Proposition of a method for stochastic analysis of value streams

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\section*{ABSTRACT}
This article aims at proposing a method to stochastically analyze value streams taking into consideration the effect of critical uncertainty sources on lead time. The proposed method combines value stream mapping (VSM) and Monte Carlo simulation to identify improvement opportunities. To illustrate this approach, we carried out a case study in the special nutrition value stream of a Brazilian public hospital. Results show that the proposed method allows the identification of improvement opportunities that would not be considered in the classical deterministic VSM approach. Further, the integration of the stochastic analysis enables the determination of a more realistic lead time, which supports a more assertive planning and scheduling of the value stream. The proposed method addresses a fundamental gap in traditional VSM without adding much complexity to the analysis procedure, which is a common practical issue in previous works that integrated other stochastic methods into VSM.

\section*{1. Introduction}
Value stream analysis of an organization allows the identification of opportunities for improvement (Karim and Biswas 2016). Among the most used tools to support this analysis, value stream mapping (VSM) conducts the systemic identification of improvement opportunities through the analysis of the relationship between information and material flows (Rother and Shook 1999; Sakthi Nagaraj et al. 2019). The importance of such relationship for companies’ performance is often neglected, culminating in the implementation of departmental improvements whose benefits are not observed in the organization as a whole (Abdelhadi and Shakoor 2014).

VSM provides a framework that supports continuous improvement initiatives, guiding them towards the greatest impacts for the company (Duggan 2012). VSM is versatile and examples of its application are found in processing industries (Abdulmalek and Rajgopal 2007), product development (Tyagi et al. 2015), civil construction (Aziz, Qasim, and Wajdi 2017), healthcare (Xie and Peng 2012; Wang, Chan, and Yang 2014; Wang et al. 2015; Tortorella et al. 2017), and in global commodity distribution chains (Badri et al. 2017). The large quantity of evidence on VSM application denotes its importance for the establishment of an integrated continuous improvement approach (Belokar, Kumar, and Kharb 2012; Dotoli et al. 2012). However, it is relevant to note some limitations related to the use of this tool. Typically, the conduction of VSM is based on a deterministic perspective. This can be observed in the works from Dickson et al. (2009), Tyagi et al. (2015) and Tortorella et al. (2017), which did not consider the probabilistic aspects related to production processes. Throughout a value stream, there are several uncertainty sources (e.g. inventories, processing and setup times) that add variability to the flow (Standridge and Marvel 2006; Seth et al. 2017; Shou et al. 2020) and negatively affect management activities.

This becomes particularly critical in the case of healthcare organisations, for example, as this variability might have a direct impact on the quality of the service provided to patients (Xie and Peng 2012). The search for efficiency improvements in healthcare value streams is primarily addressed by the use of VSM in its traditional form (Wang et al. 2015), not accounting for the stochasticity inherent to the flows under investigation (Bhuvanesh Kumar and Parameshwaran 2018). This fact is also observed in other industry sectors besides healthcare, such as manufacturing and services, featuring both a practical and theoretical opportunity to integrate stochastic methods into VSM. This article aims at proposing a method to stochastically analyse value streams taking into consideration the effect of critical uncertainty sources on lead time. The proposed method combines VSM and Monte Carlo simulation to identify improvement opportunities. Monte Carlo simulation was chosen due to its adaptability to different applications (Brandimarte 2014). Because collecting data from every single uncertainty source existing in a value stream may be unfeasible from a practical standpoint, our method integrated a multicriteria decision-making tool to rank and prioritise the most critical uncertainties, hence, considering them in the...
Optimization Models It does not require prior knowledge of the model made.
Fuzzy logic Possibility of propagating the effect of uncertainties along the model considered.
Two-stage stochastic programming Greater precision of the model made.
Monte Carlo simulation Simplicity in the treatment of variability.
Optimization Models It does not require prior knowledge of the probability distributions of the uncertain parameters.
Stochastic mixed linear programming Greater precision of the model made.
Stochastic dynamic programming Possibility of representing nonlinearities.
Systems dynamics Allows the use of feedback cycles.
Multi-period stochastic planning model It allows the creation of different scenarios based on different optimization criteria.
Multi-period mixed nonlinear programming Increased robustness in the treatment of variability.

