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System Dynamic Behavior Modeling Based on Extended GO Methodology

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ABSTRACT The GO methodology, which is a success-oriented system analysis technique, is effective for evaluating the reliability of complex systems with multiple states and time-series. It is widely used in the domain of nuclear and ship industry. However, the GO methodology has some restrictions in modeling and analyzing an intricate system that contains dynamic behavior characteristics, such as function dependency, backup dependency, and load sharing. To enhance both the capacity of the modeling and the scope of applications, we proposed an extended GO methodology in this paper to describe the dependencies of the dynamic behaviors. Integrated with the dynamic Bayesian network (DBN), the dynamic behaviors can be presented in a unified way. By using mature software, the extended GO methodology proposed in this paper can be calculated conveniently. Meanwhile, based on unified rules, the multi-operator can be mapped into the DBN, followed by a complete GO model with complex characteristics that can be converted into an isomorphic DBN and analyzed easily by utilizing DBN's powerful inference capabilities. Moreover, the approach makes the extended GO model easy to analyze and intuitive for nonexperts.

INDEX TERMS Extended GO methodology, reliability modeling, dynamic behaviors, dynamic Bayesian network.

I. INTRODUCTION

The dynamic characteristics of a large, complex system are interlaced in space and time and significantly affect the reliability and maintainability of the system. Generally, the dynamic and complexity characteristics are defined as follows: (i) the functions of the components are numerous; (ii) the states of the components are functions with time; and (iii) the components exhibit strong association relations (e.g., functional dependency, backup dependency, load sharing). With the above characteristics, reliability modeling is a common way to assess the reliability of the practical model. And the association relations with dynamic characteristics are focused on in this article.

There have been many research approaches to analyze the dynamic reliability model. For instance, Distefano and Puliafito [1], [2] developed the dynamic RBDs model, which drives the overall system reliability evaluation through all phases of modeling and analysis. Barua *et al.* [3] utilized the Dynamic Fault Tree (DFT) integrated with the Dynamic Bayesian Network (DBN) and described the dynamic system with sequential dependency. Cai *et al.* [4] proposed a novel DBN-based dynamic real-time reliability evaluation methodology for subsea blowout preventer systems, gave the ways and measures to increase the reliability, and therefore improved the system availability significantly. Based on the Continuous Time Markov Chains (CTMCs), Marin [5] proposed the Stochastic Petri Nets (SPNs) and established a correlation matrix for the network to numerically solve the dynamic reliability index.

The GO methodology, which is a success-oriented system analysis technique [6]–[8], is capable of evaluating a system's reliability and the availability of the system with both complex time-sequence problems and multi-state problems, especially for airflow and electric currents. It was initially proposed by an American company in the 1960s and uses a chart that consists of signal lines and operators. Generally, the nodes are denoted by the function of the components/subsystems/system, and the lines indicate the signal flow between the nodes. Representative research efforts on the GO methodology with shared signals, multi-state and repairable systems are reported in the literature [9]–[13]. Shen *et al.* [9] proposed an algorithm to calculate the

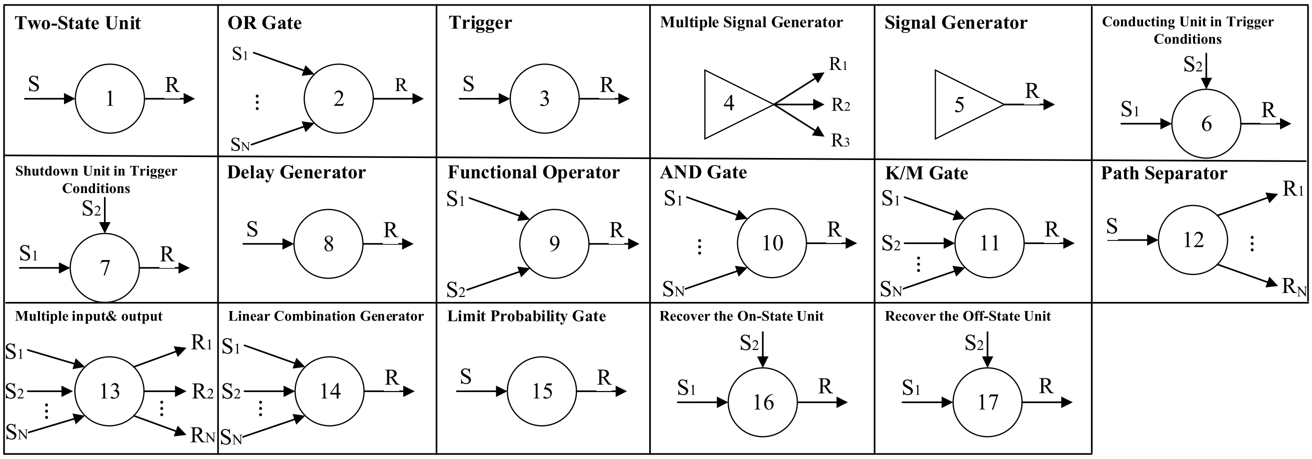


FIGURE 1. Standard operator type of the GO methodology.

reliability of the systems with repairable components. In 2005, Shen *et al.* [10] provided a supplemental algorithm for his original one that was more accurate for shared signals. Chen *et al.* [11] developed a new algorithm for the GO methodology based on the minimal path set that reduced the amount of calculations, especially complex, large-scale systems. Liu [12] extended the GO methodology to support the failure mode, effects and criticality analysis, in order to analysis the fault propagation in the system. Ren *et al.* [13] proposed an efficient algorithm for the multi-state GO model based on Multi-valued decision diagrams (MDDs) in order to avoid the complex separate process of handling shared signals in the probability formulas method. Although the approaches above expanded the traditional GO methodology through calculations and applications, independence is assumed across the components within the system when analyzing redundancy.

To address these restrictions, some pertinent improvements should be implemented when the GO methodology is applied in the reliability assessment of a system with various dynamic behaviors that have static and dynamic characteristics. In this article, a modified GO methodology integrated with the Bayesian Network (BN) and DBN is proposed to support the modeling of dynamic failure behaviors in a system.

