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Resilience Optimization for Complex Engineered Systems Based on the Multi-Dimensional Resilience Concept

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ABSTRACT Most traditional engineered systems are designed with a passive and fixed reliability capability and just required to achieve a possibly low level of failure occurrence. However, as the complexity at spatial-temporal scales and integrations increases, modern complex engineered systems (CESs) are facing new challenges of inherent risk and bottleneck for a successful and safe operation through the system life cycle when potential expected or unexpected disruptive events happen. As a prototype for ensuring the successful operation of inherently risky systems, resilience has demonstrated itself to be a promising concept to address the above-mentioned challenges. A standard multi-dimensional resilience triangle model is first presented based on the concept of the three-phase system resilience cycle, which can provide a theoretical foundation for indicating the utility objectives of resilience design. Then, the resilience design problem for CESs is proposed as a multi-objective optimization model, in which the three objectives are to maximize the survival probability, to maximize the reactive timeliness and to minimize the total budgeted cost. Furthermore, the proposed multi-objective optimization programming is solved based on the efficient multi-objective evolutionary algorithm NSGA-II. Finally, the effectiveness of the proposed models and solving procedure is illustrated with an engineered electro-hydrostatic aircraft control actuator resilience design problem, a comparative analysis on the case study is also carried out with respect to previous works. This work can provide an effective tradeoff foundation to improve the resilience of CESs.

INDEX TERMS Resilience, complex engineered systems, multi-dimensional model, multi-objective programming, NSGA-II.

I. INTRODUCTION

In the past few years, resilience has been gradually recognized as an important feature for modern complex engineered systems (CESs) [1]–[4]. Considerable efforts have been made for establishing the conceptual rationality and the measuring framework. Traditionally, engineered systems are generally designed with a passive and fixed reliability capability and just required to achieve a possibly low level of failure occurrence. However, despite component failures and unexpected accidents in CESs, new defining characteristics, e.g., complexity at spatial-temporal scales and integrations are critically challenging the resilient operation of CESs [5]–[7]. Hence, the traditional reliability-based design (RBD) with only redundancy allocation has encountered the bottleneck for a successful and safe operation through the system life cycle with potential expected or unexpected disruptive events. The shift from passive RBD to adaptive resilience-driven system design (RDSD) has gradually attracted the public's attention and the shift is proved to be effective for achieving a more resilient CES.

The resilience problem is commonly discussed as a special issue when people address how systems can continue to work safely and reliably even when a disruption occurs [8]–[11]. It is generally agreed that resilience is a system-level capability to adapt to a disturbance and then recover from the disturbance [12]–[14]. For the definition and measuring of resilience, resilience indexes are often identified according to system characteristics, for example, such as closeness centrality [15], connectivity [16], [17] and throughput capacity [18]–[20] are often adopted for networked systems when defining the network performance indexes. However, the ability of a system to successfully accomplish a mission is often emphasized for CESs [2], [21]. Despite the different definition ways, the most important thing is to specify the mechanism to achieve system resilience, otherwise the definition will only be a conceptual word and cannot instruct the resilience design of a system.

The resilience concept of CESs in the engineering domain is relatively new in comparison to other systems in organizational [22], [23], social [24], [25] and economic domains [26], [27]. Representatively, Youn *et al.* [2] defined the resilience of CESs as a sum of passive survival capability and proactive survival capability and measured it based on a function of reliability and PHM efficiency in engineering context. Youn's work interpreted the mechanism of CESs by combining reliability and PHM techniques and introduced a RDSD framework for CESs. However, this framework discussed little about the maintenance/recovery factor by fixing it to a constant success probability of 100% in the later resilience optimization case. Another definition of engineering resilience is presented by Hollnagel *et al.* [1] as the intrinsic ability of a system to adjust its functionality in the presence of disruptions, meanwhile three phases can be divided relative to the disruption to analyze the capability of resilience. This work demonstrated that the concept of phase in system operation process is important for resilience design and led a series of relevant studies. However, Hollnagel *et al.* just provided a common concept foundation and did not provide further technical details for RDSD.

To facilitate the resilience design work, a proper metric is necessary. Deterministic approaches accounting the performance loss are useful for the systems with explicit performance metric [28]–[30], however, these approaches are hard to adapt to the CESs as they barely concentrate on the system-specific characteristics while the main concern of a CES is usually the mission success rate but not the time-dependent performance. Therefore, the probabilistic approaches capturing the stochastic characteristics of system-specific behavior, e.g. survival probability or success rate [2], [31], are compatible to join the resilience metric of a CES. Despite the factor of system functionality, rapidity factor represented by recovery speed or rate and resourcefulness factor represented by recovery consumption or preparedness are often incorporated to measure the effectiveness of system resilience [32], [33]. However, most of these approaches tend to formulate all the basic factors into one unified formulary metric which would usually perplex the actual implication of resilience concept. Thus, the multi-dimensional resilience metric appears to be easily comprehended and suitable for resilience optimization in the context of decision-makers' preferences [34]–[36].

Currently, the multi-dimensional resilience metric is often represented by multi-objective mathematical model. Faturechi and Miller-Hooks [37] utilized a two-objective mathematical model considering the expectation of road network resilience over all possible disruption scenarios (functionality) and the total travel time simultaneously (timeliness) to optimize the resilience of road networks. Sahebjamnia *et al.* [38] proposed a multi-objective mixed integer linear programming (MOMILP) considering the total loss of operating level of key products (functionality) and the total recovery time of key products (timeliness) to find efficient resource allocation patterns for organizational resilience. According to the aforementioned literatures, the multi-objective approaches can commendably cater different decision preferences and help realize the resilience optimization work. However, there aren't many studies focusing on the multi-objective resilience optimization or RDSD of CESs. Youn *et al.* [2] only considered the survival probability like functionality factor for CESs but neglected the rapidity factor and resourcefulness factor. Dinh *et al.* [3] proposed six principles and five contributing factors to evaluate the resilience of engineered industrial processes. However, this identification is experiential and it can barely guide the quantification or optimization of system resilience. Thus, it's necessary to establish a multi-dimensional concept for the resilience optimization of CESs.

In this paper, we firstly propose a three-dimensional resilience triangle model based on the concept of three-phase system resilience cycle to clarify the framework for recognizing key resilience factors of CESs. For the resilience design, the primary concern is the functionality requirement which is represented by mission success rate or survival probability of a CES. On the other hand, the rapidity performance against the disruptions which is represented by reactive timeliness is also of concern. In addition, the practical resilience design is often constrained by resources which can be represented by budgeted cost. Then, the multi-objective model expressing the resilience design preferences is concluded. The objectives of this model are to maximize the survival probability, to maximize the reactive timeliness and to minimize the total budgeted cost. We need to note that the formulations of these three objectives are based on the capability recognizing work within the framework of resilience triangle model. Hence, the completeness can be guaranteed.

However, such optimal objectives would leave engineers a confusion that is how to choose the right plan for RDSD. Multi-objective optimization methodology based on advanced evolutionary algorithms can be utilized to solve this problem by generating a Pareto-optimal frontier of solutions with the consideration of the dominant optimality among optimization objectives. Over the past decades, numerous multi-objective evolutionary algorithms (MOEAs) have been developed, such as multiple objective genetic algorithm (MOGA) [39] and niched Pareto genetic algorithm (NPGA) [40]. However, many criticisms of the aforementioned MOEAs were raised because of high computational complexity of non-dominated sorting, lack of elitism and need for specifying the sharing parameter. A new MOEA named NSGA-II has well addressed these problems by generating a diverse set of solutions and converging near the true Pareto-optimal set [41]. Many studies in both theory and practice have proven NSGA-II to be one of the best algorithms for solving multi-objective optimization problems [42]–[44], helping engineers achieving optimal design plans with multiple preferences [45]–[48] and promoting a more efficient system [49], [50]. Therefore, NSGA-II is used to find the Pareto-optimal solutions to RDSD of CESs in this paper.

