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COMBINING SIMULATION WITH RELIABILITY ANALYSIS IN SUPPLY CHAIN PROJECT MANAGEMENT UNDER UNCERTAINTY: A CASE STUDY IN HEALTHCARE

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ABSTRACT

Many projects involving supply networks can be logically represented by multiple processing paths. When the supply chain is working under deterministic conditions, computing the total time requested by each path is a trivial task. However, this computation becomes troublesome when processing times in each stage are subject to uncertainty. In this paper, we assume the existence of historical data that allow us to model each stage's processing time as a random variable. Then, we propose a methodology combining Monte Carlo simulation with reliability analysis in order to (i) estimate the project survival function and (ii) the most likely 'bottleneck' path. Identifying these critical paths facilitates reducing the project makespan by investing the available budget in improving the performance of some stages along the path, e.g., by modifying the transportation mode at one particular stage in order to speed up the process. A numerical example is employed to illustrate these concepts.

1 INTRODUCTION

There are several processes that determine supply chain performance (Lambert and Cooper 2000). These include, among others, the customer relationship, the demand management, the manufacturing flow, the product commercialization, and the returns management. In particular, the distribution process is responsible for the flow of goods between each successive stage of a supply chain and constitutes one of the main drivers of the supply chain performance (Laghrabli et al. 2016). Companies aim to carry out distribution processes more efficiently in terms of shipping faster, cheaper, closer, and without disruptions. Recently, the COVID-19 pandemic has shown the lack of resilience in supply chains and the impact that disruptions may have on a global network scale as individual supply chain connections and nodes fail (Golan et al. 2020).

Many projects involving supply networks can be represented by multiple processing paths from a project starting node to an ending one. Figure 1 shows a small example that consists of six tasks and three paths. Each task represents a piece of work to be done or undertaken (e.g., developing a strategic plan, a warehousing plan, or designing KPIs). The tasks present logical precedence relationships (e.g., task #06 cannot start before task #02 has finished). A critical path is defined as the sequence of project network tasks that add up to the longest overall duration.

Typically, the processing time of a task is set to a deterministic value, which may be computed as a weighted average of an optimistic, a pessimistic, and a likely estimate. This is a simplification that may lead to wrong conclusions and suboptimal decisions. A more realistic approach is required specially in scenarios where there are hard deadlines, the uncertainty regarding processing times is not negligible, and

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small changes in the processing time of a task may have a huge impact on the efficiency of the entire distribution process. For the application of this article, we consider an illustrative example of activity planning, in this case, from the real scenario of a vaccine distribution project.

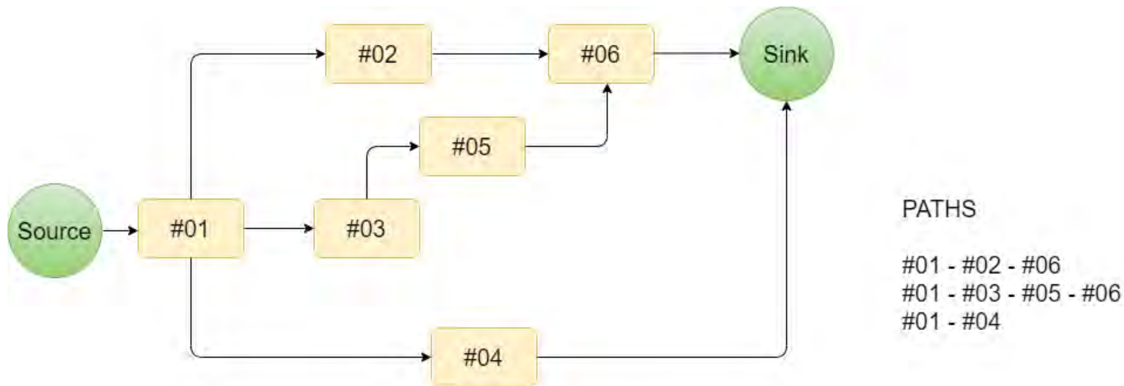

Figure 1: Representation of a small project with six tasks and three paths.

