Reliability Engineering and System Safety 251 (2024) 110330

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

Optimal component activation in multi-attempt missions with common shock process

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ARTICLE INFO

Keywords:
Common shock process
Multiple attempts
Component activation schedule
Mission success probability
Component losses

ABSTRACT

Abundant research efforts were devoted to modeling and optimizing mission systems operating in random shock environments. The existing models assumed that different components are exposed to independent shock processes. However, in many real-world applications (e.g., virtual machines in cloud computing, drones deployed in the same mission), multiple operating components may be simultaneously impacted by common shock processes during the mission, causing them to deteriorate and even crash. This paper contributes by modeling a multi-attempt mission system with heterogeneous components characterized by different performance, shock resistance and cost. Each component may start performing the mission at different times and a common shock process can negatively affect all operating components. Different activation schedules of system components may lead to dramatically different mission success probabilities and expected component losses, contributing to the expected mission losses (EML). We formulate and solve a new optimal component activation schedule (CAS) problem to minimize the EML. The proposed model is demonstrated through a case study of an aerial vehicles delivery mission system. Influences of several key model parameters (shock rate, mission failure penalty, allowed mission time, and component performance) on the mission performance metrics and the optimal CAS solutions are also investigated using the case study.

1. Introduction

Any system performing a specific task is referred to as a mission system. When systems are valuable, their operations are typically coupled with a mission aborting policy to balance the mission success probability (MSP) and the system survivability [1,2]. For example, in applications like battlefield [3], aerospace [4], healthcare [5], and chemical reactor [6,7], mission aborting may be implemented to terminate the task execution in the event of certain deterioration condition happening and a rescue procedure (RP) is then performed to save the valuable system [8].

Depending on the allowed number of attempts for completing the task, single-attempt and multi-attempt mission systems can be distinguished. Diverse aborting policies have been studied for both types of mission systems, as reviewed in Section 2. This paper focuses on the modeling and optimization of multi-attempt mission systems with the consecutive, overlapping execution mode in random shock environments. In the case of any attempt being successful, other attempts are aborted to save cost. Though several existing multi-attempt models [9–11] considered the shock environments, they assumed that different components are exposed to independent shock processes. In practice, multiple components may be affected by some common shock process. For example, multiple virtual machines hosted on the same physical server in the cloud computing may be impacted by the same attack launched to the server. Multiple drones deployed in the same mission may be affected by the same electromagnetic impulses occurring in the area.

This paper contributes by considering a common shock process affecting all simultaneously operating components attempting the same mission task. System components are heterogeneous, characterized by different levels of performance, shock resistance and cost. Following a component activation schedule (CAS), each component may start executing the mission at different times. Upon the mission completion by any of the activated components, the rest of them abort their operation and start a RP to avoid loss. Since the CAS adopted can affect the

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https://doi.org/10.1016/j.ress.2024.110330
Received 2 April 2024; Received in revised form 24 May 2024; Accepted 7 July 2024
Available online 14 July 2024

Nomenclature

J	number of components available for the mission
H	number of components activated during the mission
Λ	shocks rate
t_n	duration of time interval n
$c(j)$	index of the component for which there exist exactly j-1 components scheduled to complete the mission earlier
τ_j	operation time of component $c(j)$
a_j	activation time of component $c(j)$
b_j	scheduled time of operation completion for component $c(j)$
N_j	number of disjoint time intervals in which different subsets of components operate until time b_j
$I_{in}(j)$	indicator function ($I_{in}(j)$=1 if component $c(i)$ operates in time interval n) for components activated before b_j
$[\theta_n(j),\theta_{n+1}(j)]$	time interval during which the set of operating components does not change according to CAS for components activated before b_j
$\mu_h(j)$	total operation time of component $c(h)$ with $b_h>b_j$ when component $c(j)$ completes the mission
$w_h(j)$	probability that component $c(h)$ with $b_h>b_j$ is lost when component $c(j)$ completes the mission
E_j	event that component $c(j)$ completes the mission
r_j	occurrence probability of event E_j
C	EML
R	MSP
E	ECLC
K	maximum number of shocks that any component can survive with non-negligible probability
$P(t, i, \rho)$	the probability that i shocks occur during time t under the homogeneous Poisson process with rate ρ
$Q_{c(i)}(k)$	probability that component $c(i)$ survives k shocks
$l_{c(i)}$	cost associated with loss of component $c(i)$
x	penalty associated with the mission failure

Acronyms

AV	aerial vehicle
CAS	component activation schedule
ECLC	expected cost of lost components
EML	expected mission losses
GA	genetic algorithm
HPP	homogeneous Poisson process
MSP	mission success probability
RP	rescue procedure
VM	virtual machine

MSP, the expected cost of lost components (ECLC), and the overall expected mission losses (EML) significantly, we formulate a new optimization problem that determines the optimal CAS to minimize the EML. A probabilistic modeling method is put forward to assess the mission performance metrics of MSP, ECLC, and EML. Based on the string representation of CAS solutions suggested in this work, the genetic algorithm is further realized to solve the proposed EML minimization problem. A detailed case study of a delivery mission system is provided to demonstrate the proposed model and investigate influences of several model parameters on those mission metrics and on the optimal CAS solutions.

The rest of the paper has the following organization: Section 2 reviews some relevant works. Section 3 presents the heterogenous multi-attempt mission system model and formulates the optimal CAS problem, illustrated by two examples. Section 4 derives MSP, ECLC, and EML of the considered mission system given any CAS and describes the optimization technique used. Section 5 conducts the case study. Section 6 concludes the work with managerial suggestions and potential further research problems.

2. Literature review

Aborting policies based on different parameters have been studied for both single-attempt and multi-attempt mission systems. For instance, the aborting policies using the following parameters have been designed for diverse single-attempt mission systems:

- system degradation level (e.g., for phased-mission system [12], partially observable safety-critical systems [13])
- the number of failed elements (e.g., for warm standby systems [14], *k*-out-of-*n: F* balanced systems [15], *k*-out-of-*n: G* systems [16], unmanned aerial vehicles [17])
- completed mission work (e.g., for heterogeneous warm standby systems [18], dual-component standby systems with maintenance [19])
- the number of shocks (e.g., for multistate systems [20], drone-truck systems [21], systems with random rescue time [22])
- system predictive reliability (e.g. for multi-component systems with interactions [23])
- the number of times of entering unbalanced states (e.g., for dual-subsystem balanced systems [24])
- system age and the number of failed components (e.g., for standby systems [25], self-healing systems [26])
- system age and degradation level (e.g., for safety-critical swarm systems [27])
- system degradation level and completed mission work (e.g., for multistate systems with storage [28], load-dependent systems [29])
- operation time and the number of shocks (e.g., for resource-constrained systems [30]).

Aborting policies have also been explored for different types of multi-attempt mission systems depending on the execution modes. For instance, aborting policies using the number of shocks [31], degradation level [32,33], and the number of shocks coupled with operation time [34,35] were investigated for mission systems with multiple attempts executed sequentially by a single component. The aborting policy using the number of shocks coupled with operation time was studied for mission systems with multiple attempts executed in parallel [36] or in the consecutive, overlapping mode by different components activated according to a constant interval [9,10] or dissimilar intervals [11]. Refer to [37] for a state-of-the-art review of single-attempt and multi-attempt mission aborting models.

