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# Decision Making under Uncertainty for Reconfigurable Manufacturing Systems: a framework for uncertainty representation

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**Abstract**: Traditional manufacturing paradigms cannot deal with the current pace of uncertain events in demand, supply and beyond. Reconfigurable Manufacturing Systems (RMS) are designed to adapt to these challenges in a rapid and cost-effective way. In order to decide when and how to reconfigure an RMS, it is necessary to identify the external events which trigger change in the system. This paper proposes a framework for uncertainty representation in RMS based on three levels of uncertainty and decision horizons. An illustrative example shows how such framework can be used by researchers and practitioners to better understand RMS and its context.



*Keywords*: Reconfigurable Manufacturing Systems; Uncertainty; Decision making; Bayesian inference; Scenarios; Deep uncertainty.

## 1. INTRODUCTION

Manufacturing and logistics systems are the backbone of contemporary consumer societies. Factories all over the world integrate supply-chains, which are responsible for producing and delivering industrial goods globally. However, these systems currently operate in increasingly uncertain environments, due to several reasons, such as unexpected supply disruptions, rapidly evolving costumer`s demand, and rapid technological development (Vital-Soto and Olivares-Aguila 2023). Additionally, the need to adopt more sustainable manufacturing and logistics processes, introduces additional uncertainties for industries worldwide. Traditional manufacturing systems are not designed to deal with these challenges, with changes in production lines taking months and construction of new ones taking years.

Unlike traditional systems, Reconfigurable Manufacturing Systems (RMSs), as first conceptualized by Koren (Koren et al. 1999), can rapidly and cost effectively adapt to uncertain situations. The lifecycle of an RMS consists of the following stages (Napoleone et al. 2023):

- Configuration period, in which the system`s structure is determined in a way that ensures fast and cost-effective changes in the future;
- Ramp-up period, in which the initially unstable behaviour of the system is brought to stability (stage triggered once a configuration is determined, or once a reconfiguration takes place);
- Service life, in which the system has stable behaviour and production rate;
- Reconfiguration period, in which the system`s structure is changed based on scalability and convertibility requirements, usually triggered by an outside event (e.g. change in demand).

This structure results in the RMS having more degrees of freedom when compared to traditional manufacturing paradigms, which allows it to better respond and adapt to multiple uncertain and challenging events. Most of these events are external to the RMS direct boundaries (i.e. a factory or logistics centre) and are also the main cause of change in an RMS. So, these events can be seen as the main triggers of the system`s reconfiguration (Rodrigues et al. 2018), leading to a new ramp-up and service life periods. Such events are also referred to as change drivers in the literature (Wiendahl et al. 2007). Thus, it is necessary to continuously monitor the RMS`s context (its environment) in order to identify its reconfiguration triggers (Caesar et al. 2023), which allows to define when and how to perform the system`s reconfiguration.

This paper intends to provide a framework to facilitate the representation of uncertain reconfiguration triggers present in an RMS context, and how it can be used to select appropriate decision making methods. In order to do so, two research questions must be addressed:

1. What are the definitions and representations of uncertainty present in the RMS literature?
2. Which categories of uncertainty can be used to select appropriate decision making methods in RMS?

The remain of this paper is structured as follows. Section 2 describes the research design and how a literature review in RMS and uncertainty was conducted. In section 3, different classifications of uncertainty are presented, and common typology is defined. A brief description of the decision making methods most used in literature to deal with the different types of uncertainty is presented in section 4. In section 5, a framework for representing uncertainty in RMSs is proposed, with some common reconfiguration triggers being presented in an illustrative example. Finally, section 6 provides the conclusions of this work and point to further research opportunities.


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## 2. RESEARCH DESIGN

This paper`s main aim is to define a framework for uncertainty representation tailored to RMSs. To do so and address the first research question, a literature review was conducted to identify classifications and typologies of uncertainty present in the RMS literature. This was done by checking the abstract, keywords and title for “reconfigurable manufacturing systems” AND “uncertainty” in the SCOPUS database. The identified publications were then screened so to select the ones which contained a clear definition of a category or type of uncertainty, and which was applied to an RMS. These steps are detailed in the PRISMA flow diagram presented in Fig. 1 (Cordova-Pozo and Rouwette 2023).