### Table 1. Stochastic methods for value stream analysis – advantages and disadvantages.

| Stochastic method               | Advantages                                                                 | Disadvantages                                                                 | Uncertainty source addressed                     | Authors                                      |
|--------------------------------|---------------------------------------------------------------------------|------------------------------------------------------------------------------|-------------------------------------------------|---------------------------------------------|
| Stochastic simulation          | It allows the individual study of each component of the system, reducing uncertainty in decisions. System modelling and data analysis can be very time and resource consuming. | Demand; Processing Time/Cycle                                                  | Gurumurthy and Kodali (2011); Pujawarn et al. (2015); Villarreal, Garza-Reyes, and Kumar (2016) | Behrouzi and Wong (2013)                    |
| Fuzzy logic                    | Possibility of propagating the effect of uncertainties along the model considered. Model validation requires extensive testing. | Demand                                                                        |                                                 |                                             |
| Two-stage stochastic programming| Greater precision of the model made.                                      | It requires prior knowledge of the probability distributions of the uncertain parameters. | Demand; Inventory                                | Badri, Ghomi, and Hejazi (2016); Badri, Ghomi, and Hejazi (2017) |
| Monte Carlo simulation         | Simplicity in the treatment of variability.                               | Less accuracy as the complexity of the problem treated increases.             | Demand; Natural Disasters; Government Policies   | Deleris, Elkins, and Paté-Cornell (2004); Aamer (2017); De Souza et al. (2018) |
| Optimization Models            | It does not require prior knowledge of the probability distributions of the uncertain parameters. Depending on the complexity, the optimization model can be computationally intractable. | Demand                                                                        |                                                 | Mota et al. (2018)                          |
| Stochastic mixed linear programming| Greater precision of the model made.                                      | It requires prior knowledge of the probability distributions of the uncertain parameters. | Demand                                           | Shahparvari et al. (2018)                  |
| Stochastic dynamic programming  | Possibility of representing nonlinearities.                               | It requires prior knowledge of the probability distributions of the uncertain parameters. | Demand; Processing Time/Cycle                    | Weston, Agyapong-Koduia, and Ajafobi (2009); Kenne, Dejax, and Gharbi (2012) |
| Systems dynamics               | Allows the use of feedback cycles.                                         | The greater the complexity of the system, the greater the need for data collection. Increased complexity with increasing number of scenarios considered. | Demand                                           | Deif (2012)                                 |
| Multi-period stochastic planning model| It allows the creation of different scenarios based on different optimization criteria. | Demand                                                                        |                                                 | Al-Othman et al. (2008)                     |
| Multi-period mixed nonlinear programming| Increased robustness in the treatment of variability. High complexity for determining the programming model. | Demand                                                                        |                                                 | You and Grossmann (2008)                   |

Bold values indicate critical uncertainty sources.

stochastic analysis. To illustrate this approach, we carried out a case study in the special nutrition value stream of a Brazilian public hospital. The proposed method allows the identification of improvement opportunities that would not be considered in the traditional deterministic VSM approach. Further, the integration of the stochastic analysis enables the determination of a more realistic lead time, which supports a more assertive planning and scheduling of the value stream (Luz et al. 2020), without adding much complexity in practical terms. This work builds on De Souza et al.’s (2018) study by incorporating a structured procedure to prioritise the uncertainty sources and enhancing the data collection process, which enabled more robust results.

2. Literature review

2.1. Value stream analysis and uncertainty

Among the existing practices in lean manufacturing, VSM is a method used to apply lean principles by examining business processes (Mcmanus and Millard 2002; Löttgering and Koch 2020), culminating in waste reduction in a systematic manner (Duggan 2012). VSM favours a more holistic perspective of the organisation (Ben Fredj-Ben Alaya 2016), highlighting wastes that can be eliminated in a relatively short period of time (Rother and Shook 1999).

Although it was conceived in the context of automotive industry, traditional VSM works well in situations where the value stream is unidirectional (Braglia, Frosolini, and Zammori 2009). However, this tool becomes unrealistic for organisations with a high variety and low volume of products. Further, VSM does not contemplate variabilities derived from uncertainty sources intrinsic to the flow (De Souza et al. 2018). Belokar, Kumar, and Kharb (2012) add that uncertainty is one of the main difficulties for the effectiveness of a planning process, influencing aspects such as processing and setup time (Abdulmalek and Rajgopal 2007; Seth et al. 2017).

Different uncertainty sources can be found in the same value stream, such as: equipment, process, product, service, customer, people, suppliers, etc. (Villarreal, Garza-Reyes, and Kumar 2016). The use of stochastic methods that consider uncertainties and the entailed variability may be an alternative to assertively analyse value streams in these situations. In this sense, Table 1 consolidates the stochastic methods applied to value stream analysis and presents the advantages and disadvantages of each one. In general, the adoption of stochastic methods enables the assessment of the effect of variability on the value stream performance, identifying other wastes that would not be evidenced based on traditional VSM (Zammori, Braglia, and Frosolini 2011).

