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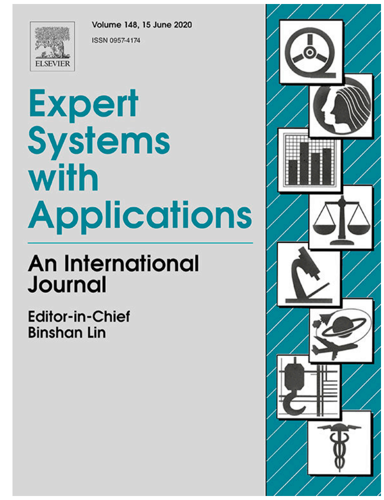

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Logic-driven, Simulation-based Risk Engineering to Ensure the Sustainability of Productive Processes even with Data Scarcity

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Abstract

Designing and operating production systems and keeping them up to date at the speed of innovation to meet competition, consumer trends and sustainability requirements is a challenging task. The problem becomes even more challenging when the production system is highly uncertain and data-poor. This complexity is increasingly recognised, as is the value that risk engineering can bring to the design, operation, maintenance and upgrading of production systems to avoid compromising their viability and ensure their continued efficiency.

The manuscript is guided by this challenge and has a twofold objective. First, it analyses and explains the importance of adopting a logic-driven and simulation-based risk engineering approach to support decision making. This objective is achieved by going to the root of the methodological constructs that characterise the methodologies available in the literature and by highlighting the main limitations. Secondly, it applies the HoRAM method to the use case of food banks to verify its suitability. The use case of food banks was chosen because it is characterised by more and unusual uncertainties compared to conventional production systems (such as uneven labour and raw material availability).

The main contributions of this research are as follows. First, it provides a critical analysis of currently available risk assessment methodologies. It highlights the weaknesses and explains the implications of these weaknesses for decision support. Secondly, it concerns the development of a complete risk engineering process, offering an approach that goes beyond conventional risk engineering approaches that stop at the identification of the critical elements associated with the problem at hand. It explains the importance of closing the risk analysis loop by verifying the efficiency of the identified mitigation solutions.

The results suggest that the proposed approach is suitable for supporting complex decision-making processes characterised by high uncertainty and data scarcity. Furthermore, due to the logic-driven nature of the proposed approach, non-experts can be involved and contribute to the analysis and engineering of risks. This allows to increase the situational awareness of decision makers and consequently their efficiency in making complex decisions.

Keywords: Risk Engineering, Logic-based Artificial Intelligence, Sustainable Decision Making, Holistic Risk Analysis, Sustainability of Food Processes, Risk-based Decision Making

1. Introduction

Competitiveness encompasses many facets of production processes: from the fundamental, historical need to ensure the efficient use of internal resources (Jayanthi *et al.*, 1999), to the integration of health, safety and environmental aspects (Kruse *et al.*, 2019) to avoid negative externalities and ensure social acceptability, to the creation of a transparent supply chain to gain consumer trust and regulatory approval (Astill et al., 2019). Sustainability is undoubtedly a key, transversal and unavoidable element to ensure competitiveness. However, it is undeniable that the multi-level complexity of production processes is constantly increasing, and the use of scenarios to explore the uncertainty associated with this complexity is becoming extremely useful to support all decision-makers involved in the design and management of production processes (Vieira *et al.*, 2023). The use of scenarios to support decision-makers is certainly not new and dates to the 1970s when the oil shock upset the entire business world (Bood & Postma, 1997). Since then, multiple scenario analysis has been considered extremely useful as "the ultimate goal of scenarios is to provide a structured means of communicating uncertainty" (Tourki et al., 2013). Although scenarios can be defined in different ways (CIS&HCCIA, 1977; Domenica et al., 2007; Gelman, 2010; Pomerol, 2001; Porter, 1985; Schwartz, 1991; Tucker, 1999; Weinstein, 2007), it is generally agreed that they are intended to anticipate the opportunities associated with the possible alternatives and not to develop new strategies (Schoemaker, 1993; Mahmoud et al., 2009; Wright et al., 2019). However, if scenarios are constructed to include the undesirable outcomes and the effort that would be required to make them less likely or less severe, they may even support strategic thinking (Porter, 1985; Cole, 2014; Means, 2005; Schoemaker, 1995; Simon, 1960; Svedung, 2002; Van der Heijden, 1996; Wright, 2000), increase situational awareness (Endsley, 1995; Wickens, 2008) and foster a questioning attitude (Weick & Sutcliffe, 2001), all of which are beneficial elements in increasing the resilience of decision makers and that of the entire organisation in which they operate. More recently, the use of scenario planning has been proposed to address the so-called wicked problems (Wright, 2019) which, according to Churchman (Churchman, 1967), are those problems that are "ill-formulated, where the information is confusing, where there are many clients and decision makers with conflicting values, and where the ramifications in the whole system are thoroughly confusing". Over the years, the use of scenarios has spread significantly and is nowadays used to address a large variety of decision-making problems: characterising social vulnerability for disaster planning and response (Orru et al., 2022), the resilience of maritime supply chains (Gu et al., 2023), the impact of the transition to a bioeconomy on ecosystem services (Immerzeel et al., 2023), energy use in residential buildings (Li et al., 2023), effects of land cover on ecosystem service provision (Padilha *et al.*, 2023), identification of trade-offs in promoting sustainable agriculture (Naranjo et al., 2023), the identification of requirements in research and development projects (Wang. & Yang, 2024), the deduction of collision accidents of ships (Zhang et al., 2024), and electricity consumption forecasting (Xie et al., 2024) to name a few. However, deriving credible and, above all, reliable scenarios is not an easy task. The reason lies not only in the conceptual model chosen (more or less consciously) to describe the business opportunity to be pursued (Andersen & Mostue, 2012; Leveson, 2004; Leveson, 2011; Rasmussen, 1997), but also on the methods and the associated tools available to perform the analysis (Connelly & Lambert, 2016; Connelly et al., 2016; Hamilton et al., 2016; Karvetski & Lambert, 2012; Lambert et al., 2013; Lambert et al., 2012; Parlak et al., 2012; You et al., 2015; Thorisson et al., 2017). Miller et al. (2023) emphasised that scenario planning (SP) is a well-established approach for assessing system response and facilitating decision-making under a wide range of conditions. However, SP lacks a defined structure for establishing objectives, quantifying trade-offs, and evaluating the performance of candidate decisions to meet those objectives. Scenarios can be created using manual and static approaches or simulation-based and dynamic ones. Siu (1994) identified potential weaknesses in manual and static methodologies. However, it is unclear whether there is an explicit link between the highlighted limitations and the methodological construct. Understanding this link is necessary to determine whether the identified limitations are inherent (i.e. insurmountable) or contingent (i.e. surmountable) to the specific methodological proposal. Goal of this work is to clarify the main methodological aspects associated with the creation of risk-based scenarios to support decision-making.

2. Literature review

2.1 Most known and widely used methods for risk assessment

Almost all methods applied in daily practice to analyse and assess risk(s), independently of their nature, have been conceptualised and created in the last thirty years of the past century. Amongst the most known and widely used, one can chronologically find the Failure Mode, Effects and Criticality Analysis (FMECA) (MIL–P–1629, 1949), the Delphi Method (DM) (Dalkey and Helmer, 1963; Woudenberg, 1991), the Preliminary Hazard Analysis (PHA) method (MIL-S-38130, 1963; MIL- STD-882, 2012), the Fault Tree Analysis (FTA) method (Haasl, 1965; Hauptmanns, 1988; Watson, 1961), the Political, Economic, Social, and Technological (PEST) method (Aguilar, 1967), the Strength, Weaknesses, Opportunity and Threats (SWOT) method (Andrews, 1971; Porter, 1980; Porter, 1985), the Hazard Analysis and Critical Control Point (HACCP) method (Bourland, 1993), the Hazard and Operability (HAZOP) method (Lawley, 1974; CIS&HCCIA, 1977), The Life Cycle Assessment (LCA) method (Boustead, 1972; Hannon, 1972; Sundstrom, 1973; Boustead, 1974), the Event Tree Analysis (ETA) (WASH-1400-MR, 1975), the Bow-Tie Method (BTM) (Gill, 1979), the Political, Economic, Social, Technological, Environmental, and Legal (PESTEL) method (Fahey and Narayanan, 1986), the Analytical Hierarchy Process (AHP) method (Saaty, 1980; Saaty, 1987), Ecological Footprint (EF) method (Wackernagel and Rees, 1996), and the Cross-Impact Analysis (CIA) method (Glenn & Gordon, 2009). All these methods have the common traits of 1) requiring the analyst to manually create scenarios and/or 2) being static. For these reasons, in the last decade of the past century, the need for simulation-based approaches to dynamically assess risks started taking shape and the Dynamic Event Tree Analysis Method (DETAM – Acosta & Siu, 1993) and the Dynamic Logical Analytical Methodology (DYLAM – Cojazzi, 1996) emerged as good references. Despite the recognised superiority of simulation-based methods compared to manual and static ones (like Fault and Ever rios. To overcome this methodological difficulty, Swaminathan & Smidts (1999) proposed the Event Sequence Diagram (ESD) framework. Despite this, as Hu and colleagues (2022) recently highlighted, these methods did not replace traditional probabilistic risk assessment methods but, rather, became supplemental tools. Hu and colleagues (2022) proposed the Simulation-based Probabilistic Risk Assessment (SIMPRA) method, which is inspired by human reasoning.

It is worth highlighting that the development of simulation-based approaches is mostly relegated to the assessment of risks associated with safety-related aspects of hazardous production systems (Jang *et al.*, 2022; Zhang *et al.*, 2023) or products (Xia *et al.*, 2023). There are only a few proposals to use simulation-based approaches to assess market risks. Nourinezhad & Rajabi (2023) proposed a simulation-based approach for cost risk analysis. Vieira et al. (2023) proposed a simulation-based approach for a multi-objective decision support tool for wine supply chain design under risk situations and sustainability objectives.

2.2 The perimeter of application

Essentially, all these methods were initially born to respond to two radically different needs, namely: 1) the need to prevent potentially harmful effects of the productive process on the health and safety of workers, the society living near the plant, and the environment, and 2) to support the corporate strategy development process in exploring the unknown and fostering innovation. Figure 1 represents the typical perimeter of the application of the above-mentioned methods with the layers of an organisation's environment proposed by Johnson (2008).

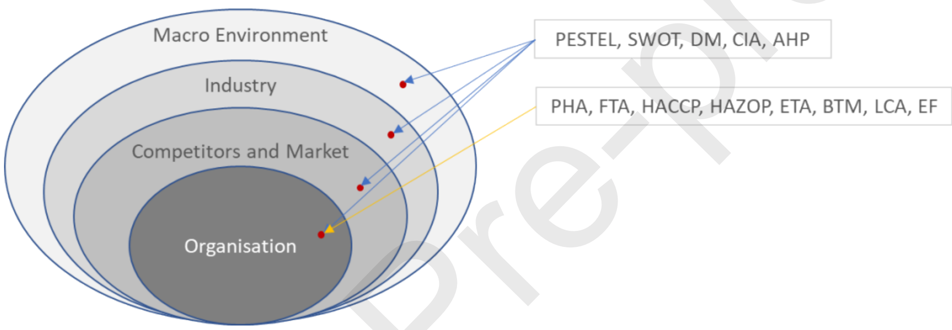

Figure 1 – Typical perimeter of application of the methods

Most methods were born in high-risk domains (i.e., nuclear, chemical and petrochemical) to prevent risks associated with the productive process. The inherently hazardous operating conditions (e.g., temperatures, pressures, concentrations) or the hazardous materials processed (e.g., toxic, pollutants, explosives) required the capability to anticipate what would have been the risks associated with the productive process. In this context the risk analysis had primarily a twofold goal: 1) acquiring permission to operate from authorities, and 2) ensuring the survivability of the business (given that major accidents may put a company out of business).

Unlike high-risk industries, all other industries historically concentrated their efforts on the identification of risks associated with their products. The reason was the different and less hazardous operating conditions and materials processed. In everyday practice, risk prevention was primarily meant as the prevention of safety problems. Still today, to provide the best products and protect customers, companies tend to invest in quality management. Yet, starting from the 70ies of the past century, all sectors began their steady increase towards complexity. The risk assessment started to assume a wider connotation, closer to the one held by high-risk industries and embracing even non-market risks i.e., occupational health & safety and environmental impact (Luther et al., 2023). The integrated Health, Safety, and Environmental (HSE) function started then to take shape (Colombo *et al.*, 2019). Today, due to the significant increase in process and technological complexity, the majority of productive processes can be considered risky. And this awareness seems to have permeated managerial roles in nearly all sectors. Yet, risk management is still primarily meant to master the *status quo* and not as a key means to increase competitiveness, foster innovation, and guarantee sustainability. When "risk management" is evoked, it is substantially interpreted either as financial risk management, when mid-to-top company activities are considered (Zhu et al., 2023), or as HSE-related risk management, when operational risks are at stake. This limited view loses the enormous beneficial opportunity that risk management can offer to assess market-related risks (e.g., efficiency, business continuity, systemic optimisation). In other words, although the development path is well on track towards that goal, risk management is not yet meant as Enterprise Risk Management in line with the ISO 31000 spirit.

2.3 Shortcomings of current approaches

2.3.1. Deductive vs. inductive approaches

Risk assessment methods can be broadly classified into two main families: deductive and inductive methods. Deductive methods are characterised by the fact that can only reveal hidden tautologies, i.e. cases in which the predicate is included, by definition, in the subject and it is then only necessary to deduce it from it. Thus, deductive methods cannot produce new knowledge as everything is implicitly contained in and bounded by the event(s) the decision maker has priorly decided to avoid or mitigate (independently on how they have been identified). On the other hand, inductive methods start the analysis from a deviation and can generate new knowledge by revealing implications that are not and cannot be included in the deviation. Therefore, they are more appropriate for performing previsional analyses to assess risks and support decision-making. Figure 2 illustrates the difference between the two logical constructs.

