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Ontology-based uncertainty management approach in designing of robust decision workflows

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ABSTRACT
The formal representation and capturing of uncertainty knowledge are always essential but difficult. Typically, the uncertainties due to incompleteness and inaccuracies of model information in engineering design necessitate the designing of robust decision workflows to improve the quality of process/product in variations. This requests extending a designer's abilities in managing various uncertainties in system design and making decisions that are robust, flexible, and comprehensive. To enable the management of various uncertainties, in this paper, we propose an ontology for robust design and a template-based ontological method that is employed to design decision workflows. We achieve the aforementioned goals through the identification of: (1) procedural knowledge – defining a procedure of designing robust decision workflows, including the sequence of activities, to determine the right combination of design information for a specific type of uncertainty, and (2) declarative knowledge – developing a frame-based ontology for the formal representation of tacit knowledge to capture and document the re-usable information of a robust design by utilising the process templates. We demonstrate the efficacy by carrying out the robust design of the hot rod rolling process based on the analysis and synthesis of the processing-microstructure (cooling module) and the microstructure-mechanical (rod module) simulation models.

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Ontology; uncertainty management; robust design; decision workflows; capture and reuse

1. Introduction

Due to the limited information and knowledge in the early stages of design, a human designer has to deal with different types of uncertainty, which is ubiquitous in any engineering systems (Yang and Calmet 2005; Allen et al. 2006; Sinha et al. 2011; Morse et al. 2018). It is necessary for a human designer to understand the effects of uncertainty and implement rational mitigation measures in the design processes chain. This depends on the uncertainty management in the designing of decision workflow, that is, the management of uncertainty information flows in decision process from one task to subsequent

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tasks through a graph topology with decision steps at certain graph nodes (Wang et al. 20192018a). Thus, the realisation of complex engineered systems using decision models and analysis models that are typically incomplete, inaccurate, and not of equal fidelity requires an understanding and prediction of process behaviours in design via managing the uncertainties in decision workflows (Wang et al. 2018a).

Two challenges are involved in managing the uncertainties associated with the model-based realisation of complex engineered systems (Wang et al. 2018b): (1) the challenge of creating knowledge about the complex engineered systems, and (2) the challenge of capturing and reusing tacit knowledge, building the ability to learn from data and cases, and developing knowledge-based methods for guided assistance in decision-making. In response to the above challenges, numerous research studies have focused on increasing design knowledge to facilitate making decisions more comprehensive under uncertainties, i.e. robust design (Ullman 2001; Park et al. 2006), which is a set of methods for minimising the effects of uncertainties on product performance. For example, a domain-independent and systematic robust design approach - Robust Concept Exploration Method (RCEM) is presented by Wei Chen et al. (1996a) to maintain design freedom and enhance the design productivity in the early stages of design, and some related works have been employed successfully on various design problems (Allen et al. 2006). Accordingly, Design Capability Indices (DCI) are proposed as a set of metrics for assessing the capability of a ranged set of design specifications and they are also incorporated in the RCEM framework (Chen et al. 1999). By extending the types of uncertainty and the corresponding robust design, Choi et al. (2005) present a mathematical construct, namely the Error Margin Index (EMI) based on the DCI. Additionally, accounting for the characteristics of uncertainty in multiscale materials design, an Inductive Design Exploration Method (IDEM) is presented to find sets of design specifications that define a feasible solution space and communicate these sets in a top-down manner, maintaining 'design freedom' as much as possible (Choi et al. 2008b). More research works that are used to create knowledge related to different types of robust design are introduced and categorised in detail by Allen et al. (2006).

In terms of knowledge formal representation and reuse, uncertainty as an inevitable feature is attracting more attention and significant research efforts for managing probabilistic uncertainty, possibilistic uncertainty, and vagueness for the Semantic Web (Lukasiewicz and Straccia 2008). For example, BayesOWL (Ding, Peng, and Pan 2005) and PR-OWL (Costa, Laskey, and Laskey 2008) were defined in order to expand the capability of capturing probabilistic knowledge about concepts, properties and relations in domains via an ontology-based Bayesian network (Fenz 2012). However, less attention has been given to the ontology of uncertainty management and robust design for complex systems (Efatmaneshnik and Reidsema 2007).

To tackle the challenge of demands of knowledge archiving and reuse in decision-based design, a Knowledge-Based Platform for Decision Support in the Design of Engineering Systems (PDSIDES) (Ming et al. 2018) has been proposed based on the software system DSIDES (Decision Support in the Design of Engineering Systems) (Mistree, Hughes, and Bras 1993). The platform PDSIDES provides well-managed design collaboration, rapid design decision making, and effective design knowledge management. In the context of platform PDSIDES, a Design Guidance System (DGS) is proposed in order to enhance the design automation and the intelligent support for the designing of decision workflows through the management of complexity and uncertainty (Wang et al. 2018b). Typical requirements for enabling the uncertainty management in decision workflows include:

- How to model and account for variability in design process chain?
- How to handle uncertainty to ensure the design's *robustness, flexibility, and comprehensiveness?*
- How to extend a designer's *abilities in order to understand and predict the process behaviours in robust design?*

To address the above requirements, the designing of robust decision workflows necessitates integrating useful information from designers working at multiple length and time scales, particularly for the integration of uncertainty information. Thus, the primary contribution of this paper is a template-based ontological method for designing robust decision workflows, which involves the identification of the procedural knowledge – define the procedure for design robust decision workflows, and the declarative knowledge – develop an ontology for robust decision process template. Using the proposed method, a human designer can determine the right combinations of design information via the creation and reuse of decision workflows, and accommodate uncertainties in input parameters, simulation models, and the process chain. An ontology-based robust decision process template will improve the ability to communicate and to understand the process behaviours in the collaborative exploration of system-level design space.

The remainder of this paper is organised as follows. In Section 2, we survey the knowledge of uncertainties in design and the robust design, as well as provide a brief of the Decision Support Problem Technique, ontology-based uncertainty knowledge modelling, and foundation of some previous relevant research. In Section 3, we propose an approach for the designing of robust decision workflows. Section 4 is devoted to developing an ontology that represents the underlying knowledge related to the identified robust design process template, as well as the instantiation approach consistent with the process template model. The efficacy of this method is illustrated by carrying out the robust design of the hot rod rolling process based on the analysis and synthesis of processing-microstructure (cooling module) and microstructure-mechanical (rod module) simulation models in Section 5, and we end with the closing remarks in Section 6.

2. Frame of reference

This section summarises the related work and research foundations of this paper. As shown in Table 1, the paper reviews the literature on knowledge of decision-making and uncertainty management in design from four aspects: decision, uncertainty, robustness, and ontology, which facilitates the understanding of contribution in this work. In the first subsection, the classification of uncertainties and robust design approaches are introduced, which draw forth the necessity of formal representation of capturing ontology-based uncertainty knowledge in engineering design. In the second subsection, the related research work in the Decision Support Problem Technique (DSPT) is explained, and previous work would be beneficial to understand the background of this study. In addition, the deficiency of ontology-based uncertainty knowledge representation in the field of engineering design is clarified, and based on that, we could identify the primary contribution of this paper.

Table 1. Overview of the knowledge of decision-making and uncertainty management.

	Decision	Uncertainty	Robustness	Ontology
Bras and Mistree 1993	Compromise decision	Noise factors	Compromise DSP with signal to noise ratio	*
Chen et al. 1996a	Compromise decision	Variations in noise factors and control factors	RCEM	*
Simpson et al. 1997	Compromise decision	Variations in noise factors and control factors	DCI	*
Chen et al. 1999	Compromise decision	Variations in noise factors and control factors	RCEM-DCI	*
Ullman 2001	Selection decision	Noise factors	12 steps for robust decision-making	*
Sim and Duffy 2003	General design evaluation	Vagueness, imprecision, etc.	*	Ontology of generic engineering design
Gurnani and Lewis 2005	Multi-attribute selection decision	Imprecise or risky attribute values	RASM	*
Ding, Peng, and Pan 2005	*	Semantic uncertainty	Bayesian network	BayesOWL
Yang and Calmet 2005	*	Semantic uncertainty	Bayesian network	OntoBayes
Choi et al. 2005	Compromise decision	System response variability and parameter uncertainty	RCEM-EMI	*
Choi et al.2008b	Compromise decision	Model structure uncertainty	IDEM	*
Costa, Laskey, and Laskey 2008	*	Probabilistic knowledge	Multi-entity Bayesian networks	PR-OWL
Hasenkamp, Arvidsson, and Gremyr 2009	*	Variation	Robust design methodology	*
Dubois and Prade 2009	General decision theories	Possibility	*	*
Rockwell et al. 2009	General collaborative design decision	*	*	Decision support ontology
Lim, Ying, and Han 2012	*	User preference uncertainty	Bayesian network	Product family design ontology
Noor, Salcic, and Wang 2016	Activity recognition decision	Data, comprehension, projection	*	Ontology of activity recognition
Ming et al. 2016	Compromise decision	*	*	Ontology of compromise DSP
Ming et al. 2017	Selection decision	*	*	Ontology of utility-based selection DSP
Howard et al. 2017	*	Variation	Variation management framework	*
Wang et al. 2018a	Compromise decision	*	Post-solution analysis	Ontology of design space exploration
Morse et al. 2018	*	Ambiguity, epistemic, aleatory, interaction	Tolerancing	Uncertainty taxonomy
Singh et al. 2019	Supply chain resilience decision	Supply chain network interruption	Hybrid particle swarm optimisation – differential evolution	Ontology of resilience
Wang et al. 2019	Selection and compromise decision	*	*	Ontology of PEI-X diagram

2.1. Uncertainties in the design process and robust design

In the model-based realisation of engineered systems, especially in simulation-based design, due to simplifying assumptions and idealizations, non-deterministic simulations, and limited experimental data considering computations and cost, etc., the design of engineered systems with hierarchical, heterogeneous, and multiscale complex characteristics faces the intellectual challenges in uncertainty management (Allen et al. 2006; Sinha et al. 2011). Uncertainty is ubiquitous in engineering design, and it could be classified depending on their causes (Morse et al. 2018). Simpson et al. (1997) define the type of uncertainty based on the source of variation for the performance, such as the variabilities in the design parameters, design variables, and constraints. Isukapalli, Roy, and Georgopoulos (1998) divide the uncertainties into three categories, namely the inherent randomness or unpredictability of the physical system, the approximations and simplifications in the model formulation, as well as the incomplete knowledge of the model parameters/inputs due to insufficient or inaccurate data. Based on above classification, Choi et al. (2008b) defined the following four types of uncertainty in engineering design: Natural Uncertainty (NU), Model Parameter Uncertainty (MPU), Model Structure Uncertainty (MSU), and Propagated Uncertainty (PU). Morse et al. (2018) identify a more detailed uncertainty taxonomy from the perspective of manufacturing tolerance and uncertainty management in design.

