Article citation info:
YU G, DU Y, YAN L, REN F. Stress-strength interference-based importance for series systems considering common cause failure. Eksploatacja i Niezawodnosc – Maintenance and Reliability 2020; 22 (2): 241–252, http://dx.doi.org/10.17531/ein.2020.2.7.

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STRESS-STRENGTH INTERFERENCE-BASED IMPORTANCE FOR SERIES SYSTEMS CONSIDERING COMMON CAUSE FAILURE

OCENA OPARTEJ NA MODELU OBCIĄŻENIOWO-WYTRZYMAŁOŚCIOWYM WAŻNOŚCI ELEMENTÓW SYSTEMU SZEREGOWEGO Z UWZGLĘDNIENIEM USZKODZEŃ WYWOŁANYCH WSPÓLNĄ PRZYCZYNĄ

Series systems, whose structures are simple, are widely discovered in practical engineering, but the interdependency between the components is complex, such as common cause failure. With the consideration of the components' strength, this paper focuses on ranking the importance measure of components considering the common cause failure based on the stress-strength interference (SSI) model. The weakest component can be identified by integrating the SSI model with the importance measure when the strength mean and variance of the component under the load stress is known. Firstly, the analytic methods are proposed to calculate the SSI-based importance of components in the series systems. Then, the monotonicity of SSI-based importance is analyzed by changing the strength mean or strength variance of one component. The results show that the SSI-based importance of components, whose parameters are changed, will reduce monotonically with the increase of strength mean or increase monotonically with the increase of strength variance. Finally, a component replacement method is developed based on the rules that both the importance of replaced component and the importance ranks should be unchanged after the replacement. SSI-based importance can help engineers to make maintenance decisions, and the component replacement method can increase the diversity of spare parts by finding the equivalent components.

Keywords: *importance measure; common cause failure; stress-strength interference; monotonicity analysis; component replacement.*

Systemy szeregowe, które są szeroko stosowane w praktyce inżynieryjnej, charakteryzują się prostą strukturą, jednak współzależności między ich elementami są złożone, czego przykładem są uszkodzenia wywołane wspólną przyczyną. Rozważając wytrzymałości składowych systemu, opracowano metodę szeregowania miar ważności składowych z uwzględnieniem uszkodzeń wywołanych wspólną przyczyną. Metoda ta pozwala zidentyfikować najsłabsze ogniwo systemu. Miarę istotności zintegrowano z modelem obciążeniowo-wytrzymałościowym (SSI), biorąc pod uwagę średnią i wariancję wytrzymałości elementu pod obciążeniem. W pierwszym kroku opracowano metody analityczne pozwalające na obliczanie opartej na SSI ważności elementów w systemach szeregowych. Następnie analizowano monotoniczność opartej na SSI ważności zmieniając średnią lub wariancję wytrzymałości jednego z elementów. Wyniki pokazują, że mierzona w oparciu o SSI ważność elementów, których parametry są zmieniane, maleje monotonicznie wraz ze wzrostem średniej wytrzymałości lub rośnie monotonicznie wraz ze wzrostem wariancji wytrzymałości. Na podstawie przeprowadzonych badań, opracowano metodę wymiany części, opartą na zasadzie polegającej na tym, że zarówno ważność zastąpionego elementu, jak i rangi ważności powinny pozostać niezmienione po wymianie. Możliwość określania ważności opartej na modelu SSI może pomóc inżynierom w podejmowaniu decyzji dotyczących konserwacji, zaś proponowana metoda wymiany elementów systemu pozwala zwiększyć różnorodność części zamiennych poprzez znalezienie równoważnych elementów.

Słowa kluczowe: *miara ważności; uszkodzenia wywołane wspólną przyczyną; model obciążeniowo-wytrzymałościowy; analiza monotoniczności; wymiana części.*

1. Introduction

The protection and security of components should be considered in the implementation of risk management, and the interdependencies within the components are a significant challenge for risk management. The common cause failure (CCF), which can cause the failure of multiple components with the common reason, is a typical reason of the interdependence between components in series systems. The importance analysis of components plays a vital role in the risk management of series systems. Importance measure is one of the significant branches of reliability theory and has a significant advance with the development of reliability engineering. It can evaluate the impact of the individual component on the system reliability when the component is failure. The results of importance measures could facilitate the reliability design, component assignment problem, redundancy allocation, system upgrading, fault diagnosis, and maintenance. Nowadays, importance measures have been widely applied in the fields of engineering, such as oil and gas transmission, railway systems, nuclear power production, manufacturing systems, and computer systems, and so on [17].

In 1968, Birnbaum first put forward the calculation method of importance measures for binary systems [4], and Birnbaum importance is classified into three categories as follows. The first category is the structure importance measure, which represents the role of the positions in the system that the components occupy; The second category is the reliability importance measure, which considered the component reliability to evaluate the effect of a component on the system reliability; The third category is the lifetime importance measure, which considered the component reliability in the life cycle to evaluate the influence of components on the system reliability. Based on the Birnbaum importance, researchers have evaluated the influence of component's reliability on the system reliability from different perspectives. So many new kinds of importance measures are proposed, such as F-V importance measure [13, 31], BP structure importance measure [1], critical importance measure [19], risk achievement worth (RAW), risk reduction worth (RRW) [32], improvement potential importance [38], and differential importance measure [5]. In recent years, some researchers have been extended importance measures to by considering the maintenance policy [9, 10], the transition rate increases over time [8], or the constraints on cost for improving the system reliability [24].

A binary system assumes that the state of the system and component only has two states: functioning and failure. However, there are a large number of multi-state systems (MSS) with more than two states in practice [22]. Barlow and Wu [2] summarized the analysis methods of MSS, where the system state was defined to be the worst state when the component is in the best minimal path set, or equivalently, the best state when the component is in the worst minimal cut set. Many of the results for the binary cases can be computed for MSS by using the binary structure and reliability function. Griffith [16] proposed the MSS performance, which described that the performance level is corresponding to different system states, and studied the effect of component improvement on the system performance. Wu and Chan [35] defined a new unity function based on the component state of MSS for measuring which component has the maximum contribution to improving the system performance. Zio and Podofillini [46] proposed the approach to evaluate the importance of all the components concerning a given performance level and expanded some binary importance measures to MSS, such as RAW, RRW, F-V, and Birnbaum importance. Ramirez-Marquez and Coit [25, 26] put forward the composite importance measures to evaluate the effect of all the states of components on the system reliability, which could break through the limitations of only considering the effect of a single state of the component on the system reliability. Levitin et al. [20] evaluated the importance measures for MSS based on the universal generating function technique and verified the effectiveness of the approach. Shrestha et al. [28] presented an analytical method based on multi-state multi-valued decision diagrams for multistate component importance analysis. Zhao et al. [42, 43] presented the mission success importance for multi-state repairable k-out-of-n systems. Do Van et al. [6, 7] put forward the multi-directional sensitivity measure within the framework of Markovian systems, which calculated the differential importance measure of risk-informed decision-making in the context of Markov reliability models. Natvig [23] raised the dynamic and stationary importance measures in repairable and non-reparable multistate coherent systems. Zhao et al. [45] introduced the redundancy importance measure into the multi-objective optimization of reliability-redundancy allocation problems for serial parallel-series systems. Si et al. [29] proposed the concept of integrated importance measure, which concerned the probability distributions and transition intensities of the component states simultaneously. Wang et al. [33] considered the improvement of system reliability based on Birnbaum importance by increasing the maintenance cost. Zhang et al. [41] proposed the Birnbaum importance-based quantum genetic algorithm for solving the component assignment problems.

