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Supply chain risk transmission monitoring based on graphic evaluation and review technique

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ABSTRACT

In the supply chain context, risk events can accumulate, amplify, and mutate as they spread through the supply chain network structure. This can lead to significant losses for supply chains and global businesses. Therefore, monitoring supply chain risk is crucial to ensure the smooth operation of the supply chain. To address this issue, our study focuses on the DongNan automobile manufacturing supply chain and examines the monitoring of lead time risk. We use the graphic evaluation and review technique (GERT) to characterize the topology of the risk transmission network in the supply chain and construct a supply chain risk transmission model. We then use the change-point control chart to monitor risk factors, specifically delayed lead time. Our study includes a case study that demonstrates the effectiveness of the change-point control chart in signaling and accurately estimating the change point and out-of-control stage in terms of performance indices. We also investigate the impact of mis-specified risk function parameters on the chart's performance, finding that it remains relatively stable. Overall, the change-point control chart is an effective tool for monitoring supply chain risk, and its monitoring effect is relatively stable.

1. Introduction

Modern supply chains have presented growth opportunities for industries but also brought a wide range of risks, including shipping delays, theft, natural disasters, severe weather, cyber-attacks, and unexpected quality issues [1,2]. The supply chain risk is 'the likelihood and impact of unexpected macro and/or micro level events or conditions that adversely influence any part of a supply chain leading to operational, tactical, or strategic level failures or irregularities [3]. These risks are prone to the negative ripple effect [4], which is a phenomenon in which the negative consequences of risks spread rapidly throughout the supply chain due to the interconnectedness of enterprises [5,6]. Essentially, disruptions or negative events in one part of the supply chain can trigger a chain reaction that affects other parts of the chain, potentially causing significant disruptions to the entire system [2]. Much of the literature on supply chain risk, e.g. Refs. [7,8], has improved our understanding of the underlying phenomena. It is essential for academia and industries to have a better understanding of risk transmission properties in the supply chain to prevent negative consequences and secure the benefits of the supply chain.

Strategies such as continuous monitoring is proposed as a necessary tool to help supply chains to identify the risk sources and analyze the reasons for the risks [9,10]. Ivanov et al. [11,12] have underlined the importance of monitoring with the purpose of

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increasing visibility along the supply chain and developing quick recovery strategies in collaboration with all supply chain partners. This can be achieved by embedding a monitoring tool such as control charts. The control chart can provide real-time visibility into key metrics and signal the need for action when a risk is identified [13]. By proactively monitoring for potential risks and responding quickly to any issues that arise, companies can build more resilient and agile supply chains that are better able to withstand disruptions and deliver value to customers. The T^2 control procedure introduced by Hotelling [14] is particularly appealing to practitioners looking for methods that effectively detect shifts in the processes.

Although extensive literature has explored supply chain risks and their transmission mechanisms, there remains a significant gap in research on the effective monitoring and management of these risks [15]. This gap is particularly evident in highly complex and interconnected supply chains, where the speed and extent of risk transmission often exceed initial expectations. This complexity complicates the identification and control of these risks [9]. Consequently, our study seeks to address the following research question.

RQ: How can the Graphic Evaluation and Review Technique (GERT) and change-point control charts be effectively utilized to monitor and manage lead-time risks in supply chains?

Our study focuses on the DongNan automobile manufacturing supply chain as a case study for several compelling reasons. First, the automotive manufacturing supply chain is inherently complex, involving a vast network of component suppliers and production processes [16], where delays in any single link can disrupt the entire supply chain. Second, the automotive manufacturing industry imposes stringent requirements on delivery times, making lead-time delays a critical and pervasive risk [17]. Third, the globalized nature of the automotive manufacturing supply chain means that risks can propagate rapidly across international borders, impacting global partners [18]. Therefore, the DongNan automotive manufacturing supply chain provides an ideal context for investigating risk monitoring strategies, with the potential to offer valuable insights for other industries.

In this study, we specifically investigate methods for monitoring lead-time risks within the DongNan automobile manufacturing supply chain. We employ the Graphic Evaluation and Review Technique (GERT) to characterize the topology of the risk transmission network within the supply chain and develop a corresponding risk transmission model. By applying change-point control charts, we are able to monitor risk factors—particularly lead-time delays—in real-time, thereby providing effective decision support for supply chain managers. For instance, the state function of "supplier delay" risk can be modeled as a function of delay time, where an increase in delay time corresponds to an elevated risk value. When the supplier delay time exceeds a predefined threshold, the trigger rule is activated, and the risk materializes as a risk event. By monitoring process activities through control charts, we can track the trend of the risk state, with the control limit serving as the trigger rule for risk events. Upon activation of a trigger, it becomes possible to identify the specific process activity where the risk originated, pinpoint the risk source, and implement appropriate control measures.

This study makes several key contributions to the literature on supply chain risk management. First, the study introduces the integration of the GERT with change-point control charts to monitor and manage supply chain risks, particularly lead-time risks. This combination is novel and provides a comprehensive approach to characterizing and monitoring risk transmission in supply chains. By utilizing GERT, the study maps the complex topology of risk transmission networks within the supply chain, while change-point control charts enable real-time monitoring of risk factors. This dual approach enhances visibility into risk propagation and improves the supply chain's responsiveness to disruptions.

Second, the study focuses on the DongNan automobile manufacturing supply chain, which is representative of a highly complex and globalized supply chain network. By investigating lead-time risks in this context, the study provides industry-specific insights that are particularly relevant to the automotive sector but also applicable to other industries. The findings offer practical implications for supply chain managers in the automotive industry, providing tools and methodologies to monitor and manage lead-time delays effectively. The study's case-based approach ensures that the results are grounded in real-world applications.

Third, the study addresses significant gaps in the literature regarding the monitoring and management of supply chain risks, particularly in highly interconnected and complex supply chains. Previous research has largely focused on identifying and understanding risks, but there has been less emphasis on effective monitoring and control mechanisms. By introducing change-point control charts to supply chain risk management, the study broadens the application of control charts beyond their traditional use in quality control. This extension demonstrates the versatility of control charts as tools for real-time risk monitoring and decision support in supply chain management.

