



Proposition of a method for stochastic analysis of value streams

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Proposition of a method for stochastic analysis of value streams

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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.

Keywords: Value stream mapping, Monte Carlo simulation, Uncertainty sources.

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 et al., 2017), healthcare (Xie and Peng, 2012; Wang et al., 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 et al., 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),

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4 Tyagi et al. (2015) and Tortorella et al. (2017), which did not consider the probabilistic aspects
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6 related to production processes. Throughout a value stream, there are several uncertainty
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8 sources (e.g. inventories, processing and setup times) that add variability to the flow
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10 (Standridge and Marvel, 2006; Seth et al., 2017; Shou et al., 2020) and negatively affect
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12 management activities.
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15 This becomes particularly critical in the case of healthcare organizations, for example, as this
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17 variability might have a direct impact on the quality of the service provided to patients (Xie
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19 and Peng, 2012). The search for efficiency improvements in healthcare value streams is
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21 primarily addressed by the use of VSM in its traditional form (Wang et al., 2015), not
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23 accounting for the stochasticity inherent to the flows under investigation (Bhuvanesh Kumar
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25 and Parameshwaran, 2018). This fact is also observed in other industry sectors besides
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27 healthcare, such as manufacturing and services, featuring both a practical and theoretical
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29 opportunity to integrate stochastic methods into VSM.
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34 This article aims at proposing a method to stochastically analyze value streams taking into
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36 consideration the effect of critical uncertainty sources on lead time. The proposed method
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38 combines VSM and Monte Carlo simulation to identify improvement opportunities. Monte
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40 Carlo simulation was chosen due to its adaptability to different applications (Brandimarte,
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42 2014). Because collecting data from every single uncertainty source existing in a value stream
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44 may be unfeasible from a practical standpoint, our method integrated a multicriteria decision-
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46 making tool to rank and prioritize the most critical uncertainties, hence, considering them in
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48 the stochastic analysis. To illustrate this approach, we carried out a case study in the special
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50 nutrition value stream of a Brazilian public hospital. The proposed method allows the
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52 identification of improvement opportunities that would not be considered in the traditional
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54 deterministic VSM approach. Further, the integration of the stochastic analysis enables the
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56 determination of a more realistic lead time, which supports a more assertive planning and
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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 prioritize 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 et al., 2002; Lödding and Koch, 2020), culminating in waste reduction in a systemic manner (Duggan, 2012). VSM favors a more holistic perspective of the organization (Seyedhosseini et al., 2015; 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 et al., 2009). However, this tool becomes unrealistic for organizations with a high variety and low volume of products. Further, VSM does not contemplate variabilities derived from uncertainty sources intrinsic to the flow (DeSouza et al., 2018). Belokar et al. (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 et al., 2016). The use of stochastic methods that consider uncertainties and the entailed variability may be an alternative to assertively analyze value streams in these situations. In this sense, Table 1 consolidates the

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4 stochastic methods applied to value stream analysis and presents the advantages and
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6 disadvantages of each one. In general, the adoption of stochastic methods enables the
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8 assessment of the effect of variability on the value stream performance, identifying other
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10 wastes that would not be evidenced based on traditional VSM (Zammori et al., 2011).

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13 Overall, literature analysis shows that as the scope of the value stream mapping increases the
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15 modeling of the value streams in a stochastic manner becomes more difficult. In most cases, it
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17 is hard to deal with a larger number of variables and uncertainties, which ends up increasing
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19 the mathematical and computational complexity (Seyedhosseini and Ebrahimi-Taleghani,
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21 2015). Thus, the application of more sophisticated stochastic analysis methods is more likely
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23 to occur in extended value streams. This fact corroborates to indications from Deif (2012),
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25 which emphasized the importance of an adequate assessment of the extended value stream to
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27 support more assertive decisions for the business. In case of value stream analysis within the
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29 company boundaries (door-to-door stream), the versatility of Monte Carlo simulation for the
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31 treatment of uncertainties inherent in the production processes stands out (Aamer, 2017; Luz
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33 et al., 2020). In fact, De Souza et al. (2018) have proposed Monte Carlo integration into VSM.
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35 However, the proposed method fell short in the prioritization of the uncertainty sources to be
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37 considered in the stochastic simulation, especially when there is a large number of uncertainties
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39 in the value stream. Our research expands on De Souza et al.'s (2018) proposition, addressing
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41 the main methodological drawbacks pointed by the authors.
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56 **2.2. Monte Carlo simulation**

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4 According to Corrado and Theophilo (2004; p. 54), the “Monte Carlo method is a technique
5 that uses random number generation to assign values to the variables of the system to be
6 investigated.” Its use is beneficial as a technique for solving problems that involve uncertainty.
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8 The application of simulation in management problems requires the translation or modeling in
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10 mathematical terms of the physical operating system under investigation. This method allows
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12 the simulation of any process with a course that depends on random factors (Gentle, 2003;
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14 Pattanayak et al., 2019).

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20 The versatility of the Monte Carlo simulation is evidenced by how research has been developed
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22 in areas such as hydrology (Vrugt et al., 2013), economic risk analysis (Arnold et al., 2015;
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24 Abdo and Flaus, 2016), medical sciences (Yang et al., 2015; Kramer et al., 2018), and
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26 ecological vulnerability assessments (Song et al., 2015). The Monte Carlo simulation
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28 demonstrates its usefulness in the treatment of uncertainty conditions present in varied areas of
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30 knowledge (De Souza et al., 2018). Specifically, for the value stream analysis, some authors
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32 (e.g. Deleris et al., 2004; Aamer, 2017) have already used Monte Carlo simulation in the
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34 treatment of uncertainties. However, these studies focused their analyses on specific
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36 uncertainty situations along the value streams, such as a risk analysis associated with failures
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38 in the delivery of supplies and the processing capacity of a distribution center.
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44 The use of Monte Carlo simulation as an alternative to verify the effects of variability along
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46 the value stream comprises a promising approach. It enables the verification of different
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48 scenarios, changing key factors such as levels of variability or probability distribution functions
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50 from some uncertainty sources (Arnold et al., 2015). This is particularly important in the search
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52 for a greater understanding of uncertainty sources that are often poorly addressed in the
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54 literature, such as the interference of human factors for value stream performance (Xie and
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56 Peng, 2012).
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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 organizations to make decisions under the influence of a variety of criteria, and is firmly rooted in an alternative concept optimization where several criteria characterize 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 et al. 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 et al. 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 analyze values streams taking into consideration the effect of critical uncertainty sources prioritized 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 rigor and objectivity (McCutcheon and Meredith, 1993). Case studies seek to investigate a phenomenon within a real and contemporary context (Yin, 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 utilization in contexts where authors seek to make a contribution by the illustration of a proposed method (Siggelkow, 2007). As suggested by Voss et al. (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 focused 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.

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4 The special nutrition value stream was chosen due to its reasonable complexity level and
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6 representativeness to hospital's cost (approximately 10% of the total costs). Special nutrition
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8 can be defined as any special purpose food with controlled nutrient intake, in an isolated or
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10 combined form, of defined or estimated composition formulated and prepared for use by probes
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12 or orally, whether industrialized or not (Petros and Engelmann, 2006). This kind of products
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14 can be used exclusively or partially to replace or supplement the oral feeding in malnourished
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16 or non-malnourished patients according to their nutritional needs in a hospital, outpatient or
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18 home regime, aiming at the synthesis or maintenance of tissues, organs, or systems. To conduct
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20 this case study, a team of fourteen leaders and professionals from the hospital was established,
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22 whose profiles can be seen in Table 2. 65% of them had more than five years of work
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24 experience in the hospital and 92% were female.
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38 **4. Proposed method** 39

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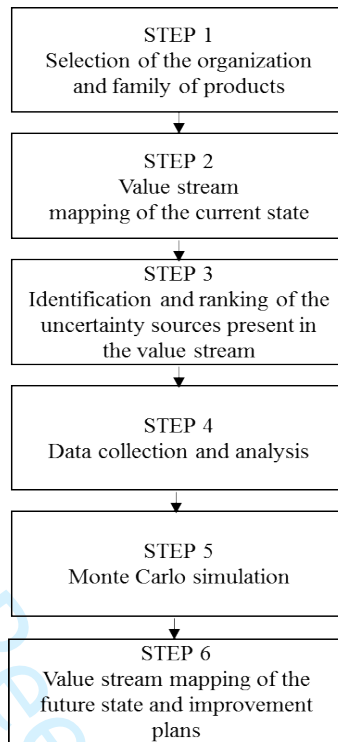


Figure 1. Steps of the proposed method

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, 2010), willingness to share operational and strategic data (Teichgraber and Bucourt, 2012), and a history of active enrollment 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

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4 targeted department's processes (Tortorella et al., 2018). Because the value stream analysis
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6 would be facilitated by the authors, it is not mandatory that team members have prior
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8 experience with lean manufacturing. This fact ensures that beginner organizations can also
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10 benefit from this method as long as they have specialized support to implement it.
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16 **4.2. Value stream mapping of the current state**

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19 In step 2, the current state map is drawn for the chosen product family, taking all processes and
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21 activities into account, from the moment the product is stored in the warehouse until it is
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23 delivered to customers. The current state map allows the estimation of the total lead time and
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25 processing times of each operation required to deliver the value to customers (Rother and
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27 Shook, 1999; Duggan, 2012). This mapping is conducted by the multidisciplinary team defined
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29 in step 1. The current state map evaluates processes in relation to waste elimination
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31 opportunities (Dickson et al. 2009; Vinodh et al. 2011; Swalmeh et al. 2014), which can be
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33 prioritized based on their impact on the lead time of the product family.
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41 **4.3. Identification and ranking of uncertainty sources present in the value stream**

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43 Step 3 identifies and ranks the uncertainty sources in the value stream according to their impact
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45 on five criteria: (a) lead time, (b) value-added time, (c) number of scheduling points, (d) non
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47 value-added time and (e) number of people involved in the value stream (Seth and Gupta,
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49 2012). For that, the utilization of the multi-criteria method Multi Attribute Utility Theory
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51 (MAUT) can be used, as it measures the attractiveness of alternatives (i.e. uncertainty sources)
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53 with respect to multiple attributes (Aqlan et al., 2017). The advantage of MAUT is that it
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55 provides a more comprehensive assessment that is easy to apply, since decision-makers can
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57 manipulate their models and assign weights involving simple mathematical operations (see
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Figure 2). It is worth mentioning that the uncertainty sources derive from the analysis of the current state map (step 2).

