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복원가능 시스템 설계를 위한 복원도 할당

Resilience Allocation for Resilient Engineered System Design

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Abstract: Most engineered systems are designed with high levels of system redundancies to satisfy required reliability requirements under adverse events, resulting in high systems' LCCs (Life-Cycle Costs). Recent years have seen a surge of interest and tremendous advance in PHM (Prognostics and Health Management) methods that detect, diagnose, and predict the effects of adverse events. The PHM methods enable proactive maintenance decisions, giving rise to adaptive reliability. In this paper, we present a RAP (Resilience Allocation Problem) whose goal is to allocate reliability and PHM efficiency to components in an engineering context. The optimally allocated reliability and PHM efficiency levels serve as the design specifications for the system RBDO (Reliability-Based Design Optimization) and the system PHM design, which can be used to derive the detailed design of components and PHM units. The RAP is demonstrated using a simplified aircraft control actuator design problem resulting in a highly resilient actuator with optimally allocated reliability, PHM efficiency and redundancy for the given parameter settings.

Keywords: resilience allocation, reliability, prognostics and health management, resilient engineered system

I. INTRODUCTION

In the past few decades, reliability has been widely recognized as of great importance in engineering product and process design. Hence, considerable advances have been made in the field of RBDO (Reliability-Based Design Optimization) [1-3] for engineered system reliability analysis and design while taking into account various variability sources (e.g., material properties, loads, geometric tolerances). In RBDO, reliability is defined as the probability that a system performance (e.g., fatigue, corrosion, and fracture) meets its marginal value under variability. Although reliability-based design can improve system reliability to some degree, most engineered systems can only be designed with a passive and fixed design capacity (the load level that the system design can withstand) and, therefore, may become unreliable in the presence of adverse events (Adverse events could include the failure of components due to internal hazards (e.g., degradation) and/or external hazards (e.g., harsh operational conditions) that occur during the mission of the systems.). To maintain the desired level of system reliability under adverse events, a great deal of system redundancy is designed into most engineered systems, resulting in a strikingly high LCC (Life-Cycle Cost) to be incurred in development, operation, and maintenance processes.

Recently, PHM (Prognostics and Health Management) methods have been developed to detect, diagnose, and predict the system-wide effects of adverse events. CM (Condition Monitoring) is the process of diagnosing health conditions based on sensory signals and related health measures. Popular tools used for CM include statistical methods [4] and artificial intelligence, such as neural networks and fuzzy logic [5]. *Real-time prognostics* research has been conducted with an emphasis on modeling the RUL (Remaining Useful Life) distribution and reliability. In general, prognostics approaches can be categorized into model-based approaches [6], data-driven approaches [7] and hybrid approaches [8]. CBM (Condition-Based Maintenance) is the maintenance decision process that exploits CM and prognostics information to maximize the availability of the system and to minimize its long-run expected cost. Component replacement in this maintenance is triggered when the system condition reaches a threshold condition or the owner's cost is minimal [9]. It is noted that PHM has been successful, in part, in lowering system maintenance costs. In addition, it was reported that PHM may have the capability to make engineered systems highly reliable with a reduced level of redundancy [10]. However, it has not been used as a means to adaptively ensuring high system reliability under adverse conditions. Capitalizing on PHM technology at an early design stage may enable the transformation of passively reliable (or vulnerable) conventional systems into adaptively reliable (or resilient) systems while considerably reducing systems' LCCs. There is, however, no definition and mathematical framework of engineering resilience to take advantage of PHM because the two interrelated disciplines (engineering reliability and PHM) have, to date, been developed in parallel and independently.

The above literature survey reveals a great potential for the advancement of PHM technology together with the system reliability technology to further make engineered systems resilient. This study aims at exploiting this potential to incorporate the resilience concept into engineering design and to transform the

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conventional RBDO to resilience-driven system design. This design framework is composed of three hierarchical tasks, namely the RAP (Resilience Allocation Problem) as a top-level design problem to define a resilience measure as a function of reliability and PHM efficiency in an engineering context, the system RBDO (Reliability-Based Design Optimization) as the first bottom-level design problem for the detailed design of components, and the system PHM design as the second bottom-level design problem for the detailed design of PHM units. We expect that the resulting system design is capable of detecting, anticipating and recovering from adverse events.

The paper is organized as follows. Section II introduces the concept of resilience to a complex engineered system. Section III presents the RAP formulation. Section IV reports the results of an engineering case study to illustrate the proposed allocation problem. The paper is concluded in Section V.

II. CONCEPT OF ENGINEERING RESILIENCE

Conceptually, engineering resilience can be characterized with the following three steps as shown in Fig. 1. Firstly, an engineered system should continuously monitor key state variables indicative of its health condition. Secondly, upon the occurrence of an incipient fault, the system should anticipate the remaining time of proper functioning before a failure occurs. Thirdly, based on the anticipation, the system should analyze various ways of restoration and identify an optimal way to restore its health condition. This section institutes a conceptual definition of a resilient engineered system and develops a mathematical definition of engineering resilience.

