A Stochastic SEIQR-Based Model for Disruption Propagation and Resilience in Transport Logistics Networks

Mohamed Abouchabane[1], *Hasna* Hajji[2], *Abdellah* Zamma[3] and *Salah* Nissabouri[4]
M2S2I laboratory, ENSET
Hassan 2nd University of Casablanca, Morocco
Corresponding author: mohamed.abouchabane-etu@etu.univh2c.ma

Abstract. This paper presents a stochastic modelling framework based on the SEIQR epidemic model to analyse the propagation of disruptions and the dynamics of resilience within transport logistics networks. Each operational unit in the network—such as a warehouse, terminal, or hub—transitions through five distinct states: Susceptible, Exposed, Infected, Quarantined, and Recovered, reflecting varying levels of risk exposure and adaptive response. The model combines a non-monotone incidence with organisational constraints in the spread of the disruption and uses stochastic differential equations to describe inherent uncertainty in system dynamics. The proposed framework provides a versatile methodology for testing the robustness of logistics systems in the presence of uncertainty and for supporting the design of more resilient network structures. The model will be further validated by using empirical data in scenario-based simulations.
Keywords: Stochastic modelling, SEIQR model, Disruption propagation, Transport logistics networks, Resilience, Network robustness, Uncertainty analysis

1 Introduction

Transport logistics networks are pivotal to global commerce and socio-economic activity. However, these systems also face an increasing range of vulnerabilities to disturbances, including natural events, pandemics, technological failures, and social uncertainties. Consequently, the investigation of how risks propagate in transport networks and how we can develop and measure resilience has become a research priority for several academic and operational studies.

One area of interest has been the development of frameworks to assess vulnerability that account for financial and temporal impacts, which triangulate to identify the critical links and nodes in networks, which have compounded cost implications upon their failure [1]. Alternatively, in another evolving area of research, network theory has been applied to hydrogen logistics incidents, to model and visualise possible risk factors and their impacts. In this case, the authors found that disruption persisted after the causal factors were removed, because failures are occurring as a consequence of chain reactions [2].

It is important to have transparency in predictive models - including the adoption of "explainable" artificial intelligence (XAI) in road safety to discern the most significant contributors to the severity of injuries arising from collisions [3]. Higher level concepts of resilience have also been established by descriptive review pieces; particularly resilient highway systems that have useful validation from real-life catastrophe data, like hurricanes [4].

Methods that characterize railway networks based on their topology or system have been evaluated; topology is criticized for being too simple, and overly reliant on structural characteristics, while system characteristics, on the other hand, capture complexities of activity, operations, and different user perspectives [5]. This divide can be used to criticize "fashionable" abstract models that struggle to include behaviour nor offer reasonable prescriptions, compromising the level of theoretical rigour, and manageable relevance [6].

To meet this demand, a monitoring-based model has been developed that makes use of structural health and functional data to evaluate resilience in real-time and assist adaptive infrastructure planning [7]. Relatedly, the disparities in flood risk and infrastructure investment by location in the UK have been explored, demonstrating that peripheral areas are often subject to high levels of exposure but receive little adaptation funding [8].

In freight transport, resilience modelling of Indian truckload (TL) systems identified three conditions that mitigate disruptions: flexibility, anticipating risks and resource allocation [9]. Resilience in Urban rail systems, in the context of flooding, has also been assessed to explore how performance loss varies based on the severity of the flooding event and how long recovery lags can compromise net system efficiency [10].

At last, mathematical models in the form of SIR and SEIQR, have also been adapted from epidemiology, to simulate disruption propagation within supply chains. Optimised adaptation of these models have been shown to greatly improve forecast accuracy in countries like Australia, Italy, and the UK [11], while similar modelling has shown the efficacy of dynamic reproduction numbers in representing public health interventions during the outbreak of COVID-19 in Mauritius [12].

Altogether these contributions provide a comprehensive analytical foundation for designing a stochastic SEIQR-based model designed to assist in resilience analysis and disruption propagation in transportation logistics systems.

The main aim of this research is to develop and evaluate a SEIQR-based stochastic model that captures the spread of disruptions and resilience responses in transport logistics networks. The intention is to employ stochastic differential equations to model the randomness of perturbations and structural constraints present in logistics systems, which will offer an empirical approach to measure robustness and adaptive recovery from disturbances in an uncertain context.