| | | Uncertainty Sources (k) | |
|--------------|--|-------------------------|------------------------------|
| Criteria (i) | Weight | Grades | Result (F) |
| | W_i | V_{ik} | $W_i * V_{ik}$ |
| Sum | | | $F_{ik} = \sum W_i * V_{ik}$ |
| k | varies from 1 to 7, because 7 uncertainty sources are considered | | |
| i | varies from 1 to 5, because we used 5 criteria | | |
| Criteria | | | |
| A | Lead Time | | |
| B | Value Added Time | | |
| C | Number of programming points | | |
| D | Value Non-Add Time | | |
| E | Number of people involved in the value stream | | |
| Grades | 3,00 | Strong | |
| | 2,00 | Moderate | |
| | 1,00 | Weak | |

Figure 2. Schematization of the MAUT

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 et al., 2014):

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

To determine the most critical uncertainty sources, f_k values are standardized. Uncertainty sources whose standardized 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:

$$s_m = s_{0m} + cS_m - CC_m \quad (2)$$

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:

$$lt = \frac{\sum s_m + s_l}{d} + \sum pt_n \quad (3)$$

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

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4 need to be feasible within this timeframe. Finally, an improvement plan is consolidated,
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6 specifying goals, activities, and people in charge of actions.
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11 **5. Results and discussion**

12 **5.1. Current state mapping**

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17 Meetings aimed at mapping the current state of this product family were held from March to
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19 May 2018 and had an average duration of two hours. During this period, five meetings were
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21 facilitated by the authors so that there was a complete understanding of the current state of the
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23 value stream. Products included in this family are particularly difficult to manage due to their
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25 high perishability. The family consisted of 37 items including probes, infant formulas, and
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27 supplements that had an average monthly demand of 1,823 units. Seven products corresponded
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29 to approximately 80% of family costs (approximately US\$ 40,000.00/year). These products
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31 were provided to many sectors of the hospital, grouped into two broad categories: inpatients
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33 (e.g. medical, surgical, pediatric, obstetric and intensive care units) and outpatients (e.g.
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35 hemodialysis unit). Results for the current state map (obtained from a deterministic standpoint)
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37 indicated a total lead time of approximately 30 days (27.7 days), as shown in Figure 3. The
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39 total processing time ranged between 180 (best-case scenario) and 305 minutes (worst-case
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41 scenario), corresponding to 0.45% and 0.76% of value-added time (VAT), respectively. It is
42
43 worth mentioning that to map the value stream under study, we have considered only the icons
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45 that were properly needed. Further, due to the complexity of the mapped value stream, we
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47 included the essential icons for the correct understanding of how the flow of materials and
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49 information occur.
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56 Specifically, for the information flow, disturbances and the absence of standardized procedures
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58 for communication between parties involved were evident. This could be observed, for
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4 example, by the existence of five different methods to obtain products' demand information;
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6 they were: (a) doctors' prescription using a printed form, (b) doctors' prescription via
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8 electronic form, (c) nutritionists' prescription by a printed form, (d) nutritionists' prescription
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10 by electronic form, and (e) emergency requests for preparation via phone calls or emails. This
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12 led to redundancy of information, which required verification and consolidation efforts. In
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14 addition, five scheduling points were identified, in which information sharing was randomly
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16 carried out. In this sense, there was a potential lack of information which could entail
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18 inefficiencies on the material flow.
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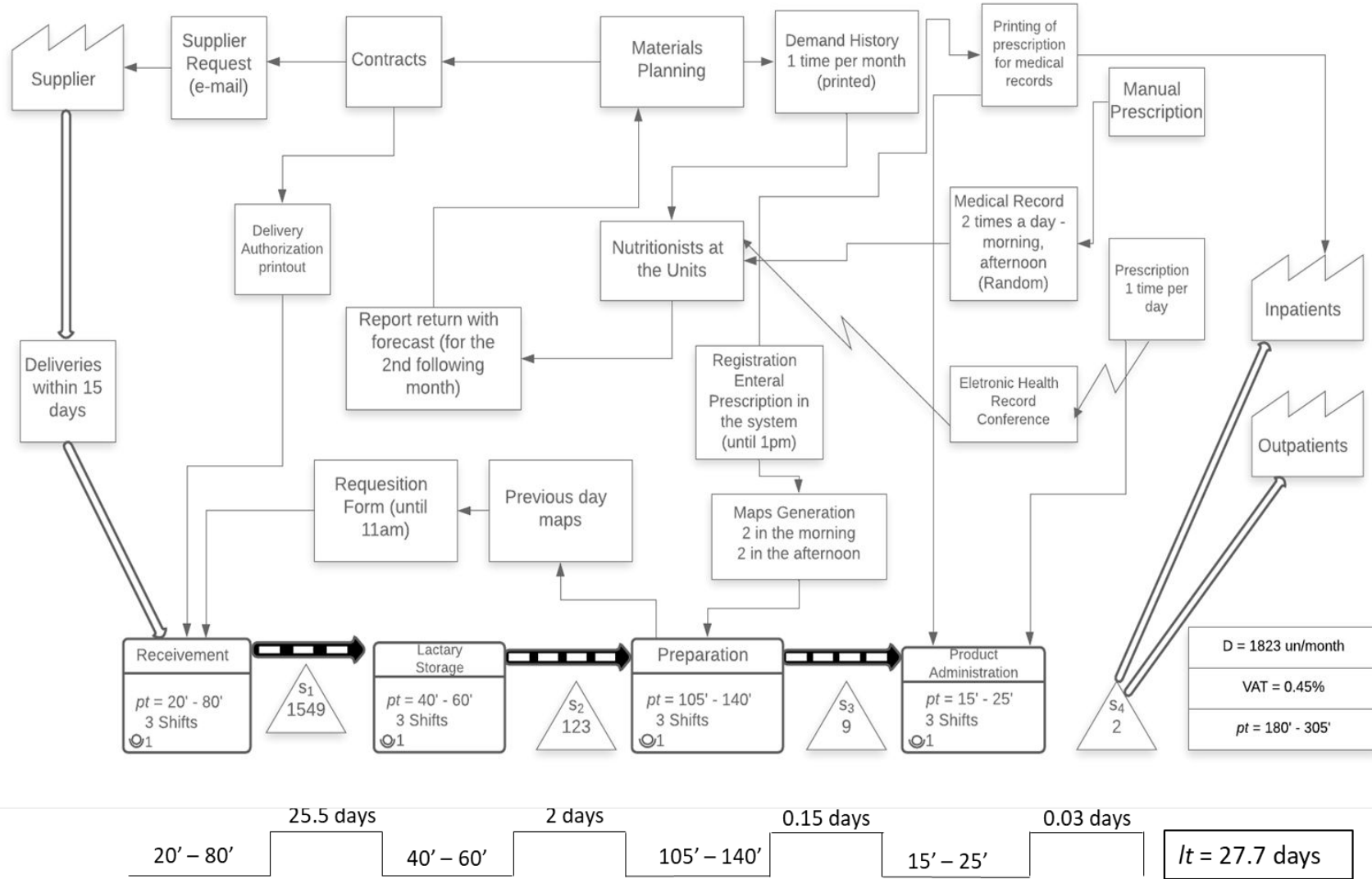


Figure 3. Current state map of the special nutrition value stream

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 and diet sector, and the third was the head of the neonatal nutrition sector. These leaders were chosen due to their vast experience with the analyzed 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 emphasized the difficulty in assertively predicting the demand, and the variation of processing times due differences in employees' skills.

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INSERT TABLE 3 ABOUT HERE

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 et al., 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 synthetized in Table 4. Because daily demand was considered one of the critical uncertainty sources in the value stream, we have carefully analyzed 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

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4 relatively inserts the greatest amount variation to the value stream (CV = 36.36%). However,
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6 this variation is not far from the others, suggesting that none of them could be neglected in the
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8 improvement activities. Curiously, although 'preparation' is the one with the highest
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10 processing time mean, it is not the one that presents the greatest variation (CV = 29.46%). In a
11
12 deterministic analysis of the value stream, managers would likely focus their efforts on
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14 reducing processing times means, neglecting the variability imposed by 'lactary storage'
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16 process, for instance.
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20 These probability distribution parameters were used to bootstrap both processing times and
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22 patients' daily demand into 10,000 random points. Particularly using processing times,
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24 processes' productive capacities were calculated by dividing the available daily time (24
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26 hours/day) by the respective process time. Then, values of s_m ($m = 1, \dots, 4$) and l_t were
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28 determined using Equations (2) and (3). It is worth mentioning that values for s_{0m} are displayed
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30 in Figure 3.
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37 INSERT TABLE 4 ABOUT HERE
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43 **5.3. Simulation results**

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45 Regarding the results for the simulation of stocks' variability (see Appendix B), Table 5
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47 consolidates the main parameters obtained. Among the four stocks, s_1 (located after material
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49 receiving) presented the highest mean value (975 units) and CV (28.92%). These results
50
51 suggest that not only the nominal value of this stock is relevant, but it also presents a large
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53 variation throughout the month, which is also an improvement opportunity. This outcome
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55 would not be evidenced in a deterministic value stream analysis. Thus, when analyzing from a
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57 stochastic perspective, the largest stock presents the greater variability and countermeasures
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3 should be adopted to mitigate its impact to the total lead time of the value stream. Such outcome
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5 converges to indications from Anzanello et al. (2017), although their research has focused on
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7 the context of a vendor managed inventory policy.
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14 INSERT TABLE 5 ABOUT HERE
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20 Finally, the variation of the total lead time is presented in Figure 4. While the lead time
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22 indicated through the deterministic analysis of the value stream was 27.7 days, the stochastic
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24 analysis showed that the probability of achieving this value is approximately 47%, which
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26 corroborates the claim that the deterministic approach represents an unlikely condition of the
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28 value stream (Braglia et al. 2009; De Souza et al., 2018). Another result worth highlighting is
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30 that for a 99% probability of attendance, the lead time is 114% higher (59.28 days) than that
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32 obtained through the deterministic approach. This fact allows a more realistic understanding of
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34 the value stream performance, with particular importance for planning and scheduling of
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36 products delivery and service level. This result illustrates the traditional trade-off between
37
38 inventory reduction and service levels widely discussed in the literature (Elsayed and Boucher,
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40 1994; Slack et al., 2013; Krajewski et al., 2013). In fact, a similar outcome was found by
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42 Frazzon et al. (2017); however, authors used a discrete simulation model to evidence the effect
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44 of processes stability on lead time and service level.
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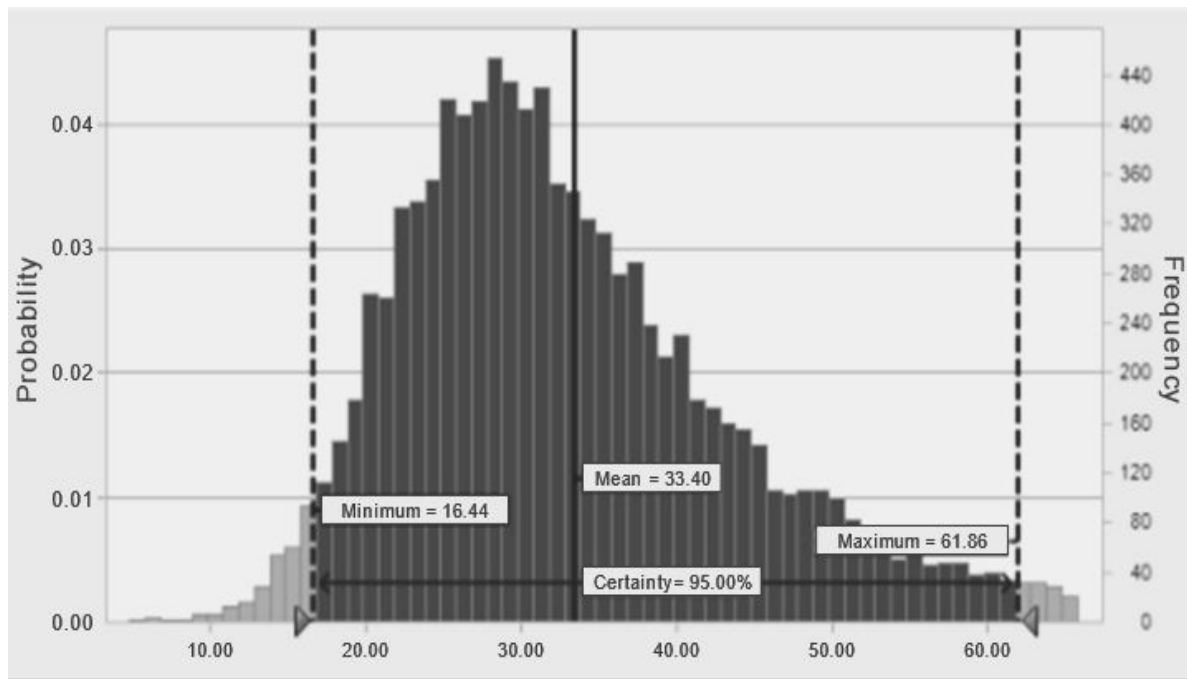