Very little work was devoted to the modeling and optimization of multi-attempt mission systems with the consecutive, overlapping execution mode, and the existing models (particularly, [9–11]) only addressed independent shock processes affecting individual components. As exemplified by the cloud computing [38] and drone [39] systems in the Introduction, common shock process affecting multiple system components simultaneously may take place during the mission and impact the mission performance greatly [40], which have not been addressed by the existing multi-attempt mission models.

This paper fills the gap by modeling and optimizing multi-attempt mission systems subject to common shock processes that affect all simultaneously operating components attempting the same mission task. Specific contributions include

- Propose a new probabilistic modeling method to evaluate several mission performance metrics including the MSP, ECLC, and EML.

- Formulate a new optimization problem that finds the optimal CAS minimizing the EML.
- Suggest a string representation of the CAS solutions and implement the genetic algorithm to solve the formulated optimization problem.
- Conduct a case study of a delivery mission system to demonstrate the proposed model.
- Investigate effects of several model parameters on mission performance metrics and the optimal CAS solutions.

3. System description and problem formulation

The system has J initially available components that are functionally identical but have different performance (speed of task accomplishment), shock resistance and cost. A mission must be accomplished by the system within the deadline T. The mission task may be attempted multiple times by different components. Each component can start performing the mission at different times. Depending on the performance, each component j needs fixed time τ_j to complete the mission.

The mission is performed in a random environment modeled by homogeneous Poisson processes (HPP) of shocks with arrival rate Λ. Each shock affects all the components that operate at the moment of shock occurrence, and can cause loss of the component affected. The probability of component loss increases as the number of shocks it experiences increases. If one of the components completes the mission, the rest of the operating components immediately abort their operation and start a RP. No components are activated after the mission completion. The RP's duration for each component is dependent on the time t elapsed from the activation of the component to the beginning of the RP, denoted by function $\varphi(t)$.

The time that each component spends in the shock environment depends on its activation time as well as on the time of the mission completion by one of other components. If component j is activated at time a_j, the mission can be completed at discrete times $a_j+\tau_j$ if $a_j+\tau_j \le T$ for $j = 1,\ldots,N$ and the time that component j surviving the mission can spend in the shock environment belongs to the discrete set of values $a_k+\tau_k-a_j+\varphi(a_k+\tau_k-a_j)$ for such $k = 1,\ldots,K$ that $a_k+\tau_k<a_j+\tau_j$ and $a_j<a_k+\tau_k$ (i.e. when component k completes the mission not later than component j, but after its activation).

3.1. Problem formulation

When all the components are activated simultaneously, they are affected by the greatest number of common shocks, which causes a decrease of the mission success probability and an increase in the expected component losses. On the other hand, activating the components one by one (sequentially) provides the lowest expected component losses, but may lead to inability of some components to complete the mission in time and contribute to probability of the mission success. The optimal scheduling of components activation should hit the balance between the cost of components' losses and the penalty associated with the mission failure.

For any component activation schedule (CAS) $\boldsymbol{A} = \{a_1,\ldots,a_J\}$, the mission success probability $R(\boldsymbol{A})$ and the expected cost of lost components $E(\boldsymbol{A})$ can be evaluated (see Section 4). The problem is to determine the optimal CAS that minimizes the expected system losses (EML)

$$C(\boldsymbol{A})=E(\boldsymbol{A})+x(1-R(\boldsymbol{A})), \tag{1}$$

where x is a penalty associated with the mission failure.

3.2. Illustrative examples

A company can use up to K offshore drilling rigs for underwater drilling in an oil-producing region under an oil proof contract. The period of work is limited by the contract. All drilling rigs operating simultaneously in the exploration area are subject to random storm impacts (common shocks). A fixed time τ_j is needed for each rig j to reach the oil-bearing layer. A storm can damage and destroy the rig, making further drilling impossible and causing losses. The rig fatal destruction probability increases with an increase in the number of experienced storms. If one of the rigs completes its work, all rigs can be evacuated. A storm can also impact the rigs during evacuation. The company's management problem is to find the rigs activation schedule balancing the losses associated with the damage to the rigs and penalty associated with the oil proof mission failure.

Consider another example of a data processing software system. It must complete a task operating with sensitive data by the deadline T. The contract between the software user and a cloud computing service provider includes creating K virtual machines (VM) on a server. The time required for each VM to accomplish the task is τ. The server is exposed to random shocks in the form of hackers' attacks. The attacks aim to access and corrupt the user's sensitive data. If a hacker succeeds to plant malicious software into the server (shock event), this software attempts to penetrate to each VM by cracking its individual protection code and to corrupt the data. Even when the penetration attempt fails, it may provide certain information about the VM protection, which can be used by the hackers in their future attacks. Consequently, as the number of attacks increases, the attack success probability increases. To decrease the time of data exposure to the attacks, the VMs can be created at different times (not simultaneously) and when one of the VMs completes the task, the remaining functioning VMs are removed from the server and their data are transferred to the safe storage. It is possible for the hackers to gain access to the data during the transfer. If no VM completes the computational task by the deadline, the mission fails. The user tries to determine the optimal VM creation schedule to balance the expected cost associated with the sensitive data corruption and the mission failure penalty.

Refer to Section 5 for another example of a delivery mission executed by multiple aerial vehicles in the shock environment.

4. Evaluating and minimizing the EML

4.1. Combinations of simultaneously operating components

Assume that the components activation schedule is such that component $c(i)$ is planned to complete its attempt at time $b_i \le T$. Let $\boldsymbol{B} = \{b_1,\ldots,b_H\}$ be an ordered set of attempt completion times for all the activated components such that $b_i<b_{i+1}$ for any i. Let $\boldsymbol{A} = \{a_1,\ldots,a_H\}$ be a set of component's activation times such that $a_i = b_i-\tau_i$. If $a_j<0$, component $c(i)$ is not activated during the mission and a_i and b_i are excluded from the corresponding sets. Therefore, the number H of components planned to be activated during the mission can be smaller than the total number of available components J.

Let $\boldsymbol{A_j} = \{a_1,\ldots,a_j\}\subset\boldsymbol{A}$ and $\boldsymbol{B_j} = \{b_1,\ldots,b_j\}\subset\boldsymbol{B}$ be the subsets containing the first j elements of the sets $\boldsymbol{A}$ and $\boldsymbol{B}$, which correspond to j components that that are planned to complete their attempts at time not later than b_j. For the given $\boldsymbol{A_j}$ and $\boldsymbol{B_j}$, one can obtain the ordered set $\boldsymbol{\Theta_j} = \boldsymbol{A_j}\bigcup B_j = \{\theta_1(j), \ldots, \theta_{N_j+1}(j)\}$, containing only different values (after excluding redundant equal values). This set contains $N_j+1\le 2j$ elements and $\theta_n(j)<\theta_{n+1}(j)$ for $1\le n\le N_j$. In any time interval $[\theta_n(j),\theta_{n+1}(j)]$ having duration $t_n = \theta_{n+1}(j)-\theta_n(j)$, different sets of components operate.

