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Analysis of the Suez Canal blockage with Queueing Theory

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Purpose: *The Suez Canal blockage in March 2021 delayed around \$9.6bn of trade each day. The delay affected more than 400 vessels and likely disrupted further Supply Chain and transport operations even after clearing the blockage.*

Methodology: *The model of this paper has two goals: first, predicting how long the queued-up vessels need to wait until continuing their voyage; second, at what time the entire queue resolves, and a new service cycle continues with steady-state behaviour.*

Findings: *The model predicted that the queued vessels' behaviour, i.e., that the last ship will pass the canal five days after the clearing, which equals the number reported by the Suez Canal Authorities. AIS-data can further validate the model's input and output. The discussed model supports the decision-making processes by proving the tool to assess at what time circumventing the blockage is more beneficial.*

Originality: *Supply Chain Management literature already established models from Queueing Theory to evaluate the efficiency of services and infrastructure. However, the literature does not use queueing models to assess Supply Chain risk. This research introduces a queueing model to Supply Chain Risk Management to analyse the recovery of a disrupted transport route, thereby forecasting delays caused by disrupted transport routes.*

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1 Introduction

1.1 Motivation

The Suez Canal blockage in March 2021 delayed around \$9.6bn of trade each day. The delay affected more than 400 vessels and is likely to propagate even further to liner trade and port operations even after clearing the blockage due to queuing processes. As Supply Chains (SC) became affected, companies discussed SC Risk Management strategies (SCRM) to mitigate the impact of the blockage; i.e., the global shipping giant Maersk warns about ripple effects lasting for weeks (Wagner, Macaya and Mahtani, 2021). Furthermore, the time of clearing was not evident during the blockage and alternatives like circumventing would take more than nine days. Therefore, the criticality of this canal for global trade has become eminent.

The mathematic discipline of Queueing Theory (QT) is well explored and established (Worthington, 2009). Some papers suggest applying models from QT to transport infrastructure, for example, in order to assess the internal procedures of crossing the Suez Canal (Griffiths, 1995). QT models are also present in the SC literature context to analyse the performance of SC operations under volatility of input parameters or demand (Bhaskar and Lallement, 2010; Van Woensel et al., 2008). QT models that provide a notion of risk in terms of statistic deviation from a service level objective are scarce (i.e., Goodfriend, H. and Pet-Edwards, 1991) and do not cover risk management.

1.2 Problem Formulation

Albeit, hundreds of waiting ships are not a performance issue but a transport disruption rippling SCs. Nevertheless, no published paper so far has applied models from QT in the context of Supply Chain Risk Management (SCRM), in which the recovery of SC services after a disruption occurred is of interest, which major review papers on SCRM and SC resilience highlight (Heckmann, Comes and Nickel, 2015; Hosseini, Ivanov and Dolgui, 2019).

Decision-makers would benefit from a prognosis of the delay of the vessels. However, there was no method at hand for stakeholders of the maritime SCs to predict the time

until the waiting vessels could continue their voyage in the Suez Canal (i.e., see HSN, 2021). Yet, each hour difference affects \$millions worth of economic activities. The time the service becomes operational again depends on the Suez Canal Authority (SCA) procedures and the number of other vessels waiting. Given the uncertainty of how long it will take to clear the blockage and resolve the initial queue, knowing when the circumvention on the alternative route around South Africa becomes viable is also beneficial. A model from QT provides these answers.

1.3 Research Goal and Structure

The application of queueing models offers insights into the restoration of transport bottlenecks, which affect SC operations: This paper introduces a novel queueing model capable of simulating the events of the Suez Canal blockage. The model allows the deduction of the vessels' waiting times and recovery of the canal's usual service based on input parameters that reflect the situation, whilst the initial queue resolves. This model demonstrates the feasibility of answering research questions of SCRM with QT by predicting the recovery of the canal operation service for the waiting vessels. The internal processes of the Suez Canal, as well as vessel-specific routines, are neglected.