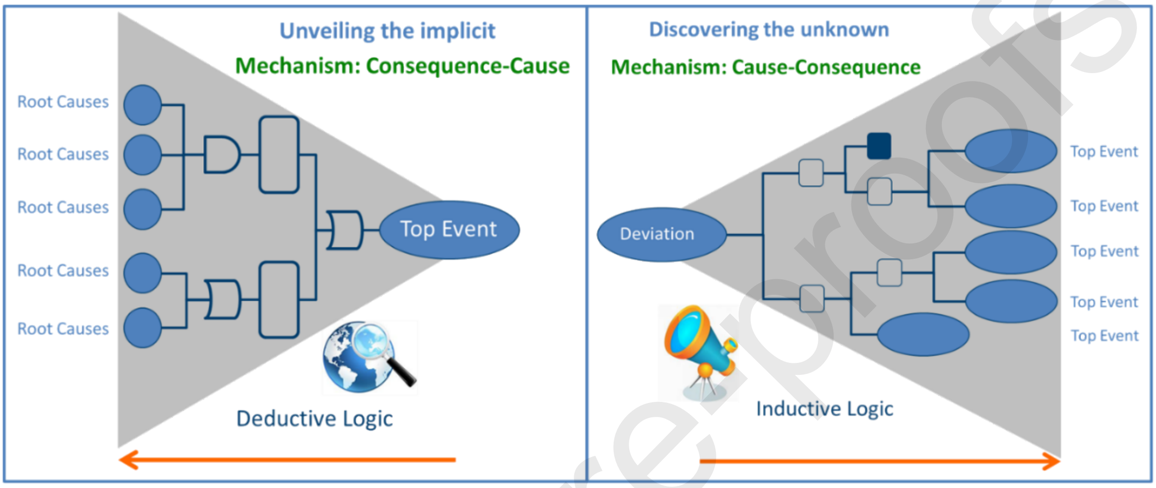

Figure 2 – Deductive vs. Inductive methods

The logical mechanism underlying deductive methods is consequence-cause, while that of inductive methods is the opposite. Deductive methods, such as the well-known and widely used FTA, begin the analysis from what needs to be prevented and/or mitigated, and move retrospectively by identifying the chain of failures that could lead to the investigated undesired consequence, known as the "Top Event" (TE). On the other hand, inductive methods, such as the well-known but less commonly used ETA, begin the analysis by identifying a possible deviation and then move forward by identifying all possible ways in which the deviation can lead to an undesired TE. For this reason, inductive methods allow for the creation of new knowledge as, by construct, they allow to identify new TEs that are previously unknown and that the risk analysis aims to identify and prevent. Skilled and experienced practitioners tend to combine inductive and deductive methods when assessing risks using manual and static approaches. The reason is because inductive methods are more suitable for identifying TEs, but they are typically qualitative and require deductive methods to quantify the probability of occurrence of the TEs. A common example of methodological coupling is the combination of the HAZOP (inductive) and FTA (deductive) methods. This approach involves identifying hazards through a systematic review of the process (HAZOP) and analysing the causes and consequences of those hazards (FTA). This practical approach overcomes inherent methodological limitations but it also creates strong inconsistencies. The translation of qualitative results into the structure of quantitative methods is not made explicit and is left to the analyst's heuristic. This limitation can create potential distortions in the analysis that are difficult to identify and correct. To overcome this gap, Piccinini & Ciarambino (1997) developed the Recursive Operability Analysis (ROA) method as an evolution of the HAZOP. The ROA was aimed at creating a systematic, consistent, and explicit link between the identification of TEs and their quantification through logic trees using the Incidental Sequence Diagram (ISD). Colombo & Demichela (2008) extended the ROA, originally focused on technology, to include the Human & Organisational Factors (HOF).

2.3.2. Quantitative vs. qualitative methods

Qualitative methods are often considered quicker and easier than quantitative methods in producing desired results. However, when analysing and assessing risks of complex systems and phenomena, qualitative methods can produce misleading previsions due to the inherent biases in the heuristics of the analyst(s). These biases are difficult to identify as the underlying conceptual model used for the analysis is often not made explicit in a readable construct, such as a logical model or graphical representation. For this reason, it cannot be tested for consistency and robustness against known facts and trends. In risk engineering, explicit quantitative methods are by far more reliable for supporting complex decision-making processes. This is the reason why the man

The first critical limitation that may affect a quantitative methodology is its practical or structural impossibility to create a partition, which refers to a complete universe of all possible, mutually exclusive alternatives (scenarios) that can stem from the considered variables (Savage, 1954; De Finetti, 1974; De Finetti, 1975; Jaynes, 2003). This limitation is crucial given that without a complete universe it is impossible to verify whether the calculated probabilities for the created scenarios are consistent with the empirical evidence or the design specifications. In other words, it is not possible to check for congruence to verify the previsional accuracy and consistency. Secondly, a complete universe is necessary to calibrate the assigned probabilities with the anchor points. The algorithm must respect the three coherence principles to guarantee that the sum of the probabilities of all produced scenarios equals 1 (one) and not something close to it (De Finetti, 1974; De Finetti, 1975). Thirdly, it is not possible to verify, but heuristically, whether the identified solutions effectively mitigate the risk along the entire consequence range. The Holistic Risk Analysis and Modelling method (Colombo, 2019) appears to be the only logic-driven method that is not affected by this first limitation. In contrast, for all other methods, including the BDN, the sum of the probabilities of all generated scenarios does not sum up to 1 (but to something close to it).

The second important limitation is the inability to create scenarios in the form of readable stories (in natural language) rather than hidden numerical combinations of the considered variables. The correctness of these hidden combinations can only be deduced through the interpretation of numerical results and/or graphical trends and/or surfaces. Creating scenarios as readable stories in natural language enables non-experts, who are typically the knowledge and risk owners, to participate both in the creation of the previsional model and the verification of its previsional capabilities . Without this methodological feature this control would only be allowed indirectly (through the interpretation of graphs and/or surfaces) and may lead to potentially misleading interpretations of the numerical trends. Therefore, a much higher caution must be exercised when interpreting the results stemming from methods that do not create scenarios as readable stories.

A third significant limitation is the inability, by methodological construct, to link the logic-stochastic part of risk with the phenomenological part. The former is necessary for generating scenarios and calculating the associated probabilities, while the latter is necessary to calculate the impact of each variable in each scenario, and each scenario in the overall universe. This is a fundamental methodological feature as a risk-based decision making process requires the possibility to assess and compare the risk and not just the probability. Amongst the methods currently available, the Belief Decision Networks (BDN) (Van de Stadt, 1994) and the HoRAM method (Colombo, 2019) guarantee this feature. The BDN was developed to transform Bayesian Believe Networks (BBN) into a risk-based decision support tool (Sadoddin *et al.*, 2005; Catenaccia and Giupponi, 2013). The BDN method has been applied in various domains to support different types of decisions (Khosravi-Farmad & Ghaemi-Bafghi, 2020; Penman *et al.*, 2020; Zhou *et al.*, 2022). The same applies to the HoRAM method (Ciotola *et al.*, 2021; Vimercati *et al.*, 2021).

A fourth important limitation is the difficulty of managing scenarios. This aspect is often underestimated given that checking the consistency, completeness, and meaningfulness of the previsional model is extremely time-consuming. For manual methods, this task is even more difficult as scenarios are not immediately readable since they are all embedded in the graphical representation of the logic tree. Therefore, identifying the biases associated with the heuristic used to generate the scenarios can be extremely challenging. Ahmed et al. (2010) noted that conventional decision support systems offer strong database, modelling, and visualization capabilities for decision-makers, but they do not explicitly support scenario management. Managing scenarios is crucial as it enables analysts to examine the decision-making problem at various levels of abstraction, from different perspectives, and for different purposes. This capability allows analysts and decision-makers to verify the quality of the analysis and gain a better understanding of the decision-making problem from various perspectives. In addition, the ability to manage scenarios can aid in the process of fine-tuning the assignment of probability values.

The fifth limitation is the difficulty (or even impossibility) of identifying what are the critical variables, amongst those considered in the model, based on their contribution to the overall risk (and not just to the probability). Without this feature it is extremely challenging for the analyst to identify efficient mitigation solutions and for decision makers understanding what are the variables to keep under control. To meet this requirement the method must account for the impact of each variable on each scenario and the impact of each scenario on the entire universe.

2.4 Data-driven vs. logic-driven methods

Jointly with theory and experimentation, simulation is the third tool of science and is extremely useful to support decision-making (Schultz, 1974; Thesen & Travis, 1989; Thesen & Travis, 1991). It imitates the behaviour of a phenomenon, such as a process or a system, over time or logical steps, producing numerical, graphical, logical, or combined results. Quantitative methods for assessing risks can be either manual or simulation based. In cases where the phenomenon being analysed is complex, manual approaches may be inadequate for identifying criticalities due to the high complexity required to the human mind (Dekker, 2014). To fully capture the complexity of the analysed phenomenon and the associated risks, simulation-based approaches become a need rather than an option. This is because limitations in the risk analysis process can lead to a distorted view of problems, which may result in identifying solutions that are not suitable for mitigating the overall risk as they may even increase it (Iovine et al., 2006; Johnson, 2006). Unfortunately, this aspect is often overlooked. While there are many efforts dedicated to developing qualitative methods that attempt to capture the complexity of productive processes (Schulte and Knuts, 2022), there are far fewer efforts focused on deve

Broadly speaking, quantitative methods can be classified into two families according to their underlying construct: logic-driven and data-driven. Table 1 and Figure 3 illustrate, for the categories of methodologies mentioned above, the driving forces, the characteristics of the underlying model(s), and the results achievable. While data-driven methodologies typically stem from the data science realm, logic-driven methodologies stem from the decision science one. Further, the term logic-driven often refers to the application of fuzzy logic principles to the development of a method, and not to the application of logic principles necessary to create partitions, i.e. complete universes.

Simulation approaches have evolved since the 1980s, from expert systems to what is nowadays known as Artificial Intelligence (AI). AI can be broadly divided into two principal areas: machine learning and cognitive computing (Hasan et al., 2021; Coccoli et al., 2016). The BDN and HoRAM methods allow for the assessment of risks, rather than just probabilities (such as Monte Carlo, BBN, DYLAM). The former belongs to the machine learning side of AI (Marcot et al., 2019), while the latter belongs to the cognitive computing one (Colombo, 2019). Figure 4 summarises the differences between these two approaches. Machine learning methods are data-driven and require statistically significant data to produce reliable previsions, as the network needs to be properly trained. Without a significant amount of data, they cannot produce useful results (Li et al., 2021). On the other hand, cognitive computing methods may be driven by logic rather than solely by data. This means they can produce accurate previsions even without statistically significant datasets through the creation of logic constructs and/or by incorporating expert judgment (Coccoli et al., 2018; Sense et al., 2022). Additionally, they can account for variables that are relevant to the decision or phenomenon but are neither measured nor measurable. From a different perspective, machine learning methods can be seen as driven by the experience as they are designed to analyse data, i.e. events already happened. Therefore, they can be useful in preventing the recurrence of past events (Coccoli et al., 2018). On the other hand, methods falling under the cognitive computing may be driven by anticipation, creating logical constructs capable of generating events that have not yet occurred but may happen in the future based on phenomenological or experiential considerations. Therefore, they are useful in preventing things from happening for the first time or again.

The underlying paradigms of the two types of methods are different. In machine learning methods, the future can be assumed to be equal to the past as they rely on recorded data (Gama et al., 2014). In contrast, logic-driven cognitive computing methods can account for variables whose manifestation has not been recorded yet, making the future not necessarily equal to the past (Ahmadi et al., 2016). Metaphorically, machine learning methods can be seen as tools that tend to substitute human decision-making, while logic-driven cognitive computing methods can be seen as tools that tend to enhance human capability in analysing complexity and making decisions (that are left to the human).

Table 1: Classification of the methods of analysis

Typology	**Driving Force**		**Models**	**Qualitative Results**	**Quantitative Results**	**Example**
Qualitative methods	-	-	-	▪ Risk Matrices ▪ Descriptive scenarios	-	HAZOP, FME(C)A, HACCP, PESTEL, SWOT, …
Quantitative methods	Logic-driven	Logic-Stochastic model	-	-	Explicit (readable or NOT readable) quantitative scenarios	FTA, ETA, DETAM, …
		Logic-Stochastic model	Deterministic phenomenological model	-	▪ Explicit readable quantitative scenarios ▪ Probability curves ▪ Risk curves	HoRAM

	model	-	-	scenarios	BBN
Data-driven	Stochastic model	Deterministic phenomenological model	-	▪ Implicit quantitative scenarios ▪ Probability curves ▪ Risk curves	BDN, DYLAM, SIMPRA, …
	Stochastic model	Stochastic phenomenological model	-	Probability curves	Monte Carlo

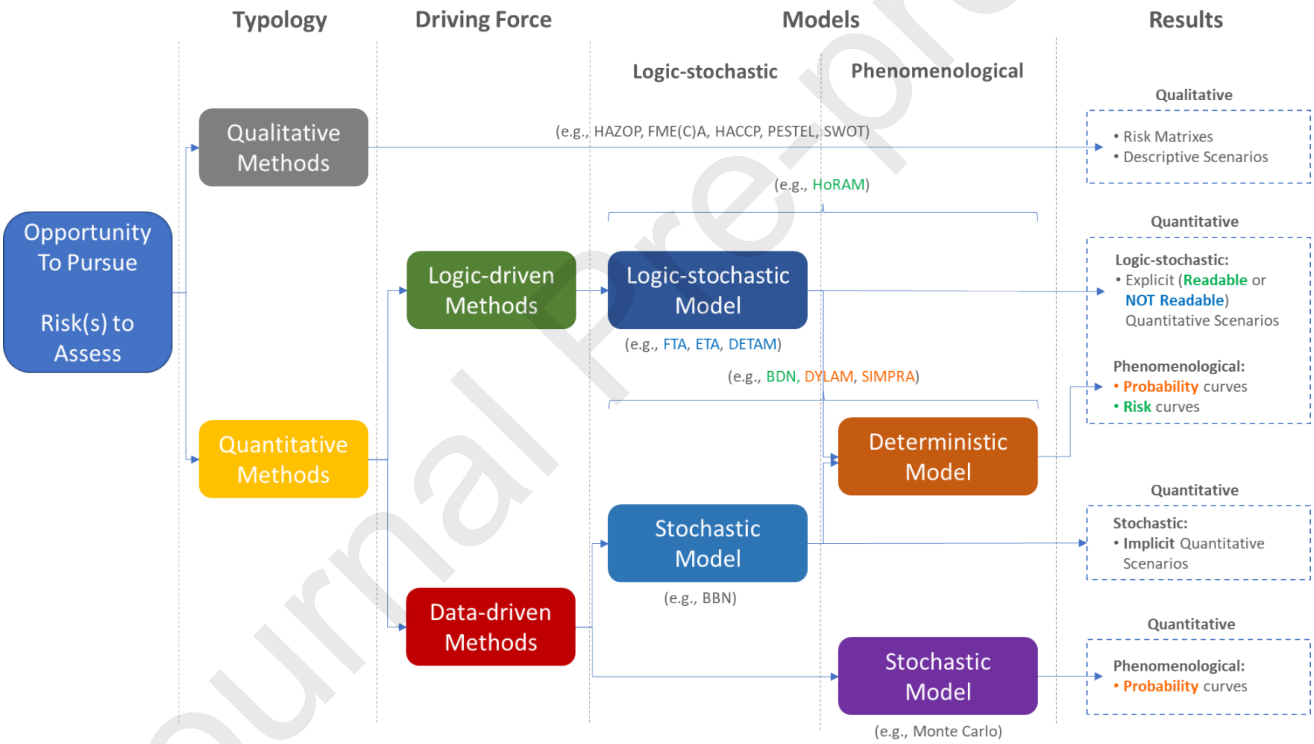

Figure 3 – Logic-driven vs. data-driven methods

Machine learning and cognitive computing approaches serve different purposes. Machine learning methods are better suited to support decisions that require the extraction of knowledge from complex datasets, which are events that have already been experienced, either directly or indirectly (Ciaburro et al., 2021). These methods can replace humans in decision-making, typically shifting them to higher, supervisory positions. On the other hand, (logic-driven) cognitive computing methods are better suited to support decisions that require the production of new knowledge, even by considering variables that have not yet been manifested but are known to influence the decision (Hasan et al., 2021). These methods capitalise on datasets that may not be statistically relevant and events that might occur but have not yet been recorded.

