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ABSTRACT

Successful bidding involves defining relevant technical bid solutions that conform to the customers' requirements, then selecting the most interesting one for the commercial offer. However, in Engineer-To-Order (ETO) industrial contexts, this selection process is complicated by issues of imprecision, uncertainty and confidence regarding the values of the decision criteria. To address this complexity, a Multi-Criteria Decision Making (MCDM) support approach is proposed in this study. This approach is based on possibility theory and the Pareto-dominance principle. It involves three main stages. First, a method is proposed to automatically model the values of the decision criteria by possibility distributions. Second, four possibilistic mono-criterion dominance relations are developed to compare two solutions with respect to a single decision criterion. Finally, an interactive method is devised to determine the most interesting technical bid solutions with respect to all the decision criteria. The method is applied to the design of a technical bid solution of a crane. The results show that this approach enables bidders to select the most interesting solution during a bidding process, while taking into account imprecision, uncertainty and their own confidence regarding the values of the decision criteria.

KEYWORDS

Bidding process; engineer-to-order; technical bid selection; multi-criteria decision making (MCDM); uncertainty and imprecision; possibilistic pareto-dominance

1. Introduction

In order to increase their business volume and to remain competitive, systems contractors (or bidders) must successfully bid to a range of different customers (Wang, Wang, and Yongwei Shan 2020). A successful bid implies that the bid proposal is attractive, profitable and feasible (Chapman, Ward, and Bennell 2000; Arslan et al. 2006). Therefore, a bidder needs to propose a solution that combines both attractiveness (good values for the evaluation criteria) and feasibility (low uncertainty or high confidence about the company's ability to develop and deliver the technical system according to these values).

In this article, we consider bid proposals related to the development and delivery of physical products (e.g. cranes, robots, machine tools). In this context, in order to submit a bid to a customer, generally, a bidder designs and evaluates several technical bid solutions that comply with the customer's requirements. Then, from this panel of potential solutions, the bidder must select the most interesting one in order to elaborate and transmit a commercial offer to the customer (Chalal and Ghomari 2008). As in (Yan et al. 2006; Guillon et al. 2020), we consider that a technical bid solution is composed of a technical system (a set of sub-systems and components) and its delivery process (a set of required activities and resources to implement the technical system). In the literature, many works offer solutions to the strategic bidding problem (Kumar, Vinod Kumar, and Edukondalu 2013; Liu et al. 2014; Egemen and Mohamed 2008; Takano, Ishii, and Muraki 2018; Rayati, Goodarzi, and Ranjbar 2019; Yadav 2020). Based on internal costs and market behaviour, various approaches are proposed to determine the optimal bid price that maximise the probability of winning and the expected profit once the bid proposal is accepted. Generally, it is assumed that the technical bid solution relevant to the customer's requirements has been identified and its cost estimated. Therefore, the problem related to the selection of the most interesting technical bid solution among several potential ones has not been widely considered in the literature. In Ling et al. (2013), the authors propose an extended Analytical Target Cascading-based method to generate a solution for customer demands which are time and cost sensitive. Their paper focuses on Make-To-Order products, which means that the technical bid solutions relevant to the customer's demand have been designed and evaluated before the bidding process. Uncertainty and confidence issues regarding the future ability of the

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bidder to deliver the technical system are not taken into account within the selection process. It is, however, a very important dimension in order to propose competitive and feasible solutions.

In an Engineer-To-Order (ETO) bidding process, taking into account uncertainty and confidence is extremely important as it allows the bidder to anticipate risk related to the development and the delivery of the technical system once the offer is accepted by the customer (e.g. cost growth and schedule slippage). In fact, in an ETO bidding process, some engineering or design activities are necessary in order to define relevant solutions that meet the customer's requirements (Johnsen and Hvam 2019; Cannas et al. 2020). However, as there is no guarantee that the bid proposal will be accepted, the bidders, very often, avoid a detailed design in order to minimise potential losses of resources and time, especially in cases where their bid proposals are not accepted by the customers (Krömker, Weber, and Wänke 1998; Sylla et al. 2017). Thus, some parts of the technical systems and the delivery processes are only partially designed. Consequently, appropriate knowledge necessary to evaluate the technical bid solutions is not fully available. The values of the evaluation criteria are imprecise and uncertain (Chapman, Ward, and Bennell 2000; Erkoyuncu et al. 2013). The confidence of the bidder about her/his ability to deliver the technical system according to these values can be low (Sylla et al. 2017). This confidence depends not only on the developmental maturity or readiness of the technical system and its delivery process, but also on the expert feeling of the designer (Sylla et al. 2017; Mankins 1995). The more a technical system and its delivery process are mature and the feeling of the designer is high, the more the confidence of the bidder to deliver the technical system according to the values of the evaluation criteria is high. Therefore, in such ETO situations, in order to choose the most attractive and feasible solutions among several potential ones, it is necessary to consider uncertainty, imprecision and, more importantly, the bidder's confidence in the values of the evaluation criteria (or decision criteria).

In this article, the design and evaluation of relevant technical bid solutions are supposed done. Their performances have been evaluated in order to provide decision criteria (e.g. the cost of the technical bid solutions and the duration of the delivery processes). In addition, each solution has been evaluated in terms of the bidder's confidence. Therefore, the focus is placed on the selection of the most interesting technical bid solution. A Multi-Criteria Decision Making (MCDM) support approach is proposed. It is based on possibility theory and the Pareto dominance principle. The aim is to help a bidder (the decision maker) to choose the best solution to propose to a customer during an ETO bidding process.

The key contributions of the proposed approach are: (i) a new method which takes into account the bidder's confidence in the technical bid solutions to automatically model the uncertain and imprecise values of the decision criteria by possibility distributions, (ii) four new generic possibilistic dominance relations which are able to compare two solutions with respect to a single decision criterion in any situations where the values of the decision criteria are modelled by possibility distributions, and (iii) a new interactive method which allows the construction of a the restricted set of the most interesting solutions (Pareto front) by taking into account the level of certainty of dominance between solutions.

The remainder of this article is organised as follows. In Section 2, relevant background on Multi-Criteria Decision Making under imprecision and uncertainty is presented in order to describe the detailed contributions of this article. In Section 3, the proposed MCDM support approach, along with the supporting algorithms, are described. In Section 4, the application of the proposed approach on an example related to the design of a technical bid solution for a crane is presented and discussed in order to validate the contributions. Conclusion and future research are provided in Section 5.

2. Multi-criteria decision making (MCDM) under imprecision and uncertainty

As mentioned in Section 1, in the literature, several research works have been reported on the strategic bidding problem (Kumar, Vinod Kumar, and Edukondalu 2013; Egemen and Mohamed 2008; Takano, Ishii, and Muraki 2018; Rayati, Goodarzi, and Ranjbar 2019). However, we did not find any work focusing on the selection of technical bid solutions (pairs of technical system/delivery process) in an Engineer-To-Order (ETO) bidding process. Therefore, in this section, some MCDM support approaches which allow imprecision and uncertainty to be taken into account in a selection process are reviewed. Various approaches have been reported in the literature (see the reviews in Durbach and Stewart 2012; Kahraman, Onar, and Oztaysi 2015; Broekhuizen et al. 2015; Pelissari et al. 2019; ZahediKhameneh and Kılıçman 2019). They differ in two aspects: (i) the uncertainty theory used to deal with imprecision and uncertainty and, (ii) the MCDM support approach used to compare the potential solutions and to model the preference (or dominance) relations between them.