This paper aims to contribute to the literature of SCRM, more specifically concerning the notion of recovery, which is present in the SC resilience literature, by predicting the time until service becomes fully operational again after a disruption.

The paper is going to address the research goal with the following five steps. First, a literature review showcases the application of QT in the SC literature, and an overview of the SCRM literature will highlight the gap that QT can close. The following section formulates a QT model to simulate the situation at the Suez Canal blockage. Then, this paper presents the findings from the model for the motivating research question. The model discusses the method and findings regarding their validity, relevancy, and applicability. Last, this paper embeds the model into the broader context of the literature and names further research opportunities.

2 Literature Review

Supply Chain Management (SCM) literature applies queueing models in several cases to optimise logistics KPIs: Van Woensel et al. (2008) develop a vehicle routing problem with queues to optimise distribution processes in logistics. Bhaskar and Lallement (2010) model a three-stage textile SC with a series of queues to optimise delivery capacity by computing the minimum response time for delivering products to their destination. Souf-Aljen et al. (2016) use QT to simulate the impact of dredging works on port sea operations in a port while making forecasts on the port's throughput. In waterway transport, Wilson (1978) uses several queueing models to test the impact of lock capacities on congestion in the US.

Literature on the Suez Canal got first published in 1956, assessing the financial-economic impact of the canal (Baer, 1956). With the help of QT, Griffiths (1995) analyses the queues and delays at the entrance of the Suez Canal to maximise the throughput of ships and minimise queuing delays. Therefore, the author provides a deep understanding of the transport operations inside the canal with their QT model. (Laih, Tsai and Chen, 2014) publish a paper from a SCM perspective on the optimal pricing at the Suez Canal. Next, Sun and Laih (2021) propose a steady-state model to minimise queues at the canal entrance with a timetable and toll scheme and that takes the extension of the Suez Canal into account. Similar problem formulations considering arrival rates but relying on other methods exist: In the case of the Kiel Canal in Germany, Andersen et al. (2021) develop a metaheuristic to study the effect of uncertainty in arrival times.

The availability of transport infrastructure is of special interest in the context of SCRM because of SCs dependencies (Heckmann, Comes and Nickel, 2015), and other SC agents influence the infrastructure's service performance. If SC links become unavailable, the recovery aspect, the time until operations perform as usual again, is of interest from a perspective of SC resilience (Hosseini, Ivanov and Dolgui, 2019). However, applying quantitative, context-sensitive models with emphasis on the time aspect is still a gap in SCRM (Heckmann, Comes and Nickel, 2015; Qazi et al., 2017). Further research efforts could explore the application from a modelling/methodological side (Li et al., 2016; Hosseini, Ivanov and Dolgui, 2019). Also, further research is required to assess the effect

that the geo-location of the disruption has which is different for many SCs, i.e., based on their market distance (Bak, 2018).

This paper identified a research gap in the application of QT for SCRM and resilience. To the best of the author's knowledge, the SCRM literature has not considered applying QT to address research questions as of this date, and the QT literature has not addressed the potential to analyse risk in transport or SCM (used search engines include but are not limited to: Google Scholar, Scopus, academia.edu). More precisely, there is no literature estimating how long it will take to reach a steady-state behaviour after a risk event.

3 Model

The model of this paper has two goals: first, predicting how long the queued-up vessels need to wait until continuing their voyage; second, at what time the entire queue resolves, and a new service cycle continues with steady-state behaviour.

Queueing models are simplifications of reality, and the objectives of the models vary depending on the analysed system. QT has been originally applied to describe queues in telephone networks in the beginning of the 20s century and established as modelling methods of operational research since a long time (Worthington, 2009). Thus, Worthington (2009) proposes a new discipline of queue modelling to focusing on practical insights for managers (decision-makers) utilising queueing models because researched models become mathematical complex and challenging to implement.