However, no single type of importance measure can fit for all systems and conditions. Various importance measures for the same system may get the different ranks of components and lead to making different decisions. With the development of science and technology, engineering systems become more complicated, such as higher order systems, multi-loop control systems, nonlinear systems, hierarchy systems, and uncertain systems. For the design and optimization of such complex systems, some new importance measures are needed to judge the relative strength of a component in a system for different criteria [18]. At present, the importance measures are always calculated based on the independent reliabilities by assuming the component failure in a system is statistical independent, such as references [44] and [30]. This assumption is accordant with the possible working conditions for electronic systems, while it could not apply to the mechanical systems with complicated failure modes and failure mechanisms.

CCF was firstly proposed by Fleming in 1975 to represent the multiple components failures caused by the common reason [12]. CCF exists widely in most kinds of complex industrial systems, especially for nuclear facilities, weapon systems, and aerospace systems. Since the 1970s, researchers have put forward many analysis models for the CCF problems, where explicit analysis and implicit substitution were two typical modelling methods [40]. The precise analysis method denotes the system reliability based on the component state directly with the large scale of computation, which is generally applicable to all kinds of CCF.

The stress-strength interference (SSI) model has been commonly used in the reliability modelling of mechanical systems [11, 47]. Bhattacharyya and Johnson [3] established the interference reliability model for k out of n system by assuming that the system component was independent and identically distributed. For the 1 out of 2: G system, Lewis [21] disposed the Poisson distributed load (stress) by Markov model and evaluated the reliability of the system with CCF. Moreover, Xie et al. [36] introduced the concept of order statistics into the SSI model and calculated the equivalent strength of series, parallel, and k out of n systems for evaluating the system reliability. With the assumption of strength degradation, Xue and Yang [39] put forward the deterministic strength degradation model and random strength degradation model based on the interference analysis methods. Wang and Xie [34] structured the equivalent load according to the probability of order statistics when the load was applied at multiple times under a Poisson process. Shen et al. [27] evaluated the structure reliability when the load was under a Poisson process, and the degradation of structural strength was under a Gamma process. Gao et al. [15] established the dynamic reliability model based on the equivalent strength degradation paths to analyze the mechanical components with uncertain strength caused by material parameters. Furthermore, Gao and Xie [14] extended the dynamic reliability models for mechanical load-sharing parallel systems with strength degradation path dependence. Generally, current importance measures cannot assist effective decision making for the complex systems with CCF or dependent components [37]. So, taking advantage of the SSI model, this paper will propose the importance measure for systems with CCF to fit for the features of complex systems.

In practice, the component reliability is hard to observe and record, but the strength information of components can be observed easily. Therefore, the SSI model can be used to simplify the analysis of CCF in the system. Considering the advantages of the importance measure and the SSI, SSI-based importance measure is developed to evaluate the importance ranking of components. The significance of SSI-based importance can be summarized as follows. (1) The evaluation method of SSI-based importance can identify the weakest link in the system, which can help engineers to make decisions for maintenance activities. (2) The component replacement method can find more equivalent components, which can increase the diversity of spare parts.

The remaining of this paper is organized as follows. Section 2 describes the ideas of SSI-based importance considering CCF in general and gives the analytic expression of component importance in series systems. Section 3 analyzes the monotonicity of SSI-based importance for series systems. Section 4 introduces two numerical experiments to verify the monotonicity of SSI-based importance. Section 5 introduces a new component replacement method based on the ideas that both the SSI-based importance of the replaced component and the importance ranks of all components should be unchanged after replacing. Section 6 concludes the research work.

2. SSI-based importance considering CCF

The performance of components is always related to the load stress and the strength parameters (mean and variance) of components. The traditional reliability importance measure considers the effect of inherent component reliability on the system reliability instead of considering the effect of the load stress and the strength parameters of the components. For series systems, each component has independent strength. If the system is under one shock, this shock will act on all the components simultaneously, as the same load stress. Supposing the component will not bear any other individual stress, the component's reliability is the interference of the same load stress and component strength, and the failure of component occurs when the stress exceeds strength. Sometimes, the components failed because of the occurrence of CCF, and the CCF can be equitant to the same stress load acting on all the components. Therefore, SSI-based importance is developed to analyze the importance of components in the system under the same load stress.

2.1. SSI-based importance in series systems considering CCF

For a system with n components, the reliability of component $j\ (1 \le j \le n)$ can be written as $R_j = R_j(l, s_j)$, which is the function of the same load stress l and component strength s_j. The system reliability is the function of system structure and components' reliabilities, which can be noted as $R_s = \phi(R_1,...,R_n) = \phi(l, s_1, s_2, \cdots, s_n)$, in which ϕ is the system structure function; l is common load stress and $s_j (j = 1, 2, \cdots, n)$ is the strength of component *j*.

According to the idea of Birnbaum importance, the SSI-based importance of component *j* can also be expressed by the system structure function, load stress, and component strength, as shown in Equation 1:

$$I_j = \frac{\partial \phi(l, s_1, s_2, \cdots, s_n)}{\partial R_j(l, s_j)} = \frac{\partial \phi(l; s_1, s_2, \cdots, s_n) / \partial s_j}{\partial R_j(l, s_j) / \partial s_j} \tag{1}$$

Since it is difficult to directly obtain the derivative of system reliability on component reliability in the form of SSI model, we will explore the relationship between importance measure and component strength. The component reliability will be improved with the improvement of component strength when the load stress is fixed. That is to say, and component reliability $R_j(l, s_j)$ is monotonic for the variable s_j when stress l remains unchanged. The inverse function $R_j(l, s_j)$ can be obtained as $s_j = s_j(R_j, l)$, so the SSI-based importance can be expressed as the following formula in Equation 1. Then the partial derivative of s_j on $R_j(l, s_j)$ can be written as reciprocal of the partial derivative of $R_j(l, s_j)$ on s_j. Therefore, the ultimate expression of SSI-based importance is shown as the ratio of two derivatives on s_j in Equation 1. The numerator of the final expression represents the influence of component strength on the system reliability, and the denominator represents the influence of component strength on the reliability of itself. The real significance of SSI-based importance represents the relative change rate caused by the change of the component strength.

