aborting defines the aborting policy (AP), which must be designed carefully to balance mission success probability and system survival probability. An abort that is either too early or too late would unnecessarily lower the mission success probability or the system survival probability, respectively. Since 2018, considerable research efforts have been devoted to the modeling and optimization of APs for diverse systems, aiming to achieve the balance between those two performance metrics [9,10].

1.1. Related AP research

The AP research has been devoted to single-attempt missions and multi-attempt missions. Different parameters (or decision variables) have been used in APs for single-attempt missions. For instance, the number of failed components was used to define the AP studied for diverse types of systems (e.g., standby systems [11], *k*-out-of-*n*: *F* balanced systems [12], *k*-out-of-*n*: *G* systems [13], *k*-out-of-*n*: *F* systems [14]). The number of external shocks experienced was used to define the AP studied for multi-state systems [15], drone-truck systems [16], and systems subject to random rescue time [17]. The completed mission work was used to define the AP studied for different standby systems [18], such as standby systems with maintenance [19], with propagated failures [20], and with state-dependent loading [21]. Other AP parameters include the number of times the system enters an unbalanced state [22], system degradation level [23], and predictive reliability [24]. In addition, the AP based on early warning signals was investigated for mission-based systems like drone systems [25].

In addition to those single-parameter APs, dual-parameter APs have also been investigated for single-attempt missions. For instance, the number of failed components and system age were used to define the AP for standby systems [26] and self-healing systems [27]. The degradation level and completed mission work were used in APs for multistate systems with storage [28] and systems operating in dynamic environments [29]. The degradation level and system age were used in APs for a drone system [30].

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Acronyms

EML	expected mission losses
GA	genetic algorithm
HPP	homogeneous Poisson process
MALP	mission aborting and loading policy
OP	operation phase
RP	return phase
RA	rescue action
AV	aerial vehicle
UGF	universal generating function
pmf	probability mass function

Notation

E	EML
W	amount of work to be accomplished for a successful mission
Ω	random amount of work completed in the entire mission
$\varphi(t,n_k)$	required RA time when OP is aborted at time t
N	number of possible loading levels
K	maximum number of attempts during the mission
n_k	system loading level in attempt k
ξ_k	time from the beginning of attempt k during which the occurrence of the m_k-th shock triggers the OP abort and RA activation
m_k	number of shocks after which the OP is aborted in attempt k
$\xi,\boldsymbol{m},\boldsymbol{n}$	MALP where $\boldsymbol{m}$={$m_1,\ldots,m_K$}, $\boldsymbol{\xi}$={$\xi_1,\ldots,\xi_K$} and $\boldsymbol{n}$={$n_1,\ldots,n_K$}
$\tau(n_k)$	time needed to complete OP in attempt k with loading level n_k
$\theta(n_k)$	time needed to complete RP in attempt k with loading level n_k
$\Lambda(n_k)$	shock rate during OP of attempt k performed with loading level n_k
$\lambda(n_k)$	shock rate during RP of attempt k performed with loading level n_k
$\mu(n_k)$	shock rate during RA of attempt k performed with loading level n_k
$\eta(n_k)$	cost of payload loss in attempt k performed with loading level n_k
$c(n_k)$	cost associated with system loss before attempt completion
σ (n_k)	cost associated with system loss after attempt completion
$w(n_k)$	amount of work completed in successful OP performed with loading level n_k
$g_{OP}(n_k)$	AV speed during OP performed with loading level n_k
$g_{RA}(n_k)$	AV speed during RA performed with loading level n_k
C_{U}	per unit cost of uncompleted work in the mission
C_{AV}	cost associated with AV loss
$P(t,i,\rho)$	occurrence probability of i shocks in [0,t) given that the shock rate is ρ
$q(i)$	conditional probability that a system survives the i-th shock given that it has survived previous shocks
$Q(i)$	probability that a system survives i shocks
Γ	survival probability upon the first shock (shock resistance factor)
γ	shock resistance deterioration factor
$a(m_k,\xi_k,n_k)$	probability that the system is lost in attempt k after completing the OP under MALP $\xi,\boldsymbol{m},\boldsymbol{n}$
$s(m_k,\xi_k,n_k)$	probability of OP success in attempt k under MALP $\xi,\boldsymbol{m},\boldsymbol{n}$
$d(m_k,\xi_k,n_k)$	probability that the system completes OP and RP in attempt k under MALP $\xi,\boldsymbol{m},\boldsymbol{n}$
$v(m_k,\xi_k,n_k)$	probability that the system aborts the OP and survives the RA in attempt k under MALP $\xi,\boldsymbol{m},\boldsymbol{n}$
$f(m_k,\xi_k,n_k)$	probability that the system is lost in attempt k leaving the OP uncompleted under MALP $\xi,\boldsymbol{m},\boldsymbol{n}$
$E_K(\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{n})$	expected losses when the mission is terminated after attempt k under MALP $\xi,\boldsymbol{m},\boldsymbol{n}$
$1(x)$	logical function: 1(TRUE)=1, 1(FALSE)=0

Both single-parameter and dual-parameter APs have also been studied for multi-attempt missions. For instance, the number of survived shocks was used in the single-parameter attempt-independent AP for a repairable multistate system [31]. The degradation level was used in the single-parameter, attempt-dependent AP for time-redundant systems [32] and standby systems [33]. The number of experienced shocks and operation time were used in the task-dependent dual-parameter AP for multi-task systems with unlimited [34] and limited [35] mission time. In the above-mentioned multi-attempt models, multiple attempts are executed sequentially by a single system (i.e., a new attempt can start only after the previous one is aborted, and the system survives or is successfully rescued). When multiple systems or units are available for mission execution, several attempts may be executed in parallel [36] or consecutively with overlapping [37–39]. For instance, the number of experienced shocks and operation time were used in the attempt-dependent dual-parameter AP for a multi-drone system where each attempt is executed by two groups of drones in parallel [36]. Such a dual-parameter AP was also studied for multi-attempt missions where multiple systems are activated one by one following a predefined constant interval [37,38] or dissimilar intervals [39] to execute different attempts. If any attempt is successful, the mission succeeds.

Despite the abundant body of the AP research, little work considered the effects of loading, which may affect the mission work progress and system loss risk significantly [14,21,29,40]. In particular, the joint modeling of loading and AP was conducted for systems operating in the dynamic environment in [29]. The joint modeling and optimization of loading, AP and rescue sites selection were studied for a drone system in [14]. The loading policy and AP were co-optimized for a heterogeneous warm standby system in [21]. All these existing models considering loading are applicable to only single-attempt mission systems, not to missions engaging multiple attempts.

1.2. Contributions

This paper models and optimizes the loading policy jointly with the AP for a system that must accomplish a specified amount of work through sequentially executed multiple attempts. The loading level selected in each attempt determines the amount of mission work accomplished during a successful operation phase (OP), the time required to accomplish the OP, the return phase (RP) following a successful OP, as well as the rescue action following an aborted OP. The loading level may also affect the shock rates during the OP, RP, and RA.

Using higher loading levels and riskier APs allows completing the mission with fewer attempts, but increases the risk of system losses. To balance the two contradictory effects and thus minimize the expected mission losses (EML), we formulate and solve the optimal mission aborting and loading policy (MALP) problem. The solution method encompasses a new numerical method for assessing the EML and an implementation of the genetic algorithm for solving the EML minimization problem.