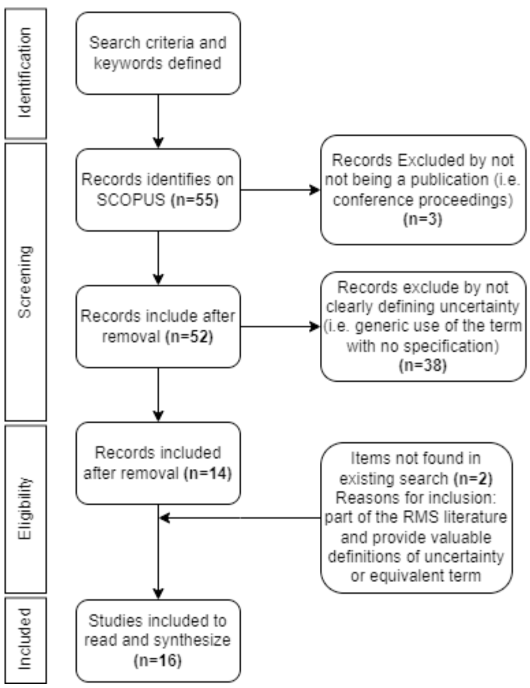


Figure 1. PRISMA flow diagram showing the different steps of the literature review.

Considering the results of this literature review, additional searches were conducted to establish the theoretical basis for the proposed framework for uncertainty representation. Other searches were conducted to identify methods for decision making under uncertainty, necessary to answer the second research question, and with the goal of complementing and enriching the framework.

## 3. UNCERTANTY REPRESENTATION

Most reconfiguration triggers are uncertain events happening in an RMS context (i.e. external entities strongly related to the RMS). Thus, an adequate representation of these events is necessary to allow for effective decision making on the reconfigurability effort. In this section, different definitions and classifications of uncertainty are given, coming from the RMS literature as well as other knowledge domains.

### *3.1 Uncertainty representation in the RMS literature*

The RMS literature provides some examples of reconfiguration triggers, and some categories of uncertain events. These were obtained in the literature review, which started with 55 records and was reduced to only 16 studies, as shown in Fig. 1, which used the term uncertainty in a precise and deliberate way.

When comparing different manufacturing paradigms, Vital-Soto and Olivares-Aguila affirm that RMSs are designed to deal with demand uncertainties, supply disruptions, and machine failure (Vital-Soto and Olivares-Aguila 2023). Demand uncertainty is the most mentioned reconfiguration trigger, with many authors considering this as the main source of uncertainty (Maganha et al. 2019; Du et al. 2006). Ostovari et al. consider both demand and exploitation cost (opportunity cost) as uncertainty parameters. However, they do not treat these as random variables with an associated probability distribution, as other authors do (Beldiceanu et al 2021; Delorme et al. 2023). Instead, they implemented a scenario-based robust optimisation model (Ostovari et al. 2023). Some authors focus on uncertainty sources internal to an RMS, such as inaccurate observation of components health and age (Achamrah and Attajer 2023), or unexpected disruptive events in machines (Gu et al. 2015).

These are cases of the representation of a single or multiple sources of uncertainty in RMS in which a clear distinction on distinct types of uncertainty is not clearly provided. At most, a methodological distinction between stochastic and scenario-based methods is mentioned (Ostovari et al. 2023). Nevertheless, other authors in the identified RMS literature do provide some categorization. For instance, in the context of manufacturing processes, uncertainty can be categorised as depending either on variation or ambiguity (Lee and Banerjee 2009). In the first category, changes in process create uncertainty in the whole manufacturing systems, with the causes of these changes being known or not. The second category is related to unclear or imprecise information about a process, which can be related to human error (e.g. improper documentation) or even automatic measurements (e.g. sensor malfunction).