Figure 4. Simulation result for lead time (lt)

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 critical uncertainty sources, such as the standardization of processes times

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4 and modelling of demand forecast. Our results not only examined of the impact of uncertainty
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6 sources on lead time, but also enabled the identification of the most prominent uncertainty
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8 sources according to their variability. This is fully aligned with lean's constant and systematic
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10 search for variation reduction (Spear and Bowen, 1999; Black, 2007; Spear, 2008),
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12 complementing a major drawback in traditional VSM analysis.
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16 Due to the context of analysis (i.e. a healthcare organization), our findings complement the
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18 study developed by Borges et al. (2020), which used a computational simulation approach to
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20 consider the variability of healthcare suppliers and customers as inputs to verify the
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22 effectiveness of the proposed inventory policies and service level achievement. This fact also
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24 raises attention to the specific benefits that healthcare organizations may obtain by
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26 incorporating the proposed method into their value stream analyses. As healthcare
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28 organizations are generally characterized by a higher level of complexity (Kannampallil et al.,
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30 2011; Long et al., 2018) in which systemic improvements are much harder to address (Ferreira
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32 and Saurin, 2019; Alemsan et al., 2020), the proposed method may find a particular relevance
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34 when applied to this kind of context.
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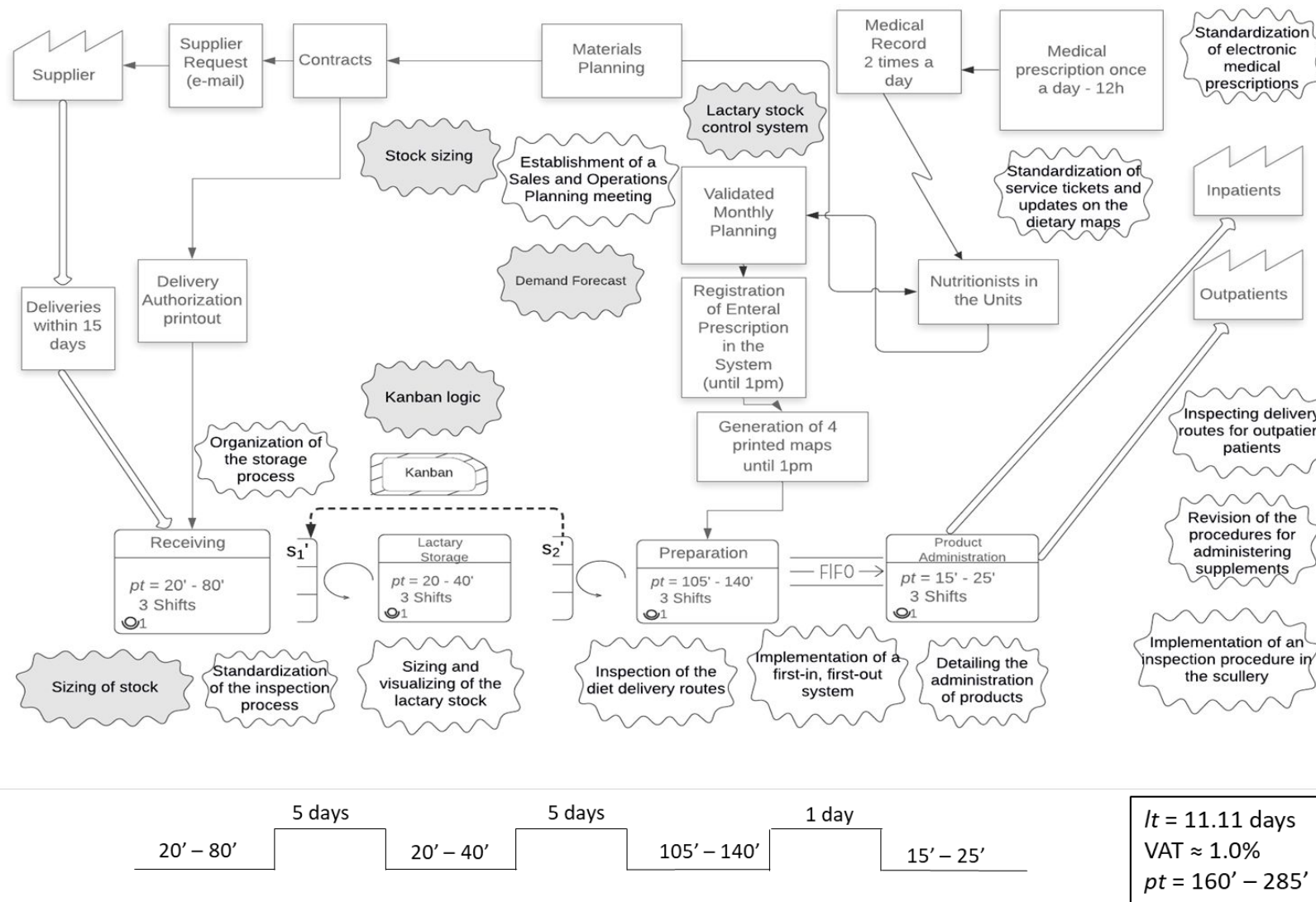


Figure 5. Future state map (grey kaizen bursts were identified from the stochastic analysis)

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.

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4 This work also presents practical contributions. Our study provides managers and practitioners
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6 guidance for the analysis of value streams considering the stochastic nature of its elements.
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8 Through the proposed method, managers can more easily identify other improvements
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10 opportunities that would not be observed in a deterministic analysis. Because these
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12 improvement opportunities are focused on variability reduction, managers can address issues
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14 that might cause significant disruptions in the value stream, hence, anticipating future
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16 difficulties. The combination of VSM with Monte Carlo simulation enables a better
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18 visualization of value streams, helping to adjust the production plan and customers deliveries'
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20 orders based on an expected service level, which is related to the probability function of the
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22 lead time. In addition, these guidelines allow the prioritization of managerial efforts that bring
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24 greater benefits to lean implementation in the context of the company in which they operate.
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26 This is especially relevant in the context of healthcare organizations, which usually struggle
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28 with high complexity levels and lack systemic approaches for their continuous improvement.
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30 Thus, this study presents an original contribution to a relevant issue for companies undergoing
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32 a lean implementation, but without adding much practical difficulty to the method. This
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34 increases the odds of its widespread utilization by managers and practitioners.
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41 Although this research was thoroughly conducted, it is worth highlighting some limitations.
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43 First, the illustration of this method occurred in a healthcare organization, and its results should
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45 be used with caution in other organizational contexts. In addition, despite presenting a ranking
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47 for the uncertainty sources indicated by hospital leaders, this data is somewhat biased on their
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49 perceptions. This limitation may generate incompatible results in other contexts because the
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51 level of understanding and sensitivity to existing uncertainty sources may vary depending on
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53 the organization. In this sense, future studies could expand the utilization of the proposed
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55 method in order to verify the possibility of replication and, hence, generalization of our
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57 findings. We encourage, for instance, the utilization of Kingman's formula (Kingman, 1961)
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4 in conjunction with a stochastic value streams analysis. Greater mathematical rigor in the use
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6 of this approach can bring benefits with regards to the problems of sequencing in the value
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8 stream. Such a combined approach is welcome for the investigation of industrial and service
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10 contexts that add significant variability to the value streams analysis. Another limitation is
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12 related to the use of the Monte Carlo simulation, as other stochastic methods could have similar
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14 or complementary results. A comparative study between stochastic methods feasible to
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16 integrate into VSM could be developed so that a better stochastic method is determined.
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18 Finally, regarding data collection, a 30-day data history was used. Although this timeframe is
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20 considered satisfactory, it may not allow the observation of seasonal issues in the uncertainty
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22 sources, thereby limiting the analysis. Future research could expand the data collection period,
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24 especially in contexts where seasonality might be an important issue for the value stream
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26 analysis, such as agribusinesses.
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34 **References**

- 35
36
37 Aamer, A. 2017. "Distribution Center capacity analysis in stochastic environment: An application of value stream
38
39 analysis and Monte Carlo simulation." *IEEM International Conference on Industrial Engineering and*
40
41 *Engineering Management*: 1396-1400.
42
43 Abdelhadi, A., and M. Shakoor. 2014. "Studying the Efficiency of Inpatient and Outpatient Pharmacies Using
44
45 Lean Manufacturing." *Leadership in Health Services* 27(3): 255-267, 2014.
46
47 Abdo, H., and J. Flaus. 2016. "Uncertainty Quantification in Dynamic System Risk Assessment: A New Approach
48
49 with Randomness and Fuzzy Theory." *International Journal of Production Research* 54(19): 5862-5885.
50
51 Abdulmalek, F., and J. Rajgopal. 2007. "Analyzing the Benefits of Lean Manufacturing and Value Stream
52
53 Mapping via Simulation: A Process Sector Case Study." *International Journal of Production Economics* 107(1):
54
55 223-236.
56
57
58
59
60