To illustrate the proposed model, a detailed case study of an aerial vehicle performing a delivery mission is conducted. We also investigate the influences of several model parameters (the allowed number of attempts, uncompleted work penalty factor, system shock resistance

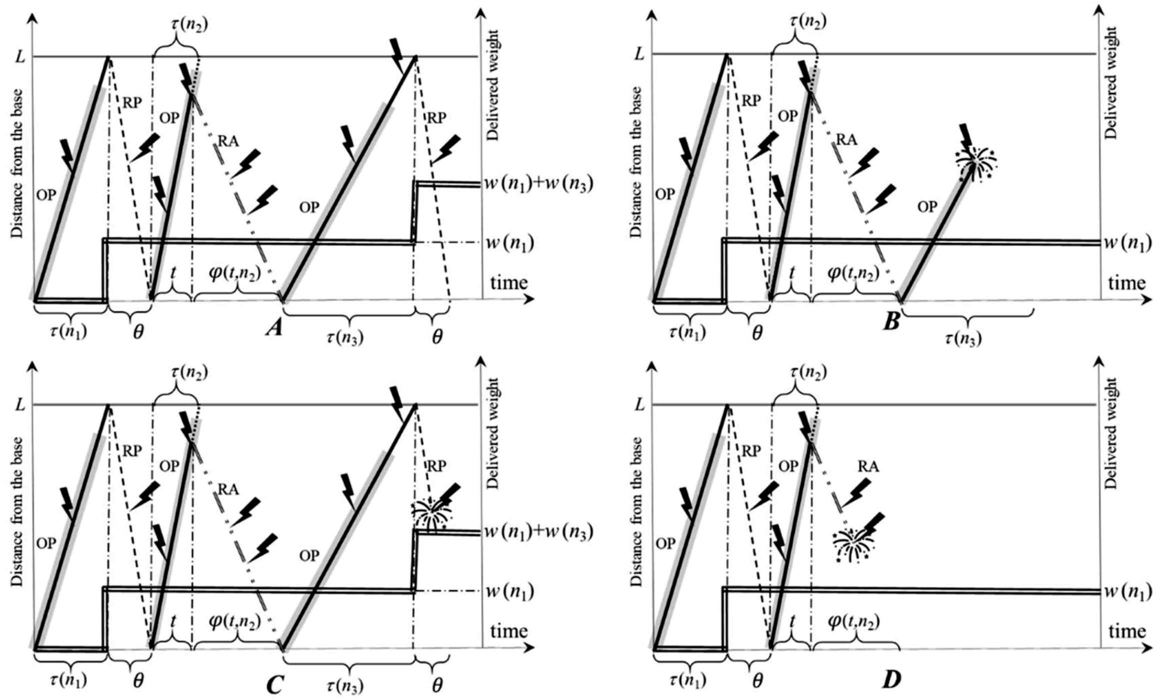

Fig. 1. Example of a three-attempt mission.

factor, and required mission work) on the EML and the optimal MALP solutions.

The rest of the paper has the following structure: Section 2 presents the system model and formulates the optimal MALP problem. An illustrative example is also presented. Section 3 derives the EML and suggests the numerical evaluation procedure. Section 4 conducts the AV case study and examine influences of several model parameters. Section 5 concludes the work and points out the future research direction.

2. System model and optimization problem formulation

2.1. System model

To accomplish a multi-attempt mission, the system is required to complete an amount of work W within K attempts. Each attempt consists of an OP and a post-operation RP. Both phases are performed in random environments modeled by homogeneous Poisson processes (HPP) of shocks. Each shock may cause deterioration to the system and the deterioration increases as more shocks happen, leading to higher risks of system loss [13]. To alleviate such a risk, the OP of the mission may be aborted before its completion, immediately followed by the activation and execution of a RA, which is also performed in random shock environments.

After a successful RA, the system can start a new attempt to complete the mission. Since the system may not accomplish all the required work in one attempt, after a successful completion of the RP, the system may also start a new attempt to complete the entire mission. In each attempt k, the system can operate with one of N loading levels. If loading level n_k is chosen, the times needed to complete the OP and RP are $\tau(n_k)$, and $\theta(n_k)$ respectively, the amount of work completed in the case of the OP success is $w(n_k)$, the shock rates during the OP and RP are $\Lambda(n_k)$ and $\lambda(n_k)$ respectively. The work completed in each successful OP is accumulated such that the total amount of work completed in the mission equals to the sum of amounts of works completed in each successful OP.

The OP abort decision is based on shocks observation. If m_k shocks occur during time ξ_k since the beginning of the OP of the k-th attempt, the system immediately aborts the OP and starts the RA. If fewer than m_k shocks happen during time ξ_k, the system continues the operation until the attempt completion or system loss.

The time required for a successful RA completion depends on the time between the OP's beginning and aborting as well as on the system loading level n_k in the attempt k. Particularly, if the OP is aborted at time t from the beginning of attempt k, the required RA time is $\varphi(t, n_k)$. The shock rate during the RA $\mu(n_k)$ also depends on the chosen load level.

If the system is lost in the OP or in the RA after aborting the OP performed with load level n_k, the incurred cost of loss is $c(n_k)$. If the system is lost in the RP after completing the OP, the incurred cost of loss is $\sigma(n_k)$.

The mission terminates when one of the following three cases occurs: 1). The required amount of work W is accomplished; 2). The predetermined number of attempts is completed; 3). The system is lost before completing the amount of work W.

If the accumulated amount of work completed before the mission termination is Ω, the incurred penalty is proportional to the amount of the uncompleted work W-Ω such that the penalty cost is

$$\max(0, W-\Omega)C_{\text{U}} \tag{1}$$

where C_{U} is per unit cost of uncompleted work in the mission.

The following assumptions are made in the model.

- The mission time is relatively short and, therefore, the probability of internal system failure is negligible compared to the probability of the system loss caused by shocks.
- 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. Formulation of optimization problem

On one hand, increasing the system loading levels in any attempt and using riskier OP aborting policy allow completing the mission after fewer attempts. On the other hand, it may increase the risk of the system loss. Considering these contradictory effects, we formulate the problem that finds the MALP providing the minimum EML associated with

Table 1
Four different three-attempt delivery mission realizations.

Mission realization	Figure	Weight of delivered payload	Cost AV and payload loss	Total mission losses
1	1A	$w(n_1)+w(n_3)$	0	$\max(0,W\text{-}\ w(n_1)-w(n_3))C_U$
2	1B	$w(n_1)$	$C_{AV}+\eta\ (n_3)$	$\max(0,W\text{-}\ w(n_1))C_U+C_{AV}+\eta\ (n_3)$
3	1C	$w(n_1)+w(n_3)$	C_{AV}	$\max(0,W\text{-}\ w(n_1)-w(n_3))C_U+C_{AV}$
4	1D	$w(n_1)$	$C_{AV}+\eta\ (n_2)$	$\max(0,W\text{-}\ w(n_1))C_U+C_{AV}+\eta\ (n_2)$.

uncompleted work and system loss.

The MALP is defined by vectors $\boldsymbol{m}=\{m_1,\dots,m_K\}$, $\boldsymbol{\xi}=\{\xi_1,\dots,\xi_K\}$ and $\boldsymbol{n}=\{n_1,\dots,n_K\}$ that determine the aborting rules and loading level option choices for each attempt $1\le k\le K$. For any specific MALP $\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{n}$, the expected amount of completed work $\Omega(\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{n})$ can be obtained and the expected penalty associated with the uncompleted work can be evaluated using (1). In addition, the probabilities of the system loss in OP, RP and RA can be obtained and the expected cost associated with the system lost can be evaluated. The total EML $E(\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{n})$ is the sum of expected penalty and expected cost associated with the system loss (see Section 3 for deriving the EML). Having an algorithm for evaluating the EML $E(\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{n})$ for any MALP $\boldsymbol{m}$, $\boldsymbol{\xi}$, $\boldsymbol{n}$, one can solve the optimization problem

$$E(\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{n})\rightarrow\min \tag{2}$$

that finds the MALP minimizing the EML. An alternative formulation of (2) is

$$\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{n}=\operatorname{argmin}E(\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{n}).$$

2.3. Illustrative example

Consider an aerial vehicle (AV) performing a delivery mission. The AV should deliver goods of the total weight W from a base to a destination point via several flights. In each flight the AV can take the payload of weight $w(n)$ when the loading level n is chosen. When carrying the weight $w(n)$, the AV can fly with a speed that determines its OP time as $\tau(n)$. If the AV aborts the OP at time t from its beginning, it flies back to the base (RA), which takes time $\varphi(t,n)$ proportional to the distance from the base at the moment when the OP is aborted. After the OP completion, the AV also returns to the base, which takes time $\theta(n)$.