In this context, we propose a hybrid methodology that aims to enhance the distribution project's makespan in a supply chain network. This methodology combines concepts and techniques of modeling, reliability, simulation, and optimization. It takes into account the uncertainty in the processing times that most tasks in supply chain project management exhibit. In particular, the methodology consists of five steps. Initially, we model the completion time of each task by fitting a given probability distribution based on historical completion times. The next step is to find the logical structure of the supply chain network, describing the relationships among the tasks. Afterwards, we simulate multiple scenarios based on the probability distributions. Each scenario is simulated by generating a random observation for the processing time of each task. For each scenario, respective estimates of the project's makespan and the critical path are stored. The fourth step builds the project's survival function from the project's completion times. Finally, the methodology proposes to enhance the project's makespan or survival function through prioritizing a budget on improving critical paths or reducing critical tasks or split large tasks into parallel sub-tasks.

The contributions of this work are: *(i)* a hybrid methodology, which considers the stochasticity in supply chain projects, able to provide statistics of a project to help decision-makers to gain insights into it and prioritize actions of improvements; and *(ii)* a comprehensive analysis of an illustrative example regarding a healthcare supply network. The rest of the paper is structured as follows: Section 2 offers a review on designing supply chains under uncertainty conditions, optimization of healthcare supply chains, and simulation-based methods in reliability analysis. Section 3 describes the problem addressed. Section 4 explains the hybrid methodology proposed. Afterwards, Section 5 presents an illustrative example while section 6 analyzes the results. Finally, Section 7 highlights the main findings of our work and identifies future research lines.

2 RELATED WORK

In this section, we provide an overview of the three topics that are related to our research: *(i)* the design of supply chains under uncertainty conditions; *(ii)* the optimization of healthcare supply chains; and *(iii)* the use of simulation-based methods to determine the reliability and time-to-completion of complex systems and networks working under uncertainty conditions.

2.1 The Process of Designing and Implementing a Supply Chain

This section aims to highlight some characteristics that are typical from the process that we want to optimize.

Supply chain network design is a concept broadly studied during the last decades, both from a qualitative and a quantitative perspective. Chopra and Meindl 2003 (p. 99) state that ”Supply chain network design decisions include the location of manufacturing, storage, or transportation-related facilities and the allocation of capacity and roles to each facility”. These decisions are related to a strategic level, and must be optimized considering a long-term (usually several years) efficient operation of the supply chain as a whole (Altiparmak et al. 2006). One of the more challenging tasks in supply chain design is addressing uncertainty. Anticipating the future is crucial in planning and design processes. Blackhurst et al. (2004) state that one of the causes of supply chain complexity is their dynamic nature, and the uncertainty in variables such as demand, capacities, transportation times, or manufacturing times.

A review about the use of quantitative approaches in supply chain risk management is carried out by Oliveira et al. (2019). When risks cause a disruption in a few nodes, their effects can easily spread to other parts of the supply chain (Li and Zobel 2020). According to Dolgui et al. (2018), these disruptions are responsible for lower revenues, delivery delays, loss of market share and reputation, as well as stock return decreases, hence affecting the global performance of the supply chain. Particularly in 2020 and 2021, the global pandemic caused by the COVID-19 disease has largely affected all areas of the economy and society worldwide. Some supply chains have experienced an increase of demand that they are not able to satisfy (facial masks, ventilators, etc.), while others are suffering long-time production stops like the ones of non-essential products. As pointed out by Ivanov and Dolgui (2020), supply availability in global supply chains has been largely decreased and imbalanced with the demands. Thus, this pandemic is an unprecedented and extraordinary situation that clearly shows the need for advancing in research and practices of improving delivery projects in supply chains.

2.2 Optimization of Healthcare Supply Chains

Following Mathew et al. (2013), the healthcare supply chain involves the flow of many different types of products. The primary goal of the healthcare supply chain is to deliver products in a timely manner, so that the demand from the end consumers is properly satisfied. In addition, there is the participation of different stakeholders, such as government institutions, regulatory agencies, and insurance companies, which increases the complexity of the distribution process. Thus, the industry is highly interdependent and one party cannot perform efficiently leaving the other parties behind. Moons et al. (2019) state that healthcare logistics ranges from the process of handling physical goods (such as pharmaceutical products, surgical items, medical equipment, sterile items, bedding, food, etc.) to the information flows associated with these goods – i.e. from the receipt of these goods in a hospital to their delivery to the patient at their place of care. A specific challenge for the transportation of these goods is that many supplies require special precautions. For instance, medicines may require transportation and storage within certain temperature ranges, have a short shelf life, or suffer from supply disruptions (Skipworth et al. 2020). Therefore, reducing the transportation and distribution process time in these cases is a key factor.