Any component $c(i)$ operates in time interval $[\theta_n(j),\theta_{n+1}(j)]$ if $a_i\le\theta_n(j)$, and $b_i\ge\theta_{n+1}(j)$. Thus,

$$I_{in}(j) = \begin{cases} 1 \text{ if } a_i \le \theta_n(j) \text{ and } b_i \ge \theta_{n+1}(j) \\ \quad 0 \text{ otherwise}, \end{cases} \tag{2}$$

can be used as an indicator that component $c(i)$ operates in time interval $[\theta_n(j),\theta_{n+1}(j)]$.

Consider, for example, an activation schedule $\boldsymbol{A} = \{0,4,2,7\}$ and $\boldsymbol{B} = \{4,7,8,10\}$ for four components (where $\tau_{c(1)}=4$, $\tau_{c(2)}=3$, $\tau_{c(3)}=6$,

Table 1
Example of component activation schedule.

j	A_j	B_j	Θ_j	N_j	Intervals' durations	Nonzero indicators
1	{0}	{4}	{0,4}	1	t_1=4-0=4	$I_{11}(1)$
2	{0,4}	{4,7}	{0,4,7}	2	t_1=4-0=4, t_2=7-4=3	$I_{11}(2)$,$I_{22}(2)$
3	{0,4,2}	{4,7,8}	{0,2,4,7,8}	4	t_1=2-0=2, t_2=4-2=2, t_3=7-4=3, t_4=8-7=1	$I_{11}(3)$,$I_{12}(3)$,$I_{23}(3)$, $I_{32}(3)$,$I_{33}(3)$,$I_{34}(3)$
4	{0,4,2,7}	{4,7,8,10}	{0,2,4,7,8,10}	5	t_1=2-0=2, t_2=4-2=2, t_3=7-4=3, t_4=8-7=1, t_5=10-8=2	$I_{11}(4)$,$I_{12}(4)$,$I_{23}(4)$, $I_{32}(4)$,$I_{33}(4)$,$I_{34}(4)$, $I_{44}(4)$,$I_{45}(4)$

$\tau_{c(4)}$=3). Table 1 presents the subsets $\boldsymbol{A_j}$, $\boldsymbol{B_j}$ and $\boldsymbol{\Theta_j}$, the numbers of non-overlapping intervals $N_j = 1$, the durations of the intervals and the lists of non-zero indicators $I_{in}(j)$ for $1 \le j \le 4$.

4.2. Component survivability

Based on the shock model in [41], the conditional probability that a component j can survive the n-th shock given that it survived previous shocks is computed as

$$q_j(n) = \Gamma_j \gamma_j(n) \text{ for } n > 0, \tag{3}$$

In (3), Γ_j is the survival probability of component j upon the first shock, and $\gamma_j(n)$ is the shock resistance deterioration factor which is defined as a decreasing function of its argument with

$$\gamma_j(n) = \gamma_j^{\,n-1},\ 0 < \gamma_j < 1 \text{ and } \gamma_j(0) = 1. \tag{4}$$

Eq. (4) models the decreasing survival probability upon each shock as the number of survived shocks increases. Eq. (5) gives the probability that component j can survive k shocks, where $q_j(0)\equiv 1$.

$$Q_j(k) = \prod_{n=0}^{k} q(n) = \Gamma_j^{\,k} \gamma_j^{\frac{k(k-1)}{2}}. \tag{5}$$

4.3. Evaluating the MSP

Consider event E_j that component $c(j)$ completes the mission before time T. Event E_j occurs at time b_j since the beginning of the mission if $b_j \le T$, any component k with $b_k \le b_j$ fails to complete the mission and component j survives the OP during time τ_j. The number of disjoint time intervals in which different subsets of the components operate till time b_j is N_j. The probability that in these time intervals 1,2,…,N_j exactly $k_1, k_2, \ldots, k_{N_j}$ shocks respectively occur is

$$\prod_{n=1}^{N_j} P(t_n, k_n, \Lambda), \tag{6}$$

where $P(t,i,\rho) = e^{-\rho t}\frac{(\rho t)^i}{i!}$ is the probability that i shocks occur during time t under the homogeneous Poisson process with rate ρ. The number of shocks component $c(i)$ (for $i<j$) experiences in this case from the mission beginning till time b_j is $\sum_{n=1}^{N_j} k_n I_{in}(j)$, and the probability that component $c(i)$ survives all these shocks is

$$Q_{c(i)}\left(\sum_{n=1}^{N_j} k_n I_{in}(j)\right). \tag{7}$$

Thus, the probability that component $c(j)$ completes the mission (i.e. it survives all the shocks it was exposed to before time b_j, whereas all the components $c(i)$ with $b_i<b_j$ are lost in operation before time b_j) can be obtained as

$$r_j = \sum_{k_1=0}^{\infty} P(t_1,k_1,\Lambda) \sum_{k_2=0}^{\infty} P(t_2,k_2,\Lambda) \ldots \sum_{k_{N_j}=0}^{\infty} P\left(t_{N_j},k_{N_j},\Lambda\right) \times Q_{c(j)}\left(\sum_{n=1}^{N_j} k_n I_{jn}(j)\right) \prod_{i=1}^{j-1}\left(1 - Q_{c(i)}\left(\sum_{n=1}^{N_j} k_n I_{in}(j)\right)\right). \tag{8}$$

A recursive procedure for obtaining r_j with any predetermined precision is presented in Appendix 1. The computational complexity of the procedure is $O(K^{N_j})$ where K is the maximum number of shocks that can occur in at least one of the time intervals t_n with non-negligible probability.

As the events that different components complete the mission are mutually exclusive, the total probability of the mission success can be obtained as

$$R = \sum_{j=1}^{H} r_j. \tag{9}$$

4.4. Evaluating the ECLC

When event E_j occurs, all j-1 components with $b_i<b_j$ are lost and the rest of components immediately abort their attempts. The time during which any component $c(h)$ with $b_h>b_j$ must operate to survive when event E_j occurs can be obtained as

$$\mu_h(j) = \begin{cases} 0 \text{ if } a_h \ge b_j \\ b_j - a_h + \varphi(b_j - a_h) \text{ otherwise,} \end{cases} \tag{10}$$

where $b_j - a_h$ is the time which component $c(h)$ spends in operation before event E_j. The conditional probability that component $c(h)$ is lost given that event E_j occurs is

$$w_h(j) = 1 - \sum_{k=0}^{\infty} P(\mu_h(j),k,\Lambda) Q_{c(h)}(k). \tag{11}$$

The expected cost of lost components in the case where event E_j occurs is

$$\sum_{h=1}^{H} l_{c(h)} 1(b_h < b_j) + \sum_{h=1}^{H} l_{c(h)} w_h(j) 1(b_h > b_j). \tag{12}$$

Thus, the overall expected number of lost components when the mission succeeds is

$$\sum_{j=1}^{H} r_j \left(\sum_{h=1}^{H} l_{c(h)} 1(b_h < b_j\right) + \sum_{h=1}^{H} l_{c(h)} w_h(j) 1(b_h > b_j)). \tag{13}$$

The mission fails when all the activated components are lost. The probability of this event is 1-R. Thus, the overall expected number of lost components in the mission is

$$E = (1-R)\sum_{h=1}^{H} l_{c(h)} + \sum_{j=1}^{H} r_j \left(\sum_{h=1}^{H} l_{c(h)} 1(b_h < b_j\right) + \sum_{h=1}^{H} l_{c(h)} w_h(j) 1(b_h > b_j)). \tag{14}$$

The total EML is evaluated using (1).