Depending on the payload weight, the AV can fly on different altitudes at different mission stages (OP, RP, and RA). During the flight, the AV is exposed to electromagnetic interference from high voltage power lines, cell phone towers, large metal structures and other sources [10,34], which usually causes overheat deteriorating or damaging the AV or its key components [41,42]. The electromagnetic impulses arrive at random times with specific rates depending on the AV altitude. The shock resistance of the AV deteriorates with the number of shocks and the AV can abort the OP according to policy $\boldsymbol{m}$, $\boldsymbol{\xi}$.

If the AV is lost during the flight when its payload is not delivered, the cost of incurred losses $c(n)$ is composed of the cost of AV loss C_{AV} and payload loss $\eta(n)$. If the AV is lost during the return flight after downloading the payload, the cost of incurred losses is $\sigma(n)=C_{AV}$. When the mission results in delivering goods with the total weight of Ω, the total penalty is proportional to the weight of undelivered payload (as defined in (1)).

Fig. 1 and Table 1 present an example of a three-attempt delivery mission realizations by an AV. Solid and dashed lines correspond to OP (flight to the destination point) and RP/RA (return flight), respectively. Grey rectangles indicate the parts of OP during which the OP aborts are allowed (determined by time ξ_k). In the example, $m_k=2$ for any k. In Fig. 1A the AV starts the first attempt with loading option n_1 and delivers amount of payload $w(n_1)$ at time $\tau(n_1)$ from the beginning of the attempt. Then it successfully returns to the base without any payload, which takes time $\theta(n_1)=\theta$ and starts the second attempt with payload weight $w(n_2)$. The AV aborts the OP of the second attempt at time t from its beginning upon experiencing the second shock and performs the RA taking time $\varphi(t,n_2)$. After successful completion of the RA, the AV starts the third attempt with payload weight $w(n_3)$ and succeeds to deliver the payload. After flying back to the base (which takes time $\theta(n_3)=\theta$), it completes the mission. The mission terminated after delivering the total payload weight of $w(n_1)+w(n_3)$. As the AV is not lost during the mission, the total mission losses are $\max(0,W\text{-}\ w(n_1)-w(n_3))C_U$.

In Fig. 1B, the AV crashes during the OP of the third attempt before delivering the payload. The total amount of delivered payload is $w(n_1)$. The cost of AV and payload loss is $C_{AV}+\eta\ (n_3)$. The total mission losses are $\max(0,W\text{-}\ w(n_1))C_U+C_{AV}+\eta\ (n_3)$. In Fig. 1C, the AV crashes during the return flight (RP) after successfully completing the third attempt. The total mission losses are $\max(0,W\text{-}\ w(n_1)-w(n_3))C_U+C_{AV}$. In Fig. 1D, the AV crashes during the RA of the second attempt. The total amount of delivered payload is $w(n_1)$. The cost of AV and payload loss is $C_{AV}+\eta(n_2)$. The total mission losses are $\max(0,W\text{-}\ w(n_1))C_U+C_{AV}+\eta\ (n_2)$.

A detailed case study of the multi-attempt delivery mission is presented in Section 5.

3. Numerical EML evaluation algorithm

This section presents the probabilistic model of deriving the EML followed by a numerical algorithm proposed to implement the EML evaluation.

3.1. System survivability as a function of number of experienced shocks

According to the shock model of [43,44], the conditional survival probability of a system upon the h-th shock given that it has survived previous shocks can be evaluated as

$$q(0)\equiv 1;q(h)=\Gamma\gamma(h)\text{for}\,h>0, \tag{3}$$

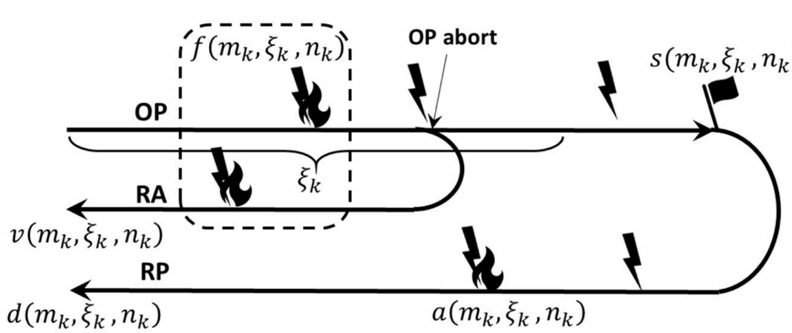

Fig. 2. Probabilities of attempt outcomes.

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 $(0)=1$ and $\gamma(h)=\gamma^{h-1}, 0<\gamma<1$. Thus, the probability that the system can survive $H\geq 0$ shocks can be evaluated as the product of the probabilities $q(0),\ldots,q(H)$, that is,

$$Q(H)=\prod_{h=0}^{H}q(h)=\Gamma^{H}\gamma^{\frac{H(H-1)}{2}}. \quad (4)$$

3.2. Probabilities of outcomes of attempt k

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

$$P(t,i,\rho)=e^{-\rho t}\frac{(\rho t)^{i}}{i!},\ \text{for } i=0,1,2,\cdots \quad (5)$$

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

$$P(t,i-1,\rho)\rho dt=\rho e^{-\rho t}\frac{(\rho t)^{i-1}}{(i-1)!}dt. \quad (6)$$

Fig. 2 presents the possible outcomes of attempt k. In this attempt the system operates in environment with shock rate $\Lambda(n_k)$ and completes the OP 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 $\tau(n_k)$. 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 $[\xi_k,\tau(n_k)]$, then the system survives these shocks and completes the OP with probability $Q(h+j)$. The probability of OP success is

$$s(m_k,\xi_k,n_k)=\sum_{h=0}^{m_k-1}P(\xi_k,h,\ \Lambda(n_k))\sum_{j=0}^{\infty}P(\tau(n_k)-\xi_k,j,\ \Lambda(n_k))Q(h+j). \quad (7)$$

The system completes the OP and the subsequent RP in attempt k when fewer than m_k shocks take place in $[0,\xi_k)$ and the system survives all shocks that occur with rate $\Lambda(n_k)$ during time $\tau(n_k)$ in the OP and with rate $\lambda(n_k)$ during time $\theta(n_k)$ in the RP. The occurrence probability of such attempt outcome is

$$d(m_k,\xi_k,n_k)=\sum_{i=0}^{m_k-1}P(\xi_k,i,\ \Lambda(n_k))\sum_{k=0}^{\infty}P(\tau(n_k)-\xi_k,k,\ \Lambda(n_k))\sum_{h=0}^{\infty}P(\theta(n_k),h,\lambda(n_k))Q(i+k+h). \quad (8)$$

The probability that the system is lost in attempt k after completing the OP is

$$a(m_k,\xi_k,n_k)=s(m_k,\xi_k,n_k)-d(m_k,\xi_k,n_k). \quad (9)$$

The system aborts the OP and starts the RA in environment with shock rate $\mu(n_k)$ if the m_k-th shock occurs at any time t belonging to interval $[0,\xi_k)$. The time needed to complete the RA is $\varphi(t,n_k)$. The system completes the aborted attempt if it survives m_k shocks in the OP during the time interval $[0,t)$ and all the shocks in RA during time $\varphi(t,n_k)$. Thus, the probability that the system following the MALP m_k,ξ_k,n_k completes the RA and survives the k-th attempt, but fails to complete the mission in this attempt is

$$v(m_k,\xi_k,r_k)=\Lambda(n_k)\int_{0}^{\xi_k}P(t,m_k-1,\ \Lambda(n_k))\times\sum_{j=0}^{\infty}P(\varphi(t,n_k),j,\mu(n_k))Q(m_k+j)dt. \quad (10)$$

The system that does not complete the OP can survive only if it aborts the OP and survives the subsequent RA. Therefore, the probability that the system is lost in the attempt leaving the OP uncompleted is

$$f(m_k,\xi_k,n_k)=1-s(m_k,\xi_k,n_k)-v(m_k,\xi_k,n_k). \quad (11)$$

3.3. Deriving EML

To obtain the EML we use the universal generating function (UGF) technique, which is a straightforward universal approach of obtaining the discrete distribution of function of random variables. This approach proved to be effective for diverse types of systems [45] because it allows obtaining the probability mass function (*pmf*) in a short time.

