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Availability-based engineering resilience metric and its corresponding evaluation methodology

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ABSTRACT

Several resilience metrics have been proposed for engineering systems (e.g., mechanical engineering, civil engineering, critical infrastructure, etc.); however, they are different from one another. Their difference is determined by the performances of the objects of evaluation. This study proposes a new availability-based engineering resilience metric from the perspective of reliability engineering. Resilience is considered an intrinsic ability and an inherent attribute of an engineering system. Engineering system structure and maintenance resources are principal factors that affect resilience, which are integrated into the engineering resilience metric. A corresponding dynamic-Bayesian-network-based evaluation methodology is developed on the basis of the proposed resilience metric. The resilience value of an engineering system can be predicted using the proposed methodology, which provides an implementation guidance for engineering planning, design, operation, construction, and management. Some examples for common systems (i.e., series, parallel, and voting systems) and an actual application example (i.e., a nine-bus power grid system) are used to demonstrate the application of the proposed resilience metric and its corresponding evaluation methodology.

1. Introduction

Resilience is the capability of an entity to recover from an external disruptive event. To date, the concept of resilience has been spread from ecology [1,2] to various fields, such as economics [3,4], psychology [5,6], and sociology [7,8]. In comparison with the research in non-engineering contexts, only a small proportion of resilience-related research exists in the field of engineering [9–11]. For engineering systems, such as mechanical engineering, civil engineering, critical infrastructure, etc., different definitions are proposed depending on the objects of evaluation. The National Infrastructure Advisory Council defines critical infrastructure resilience as the capability to reduce the magnitude and/or duration of disruptive events. The effectiveness of a resilient infrastructure or enterprise depends upon its capability to anticipate, absorb, adapt to, and/or rapidly recover from a potentially disruptive event [12]. The American Society of Mechanical Engineers defines resilience as the capability of a system to sustain external and internal disruptions without discontinuity of performing the system function or, if the function is disconnected, to fully recover the functions rapidly [13]. Haimes [45] defined resilience as the capability of the system to with-stand a major disruption within acceptable degradation parameters, and recover within an acceptable time and composite costs and risks. Many other researchers have also proposed their own engineering resilience definitions from different perspectives [14–17].

According to the definitions above, various resilience metrics and their corresponding evaluation methodologies have been developed [18–23]. For example, Dessavre et al. [18] defined a new model and visual tools that improve the capabilities to characterize the resilience behavior of complex systems by extending existing time-dependent resilience functions. Bruneau et al. [19] defined four dimensions of resilience, namely, robustness, rapidity, resourcefulness, and redundancy, in the well-known resilience triangle model in civil infrastructure and proposed a deterministic static metric for measuring the resilience loss of a community to an earthquake. Henry et al. [20] proposed a time-dependent quantifiable resilience metric corresponding to a specific figure-of-metric, which was evaluated at a certain time period under disruptive events. Francis et al. [21] proposed a resilience metric that incorporates three resilience capabilities, including adaptive capacity, absorptive capacity, recoverability, and the time to recovery. Hosseini et al. [22] used static Bayesian networks to model infrastructure re-

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Fig. 1. Resilience-related properties of engineering system.

Fig. 2. Availability of a system subject to degradation and shock.

silence and used a case of inland waterway port to demonstrate the proposed method.

Although various resilience metrics have been developed, quantifying the resilience for a specific engineering system remains a challenge because of internal and external factors involved in such metrics. From the above definitions and metrics, resilience overlaps with a number of existing concepts, such as adaptability [24], robustness [24,25], redundancy [26], flexibility [27], survivability [27], recoverability [28,29], rapidity [25,30], and resourcefulness [30]. Here, we consider resilience as an intrinsic capability and an inherent attribute of an engineering system itself. It is composed of two properties, namely, performance- and time-related properties. System structure determines performance-based properties, such as robustness, adaptability, redundancy, flexibility, and survivability, whereas maintenance resource determines time-related properties, such as reparability, recoverability, rapidity, and resourcefulness. Similar with the reliability in reliability engineering, external factors, such as disturbance, attack, and disaster events, are not intrinsic properties of resilience in engineering system and are thus not involved in the resilience metric (see Fig. 1). Therefore, when an engineering system is designed and maintenance resource is allocated, the resilience of this system is determined. Hence, the structure and maintenance resource in the engineering system form a unified whole, thereby determining the engineering resilience of the system. The promoted viewpoint may be different from the dominant ones [46,47]; however, it can provide an implementation guidance for engineering planning, design, operation, construction, and management.

In this study, we aim to develop a new availability-based engineering resilience metric from the essence and property of resilience in engineering system. From the perspective of reliability engineering, steady-state availability and steady-state time can be used to represent the performance- and time-related properties. Each engineering system has its own availability; thus, the resilience value can be obtained easily according to the steady-state availability and steady-state time. Therefore, the metric is suitable for every engineering system. The rest of this paper is organized as follows. Section 2 presents the proposed availability-based engineering resilience metric and its corresponding evaluation methodology. Section 3 adopts some examples for common systems to demonstrate the application of the proposed resilience metric and its evaluation methodology. Section 4 adopts an actual example for a nine-bus power grid system to demonstrate the application of the proposed method. Section 5 summarizes the contributions of this paper.
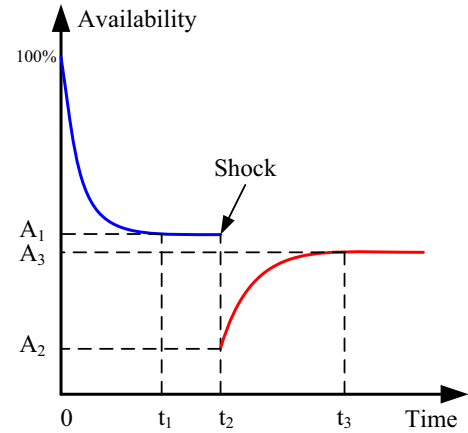
2. Resilience metric and evaluation methodology

2.1. Availability-based engineering resilience metric

Each engineering system has its own availability, where an item is capable to be in a state of performing a required function under given conditions at a given time or time interval, assuming that the required external resources are provided. The availability of an engineering system decreases continuously to reach a steady-state availability A_1 at steady state t_1 from the initial time with the initial availability of 100%. This progress is caused by degradation of components and daily maintenance of the system. Suppose an external shock occurs at time t_2, the availability instantaneously decreases to a post-shock transient-state availability A_2 and then increases to a new equilibrium state A_3. This progress is also caused by emergency repair after shock, as well as degradation of components. The blue line in Fig. 2 represents the availability considering the degradation of components and daily system maintenance without external shocks, and the red line represents the availability considering the emergency repair after shock and degradation of components.