SSI-based importance extends the connotations of Birnbaum importance from component reliability to component strength. It is easy to obtain the specific value of SSI-based importance, but it is hard to determine the derivative of the system reliability. Therefore, Equation 1 can be transformed as the limit format based on the definition of the derivative as

$$I_j = \lim_{\Delta s_j \to 0} \frac{[R_s(t_1) - R_s(t_2)] / \Delta s_j}{[R_j(t_1) - R_j(t_2)] / \Delta s_j} \tag{2}$$

where $R_s(t_1)$ and $R_s(t_2)$ denote the system reliability before (at the time t_1) and after (at the time t_2) the change of component strength, respectively; $R_j(t_1)$ and $R_j(t_2)$ denote the component reliability before and after the change of component strength; Δs_j is the change of the strength for component *i*.

2.2. Analytic evaluation of SSI-based importance in series systems considering CCF

The structures of some systems are the series system, which will fail if any component fails, and the reliability block diagram of the series system is shown in Fig. 1.

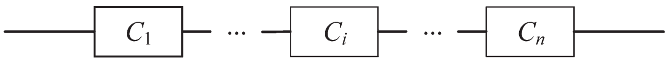

Fig. 1. Reliability block diagram of the series system

Assume the probability density function (PDF) of the strength for component *i* is $f_{si}(s)$, $i = 1, \cdots, n$. All components in the system bear the same load stress, and the corresponding PDF is $f_l(l)$. The reliability of series system can be expressed based on SSI in Equation 3:

$$R_{seri}(t) = \int_0^\infty f_l(l) \prod_{i=1}^{n} [1 - \int_0^l f_{si}(s)ds]dl \tag{3}$$

Assume that only the strength of component *j* changes. According to Equations 2 and 3, the SSI-based importance of component *j* can be described as follows:

$$\begin{aligned} I_j^{seri} &= \lim_{\Delta sj \to 0} \frac{\left\{ \int_0^\infty f_l(l) \prod_{i=1, i \ne j}^{n} [\int_l^\infty f_{si}(s)ds][\int_l^\infty (f_{sj1}(s) - f_{sj2}(s))ds]dl \right\} / \Delta s_j}{\left\{ \int_0^\infty f_l(l)[\int_l^\infty \Delta_j(s)ds]dl \right\} / \Delta s_j} \\ &= \frac{\int_0^\infty f_l(l) \prod_{i=1, i \ne j}^{n} [\int_l^\infty f_{si}(s)ds][\int_l^\infty \lim_{\Delta sj \to 0} (\Delta_j(s) / \Delta s_j)ds]dl}{\int_0^\infty f_l(l)[\int_l^\infty \lim_{\Delta sj \to 0} (\Delta_j(s) / \Delta s_j)ds]dl} \end{aligned} \tag{4}$$

where the initial strength PDF of component *j* is $f_{sj1}(s)$, and the after-change PDF is $f_{sj2}(s)$, $\Delta_j(s) = f_{sj1}(s) - f_{sj2}(s)$ denotes the strength change of component *j*.

In order to analyze the SSI-based importance clearly, we have discussed the three forms of SSI-based importance of component *j* in series systems as follows. If the strength of component *j* follows a continuous univariate distribution, Equation 4 can be simplified as follows:

$$\begin{aligned} I_j^{seri} &= \frac{\int_0^\infty f_l(l) \prod_{i=1, i \ne j}^{n} [\int_l^\infty f_{si}(s)ds][\int_l^\infty (df_{sj}(s) / ds)ds]dl}{\int_0^\infty f_l(l)[\int_l^\infty (df_{sj}(s) / ds)ds]dl} \\ &= \frac{\int_0^\infty f_l(l) \prod_{i=1, i \ne j}^{n} [\int_l^\infty f_{si}(s)ds][f_{sj}(\infty) - f_{sj}(l)]dl}{\int_0^\infty f_l(l)[f_{sj}(\infty) - f_{sj}(l)]dl} \end{aligned} \tag{5}$$

Generally, the variable PDF tends to be '0' when the variable tends to be endless. So the SSI-based importance for the series system can be written as:

$$I_j^{seri}=\frac{\int_0^\infty f_l(l)f_{sj}(l)\prod_{i=1,i\neq j}^{n}[\int_l^\infty f_{si}(s)ds]dl}{\int_0^\infty f(l)f_{sj}(l)dl}. \tag{6}$$

Supposing that the failure of components in the system is independent, the importance measure for independent components can be expressed as:

$$I_{j\_indep}^{seri}=\prod_{i=1,i\neq j}^{n}\int_0^\infty f_l(l)[\int_l^\infty f_{si}(s)ds]dl=\prod_{i=1,i\neq j}^{n}R_i, \tag{7}$$

where R_i is the reliability of component C_i.

According to Equation 6, it is clear that the strength distribution of all components is taken into consideration for calculating the SSI-based importance. However, the importance of component is independent with its strength in Equation 7. In production practice, the distribution of component strength is the statistical result of test data, which may be different because of different quality levels and different processes. Therefore, the proposed importance measure can describe the influence of strength change on system reliability well for engineering applications. The SSI-based importance can be evaluated by solving the complex analytic geometry integration for series system.

3. Monotonicity analysis of SSI-based importance for series system

The degradation of components is related to the inherent reliability, the strength mean, and the strength variance. For the traditional Birnbaum importance, the component importance has no concern with its inherent reliability, which is related to the reliabilities of other components. For the SSI-based importance of component *i*, its importance measure also has nothing to do with the inherent reliability of component *i*, but its importance measure has a close relationship with the strength mean and the strength variance. The reduction of strength mean or the increment of strength variance appears in component, which means the component begins to degrade. Therefore, the monotonicity analysis of SSI-based importance is discussed based on the changes of strength mean and the strength variance.

3.1. Monotonicity of SSI-based importance about strength mean

When component strength and stress distributions are a normal distribution, Equation 6 can be simplified base on the PDF of the normal distribution as Equation 8:

$$I_j^{seri}=\frac{\int_0^\infty \exp(-\frac{(l-\mu_l)^2}{2\sigma_l^2})\exp(-\frac{(l-\mu_j)^2}{2\sigma_j^2})\prod_{i=1,i\neq j}^{n}[\int_l^\infty \exp(-\frac{(s-\mu_i)^2}{2\sigma_i^2})ds]dl}{(2\pi)^{\frac{n-1}{2}}\prod_{i=1,i\neq j}^{n}\sigma_i\int_0^\infty \exp(-\frac{(l-\mu_l)^2}{2\sigma_l^2})\exp(-\frac{(l-\mu_j)^2}{2\sigma_j^2})dl}$$
$$=\frac{\int_0^\infty f(l)f_j(l;\mu_j,\sigma_j)\prod_{i=1,i\neq j}^{n}H_i(l)dl}{p\int_0^\infty f(l)f_j(l;\mu_j,\sigma_j)dl} \tag{8}$$

where $f(l)=\exp(-\frac{(l-\mu_l)^2}{2\sigma_l^2})$ is the function of variables μ_l and σ_l, $f_j(l;\mu_j,\sigma_j)=\exp(-\frac{(l-\mu_j)^2}{2\sigma_j^2})$ is the function of variables μ_j and σ_j, $H_i(l)=\int_l^\infty \exp(-\frac{(s-\mu_i)^2}{2\sigma_i^2})ds$ is the function of parameters of all components except component j, $p=(2\pi)^{\frac{n-1}{2}}\prod_{i=1,i\neq j}^{n}\sigma_i$.