- 1
2
3
4 Ait-Alla, A., M. Teucke, M. Lütjen, S. Beheshti-Kashi, and H. Karimi. 2014. "Robust Production Planning in
5 Fashion Apparel Industry under Demand Uncertainty via conditional Value at Risk." *Mathematical Problems in*
6 *Engineering* 2014: 1-10.
7
8
9
10 Alem, D., and R. Morabito. 2015. "Production Planning under Uncertainty: Stochastic Programming Versus
11 Robust Optimization." *Gestão & Produção* 22(3): 539-551.
12
13
14 Alemsan, N., Tortorella, G., Mac Cawley, A., and Sawhney, R. 2020. "A review on methods for materials planning
15 and control in Healthcare Organizations." *International Journal of Services and Operations Management*,
16 (forthcoming).
17
18
19
20 Al-Othman, W., H. Lababidi, I. Alatiqi, and K. Al-Shayji. 2008. "Supply Chain Optimization of Petroleum
21 Organization under Uncertainty in Market Demands and Prices." *European Journal of Operational Research*
22 189(3): 822-840.
23
24
25
26 Alshamrani, O., A. Alshibani, and M. Alogaili. 2018. "Analytic Hierarchy Process and Multi Attribute Utility
27 Theory Based Approach for the Selection of Lighting Systems in Residential Buildings: A Case Study. *Buildings*
28 8(6): 73.
29
30
31
32 Anzanello, M., Mazzillo, C., Tortorella, G., and Marodin, G. 2017. "Variable selection framework for allocating
33 products to recommended replenishment models in VMI applications." *Journal of Advances in Management*
34 *Research*, 14(2): 128-142.
35
36
37
38 Aqlan, F., A. Ahmed, O. Ashour, A. Shamsan, and M. Hamasha. 2017. "An Approach for Rush Order Acceptance
39 Decisions Using Simulation and Multi-Attribute Utility Theory." *European Journal of Industrial Engineering*
40 11(5): 613.
41
42
43
44 Arnold, U., and Ö. Yildiz. 2015. "Economic Risk Analysis of Decentralized Renewable Energy Infrastructures: a
45 Monte Carlo Simulation Approach." *Renewable Energy* 77: 227-239.
46
47
48
49 Augusto, B., and G. Tortorella. 2019. "Literature Review on Lean Healthcare Implementation: Assessment
50 Methods and Practices." *International Journal of Services and Operations Management* 32(3): 285-306.
51
52
53
54 Aziz, Z., R. Qasim, and S. Wajdi. 2017. "Improving productivity of road surfacing operations using value stream
55 mapping and discrete event simulation." *Construction Innovation* 17(3): 294-323.
56
57
58
59
60

- 1
2
3
4 Badri, H., S. Ghomi, and T. Hejazi. 2017. "A Two-Stage Stochastic Programming Approach for Value-Based
5 Closed-Loop Supply Chain Network Design." *Transportation Research Part E: Logistics and Transportation*
6 *Review* 105: 1-17.
7
8
9
10 Badri, H., S. Ghomi, and T. Hejazi. 2016. "A Two-Stage Stochastic Programming Model for Value-Based Supply
11 Chain Network Design." *Scientia Iranica Transaction E: Industrial Engineering* 23(1): 348-360.
12
13
14 Barraza, M., and T. Lingham. 2008. "Kaizen within kaizen teams: continuous and process improvements in a
15 Spanish municipality." *The Asian Journal of Quality* 9(1): 1.
16
17
18 Behrouzi, F., and K. Wong. 2013. "An Integrated Stochastic-Fuzzy Modeling Approach for Supply Chain
19 Leanness Evaluation." *The International Journal of Advanced Manufacturing Technology* 68(5-8): 1677- 1696.
20
21
22 Belokar, R., V. Kumar, and S. Kharb. 2012. "An Application of Value Stream Mapping in Automotive Industry:
23 a Case Study." *International Journal of Innovative Technology and Exploring Engineering* 1(2): 152-157.
24
25
26 Ben Fredj-Ben Alaya, L. 2016. "VSM a Powerful Diagnostic and Planning Tool for a Successful Lean
27 Implementation: a Tunisian Case Study of an Auto Parts Manufacturing Firm." *Production Planning & Control*,
28 1-16.
29
30
31
32
33 Bhuvanesh Kumar, M., and R. Parameshwaran. 2018. "Fuzzy Integrated QFD, FMEA Framework for the
34 Selection of Lean Tools in a Manufacturing Organisation." *Production Planning & Control* 29(5): 403-417.
35
36
37 Black, J. 2007. "Design rules for implementing the Toyota Production System." *International Journal of*
38 *Production Research*, 45(16): 3639-3664.
39
40
41
42 Borges, G., Tortorella, G., Martínez, F., and Thurer, M. 2020. "Simulation-based analysis of lean practices
43 implementation on the supply chain of a public hospital." *Production*, 30: e20190131.
44
45
46 Braglia, M., M. Frosolini and F. Zammori. 2009. "Uncertainty in Value Stream Mapping Analysis." *International*
47 *Journal of Logistics: Research and Applications* 12(6): 435-453.
48
49
50 Brandimarte, P. 2014. *Handbook in Monte Carlo simulation: applications in financial engineering, risk*
51 *management, and economics*. John Wiley & Sons, London.
52
53
54
55 Childe, S. 2011. "Case studies in operations management." *Production Planning and Control*, 22(2): 107.
56
57
58 Cinelli, M., S. Coles, and K. Kirwan. 2014. "Analysis of the Potentials of Multi Criteria Decision Analysis
59 Methods to Conduct Sustainability Assessment." *Ecological Indicators* 46: 138-148.
60

- 1
2
3
4 Deif, A. 2012. "Dynamic Analysis of a Lean Cell under Uncertainty." *International Journal of Production*
5 *Research* 50(4): 1127-1139.
6
7
8 Deleris, L., D. Elkins, and M. Paté-Cornell. 2004. "Analyzing Losses from Hazard Exposure: A Conservative
9 Probabilistic Estimate Using Supply Chain Risk Simulation." *Proceedings of the 36th conference on Winter*
10 *simulation*, Winter Simulation Conference: 1384-1391.
11
12
13
14 De Souza, L., G. Tortorella, P. Cauchick-Miguel, and D. Nascimento. 2018. "Application of Value Stream
15 Mapping and Monte Carlo Simulation in a University Hospital." *Proceedings of the International Conference on*
16 *Industrial Engineering and Operations Management Paris*, 26-27.
17
18
19
20 Dickson, E., S. Singh, D. Cheung, C. Wyatt, and A. Nugent. 2009. "Application of Lean Manufacturing
21 Techniques in the Emergency Department." *The Journal of emergency medicine* 37: 177-182.
22
23
24
25 Dotoli, M., M. Fanti, G. Iacobellis, and G. Rotunno. 2012. "A Lean Manufacturing Strategy Using Value Stream
26 Mapping, the Unified Modeling Language, and Discrete Event Simulation." *International Conference on*
27 *Automation Science and Engineering* 668-673, 2012.
28
29
30
31 Duggan, K. 2012. *Creating mixed model value streams: practical lean techniques for building to demand*.
32 Productivity Press.
33
34
35
36 Elsayed, E., and Boucher, T. 1994. *Analysis and control of production systems*. Prentice Hall, London.
37
38
39 Ferreira, D., & Saurin, T. 2019. "A complexity theory perspective of kaizen: a study in healthcare." *Production*
40 *Planning & Control*, 30(16): 1337-1353.
41
42
43 Frazzon, E., Tortorella, G., Dávalos, R., Holtz, T. and Coelho, L. 2017. "Simulation-based analysis of a supplier-
44 manufacturer relationship in lean supply chains." *International Journal of Lean Six Sigma*, 8(3): 262-274.
45
46
47 Gentle, J. 2003. *Random Number Generation and Monte Carlo Methods*. New York: Springer.
48
49
50 Gurumurthy, A., and R. Kodali. 2011. "Design of Lean Manufacturing Systems Using Value Stream Mapping
51 with Simulation: A Case Study." *Journal of Manufacturing Technology Management* 22(4): 444-473.
52
53
54 Harmancioglu, N., C. Droge, and R. Calantone. 2009. "Theoretical Lenses and Domain Definitions in Innovation
55 Research." *European Journal of Marketing* 43(1/2): 229-263.
56
57
58 Henrique, D., A. Rentes, M. Godinho Filho, and K. Esposto. 2015. "A New Value Stream Mapping Approach for
59 Healthcare Environments." *Production Planning & Control*, 27(1): 24-48.
60

- 1
2
3
4 Hogg, R.V., E. Tanis, and D. Zimmerman. 2010. *Probability and statistical inference*. Pearson/Prentice Hall,
5
6 Boston.
- 7
8 Holden, R. 2010. "Lean thinking in emergency departments: a critical review." In *Proceedings of Annals of*
9
10 *Emergency Medicine*, March.
- 11
12 Kailiponi, P. 2010. "Analyzing Evacuation Decisions Using Multi-Attribute Utility Theory (MAUT)." *Procedia*
13
14 *Engineering* 3: 163-174.
- 15
16 Kannampallil, T., Schauer, G., Cohen, T., and Patel, V. 2011. "Considering complexity in healthcare systems."
17
18 *Journal of Biomedical Informatics*, 44(6): 943-947.
- 19
20
21 Karim, R., and J. Biswas. 2016. "Value Stream Analysis of Vegetable Supply Chain in Bangladesh: a Case Study."
22
23 *International Journal of Managing Value and Supply Chains* 7(2): 41-61.
- 24
25 Keeney, R., and H. Raiffa. 1976. *Decisions with Multiple Objectives: Preference and Value Tradeoffs*. New York:
26
27 John Wiley & Sons.
- 28
29 Ketokivi, M., and T. Choi. 2014. "Renaissance of Case Research as a Scientific Method." *Journal of Operations*
30
31 *Management* 32(5): 232-240.
- 32
33
34 Kenne, J., P. Dejax, and A. Gharbi. 2012. "Production Planning of a Hybrid Manufacturing-Remanufacturing
35
36 System under Uncertainty within a Closed-Loop Supply Chain." *International Journal of Production Economics*
37
38 135(1): 81-93.
- 39
40 Kentel, E., and M. Aral. 2005. "2D Monte Carlo versus 2D Fuzzy Monte Carlo Health Risk Assessment."
41
42 *Stochastic Environmental Research and Risk Assessment* 19(1): 86-96.
- 43
44 Kingman, J. 1961. "The single server queue in heavy traffic." In *Mathematical Proceedings of the Cambridge*
45
46 *Philosophical Society* (Vol. 57, No. 4, pp. 902-904). Cambridge University Press.
- 47
48
49 Kovačević, M. S., M. Bačić, I. Stipanović, and K. Gavin. 2019. "Categorization of the Condition of Railway
50
51 Embankments Using a Multi-Attribute Utility Theory." *Applied Sciences* 9 (23): 5089.
- 52
53 Krajewski, L., Ritzman, L., and Malhotra, M. 2013. *Operations management*. Pearson, New York.
- 54
55
56 Kramer, C., C. Ye, S. Campbell, and R. Retnakaran. 2018. "Comparison of New Glucose-Lowering Drugs on
57
58 Risk of Heart Failure in Type 2 Diabetes: a Network Meta-Analysis." *JACC: Heart Failure* 6(10): 823-830.
- 59
60