With the integrated DBN [12], [14], a modified algorithm of various GO-FLOW operators is proposed. The traditional GO methodology is extended to support system dynamic behaviors: functional dependency, backup dependency and load sharing. Inheriting the advantages of the traditional GO methodology, the novel modeling rules can be presented for a static system, non-repairable system or repairable system. Then, by unifying the dynamic failure behaviors and repairable operators, a universal algorithm is proposed that integrates the DBN with the GO methodology. Based on the unified rules, the dynamic failure behaviors can be mapped into the DBN. Finally, the Water Supply System (WSS) of an aircraft is analyzed as an example to illustrate the accuracy and practicality of the approach.

The remainder of this paper is organized as follows. The discussions of this paper start with a brief description of the GO methodology, BN and DBN in Section II. Next, Section III defines the typical dynamic relationship between the components. Meanwhile, the mapping rules from the GO operators into the BN are proposed while considering the dynamic relationships. In Section IV, a case study of the water supply system is conducted in the aspect of reliability evaluation by the GO methodology, and the calculated reliability results are explained. Finally, the conclusions are presented in Section V.

II. BACKGROUND

A. GO METHODOLOGY

The GO methodology is a system analysis technique that can evaluate the system reliability and availability. From the initial operator to the end, the model is calculated sequentially from the system configuration to obtain the probability analysis results of the integral system. Seventeen different types of GO operators [9], [10] are currently defined to model the function or failure of the physical equipment and to represent the logical relations and signal equipment, as shown in Fig. 1. The signals among the operators are utilized to simulate the input/output relationships. Evolving from the decision tree, the schematic diagram and route chart of the system can be translated into a GO chart directly, and there is a one-to-one correspondence between the actual physical system and the operators of the GO methodology through the signals. The GO methodology possesses the following vital features: (i) the GO methodology is a visualized modeling approach, and it is available for back trace and fault detection [15], [16]; (ii) the GO chart corresponds to the physical layout of the system and is easily constructed and validated; (iii) the GO chart is similar to the functional block diagram of the system, and is convenient for engineers to comprehend and implement; and (iv) the multi-state can be described by the operators and signals, and the failure probability of system can be simultaneously obtained.

Seventeen different types of GO operators are currently defined to model the function or failure of the physical equipment and to represent the logical relations and signal equipment. The procedures for the reliability analysis with the GO method are as follows:

(i) According to the rules, translate the system schematic or the engineering structure chart into the GO diagram;

(ii) Replace the practical components into the corresponding operators in the GO methodology;

(iii) Connect the operators with signal flows;

(iv) Input the data according to the operators;

(v) Calculate the probabilities based on the rules of the operators;

(vi) Evaluate the reliability of the system.

B. BAYESIAN NETWORK

The BN is a kind of graphical network that is based on probabilistic inference. If $N =\ll V, T >, P >$ represents a network model with N nodes, then $< V, T >$ is a directed acyclic graph with N nodes, and $V = \{V_1, \cdots V_n\}$ presents the set of N variables. The directed line segments between nodes represent the parent-child or causal relationship of the nodes [17], [18]. For $T_i = (V_i, V_j)$, V_i is the parent node of V_j, or V_j is the child of V_i. Root nodes are those that have no parent node, and leaf nodes are those that have no child nodes. In addition, the parent node set of note V_i is represented by $Parent(V_i)$ [19], [20]. According to the conditional independence assumption, the joint probability distribution of all variables is shown in (1).

$$P(V_1, V_2, \cdots V_n) = \prod_{i=1}^{n} P(V_i|Parent(V_i)) \tag{1}$$

The BN allows both forward (or predictive) and backward (diagnostic) analyses [21], where the posterior probability of any set of variables can be calculated. The inference in the BN is to calculate the probability of each node when the other variables are known. The Bayesian theorem is used to compute the conditional probabilities [4], [22]. Given the variable Y, the conditional probability of X is given by

$$P(X|Y) = \frac{P(X)P(Y|X)}{P(Y)} \tag{2}$$

The probability of BN nodes can be obtained from the state probability of the parent nodes and Conditional Probability Table (CPT). The inference specialty of the BN makes it available in the domain of complex system modeling and analysis [23]. In the representative research, the BN are classified into two types: static BN and DBN. Expanding the network into multiple time intervals, the static BN can also be utilized to describe the time dimension, as shown in Fig. 2. However, this can be accomplished in a finite number of time slices. If the number of time slices are abundant, the structure of the model may be extremely complex. Mindful of the difficulties, the authors have utilized the DBN to enhance the algorithm of the GO methodology [24], [25].

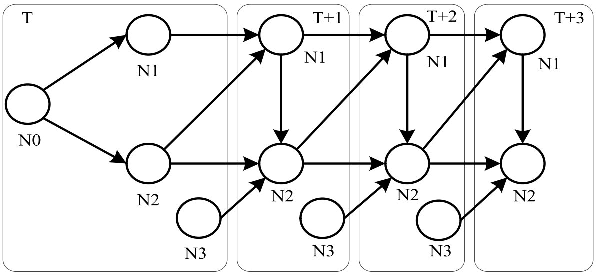


FIGURE 2. Multi-time dimension of the static BN.

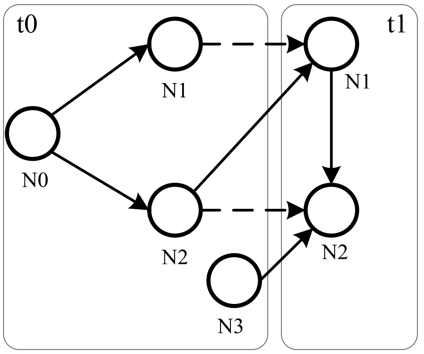


FIGURE 3. Schematic diagram of DBN.

The DBN is a graph structure that is based on static BN and the hidden Markov model, which has the following advantages: i) description of multi slices

provides a more practical method to describe the stochastic dynamic system [26], [27]. The assumptions of DBN are as follows:

(i) the transition of the system states is described by Markov process;

(ii) the structure of system is time invariant.