Another typology of uncertainty in RMS assumes that uncertainties arise throughout the product value chain and can be categorised into three areas (Milisavljevic-Syed et al. 2023). The first one is problem modelling, in which both internal (e.g. assumptions, simplifications) and external factors (e.g. customer satisfaction) introduce uncertainties to the model of complex engineering systems. The second area, decision process, is concerned with the representation of interconnected subsystems and the propagation of uncertainty in the model and process chain. In the third area, design exploration, both incomplete models and decision preferences should be considered as these factors can lead to error accumulation in design decisions.

The results of this literature review show that, although some examples of uncertainty sources are given, not many categories or typologies of uncertainty are proposed in the RMS literature. The lack of a systematic categorisation of uncertain events makes it harder to choose adequate decision support tools to address them. Therefore, additional concepts from different knowledge domains are needed to form the theoretical basis of the intended uncertainty representation framework.

### *3.2 Uncertainty representation in other knowledge domains*

Uncertainty representation encompasses various levels that reflect the varying degrees of predictability and randomness inherent in different processes. Lev Tarorasov (Tarorasov 1988), when talking about decision making, defines two types of uncertainty: stochastic, which can be treated using probability theory, and "bad" uncertainty, which does not present statistical stability, thus not having a notion of probability.

Another classification, which can be seen as more nuanced version of the previous one, consists of four levels of uncertainty located between complete determinism and total ignorance (Marchau et al. 2019). The first level regards a future that is clear enough where processes are primarily treated as deterministic, with point estimates for each outcome. In this level, only small fluctuations are expected (e.g. derived from measurement noise), and no notion of probability is needed. The second, "stochastic uncertainty", acknowledges the presence of random variables, which represents a higher level of unpredictability in the system, requiring the use of probability distributions. In manufacturing, this could involve factors such as machine breakdowns or variations in production times.

Moving further along the spectrum, the third level is characterized by "scenario-based uncertainty". This level recognizes the complexity of both internal and external events that are challenging to predict individually. Instead of attempting to model every possible outcome, scenario-based approaches consider a range of plausible future situations. In the context of manufacturing, this could involve changes in market demand, evolving regulatory landscapes, or unexpected disruptions in the supply chain. The fourth and most challenging level is "deep uncertainty". Here, the inherent unpredictability of certain events leads to many plausible future scenarios, making it impractical to use conventional scenario planning. Deep uncertainty arises when there is limited knowledge about the parameters and dynamics of a system. Predicting disruptive technological shifts is an example where deep uncertainty prevails.

Considering these broader classifications of uncertainty and their link to decision making methods, they provide an appropriate theoretical basis for the representation of a multitude of uncertain events relevant in RMSs. In particular, the three most uncertain levels (stochastic, scenario-based, and deep) in the classification scheme presented by Marchau et al. are a good reference for the proposed framework for uncertainty representation. Thus, these types of uncertainty are used to both classify reconfiguration triggers and to determine appropriate decision support tools and methods to assist on decision making in RMSs.

## 4. METHODS FOR DECISION MAKING UNDER UNCERTAINTY

A clear characterisation of the types of uncertainty present in manufacturing systems, and its representation, is the first step in dealing with the uncertainty. The next step is to use adequate methods to incorporate uncertainty into decision making, improving the reliability and robustness of manufacturing systems. Considering the stochastic, scenario-based, and deep uncertainty levels (Marchau et al. 2019), multiple methods are available to deal with each one. They are grouped according to the level/type of uncertainty they address. The goal of this section is to provide a general overview of such methods and serve as an initial reference for researchers and practitioners.

It is worth noting that risk management is one of the most used families of methods to deal with uncertainty. However, due to its broad scope and different formulations, it is not presented in the three uncertainty classes shown here. For a specific view on risk management methods, the interested reader is encouraged to look at the work of Aven (Aven 2016).