- 1
2
3
4 Jauhari, W., and R. Saga. 2017. "A Stochastic Periodic Review Inventory Model for Vendor–Buyer System with
5 Setup Cost Reduction and Service–Level Constraint." *Production & Manufacturing Research* 5(1): 371-389.
6
7
8 Larson, J. 2013. "Management Engineering: a Guide to Best Practices for Industrial Engineering in Health Care."
9 *CRC Press*.
10
11
12 Liu, M. 2015. "Optimal Scheduling of Logistical Support for Medical Resources Order and Shipment in
13 Community Health Service Centers." *Journal of Industrial Engineering and Management* 8(5): 1362.
14
15
16 Lödding, H., and C. Koch. 2020. "Value stream analysis and design for make-to-order companies." *Production*
17 *Planning & Control*, (forthcoming).
18
19
20
21 Long, K., McDermott, F., and Meadows, G. 2018. "Being pragmatic about healthcare complexity: our experiences
22 applying complexity theory and pragmatism to health services research." *BMC Medicine*, 16(1): 1-9.
23
24
25 Luz, G., G. Tortorella, G. Narayanamurthy, P. Gaiardelli, R. Sawhney. 2020. "A Systematic Literature Review
26 on the Stochastic Analysis of Value Streams." *Production Planning & Control*, 1-11.
27
28
29
30 Mahfouz, A., J. Crowe, and A. Arisha. 2011. "Integrating Current State and Future State Value Stream Mapping
31 With Discrete Event Simulation: a Lean Distribution Case Study." *The Third International Conference on*
32 *Advances in System Simulation*, 161-168.
33
34
35
36 McCutcheon, D., and Meredith, J. 1993. "Conducting case study research in operations management." *Journal of*
37 *Operations Management*, 11(3): 239-256.
38
39
40 Mcmanus, H., and R. Millard. 2002. "Value Stream Analysis and Mapping for Product Development" *MIT and*
41 *International Council for aeronautical Sciences*.
42
43
44 Meredith, J. 1998. "Building operations management theory through case and field research." *Journal of*
45 *Operations Management*, 16(4): 441-454.
46
47
48
49 Mota, B., M. Gomes, A. Carvalho, and A. Barbosa-Povoa. 2018. "Sustainable Supply Chains: an Integrated
50 Modeling Approach under Uncertainty." *Omega* 77: 32-57.
51
52
53 Pattanayak, A., A. Prakash, and R. Mohanty. 2019. "Risk analysis of estimates for cost of quality in supply chain:
54 a case study." *Production Planning & Control*, 30(4): 299-314.
55
56
57 Petros S., L. Engelmann. 2006. "Enteral Nutrition Delivery and Energy Expenditure in Medical Intensive Care
58 Patients." *Clinical Nutrition* 25(1): 51-9.
59
60

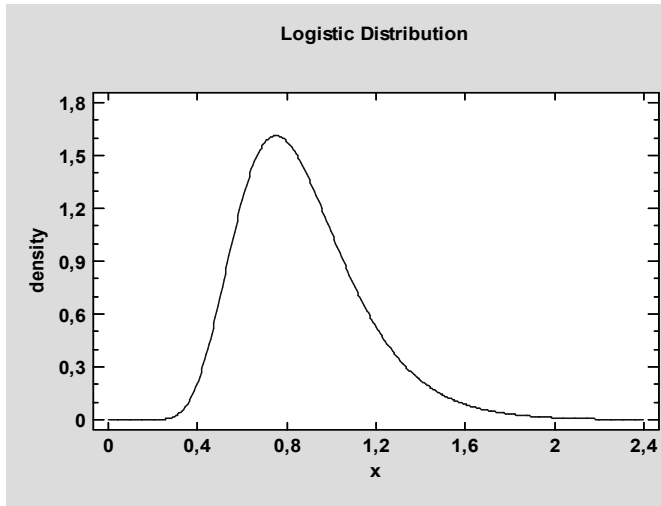
- Pujawan, N., M. Arief, B. Tjahjono, and D. Kritchanhai. 2015. "An Integrated Shipment Planning and Storage Capacity Decision under Uncertainty: A Simulation Study." *International Journal of Physical Distribution & Logistics Management* 45(9/10): 913-937.
- Rother, M., and J. Shook. 1999. *Learning to See: Value Stream Mapping to Add Value and Eliminate Muda*. Massachusetts: Brookline.
- Sakthi Nagaraj, T., R. Jeyapaul, K. Vimal, and K. Mathiyazhagan. 2019. "Integration of human factors and ergonomics into lean implementation: ergonomic-value stream map approach in the textile industry." *Production Planning & Control*, 30(15): 1265-1282.
- Seth, D., and V. Gupta. 2012. "Application of Value Stream Mapping for Lean Operations and Cycle Time Reduction: an Indian Case Study." *Production Planning & Control* (October): 37-41.
- Seth, D., N. Seth, and P. Dhariwal. 2017. "Application of Value Stream Mapping (VSM) for Lean and Cycle Time Reduction in Complex Production Environments: A Case Study." *Production Planning & Control*, 28(5): 398-419.
- Seyedhosseini, S., and A. Ebrahimi-Taleghani. 2015. "A Stochastic Analysis Approach on the Cost-Time Profile for Selecting the Best Future State Map." *The South African Journal of Industrial Engineering* 26(1): 267-291.
- Shahparvari, S., P. Chhetri, C. Chan, and H. Asefi. 2018. "Modular Recycling Supply Chain under Uncertainty: A Robust Optimisation Approach." *The International Journal of Advanced Manufacturing Technology* 96(1-4): 915-934.
- Shou, W., J. Wang, P. Wu, and X. Wang. 2020. "Value adding and non-value adding activities in turnaround maintenance process: classification, validation, and benefits." *Production Planning & Control*, 31(1): 60-77.
- Siggelkow, N. 2007. "Persuasion with case studies." *Academy of Management Journal*, 50(1): 20-24.
- Slack, N., Brandon-Jones, A., and Johnston, R. 2013. *Operations Management*. 7th Edition, Pearson, New York.
- Song, G., Z. Li, Y. Yang, H. Semakula, and S. Zhang. 2015. "Assessment of Ecological Vulnerability and Decision-Making Application for Prioritizing Roadside Ecological Restoration: a Method Combining Geographic Information System, Delphi Survey and Monte Carlo Simulation." *Ecological Indicators* 52: 57-65.
- Spear, S. 2008. *Chasing the rabbit: how market leaders outdistance the competition and how great companies can catch up and win*. McGraw Hill Professional, New York.

- 1
2
3
4 Spear, S., & Bowen, H. 1999. "Decoding the DNA of the Toyota production system." *Harvard Business Review*,
5 77: 96-108.
6
7
8 Standridge, C., and J. Marvel. 2006. "Why Lean Needs Simulation." *Winter Simulation Conference: 1907–1913*.
9
10 Swallmeh, E., A. Tobail, W. Abo-Hamad, J. Gray, and A. Arisha. 2014. "Integrating Simulation Modelling and
11 Value Stream Mapping for Leaner Capacity Planning of an Emergency Department." *Sixth International
12 Conference on Advances in System Simulation*.
13
14
15
16 Teichgraber, U., and M. Bucourt. 2012. "Applying value stream mapping techniques to eliminate non-value-added
17 waste for the procurement of endovascular stents." *European Journal of Radiology* 81: e47.
18
19
20
21 Tortorella, G., and F. Fogliatto. 2014. "Method for assessing human resources management practices and
22 organisational learning factors in a company under lean manufacturing implementation." *International Journal of
23 Production Research* 52(15): 4623-4645..
24
25
26
27 Tortorella, G., F. Fogliatto, M. Anzanello, G. Marodin, M. Garcia, and R. Reis Esteves. 2017. "Making the Value
28 Flow: Application of Value Stream Mapping in a Brazilian Public Healthcare Organization." *Total Quality
29 Management & Business Excellence* 28(13-14): 1544-1558.
30
31
32
33 Tortorella, G., G. Silva, L. Campos, C. Pizzeta, A. Latosinski, and A. Soares. 2018. "Productivity improvement
34 in solid waste recycling centres through lean implementation aided by multi-criteria decision analysis."
35 *Benchmarking: An International Journal* 25(5): 1480-1499.
36
37
38
39 Tyagi, S., A. Choudhary, X. Cai, and K. Yang. 2015. "Value Stream Mapping to Reduce the Lead-Time of a
40 Product Development Process." *International Journal of Production Economics* 160: 202-212.
41
42
43
44 Velasquez, M., and P. T. Hester. 2013. "An Analysis of Multi-Criteria Decision Making Methods." *International
45 Journal of Operations Research* 10 (2): 56-66.
46
47
48 Villarreal, B., J. Garza-Reyes, and V. Kumar. 2016. "A Lean Thinking and Simulation-Based Approach for the
49 Improvement of Routing Operations." *Industrial Management & Data Systems* 116(5): 903-925.
50
51
52
53 Vinodh, S., K. Arvind, M. Somanathan. 2011. "Tools and Techniques for Enabling Sustainability Through Lean
54 Initiatives." *Clean Technologies and Environmental Policy* 13(3): 469-479.
55
56
57 Voss, Chris, Nikos Tsikriktsis, and Mark Frohlich. 2002. "Case research in operations management."
58 *International Journal of Operations and Production Management*.
59
60