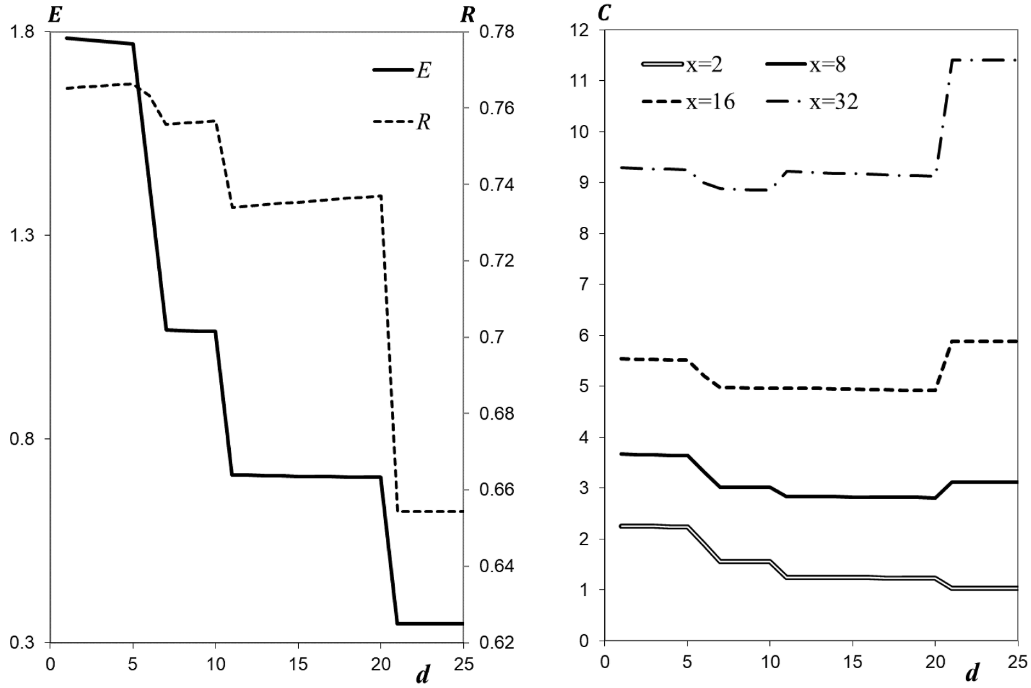

Fig. 1. MSP R, ECLC E and EML C as functions of the delay d for different values of the penalty x.

4.5. Optimization procedure for minimizing the EML

Finding the optimal CAS $\boldsymbol{A}$ minimizing the EML $C(\boldsymbol{A})$ is a multidimensional optimization problem, in which J parameters $\{a_1,\ldots,a_J\}$ must be obtained. When each parameter a_i can take B discrete values from the set $\{0,dt,2dt,\ldots,T\}$, where the step is $dt = T/(B\text{-}1)$, the size of the search space is B^J. To solve the optimization problem, the widely applied genetic algorithm (GA) [42] is implemented. GA requires solutions to be represented in strings. To represent the CAS solution, it is proposed that the string contains J real numbers $b_1,\ldots, b_J$ ranging from 0 to T and corresponding to times of mission completion for the J system components. The CAS parameters (component activation times) are obtained as $a_k = b_k\text{-}\tau_k$. If $a_k<0$, the component k is not activated during the mission. This allows checking different numbers of activated components and different sequences of components activation during the optimization search.

With the suggested string representation of CAS solutions, the standard operations of mutation, crossover, and selection engaged in the GA optimization process (see Appendix 2) are implemented for solving the proposed optimization problem.

5. Case study of the multi-AV delivery mission

5.1. System description

Consider a group of $J = 5$ AVs performing a delivery mission. To complete the mission successfully, a payload must be delivered from a base to a destination point. Each AV j can accomplish the mission if it is not lost during the flight to the destination point. Each AV j has its specific speed that determines the flight time τ_j required for delivering the payload.

During the flight, the AVs are exposed to a process of shocks caused by electromagnetic impulses such that any impulse affects all AVs operating in the area. The shocks may destroy the control equipment of any AV affected and cause the AV to crash. The number of shocks arrivals during the flight obeys the HPP with rate Λ. The performance of the interference filters that protects the AVs' equipment degrades as more shocks happen. Such deterioration is modelled using the shock resistance model (5) with specific values of Γ_j and γ_j for AV j.

If any AV reaches the destination point, the rest of the already en route AVs abort their mission and start the RP, which presumes dropping the payload and flying with an increased speed to the closest landing position between the base and the destination point. Thus, if AV j aborts its mission at time t from its beginning, it needs time $\varphi(t)$=0.8min(t,τ_j-t) to complete the RP. The penalty x is imposed if the delivery mission is not completed during time T.

5.2. Identical AVs

Assume that for all the AVs, $\tau_j = 80$, $\Gamma_j = 0.8$, $\gamma_j = 0.95$ and the cost of lost component is $l_j = 1$. The mission time is $T = 100$ and the shock rate is $\Lambda = 0.01$. The first AV is activated at time $a_1 = 0$ and each next AV is activated with delay d after the previous one i.e. $a_i=a_{i\text{-}1}+d=(i\text{-}1)d$ for $i = 2,\ldots,5$.

Fig. 1 presents MSP R and ECLC E as functions of the delay d. It can be seen that as d increases, the MSP increases and the ECLC decreases because the time when all the AVs are exposed to shocks simultaneously decreases. However, as d reaches the values when the number of AVs having enough time to complete the mission decrements, both MSP and ECLC sharply drop. Indeed, when fewer AVs have enough time to complete the mission, fewer AVs participate in the mission as an AV is not activated if it has no chance to contribute to the mission success. When the number of activated AVs decreases, the probability that at least one of them succeeds to complete the mission (MSP) decreases and the number of AVs exposed to shocks decreases, which causes the decrease in the ECLC. When the delay d exceeds 20, only one AV performs the mission and the MSP and ECLC do not depend on d anymore.

Fig. 1 also presents EML C as a function of the delay d for different values of the penalty x. The EML can behave non-monotonically. When the penalty x is low ($x = 2$), the mission completion is less important than saving the AVs and only one AV should be used in the mission ($d>20$) to minimize the EML. When the penalty increases, more AVs should be activated to deliver the payload with the maximum possible delay among their activation. For $x = 8$ and $x = 16$, the minimum EML is achieved for $d = 20$, which corresponds to two activated AVs. For $x = 32$, the minimum EML is achieved for $d = 10$, which corresponds to three

Table 2
Parameters of available AVs.

j	τ_j	Γ_j	γ_j	l_j
1	90	0.80	0.95	0.9
2	85	0.85	0.92	1.2
3	85	0.90	0.90	1.2
4	80	0.86	0.93	1.4
5	70	0.90	0.92	1.7

activated AVs. Whereas the CAS solutions with the constant delay and $a_i = (i\text{-}1)d$ are optimal when no more than two AVs are activated, the best solution for $x = 32$ when three AVs are activated is $a_1 = 0$, $a_2 = a_3 = 20$ where both the second and third AVs have chances to complete the mission, but are exposed to shocks during the minimal time in the case where the first AV completes the mission. Such a CAS provides $R = 0.7570$, $E = 1.059$ and $C = 8.832$ whereas the CAS with $a_1 = 0$, $a_2 = 10$, $a_3 = 20$ provides $R = 0.7567$, $E = 1.064$ and $C = 8.850$.