The rest of this paper is organized as follows. The second section introduces the resilience triangle model based on the concept of the three-phase system resilience cycle. Then, the three-dimensional resilience design preferences are concluded and the multi-objective resilience design model for CESs is formulated in section three. Section four utilizes NSGA-II to find the Pareto-optimal solutions to multi-objective design problem. To demonstrate the effectiveness of proposed models and solving procedure, section five presents a case study on an engineered aircraft control actuator. Finally, section six concludes this paper.

II. RESILIENCE TRIANGLE CONCEPT MODEL

Many aspects can be considered when evaluating the level of system resilience. However, it can be very difficult to achieve a comprehensive definition of resilience when there are too many concerns, and furthermore, simple reuse or renovation could be greatly hindered. Therefore, this section is devoted to presenting a standard three-dimensional resilience triangle model for CESs, which is derived from the three-phase concept, i.e., the system resilience cycle encompassing the phases before, during and after a disruptive event.

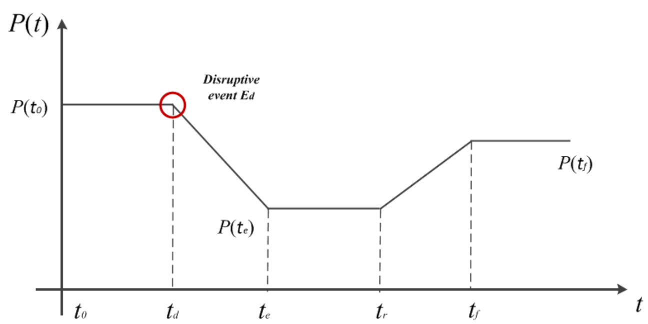

FIGURE 1. Three phases in the system performance cycle.

As a key item in the resilience definition, the disruptive event can be embodied in a variety of forms such as attacks, hazards, perturbations, disturbances and disasters for different systems. As depicted in Fig. 1, the time dimension can be divided into three phases relative to the occurrence of a disruptive event E_d:

- *Pre-disaster phase*: $T_{pre} \in [t_0, t_d]$, representing that the system remains in a relatively stable state;
- *During-disaster phase*: $T_{during} \in [t_d, t_e]$, representing that the system suffers E_d; in particular, the performance of the system may possibly suffer a degradation from $P(t_0)$ to $P(t_e)$, while there may be likely no degradations for specific systems;
- *Post-disaster phase*: $T_{post} \in [t_e, \infty]$, representing that the system recovers from the disruptive state with resilience actions; in particular, the time between t_e and t_r represents a decision-making period for resilience actions and in this period the system is in a disrupted stable state; on the other hand, the time between t_r and t_f represents the recovery process of the system and the system achieves a complete recovery at t_f.

In Fig. 1, we can obviously see a sequential system performance cycle consisting of three phases, pre-disaster phase, during-disaster phase and post-disaster phase, which are determined by the time points t_0, t_d, t_e, t_r, t_f. In what follows, we will give a detailed explanation about the three phases.

In the pre-disaster phase, i.e., the time before the occurrence of a disruptive event, generally, two types of disruptions can impact the normal performance during system operation—an inner component failure of the fundamental elements and external intentional destructions. To improve the resilience, both of these impacts should be considered; however, the detailed approaches are beyond the scope of this paper. In a CES, when we analyze this dimension of resilience capability, both types of disruptions can be represented by deviations of basic components for simplicity, thus they can be summarized into the unified Defensive Capability C_d which can be quantified by a statistic failure rate.

In the during-disaster phase, the disruptive event has impacted the normal operation of basic devices and has caused a holistic impact on the system. Note that a delayed recognition of deviations may lead a spread of failure impact and finally result in an accident. Thus, a more resilient system should shrink the impact scope and spread probability by applying proper approaches e.g. fault diagnosis. Here, we define this part of ability as Adaptive Capability C_a, which can be measured by fault diagnosis rate and time, etc.

In the post-disaster phase, the system has come to a stable disruptive state and has started to recover in the post-disaster phase. Theoretically, the recovery actions can be presented before the end of the disaster; however, this can be very risky in reality, e.g., in an earthquake scenario, it can be dangerous to arbitrarily conduct rescues before a credible safety estimation of potential conditions is performed. Recovery efforts attempt to repair or replace failed devices and bring a system back to normal; however, manpower and material resources may limit the idealized implementation of system recovery. Therefore, the performance recover rate and time would be different and represent a different resilience level, in another word, the defined Recovery Capability C_r can be different in accordance with different scenarios.

In summary, resilience is regarded as a three-dimensional system-level capability of a system to defend against, adapt during and recover from a disruptive event in this paper. In addition, based on the concept of the three-phase system resilience cycle, the three-dimensional resilience triangle model, including Defensive Capability C_d, Adaptive Capability C_a, and Recovery Capability C_r, can be derived (Fig. 2).

Examples are provided in Table. 1 to illustrate that this three-dimensional resilience triangle model is compatible with previous dimension-based-definition works. As we

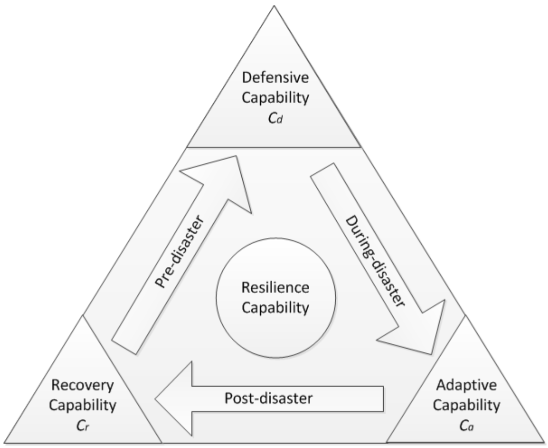

FIGURE 2. Three-dimensional resilience triangle model.

TABLE 1. Illustration of the fitness with previous definition works.

		Pre-disaster Defensive Capability C_d	During-disaster Adaptive Capability C_a	Post-disaster Recovery Capability C_r
Typical dimension -based definition	Bruneau [28]	Robustness, redundancy	/	Rapidity, resourceful
	Sterbenz [16]	Defend	Detect, diagnose	Remediate, refine, recover
	Youn [2]	Reliability	/	Restoration
	Zobel [29]	Robustness	/	Rapidity
	Dinh [3]	Minimization of failure	Limitation of effects, early detection	Administrative controls/procedures, flexibility, controllability
	National Infrastructure Advisory Council [51]	Predict, absorb	Adapt	Quickly recover

can see, the three-dimensional resilience triangle model can gracefully accommodate the basic concerns of resilience capability and provide holistic guidance for the identification of system resilience along the three-phase operation cycle, whereas previous dimension-based definitions simply propose detached requirements of resilience capability. Similar to the definitions and measures of Bruneau [28], Youn [2] and Zobel [29], they all provide minimal discussion on the adaptive capability during a disaster; on the other hand, although the definitions of Sterbenz [16], Dinh [3], and the National infrastructure advisory council [51] encompass all three dimensions, there is overlap, with poor holistic cooperation between them. It is widely stated that there is overlap between resilience and many existing concepts, such as robustness, fault tolerance, and survivability, and this can easily lead to confusion without careful discrimination. Thus, this three-phase classification method can clearly indicate the relations between them. Moreover, this unifying framework can serve as an important foundation for indicating the utility objectives of resilience design. In the following section, we would quantify the design objectives of CESs under this framework.

III. THREE-DIMENSIONAL RESILIENCE DESIGN MODEL

The resilience design for CESs is essentially a multi-objective optimization problem, which aims to generate a Pareto-optimal set of design plans by balancing between maximizing survival probability and reactive timeliness and minimizing total budgeted cost. In this section, the resilience design model consisting of three dimensions is introduced and the multi-objective optimization function is proposed.

As mentioned in the above section, the three dimensions are functionality, rapidity and resourcefulness respectively, and the main work here is to identify the measure of these dimensions based on the resilience triangle concept model.

