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Measuring the Resilience of Supply Chain Systems Using a Survival Model
Ratan Raj, J. W. Wang, Ashutosh Nayak, M. K. Tiwari, B. Han, C. L. Liu, and W. J. Zhang

Abstract—Disruptions at any stage of a supply chain system can cause mammoth operational and financial losses to a firm. When there is a disruption with a supply chain system, it is highly desired that the system quickly recover. The ability of recovery is, in short, called resilience. This paper proposes a new measure of the resilience of a supply chain system based on the concept of survival and, subsequently, a survival model [Cox proportional hazard (Cox-PH) model]. The survival model represents a time interval or period from the time the system failed to function to the time the system gets back with its function (i.e., recovery). The input to the model is, thus, a failure event; the output from the model is the recovery time. This model has been implemented. There is a case study to illustrate how the model is used to give a quantitative measurement of resilience, in terms of recovery time.

Index Terms—Cox proportional hazard (Cox-PH) model, supply chain, supply chain resilience, survival analysis.

I. INTRODUCTION

RESILIENCE has been an important concept in engineering recently. A summary of resilience for general systems and information systems can be found in [1]–[3]. The concept of resilient manufacturing systems can be found in [4]. Supply chain resilience addresses the supply chain’s ability to cope with the consequences of unavoidable risk events or disruptions, such as the loss of a critical supplier, a major fire at a manufacturing plant, or an act of terrorism, in order to return to its original operations or move to a new and more desirable state after being disturbed [5]–[8]. These events can take many forms, as highlighted in many recent highly publicized events, including the 2004 Indian Ocean Tsunami, the 2010 Haiti and Chile Earthquakes, the recent global financial crisis, and the 2010 eruption of Icelandic Volcano Eyjafjallajökull [9]. Natural disasters, pandemic disease, terrorist attacks, economic recession, equipment failure, and human error can all pose both a potentially unpredictable and severe threat to the continuity of an organization’s operation.

Resilience is a function of both vulnerability of a system and its adaptive capacity [10]–[12]. Fiksel identifies four major system characteristics that contribute to resilience [13]. These are diversity, adaptability, efficiency, and cohesion. To date, many definitions have been proposed by researchers for supply chain resilience, but theoretical justifications are still in their infancy.

For resilience with respect to ecological systems, the Canadian ecologist Holling was one of the first researchers to note resilience in an ecological perspective [14]. According to him, any system has two distinct properties: resilience and stability. Resilience determines the ability of systems to absorb changes, and stability is the capacity of systems to return to an equilibrium state after a temporary disturbance. The faster a system returns to equilibrium, the greater its stability [14]. Gunderson and Holling defined resilience as the capacity of a system to experience disturbance and maintain its functions and controls [15]. Carpenter et al. [16] extended the research by examining the magnitude of disturbance that a system could tolerate before it fundamentally changes into a different region with a different set of controls. The psychological perspective on resilience is well studied and widely represented in the literature. It has its roots in developmental theory that deals with the examination of people’s behavior across the life span, and encompasses an understanding of biopsychological factors as well as the spiritual realm [17]. From an economic perspective, static economic resilience refers to the ability or capacity of a system to absorb or cushion against damage or loss [14], [18]. From an organizational perspective, supply chain resilience is the capacity to adjust and maintain desirable functions under challenging or straining conditions [19]–[21]. Hamel and Valikangas [22] stress that resilience is not just concerned with recovery, flexibility, or crisis preparedness but
also a distinct source of sustainable competitive advantage. In
the area of supply chain systems, Ponomarov and Holcomb [23]
defined supply chain resilience as “the adaptive capability of
a supply chain to prepare for unexpected events, respond to
disruptions and recover from them by maintaining continuity
of operations at the desired level of connectedness and control
over structure and function.” In this paper, this definition is
taken for studying the problem of measuring supply chain
resilience.

Very limited research work has been done on resilience mea-
surement until now [24]–[27]. Mauro et al. [28] built a decision-
making model based on supply chain density, complexity, and
the number of key nodes from the qualitative point of view.
Zhu and Su [29] built a mathematical model based on Hooke’s
law. At present, studies on the measuring method of supply
chain resilience are limited, and quantitative studies are scarce,
which is not enough to provide an accurate theoretical basis
for practical applications. Rosenkrantz et al. [24] measured
the resilience through the number of node failures and edge
failures while the network can remain its function. Wang and Ip
[26] proposed an approach to evaluate the logistics network re-
covery from the former. The aforementioned studies were focused
furthermore, a supply chain system was modeled as a biological
chain system so that the measurement method for the latter can be
applied to the former. The Cox-PH model is a model that describes the survival of
a system, including a supply chain system, from the perspective of
recovery of a system’s function or service and by taking an
entire system as a black box. Note that the structure of the
black-box system in responding failure is determined based on
the historical data, and as such, the proposed measure is
applicable to any system. In particular, the present measure is based on the so-called Cox proportional hazard (Cox-PH)
model [31], [32].