The situation at the Suez Canal is as follows: During the blockage, vessels queued up and waited for the clearing. After clearing, vessels now enter the canal entrances and continue their voyage by being assigned to a convoy that achieves their goal. The convoy assignment depends on their arrival position in the waiting line. The North and South convoys are almost working independently due to the canal extension in 2016 preventing transshipment traffic; they start at the same time and contain about the same number of vessels each day. Therefore, the modelling of the situation gets simplified by aggregating the entrances altogether into a single service system with a deterministic service rate,

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namely the convoy schedule and the cumulated arrival rates of new vessels at both entrances.

3.1 Model formulation

In the Kendall notation, the proposed model is the M/Dk/1 queue model considering a single queue (".../1"). M denotes the exponentially distributed arrival rate of a new vessel, D is the convoy's batch-service with a deterministic service rate μ , additionally a fixed service time, and an average convoy capacity of k vessels. The waiting area for arriving vessels is hypothetically infinite, and new vessels arrive at an arrival rate λ according to a Poisson process. The arrival of a new vessel alters the queue process from state i to $i + 1$, where i denotes the number of vessels in the system, including those currently assigned to a convoy.

Vessels are assumed to arrive individually in the waiting area and not in batches. The convoy assignment operates according to the principle "first come – first serve", although different prioritisation strategies would be possible. The service convoys have a fixed capacity, and the vessel size does not matter: This model does not account for a variable service rate depending on the number of pilots from the SCA and guidelines like the minimum safety distance between ships sailing in the same convoy. The anonymous vessels are numbered and served according to their time of arrival in the queueing line.

This paper does not undertake to analyse the internal traffic of the canal. The internal services of the Suez Canal were investigated by (Griffiths 1995). This delineation is reflected in Figure 1, which draws a schema of the proposed M/Dk/1 model with the simplifying assumptions: the North- and South-Convoy get aggregated to a single service server to which vessels from the North and South waiting lines are assigned. Though implementable, the model does not consider the actual transit of the canal and continuation of the voyage.

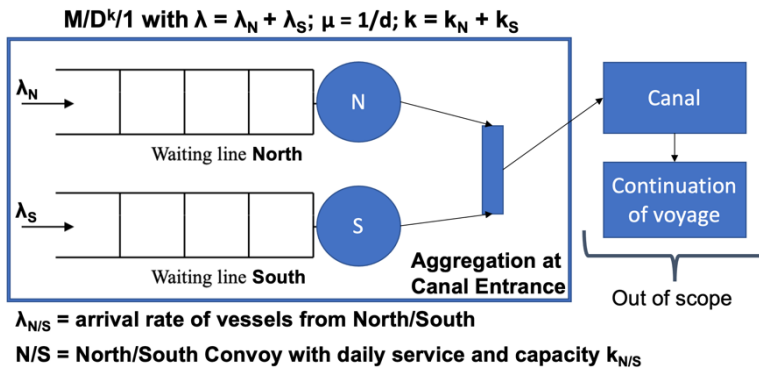


Figure 1: Schema of the $M/D^k/1$ model

For the steady-state, classic performance metrics are easily obtained. In the steady-state, the average arrival rate is less than the average service rate and service capacity – “business is as usual”. However, the studied $M/D^k/1$ is initially not in a steady-state because numerous vessels queued up due to the Suez Canal blockage, whereas the service rate had been zero. Also, the time-dependent properties are of interest for this research, namely, to determine the initial queue’s resolving. Thus, a transient model is required, which describes the busy period from the time of blockage when vessels start to queue up to when the entire queue becomes empty again, and business is as usual again.