2.3 Simulation-based Methods in Reliability Analysis

Reliability or survival analysis has been a major research topic in areas as diverse as Industrial Engineering and Biostatistics during the last decades (Gardoni 2017). While engineers tend to use parametric statistical methods to study the time-to-failure of electronic or mechanical components and systems, biostatisticians usually employ non-parametric methods to study the durability of patients subject to different treatments or biological entities under specific environmental conditions (Emmert-Streib and Dehmer 2019). Especially when dealing with system reliability, often both the individual components of the system as well as the system logical topology play a key role in its durability. Since the time-to-failure of individual components is typically modeled as a random variable following a Weibull or lognormal probability distribution (Elsayed 2020), the durability of the system itself becomes a random variable as well. The complexity of most modern systems (e.g., supply chain networks, telecommunication systems, civil engineering infrastructure, military instruments, etc.) makes it quite challenging to analyze their durability just by employing analytical expressions. As a consequence, Monte Carlo and discrete event simulation have become a popular tool among system reliability engineers. One excellent review on the use of Monte Carlo simulation in systems reliability is provided by Marseguerra and Zio (2002). Also, Juan and Vila (2002) propose a simulation-based algorithm, developed in Excel/VBA, which makes use of Monte Carlo simulation to estimate the reliability or survival function of a complex system. This work was then extended by Faulin et al. (2007) and Faulin et al. (2008), who incorporated new simulation-based algorithms for studying system availability concepts – i.e., considering repairing policies and not just failures. Finally, a complete collection of articles related to this topic can be found in Faulin et al. (2010), while recent applications of simulation-based methods to study the reliability of logistics systems can be found in Wang et al. (2018) and Vojtov et al. (2018).

3 PROBLEM DESCRIPTION

There is a supply chain project composed of n tasks. Each task a has a processing time t_a that may be modeled as a random variable following either a theoretical or empirical probability distribution.

The first stage of the problem is to find the logical structure of the supply chain. The result may be represented as a directed acyclic graph $G = (V, E)$ (such as that in Figure 1), where V is the set of nodes (there are $n+2$ nodes: each of the tasks, a starting node, and an ending node) and E is a set of paired vertices, whose elements are called edges or links. These edges reveal the precedence relationships among tasks; a task cannot be started before the previous ones have finished. The graph can be decomposed into a set of paths P. Some tasks might be included in several paths. The project will only finish once all the required paths have been completed. Since we consider random processing times for each task, the project duration becomes stochastic.

The second stage consists in designing and selecting strategies to enhance the project's makespan or survival function. Different strategies may be implemented. We considered the following ones (which are further described in the next section): (*i*) prioritizing a given budget B and (*ii*) reducing critical tasks or split a large task into parallel sub-tasks.

4 A SIMULATION-BASED METHODOLOGY

This section describes a general methodology that can be employed to enhance the distribution project's makespan in a supply chain network. As displayed in Figure 2, our approach consists of five steps and combines inputs modeling, reliability concepts, simulation and, optimally, a heuristic procedure based on the outcomes of the simulation. The first step consists in using historical data (e.g., from similar projects carried out in the past) to fit the completion times of each individual task in a given distribution project. Alternatively, the data may also come from experts in industry. Frequently, these completion times will be modeled as Weibull or lognormal probability distributions, since these are extraordinarily flexible distributions, which are frequently employed in reliability analysis to model failure and repair times (Brot 2019). At this stage, the logical structure of the distribution project has to be identified and modeled in a processable manner. One way to do this is by considering the path representation of the project, i.e., the set of paths that have to be completed in order for the project to be finished. Next, using the probability distributions that model the completion times of each task, random observations on these times can be generated, and the project's makespan can be estimated as the finishing time of the most durable (critical) path. In addition to this, the simulation can also provide estimates of the probability that the project is completed on or before a given target time. The latter information lead to the construction of the survival function, which shows the probability that the project has not been completed yet (i.e., it is still 'alive') at any time. A guided enhancement of the project performance can be achieved by employing the information about the critical paths: As far as there is some budget available, this can be used to either reduce some task completion times in the most critical path (thus, reducing the path completion time as well as the project's expected makespan) or to split long tasks in the critical path into sub-tasks (i.e., changing the network topology), in such a way that these sub-tasks can be executed in parallel. After these changes, a new simulation can be run and new values for the expected project's makespan and its associated reliability function are obtained. These iterative steps can be automatized by a simple heuristic, which can order a list of potential improvements by their cost and their expected effect on the probability distributions of the tasks involved, and run until all the budget available for improvements has been exhausted. Notice that the goal does not necessarily have to be minimizing the expected project's makespan, since another interesting objective could be to minimize the probability that the project has not finished on or before a given deadline – this information can be obtained from the survival function.