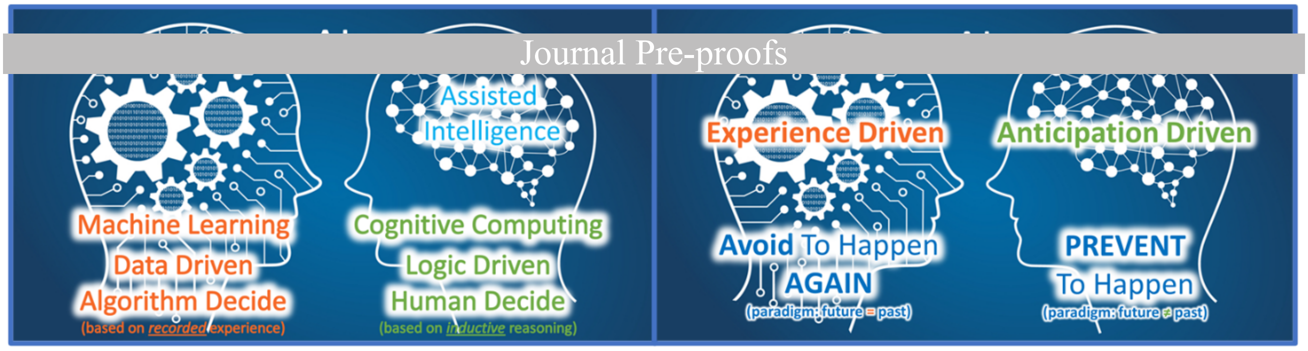

Figure 4 – Data-driven vs. Logic-driven Methods

Operationally, logic-driven cognitive computing methods enhance human decision-making capabilities and offer the possibility to analyse types of uncertainty that neither the human mind nor machine learning can offer alone. From a different perspective, (logic-driven) cognitive computing methods are more suitable for supporting decisions typically faced by mid- to top-level managers. Machine learning methods are better suited for decisions typically faced by people working from mid-management to the shop floor level. The reason for this lies in the different availability of data. Individuals working from mid-management to shop floor level can typically rely on statistically relevant datasets to make decisions. On the other hand, mid- to top-managers must consider variables that are not statistically relevant, as they may not be measured or recorded, and therefore cannot rely solely on machine learning methods and algorithms to support their strategic decisions.

2.5 Motivation

Considering the evolving landscape surrounding risk assessment methodologies and the increasing complexity of modern systems, it is evident that there is still ample room for development and innovation. The integration of AI presents a promising avenue for addressing these challenges and unlocking new opportunities. In this context, the authors seek to highlight the potential benefits of using a logic-driven methodology, particularly in systems characterized by high uncertainty and limited historical data. To that end, authors have selected the HoRAM method for all the potential benefits and remarkable results achievable with it with respect to the other methods analysed and currently available in the literature. HoRAM is a quantitative simulation-based approach driven by logic. It leverages both simulation techniques and logic-based artificial intelligence to analyse and assess risks in complex systems.

The aim of the work was to assess and demonstrate the suitability of the HoRAM method in supporting strategic decision-making processes also under highly uncertain conditions. By means of a practical use case, the authors illustrate the potential of the HoRAM method and its capacity to enhance decision-making in complex and dynamic environments.

3. Methodology

This section explains the reasons for the methodological choice. The use case developed was characterized by data scarcity and high uncertainty in the production process. Furthermore, the main goal of the use case was to support the top management of the charity organization in making a strategic decision. The HoRAM method is logic-driven and allows for the consideration of variables that are not measured or measurable. Therefore, it was a potential candidate. Additionally, it has demonstrated its adequacy in analysing risks of two radically different problems with data scarcity and high uncertainty (Ciotola et al., 2021; Vimercati et al., 2021). Another important aspect that distinguishes HoRAM is the ability to consider both pure and speculative risks. The former only accounts for occurrences associated with negative impacts, while the latter can account for occurrences that can generate positive impacts as well. This distinctive feature allows analysts to perform risk assessments in line with the ISO 31000 standard, which defines risk as the "uncertainty on objectives" rather than the "uncertainty of possible negative occurrences on objectives".

Technically, HoRAM respects the three coherence principles and can generate a complete universe. This capability has three benefits. First, it enables the analyst(s) to calibrate the probability assignments with the identified anchor points. Second, it allows the analyst(s) to compare the previsional results with the empirical evidence or the design intent. Third, it enables verification of the efficiency of envisaged solutions to mitigate the risk. Another fundamental aspect that makes HoRAM interesting to apply is that it was built to assess risks, not just probabilities. HoRAM forces analysts to consider both probabilities and impacts and allows to identify critical variables prioritized based on their contribution to overall risk. This feature enables analysts to identify mitigation solutions based on the variables that contribute the most to total risk, rather than relying on heuristics.

In the analysis of the process, HoRAM allows non-experts to be involved as it produces scenarios in the form of readable stori

scenario management is made easy thanks to logical selections. This feature enables both the extraction of subsets of scenarios (from the complete universe) which adhere to specific logical conditions and verify their stochastic consistency with the experience of knowledge owners or the desired intents of decision-makers.

The HoRAM methodology divides the analysis into three steps: system characterisation, risk level identification, and risk treatment. Figure 5 provides an overview of the three steps and the associated tasks.

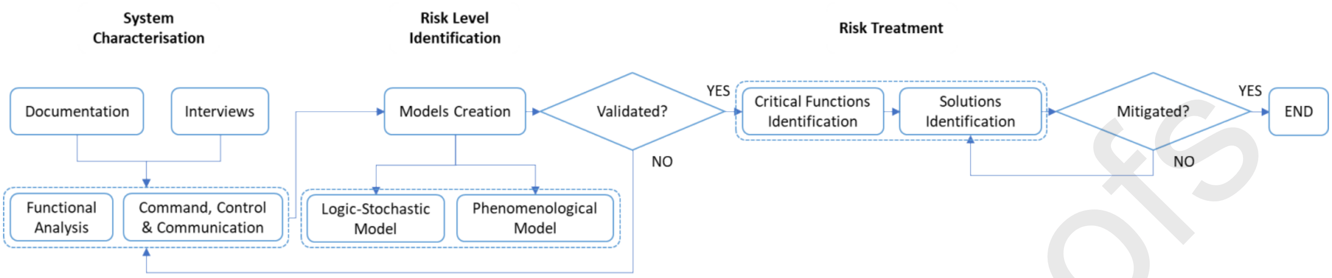

Figure 5 – Overview of the main steps required by HoRAM

The system characterisation requires the analyst(s) to perform the functional analysis of the decision and clarify the organisational aspects through the command, control, and communication diagram. To perform these analyses, the analyst(s) use the available documentation and complement it with interviews of the process and risk owners. The quality manual, which explains the production processes and associated procedures, is typically studied for a production system. The functional analysis is used to represent business processes and associated activities in a schematic way. It is created using the GANTT chart representation, which allows for the representation of variables involved at different levels of abstraction and their correlations in a single picture. The previsional model is created based on the functional analysis and is integrated with the information clarified in the command, control, and communication diagram. The creation of the model using HoRAM follows a discrete-event simulation (DES) approach rather than an agent-based simulation (ABS) (Brailsford, 2014). Conducting interviews during the model creation process is essential for extending the structure and incorporating system behaviour in case of possible deviations. Interviews are also crucial for interpreting data and assigning probability values. The previsional model is validated in two parts using a recursively simulation and learning approach. Once validated, the analyst calculates the risk level of the system, visualises the critical functions, identifies mitigation solutions to incorporate into the model and verifies their efficiency.

4. Case study

The aim of the following sections of the manuscript is to demonstrate the potential of applying a structured risk engineering approach to support decision-making using a simple yet not trivial example. The chosen use case is the recovery of nectarines surplus by food banks from either agricultural production or the market. This use case was chosen due to its complexity, which is not attributable to the productive process but, rather, to the extremely high uncertainty of the operating conditions. This use case builds upon a previous study (Colombo et al., 2021) where a preliminary analysis of nectarines recovery by European Food Banks was conducted.

4.1 The problem

Food banks are a mitigation solution to food poverty and hunger reduction (Karki *et al.*, 2021) directly addressing the 12th Sustainability Development Goal (SDG) set by the United Nations in 2015 “Responsible Production and Consumption” and indirectly contributing to SDG 2 “Zero Hunger”, SDG 3 “Good Health and Well-Being”, and SDG 13 “Climate Action”. The chosen use case, although simple in terms of production process, was selected due to its numerous unconventional uncertainties.

The first is the raw material used in the process. While most production processes have uncertainty in the procurement of raw materials required for the production, they can generally assume that there will be raw materials available for processing. The uncertainty lies in the price. In other words, the raw materials can be sourced and purchased on the market. However, this perspective does not apply to a food bank. Raw materials cannot be taken for granted as there may be seasons where production is scarce or consumption is high, making it difficult to guarantee an excess to be recovered and a production to be guaranteed by the food bank. Another unconventional uncertainty is the workforce. In contrast to a company, where the workforce is relatively stable and can be planned according to production needs and available resources, a food bank cannot rely on a consistent pool of volunteers. This is particularly challenging when it comes to recovering nectarines, as this activity must be carried out during the two-

tries where nectarines are produced. Linked to this aspect is the availability of competencies. Companies can recruit the necessary competencies from the market and, if not possible, they can invest in training to develop the required skills. However, food banks cannot do the same as they must rely on availability of volunteers at the time they are needed, making competencies planning an extremely challenging task. The time for volunteering is easily substitutable, which further complicates the situation. Another uncertainty faced by food banks is the availability of storage space and refrigeration capabilities. This is particularly challenging due to the limited economic resources available to these charity organisations. It is important to note that this uncertainty is closely linked to the availability of raw materials. Companies should plan their need for warehouse space and refrigeration based on their estimated production capabilities and the procurement of raw materials. In contrast, food banks face a unique challenge as they cannot predict the type or amount of raw materials they will receive. Therefore, sizing the warehouse and refrigeration needs is not just an economic problem, but also a production problem.

These uncertainties are inherent in the production nature of food banks. However, food banks, like all other charitable organisations, face a significant constraint in their need to aggregate as many people as possible to fulfil their societal role, which contradicts the scarcity of human resources. Therefore, the designer must create a new process that increases the process mechanisation, while maintaining a low level of automation to ensure a high number of people are required to operate it. The requirement contradicts the automation concept which tends to promote people to higher supervisory positions that require higher education profiles. However, this process would not be sustainable for food banks due to the high turnover of volunteers and the significant training demand it would entail. Therefore, the process must be more mechanised than automated.

4.2 The decision-making problem at hand

To improve the recovery and shelf life of nectarines, a possible solution would be to incorporate a basic food processing step into the standard food bank business process. Figure 6 illustrates the use case.

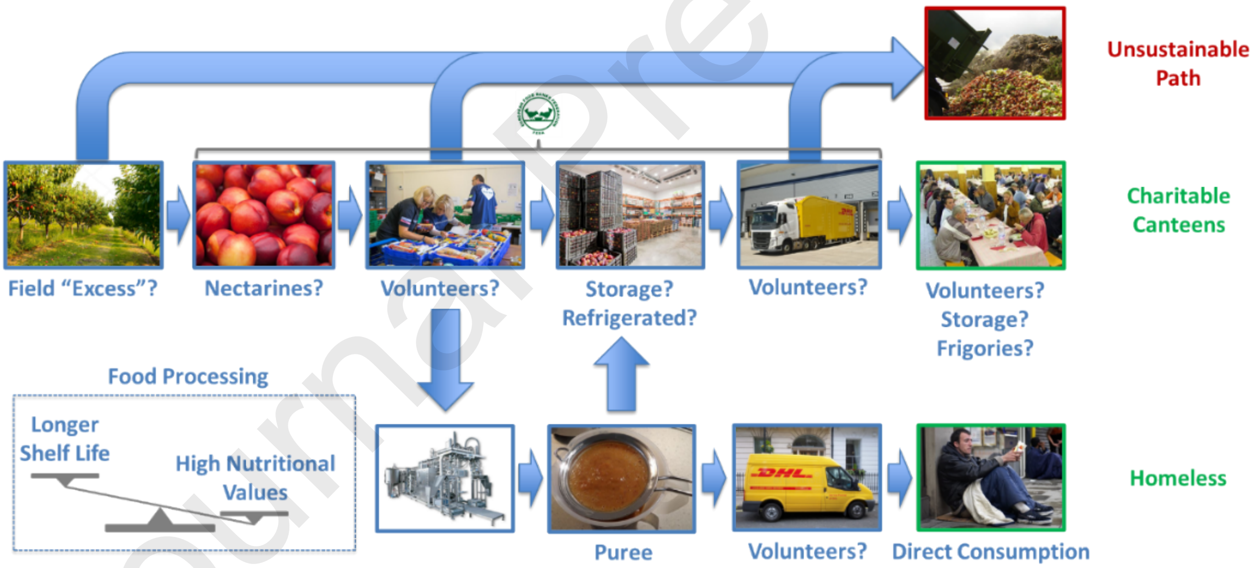

Figure 6 – Use case of nectarines recovery

The initial waste occurs in the field, as any excess produced that is not donated to food banks is discarded. However, even if peaches are donated, if there are not enough volunteers at the food bank to select and distribute them, a portion will still be wasted. This is where simple food processing steps can be implemented to make the overall process more sustainable, by transforming excess peaches into puree. Food processing can help extend the shelf-life of excess nectarines that cannot be consumed before they expire. This ensures that the excess fruit is not wasted and can be used to help those in need. In any case, peaches can be transformed into puree and distributed to homeless or charitable canteens. However, despite the uncertainties mentioned above, food banks are still faced with additional uncertainties that are not present in a normal production process. This raises doubts about whether investing would reduce the overall risk of wasting nectarines. Therefore, a decision-making opportunity is defined, along with the need to investigate and clarify the uncertainties involved to make a sustainable decision. It should be evident from the preceding discussion that converting a business process into a new one that can handle a degree of uncertainty is a challenging task. The best approach is to adopt a risk-based perspective, which enables the management of both deterministic and uncertain aspects of the problem. It is important to note that the term "risk" is incorrectly associated with negativity when compared to the term opportunity. However, according to the ISO31000 definition, risk is defined as the “effect of u thus restoring its dualistic connotation.