The Cox-PH model is a model that describes the survival of
a system. The model relates events to times with the so-called
resource variables, representing the sources of failures, when
the Cox-PH model is applied to survival analysis. The event-
time historical data are assumed to be available, and these data
are used to determine or train the coefficients of the resource
variables or resources. If the event is a failure of the system, the
time represents the period from a time before the failure to the
time the failure occurs.

The remainder of this paper is organized as follows. In
Section II, the procedure to construct a Cox-PH model is
presented. The effectiveness of the proposed model has been
confirmed through simulation in Section III. Conclusions are
drawn and insights in need of further research are discussed in
Section IV.

II. BUILDING THE COX-PH MODEL

In the Cox-PH model, the hazard function, which is also
called the conditional failure rate function, is defined as follows:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T \leq t + \Delta t | T \geq t)}{\Delta t} = \frac{f(t)}{S(t)}$$

(1)

where

- $T$ time the hazard function is estimated;
- $h(t)$ hazard function;
- $f(t)$ probability density function of $T$;
- $S(t)$ $\Pr(T > t)$, the survival function of $T$.

Notations

- $\mu = [\mu_1, \mu_2, ..., \mu_n]$ set of coefficients of the covariates in the model;
- $z = [z_1(t), z_2(t), ..., z_n(t)]$ set of decision variables for the model ($z_i(t) = z_i(t')$ if $t \leq t'$ and $= 0$ otherwise);
- $P_q$ time at which the estimation is made;
- $S(t|z(t'))$ residual survival function of the system;
- $S_n(t)$ base survival function;
- $h_0(t)$ base hazard function.

The failure rate is described as follows:

$$f(t) = \frac{d}{dt}[1 - S(t)].$$

(2)

From (2), we obtain

$$f(t) = -S'(t).$$

(3)

The Cox-PH model is used to describe the relationship
between the system hazard function and covariates, as shown in the following equation:

$$h(t|z(t)) = h_0(t) \mu^t z(t) = h_0(t) \sum_{i=1}^{n} \mu_i z_i(t).$$

(4)

From (1) and (3), we obtain

$$h(t) = \frac{-S'(t)}{S(t)}.$$ 

(5)

By solving (5) and simplifying it, we obtain

$$S(t|z(t)) = \exp \left( \int_{0}^{t} h_0(t) \exp \left( \sum_{i=1}^{n} \mu_i z_i(t) \right) \right).$$

(6)

The conditional probability of the survival of a system
$\Pr(T > t|z(t'))$, which is the probability that the system
survives for a time $T$ given that it has survived until time $t'$,
is given by

$$\frac{S(t|z(t'))}{S(t'|z(t'))} = S(t|z(t')).$$

(7)

Using (6), (7) can be simplified as

$$S(t|z(t')) = \left( \frac{S_0(t)}{S_0(t')} \right)^{\exp[\mu^t z(t)]}.$$ 

(8)
The failure point of the system is predicted when the survival probability (residual life of the system) estimated at \( t' \) is \( P_q \). Therefore, the estimated failure time \( t \) can be obtained from the following equation:

\[
\left( \frac{S_o(t)}{S_o(t')} \right)^{\exp[\mu^t z(t)]} \leq (1 - P_q). \tag{9}
\]

From (9) and assuming that the survival function is continuous and invertible, the failure time can be estimated by

\[
t = S_o^{-1}(S_o(t)(1 - P_q)^{\exp(\mu^t z(t))}) \tag{10}
\]

To estimate the recovery time from the failure events, it can be assumed that no failure event has occurred; the value of the decision variables is 0 in this case, i.e.,

\[
z_1 = z_2 = z_3 = \ldots = z_n = 0. \tag{11}
\]

Equation (11) corresponds to the no failure event. Thus, by modifying (10), we can get the recovery time as follows:

\[
T_{rc} = T_{nf} - T_f \tag{12}
\]

where

- \( T_{rc} \) recovery time;
- \( T_{nf} \) estimated time for the system to have \( P_q \) residual life but with no source of disruption;
- \( T_f \) estimated time for system to have \( P_q \) residual life with sources of disruption.