The rest of the paper is organized as follows. The next section presents a literature review on supply chain risk transmission and control. Section 3 presents the supply chain risk transmission model-based GERT. Sections 4 describes the change-point chart based on Hotelling T^2 statistics. A case study and sensitivity analysis are presented in Section 5 and Section 6, respectively. The conclusions, implications and future research are provided in Section 7.

2. Supply chain risk transmission and control

2.1. Theoretical foundations of supply chain risk transmission

The transmission of risks within supply chains has been a focal point for both qualitative and quantitative research methodologies. These methodologies encompass risk identification, assessment, mitigation, and monitoring [3,19]. While risk monitoring has received less attention, it is crucial for understanding how risks propagate and influence supply chain dynamics [6,20,21].

The phenomenon often referred to as the "supply chain ripple effect" describes the cascading impacts of disruptions throughout the supply chain network. This effect has been characterized by various terms, including 'domino effect', 'snowball effect', and 'cascading failure' [4,22,23]. To manage this ripple effect, resilient supply chain design and planning are imperative, supported by methods such as graph theory, complex network theory, and Bayesian networks [24,25].

Optimization techniques and analytical methods, such as mixed-integer programming and system dynamics, have been applied to study supply chain design [26], while stability and robustness analyses often utilize control theory and Monte Carlo simulations [27,28]. These frameworks help in understanding the propagation and control of risks within supply chains.

2.2. *Application of GERT in supply chain risk analysis*

The Graphical Evaluation and Review Technique (GERT) is a powerful tool for analyzing and mitigating supply chain risks, particularly those associated with the SC ripple effect. Pritsker and Happ [29] developed GERT to model networks with probabilistic activities and variable durations, making it suitable for complex supply chain scenarios [30]. GERT's flexibility and probabilistic modeling capabilities allow for a nuanced representation of risk propagation [31,32].

GERT can model supply chains with multiple paths or loops, enhancing its utility in complex network analysis [33,34]. Its dynamic analysis capabilities facilitate the simulation of supply chain performance under various disruption scenarios, providing insights into potential risk pathways [35]. Furthermore, GERT's visualization features make risk propagation analysis accessible and actionable for decision-makers.

Given these strengths, this study employs GERT to model the risk transmission process within supply chains, aiming to provide a comprehensive framework for understanding and mitigating these risks.

2.3. *Integration of risk control mechanisms*

Effective risk control in supply chains is critical, especially in the context of increasing globalization and technological advancements that heighten risk complexity [36,37]. Traditional strategies, such as inventory management, capacity flexibility, and backup facilities, are often discussed in isolation from the complex dynamics of risk transmission [38,39].

Recent studies highlight the need for proactive risk detection and integrated control mechanisms [40]. For example, Lei et al. [41] combined the susceptible-infectious-susceptible model with complex network theory to optimize risk control strategies, while Yue et al. [42] used hub and spoke networks to identify hidden disruption sources. However, the integration of risk monitoring with control mechanisms remains underexplored [41–43].

Control charts have traditionally been used for monitoring supply chain risks, but their application is limited by the increasing complexity of modern supply chains [13,44]. Therefore, this study introduces a novel control chart tailored for modeling risk transmission, enhancing the proactive management of supply chain risks.

2.4. *Contribution of the current study*

This study bridges the gap between risk transmission and control by utilizing GERT to model the dynamic process of risk propagation within supply chains. It also introduces an innovative control chart specifically designed to account for risk transmission, providing a more comprehensive and proactive approach to supply chain risk monitoring and management. This integrated approach aims to enhance organizational capabilities in anticipating, detecting, and responding to risks, thereby improving supply chain resilience and stability.

3. Supply chain risk transmission model based on GERT

3.1. *Model assumptions*

Consider a multistage supply chain system including n stages and one loop (as shown in Fig. 1). In this automobile supply chain, delivery delays are a common risk, which can lead to many problems such as production interruptions, inventory buildup, and customer dissatisfaction [3]. Therefore, we choose delivery delays as the monitoring object. And the proposed approach to monitor risks in the supply chain is generalizable to other types of risks as well. The key is to assess potential risks likelihood and design the corresponding control chart to mitigate or manage them, regardless of the specific type of risk.

In detail, when the upstream node enterprise i delivers materials to the node enterprise j, the probability of timely delivery is p_{ij}, and the time required is t_{ij}. The time of delivery delay directly caused by disruptions is st_{ij}. The delay will also be transmitted to downstream enterprises, and each node enterprise along the downstream line will have new delays in their respective delivery links. In the case of delay, the probability of node enterprise i completing material delivery to node enterprise j is $p_{d,ij}$, the probability of delay aggravation caused by node enterprise i's improper response is $p_{d,ii}$, and the probability of delay superposition caused by node enterprise j's improper response is $p_{d,jj}$. The intensity of risk transmit from the node enterprise of i to the node enterprise j is $p_{R,ij}$, and the amount of

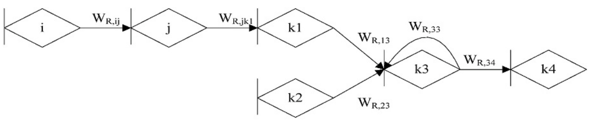

Fig. 1. Supply chain network structure.

risk transmitted to the downstream enterprise $j, k, \ldots n$ in the link (i,j) is $r_{j,ij}, r_{k,ij}, \ldots, r_{n,ij}$, respectively. The amount of risk $r_{j,ij}, r_{k,ij}, \ldots, r_{n,ij}$ can be regarded as a function of the final delay time Δt_{ij} in the link (i,j), i.e., $r_{j,ij} = r_j(\Delta t_{ij})$, $r_{k,ij} = r_k(\Delta t_{ij}), \ldots, r_{n,ij} = r_n(\Delta t_{ij})$.

Furthermore, the following assumptions are made, and the symbols and notation are shown in Table 1.

(1) To maintain system stability, it is assumed that the transition probability between nodes remains constant over time. When moving from node enterprise i to node enterprise j, the latter is solely dependent on the former and is independent of the path taken to reach node enterprise i.
(2) During the process of transmission, the inherent nature of risk remains unchanged from its original state at the beginning, but the quantity of risk changes during transmission. This type of transmission is known as steady-state transmission.