5.3. Different AVs

When the AVs have different characteristics, the order of their activation as well as the delays between their activations affect the EML. The times needed for AVs to reach the destination point, the shock resistance function parameters and the costs are presented in Table 2.

5.3.1. Effects of mission failure penalty and shock rate

Fig. 2 presents the mission metrics corresponding to the best obtained CAS as functions of the penalty x for different values of the shock rate Λ. Tables 3 and 4 present the best obtained CAS and the corresponding values of the mission metrics for $\Lambda = 0.005$ and $\Lambda = 0.02$. For convenience, the CAS solutions are represented in the form of list, $i{:}a_i,\ldots, k{:}a_k$ containing only indices and activation times of AVs activated during the mission.

It can be seen that when the penalty increases, more AVs are activated to perform the mission and the MSP R increases by the price of increasing ECLC E. The increase in the shock rate Λ causes a decrease of the MSP and an increase of the ECLC.

The number of activated AVs increases with an increase in the penalty. It also increases when the shock rate increases to compensate the greater probability that AVs fail to complete the mission. The fastest and most shock resistant AV 5 is always activated first, which gives chances for the rest of AVs to abort their mission being exposed to shocks during the minimal time in the case of AV 5 success. AV 3 is also always activated. AV 2 is never activated when $\Lambda = 0.005$ and is activated only when all the five AVs contribute to the mission success when $\Lambda = 0.02$. When $\Lambda = 0.02$, the CAS for $x>160$ does not change because all five available AVs are already activated and no further MSP improvement can be achieved.

Table 3
Best obtained CAS and the corresponding mission metrics for different values of penalty when $\Lambda = 0.005$.

x	A	R	E	C
10	5:0,3:15	0.870	0.465	1.762
20	5:0,3:15	0.870	0.465	3.058
40	5:0,3:15	0.870	0.465	5.652
80	5:0,1:10,3:14	0.873	0.645	10.805
160	5:0,3:14,4:20	0.874	0.708	20.927
320	5:0,1:10,3:13,4:19	0.874	0.887	41.134

Table 4
Best obtained CAS and the corresponding mission metrics for different values of penalty when $\Lambda = 0.02$.

x	A	R	E	C
10	5:0,3:15	0.754	1.028	3.493
20	5:0,3:15	0.754	1.028	5.958
40	5:0,3:15,4:19	0.779	1.578	10.411
80	5:0,1:9,3:15,4:18	0.787	1.993	19.068
160	5:0,1:8,2:14,3:15,4:17	0.791	2.497	35.898
320	5:0,1:8,2:14,3:15,4:17	0.791	2.497	69.299

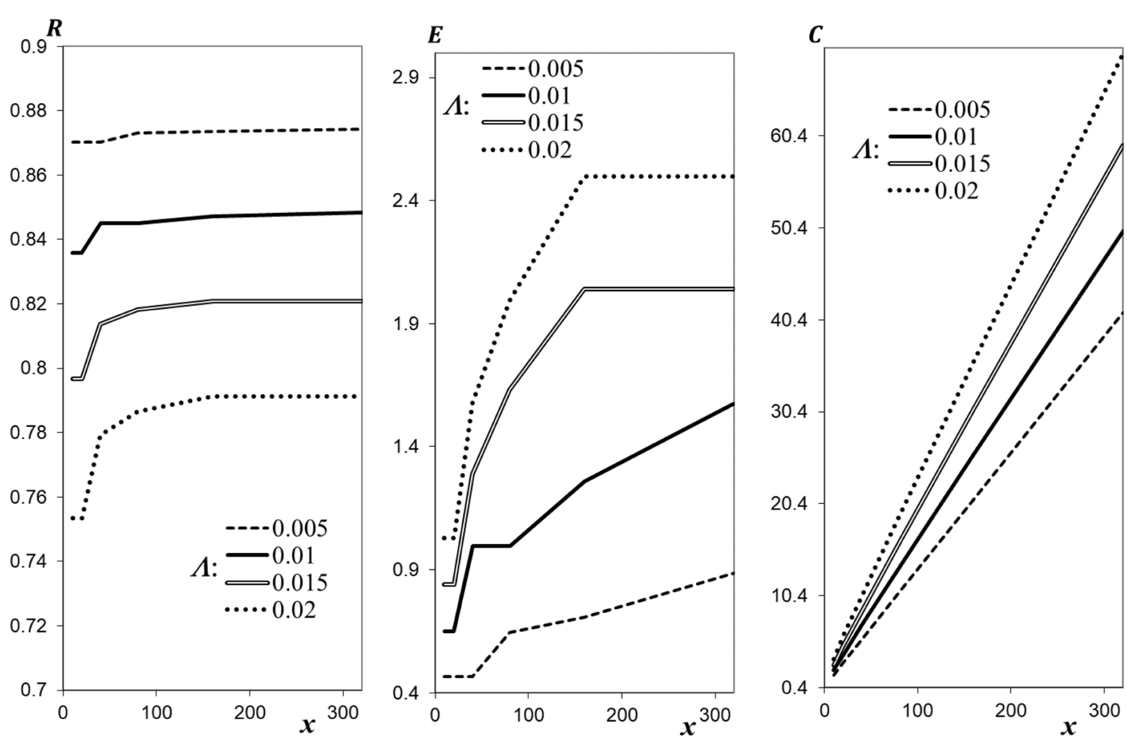

Fig. 2. The mission metrics corresponding to the best obtained CAS as functions of the penalty x for different values of the shock rate Λ.