Generally, it is expensive or even impossible to remove the sources of uncertainty, but they can have a profound impact on the prediction of the system model and the performance of the final system. As George Box said, ‘essentially, all models are wrong but some are useful’ (1976), decision and analysis models used for the design synthesis are typically incomplete and inaccurate, and the designers have to look for ways to somehow optimise the design given the input variation. Since multiplying safety factors in an *ad hoc* manner is no longer plausible for design reliability (Choi et al. 2008a), the current research has shifted attention to handling the uncertainty that is different according to the modelling of the variabilities in design, such as, Gurnani and Lewis (2005) model the imprecise of design alternatives attribute values and inabilities of the decision-maker, so as to investigate the multiple, conflicting, and uncertain criteria in robust multi-attribute decision making. Dubois and Prade (2009) have given their suggestions for the formal representation of uncertainty knowledge from the perspective of Decision Theory and Artificial Intelligence. Often in engineering design, the uncertainty can be modelled with interval sets, fuzzy sets, and probability distributions (Simpson et al. 1997). For example, in the Taguchi method (Taguchi and Clausing 1990), the variation of the system response caused by the noise factors is described as the quality loss function, and the signal-to-noise ratios combine the mean response and the standard deviation, which is used to measure the overall quality of the system. Chen, Allen, and Mistree (1997) further develop the Taguchi method and use normal distributions to model the variability in the design parameters by considering the variation of the design variables. Choi et al. (2005) model the unparameterizable variability as intervals in the parameters of a metamodel.

Two primary approaches are available to minimise the uncertainty impact on product performance: one is mitigating or eliminating uncertainty, and the other is managing uncertainty (Allen et al. 2006; Choi et al. 2008a). The former is attainable by developing a ‘perfect’ model with a larger amount of data and system knowledge, e.g. Monte Carlo Analysis (Choi et al. 2008b), an assessment of the various factors using fuzzy sets (Gurnani and

Lewis 2005). Obviously, it is not the focus of this paper, our purpose of managing uncertainty is to design a system that is relatively insensitive to uncertainties without removing the sources, namely robust design. Some methods and tools of robust design have been developed to the management of uncertainty and variation (Ullman 2001; Park et al. 2006; Howard et al. 2017), and they are effective in improving product reliability and reducing design risk. However, it is a universal awareness that robust design methods do not experience widespread success in the industry (Howard et al. 2017), and one reason for this is the lack of a coherent robust process (Göhler, Ebro, and Howard 2017). There are many interesting design approaches and applications used to formulate a strategy for uncertainty management and facilitate the exploration of a broad design space via the integration of statistical experimentation and approximate models, robust design techniques, multidisciplinary analyses, and multi-objective decisions (Allen et al. 2006; Hasenkamp, Arvidsson, and Gremyr 2009).

2.2. Decision support problem technique

The philosophy of Decision-Based Design (DBD) holds the perspective that the primary role of designers is to make robust design decisions given the uncertainties associated with the system and models (Ullman 2001). The Decision Support Problem Technique (DSPT) is a framework for a system design in view of the DBD mindset (Mistree, Hughes, and Bras 1993). In the DSPT, the compromise Decision Support Problem (cDSP) is a generic mathematical formulation of a decision construct (as shown in Figure 1), which is based on mathematical programming and goal programming (Mistree, Hughes, and Bras 1993), and it assists the designers in carrying out trade-offs among multiple conflicting goals. By using the cDSP, the designers' goal is to find satisfying solutions for the desired system performance rather than optimum solutions that are valid only in a narrow range of conditions. In the context of the DSPT, the apparent strength of the cDSP is the handling of highly constrained environments (Murphy, Tsui, and Allen 2005), and also been verified to achieve robust design (Bras and Mistree 1993). Many extensions of the cDSP that enable it to be strengthened and/or specialised through augmentation are defined. The most relevant to this paper is the robust design decision formulations of the cDSP and their corresponding integrated computational approaches, such as the Robust Concept Exploration Method (RCEM) (Chen et al. 1996a), RCEM – Design Capability Indices (DCI) (Chen et al. 1999), RCEM – Error Margin Index (EMI) (Choi et al. 2005), and Inductive Design Exploration Method (IDEM) (Choi et al. 2008b).

In the approach proposed by Chen et al. (1999), a cDSP-DCI based computational procedure in RCEM that generates multidisciplinary design solutions for probability-based robust design and also defines a design process as either a robust design Type I or Type II. Building on that work, Choi et al. (2005) propose a cDSP-EMI for robust design Type III (as shown in Figure 1), where the EMI is capable of indicating the location of the mean system performance and the spread of the performance considering the variabilities in both the design variables and the system models. Taking into account the propagation of the above three types of uncertainty (Allen et al. 2006), especially in a multiscale material design, Choi et al. (2008b) propose a multi-level and robust design method – IDEM, which effectively facilitates the robust design for the analysis and design chain of the models with the presence of the MSU in the hierarchical design of the multiscale systems.

Baseline cDSP	cDSP-DCI/EMI with Robust Design Goal Formulation
Given n number of system variables m number of system goals q number of inequality constraints $p+q$ number of system constraints $g_i(x)$ system constraint functions G_i system goals $A_i(x)$ performance functions $f_k(d_i)$ function of deviation variables to be minimized **Find** x_i system variables $i = 1, \ldots, n$ d_i^+, d_i^- deviation variables $i = 1, \ldots, m$ **Satisfy** *System constraints (linear, nonlinear)* $g_i(x) = 0 \quad i = 1, \ldots, p$ $g_i(x) \geqslant 0 \quad i = p+1, \ldots, p+q$ *System goals (linear, nonlinear)* $A_i(x) + d_i^- - d_i^+ = G_i \quad i = 1, \ldots, m$ *Bounds* $x_i^{min} \leq x_i \leq x_i^{max} \quad i = 1, \ldots, n$ $d_i^+, d_i^- \geq 0;\ d_i^+ \cdot d_i^- = 0 \quad i = 1, \ldots, m$ **Minimize** Archimedean: $Z = \sum_{i=1}^{m} w_i(d_i^-, d_i^+)$ Preemptive: $Z = [f_i(d_i^-, d_i^+), \ldots, f_k(d_i^-, d_i^+)] \quad i = 1, \ldots, m$	**Given** n number of system variables m number of system goals q number of inequality constraints $f_{0.i}(x)$ multiple mean response functions $f_{1.i}(x)$ multiple upper uncertainty bound functions $f_{2.i}(x)$ multiple lower uncertainty bound functions $g_{0.i}(x)$ multiple mean constraint functions $g_{1.i}(x)$ multiple upper constraint bound functions $g_{2.i}(x)$ multiple lower constraint bound functions URL_i/LRL_i performance requirements Δx deviations of system variables $DCI_{target,i}$ targets of *DCI* $EMI_{target,i}$ targets of *EMI* **Find** μ_x mean of system variables d_i^+, d_i^- deviation variables i = 1, …, m **Satisfy** *System constraints:* $DCI_{constraints,i}(x) \geqslant 1 \quad i = 1, \ldots, q$ *or/and* $EMI_{constraints,i}(x) \geqslant 1 \quad i = 1, \ldots, q$ *System goals* $DCI_i(x)/DCI_{target.i} + d_i^- - d_i^+ = 1 \quad i = 1, \ldots, m$ *or/and* $EMI_i(x)/EMI_{target.i} + d_i^- - d_i^+ = 1 \quad i = 1, \ldots, m$ *Bounds* $x_i^{min} \leq x_i \leq x_i^{max} \quad i = 1, \ldots, n$ $d_i^+, d_i^- \geq 0;\ d_i^+ \cdot d_i^- = 0 \quad i = 1, \ldots, m$ **Minimize** Archimedean: $Z = \sum_{i=1}^{m} w_i(d_i^-, d_i^+)$ Preemptive: $Z = [f_i(d_i^-, d_i^+), \ldots, f_k(d_i^-, d_i^+)] \quad i = 1, \ldots, m$

Figure 1. Mathematical formulations of baseline cDSP and cDSP-DCI/EMI for robust design.

In the context of DSPT, various design activities related to decision-making are organised as a domain-dependent process (Mistree, Smith, and Bras 1993), then formulated as decision workflows via using the PEI-X (Phase-Event-Information – X) diagram. Furthermore, the PEI-X diagram is used to achieve the designing of decision workflows from a perspective of event-based time, where the X can be identified as Decision, Task, System, Knowledge, as well as other essential elements that enable to extend a designer's ability of decision-making (Wang et al. 2019). As an uniform representation schemes of meta-design, the DSPT palette entities are used to modelling the design processes in PEI-X diagram, as shown in Figure 2, which enables the designers to plan the Support Problems (SPs) and order the various information aspects of the design problem.

As a meta-level of designing systems/processes, meta-design includes the partitioning of a design problem, the decomposing of the design processes into a set of decisions and the planning of the sequence of decision-making activities (Wang et al. 2019). Compared with the traditional process models, such as the Business Process Modeling Notation (BPMN), IDEF0, Design Structure Matrix (DSM), and Event-driven Process Chain (EPC), the Decision-Based Design (DBD) puts more emphasis on the partnership between humans and computers, and its guiding philosophy is emphasising the core role of designers in the computer design environment is the decision makers (Mistree, Smith, and Bras 1993). The PEI-X diagram enables the visualisation of the decision-centric design process and the decision-making problem formation (Schönberg and Messer 2018), where the decisions are

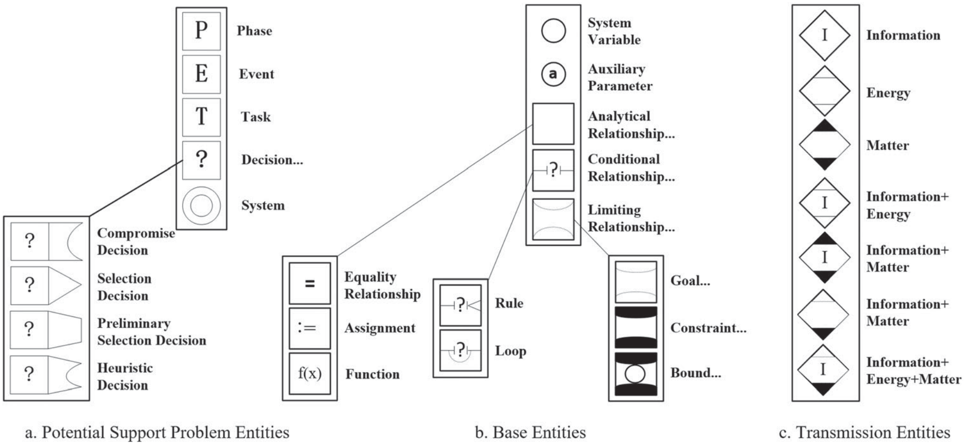

Figure 2. The DSPT palette entities for decision process modelling (Mistree, Smith, and Bras 1993).

categorised in two main types of DSP, i.e. selection decision and compromise decision. In this paper, we will expand the capability of the PEI-X diagram in designing of robust decision workflows.