4.2.1. The phenomenon characterisation (Phase 1)

From the outset, it was evident that the process needed to meet several significant requirements, namely 1) it must be straightforward as the workforce consists of volunteers with diverse competencies and, on average, limited education; 2) to maintain the social mission of food banks it is important to avoid excessive automation in the processing of nectarines and to keep the highest number of volunteers involved in the process; 3) the processing system should be designed to function with small quantities of raw materials, without requiring a minimum amount to operate; 4) the process must be flexible enough to allow food banks to use it with raw materials other than nectarines, such as tomatoes or apples, to expand the range of food recoverable food; 5) the process should not require high operational costs, as food banks can more easily find donations, even significant ones, for purchasing equipment rather than covering operational costs. In other words, the project should prioritise CAPEX and keep OPEX as low as possible.

In addition to the constraints related to food banks, it is important to consider the needs of the recipients, particularly the nutritional value of the processed products. To assess this aspect, it was used the nutritional nutrient database provided by the U.S. Department of Agriculture (2011) to extract information about nectarines. The summary is presented in Table 2.

Table 2: Nutritional values of possible transformation alternatives (USDA, 2011)

Product	Shelf Life	Calories [kcal]	Water [g]	Carbs [g]	Proteins [g]	Lipids [mg]	Vitamin A [mg]	Vitamin C [mg]	Calcium [mg]	Iron [mg]	Potassium [mg]
Sliced Fruit	5 days @ 5°C or 6-9 months frozen	39	88.87	8.7	0.8	5	0.1	6.6	6	0.25	190
Fruit Juice	12-18 months @ room T	54	85.64	13.9	0.27	-	0.08	5.3	5	0.19	40
Puree	24 months frozen	42.6	-	10.5	0.8	-	0.3	8	8	0.22	40
Light Jam	24 months @ room T	117	-	12.6	0.4	3	0.03	8.8	20	0.49	77
Dehydrated Fruit	6-12 months @ room T	357	3	8.8	0.48	9	0.05	5	62	0.25	122
Canned Fruit	12-18 months @ room T	72	80.62	14.9	0.5	-	0.11	3.6	6	0.27	128

When transforming a raw material, it is important to consider the most valuable nutrients, such as vitamins, iron and potassium. Ther[illegible]s of education and in need, the number of calories should be the first aspect to consider from a nutritional standpoint. The reason for this is that the recipients might not be able to accurately assess the risks associated with consuming a large amount of highly concentrated processed food products. Therefore, the closest alternative to fresh sliced fruit is puree. Despite being a processed product, it contains a relatively low amount of carbohydrates and maintains a similar protein level of the fresh product although lipids may be entirely degraded. It was then decided to verify the transformation of fresh nectarines into puree. The puree also satisfies the design requirement of being easy to consume, as it is typically packed in small, flexible aluminium pans, making distribution by food banks easier. Figure 7 illustrates a simplified schematization of the process that requires verification of its efficiency in terms of nectarines recovery through risk analysis.

Figure 7 – Schematization of the process line to produce nectarines' puree

The puree of the nectarines, as well as that of most other stone fruits, is produced using ripe fruits that are washed and sorted by operators. The raw materials are then sent to a destoning machine and a pulper. Once the nectarines are crushed, the pulp is cooked and sterilized. It is important to note that the cooking and the sterilisation processes, typically performed in one step, are kept separated to allow for greater plant flexibility.
The puree of nectarines is usually supplied in a sterilised form after undergoing high-temperature treatment. It is commonly packed in drums, bags-in-boxes, or delivered in single-portion packaging (Groenewald et al., 2009).

4.2.2. The risk level and profile identification (Phase 2)

According to the HoRAM scheme (Colombo, 2019), the decision-making problem is modelled as a progressive sequence of random events. These events are derived from the functional analysis and the Command, Control and Communication (C3) schematisation that the analyst produces to aid in understanding the phenomenon and support the creation of the model. Please note that the functional analysis and the command, control and communication schematisation are not included in this manuscript.

To facilitate the calculation of probability values and avoid ambiguity, each random event must be formulated clearly so that the hypothetic gambler has no doubts about what they are betting on. The random variables derived from Phase 1 should be only the elective ones (i.e., those that matters) and described according to the Artificial Logic Bayesian Algorithm (ALBA) syntax of the HoRAM method. Figure 8 shows an excerpt of the overall logic-stochastic model, which includes 123 variables.

The purpose of the model is to analyse both the process currently in place and the modified one including the production of the puree, which is made up of all the distinct phases shown in figure 6 and 7 of the previous paragraph. It includes fresh fruit distribution, which involves the fresh fruit recovery, washing and sorting, packaging and distribution steps, as well as a mixed process. The two methods of treating nectarines can be analysed independently, i.e. fresh fruit distribution, puree production, or a combination of both. External conditions can alter the preference for one alternative over another. For example, if the amount of fruit recovered is below the minimum required for puree production, the process will be directed towards fresh fruit distribution only.

The logic-stochastic model is used to generate the universe of scenarios through the Klarisk® webapp. As a result, the software proc [illegible] ories ensure transparency in the simulation process, which is not possible with other computational methods such as the Monte Carlo or the Neural Networks. Traditional methods require interpretation of stochastic curves to verify the results, making it difficult to verify the consistency with represented phenomenon. HoRAM provides readable scenarios (in natural language) for risk and stochastic curves enabling transparent and reliable and transparent semantic checks.

```
:
1 0. 0. 2 2 3 "Analysis starts" "" ""

:
2 0. 0. 3 3 3 "Impacts definition" "" ""

;Exogenous variables

:
3 0. 0. 4 4 3 "Degree of knowledge of BA" "Well known" "Not so well known"
20 11 3e-1 0.

:
4 0. 0. 5 5 3 "Adverse climatic conditions" "Not present" "Present"
20 11 3e-1 0.

:
5 0. 0. 6 6 3 "Degree of ripeness" "" "High"
20 12 3e-1 0.

:
6 0. 0. 7 7 3 "Degree of ripeness" "" "Low"
25 12 0. 0.

:
7 0. 0. 8 8 3 "Cold storage room" "Available" "Not available"
20 12 9e-1 0.

:
8 0. 0. 9 9 3 "Volunteers" "Available" "Not available"
20 24 5e-1 0.
20 32 5e-1 0.
20 42 5e-1 0.
20 59 5e-1 0.
20 60 5e-1 0.
20 86 5e-1 0.
20 87 5e-1 0.

:
9 1. 0. 10 13 3 "Process choice and comparison" "" "Puree"

:
10 0. 0. 11 14 3 "Process choice and comparison" "" "Fresh fruit"
```

Figure 8 – Extract of the logic-stochastic model created (made up of 123 variables)

After a few seconds of simulation using an edgy yet commercial cloud server (or a standard PC, which would take a couple of minutes), it was possible calculated that there are 168.569 possible ways (scenarios) for distributing fresh fruit (figure 9). The “Lowest Probability” (i.e. probability cut) applied is 1E-10 and the calculated “Residual Probability” is a sufficiently conservative 6.44E-06 (i.e. the sum of the probability of all scenarios not analysed). The initial scenario, which represents the design intent (i.e. when everything goes according to the plan both technologically and organisationally), has a probability of occurrence of 21.3% (figure 10).

```
GENERAL PICTURE on the SET of POSSIBLE ALTERNATIVES
====================================================

Model Name              : \UNIVERSE_1626698711991_FreshFruitP\\FreshFruitP.INP
Universe Name           : \UNIVERSE_1626698711991_FreshFruitP\\FreshFruitP.OUT

Starting Level          :    1

Lowest Probability      : 1.0000E-10
Highest Probability     : 1.0000E+00

    Mission Time                :

    Total Nr. of Constituents   :    168569

    Cumulative Probability      : 9.9999355E-01
    Residual Probability        : 6.4470593E-06

    Partition Entropy           : 7.7090270E+00


Simulation STARTED on 2021/07/19 at 14:45:15
Simulation FINISHED on 2021/07/19 at 14:45:33

CPU Time:    00 hrs. : 00 min. : 18 sec.
```

Figure 9 – Extract of the first constituent/scenario for the fresh fruit distribution process

```
      ----------------------------
      CONSTITUENT Ordinal :      1

  1  Analysis starts                                            + V    1.-0.00E+00    1.00E+00
  2  Impacts definition                                         + V    1.-0.00E+00    1.00E+00
  3  Degree of knowledge of BA        Well known                + V    1.-0.00E+00    1.00E+00
  4  Adverse climatic conditions      Not present               + V    1.-0.00E+00    1.00E+00
  5  Degree of ripeness                                         + V    1.-0.00E+00    1.00E+00
  6  Degree of ripeness                                         + V    1.-0.00E+00    1.00E+00
  7  Cold storage room                Available                 + V    1.-0.00E+00    1.00E+00
  8  Volunteers                       Available                 + V    1.-0.00E+00    1.00E+00
  9  Process choice and comparison                              + V    1.-0.00E+00    1.00E+00
 10  Process choice and comparison    Fresh fruit               - V       1.00E+00    1.00E+00
 ...                                  ...                                 ...
 41  Number of operators packaging    Adequate                  +      1.-1.00E-01    3.58E-01
 42  Packaging for distribution       On time                   +      1.-5.00E-02    3.40E-01
 43  Fruit packaging hygiene standard Respected                 +      1.-5.00E-04    3.40E-01
 48  HSE implications fruit distrib.  No HSE consequences       +      1.-1.00E-04    3.40E-01
100  Means of transport distribution  Available                 +      1.-5.00E-03    3.38E-01
101  Truck driver distribution        Available                 +      1.-5.00E-02    3.21E-01
102  Forklift loading distribution    Available                 +      1.-5.00E-04    3.21E-01
103  Forklift loading operator        Available                 +      1.-3.00E-01    2.25E-01
104  Transportation accident distrib. Not involved              +      1.-1.00E-04    2.25E-01
109  Distribution                     On time                   +      1.-5.00E-02    2.13E-01
208  Process nutritional values       Respected                 - V       1.00E+00    2.13E-01
213  Process waste                    Not wasted                - V       1.00E+00    2.13E-01
300  Fruit delivery                   As expected               + V    1.-0.00E+00    2.13E-01

                              PROBABILITY equal to  :  2.13E-01
```

Figure 10 – Extract of the overall numerical results of the simulation for the fresh fruit distribution process

The first scenario is a subset of the sub-universe consisting of all scenarios that conclude positively despite any "natural", unavoidable failures, whether they are human, organisational, or technological in nature, that the system experiences during execution. To determine the probability of the system concluding as expected (i.e., without wasted nectarines) despite the failures encountered, it is necessary to add up all the scenarios that ended positively. To have this information is necessary to easily man not properly supported by available tools and technologies. They support neither the top-down approach — the breaking down of a scenario into executable and assessable component scenarios at various levels of abstraction; nor the bottom-up approach — the combining of small scenarios into the development of a high-level scenario that represents a complex set of problems". In this respect, HoRAM enables analysts to efficiently manage scenarios by selecting the logical conditions that must be met to derive satisfied to derive the specific event of interest, regardless of the level of abstraction. For instance, an event of interest could be the subset of scenarios that conclude positively, i.e. meaning without wasting nectarines, despite an unavoidable delay in unloading the truck due to the absence of the forklift operator. The forklift operator is one of the most highly skilled individuals required to operate the food bank process. In practice a logical selection matrix is used to select each variable in the model in all possible states. This methodological feature is crucial as it allows the analyst to calculate the probability associated with events of interest for the decision at hand through logical conditions. This provides different perspectives and levels of abstraction for the decision-making process. Table 3 presents the probability values calculated for 10 events (i.e. 10 logical selections) of interest for fresh fruit distribution.

The fresh fruit distribution system has a high probability of wasting nectarines throughout the food recovery process. Specifically, there is 72.6% probability of not achieving the expected outcome, and only a 27.4% probability of fully recovering the fruit. Further, there is a 33.3% probability of total fruit waste.

Table 3: Selection of events (meaningful variables) for the fresh fruit distribution process

Fresh Fruit Process			
As expected	27.4%		
Not as Expected	72.6%		
Food Totally Recovered	27.4%		
Food Partly Wasted	39.3%		
Food Totally Wasted	33.3%		
HSE Implications	2.11E-4	Minor HSE	1.16E-3
		Major HSE	7.33E-5
Hygiene standards not respected	4.99E-4	With law issues	2.49E-4

To move from a stochastic to a risk-based perspective, given that risk is the product between the probability of occurrence of the ever it is possible to calculate the risk associated with the process. The phenomenological model can be either a direct assignment of impact values to each variable producing an impact, or an algorithm that calculates the impact value according to the phenomenon being represented. In the latter case, the algorithm describing the phenomenology takes the form of a dynamic process simulator (i.e. a mathematical simulation of the process). In any case, it is the logic-stochastic side of the model that drives the computation, as it prompts the phenomenological side. As a first step, the direct assignment of relative weights between 0 and 100 was chosen as the impact model. Table 4 shows the choices made.

Table 4: Impact reference values for the example at stake

Variables	**Impact value**
Major HSE	100
Delay not recoverable of the fresh fruit distribution	90
Product loss during the transportation for the distribution	80
Major law issues due to scarce hygiene	70
Fruit waste during the processing	60
Fruit partial loss during the transportation for the processing	40
Minor law issues due to scarce hygiene	30
Fruit damage during the transportation for the processing	20
Puree distribution delay	5

As can be noticed, the impacts considered are of different nature. Firstly, delays that have an indirect effect on the deterioration of the fruit. For example, a delay in unloading the nectarines from the lorry will have a negative effect on the texture of nectarines, contributing to their loss of quality and the erosion of valuable shelf life. In addition, the direct waste of fruit in the intermediate stages of the process was considered, as well as those affecting the workers and the hygiene of the product (be it the fresh fruit or the puree). It is worth noting that it would even have been possible to use economic values for the impacts, since the impact could be seen as any measurable or even unmeasurable number.

The coupling of the two parts of the model (i.e. the logic-stochastic and phenomenological part), allows the calculation of the risk parameters, as well as the curves which, from the HoRAM point pf view, are the well-known risk curve (i.e. the Complementary Cumulative Distribution Function – CCDF), represented in figure 11, and the newly defined risk spectrum (i.e. the Risk Distribution Function – RDF), represented in figure 12.