In the rest of the paper, Section 2 will provide a full literature review by discussing the literature on resilience in logistics first, then uncertainty and disruption and transport systems second, and finally, the use of compartmental propagation models in non-epidemiological fashion. In Section 3 we present the model whereby a deterministic SEIQR model is formulated, the assumptions that are made, a system of stochastic differential equations (SDEs) with a concise explanation of each term, a non-monotone incidence function, and how the basic reproduction number is determined along with a rigorous mathematical analysis. Section 4 refers to the numerical implementation of the model including a description of the system and then the results of simulation.

2 Literature Review

1.1 Resilience Concepts and Strategies in Logistics

In recent studies concentrating on logistics resilience, findings are primarily stressing the development of adaptive measures, modelling quantitatively, and making disruption-aware decisions. A resilience framework for international express logistics provides opportunities to reallocate resources and reroute movements should there be stress [13]. A scheduling model, using two-stages aimed at improving supply chain resilience through both routine and emergency operations [14]. A maritime framework, inclusive of multiple marine stakeholders, provides the resilience capabilities and performance measures across ports and shipping networks [15]. In an urban context, resilience is demonstrated in shifting service capabilities in the planning response, as well as the equity vs efficiency trade-offs [16]. If assessing global transport in logistics, a logistic model of control-initiated banking for fuzzy real-time regulation of freight delays through the introduction of a concept of loading time; which the author found impossible to quantify as the regulation of recovery [17]. This mix of information represents a systematic and data-driven dimension of logistic resilience research.

1.2 Uncertainty and Disruptions in Transport Logistics

Transport logistics can have multiple sources of uncertainty in operations such as delays in delivery, unexpected demand, and lack of integration in the supply train. All of these factors create economic and environmental impact especially in industries with frequent unplanned congestion [18].

Operations in the courier sector are also subject to a variety of risks, such as road closures, volatile fuel prices and customer error, that decrease company performance and increase an organization's cost of operations. The specific challenges in this sector (for example, the speed of delivery and direct interaction with customers) also contribute to the sector's risk exposure [19].

Last-mile and reverse logistics operations in Spain are also experiencing a statistically high service incompletion distribution of positive deficient obligations due to customer absences, system errors and timing of couriers. Improved classification of disruption and data sharing are necessary to improve reliability [20].

In the offshore logistics context, increasingly immense environmental conditions and mechanical deterioration emphasize the use of probabilistic models to explore the difference in risk associated with real time management. The authors discuss a hybrid Bayesian-Monte Carlo approach to explore both disruption forecasting and cost variables [21].

In summary, I located some of the same constraints when transporting food grains. In their study completed on robust optimization on the delivery of food grains subject to uncertainty for stock and disturbance, the authors discover that coupling collaboration with capacity expansion greatly encourages redoubled commitment to strength and sustainability in network [22].

1.3 Application of Compartmental Propagation Models (SEIR, SEIQ, SEIQR) in Non-Epidemiological Contexts

In recent years, researchers have used compartmental models from epidemiology such as SIR, SEIR, and SEIQR models in areas not related to health, especially finance, risk management and strategic planning. These models reproduce the dynamic propagation of disruptive events in complex systems by including dependence, contagion and response mechanisms. The next table synthesizes a selection of key papers that have used these approaches in non-epidemiological fields, identifies their area of application, their method of application, and contributions to analysis.

Table 1. Non-Epidemiological Applications of Compartmental Models.