The steady-state availability A_1, post-shock transient-state availability A_2, post-shock steady-state availability A_3, steady-state time t_1, and post-shock steady-state time $(t_3 - t_2)$ are determined by the structure of the engineering system and maintenance resource, such as redundant structure, failure rate, and repair rate. High redundancy, low failure rate, or high repair rate results in high steady-state availability and short steady-state time before and after any shocks. This condition accords with the essence and property of resilience. Therefore, steady-state availability and low steady-state time are used to represent the performance- and time-related properties of engineering resilience. Thus, quantifying the resilience with an appropriate resilience metric is no longer a challenge given that steady-state availability and steady-state time are easy to obtain.

The proposed resilience metric aims to compare the resilience of different systems that achieve the same functions, thereby identifying the different internal factors that contribute to it. In this study, we develop a resilience metric that incorporates performance- and time-related properties using steady-state availability and steady-state time before and after external shocks. The value of resilience increases with the increase of availability A and the decrease of recovery time t. Thus, $A/\ln(t)$ is used to describe the degree of resilience. The natural logarithm function $\ln(x)$ is used to balance the level of effects between availability A and recovery time t. The resilience metric is considered to be the product of $A/\ln(t)$ before and after external shocks. Therefore, the final developed resilience metric is given as follows:

$$\rho = \frac{A_1}{n \ln(t_1)} \sum_{i=1}^{n} \frac{A_2^i A_3^i}{\ln(t_3^i - t_2^i)}, \tag{1}$$

where n is the number of shocks, and $i \in [1, n]$.

Given that the external factors are random and unpredictable, they are not factors of resilience and not involved in the resilience metric. The external factors only trigger a "bounce back," which is similar to the spring system, where an external force F can extend or compress a spring by some distance X and the spring can bounce back to the initial balance once the force F is removed. According to Hooke's law, the stiffness of the spring can be expressed as $k = F/X$. It is a constant factor characteristic of spring, which is determined by the spring itself and not by the force. The defined resilience ρ is similar with k; however, for the engineering system, the external factors and responses of this system are not directly proportional. Therefore, we determine a series of shocks on the engineering system, which result in the common cause failure of components. The prior probability of common cause failure for each component is defined as

$$p_i = \frac{i}{n+1},\tag{2}$$

where $i \in [1, n]$. A shock can lead to a common cause failure of components with any prior probability. The proposed resilience metric is used to evaluate, optimize, compare, and design systems only if n is the same for each system. A larger value of n indicates more simulated shocks. When the number of shocks is more than 9, the resilience slightly changes. Therefore, we select $n = 9$ to evaluate system resilience.

For different shocks, the repair rates of components are completely different with fixed maintenance resources. When a shock is serious, the maintenance resources are dispersed, thereby causing low repair rates of components. That is, a larger prior probability of common cause failure indicates a smaller repair rate of components. To simplify, we define the repair rate of component under different shocks as

$$\mu_i = (1 - p_i)\mu,\tag{3}$$

where μ is the repair rate of each component under normal circumstances. Notably, other relationships between repair rate and prior probability of common cause failure, $\mu_i = f(p_i)$, can also be modeled and used to calculate the availability and subsequent resilience.

Based on the prior probabilities of common cause failure and corresponding repair rates of components, the steady-state availability of the engineering system can be obtained as follows:

$$A(\infty) = \lim_{t \to \infty} A(t),\tag{4}$$

Notably, a real steady-state availability does not exist. In practice, we therefore define steady-state availability as the availability when the difference within five continuous time point (hour) is equal to or less than 10^{-5}, and the time is termed as steady-state time.

2.2. Engineering resilience evaluation methodology

Evaluating the availability of engineering systems is important in resilience evaluation. Several approaches can be used to evaluate the steady-state availability, such as reliability block diagram [31], fault tree [32], Monte Carlo simulation [33], and Markov chain [34]. In this current work, a dynamic-Bayesian-network-based evaluation methodology is proposed to calculate the steady-state availability, steady-state time, and subsequent resilience of engineering systems. Bayesian network is a probabilistic graphical model that represents a set of random variables, including their conditional dependencies through directed acyclic graphs. It is considered to be one of the most useful models in the field of probabilistic knowledge representation and reasoning [35,43,44]. Dynamic Bayesian networks are a long-established extension to ordinary Bayesian networks and allow the explicit modeling of changes over time. In view of classical probabilistic temporal models, such as Markov chains, dynamic Bayesian networks are stochastic transition models factored over a number of random variables, over which a set of conditional dependency assumption is defined [36]. We adopt dynamic Bayesian networks to predict the future state of variables considering the current observation of variables. That is, we can predict the

steady-state availability and steady-state time of an engineering system on the basis of the current state of components, such as when external shocks destroy some components.

Engineering resilience evaluation methodology with dynamic Bayesian networks consists of the following five procedures:

(1) Structural modeling of dynamic Bayesian networks is completed by using structural relationship methods, mapping algorithms, or structure learning methods;
(2) Expert elicitation with noisy models or parameter-learning methods are used to model the parameters of dynamic Bayesian networks;
(3) Availability is evaluated by using exact or approximated inference algorithms;
(4) Resilience is evaluated using the resilience metric shown in Eqs. (1)–(4); and
(5) Sensitivity analysis is conducted to research the influences of failure and repair actions on the resilience of engineering systems.

3. Examples for common systems

3.1. Series, parallel, and voting systems

Many systems in practical engineering can be abstracted as series, parallel, or voting system. Taking subsea blowout preventer system as an example, the control stations, control pods, annular preventer, and ram preventer are redundantly configured; thus, three control stations, two control pods, several annular preventers, and several ram preventers are considered in parallel. The entire system can be considered a series of control stations, triple modular redundancy controllers, subsea control pods, annular preventers, lower marine riser package connector, ram preventer, and wellhead connector because the complete failure of each component category causes failure of the subsea blowout preventer system [34]. In the current work, we adopt some examples for the common systems to demonstrate the application of the availability-based resilience metric and its evaluation methodology.