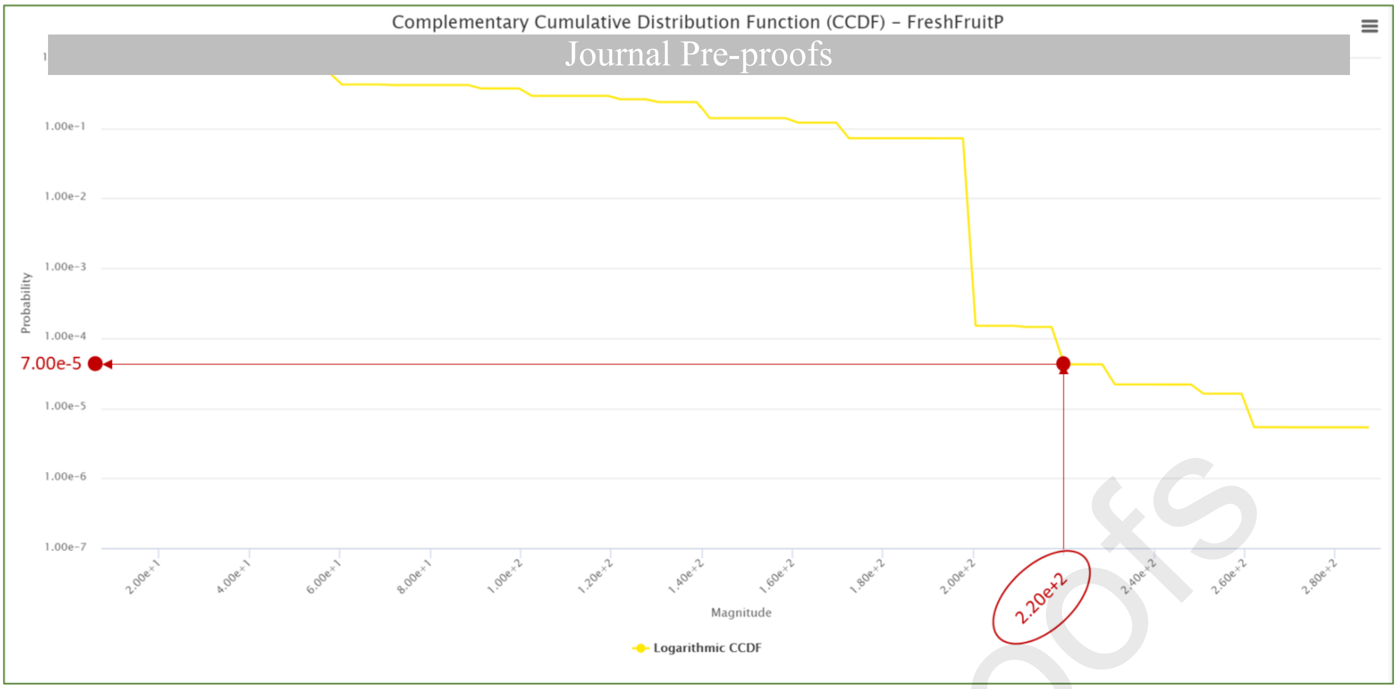

Figure 11 – Risk curve (CCDF) for the fresh fruit distribution process

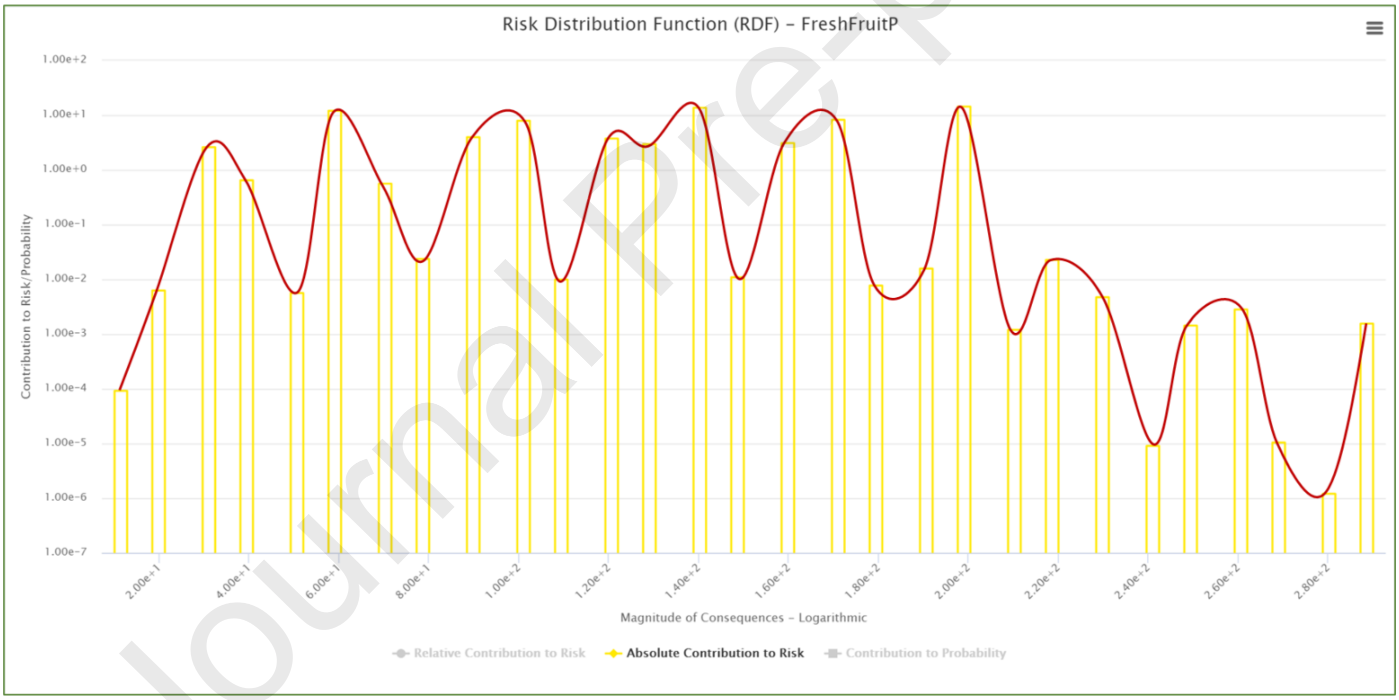

Figure 12 – Risk spectrum (RDF) for the fresh fruit distribution process

The risk curve (CCDF) is the complementary of the Cumulative Distribution Function (CDF) $F_x(x)$ and is defined by equation (1) for a real-valued random variable and by equation (2) for a continuous variable.

$$\overline{F_x}(x) = P(X > x) = 1 - F_x(x) \tag{1}$$

$$\overline{F_x}(x) = \int_x^{+\infty} f_x(t)dt \tag{2}$$

From the HoRAM point of view, it is considered much more useful to identify the probability value of exceeding a chosen impact value (as the complementary does) than the probability of being lower or equal to it (as the cumulative does instead). From a decision-making point of view the CCDF serves to understand the risk level. In figure 11 the value 220 in the abscissa (impact) has a probability of being exceeded is equal to 7.00e-5 (ordinate).

The risk Distribution Function (RDF), i.e. the risk spectrum, divides the impact range into 100 homogenous classes according to equation (3).

$$Class = \frac{C_{Max} - C_{Min}}{100} \qquad (3)$$

The generated scenarios are clustered into 100 classes according to their impact value. The higher the class the higher the number of scenarios contained in the class and, consequently, the higher the risk and probability contribution of the class. Although there are no good or bad risk spectrums *per se*, the rule of thumb is that the more scenarios are concentrated to the left, the better. In terms of spectrum composition, lower impact risk classes should be taller and more numerous than high impact risk classes, which should be shorter and fewer in number. For the case analysed (figure 12), with the exception of the up and down behaviour (red line), it is evident that the risk classes tend to be homogeneously distributed along the impact range, as they only begin to decrease in height only at high impact values and, moreover, they do not tend to become thinner as the impact value increases. This gives the decision maker the immediate message that the risk associated with processing fresh fruit tends to be high. This result should not be overlooked when considering the specifics of the food bank process in terms of availability of raw materials, labour, and skills. Tables 5 shows a summary of the risk values.

Table 5: Risk parameters for the fresh fruit distribution process

Fresh Fruit Process			
Max Loss	**Min Loss**	**Expected Loss**	**Risk**
290.00	10.00	101.65	73.79

In addition to the values shown in Table 5, HoRAM calculates for each class the risk, its contribution to the total risk (in percentage), the probability and the average impact (details are not shown as not considered particularly useful for the purpose of the manuscript).

As a final step in the analysis, HoRAM allows the calculation of the Critical Functions List (CFL), which is the list of critical functions prioritised by their contribution to the overall risk. Table 6 shows the results.

Table 6: Critical functions for the distribution of fresh fruit

Fresh fruit process

Prio				
1	Forklift operator unloading phase	Not available	45.0%	45.0%
2	Sorting operations	Delayed	20.5%	65.5%
3	Forklift operator loading phase	Not available	10.1%	75.6%
4	Unloading operations	Delayed	9.6%	85.2%
5	Packaging for distribution	Delayed	8.0%	93.2%

The CFL is a fundamental piece of information both for the identification of mitigation actions and for risk management, as it tells decision-makers which are the most important variables among all those taken into account in the model in terms of risk contribution. This is an essential information to avoid wasting the limited and scarce resources available (even for risk mitigation). The first aspect that emerges from the CFL is that the critical functions for the distribution of fresh fruit can be traced back to the availability of volunteers, be they specialised, such as forklift drivers, or non-specialised such as for sorting and packaging. This result is in line with the above-mentioned vocation of the food bank as a social aggregator (i.e. to make the process as manual as possible).

More specifically, the forklift driver plays a crucial role, as s/he contributes to directly causing more than 50% of the total risk (precisely 45% + 10.1% = 55.1%). Furthermore, if the direct and indirect effects of the forklift operator are taken into account, the risk caused by this function increases to almost 65% (45% + 10.1% + 9.6% = 64.7%), since the unloading operations are necessarily delayed, either because they are postponed to a later time or because the available volunteers are asked to unload the fruit manually from the lorry.

4.2.3. The risk treatment (Phase 3)

In the spirit of ISO31000, once the risk associated with the nominal condition (be it a design intent or the current operating conditions of a running process) has been defined, the risk needs be mitigated (i.e. engineered). In other words, its negative potential should be reduced by introducing preventive measures (which reduce the probability of occurrence), protective measures (which reduce the impact), or a mixture of both. Typically, risk modelling is the weakest part of the risk engineering process. This is because analysts tend either to assume that the beneficial effects of the identified mitigation solution(s) are also positive even at system level (and not just "locally" where the solution has its direct and apparently obvious beneficial effects) or assess their impact heuristically. In other words, the risk analysis for the new configuration (i.e. the one with the solution implemented) is usually not performed. However, this is a very risky approach, as the complexity of today's systems is so high that the heuristic anticipation of the possible effects of the solution(s) on the behaviour of the overall system being analysed goes far beyond human cognitive capabilities (Dekker, 2014). It may then happen that the envisaged solutions are not only neutral with respect to the negative potential of the overall risk, i.e. do not reduce it, but even increase it somewhere, thus leading the decision-making process in the wrong direction. In HoRAM terms, the risk could worsen its profile by encouraging the shift of scenarios from lower impact classes to higher impact classes. And this could happen even if the numerical value of the risk remains unchanged; a condition that is very risky because it is deeply misleading.

In HoRAM's view this condition would never occur, since the quality of the envisaged solution(s) must be methodologically verified at least by comparing both the risk curve and the risk spectrum, as well as the calculated risk parameters. This step is carried out by introducing the envisaged solutions into model (both for the logic-stochastic side and the phenomenological side).

In the case of nectarine recovery, the risk reduction solution to be tested was the production of fruit puree. As a first step, only the production of fruit puree was calculated, which is considered an extreme measure as it tends to highly automate the system (and not simply mechanise it), thus removing the human from the loop.

Using the same probability cut of 1E-10 as for the fresh fruit process, after a simulation time of just 2 minutes, it was possible to determine that the universe is made up of 627,137 possible scenarios (i.e. almost 4 times the one for the fresh fruit distribution) with and a residual probability of 3.758E-05 (figure 13).

As can be seen from the first nominal scenario (figure 14), the “perfect” production of fruit puree has a probability of 19.9%, which is sli any conclusions, as the first scenario is only one of the many that have the same positive outcome. However, from a risk engineering point of view, this information is valuable as it indicates that the process is more complicated.

Table 7 shows the results of the same 10 scenarios extracted for the fresh fruit.

It is immediately evident that the probability of achieving the expected outcome and probability of not achieving the expected outcome are literally reversed when compared to that of the fresh fruit distribution. Furthermore, the probability of complete recovery of nectarines increases from a mild 27.4% for fresh fruit to a much more generous 76.9% for puree only. Even the total waste of nectarines decreases from 33.3% to 0.1%. The only negative parameter that has almost doubled its value, from 4.99E-04 to 9.93E-04, is the compliance with hygiene standards. Even this result seems to be consistent with the fact that a processing plant for fruit puree, however simple it may be, tends to push the whole system towards the generation of hygienic problems, not least because it needs to be kept clean and maintained (which is much more complicated, time-consuming, and skill-intensive than the simple handling and selection of fresh fruit).

```
                 ANALYSIS of "\UNIVERSE_1626699371048_PureeP\\PureeP

GENERAL PICTURE on the SET of POSSIBLE ALTERNATIVES
===================================================

Model Name               : \UNIVERSE_1626699371048_PureeP\\PureeP.INP
Universe Name            : \UNIVERSE_1626699371048_PureeP\\PureeP.OUT

Starting Level           :    1

Lowest Probability       : 1.0000E-10
Highest Probability      : 1.0000E+00

    Mission Time                :

    Total Nr. of Constituents   :     627137

    Cumulative Probability      : 9.9996241E-01
    Residual Probability        : 3.7589065E-05

    Partition Entropy           : 7.6869727E+00


Simulation STARTED on 2021/07/19 at 14:56:14
Simulation FINISHED on 2021/07/19 at 14:58:21

CPU Time:    00 hrs. : 02 min. : 07 sec.
```

Figure 13 – Overall numerical results of the simulation for the fruit puree processing line

```
  1  Analysis starts                                                  + V    1.-0.00E+00    1.00E+00
  2  Impacts definition                                               + V    1.-0.00E+00    1.00E+00
  3  Degree of knowledge of BA          Well known                    + V    1.-0.00E+00    1.00E+00
  4  Adverse climatic conditions        Not present                   + V    1.-0.00E+00    1.00E+00
  5  Degree of ripeness                                               + V    1.-0.00E+00    1.00E+00
  6  Degree of ripeness                                               + V    1.-0.00E+00    1.00E+00
  7  Cold storage room                  Available                     + V    1.-0.00E+00    1.00E+00
  8  Volunteers                         Available                     + V    1.-0.00E+00    1.00E+00
  9  Process choice and comparison      Puree                         - V       1.00E+00    1.00E+00
 ...                                    ...                                  ...
 31  Number of operators sorting        Adequate                      +      1.-1.50E-01    4.46E-01
 34  Sorting operations                 Efficient                     +      1.-1.00E-02    4.42E-01
 35  Sorting operations                 On time                       +      1.-1.00E-01    3.98E-01
 36  HSE implications sorting           No HSE consequences           +      1.-1.00E-04    3.98E-01
 ...                                    ...                                  ...
100  Means of transport distribution    Available                     +      1.-5.00E-03    3.15E-01
101  Truck driver distribution          Available                     +      1.-5.00E-02    3.00E-01
102  Forklift loading distribution      Available                     +      1.-5.00E-04    2.99E-01
103  Forklift loading operator          Available                     +      1.-3.00E-01    2.10E-01
104  Transportation accident distrib.   Not involved                  +      1.-1.00E-04    2.10E-01
109  Distribution                       On time                       +      1.-5.00E-02    1.99E-01
209  Process nutritional values         Partly respected              - V       1.00E+00    1.99E-01
213  Process waste                      Not wasted                    - V       1.00E+00    1.99E-01
300  Fruit delivery                     As expected                   + V    1.-0.00E+00    1.99E-01

                 PROBABILITY equal to  :  1.99E-01
```

Figure 14 – Extract of the first constituent/scenario for the fruit puree processing line

Table 7: Selection of events (meaningful variables) for the puree production process

Puree Production Process			
As expected	74.6%		
Not as Expected	25.4%		
Food Totally Recovered	76.9%		
Food Partly Wasted	25.2%		
Food Totally Wasted	1.11E-3		
		Minor HSE	1.07E-3
HSE Implications	1.25E-4		

Hygiene standards not respected	9.93E-4	With law issues	4.96E-4

The risk curve and the risk spectrum were then calculated using the same procedure as described above. The results are shown in figure 15 (CCDF) and 16 (RDF).