- 1
2
3
4 Vrugt, J., C. Ter Braak, C. Diks, and G. Schoups. 2013. "Hydrologic Data Assimilation Using Particle Markov
5 Chain Monte Carlo Simulation: Theory, Concepts and Applications." *Advances in Water Resources* 51: 457-478.
6
7
8 Wang, T., F. Chan, and T. Yang. 2014. "The Integration of Group Technology and Simulation Optimization to
9 Solve the Flow Shop with Highly Variable Cycle Time Process: A Surgery-Scheduling Case
10 Study." *Mathematical Problems in Engineering* 2014: 1-10.
11
12
13
14 Wang, T., T. Yang, C. Yang, and F. Chan. 2015. "Lean Principles and Simulation Optimization for Emergency
15 Department Layout Design." *Industrial Management & Data Systems* 115(4): 678-699.
16
17
18 Weston, R., K. Agyapong-Kodua, and J. Ajaefobi. 2009. "Modelling Dynamic Value Streams in Support of
19 Process Design and Evaluation." *International Journal of Computer Integrated Manufacturing* 22(5): 411-427.
20
21
22
23 Womack, J., and D. Jones. 1996. *Lean Thinking: Banish Waste and Create Wealth for your Corporation*. New
24 York: Simon and Schuster.
25
26
27 Womack, J., and D. Jones. 2002. *Seeing the Whole: Mapping the Extended Values Stream*. Massachusetts:
28 Brookline.
29
30
31 Xie, Y., and Q. Peng. 2012. "Integration of Value Stream Mapping and Agent-Based Modeling for OR
32 Improvement." *Business Process Management Journal* 18(4): 585-599.
33
34
35
36 Yang, Y., M. Geurts, J. Smilowitz, E. Sterpin, and B. Bednarz. 2015. "Monte Carlo Simulations of Patient Dose
37 Perturbations in Rotational-Type Radiotherapy Due to a Transverse Magnetic Field: a Tomotherapy
38 Investigation." *Medical physics* 42(2): 715-725 2015.
39
40
41
42 Yin, R. K, Davis, D. 2007. "Adding new dimensions to case study evaluations: the case of evaluating
43 comprehensive reforms." *New Directions for Program Evaluation: Informing Federal Policies for Evaluation*
44 *Methodology* 113: 75-93.
45
46
47
48 Zammori, F., M. Braglia, and M. Frosolini. 2011. "Stochastic Overall Equipment Effectiveness." *International*
49 *Journal of Production Research* 49(21): 6469-6490.
50
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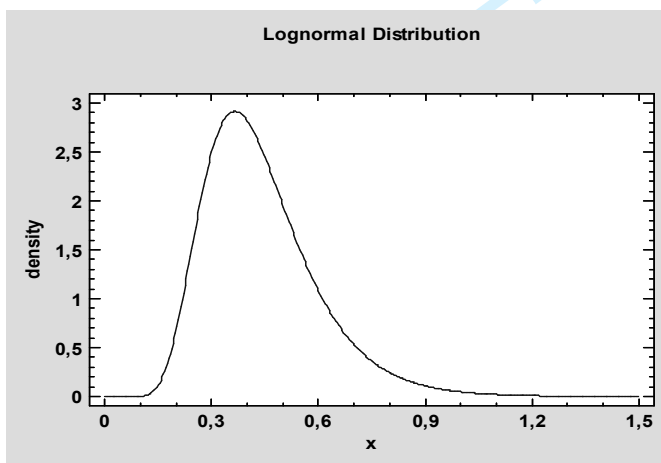
APPENDIX A – Distributions used in the simulation

Distribution of processing times for Receiving



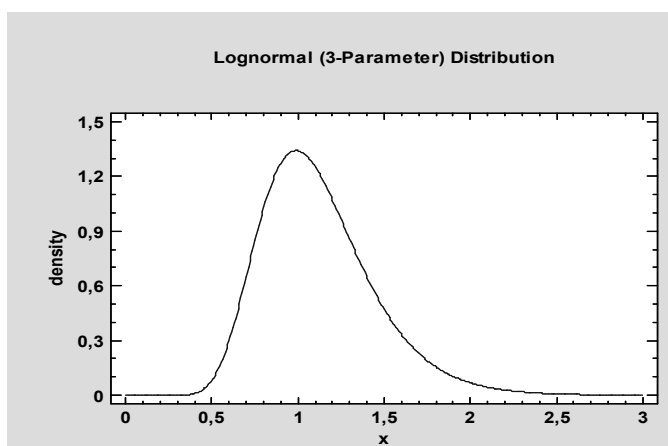
| | |
|--------------------|----------|
| Distribution | Logistic |
| Parameters | (hours) |
| Local | 0.21 |
| Mean | 0.87 |
| Standard Deviation | 0.28 |

Distribution of processing times for Lactary Storage



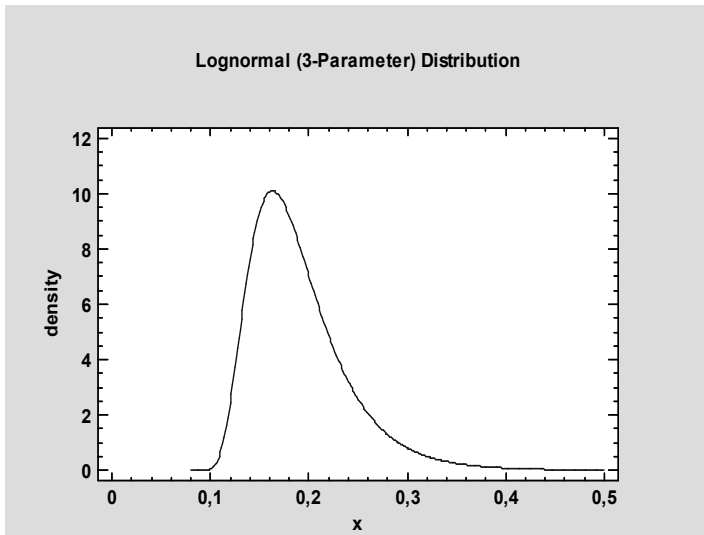
| | |
|--------------------|-----------|
| Distribution | Lognormal |
| Parameters | (hours) |
| Local | 0.31 |
| Mean | 0.44 |
| Standard Deviation | 0.16 |

Distribution of processing times for Preparation



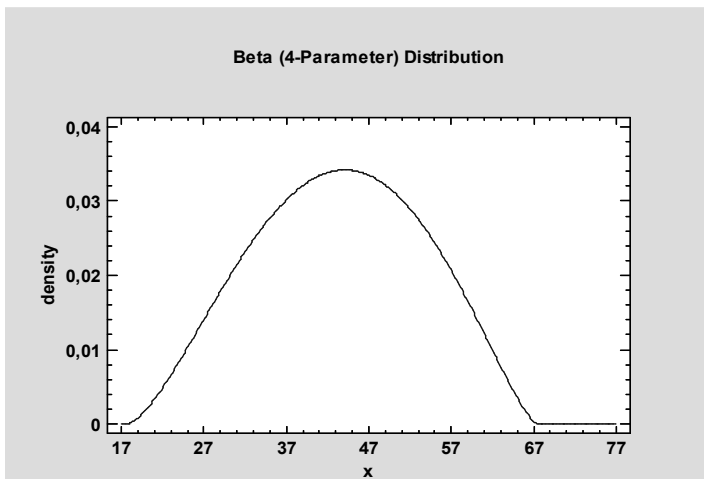
| | |
|--------------------|-----------|
| Distribution | Lognormal |
| Parameters | (hours) |
| Local | 0.00 |
| Mean | 1.12 |
| Standard Deviation | 0.33 |

Distribution of processing times for Product Administration



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

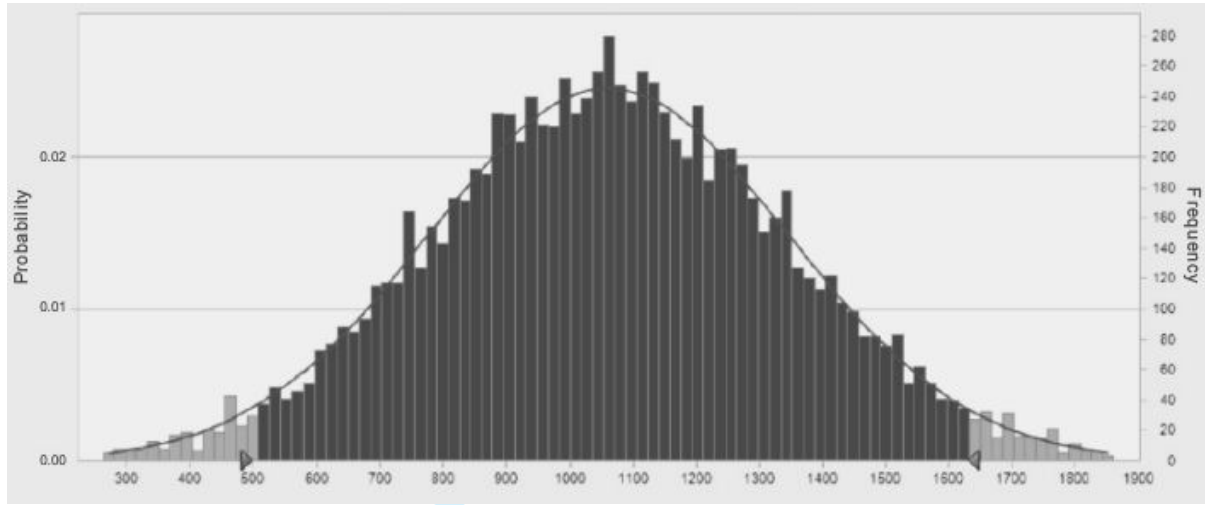
Distribution of patients' daily demand



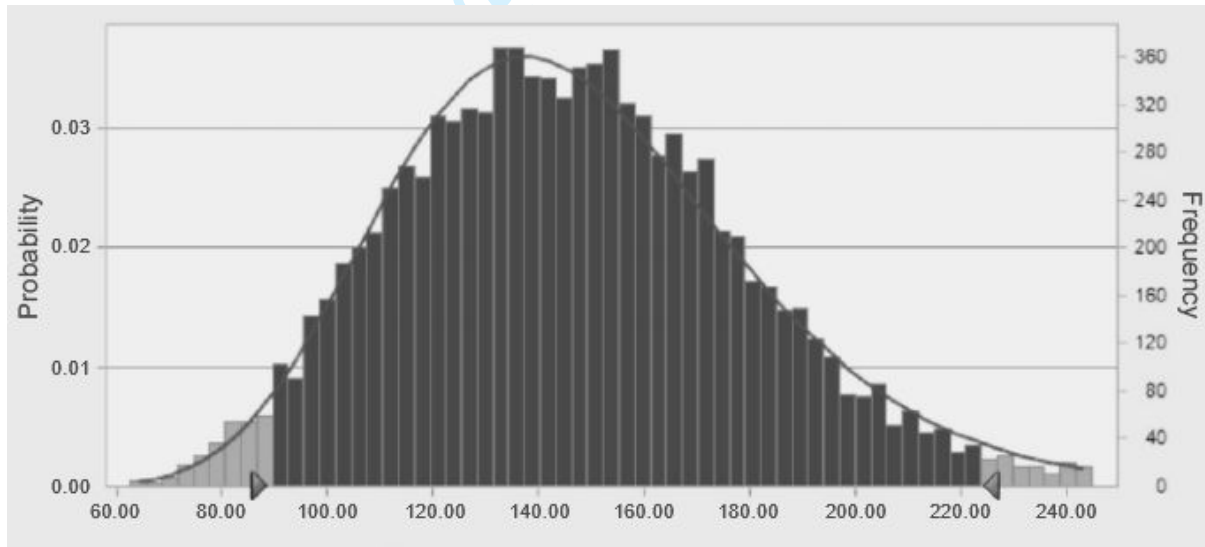
| | |
|--------------------|---------|
| Distribution | Beta |
| Parameters | (units) |
| Mean | 43.44 |
| Standard Deviation | 10.43 |
| Maximum | 67.46 |
| Minimum | 17.57 |
| Alpha | 2.61 |
| Beta | 2.42 |