Series, parallel, and voting systems are an abstract system composed of three series components, three parallel components, and three voting components, denoted by S3P3V3 (See Fig. 3a). The series subsystem works only when all of the three series components S1, S2, and S3 work; the parallel subsystem works when any of the three components P1, P2, or P3 works; the 2-out-of-3 (2oo3) voting system works when at least 2 components of V1, V2, and V3 work. The entire system works only when all of the three subsystems work, which is equivalent to a series system. Similarly, we use S2P3V3 to denote a series system composed of two series components, three parallel components, and three voting components (See Fig. 3b), and S3P2V3 to denote a series system composed of three series components, two parallel components, and three voting components (See Fig. 3c).

3.2. Structural modeling of dynamic Bayesian networks

For these series, parallel, and voting systems, the structural models of dynamic Bayesian networks are established by using the structural relationship of each component. Taking S3P3V3 system as an example, the components and their states are denoted by root nodes, including S1, S2, S3, P1, P2, P3, V1, V2, and V3 at a specific time slice of dynamic Bayesian networks (e.g., Slice1: t; see Fig. 4). A is the final leaf node of the network, which represents the state of the entire system. Each root node has two states (i.e., *work* and *fail*). For node A, the probabilities of work and fail indicate the transient availability and transient unavailability, respectively. We artificially added several intermediate nodes, including S, P, and V, to simplify the conditional probability table of related nodes. The causal relationship between the nodes are connected by intra slice arcs.

Dynamic Bayesian networks are essentially replications of static Bayesian networks over n time slices between t and $t + (n-1)\Delta t$. A set
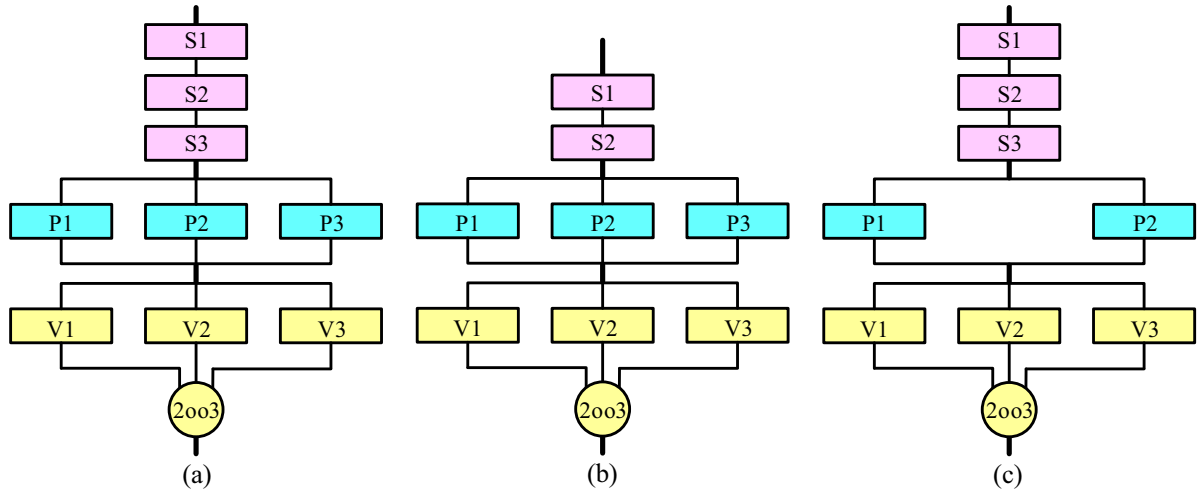
Fig. 3. Simple systems composed of series, parallel, and voting subsystems: (a) S3P3V3, (b) S2P3V3, and (c) S3P2V3.
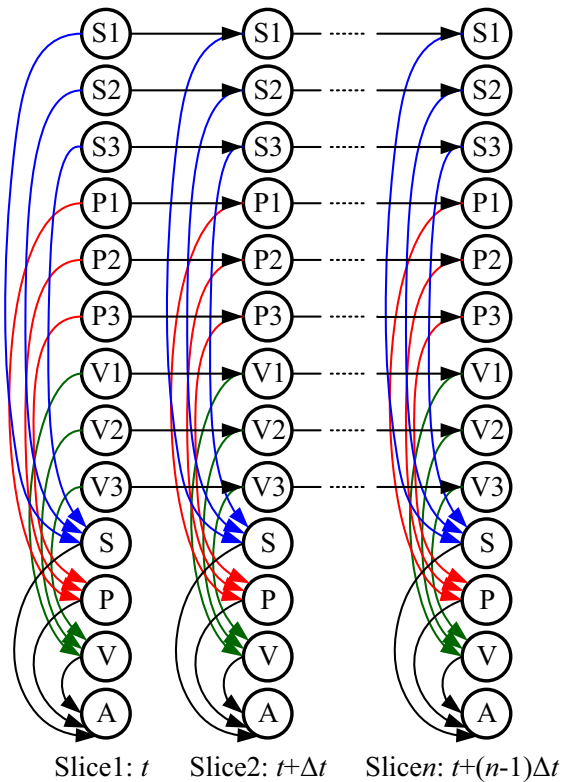

Fig. 4. Dynamic Bayesian networks of S3P3V3 system.

of inter arcs between adjacent time slices t and $t+\Delta t$ connects the corresponding nodes of components, which represent the dynamic degradation process and daily maintenance or emergency repair of components. All the information required to predict a state at time $t+\Delta t$ is contained in the description at time t, and no information about earlier times is required; thus, the process possesses the Markov property.

3.3. Parameter modeling of dynamic Bayesian networks

The parameter model of dynamic Bayesian networks is composed of intra and inter slice parameter models. For the intra slice parameter model, the marginal prior probabilities are assigned to them according to the resilience metric in Eq. (2), and the conditional probability tables

Table 1
Failure and repair rates of components in series, parallel, and voting systems.