5 AN ILLUSTRATIVE EXAMPLE

In order to illustrate our simulation-based approach, we consider a fictitious (but realistic) case example from the healthcare industry. It is based on data provided by an expert in supply chain planning, in this particular case, distribution of a vaccine. The method may be extended to projects in other fields, in which there is a logical sequence of activities.

In this case, the distribution project refers to the distribution of a vaccine, for which a series of tasks need to be accomplished. For each task in the project, Table 1 shows the following information: *(i)* a task identifier (number); *(ii)* a short description; and *(iii)* a probability distribution modeling the processing time of the task, which also includes the specific parameter values. For our computational experiments, we have modeled each task processing time as a Weibull distribution with shape and scale generated from the user specified mean and standard deviation (both in days). In a real-life application, the specific probability distribution can be fitted from historical data, which allows for obtaining the best-fit probability distribution, including its parameters (Law 2013). Still, the Weibull distribution is largely employed to model random times due to its extraordinary flexibility, which makes it the predominant probability distribution in most reliability studies (McCool 2012).

Table 1: Detailed information on each task and its random processing time.

Task	Description	Distribution	Shape	Scale	Mean	StDev
#01	Strategic plan	Weibull	2.6955	16.8678	15	6
#02	Permit agreements	Weibull	2.6955	16.8678	15	6
#03	Warehousing plan	Weibull	2.6956	22.4913	20	8
#04	Distribution plan	Weibull	2.6956	22.4913	20	8
#05	OPEX control	Weibull	2.6958	67.4737	60	24
#06	Distribution permits	Weibull	2.6956	33.7370	30	12
#07	Loading/unloading permits	Weibull	2.6956	33.7370	30	12
#08	Training and action protocols	Weibull	2.6956	11.2455	10	4
#09	Logistics components procurement	Weibull	2.6956	22.4913	20	8
#10	KPIs design and monitoring	Weibull	2.6956	44.9825	40	16
#11	Delivery and pickup agreements	Weibull	2.6956	11.2455	10	4
#12	Conservation control	Weibull	2.6956	22.4913	20	8
#13	Warehousing Logistics	Weibull	2.6955	16.8678	15	6
#14	Delivery to vaccination center	Weibull	2.7037	5.6373	5	2
#15	Visit to warehouses	Weibull	2.6956	11.2455	10	4
#16	Route records	Weibull	2.7037	5.6373	5	2
#17	Suppliers negotiation	Weibull	2.7037	5.6373	5	2

As shown in Figure 3, the aforementioned tasks present some logical precedence relationships. Thus, for instance, task #14 can only start once task #13 has been completed. Each path in Figure 3 displays a series of tasks that need to be processed in order for that path to be completed, i.e., the upper path will