It should be immediately evident that the spectrum is denser, confirming the perception of a higher complexity of the new system configuration (i.e. puree production). Furthermore, it seems to have a less risky shape, as the higher risk classes are concentrated significantly to the left and, in addition, the more the impact value increases, the shorter they tend to be (i.e. scenarios with high impact are lower than those with low impact). To check the real effect of the solution, the two curves and the two risk spectrums can be compared. Figure 17 and 18 show the results.

As well as confirming the impression that the risk profile (delineated by the spectrum) is less risky, the comparison allows analysts to derive other valuable information. Firstly, the curve shows that the risk level is decreasing, as the green curve is always below the yellow curve. Secondly, it confirms the impression that the spectrum has a less risky shape, as essentially all green risk classes, from medium to high impact values, are shorter than the yellow ones. Thirdly, it is highlighted that the puree production process (green spectrum) by shifting the risk classes to the left, thus eliminating the last 4 risk classes (in yellow) with the highest impact value.

The two situations, reflecting the curves and spectra, are represented numerically in Table 8. It is clear that the risk of producing puree, in all its facets, is much lower. In other words, although the process is more complicated to operate, the risk of wasting nectarines is significantly reduced. Specifically, the total risk is reduced from 73.79 to 27.16 and the expected loss from 101.65 to 38.22 (and even the two extremes are lower).

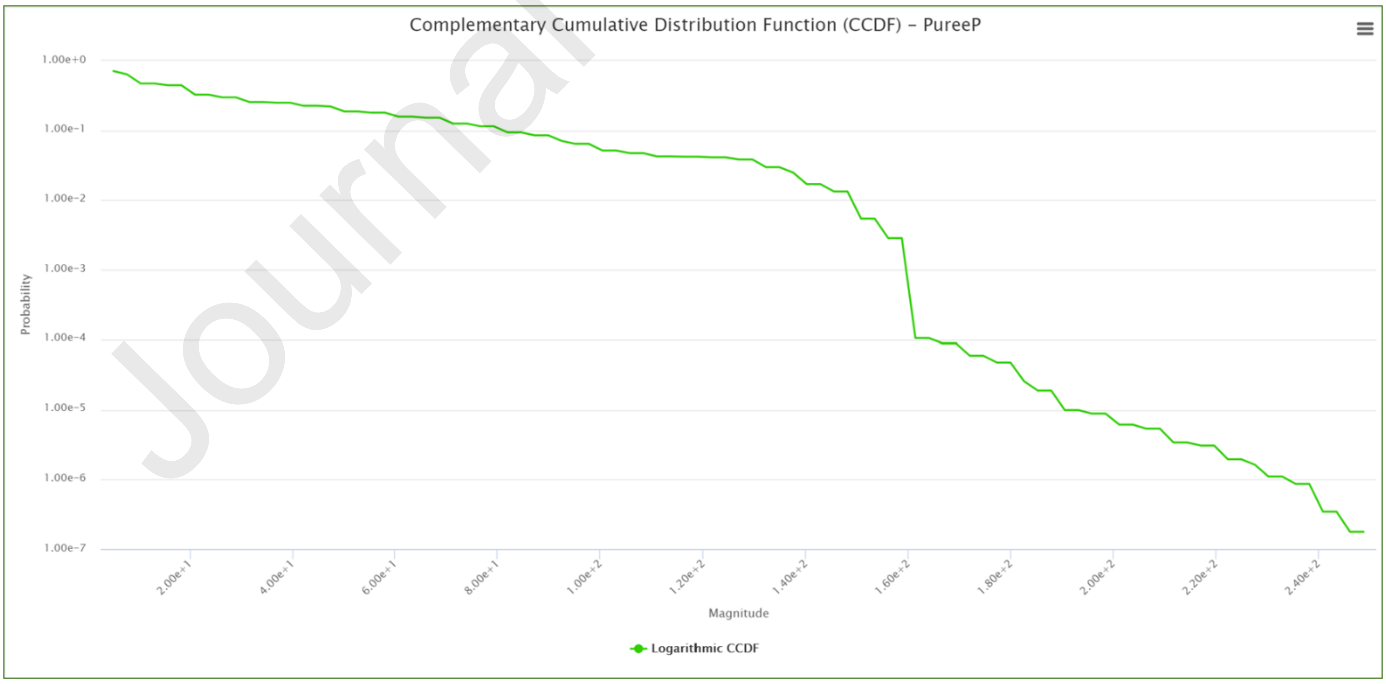

Figure 15 – Risk curve (CCDF) for the fruit pure (only)

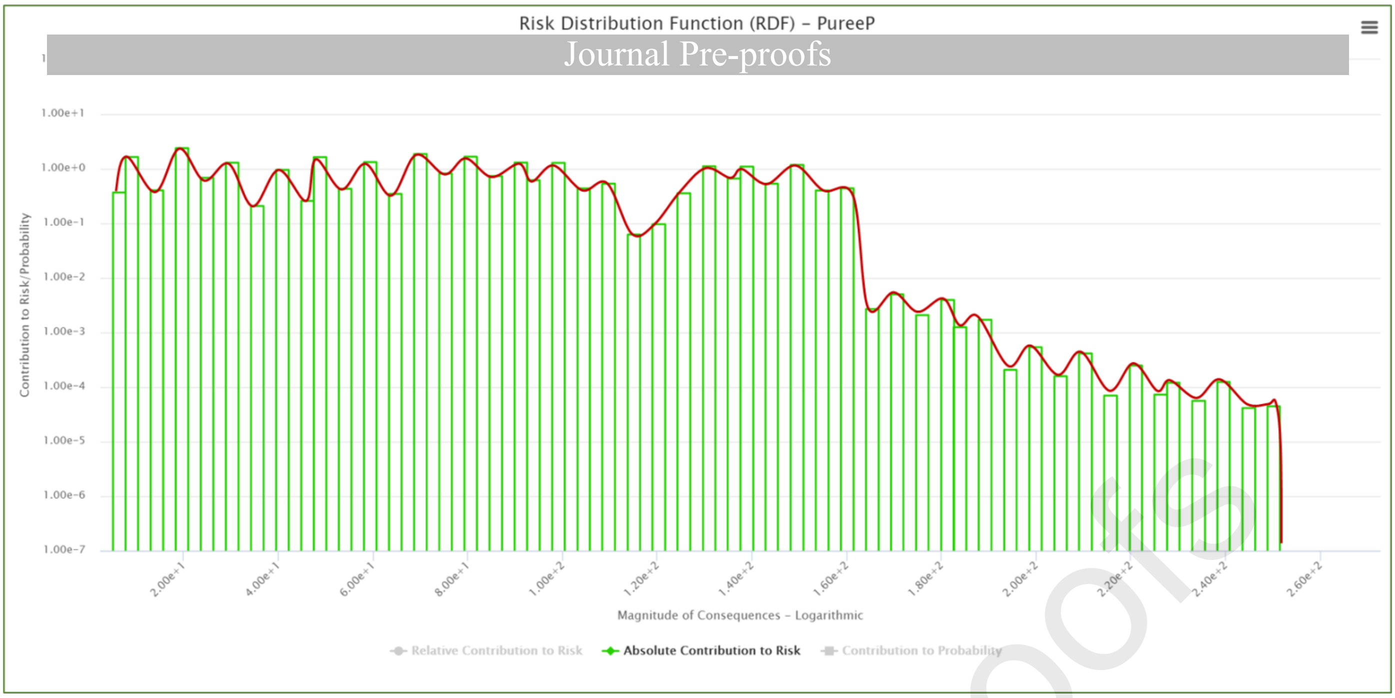

Figure 16 – Risk spectrum (RDF) for the fruit pure (only)

The last step was to calculate the CFL. Table 9 shows the results. The functions that were present in the fresh fruit process (Table 6) but with a different priority are highlighted in blue and the "newcomers", i.e. the functions that were not in the CFL, are highlighted in red. It can be seen that the "loading phase by the forklift operator" has moved from position 3 to position 5, reducing its contribution to the total risk from 10.10% to 3.7%. This behaviour seems to be in accordance with the new phenomenology, since nectarines can be processed into produce puree in the event of a distribution problem, leaving much more time for the loading phase (since the puree has a much longer shelf life).

Overall, in the new configuration, what gains weight are the unloading phase and its operations, meaning that once the nectarines are unloaded from the truck, even if they cannot be distributed fresh, they can be processed to avoid wasting them. Although these results are numerically more than positive and phenomenologically coherent, they do not satisfy the social vocation of the food bank. In other words, a complete switch from fresh fruit to puree would not be the best solution for at least two good reasons: the reduction in nutritional value, as puree is less nutritious than fresh fruit, and the reduction in the number of people needed to operate the process.

The optimal solution would be to integrate, rather than replace, the fresh fruit distribution process with puree production to reduce the risk of nectarines going to waste. Puree production would then be used to avoid wasting nectarines only when full distribution would not be feasible for whatever reason (e.g. lack of volunteers, excess of nectarines…).

As anticipated above, the model was specifically designed to test all these possibilities. Figures 19 and 20 show the results. Using the same probability cut of 1E-10 as for the fresh fruit and the puree processes, after a simulation time of almost 3 minutes (figure 19), it was possible to determine that the universe is made up of 865,143 possible scenarios (i.e., more than 5 times that of the fresh fruit distribution and almost 1.4 times that of the puree), with a residual probability of 5.327E-05 (figure 19). In this case, the first scenario has a probability of occurrence of 17.9% (figure 20), which is slightly lower than for puree production. For a hybrid process, this should not be a surprising result.

It was then possible to extract the same 10 scenarios extracted for the fresh fruit and the puree. Table 10 shows the results.

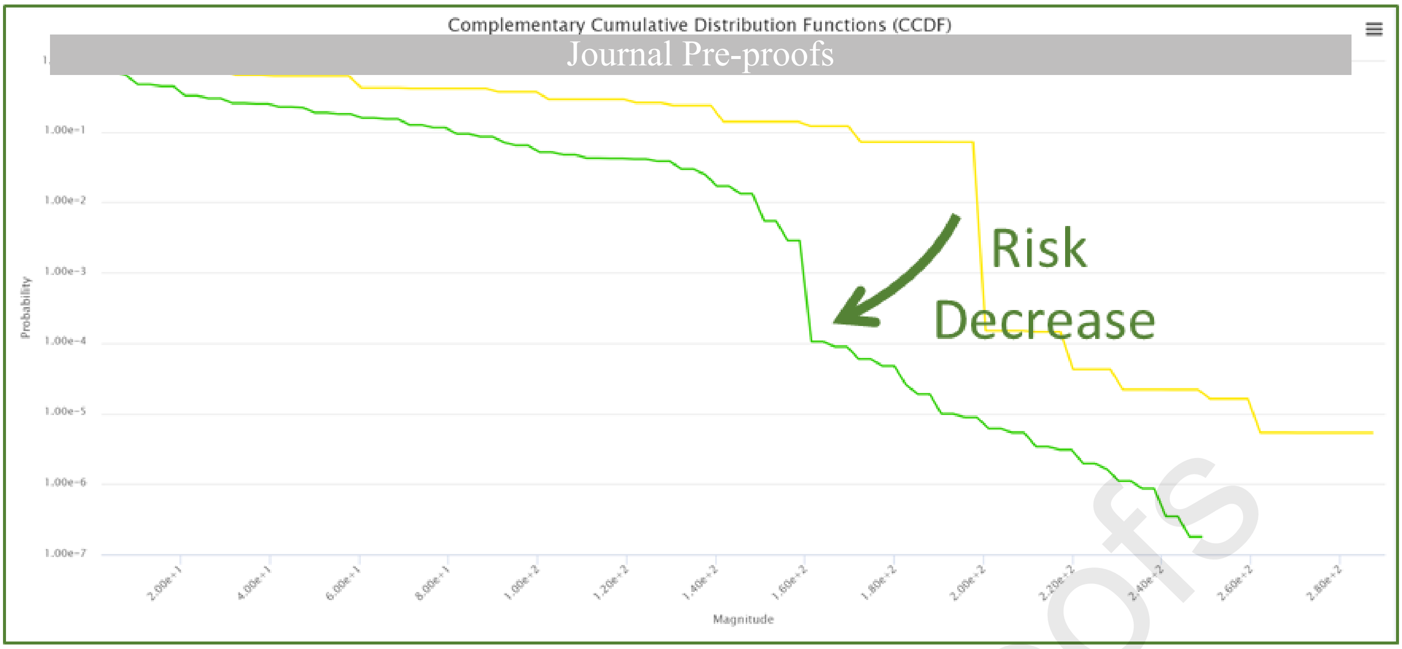

Figure 17 – Risk curve comparison between fresh fruit (yellow) and puree production (green)