Overall, literature analysis shows that as the scope of the value stream mapping increases the modelling of the value streams in a stochastic manner becomes more difficult. In most cases, it is hard to deal with a larger number of variables and uncertainties, which ends up increasing the mathematical and computational complexity (Seyedhosseini and...
Thus, the application of more sophisticated stochastic analysis methods is more likely to occur in extended value streams. This fact corroborates to indications from Deif (2012), which emphasised the importance of an adequate assessment of the extended value stream to support more assertive decisions for the business. In case of value stream analysis within the company boundaries (door-to-door stream), the versatility of Monte Carlo simulation for the treatment of uncertainties inherent in the production processes stands out (Aamer 2017; Luz et al. 2020). In fact, De Souza et al. (2018) have proposed Monte Carlo integration into VSM. However, the proposed method fell short in the prioritisation of the uncertainty sources to be considered in the stochastic simulation, especially when there is a large number of uncertainties in the value stream. Our research expands on De Souza et al.’s (2018) proposition, addressing the main methodological drawbacks pointed by the authors.

2.2. Monte Carlo simulation

According to Corrar and Theophilo (2004; p. 54), the ‘Monte Carlo method is a technique that uses random number generation to assign values to the variables of the system to be investigated.’ Its use is beneficial as a technique for solving problems that involve uncertainty. The application of simulation in management problems requires the translation or modelling in mathematical terms of the physical operating system under investigation. This method allows the simulation of any process with a course that depends on random factors (Gentle 2003; Pattanayak, Prakash, and Mohanty 2019).

The versatility of the Monte Carlo simulation is evidenced by how research has been developed in areas such as hydrology (Vrugt et al. 2013), economic risk analysis (Abdo and Flaus 2016), medical sciences (Yang et al. 2015; Kramer et al. 2018), and ecological vulnerability assessments (Song et al. 2015). The Monte Carlo simulation demonstrates its usefulness in the treatment of uncertainty conditions present in varied areas of knowledge (De Souza et al. 2018). Specifically, for the value stream analysis, some authors (e.g. Deleris et al. 2004; Aamer 2017) have already used Monte Carlo simulation in the treatment of uncertainties. However, these studies focussed their analyses on specific uncertainty situations along the value streams, such as a risk analysis associated with failures in the delivery of supplies and the processing capacity of a distribution centre.

The use of Monte Carlo simulation as an alternative to verify the effects of variability along the value stream comprises a promising approach. It enables the verification of different scenarios, changing key factors such as levels of variability or probability distribution functions from some uncertainty sources (Arnold et al. 2015). This is particularly important in the search for a greater understanding of uncertainty sources that are often poorly addressed in the literature, such as the interference of human factors for value stream performance (Xie and Peng 2012).

2.3. Multi-attribute utility theory

Multicriteria decision support or multicriteria decision making is a set of methods and techniques to help and support people and organisations to make decisions under the influence of a variety of criteria, and is firmly rooted in an alternative concept optimisation where several criteria characterise the most satisfactory alternative (Kailiponi 2010). A multicriteria decision problem consists of a situation in which there are at least two alternatives of action to choose from, and this choice is driven by the desire to attend to multiple objectives. These alternatives often conflict with each other, so the decision-making processes that involve a high degree of complexity are not based on just one criterion (Alshamrani, Alshibani, and Alogali 2018). The preferences of decision makers need to be precise, providing specific weights for each of the criteria and requiring stronger assumptions at each level.

In this sense, Multi-Attribute Utility Theory (MAUT) can be used to measure the attractiveness of alternatives with respect to multiple attributes (Aqlan et al. 2017). To solve the ranking problem, an additive aggregation method is usually used, which is considered as a compensatory method, in which the evaluation of alternative methods takes into account the trade-offs between standards or compensation in methodology (Alshamrani, Alshibani, and Alogali 2018). The advantage of MAUT compared to other methods is that it provides a more comprehensive assessment and allows comparison of several alternative methods (Velasquez and Hester 2013). Besides, MAUT is considered to be a transparent method that is easy to apply because decision-makers can manipulate their models, assign weights to assigned standards, and involve simple mathematical operations making it a widely understood, multi-standard method. Finally, another major advantage of MAUT is that it considers uncertainty in decision making (Kovačević et al. 2019).

3. Research design

This research proposes a method to stochastically analyse value streams taking into consideration the effect of critical uncertainty sources prioritised by a multicriteria decision-making tool. Hence, due to the exploratory nature of our research, a case study was conducted to illustrate the application of the proposed method, helping researchers and managers to better understand its implications (Childe, 2011). Case study research is a primary means of exploring field conditions, as long as conducted with rigour and objectivity (McCutcheon and Meredith 1993). Case studies seek to investigate a phenomenon within a real and contemporary context (Yin and Davis 2007), relating variables and the links they have to each other.

Although results from a single case study might be subject to bias, this research design was chosen due to its valuable utilisation in contexts where authors seek to make a contribution by the illustration of a proposed method (Siggeklow 2007). As suggested by Voss, Tsikriktsis, and Frohlich (2002), we conducted this case study to investigate...
the main key variables that impose variability on the value stream studied. Our study, therefore, is a refinement of the current theory (Ketokivi and Choi 2014) regarding the stochasticity inherent to value streams and ways to mitigate the effect of variability on the flow of information and materials.