With empirical data reported by news media (Greg Chang, 2021; Ankur Kundu, 2021), the model is parametrised as followed:

- λ : The arrival rate is 50 vessels per day.
- μ : two service convoys per day start from the two entrances with a constant service time of 11 hours with a service interval time of 12h for convoys.
- k : 85 vessels can pass the canal in convoy from the two directions.
- V_0 : 494 vessels were queued and waiting in total at the North and South entrance at the time of clearing on 29 Mar at 3 pm, of which 72 are waiting inside the canal at the Great Bitter Lake.

3.2 Simulation and method validation

Time-dependent solutions often require sets of differential equations (Worthington, 2009); for a transient M/Dk/1 model, an analytical solution was published (Baek et al., 2016). However, the literature suggests that simulation results are sufficiently close to results from the analytical form (i.e., see Griffiths, Leonenko and Williams, 2008) while making them less mathematically complex and easier to implement (Worthington, 2009).

This paper uses the simulation approach due to the ease of application and better potential for modification. The simulation is conducted with the python simulation API SimPy, version 4.0.1 (SimPy, 2021). With this setup, a Monte Carlo simulation is performed to draw the queue model states from the distribution of the arriving vessels.

Consider an M/D^k/1 queueing system with infinite waiting room, arrival rate λ and deterministic service time $1/\mu$ with capacity k . V_0 is the number of the initial waiting vessels at the time of clearing $t=0$. Let $V(t)$ be the number of vessels at time t . Equation 1 depicts the time-dependent queue length probability:

$$Q_n^{(j)}(t) = \Pr[V(t, k) = n | V_0 = j], (\tau > t > 0) \quad (1)$$

where $n \geq 0$ is the state of the queue with $k = 85$, the batch-service capacity of the convoys, and $j = 494$ is the number of the initial vessels. τ is the first passage time of the M/D/1 queue defined as the point where the original queue becomes empty, meaning the Suez Canal can operate as usual again.

The time-dependent waiting time distribution of the vessels until their respective convoy starts is then, as equation 2 shows:

$$W_q^{(j)}(t, x) = \Pr[T_q(t) \leq x | V_0 = j] \quad (2)$$

with q being the vessel number $\in \{0, \dots, j, j+1, \dots, \max V\}$ with $\max V$, the number of the last vessel entering the system in the considered runtime period of the simulation model.

The conflict between the applicability of QT models and engineering model properties to reflect real system's behaviour arises, and this paper states many simplifying assumptions. Nevertheless, the simplistic M/Dk/1 simulation model obtains the

properties relevant for decision-making, which is according to the research goal to predict the behaviour of the queue of waiting vessels due to the Suez Canal blockage.

The findings consist of one random simulation simulating 14 days because multiple simulation runs do not change the characteristics significantly. The code is available on request.

4 Findings

Figure 2 shows the situation for the queued vessels, which are numbered according to their arrival in the system, at the time of clearing regarding their waiting time: The first 85 vessels transited the channel with the first convoy, whereas the convoy assignment serves the next vessels waiting in line in the following days. Thereby, the vessels accumulate waiting time equal to the time passing. This model omits the vessel's waiting time during the 6 days blockage before the clearing is easy to add.

The maximum waiting time of a vessel was 5.6 days. Afterwards, benefit from the diminishing queue length when the original vessels were processed. The 1089th ship, arriving 12.09 days after the clearing, encounters an empty queue and thus does not accumulate any waiting time anymore.

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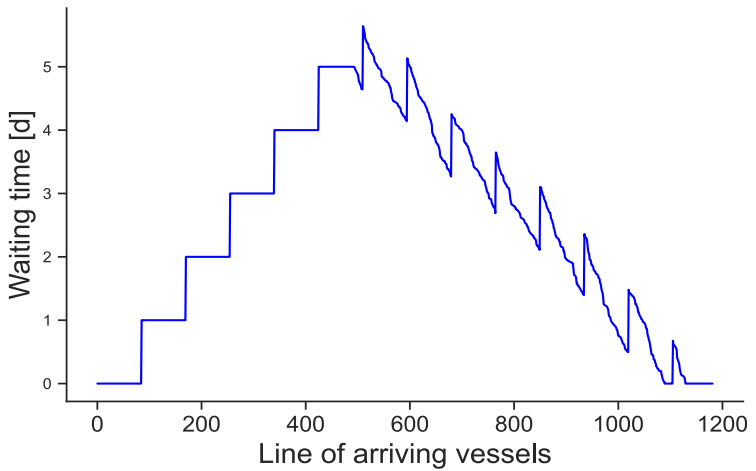