A. FUNCTIONALITY DIMENSION-SURVIVAL PROBABILITY

Survival probability is generally defined to quantify the probability that a system or individual could survive through a certain period of time under a certain condition. This concept is comparable with the essence of resilience that is an ideal system is expected to operate successfully and safely even after a disruption occurs. Thus, it is reasonable to adopt survival probability as the index of functionality dimension. According to the mechanism analysis in section two, the quantification of survival probability is essentially a synthetical evaluation of the defensive, adaptive and recovery capability.

For engineered systems, the defensive capability can be generally treated as a synthesis of reliability, i.e., the capability to refrain from disruptive events and keep the system's state above the safe margin. Thus, the defensive capability can be quantified by a probability parameter r and statistically measured by:

$$r = \frac{N_P - N}{N_P} \times 100\% \tag{1}$$

where N_P is the potential number of failures that may occur in a certain period and N is the number of occurred failures.

The adaptive capability of engineered systems is generally defined as the diagnostic ability to detect and isolate adverse events once failed to defense. For the design of engineered systems, however, diagnostic ability can be generally regarded as a synthetical capability to adapt adversities. Therefore, this adaptive dimension of capability can be quantified by a unified probability parameter ρ and statistically measured by:

$$\rho = \frac{N_D}{N} \times 100\% \tag{2}$$

where N_D is the number of failures that are successfully diagnosed and N is the number of occurred failures.

After a successful diagnosis, to sustain a reliable and safe system operation, recovery actions represented by maintenance or reconfiguration should be performed. The probability of a successful recovery action can be quantified by a parameter γ and statistically measured by:

$$\gamma = \frac{N_{Re}}{N_D} \times 100\% \tag{3}$$

where N_{Re} is the number of failures that are successfully recovered and N_D is the number of failures that are successfully diagnosed.

After the multi-dimensional identification of survival probability, the measure can be formulated as:

$$\Psi\,(resilience, SP) = r + (1 - r) \cdot \rho \cdot \gamma \tag{4}$$

which is a joint probability of passive survival rate of defensive probability r and reactive survival rate represented by adaptive probability ρ and recovery probability γ after an unsuccessful defense $(1 - r)$.

Typically, engineered systems often have series-parallel feature, where a system can be divided into several subsystems with basic components. On the survival probability calculating of a system with series relationship, since there is only one path to successful survival, the system-level survival probability should have an intersection relationship with the subsystem-level survival probability:

$$\Psi_{system}\,(resilience, SP) = \prod_{i=1}^{n} \Psi_i\,(resilience, SP) \tag{5}$$

while for the system with parallel relationship, since the system will survive if any of the subsystems is in normal, therefore, the system-level survival probability can be obtained by:

$$\Psi_{system}(resilience, SP) = 1 - \prod_{i=1}^{n} [1 - \Psi_i(resilience, SP)] \tag{6}$$

B. RAPIDITY DIMENSION-REACTIVE TIMELINESS

Reactive timeliness is identified in this paper to quantify the capability of resilience from the rapidity dimension. Considering the performance curve in the system resilience cycle (adopted from Fig. 1), there are four key time points representing the resilience capability:

- t_d: the time point that a disruptive event E_d occurs;
- t_e: the time point that system performance stops declining (the system enters into a relative stable state after E_d);
- t_r: the time point that a recovery action starts;
- t_f: the time point that a recovery action ends (the system enters into a final stable state after recovery).

Accordingly, three time periods can be obtained in the time axis of reactive timeliness (as shown in Fig. 3):

- $T_a = t_e - t_d$:the time period when system performance declines or the system is just suffering the impact of E_d with potential performance decline;
- $T_s = t_r - t_e$:the time period when system stays in a relative stable state or just waits the recovery decision;
- $T_r = t_f - t_r$:the time period when recovery actions take effect and system performance recovers.

Need to note that, the performance of an engineered system may be not affected by the E_d (usually a failure of unit) with the help of redundancy. Thus, T_a can be generally represented by the diagnosis time T_D for an engineered system, representing the time of a system suffering from an undiagnosed failure. On the other hand, T_s can be generally regarded as

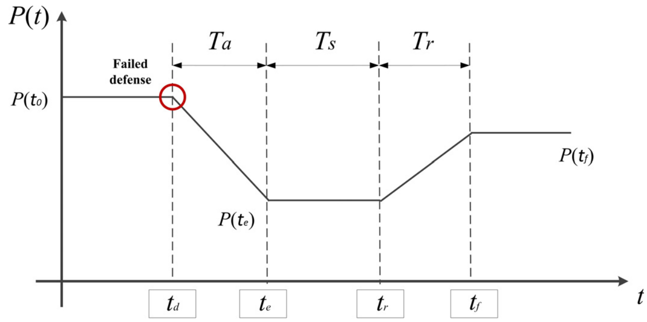

FIGURE 3. Time periods in the time axis of reactive timeliness.

the decision-making time of a proper recovery action for the engineered system, i.e., maintenance or reconfiguration, and then T_r is correspondingly regarded as the execution time of the recovery action. Thus, T_s and T_r are jointly represented by the joint recovery time T_{Re}, i.e., $T_{Re} = T_s + T_r$.

Further, we can obtain the total consumption of reactive time $T = T_a + T_s + T_r$ and define the reactive timeliness for rapidity dimension of resilience design model as:

$$\Psi\,(resilience, T) = a\left(\frac{1}{T_a}\right) + b\left(\frac{1}{T_s}\right) + c\left(\frac{1}{T_r}\right) \tag{7}$$

where the reciprocal form of timeliness factors $1/T_a$, $1/T_s$, $1/T_r$ indicates the inverse correlation between reactive timeliness and time consumption. Further, considering the different preference of timeliness factors, weighting factors *a, b* and *c* are added with the constraint of $a + b + c = 1$. Note that, in this paper, we unify the unit of timeliness factors with per-unit value, thus the range of $\Psi\,(resilience, T)$ of a basic component can be restricted between 0 and 1.

Typically, for the system with series relationship, since system-level performance recovery is achieved only if all subsystems complete the resilient recovery process, therefore, the system-level reactive timeliness should be the sum of subsystem-level reactive timeliness:

$$\Psi_{system}\,(resiilience, T) = \sum_{i=1}^{n} \Psi_i\,(resilience, T) \tag{8}$$

while for the system with parallel relationship, the reactive timeliness of a subsystem should be equal to the maximum reactive timeliness of the parallel components since only one completion of resilient recovery in parallel branch will help recover the subsystem:

$$\Psi_i\,(resilience, T) = Max[\Psi_{1\sim m_i}\,(resilience, T)] \tag{9}$$

From the definition, reactive timeliness for rapidity dimension mainly characterizes the adaptive capacity and recovery capacity of resilience, in another word, it mainly accounts for the extent of suffering duration after a failed defense of disruptive event E_d which is cognitively desired to be as short as possible. However, blind pursuit of rapidity is bound to increase the investment of system design, therefore the budgeted cost of resourcefulness dimension should be considered.

C. RESOURCEFULNESS DIMENSION-BUDGETED COST

Budgeted cost is often limited for a system resilience design work; therefore, it should be formulated for optimization. In this paper, based on the concept of Life Cycle Cost (LCC), we derive the budgeted cost model by modifying an existing LCC model presented by [52]. For a general engineered system, the budgeted cost is allocated to the development of defensive capability C_d represented by system reliability vector $\boldsymbol{r}$, adaptive capability C_a represented by system diagnosis vector $(\boldsymbol{\rho}, \boldsymbol{T_D})$, and recovery capability C_r represented by system recovery vector $(\boldsymbol{\gamma}, \boldsymbol{T_{Re}})$. Note that, the basic resilience design unit for engineered systems is the component which can be assigned with a specific set of design vector $\boldsymbol{\eta_i} = (r_i, \rho_i, T_i^D, \gamma_i, T_i^{Re})$. Therefore, the budgeted cost model can be expressed as:

$$\Psi\,(resilience, C) = C_R + C_D + C_{Re} \tag{10}$$

where $C_R = f(\boldsymbol{r})$ denotes the development cost of reliability for defensing against disruptions, $C_D = f(\boldsymbol{\rho}, \boldsymbol{T_D})$ denotes the development cost of diagnosis for adapting to disruptions and $C_{Re} = f(\boldsymbol{\gamma}, \boldsymbol{T_{Re}})$ denotes the development cost of recovery for recovering from disruptions. The three parts are discussed in detail as below.