The most common uncertainty theories used to deal with imprecision and uncertainty in decision making is probability theory and fuzzy set theory (or possibility theory) (Mardani, Zavadskas, and Zare 2018; Kaya, Colak, and Terzi 2019). With the probability theory, uncertain values of each potential solution S_i following a decision criterion k, is modelled with a probability distribution function F_i^k. Two methods are very often used to compare the potential solutions: (i) Muti-Attributes Utility Theory (MAUT) (see von Neumann and Morgenstern 1953; Grabisch, Kojadinovic, and Meyer 2008; Wilson and Quigley 2016) and (ii) Stochastic Dominance approach (SD) (see Nowak 2004; D'Avignon and Vincke 1988; Zhang, Fan, and Liu 2010). In MAUT, based on the probability distributions of all the criteria, a function permits to compute the expected utility of each solution. Then a solution S_i is preferred to another one S_j if and only if the expected utility of S_i is greater than that of S_j. In the SD approach, a pairwise comparison of probability distributions is first performed in order to compare the potential solutions and to establish preference (or dominance) relations between them, following each decision criterion. Then, a method is used to built deterministic/stochastic preference (or dominance) relations following all the decision criteria.

With the fuzzy set theory, the imprecise and uncertain values of the decision criteria are modelled with fuzzy numbers (Durbach and Stewart 2012; Longaray et al. 2019). The possibility theory is known to be a very good framework to simultaneously deal with imprecision (vagueness) and uncertainty due to a lack of accurate and complete information (knowledge) (French 1995; Solaiman and Éloi Bossé 2019; Hose, Mäck, and Hanss 2019; Denœux, Dubois, and Prade 2020). Moreover, it also permits to easily and effectively take into account expert's points of view (thus to take into account the confidence of the bidders in each technical bid solution) (Dubois and Prade 2012). Therefore, in this article, we consider the possibility theory framework to cope with uncertainty, imprecision and confidence related to the values of the decision criteria.

According to the reviews presented in Broekhuizen et al. (2015), Mardani, Zavadskas, and Zare (2018) and Kaya, Colak, and Terzi (2019), the Analytic Hierarchy Process (AHP) is the most common MCDM support approach used with fuzzy set theory. Indeed, in AHP, the estimation of the weights and the values of the decision criteria is based on judgments. These judgments have a qualitative nature and may be inconsistent (Durbach and Stewart 2012). Therefore, the fuzzy set theory is very often used: (i) to model the weight and/or values of the decision criteria with fuzzy numbers, and (ii) to perform the aggregation of these values into a global score for each potential solution, which is used to select the most interesting solution. Some recent applications of AHP with fuzzy set theory are related to supplier selection (Burney and Ali 2019; Lu et al. 2019; Liu et al. 2019) and product design (Chakraborty, Mondal, and Mukherjee 2017; Mondragon et al. 2019; Khamhong, Yingviwatanapong, and Ransikarbum 2019; Haber, Fargnoli, and Sakao 2020). There is another stream of methods, named outranking methods (ELECTRE and PROMETHEE), which are used with fuzzy set theory (Broekhuizen et al. 2015; Kaya, Colak, and Terzi 2019; Liao, Yang, and Xu 2018). In the outranking methods, first, for each decision criterion and for each pair of potential solutions (S_i, S_j), based on the estimation of the two solutions, the preference degree of S_i over S_j is computed. Based on this and the relative importance of the decision criteria, the overall preference degree of the solution S_i over S_j with respect to all the decision criteria is computed. This overall preference degree is exploited in order to select the most interesting solution. These methods have also been used with fuzzy set theory for supplier selection (Krishankumar, Ravichandran, and Saeid 2017; Fei et al. 2019; Ping Wan et al. 2020) and for product design (Barajas and Agard 2010; Gul et al. 2017).

For both AHP and outranking methods, a formal definition of the relative importance of the decision criteria is required. However, in the context of a bidding process, in many situations, the bidders do not know to which criterion the customer demand is more sensitive (Ling et al. 2013). Moreover, even in situations where they have this information, most of the time, a non-expert decision maker cannot explicitly formalise the relative importance of each decision criterion. He/She may be able to choose a good solution according to her/his feeling with regard to many criteria but he/she is not able to provide a formal importance or weight for each criterion. Therefore, the MCDM problem considered in this article does not involve a formal prioritisation of the relative importance of the criteria. Moreover, as far as we know, the approaches found in the literature do not permit taking into account the confidence of the bidder in the decision process.

The Pareto-dominance approach is another approach used with fuzzy set theory for decision making under imprecision and uncertainty (Köppen, Vicente-Garcia, and Nickolay 2005; Ganguly, Sahoo, and Das 2013; Asrari, Lotfifard, and Payam 2016; Bahri, Talbi, and Ben Amor 2018). It is based on the conventional Pareto-dominance method. First, a pairwise comparison of the potential solutions is performed with respect to a single decision criterion in order to establish mono-criterion dominance relations between them. Second, based on the mono-criterion dominance relations, a pairwise comparison of the potential solutions is performed with respect to all the decision criteria in order to establish

Pareto-dominance relations between them and determine the restricted set of the most interesting solutions (Pareto front). In the fuzzy Pareto-dominance approach, a degree of dominance characterises the dominance relation between two solutions (Ganguly, Sahoo, and Das 2013).

This approach is suitable for the decision problem considered in this article because it does not require a formal definition of the relative importance of the decision criteria. Moreover, this approach can provide the decision maker with more flexibility in choosing the most interesting solution from a set of non-dominated solutions during the offer elaboration process (Asrari, Lotfifard, and Payam 2016; Pitiot et al. 2019). In Bahri, Ben Amor, and El-Ghazali (2014); Bahri, Talbi, and Ben Amor (2018), the authors have proposed an empirical approach where fuzzy triangular numbers model criteria values. By comparing two fuzzy numbers, following the overlapping of their possibility distributions, three relations of dominance are defined for a single criterion (mono-criterion dominance relations): total dominance, partial strong-dominance and partial weak-dominance. These relations are easy to implement and make it possible to define the Pareto front. However, they are not generic enough to be used in situations where the values of the decision criteria are modelled with fuzzy numbers other than triangular ones. Moreover, as with the other approaches, these approaches do not allow the bidder's confidence to be taken into account in the selection process.

With regard to this literature analysis, in this article, a new Multi-Criteria Decision Making (MCDM) support approach is proposed for the selection of the most interesting technical bid solution in an Engineer-To-Order (ETO) bidding process. It takes into account imprecision, uncertainty and the bidder's confidence in the decision process. The main contributions developed in this article are:

- A method is proposed to model the values of the decision criteria by possibility distributions. The originality of this method is that the possibility distributions are automatically built using two confidence indicators OCS (Overall Confidence in System) and OCP (Overall Confidence in Process) which have been defined in our previous work (Sylla et al. 2017). They represent the bidder's confidence in the technical bid solutions and gather reliable knowledge about their feasibility. Therefore, this method allows the confidence to be taken into account in the decision process.
- Four new possibilistic mono-criterion dominance relations are developed in order to perform the comparison of two solutions with respect to a single decision criterion. As opposed to the dominance relations proposed in Bahri, Talbi, and Ben Amor (2018), the dominance relations proposed in this article are generic and can be used in any situation where the values of the decision criteria are modelled with fuzzy numbers or possibility distributions. They are developed based on the indexes proposed in Dubois and Prade (1983, 2012) which are powerful theoretical materials, and their computation is fully automated.
- A method is proposed to help the decision maker to interactively construct the restricted set of the most interesting solutions (Pareto front). The Pareto front is built by taking into account the certainty of dominance between solutions. Only solutions which are dominated with a level of certainty defined by the decision maker are removed from the Pareto front. To the best of our knowledge this is the only method which allows the decision maker to interactively select the most interesting technical bid solutions following a required level of certainty of dominance between solutions.