3.2. Model building

Assume that all nodes are exclusive OR nodes (i.e., the flow of the network can only go through one of the outgoing branches of each node at a time), and the node enterprise i is directly impacted by disruptions and the delivery time delay st_i is a constant. In the case of delay, the probability density function of the actual delivery time $lt_{ij} = t_{ij} + st_i$ is $f_{d,ij}(lt_{ij})$, then the corresponding moment generating function can be expressed as Equation (1),

$$M_{d,ij}(s) = \int_{-\infty}^{+\infty} e^{slt_{ij}} f_d(lt_{ij}) dlt_{ij} = \int_{-\infty}^{+\infty} e^{s(t_{ij}+st_i)} f_T(t_{ij}) dt_{ij}. \tag{1}$$

And its equivalent transfer function can be expressed as Equation (2),

$$W_{d,ij}(s) = p_{d,ij} M_{d,ij}(s). \tag{2}$$

The expected delivery time and variance from node enterprise i to node enterprise j are shown in Equation (3),

$$E_d(lt_{i\to j}) = \frac{\partial}{\partial s}\left[M_{d,ij}(s)\right]|_{s=0} = \frac{\partial}{\partial s}\left[\frac{W_{d,ij}(s)}{W_{d,ij}(0)}\right]|_{s=0},$$

$$V_d = E_d\left(lt^2_{i\to j}\right) - \left[E_d(lt_{i\to j})\right]^2 = \frac{\partial^2}{\partial s^2}\left[\frac{W_{d,ij}(s)}{W_{d,ij}(0)}\right]|_{s=0} - \left\{\frac{\partial}{\partial s}\left[\frac{W_{d,ij}(s)}{W_{d,ij}(0)}\right]|_{s=0}\right\}^2 \tag{3}$$

respectively.

On this basis, the final delay time of each node can be obtained as Equation (4),

$$\Delta t = E_d(lt_{ij}) - E(t_{ij}). \tag{4}$$

Further, assume that the probability density functions of risk size $r_{j,ij}$ and final delay time Δt_{ij} are $f_R(r_{j,ij})$ and $f_{\Delta T}(\Delta t_{ij})$, respectively. Then the corresponding moment generating function can be expressed as Equation (5)

$$M_{R,j,ij}(s) = \int_{-\infty}^{+\infty} e^{sr_{j,ij}} f_R(r_{i,ij}) dr_{i,ij} = \int_{-\infty}^{+\infty} e^{sr_j(\Delta t_{ij})} f_{\Delta T}(\Delta t_{ij}) d\Delta t_{ij}\ . \tag{5}$$

Currently, the transfer function of risk from node enterprise i to node enterprise j is shown in Equation (6)

$$W_{R,j,ij}(s) = p_{R,ij} \cdot M_{R,j,ij}(s). \tag{6}$$

where $p_{R,ij}$ represents the possibility of risk transmission from node enterprise i to node enterprise j.

Based on the signal flow graph theory, according to the basic properties of Mason formula and moment generating function, risk is

Table 1
Symbols and notation.

Symbols	Notation
t_{ij}	the time required when the upstream node enterprise i delivers materials to the node enterprise j
p_{ij}	the probability of timely delivery when the upstream node enterprise i delivers materials to the node enterprise j
Δt_{ij}	the final delay time in the link (i,j)
$f_{\Delta T}(\Delta t_{ij})$	the probability density functions of final delay time Δt_{ij}
st_{ij}	the time of delivery delay directly caused by disruptions in the link (i,j)
$p_{d,ij}$	the probability of node enterprise i completing material delivery to node enterprise j in the case of delay
$p_{d,ii}$	the probability of delay aggravation caused by node enterprise i's improper response in the case of delay
$p_{R,ij}$	the intensity of risk transmit from the node enterprise of i to the node enterprise j
$r_{j,ij}, r_{k,ij}, \ldots, r_{n,ij}$	the amount of risk transmitted to the downstream enterprise $j, k, \ldots n$ in the link (i,j)
$f_R(r_{j,ij})$	the probability density functions of risk size $r_{j,ij}$
$f_{d,ij}(lt_{ij})$	the probability density function of the actual delivery time $lt_{ij} = t_{ij} + st_i$

transmitted from node enterprise i to any downstream associated node enterprise j, and its equivalent transfer function of risk quantification is shown in Equation (7),

$$W_{R,i,j}(s)=\frac{\sum_{d=1}^{n}W_{R,j,d}(s)\left[1-\sum_{m}\sum_{g\neq d}(-1)^{m}W_{R,j,g}(L_m)\right]}{1-\sum_{m}\sum_{g}(-1)^{m}W_{R,j,g}(L_m)}, \tag{7}$$

where $W_{R,j,d}(s)$ represents the equivalent transfer function of the d th direct path from node enterprise i to node enterprise j, when node enterprise j is the object of risk quantification. $\sum_m\sum_g(-1)^m W_{R,j,g}(L_m)$ denotes the characteristic formula of GERT network of node enterprise i and node enterprise j.

The equivalent transfer probability and equivalent moment generating functions of risk transfer from node enterprise i to node enterprise j are as shown in Equation (8),

$$p_{R,j,ij}=W_{R,i,ij}(0)$$

and

$$M_{R,y,xy}(s)=\frac{W_{R,y,xy}(s)}{p_{R,y,xy}}=\frac{W_{R,y,xy}(s)}{W_{R,y,xy}(0)}, \tag{8}$$

respectively.