For $C_R = f(\boldsymbol{r})$, it is often assumed that there is an inverse power relationship between cost and failure rate for binary-state systems [53]. Thus, the cost of a system with m_i parallel components/redundancies can be expressed as:

$$C_i^R = \alpha_i^R \left(-\frac{T_R}{ln(r_i)}\right)^{\beta_i^R} \times \left[m_i + \exp\left(\frac{m_i}{4}\right)\right] \tag{11}$$

where T_R is the required system mission time, α_i^R and β_i^R are constant parameters representing the physical features which can be determined by collected data or experience. The exponent part exp $(\cdot)$ denotes the extra cost of interconnecting parallel components/redundancies.

Sine a series system can be generally regarded as a sum of multiple parallel subsystems, thus the total cost of a system with n subsystems is:

$$C_R = \sum_{i=1}^{n} C_i^R = \sum_{i=1}^{n} \alpha_i^R \left(-\frac{T_R}{ln(r_i)}\right)^{\beta_i^R} \times \left[m_i + \exp\left(\frac{m_i}{4}\right)\right] \tag{12}$$

For $C_D = f(\boldsymbol{\rho}, \boldsymbol{T_D})$, it is assumed that there is an inverse power relationship between cost and diagnosis rate [2]. Since the diagnosis capability embedded in a component is also represented by diagnosis time T_i^D, therefore, we assume that there is an extra exponential relationship between cost and diagnosis time. And then the development cost of diagnosis can be expressed as:

$$C_D = \sum_{i=1}^{n} C_i^D = \sum_{i=1}^{n} \alpha_i^D \left(-\frac{1}{ln(\rho_i)}\right)^{\beta_i^D} \times \exp(-\mu_i^D T_i^D) \times m_i \tag{13}$$

where ρ_i and T_i^D are performance parameters of diagnostic facility equipped within a component, e.g., Built-in Test (BIT). α_i^D, β_i^D and μ_i^D are constant parameters representing physical and technical features.

For $C_{Re} = f(\boldsymbol{\gamma}, \boldsymbol{T_{Re}})$, like C_D, we assume that the C_{Re} has an inverse power relationship with recovery rate and an exponential relationship with recovery time:

$$\begin{aligned} C_{Re} &= \sum_{i=1}^{n} C_i^{Re} \\ &= \sum_{i=1}^{n} \alpha_i^{Re} \left(-\frac{1}{ln(\gamma_i)}\right)^{\beta_i^{Re}} \times \exp(-\mu_i^{Re} T_i^{Re}) \times m_i \end{aligned} \tag{14}$$

where γ_i and T_i^{Re} are performance parameters of recovery action. α_i^{Re}, β_i^{Re} and μ_i^{Re} are constant parameters representing physical and technical features.

In summary, the identification relationship between capabilities in the resilience triangle concept model and objectives in the three-dimensional resilience design model is summarized in Table. 2.

TABLE 2. Identification relationship between resilience capabilities and design objectives.

	Pre-disaster C_d	During-disaster C_a	Post-disaster C_r
Functionality	r	ρ	γ
Rapidity	/	T_D	T_{Re}
Resourcefulness	C_R	C_D	C_{Re}

Relative to the three resilience capabilities, i.e., C_d, C_a, and C_r, in the resilience triangle concept model, the functionality dimension in the resilience design model is quantified by r, ρ, and γ respectively, the rapidity dimension is quantified by T_D and T_{Re}, and the resourcefulness dimension is quantified by C_R, C_D, and C_{Re}.

D. MULTI-OBJECTIVE RESILIENCE DESIGN MODEL

After the identification of objectives, the design model can be formulated. Generally, the design variables are constrained for resilience design plans. Thus, we should add some constrains on design variables: (i) the lower and upper bounds of rate for r, ρ, γ are R_L and R_U; (ii) the lower and upper bounds of time consumption for T_a, T_s, T_r are T_L and T_U.

Finally, the multi-objective resilience optimization model for resilience allocation is expressed as follows:

$$\begin{aligned} &max\ \Psi\,(resilience, SP) = r + (1-r)\cdot\rho\cdot\gamma \\ &max\ \Psi\,(resilience, T) = a\left(\frac{1}{T_a}\right) + b\left(\frac{1}{T_s}\right) + c\left(\frac{1}{T_r}\right) \\ &min\ \Psi\,(resilience, C) = C_R + C_D + C_{Re} \\ &s.t.\ R_L \le r, \rho,\ \gamma \le R_U \\ &\qquad T_L \le T_a, T_s, T_r \le T_U \\ &\qquad a + b + c = 1 \\ &\qquad a, b, c \in (0, 1) \end{aligned} \tag{15}$$

Then, the Pareto-optimal resilience design plans $\boldsymbol{\eta}^* = (\boldsymbol{C}_d^*, \boldsymbol{C}_a^*, \boldsymbol{C}_r^*) = (\boldsymbol{r}^*, \boldsymbol{\rho}^*, \boldsymbol{T}_D^*, \boldsymbol{\gamma}^*, \boldsymbol{T}_{Re}^*)$ can be obtained by solving the above model.

IV. FINDING PARETO-OPTIMAL RESILIENCE DESIGN PLANS BASED ON NSGA-II

This section will introduce the multi-objective algorithm NSGA-II implemented to find the Pareto-optimal resilience design plans. Basic steps to solve the aforementioned multi-objective resilience design model are described in what follows.

A. INITIALIZATION

Firstly, parameters of NSGA-II including the maximum generation number G_{max}, the generation counter n_g, the individual number in one population n_p, the proportion of crossover P_c, the proportion of mutation P_m and the probability of mutation μ. Then, randomly generate the initial population $\mathcal{P}_g(g = 1)$ with n_p encoded chromosomes $\boldsymbol{\eta}$ based on the constrains of design variables.

B. NON-DOMINATED SORTING

Non-dominated sorting aims to sort the individuals in current population $\mathcal{P}_g$ into different non-dominated fronts. Note that, an individual of chromosome is regarded to dominate another if all the objective functions of it is not worse than the other and at least one of its objective functions is strictly better. The first front denotes a completely non-dominated set of individuals which are assigned with the rank value $\eta_{rank} = 1$ in current population, and the second front consists of the individuals ($\eta_{rank} = 2$) just dominated by those in the first front, and so on.

C. CROWDING DISTANCE

To distinguish the individuals in the same front, crowding distance ($\eta_{distance}$) is utilized to find the euclidian distance between each individual based on their d objective functions in the d dimensional hyper space. Note that, comparing the crowding distance between two individuals in different fronts is meaningless. Hence, the optimal individual can be selected based on the non-dominated rank and crowding distance together.

D. SELECTION

Once the individuals are sorted by non-dominated rank and crowding distance, the selection process based on the binary tournament can be carried out using the crowded comparison operator ($\prec$), where $\eta_i \prec \eta_j$ if ($\eta^i_{rank} < \eta^j_{rank}$) or ($\eta^i_{rank} = \eta^j_{rank}$ and $\eta^i_{distance} > \eta^j_{distance}$). The selection process can be used to choose better individuals for genetic operations, which can improve the convergence capability of algorithm.

E. GENETIC OPERATORS

Real-coded genetic algorithm (GA) often use two kinds of genetic operators: crossover and mutation, the crossover operator is used to vary the programming of chromosomes from one generation to the next while the mutation operator is used to maintain the genetic diversity. In NSGA-II, the two genetic operators are adopted to improve the convergence performance and help achieving the Pareto-optimal solutions.