Figure 2: Average waiting times for initial queue length

Figure 3 depicts the queue length (brown line; left side) with an initial 494 waiting vessels at the time of clearing. The queue gets stepwise reduced as vessels get assigned to the convoys starting on day one after clearing. Meanwhile, the average waiting time of vessels increases as the backlog gets processed (blue line; right side). On day 5, the average waiting time reaches its peak and diminishes after that; the steep slope at day 12 means that the initial queue becomes empty, the average waiting time resets, and the busy period is over: the transport service through the Suez Canal has fully recovered. The findings imply that not only the initial 494 vessels got affected by the blockage but further 595 vessels in the next 12 days after clearing.

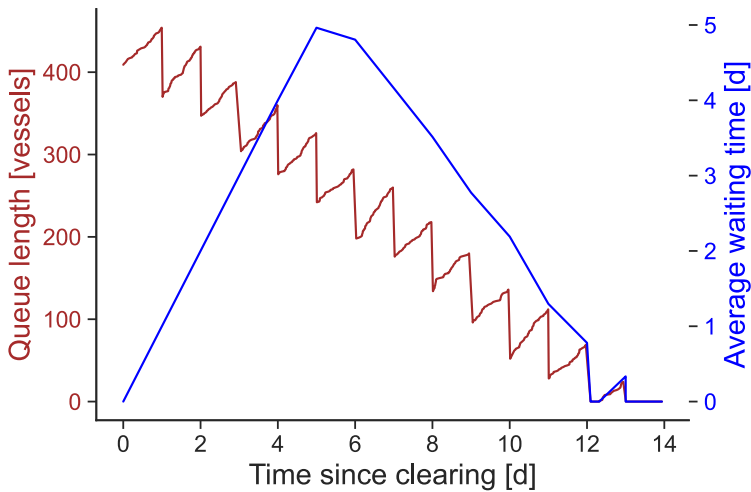


Figure 3: Mean waiting times for ships arriving since clearing at $t = 0$ d

After examining the relationship between vessel position, queue length, and waiting time, Figure 4 depicts the prognosis of recovery depending on the point of clearing $t = 0$ and duration of blockage resembled by the initialising waiting vessels, which are calculated with a constant of 50 vessels per day of blockage. Note how the queue length in case of 2 days blockage (orange line) does not increase that steeply because most of the initial queue can already be assigned to the first convoy starting at day one after clearing. With the support of such a prognosis, a decision-maker can deduce risk mitigation strategies for their vessels with their estimated arrival and associated waiting time depending on the scenarios when the Suez Canal blockage gets cleared.

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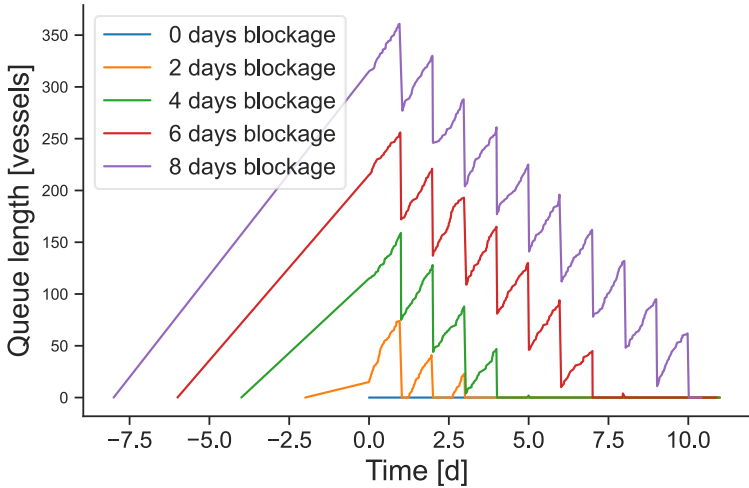