2.3. Ontology-based uncertainty knowledge representation

In the computational environment, the modelling of design process is used as a template in order to facilitate the reusability and executability of the domain-dependent information via the separation of the declarative knowledge (i.e. problem-specific information) from the procedural knowledge (i.e. process-specific information) (Panchal et al. 2004; Panchal et al. 2009; Schönberg and Messer 2018). A template-based approach for modelling various design decisions and uniform representation of specific mathematical models is presented and validated in different application cases (Panchal et al. 2004; Ming et al. 2016; Ming et al. 2017), and it provides modular support for human judgment in system design by means of the structured decision information content. Decision templates are created by developing a set of Extensible Markup Language (XML) schemas which provides a convenient and standardised means of capturing information (Panchal et al. 2009). However, the consistency and inherent structure of the manner in which the reusable information is used necessitates the formalisation and representation of knowledge in the decision-making process. As specifications of conceptualisation, ontologies provide common vocabularies or terms, as well as their relationships, to enable the formal representation of domain-specific knowledge (Noy and McGuinness 2001), which can used to facilitate the creation and reuse of decision templates.

Ontologies have been widely used in various application areas such as information integration, semantic retrieval, knowledge exchange, management, etc. (Torga, Andreasen, and Marjanoviä 2010), which benefit from their characteristics of flexibility, intelligent behaviour, semantic interoperability, and expressiveness (Wang et al. 2018b). Some valuable design information will be captured and archived in a general way, along with a set of concepts describing an area of knowledge that can be shared and reused among teams and even software agents in a distributed design environment (Moon et al. 2009). Such as, Rockwell et al. (2009) develop a Decision Support Ontology (DSO) to support the information communication of decision making within collaborative design. Noor, Salcic, and Wang (2016) illustrate the significant value and benefits of ontology in the activity identification under uncertainty.

Meanwhile, a series of ontologies also are developed to facilitate the efficiency and effectiveness of a human designer who uses a DGS in PDSIDES to design the decision workflows. These ontologies include a PEI-X ontology for meta-design process hierarchies that integrates the information related problem, product, and process in the decision-making processes (Wang et al. 2019), ontologies for compromising DSP template (Ming et al. 2016) and the utility-based selection DSP template (Ming et al. 2017) that represent and document the knowledge of the decision-solving model, and an ontology for systematic design space exploration that integrates the decision-centric design problem-solving process (Wang et al. 2018a). Additionally, based on the corresponding ontologies, the template-based ontological method is validated effectively in terms of capturing and reusing the information of decision support in various design problem applications, such as the adaptive design of cylindrical pressure vessel, a rapid prototyping resource selection problem, the design of a shell and tube heat exchanger, and a hot rod rolling process chain.

Numerously published research in the semantic community is focused on the extension of the ontologies' capability to facilitate the formal representation of uncertain knowledge and to support reasoning with inaccurate information (Yang and Calmet 2005; Ding, Peng, and Pan 2005; Costa, Laskey, and Laskey 2008). The primary idea of these work augments and supplements the Web Ontology Language (OWL) as an underlying ontology modelling language with uncertainty and annotates it with Bayesian networks (also referred to as probabilistic networks), which facilitate the ability to express and assess probabilistic knowledge (Yang and Calmet 2005; Fenz 2012). For example, the customer preference uncertainty in the product family design is modelled as a feature preference probability towards certain product attributes using the customer preference survey data, and the propagation and the impact of the preference uncertainty are evaluated quantitatively through the ontology-based Bayesian network (Lim, Ying, and Han 2012). Further, Costa et al. (2012) define an ontology reference model developed as part of the uncertainty representation and reasoning evaluation framework (URREF), which is being carried out by the Evaluation of Technologies for Uncertainty Representation Working Group (ETURWG). Also, PR-OWL (Probabilistic Web Ontology Language) is developed as a Bayesian ontology language to serve as a supporting tool for applications (Costa, Laskey, and Laskey 2008).

However, some practical limitations have also been realised with regards to industrial implementations, especially in terms of robust design for model-based complex engineered systems, the attention to the representing and capturing process-related knowledge that refers to the uncertainty management is still not enough. Sim and Duffy (2003) identify an ontology of generic engineering design activities, where the ambiguity and uncertainty are integrated into the activity of defining. Singh et al. (2019) developed a decision support ontology to enhance the resilience of the supply chain with the uncertainty of disruptions. In the context of DSPT, the most previous work related to decision-making knowledge representation has been focused on the information under the case of certainty in design, nevertheless, uncertainty is a more commonly encountered factor during the engineering design process. Thus, the typical requirements of uncertainty management identified in Section 1 are addressed in this paper, and it enables the users of PDSIDES to design the decision workflows with uncertainty.

3. Uncertainty management approach in designing of decision workflows

3.1. Requirements for uncertainty management in decision workflows

Since leveraging the knowledge related to the design process has become crucial to improving enterprise agility, the strategic methods for the effective management of enterprise intellectual capital also have drawn more attention (Wang et al. 2019). Most of the design processes for complex engineered systems are structured in an *ad-hoc* fashion based on previous design experience (Panchal et al. 2009). Therefore, we have realised that the quality of processes for systems designs have a great influence on cost and design efficiency (Wang et al. 2018a). As Herbert Simon pointed out 'design process strategies can affect not only the efficiency with which resources for designing are used but also the nature of final design as well' (Simon 1996). Hence designing the design processes, namely, meta-design, is an essential component in the systems-based design strategy for designing complex systems, particularly for multiscale systems with high degrees of nonlinearity and uncertainty (Panchal et al. 2007).

Due to the coexistence of various uncertainties in design, from the perspective of a model-based realisation of complex engineered systems, the application of existing processes, methods, and tools in the management of various uncertainties necessitates a computational environment that enable the system model to integrate the associated information of robust design (Wang et al. 2018b). Since the semantic interoperability of ontology in the computer environment, a template-based ontological method is employed in Section 4 to represent and capture the uncertain knowledge in engineering design on the foundation of Decision Support Problem Technique (DSPT) introduced below. The developed ontology for the robust decision process will enable human designers to understand and predict the process behaviours in decision-making.

In the context of DSPT, robust decision-making refers to a particular set of methods aiming to help human designers identify potential robust strategies under the conditions of complexity and uncertainty. A decision-centric meta-design for the complex system design requires the information flows of the decision processes to be effectively organised and combined, which will assist a human designer in accommodating uncertainty and making a robust decision in design. The traditional design process models, such as the IDEF0, BPMN, and EPC, are unsuitable for describing the information of the existence of uncertainty in the process chain. Phadke (1989) proposes a P-Diagram to represent the quality characteristics of a process/product that is useful for describing a robust design task based on a semantic graphical representation. From the perspective of DBD, the PEI-X diagram has the ability to visualise hierarchical decision processes, which provides a basis for the graphical representation of robust design information between decision-making activities. However, it is difficult to use the P-Diagram and PEI-X diagram to express a series of activities associated with the robust design and the impact of the uncertainty on the decision-making processes. Therefore, it is necessary to use a hierarchical process model with a stronger semantically graphical expression to explicitly depict the value of the parameters interlinked with individual subsystems and the propagation characteristics of the uncertainty in the model and the process chain.

3.2. Procedure for designing robust decision workflows

In this paper, a domain-independent approach is proposed to assist the designers in defining and creating the reusable and computational decision workflows that involve experimental design, statistical analysis, and decision-making. The approach includes the following steps:

3.2.1. STEP 1: identify the types of uncertainty

Numerous research studies have clarified and verified that variations in the early design phase will have a significant impact on the quality and performance of the subsequent design. Thus, the most important part of implementing the effective management of the various uncertainties in design is the identification of the uncertainty types, which involves determining whether the uncertainty is quantifiable. Therefore, the primary task of specifying the design problem is to distinguish the attribute types and numeric types of the design parameters. There are four attribute types defined for the parameters of the simulation model, which cover control factors, noise factors, the response, and the fixed parameter. Additionally, the numeric types of parameters need to be specifically described as intervals or discrete values. The influence of uncertainty on the system itself is considered, namely the attribute types of the simulation model that need to be defined. To assist the designers in completing the above work, a graphical expression for designing the hierarchies of a robust design is defined, which uses strong semantics to represent the features of each element in the robust design model layer. As shown in Table 2, a revised graphical expression adopted by (Choi 2005) is used to capture three semantic information items of the model entity, the data attribute, and the composite pattern. The graphical representation of the robust design process facilitates the identification of uncertainty management types. Furthermore, the robust design hierarchy is represented explicitly in the form of graphics, which will also increase the understanding of the relationship between the elements of the simulation model and the propagation of uncertainty between them.

Table 2. Graphical expression for the hierarchies in robust decision workflows.

Entity	Symbols	Semantics
Rhombus box	◇	Control factors, noise factors, the response, and the fixed parameter
Pentagon box	⬠	Certain model
Hexagon box	⬡	Uncertain model
Arrow Line	**Symbols**	**Semantics**
Single solid line	⟶	Discrete & certain
Single dotted line	⇢	Discrete & uncertain
Double solid line	⟹	Ranged & certain
Double dotted line	⤃	Ranged & uncertain
Composite Pattern	**Symbols**	**Semantics**
Arrow from the left into the box	→⬡	Given value/parameter
Arrow from the top into the box	↓⬡	Goal/required response
Arrow out of the box to the right	⬡→	Determined variable
Arrow out of the box to the bottom	⬡↓	Output response

For quantifiable sources of uncertainty, we define three variations based on the probability distributions of the parameters of a system, namely certain mean (μ), variance (σ^2), and deviation (Δx). The acquisition of these quantifiable variation values will be used to determine the estimation of the system response, which will be managed with two different methods.

- One method is the management of the Input Parameter Uncertainty (IPU), which means handling the uncertainty that is caused by the variability of input parameters (i.e. noise factors and control factors) in the system model. This method also ensures that the obtained solutions are relatively insensitive to the variation generated by the input parameters. The corresponding robust design for this type of uncertainty management type is Type I (for noise factors) or Type II (for control factors).
- Another method is the management of the Model Parameter Uncertainty (MPU), which means handling the uncertainty that is caused by the unparameterisable variability in the system model. The corresponding robust design is Type III, and it is used to identify a ranged set of solutions that are relatively insensitive to the variability within the system model.

Due to the limited knowledge of the system, there are some assumptions and simplifications in the simulation, which will cause the propagated uncertainty in a chain of models. This type of uncertainty source is unquantifiable, which is managed by the method of Model Structure Uncertainty (MSU). MSU belongs to the Type IV robust design, which may include two other types of uncertainty management. Various types of robust design will be performed in Step 3.

3.2.2. STEP 2: design the hierarchical decision workflows

20192019The robust design problem is modelled structurally with the graphical expression defined in Step 1. Most of the information used to describe the specific problem will be organised in a displayable manner. The remaining issue is how to use this information to solve the design problem through a reasonable process. In the context of the DSPT, various sequences of the computational tasks related decision-making are organised in the decision workflows. The process granularity of the different levels is partitioned and planned in order to form the meta-design hierarchy of decision workflows. According to the identified methods of uncertainty management and the types of robust design, the hierarchical decision workflows are further defined to provide the executable processes that can be used to obtain solutions that satisfy the design requirement in the given design space. To increase the efficiency and effectiveness of the meta-design for decision workflows, a graphical decision-making process is modelled on the format of PEI-X diagram process language. Depending on the focus of the functional goals, the decision workflows consists of five types of process templates, namely 'Design', 'Phase', 'Event', 'Decision', and 'Task' (Wang et al. 2019). The iteration of the specific activities is implemented in each executable process template via the embedded computable module. The generated information will be used for the uncertainty management in Step 1.