With the above assumptions, we can divide the model into two time slices, as shown in Fig.3 [28]. Fig.2 can be replaced by Fig. 3, which is not limited to the number of time slices. In Fig. 3, the left panel presents the initial network at time t0, and the right panel denote the transfer network at time t1 [29]. The process of transformation is shown with the dotted lines. To make inferences from the data that have multi-original inputs, the following data are also essential for the inference: (i) the prior probability of the root node at the initial time and (ii) the conditional probability table of each node, except for the root nodes. Based on this method, the DBN mode is generally called the Two Time-slice Temporal BN (2TBN) [24], [30], [31].

III. DYNAMIC EVALUATION METHODS OF THE RELIABILITY MODEL WITH DBN

A. THE DEFINITION OF TYPICAL COMPONENT STATES IN THE DYNAMIC SYSTEM

According to the components in the repairable system, as shown in Fig. 4, the system parameters and states at time t depend on the state of time t and the event series before time t.

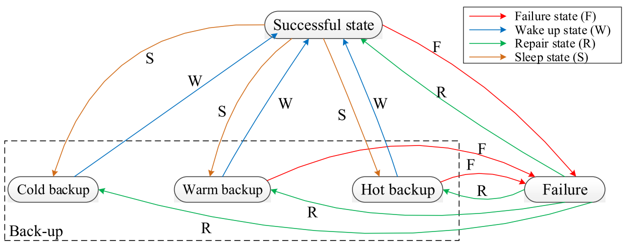


FIGURE 4. State machine of the components.

The component states are classified into 3 types: successful, failure and back-up state.

(i) Successful state: the initial state of the component without any degradation.

(ii) Failure state: the state where failures have acted on the component.

(iii) Back-up state: the redundancy components.

Cold, warm and hot backup are the three forms of back-up. (i) Cold backup: the component is out of work. The failure rate of the cold backup component is $\alpha\lambda$, and the variant α is equal to 0. The backup component starts to work when the primary one breaks down. (ii) Warm backup: the component is in the state of preliminary work, and its failure rate is $\alpha\lambda$ where $\alpha \in (0, 1)$. (iii) Hot backup: the component is in the state of working the same as the primary one. Its failure rate is $\alpha\lambda$, which is equal to the parallel model, and the variant is $\alpha = 1$.

The events represent the transformation among the various component states, as shown in Fig. 4. There are four events that may occur: failure state (denoted by F), wake up state (denoted by W), repair state (denoted by R) and sleep state (denoted by S).

(i) Failure state (F): the transformation from the successful and hot/warm backup state to the failure state.

(ii) Wake up state (W): the transformation from the backup state to the success state.

(iii) Repair state (R): the transformation from the failure state to the other states.

(iv) Sleep state (S): the transformation from the success state to backup states.

B. THE DYNAMIC RELATIONSHIP BETWEEN COMPONENTS

The correlativity between components is a specific logic relationship between the trigger and target components. Detonated by the specific events, the target components would be in the specified state with the help of the trigger components. The events that activate the correlativity are called the activity events, and the events that occurred are called the reactivity events. Compared with the Dynamic fault tree analysis (DFTA) and the Dynamic reliability block diagram (DRBD), the dynamic behaviors are classified into three categories: functional dependency, backup dependency and load sharing [32].

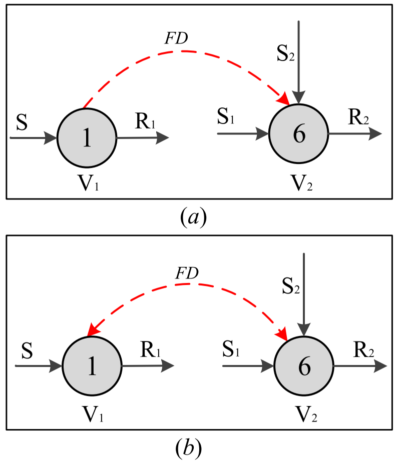


FIGURE 5. Schematic diagram of the functional dependency.

1) FUNCTIONAL DEPENDENCY

If the activity events occur, the target components would be forced to execute the specific reactivity events. In this article, the functional dependency (FD) is denoted by the directed dotted lines between the components.

Fig. 5(a) shows that the active component V_1 (denoted by the type 1 operator) can lead to the failure state of the reactivity component V_2 (denoted by the type 6 operator) with the help of the trigger event. This one-way causation is described by a dotted line with an arrow. Meanwhile, if the two components have functional dependencies with each other, it would be denoted by a dotted line with a double arrow, as shown Fig. 5(b).

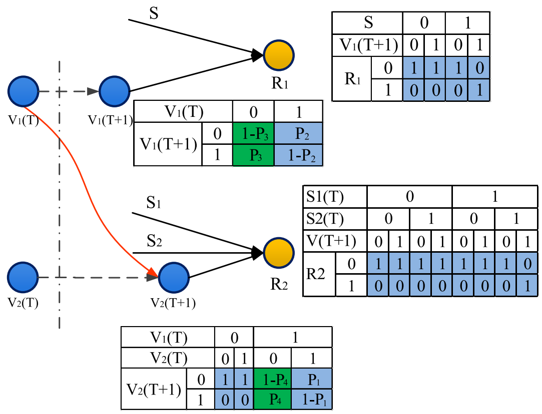
In Fig. 5, S is the input signal of component V_1; S_1 and S_2 are the input signals of component V_2; R_1 represents the output signal of component V_1; and R_2 represents the output signal of component V_2. By expanding the traditional GO methodology, the functional dependencies are visual in Fig. 5(a). V_1 and V_2 are the repairable components with functional dependencies, and V_1 is the trigger component, with V_2 being the target component [33]. We assume the following: (i) if V_1 is in the failure state, then the repair rate of V_2 is $\mu_{V_1}(t) = 0$; and (ii) if V_1 is in the success state, then the repair rate of V_2 is $\mu_{V_2}(t)$. The DBN of V_1 and V_2 are shown in Fig. 6 (0-successful state, 1-failure state).

$$P_1 = P(V_2(T+1)=0|V_2(T)=1,\, V_1(T)=1) = \int_T^{T+1} f_{V_2}(t)dt \tag{3}$$

$$P_2 = P(V_1(T+1)=0|V_1(T)=1) = \int_T^{T+1} f_{V_1}(t)dt \tag{4}$$

$$P_3 = P(V_1(T+1)=1|V_1(T)=0) = \int_T^{T+1} \mu_{V_1}(t)dt \tag{5}$$

$$P_4 = P(V_2(T+1)=1|V_1(T)=1,\, V_2(T)=0) = \int_T^{T+1} \mu_{V_2}(t)dt \tag{6}$$