In the next section, the proposed MCDM approach along with the supporting algorithms are presented.

3. Possibilistic Pareto-dominance approach for technical bid selection

The proposed approach is organised in three main steps: (i) the first step corresponds to the modelling of the values of the decision criteria by possibility distributions, (ii) the second step corresponds to the pairwise comparison of the potential solutions with respect to a single decision criterion, and (iii) the third step corresponds to the interactive construction of the restricted set of the most interesting solutions (Pareto front). In the following sections, the methods and algorithms that support the three steps are described.

3.1. *Modelling of the values of the decision criteria as possibility distributions*

The possibility theory together with the confidence indicators offer a good opportunity to model the uncertain and imprecise values of the decision criteria by possibility distributions. For a solution S_i, the possibility distribution μ^k_{Si} corresponding to the possible values of the decision criterion k, is characterised with five parameters: a, b, c, d and e (see Figure 1). Moreover, it can be formally defined by Equation (1). For every value of the criterion k for the solution i (noted S^k_i), $\mu^k_{Si}(S^k_i)$ is the possibility of the value S^k_i.

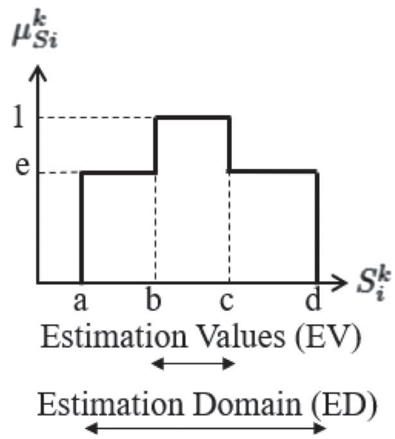

Figure 1. Possibility distribution $\mu_{Si}^{k}(S_i^k)$ of a criterion k for a solution S_i.

- Parameters a and d represent respectively the lower and upper bounds of the Estimation Domain (ED) of a criterion. This domain is supposed certain. It means that the value of a criterion for a technical bid solution is, with certainty, included in this domain.
- Parameters b and c represent respectively the lower and upper bounds of the interval of the Estimation Values (EV). The interval EV corresponds to the most possible values (the values that have their possibility level at the maximum level). Given the estimation domain of a criterion, based on experience, an expert (or a computerised system) estimates the interval of the most possible values. For instance, a configuration software can be used to compute these intervals (Sylla et al. 2017).

$$\mu_{Si}^{k}(S_i^k) = \begin{cases} 0 & \text{if} \quad (S_i^k < a) \vee (S_i^k > d) \\ e & \text{if} \quad (a \leq S_i^k < b) \vee (c < S_i^k \leq d) \\ 1 & \text{if} \quad (b \leq S_i^k \leq c) \end{cases} \tag{1}$$

$$e = 1 - (\alpha * OCS + (1 - \alpha) * OCP)/9 \tag{2}$$

- Parameter e represents the possibility of a value being outside of the interval EV. It depends on the confidence indicators (OCS and OCP) which represent the bidder's confidence in the technical bid solution. It is calculated using the Equation (2). The value '9' represents the maximum level on the OCS and OCP scales. Thus the values of e belong to the real interval [0, 1].

The parameter α makes it possible to take into account the relative importance of each item (technical system and delivery process) according to the criterion in consideration. In the context of the elaboration of a technical bid solution in a bidding process, for a criterion that characterises the two items (e.g. the *cost* of the technical bid solution), both the OCS and OCP indicators are relevant. Therefore, assuming that the two items have the same importance, α is equal to 0.5. For a criterion, that characterises only the delivery process (e.g. the *duration* of the delivery process), only the OCP indicator is relevant, α is equal to 0. For a criterion, that characterises only the technical system (e.g. a *technical performance* of the technical system), only the OCS indicator is relevant, α is equal to 1.

For example, let us consider the estimation of the cost of a technical bid solution for a crane, (which is composed of the crane technical system and its delivery process). As this criterion characterises both the technical system and its delivery process, α is equal to 0.5. In this estimation, it is known with certainty that the Estimation Domain (ED) of the technical bid solution for the crane is equal to [60, 100] k\$. Based on the available information, an expert (or a computerised system) indicates that it is more possible that the cost of this solution be equal to [75, 85] k\$. This interval [75, 85] k\$ represents the interval of the Estimation values (EV). The system also provides the values of the confidence indicators OCS and OCP.

- If OCS $=$ 9 and OCP $=$ 9 (high confidence), then according to Equation (2), $e = 0$. The possibility e to have a value outside of this interval [75, 85] k\$ is then equal to 0. That means that the bidder is, with certainty, able to develop and deliver the technical system according to the Estimation Values (EV) [75, 85] k\$. Therefore, it is certain that the cost of this technical bid solution will be in the interval of the EV [75, 85] k\$.
- If OCS $=$ 7 and OCP $=$ 6, then according to the Equation (2), $e = 0.28$. This means that it is not certain that the bidder is able to develop and deliver the technical system according to the EV [75, 85] k\$. Therefore, there is a possibility that the cost of the technical bid solution will be outside the interval of the EV [75, 85] k\$. This possibility e is equal to 0.28.

For a technical bid solution, given the four parameters (a, b, c and d) and the confidence indicators (OCS and OCP), this method allows the corresponding possibility distribution for each decision criterion to be built automatically. Thus it allows imprecision, uncertainty and confidence in the decision making process to all be taken into account. In the next section, the possibilistic mono-criterion dominance relations developed to compare the potential technical bid solutions with respect to a single decision criterion are presented.

3.2. Comparison of technical bid solutions with respect to a single criterion

In this section, four generic dominance relations are proposed in order to automatically compare two solutions S_i and S_j in any situations where the values of a decision criterion k are modelled by possibility distributions (μ^k_{Si} for S_i and μ^k_{Sj} for S_j). They are developed based on the indexes (POD, PSD, NOD and NSD) suggested in Dubois and Prade (2012). In fact, as shown in many works (Dubois and Prade 2012; Bortolan and Degani 1985; Iskander 2005; Wang and Kerre 2001), these indexes, described in Table 1 , provide for each distribution (μ^k_{Si} and μ^k_{Sj}) four values in the interval [0,1] corresponding to their possibility and necessity of being smaller than the other one. However, they do not indicate globally which distribution has to be considered as the smaller (Wang and Kerre 2001). Moreover, they cannot be used in this form by a decision-maker to compare two solutions and to establish dominance relations between them. An expert who understands their meaning is required. But, even for an expert, in a real decision problem, it is not possible to analyse, for each pair of potential solutions, eight values (four for each solution) in order to decide the dominance relations between these solutions. Some relations that enable an automatic comparison of the potential solutions and establish dominance relations between them are required.