Study	Epidemiological Model Variant	Area of Application	Aim of the Study	Analytical / Computational Approach	Critical Analysis
[24]	SEIR (Susceptible–Exposed–Infectious–Recovered) / SIERS (Susceptible–Infectious–Exposed–Recovered–Susceptible)	Healthcare logistics during epidemics	Enhance dynamic allocation of medical resources in outbreak conditions	Integration of epidemic diffusion models (SEIR/SIERS) with demand forecasting and multi-stage linear programming	**Strengths:** Combines epidemic diffusion and logistics planning effectively. **Limitations:** Fully deterministic; ignores uncertainty and stochastic variability.
[25]	Modified SEIAR (Susceptible–Exposed–Infectious–Asymptomatic–Recovered)	Emergency relief logistics	Optimize multi-period distribution of medical supplies while considering asymptomatic carriers	Adapted SEIAR model (including asymptomatic spread and mobility); stochastic multi-objective programming; solved with 2D immune algorithm; case validation in Hubei, China	**Strengths:** Captures asymptomatic effects; realistic case validation. **Limitations:** Complex and computationally heavy; still lacks explicit stochastic dynamics.
[26]	Fractional-order SEIR	Cybersecurity (computer virus diffusion)	Model and analyze computer virus spread incorporating memory effects and convergence dynamics	Caputo fractional-order SEIR model (5 compartments); stability checked via LaSalle's principle & Lyapunov functions; R_0 estimated with next-generation matrix; simulations + sensitivity analysis	**Strengths:** Integrates memory effects; advanced theoretical rigor. **Limitations:** Limited empirical validation; abstract context outside logistics.
[27]	Time-discretized SEIR	Epidemic-related medical logistics	Couple epidemic forecasting with logistics planning in a closed-loop adaptive framework	FPEA cycle (Forecast–Planning–Execution–Adjustment); SEIR-based demand prediction; binary integer programming for allocation; parameter tuning with quadratic programming	**Strengths:** Adaptive feedback between forecasting and logistics. **Limitations :** Simplifies continuous dynamics; ignores random disturbances.
This study	Stochastic SEIQR (Susceptible–Exposed–Infectious–Quarantined–Recovered)	Transport logistics networks	Model disruption propagation and resilience under uncertainty	SEIQR-based stochastic differential equations; non-monotone incidence; simulation of randomness in network performance	**Strengths:** Introduces explicit stochasticity; realistic modeling of uncertainty and resilience; bridges theoretical and applied logistics. **Limitations:** Requires advanced parameter calibration.

Prior research using compartmental models in non-epidemiological contexts has contributed important knowledge of diffusion mechanisms and adaption behaviors following disturbances. M. Liu, J. Cao, J. Liang [24] and C. Hou and H. Jiang [25] provide examples of studies that successfully combined epidemic models with logistics planning to increase allocation efficiency. However, both studies depend on deterministic assumptions regarding events (e.g. demand and supply) that neglect random perturbations and structural uncertainty in logistics networks. Likewise, researchers proposing components of fractional-order models, which capture memory effects, are often not able to put their studies into empirical contexts in transport logistics [26]. Authors have also begun work on time-discretized mechanics, which is a step toward computational tractability, but could simplify dynamics of feedback mechanisms in calculating effects [27].
The current study seeks to build on prior attempts by developing a stochastic SEIR-based model that explicitly includes randomness and uncertainty to achieve a more realistic representation of resilience in transport logistics systems.

2 Model Formulation

This section provides the mathematical formulation of the SEIQR model in the context of transport logistics networks. We begin with the deterministic version of the model, which was originally developed to represent the structured dynamics of operational units during disruption. We acknowledge the shortcoming of only considering a deterministic context in the presence of real-world uncertainty, and we extended the model within a stochastic framework. The resulting model and system of equations incorporates uncertainty through stochastic differential equations to allow for a more realistic representation of the propagation of disruption and recovery resilience.

2.1 Deterministic SEIQR Model

Although this deterministic derivative offers some valuable understanding of average system performance in relation to the average response, it assumes that transitions are uniform, smooth, and direct, when in reality, various disruptions do not have a prescribed pattern. For instance, unexpected unavailability of assets, delays in supplies, the timing of the intervention, and the variation in process resources all contribute to the elements of randomness and uncertainty found in the variety of dynamic system factors, which cannot be simply defined by a deterministic model.

$$\begin{cases} \dfrac{dS}{dt} = \Lambda - dS - \dfrac{\beta' SI}{1+kI^2} \\ \dfrac{dE}{dt} = \dfrac{\beta' SI}{1+kI^2} - \sigma' E - dE \\ \dfrac{dI}{dt} = \sigma' E - (\gamma' + \delta' + d)I \\ \dfrac{dQ}{dt} = \delta' I - (\rho' + d)Q \\ \dfrac{dR}{dt} = \gamma' I + \rho' Q - dR \end{cases} \tag{1}$$

To resolve the issue of the limitation found in this deterministic approach, we will add on the stochastic SEIQR model. It will incorporate stochastic differential equations (SDE) accounting for random changes in each compartment, due to either the unpredictable mis-managed shocks or because of the inherent variability of internal measures. This will assist in better describing the complexity and variability of how disruptions propagate in logistical networks while enhancing the model's capability to consider approximate set of realistic elements of uncertainty for modelling stochastic behaviour. The stochastic formulation offered in this paper will yield a more useful analytical tool for consideration of resiliency during prior decision-making, and future logistical actions in uncertain environments.