The proposed method was illustrated in a case study conducted in the special nutrition value stream of a Brazilian public hospital. This hospital has started its lean manufacturing implementation four years ago and has developed several collaborative activities with some of the authors, which facilitated the contact and increased openness from senior management to develop the research. However, those initiatives were focussed on specific departments, and did not involve the whole hospital. In this sense, individuals from the special nutrition department have not had any previous experience with lean manufacturing.

The special nutrition value stream was chosen due to its reasonable complexity level and representativeness to hospital’s cost (approximately 10% of the total costs). Special nutrition can be defined as any special purpose food with controlled nutrient intake, in an isolated or combined form, of defined or estimated composition formulated and prepared for use by probes or orally, whether industrialised or not (Petros and Engelmann 2006). This kind of products can be used exclusively or partially to replace or supplement the oral feeding in malnourished or non-malnourished patients according to their nutritional needs in a hospital, outpatient or home regime, aiming at the synthesis or maintenance of tissues, organs, or systems. To conduct this case study, a team of fourteen leaders and professionals from the hospital was established, whose profiles can be seen in Table 2. 65% of them had more than five years of work experience in the hospital and 92% were female.

4. Proposed method

The proposed method in our research is comprised by six main steps (see Figure 1). These steps are detailed in the subsequent subsections.

4.1. Selection of organization and products family

Step 1 comprises the selection of the organization and product family. In terms of selection of the organization, a few requirements are recommended, such as top management commitment to lean implementation (Holden 2011), willingness to share operational and strategic data (Teichgraber and Bucourt 2012), and a history of active enrolment of employees in process improvement initiatives (Barraza and Lingham 2008). Regarding the product family with which VSM will be applied, historical operational and financial indicators should be analyzed so that a rationale for its selection is established. Duggan (2012) suggests that the product family definition should be performed with the aid of a matrix of products and processes. The aim is to determine product families with similar processing needs, which simplifies the mapping activity to be performed in step 2. A minimum value of 80% of process similarity is considered satisfactory for determining the product family (Rother and Shook 1999). Finally, an improvement team should be put together,
including employees knowledgeable about the targeted department’s processes (Tortorella et al. 2018). Because the value stream analysis would be facilitated by the authors, it is not mandatory that team members have prior experience with lean manufacturing. This fact ensures that beginner organizations can also benefit from this method as long as they have specialized support to implement it.

4.2. Value stream mapping of the current state

In step 2, the current state map is drawn for the chosen product family, taking all processes and activities into account, from the moment the product is stored in the warehouse until it is delivered to customers. The current state map allows the estimation of the total lead time and processing times of each operation required to deliver the value to customers (Rother and Shook 1999; Duggan 2012). This mapping is conducted by the multidisciplinary team defined in step 1. The current state map evaluates processes in relation to waste elimination opportunities (Dickson et al. 2009; Vinodh, Arvind, and Somanaathan 2011; Sialmeh et al. 2014), which can be prioritised based on their impact on the lead time of the product family.

4.3. Identification and ranking of uncertainty sources present in the value stream

Step 3 identifies and ranks the uncertainty sources in the value stream according to their impact on five criteria: (a) lead time, (b) value-added time, (c) number of scheduling points, (d) non-value-added time and (e) number of people involved in the value stream (Seth and Gupta 2012). For that, the utilisation of the multi-criteria method Multi Attribute Utility Theory (MAUT) can be used, as it measures the attractiveness of alternatives (i.e. uncertainty sources) with respect to multiple attributes (Aqlan et al. 2017). The advantage of MAUT is that it provides a more comprehensive assessment that is easy to apply, since decision-makers can manipulate their models and assign weights involving simple mathematical operations (see Figure 2). It is worth mentioning that the uncertainty sources derive from the analysis of the current state map (step 2).

Leaders of the value stream under analysis are interviewed to assign weights $w_i$ (ranging from 0 – ‘no important’ to 10 – ‘highly important’) to criteria and values to each pairwise relationship $V_{ik}$ (varying from 1 – ‘weak’ to 3 – ‘strong’) between criterion $i$ and uncertainty source $k$. The final criticality score $f_k$ for each uncertainty source is given by the expression (Cinelli, Coles, and Kirwan 2014):

$$f_k = \sum w_i V_{ik} \quad (i = 1, \ldots , 5)$$

To determine the most critical uncertainty sources, $f_k$ values are standardised. Uncertainty sources whose standardised values are greater than 1.0 are considered extremely critical (Tortorella and Fogliatto 2014) and, hence, have their variability considered in the following steps.