Therefore, in order to provide a decision maker with tools that allow her/him to automatically compare two solutions, we take advantage of these indexes to develop new generic possibilistic mono-Criterion Dominance Relations (mono-CDR). In order to do that, an empirical study was performed. All possible configurations of the possibility distributions μ^k_{Si} and μ^k_{Sj} were generated and studied. For each configuration, and for each of the two solutions S_i and S_j, the four dominance indexes (POD^k, PSD^k, NOD^k and NSD^k) were computed and summarised in a vector (noted $D^k_{Si\prec Sj}$ for the solution S_i and $D^k_{Sj\prec Si}$ for the solution S_j, see Equations (3) and (4)). For details about the computation method of the indexes, consult (Dubois and Prade 2012). $D^k_{Si\prec Sj}$ provides the possibility and necessity of μ^k_{Si} being smaller than μ^k_{Sj} whereas $D^k_{Sj\prec Si}$ provides the possibility and necessity of μ^k_{Sj} being smaller than μ^k_{Si}. The two vectors are shown in Equations (3) and (4).

$$D^k_{Si\prec Sj} = [POD^k_{Si\prec Sj},\ PSD^k_{Si\prec Sj},\ NOD^k_{Si\prec Sj},\ NSD^k_{Si\prec Sj}] \tag{3}$$

$$D^k_{Sj\prec Si} = [POD^k_{Sj\prec Si},\ PSD^k_{Sj\prec Si},\ NOD^k_{Sj\prec Si},\ NSD^k_{Sj\prec Si}] \tag{4}$$

For each configuration, the values of the two vectors were thoroughly analysed with regard to the definition of the four dominance indexes. This analysis made it possible to define three categories of dominance (certain dominance, strong possibility of dominance, weak possibility of dominance) and one category of indifference between two solutions S_i and S_j. They are formalised with four new generic possibilistic dominance relations. Considering a single decision criterion, these relations make it possible: (i) to indicate if a solution S_i dominates (or not) another one S_j and (ii) if it dominates it, to indicate the necessity or possibility of dominance (certain, strong and weak). They are presented as follows.

1. Certain Dominance (denoted $\prec_{CD}$). This relation corresponds to situations where the two possibility distributions (μ^k_{Si} for the solution S_i and μ^k_{Sj} for the solution S_j) are completely disjoint (see Figure 2). Whatever the value of each variable, one of them is (with certainty) smaller than the other one. Therefore, one solution certainly dominates the other one following the criterion k. A solution S_i certainly dominates a solution S_j, if the value of NSD$^k_{Si\prec Sj}$ (Necessity of Strict Dominance of S_i over S_j) is equal to 1 (see Equation (5) and Figure 2(a)). Then, $S_i \prec_{CD} S_j$ if:

$$D^k_{Si\prec Sj}(4) = 1 \tag{5}$$

2. Strong Possibility of Dominance (denoted $\prec_{SPD}$). This relation corresponds to situations where the two possibility distributions (μ^k_{Si} for the solution S_i and μ^k_{Sj} for the solution S_j) are not disjoint (see Figure 2(b)). However, all the four dominance indexes of the two vectors $D^k_{Si\prec Sj}$ and $D^k_{Sj\prec Si}$ indicate that one variable is generally smaller than the other one. Accordingly, one solution dominates the other one, not certainly, but with a strong possibility. A solution S_i uncertainly, but with a strong possibility, dominates a solution S_j, if all the values of the four elements of the vector $D^k_{Si\prec Sj}$ are respectively greater than those of the vector $D^k_{Sj\prec Si}$ (see Equation (6) and Figure 2(b)). Then, S_i

Table 1. POD, PSD, NOD and NSD indexes.

Indexes	Definition
Possibility of Dominance (POD)	the possibility that S^k_i is not greater than S^k_j
Possibility of Strict Dominance (PSD)	the possibility that S^k_i is smaller than S^k_j
Necessity of Dominance (NOD)	the necessity that S^k_i is not greater than S^k_j
Necessity of Strict Dominance (NSD)	the necessity that S^k_i is smaller than S^k_j

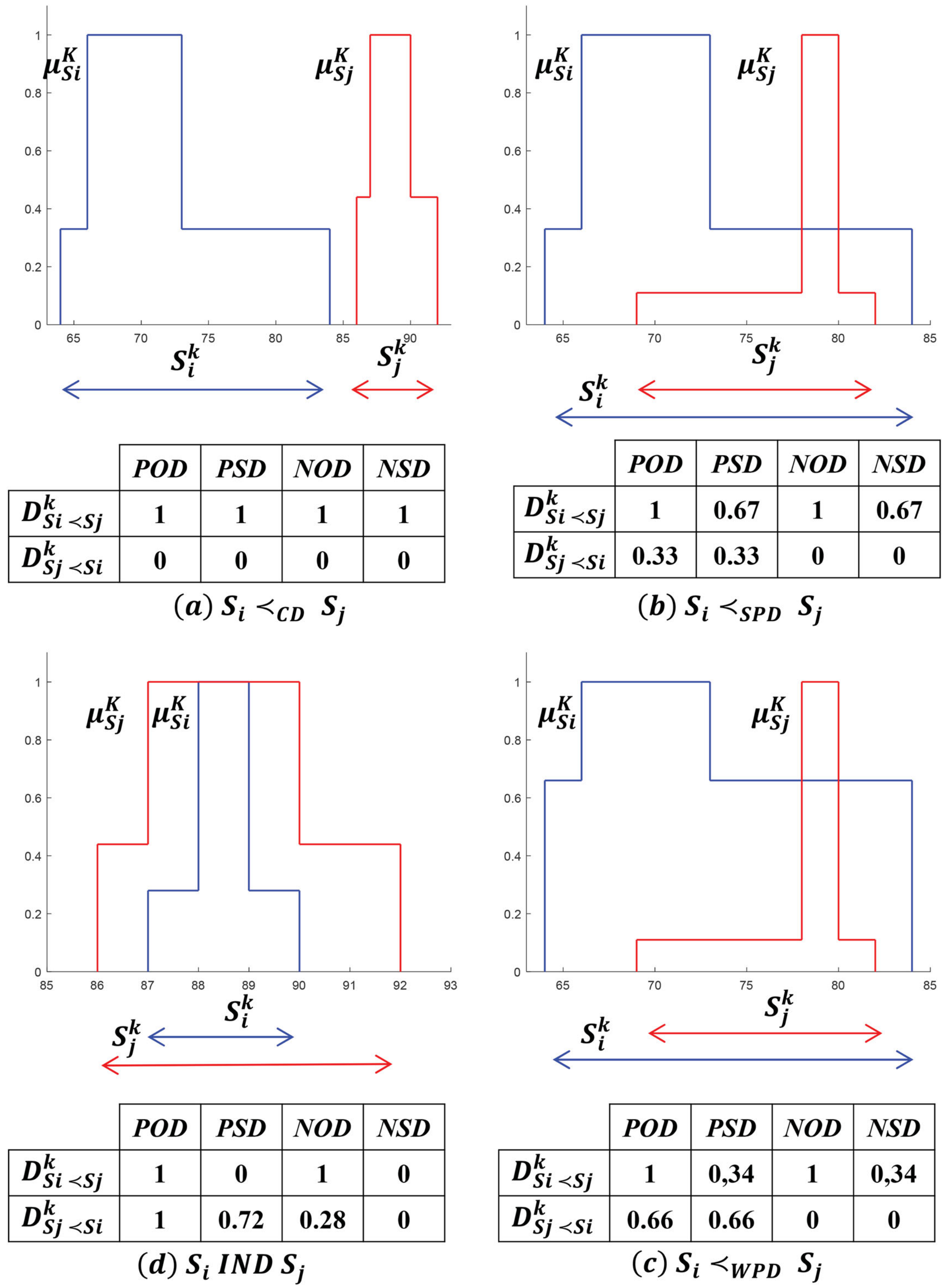

Figure 2. Examples of the dominance relations.