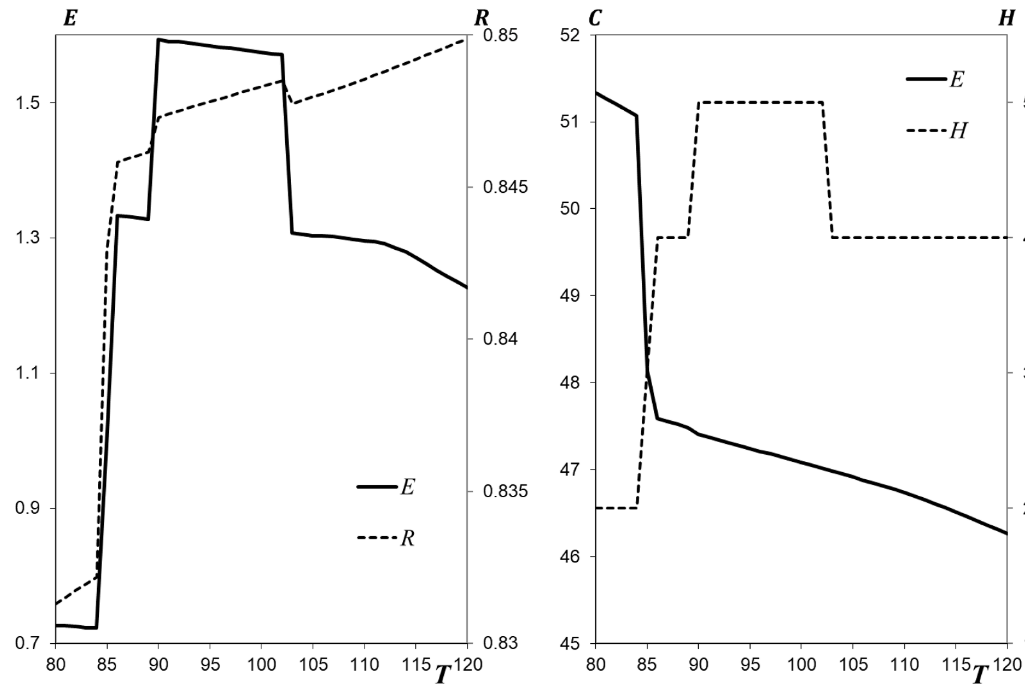

Fig. 3. Mission metrics corresponding to the best obtained CAS as functions of the allowed mission time T for $x = 300$ and $\Lambda = 0.01$.

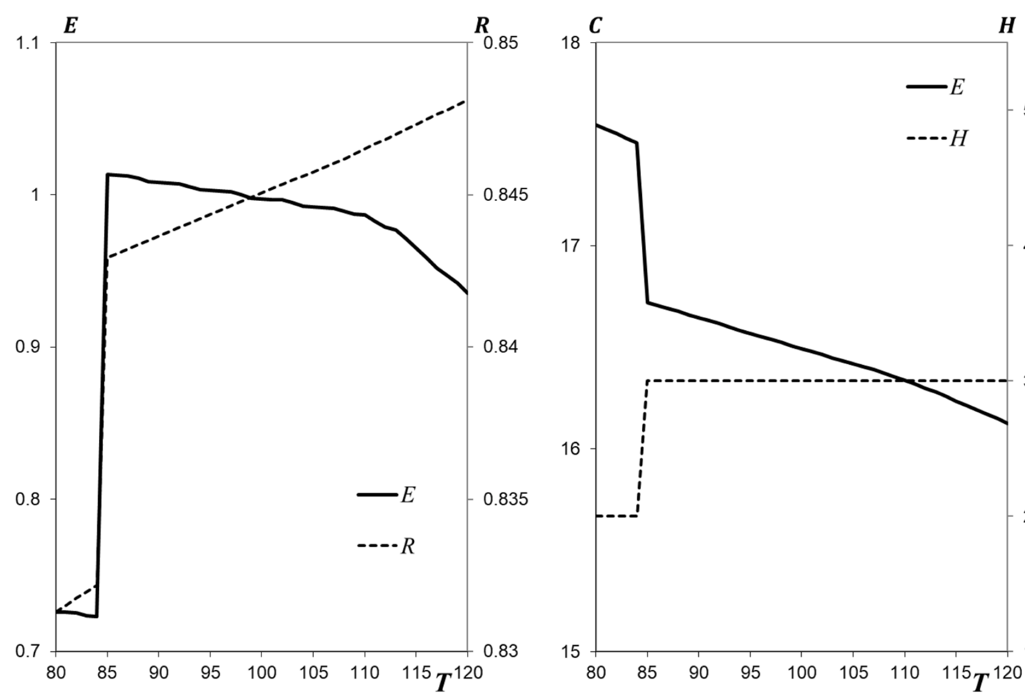

Fig. 4. Mission metrics corresponding to the best obtained CAS as functions of the allowed mission time T for $x = 100$ and $\Lambda = 0.01$.

5.3.2. *Effects of allowed mission time*

Figs. 3 and 4 present the mission metrics corresponding to the best obtained CAS as functions of the allowed mission time T for shock rate $\Lambda = 0.01$ and penalty values $x = 300$ and $x = 100$. Figs. 5 and 6 presents the AV operation schedules corresponding to the best obtained CAS for three different mission times T and two values of penalty x. Tables 5 and 6 present the best obtained CAS and the corresponding values of the mission metrics for some of solutions. When $T<85$, the first three AVs have no chance to complete the mission in time. Therefore, only AVs 4 and 5 can be used. When T increases above 85, AVs 2 and 3 can be activated, and when T increases above 90, all available AVs can be activated. The possibility to activate additional AVs when $T>85$ causes a sharp increase in MSP and a drop of EML. When T further increases, the AVs operation overlapping can be reduced, which leads to an increase of the MSP and a decrease of the ECLC.

Therefore, for $x = 300$ and $T>102$, the minimum EML can be achieved with activating only part of the available AVs and the number of activated AVs drops to 4. For $x = 100$, the AVs survival remains more important than for $x = 300$ and no more than three AVs are activated during the mission to keep the ECLC low.

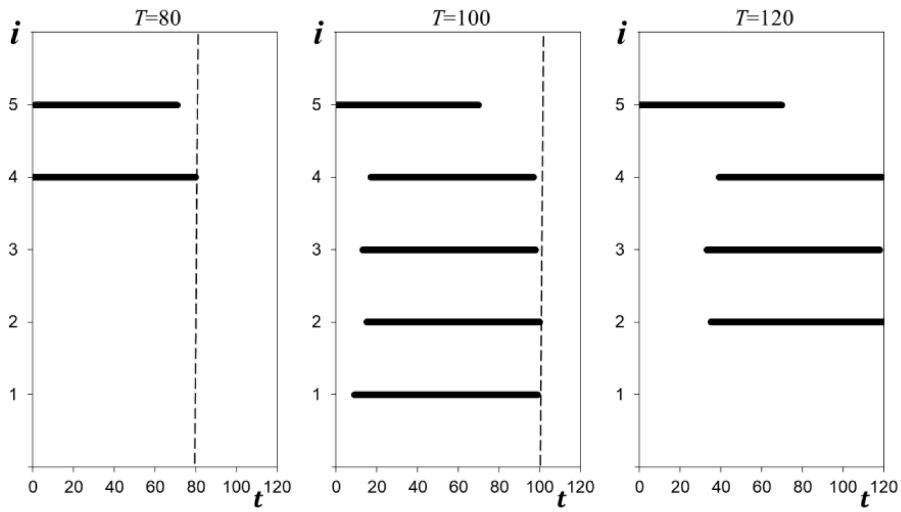

Fig. 5. AV operation schedules corresponding to the best obtained CAS for three different mission times T when $x = 300$ and $\Lambda = 0.01$.