S	0		1	
$V_1(T+1)$	0	1	0	1
R_1 = 0	1	1	1	0
R_1 = 1	0	0	0	1

$V_1(T)$	0	1
$V_1(T+1)$ = 0	$1-P_3$	P_2
$V_1(T+1)$ = 1	P_3	$1-P_2$

$S_1(T)$	0				1			
$S_2(T)$	0		1		0		1	
$V(T+1)$	0	1	0	1	0	1	0	1
R2 = 0	1	1	1	1	1	1	1	0
R2 = 1	0	0	0	0	0	0	0	1

$V_1(T)$	0		1	
$V_2(T)$	0	1	0	1
$V_2(T+1)$ = 0	1	1	$1-P_4$	P_1
$V_2(T+1)$ = 1	0	0	P_4	$1-P_1$

FIGURE 6. The mapping of the repairable components with functional dependency.

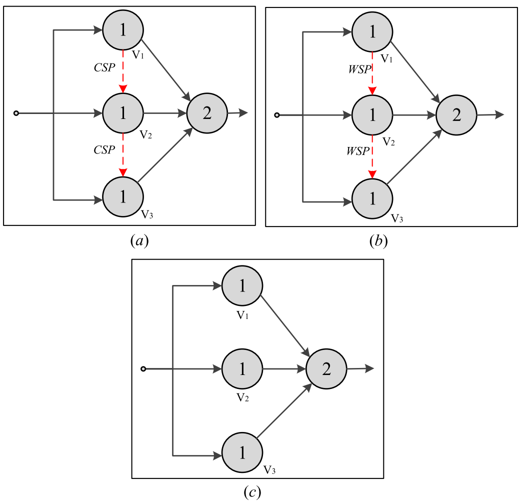


FIGURE 7. Schematic diagram of the backup dependency.

where $f_{V1}(t)$ and $f_{V2}(t)$ are the fault probability functions of components V_1 and V_2, respectively; and $\mu_{V_1}(t)$ and $\mu_{V_2}(t)$ are the repair probability functions of components V_1 and V_2, respectively.

2) BACKUP DEPENDENCY

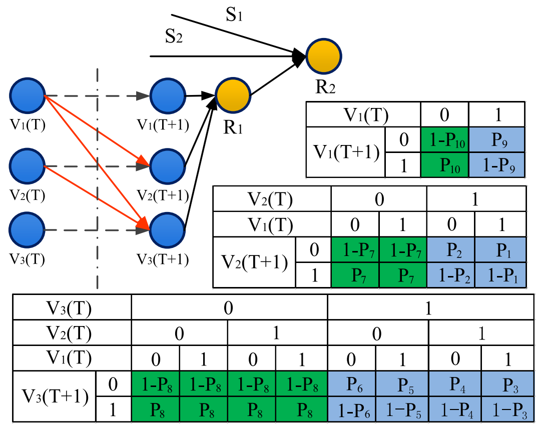
In the backup system, there usually exists one main component and more than one backup component [34], [35]. If the main component is in the success state, the backup ones are in the back up state. If the main component fails, the first backup one begins to work. Subsequently, the second backup component would start working after the first one breaks down. The other components work in sequence through this analogy. The failure of the system is defined in that all components are in the state of failure [36]. The three types of backup are shown in Fig. 7.

In Fig. 7(a), the Cold-Spare (CSP) represents the cold backup denoted by a dotted line with an arrow. The arrow describes the direction of the events. In Fig. 7(b), the Warm-Spare (WSP) represents the order of components in the warm backup. Fig. 7(c) shows the parallel connection. To analyze the backup system with repairable components, we assume the following:

(i) If arbitrary components break down, they would be repaired immediately; and

(ii) If the failure component has been repaired, it would be in the backup state.

The DBN and its CPT are shown in Fig. 8 (0-the success state, 1-the failure state).



$V_1(T)$	0	1
$V_1(T+1)$ = 0	$1-P_{10}$	P_9
$V_1(T+1)$ = 1	P_{10}	$1-P_9$

$V_2(T)$	0		1	
$V_1(T)$	0	1	0	1
$V_2(T+1)$ = 0	$1-P_7$	$1-P_7$	P_2	P_1
$V_2(T+1)$ = 1	P_7	P_7	$1-P_2$	$1-P_1$

$V_3(T)$	0				1			
$V_2(T)$	0		1		0		1	
$V_1(T)$	0	1	0	1	0	1	0	1
$V_3(T+1)$ = 0	$1-P_8$	$1-P_8$	$1-P_8$	$1-P_8$	P_6	P_5	P_4	P_3
$V_3(T+1)$ = 1	P_8	P_8	P_8	P_8	$1-P_6$	$1-P_5$	$1-P_4$	$1-P_3$

FIGURE 8. Mapping of the repairable components with backup dependency.

$$P_1 = P(V_2(T+1)=0\,|V_1(T)=1,\, V_2(T)=1) = \int_T^{T+1} f_{\alpha V_2}(t)dt \tag{7}$$

$$P_2 = P(V_2(T+1)=0\,|V_1(T)=0,\, V_2(T)=1) = \int_T^{T+1} f_{V_2}(t)dt \tag{8}$$

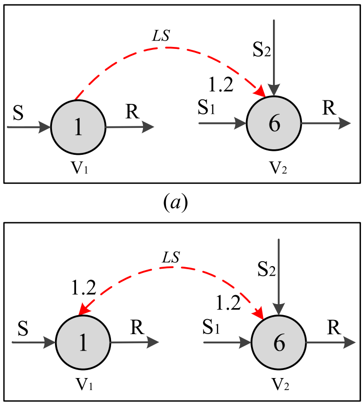
$$P_3 = P\left(V_3(T+1)=0 \,\middle|\, \begin{array}{l} V_1(T)=1,\, V_2(T)=1, \\ V_3(T)=1 \end{array}\right) = \int_T^{T+1} f_{\alpha V_3}(t)dt \tag{9}$$

$$P_4 = P\left(V_3(T+1)=0 \,\middle|\, \begin{array}{l} V_1(T)=0,\, V_2(T)=1, \\ V_3(T)=1 \end{array}\right) = \int_T^{T+1} f_{\alpha V_3}(t)dt \tag{10}$$

$$P_5 = P\left(V_3(T+1)=0 \,\middle|\, \begin{array}{l} V_1(T)=1,\, V_2(T)=0, \\ V_3(T)=1 \end{array}\right) = \int_T^{T+1} f_{\alpha V_3}(t)dt \tag{11}$$

$$P_6 = P\left(V_3(T+1)=0 \,\middle|\, \begin{array}{l} V_1(T)=0,\, V_2(T)=0, \\ V_3(T)=1 \end{array}\right) = \int_T^{T+1} f_{V_3}(t)dt \tag{12}$$

$$P_7 = P(V_2(T+1)=1|V_2(T)=0) = \int_T^{T+1} \mu_{V_2}(t)dt \tag{13}$$



(a)