The u-functions representing the *pmf* of s-independent random variables G_i can be defined as polynomials

$$u_i(z)=\sum_{n_i=0}^{N_i}p_{i,n_i}z^{g_{i,n_i}}, \quad (12)$$

where g_{i,n_i} is the n_i-th realization G_i and $p_{i,n_i}=Pr\left(G_i=g_{i,n_i}\right)$. To obtain the u-function representing the distribution of function ϑ $(G_1(t),\ldots,G_J(t))$, the following composition operator is used.

$$U(z)=\otimes_{\vartheta}(u_1(z),\ldots,u_J(z))=\otimes_{\vartheta}\left(\sum_{n_1=0}^{N_1}p_{1,n_1}z^{g_{1,n_1}},\ldots,\sum_{n_J=0}^{N_J}p_{J,n_J}z^{g_{J,n_J}}\right)=\sum_{n_1=0}^{N_1}\sum_{n_2=0}^{N_2}\ldots\sum_{n_J=0}^{N_J}\left(\prod_{i=1}^{J}p_{i,n_i}z^{\vartheta\left(g_{1,n_1},\ldots,g_{J,n_J}\right)}\right). \quad (13)$$

The polynomial $U(z)$ represents all the possible mutually exclusive combinations of realizations of the s-independent variables $G_1(t),\ldots,G_J(t)$ by relating the probability of each combination to the value of function $\vartheta(G_1(t),\ldots,G_J(t))$ for this combination. Eventually, this polynomial takes the form $U(z)=\sum_{i=0}^{I}p_i z^{g_i}$, which represents the *pmf* of $(G_1(t),\ldots,G_J(t))$.

Let X_k represent the random amount of work completed after the k-th attempt when the system survives this attempt and $u_k(z)$ represent the *pmf* of X_k. $X_0=0$ and $u_0(z)=z^0$ by definition. In what follows, we present the recursive derivation of $u_k(z)$ based on $u_{k-1}(z)$.

The attempt k can start when the system survives k-1 previous attempts and when the amount of work completed in these previous attempts is less than W. Having the function $u_{k-1}(z)$ representing the completed work distribution at the end of attempt k-1, one can obtain the function representing the completed work distribution at the beginning of attempt k by applying the following operator

$$\pi(u_{k-1}(z))=\pi\left(\sum_{i=0}^{I}p_{k-1,i}z^{g_{k-1,i}}\right)=\sum_{i=0}^{I}1\left(g_{k-1,i}<W\right)p_{k-1,i}z^{g_{k-1,i}}=\sum_{j=0}^{J}p_{k-1,j}z^{g_{k-1,j}}, \quad (14)$$

which removes the terms corresponding to the amount of work reaching the level of W from $u_{k-1}(z)$. In (14), I is the total number of different possible realizations of the random value X_{k-1} and J is the number of different possible realizations of X_{k-1} that are less than W.

If the system completes the OP and the RP in attempt k (which happens with probability $d(m_k,\xi_k,n_k)$), the completed work is $X_k=X_{k-1}+w(n_k)$.

If the system aborts the OP and completes the RA in attempt k (which happens with probability $v(m_k,\xi_k,n_k)$), the completed work is $X_k=X_{k-1}$. Thus,

$$u_k(z)=\pi(u_{k-1}(z))\times\left(d(m_k,\xi_k,n_k)z^{w(n_k)}+v(m_k,\xi_k,n_k)z^0\right)=\sum_{j=0}^{J}\left(p_{k-1,j}d(m_k,\xi_k,n_k)z^{g_{k-1,j}+w(n_k)}+p_{k-1,j}v(m_k,\xi_k,n_k)z^{g_{k-1,j}}\right). \quad (15)$$

The mission can be terminated after attempt k if the system survives

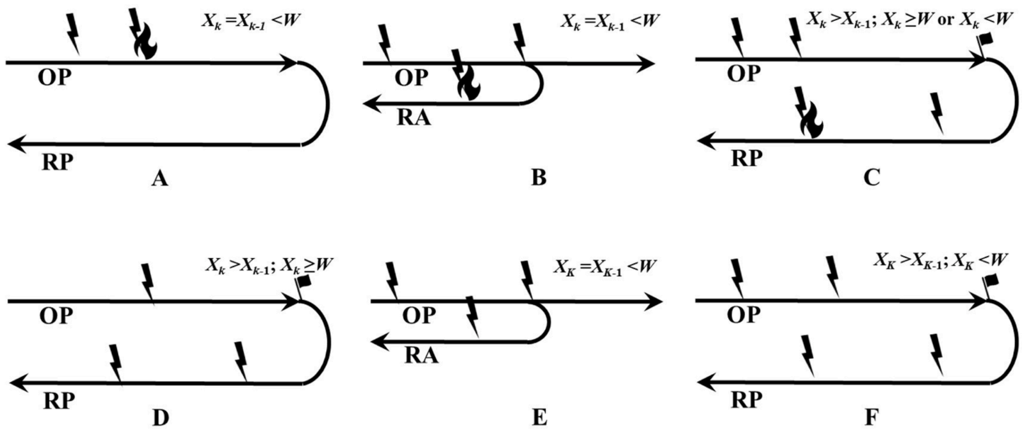

Fig. 3. Possible cases of mission termination.

the previous k-1 attempts, the amount of work completed after the attempt k-1 is less than W and the following outcomes of the attempt k take place.

1) The system is lost before completion of OP in attempt k (which happens with probability $f(m_k, \xi_k, n_k)$ see Fig. 3A, 3B), the completed work is X_k=X_{k-1} and the expected loss is

$$(W - X_{k-1})C_U + c(n_k) \tag{16}$$

2) The system is lost after completion of OP in attempt k (which happens with probability $a(m_k, \xi_k, n_k)$ see Fig. 3C), the completed work is X_k =X_{k-1}+$w(n_k)$ and the expected loss is

$$\max(0, W - X_{k-1} - w(n_k))C_U + c(n_k). \tag{17}$$

3) The system completes the OP and the RP in attempt k (which happens with probability $d(m_k, \xi_k, n_k)$ see Fig. 3D), X_k =X_{k-1}+$w(n_k) \geq W$ and the expected loss is zero.

Therefore, the expected mission losses when the system completes the mission in attempt $k < K$ can be obtained using the following operator over the function $\pi(u_{k-1}(z))$.

$$E_k(\boldsymbol{m}, \boldsymbol{\xi}, \boldsymbol{n}) = \chi(\pi(u_{k-1}(z)), m_k, \xi_k, n_k) = \sum_{j=0}^{J} p_{k-1,j}\Big\{f(m_k, \xi_k, n_k)\Big[\Big(W - g_{k-1,j}\Big)C_U + c(n_k)\Big] + a(m_k, \xi_k, n_k)\Big[\max\Big(0, W - g_{k-1,j} - w(n_k)\Big)C_U + \sigma(n_k)\Big]\Big\}. \tag{18}$$

If k=K, i.e., the mission is terminated independently from the K-th attempt outcome. In this case, besides the outcomes considered for $k<K$, the following two additional outcomes incur the system losses.