In order to analyze the monotonicity of SSI-based importance, we can conduct the partial derivation of Equation 8 about μ_j when σ_j is constant. The result is represented by Equation 9:

$$\frac{\partial I_j^{seri}}{\partial\mu_j}=\frac{\partial I_j^{seri}}{\partial f_j(l,\mu_j)}\times\frac{\partial f_j(l,\mu_j)}{\partial\mu_j}$$
$$=\frac{\int_0^\infty f(l)\prod_{i=1,i\neq j}^{n}H_i(l)g(l)dl\int_0^\infty f(l)f_j(l,\mu_j)dl}{p[\int_0^\infty f(l)f_j(l,\mu_j)dl]^2}$$
$$-\frac{\int_0^\infty f(l)f_j(l,\mu_j)\prod_{i=1,i\neq j}^{n}H_i(l)dl\int_0^\infty f(l)g(l)dl}{p[\int_0^\infty f(l)f_j(l,\mu_j)dl]^2} \tag{9}$$

where $g(l)=\frac{\partial f_j(l,\mu_j)}{\partial\mu_j}$, $f_j(l,\mu_j)$ represents $f_j(l;\mu_j,\sigma_j)$ when σ_j is a constant.

Since the integral operation in Equation 9 is complex, a unique series system with four components is introduced to illustrate the monotonicity of SSI-based importance. The strength of components follows the normal distribution of $s_1\sim N(\mu_1,50)$, $s_2\sim N(420,50)$, $s_3\sim N(440,50)$, $s_4\sim N(460,50)$, and the same load stress on these four components follows $l\sim N(300,60)$. When μ_1 varies in the interval [350, 700], the SSI-based importance and the partial derivation of importance measure can be evaluated by Equations 8 and 9.

In order to analyze the changes of the SSI-based importance and its rate, the strength variances of components in the series systems are the same. The evaluation results are shown in Fig. 2. From the top figure, the importance value decreases when the strength mean increases, which indicates that the better the component quality is, the lower its importance value is. The bottom figure presents the partial derivative of importance, which means the change rate of importance. It is noteworthy that when the strength mean of component 1 reaches 462, the change rate is the highest at the point. The parameters of components 1 are almost the same as that of component 4 at this moment. Both of them have similar reliability because they have the same strength mean and strength variance.

3.2. Monotonicity of SSI-based importance about strength variance

In order to analyze the monotonicity of SSI-based importance, we can assume μ_j as a constant and conduct the partial derivation of Equation 8 about σ_j. The result is represented by Equation 10.

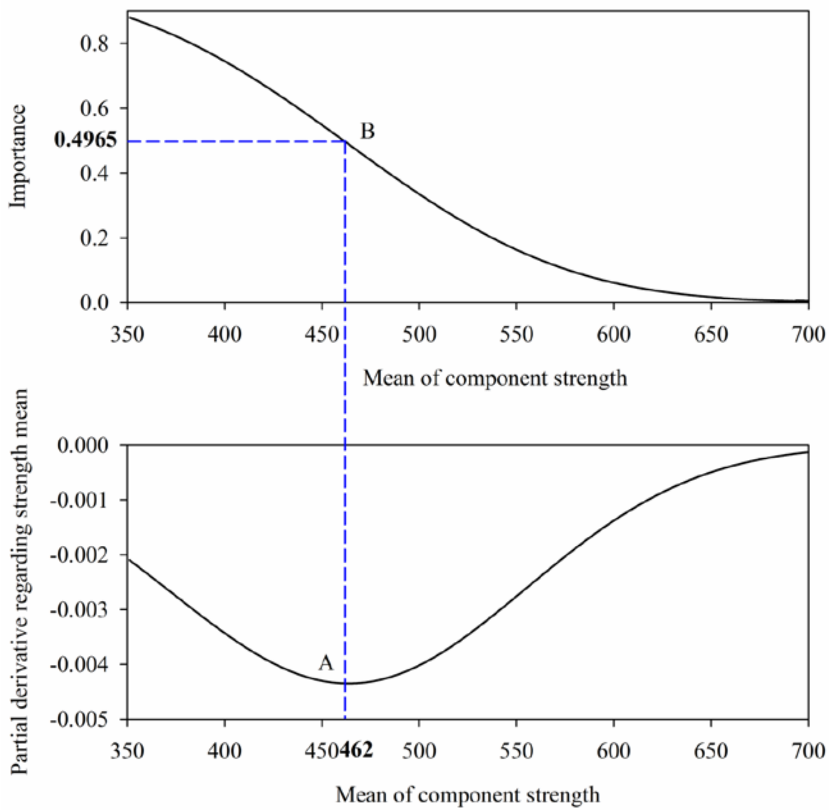

Fig. 2. The tendency of importance on the strength mean of component

tance of component will increases, which is the top one in Fig. 3. In the bottom of Fig. 3, the change rate reaches the highest value when the variance of component 1 is 22. The corresponding reliabilities of 4 components are R_{C1}=0.9698, R_{C2}=0.9635, R_{C3}=0.9797, R_{C4}=0.9894, respectively. This phenomenon illustrates that SSI-based importance increases fast when its inherent reliability is equal to the lowest reliable component.

4. Numerical experiments

In this section, we applied two numerical experiments to illustrate the methods in Sections 2 and 3 clearly. Experiment I shows the SSI-based importance ranking of 5 series systems with different component strength distributions, whose parameters are unchanged. Experiment II illustrates the changes of SSI-based importance of each component in series systems when the parameters of component 1 change, but the parameters of other components remain unchanged.

4.1. Experimental design

Experiment I: There are 5 series systems with different numbers of components, and the parameters of components are shown in Table 1. The experiment is established to illustrate the evaluation of SSI-based importance according to Equation 6, which also can determine the importance ranking of components in the series systems. The same load stress follows $l \sim N(200,30)$.

$$\frac{\partial I_j^{seri}}{\partial \sigma_j} = \frac{\partial I_j^{seri}}{\partial f_j(l,\sigma_j)} \times \frac{\partial f_j(l,\sigma_j)}{\partial \sigma_j}$$
$$= \frac{\int_0^\infty f(l) \prod_{i=1,i\neq j}^{n} H_i(l)h(l)dl \int_0^\infty f(l) f_j(l,\sigma_j)dl}{p[\int_0^\infty f(l) f_j(l,\sigma_j)dl]^2}$$
$$- \frac{\int_0^\infty f(l) f_j(l,\sigma_j) \prod_{i=1,i\neq j}^{n} H_i(l)dl \int_0^\infty f(l)h(l)dl}{p[\int_0^\infty f(l) f_j(l,\sigma_j)dl]^2} \quad (10)$$

where $h(l) = \frac{\partial f_j(l,\sigma_j)}{\partial \sigma_j}$, $f_j(l,\sigma_j)$ represents $f_j(l;\mu_j,\sigma_j)$ when μ_j is constant.