2.2 Model Assumptions

In order to present the uncertain advancement of disruptions in logistics networks, we implement a compartmental model based on epidemic modelling. In this model each operational unit (e.g. a warehouse, terminal, logistics centre) can be seen as an active entity which evolves over time based on risk exposure and resilience actions. An operational unit can move through five states: Susceptible (S), Exposed I, Infected (I), Quarantined (Q), and Recovered I. Transitions are shaped by a logic which provides deterministic rules and stochastic variability.

The overarching assumptions of the model can be summarized as follows:

- The system involved consists of a continuous influx of operational units at a rate, Λ, representing new logistics nodes or infrastructure.
- Units will exit the system at a constant rate, d, as the process of retiring, destroying and permanently closing structural units progresses.
- Units that are susceptible can become exposed through contact with currently infected units; this is captured by a non-monotone incidence function, $\frac{\beta' SI}{1+kI^2}$, that recognizes saturation and organizational mitigation strategies.
- Exposed units can become infected at a transfer rate, σ′, which is indicative of the activation of interference.
- Infected units can recover directly (γ′) or are quarantined (δ′) – quarantined units are reactivated at the recovery rate, ρ′.
- All transitions are subject to stochastic variability to account for the uncertain behaviours evident in network functioning.

2.3 Parameters and Notation

Table 2. Description of the parameters used in the SEIQR model.

Notations	Parameters with description
Λ	Rate of arrival of new operational units
d	Natural removal rate of units
β'	Effective exposure coefficient
k	Saturation factor
σ'	Progression rate from exposed to disrupted
γ'	Direct recovery rate of disrupted units
δ'	Isolation (quarantine) rate of disrupted units
ρ'	Recovery rate of quarantined units
σ_X	Stochastic volatility in compartment $X \in \{S, E, I, Q, R\}$
$W_i(t)$	Standard Wiener process (Brownian motion) for state *i*

2.4 System of SDEs with explanation of each term

The dynamics of the system are expressed using a series of stochastic differential equations (SDEs), with each compartment being subject to random variations that are modelled as Wiener processes. The general process for a stochastic SEIQR model is as follows:

$$\begin{cases} dS(t) = \left(\Lambda - dS(t) - \dfrac{\beta' S(t)I(t)}{1+kI(t)^2}\right)dt + \sigma_S S(t)\, dW_1(t) \\ dE(t) = \left(\dfrac{\beta' S(t)I(t)}{1+kI(t)^2} - \sigma' E(t) - dE(t)\right)dt + \sigma_E E(t)\, dW_2(t) \\ dI(t) = \big(\sigma' E(t) - (\gamma' + \delta' + d)I(t)\big)dt + \sigma_I I(t)\, dW_3(t) \\ dQ(t) = \big(\delta' I(t) - (\rho' + d)Q(t)\big)dt + \sigma_Q Q(t)\, dW_4(t) \\ dR(t) = \big(\gamma' I(t) + \rho' Q(t) - dR(t)\big)dt + \sigma_R R(t)\, dW_5(t) \end{cases} \quad (2)$$

In our stochastic SEIQR model applied to transport logistics networks, perturbation terms are included in the form of $\sigma_X X(t)\, dW_X(t)$, where $dW_X(t)$ is interpreted to be a standard Wiener process. Logistical risks are often framed in terms of negative consequences such as; Deley, breakdown, or disruption. The function of the stochastic term is not a measure or direct modelling of dilution', but rather introduces dynamic uncertainty regarding the evolution of the system.

As previously mentioned, Brownian motion $dW_X(t)$ is a zero-mean Gaussian process, which exhibits both positive and negative shifts. Therefore, you can think of the term $\sigma_X X(t)\, dW_X(t)$ as providing a symmetrical range of fluctuations about the mean trajectory, while also accounting for uncertainty in the distribution of the magnitude of the disruptive effect and when that impact may occur. This modelling reflects conventional uses in the literature with stochastic terms incorporated in epidemiological modelling, finance, and logistics where a stochastic component represents some form of randomness that is non-directional, as opposed to deterministic 'losses'. Therefore, on account of the argument made above, there is nothing inherently wrong or illogical mathematically with having a positive sign in front of the stochastic term, as a non-directed measure of risk. The antecedent statement is especially relevant in evaluating systems resiliency in the face of uncertain variable disturbance ranges which can effect the firm.