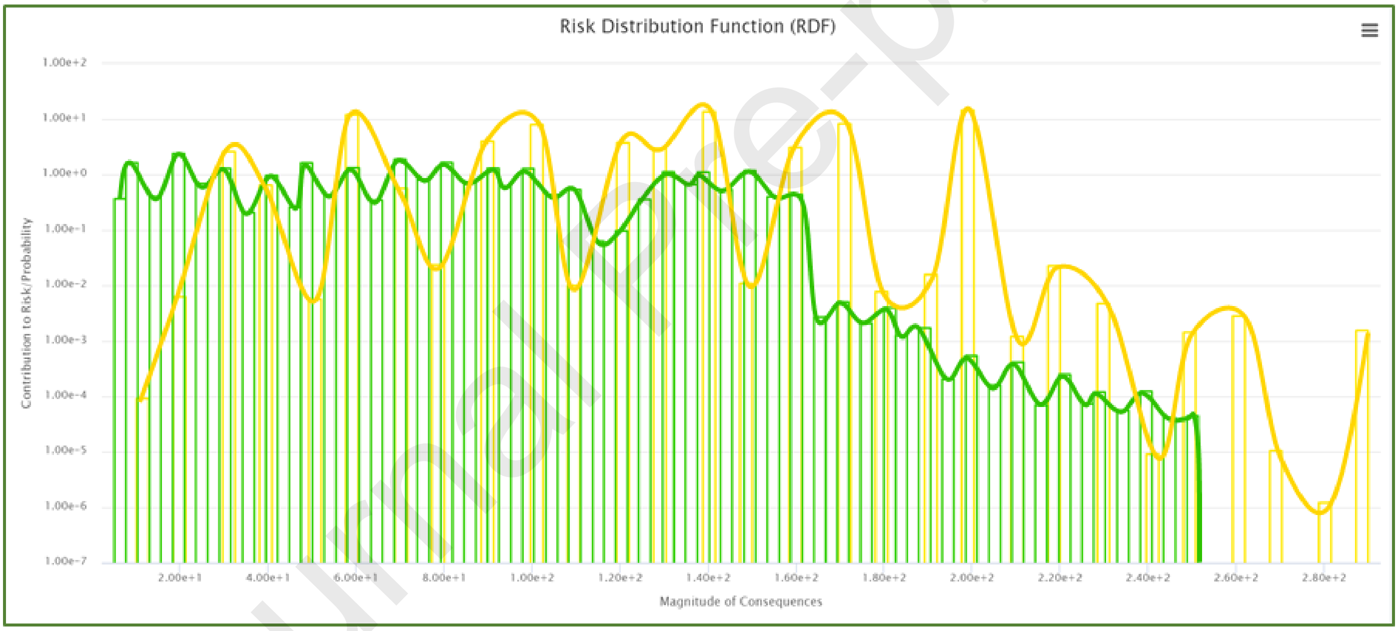

Figure 18 – Risk spectrum comparison between fresh fruit (yellow) and puree production (green)

Table 8: Risk comparison between fresh fruit (left) and puree production (right)

Fresh Fruit Process			
Max Loss	**Min Loss**	**Expected Loss**	**Risk**
290.00	10.00	101.65	73.79

Puree Production Process			
Max Loss	**Min Loss**	**Expected Loss**	**Risk**
270.00	5.00	38.22	27.16

Table 9: CFL for the puree production

Puree production process				
Priority	**Variable Name**		**Risk**	**Cumulative Risk**
1	Forklift operator unloading phase	Not available	46.1%	46.1%
2	Sorting operations	Delayed	29.0%	75.1%
3	Unloading operations	Delayed	10.7%	85.7%
4	Unloading phase	Delayed	5.7%	91.4%
5	Forklift operator loading phase	Not available	3.7%	95.1%

```
ANALYSIS of "\UNIVERSE_1626717135806_FullP\\FullP

GENERAL PICTURE on the SET of POSSIBLE ALTERNATIVES
===================================================

Model Name             : \UNIVERSE_1626717135806_FullP\\FullP.INP
Universe Name          : \UNIVERSE_1626717135806_FullP\\FullP2.OUT

Starting Level         :    1

Lowest Probability     : 1.0000E-10
Highest Probability    : 1.0000E+00

    Mission Time                 :

    Total Nr. of Constituents    :     865143

    Cumulative Probability       : 9.9994673E-01
    Residual Probability         : 5.3273949E-05

    Partition Entropy            : 8.1601678E+00


Simulation STARTED on 2021/07/19 at 19:52:18
Simulation FINISHED on 2021/07/19 at 19:55:18

CPU Time:     00 hrs. : 02 min. : 59 sec.
```

Figure 19 – Overall numerical results of the simulation for the hybrid process

```
     ----------------------------
     CONSTITUENT Ordinal :      1

  1  Analysis starts                                           + V    1.-0.00E+00    1.00E+00
  2  Impacts definition                                        + V    1.-0.00E+00    1.00E+00
  3  Degree of knowledge of BA     Well known                  + V    1.-0.00E+00    1.00E+00
  4  Adverse climatic conditions   Not present                 + V    1.-0.00E+00    1.00E+00
  5  Degree of ripeness                                        + V    1.-0.00E+00    1.00E+00
  6  Degree of ripeness                                        + V    1.-0.00E+00    1.00E+00
  7  Cold storage room             Available                   + V    1.-0.00E+00    1.00E+00
  8  Volunteers                    Available                   + V    1.-0.00E+00    1.00E+00
  9  Process choice and comparison                             + V    1.-0.00E+00    1.00E+00
 10  Process choice and comparison                             + V    1.-0.00E+00    1.00E+00
 11  Fresh fruit flowrate          Higher than minimum requested +    1.-1.00E-01    9.00E-01
 13  Fresh fruit                   To process                  - V       1.00E+00    9.00E-01
...                                ...                                   ...
 85  Packaging line                Working                     +      1.-5.00E-04    3.17E-01
 88  Number of operators packaging Adequate                    +      1.-1.00E-01    2.85E-01
 89  Packaging                     On time                     +      1.-1.00E-04    2.85E-01
 91  Fruit packaging hygiene standard Respected                +      1.-5.00E-04    2.85E-01
 96  HSE implications packaging    No HSE consequences         +      1.-1.00E-05    2.85E-01
100  Means of transport distribution Available                 +      1.-5.00E-03    2.84E-01
101  Truck driver distribution     Available                   +      1.-5.00E-02    2.70E-01
102  Forklift loading distribution Available                   +      1.-5.00E-04    2.69E-01
103  Forklift loading operator     Available                   +      1.-3.00E-01    1.89E-01
104  Transportation accident distrib. Not involved             +      1.-1.00E-04    1.89E-01
109  Distribution                  On time                     +      1.-5.00E-02    1.79E-01
209  Process nutritional values    Partly respected            - V       1.00E+00    1.79E-01
213  Process waste                 Not wasted                  - V       1.00E+00    1.79E-01
300  Fruit delivery                As expected                 + V    1.-0.00E+00    1.79E-01

                              PROBABILITY equal to  :  1.79E-01
```

Figure 20 – Extract of the first constituent/scenario for the hybrid process

Table 10: Selected events for the hybrid process

Full Production Process (puree & fresh fruit)

As e			
Not as Expected	25.5%		
Food Totally Recovered	76.8%		
Food Partly Wasted	25.2%		
Food Totally Wasted	1.27E-3		
		Minor HSE	1.07E-3
HSE Implications	1.24E-4		
		Major HSE	6.71E-5
Hygiene standards not respected	9.91E-4	With law issues	4.95E-4

As it can be seen, the results of the hybrid solution are very much similar in all values to those of the pure production (table 7). To further test the efficiency of the hybrid solution, risk curves and risk spectra were compared. Figures 21 and 22 show the results.

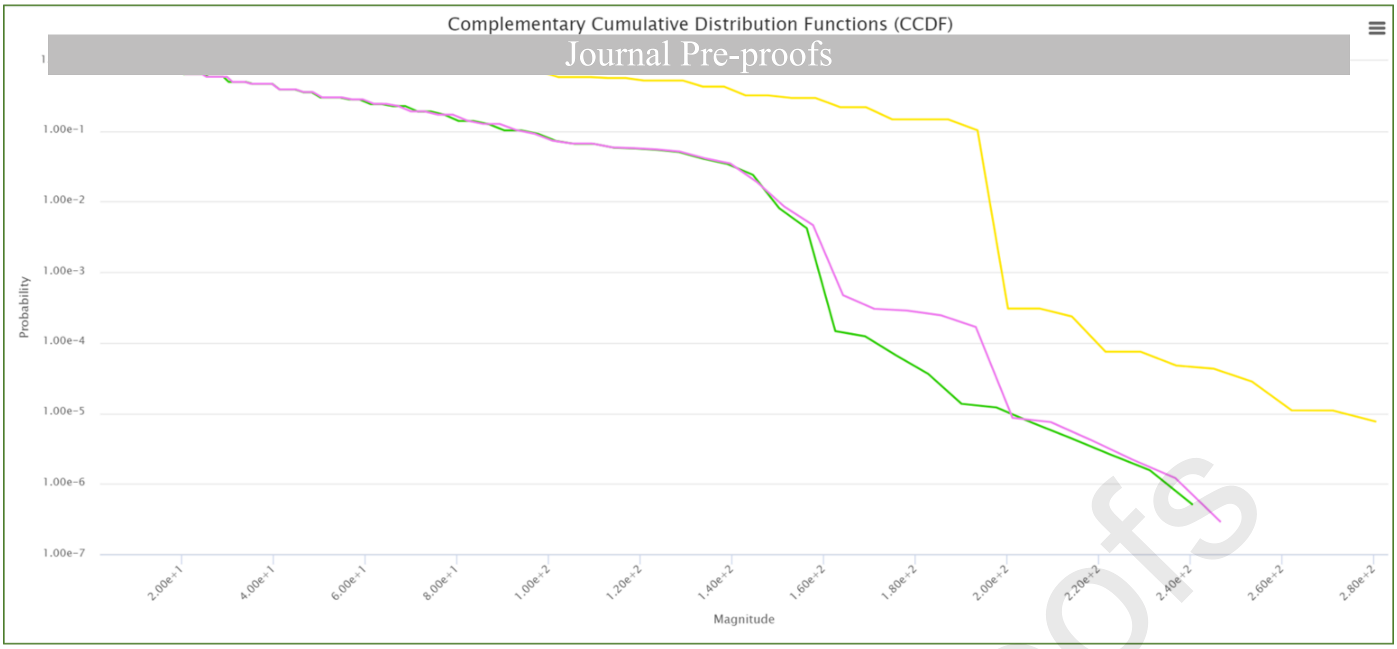

Figure 21 – Risk curves (CCDF) comparison: fresh fruit (yellow), puree production (green), and hybrid process (pink)

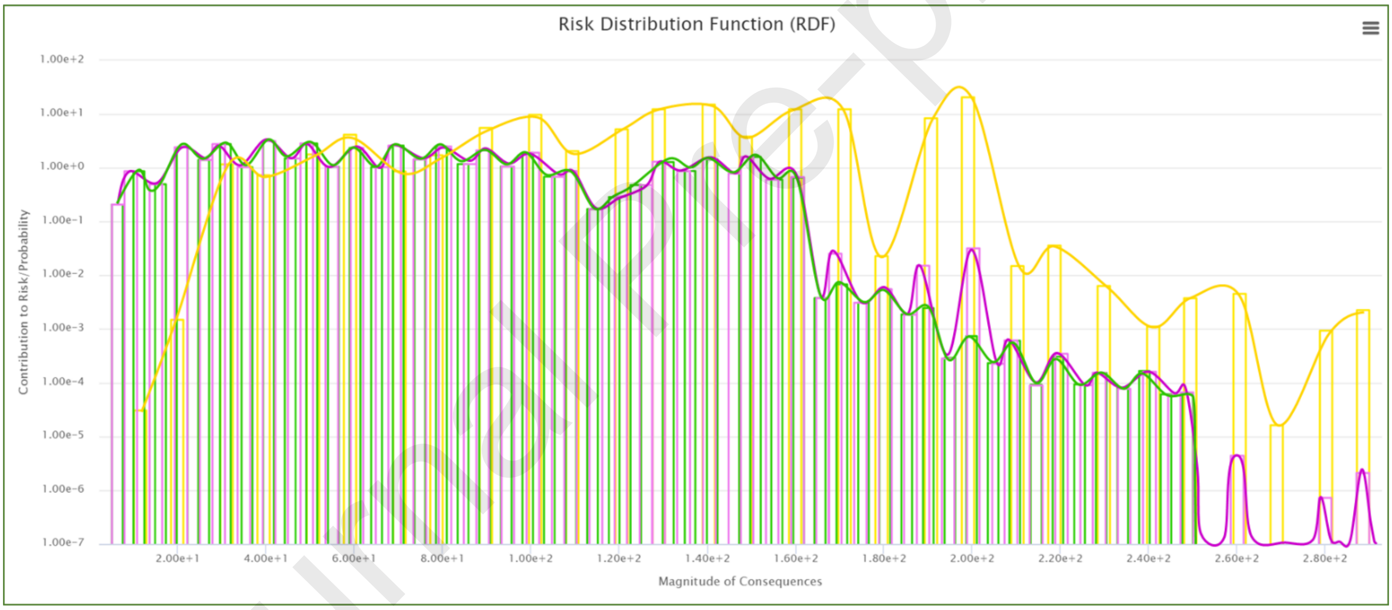

Figure 22 – Risk spectra (RDF) comparison: fresh fruit (yellow), puree production (green), and hybrid process (pink)

It is evident that the hybrid process (pink) has basically the same shape as the puree production (green), with the only exception that it generates two small classes at the highest impact values of the spectrum (extreme right). This means that the hybrid solution can cause more negative consequences than the pure production. This can be seen as the "price to pay" (i.e. risk to take) for increasing the nutritional value and societal impact of the food bank.

The numerical results of the two situations reflecting the curves and spectra of the fresh fruit and the hybrid process are presented in Table 11.

Table 11: Risk comparison between the fresh fruit process and hybrid process

Fresh Fruit Process

Max			
290.00	10.00	101.65	73.79

Full Process			
Max Loss	**Min Loss**	**Expected Loss**	**Risk**
290.00	5.00	38.25	27.19

The only notable aspects are the two extreme values of loss: the maximum loss of 290.00 was inherited from the fresh fruit while the minimum loss of 5.0 was inherited from the puree process. Overall, the hybrid process designed is much less risky than the one currently managed by the food bank.

As a final step, the CFL for the hybrid process were derived, table 12 shows the results. It is evident that there is no difference between the puree process (table 9) and the hybrid process in terms of critical elements/functions (i.e. elements that need to be kept under control or mitigated). The results then show that even the hybrid process (or the full process if one prefers) seems to be a convenient step for the food bank, as it would allow to significantly reduce the risk of wasting nectarines.

Table 12: CFL for the hybrid process

Full production process				
Priority	**Variable Name**		**Risk**	**Cumulative Risk**
1	Forklift operator unloading phase	Not available	46.1%	46.1%
2	Sorting operations	Delayed	29.0%	75.1%
3	Unloading operations	Delayed	10.7%	85.7%
4	Unloading phase	Delayed	5.7%	91.4%
5	Forklift operator loading phase	Not available	3.7%	95.1%

4.2.4. Resilience analysis (Phase 3)

Once the viability of the identified solution has been clarified, it is possible to check whether the system in its new configuration is as resilient as in its original configuration (i.e. hybrid vs. fresh distribution). To this end, two key variables were variated to see their effects: the availability of nectarines and the availability of volunteers.