### *4.1 Stochastic methods*

Bayesian inference provides the optimal way to update probabilities in the context of stochastic uncertainty (Murphy, 2023). Multiple mathematical and computational methods provide an updated *posterior* belief, given *prior* evidence/data, while balancing the trade-off between accuracy and computational efficiency. These methods can be grouped in three categories: Variational, sampling, and analytical (Lukashchuk et al. 2023). In Bayesian inference, only linear Gaussian systems have analytical solutions available, which limits its applications. For more complex systems, including manufacturing ones, the posterior distributions need to be approximated either by Monte Carlo sampling or by variational optimisation of a bound on the data evidence (Lukashchuk et al. 2023).

Monte Carlo sampling methods work by constructing a Markov chain that has an equilibrium distribution proportional to the desired posterior distribution (i.e. the intended result from the inference procedure). These are commonly known as Markov chain Monte Carlo (MCMC) methods. Some commonly used examples are Metropolis-Hastings, Gibbs sampling and No-U-Turn Sampler (NUTS) (Robert et al. 2018). The strength of these methods is the guarantee of convergence for almost any distribution, making them widely applicable. However, this universality usually comes at a large computational cost, leading to slow convergence behaviour. Some techniques to accelerate MCMC algorithms are presented by Robet et al. (Robert et al. 2018).

Variational inference (VI) or variational Bayesian methods also aim at approximating a posterior distribution, but while MCMC methods provide a numerical approximation to the exact posterior, variational methods give the locally optimal values for an approximation of the posterior distribution. By relying on fast optimization techniques, VI methods tend to be preferred with respect to MCMC when accuracy is not paramount. Different techniques are used to solve the optimization problem in VI, some like Automated Differentiation Variational Inference (ADVI) rely on information from the derivative of the objective function. Other algorithm use message passing to solve the optimization problem using the principle of dynamic programming (Murphy 2023). Some examples of this type of algorithm are:

Stochastic Variational Message Passing (SVMP), Approximate Nonlinear Gaussian Message Passing (ANGMP) and Conjugate-computational Variational Message Passing (CVMP) (Lukashchuk et al. 2023).

*4.2 Scenarios methods*

Moving to scenario-based uncertainty, multiple techniques were developed by three groups, also known as scenario planning schools, these are: Intuitive Logic method (ILM), La Prospective (LP) and the Probabilistic Modified Trends (PMT) (Cordova-Pozo and Rouwette 2023). They mainly differ in terms of a more qualitative or quantitative approach: ILM for instance, is more qualitative, while PMT is strongly quantitative, and LP mixes the qualitative techniques from ILM with more elaborate quantitative analysis. Cordova-Pozo and Rouwette identified 29 different techniques, from which the most cited ones like dynamic scenarios, cognitive fuzzy maps and cross-impact analysis belong to the PMT school. Some notorious methods, like role playing and Delphi, were identified, but were considered too generic by the authors, who focused on the already mentioned techniques.

The two most important recently developed techniques are dynamic scenarios and cognitive fuzzy maps. Both methods are suited for short- to long-term decisions and present a cause-and-effect perspective. They differ in terms of the type of information used, with both methods using (qualitative) experts and stakeholder judgement, but only dynamic scenarios considering different (quantitative) probabilistic data.

*4.3 Deep Uncertainty methods*

Regarding deep uncertainty, multiple approaches with some common features are presented in literature (Marchau et al. 2019). They are all based on the need to reduce vulnerability of policies or strategies to uncertain future events, and they are structured with (most of) the following elements: Frame analysis; Perform exploratory uncertainty analysis; Chose initial actions and contingent actions; Iterate and Re-examine.

One of the first proposed approaches for decision making under deep uncertainty (DMDU) is Info-Gap Decision Theory (IG). It is a non-probabilistic decision theory with the aim of optimizing robustness to failures in a system. This is done by reducing the information gap, which is understood as the difference between what is known and what needs to be known in order to make a reliable decision (Ben-Haim 2006). Two other approaches, Robust Decision Making (RDM) and Dynamic Adaptive Planning (DAP), were developed by the RAND Corporation. Both approaches do not try to make predictions about the future, rather, they used computational tools (in the case of RDM) and define adaptation strategies for initial plans as added information is acquired.