2.1 Definition of resilient engineered systems

Conventionally, an engineered system is composed of hardware, software, and human elements in a physical domain, which interact through a functional decomposition in a functional domain. This conventional system could fail catastrophically in the presence of adverse events (e.g., extreme weather, hardware fault, human error) because the system can neither respond nor adapt to the adverse events. There is thus a desperate need to build resilient engineered systems by introducing a pioneering feature, engineering resilience, into conventional engineered systems (see Fig. 2).

We then investigate a conceptual definition of a complex engineered system having engineering resilience, characterized with three key functions including:

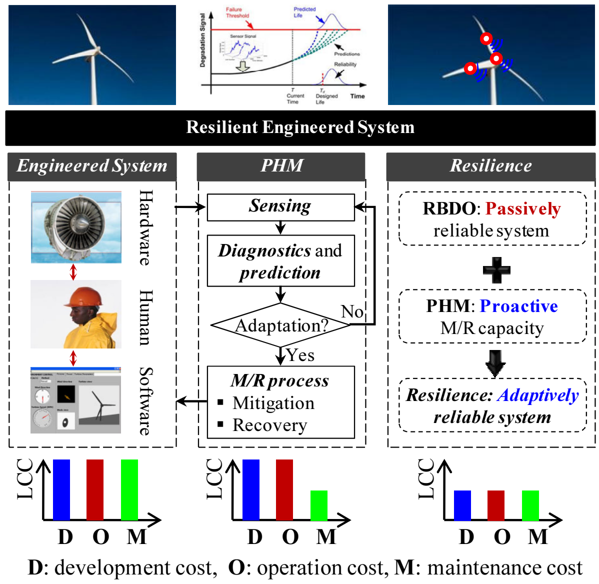


그림 2. 복원가능 시스템에서의 복원 수행.

Fig. 2. Resilience practice in a resilient engineered system.

- *Sensing function*: It senses the effect of adverse events on engineered systems. The sensing function can be realized by employing an optimally designed sensor network.
- *Reasoning (diagnostics and prediction) function*: It extracts system health-relevant information in real-time with feature extraction techniques, classifies system health condition with health classification techniques, and predicts the time remaining before an engineered system no longer performs the required function(s) or the RUL (Remaining Useful Life) in real-time with advanced machine learning techniques. The system health condition and RUL provide valuable information for field engineers to make proactive M/R (Mitigation/Replacement) actions to prevent catastrophic system failure.
- *M/R (Mitigation or Recovery) action process*: This process enables engineered systems to respond to and quickly recover from catastrophic system failures. It employs two types of actions, namely, mitigation and recovery. In general, the mitigation can be categorized as an M/R action for a short-term resilience while the replacement contributes to a long-term resilience.

In what follows, the focus is to seek for a mathematically definition of engineering resilience, which then gives rise to a

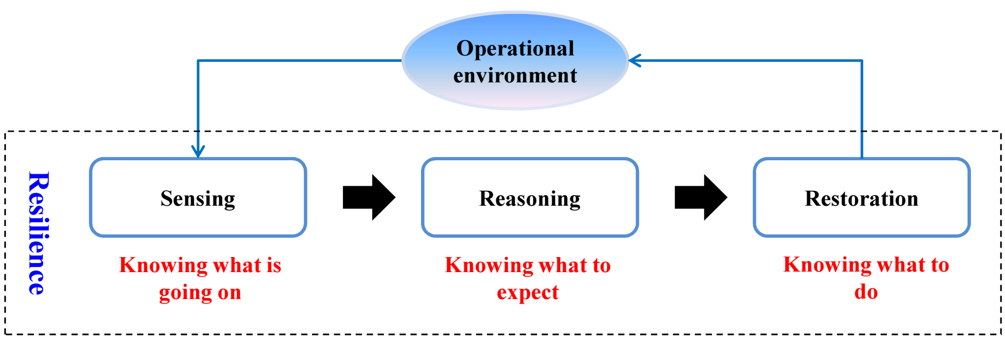


그림 1. 공학 복원의 수행 과정.

Fig. 1. Engineering resilient practice.

design framework of engineering resilience, namely resilience-driven system design.