Figure 4: Resolving of vessels depending on initial queue length

5 Discussion

This paper computes findings close to the observations in reality: The model predicts five days until the last waiting vessel at the time of clearing passed the entrance; this is equal to the retrospectively announced five days by the SCA. The complete recovery of business-as-usual happens in 12 days. For the latter, the reported figures vary, depending on the source and definition of business-as-usual (i.e., 7 days by the SCA (Greg Chang, 2021), 10 days by Maersk (2021) and more than 11 days by (Kemmsies, 2021)).

The predicted behaviour regarding the queue length and vessel's waiting times are close to the reported numbers. However, the danger exists to cherry-pick the proper set of parameters that calculate the desired results observed. Using AIS-data allows for a data-based validation of the model by providing more precise arrival and service rates for the case of the Suez Canal and other situations where vessels with AIS-transponders are mainly present (i.e., see, Yang et al., 2019). Nevertheless, with the parametrisation from

news media, the model output reflects the determining behaviour of the waiting vessels and thereby reflects the notion that queueing models need to rely on the weight of empirical evidence (Worthington, 2009).

This paper aimed to analyse the new aspect of recovery due to the risk event of the Suez Canal blockage. As stated beforehand, the model did not consider performance-based aspects of the Suez Canal case, which are already present in the literature. However, due to the compatibility of QT models (see Worthington, 2009), this paper's model and the queueing service model by Griffiths (1995) can be integrated into a holistic model integrating the risk and performance-based view. Furthermore, the formulation from QT allows consistency to other models from QT, thereby extending the model further by, i.e., further analysing port operations in the waiting vessels' destinations.

The simplistic $M/D^k/1$ model has been formulated to demonstrate the feasibility to model the behaviour relevant for decision-making after the disruptive risk event of the Suez Canal blockage. The model assigns each vessel in line with an associated waiting time, thereby anticipating the delay of the affected SCs that put cargo onto the vessel. A risk assessment of said SCs can use this value because decision-makers base risk mitigation strategies on the duration of the risk event (Heckmann, Comes and Nickel, 2015). Therefore, this paper's model contributes to SCRM research gaps as it provides a quantitative method with particular emphasis on the time aspect from which decision-points are derived (see Heckmann, Comes and Nickel, 2015).

6 Conclusion

This paper proposes applying models from QT to derive essential parameters relevant to SCRM: the behaviour of the recovery process after a disruptive risk event occurred. The proposed Queueing Theory model with a risk-based view extends the performance-based view of queueing models in the SCM literature by analysing the backlog queue and cycle until the busy period is over. The proposed method is novel to SCRM.

The $M/D^k/1$ model allowed a quick analysis of the Suez Canal Blockage and predicted a close estimate of when the queue eventually resolved with the associated waiting times

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for individual vessels. In the case of infrastructure-based disruptions, the application of this model provides insights into the backlog behaviour and supports data-driven decision-making to mitigate risk effects by providing method-driven transparency. Stakeholders of waterway-dependent transport routes like the Kiel Canal can benefit from this model by assessing the associated time costs of queueing and deducing appropriate risk mitigation strategies like circumventing or modal shift.

The application of this model provided a quantitative method to gain insights into the Suez Canal blockage from a SCRM perspective. Moreover, a whole methodological toolset is presented to analyse the situation further with QT. Furthermore, applying queueing models brings along the performance measures and cost-optimising strategies transferred to decision-making in the context of SCRM.

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