1) The system survives after aborting the OP in attempt K (which happens with probability $v(m_K, \xi_K, n_K)$ see Fig. 3E), the completed work is X_K =X_{K-1} and the expected loss is

$$(W - X_{K-1})C_U. \tag{19}$$

2) The system completes the OP and the RP in attempt K (which happens with probability $d(m_K, \xi_K, n_K)$ see Fig. 3F), X_K =X_{K-1}+$w(n_K)<W$ and the expected loss is

$$(W - X_{K-1} - w(n_K))C_U. \tag{20}$$

Thus,

$$E_K(\boldsymbol{m}, \boldsymbol{\xi}, \boldsymbol{n}) = \psi(\pi(u_{K-1}(z)), m_K, \xi_K, n_K) = \sum_{j=0}^{J} p_{K-1,j}\Big\{f(m_K, \xi_K, n_K)\Big[\Big(W - g_{K-1,j}\Big)C_U + c(n_K)\Big] + a(m_K, \xi_K, n_K)\max\Big(0, W - g_{K-1,j} - w(n_K)\Big)C_U + \sigma(n_K) + v(m_K, \xi_K, n_K)\Big(W - g_{K-1,j}\Big)C_U + d(m_K, \xi_K, n_K)\Big(W - g_{K-1,j} - w(n_K)\Big)C_U\Big\}. \tag{21}$$

As the mission termination after different numbers of attempts are mutually exclusive events, the total EML can be obtained as

$$E(\boldsymbol{m}, \boldsymbol{\xi}, \boldsymbol{n}) = \sum_{k=1}^{K} E_k(\boldsymbol{m}, \boldsymbol{\xi}, \boldsymbol{n}). \tag{22}$$

3.4. Numerical algorithm for the EML evaluation

The pseudo-code of the numerical algorithm that realizes recursive derivations presented in Section 3.3 is given below. It determines the EML for any given MALP $\boldsymbol{m}, \boldsymbol{\xi}, \boldsymbol{n}$.

1	Set E=0, $u_0(z)$=z^0
2	For k=1,…,K:
3	Obtain $a(m_k, \xi_k, n_k)$, $v(m_k, \xi_k, n_k)$, $f(m_k, \xi_k, n_k)$ and $d(m_k, \xi_k, n_k)$ using (7)-(11);
4	Obtain $\pi(u_{k-1}(z))$ using (14);
5	$u_k(z) = \pi(u_{k-1}(z)) \times \left(d(m_k, \xi_k, n_k)z^{w(n_k)} + v(m_k, \xi_k, n_k)z^0\right)$ using (15);
6	If $k<K$ then $E = E + \chi(\pi(u_{k-1}(z)), m_k, \xi_k, n_k)$ using (18);
7	If k=K then $E = E + \psi(\pi(u_{k-1}(z)), m_k, \xi_k, n_k)$ using (21);

Step 1 of the algorithm initializes the value of EML E and the function $u_0(z)$. Step 3 obtains the attempt outcome probabilities based on (7)-(11). Observe that $Q(J) = \prod_{j=0}^{J} q(j)$ is a decreasing function of J. Therefore, in practice the infinite sums in (7), (8) and (10) can be replaced by the sum in which the total number of shocks is limited by the value of J, where $Q(J)$ is negligible. The computational aspects of obtaining the infinite sums in (7), (8) and (10) and an example of determining the value of J are presented in [43]. The computational complexity of Step 3 is $O(J\tau/dt)$ [43]. Steps 4 and 5 obtain the function $u_k(z)$ and steps 6 and 7 obtain the value of the EML according to (18) and (21).

As it can be seen from the pseudo code above, the computational complexity of the algorithm is $O(K2^K)$, because the maximum size of the

Table 2
System and mission attempt parameters corresponding to different loading levels.

n	$\tau(n)$	$\varphi(t,n)/t$	$\Lambda(n)$	$\lambda(n)$	$c(n)$	$w(n)$
1	10	0.85	0.65	0.65	22.0	1
2	16	0.87	0.72	0.65	24.5	2
3	20	0.92	0.85	0.85	28.0	6
4	22	1.00	0.87	0.90	31.2	10

polynomial $u_k(z)$ is 2^K.

4. AV case study

4.1. System and mission description

Consider an AV performing a delivery mission. The AV should deliver goods of the total weight W from a base to a destination point engaging several flights. Each flight can be accomplished with one of N=4 load levels, depending on the payload weight $w(n)$. When carrying the weight $w(n)$, the AV can fly with speed $g_{OP}(n)$, which determines its OP time (flight from the base to the destination point) $\tau(n)$. If the AV aborts the OP at time t from its beginning, it flies back (i.e., performing the RA) with increased speed $g_{RA}(n)$, which depends on the payload weight. Therefore $\varphi(t,n)=tg_{OP}(n)/g_{RA}(n)$. After the OP completion, the AV is downloaded and fueled at the destination point and it returns to the base with maximal speed not depending on the delivered payload weight. The return flight (RP) time is $\theta(n)$=8.0. The payload weights and AV speeds corresponding to different loading levels are presented in Table 2.

Depending on the payload weight, the AV can fly on different altitudes. At any altitude, the AV is exposed to shocks caused by electromagnetic interference. The shocks may destroy the control equipment of the AV and cause its crash. The number of shocks arrivals during the OP flight on an altitude corresponding to the load level n obeys the HPP with rate $\Lambda(n)$. The interference filter that protects the AV deteriorates as the number of experienced shocks increases due to overheating. Such

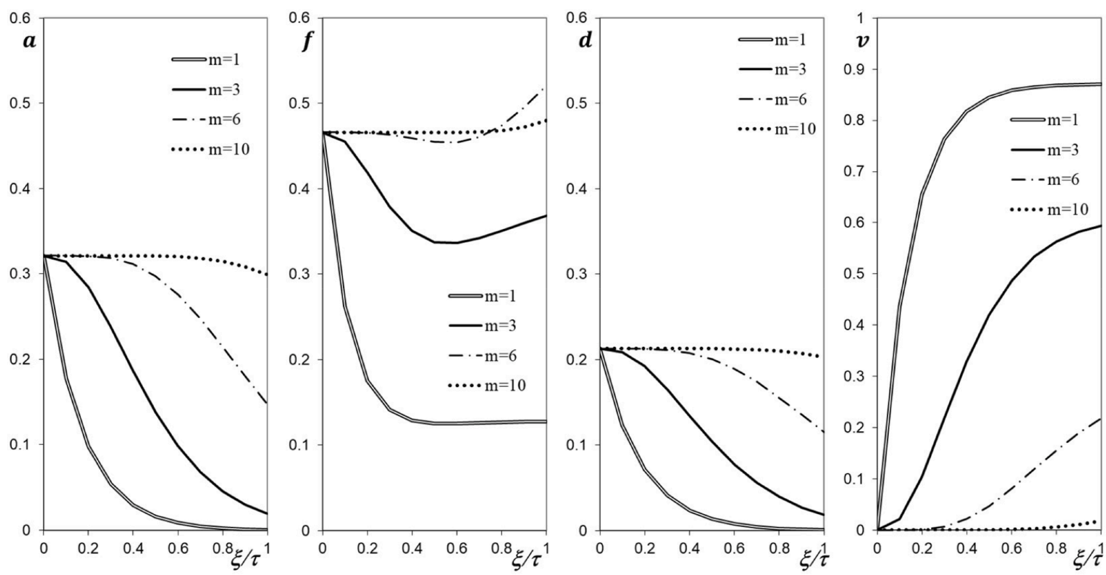

Fig. 4. Probabilities of attempt outcomes for load level n=1.