Similarly, a unique series system with four components is adopted to analyze the monotonicity of SSI-based importance with strength variance. The component follows the normal distributions as $s_1 \sim N(400,\sigma_1)$, $s_2 \sim N(440,50)$, $s_3 \sim N(460,50)$, $s_4 \sim N(480,50)$. The same load stress follows $l \sim N(300,60)$. In order to analyze the changes in the SSI-based importance and its rate with the increase of component variance, the strength mean of components in the series systems is unchanged. If σ_1 varies in the interval [10, 110], the SSI-based importance and its rate can be evaluated by Equations 8 and 9, which are shown in Fig. 3. Since the increase of strength variance indicates the component quality decreases, the SSI-based impor-

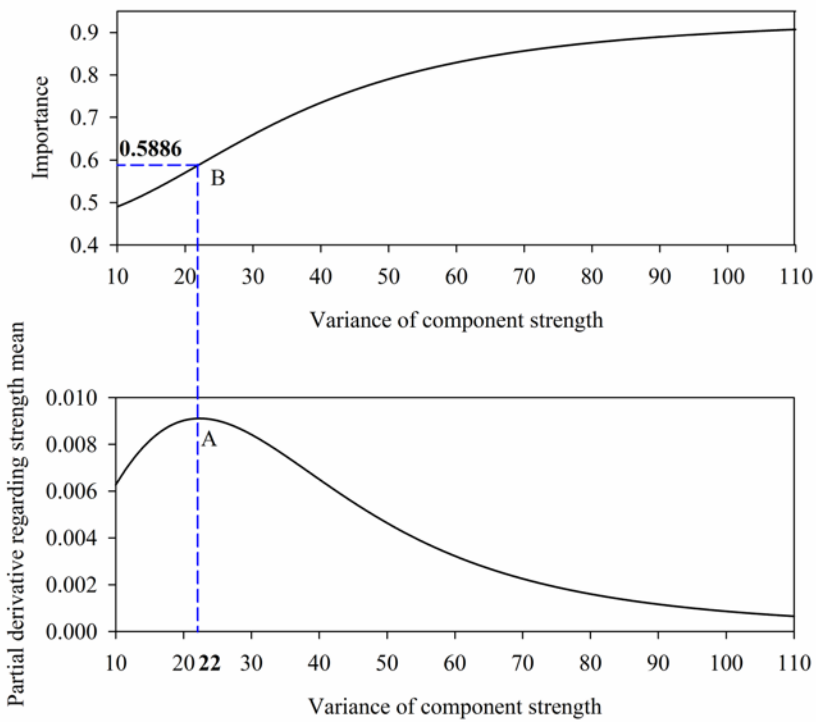

Fig. 3. The tendency of importance on strength variance of component

Experiment II: A four-component series system is introduced to illustrate the changes of SSI-based importance if the parameters of component 1 change and the parameters of other components are un-

Table 1. The parameters of components in Experiment I

Component #	System 1	System 2	System 3	System 4	System 5
1	$N(270,35)$	$N(290,30)$	$N(400,35)$	$N(315,45)$	$N(350,45)$
2	$N(370,60)$	$N(350,15)$	$N(300,45)$	$N(310,50)$	$N(255,10)$
3	/	$N(350,20)$	$N(335,55)$	$N(365,25)$	$N(380,25)$
4	/	$N(360,55)$	$N(280,60)$	$N(370,45)$	$N(390,10)$
5	/	/	$N(360,40)$	$N(280,40)$	$N(350,15)$
6	/	/	$N(290,15)$	$N(320,20)$	$N(360,50)$
7	/	/	/	$N(310,15)$	$N(360,45)$
8	/	/	/	$N(350,35)$	$N(300,25)$
9	/	/	/	/	$N(350,60)$
10	/	/	/	/	$N(275,10)$

Table 2. The parameters of components in Experiment II

Case #	Component 2	Component 3	Component 4
1	$N(200,30)$	$N(250,30)$	$N(300,30)$
2	$N(200,30)$	$N(250,30)$	$N(300,50)$
3	$N(200,30)$	$N(250,50)$	$N(300,30)$
4	$N(200,50)$	$N(250,30)$	$N(300,30)$
5	$N(200,30)$	$N(250,50)$	$N(300,50)$
6	$N(200,50)$	$N(250,50)$	$N(300,30)$
7	$N(200,50)$	$N(250,30)$	$N(300,50)$
8	$N(200,50)$	$N(250,50)$	$N(300,50)$

changed. The purposes of this experiment are to illustrate the changes of SSI-based importance for component 1 and analyze the changes of importance for other components except for the component 1. There are 6 cases that depend on the variance of components 2-4 comparing with the variance of stress. All the parameters of components are listed in Table 2 because the variance of component is 30 or 50, which means the strength variance of component is lower or higher than that of load stress. This experiment is introduced to analyze the changes of importance ranking for this specific series system. The same load stress follows $l \sim N(150,40)$, and the strength of component 1 follows $s_1 \sim N(\mu_1,\sigma_1)$. Let σ_1 vary in the interval [20, 50], and let μ_1 vary in the interval [180, 400].

4.2. Results analysis of experiments

4.2.1 Results of Experiment I

The SSI-based importance of all components in the series systems can be evaluated based on Equation 6, and the importance ranks of all components also can be obtained by comparing the importance values of all components. The results of Experiment I are shown in Table 3, which lists the importance value and importance ranks of all components in 5 series systems.

From Table 3, the strength of components with lower mean and higher variance has a higher importance measure, such as component 1 is more important than components 2 and 3 in System 2. If the strength mean of component is the same, the strength of component with higher variance has higher importance, such as component 2 ($s_2 \sim N(310,50)$) is more important than component 7 ($s_7 \sim N(310,15)$) in System 4. Similarly, if the strength variance of component is the same, the higher the strength mean of component is, the less important the component is, such as the component 10 ($s_{10} \sim N(275,10)$) is less important than component 2 ($s_2 \sim N(255,10)$) in System 5. If the variance and mean of component strength has a similar percentage increase (or decrease), the importance will decrease (or increase), which means the mean of component strength has more effect on the changes of component importance. For example, the strength mean of component 6 decreases 27.5% compared with that of component 1 in System 3, and the strength variance increases 57.1% from component 1 to component 7; but the SSI-importance of component increases with the decrease of strength mean. Therefore, the SSI-based importance of components is

Table 3. The SSI-based importance ranks of 5 series systems in Experiment I

System #	SSI-based importance value	SSI-based importance ranks
1	[0.9856, 0.7928]	$I_1 > I_2$
2	[0.9743, 0.0001, 0.2981, 0.9091]	$I_1 > I_4 > I_3 > I_2$
3	[0.2067, 0.7378, 0.7033, 0.9178, 0.4603, 0.3545]	$I_4 > I_2 > I_3 > I_5 > I_6 > I_1$
4	[0.7586, 0.8192, 0.1328, 0.5754, 0.8847, 0.2520, 0.1996, 0.4634]	$I_5 > I_2 > I_1 > I_4 > I_8 > I_6 > I_7 > I_3$
5	[0.5918, 0.8648, 0.0063, 2.36E-40, 1.04E-07, 0.6412, 0.5460, 0.3893, 0.7914, 0.1527]	$I_2 > I_9 > I_6 > I_1 > I_7 > I_8 > I_{10} > I_3 > I_5 > I_4$

higher when the strength mean of component is lower, or the strength variance of component is higher, and the mean has a higher effect on the SSI-based importance than that of variance.