Moreover, the expected risk quantity and variance of the risk transfer from node enterprise x to node enterprise y are shown in Equation (9),

$$E_R(r_{x\to y})=\frac{\partial}{\partial s}\left[M_{R,y,xy}(s)\right]|_{s=0}=\frac{\partial}{\partial s}\left[\frac{W_{R,y,xy}(s)}{W_{R,y,xy}(0)}\right]|_{s=0}$$

$$V_R=E_R\left(r_{x\to y}^2\right)-\left[E_R\left(r_{x\to y}\right)\right]^2=\frac{\partial^2}{\partial s^2}\left[\frac{W_{R,y,xy}(s)}{W_{R,y,xy}(0)}\right]|_{s=0}-\left\{\frac{\partial}{\partial s}\left[\frac{W_{R,y,xy}(s)}{W_{R,y,xy}(0)}\right]|_{s=0}\right\}^2. \tag{9}$$

In the context of series structure, the moment generating function of the sum of independent random variables is equal to the product of the moment generating functions of each individual random variable (Pritsker, 1966). Therefore, in the series GERT network, the equivalent transfer function of the risk factors is represented by Equation (10),

$$W_{R,ik}=W_{R,ij}W_{R,jk} \tag{10}$$

The expected quantity of risk transferred from node enterprise i to node enterprise k_1 via node enterprise j is shown in Equation (11),

$$E_R(r_{i\to k1})=\frac{\partial}{\partial s}\left[M_{R,ik1}(s)\right]|_{s=0}=\frac{\partial}{\partial s}\left[\frac{W_{R,ik1}(s)}{W_{R,ik1}(0)}\right]|_{s=0}=\frac{\partial}{\partial s}\left[\frac{W_{R,ij}(s)\cdot W_{R,jk1}(s)}{W_{R,ij}(0)\cdot W_{R,jk1}(0)}\right]|_{s=0}. \tag{11}$$

In the context of parallel structure, the transfer relationship of independent random variables is the sum of the transfer relationships on each parallel branch line, so the equivalent transfer function for the risk transferred from node enterprises k_1, k_2 to node enterprise k_3 in the parallel GERT network can be expressed as the sum of the transfer functions of each individual branch line, i.e., Equation (12):

$$W_{R,k}=W_{R,13}+W_{R,23}. \tag{12}$$

The expected quantity of risk transferred from node enterprises k_1, k_2 to node enterprise k_3 is shown in Equation (13),

$$E_R\left(r_{k1,k2\to k3}\right)=\frac{\partial}{\partial s}\left[M_{R,k}(s)\right]|_{s=0}=\frac{\partial}{\partial s}\left[\frac{W_{R,k}(s)}{W_{R,k}(0)}\right]|_{s=0}=\frac{\partial}{\partial s}\left[\frac{W_{R,13}(s)+W_{R,23}(s)}{W_{R,13}(0)+W_{R,23}(0)}\right]|_{s=0}. \tag{13}$$

In the case of self-circulation (i.e., a situation where a node can be reached from itself by traversing a cycle of paths in the network), the transfer relation is the product of the entry node's branch line value and $\frac{1}{1-\beta}$ (where β is the transfer coefficient in self-circulation), then the equivalent transfer function and expected risk quantity of risk are shown in Equation (14),

$$W_{R,k3k4}=\frac{W_{R,34}}{1-W_{R,33}}, \text{ and}$$

$$E_R(r_{i\to k1})=\frac{\partial}{\partial s}\left[M_{R,k3k4}(s)\right]|_{s=0}=\frac{\partial}{\partial s}\left[\frac{W_{R,k3k4}(s)}{W_{R,k3k4}(0)}\right]|_{s=0}=\frac{\partial}{\partial s}\left[\frac{W_{R,34}(s)/\left[1-W_{R,33}(s)\right]}{W_{R,34}(0)/\left[1-W_{R,33}(0)\right]}\right]|_{s=0}. \tag{14}$$

4. The change-point chart based on Hotelling T^2 statistics

Suppose a normally distributed random variable Y_l conditioned on the parameter τ, called the 'change-point' which is unknown a priori. The original model

$$Y_l \sim \begin{cases} N(\mu_1, \sigma^2), \text{if } l \le \tau \\ N(\mu_2, \sigma^2), \text{if } l > \tau \end{cases}$$

specifies the change-point formulation in the case of a normal distribution. The model includes three additional unknown parameters: μ_1 and μ_2 represent the in- and out-of-control means respectively, while σ^2 represents the constant in-control and out-of-control variance. The mean of the first l samples and the mean of the last $m-l$ samples is $\bar{y}_l = \frac{1}{l}\Sigma_{j=1}^{l} y_j$ and $\bar{y}_{m-l} = \frac{1}{m-l}\Sigma_{j=l+1}^{m} y_j$, respectively. Then, the variance matrix of m samples can be expressed as Equation (15),

$$W_l = \frac{1}{m-2}\left\{ \sum_{j=1}^{l} \left(y_j - \bar{y}_l\right)\left(y_j - \bar{y}_l\right)^T + \sum_{j=l+1}^{m} \left(y_j - \bar{y}_{m-l}\right)\left(y_j - \bar{y}_{m-l}\right)^T \right\}. \tag{15}$$

When the change point τ appears between the observations of two adjacent samples, only when $l \le \tau < l+1$, W_l is the unbiased estimation of Σ.

Then, the standard deviation between the sample observations before and after the change point is $t_l = \sqrt{\frac{l(m-l)}{m}}(\bar{y}_l - \bar{y}_{m-l})$, and the corresponding Hotelling T^2 statistic is shown in Equation (16),

$$T_l^2 = t_l' W_l^{-1} t_l, l = 1, 2....m-1. \tag{16}$$

If $\max_{1 \le l \le m-1} T_l^2$ is large enough, H_0 is rejected. The maximum likelihood estimation of change point τ is shown in Equation (17),

$$\hat{\tau} = \underset{l=1,\ldots,m-1}{\arg} \max T_l^2. \tag{17}$$

The transmission of supply chain risk follows a specific path and direction. To take full advantage of this directional information, Zou et al. [45] developed a multivariate change point method that incorporates direction information. This approach is particularly effective in detecting small mean shifts that may otherwise be difficult to identify. In detail, assume that the mean shift occurs at a certain stage ζ, the expectation of y_j becomes $\mu_2 = \delta_\zeta$, and the hypothesis test can be described as

$$H_0 : \mu_1 = 0 \leftrightarrow H_2 : \mu_2 = \delta d_1 or \ \mu_2 = \delta d_2 \cdots or \ \mu_2 = \delta d_p$$

where the shift size δ is an unknown constant, and d is directional information, $\mathrm{d}_\varsigma = \left(\mathrm{d}_{\varsigma,1}, \mathrm{d}_{\varsigma,2}, \ldots, \mathrm{d}_{\varsigma,p}\right)'$, $d_{\xi,k} = \begin{cases} C_k \prod_{i=\xi+1}^{k} A_i & \text{if} \quad k \ge \xi \\ 0 \quad other \end{cases}$.