4.4. Data collection and analysis

Step 4 comprises the data collection related to the critical uncertainty sources determined in step 3. This aims at verifying the variability of the uncertainty sources throughout a minimum period of analysis (De Souza et al. 2018), allowing the identification of the respective probability distribution.
and parameters that best describe the data. For that, Oracle Crystal Ball® software is used as a supporting tool. The probability distributions and their parameters are used as inputs in the next step.

### 4.5. Monte Carlo simulation

Step 5 encompasses the Monte Carlo simulation, in which probability distributions are inputted and variability of the lead time is verified (Aamer 2017). Random data are generated based on probability distributions of each critical uncertainty source, bootstrapping observations to ten thousand iterations (considering a 95% confidence interval) (Kentel and Aral 2005). The bootstrapped dataset allows the determination of the variability of the productive capacity of value stream processes. As total lead time is mainly defined by the inventory level, the variability of each intermediate stock $s_m$ is calculated based on the differences of productive capacities between supplier and customer processes at point $m$ of the value stream, and given by:

$$s_m = s_{0m} + cs_m - cc_m$$  \hspace{1cm} (2)

Where:
- $s_{0m}$ = initial stock obtained from the deterministic current state map at point $m$ of the value stream;
- $cs_m$ = productive capacity of the supplier process of the stock located before point $m$ of the value stream; and
- $cc_m$ = productive capacity of the customer process of the stock located after point $m$ of the value stream.

Particularly for the stock at the last point $m$ of the value stream (i.e. before customers delivery), the consumption of this stock is directly affected by customers’ daily demand $d$. Hence, the variable $cc_m$ is substituted by $d$ in this case. The total lead time ($lt$) is then obtained from the following expression:

$$lt = \frac{\sum s_m + s_0}{d} + \sum pt_n$$  \hspace{1cm} (3)

Where:
- $pt_n$ = process time of process $n$ of the value stream indicated as days/part.

### 4.6. Value stream mapping of the future state and improvement plans

Step 6 aims at mapping the future state and elaborating an improvement plan. Designing the future state clearly defines the improvement opportunities that will lead to waste elimination (Womack and Jones 1996). The same multidisciplinary team is used for this step, enabling a shared vision of the value stream as a whole (Larson 2013). The design of the future state map is based on four principles: (a) increasing system flexibility to allow rapid adaptation to changes in demand, (b) eliminating waste, (c) minimizing stock, and (d) increasing the efficiency of information and material flows (Rother and Shook 1999). A threshold of one year is established as a horizon for implementing the future state, so that the improvement ideas need to be feasible within this timeframe. Finally, an improvement plan is consolidated, specifying goals, activities, and people in charge of actions.

### 5. Results and discussion

#### 5.1. Current state mapping

Meetings aimed at mapping the current state of this product family were held from March to May 2018 and had an average duration of two hours. During this period, five meetings were facilitated by the authors so that there was a complete understanding of the current state of the value stream. Products included in this family are particularly difficult to manage due to their high perishability. The family consisted of 37 items including probes, infant formulas, and supplements that had an average monthly demand of 1,823 units. Seven products corresponded to approximately 80% of family costs (approximately US$40,000.00/year). These products were provided to many sectors of the hospital, grouped into two broad categories: inpatients (e.g. medical, surgical, paediatric, obstetric and intensive care units) and outpatients (e.g. haemodialysis unit). Results for the current state map (obtained from a deterministic standpoint) indicated a total lead time of approximately 30 days (27.7 days), as shown in Figure 3. The total processing time ranged between 180 (best-case scenario) and 305 minutes (worst-case scenario), corresponding to 0.45 and 0.76% of value-added time (VAT), respectively. It is worth mentioning that to map the value stream under study, we have considered only the icons that were properly needed. Further, due to the complexity of the mapped value stream, we included the essential icons for the correct understanding of how the flow of materials and information occur.

Specifically, for the information flow, disturbances and the absence of standardized procedures for communication between parties involved were evident. This could be observed, for example, by the existence of five different methods to obtain products’ demand information; they were: (a) doctors’ prescription using a printed form, (b) doctors’ prescription via electronic form, (c) nutritionists’ prescription by a printed form, (d) nutritionists’ prescription by electronic form, and (e) emergency requests for preparation via phone calls or emails. This led to redundancy of information, which required verification and consolidation efforts. In addition, five scheduling points were identified, in which information sharing was randomly carried out. In this sense, there was a potential lack of information which could entail inefficiencies on the material flow.

Regarding the material flow, none of the sectors involved in the value stream had clear inventory management policies. The need for product replenishment was based on employees’ experience and it was not consistent. There were four intermediate stocks throughout the value stream ($m = 4$). These stocks were poorly controlled, hindering the traceability of products. Another important aspect was the lack of a visual system for managing information. Finally, the analysis of the current state map together with previous situations experienced by the multidisciplinary team indicated seven main uncertainty sources; they were: (a) demand, (b) supplier lead
time, (c) product quality, (d) processing time, (e) natural disasters, (f) infrastructure, and (g) government policies.