2.5 Non-Monotone Incidence Function

The model has a non-monotone incidence function of the type:

$$\frac{\beta' SI}{1+kI^2}$$

The model departs from the traditional bilinear term $\beta' SI$ in many epidemic models. The addition of a denominator $1 + kI^2$ here has a saturating effect that removes transmission dynamics as the number of disrupted units I increases to the limit. This behaviour is intended to reflect real-world observations in logistics networks whereby, with severe disruption, the likelihood of further propagation if a great number of units are disrupted is reduced due to: organisational awareness, emergency protocols, physical or managerial capacity limits. As a result, the function encodes the essential nonlinear and self-regulatory features of disruption's dynamics in complex operational systems. In addition, it enables the model to represent resilience mechanisms when disruption arises, that include containment of the disruption, rerouting of disrupted units or reallocation of resources in response.

2.6 Basic Reproduction Number

The basic reproduction number R_0, is a threshold parameter that provides a measure of the potential for a disruption to spread through a fully functioning logistics network. For this SEIQR-based model: R_0 is the expected number of secondary disruptions from a single initially disrupted unit with all other units in a functional (susceptible) state. Thus, the R_0 value indicates the systems potential vulnerability to cascading failures without any mitigation or saturation effects. In order to determine this value, we applied the next-generation matrix method, or spectral expansion which allows for R_0 to be derived from the rate of new exposures and the expected time a unit spends in each infectious state. This formal approach gives rise to the following for our model:

$$R_0 = \frac{\beta' \Lambda \sigma'}{d(\sigma' + d)(\gamma' + \delta' + d)} \tag{3}$$

Using this formulation, we confirm that R_0 depends on the magnitude of exposure β', the arrival rate of new units Λ, and the removal rates (recovery, quarantine, and natural removal units). If $R_0 > 1$ the disruption is expected to spread, if $R_0 < 1$ the system is resilient enough to contain it.

2.7 Mathematical analysis

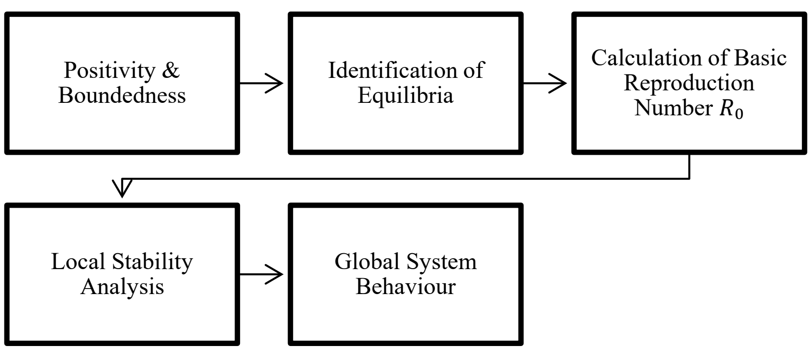

Fig. 1. Analytical Framework for SEIQR Model.

This structured manner of working includes several essential steps that one would typically consider when investigating compartmental dynamic systems. These steps include: identifying positivity and boundedness of the model; finding equilibria; determining the basic reproduction number R_0, and exploring the local and global stability of the system. While the current work emphasises the model development and stochastic extension largely in a qualitative way, these analytical steps will be explored in future research to add a more thorough theoretical reflection and understanding of the system's dynamics. In particular, identifying positivity and boundedness will show whether or not the model behaves correctly within realistic operational limits, while identifying equilibria and R_0 are crucial for understanding limits where disruption occurs and the stability automates assessment about how fast the system may restore to its previous state after perturbation.