APPENDIX B – Stocks simulation

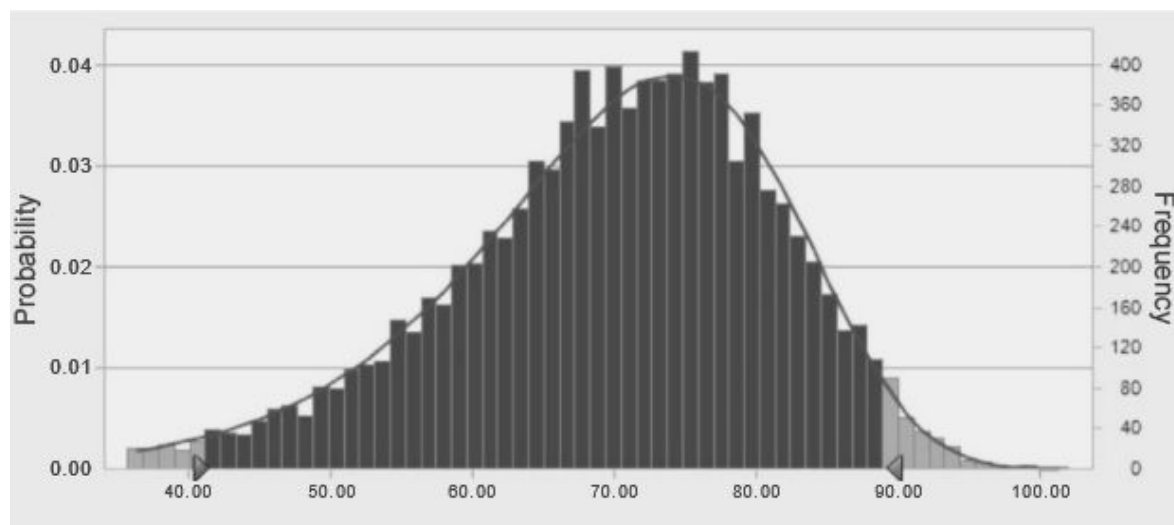
Simulation result for stock (s_1)



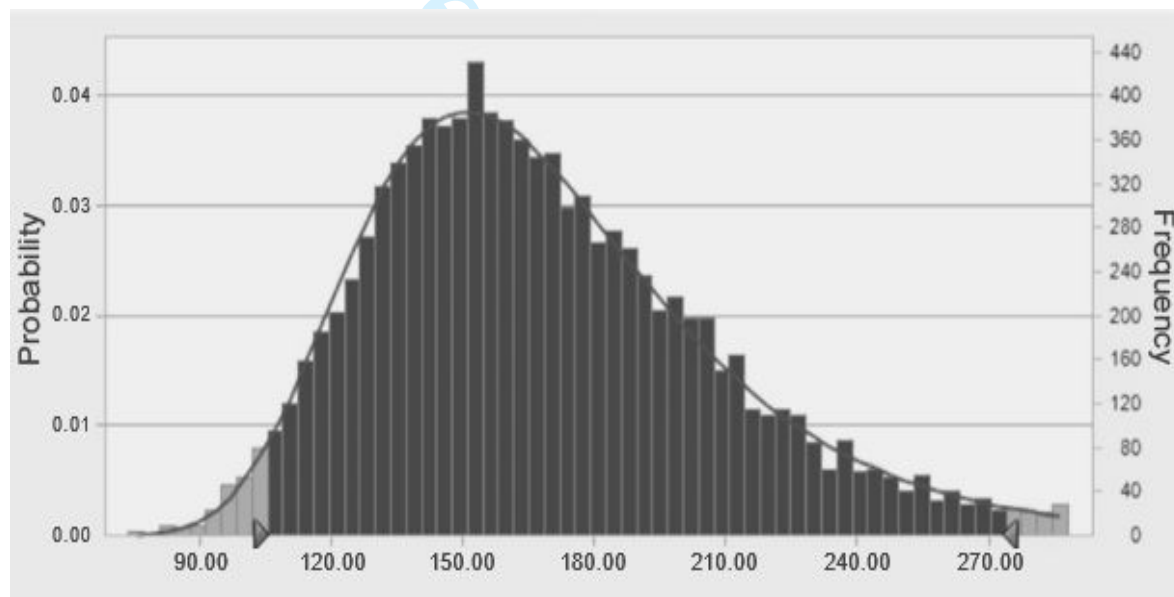
Simulation result for stock (s_2)



Simulation result for stock (s_3)



Simulation result for stock (s_4)



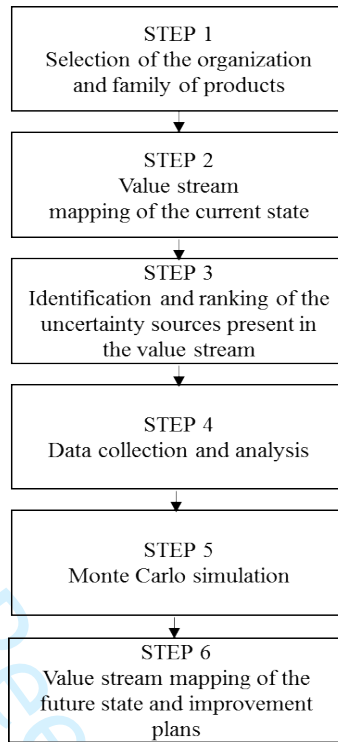


Figure 1. Steps of the proposed method

| | | Uncertainty Sources (k) | |
|--------------|--|-------------------------|------------------------------|
| Criteria (i) | Weight | Grades | Result (F) |
| | W_i | V_{ik} | $W_i * V_{ik}$ |
| Sum | | | $F_{ik} = \sum W_i * V_{ik}$ |
| k | varies from 1 to 7, because 7 uncertainty sources are considered | | |
| i | varies from 1 to 5, because we used 5 criteria | | |
| Criteria | | | |
| A | Lead Time | | |
| B | Value Added Time | | |
| C | Number of programming points | | |
| D | Value Non-Add Time | | |
| E | Number of people involved in the value stream | | |
| Grades | 3,00 | Strong | |
| | 2,00 | Moderate | |
| | 1,00 | Weak | |

Figure 2. Schematization of the MAUT

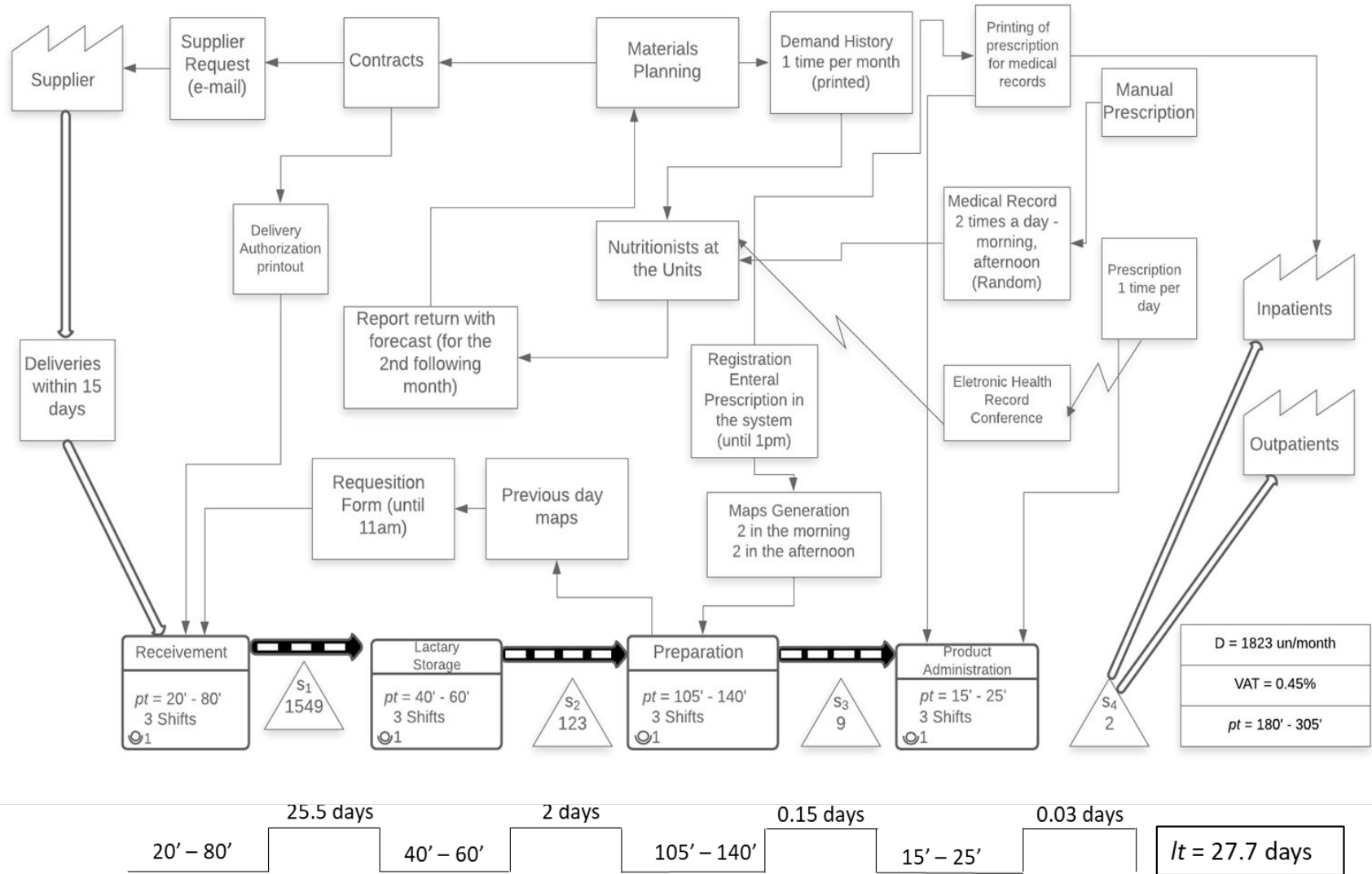


Figure 3. Current state map

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For Peer Review Only

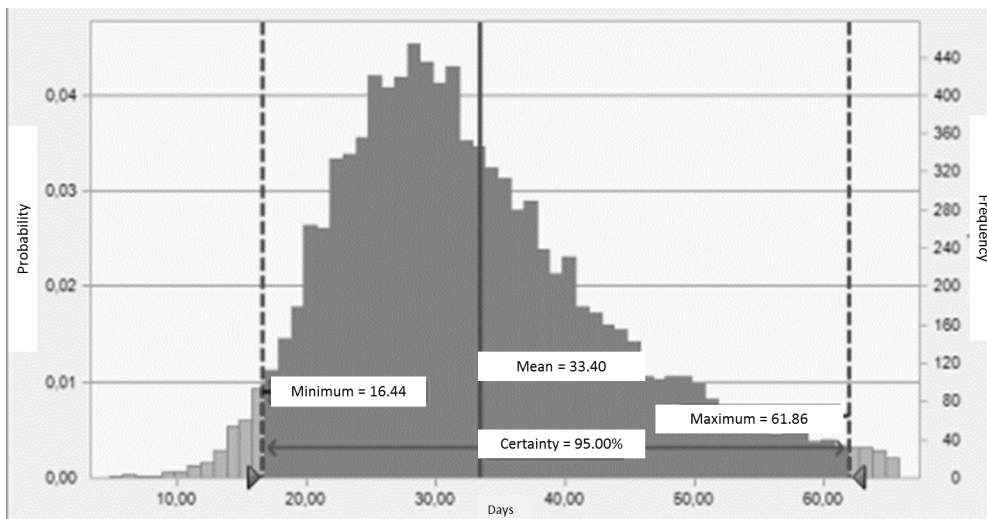


Figure 4. Simulation result for the total lead time (lt)