4.2.2 Results of Experiment II

If the strength mean or strength variance of component 1 changes, then the changing tendency of SSI-based importance for all components can be recorded by Experiment II. From the results of Experiment II, we can find the SSI-based importance of any components in 8 cases has a similar change tendency. For component 1, the SSI-based importance decreases with the increase of strength mean of component 1, while the importance increases with the increase of strength variance. However, for components 2, 3, and 4, the SSI-based importance increases with the increase of strength mean of component 1, and the importance almost remains unchanged with the increase of variance when the strength mean is determined. In order to illustrate the detailed changes of importance, the results of cases 1 and 8 are shown in Fig. 4 and Fig. 5, respectively.

From Fig. 4, the SSI-based importance of component is close to 0 when strength mean is 25 and strength variance is 400. When the strength mean is fixed, the importance decreases with the decrease of the strength variance. Such as the importance is almost 0.2 when strength mean is 400 and strength variance is 56. However, the importance of the other three components increases with the increase of the strength mean for component 1, such as the importance of component 2 is 0.96 when strength mean is 390 while the importance becomes 0.47 when strength

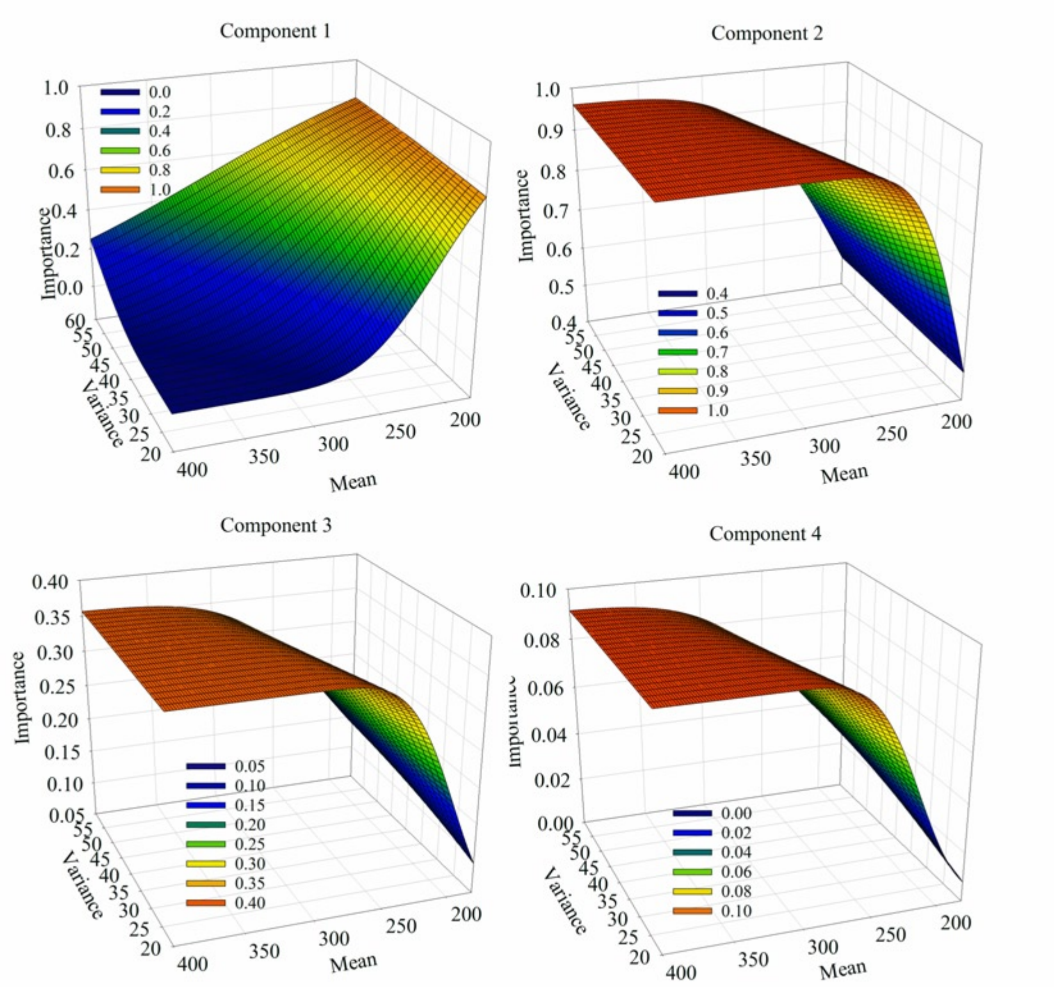

Fig. 4. The changes of SSI-based importance for case 1 in Experiment II

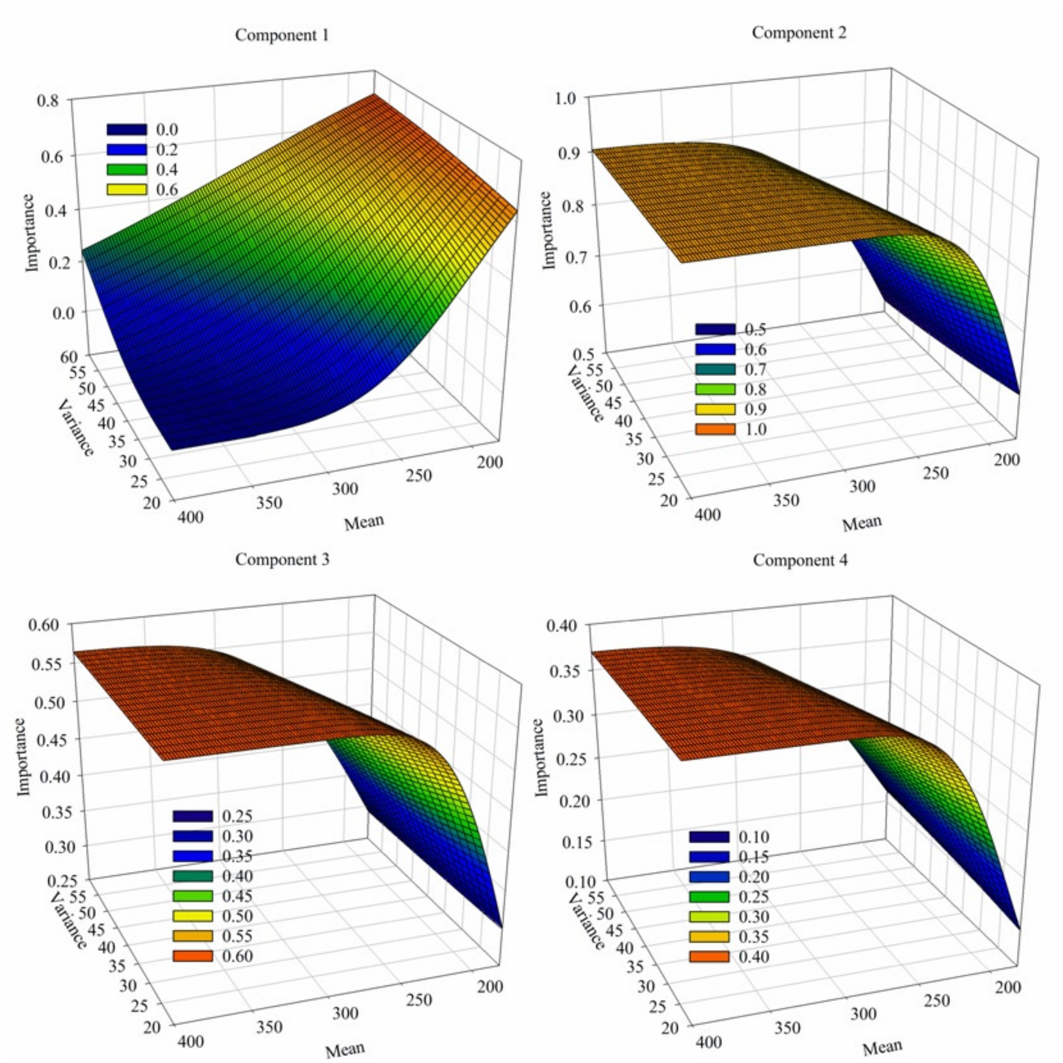

Fig. 5. The changes of SSI-based importance for case 8 in Experiment II

mean is 180. When the strength mean is known, the importance of these three components is almost unchanged. Component 1 has the lowest importance value, and component 2 has the highest importance when the strength mean of component 1 is higher.

From Fig. 5, we can find that the results of case 8 are similar to that of case 1 while the importance values are different. Because the strength variance of components 2, 3, and 4 becomes higher, the importance value of these three components is higher than that of case 1, but the change tendency is also the same with case 1.