2.2 Definition of engineering resilience

This subsection aims at proposing a conceptual definition of engineering resilience, which will facilitate the derivation of its generic formula in terms of reliability and other key PHM attributes. Non-resilient system designs encounter gradual degradation of system capacity and performance due to adverse events (see Fig. 3(a)). In contrast, resilient system designs will be able to recover from their critical health states by restoring the system capacity (see Fig. 3(b)). PHM will support logical decisions about when and how to restore the system capacity. The capacity restoration (ρ) can be defined as the degree of reliability recovery. It can be found that the restoration is a joint probability of a system failure event (E_{sf}), a correct diagnosis event (E_{cd}), a correct prognosis event (E_{cp}), and an M/R action success event (E_{mr}), expressed as

$$\begin{aligned}\rho(R,\Lambda_P,\Lambda_D,\kappa) &\triangleq \Pr(E_{sf}E_{cp}E_{mr})\\ &= \Pr(E_{mr}|E_{cp}E_{cd}E_{sf})\cdot\Pr(E_{cp}|E_{cd}E_{sf})\\ &\quad\cdot\Pr(E_{cd}|E_{sf})\cdot\Pr(E_{sf})\\ &= \kappa\cdot\Lambda_P\cdot\Lambda_D\cdot(1-R)\end{aligned} \tag{1}$$

where κ, Λ_P and Λ_D are the conditional probabilities of the M/R action success, correct prognosis and diagnosis, and $(1-R)$ is the probability of system failure. In this study, the value of κ is held constant here by assuming that M/R maintenance actions are consistently performed. However, there is no restriction on the form of κ. In particular, κ can be a nonlinear function of the system reliability R, indicating that the performance of an M/R action is affected by the health condition of the engineered system.

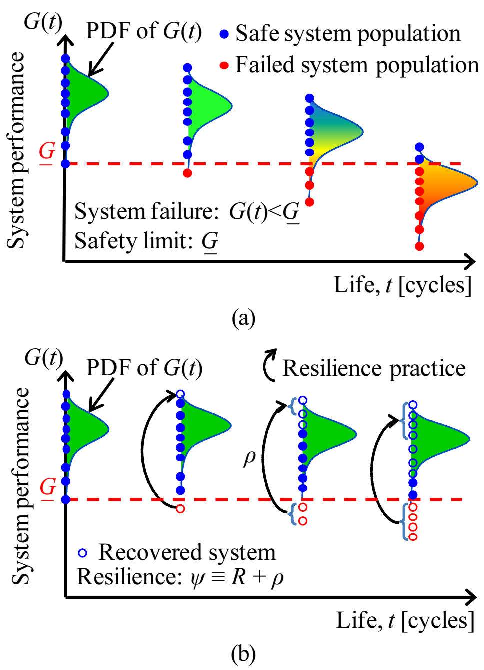


그림 3. (a) 복원 수행이 없을 때와 (b) 있을 때의 사용 시간에 따른 시스템 성능 변화.

Fig. 3. System performance changes over lifetime without (a) and with the resilience practice (b).

The conceptual definition of engineering resilience is the degree of a passive survival rate (or reliability) plus a proactive survival rate (or restoration). Mathematically, the resilience measure can be defined as the addition of reliability and restoration as (see Fig. 3(b))

$$\begin{aligned}&\text{Resilience}(\Psi)\triangleq\text{Reliability}(R)+\text{Restoration}(\rho)\\ &\rightarrow\quad \Psi\triangleq R+\rho(R,\Lambda_P,\Lambda_D,\kappa)\end{aligned} \tag{2}$$

It is noted that the above definition enable the quantitative analysis of the resilience potential of an engineered system.

III. RESILIENCE ALLOCATION PROBLEM

This section presents the resilience allocation problem (RAP) with the aim to allocate resilience levels—redundancy, reliability and PHM efficiency levels—to components.

3.1 Problem formulation

The resilience of a system can be enhanced by increasing the degree of redundancy, reliability, and/or PHM efficiency at a component level. A rise in the resilience of a system, however, could lead to an increase in system LCC. Thus, based on the resilience definition above, a systematic trade-off can be formulated as an original RAP in this subtask. This original problem can be formulated as

$$\begin{aligned}&\underset{\mathbf{r},\boldsymbol{\lambda},\mathbf{m}}{\text{minimize}} && LCC(\mathbf{r}^t,\boldsymbol{\lambda}^t,\mathbf{m})\\ &\text{subject to} && \Psi\big(\boldsymbol{\psi}(\mathbf{r}^t,\boldsymbol{\lambda}^t,\mathbf{m})\big)\geq\Psi^t;\ \ \mathbf{0}\leq\mathbf{r}^t,\boldsymbol{\lambda}^t\leq\mathbf{1}\\ &&& m_j^L\leq m_j\leq m_j^U,\ \ j=1,2,\ldots,N\end{aligned} \tag{3}$$