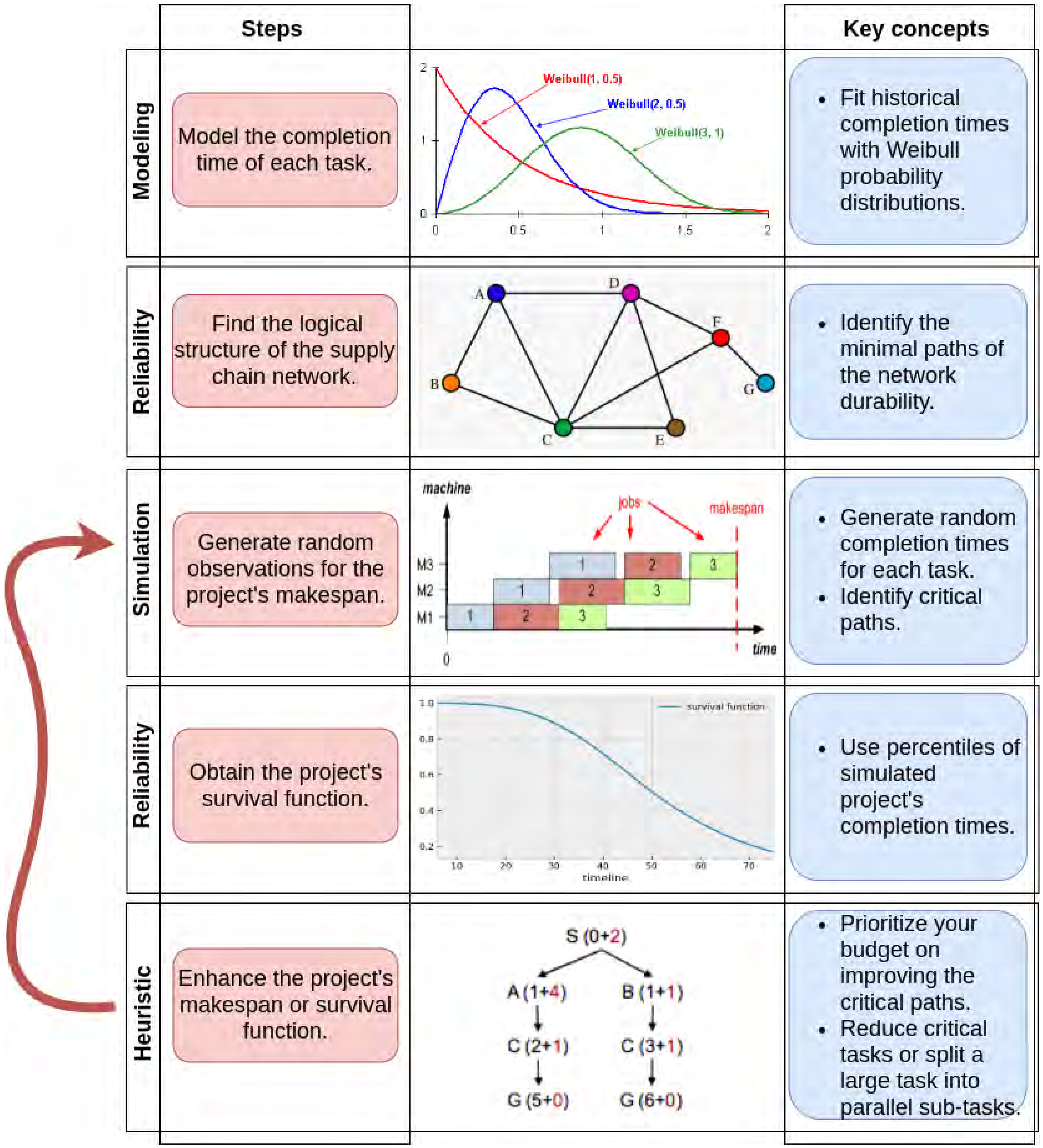

Figure 2: Scheme of the proposed methodology.

consist in processing tasks #02, #06, #11, #13, and #14. Nne of the aforementioned tasks can be started before the previous ones have finished. Some tasks might be included in several paths (e.g., tasks #02, #11, #13, and #14 belong to the two upper paths). The project will only finish once all the required paths have been completed as well. Should the processing times of each task be deterministic, computing the project duration would be trivial. However, once we consider random processing times for each task, the project duration becomes stochastic and the combination of simulation with concepts from survival analysis can be useful to better understand what is happening in this supply chain.