$\prec_{SPD} S_j$ if:

$$[D^k_{Si \prec Sj}(4) < 1] \wedge [\forall\, t \in \{1, \ldots, 4\};$$
$$D^k_{Si \prec Sj}(t) > D^k_{Sj \prec Si}(t)] \qquad (6)$$

3. *Weak Possibility of Dominance (denoted $\prec_{WPD}$).* The two possibility distributions (μ^k_{Si} for the solution S_i and μ^k_{Sj} for the solution S_j) are not disjoint. However, in contrast to the $\prec_{SPD}$ relation, all the dominance indexes of the two vectors $D^k_{Si \prec Sj}$ and $D^k_{Sj \prec Si}$ are not consistent for the comparison of the two variables S^k_i and S^k_j. Most of

the indexes of the two vectors indicate that one variable is generally smaller than the other one, but some of them are not consistent with that. Three cases have been identified:

(a) In the first case, formalised in Equation (7), three indexes (POD^k, NOD^k and NSD^k or POD^k, PSD^k and NSD^k) indicate that the variable S_i^k of the solution S_i is generally smaller than the variable S_j^k of the solution S_j, and one index (PSD^k or NOD^k) indicates whether: (i) the variable S_j^k of the solution S_j is generally smaller than that of the solution S_i or (ii) the variable S_j^k of the solution S_j is equal to S_i^k.

(b) In the second case, formalised in Equations (8) and (9), two indexes (POD^k and NSD^k or PSD^k and NOD^k) indicate that the variable S_i^k of the solution S_i is generally smaller than the variable S_j^k of the solution S_j and the two other indexes (PSD^k and NOD^k or POD^k and NSD^k) indicate that the variable S_i^k of the solution S_i is equal to that of the solution S_j.

(c) In the third case, formalised in Equation (9), one of the indexes PSD^k or NOD^k indicates that the variable S_i^k of the solution S_i is generally smaller than the variable S_j^k of the solution S_j and the other indexes (POD^k, NSD^k and NOD^k or POD^k, NSD^k and PSD^k) indicate that the variable S_i^k of the solution S_i is equal to S_j^k.

Therefore, a solution S_i uncertainly dominates, but with a weak possibility, a solution S_j (denoted $S_i \prec_{WPD} S_j$), if it satisfies one of the four Equations (7), (8), (9) or (10) below.

$$[\exists\, t \in \{1, \dots, 4\} : D^k_{Si\prec Sj}(t) \le D^k_{Sj\prec Si}(t)] \wedge [\forall\, l \neq t : D^k_{Si\prec Sj}(l) > D^k_{Sj\prec Si}(l)] \quad (7)$$

$$[\forall\, t \in \{1, 4\} : D^k_{Si\prec Sj}(t) = D^k_{Sj\prec Si}(t)] \wedge [\forall\, l \neq t : D^k_{Si\prec Sj}(l) > D^k_{Sj\prec Si}(l)] \quad (8)$$

$$[\forall\, t \in \{1, 4\} : D^k_{Si\prec Sj}(t) > D^k_{Sj\prec Si}(t)] \wedge [\forall\, l \neq t : D^k_{Si\prec Sj}(l) = D^k_{Sj\prec Si}(l)] \quad (9)$$

$$[\exists\, t \in \{1, \dots, 4\} : D^k_{Si\prec Sj}(t) > D^k_{Sj\prec Si}(t)] \wedge [\forall\, l \neq t : D^k_{Si\prec Sj}(l) = D^k_{Sj\prec Si}(l)] \quad (10)$$

The example shown in Figure 2(c) corresponds to the first case (Equation (7)). It can be seen through this Figure 2 (c) that the two distributions μ^k_{Si} and μ^k_{Sj} have almost the same positions as in Figure 2(b). The only difference is that, in Figure 2(c), the possibility to have a value of S_i^k that is greater than S_j^k has been increased. That is why the strength of the dominance of S_i over S_j has been decreased from $\prec_{SPD}$ (in Figure 2(b)) to $\prec_{WPD}$ (in Figure 2(c)).

4. Indifference (denoted IND). This relation corresponds to situations where the two possibility distributions μ^k_{Si} and μ^k_{Sj} strongly overlap (see Figure 2(d)). The dominance indexes of the two vectors $D^k_{Si\prec Sj}$ and $D^k_{Sj\prec Si}$ are not consistent for the comparison of the two variables S_i^k and S_j^k. In addition, in contrast to the previous dominance relations, none of the two variables exceeds the other one in number of indexes indicating that it is smaller than the other one. Two cases have been identified:

(a) In the first case, formalised in Equation (11), the four dominance indexes (POD^k, PSD^k, NOD^k and NSD^k) indicate that the two variables S_i^k and S_j^k are equal.

(b) In the second case, formalised in Equations (12) and (13), two dominance indexes (POD^k and NSD^k) indicate that the two variables S_i^k and S_j^k are equal and for the two others, each variable has one dominance index (PSD^k or NOD^k) that indicates that it is smaller than the other one. The example shown in Figure 2(d) corresponds to this case.

Therefore, two technical bid solutions S_i and S_j are indifferent (denoted S_i IND S_j) if one of the three Equations (11), (12) and (13) is true:

$$[\forall\, t \in \{1, \dots, 4\} : D^k_{Si\prec Sj}(t) = D^k_{Sj\prec Si}(t)] \quad (11)$$

$$[\forall\, t \in \{1, 4\} : D^k_{Si\prec Sj}(t) = D^k_{Sj\prec Si}(t)] \wedge [D^k_{Si\prec Sj}(2) > D^k_{Sj\prec Si}(2)] \wedge [D^k_{Si\prec Sj}(3) < D^k_{Sj\prec Si}(3)] \quad (12)$$

$$[\forall\, t \in \{1, 4\} : D^k_{Si\prec Sj}(t) = D^k_{Sj\prec Si}(t)] \wedge [D^k_{Si\prec Sj}(2) < D^k_{Sj\prec Si}(2)] \wedge [D^k_{Si\prec Sj}(3) > D^k_{Sj\prec Si}(3)] \quad (13)$$

In the proposed approach, these relations CD, SPD, WPD and IND are used to compare two solutions S_i and S_j with respect to a single criterion. The Equations (5) to (13) present the conditions to be satisfied for a solution S_i: (i) to dominate another solution S_j (Equations (5), (6), (7), (8), (9) and (10)), or (ii) to be indifferent to a solution S_j (Equations (11), (12) and (13)). In the following parts, the mono-criterion dominance relation of a solution S_i over a solution S_j is noted mono-CDR(S_i, S_j). Comparing two solutions S_i and S_j, if none of the four mono-CDR is applicable (which means that the solution S_i is dominated by the solution S_j), the mono-CDR(S_i, S_j) takes the value 'NA' (Not Applicable) and it is noted by S_i

$\not\prec S_j$. In the next section, the construction method of the Pareto front is developed.