5.2. Criticality and variability of uncertainty sources

To determine the criticality of uncertainty sources, we interviewed three leaders of the hospital’s steering committee: the first one was part of the hospital administration, the second was the head of the nutrition sector, and the third was the head of the neonatal nutrition sector. These leaders were chosen due to their vast experience with the analysed value stream (38, 18 and 11 years, respectively). Interviews were conducted individually in September 2019 and lasted 30 minutes each. Final values for both criteria weights ($w_i$) and relationship intensities ($v_{ik}$) were determined by the average of responses, as displayed in Table 3. In general, leaders attributed greater weight to the criterion ‘lead time’. Further, based on the differentiation index, the most critical uncertainty sources were ‘demand’ and ‘processing time’, which were then considered in the Monte Carlo simulation. These results were somewhat expected by the researchers, as the discussions during the current state map meetings frequently emphasised the difficulty in assertively predicting the demand, and the variation of processing times due differences in employees’ skills.

To collect data on the variability of demand and processing times, a period of 30 subsequent days was considered. Although this period is relatively short, a dataset larger than 25 or 30 observations is considered reasonable to describe the probability function of a certain process (Hogg, Tanis, and Zimmerman 2010). Data from demand was gathered from the daily patients’ prescriptions used to schedule the nutrition department. With respect to processing times, data for each one of the four main processes (i.e. receiving, lactary storage, preparation and product administration) was collected in loco by one of the researchers during the 30 days. Every day processes were timed 30 times, which allowed us to check for process variability with the same employee and variability among employees. Based on these data, probability distributions were generated for processing times and patients’ daily demand (see Appendix A), which are synthesized in Table 4. Because daily demand was considered one of the critical uncertainty sources in the value stream, we have carefully analysed its variation so that a more robust future state map could be drawn. As takt time is mostly a deterministic parameter (Rother and Shook 1999), and we wanted to comprehend the effect of stochasticity on the value stream performance, we decided to approach the probability distribution of daily demand as our parameter. However, as the daily availability in the hospital is pretty much fixed (i.e. 24 hours per day), this probability distribution of daily demand could be used as proxy for takt time. In this sense, we argue that in this stochastic scenario, takt time would be more accurately represented by the probability distribution of daily demand.

The coefficients of variation (CV) represent the variability imposed on the value stream by each uncertainty source. Results showed that the ‘lactary storage’ process is the one that relatively inserts the greatest amount variation to the

![Figure 3. Current state map of the special nutrition value stream.](image-url)
value stream (CV = 36.36%). However, this variation is not far from the others, suggesting that none of them could be neglected in the improvement activities. Curiously, although ‘preparation’ is the one with the highest processing time mean, it is not the one that presents the greatest variation (CV = 29.46%). In a deterministic analysis of the value stream, managers would likely focus their efforts on reducing processing times means, neglecting the variability imposed by ‘lactary storage’ process, for instance.

These probability distribution parameters were used to bootstrap both processing times and patients’ daily demand into 10,000 random points. Particularly using processing times, processes’ productive capacities were calculated by dividing the available daily time (24 hours/day) by the respective process time. Then, values of \( s_m \) (\( m = 1, \ldots, 4 \)) and \( l_t \) were determined using Equations (2) and (3). It is worth mentioning that values for \( s_{0\text{m}} \) are displayed in Figure 3.

### 5.3. Simulation results

Regarding the results for the simulation of stocks’ variability (see Appendix B), Table 5 consolidates the main parameters obtained. Among the four stocks, \( s_1 \) (located after material receiving) presented the highest mean value (975 units) and CV (28.92%). These results suggest that not only the nominal value of this stock is relevant, but it also presents a large variation throughout the month, which is also an improvement opportunity. This outcome would not be evidenced in a deterministic value stream analysis. Thus, when analyzing from a stochastic perspective, the largest stock presents the greater variability and countermeasures should be adopted to mitigate its impact to the total lead time of the value stream. Such outcome converges to indications from Anzanello et al. (2017), although their research has focussed on the context of a vendor managed inventory policy.

| Criteria                | Weights | \( v_{11} \) | \( v_{12} \) | \( v_{13} \) | \( v_{14} \) | \( v_{15} \) | \( v_{16} \) |
|-------------------------|---------|--------------|--------------|--------------|--------------|--------------|--------------|
| Lead time               | 10.00   | 22.22        | 3.00         | 3.00         | 2.33         | 3.00         | 2.33         |
| Value-added time        | 9.50    | 21.11        | 2.3           | 1.33         | 2.33         | 2.00         | 2.00         |
| Non value-added time    | 8.50    | 18.89        | 1.67          | 1.33         | 1.00         | 2.00         | 2.00         |
| Criticality scores      | 8.00    | 17.78        | 1.67          | 1.33         | 1.00         | 2.67         | 2.00         |

Table 3. MAUT method.