$W_l (1 \le l \le m)$ can be used as the estimated value of Σ, and the statistics using generalized likelihood ratio is shown in Equation (18),

$$U_l = \max_{1 \le k \le p} \left\{ \left(d_k' W_l^{-1} t_l\right)^2 \Big/ \left(d_k' W_l^{-1} d_k\right) \right\} \quad l = 1, 2, 3, \ldots, m-1. \tag{18}$$

If $\max_{1 \le l \le m-1} U_l > c$ (c is a constant), H_0 is rejected. It can be judged that the quality risk is abnormal, and the supply chain system runs out-of-control. And the estimates of change point $\hat{\tau}$ and out-of-control stage $\hat{\varsigma}$ are shown in Equation (19),

$$\begin{aligned} \hat{\tau} &= \underset{1 \le l < m}{\arg\max} \left\{ \max_{1 \le k \le p} \left(d_k' W_l^{-1} t_l\right)^2 / \left(d_k' W_l^{-1} d_k\right) \right\} \\ \hat{\varsigma} &= \underset{1 \le k \le p}{\arg\max} \left\{ \left(d_k' W_l^{-1} t_l\right)^2 / \left(d_k' W_l^{-1} d_k\right) \right\} \end{aligned} \tag{19}$$

respectively.

Set $G_{l,k} = \left(d_k' W_l^{-1} t_l\right)^2 / \left(d_k' W_l^{-1} d_k\right)$ and $V_k = \max_{1 \le l \le m-1} \left(\left(d_k' W_l^{-1} t_l\right)^2 / d_k' W_l^{-1} d_k \right)$, according to $\Pr(V_k > c), k = 1, 2, 3..p$, approximate values $\hat{c}$ can be calculated. When the supply chain system is in-control, $G_{l,k}$ follows the following distribution

$$G_{l,k} \sim \frac{m-2}{m-p-1} F_1 \left(1 + \frac{p-1}{m-p} F_2\right).$$

where $F_1 \sim F(1, m-p-1)$, $F_2 \sim F(p-1, m-p)$, and the variables F_1 and F_2 are independent of each other. Then when $m \to \infty$, $G_{l,k}$ follows approximately χ_1^2 distribution. Hence, in the mean testing, the approximate distribution of V_k ($V_k = Z_m$) can be obtained by calculating the classical likelihood rate Z_m, as shown in Equation (20),

$$\Pr\left(Z_m^{1/2} > x\right) \approx \frac{x \exp(-x^2/2)}{\sqrt{2\pi}} \left\{ \ln(s) - \frac{1}{x^2}\ln(s) + \frac{4}{x^2} \right\}, \tag{20}$$

where $s = \frac{(1-h)(1-l)}{hl}$, $h = l = (\ln(m))^{3/2}/m$. Then based on $\Pr(V_k > c_1) = \alpha$ (α is type I error), c_1 can be calculated. The approximate value $\widehat{c}$ of c can be obtained with Equation (21):

$$F(\widehat{c}) \equiv \Pr\left(G_{l,k} < \widehat{c}\right) = F_{\chi_2^1}(c_1) \tag{21}$$

where $F(\cdot), F_{\chi_1^2}(\cdot)$ are cumulative distribution probability function of $G_{l,k}$ and χ_1^2, respectively. In order to ensure that the change-point control chart can maintain a small false alarm rate when the number of Stage p is not large, the classical Bonferroni procedure is used for correction. Given type I error α, according to $\Pr\left(\max_{1\le k\le p} V_k > c\right) = \Sigma_{k=1}^{p} \Pr(V_k > c) = \alpha$, the control limit $\widehat{c}$ of the change point control chart is determined. Zou et al. [45] suggested that the basic criterion for evaluating the monitoring effect of the change-point control chart is the accuracy of abnormal point detection. Therefore, we take the detection rate, the accuracy of change point estimation and out-of-control stage estimation as the evaluation criteria.

To ensure the study is clear and precise enough to be replicated, the specific steps are as follows.

Step 1 Analyze the logical relationships among risk factors (such as series and parallel), and construct the GERT network model of risk factor transmission based on the fundamental features of the actual supply chain system and the risk events.

Step 2 Estimate the parameters of the supply chain system operation using historical data, such as the probability density function and risk function of delayed delivery. Use the product of the characteristic function and transfer probability between node enterprises as a parameter to describe the transfer relationship of risk factors between node enterprises.

Step 3 Employ the Mason formula of the signal flow graph to determine the characteristic transfer function and equivalent probability of the supply chain system. Based on this, calculate the cumulative expected risk transmitted from the risk source enterprise to each node enterprise along the downstream link.

Step 4 Use the expected risk quantity as the monitoring object, and apply the change-point control chart based on Hotelling statistics to monitor the supply chain risk. The expected risk quantity is taken as the monitoring object, and the change-point control chart based on Hotelling T^2 statistics is used to monitor the supply chain risk.

5. Case study

To illustrate and validate the modeling, DongNan (DN) Automotive, the largest cross-strait joint venture automobile manufacturer in China, based in Fuzhou, is used as an example. DN Automotive produces cars, SUVs, and commercial vehicles for low-end customers. A portion of DN Automotive's supply chain network is selected for simulation (as depicted in Fig. 2). It is assumed that node enterprise 1 is directly impacted by disruptions, leading to delayed delivery. This delay may also affect downstream node enterprises along the supply chain. Additionally, downstream node enterprises may experience new delays due to improper handling of their own operations. For instance, serious delay accumulation in multiple stages could result in Stage 4 bearing more risks, leading to more severe consequences, and ultimately causing a supply chain disruption.