3.3. Construction of the Pareto front

In this section, the method which allows the comparison of technical bid solutions with respect to all the decision criteria and the determining of the set of non-dominated solutions (Pareto front) is described.

In the context of the bidding process, when selecting the most interesting technical bid solutions, in situations where the values of the decision criteria are imprecise and uncertain, it is necessary to take into account the point of view of the decision maker about the level of certainty or possibility required on the dominance of one solution over another one. Therefore, the concept of Required Level of Dominance for a decision criterion (RLD) is introduced to capture this point of view and take it into account in the decision making process. For a decision criterion k, the required level of dominance is noted RLD^k. In this article, we consider four possible values for RLD^k. These values correspond to the four possibilistic mono-CDR (CD, SPD, WPD and IND). For n decision criteria ($n > 1$), all possible combinations of the four values are allowed, except that combining only the value IND. Indeed, in that case, none of the two solutions Pareto-dominates the other one.

Accordingly, let us consider two technical bid solutions S_i and S_j to be compared following n decision criteria. Given a RLD^k for each decision criterion k, a technical bid solution S_i Pareto-dominates another one S_j (denoted $S_i \prec S_j$), if and only if, for each decision criterion k, the possibilistic mono-criterion dominance of the solution S_i over S_j (mono-$\text{CDR}^k(S_i, S_j)$) is at least stronger (noted by $\geq$) than the required level of dominance on this decision criterion (RLD^k). The mono-CDR value CD is stronger than SPD, which is stronger than WPD, which is also stronger than IND which in turn is stronger than NA (CD > SPD > WPD > IND > NA). Equation (14) represents the Pareto-dominance relation of a solution S_i over S_j with respect to n decision criteria. Moreover, a solution belongs to the Pareto Front (PF) if there is no other solution that Pareto-dominates it. Let S be the set of m potential technical bid solutions. Let PF be the Pareto front. PF is defined by Equation (15).

$$S_i \prec S_j \text{ if } \forall\, k \in \{1, \ldots, n\},$$

$$mono - CDR^k(S_i, S_j) \geq RLD^k \tag{14}$$

$$PF = \{S_l, S_l \in S, \nexists\, S_t / S_t \prec S_l\} \tag{15}$$

Therefore, by performing a pairwise comparison of the potential solutions using Equation (14), the Pareto front is built based on Equation (15). Thus, this method enables the decision maker to interactively determine the set PF (which is the set of the most interesting technical bid solutions) according to the required level of dominance on each decision criterion. In the next Section 3.4, the algorithms that support the proposed approach are described.

3.4. Description of the algorithms to support the proposed approach

The first algorithm (Algorithm 1) computes the possibilistic mono-criterion dominance of solution S_i over solution S_j. It corresponds to the function mono-$\text{CDR}^k(S_i, S_j)$.

The function mono-$\text{CDR}^k(S_i, S_j)$ has two arguments S_i and S_j. First the vectors $D^k_{Si \prec Sj}$ and $D^k_{Sj \prec Si}$ are computed. Then, using Equations (5) to (13) described in Section 3.2, the mono-CDR value is selected among Certain Dominance (CD), Strong Possibility of Dominance (SPD), Weak Possibility of Dominance (WPD), Indifference (IND) and Not Applicable (NA) when S_i is dominated by S_j.

The second algorithm (Algorithm 2) defines the function Pareto-front(S, $\{RLD^1, RLD^2, \ldots, RLD^n\}$) which returns the set of non-dominated solutions (i.e. the Pareto-front). This function has several arguments: (i) S, the set of the potential technical bid solutions, (ii) $\{RLD^1, RLD^2, \ldots, RLD^n\}$, the set of n required levels of dominance corresponding to the n decision criteria. The function 'Pareto-front' realises a pairwise comparison of the potential solutions of the set S. Each solution is compared to each of the others. For each pair (S_i, S_j) of solutions (with $i \neq j$) and for each decision criterion k (with $k \in \{1, 2, \ldots, n\}$), the function mono-$\text{CDR}^k(S_i, S_j)$ is called. The result is the possibilistic mono-criterion dominance of solution S_i over S_j with respect to the decision criterion k. If for any decision criterion k, the mono-$\text{CDR}^k(S_i, S_j)$ is stronger than the corresponding RLD^k, then solution S_i Pareto-dominates solution S_j, and consequently S_j is removed from the set PF. At the end, the resulting PF is returned by the function Pareto-front.

4. Illustrative application of the proposed approach

This application is inspired by a real industrial case of the design of a technical bid solution for a crane in a French company. The company has to select one solution from a panel of twelve potential ones designed and estimated using a configuration software. For the sake of simplicity and clarity, we consider only two decision criteria: (i) the cost of the technical bid solution (cost) which

Algorithm 1 $Mono-CDR^k(S_i, S_j)$

$Compute\ D^k_{Si \prec Sj}$ *# Dubois and Prade's dominance indexes for Si*
$Compute\ D^k_{Sj \prec Si}$ *# Dubois and Prade's dominance indexes for Sj*
if (equation 13 is TRUE) **then**
  return CD *# Si certainly dominates Sj ($S_i \prec_{CD} S_j$)*
else if (equation 14 is TRUE)
  return SPD *# Si dominates Sj, with a strong possibility ($S_i \prec_{SPD} S_j$)*
else if ((equation 15 is TRUE) $\vee$ (equation 16 is TRUE) $\vee$ (equation 17 is TRUE) $\vee$ (equation 18 is TRUE))
  return WPD *# Si dominates Sj, with a weak possibility ($S_i \prec_{WPD} S_j$)*
else if ((equation 19 is TRUE) $\vee$ (equation 20 is TRUE) $\vee$ (equation 21 is TRUE))
  return IND *# Si is indifferent to Sj ($S_i\ \ IND\ \ S_j$)*
else
  return NA *# Si is dominated by Sj ($S_j \prec\ \ S_i$)*
end if

Algorithm 2 Pareto-front(S, $\{RLD^1, RLD^2, \ldots, RLD^n\}$)

$PF \leftarrow S$ *# The initial Pareto front includes all the solutions*
for S$_j \in$ S do
  for S$_i \in$ S / S$_i \neq$ S$_j$ do
    $NbDom \leftarrow 0$ *# Number of decision criteria by which Si dominates Sj*
   for k $\in \{1, ..., n\}$ **do**
    if Mono-CDR^k(S$_i$,S$_j$) $\geq$ RLD^k
    $NbDom \leftarrow NbDom + 1$ *# NbDom is increased by 1*
    end if
   end for
   if NbDom = n **then**
    $PF \leftarrow PF - \{S_j\}$ *# Sj is removed from PF because it is dominated*
   end if
  end for
end for
return PF *# The most interesting solutions with regard to the RLDs*

gathers both the technical system cost and the delivery process cost, and (ii) the duration of the delivery process (duration). The details are provided in the following sub-section.