3.2.3. STEP 3: Execute the sequential computability routines

The partitioning and planning of the executable design activities are implemented in Step 2. To obtain the solution that meets defined design requirements, the sequential computability routines embedded in the process template need to be executed. The definition of the computability routines in the decision workflows is relevant to the goals of the design activities. Some of the goals associated with design space exploration have been described in (Wang et al. 2018a), such as the response surface modelling in the Design of Experiments module and the design preferences exploring in the Post-Solution Analysis (PSA) module. In this paper, we focus on other computability routines associated with the three types of uncertainty management identified in Step 1.

- *The computability routines for the IPU management.* In the IPU management, the formulations of the mean and the variance of the response defined in (Chen et al. 1996b) are employed in the robust designs Type I and Type II. The solutions that satisfy a set of performance requirement targets are found by taking into account the system performance deviation that resulted from the variation of noise factors and control factors. The Design Capability Indices (DCI) also need to be calculated in the robust design Type III, since the design variables can be identified as adjustable ranges rather than a single value. This means that the solutions satisfy a ranged set of performance requirements (Simpson et al. 1997).
- *The computability routines for the MPU management.* In the robust design Type III, the premise of the above design scenario is that the simulation model is certain. When the simulation model is identified as uncertain in Step 1, the Error Margin Index (EMI) needs to be calculated based on the formulation of the variability interval in the system response. The approach for estimating the lower/upper response bound function is developed by Choi et al. (2005).
- *The computability routines for the MSU management.* All of above computability routines may appear in the robust design Type IV because of the identification of the uncertainty type for each model in the chain of simulation models. To find the adjustable ranges for the given design space under the uncertainty propagation, the designers need to evaluate discrete points in the simulation model. The most important part of the evolution processes is searching the feasible region for the interdependent space between two models, based on the hyper-dimensional EMI (HD-EMI) and using the discrete points generated from the mean, minimum, and maximum response functions. The detailed calculation procedure is developed in the IDEM (Choi et al. 2008b).

4. Ontology development for robust design decision process

Following the requirements of uncertainty management presented in Section 1, a modular template for the robust design decision process is defined in order to achieve the goals of reusability and executability. Further, a frame-based ontology is developed based on the module elements embedded in the robust design template, which enhances the designer's understanding of process behaviour. Then the instantiation procedure of the ontology-based template is elaborated in keeping with the design approach of the robust decision workflows. Instead of using visual tools (e.g. OWL-VisMod) to display the ontology structure, the visualisation of meta-design in robust decision workflows is achieved via a graph-based editing tool in Protégé[1] (Garcíapeñalvo et al. 2014).

4.1. The modular template for the robust design

In the computational environment, a modular-based design approach enables a designer to construct reconfigurable and executable process templates, which can implement flexible configurations for the different types of uncertainty management identified in the proposed method in Section 3. Thus, a modular-based template for robust design is developed for enhancing the capabilities of reusability and executability.

As shown in Figure 32019, the robust design template is visualised as a structure similar to a printed board assembly having some electronic components, where the elements are represented by 'chips' and the procedure for achieving the design of robust decision workflows is represented by the 'breadboard'. Three reuse scenarios defined in (Wang et al. 2019) and some modules and templates developed by (Wang et al.2019 ; Wang et al. 2018a), which are reused in order to capture the information of the decision process and related problem model in the robust design. The *Process Template* for integrating the meta-design of decision workflows is reused in the form of an assembly, and the instantiated *Process Template* with specific information corresponding to the 'chips' (e.g. the *Support Problems* or the *cDSP template*) is used to populate the related property `Slots` of the robust template. For example, the parameter information of the factors (i.e. the control factor or the noise factor), responses, and fixed parameters for the simulation mode is captured and documented by the module of the *Response Surface Model* developed in the design space exploration ontology. In this paper, we will define other new modules associated with uncertainty management, which include the *Response Function*, *Variation*, and *Uncertainty*. The functions of each module are described in detail in Section 4.2.

4.2. Definition of Classes and Slots

A frame-based ontology for the robust design decision process template is developed using Protégé 3.5,[2] which has ability to capture and document the re-usability information in the robust design and support the integrated management of uncertainty in design. The robust design decision ontology consists of the `Classes` and `Slots`, and by mapping to the robust design template, the 'chips' embedded in the 'breadboard' identify the main `Classes` of the ontology. Meanwhile, some `sub-classes` are also identified to increase the semantic richness and integrity of the robust design template ontology. Here, we focus

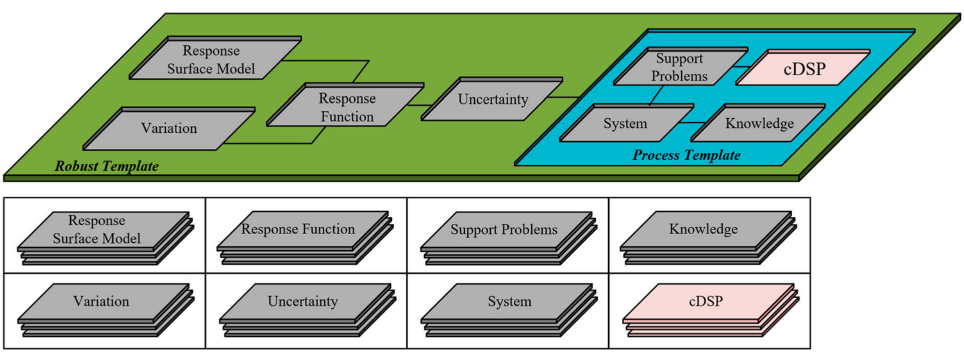

Figure 3. The modular template for the robust design.

Table 3. Classes of the robust design process ontology.

Class	Definition
Robust_Template	A formulation that integrates all the associated modules and represents the information structure of the robust design
Uncertainty	A class that represents the different management types under the various source of the types of uncertainty
ResponseFunction	A class that represents the functional relationship of the system performance response under uncertainty
Variation	A class that represents the quantitative degree of variation of the factors in the uncertainty
InputParameterUncertainty	A sub-class of '*Uncertainty*' that represents the management of the robust design information due to the uncertainty from the system input parameters (i.e. 'control factors' and 'noise factors')
ModelParameterUncertainty	A sub-class of '*Uncertainty*' that represents the management of robust design information due to the uncertainty from the system simulation model parameters (i.e. the unparameterizable variability of the model)
ModelStructureUncertainty	A sub-class of '*Uncertainty*' that represents the management of the robust design information due to the uncertainty from the system model structure formulation (i.e. the approximations and simplifications in a model)
MeanResponseFunction	A sub-class of '*ResponseFunction*' that represents the mean function of the response under different types of uncertainty
VarianceResponseFunction	A sub-class of '*ResponseFunction*' that represents the variance function of the response
LowerResponseBoundFunction	A sub-class of '*ResponseFunction*' that represents the lower deviation function of the response
UpperResponseBoundFunction	A sub-class of '*ResponseFunction*' that represents the upper deviation function of the response
Mean	A sub-class of '*Variation*' that represents the given mean value of the factors (including the control factors and noise factors)
Variance	A sub-class of '*Variation*' that represents the given variance value of the factors (including the control factors and noise factors)
Deviation	A sub-class of '*Variation*' that represents the given variance value of the control factors

on the definition of the `Classes`: *ResponseFunction*, *Variation*, and *Uncertainty*, the semantic relationships captured using `Slots` among those `Classes`. There are two types of `Slots` – data slots and object slots. Data slots are used to link the classes to the end data, while object slots are used to link the classes to the other classes. The detailed definitions of the `Classes` and `Slots` are shown in Tables 3–5. Some `Classes` and `Slots` that reuse the previously developed ontologies (Ming et al. 2016; Wang et al. 2019; Wang et al. 2018a) are not described here, such as *Process_Template*, *hasParameter*, *name*, *value*, etc.

4.3. Instantiation procedure of the robust decision process template

According to the design method for robust decision workflows defined in Section 3, the robust design template is assembled by the following modules and templates: *Response Surface Model*, *Variation*, *Uncertainty*, and *Process Template*, as shown in Figure 4. In the instantiation procedure of the robust design template, one of the important aspects is to create a PEI-X process template with the appropriate granularity, which is used to solve the defined design problem under uncertainty. The approach for creating and populating the property slots in the process template is explained in (Wang et al. 2019). Here, we focus on the designing of robust decision workflows and achieving uncertainty management through the reuse of `Instances` *Information* that is created in the *Process_Template*. Based on the developed ontology, the instantiation procedure of robust decision workflows involves three key steps:

Table 4. Object slots of the robust design process ontology.

Class	Definition	Type
robustDesignType	Specifies the type of the robust design	Instance
hasSM	Specifies the surrogate model instance of the *Robust_Template*	Instance
hasTEM	Specifies the theoretical empirical model instance of the *Robust_Template*	Instance
hasCFs	Specifies the control factor instance of the *Robust_Template*	Instance
hasNFs	Specifies the noise factor instance of the *Robust_Template*	Instance
hasUncertainty	Specifies the type of uncertainty instance of the *Robust_Template*	Instance
hasMeanResponseFunction	Specifies the *MeanResponseFunction* instance of the *InputParameterUncertainty* and the *ModelParameterUncertainty*	Instance
hasVarianceResponseFunction	Specifies the *VarianceResponseFunction* instance of the *InputParameterUncertainty* and the *ModelParameterUncertainty*	Instance
hasUpperResponseBoundFunction	Specifies the *UpperResponseBoundFunction* instance of the *InputParameterUncertainty* and the *ModelParameterUncertainty*	Instance
hasLowerResponseBoundFunction	Specifies the *LowerResponseBoundFunction* instance of the *InputParameterUncertainty* and the *ModelParameterUncertainty*	Instance
MeanOfCF	Specifies the *Mean* instance for the control factor	Instance
MeanOfNF	Specifies the *Mean* instance for the noise factor	Instance
VarianceOfCF	Specifies the *Variance* instance for the control factor	Instance
VarianceOfNF	Specifies the *Variance* instance for the noise factor	Instance
deviationOfCF	Specifies the *Deviation* instance for the control factor	Instance
designSpace	Specifies the generated discrete points for the defined design variables instance in the design space	Instance
interdependentSpace	Specifies the generated discrete points for the defined design variables instance in the interdependent space	Instance

Table 5. Data slots of the robust design process ontology.