(b)

FIGURE 9. Schematic diagram of load sharing.

$$P_8 = P(V_3(T+1)=1|V_3(T)=0) = \int_T^{T+1} \mu_{V_3}(t)dt \tag{14}$$

$$P_9 = P(V_1(T+1)=0|V_1(T)=1) = \int_T^{T+1} f_{V_1}(t)dt \tag{15}$$

$$P_{10} = P(V_1(T+1)=1|V_1(T)=0) = \int_T^{T+1} \mu_{V_1}(t)dt \tag{16}$$

where $f_{V_1}(t)$, $f_{V_2}(t)$ and $f_{V_3}(t)$ are the fault probability functions of components V_1, V_2 and V_3, respectively; $\mu_{V_1}(t)$, $\mu_{V_2}(t)$ and $\mu_{V_3}(t)$ are the repair probability functions of components V_1, V_2 and V_3, respectively; and $f_{\alpha V_2}(t)$ and $f_{\alpha V_3}(t)$ are the backup fault probability functions of components V_2 and V_3, respectively.

3) LOAD SHARING

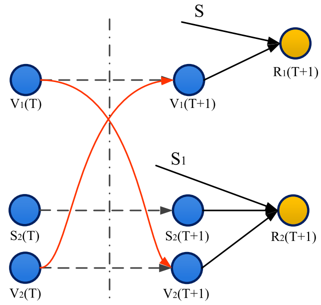
In practical systems, the load is shared by multiple components [37]. If one of the loading components has a loss of function, the other components would be enhanced compared with their original loading. This setup is commonly used in parallel systems, and is described by a factor of load, denoted by $\beta (\beta > 1)$. The load sharing (LS) system can be presented in the extended GO methodology, as shown in Fig. 9. Similar to the functional dependency, the load sharing can also be affected by one-way or bi-directional load sharing. As shown in Fig. 9(a), when component V_1 breaks down, the failure rate of component V_2 increases to 1.2λ from λ. Similarly, Fig. 9(b) shows the bi-direction relationship in load sharing.

The DBN and its CPT are shown in Fig. 10 for components V_1 and V_2 if they are repairable (0-the success state, 1-the failure state).

$$\begin{aligned} P_1 &= P(V_1(T+1)=0\,|V_1(T)=1\ ,\ V_2(T)=1) \\ &= \int_T^{T+1} f_{V_1}(t)dt \end{aligned} \tag{17}$$

$$\begin{aligned} P_2 &= P(V_1(T+1)=0\,|V_1(T)=1\ ,\ V_2(T)=0) \\ &= \int_T^{T+1} f_{\beta V_1}(t)dt \end{aligned} \tag{18}$$

$$\begin{aligned} P_3 &= P(V_2(T+1)=0\,|V_1(T)=1\ ,\ V_2(T)=1) \\ &= \int_T^{T+1} f_{V_2}(t)dt \end{aligned} \tag{19}$$



V1(T)		0		1	
V2(T)		0	1	0	1
V1(T+1)	0	1-P5	1-P5	P2	P1
	1	P5	P5	1-P2	1-P1

V2(T)		0		1	
V1(T)		0	1	0	1
V2(T+1)	0	1-P6	1-P6	P4	P3
	1	P6	P6	1-P4	1-P3

FIGURE 10. Mapping of repairable components with load sharing.

$$\begin{aligned} P_4 &= P(V_2(T+1)=0\,|V_1(T)=0\ ,\ V_2(T)=1) \\ &= \int_T^{T+1} f_{\beta V_2}(t)dt \end{aligned} \tag{20}$$

$$P_5 = P(V_1(T+1)=1|V_1(T)=0) = \int_T^{T+1} \mu_{V_1}(t)dt \tag{21}$$

$$P_6 = P(V_2(T+1)=1|V_2(T)=0) = \int_T^{T+1} \mu_{V_2}(t)dt \tag{22}$$

where $f_{V_1}(t)$, and $f_{V_2}(t)$ are the fault probability functions of components V_1 and V_2; $\mu_{V_1}(t)$ and $\mu_{V_2}(t)$ are the repair probability functions of components V_1 and V_2; and $f_{\beta V_1}(t)$ and $f_{\beta V_2}(t)$ are the load sharing fault probability functions of components V_1 and V_2.

C. MODELING RULES OF THE EXTENDED GO METHODOLOGY WITH THE DBN

To establish the assessment model of the complex product with the functional dependency, backup dependency and load sharing, some modeling rules have been formulated as follows:

(i) Each component can be the trigger, except the logic operators;

(ii) Two or more arbitrary components can be covered in the functional dependency;

(iii) The backup components cannot be in load sharing system simultaneously; and

(iv) Each component can exist at most in one load sharing system.