For crossover operator, notable approaches include the single-point, the two-point, and the uniform types. Considering of the proposed chromosome programming, we adopt the crossover operator illustrated in Fig. 4. We firstly select two segments, i.e., the third and the sixth gene, as the crossover objects in parent chromosomes, and then exchange them to generate two new offspring chromosomes.

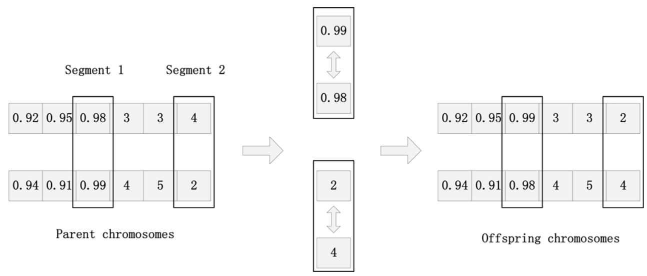

FIGURE 4. Illustration on crossover operator.

For mutation operator, it mainly alters the gene values in a chromosome from its initial state into entirely new values. Different types of mutation, such as the single-point type and the multi-point type, can be used according to the feature of chromosome programming. The mutation operator adopted in this paper is illustrated in Fig. 5. The genetic information in the third and the sixth gene of the parent chromosome is randomly changed, and then a new offspring chromosome is generated.

F. RECOMBINATION AND SELECTION

In this part, the offspring population $\mathcal{Q}_g$ generated by genetic operators is firstly combined with the current population $\mathcal{P}_g$, and a temporary population is generated $\mathcal{R}_g = \mathcal{P}_g \cup \mathcal{Q}_g$. Since all the previous and current best chromosomes are included in $\mathcal{R}_g$, the elitism of population can be ensured. Then, the temporary population $\mathcal{R}_g$ is sorted based on non-dominated rank and crowding distance. Finally, a new generation is selected by sorting results with the limit of maximum population size.

In summary, the logical diagram of the multi-objective algorithm NSGA-II for resilience design is shown in Fig. 6.

V. CASE STUDY AND ANALYSIS

In this section, an electro-hydrostatic aircraft control actuator (EHA) case adapted from [2] and [54] is proposed to demonstrate the approach of resilience optimization for engineered systems. Note that, the EHA system has a predetermined structure, and the resilience optimization problem generally refers to the parameters assignment of each component $(r_i, \rho_i, T_i^D, \gamma_i, T_i^{Re})$ with the system-level resilience objectives, and finally the optimal system design plan $\boldsymbol{\eta}^* = (\boldsymbol{r}^*, \boldsymbol{\rho}^*, \boldsymbol{T_D}^*, \boldsymbol{\gamma}^*, \boldsymbol{T_{Re}}^*)$ consisting of basic resilience parameters of components can be obtained.

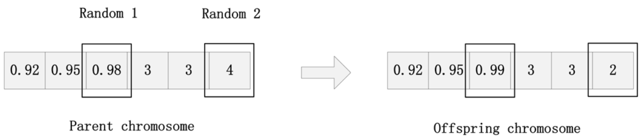

FIGURE 5. Illustration on mutation operator.

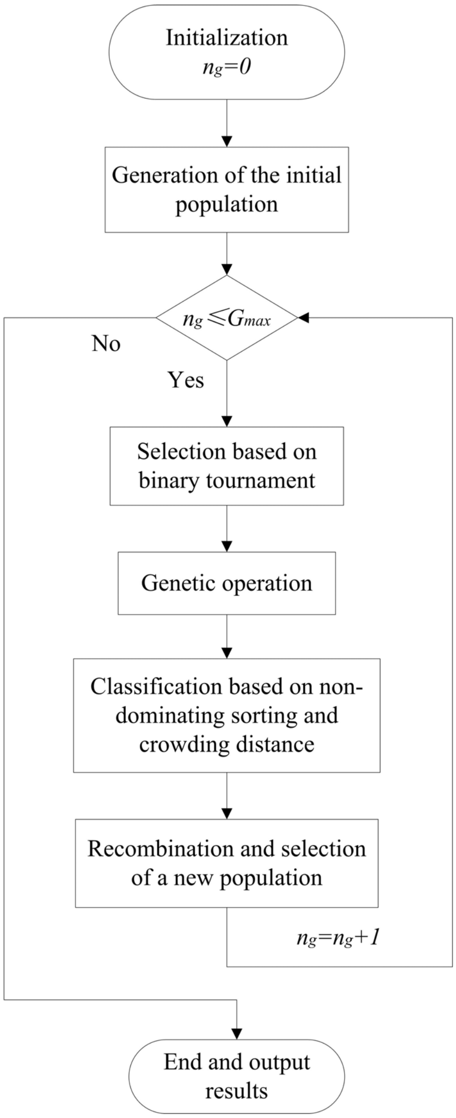

FIGURE 6. Logical diagram of NSGA-II for resilience design.

A. PROBLEM DESCRIPTION

The EHA system mainly consists of four subsystems in series, they are electronic control unit (E), variable-speed electronic motor (M), fixed-displacement hydraulic pump (P) and hydraulic piston actuator (H). In each subsystem, some uniform components are equipped in parallel. System block diagram is depicted to show the structure of EHA in Fig. 7.

Basic parameters representing the physical technical features of components in EHA are given in Table 3, and the system mission time $T_R = 1000$.

With preliminary analysis, this EHA is a typical series-parallel system, hence the system-level survival probability

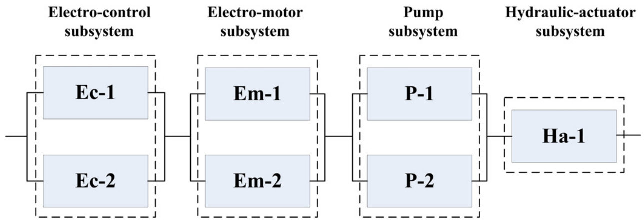

FIGURE 7. EHA system structure.

TABLE 3. Parameters of EHA.

Subsystem	(a_i, b_i, c_i)	(α_i^R, β_i^R)	$(\alpha_i^D, \beta_i^D, \mu_i^D)$	$(\alpha_i^{Re}, \beta_i^{Re}, \mu_i^{Re})$
E	(0.5,0.3,0.2)	(5e-6,1.5)	(3.3e-6,1.5,2)	(4e-5,2,2)
M	(0.5,0.2,0.3)	(8e-6,1.5)	(5.3e-6,1.5,2)	(7e-5,2,2)
P	(0.5,0.2,0.3)	(1e-5,1.5)	(6.7e-6,1.5,2)	(8e-5,2,2)
H	(0.6,0.1,0.3)	(7e-6,1.5)	(4.7e-6,1.5,2)	(4e-5,2,2)

has an intersection relationship with the four subsystem-level survival probabilities:

$$\Psi_{EHA}(resilience, SP) = \prod_{i=1}^{4} \Psi_i(resilience, SP) \quad (16)$$

while the subsystem will survive if any of the m_i parallel components survives:

$$\Psi_i(resilience, SP) = 1 - (1 - r_i)^{m_i}(1 - \rho_i)^{m_i}(1 - \gamma_i)^{m_i} \quad (17)$$

For the reactive timeliness of rapidity dimension, the system-level reactive timeliness is the sum of subsystem-level reactive timeliness:

$$\Psi_{EHA}(resilience, T) = \sum_{i=1}^{4} \Psi_i(resilience, T) \quad (18)$$

while the reactive timeliness of a subsystem is equal to the reactive timeliness of the parallel component, since the parallel components are homogeneous:

$$\Psi_i(resilience, T) = \Psi_{1\sim m_i}(resilience, T) \quad (19)$$

In addition, for the budgeted cost of resourcefulness dimension, the system-level budgeted cost can be easily comprehended and obtained by a sum of subsystem-level costs:

$$\Psi_{EHA}(resilience, C) = \sum_{i=1}^{4} \Psi_i(resilience, C) \quad (20)$$

while the subsystem-level budgeted cost is a sum of basic component costs:

$$\Psi_i(resilience, C) = C_i^R + C_i^D + C_i^{Re} \quad (21)$$

Furthermore, considering the constrains on design variables from practical and solving perspectives, the lower and upper bounds of r, ρ, γ are assigned to 0.90 and 0.99, and the lower and upper bounds of T_a, T_s, T_r are assigned to 2 and 5 units of time with normalization. Then, the resilience optimization problem for EHA is formulated as follows:

$$\max\ \Psi_{EHA}(resilience, SP) = \prod_{i=1}^{4} [1 - (1 - r_i)^{m_i}(1 - \rho_i)^{m_i}(1 - \gamma_i)^{m_i}]$$

TABLE 4. Optimal solutions for resilience design.