where LCC is the system life-cycle cost, Ψ and Ψ^t are system resilience and its target value, $\boldsymbol{\psi}=(\psi_1,\psi_2,\ldots,\psi_N)^{\mathrm{T}}$ is an allocated resilience vector for all subsystems, N is the number of the subsystems, and the allocation decision variables include the target component-reliability vector $\mathbf{r}^t=(r_1^t, r_2^t, \ldots, r_N^t)^{\mathrm{T}}$ with r_j^t being the target component-reliability of the j^{th} subsystem, the target component-PHM efficiency vector $\boldsymbol{\lambda}^t=(\lambda_1^t, \lambda_2^t, \ldots, \lambda_N^t)^{\mathrm{T}}$ with λ_j^t being the component-PHM efficiency of the j^{th} subsystem, and the target component-redundancy vector $\mathbf{m}=(m_1, m_2, \ldots, m_N)^{\mathrm{T}}$ with m_j being the target redundancy level of the j^{th} subsystem. The RAP in Eq. (3) makes it possible to optimally allocate target resilience levels—redundancy, reliability, and PHM efficiency levels—to components while meeting the target system resilience (Ψ^t). This problem is a mixed-integer non-linear programming problem. It can be solved using a genetic algorithm [11], ant colony optimization [12], particle swarm optimization [13], or other optimization techniques. Solving this problem will be computationally economic since the system resilience function Ψ can be analytically expressed in terms of the target component reliability vector $\mathbf{r}^t$, the component-PHM efficiency vector $\boldsymbol{\lambda}^t$ and the target component-redundancy vector $\mathbf{m}$. The proposed RAP incorporates the PHM efficiency in design, where the reliability allocation can be considered as one special case in which PHM efficiencies for all components equal zero. For a series-parallel system (see Fig. 4), each component in a subsystem is supported by a PHM unit which provides anticipation/prevention of failure

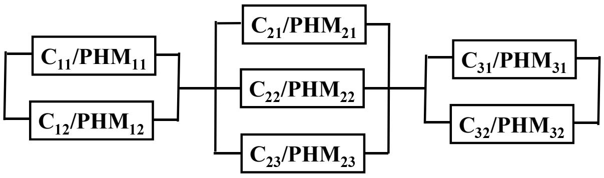


그림 4. 병렬 시스템에서의 복원도 할당 구조도.

Fig. 4. Structure of resilience allocation problem for a series-parallel system.

events for the component. By conducting the RAP, we can derive the optimally allocated values for the target attributes (PHM efficiency and reliability levels) and the target structures (redundancy levels) for this series-parallel system. In what follows, the system resilience and LCC will be analyzed in details to evaluate the constraints objective functions in Eq. (3), respectively.

3.2 Top-level system resilience analysis

For different system configurations [14] (e.g., series-parallel, parallel-series, and general mixed system), the system resilience function can be built with the following two steps:

Step 1: Derive the system resilience function in terms of subsystem resilience levels, i.e., $\Psi(\psi) = \Psi(\psi_1, ..., \psi_N)$. Since the system resilience is evolved from the system reliability, a reliability block diagram [15] and the analogy between the system reliability and resilience can be readily used to develop the analytic expression for the system resilience function.

Step 2: Build the subsystem resilience functions in terms of the target component-reliability, component-PHM efficiency and component-redundancy vectors, i.e., $\psi_j = \psi_j(r_j^t, \lambda_j^t, m_j)$ for $j = 1, 2, ..., N$. Take a series-parallel system (see Fig. 4) as an example. Based on the generic resilience formula in Eq. (2), we can build the resilience function for the j^{th} subsystem being a parallel system, expressed as

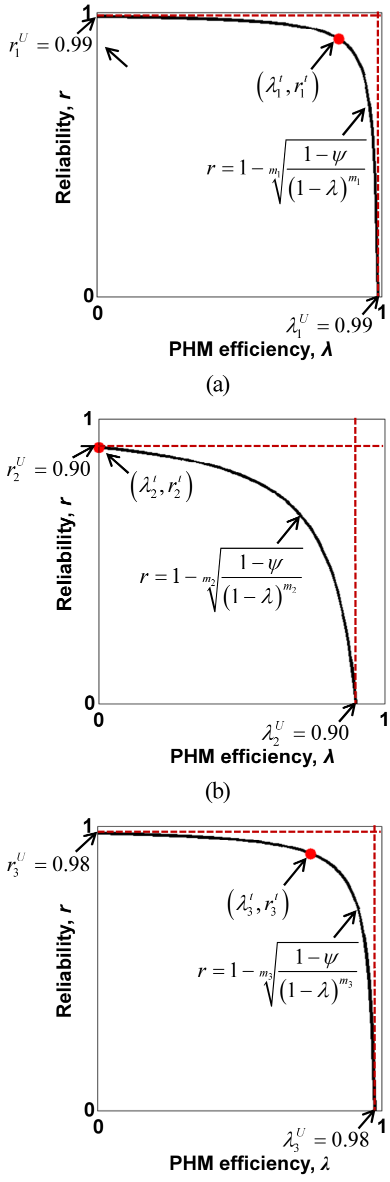
$$\psi_j \triangleq R_j^t + \Lambda_j^t \cdot (1 - R_j^t) = 1 - (1 - r_j^t)^{m_j}(1 - \lambda_j^t)^{m_j} \tag{4}$$

where R_j^t and Λ_j^t are the j^{th} subsystem reliability and PHM efficiency. In this series-parallel system, the components in the same subsystem possess the same reliability (r_j^t) because the components in parallel are identical and redundant, as are the PHM units.