Peer Review Only

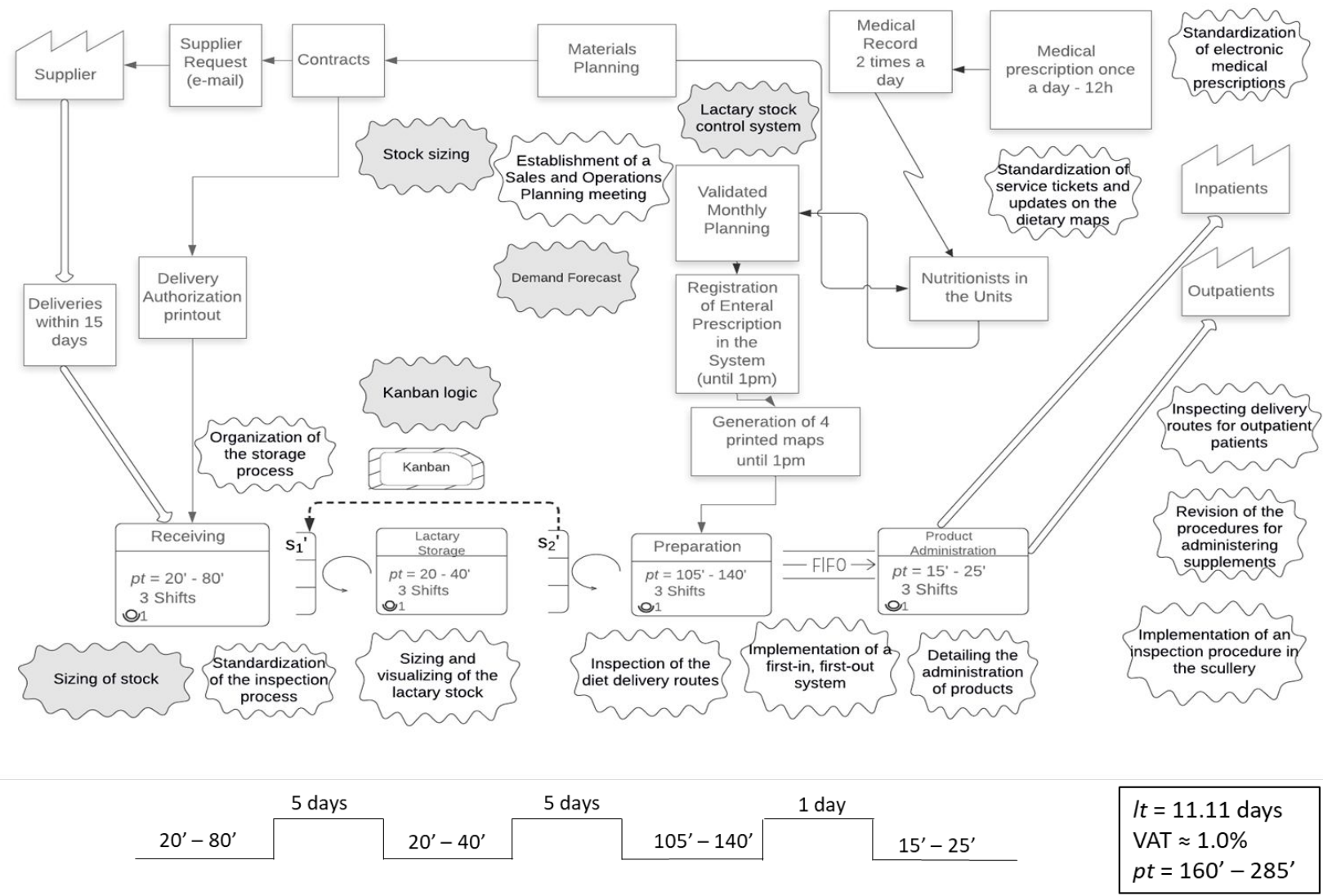


Figure 5. Future state map (grey kaizen bursts were identified from the stochastic analysis)

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 modeling and data analysis can be very time and resource consuming. | Demand; Processing Time/Cycle | Gurumurthy et al. (2011); Pujawan et al. (2015); Villarreal et al. (2016) |
| Fuzzy Logic | Possibility of propagating the effect of uncertainties along the model considered. | Model validation requires extensive testing. | Demand | Behrouzi et al. (2013) |
| Two-stage stochastic programming | Greater precision of the model made. | It requires prior knowledge of the probability distributions of the uncertain parameters. | Demand; Inventory Demand; Natural | Badri et al. (2016); Badri et al. (2017) |
| Monte Carlo Simulation | Simplicity in the treatment of variability. | Less accuracy as the complexity of the problem treated increases. | Disasters; Government Policies | Deleris et al. (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 et al. (2009); Kenne et al. (2012) |
| Systems Dynamics | Allows the use of feedback cycles. | The greater the complexity of the system, the greater the need for data collection. | Demand | Deif (2012) |
| Multi-period stochastic planning model | It allows the creation of different scenarios based on different optimization criteria. | Increased complexity with increasing number of scenarios considered. | 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 et al. (2008) |

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Table 2. Demographic profile of multidisciplinary team

| Position | Gender | Age (years) | Experience with Lean Manufacturing | Company time (years) | Functional area |
|---------------------------------|--------|-------------|------------------------------------|----------------------|-------------------------------------|
| Nutritionist | Female | 20-35 | None | 10 | ICU-NEO, Pediatrics |
| Head of the nutrition unit | Female | above 50 | None | 21 | Division of Nutrition and Dietetics |
| Head nurse | Female | 20-35 | None | 23 | Inpatient nursing |
| Assistant | Female | 20-35 | 1-5 years | 5 | Materials planning / OPME |
| Nutritionist | Female | 20-35 | None | 11 | Division of Nutrition and Dietetics |
| Nutrition assistant | Female | above 50 | None | 3.5 | Division of Nutrition and Dietetics |
| Nurse | Female | 35-50 | None | 15 | Pediatrics |
| Manager | Female | above 50 | None | 38 | Management |
| Nurse | Female | 35-50 | None | 8 | Materials Planning |
| Assistant | Female | 20-35 | None | 3 | Hospital administration |
| Nutritionist | Female | above 50 | None | 15 | Clinical Nutrition Unit |
| Nutritionist | Female | 20-35 | None | 2 | Division of Nutrition and Dietetics |
| Storekeeper | Male | 35-50 | None | 3 | Division of Nutrition and Dietetics |
| Head of infrastructure division | Female | 35-50 | 0-1 year | 8 | Management |

Table 3. MAUT method

| Criteria | Weights | % | Demand | Supplier lead time | Product quality | Processing time | Natural disasters | Infrastructure | Government policies |
|-------------------------|---------|-------|-------------|--------------------|-----------------|-----------------|-------------------|----------------|---------------------|
| | | | v_{i1} | v_{i2} | v_{i3} | v_{i4} | v_{i5} | v_{i6} | v_{i7} |
| Lead time | 10.00 | 22.22 | 3.00 | 3.00 | 2.33 | 3.00 | 2.33 | 2.67 | 2.33 |
| Value-added time | 9.50 | 21.11 | 2.3 | 1.33 | 2.33 | 2.00 | 2.67 | 2.00 | 2.00 |
| N° of scheduling points | 9.00 | 20.00 | 2.33 | 1.00 | 1.33 | 1.33 | 1.00 | 1.33 | 1.33 |
| Non value-added time | 8.50 | 18.89 | 1.67 | 1.33 | 1.00 | 2.00 | 2.00 | 2.00 | 2.00 |
| N° of people involved | 8.00 | 17.78 | 1.67 | 1.33 | 1.00 | 2.67 | 1.33 | 1.00 | 1.33 |
| Criticality scores | | | 223.69 | 163.51 | 164.23 | 220.73 | 189.57 | 183.71 | 182.02 |
| Differentiation Index | | | 1.51 | -1.16 | -1.12 | 1.38 | -0.002 | -0.26 | -0.34 |

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

| | Receiving | Lactary storage | Preparation | Product administration | Patient daily demand |
|--------------------|-----------|-----------------|-------------|------------------------|----------------------|
| Distribution | Logistic | Lognormal | Lognormal | Lognormal | Beta |
| Parameters | (hours) | (hours) | (hours) | (hours) | (units) |
| Local | 0.21 | 0.31 | 0.00 | 0.08 | - |
| Mean | 0.87 | 0.44 | 1.12 | 0.19 | 43.44 |
| Standard deviation | 0.28 | 0.16 | 0.33 | 0.05 | 10.43 |
| Maximum | - | - | - | - | 67.46 |
| Minimum | - | - | - | - | 17.57 |
| Alpha | - | - | - | - | 2.61 |
| Beta | - | - | - | - | 2.42 |
| CV | 32.18% | 36.36% | 29.46% | 26.31% | 24.01% |

Table 5. Stocks variation analysis

| Stocks | s_1 | s_2 | s_3 | s_4 |
|----------------------------|--------|--------|-------|-------|
| Initial Value (s_{0m}) | 1,549 | 123 | 9 | 2 |
| Mean | 975 | 149 | 74 | 169 |
| Standard deviation | 282 | 27 | 7 | 4 |
| Minimum | 287 | 67 | 35 | 81 |
| Maximum | 1,877 | 257 | 98 | 277 |
| CV | 28.92% | 18.12% | 9.46% | 2.37% |