The shortage of nectarines can be a problem not only when they are in short supply (as the food bank cannot fulfil its social miss

ugh to use the process to make puree. Lack of volunteers is always a problem. Figure 23 shows the results of the simulations.

As can be seen, the modified process, be it the puree process (indicated as “B” – green) or the hybrid one (indicated as “C” – pink), is more resilient than the fresh fruit process (indicated as “A” – yellow), since the variation between the nominal and the stressed states (i.e., the green vs. red, for condition “B”, or the pink vs. red, for condition “C”) is lower than that between the current process (i.e., the distribution of the fresh fruit) and the stressed condition (yellow vs. red – condition “A”). The numerical differences are shown in Table 13. In the stressed condition, the fresh fruit process dramatically reduces its efficiency as the probability of the process running as expected drops from 27.4% to 6.4% (i.e. less than a third of the nominal condition). The probability of complete recovery of nectarines decreases from 27.4% to 6.4% (i.e., less than a quarter of the nominal condition) and the probability of complete waste increases from 33.3% to 53.1%. Furthermore, it is evident that both the risk and the expected loss are lower than for fresh fruit, even under stressed conditions. For both the puree and the hybrid/full process, the difference between the nominal and the stressed condition is significantly lower, confirming a much higher resilience of the new modified process compared to the one currently operated by the food bank.

In addition to the overall risk values, for each of the three processes the 10 selected events were also calculated under stressed conditions. Table 14 shows the results.

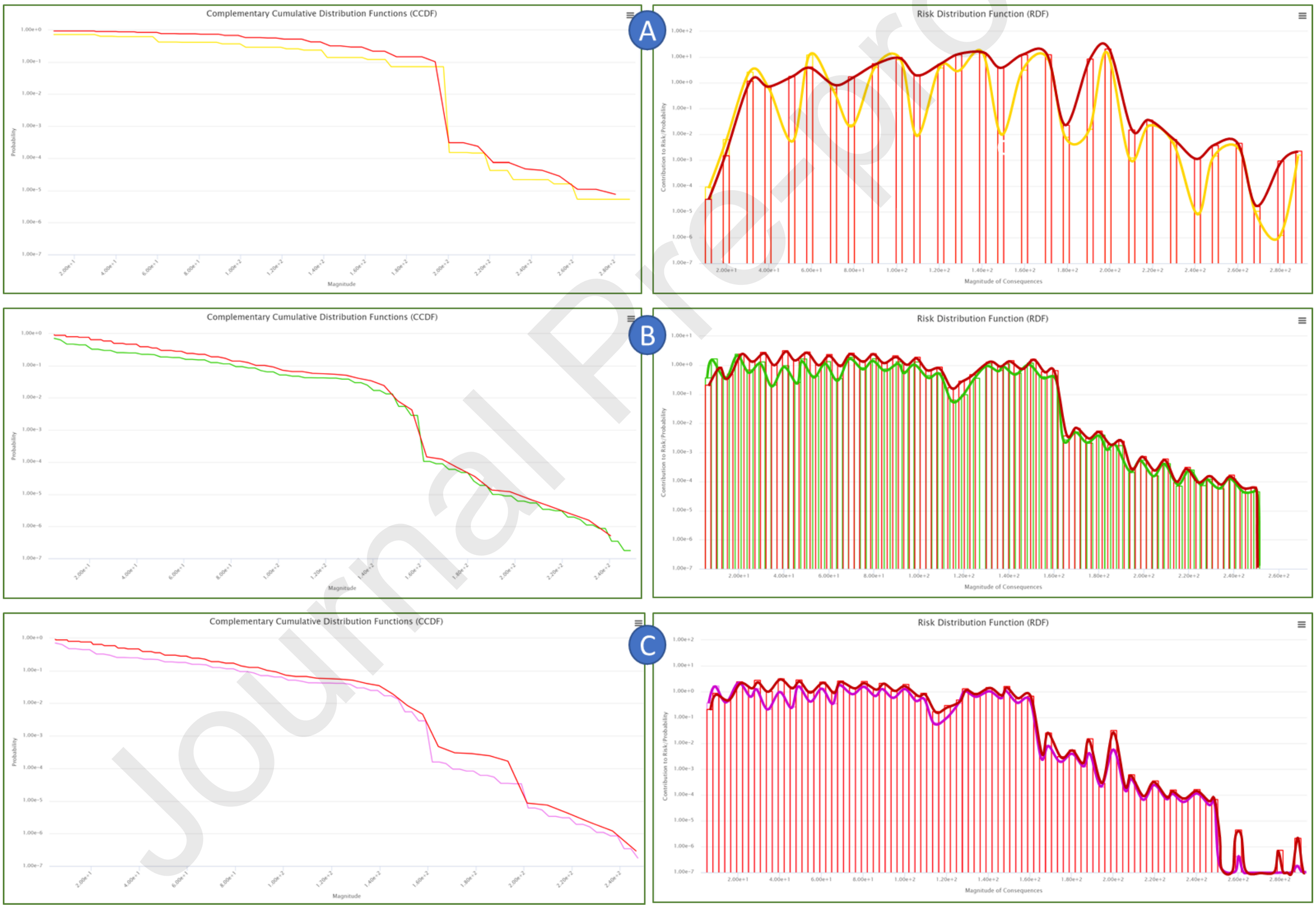

Figure 23 – Risk curve and risk spectrum comparison amongst the fresh fruit (yellow - A), the puree production (green - B) and the hybrid process (pink - C)

Table 13: Risk comparison between nominal and stressed conditions for the three processes

Fresh Fruit Process

Nominal	290.00	10.00	101.65	73.79
Stressed	290.00	10.00	125.24	117.27

Puree Production Process

	Max Loss	Min Loss	Expected Loss	Risk
Nominal	270.00	5.00	38.22	27.16
Stressed	270.00	5.00	46.88	43.40

Full Process

	Max Loss	Min Loss	Expected Loss	Risk
Nominal	290.00	5.00	38.25	27.19
Stressed	290.00	5.00	46.99	43.50

Table 14: Comparison of selected events for the different processes in nominal and stressed conditions

Fresh Fruit Process					
	Nominal	Stressed		Nominal	Stressed
As expected	27.4%	6.4%			
Not as Expected	72.6%	93.6%			
Food Totally Recovered	27.4%	6.4%			
Food Partly Wasted	39.3%	40.5%			
Food Totally Wasted	33.3%	53.1%			
			Minor HSE	1.16E-3	1.17E-3
HSE Implications	2.11E-4	2.25E-4			
			Major HSE	7.33E-5	7.39E-5
Hygiene standards not respected	4.99E-4	4.98E-4	With law issues	2.49E-4	2.49E-4

Puree Production Process					
	Nominal	Stressed		Nominal	Stressed
As expected	74.6%	59.7%			
Not as Expected	25.4%	40.3%			

Food					
Food Partly Wasted	25.2%	40.1%			
Food Totally Wasted	1.11E-3	1.53E-3			
HSE Implications	1.25E-4	1.32E-4	Minor HSE	1.07E-3	2.27E-4
			Major HSE	6.74E-5	6.72E-5
Hygiene standards not respected	9.93E-4	9.90E-4	With law issues	4.96E-4	4.94E-4

Full process

	Nominal	Stressed		Nominal	Stressed
As expected	74.5%	59.6%			
Not as Expected	25.5%	40.4%			
Food Totally Recovered	76.8%	62.5%			
Food Partly Wasted	25.2%	40.1%			
Food Totally Wasted	1.27E-3	2.32E-3			
HSE Implications	1.24E-4	1.30E-4	Minor HSE	1.07E-3	1.08E-3

Hygiene standards not respected	9.91E-4	9.84E-4	With law issues	4.95E-4	4.91E-4

The results show that the full/hybrid process is the best compromise as it has the advantage of having the risk of the puree process (which is much lower compared to the nominal one) while maintaining the nutritional and social values of the nominal process. The only disadvantage of the hybrid/full solution is that it may have a higher impact than the puree process. Fortunately, this condition has a low risk because the two additional classes generated by the hybrid process at the highest impact value are very short. This tendency of the full/hybrid process to have a higher risk is confirmed by the profile shown in its stressed conditions (figure 23 part "C"). At the highest values (extreme right), a third new class appears in the spectrum, adding to the two existing classes of the nominal condition.

5. Discussion and Conclusion

5.1 Findings

Adopting a risk-based approach, rather than a purely opportunity-based one, in the design, management and revamping of productive systems is nowadays of vital importance as it allows decision-makers to consider potential negative outcomes and take steps to mitigate their likelihood or impact. Scenario analyses allow to clarify the uncertainty associated with any decision. Due to the increasing complexity of considered systems, adopting a simulation-based approach to perform scenario analyses, understand, and anticipate the effects of decisions, is slowly becoming an imperative. While simulation-based approaches are nowadays a good practice in most engineering fields, they are still not as common in risk engineering where heuristic, manual approaches tend to prevail due to challenges in data availability and usability. Indeed, data are not just expensive to collect, manipulate and keep up to date, but, sometimes, not even recordable. Without data, or with poor datasets, data-driven approaches, such as the simulation-based ones belonging to the machine learning world, are unusable or might produce distorted previsions. Logic-based approaches, instead, offer the opportunity to leverage the data available (even when not statistically relevant) and capitalise the knowledge and experience hold by people operating in the organisation to produce reliable previsions. This opens a new perspective on the use of simulation-based approaches as it allows also (mid to) top managers to quantitively anticipate the effects of their decisions, even by accounting for the unmeasured or unmeasurable exogenous variables that could impact the system (e.g., the geopolitical stability, the raw material market, the climate change…).

The manuscript presented, through a practical use case, how the HoRAM method can be conveniently applied to assess the efficiency of potential business process transformation opportunities. HoRAM is a simulation-based method grounded on artificial logic (or logic-based artificial intelligence) and, as such, has the invaluable, practical benefit to allow making reliable previsions even without statistically relevant datasets. The use case analysed was the recovery of nectarines by a food bank. The decision-making challenge was to assess whether the introduction of a process to transform nectarines into puree, with the goal of recovering the maximum quantity of nectarines also in case of an agricultural or market excess or a shortage of volunteers, would have been an efficient decision. HoRAM allowed to analyse the decisional problem from different perspectives and offered the decision maker a set of structured results. Specifically, it was initially calculated the risk level and profile of the current process operated by a food bank, i.e., the fresh fruit distribution. Next, it was tested whether the solution of producing puree (only) would have decreased the risk. The results showed that the complete transformation of the business process, from a pure distribution of fresh fruit to that of puree production, would have significantly increased the probability of completely recovering nectarines, from 27.4% to a much more generous 76.9%, and drastically reduced that of totally wasting nectarines, dropping from 33.3% to 0.1% (i.e., more than two orders of magnitude lower). Yet, this important gain would have been compensated by a near doubling of the probability of facing hygiene-related issues, which would increase from 4.99E-04 to 9.93E-04 (results which are consistent with the complexity of the new process). Given that the complete transformation of nectarines into puree only would be against the societal vocation of the food bank, it was also tested the possibility of operating a hybrid process that would use the processing of nectarines only in case of an excess of fruit that could not allow the fresh distribution alone. It was made evident that the full process would have been slightly riskier than the mere puree production, but far less risky than the fresh fruit distribution only. Indeed, for the fresh fruit distribution process the probability of going as expected was calculated to be 27.4% (and that of not going as expected 72.6%), while that of the hybrid process was calculated to be 74.5%, thus confirming that adopting a hybrid process would be a convenient move for the food bank. In terms of risk parameters, the risk reduced from 73.79 down to 23.19, the expected loss from 101.65 down to 73.79. Finally, and this is the advantage of working with model-based simulation approaches, it was tested the resilience of the processes against high uncertainty on the amount of available fruit and the availability of volunteers. Even looked from this perspective the choice of introducing a food process to produce puree, to com cess currently in place. To help decision makers understanding the complexity of the decisional problem at stake, graphical representations of the risk level are extremely useful. In that respect, it was shown that, besides the numerical values, HoRAM offers graphical tools to allow decision makers to immediately understand the risk associated with the decision at stake. Specifically, it provides the risk curve, well known in the risk engineering community, and the newly defined risk spectrum. The former is useful to understand the risk level and, comparatively, whether the risk increases or decreases, where, and to which extent. The latter is useful to understand the risk profile (i.e., how scenarios distribute along the consequences range) and, comparatively, whether in two different conditions the risk changes its profile (i.e., some classes are eliminated, or the existing ones are reduced). Furthermore, HoRAM allows to identify and prioritise the variables that count the most in terms of risk production amongst those considered in the model, allowing to concentrate the always scarce and limited resources on what really matters. In the case of nectarines recovery, it was calculated that the absence of the forklift operator (one the highest specialised profiles required by the process), jointly with the shortage of volunteers for the sorting and packaging, would contribute to produce something around 95% of the overall risk; and this would happen both for the fresh fruit and the hybrid process. This methodological feature is extremely important both to identify the solutions to mitigate the risk and, once the decision is made, to support the risk governance that follows.

5.2 Limitations and future research

The use case presented has served to illustrate the potential of applying a logic-driven, simulation-based (specifically HoRAM) to analyse risk of complex decision-making systems characterized by high uncertainty and data scarcity. The risk analysis performed lacks economic considerations. A possible avenue for further development would be to extend the model underlying the analysis by incorporating economic and environmental aspects. This extension would allow for a more comprehensive analysis of the use case, allowing managers to understand the decision-making opportunity even from an economic perspective. In particular, the addition of economic considerations could further demonstrate the benefits of using HoRAM as a strategic planning tool, given its ability to visualise the possible uncertainties (in terms of gains and losses) on the objectives of the process. In addition, extending the model by incorporating the environmental implications would allow to have a more thorough assessment of the solution sustainability.

However, it should be noted that the inclusion of economic and environmental considerations could lead to different results. Indeed, the inclusion of economic considerations, in particular the costs associated with operational and capital changes, plays an essential role in companies and is even more critical for charitable organisations such as food banks. It is therefore recommended not to rely solely on the results presented, but to interpret them as a demonstration of the potential improvements achievable by using a structured risk engineering approach to a possible business process transformation opportunity.

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7. Conflicts of interest

Authors have no conflicts of interest.

8. CRediT authorship contribution statement

Simone Colombo: Conceptualisation (lead), Methodology (lead), Writing – Original Draft (lead), Formal Analysis (equal), Supervision. **Angela Ciotola**: Data Curation, Formal Analysis (lead), Writing – Original Draft (equal), Review & Revision. **Laura Piazza**: Resources, Writing – Original Draft (equal), Review & Revision

9. Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors did not use any AI-assisted tool to write the article.

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11. CRediT authorship contribution statement

Simone Colombo: Conceptualisation (lead), Methodology (lead), Writing – Original Draft (lead), Supervision. **Angela Ciotola**: Data Curation, Formal Analysis (lead), Writing – Original Draft (equal), Review & Revision. **Laura Piazza**: Resources, Writing – Original Draft (equal), Review & Revision