The relationship between the component-reliability and component-PHM efficiency of the three subsystems in Fig. 4 is plotted in Fig. 5, where the target subsystem resilience levels for the three subsystems are set as 99.98%, 99.90% and 99.94%, respectively. We can see that a highly nonlinear relationship between these two measures.

3.3 LCC (Life-Cycle Cost) analysis with PHM

In this study, we derive a LCC model by modifying and adding PHM relevant cost elements to an existing LCC model for deteriorating structural systems [16]. The LCC model consists of four cost elements: the expected initial development cost of components, the expected cost of preventive maintenance, the expected cost of corrective maintenance, and the expected development cost of PHM. Given the target component-reliability vector $\mathbf{r}^t$, the target component-PHM efficiency vector λ^t, and the target component- redundancy vector $\mathbf{m}$, this LCC model can be expressed as



(c)

그림 5. 서브 시스템 목표 복원 등급을 만족하기 위한 요소 신뢰도와 요소 PHM 효율 간의 관계.

Fig. 5. Relationship between component-reliability and component-PHM efficiency for given target subsystem resilience levels.

$$C(\mathbf{r}, \mathbf{m}, \boldsymbol{\lambda}) = C^I + C^{PM} + C^{CM} + C^{PHM} \tag{5}$$

where C^I denotes the initial development cost of components, C^{PM} denotes the cost of preventive maintenance, C^{CC} denotes the cost of corrective maintenance, and C^{PHM} denotes the cost of PHM units. In the following sections, the four cost elements will be discussed in details.

• *System Development Cost C^I*

In the binary-state reliability-redundancy allocation problem, it is often assumed that there is an inverse power relationship between component cost and component failure rate [17,18].

Under the assumption of a constant failure rate, the initial development cost of the j^{th} subsystem with m_j parallel components can be expressed as [17,18]

$$C_j^I = c_j^I\left(r_j^t\right)\cdot\left[m_j + \exp\left(\frac{m_j}{4}\right)\right],$$
$$\text{with } c_j^I\left(r_j^t\right) = \alpha_j^C\left(-\frac{T}{\ln\left(r_j^t\right)}\right)^{\beta_j^C} \tag{6}$$

where $c_j^I(r_j^t)$ is the cost function of a component in the j^{th} subsystem, $c_j^I(r_j^t)\cdot m_j$ is the cost of components in the j^{th} subsystem, an additional cost $c_j^I(r_j^t)\cdot\exp(m_j/4)$ accounts for the cost for interconnecting parallel components, T is the required system mission time, α_j^C and β_j^C denote constants representing the physical characteristics of each component in the j^{th} subsystem.

• *Preventive Maintenance Cost* C^{PM}

That preventive maintenance occurs if PHM successfully detects critical system health states and accurately predicts the system RUL. As a function of the component reliability, subsystem redundancy and PHM efficiency, the preventive maintenance cost can be expressed as

$$C^{PM} = \sum_{j=1}^{N} m_j \lambda_j^t\left(1-r_j^t\right)C_j^{PM} \tag{7}$$

where C_j^{PM} denote the preventive maintenance cost of each component in the j^{th} subsystem. The assumption here is that a preventive maintenance occurs when any component approaches its end of life predicted by the PHM and that all the components and PHM systems fail independently.

• *Corrective Maintenance Cost* C^{CM}

The corrective maintenance occurs if PHM fails in detecting critical system health states and making an accurate prediction of the system RUL. As a function of the component reliability, subsystem redundancy and PHM efficiency, the corrective maintenance cost can be expressed as

$$C^{CM} = \sum_{j=1}^{N} m_j\left(1-\lambda_j^t\right)\left(1-r_j^t\right)C_j^{CM} \tag{8}$$

where C_j^{CM} denote the corrective maintenance cost of each component in the j^{th} subsystem and is far higher than the preventive maintenance cost C_j^{PM}. The assumption here is that a corrective maintenance occurs upon the failure of any component and that all the components and PHM systems fail independently. In contrast to the preventive maintenance which always takes place before system failure, the corrective maintenance occurs after system failure and restores the system to a healthy state [19].