Because the strength variance has little effect on the importance ranks, the importance ranks should be discussed with the increase of strength mean when the strength variance is determined. For each case, the strength variance is determined randomly, and the change of importance ranks is shown in Fig. 6. From Fig. 6, the SSI-based importance of component 1 decreases with the increase of the strength mean of component 1, but the importance of other components increases with the increase of the strength mean of component 1. The importance ranks of components 2, 3, and 4 are fixed no matter the parameters of component 1 are, and the importance of component 1 decreases from the highest to the lowest with the increase of strength mean. From example, the SSI-based importance of component ranks as the highest one when the strength mean is less than 205 in case 3, and the importance ranks of components is $I_1 > I_2 > I_3 > I_4$; the importance ranks of components is $I_2 > I_1 > I_3 > I_4$ when the strength mean of component is in the interval [205, 225]; the importance ranks of components is $I_2 > I_3 > I_1 > I_4$ when the strength mean of component is in the interval [225, 331]; the importance ranks of components is $I_2 > I_3 > I_4 > I_1$ when the strength mean of component is larger than 331.

Therefore, these two experiments illustrated the contributions of the proposed importance. Experiment I described how to determine the importance ranks once the parameters of components are known; Experiments II verified the monotonicity of SSI-based importance about strength mean or strength variance, and the changes of importance ranks in series systems are illustrated.

5. Component replacement method considering SSI-based importance

From the results in Section 4, the components with different combinations of strength mean and strength variance may have different SSI-based importance. For the component whose parameters can be adjusted, the SSI-based importance of this component increases with the increment of the strength mean but decreases with the increment of strength variance, There are different combinations of strength mean and variance for the component to remain the importance unchanged. However, sometimes although the importance of components with different combinations of strength mean and variance are the same while the combination may change the importance ranks of components. The SSI-based importance and the importance ranks of this component after replacing should be the same as before replacing. Therefore, a new component replacement method is developed where

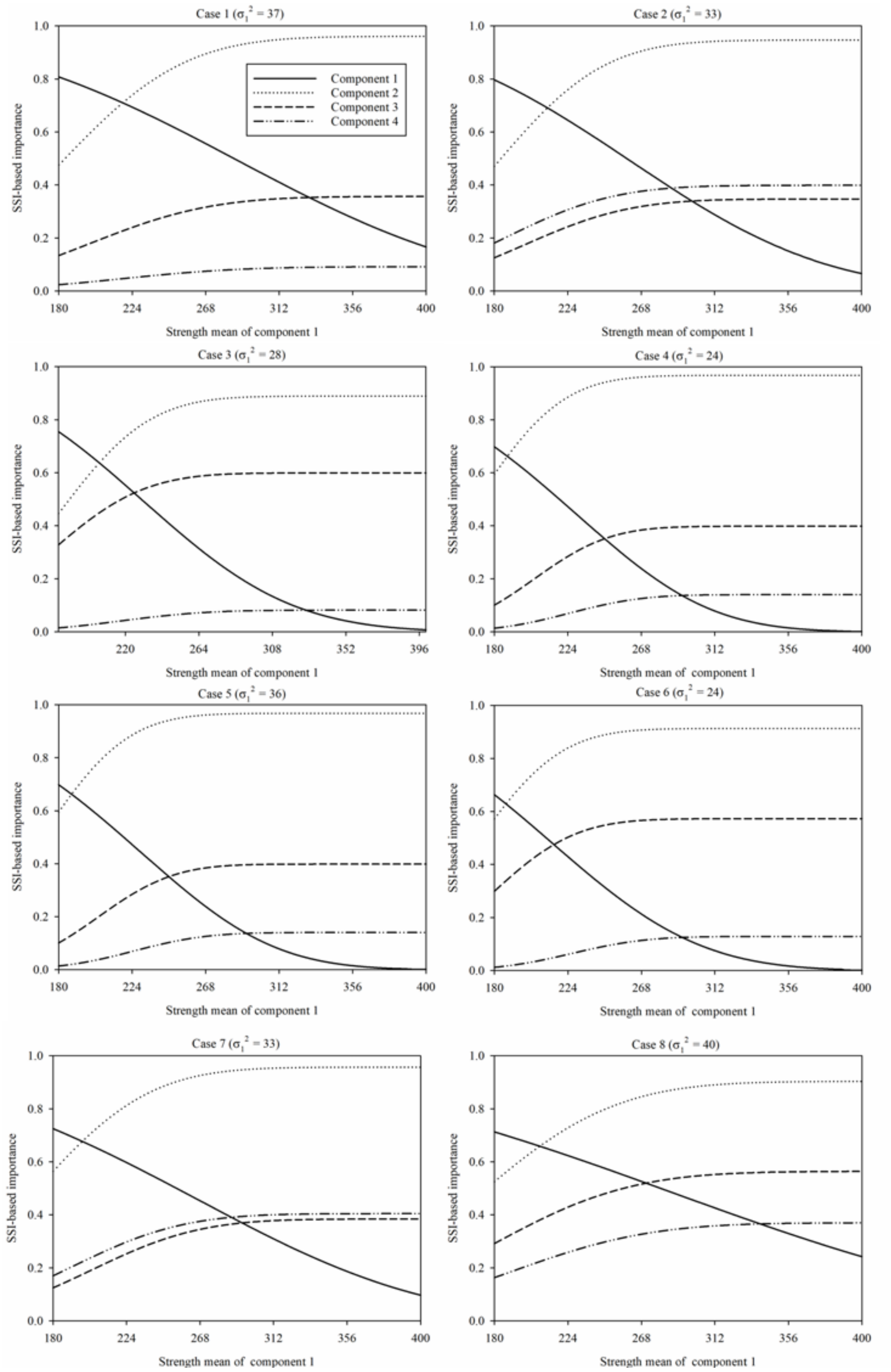

Fig. 6. The changes of SSI-based importance for case 8 in Experiment II

both the importance value and the importance ranks should remain unchanged after replacing the component.