Class	Definition	Type
lowerRequirementLimit	The value of the lower requirement limit for the system performance design requirement	Float
upperRequirementLimit	The value of the upper requirement limit for the system performance design requirement	Float
targetForDCI	The target value for the design capability index	Float
targetForEMI	The target value for the error margin index	Float
targetForHD-EMI	The target value for the hyper-dimensional error margin index used to estimate interdependent space	Float
valueOfHD-EMI	The value of the hyper-dimensional error margin index used to estimate design space	Float
CL(1-α)	The value of the confidence level used to predict the interval estimation with the Student t-distribution	Float
numOfPredictors	The number of predictors in an approximate model used to predict the interval estimation with the Student t-distribution	Integer
numOfSamples	The number of samples used to predict the interval estimation with the Student t-distribution	Integer
decisionCriterion	The decision preference used to indicate the location of the system response	String

(1) Create the `Instance` of *Robust_Template* and the associated modules (i.e. *Response-Function*, *Variation*, and *Uncertainty*). Based on the characteristics of the parameters in the defined design problem (i.e. the variation of parameters in the simulation model), the designer selects and edits the relevant box, arrow line, and composite pattern to depict the graphical hierarchies for the simulation model using the graphical expression defined in Step 1 (see the Section 3.2). This will facilitate the identification of robust design types and the uncertainty management involved.

(2) Create the `Instance` of *Process_Template* and the associated modules (i.e. *SPs_Entity*, *Sys_Entity*, *cDSP_Template*, *Information*, *GeneralDesign_Knowledge*, and *Interface*).

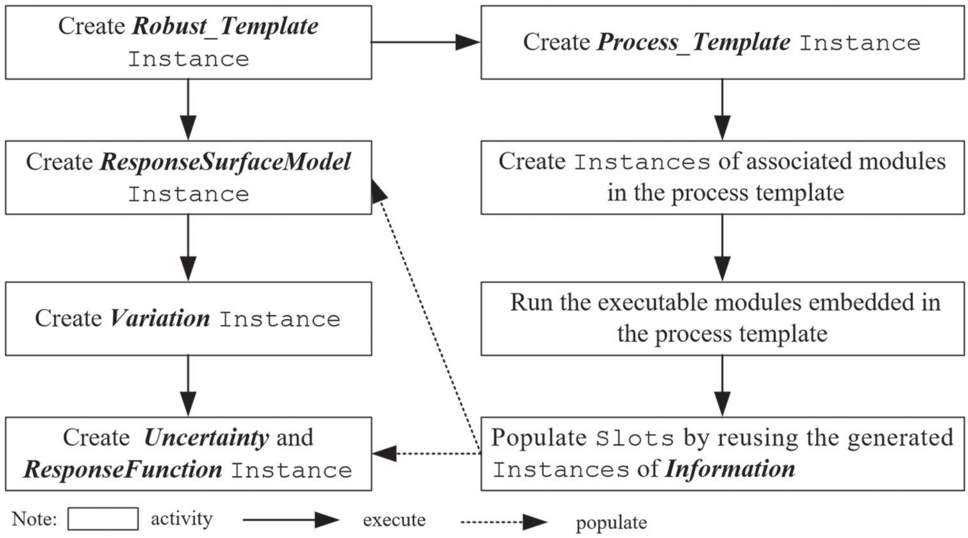

Figure 4. Instantiation procedure of the robust design template.

Based on the identified robust design type, the designers select and edit the relevant process entity, information, and interface in order to depict the graphical hierarchical decision workflows, which mainly refer to the partitioning and planning of the support problems.

(3) Run the executable modules that are embedded into the defined decision workflows, and populate the property `Slots` in the `Instance` of *Robust_Template* by reusing the created `Instance` of *Information*. In the `Instance` of *Process_Template*, the executable computing modules (e.g. developing the response surface model, calculating the functions of DCI/EMI, solving the cDSP-DCI/EMI model) will be embedded in the process templates at different levels in the format of knowledge. Through invoking and instantiating these modules, the generated information is reused and populated into the property `Slots` of *Uncertainty* and *ResponseFunction* in the robust design template, such as determining the information instances of response function by the instantiating the designing of experiments or reusing empirical models.

5. Case study

In this section, the utility of robust decision process template ontology is illustrated via a hot rod rolling (HRR) process design problem – an integrated design of product, material and associated manufacturing processes that calls for a series of hierarchical decisions to manage the uncertainties involved. The goal of designer (decision-maker) is to identify the material structures and processing paths that achieve/satisfy certain required product and manufacturing process-level properties and performances (Nellippallil et al. 2018b). Some model-based methods for the realisation of engineered products, materials, and associated manufacturing processes are presented to couple the material processing-structure–property-performance spaces (Olson 1997; Sinha et al. 2011). Here, the robust decision process chain of hot rod rolling simulation models are explained and the uncertainty knowledge of robust design for simulation models is represented and captured by using the developed ontology in this paper.

5.1. Hot rod rolling process design problem

In steel manufacture process, the products (e.g. rod, bar) involve a series of unit operations like continuous casting, reheating, rolling, cooling, etc. Integrating vertical and horizontal information flows for hot rod rolling process chain problem is achieved by carrying out the modelling of material behaviours at different scales within different unit operations (Nellippallil et al. 2017). The development of steels with high-quality performance and a range of properties are pursued by manufacturing designers, and the steel products' performance and mechanical property could be improved by managing the material processing and tailoring the microstructure of steel material generated (Wang et al. 2018a). In this way, the designer has to deal with the highly complex decision process chain to identify the process parameters, system variables, constraints and bounds, conflicting goals, etc., because of a large amount of information for the sequential manufacturing process and material processing flows.

Traditional plant trials are usually expensive and time-consuming, thus simulation-supported that involve by exploiting the computational modelling at different scales are carried out to obtain the desired mechanical performance and properties for the steel products. The showcase simulation model chain of HRR in Figure 5, Nellippallil et al. (2017, 2018b) define the forward information flows of two manufacturing stages in hot rod rolling process, namely hot rolling and cooling. The rod as the end product is measured by the identified mechanical property space, i.e. yield strength (*YS*), tensile strength (*TS*), and hardness (*HV*), which dependent on the final microstructure after cooling like the phase fractions of ferrite (X_f) and pearlite (X_p), ferrite grain size after the transformation of austenite to ferrite and pearlite (FGS, D_α), the pearlite interlamellar spacing (S_o) and the chemical composition of the material (e.g. silicon [Si], nitrogen [N], manganese [Mn], etc.). Hence the microstructure space is generated during the cooling state of HRR process, where the inputs involve the final austenite grain size (AGS, D), the cooling rate (CR), and the chemical composition of after rolling stage process. The integrated design of hot rolling and cooling processes completes the forward material workflow for the HRR we are addressing and establishes the process-structure–property-performance hierarchy for the material system.

Many have highlighted the challenges associated with the simulation-based multiscale material design (Sinha et al. 2011; McDowell 2018), among these are the challenges arising: (1) uncertain material models (that includes input factors, parameters, responses, etc.) due to simplification/idealization or a lack of complete knowledge, and (2) the propagation of uncertainty due to hierarchical information dependence in a multiscale model chain or in Olson's relationship of processing-structure–property-performance. To find the satisfying robustness solution for specific design requirements, the vertical and horizontal integration of simulation model chain for HRR design problem further ask for the designer to carry out the decision-based robust design exploration of the manufacturing process chain. Hence the uncertainty management in designing robust decision workflows is critical. This requests the designer to determine the sequence of activities needed for the

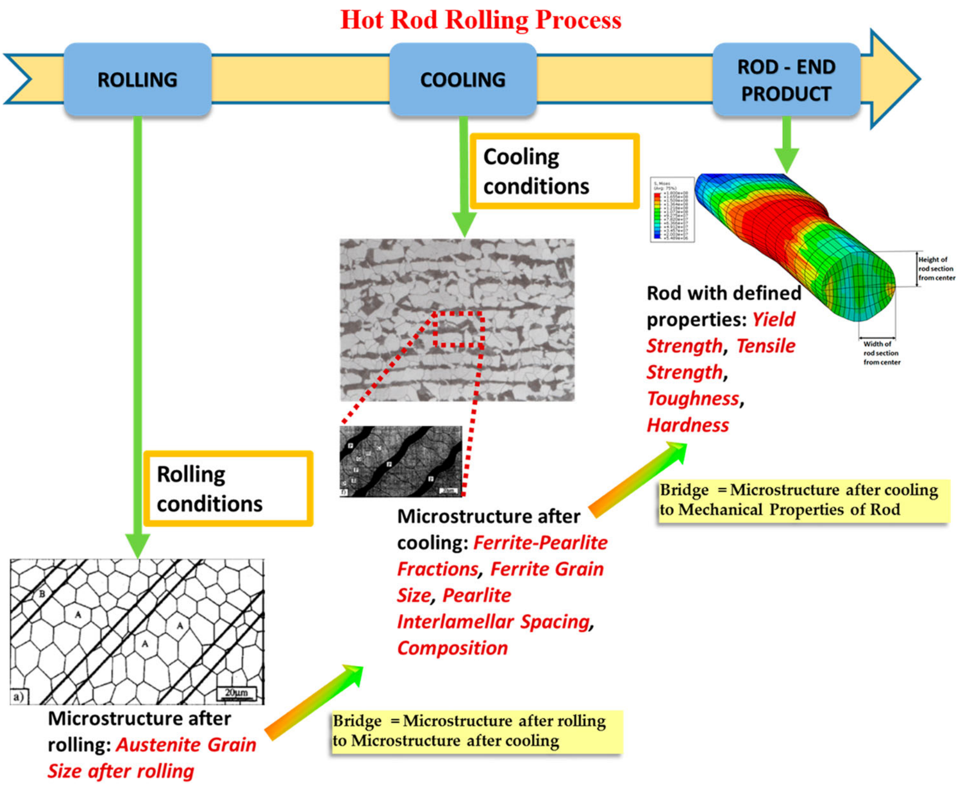

Figure 5. The simulation model chain of hot rod rolling process.

systematic exploration of design space under uncertainty and ensure the determination of the right combination of robust design information that meets the various conflicting goals and constraints. To illustrate the uncertainty management of designing decision workflows, our focus in this work is to demonstrate how a designer can capture, represent, and document the re-usability information in the hot rod rolling problem and thereby support the designers to explore the design space via using the robust decision process template.