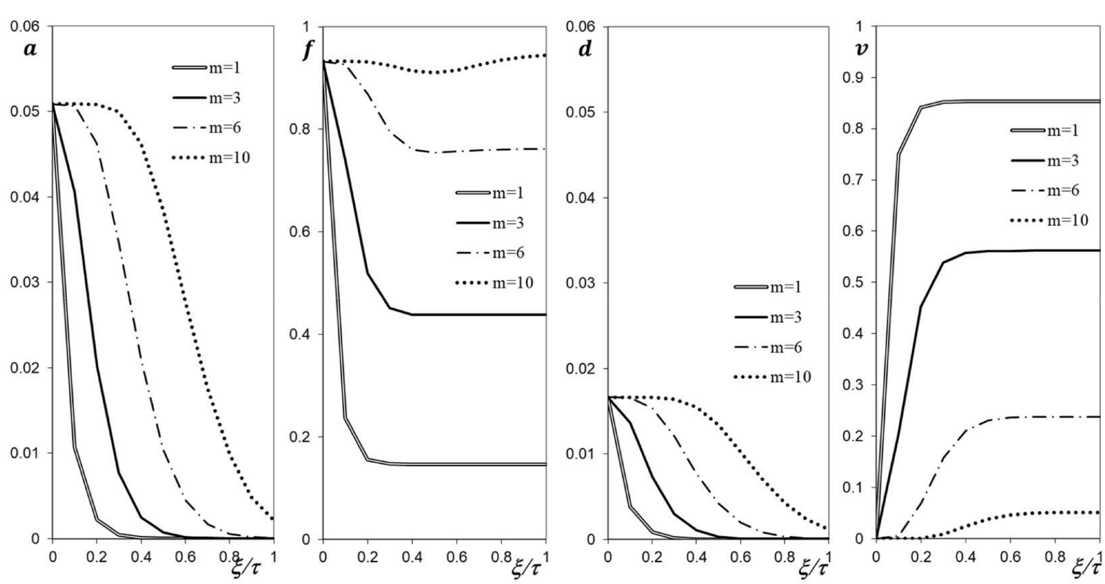

Fig. 5. Probabilities of attempt outcomes for load level n=4.

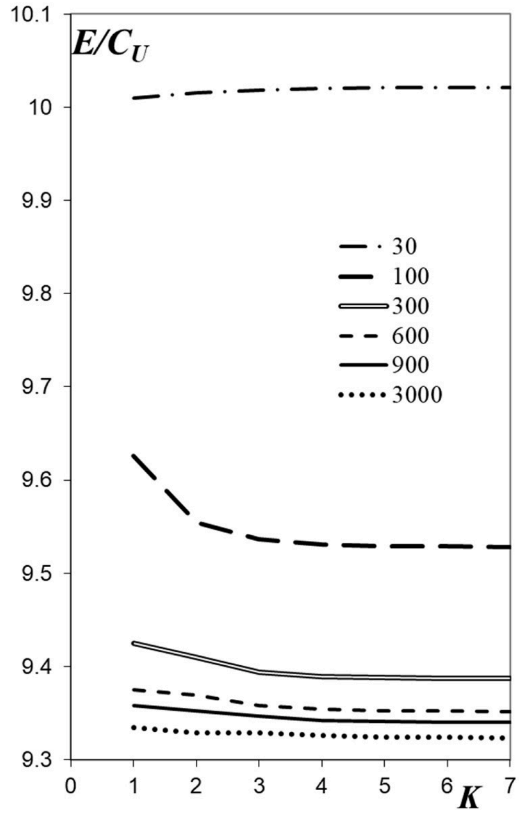

Fig. 6. Normalized EML E/C_U corresponding to the best obtained MALP as function of the allowed number of attempts K.

deterioration is considered using (3) with Γ=0.93, γ=0.99. To alleviate the risk of the AV loss, the k-th 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 AV starts the RA by flying back to the base on the altitude depending on its loading level n and is exposed to shock process with rate $\lambda(n)$. When the unloaded AV flies back after the OP completion, it is exposed to the HPP shock process with rate $\mu(n)$=0.8 (independent from the load level during the completed OP).

If the AV is lost during the flight before delivering its payload (i.e., during OP or RA), the cost of incurred losses is composed of the cost of AV loss C_{AV} and payload loss $\eta(n)$ such that $c(n)=C_{AV}+\eta(n)$. If the AV is lost during the return flight (RP) after downloading the payload, the cost of incurred losses is $\sigma(n_k)=C_{AV}$=20. When the mission results in delivering goods with the total weight of Ω, the total penalty, associated with undelivered goods is $\max(0,W\text{-}\Omega)C_U$. The shock rates and costs are also presented on Table 2.

4.2. Single attempt outcome parameters

Figs. 4 and 5 present the probabilities of a single attempt outcome as functions of abort parameters m, ξ/τ for two AV loading levels n=1 and n=4. It can be seen that the probabilities that the OP succeeds and the AV survives $d(m,\xi)$ and that the OP succeeds and the AV is lost $a(m,\xi)$ both decrease as ξ increases and increase as m increases. The reason is that 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 OP. On the contrary, the probability that the AV aborts the OP and survives the attempt $v(m,\xi,n)$ increases as ξ increases and decreases as m increases because with a more cautious abort policy (smaller m and greater ξ), the system aborts the attempt earlier and has greater chances to survive. The probability $f(m,\xi,n)$ that the AV fails before completing the OP can behave non-monotonically. When no aborts are allowed ($\xi = 0$), $f(m,\xi,n)$ equals to the probability that the AV fails during the OP. When ξ increases and/or m decreases, the aborting policy becomes more cautious and the probability that the AV fails in the OP decreases. However, a further increase in ξ allows the OP aborting in the later stages of the OP when the RA takes a greater time and the probability of the AV failure during the RA increases. This causes the increase of the overall failure probability during OP and RA.

Table 3
Best obtained MALP solutions for C_U=30 and different values of allowed number of attempts K.

K	E	MALP
1	300.291	(1,0.1,1)
2	300.454	(1,0.1,1)(1,0.1,1)
3	300.545	(1,0.1,1)(1,0.1,1)(1,0.1,1)
4	300.596	(1,0.1,1)(1,0.1,1)(1,0.1,1)(1,0.1,1)
5	300.625	(1,0.1,1)(1,0.1,1)(1,0.1,1)(1,0.1,1)(1,0.1,1)
6	300.641	(1,0.1,1)(1,0.1,1)(1,0.1,1)(1,0.1,1)(1,0.1,1)(1,0.1,1)
7	300.649	(1,0.1,1)(1,0.1,1)(1,0.1,1)(1,0.1,1)(1,0.1,1)(1,0.1,1)(1,0.1,1)

Table 4
Best obtained MALP solutions for C_U=300 and different values of allowed number of attempts K.

K	E	MALP
1	2827.526	(-,4)
2	2822.846	(4,0.1,1)(-,3)
3	2818.253	(2,0.1,1)(4,0.1,1)(-,3)
4	2816.847	(2,0.1,1)(2,0.1,1)(4,0.1,1)(-,3)
5	2816.417	(2,0.1,1)(2,0.1,1)(2,0.1,1)(4,0.1,1)(-,3)
6	2816.186	(1,0.1,1)(2,0.1,1)(2,0.1,1)(2,0.1,1)(4,0.1,1)(-,3)
7	2816.056	(1,0.1,1)(1,0.1,1)(1,0.1,1)(2,0.1,1)(2,0.1,1)(4,0.1,1)(-,3)

Table 5
Best obtained MALP solutions for C_U=3000 and different values of allowed number of attempts K.