Based on the modeling rules above, the BN transformation procedure for the complete GO model is proposed [12], [14], as shown in Fig. 11. The detailed procedure is described below:

Step 1: Traverse the signal set $S = \{S_1, S_2, \cdots, S_N\}$ of the GO model according to the index i;

Step 2: For each signal flow i of the GO model, create a corresponding root node S_i in the BN;

Step 3: Visit the precursive operator O_i of the signal flow i and judge its type:

If O_i is a repairable operator, skip to Step 4;

If O_i is not a repairable operator, skip to Step 5;

Step 4: Judge the type of O_i:

If O_i is an initial operator (operator 5), establish the BN node state distribution in terms of the state of operator O_i;

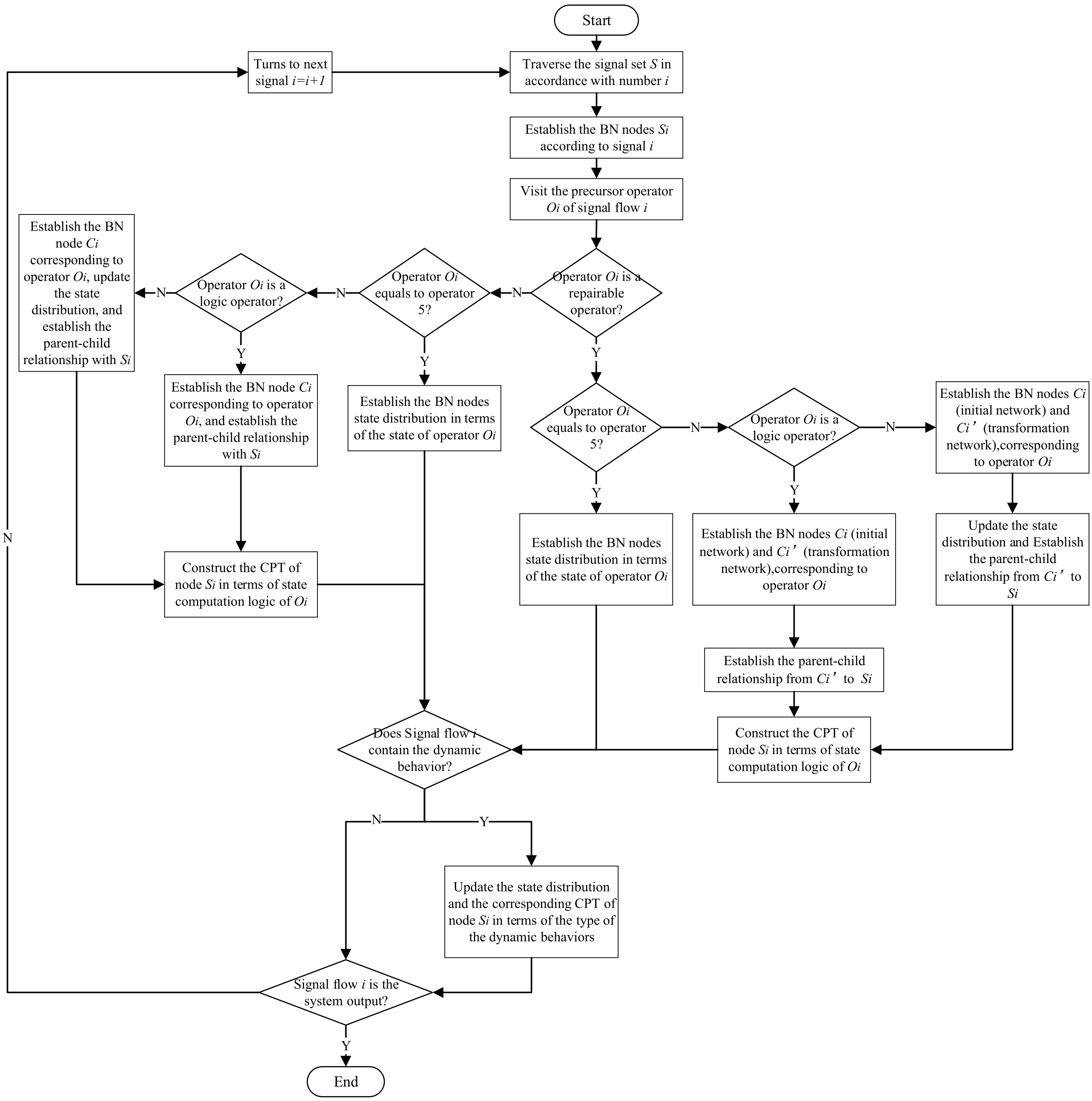


FIGURE 11. The BN conversion procedure of the extended GO model.

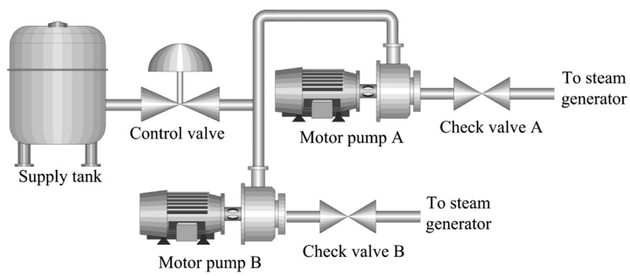


FIGURE 12. Simplified scheme of the water supply system.

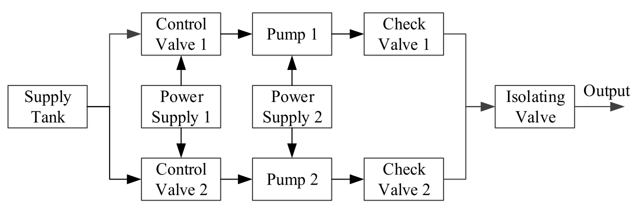


FIGURE 13. Structure of the water supply system.

If Oi is a logical operator, establish the BN nodes C_i (initial network) and $C_i^{'}$ (transformation network), corresponding to operator O_i. Then, establish the parent-child relationship from $C_i^{'}$ to S_i. Meanwhile, construct the CPT of node S_i in terms of the state computation logic of O_i.