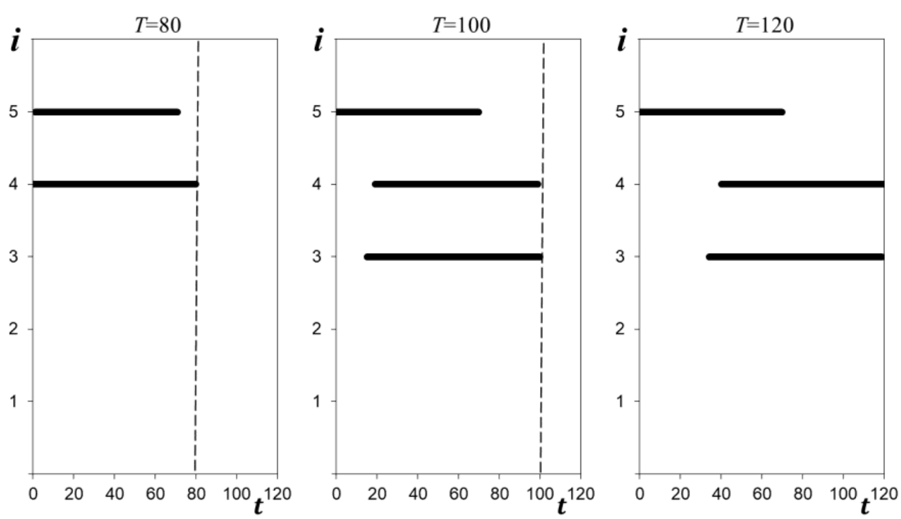

Fig. 6. AV operation schedules corresponding to the best obtained CAS for three different mission times T when $x = 300$ and $\Lambda = 0.01$.

Table 5
Best obtained CAS and the corresponding mission metrics for different values of mission time T penalty when $x = 100$ and $\Lambda = 0.01$.

T	***A***	*R*	*E*	*C*
80	4:0,5:1	0.831	0.726	17.596
85	3:0, 5:0,4:4	0.843	1.013	16.721
88	5:0,3:3,4:7	0.843	1.011	16.675
100	5:0,3:15,4:19	0.845	0.997	16.492
120	5:0,3:34,4:40	0.848	0.935	16.124

Table 6
Best obtained CAS and the corresponding mission metrics for different values of mission time T penalty when $x = 300$ and $\Lambda = 0.01$.

T	***A***	*R*	*E*	*C*
80	4:0,5:1	0.831	0.726	51.335
85	3:0,5:0,4:4	0.843	1.013	48.135
88	5:0,3:2,2:3,4:6	0.846	1.329	47.517
100	5:0,1:9,3:13,2:15,4:17	0.848	1.574	47.083
120	5:0,3:33,2:35,4:39	0.850	1.227	46.265

5.3.3. *Effects of component performance*

The presented CAS optimization methodology allows evaluating the influence of performance improvement of system components on the EML. For example, if the speed of the AVs (except the fastest AV 5) can be increased, the question of "which AV should be upgraded first to achieve the greatest EML reduction" arises.

Fig. 7 presents the mission metrics corresponding to the best obtained CAS as functions of the AV operation times τ_i ($i = 1,2,3,4$) for shock rate $\Lambda = 0.01$ and penalty values $x = 300$ (when τ_i varies, the values of τ_j for any $j \neq i$ remain the same as in Table 2). Table 7 presents the best obtained CAS and the corresponding values of the mission metrics for some of solutions. When the AVs are fast, they are activated in later stages of the mission and the relatively low overlapping in the AVs operation allows to achieve the minimal EML using 4 out of 5 AVs.

With an increase in τ_i the overlapping increases, causing the decrease of the MSP that must be compensated by using all five AVs. However, when the AVs become too slow, their contribution to the increase of the ECLC can become greater than to the increase of the MSP and it can become beneficial to avoid activating these AVs (except AV3, which is always activated).

For example, when $\tau_1 = 70$, the AV1 is activated last ($a_1 = 29$) and has good chances to complete the mission. The slowest AV2 is not activated in this case. When τ_1 increases to 85, the chances of AV1 to

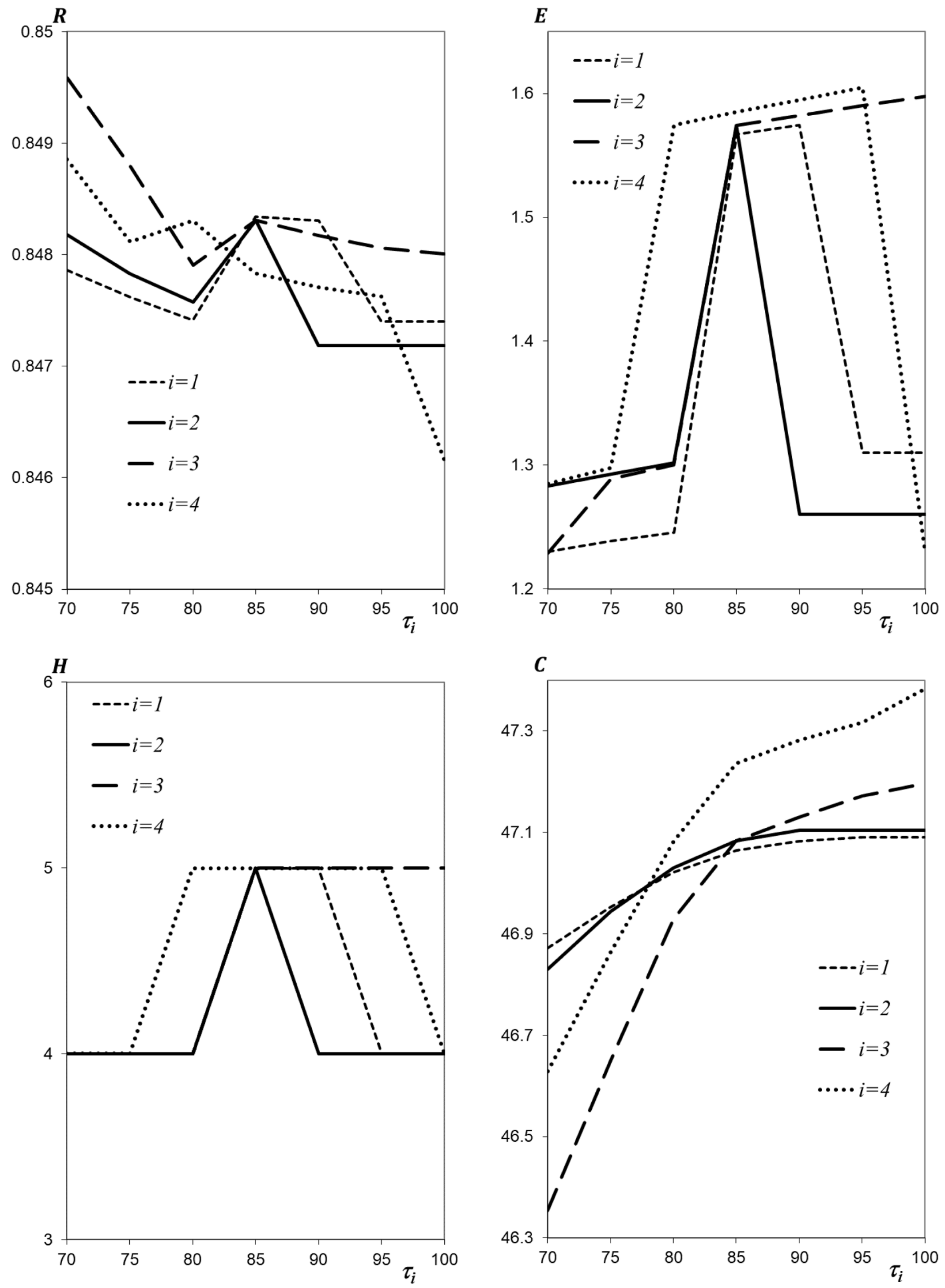

Fig. 7. Mission metrics corresponding to the best obtained CAS as functions of the AV operation times τ_i for $T = 100$, $x = 300$ and $\Lambda = 0.01$.

complete the mission become lower and it must be activated earlier to have enough time for mission completion. To compensate the decrease in the MSP caused by the increased τ_1, AV2 is also activated during the mission and the number of AVs participating in the mission increases to $H = 5$. When τ_1 increases to 100, the chances of AV1 to complete the mission become so low that its contribution to the MSP increase becomes less than its contribution to the ECLC increase. In this case, the activation of AV1 is not beneficial and the number of AVs participating in the mission drops to $H = 4$.