K	E	MALP
1	28,004.258	(-,4)
2	27,987.204	(4,0.1,4)(-,4)
3	27,985.903	(4,0.1,4)(4,0.1,4)(-,4)
4	27,976.823	(2,0.1,1)(2,0.1,1)(3,0.1,1)(-,3)
5	27,972.972	(1,0.1,1)(2,0.1,1)(2,0.1,1)(3,0.1,1)(-,3)
6	27,970.851	(1,0.1,1)(1,0.1,1)(2,0.1,1)(2,0.1,1)(3,0.1,1)(-,3)
7	27,969.669	(1,0.1,1)(1,0.1,1)(1,0.1,1)(2,0.1,1)(2,0.1,1)(3,0.1,1)(-,3)

As it can be seen from Figs. 4 and 5, when the AV is heavily loaded (n=4) it has a much lower chance to complete the delivery mission and survive because it flies with a lower speed, which increases the time of its exposure to shocks. Moreover, the heavily loaded AV flies during the OP on the altitude where the shock rate is high (being unable to rise higher). Thus, on one hand, the greater AV loading reduces chances on the delivery mission success. On the other hand, using a lighter payload requires performing more attempts (flights) to deliver the required amount of payload, which also increases the overall time of AV exposure to the shocks. In the next section, we consider MALP optimization for different numbers of attempts.

4.3. EML minimization solution method

Finding the optimal MALP minimizing the EML $E(\boldsymbol{m},\boldsymbol{\xi},\boldsymbol{n})$ is a multi-dimensional optimization problem in which 3K parameters$\{m_1,\xi_1,n_1,\ldots, m_K,\xi_K,n_K\}$ should be obtained. To solve this problem, the genetic algorithm (GA) is applied in this work, which requires solutions to be represented in strings [46,47].

To represent the solution in the EML minimization problem, we use a string consisting of 3K integer numbers $\zeta_{11},\ldots, \zeta_{13},\ldots,\zeta_{K1},\ldots,\zeta_{K3}$ ranging from 0 to 100. The MALP parameters are obtained as m_k=1+0.1ζ_{k1},

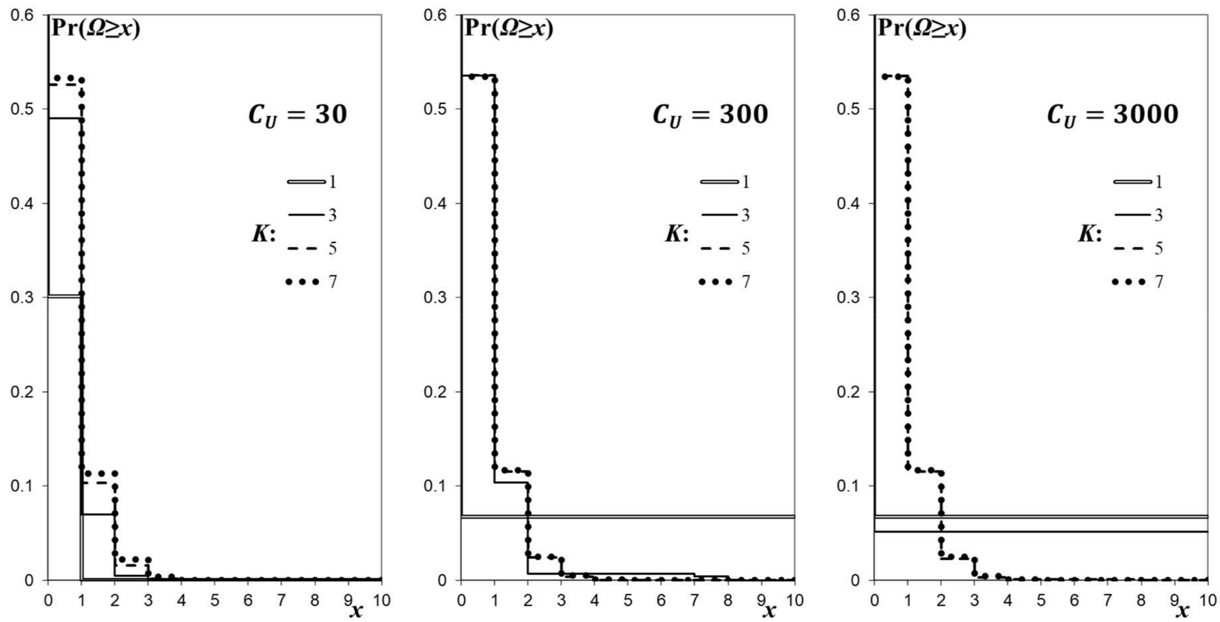

Fig. 7. Delivered weight distribution Pr(Ω≥x) corresponding to the best obtained MALP for different values of C_U and allowed number of attempts K.

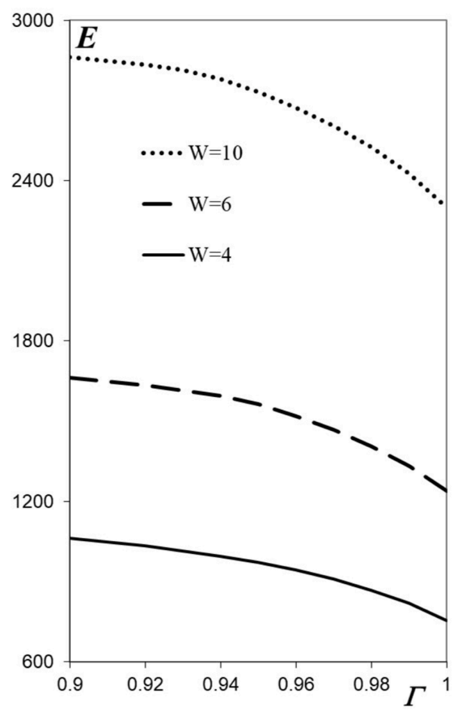

Fig. 8. EML corresponding to the best obtained MALP as function of the AV shock resistance factor Γ and demand weight W for C_U=300 and K=5.

$\xi_k=0.01\tau(n_k)\zeta_{k2}$, $n_k=1+\text{mod}_3\zeta_{k3}$. Such encoding provides variation of the parameters in the ranges $m_k\in[1,11]$, $\xi_k/\tau(n_k)\in[0,1]$, $n_k\in[1,4]$.

With the proposed string solution representation, the standard GA operations (i.e., mutation, crossover, selection) [46,47] are implemented to solve the proposed MALP optimization problem in (2).

4.4. Influence of the allowed number of attempts K and penalty C_U

Fig. 6 presents the values of the normalized EML E/C_U corresponding to the best obtained MALP as a function of the allowed number of attempts K for W=10 and different values of penalty C_U. Tables 3–5 present some of the best obtained MALP in the format $(m_1,\xi_1/\tau(n_1),n_1)\ldots(m_K,\xi_K/\tau(n_K),n_K)$. No aborting policy (when ξ_k=0) is represented in format (-,n_k). Fig. 7 presents the delivered weight distribution Pr(Ω≥x) corresponding to the best obtained MALP for different values of C_U and K.

Table 6
Best obtained MALP solutions for C_U=300, K=5, W=10 and different values of AV shock resistance factor Γ.

Γ	E	MALP
0.9	2863.301	(1,0.05,1)(1,0.05,1)(1,0.05,1)(-,1)(-,1)
0.92	2833.410	(1,0.05,1)(1,0.05,1)(2,0.05,1)(5,0.1,1)(-,1)
0.94	2779.485	(1,0.05,4)(1,0.05,4)(1,0.05,4)(2,0.05,4)(-,4)
0.96	2674.530	(1,0.05,4)(1,0.05,4)(1,0.05,4)(1,0.05,4)(-,4)
0.98	2525.336	(1,0.05,4)(1,0.05,4)(1,0.05,4)(1,0.05,4)(-,4)
1.0	2301.460	(1,0.1,4)(1,0.1,4)(2,0.1,4)(2,0.1,4)(-,4)

Table 7
Best obtained MALP solutions for C_U=300, K=5, W=6 and different values of AV shock resistance factor Γ.