If O_i is a functional operator, establish the BN nodes C_i (initial network) and $C_i^{'}$ (transformation network), corresponding to operator O_i. Then, update the state distribution

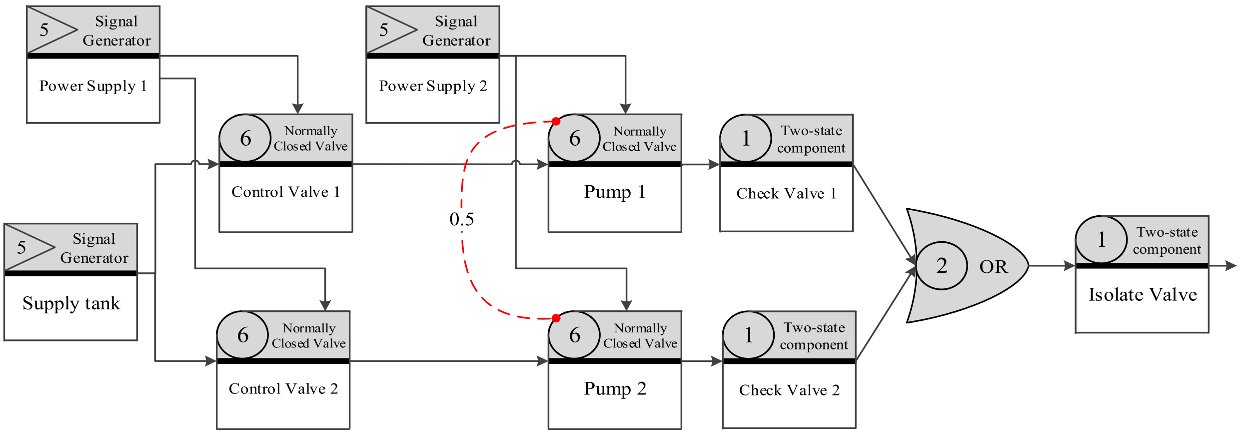


FIGURE 14. The GO model of the water supply system.

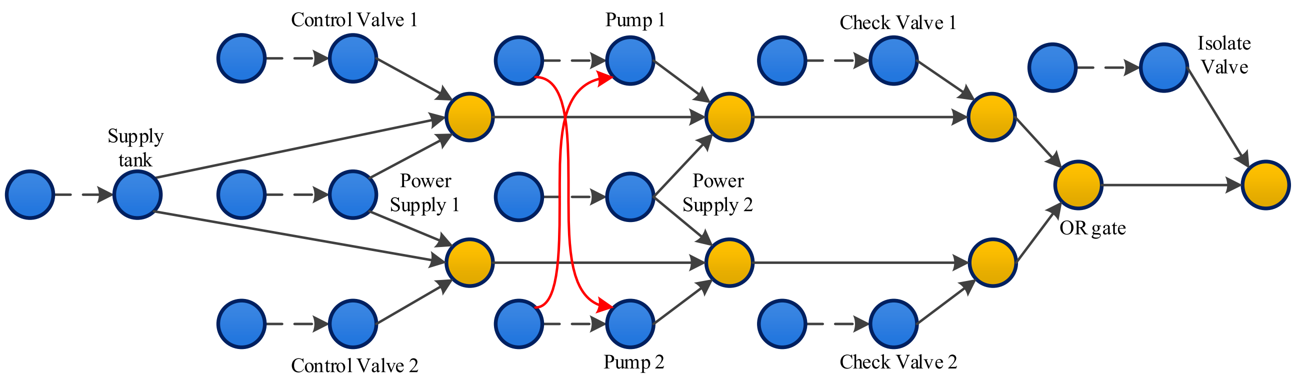


FIGURE 15. The DBN of the water supply system.

TABLE 1. Failure and maintenance rate of the system.

Name	Failure rate/10^{-4}	MTTR/h
Supply tank	0	
Power supply	0.3	8.0
Control valve	0.7	8.0
Pump	0.2	8.0
Check valve	2.5	8.0
Isolating valve	0.5	8.0

and establish the parent-child relationship from C_i' to S_i. Meanwhile, construct the CPT of node S_i in terms of the state computation logic of O_i.

Step 5: judge the type of O_i:

If O_i is an initial operator (operator 5), establish the BN node state distribution in terms of the state of operator O_i;

If O_i is a logical operator, establish the BN node C_i corresponding to operator O_i, and establish the parent-child relationship with S_i. Then, construct the CPT of node S_i in terms of the state computation logic of O_i.

If O_i is a functional operator, establish the BN node C_i corresponding to operator O_i, update the state distribution,

TABLE 2. Success probability for each component in the system.

Name	Success probability (T=100)	Success probability (T=500)	Success probability (T=1000)
Power Supply 1	0.99974476	0.99974476	0.99974476
Control Valve 1	0.99914956	0.99914955	0.99914955
Control Valve 2	0.99914956	0.99914955	0.99914955
Power Supply 2	0.99974476	0.99974476	0.99974476
Pump 1	0.99872451	0.99872451	0.99872451
Pump 2	0.99872451	0.99872451	0.99872451
Check Valve 1	0.99660441	0.99660439	0.99660439
Check Valve 2	0.99660441	0.99660439	0.99660439
Isolate Valve	0.99905612	0.99905611	0.99905611

and establish the parent-child relationship with S_i. Then, construct the CPT of node S_i in terms of the state computation logic of O_i.

Step 6: Whether the signal flow i contains dynamic behavior or not:

If the signal flow contains dynamic behavior, skip to Step 7;

If the signal flow does not contain dynamic behavior, skip to Step 8;