When AVs are slower, they tend to be activated earlier (for example, when $\tau_1 = 70$, AV1 is activated last at time $a_1 = 29$; when $\tau_1 = 85$, AV1 is activated before AV2 and AV4 at time $a_1 = 14$; when $\tau_3 = 70$, AV3 is activated last at time $a_3 = 28$; when $\tau_3 = 85$, AV3 is activated before AV2 and AV4 at time $a_3 = 13$; when $\tau_3 = 100$, AV3 is activated before AV1, AV2 and AV4 at time $a_1 = 3$). The EML increases when the AV operation time increases if the AV participates in the mission. When the AV becomes too slow and is excluded from the mission execution, a further increase of its operation time does not affect the EML. It can be seen that the EML is the most sensitive to variation of the operation times of AVs 3 and 4 and the least sensitive to variation of the operation time of AVs 1

Table 7
Best obtained CAS and the corresponding mission metrics for different values of AV operation times τ_i when $T = 100$, $x = 300$ and 4ld = 0.01.

i	τ_i	***A***	R	E	C
	70	5:0, 3:15,4:18,1:29	0.848	1.230	46.872
1	85	5:0, 3:13,1:14,2:15,4:17	0.848	1.567	47.065
	100	5:0,3:14,2:15,4:18	0.847	1.310	47.090
	70	5:0,3:15,4:18,2:29	0.848	1.283	46.830
2	85	5:0,1:9,3:13,2:15,4:17	0.848	1.574	47.083
	100	5:0,1:10,3:14,4:18	0.847	1.261	47.105
	70	5:0,1:10,4:19,3:28	0.850	1.229	46.354
3	85	5:0,1:9,3:13,2:15,4:17	0.848	1.574	47.083
	100	5:0,3:3,1:9,2:15,4:17	0.848	1.590	47.172
	70	5:0,3:14,2:15,4:28	0.849	1.285	46.629
4	85	5:0,1:9,3:12,4:13,2:15	0.848	1.585	47.236
	100	5:0,1:9,3:13,2:15	0.846	1.229	47.383

and 2.

6. Conclusion and future work

This paper models a heterogeneous mission system with multiple components activated according to a certain schedule to perform the required mission by a deadline. All the operating components may deteriorate due to common shocks. We formulate a new optimization problem, which finds the activation schedule of heterogeneous system components minimizing the EML. A probabilistic model encompassing a recursive procedure has been proposed to assess the mission performance metrics of MSP, ECLC, and EML. On the basis of a suggested string representation of CAS solutions, the GA is implemented to solve the proposed EML minimization problem. We demonstrate the proposed model and examine the influences of several model parameters on the mission performance and on the optimization solutions using a case study of a multi-AV mission system. Some managerial suggestions are revealed, including 1) As the mission failure penalty increases, more components tend to be activated to complete the mission; 2) As the shock rate increases, more components tend to be activated to compensate the greater component loss probabilities; 3) The fastest and most shock resistant component tends to be activated first; for other components, the ones with lower performance tend to be activated earlier; 4) When the allowed mission time is large, the components operation overlapping can be reduced, leading to increasing MSP and decreasing ECLC.

In the future, in addition to the common shock processes deteriorating the system components, the individual aging processes contributing to the component failures will be considered. Another direction is to extend the model to consider both common shock processes and independent shock processes for the mission performance evaluation and EML minimization. The proposed model assumes the attempt aborting only when one of the system components accomplishes the mission. We are interested in designing aborting policies based on the number of shocks that have happened and mission work progress to abort attempts earlier to decrease the ECLC.

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.

Acknowledgment

The work of L. Xing was partially supported by the National Science Foundation under grant no. 2302094

Appendix 1

The procedure **PrR**(n,p) for recursive computing of the probability r_j that the mission is completed by component $c(j)$ is presented below.
Procedure **PrR**(n,p):

1	If $n>N_j$ then	
2		$x = p \times \prod_{i=1}^{j-1}\left(1 - Q_{c(i)}\left(\sum_{h=1}^{n-1} k_h I_{ih}(j)\right)\right)$;
3		$r_j = r_j + x \times Q_{c(j)}\left(\sum_{h=1}^{n-1} k_h I_{jh}(j) + k_n\right)$;
4	else	
5		$k_n = 0$;
6		$q = p \times P(t_n, k_n, \Lambda)$;
7		If $q < \varepsilon$ return;
8		**PrR** (n+1,q);
9		k_n=k_n+1, go to Step 6;

In this procedure, ε is the required precision value, n is the index of the disjoint interval, p is the probability of occurrence of $k_1,\ldots,k_n$ shocks in time intervals 1,…,n, respectively, t_n is the duration of interval n. The procedure recursively generates all the possible combinations of numbers of shocks $k_1,\ldots, k_{N_j}$ that have the probability of occurrence exceeding ε and calculates the probability that all components except $c(j)$ do not survive all the shocks they are exposed to in time intervals where they operate and component $c(j)$ survives all of the shocks it was exposed to. The value of r_j must be zeroed before activating the procedure. The initial values of procedure parameters are n=p=1.

Appendix 2

The basic steps of the GAs:

1. Generate an initial population of K_{pop} randomly constructed solutions (strings) and evaluate their fitness values equal to EML C.
2. Select two solutions randomly, and produce a new solution (offspring) using a crossover procedure which first copies the entire string of the first solution to the offspring and then copies a randomly chosen string fragment from the second parent to the same positions of the offspring.
3. Allow the offspring to mutate with probability p_{mut}. The mutation randomly increments or decrements the number in a randomly chosen string position.
4. Evaluate the offspring fitness (EML) and apply a selection procedure that compares the new offspring with the worst solution in the population and selects the one that is better. The better solution joins the population, and the worse one is discarded. If the population contains equivalent solutions following the selection process, redundancies are eliminated, and the population size decreases.
5. Generate new randomly constructed solutions to replenish the population after repeating steps 2-4 K_{cross} times.
6. Terminate the GA after repeating the genetic cycle (steps 2-5) K_{cycle} times or when no the best solution improvement is achieved after 10 cycles of steps 2-5.

In this work, the parameters $K_{pop} = 50$, $p_{mut} = 0.8$, $K_{cross} = 2000$ and $K_{cycle} = 100$ are chosen. Running the GA 10 times for solving the same problems (from Table 3) with different randomly generated initial populations of solutions shows the difference of the obtained EML not exceeding 0.8 %.

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