System	Component	Failure rate	Repair rate
Series, parallel, and voting systems	S	0.833e-3	0.500
	P	2.083e-3	0.330
	V	1.389e-3	0.670

are determined using the series, parallel, and voting relationship. For the inter slice parameter model, we use Markov state transition relationship to determine the dynamic degradation process and daily maintenance or emergency repair of components.

In dynamic Bayesian networks, the inter slice parameter model is the probability of nodes between time slices t and $t+\Delta t$. For the components of S3V3P3 system, we suppose that the failure and repair follow an exponential distribution, that is, all of the transition rates, including failure and repair rates, are constant. Given that the process possesses the Markov property, the probability is determined using a Markov-state transition relationship. Hence, the transition relationships between consecutive nodes can be expressed as follows:

$$p(X_{t+\Delta t} = work | X_t = work) = e^{-\lambda \Delta t}, \tag{5}$$

$$p(X_{t+\Delta t} = fail | X_t = work) = 1 - e^{-\lambda \Delta t}, \tag{6}$$

$$p(X_{t+\Delta t} = fail | X_t = fail) = e^{-\mu \Delta t}, \tag{7}$$

$$p(X_{t+\Delta t} = work | X_t = fail) = 1 - e^{-\mu \Delta t}, \tag{8}$$

where X is the root node, λ is the failure rate of a component, and μ is the repair rate of a component. For the S3P3V3, S2P3V3, and S3P2V3 systems, we provide the same failure and repair rates for each component (see Table 1).

3.4. Resilience evaluation

The goal of inference in a dynamic Bayesian network is to compute the marginal $p(X_{t+h}|y_{1:t})$ when $y_{1:t}$ is observation. $h=0$, $h<0$, and $h>0$, indicate filtering, smoothing, and prediction, respectively. We use the following prediction of dynamic Bayesian networks to evaluate the resilience value of engineering systems. Junction tree algorithm for propagation analysis is conducted, where the joint probability for the model from the conditional probability structure of the dynamic Bayesian networks is calculated in a computationally efficient manner.

$$p(Y_{t+h} = h|y_{1:t}) = \sum_x p(Y_{t+h} = h | X_{t+h} = x) p(X_{t+h} = x|y_{1:t}) \tag{9}$$

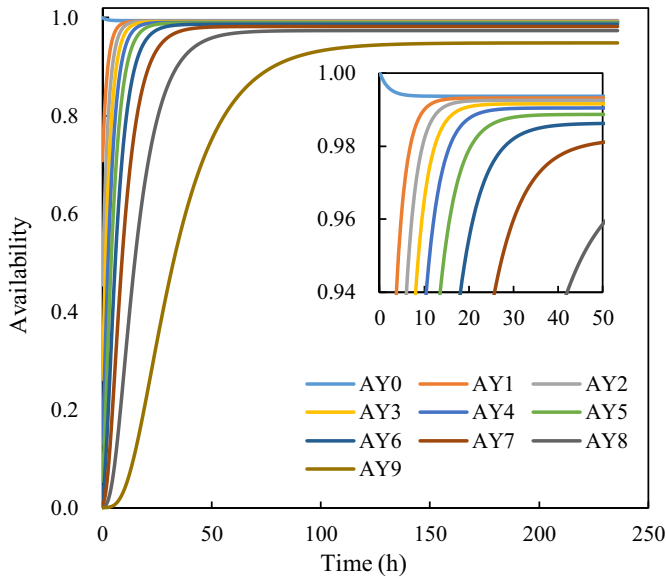Fig. 5. Availability of S3P3V3 system subject to degradation and different shocks.

Fig. 6. Sensitivity of failure rates of components of S3P3V3 system.

Fig. 7. Sensitivity of repair rates of components of S3P3V3 system.

The trends of availability without external shocks or with different external shocks are different (See Fig. 5). The curve AY0 indicates the availability without any shocks, and the curves AY1–AY9 indicate the availability with different shocks, that is, different prior probabilities (p1–p9) of common cause failure for each component. When no shocks occur, that is, during normal running of the S3P3V3 system, the availability decreases rapidly from 100% and reaches a stable level of 99.365% at the 15th hour. The steady-state availability and steady-state time are therefore 99.365% and 15, respectively. During emergency circumstances, the availabilities decrease to a minimum valve the moment shocks occur and then increase to reach different stable levels. Taking AY1 as an example, the prior probability of 10% of common cause failure are assigned to each component at the original time. The availability decreases to 70.790% immediately, increases rapidly with emergency repair, and reaches a stable level of 99.311% at the 27th hour. Hence, the post-shock transient-state availability, post-shock steady-state availability, and post-shock steady-state time are 70.790%, 99.311%, and 27, respectively. With the increase in probability of shocks, the post-shock transient-state availability and the post-shock steady-state availability decrease, and the post-shock steady-state time increases. This finding agrees with the fact. Using all the characteristic values, we obtain the resilience value of the S3P3V3 system of 1.90% using the proposed availability-based resilience metric.

Resilience is determined by the engineering system itself and not by external shocks; thus, the factors that affect system performance are certain to affect the resilience value. System structures and failure and repair rates of components are main influencing factors.