Specifically, after the node enterprise 1 suffers a disruption directly, the expected delivery time delay $st_1 = 21$ is a constant. Taking link (1,2) as an example, in the case of delay, the probability density function of the actual delivery time $lt_{12} = t_{12} + st_1$ is $f_{d,12}(lt_{12})$, and the corresponding moment generating function can be expressed as Equation (22),

$$M_{d,12}(s) = \int_{-\infty}^{+\infty} e^{slt_{12}} f_d(lt_{12}) dlt_{12} = \int_{-\infty}^{+\infty} e^{s(t_{12}+21)} f_T(t_{12}) dt_{12}. \tag{22}$$

And its equivalent transfer function can be expressed as Equation (23),

$$W_{d,12}(s) = \frac{0.35\exp(4s + 0.125s^2)}{1 - 0.4\exp(4s)}. \tag{23}$$

According to the historical data, the probability of delayed delivery and its distribution function are shown in Table 2.

According to historical data, the functional relationships between the amount of risk and delay time for node enterprise 2,3,4 and 5 are as follows:

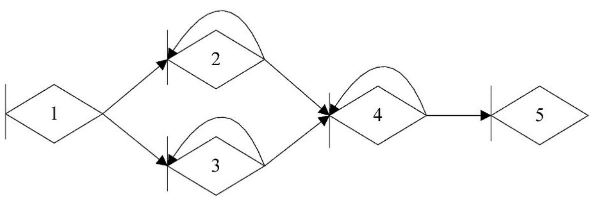

Fig. 2. DN supply chain network structure.

Table 2
Parameters of various delivery activities in the supply chain.

link	timely delivery probability	Parameters of timely delivery distribution	late delivery probability
(1,2)	0.45	N(4,0.5)	0.35
(1,3)	0.5	N(5,0.5)	0.4
(2,4)	0.3	N(12,2)	0.2
(3,4)	0.35	N(6,1.5)	0.35
(4,5)	0.5	N(6,0.5)	0.4
(2,2)		N(5,0.5)	0.55
(3,3)		N(6,1)	0.65
(4,4)		N(2,0.5)	0.35

$$r_2(\Delta t_{12}) = 0.3\Delta t_{12}^2, r_3(\Delta t_{12}) = 0.45\Delta t_{12}^2, r_4(\Delta t_{12}) = 6.5\Delta t_{12}, r_5(\Delta t_{12}) = 75\ \ln(0.2\Delta t_{12} + 1).$$ Thus, the cumulative expected risk can be obtained as $E_R(r_{1\to 2}), E_R(r_{1\to 3}), E_R(r_{1\to 4}), E_R(r_{1\to 5})$.

For the mean step change of the delivery time, the change-point control chart based on direction information and the Hotelling T^2 chart is used to monitor the cumulative expected risk quantity of the supply chain system to judge the risk shift trend. Setting $m = 50$, $p = 5$, $\alpha = 0.05$ and after some calculations, the control limit of the change-point control chart is $c = 183.57$.

When the change point τ occurs, the delay of the order $\tau + 1$ will appear in the stage ξ. Suppose the change point is $\tau = 20$, the process mean shift size is $\delta = 20$, $\delta = 30$, $\delta = 40$, and $\delta = 50$. And the out-of-control stages are $\xi = 1, \xi = 3$. The detection rate of the change point control chart, the accuracy of the estimated value $(\hat{\tau})$ of the change point, and the accuracy of the estimated value $(\hat{\xi})$ of the out-of-control stage are used as the performance indicators of the change point control chart, respectively. The MATLAB software is used to simulate 10000 times, and the results are shown in Table 3.

From Tables 3 and in the case $\xi = 1$, when the mean shift is small (i.e., $\delta = 20$), the detection rate of change point control chart is about 51 %, but it increases with the increase of mean shift.

Under the four studied mean shift sizes, according to the mean and standard deviation of $\hat{\tau}$, its diagnostic performance is consistent and mainly concentrated in the range $\tau \pm 3$. As the mean shift increases, the estimated value of the change point $(\hat{\tau})$ gradually approaches to the true value (Columns 4–8 in Table 3).

The estimated value $(\hat{\xi})$ of the out-of-control stage is relatively accurate. Even in the case of $\delta = 20$, it can still maintain a diagnostic accuracy of 94 %, and gradually tends to 1 with the increase of mean shift. In the case of $\xi = 3$, even if the change point occurs in different stages, the monitoring effect of the change-point control chart is not significantly different.

6. Sensitivity analysis

The sensitivity analysis explores how inaccuracies in parameter estimates affect the performance of the change-point control chart, particularly in terms of detection rates and estimation accuracy.

6.1. *Impact of parameter estimation on control chart performance*

When constructing a risk transmission model, parameters are often estimated based on multiple samples or managerial experience. However, in practice, these estimates may be inaccurate. Inaccurate parameter estimates can result in incorrect estimation of the mean shift direction vector, ultimately affecting the performance of the control chart [46], particularly the accuracy of change point detection.

For simplicity, set $\alpha = 0.05$, $p = 6$, $m = 50$, $\xi = 3$, $\tau = 20$, the coefficient of the risk function varied by 10 % (i.e., increased and decreased by 10 %), as shown in Table 4. Similarly, the detection rate of the change-point control chart, the accuracy of the estimated value $(\hat{\tau})$ of the change point, and the accuracy of the estimated value $(\hat{\xi})$ of the out-of-control stage, respectively, are used as the performance indicators of the change-point control chart. MATLAB software is used to simulate 10000 times, and the results are shown

Table 3
The performance of the control chart if $\tau = 20$ $\xi = 1$ and $\xi = 3$

Out-of-control stage	Mean shift (δ)	Detection rate	$\hat{\tau}$					
			AVE	SD	$P(\lvert\hat{\tau} - \tau\rvert \le 1)$	$P(\lvert\hat{\tau} - \tau\rvert \le 2)$	$P(\lvert\hat{\tau} - \tau\rvert \le 3)$	$P(\hat{\xi} = \xi)$
$\xi = 1$	20	0.51	21.8	10.3	0.60	0.68	0.73	0.94
	30	0.64	20.3	4.7	0.69	0.74	0.82	0.96
	40	0.93	20	1.8	0.82	0.85	0.90	0.99
	50	1.00	20	0.9	0.91	0.94	0.96	1.00
$\xi = 3$	20	0.44	22.3	12.1	0.53	0.59	0.69	0.91
	30	0.56	21.6	10.7	0.61	0.70	0.75	0.97
	40	0.92	20.2	5.6	0.72	0.82	0.87	0.99
	50	1.00	20	2.4	0.84	0.91	0.94	1.00