• *PHM Unit Cost* C^{PHM}

The PHM unit cost is specifically the costs associated with developing PHM units to be integrated with components. In this study, the PHM unit cost will be formulated as a parametric model with the subsystem redundancy and component PHM efficiency as inputs. Inspired by the component cost function for reliability-redundancy allocation, shown in Eq. (3), we define the PHM unit cost as

$$C^{PHM} = \sum_{j=1}^{N}\alpha_j^{PHM}\left(-\frac{T}{\ln\left(\lambda_j^t\right)}\right)^{\beta_j^{PHM}}\cdot m_j \tag{9}$$

where α_j^{PHM} and β_j^{PHM} denote constants representing the physical characteristics of each PHM unit in the j^{th} subsystem. Prior to solving the optimization problem in Eq. (3), these constants can be determined based on the collected data of the PHM unit cost and efficiency. We derive the PHM unit cost model in Eq. (9) based on the component cost model [17,18] in Eq. (6) by replacing the target reliability r_j^t with the target PHM efficiency λ_j^t. It is noted that, in general, there is no interconnections between parallel PHM units. Therefore, unlike the component cost, the additional cost for interconnecting parallel elements is not considered in the PHM unit cost.

IV. AIRCRAFT CONTROL ACTUATOR CASE STUDY

This section presents a case study for the design of a simplified aircraft control actuator. The aircraft control actuator considered is the EHA (Electro-Hydrostatic Actuator) [20]. In this case study, we aim at designing a highly resilient EHA with optimally allocated reliability, PHM efficiency and redundancy.

4.1 Problem description

The EHA (see Fig. 6), as a closed-loop, hydrostatic control system, mainly consists of an ECU (Electronic Control Unit), a variable-speed EM (Electric Motor), a fixed-displacement hydraulic pump and a hydraulic piston actuator [22]. In the EHA, a variable-speed electric motor (typically DC) is used to drive a fixed-displacement hydraulic pump, which in turn, powers a hydraulic piston actuator. Compared to a conventional hydraulic actuator, the EHA can achieve higher energy efficiency (with on-demand usage) and positional accuracy with enhanced compactness. These advantages have led to the wide use of the EHA for flight surface actuation in today's commercial and military aircrafts. Failures of the EHAs in these safety critical applications can be catastrophic, resulting in great loss of lives. Therefore, the EHA must be designed to achieve a sufficiently high reliability level. To this end, a common practice is to introduce a great deal of redundancy into the EHA (e.g., a triplex-redundant flight control system [23]). While a high redundancy

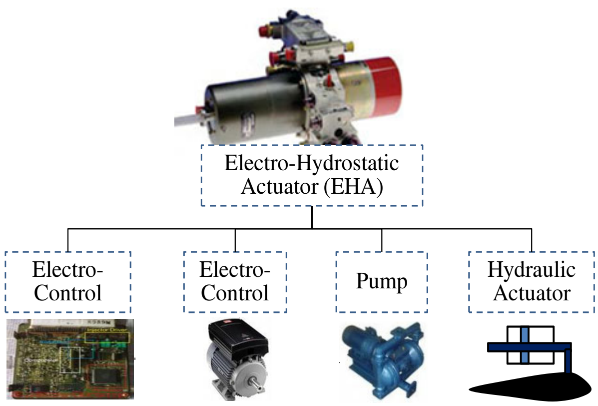


그림 6. EHA와 직렬 연결된 서브 시스템.

Fig. 6. An airplane control actuator with series-connected sub-systems.

level improves reliability, it results in a strikingly high LCC (Life-Cycle Cost) to be incurred in development, operation, and maintenance processes. To reduce the LCC while still maintaining an equivalent reliability level, we apply the proposed RAP to the EHA with an aim to compensate the redundancy reduction with the PHM technology. It is worth noting that the RAP leads to the possibility to implement this compensation in an optimum manner.

4.2 RAP formulation

Solving the top-level RAP will allocate a target system resilience level into the target resilience levels of the four subsystems. Assumptions under which this design problem is solved are listed as follows:

(1) The failure times all components considered in the example are exponentially distributed, leading to constant failure rates.
(2) PHM will detect critical system health states and predict system RUL through health diagnostics and prognostics
(3) The redundancy level of each subsystem should be no more than nine due to subsystem weight and volume constraints.
(4) All the components and PHM units fail independently. An observed failure is due to the loss of resilience, i.e., the failures of both a component and its associated PHM unit.