5.1. The component replacement search algorithm

In order to find the general solutions, assuming component strength and stress distributions are normal distribution in a series system, and all parameters of distributions are known. If the component k can be replaced by the component j, the SSI-based importance of these two components should be the same. If I_k is equal to I_j, the relationship of strength mean and strength variance between components C_k and C_j based on Equation 11, which is shown as follows:

$$\int_0^{\infty} \exp\left(-\frac{(l-\mu_l)^2}{2\sigma_l^2}\right)\exp\left(-\frac{(l-\mu_j)^2}{2\sigma_j^2}\right)\left\{\prod_{i=1,i\neq j}^{n}\left[\int_l^{\infty}\exp\left(-\frac{(s-\mu_i)^2}{2\sigma_i^2}\right)ds\right]-p\right\}dl=0 \tag{11}$$

where $p = I_k(2\pi)^{\frac{n-1}{2}}\prod_{i=1,i\neq j}^{n}\sigma_i$ is a constant, μ_j and σ_j are unknown parameters.

Considering that the difficulty of solving μ_j with σ_j explicitly, a component replacement search algorithm is proposed to determine the parameters of component after replacing, the process of component replacement considering SSI-based importance can be summarized in Fig. 7.

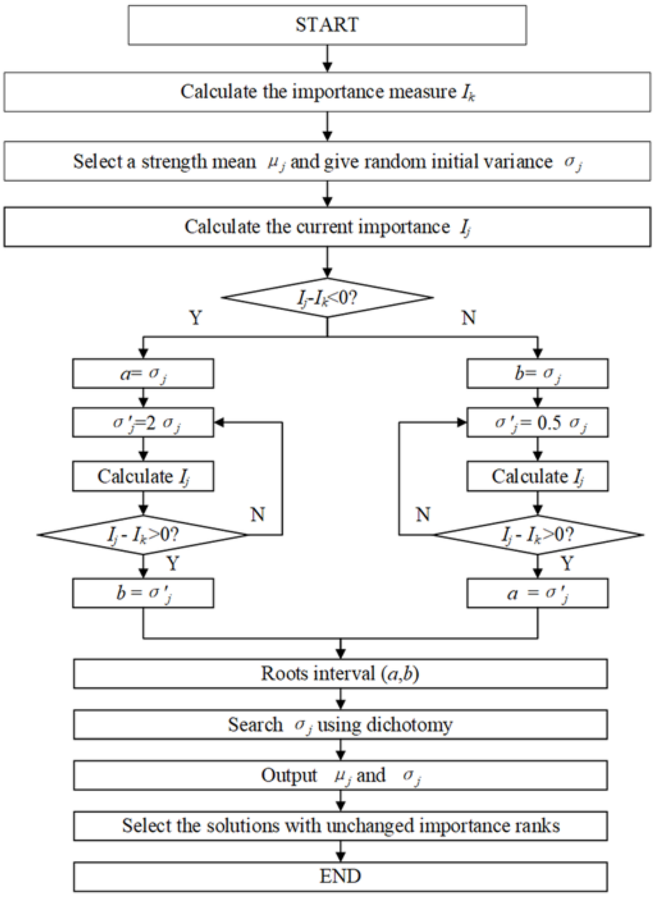

Fig. 7. The component replacement search algorithm

5.2. An example to illustrate the search process

A simple series system contains four infrastructures {C_1, C_2, C_3, C_4} with $s_1 \sim N(800,45)$, $s_2 \sim N(850,60)$, $s_3 \sim N(850,50)$, $s_4 \sim N(870,55)$, and the stress follows $l \sim N(600,40)$. The initial importance measure of component 1 is 0.9877, which can be calculated by Equation 6.

If we select

μ_1=[801,803,805,807,809,811,813,815,817,819,821,823,825,827,829] respectively, the strength variance σ_1 of component 1 can be obtained based on the component replacement search algorithm. The strength variance of component 1 and the importance ranks of components are listed in Table 4.

From Table 4, the solutions are listed with the increase of the strength mean of component 1, and the importance ranks of components are changed when the strength mean is larger than 817. According to the previous analysis, the solution that changes the importance ranking should be excluded from the available set, because the importance ranks of all components in the system should be unchanged after replacement. Sometimes, the available solution may not exist; we need to narrow the interval of strength mean. Actually, for engineering practice, other factors, such as the constraints of cost and resources should be considered to determine the available replacement solution.

Table 4. The result of the component replacement search algorithm

μ_1	σ_1	Importance ranks	Available solution
800	45.00	$I_1 > I_2 > I_4 > I_3$	✓
801	45.24	$I_1 > I_2 > I_4 > I_3$	✓
803	45.70	$I_1 > I_2 > I_4 > I_3$	✓
805	46.19	$I_1 > I_2 > I_4 > I_3$	✓
807	46.65	$I_1 > I_2 > I_4 > I_3$	✓
809	47.11	$I_1 > I_2 > I_4 > I_3$	✓
811	47.56	$I_1 > I_2 > I_4 > I_3$	✓
813	48.01	$I_1 > I_2 > I_4 > I_3$	✓
815	48.45	$I_1 > I_2 > I_4 > I_3$	✓
817	48.89	$I_1 > I_2 > I_4 > I_3$	✓
819	49.33	$I_2 > I_1 > I_4 > I_3$	×
821	49.77	$I_2 > I_1 > I_4 > I_3$	×
823	50.21	$I_2 > I_1 > I_4 > I_3$	×
825	50.63	$I_2 > I_1 > I_4 > I_3$	×
827	51.04	$I_2 > I_1 > I_4 > I_3$	×
829	51.46	$I_2 > I_1 > I_4 > I_3$	×

6. Conclusions

Some conclusions of SSI-based importance can be summarized as follows. (1) SSI-based importance of components, whose parameter changes, reduces monotonically with the increase of strength mean or increases monotonically with the increase of strength variance. (2) The strength mean has more impact on the SSI-based importance change, while the strength variance has less effect on the change of SSI-based importance. (3) The components with different combinations of strength mean and strength variance can be replaced when the importance ranks of components are unchanged after replacement. In future, the complex interdependency of components and systems should be considered, and the SSI model also can be applied to the system with more complicated structure.

Acknowledgment

The authors gratefully acknowledge the financial support for this research from the Xi'an Technological University Teaching Reform Research Project (No. 16JGY07).

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