### Table 4. Parameters of the probability distributions for the uncertainty sources.

| Distribution          | Receiving | Lactary storage | Preparation | Product administration | Patient daily demand |
|-----------------------|-----------|-----------------|-------------|------------------------|----------------------|
| Parameters (hours)    | Logistic  | Lognormal       | Lognormal   | Lognormal              | Beta                 |
| Local                 | 0.21      | 0.31            | 0.00        | 0.08                   | –                    |
| Mean                  | 0.87      | 0.44            | 1.12        | 0.19                   | 43.44                |
| Minimum               | –         | –               | –           | –                      | 67.46                |
| Alpha                 | –         | –               | –           | –                      | 17.57                |
| Beta                  | –         | –               | –           | –                      | 2.61                 |
| CV (%)                | 32.18     | 36.36           | 29.46       | 26.31                  | 24.01                |

Table 5. Stocks variation analysis.

Finally, the variation of the total lead time is presented in Figure 4. While the lead time indicated through the deterministic analysis of the value stream was 27.7 days, the stochastic analysis showed that the probability of achieving this value is approximately 47%, which corroborates the claim that the deterministic approach represents an unlikely condition of the value stream (Braglia, Frosolini, and Zammmori 2009; De Souza et al. 2018). Another result worth highlighting is that for a 99% probability of attendance, the lead time is 114% higher (59.28 days) than that obtained through the deterministic approach. This fact allows a more realistic understanding of the value stream performance, with particular importance for planning and scheduling of products delivery and service level. This result illustrates the traditional trade-off between inventory reduction and service levels widely discussed in the literature (Elsayed and Boucher 1994; Slack, Brandon-Jones, and Johnston 2013; Krajewski, Ritzman, and Malhotra 2013). In fact, a similar outcome was found by Frazzon et al. (2017); however, authors used a discrete simulation model to evidence the effect of processes stability on lead time and service level.

### 5.4. Future state design

Proceeding with the proposed method, the same team involved in the preparation of the current state map supported the design of the future state map. Meetings were held in November 2018 and had an average duration of two
hours. During this period, four meetings were conducted so that members could suggest improvements in the value stream loops. Based on the deterministic analysis, eleven improvement opportunities (white kaizen bursts in Figure 5) predominantly associated with the value stream loop between preparation and product administration were identified in both material (e.g. organization of the storage process, sizing and visualizing the lactary stock, among others) and information flows (e.g. standardization of electronic medical prescription). Seven additional improvement opportunities were raised from the stochastic analysis (grey kaizen bursts in Figure 5), mostly related to the value stream loop between receiving and lactary storage. In general, these improvements are focused on reducing the variability of the

Figure 4. Simulation result for lead time ($lt$).

Figure 5. Future state map (grey kaizen bursts were identified from the stochastic analysis).
critical uncertainty sources, such as the standardization of processes times and modelling of demand forecast. Our results not only examined the impact of uncertainty sources on lead time, but also enabled the identification of the most prominent uncertainty sources according to their variability. This is fully aligned with lean’s constant and systematic search for variation reduction (Spear and Bowen 1999; Black 2007; Spear 2008), complementing a major drawback in traditional VSM analysis.

Due to the context of analysis (i.e. a healthcare organization), our findings complement the study developed by Borges et al. (2020), which used a computational simulation approach to consider the variability of healthcare suppliers and customers as inputs to verify the effectiveness of the proposed inventory policies and service level achievement. This fact also raises attention to the specific benefits that healthcare organizations may obtain by incorporating the proposed method into their value stream analyses. As healthcare organizations are generally characterized by a higher level of complexity (Kannampallil et al. 2011; Long, McDermott, and Meadows 2018) in which systemic improvements are much harder to address (Ferreira and Saurin 2019; Alemsan et al. 2020), the proposed method may find a particular relevance when applied to this kind of context.

6. Conclusion

This article proposed a method for the stochastic analysis of value streams considering the most critical uncertainty sources based on a multicriteria decision-making tool. The method integrates Monte Carlo simulation into VSM, and it is illustrated through a single case study in a healthcare organization, more specifically in the special nutrition value stream. Such illustration allowed a better understanding of the effects of stochasticity on the value stream performance, which is usually neglected or underrated in most value stream analyses. Although the incorporation of stochastic methods into VSM has already been a topic of previous studies, the methodological complexity somewhat undermines their practical utilization. Thus, we argue that implications of the proposed method are valid for both theory and practice, which are subsequently discussed.