4.1. Description of the example

As shown in Figure 3, each solution is composed of two interconnected parts. The first part is the technical system which is composed of four sub-systems: an engine (EN), a jib (JI), a tower (TO) and a basket (BA). The jib sub-system is integrated with the tower and the engine sub-systems whereas the basket sub-system is integrated with the tower sub-system. For each sub-system, there are three possible solutions (for instance: EN1, EN2 and EN3 for the engine sub-system). Each sub-system i is characterised with a cost$_i$ (see Table 4). For the sake of clarity, we do not consider the costs of the integrations between

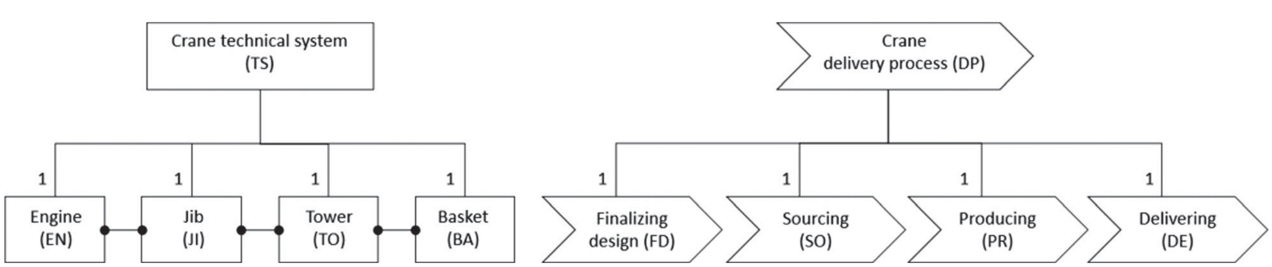

Figure 3. A crane technical bid solution.

Table 2. Integration readiness Level IRL_{ij}/Confidence In Sub-systems *i* and *j* CIS_{ij}.

IRL_{ij}/CIS_{ij}	EN1	EN2	EN3	JI1	JI2	JI3	TO1	TO2	TO3	BA1	BA2	BA3
EN1	9/5	–	–	5/4	–	–	0/0	–	–	0/0	–	0/0
EN2	–	9/5	–	6/5	5/3	–	0/0	0/0	–	0/0	0/0	0/0
EN3	–	–	9/5	–	–	8/5	0/0	0/0	0/0	0/0	0/0	0/0
JI1	5/4	6/5		9/5	–	–	6/4	–	–	0/0	–	0/0
JI2	–	5/3	–	–	9/5	–	–	5/3	6/3	–	0/0	0/0
JI3	–	–	8/5	–	–	9/5	7/5	8/5	6/5	–	0/0	0/0
TO1	0/0	0/0	0/0	6/4		7/5	9/5	–	–	8/4	–	5/4
TO2	–	0/0	0/0	–	5/3	8/5	–	9/5	–	–	7/4	0/0
TO3	–	0/0	0/0	–	6/3	6/5	–	–	9/5	–	5/4	6/5
BA1	0/0	0/0	0/0	0/0	–	0/0	8/4	–	–	9/5	–	–
BA2	–	0/0	0/0	–	0/0	0/0	–	7/4	5/4	–	9/5	–
BA3	0/0	0/0	0/0	0/0	0/0	0/0	5/4	–	6/5	–	–	9/5

Table 3. AFL_l and CIP_l of the crane delivery process activities.

	Finalising design		Sourcing		Producing		Delivering	
Cranes	AFL_l	CIP_l	AFL_l	CIP_l	AFL_l	CIP_l	AFL_l	CIP_l
CR1	3	4	4	4	3	4	4	4
CR2	3	3	3	3	3	3	4	4
CR3	4	4	4	4	4	4	4	4
CR4	4	5	4	5	4	5	4	5
CR5	3	4	4	4	3	4	4	4
CR6	4	5	4	5	4	5	4	5
CR7	3	3	3	4	3	3	4	4
CR8	4	4	4	5	4	5	4	4
CR9	3	4	3	4	3	4	4	4
CR10	3	3	3	4	3	3	4	4
CR11	3	4	4	5	3	4	4	4
CR12	3	3	4	4	3	3	4	4

solutions. Therefore, the cost of a technical system is the sum of the costs of its sub-systems (see Table 5). The composition of technical systems which satisfy the customer's requirements is presented in Table 5.

The second part is the delivery process of the crane technical system. It is composed of four main activities: finalising design (FD), sourcing (SO), producing (PR) and delivering (DE). Each activity *l* is characterised with a $cost_l$ and a $duration_l$. For each activity, a same resource is used independently to the technical systems. For instance, the same designer performs the design of the twelve technical systems. Therefore, the duration of an activity depends solely on the technical systems. The costs of the FD and PR activities are computed as their duration multiplied by *2* ($cost_l = duration_l*2$). Whereas the costs of the SO and DE activities are computed as their duration multiplied by *1.5* ($cost_l = duration_l*1.5$). The duration and cost of the activities are presented in Table 6. The cost and the duration of a delivery process are computed as the sum of the costs and durations of its activities (see Table 7). The cost of a crane technical bid solution is computed as the sum of the cost of the technical system and the cost of its delivery process (see Table 8).

Moreover, each technical bid solution is characterised with the confidence indicators OCS (Overall Confidence in System) and OCP (Overall Confidence in Process) which represent the bidder's confidence in this solution. Both OCS and OCP indicators are based on two kinds of metrics: (i) factual ones which relate on the readiness of the technical system and the feasibility of the delivery process, and (ii) subjective ones which are the expert feeling of the designer (Sylla et al. 2017; Sauser et al. 2008).

Therefore, in order to compute the OCS of a technical system, each sub-system i is characterised with a readiness level (TRL_i) and a designer feeling (CIS_i). The TRL_i and CIS_i indicators are measured on a nine-level scale and a five-level scale, respectively (see Table 4). Each integration between two sub-systems i and j is also characterised with a readiness level (IRL_{ij}) and a designer feeling CIS_{ij}. Like the TRL_i and CIS_j, the IRL_{ij} and CIS_{ij} indicators are measured on a nine-level scale and a five-level scale (see Table 2). In Table 2, the IRL_{ij}/CIS_{ij} of the integration of two sub-systems *i* and *j* are presented once these subsystems are present in the same system. If there is no integration between two subsystems *i* and *j* which are present in the same system, their IRL_{ij}/CIS_{ij} are equal to 0. Furthermore, according to the method presented in Sylla et al. (2017) and Sauser et al. (2008), the IRL_{ii}/CIS_{ii} of a subsystem *i* with itself is equal to the highest values (9/5). The readiness level (SRL), the designer feeling (CIS) and the OCS of a technical system are computed using the methods presented in Sylla et al. (2017) and Sauser et al. (2008). The SRL and CIS

Table 4. The sub-system solutions.

Sub-systems	$Cost_i$ (K$) a	b	c	d	TRL_i [1–9]	CIS_j [1–5]
EN1	15	16	18	20	5	4
EN2	18	19	20	21	7	5
EN3	22	23	23,5	24	8	5
JI1	15	16	17	20	7	5
JI2	15	17	18	19	6	3
JI3	16	16,5	17,5	18	8	5
TO1	25	27	28	30	8	5
TO2	18	19	25	28	8	5
TO3	32	35	36	37	7	5
BA1	9	10	12	14	8	4
BA2	12	13	14	15	8	4
BA3	9	9,5	10	11	7	5

Table 5. The crane technical systems.