3 Numerical Simulation

3.1 Schematic Diagram of the Proposed SEIR Model

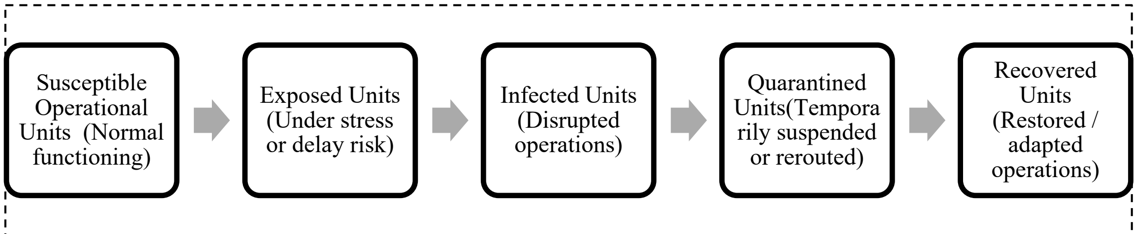

Fig. 2. Schematic diagram of SEIQR model.

The SEIQR model's stochastic quality enables the incorporation of variability and uncertainty that is intrinsic to the transitions between states. For instance,
between S → E, it addresses the stochastic variability of exposure and risk transmission.
between E → I, it addresses the timing with which a disruption becomes effective, which could vary based on the sensitivity of operational units.
Between I → Q, it represents the temporal and structural diversity of stabilisation responses.
Finally, between Q → R, it describes the dispersion of recovery processes and the differentiated trajectories of resilience.
These behaviours are represented in the model with stochastic diffusion terms in the model's differential equations. Each compartment is associated with a random component modelled by a Wiener process, where the amplitude is parameterised by a particular volatility for each state.
In this way, transitions are modelled as probabilistic processes in relation to time that have continuous variations, and a range of possible trajectories can be observed rather than deterministic evolution. Accordingly, the model does more than account for the average propagation of disruptions it represents quantifiable system resilience attributes, while acknowledging variability, uncertainty, and the nonlinear dynamic behaviours present in transport logistics networks.

3.2 Numerical Simulation

Table 3. Analytical setup for the anticipated simulation of the SEIQR model.

Component	Description
● Objective	● To explore the dynamic behaviour of risk propagation and assess the influence of key parameters under various disruption scenarios.
● Model Parameters	● Parameters such as β (transmission), k (saturation), σ, δ, γ, ρ, and μ will be defined using realistic data from logistics or epidemiological contexts.
● Initial Conditions	● Initial values for S(0), E(0), I(0), Q(0), and R(0) will represent the system's state at time $t = 0$, based on application-specific considerations.
● Numerical Methods	● Numerical solvers such as MATLAB will be used to approximate the system's behaviour over time.
● Scenarios	● Several simulation scenarios will vary parameters like β, k, and δ to assess system sensitivity and the effect of resilience strategies or interventions.
● Expected Results	● Simulations are expected to confirm analytical properties (positivity, boundedness, stability) and illustrate disruption dynamics and system resilience.

This table outlines the conceptual framework for future simulations of the SEIQR model. It defines the key components required to analyse risk propagation dynamics, including parameter settings, initial conditions, numerical methods, and scenario design. Although no computational experiments are conducted at this stage, this structure establishes a solid analytical foundation for subsequent simulation-based validation.

Conclusion

This work has introduced a stochastic SEIQR-based model to examine disruption propagation and resilience dynamics in transport logistics networks. The model has taken an epidemiological compartment type approach and adapted it to a non-health-related context to highlight the different states that operational units will go through (vulnerability, recovery, etc.) and to take into account the uncertainty that occurs in actual systems. The introduction of a non-monotone incidence function and stochastic differential equations has enabled a more realistic representation of saturation effects, random disturbances, and a mitigation process that can affect practical attempts within the complex logistical environment. Apart from the theoretical contributions provided from this model; the model provides an articulated tool for investigating resilience in logistics systems and supporting the design of active adaptations in uncertain scenarios. It therefore can be used as a relevant basis for planning resilience in this case for responding to disruptions.
Looking forward, many directions are foreseen:

- to expand the mathematical analysis focussing on global stability, equilibrium points and boundedness of the stochastic system,
- to develop a complete numerical simulation framework that can validate the model dynamics for a variety of realistic disruption cases,
- and to carry out sensitivity analysis, so that we pay attention to the parameters that have the most influence on the propagation of disruption and resilience of the system.

These will strengthen the robustness of the model and lead to its increased utility for managing transport logistics networks coping with stress.

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