3.5. Sensitivity analysis

The sensitivity analysis of the failure rates of components S, P, and V are conducted by changing the failure rates of each component of the same category in multiples. The curves represent the resilience values with the changes of the failure rates from 0.5 times to 2.5 times of series, parallel, and voting components. The resilience of the S3P3V3 system decreases with the increase in time of failure rates (See Fig. 6). For components S and P, the resilience values present a ladder-form decrease with the increase of failure rates. For component V, the resilience values continuously decrease with the increase of failure rates. Under the same time variation of failure rates of components, the resilience value for S decreases fastest, that for V decreases slowest, and that for P is in between. Therefore, the resilience of the S3P3V3 system is the most
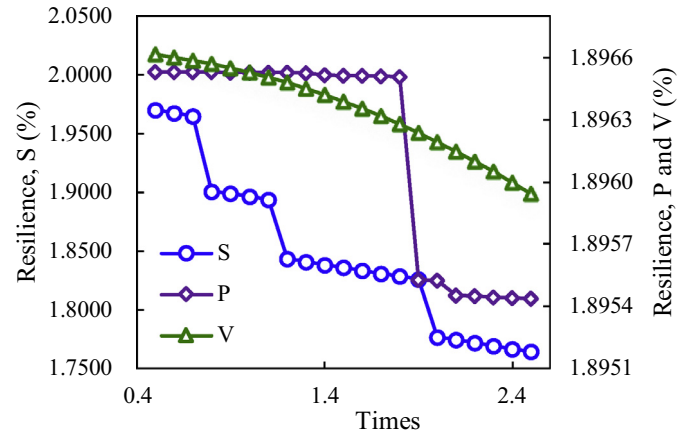
sensitive to the failure rates of component S and is the least sensitive to the failure rates of component V.
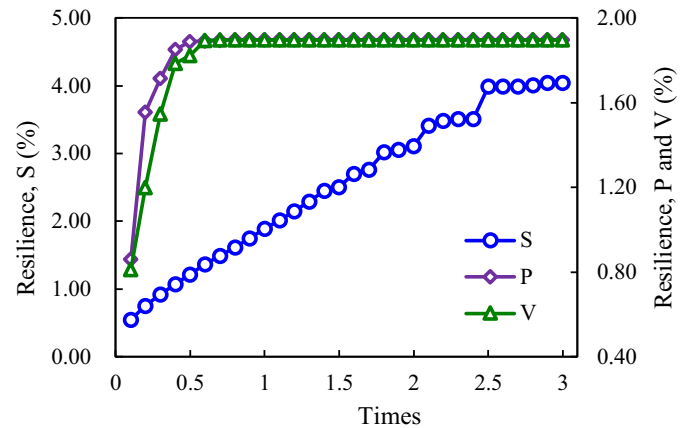
The sensitivity analysis of the repair rates of components S, P, and V are conducted by changing the repair rates of each component of the same category in multiples. The curves represent the resilience values with the changes of the repair rates from 0.1 times to 3.0 times of series, parallel, and voting components. The resilience of the S3P3V3 system increases with the increase in time of repair rates (See Fig. 7). With the increase of repair rates, the resilience value for component S continuously decreases when time is minimal, whereas it presents a ladder-form increase when the time is considerable. For components P and V, the resilience values increase rapidly when the times is minimal and then reach stable levels with the increase of repair rates. Under the same time variation of repair rates of components, the resilience value for S increases fastest, and those for P and V increase slowest; the resilience value of V is slightly higher than that for P. Therefore, the resilience of the S3P3V3 system is the most sensitive to the repair rates of component S and is the least sensitive to the failure rates of components P and V.

We suppose that S3P3V3, S2P3V3, and S3P2V3 systems can achieve the same functions. Comparison of S2P3V3 and S3P3V3 systems reveal that less series components improve engineering resilience; comparison of S3P2V3 and S3P3V3 systems show that less parallel components can reduce engineering resilience (See Fig. 8). Therefore, redundancy of engineering systems plays an important role in engineering resilience.
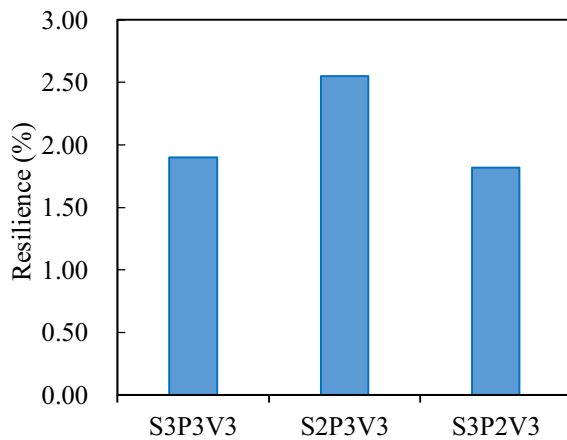
Fig. 8. Resilience values of S3P3V3, S2P3V3, and S3P2V3 systems.

Table 2
Failure and repair rates of components in the nine-bus power grid system.

System	Component	Failure rate	Repair rate
Nine-bus power grid system	Generator	1.631e-5	0.050
	Transformer	1.903e-5	0.067
	Line	2.854e-5	0.083
	Bus	0.951e-5	0.250

4. Actual application example for nine-bus power grid system

4.1. Resilience of nine-bus power grid system

Aside from abstracting the series, parallel, and voting systems, using a practical engineering system is necessary to demonstrate the application of the proposed availability-based resilience metric. Various resilience indexes or evaluation methods have been demonstrated using power systems [37,38]. Here, we study the resilience of a nine-bus power grid system (See Fig. 9). The system consists of nine buses, three generators, three two-winding power transformers, six lines, and three loads. To simplify, we ignore the power energy volume and dynamic response and focus on the system structure. Hence, when loads A, B, and C are powered, the entire nine-bus power grid system works.

The dynamic Bayesian network model of the nine-bus power grid system is established similar to the S3P3V3 system, and the resilience is evaluated (See Fig. 10 and Table 2). Node B denotes the bus; G denotes the generator; T represents the transformer; L represents the line; and LA, LB, and LC are loads A, B, and C, respectively. Node S represents the state of the entire power grid system. Each root node has two states (i.e., *work* and *fail*). For node S, the probabilities of work and fail indicate the transient availability and transient unavailability of this power system, respectively. For the nine-bus power grid system, we review the literature [39] and determine the failure and repair rates of each components. Additional general distributions, such as Weibull distribution, can also be modeled using dynamic Bayesian networks [40]. The results show that the resilience value of the system is 0.54%. Although the resilience of the S3P3V3 system is larger than the nine-bus power grid system, comparing these two systems is illogical because they do not achieve the same functions. That is, the resilience of engineering systems that achieve the same functions is comparable. Therefore, for a specified engineering system, resilience provides an implementation guidance for planning, design, operation, construction, and management.