NO.	η						SP(η) (%)	T(η)	C(η)
	r (%)	ρ (%)	γ (%)	T_a	T_s	T_r			
1	(90.98,92.22,90.78,90.28)	(92.96,92.87,98.12,98.70)	(97.83,93.59,90.01,94.64)	(5,5,5,5)	(4,4,4,3)	(4,5,5,5)	99.9932	18.9	113.71
2	(92.68,97.39,95.24,98.06)	(96.68,97.49,93.38,98.94)	(90.56,91.29,97.31,98.84)	(4,5,4,4)	(4,5,4,4)	(5,2,5,5)	99.9998	16.9	533.66
4	(92.68,97.39,95.24,98.06)	(96.68,97.49,93.38,98.94)	(90.56,91.29,97.31,98.84)	(4,5,4,4)	(4,4,4,3)	(4,5,5,5)	99.9998	17.3	533.66
6	(91.27,96.39,91.78,90.32)	(91.15,94.57,94.05,98.76)	(94.68,93.50,98.91,98.26)	(5,5,5,5)	(4,4,4,3)	(4,5,5,5)	99.9978	18.9	213.32
8	(90.98,92.22,90.78,90.28)	(92.96,92.87,98.12,98.70)	(94.68,93.50,98.91,98.26)	(5,5,5,5)	(4,4,4,3)	(4,5,5,5)	99.9978	18.9	113.71
9	(93.20,92.10,94.09,98.76)	(98.83,94.45,95.39,97.78)	(94.68,93.50,98.91,98.26)	(5,5,5,5)	(4,4,4,3)	(4,5,5,5)	99.9995	18.9	509.46
10	(94.19,95.27,96.80,94.20)	(97.18,94.48,92.18,98.88)	(90.56,91.29,97.31,98.84)	(4,5,4,4)	(4,4,4,3)	(4,5,5,5)	99.9992	17.3	357.27
12	(94.19,95.27,96.80,94.20)	(97.18,94.48,92.18,98.88)	(94.68,93.50,98.91,98.26)	(5,5,5,5)	(4,4,4,3)	(4,5,5,5)	99.9989	18.9	357.27
13	(93.20,92.10,94.09,98.76)	(98.83,94.45,95.39,97.78)	(90.56,91.29,97.31,98.84)	(4,5,4,4)	(4,4,4,3)	(4,5,5,5)	99.9997	17.3	509.46
14	(90.98,92.22,90.78,90.28)	(92.96,92.87,98.12,98.70)	(90.56,91.29,97.31,98.84)	(4,5,4,4)	(4,4,4,3)	(4,5,5,5)	99.9985	17.3	113.71
15	(94.44,91.17,90.27,97.80)	(93.13,92.49,91.55,96.74)	(90.56,91.29,97.31,98.84)	(4,5,4,4)	(4,4,4,3)	(4,5,5,5)	99.9991	17.3	262.62
16	(94.44,91.17,90.27,97.80)	(93.13,92.49,91.55,96.74)	(94.68,93.50,98.91,98.26)	(5,5,5,5)	(4,4,4,3)	(4,5,5,5)	99.9987	18.9	262.62
17	(91.27,96.39,91.78,90.32)	(91.15,94.57,94.05,98.76)	(90.56,91.29,97.31,98.84)	(4,5,4,4)	(4,4,4,3)	(4,5,5,5)	99.9985	17.3	213.32
18	(90.98,92.22,90.78,90.28)	(92.96,92.87,98.12,98.70)	(90.56,91.29,97.31,98.84)	(4,5,4,4)	(4,5,4,4)	(5,2,5,5)	99.9985	16.9	113.71
19	(92.68,97.39,95.24,98.06)	(96.68,97.49,93.38,98.94)	(94.68,93.50,98.91,98.26)	(5,5,5,5)	(4,4,4,3)	(4,5,5,5)	99.9996	18.9	533.66
21	(94.19,95.27,96.80,94.20)	(97.18,94.48,92.18,98.88)	(90.56,91.29,97.31,98.84)	(4,5,4,4)	(4,5,4,4)	(5,2,5,5)	99.9992	16.9	357.27
22	(94.44,91.17,90.27,97.80)	(93.13,92.49,91.55,96.74)	(90.56,91.29,97.31,98.84)	(4,5,4,4)	(4,5,4,4)	(5,2,5,5)	99.9991	16.9	262.62
32	(93.20,92.10,94.09,98.76)	(98.83,94.45,95.39,97.78)	(90.56,91.29,97.31,98.84)	(4,5,4,4)	(4,5,4,4)	(5,2,5,5)	99.9997	16.9	509.46
33	(91.27,96.39,91.78,90.32)	(91.15,94.57,94.05,98.76)	(90.56,91.29,97.31,98.84)	(4,5,4,4)	(4,5,4,4)	(5,2,5,5)	99.9985	16.9	213.32

$$
\begin{aligned}
&max\ \Psi_{EHA}\left(resilience, T\right) \\
&\quad = \sum\nolimits_{i=1}^{4}\left[a_i\left(\frac{1}{T_i^a}\right)+b_i\left(\frac{1}{T_i^s}\right)+c_i\left(\frac{1}{T_i^r}\right)\right] \\
&min\ \Psi_{EHA}\left(resilience, C\right) \\
&\quad = \sum\nolimits_{i=1}^{4}\left(C_i^R+C_i^D+C_i^{Re}\right) \\
&\qquad s.t.\ 0.9 \le r, \rho,\ \gamma \le 0.99 \\
&\qquad\quad 2 \le T_a, T_s,\ T_r \le 5 \\
&\qquad\quad a+b+c=1 \\
&\qquad\quad a, b, c \in (0, 1)
\end{aligned} \tag{22}
$$

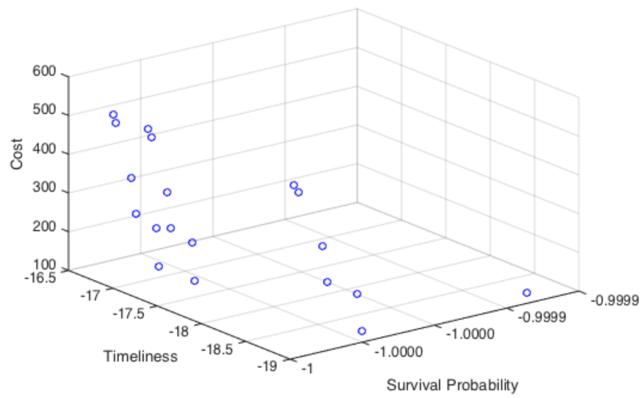

FIGURE 8. Pareto solutions of the EHA resilience optimization model.

B. NUMERICAL RESULTS AND ANALYSIS

After the formulation of resilience optimization for EHA, by performing the NSGA-II algorithm introduced in section four, the Pareto solutions of the optimization model are depicted in Fig. 8, and the details of these Pareto optimal results, i.e., resilience design plans, are shown in Table. 4. Note that, the main parameters of NSGA-II are assigned as follows: the maximum generation number $G_{max} = 20$, individual number in one population $n_p = 100$, the proportion of crossover $P_c = 0.8$, the proportion of mutation $P_m = 0.3$, the probability of mutation $\mu = 0.7$.