With respect to theoretical implications, the integration of the stochastic analysis enables the understanding of the impact of the uncertainty sources on value stream performance, leading to the determination of a more realistic lead time. This supports a more assertive planning and scheduling of the value stream, as well as the identification of improvement opportunities that would otherwise be neglected with the deterministic analysis. Hence, the proposed method addresses a fundamental gap in traditional VSM (Luz et al. 2020), especially contributing to the analysis of value streams whose processes and products present a high variability. Our research complements the method and validates the findings from De Souza et al. (2018), adding evidence to the benefits from integrating Monte Carlo into VSM supported by a multicriteria decision-making tool. To the best of our knowledge, no previous work has systematically encompassed all three concepts (i.e. stochasticity, value stream analysis and multicriteria decision-making), resulting in the methodological contribution of our research.

This work also presents practical contributions. Our study provides managers and practitioners guidance for the analysis of value streams considering the stochastic nature of its elements. Through the proposed method, managers can more easily identify other improvements opportunities that would not be observed in a deterministic analysis. Because these improvement opportunities are focussed on variability reduction, managers can address issues that might cause significant disruptions in the value stream, hence, anticipating future difficulties. The combination of VSM with Monte Carlo simulation enables a better visualization of value streams, helping to adjust the production plan and customers deliveries’ orders based on an expected service level, which is related to the probability function of the lead time. In addition, these guidelines allow the prioritization of managerial efforts that bring greater benefits to lean implementation in the context of the company in which they operate. This is especially relevant in the context of healthcare organizations, which usually struggle with high complexity levels and lack systemic approaches for their continuous improvement. Thus, this study presents an original contribution to a relevant issue for companies undergoing a lean implementation, but without adding much practical difficulty to the method. This increases the odds of its widespread utilization by managers and practitioners.

Although this research was thoroughly conducted, it is worth highlighting some limitations. First, the illustration of this method occurred in a healthcare organization, and its results should be used with caution in other organizational contexts. In addition, despite presenting a ranking for the uncertainty sources indicated by hospital leaders, this data is somewhat biased on their perceptions. This limitation may generate incompatible results in other contexts because the level of understanding and sensitivity to existing uncertainty sources may vary depending on the organization. In this sense, future studies could expand the utilization of the proposed method in order to verify the possibility of replication and, hence, generalization of our findings. We encourage, for instance, the utilization of Kingman’s formula (Kingman 1961) in conjunction with a stochastic value streams analysis. Greater mathematical rigour in the use of this approach can bring benefits with regards to the problems of sequencing in the value stream. Such a combined approach is welcome for the investigation of industrial and service contexts that add significant variability to the value streams analysis. Another limitation is related to the use of the Monte Carlo simulation, as other stochastic methods could have similar or complementary results. A comparative study between stochastic methods feasible to integrate into VSM could be developed so that a better stochastic method is determined. Finally, regarding data collection, a 30-day data history was used. Although this timeframe is considered satisfactory, it may
not allow the observation of seasonal issues in the uncertainty sources, thereby limiting the analysis. Future research could expand the data collection period, especially in contexts where seasonality might be an important issue for the value stream analysis, such as agribusinesses.

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Appendix A. Distributions used in the simulation.

Distribution of processing times for Receiving

| Distribution | Logistic |
|--------------|----------|
| Parameters   | (hours)  |
| Local        | 0.21     |
| Mean         | 0.87     |
| Standard Deviation | 0.28 |

Distribution of processing times for Lactary Storage

| Distribution | Lognormal |
|--------------|-----------|
| Parameters   | (hours)   |
| Local        | 0.31      |
| Mean         | 0.44      |
| Standard Deviation | 0.16 |

Distribution of processing times for Preparation

| Distribution | Lognormal |
|--------------|-----------|
| Parameters   | (hours)   |
| Local        | 0.00      |
| Mean         | 1.12      |
| Standard Deviation | 0.33 |
Distribution of processing times for Product Administration

Lognormal (3-Parameter) Distribution

| Distribution  | Lognormal |
|---------------|-----------|
| Parameters    | (hours)   |
| Local         | 0.08      |
| Mean          | 0.19      |
| Standard Deviation | 0.05 |

Distribution of patients' daily demand

Beta (4-Parameter) Distribution

| Distribution  | Beta |
|---------------|-----|
| Parameters    | (units) |
| Mean          | 43.44 |
| Standard Deviation | 10.43 |
| Maximum       | 67.46 |
| Minimum       | 17.57 |
| Alpha         | 2.61 |
| Beta          | 2.42 |
Appendix B. Stocks simulation.

Simulation result for stock ($s_1$)

Simulation result for stock ($s_2$)

Simulation result for stock ($s_3$)
Simulation result for stock ($s_t$)