4.2. Discussion of the proposed resilience metric

4.2.1. Resilience is an intrinsic capability and an inherent attribute

We consider resilience as an intrinsic capability and an inherent attribute of an engineering system itself. It is not influenced by external factors, such as disturbance, attack, and disaster events. This definition is different from other viewpoints [41,42]. The developed availability-based resilience metric in this study involves the performance- and time-related properties of the engineering system but not the external factors. We adopt steady-state availability and steady-state time before and after several shocks to define the metric. Therefore, the resilience value of the system is determined when a system is developed and the repair resources are assigned and fixed in this system. Resilience value is helpful in planning, design, operation, construction, and management of an engineering system. When an emergency incident occurs (e.g., an earthquake destroys some components of a power grid system), although some emergency maintenance teams outside the system might be assigned to this system and hence shorten the repair time, the primary system does not possess this intrinsic capability. Therefore, the repair actions of the emergency maintenance teams from other systems cannot improve the resilience of this system. Another example is two similar systems in earthquake-prone area and non-earthquake area; these systems should have the same resilience values when the same maintenance teams are involved because the systems have the same capability to suffer from an earthquake and recover from the destruction. To improve the capability against earthquakes, one should improve the performance of the system or increase the maintenance teams of the system itself, but not to obtain help from other systems.

4.2.2. Comparison of resilience-based engineering systems

The proposed availability-based resilience metric aims to compare the resilience values of different systems that achieve the same functions, thereby identifying different internal factors that contribute to it. For systems with the same functions, a larger resilience value indicates that the system is more resilient. Notably, the objects for comparison should be systems that achieve the same functions. In this study, the series, parallel, and voting systems S3P3V3, S2P3V3, and S3P2V3 aim to connect two terminations, and the nine-bus power grid system aims to supply power for loads A, B, and C. Comparing the resilience values of S3P3V3, S2P3V3, and S3P2V3 systems seems logical, whereas comparing the S3P3V3 system with the nine-bus power grid system is irrational. Similarly, if we develop a new power grid system to supply power for loads A, B, and C, then comparing it with the nine-bus power grid system and selecting a more resilient system are important.

4.2.3. Optimization of resilience-based engineering system

When an engineering system is planned and designed, identifying the weak components that affect the resilience significantly is important. Resilience is influenced by the internal factors of an engineering system; thus, the sensitivity of these factors (e.g., redundancy and failure and repair rates) to resilience can be quantified. We can change the system structure and failure or repair rates in multiples to evaluate the resilience values and analyze the sensitivity. We should pay more attention to the structure or component that is most sensitive to resilience (e.g., increase the redundancy of that structure to decrease the failure rate or increase the repair rate of that component).

4.2.4. Design of resilience-based engineering system

From the perspective of reliability engineering, several reliability-based engineering system design methods are available. For example, we can design an automation control system of subsea blowout preventers with the reliability of 99.9999%. Similarly, a resilience-based engineering system design method might be useful because it involves the characteristics of recovery after shocks. In practical guidance documents, the recommended resilience value of engineering systems should be specified. For example, suppose that the resilience value for a power
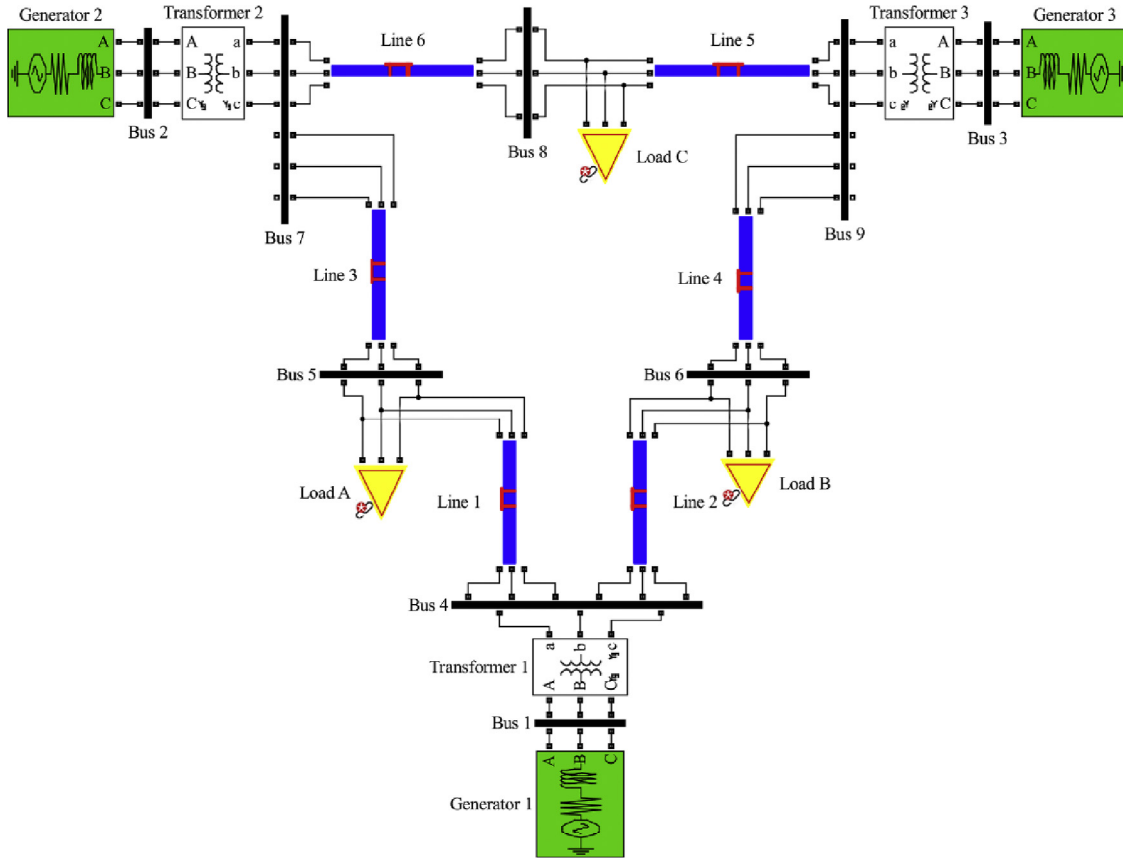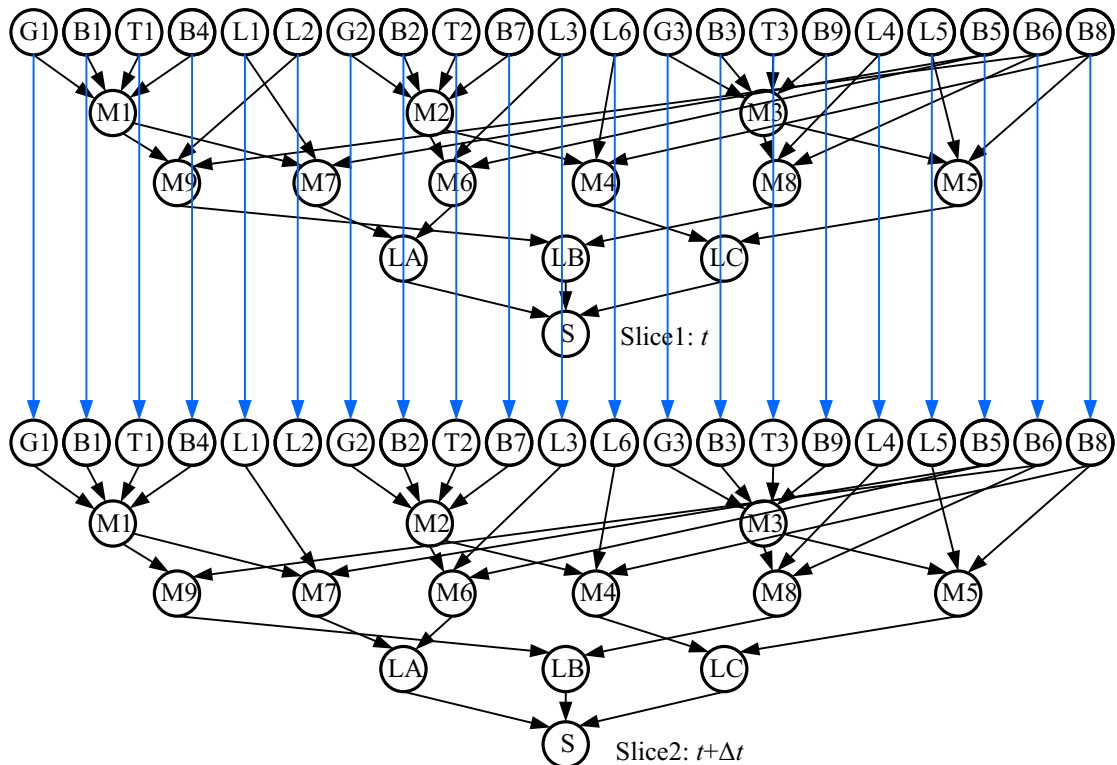
Fig. 9. Nine-bus power grid system.