5.2. Robust decision process for the processing-microstructure simulation models

In the cooling stage of HRR process, the process designer needs to initially determine the basic elements of the problem model before he/she creates the processes of solving and exploring the problem identified. That is the purposes of the robust design template are to allow the designer to define the initial robust design space of the problem to be solved, which refers to factors (i.e. signal factor, control factor, and noise factor), response, fixed parameter, and the process/product model. As shown in Figure 6, an instance of the robust template for the cooling module is created based on Step 1 of the approach defined in Section 3, where a graphical expression for designing the hierarchies of robust design is displayed. Further, the integrated information of uncertainty management and its associated robust decision process also should be captured and documented to support

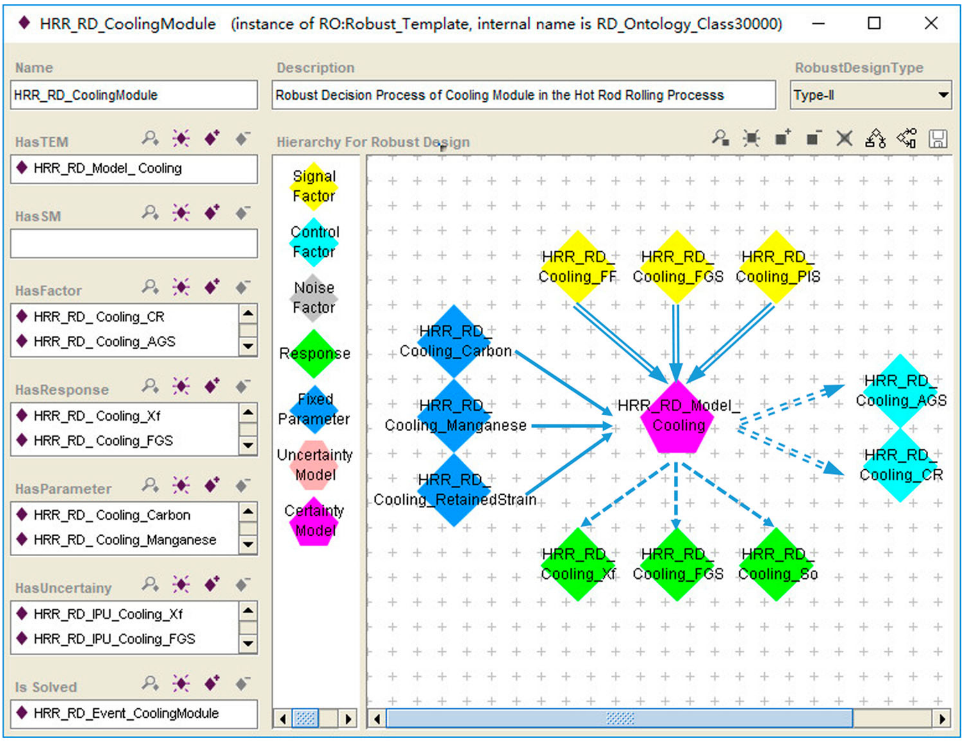

Figure 6. Instance of the robust design template for cooling module in HRR process.

the process designer in find the robust solution. For the cooling module of HRR problem addressed in this paper, the `Instance` of *Robust_Template* 'HRR_RD_CoolingModule' is created and the `Slots` are populated by the corresponding instances. Here we showcase the same using Figure 5, the designer is adopting the empirical models for processing-microstructure simulation chain (Nellippallil et al. 2018a), where the responses (i.e. ferrite fraction X_f, ferrite grain size D_α, and pearlite interlamellar spacing S_o) are defined as the function of the control factors (inputs of microstructure space) and some related fixed parameters. Meanwhile, the details of this information are identified in the `Instance` of PEI-X process template 'HRR_RD_Event_ CoolingModule' embedded in the robust design template.

As shown in Figure 7, the hierarchical decision workflows are created based on the Step 2 of the approach defined in Section 3. According to the definition of the different types of process templates in (Wang et al. 2019), the `Instance` 'HRR_RD_Event_CoolingModule' is an 'Event' process template. The prime function of event process template is to partition the design problem into some decision support problem and associated task support problem, then plan their execution sequences. Also, the design object along with its attribute information of the design decision and task, as well as the necessary knowledge reused in the design activities are populated. In the case of cooling module, the inputs of the event instance are constituted of the embedded `Instances` 'HRR_RD_Cooling_DesignRequirement' and 'HRR_RD_Cooling_DesignSpace', and the outputs is 'HRR_RD_Cooling_Solution'. And the instance of event support problem is divided

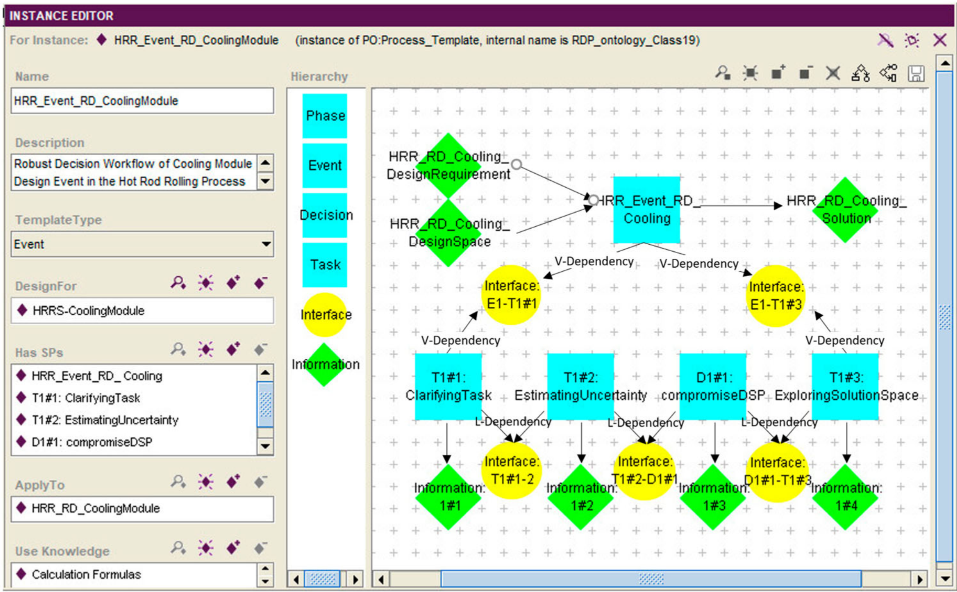

Figure 7. Instance of the hierarchical decision workflow embedded in the robust template for cooling module.

into three related tasks and one decision activities, where the `Instances` 'T2#1: ClarifyingTask', 'T2#2: EstimatingUncertainty', 'D1#1: compromiseDSP', and 'T2#3: ExploringSolutionSpace' are created and populated, the detailed procedure and slots for each template instance have been illustrated in (Wang et al. 2018a) and (Ming et al. 2016). The information flows among those support problem entities are represented via the interface `Instances` like 'Interface: E1-T1#1', 'Interface: 1#1-2', etc, the detailed description of the interface for the process template is explained in (Ming et al. 2017).

The different activity modules in the process template focus on identifying and processing related attributes, the main information embedded in the event process template instance is shown in Table 6. For example, the information instance for design requirement and design space are populated to capture and document the given problem statement of the cooling module in HRR process and relevant target and boundary like upper requirement limit (URL) for signal factors. This attribute information will be beneficial for the designer to identify and clarify the basic elements of the problem/process model in 'Task1#1', which is extremely important for the instantiation of the robust design template mentioned above. More critical is to identify the type of uncertainty management based on this information and to estimate the associated uncertainty in subsequent tasks. Here the `Instance` 'Task1#2' is performed following the Type II of robust design, the DCIs as metric for system performance and robustness are calculated by using mean response function and response variation function.

Based on the aforementioned tasks and attribute information, the uncertainty management module in the robust design template can be determined accordingly. For example, the management instances of input parameter uncertainty for each response in the product/process model for cooling module are populated. As shown the window '①' in Figure 8, the `Instance` 'HRR_RD_Cooling_X_f' is created and the embedded instances of variance

Table 6. Main attribute content of the information embedded in the event process template for cooling module.

Information	Main attribute content
HRR_PM_Design Requirement	• Achieving the lower value of the Microstructure Space (X_f, Ferrite Fraction; D_α, Ferrite Grain Size; S_o, Pearlite Interlamellar Spacing) • URL, X_f = 0.75; URL, D_α = 30 μm; URL, S_o = ï£¡ï£¡0.2 μm • $\text{DCI}_{\text{target},}$ X_f = 10; $\text{DCI}_{\text{target},}$ D_α = 10; $\text{DCI}_{\text{target},}$ S_o = 10
HRR_PM_Design Space	• x_1, Cooling Rate (*CR*) • x_1 = [11, 100] (K/min) • $\Delta x_1 = \pm 10$ (K/min) • x_2, Austenite Grain Size (*D*) • x_2 = [30, 100] (μm) • $\Delta x_2 = \pm 10$ (μm)
HRR_PM_Solution Space	• System Constraints: DCI_{X_f}, DCI_{D_α}, DCI_{S_o} • System Goals: X_f, D_α, S_o • System Variables: *CR*, *D*
Information2#1	• Factor (control factors: *CR*, *D*; signal factors: X_f, D_α, S_o) • Response • Variation (deviation: Δx) • Fixed Parameter ([C], [Mn], ε_r) • Response Model
Information2#2	• The Type of Robust Design (Type II) • Response Functions (mean response function and response variation function) • The DCI for each response
Information2#3	• The results of robust cDSP model with different design preference
Information2#4	• The satisfying robust solution

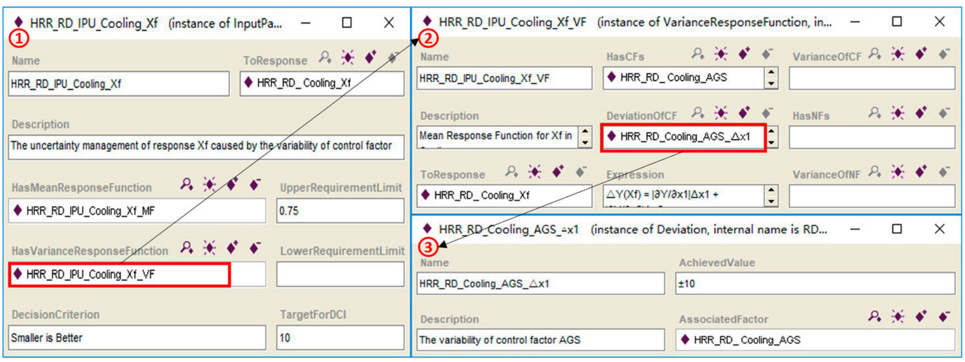

Figure 8. Instances of the uncertainty management (IPU) embedded in the robust template for cooling module.

response function and deviation of control factor are presented in the window '②' and '③', respectively. The essential information involved in a specific design problem for robust design is captured by the `Slots` in these template modules.