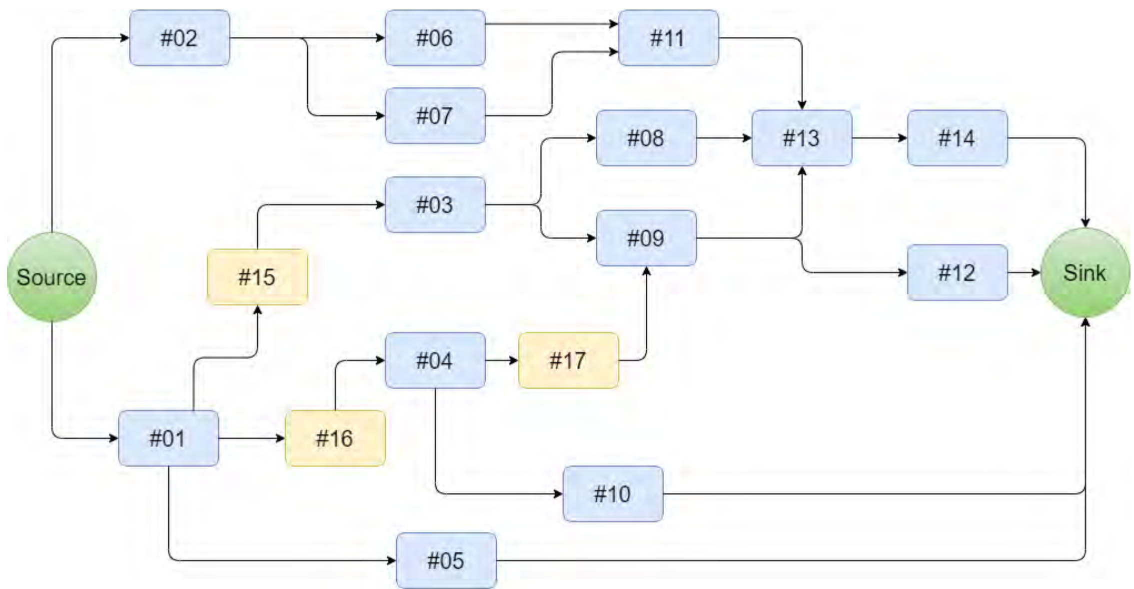

Figure 3: Precedence network diagram for the illustrative example.

6 COMPUTATIONAL EXPERIMENTS

The algorithm has been implemented in R version 4.0.3 (Stowell and Pace 2014). In this particular experiment, the average project duration is 102.2 days, with a standard deviation of 13.4 days. Figure 4 displays the survival function for the analyzed distribution project with the data provided in Table 1. This survival function provides the probability that the project is still active (not finished yet) as time evolves. Hence, for instance, the probability that the project's makespan exceeds the 101 days is about 0.51, the probability that the project's makespan exceeds 90 days is about 0.82, while the probability that the project's makespan exceeds 110 days is about 0.25.

The algorithm is capable of registering the critical path in each simulation run. Knowing the relative frequencies in which each path is responsible for a delay in the project completion, it is possible to focus our efforts on incorporating additional resources to the tasks in that path – so that their processing times are reduced – or to decompose the most critical paths – so different sub-paths can work in parallel. This procedure can be generalized for supply networks with many tasks and paths. In our example, the two lower paths in Figure 3, #01 − #05 and #01 − #16 − #04 − #10, are the most durable paths in about 18.3 % and 17.7 % of the simulation runs, respectively. Notice that, despite the last path contains just two tasks, the first of these (task #05) has a high standard deviation (25) and an elevated mean (60), which explains why the corresponding path can easily become the most durable in the entire project. A natural question arises here: what would be the effect on the project's duration of reducing the duration of these two critical paths? For instance, how would the survival function of the project change if we were able to reduce the standard deviation of task #05 from 24 to 5 (i.e., new shape = 14.7089 and new scale = 62.1721) and the mean of task #06 from 30 to 15 (i.e., new shape = 1.2582 and new scale = 16.1289)? After running again

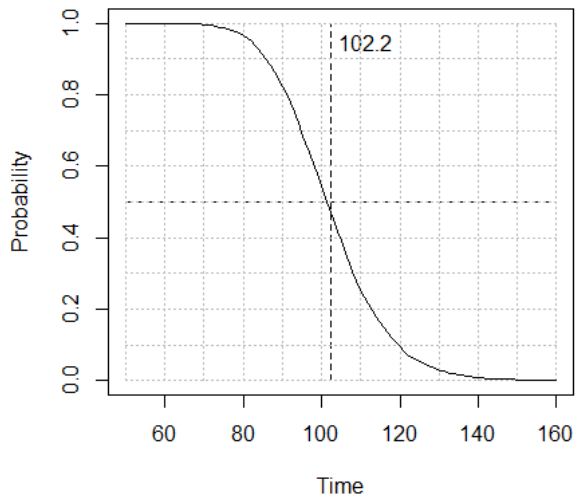

Figure 4: Survival function for the initial supply chain configuration.

the simulation-based algorithm, we obtain that the average duration of the distribution project is reduced from 102.2 to 98.9 days. Also, Figure 5 displays the new survival function, which – as expected – is shifted to the left when compared with the original one (e.g., now there is a 0.5 probability that the project is completed after 98 days).