Γ	E	MALP
0.9	1663.301	(1,0.05,1)(1,0.05,1)(1,0.05,1)(-,1)(-,1)
0.92	1633.410	(1,0.05,1)(1,0.05,1)(2,0.05,1)(6,0.1,1)(-,1)
0.94	1594.467	(1,0.05,1)(1,0.05,1)(2,0.05,1)(5,0.10,1)(-,2)
0.96	1519.402	(1,0.05,3)(1,0.05,3)(1,0.05,3)(1,0.05,3)(-,3)
0.98	1406.151	(1,0.05,3)(1,0.05,3)(1,0.05,3)(1,0.05,3)(-,3)
1.0	1237.732	(1,0.10,3)(1,0.1,3)(2,0.1,3)(2,0.1,3)(-,3)

Table 8
Best obtained MALP solutions for C_U=300, K=5, W=4 and different values of AV shock resistance factor Γ.

Γ	E	MALP
0.9	1063.328	(1,0.05,1)(1,0.05,1)(1,0.05,1)(-,1)(-,1)
0.92	1033.495	(1,0.05,1)(1,0.05,1)(1,0.05,1)(5,0.1,1)(-,1)
0.94	994.753	(1,0.05,1)(1,0.05,1)(2,0.1,1)(5,0.1,1)(-,1)
0.96	942.366	(1,0.1,1)(1,0.05,1)(2,0.1,1)(5,0.05,1)(-,1)
0.98	867.680	(1,0.1,1)(2,0.15,1)(3,0.15,1)(7,0.15,1)(-,1)
1.0	754.779	(2,0.25,1)(2,0.2,1)(2,0.15,1)(4,0.2,1)(-,2)

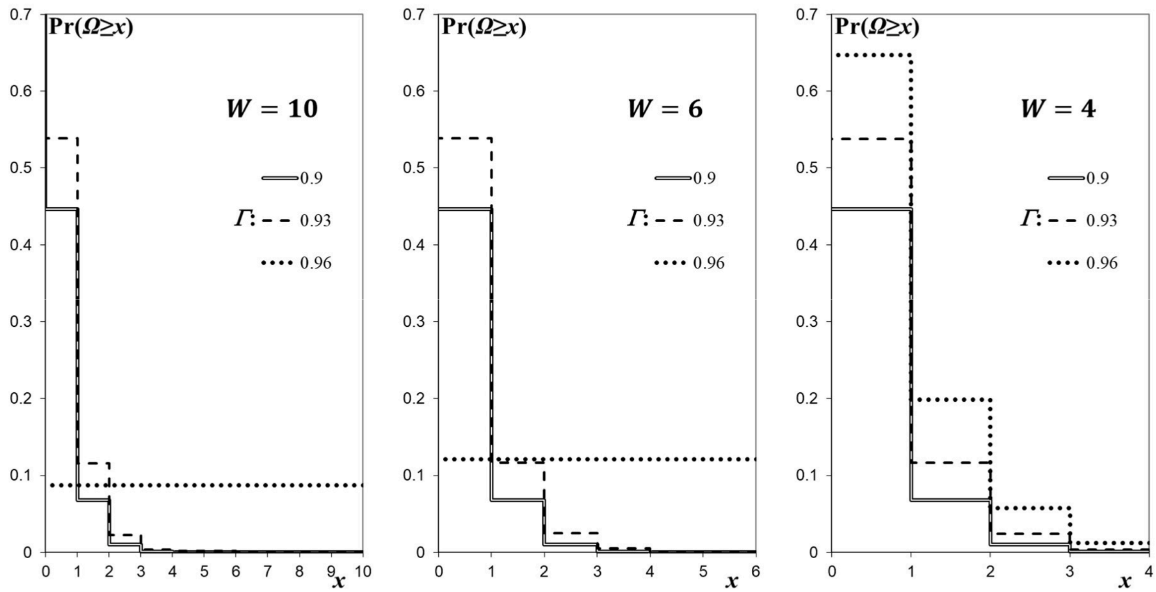

Fig. 9. Delivered weight distribution Pr(Ω≥x) corresponding to the best obtained MALP for different values of AV shock resistance factor Γ and demand weight W for C_U=300 and K=5.

The increase in the number of attempts gives chances to deliver greater weight, but, on the other hand, it increases the AV exposure to shocks, which leads to a greater probability of the AV loss. When the penalty is low (C_U=30), the AV survival is more important than the weight delivery and the EML increases with the increase in the number of attempts. Therefore, the optimal number of attempts is K=1. When the penalty increases, the delivery success becomes more important than the AV survival, and the EML decreases with the increase in the number of attempts because the chance of delivering a greater weight increases. However, the reduction of EML when K exceeds 5 becomes negligible.

When only one attempt is allowed with high C_U, the greatest loading level with no aborting policy is chosen to maximize the chance to deliver the greatest possible weight. With an increase in the allowed number of attempts, the lowest loading and cautious aborting policies are chosen in earlier attempts. In later attempts, the riskier attempt policies with greater m_k are chosen and, finally, in the last attempt the riskiest no aborting policy with loading level 3 is chosen.

4.5. Influence of the shock resistance factor Γ and required mission work W

Fig. 8 presents the values of the EML E corresponding to the best obtained MALP as a function of the AV shock resistance factor Γ for C_U=300, K=5 and different values of the demand weight W. Tables 6–8 present some of the best obtained MALP. Fig. 9 presents the delivered weight distribution Pr(Ω≥x) corresponding to the best obtained MALP for different values of Γ and W.

When the AV shock resistance factor Γ increases, the AV failure probability decreases and greater levels of AV loading can be used, especially when the required delivered weight is large. In all obtained MALP, the last attempt is performed without the aborting option to achieve the maximal delivery success probability. Intuitively, the EML decreases when the AV becomes more shock resistive and when the required delivered weight decreases.

5. Conclusion and future work

This paper models a new mission system that must accomplish a specified amount of work through multiple attempts. Depending on the loading, a portion of required work may be accomplished during each successful OP, followed by the RP. After a successful completion of the RP, the system starts a new attempt to accomplish more work. According to a dual-parameter aborting policy, the OP in an attempt may be aborted followed by the RA to survive the system. No work is accomplished for an aborted attempt. As the total number of attempts is upper bounded by K, some uncompleted work may be incurred contributing to the EML in addition to the cost associated with the possible system loss. As both the aborting policy and loading level adopted in each attempt impact the EML, we formulate a new optimization problem, the optimal MALP problem to minimize the EML. Based on the probabilistic derivation, a new numerical algorithm is put forward to assess the EML. Further, the GA is implemented solve the proposed optimization problem. We conduct a detailed case study of an AV goods delivery mission system to illustrate the proposed model and methodology. Influences of several model parameters on the EML and the optimal MALP solutions are also investigated.

Several managerial suggestions and insights are derived from the case study, including 1) As the allowed number of attempts increases, the system has a greater chance to accomplish the required work but has a greater loss probability due to its longer exposure to shocks; 2) As the allowed number of attempts increases, the earlier attempts tend to choose the lowest loading and cautious aborting policies while the later attempts tend to choose riskier aborting policies with greater loading level; 3) The last attempt tends to choose the riskiest no aborting policy to achieve the maximal OP success probability; 4) As the system becomes more shock resistive, the EML decreases; 5) As the required mission work decreases, the EML decreases.

The proposed model assumes only one system is available to perform the task. In the future, multiple systems that can perform the task will be considered (e.g., multiple AVs deliver the required amount of goods). Different working modes (sequential, in parallel, consecutive but overlapping) will be investigated and compared. In addition, both independent and common shock processes will be studied under the multi-system multi-attempt mission system model.

CRediT authorship contribution statement

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

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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