Based on the RAP formulation in Eq. (3), this problem is formulated as follows:

$$\begin{aligned} &\text{find } \ \mathbf{r}^t = \left(r_1^t, r_2^t, r_3^t, r_4^t\right),\ \boldsymbol{\lambda}^t = \left(\lambda_1^t, \lambda_2^t, \lambda_3^t, \lambda_4^t\right), \\ &\qquad \mathbf{m} = (m_1, m_2, m_3, m_4) \\ &\text{to minimize } \ LCC = \sum_{j=1}^{4}\left(C_j^I + C_j^{PM} + C_j^{CM} + C_j^{PHM}\right) \qquad (10) \\ &\text{subject to } \quad \Psi = \prod_{j=1}^{4}\left[1-\left(1-r_j^t\right)^{m_j}\left(1-\lambda_j^t\right)^{m_j}\right] \geq \Psi^t \\ &\qquad \mathbf{0} \leq \mathbf{r}^t, \boldsymbol{\lambda}^t \leq \mathbf{1}, \quad \mathbf{1} \leq \mathbf{m} \leq \mathbf{9} \end{aligned}$$

where LCC is the system life-cycle cost, which consists of the initial development cost of components C^I, the cost of preventive maintenance C^{PM}, the cost of corrective maintenance C^{CC}, and the cost of PHM units C^{PHM}, Ψ and Ψ^t are system resilience and its target value, the lower and upper bounds for any target component-reliability or target component-PHM efficiency are 0 and 1, respectively, and the lower and upper bounds for any target component-redundancy are 1 and 9, respectively. The parameters for the cost models are listed in Table 1 and the system mission time T = 1000. The RAP problem is a mixed-integer non-linear programming problem. To determine an optimum solution of the RAP problem, we employed a genetic algorithm of which the details will be presented in the subsequent section.

4.3 Genetic algorithm as the optimization solution method

The RAP is a MINLP (Mixed-Integer Nonlinear Programming) problem. To the best of the authors' knowledge, MINLP problems are generally solved by heuristic algorithms as an exhaustive search of the optimum solution is usually impractical. One of the most widely used algorithms is the so-called GA (Genetic Algorithm) [11] due to the following advantages: (i) the encoding scheme (binary or decimal encoding) in the GA leads to the flexibility to represent both continuous and discrete design variables; and (ii) the search in the solution space for optimal solutions can be very efficient due to the use of fitness evaluation and genetic operator functions. Although the GA is employed to solve the top-level RAP, the computational cost for function evaluations can be negligible since the system LCC and resilience are computed through the evaluation of analytic models.

In the GA, each candidate solution is called a chromosome and a set of candidate solutions is called a population. The GA for solving the RAP in this case study employed the decimal encoding. The solution procedures are presented as follows [24]:

Step 1 (Initialization): Set the population size and maximum number of iterations as 500 and 100, respectively. Since one decimal digit represents one design variable in the RAP shown in Eq. (3), the length L of a chromosome reads: L = 3N. Set the upper and lower bounds for both component-reliability and component efficiency to 0 and 1, respectively. Set the upper and lower bounds for component-redundancy to 1 and 9, assuming the redundancy level should not be too high. Set the generation index k_g = 1 and randomly generate an initial population $\boldsymbol{\Gamma}(1)$.

Step 2 (Evaluation): Evaluate the fitness function *ftn* for each chromosome in the current population $\boldsymbol{\Gamma}(k_g)$. The fitness function used here is a composite of both the objective value (i.e., system LCC) and the penalty arising from the violation of the constraint (i.e., system resilience). Mathematically, the fitness function *ftn* can be expressed as

$$ftn = \begin{cases} LCC(\mathbf{r}^t, \boldsymbol{\lambda}^t, \mathbf{m}), & \text{if } \Psi \geq \Psi^t \\ \text{inf}, & \text{otherwise} \end{cases} \qquad (11)$$

Step 3 (Parent Selection): Select chromosomes from the current population based on their fitness values to form a new generation $\boldsymbol{\Gamma}(k_g + 1)$. Here the roulette-wheel selection scheme is used. These chromosomes are called parent and will be used in the next step to generate new chromosomes in the new generation.

Step 4 (Crossover & Mutation): Implement the two-point crossover operator with a crossover rate of 0.85 and the uniform mutation operator with a mutation rate of 0.10 to generate new chromosomes in the new population.

Step 5 (Termination Check): If the generation index k_g exceeds the maximal number of iterations, terminate the iteration and report the solution. Otherwise, increase the generation index: $k_g = k_g + 1$, and go back to Step 2.

4.4 Results and discussion

We would like to investigate scenarios with different target system resilience levels. First let us look at the scenario in which the target system resilience Ψ^t is set as 0.90. The optimum solution is shown in Table 2. It can be seen that the incorporation of PHM by the proposed RAP reduces the system redundancy from $\mathbf{m}$ = (3, 2, 3, 2) to $\mathbf{m}$ = (2, 2, 2, 1). As a consequence, the system LCC decreases from 73.6301 under the traditional design

표 1. EHA 사례 연구를 위한 모델 매개 변수.
Table 1. Model parameters for the EHA case study.