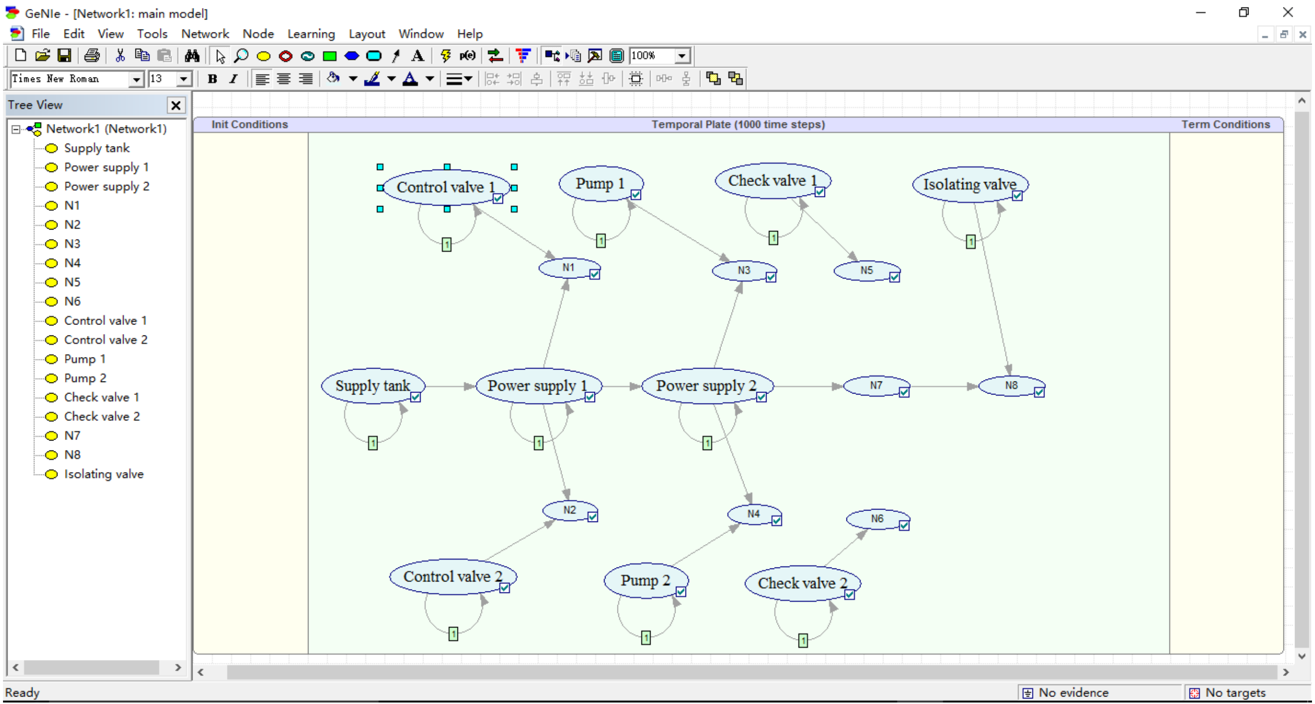


FIGURE 16. The DBN of the water supply system in GeNIe.

Step 7: Update the state distribution and the corresponding CPT of node S_i in terms of the type of dynamic behaviors;

Step 8: Judge whether the signal flow Si is the output of this system or not (namely, judge whether i is equal to N or not):

If not, skip to step 1 to visit the next signal flow (namely, $i = i + 1$);

Otherwise, skip to step 9;

Step 9: End.

IV. CASE STUDY

In this section, a model of the water supply system of an aircraft is created by using the extended GO methodology to verify that the approach is accurate and practical. As one of the engineered safety facilities, the water supply system acts as a heat sink to remove the decay heat from the reactor core during accident scenarios [38]. This cools down the steam generator secondary side and eventually removes the decay heat from the reactor core through a natural circulation mechanism. The simplified scheme of this process is shown in Fig. 12.

The system consists of two roads for the water supply. Each road goes through the control valve, the pump and the check valve. Finally, the water can be successfully supplied. The structure of the system is shown in Fig. 13. Meanwhile, if one of the pumps fails, the failure rate of the other pump would increases [40].

Additionally, the water supply system can be repairable. The water and power source are the inputs to the system, and they are described by the signal generators. The other equipment in the system are all two-state components. The control valves and pumps are denoted as a normally closed valve. The check valve and isolating valve are presented as two-state components, and the two branches are logically output with an OR gate. We assume that the failure of the supply tank can be ignored and that if one of the pumps breaks down, the failure rate of the other pump would increase to $\alpha\lambda$ ($\alpha = 2$). The data for the failure and maintenance rate are shown in Table 1.

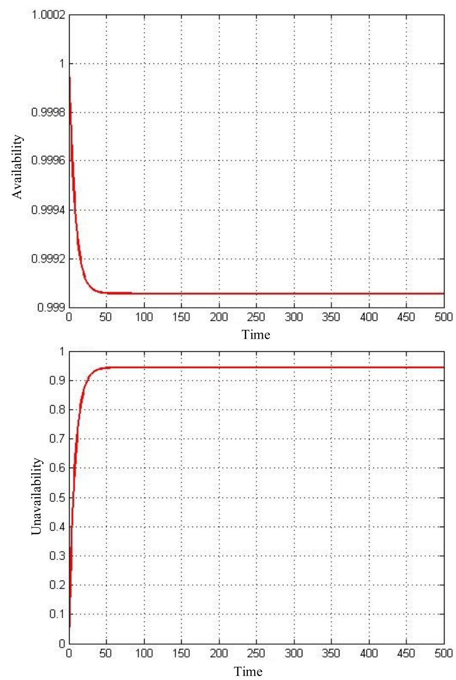


FIGURE 17. Results of the water supply system.

Based on the structure of the water supply system, the GO model can be created. Due to the loading share of pumps, the load factor is additive on their model, as shown in Fig. 14.

According to the mapping rules mentioned previously, the GO model is mapped onto the DBN, as shown in Fig. 15. With the help of mature software, namely GeNIe, DBN model could be drawn and calculated efficiently, as shown in Fig. 16 and Table 2. Moreover, we utilize the MATLAB to verify the accuracy of results that proposed by GeNIe. The availability and unavailability curves are shown in Fig. 17. We can find that the curves tend to a stable value, which are called the long-term stable availability and unavailability. The final average working probability of Isolate Valve is 0.99905601 at $T = 1000$, nearly equal to the results of the software. Simultaneously, the comparative results could also prove the accuracy of the approach.

V. CONCLUSION

This paper proposed a dynamic graphical aggregation approach to extend the GO methodology to model the reliability of the complex system with dynamic failure behaviors. The DBN is employed to map the modeling elements of the extended GO methodology. Based on the mapping rules, each type of operator, the signals and the three typical dynamic relationships (functional dependency, backup dependency, and load sharing) were aggregated into the DBN nodes, and the BN toolkit was used to quantitatively calculate the reliability of the complex system.

Ultimately, the validity and efficiency of the approach were verified in the case of the water supply system. Several advantages were listed as follows: (i) the dynamic relationships in system can be created visually with the GO methodology; (ii) the unified mapping rules of from static and dynamic GO model to the BN are established conveniently; and (iii) the quantitative calculation of the dynamic GO models is empowered by various matured BN software toolkits.

In the future, the uncertainties and larger-scale issues should be considered, such as i) how to evaluate the quantitative results considering the human factors and statistical uncertainties; ii) how to efficiently analyze a large-scale model by utilizing new computation platforms, e.g., Hadoop and Spark.

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