The ultimate goal of uncertainty management is to assist the designer to determine the right combination of robust design information that meets the various conflicting goals and constraints. Thus, the cDSP template for microstructure space (the `Instance` 'D1#1: compromise DSP') is formulated with DCI goals that captures microstructure requirements identified under uncertainty, see (Ming et al. 2016) and (Nellippalli et al. 2018a). The solution space formed based on the results of cDSP-DCI model with different design preference can be explored by the designer in task `Instance` 'T1#3: ExploringSolution-Space' mentioned in Figure 7. The weight sensitivity analysis embedded in the instance of solution space exploration is shown in Figure 9, and here the superimposed ternary

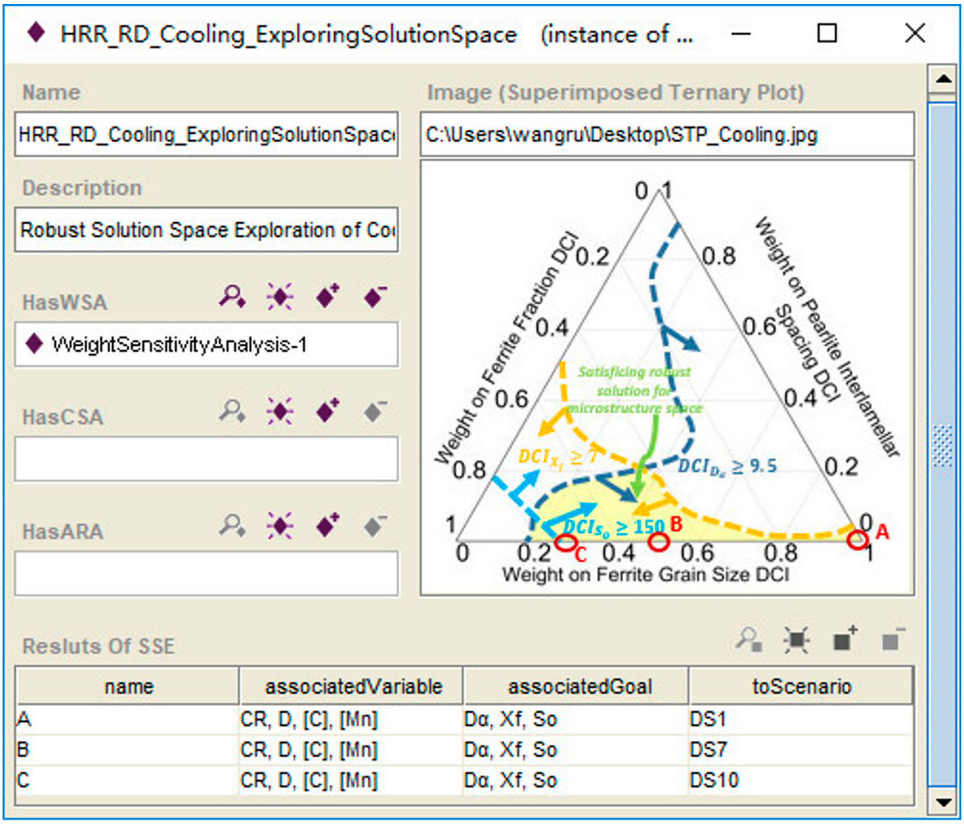

Figure 9. Task Instance of the solution space exploration for cooling module.

plot (microstructure solution space) with all the solution spaces of interest is used to identify the satisficing robust solution regions for the multiple conflicting goals. For cooling module, the designer defines a region with $DCI_{X_f} \geq 7$, $DCI_{D_\alpha} \geq 9.5$, and $DCI_{S_o} \geq 150$ on account of requirements for each goal and decision criterion. Also, to analyse further and assist the decision-making we select 3 solution points (A, B, C) from the region identified, which lie within the region that satisfies all the robust design goals in the best possible manner. The details of solution space exploration template are introduced in (Wang et al. 2018a).

5.3. Robust decision process for the microstructure-mechanical simulation models

In Section 5.2, a robust design template for cooling module in HRR is created by instantiating the embedded PEI-X process template and uncertainty management template, and the re-usability information of robust decision workflows is populated. In that case, the adopted response functions are defined based on the empirical models, which are usually response surface model developed through the design of experiments, thus there are uncertainties of the response model in some sense. The process designer has sufficient confidence to ignore the impact of this uncertainty, and only manage the variations of control factors (IPU) mentioned in Section 5.2. In this section, another case that here

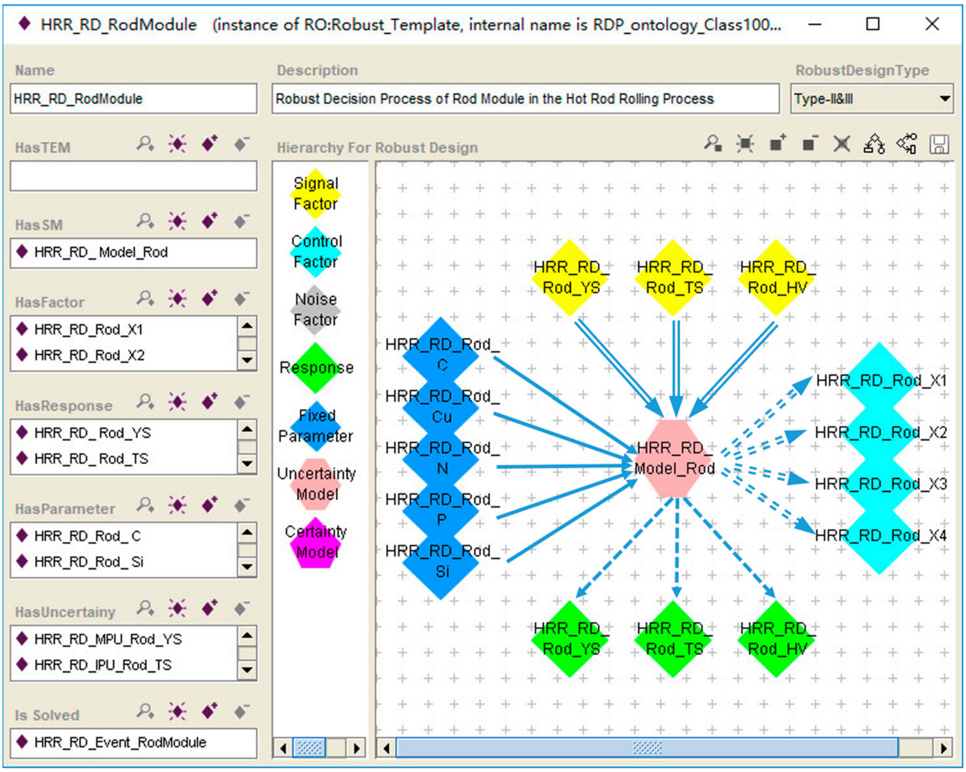

Figure 10. Instance of the robust template for rod module in HRR process.

there is a situation that the uncertainty derived from the response model is discussed via instantiating the robust design template of rod module in HRR process chain, as shown in Figure 10.

In the HRR problem defined in Section 5.1, the subsequent simulation model chain after microstructure correlation calculation (cooling module) is the rod module for predicting the mechanical properties, which are identified as yield strength (YS), tensile strength (TS), and hardness (HV). Also similar to the above mentioned, the design requirements for the rod module are shown in Table 7, and based on this information, the basic elements of robust design like control factors, signal factors, responses, and fixed parameters are populated. The difference is that the process/product model `Instance` 'HRR_RD_Model_Rod' is created in the robust design template instance by taking into account the uncertainty of the response function itself. The designer can organise these robust design elements with a graphical hierarchy, while also identifying robust design type based on attribute information for each element. For example, in the case of rod module, there are two types of robust design (Type II and Type III) due to the uncertainty sources from input parameters and model parameters (i.e. IPU and MPU). Also, the hierarchical decision workflows are created to address the corresponding robust design. Here, the designer can reuse the PEI-X process template created for the cooling module.

As mentioned, the `Instance` 'HRR_RD_MPU_Rod_YS' is used to manage the model parameter uncertainty for response yield strength (YS). During the carrying out of the instance of estimating uncertainty task, the detailed information attributes will be created

Table 7. Main information embedded in the robust design template for rod module.

Item	Main information
Design requirement	• Achieving the larger value of the mechanical property space (*YS*, Yield Strength; *TS*, Tensile Strength; *HV*, Hardness) • $\mathrm{LRL}_{YS} = 200$ MPa; $\mathrm{LRL}_{TS} = 450$ MPa; $\mathrm{LRL}_{HV} = 130$ • $\mathrm{EMI}_{\mathrm{target},}$ $YS = 3$; $\mathrm{DCI}_{\mathrm{target},}$ $TS = 8$; $\mathrm{DCI}_{\mathrm{target},}$ $HV = 8$
Control factors	• x_1, Ferrite Grain Size (D_α) • x_2, Ferrite Fraction (X_f) • x_3, Pearlite Interlamellar Spacing (S_o) • x_4, Manganese concentration after cooling ([Mn]) • $x_1 = [5, 25]$ (μm) • $x_2 = [0.1, 1]$ • $x_3 = [0.15, 0.25]$ (μm) • $x_4 = [0.7, 1.5]$ (%) • $\Delta x_1 = \pm 3$ (μm) • $\Delta x_2 = \pm 0.1$ • $\Delta x_3 = \pm 0.01$ (μm) • $\Delta x_4 = \pm 0.01$
cDSP-EMI/DCI	• System Variables: D_α, X_f, S_o, [Mn] • System Goals: Maximize EMI for *YS*, Maximize DCI for TS, Maximize DCI for *HV* • System Constraints: $\mathrm{EMI}_{YS} \geq 1$, $\mathrm{DCI}_{TS} \geq 1$, $\mathrm{DCI}_{HV} \geq 1$

and populated by executing the related sequential computability routines based on Step 3 in Section 3. As shown in Figure 11, the variation of the model response (YS) is depicted in term of the mean response function and the maximum/minimum prediction intervals functions (i.e. lower/upper uncertainty bound function). Using these mathematical functions, the designer can calculate the upper and lower deviation of response, then obtain the EMI according to the decision criterion. For the simulation model of rod module, the decision criterion for the EMI/DCI is 'Larger is Better', which signifies that the mean responses (i.e. *YS*, *TS*, *HV*) need to be located further from the defined lower requirement limit (LRL) and as close as possible to the defined target for the EMI/DCI. The objective of the cDSP

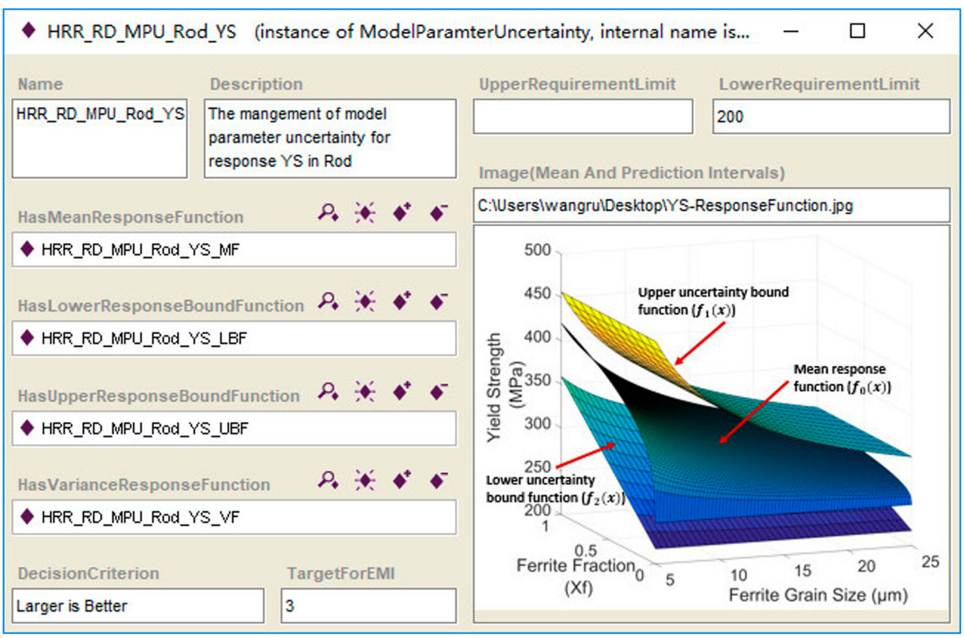

Figure 11. Instance of the uncertainty management (MPU) embedded in the robust template for cooling module.

formulation for the EMI/DCI is to find the mean value of the control factors ($x_1 \sim x_4$) that satisfies the given performance goals and bounds.