It is interesting to notice that some changes in the mean or the standard deviation of some tasks may result in a different survival function that crosses the original one. For instance, suppose efforts are conducted to reduce the standard deviation of all tasks in 20 % but, as a result, the means of activities #01 and #02 are incremented in 20 %. The new survival function is depicted in Figure 6. The probability that the project exceeds x days, being $x < 97$, is higher with the new configuration. However, the probability is higher with the original configuration when $x > 97$.

This process of shortening the distribution project's makespan could be iteratively applied while there is available budget as to increase the number of resources in critical paths, hence reducing their expected process time or the associated variability. Actually, by automating this process with a biased-randomized heuristic (Grasas et al. 2017), it could be possible to quickly generate high-quality solutions to the problem of minimizing the project's makespan subject to a maximum available budget.

7 CONCLUSIONS

Efficiency in distribution is a key metric for decision-making in the improvement of the supply chain and has a direct impact on cost savings. When the supply chain is working under deterministic conditions, computing the total time requested is trivial. However, there are many factors that affect the processing time of each task of the supply chain (such as traffic congestion, weather conditions, route problems, or unexpected delays) and ignoring this uncertainty may lead to erroneous conclusions and strategies.

In this context, our work has proposed a hybrid methodology that aims to study and enhance the distribution project's makespan in a project network where each task has associated a random processing time. This methodology relies on the following steps: (i) model the completion time of each task; (ii) find the logical structure of the network; (iii) simulate scenarios and compute the project's makespan for each one; (iv) fit the project's survival function; and (v) enhance the project's makespan or survival function by prioritizing the budget on improving critical tasks or paths, reducing critical tasks, or splitting a large task

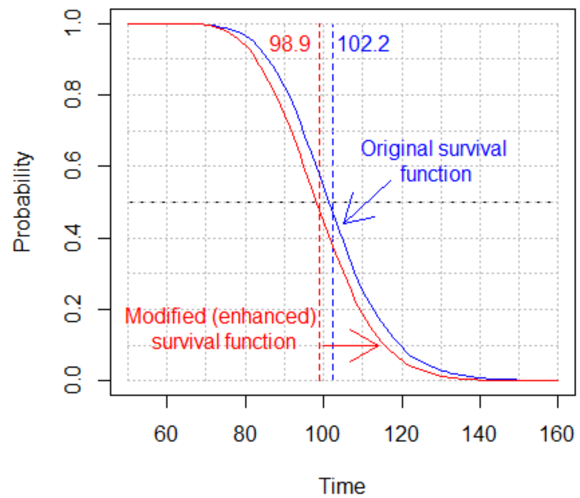

Figure 5: Survival function for the modified supply chain configuration (shift to the left).

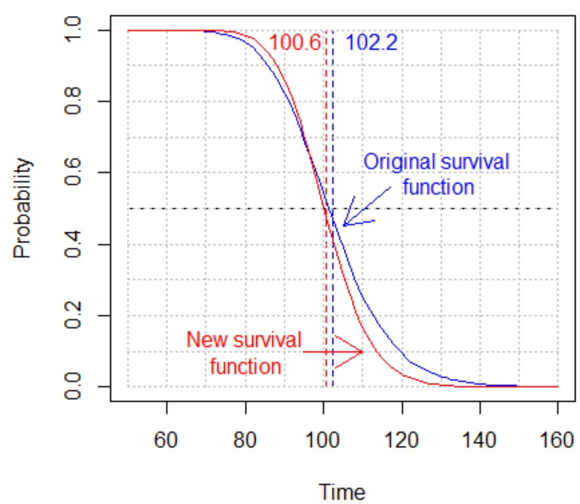

Figure 6: Survival function for the modified supply chain configuration (crossing functions).

into parallel sub-tasks. This simple yet powerful methodology has been illustrated through an example of a vaccine distribution project in the healthcare industry. Several interesting lines of future research stem from this work. For instance, different heuristics or metaheuristics could be designed and compared to improve our methodology. Moreover, more comprehensive computational experiments could provide much more insights on the potential of the methodology to enhance distribution projects in the healthcare industry and other industries.

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