Fig. 10. Dynamic Bayesian networks of the nine-bus power grid system.

grid system in Qingdao City is specified to be 0.60%; a new power grid system should be designed to meet this requirement. Notably, the specified resilience values are determined by practical engineering environment even for the same system. For example, the resilience value for a power grid system in a large city might be 0.80%, but 0.50% in a small village, 0.90% in an industrial park, and 0.60% in a residential area. Such values are determined by practical guidance documents produced by experts.

5. Conclusion

A new availability-based engineering resilience metric is proposed from the perspective of reliability engineering. The corresponding dynamic-Bayesian-network-based evaluation methodology is developed based on the proposed metric. Series, parallel, and voting systems and a nine-bus power grid system are used to demonstrate the application of the metric and its corresponding evaluation methodology. The results show that the engineering resilience metric is reasonable and that the corresponding evaluation methodology is precise. System structures and failure and repair rates of components are the main influencing factors of engineering resilience. Redundancy of components plays an important role in increasing resilience. The proposed metric can be used for engineering comparison, optimization, and design. Therefore, we can use the metric to compare the resilience of different systems that achieve the same functions, thereby identifying different internal factors that contribute to it. Moreover, we can change the system structure and failure or repair rates in multiples to evaluate resilience values and analyze the sensitivity. Furthermore, we can conduct resilience-based design for engineering systems based on the required resilience values determined by practical guidance documents.

Notably, only the series, parallel, voting, and nine-bus power grid systems with binary state are used in this study to demonstrate the proposed availability-based resilience metric and its corresponding evaluation methodology. Bayesian networks are a powerful tool in modeling any complex system, such as multistate system, linear consecutively connected systems, and general networks with sources and sinks. Therefore, the proposed metric and methodology are general for any complex systems. Future scopes of work can be directed toward resilience evaluation of a complex system (not limited to the binary state systems) and further system comparison, system optimization, and system design by using the proposed metric and methodology.