Through the solving of cDSP-EMI/DCI model with different design preference, the designer obtains the values of system goals under the identified uncertainties, namely EMI_{YS}, DCI_{TS}, and DCI_{HV}. To achieve high *EMI* and *DCI* for the model response *YS*, *TS*, and *HV*, the designer is interested in defining satisficing robust solution regions for the multiple conflicting goals. In Figure 12, a common robust solution region (light-yellow region) with $\mathrm{EMI}_{YS} \geq 1.5$, $\mathrm{DCI}_{TS} \geq 6$, and $\mathrm{DCI}_{HV} \geq 7$ is identified in the task instance of exploring solution space, which satisfices the robust design requirements identified for the conflicting mechanical property goals. Also, here we highlight three solution points (A, B, C) to assist the designer's decision-making. The point A is the most robust region for *YS* with high *EMI* but lowest for *TS* and *HV* with low *DCIs*. Similarly, the point B is the most robust region for *TS* with high DCI_{TS} but lowest for *YS* with low EMI. In contrast, the point C lying inside the satisficing robust solution regions achieves the highest DCI_{HV} and is the most robust region for *HV* goal satisficing the robust design requirements of other goals. Thus, the point

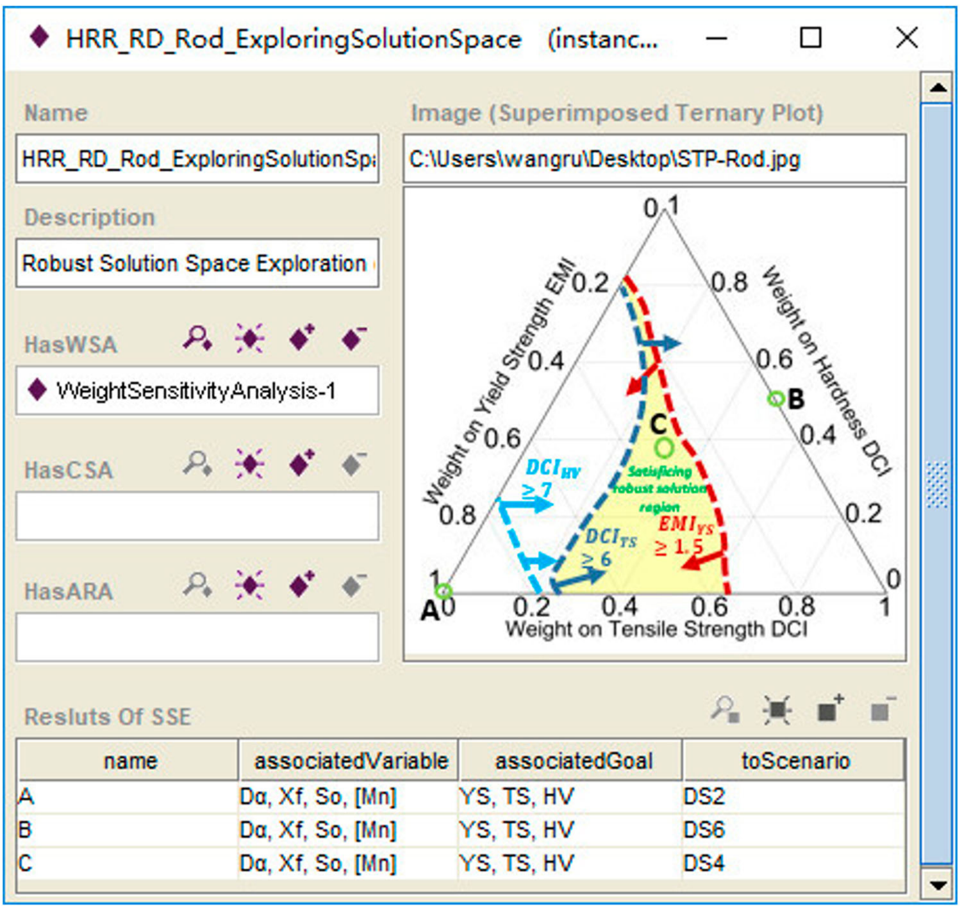

Figure 12. Task instance of the solution space exploration for rod module.

C has the most potential to be selected as the recommended solution to the subsequent manufacturing operations.

5.4. Summary and Discussion

Using an analysis and synthesis simulation model chain identified in the HRR design problem, we instantiate two ontology-based templates of robust design by capturing and populating the re-usability information for the uncertainty management and the corresponding decision processes. Meanwhile, the graphical hierarchies for their simulation models are depicted. In the robust design for processing-microstructure simulation models, the robust design template for the cooling module is created in Section 5.2, and it provides a combination of the right information for IPU management and the corresponding decision processes. In this case, the control factor variability of process/product model is taken into account, and the robust system responses with sets of design specification are obtained by the implementation of a series of design activities, namely clarifying task, estimating uncertainty, formulating cDSP-DCI model, and exploring solution space. In the robust design for microstructure-mechanical simulation models, the robust design template for the rod module is created in Section 5.3, In this case, two types of uncertainty management are populated to manage the uncertainty sources from input parameters and response mode. Further, as for the PEI-X process template embedded in the robust design instance of rod module, the designer reuses the decision processes created in the previous instance of cooling module, which reflects the flexibility and configurability of the proposed ontology-based template in designing of robust decision workflows.

Since most of the decisions in the engineering design problem refer to the rigid constraints and bounds on the system variables, which are quantified using analysis-based 'hard', while some insight-based 'soft' information can be modelled as a multiobjective,

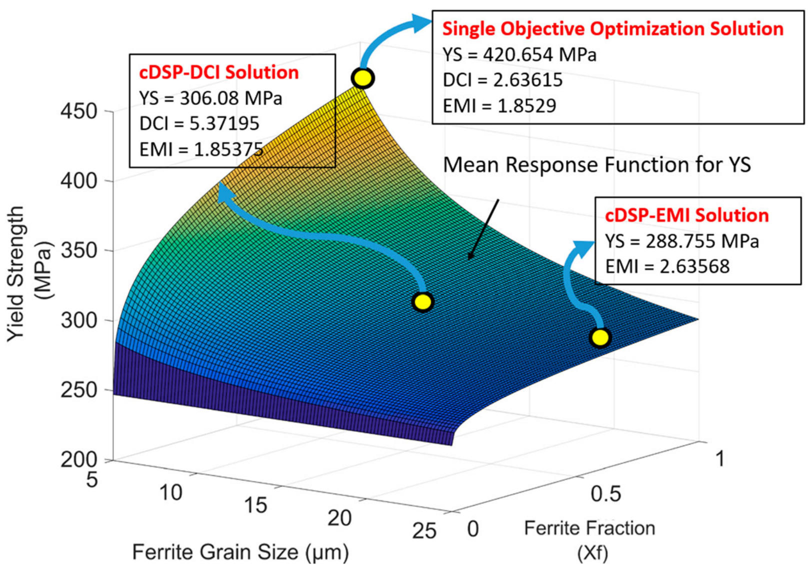

Figure 13. Comparison of solution obtained for yield strength using different formulations.

nonlinear optimisation problem. In this work, we prefer to suggest a designer find 'satisfying' robust solutions, which means designing a process/product that is relatively insensitive to uncertainties without removing the sources. To further illustrate the effectiveness of the proposed robust decision workflow design method for specific design problems, we compare three different formulations using the response Yield Strength for the Property-Performance space. The results associated with this comparative study are plotted in Figure 13 with ferrite fraction and ferrite grain size as the input factors for the yield strength model. We see that: (1) the value of solution point with EMI is less than using DCI formulation because the DCI formulation overlooks the uncertainty associated with the model and thus achieve a lower EMI value for the design solutions, (2) the optimal solution predicts the highest response but the value of DCI and EMI are low, which means that the optimal solution points obtained are susceptible to the uncertainties derived from input parameters and model parameter, namely are less robust. On the other hand, we use the same design problem to verify the effectiveness of the proposed method in this paper and previous research work, see Ref. (Wang et al. 2018a), which would be useful to understand the comparison between the baseline model of cDSP and the robust model (cDSP-DCI/EMI).

6. Closure

It is always essential but difficult to represent and capture the uncertainty knowledge, some practical limitations have also been realised with regards to industrial implementations, especially in the context of knowledge-intensive complex engineered systems. In view of DBD, system design involves a sequence of decision-making, that is decision workflows, which require a combination of analytical models and a way to synthesise the information generated by decision models. Typically, the uncertainties due to the incompleteness, inaccuracies, and not of equal fidelity in engineering design necessitate the robust design of decision workflows. In this paper, we focus on the knowledge reuse of uncertainty management to minimise the uncertainty impact on systems' performance and to expand the human designers' ability of understanding and prediction of process behaviour in decision workflows. Therefore, a template-based ontological method for robust design is introduced that supports the designing of decision workflows to ensure decision-making with the features of robustness, feasibility, and comprehensiveness, taking account of the goals of enhancing the design automation and intelligence in designing of decision workflows.

In the proposed method, the designing of robust decision workflows refers to a particular set of procedures aiming to help human designers identify potential robust strategies under the conditions of complexity and uncertainty. A hierarchical process model with a stronger semantically rich graphical expression and an executable template-based flexible decision process configuration will facilitate the meta-design of decision workflows. In addition, a frame-based ontology is developed in order to integrate the management of varied uncertainty information and improve the ability to communicate and to understand the process behaviours in the collaborative exploration of a system-level design space. Finally, we demonstrate the efficacy of this template-based ontological method for designing the robust decision workflows by carrying out the robust design of Hot Rod Rolling (HRR) process based on the analysis and synthesis of processing-microstructure (cooling module) and microstructure-mechanical (rod module) simulation models.

The research foundation of this paper mainly focuses on the DSPT, and the uncertainty knowledge involves the identified four types of robust design. Furthermore, there are some other uncertainties in engineering design that need to be captured and reused, such as the designers' preference and fuzzy epistemic, which will be an extension of this work. Although, the template-based ontological method for robust decision workflows effectively facilitates the improvement of the quality of products/processes in variations, and maintains semantic associativity and consistency of relevant robust design information and data in decision workflows.

Notes

1. Graph Widget of Protégé, Stanford University, http://protegewiki.stanford.edu/wiki/Graph_Widget_Tutorial_OWL, Accessed on 1 February 2016.
2. https://protege.stanford.edu/.

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