As we can see, instead of a single optimal solution, solving optimization model based on NSGA-II gives a set of Pareto-optimal solutions. In the absence of further information, any of these solutions cannot be said to be better than others. However, the Pareto solutions obtained by NSGA-II are just optimal from the perspective of mathematics, and the alternative solutions are generally too many for decision makers to select. Thus, a further analysis is often needed for practical engineering application.

Obviously, in this work, the optimal solutions have very similar results of survival probability and reactive timeliness, but the budgeted cost is dramatically different. It reveals an obvious long-tail effect for budgeted cost when increasing the survival probability and reactive timeliness among the 19 optimal solutions. Therefore, we can make a succinct reduction of the mathematical Pareto-optimal solutions and select the representative ones with less cost, namely the 4 optimal solutions with $\Psi_{EHA}\left(resilience, C\right) = 113.71$

are finally selected for the resilience designers (shadowed in Table. 4).

As the electro-hydrostatic aircraft control actuator (EHA) case is adapted from [54], therefore we make a further comparison with Youn's work which is belong to the traditional single objective optimal design methodology. Firstly, in the top-level resilience allocation work, the single objective optimal result is obtained by minimizing the only one specified expected utility life-cycle cost (LCC) with the constraint of a target system resilience level, the result only provides a survival probability like design suggestion which is a function of reliability and PHM efficiency, in another word, the information derived from the result is very limited. On the contrary, the result we obtain from the multi-objective optimization methodology encompasses more design concerns, i.e., the rapidity factor and the resourcefulness factor, which can serve as a more comprehensible and credible design suggestion for decision-makers. Furthermore, the optimal objectives we select are derived from a standard resilience triangle concept model which gives a precise identification on the mechanism to achieve system resilience, this can provide a strong theoretical foundation for our resilience design work, however, most of the previous works are weak at this part.

VI. CONCLUSION

This paper mainly presents a resilience design approach motivated by multi-objective optimization concept for complex engineered systems (CESs). A standard multi-dimensional resilience triangle model indicating the utility objectives of resilience design is derived from the concept of a three-phase system resilience cycle, which provides a theoretical foundation for resilience design work. Three resilience capabilities, the Defensive Capability C_d, the Adaptive Capability C_a, and the Recovery Capability C_r, are summarized in the resilience triangle model and three dimensions consisting of functionality, rapidity and resourcefulness are indicated for design preference. The resilience design for CESs is formulated into a multi-objective optimization problem, aiming to generate a Pareto-optimal set of design plans by maximizing survival probability and reactive timeliness and minimizing total budgeted cost. By solving the multi-objective model based on NSGA-II, a set of optimal design plans instead of a single solution is obtained for designers, practical reduction of mathematical Pareto-optimal solutions is also considered which can provide a more comprehensible and exercisable suggestion for decision-makers. To demonstrate the effectiveness, the above methodology is applied to an electro-hydrostatic aircraft control actuator (EHA) system which has typical engineered series-parallel features. A comparative analysis on the case study is also carried out to illustrate the significance of the proposed approach with respect to the previous works.

In this paper, the resilience optimization work is generally restricted to the system with predetermined structure and the main concern refers to the assignment of resilience parameters to basic components. In the future, since structure design is another important work for CESs, the resilience optimization considering variable structure will be further studied, and this resilience design approach will be applied to more complex real systems, such as networked systems and integrated modular systems.

REFERENCES

[1] E. Hollnagel, D. D. Woods, and N. Leveson, *Resilience Engineering: Concepts and Precepts*. Aldershot, U.K.: Ashgate, 2006.

[2] B. D. Youn, C. Hu, and P. Wang, "Resilience-driven system design of complex engineered systems," *J. Mech. Des.*, vol. 133, no. 10, pp. 1179–1188, 2011.

[3] L. T. T. Dinh, H. Pasman, X. Gao, and M. S. Mannan, "Resilience engineering of industrial processes: Principles and contributing factors," *J. Loss Prevention Process Ind.*, vol. 25, no. 2, pp. 233–241, 2012.

[4] H. Mehrpouyan, B. Haley, A. Dong, I. Y. Tumer, and C. Hoyle, "Resiliency analysis for complex engineered system design," *Artif. Intell. Eng. Des. Anal. Manuf.*, vol. 29, no. 1, pp. 93–108, 2015.

[5] S. Andersen and B. A. Mostue, "Risk analysis and risk management approaches applied to the petroleum industry and their applicability to IO concepts," *Saf. Sci.*, vol. 50, no. 10, pp. 2010–2019, 2012.

[6] E. Zio, "Challenges in the vulnerability and risk analysis of critical infrastructures," *Rel. Eng. Syst. Saf.*, vol. 152, pp. 137–150, Aug. 2016.

[7] C. L. Bloebaum and A. M. R. Mcgowan, "The design of large-scale complex engineered systems: Present challenges and future promise," in *Proc. AIAA Aviation Technol. Integr. Oper. Conf.*, 2012, pp. 1–2.

[8] W. Najjar and J.-L. Gaudiot, "Network resilience: A measure of network fault tolerance," *IEEE Trans. Comput.*, vol. 39, no. 2, pp. 174–181, Feb. 1990.

[9] K. S. Trivedi, D. S. Kim, and R. Ghosh, "Resilience in computer systems and networks," in *Proc. IEEE/ACM Int. Conf. Comput.-Aided Des.*, Nov. 2009, pp. 74–77.

[10] R. Francis and B. Bekera, "A metric and frameworks for resilience analysis of engineered and infrastructure systems," *Rel. Eng. Syst. Saf.*, vol. 121, no. 1, pp. 90–103, 2014.

[11] S. Hosseini, K. Barker, and J. E. Ramirez-Marquez, "A review of definitions and measures of system resilience," *Rel. Eng. Syst. Saf.*, vol. 145, pp. 47–61, Jan. 2016.

[12] A. Carmeli, Y. Friedman, and A. Tishler, "Cultivating a resilient top management team: The importance of relational connections and strategic decision comprehensiveness," *Saf. Sci.*, vol. 51, no. 1, pp. 148–159, 2013.

[13] J. Lundberg and A. Rankin, "Resilience and vulnerability of small flexible crisis response teams: Implications for training and preparation," *Cognit. Technol. Work*, vol. 16, no. 2, pp. 143–155, 2014.

[14] S. Dekker and S. Pruchnicki, "Drifting into failure: Theorising the dynamics of disaster incubation," *Theor. Issues Ergon. Sci.*, vol. 15, no. 6, pp. 534–544, 2014.

[15] M. Omer, A. Mostashari, and U. Lindemann, "Resilience analysis of soft infrastructure systems," *Proc. Comput. Sci.*, vol. 28, pp. 565–574, Jan. 2014.

[16] J. P. G. Sterbenz, E. K. Cetinkaya, M. A. Hameed, and A. Jabbar, "Modeling and analysis of network resilience," in *Proc. IEEE Int. Conf. Commun. Syst. Netw.*, Jan. 2011, pp. 1–10.

[17] S. G. Perz *et al.*, "Connectivity and resilience: A multidimensional analysis of infrastructure impacts in the southwestern Amazon," *Social Indic. Res.*, vol. 106, no. 2, pp. 259–285, 2012.

[18] L. Chen and E. Miller-Hooks, "Resilience: An indicator of recovery capability in intermodal freight transport," *Transp. Sci.*, vol. 46, no. 1, pp. 109–123, 2012.

[19] M. J. Alenazi, A. M. Peck, J. P. Rohrer, and J. P. Sterbenz, "Multilevel resilience analysis of transportation and communication networks," *Telecommun. Syst.*, vol. 60, no. 4, pp. 515–537, 2015.