## 5. FRAMEWORK FOR UNCERTAINTY REPRESENTATION IN RMS

As previously mentioned, reconfiguration in an RMS is triggered by events coming from some external entity (e.g. demand, supply, regulation), which in turn leads to uncertainty in the new ramp-up and service life stages. Thus, it is necessary to model the main external uncertainties to the RMS to decide when and how to start a reconfiguration process. In this section, the findings from the previous sections are combined in a framework for uncertainty representation suited for the needs of different RMSs.

*5.1 Framework definition*

The proposed framework is organized in four steps, going from the definition of the external entities of interest to the selection of appropriate decision making methods to deal with distinct groups of reconfiguration triggers. The complete process is shown in the flow diagram in Fig. 2, with the four steps identified by a number in its lower-right corner. These processes of uncertainty representation are analogous to a continuous improvement cycle such as Deming`s PDCA (Deming 1982), with significant changes in the RMS environment, its context, causing the entire process to repeat itself.

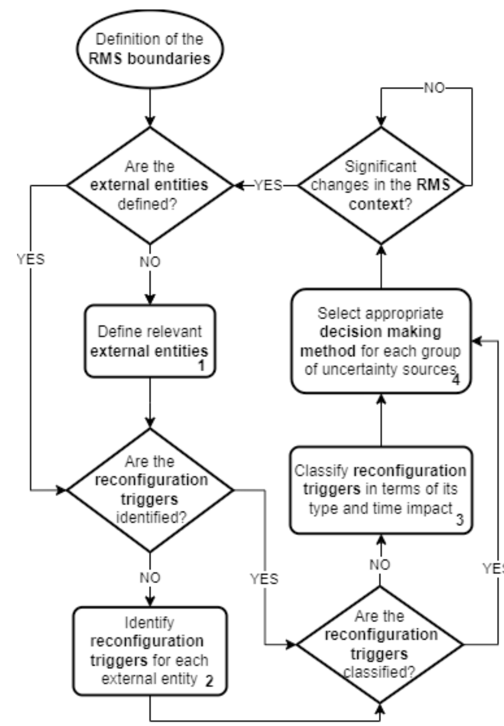


Figure 2. Flow diagram of the uncertainty representation framework.

The starting point, or step zero, is the definition of the RMS and its boundaries. Then, the first step consists in identifying the external entities of interest, which represent the sources of uncertainty for the RMS. On step two, each external entity is analysed with the goal of identifying the reconfiguration triggers associated with them. As uncertain events, these reconfiguration triggers are classified in step three, both in terms of their uncertainty level (i.e. stochastic, scenario-based, and deep) and the time impact in decision making (i.e. short, mid, and long-term). On step four, decision making methods and tools are selected to address each class of triggers previously identified. Such methods and tool can be used until a significant change to the RMS context takes place, in which case the process is restarted, and the four steps can be repeated.

The proposed framework shows some similarities with the one presented by Wiendahl et al., in which change drivers help to define the change objectives for a company (Wiendahl et al. 2007). However, by explicitly defining the external sources of uncertainty and the trigger events associated with them, the proposed framework may represent a larger variety of change drivers and show them with greater transparency then the one found in the literature. Also, the presented framework is setup as a cycle, allowing for constant redefinition of the main sources of uncertainty. This could be made either by a systematic analytical process performed at fixed frequency, or by an event driven approach, in which major external events (e.g. supply-chain disruption) would indicate the need to perform a new evaluation cycle.

The result from the first three steps can be graphically represented as an uncertainty graph, in which the RMS and the external entities are represented by nodes and the reconfiguration triggers is given by directed edges. Using the uncertainty-level-time-horizon classification, it is possible to distinguish each type of trigger, for instance, by colour and line type. Such uncertainty graph allows to easily visualise all (or at least the most important) reconfiguration triggers, their source and type.

### *5.2 Uncertainty Graph example*

In order to better illustrate the use of the uncertainty representation framework, an example is given considering an (illustrative) RMS in the automotive sector present in Europe. An uncertainty graph for this example is presented in Fig 3.