From (10), the following equations can be obtained:

\[
T_f = S_o^{-1}(S_o(t)(1 - P_q)^{\exp(\mu^t z(t))}) \tag{13}
\]

\[
T_{nf} = S_o^{-1}(S_o(t)(1 - P_q)) \tag{14}
\]

Equation (12) can be used to estimate the recovery time of the system from a failure event. From the coefficients obtained and the recovery time estimated from each failure event, the influence of the various sources of disruptions on the health of a supply chain system can then be analyzed as well.

### III. Simulation Model

As an illustration, a simulation model of the supply chain is developed based on the aforementioned theory to estimate the recovery time of a supply chain after disruption. In particular, the 12 different sources of disruptions have been considered. The 12 sources include both external and internal factors. The examples of external sources are fire, extreme weather, strikes, high-cost labors, and epidemics. The examples of internal sources are shortage of qualified labors, inflexible production capacity, long setup and lead time, overly leaned inventory, and process issues.

In the simulation model, 2000 general events have been generated randomly. The inability of the supply chain of the firm to meet at least 95% of the demand has been considered as a failure event for the purpose of this study. In the 2000 events, 142 failure events with the different sources responsible for the failures have been identified.

Cox-PH model fitting has been developed on these 12 sources of disruptions. After that, it has been observed that sources 3 and 6 are statistically insignificant. Thus, sources 3 and 6 are ignored, and a refitting to the model has been performed. The coefficient of the resources of the different sources after the refitting is shown in Table I.

The exponential coefficients of the variables in the Cox-PH model are interpretable as the multiplicative effects of the variable. Thus, for example, holding other covariates (sources in the model) constant, an additional occurrence of source 1 increases the chances of failure of the system and, in this case, disruption in the supply chain by the factor of \( e^{3.576} \approx 35.75 \). Thus, the coefficients of the sources, after encoding into the Cox-PH model, relatively estimate the significance of the different sources responsible for disruption. The recovery time of the supply chain from the disruption for all the 142 events can be estimated, as shown in Fig. 1.

In the simulation model, estimation of the recovery period has been done on the basis of 10% residual life. This means that the estimation of the recovery period is done when the supply chain health is 10% only. At the health of 1, the supply chain is considered to be perfectly fit. For all the different 142 failure events, different combinations of sources are recognized imbibing different recovery times of the supply chain. The average number of days taken by the system to recover from the disruption due to a particular source is given in Table II. It is noted that the procedure for calculating the recovery time has been thoroughly explained in Section II, in (14).
The recovery time after failure event due to different sources is indicative of the estimated recovery time since some interaction pattern may also be present between the sources affecting the recovery time. The observations from the model developed can be summarized as in Table III.

The Cox-PH model has been developed using the R-software run in Windows 7 environment. The R-square value obtained in the simulation model is 0.25 (the details for the R-value have already been provided using the R-software run in Windows environment).

IV. CONCLUSION AND DIRECTIONS FOR FURTHER RESEARCH

This paper focused on the measurement of supply chain resilience. The definition of the resilience of supply chain taken in this paper was decribed as follows: it is the ability of the supply chain to bounce back to its normal operating status following a disruption. The paper proposed a new measure of resilience, in terms of recovery time. The new measure is based on the Cox-PH model, which is a semiparametric model. In the Cox-PH model, the variables represent various sources of disruptions, the input variable represents an event (failure event for survival or resilience analysis), and the output variable is the time. It is remarkable that the model can capture the multiple sources of failures, as this is the more accurate case in real-world systems.

However, the mathematical model presented in this paper is just one of the possible views. As such, it has some limitations, which leads to some potential future works. First, further conceptualization using different research perspectives would be highly recommended. For instance, increasing the number of variables for representing disruption in a supply chain could help to develop a broader perspective of supply chain resilience measurement. Second, different risk assessment paradigms, such as probabilistic choice, systems theory, and the theory of constraints, could also be applied to the problem. Third, the present model is based on the assumption that the survival function of a system depicting the health of the supply chain follows the Cox-PH model exactly, which seems to be a highly strong condition. Fourth, the number of sources of disruptions is limited for Cox-PH model fitting. Fifth, the model is based on the assumption that the sources are independent of each other; however, in real life, one source might have impact on the other source.


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