Table 4
Coefficient combination of risk function.

combination	1	2	3	4	5	6	7	8
r2	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.33
r3	0.495	0.495	0.495	0.495	0.405	0.405	0.405	0.405
r4	7.15	7.15	5.85	5.85	7.15	7.15	5.85	5.85
r5	0.22	0.18	0.22	0.18	0.22	0.18	0.22	0.18
combination	9	10	11	12	13	14	15	16
r2	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
r3	0.495	0.495	0.495	0.495	0.405	0.405	0.405	0.405
r4	7.15	7.15	5.85	5.85	7.15	7.15	5.85	5.85
r5	0.22	0.18	0.22	0.18	0.22	0.18	0.22	0.18

Table 5
The detection rate of the change point control chart with incorrectly estimated risk function parameters.

δ	true	1	2	3	4	5	6	7	8
20	0.44	0.48	0.46	0.43	0.43	0.45	0.44	0.41	0.40
30	0.56	0.61	0.60	0.54	0.53	0.58	0.57	0.53	0.51
40	0.92	0.94	0.93	0.91	0.90	0.92	0.92	0.90	0.90
50	1.00	1.00	1.00	0.99	0.99	1.00	1.00	0.98	0.98
δ	true	9	10	11	12	13	14	15	16
20	0.44	0.46	0.45	0.42	0.40	0.43	0.42	0.39	0.36
30	0.56	0.60	0.59	0.53	0.50	0.55	0.54	0.48	0.45
40	0.92	0.92	0.91	0.89	0.88	0.92	0.91	0.87	0.84
50	1.00	1.00	1.00	0.97	0.97	1.00	1.00	0.96	0.95

in Table 5.

6.2. Detection rate analysis

Table 5 presents the detection rate of the change-point control chart with incorrectly estimated risk function parameters. The results show that there is a slight difference in the detection rate compared to the real value when there is an error in parameter estimation. However, the detection rate under combination 1 and combination 2 is slightly higher than that under the real value, which may be due to the increased coefficient amplifying the risk of the source enterprise. On the other hand, the detection rate under combination 11 and combination 12 is significantly lower than that under the real value, which may be due to the reduced coefficient lowering the risk of the source enterprise. Overall, the detection rate of the change-point control chart increases with larger mean shifts.

6.3. Accuracy of change point and out-of-control stage estimation

Table 6 displays the accuracy of change point estimation and out-of-control stage estimation under incorrect parameter estimation of the risk function. The accuracy of change point estimation (i.e., $\mu_{\hat{\tau}}, P(|\hat{\tau} - \tau| \leq 1)$) and the out-of-control stage estimation ($\mu_{\hat{\xi}}$) exhibit some difference compared to the real scenario, but it is not substantial. Similarly, the accuracy of change point estimation and out-of-control stage estimation under combination 1 and combination 2 is marginally higher than that in the real scenario, possibly due to the amplified risk of the source enterprise resulting from the increase in the coefficient. In contrast, the accuracy of change point estimation and out-of-control stage estimation under combination 11 and combination 12 is significantly lower than that in the real scenario because the reduction in the coefficient reduces the risk of the source enterprise. However, the accuracy of estimation remains above 54 %. In conclusion, a higher mean shift leads to better accuracy in change point and out-of-control stage estimation.

In summary, our sensitivity analysis demonstrates that inaccuracies in parameter estimates can significantly impact the performance of the change-point control chart. Notably, higher mean shifts correlate with better accuracy in both change point and out-of-control stage estimations. This highlights the importance of accurate parameter estimation in ensuring the effective functioning of control charts in risk management settings. Future research should focus on refining parameter estimation techniques to enhance the reliability of change point detection and improve overall control chart performance.

7. Conclusions and implications

7.1. Discussion and conclusions

This study aims to monitor supply chain disruptions by developing a risk transmission model utilizing the GERT network alongside

Table 6
The accuracy of change point estimation and out-of-control stage estimation with incorrectly estimated risk function parameters.