[20] M. Janić, "Modelling the resilience, friability and costs of an air transport network affected by a large-scale disruptive event," *Transp. Res. A Policy Pract.*, vol. 71, pp. 1–16, Jan. 2015.

[21] *Innovative Technological Institute (ITI)*, American Society Mechanical Engineers, Washington, DC, USA, 2009.

[22] L. Riolli and V. Savicki, "Information system organizational resilience," *Omega*, vol. 31, no. 3, pp. 227–233, 2003.

[23] Y. Sheffi, *The Resilience Enterprise: Overcoming Vulnerability for Competitive Enterprise*. Cambridge, MA, USA: MIT Press, 2005.

[24] W. N. Adger, T. P. Hughes, C. Folke, S. R. Carpenter, and J. Rockström, "Social-ecological resilience to coastal disasters," *Science*, vol. 309, no. 5737, pp. 1036–1039, 2005.
[25] N. J. Turner, I. J. Davidson-Hunt, and M. O'Flaherty, "Living on the edge: Rcological and cultural edges as sources of diversity for social-ecological resilience," *Hum. Ecol.*, vol. 31, no. 3, pp. 439–461, 2003.
[26] A. Rose and S. Y. Liao, "Modeling regional economic resilience to disasters: A computable general equilibrium analysis of water service disruptions," *J. Reg. Sci.*, vol. 45, no. 1, pp. 75–112, 2005.
[27] A. Rose, "Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions," *Environ. Hazard*, vol. 7, no. 4, pp. 383–398, 2007.
[28] M. Bruneau *et al.*, "A framework to quantitatively assess and enhance the seismic resilience of communities," *Earthquake Spectra*, vol. 19, no. 4, pp. 733–752, 2003.
[29] C. W. Zobel, "Representing perceived tradeoffs in defining disaster resilience," *Decision Support Syst.*, vol. 50, no. 2, pp. 394–403, 2011.
[30] D. Henry and J. E. Ramirez-Marquez, "Generic metrics and quantitative approaches for system resilience as a function of time," *Rel. Eng. Syst. Saf.*, vol. 99, no. 99, pp. 114–122, 2012.
[31] S. E. Chang and M. Shinozuka, "Measuring improvements in the disaster resilience of communities," *Earthquake Spectra*, vol. 20, no. 3, pp. 739–755, 2004.
[32] B. M. Ayyub, "Systems resilience for multihazard environments: Definition, metrics, and valuation for decision making," *Risk Anal.*, vol. 34, no. 2, pp. 340–355, 2014.
[33] R. Pant, K. Barker, J. E. Ramirez-Marquez, and C. M. Rocco, "Stochastic measures of resilience and their application to container terminals," *Comput. Ind. Eng.*, vol. 70, pp. 183–194, Apr. 2014.
[34] X. Zhao, Z. Chen, and H. Gong, "Effects comparison of different resilience enhancing strategies for municipal water distribution network: A multidimensional approach," *Math. Prob. Eng.*, vol. 2015, Jul. 2015, Art. no. 438063. [Online]. Available: http://dx.doi.org/10.1155/2015/438063
[35] D. G. Dessavre, J. E. Ramirez-Marquez, and K. Barker, "Multidimensional approach to complex system resilience analysis," *Rel. Eng. Syst. Saf.*, vol. 149, pp. 34–43, May 2016.
[36] I. Bachmann, P. Reyes, J. Bustos, and A. Silva, "Multidimensional network resilience analysis," *IEEE Latin Amer. Trans.*, vol. 14, no. 6, pp. 2912–2914, Jun. 2016.
[37] R. Faturechi and E. Miller-Hooks, "Travel time resilience of roadway networks under disaster," *Transp. Res. B.*, vol. 70, pp. 47–64, Dec. 2014.
[38] N. Sahebjamnia, S. A. Torabi, and S. A. Mansouri, "Integrated business continuity and disaster recovery planning: Towards organizational resilience," *Eur. J. Oper. Res.*, vol. 242, no. 1, pp. 261–273, 2015.
[39] C. M. Fonseca and P. J. Fleming, "Genetic algorithms for multi-objective optimization: Formulation discussion and generalization," in *Proc. Int. Conf. Genet. Algorithms*, 1993, pp. 416–423.
[40] J. Horn, N. Nafpliotis, and D. E. Goldberg, "A niched Pareto genetic algorithm for multiobjective optimization," in *Proc. IEEE Conf. Comput. Intell.*, Jun. 1994, pp. 82–87.
[41] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Feb. 2000.
[42] Y. K. Lin and C. T. Yeh, "Multi-objective optimization for stochastic computer networks using NSGA-II and TOPSIS," *Eur. J. Oper. Res.*, vol. 218, no. 3, pp. 735–746, 2012.
[43] J. Neale, S. Nettleton, L. Pickering, and J. Fischer, "Pareto optimal reconfiguration of power distribution systems using a genetic algorithm based on NSGA-II," *Energies*, vol. 6, no. 3, pp. 1439–1455, 2013.
[44] L. A. Pereira, S. Haffner, G. Nicol, and T. F. Dias, "Multiobjective optimization of five-phase induction machines based on NSGA-II," *IEEE Trans. Ind. Electron.*, to be published, doi: 10.1109/TIE.2017.2701768.
[45] M. H. Ahmadi, H. Sayyaadi, S. Dehghani, and H. Hosseinzade, "Designing a solar powered Stirling heat engine based on multiple criteria: Maximized thermal efficiency and power," *Energy Convers. Manage.*, vol. 75, pp. 282–291, Nov. 2013.
[46] M. H. Ahmadi and M. A. Ahmadi, "Multi objective optimization of performance of three-heat-source irreversible refrigerators based algorithm NSGAII," *Renew. Sustain. Energy Rev.*, vol. 60, pp. 784–794, Jul. 2016.
[47] M. H. Ahmadi, M. A. Ahmadi, F. Pourfayaz, and M. Bidi, "Thermodynamic analysis and optimization for an irreversible heat pump working on reversed Brayton cycle," *Energy Convers. Manage.*, vol. 110, pp. 260–267, Feb. 2016.
[48] M. H. Ahmadi, M. A. Ahmadi, A. Maleki, F. Pourfayaz, M. Bidi, and E. Açikkalp, "Exergetic sustainability evaluation and multi-objective optimization of performance of an irreversible nanoscale Stirling refrigeration cycle operating with Maxwell–Boltzmann gas," *Renew. Sustain. Energy Rev.*, vol. 78, pp. 80–92, Oct. 2017.
[49] H. M. Alsaket, K. R. Mahmoud, H. M. Elattar, and M. A. Aboul-Dahab, "Exploring evolutionary multi-objective techniques in self-organizing networks," *IEEE Access*, vol. 5, pp. 12049–12060, 2017.
[50] H. Zheng, Y. Feng, and J. Tan, "A hybrid energy-aware resource allocation approach in cloud manufacturing environment," *IEEE Access*, vol. 5, pp. 12648–12656, 2017.
[51] *Critical Infrastructure Resilience: Final Report and Recommendations*, National Infrastructure Advisory Council, New York, NY, USA, 2009.
[52] D. M. Frangopol, K. Y. Lin, and W. Kuo, "Life cycle cost design of deteriorating structures," *Struct. Eng.*, vol. 123, no. 10, pp. 1390–1401, 1997.
[53] A. K. Dhingra, "Optimal apportionment of reliability and redundancy in series systems under multiple objectives," *IEEE Trans. Rel.*, vol. 41, no. 4, pp. 576–582, Dec. 1992.
[54] S. Frischermeier, "Electrohydrostatic actuators for aircraft primary flight control—Types, modelling and evaluation," in *Proc. 5th Scandinavian Int. Conf. Fluid Power*, 1997, p. 5.

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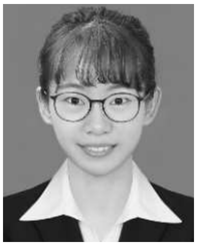

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