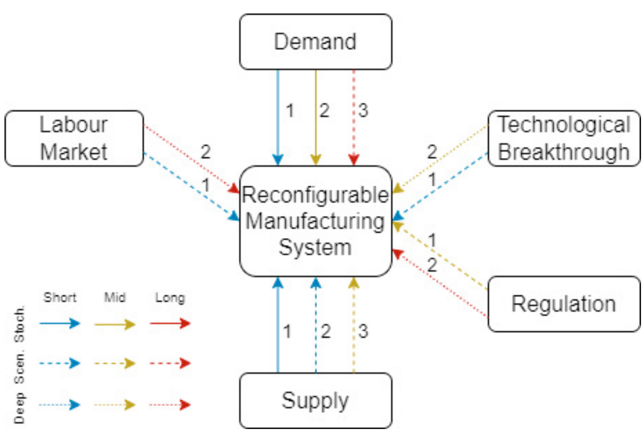


Figure 3. Example of an Uncertainty Graph for a RMS.

*Step 1:* As common to all manufacturing systems, two external entities to this RMS are the Demand and Supply. Due to characteristics of its sector, both Regulation and Technological Breakthrough are considered as important sources of uncertainty. Also, considering its location, uncertainties related to the Labour Market are included.

*Steps 2&3:* For each of the five external entities, some reconfiguration triggers were identified. They were also classified using the uncertainty-level-time-horizon labels shown in Fig. 3. An explanation of these reconfiguration triggers is given as follows:

Demand: **1.** Number of sales of a specific vehicle model in the next quarter (Stochastic short-term); **2.** Aggregate number of sales in the next year (Stochastic mid-term); **3.** Number of sales of a new vehicle family in the next five years (Scenario-based long-term).

Supply: **1.** Delivery lead time of brake pads (Stochastic short-term); **2.** Delivery lead time of specific microchips (Scenario-based short-term); **3.** Disruption in the production of a key microchip`s supplier (Scenario-based mid-term).

Technological Breakthrough: **1.** Commercialization of more power dense batteries (Scenario-based short-term); **2.** Reliable level 5 autonomous vehicles (Deep uncertainty mid-term).

Regulation: **1.** Phase-out of internal combustion engines (Scenario-based mid-term); **2.** Bans or import limitations on critical components (Deep uncertainty long-term).

Labour Market: **1.** Shortage of electricians in the sector (Scenario-based short-term); **2.** Number skilled workers in the country in 10-15 years (Deep uncertainty long-term).

*Step 4:* Some trigger classes are shared by multiple external entities, like the stochastic short-term trigger (solid blue arrows). Thus, similar methods could be used to deal with different triggers belonging to the same class. For instance, Variational Inference or MCMC methods could be used to give updated estimates on both the number of sales of a vehicle and the delivery lead time of specific parts.

## 6. CONCLUSIONS

This paper presents a framework for uncertainty representation suited for the types of uncertain events faced by Reconfigurable Manufacturing Systems. A review on how the growing RMS literature treats the concept of uncertainty was conducted. From it, a gap in the RMS literature regarding uncertainty classification was identified. Concepts from other knowledge domains were used to set the theoretical basis of the proposed framework. The framework is presented together with an illustrative example on how researchers and practitioners in RMS could use it to identify and classify reconfiguration triggers, and which decision making methods and tools can be used. Since this framework relies on experts or sufficiently advanced decision support systems (DSS) to identify and monitor the sources of uncertainty, it can be seen as a limitation of the framework`s applicability by some companies.

Such limitations can inspire further investigation into DSS that can help with the implementation and use of such framework. One line of research could be the use of machine learning techniques and other AI methods, such as process mining, in helping with the construction of uncertainty graphs and keeping them updated. Another research direction is the integration of this framework with other decision making tools, such as factory Digital Twins, which could streamline different decision making processes, resulting in more efficient and robust RMSs. Finally, case studies may identify further barriers in the implementation and practical use of the proposed framework, allowing for its continuous improvement.

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