δ		true	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
20	$\mu_{\hat{\tau}}$	22.3	21.7	21.9	22.6	22.7	22.0	22.2	22.7	22.9	21.9	22.1	22.6	22.9	22.5	22.7	23.3	23.5
	$\mu_{\hat{\xi}}$	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3	4	4
	$P(\lvert\hat{\tau}-\tau\rvert \le 1)$	0.53	0.57	0.55	0.49	0.47	0.52	0.50	0.45	0.41	0.55	0.54	0.45	0.42	0.48	0.45	0.38	0.35
	$P(\lvert\hat{\tau}-\tau\rvert \le 2)$	0.59	0.64	0.65	0.55	0.54	0.59	0.57	0.51	0.48	0.61	0.60	0.52	0.49	0.55	0.53	0.42	0.40
	$P(\lvert\hat{\tau}-\tau\rvert \le 3)$	0.69	0.75	0.74	0.66	0.65	0.70	0.68	0.62	0.60	0.72	0.69	0.63	0.61	0.65	0.64	0.57	0.54
30	$\mu_{\hat{\tau}}$	21.6	20.9	21.3	21.9	22.1	21.5	21.6	22.2	22.1	21.3	21.5	22.1	22.4	21.9	22.1	22.8	23.1
	$\mu_{\hat{\xi}}$	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3	4	4
	$P(\lvert\hat{\tau}-\tau\rvert \le 1)$	0.61	0.65	0.63	0.62	0.59	0.63	0.62	0.59	0.57	0.63	0.64	0.59	0.55	0.63	0.59	0.51	0.45
	$P(\lvert\hat{\tau}-\tau\rvert \le 2)$	0.72	0.76	0.73	0.72	0.70	0.73	0.73	0.70	0.69	0.72	0.72	0.71	0.64	0.72	0.72	0.59	0.50
	$P(\lvert\hat{\tau}-\tau\rvert \le 3)$	0.77	0.81	0.79	0.77	0.74	0.79	0.78	0.74	0.72	0.78	0.77	0.75	0.70	0.79	0.76	0.66	0.58
40	$\mu_{\hat{\tau}}$	20.3	20	20	20.5	20.7	20.1	20.2	20.9	21.2	20	20.1	20.8	21.2	20.5	20.8	22.1	22.5
	$\mu_{\hat{\xi}}$	3	3	3	3	3	3	3	3	3	3	3	3	4	3	3	4	4
	$P(\lvert\hat{\tau}-\tau\rvert \le 1)$	0.75	0.80	0.79	0.77	0.73	0.75	0.74	0.72	0.71	0.78	0.73	0.73	0.66	0.77	0.73	0.60	0.56
	$P(\lvert\hat{\tau}-\tau\rvert \le 2)$	0.84	0.89	0.88	0.85	0.82	0.84	0.83	0.81	0.79	0.88	0.83	0.81	0.73	0.85	0.82	0.69	0.63
	$P(\lvert\hat{\tau}-\tau\rvert \le 3)$	0.88	0.94	0.92	0.90	0.87	0.88	0.87	0.85	0.84	0.91	0.88	0.87	0.80	0.91	0.88	0.74	0.69
50	$\mu_{\hat{\tau}}$	20	20	20	20.2	20.3	20	20.1	20.5	20.9	20	20	20.4	20.9	20.2	20.4	21.4	22.0
	$\mu_{\hat{\xi}}$	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	4
	$P(\lvert\hat{\tau}-\tau\rvert \le 1)$	0.86	0.92	0.91	0.88	0.84	0.87	0.85	0.83	0.81	0.91	0.87	0.83	0.81	0.89	0.83	0.78	0.70
	$P(\lvert\hat{\tau}-\tau\rvert \le 2)$	0.93	0.96	0.95	0.94	0.92	0.93	0.92	0.90	0.88	0.94	0.93	0.91	0.84	0.94	0.92	0.85	0.76
	$P(\lvert\hat{\tau}-\tau\rvert \le 3)$	0.95	0.98	0.98	0.96	0.93	0.96	0.93	0.92	0.90	0.96	0.95	0.92	0.89	0.97	0.93	0.89	0.86

a change-point control chart based on Hotelling T^2 statistics. We validated the effectiveness of the change-point control chart by analyzing the transmission of delayed delivery risk from source enterprises to downstream entities within a simplified automotive supply chain case study involving DongNan Automotive. Our evaluation employed Monte Carlo simulations, focusing on detection rates, accuracy of change-point estimation, and identification of out-of-control stages. The results reveal that the change-point control chart demonstrates exceptional performance, enabling quick responses to supply chain risk factors and precise estimations of change points and out-of-control conditions.

The findings of this research contribute significantly to the existing literature on supply chain risk management in several ways. First, while previous studies have primarily focused on static assessments of risk, our integration of GERT with change-point analysis offers a dynamic perspective on risk propagation within supply chains. This approach emphasizes the temporal aspects of risk, allowing for a more nuanced understanding of how risks evolve over time. This is crucial as supply chains become increasingly complex and interconnected, necessitating real-time monitoring and response mechanisms.

Past research has often addressed risk management through static models or isolated case studies, but our study advances this by demonstrating the practical application of dynamic risk monitoring tools in a real-world context. For instance, we have shown that the change-point control chart can quickly identify shifts in risk levels, which is particularly valuable for supply chain practitioners. In environments where delays and disruptions can have cascading effects, the timely identification of such changes can enable organizations to implement corrective actions proactively, thereby minimizing potential losses. This supports the argument made by existing literature that timely risk identification is essential for effective supply chain management.

Moreover, our findings align with recent calls for more integrated risk management frameworks within the supply chain literature. By utilizing control charts, companies can foster a proactive approach to risk management, shifting from reactive strategies that respond to disruptions after they occur to anticipatory strategies that aim to mitigate risks before they escalate. This cultural shift towards risk awareness and proactive management is essential for modern supply chains operating in volatile environments.

In summary, this study not only validates the effectiveness of the change-point control chart but also bridges a gap in the literature by providing a practical, dynamic tool for real-time risk monitoring and response in supply chains. Our work underscores the importance of integrating temporal risk analysis with traditional risk management practices, offering new insights and practical applications for both researchers and practitioners in the field.

7.2. Implications

The implementation of control charts for monitoring supply chain risks offers several organizational benefits. Firstly, it aids in identifying potential risks within the supply chain process, allowing for timely interventions to mitigate adverse effects. Secondly, optimizing the supply chain becomes feasible as control charts can pinpoint areas requiring improvement. Thirdly, a robust supply chain network can be established, capable of withstanding various risks, including supplier failures, transportation disruptions, and demand fluctuations.

To fully leverage the advantages of control charts, organizations should consider several managerial implications. Regular monitoring of supply chain performance using control charts is essential for early identification of risks, enabling corrective measures before operational impacts occur. Additionally, developing a proactive risk management strategy that anticipates potential disruptions and identifies alternative suppliers, transportation modes, or inventory management strategies is crucial for resilience. Training employees to interpret control charts effectively will empower them to identify trends and potential issues within the supply chain. Finally, utilizing insights gained from control charts to optimize processes can lead to reduced lead times and enhanced efficiency.

7.3. Future directions

However, it is important to acknowledge some limitations associated with the use of GERT. A primary concern is the assumption of independence among event probabilities and activities, which may not always hold true in real-world supply chains. Furthermore, our study focused on a stationary process within a serial-parallel-cyclic supply chain structure. Future research should explore additional modeling aspects, such as distribution types, nonparametric approaches, nonstationary processes, and multiple shift levels, to provide a more comprehensive understanding of risk dynamics in supply chains.

CRediT authorship contribution statement

Jianlan Zhong: Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Fu Jia:** Writing – review & editing.

Data availability statements

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy restrictions.

Ethical statements

This research was conducted in strict accordance with ethical principles and standards. The study did not involve any human subjects, animal experiments, or the use of sensitive personal data.

Declaration of generative AI in scientific writing

We declare that generative AI and AI-assisted technologies were not used in the process of this scientific writing. All the content was created based on my own research, thinking and writing. I have independently created and rigorously reviewed every part of the paper to ensure its accuracy, completeness and originality.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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