Subsystem	α_j^C(×10^{-5})	β_j^C	C_j^{PM}	C_j^{CM}	α_j^{PHM}(×10^{-6})	β_j^{PHM}
1	0.5	1.5	2.5	7.5	3.3	1.5
2	0.8	1.5	5.0	15.0	5.3	1.5
3	1.0	1.5	6.5	19.5	6.7	1.5
4	0.7	1.5	12.5	37.5	4.7	1.5

표 2. 기존 설계와 RAP에 의한 최적해 비교 (Ψ^t = 0.90).
Table 2. Optimum results of traditional design and RAP with Ψ^t = 0.90.

Subsystem	Traditional design (without PHM)					RAP (with PHM)				
	r_j^t	m_j	λ_j^t	LCC	Ψ	r_j^t	m_j	λ_j^t	LCC	Ψ
1	0.7371	3	0	73.6301	0.9000	0.6291	2	0.6721	38.3416	0.9000
2	0.8088	2	0			0.6412	2	0.6682		
3	0.7287	3	0			0.6519	2	0.6732		
4	0.8292	2	0			0.7363	1	0.7679		

표 3. 기존 설계와 RAP의 최적해 비교 (Ψ^t = 0.95).
Table 3. Optimum results of traditional design and RAP with Ψ^t = 0.95.

Subsystem	Traditional design (without PHM)					RAP (with PHM)				
	r_j^t	m_j	λ_j^t	LCC	Ψ	r_j^t	m_j	λ_j^t	LCC	Ψ
1	0.7901	3	0	82.2774	0.9500	0.6152	2	0.6448	45.9357	0.9500
2	0.7731	3	0			0.6437	2	0.6644		
3	0.7872	3	0			0.6486	2	0.6677		
4	0.8574	2	0			0.7539	2	0.7423		

표 4. 기존 설계와 RAP의 최적해 비교 (Ψ^t = 0.99).
Table 4. Optimum results of traditional design and RAP with Ψ^t = 0.99.

Subsystem	Traditional design (without PHM)					RAP (with PHM)				
	r_j^t	m_j	λ_j^t	LCC	Ψ	r_j^t	m_j	λ_j^t	LCC	Ψ
1	0.8102	4	0	111.6017	0.9900	0.6488	3	0.6772	55.0199	0.9900
2	0.7745	4	0			0.6483	3	0.7049		
3	0.7850	4	0			0.6567	2	0.8014		
4	0.8411	3	0			0.7720	2	0.7678		

(without PHM) to 38.3416 under the RAP (with PHM). It is noted that, even though the target component-reliabilities are relatively low for both traditional design (below 0.8500) and RAP (below 0.7500), the incorporation of redundant components (traditional design and RAP) and PHM (RAP) still leads to high subsystem reliabilities (above 0.90). Finally, the system resilience levels under both optimum designs read 0.9000, which just satisfies the system resilience requirement.

Raising the target system resilience to 0.95, we then obtained another optimal design, which is listed in Table 3. Again, the incorporation of PHM by the proposed RAP reduces the system redundancy from $\mathbf{m}$ = (3, 3, 3, 2) to $\mathbf{m}$ = (2, 2, 2, 2). As a consequence, the system LCC decreases from 82.2774 under the traditional design (without PHM) to 45.9357 under the RAP (with PHM). The results further verify the fact that, compared with the traditional design, the RAP yields an optimum design with a much lower LCC by considering PHM in the early design stage. The incorporation of redundant components (traditional design and RAP) and PHM (RAP) compensates for the relatively low target component-reliabilities for traditional design (below 0.8600) and RAP (below 0.7600), still leading to high subsystem reliabilities (above 0.95). Finally, the system resilience levels under both optimum designs read 0.9500, which just satisfies the system resilience requirement. We further observe that, in order to meet a higher target system resilience level than the case with Ψ^t = 0.90, more components are used with higher component-reliabilities and PHM efficiencies.

Further raise the target system resilience to 0.99, we then obtained another optimal design, which is listed in Table 4. Similar observations can be made compared to those in the case with Ψ^t = 0.95, except that we have more components as well as higher component-reliabilities and PHM efficiencies. The consideration of PHM in the early design stage significantly reduces the LCC compared to the traditional design.

Finally, we note that the target component-reliabilities and component-PHM efficiencies allocated in this RAP can serve as design specifications for the system RBDO and PHM design, which will not be covered in this paper.

V. CONCLUSION

This paper presents a RAP (Resilience Allocation Problem) to incorporate resilience characteristics into engineered systems. The RAP, supported by a rigorous theoretical basis of engineering resilience, is expected to ensure highly resilient system designs under various loading/environmental conditions and system-wide effects of adverse events while considerably reducing systems' LCC. The RAP is demonstrated with a simplified aircraft control actuator design problem, in which the incorporation of PHM significantly reduces the system LCC. Future research will focus on the verification of the proposed RAP using testing data from a real complex engineered system.

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