References

[1] Cole LE, Bhagwat SA, Willis KJ. Recovery and resilience of tropical forests after disturbance. Nat Commun 2014;5:3906.
[2] Oliver TH, Isaac NJ, August TA, Woodcock BA, Roy DB, Bullock JM. Declining resilience of ecosystem functions under biodiversity loss. Nat Commun 2015;6:10122.
[3] Martin R. Regional economic resilience, hysteresis and recessionary shocks. J Econ Geogr 2011;12:1–32.
[4] Rose A, Liao SY. Modeling regional economic resilience to disasters: a computable general equilibrium analysis of water service disruptions. J Region Sci 2005;45(1):75–112.
[5] Southwick SM, Charney DS. The science of resilience: implications for the prevention and treatment of depression. Science 2012;338:79–82.
[6] Pan JY, Chan CLW. Resilience: a new research area in positive psychology. Psychologia 2007;50(3):164–76.
[7] Olsson L, Jerneck A, Thoren H, Persson J, O'Byrne D. Why resilience is unappealing to social science: theoretical and empirical investigations of the scientific use of resilience. Sci Adv 2015;1(4):e1400217.
[8] Keck M, Sakdapolrak P. What is social resilience? Lessons learned and ways forward. Erdkunde 2013;67(1):5–19.
[9] Hosseini S, Barker K, Ramirez-Marquez JE. A review of definitions and measures of system resilience. Reliab Eng Syst Safety 2016;145:47–61.
[10] Gao J, Barzel B, Barabási AL. Universal resilience patterns in complex networks. Nature 2016;530:307–12.
[11] Fang YP, Pedroni N, Zio E. Resilience-based component importance measures for critical infrastructure network systems. IEEE Trans Reliab 2016;65(2):502–12.
[12] National Infrastructure Advisory Council (US) Critical infrastructure resilience: final report and recommendations.. Natl Infrastruct Advis Council 2009.
[13] American Society of Mechanical Engineers (US) All-Hazards risk and resilience: prioritizing critical infrastructures using the RAMCAP Plus^SM approach. Am Soc Mech Eng 2009.
[14] Youn BD, Hu C, Wang P. Resilience-driven system design of complex engineered systems. J Mech Design 2011;133(10):101011.
[15] Ouyang M, Wang Z. Resilience assessment of interdependent infrastructure systems: with a focus on joint restoration modeling and analysis. Reliab Eng Syst Safety 2015;141:74–82.
[16] Yodo N, Wang P. Resilience modeling and quantification for engineered systems using Bayesian networks. J Mech Design 2016;138(3):031404.
[17] Roege PE, Collier ZA, Mancillas J, McDonagh JA, Linkov I. Metrics for energy resilience. Energy Policy 2014;72:249–56.
[18] Dessavre DG, Ramirez-Marquez JE, Barker K. Multidimensional approach to complex system resilience analysis. Reliab Eng Syst Safety 2016;149:34–43.
[19] Bruneau M, Chang SE, Eguchi RT, Lee GC, O'Rourke TD, Reinhorn AM, von Winterfeldt D. A framework to quantitatively assess and enhance the seismic resilience of communities. Earthquake spectra 2003;19(4):733–52.
[20] Henry D, Ramirez-Marquez JE. Generic metrics and quantitative approaches for system resilience as a function of time. Reliab Eng Syst Safety 2012;99:114–22.
[21] Francis R, Bekera B. A metric and frameworks for resilience analysis of engineered and infrastructure systems. Reliab Eng Syst Safety 2014;121:90–103.
[22] Hosseini S, Barker K. Modeling infrastructure resilience using Bayesian networks: a case study of inland waterway ports. Comput Ind Eng 2016;93:252–66.
[23] Zhao S, Liu X, Zhuo Y. Hybrid hidden Markov models for resilience metrics in a dynamic infrastructure system. Reliab Eng Syst Safety 2017;164:84–97.
[24] Woods DD. Four concepts for resilience and the implications for the future of resilience engineering. Reliab Engi Syst Safety 2015;141:5–9.
[25] McDaniels T, Chang S, Cole D, Mikawoz J, Longstaff H. Fostering resilience to extreme events within infrastructure systems: Characterizing decision contexts for mitigation and adaptation. Global Environ Change 2008;18(2):310–18.
[26] Molyneaux L, Brown C, Wagner L, Foster J. Measuring resilience in energy systems: Insights from a range of disciplines. Renewable Sustainable Energy Rev 2016;59:1068–79.
[27] Arghandeh R, von Meier A, Mehrmanesh L, Mili L. On the definition of cyber-physical resilience in power systems. Renewable Sustainable Energy Rev 2016;58:1060–9.
[28] Filippini R, Silva A. A modeling framework for the resilience analysis of networked systems-of-systems based on functional dependencies. Reliability Eng Syst Safety 2014;125:82–91.
[29] Lundberg J, Johansson BJ. Systemic resilience model. Reliability Eng Syst Safety 2015;141:22–32.
[30] Zobel CW, Khansa L. Characterizing multi-event disaster resilience. Comput Oper Res 2014;42:83–94.
[31] Bourouni K. Availability assessment of a reverse osmosis plant: comparison between reliability block diagram and fault tree analysis methods. Desalination 2013;313:66–76.
[32] Choi IH, Chang D. Reliability and availability assessment of seabed storage tanks using fault tree analysis. Ocean Eng 2016;120:1–14.
[33] Naseri M, Baraldi P, Compare M, Zio E. Availability assessment of oil and gas processing plants operating under dynamic arctic weather conditions. Reliability Eng Syst Safety 2016;152:66–82.
[34] Cai B, Liu Y, Liu Z, Tian X, Zhang Y, Liu J. Performance evaluation of subsea blowout preventer systems with common-cause failures. J Petroleum Sci Eng 2012;90:18–25.
[35] Cai B, Zhao Y, Liu H, Xie M. A data-driven fault diagnosis methodology in three-phase inverters for PMSM drive systems. IEEE Trans Power Electron 2017;32(7):5590–600.
[36] Cai B, Huang L, Xie M. Bayesian networks in fault diagnosis. IEEE Trans Ind Inform 2017;13(5):2227–40.
[37] Fang Y, Sansavini G. Optimizing power system investments and resilience against attacks. Reliability Eng Syst Safety 2017;159:161–73.
[38] Fotouhi H, Moryadee S, Miller-Hooks E. Quantifying the resilience of an urban traffic-electric power coupled system. Reliability Eng Syst Safety 2017;163:79–94.
[39] Yssaad B, Khiat M, Chaker A. Reliability centered maintenance optimization for power distribution systems. Int J Electric Power Energy Syst 2014;55:108–15.
[40] Zaidi A, Ould Bouamama B, Tagina M. Bayesian reliability models of Weibull systems: state of the art. Int J Appl Math Comput Sci 2012;22(3):585–600.
[41] Panteli M, Mancarella P. Modeling and evaluating the resilience of critical electrical power infrastructure to extreme weather events. IEEE Syst J 2015. doi:10.1109/JSYST.2015.2389272.
[42] Ji C, Wei Y, Mei H, Calzada J, Carey M, Church S, White J. Large-scale data analysis of power grid resilience across multiple US service regions. Nat Energy 2016;1:16052.

[43] Cai B, Liu H, Xie M. A real-time fault diagnosis methodology of complex systems using object-oriented Bayesian networks. Mech Syst Signal Process 2016;80:31–44.

[44] Cai B, Liu Y, Fan Q, Zhang Y, Liu Z, Yu S, Ji R. Multi-source information fusion based fault diagnosis of ground-source heat pump using Bayesian network. Appl Energy 2014;114(2):1–9.

[45] Haimes YY. On the definition of resilience in systems. Risk Anal 2009;29(4):498–501.

[46] Hollnagel E, Woods D, Leveson N. Resilience engineering, concepts and precepts. Ashgate Publishing; 2006.

[47] Attoh-Okine NO. Resilience engineering, models and analysis. Cambridge University Press; 2016.