Cranes	Composition EN	JI	TO	BA	Cost (K$) a	b	c	d	SRL [1–5]	CIS [1–5]	OCS [1–9]
CR1	EN1	JI1	TO1	BA1	64	69	75	84	3	4	6
CR2	EN2	JI2	TO2	BA2	63	68	77	83	3	3	5
CR3	EN2	JI1	TO1	BA1	67	72	77	85	3	4	6
CR4	EN3	JI3	TO1	BA1	72	76,5	81	86	4	5	8
CR5	EN3	JI3	TO3	BA3	79	84	87	90	3	5	7
CR6	EN1	JI1	TO1	BA3	64	68	75	81	3	4	6
CR7	EN2	JI2	TO3	BA2	77	84	88	92	3	3	5
CR8	EN3	JI3	TO2	BA2	68	71,5	80	85	4	5	8
CR9	EN2	JI1	TO1	BA3	67	71,5	75	82	3	5	8
CR10	EN2	JI2	TO3	BA3	74	80,5	84	88	3	3	5
CR11	EN3	JI3	TO3	BA2	82	87,5	91	94	3	5	7
CR12	EN3	JI3	TO1	BA3	72	76	79	83	3	5	7

indicators are measured on a five-level scale. The OCS indicator is measured on a nine-level scale. They are presented in Table 5.

On the other side, in order to compute the OCP of the delivery process, each activity l is characterised with a feasibility level (AFL_l) and a designer feeling (CIP_l). The AFL_l and CIP_l are measured on a five-level scale (see Table 3). The feasibility level (PFL), the designer feeling (CIP) and the OCP of a delivery process are computed using the methods presented in Sylla et al. (2017). The PFL and CIP indicators are measured on a five-level scale. The OCP indicator is measured on a nine-level scale. They are presented in Table 7. For more detail about the OCS and OCP indicators, consult (Sylla et al. 2017; Sauser et al. 2008).

The proposed Multi-Criteria Decision (MCDM) support approach is used to provide the decision maker with a restricted set of the most interesting technical bid solutions while taking into account: (i) uncertainty, imprecision and, more importantly, the bidder's confidence in the values of the decision criteria, and (ii) the required level of certainty on the dominance of one solution S_i over another one S_j. Thus, from this Pareto front, the decision maker has the flexibility to choose the most interesting solution to propose to a customer during the offer elaboration process. The application is performed using the Matlab software (MATLAB R2018b). In the following section, the main results are presented and discussed.

4.2. Results and discussion of the experiments

In this section, first, for each decision criterion, the dominance relations between the potential solutions are computed and presented. Then, three different Pareto fronts are interactively built according to particular combinations of RLDs imputed by the decision maker. Finally, two different ways to exploit the Pareto front are presented.

4.2.1. The dominance relations between the potential solutions

Before computing the possibilistic mono-criterion dominance relations (mono-CDR), the possibility distributions which represent the evaluation of the potential solutions are computed using the method presented in Section 3.1. Then, these possibility distributions are used to compute the two vectors $D^k_{Si \prec Sj}$ and $D^k_{Sj \prec Si}$ for each

Table 6. Duration of the crane delivery process activities.

	(a) Duration of the crane delivery process activities															
	Finalising design (Weeks)				Sourcing (Weeks)				Producing (Weeks)				Delivering (Weeks)			
Cranes	a	b	c	d	a	b	c	d	a	b	c	d	a	b	c	d
CR1	18	19	22,5	26	10	10,3	11	12	26	26,5	30	34	9	9,2	10,5	11
CR2	15	15,3	16,5	18	7	7,2	7,5	8	23	23,3	24	25,5	7	7,2	8	8,5
CR3	16	17	18	19	8	8,5	9	9,5	24	24,5	25,8	26	9	10	10,2	10,5
CR4	14,5	15	15,3	15,5	7,5	8	8,2	8,4	24	24,5	24,8	25,2	9	9,5	9,7	9,9
CR5	19	19,5	20	21	10	10,3	10,5	11	25,5	26	26,5	27	9,5	10,2	10,5	11
CR6	20,5	21	22,3	24	10,5	11	11,2	11,5	26,5	27	27,3	28	10,5	11	11,2	11,5
CR7	15	15,3	16	16,3	7,5	7,7	8	8,2	23,5	23,8	25	25,2	7	7,2	8	8,3
CR8	13	15	17	18	7	8	8,5	9	22	23	24	27	7	8	8,5	9
CR9	19,5	19,8	20	22	9,5	9,7	10,2	10,5	23	23,2	25	26	8	8,3	8,8	9
CR10	19	19,2	20,4	21,5	10	10,3	10,5	10,8	25	26	26,5	28,5	10	10,2	10,6	11,2
CR11	13,5	14	15	17	7	7,5	7,8	10	22,5	23	24	25,5	7	7,5	7,8	8,5
CR12	20	21	22	24	10	10,3	10,5	11	26	27	30	35	10	10,2	10,5	11

	(b) Cost of the delivery process activities															
	Finalising design (K$)				Sourcing (K$)				Producing (K$)				Delivering (K$)			
Cranes	a	b	c	d	a	b	c	d	a	b	c	d	a	b	c	d
CR1	36	38	45	52	15	15,45	16,5	18	52	53	60	68	13,5	13,8	15,75	16,5
CR2	30	30,6	33	36	10,5	10,8	11,25	12	46	46,6	48	51	10,5	10,8	12	12,75
CR3	32	34	36	38	12	12,75	13,5	14,25	48	49	51,6	52	13,5	15	15,3	15,75
CR4	29	30	30,6	31	11,25	12	12,3	12,6	48	49	49,6	50,4	13,5	14,25	14,55	14,85
CR5	38	39	40	42	15	15,45	15,75	16,5	51	52	53	54	14,25	15,3	15,75	16,5
CR6	41	42	44,6	48	15,75	16,5	16,8	17,25	53	54	54,6	56	15,75	16,5	16,8	17,25
CR7	30	30,6	32	32,6	10,5	11,55	12	12,3	47	47,6	50	50,4	10,5	10,8	12	12,45
CR8	26	30	34	36	10,5	12	12,75	13,5	44	46	48	54	10,5	12	12,75	13,5
CR9	39	39,6	40	44	14,25	14,55	15,3	15,75	46	46,4	50	52	12	12,45	13,2	13,5
CR10	38	38,4	40,8	43	15	15,45	15,75	16,2	50	52	53	57	15	15,3	15,9	16,8
CR11	27	28	30	34	10,5	11,25	11,7	15	45	46	48	51	10,5	11,25	11,7	12,75
CR12	40	42	44	48	15	15,45	15,75	16,5	52	54	60	70	15	15,3	15,75	16,5

Table 7. Duration, cost, PFL and CIP of the crane delivery processes.

	Duration (Weeks)				Cost(K$)				PFL	CIP	OCP
Cranes	a	b	c	d	a	b	c	d	[1–5]	[1–5]	[1–9]
CR1	63	65	74	83	116,5	120,25	137,25	154,5	3	4	6
CR2	52	53	56	60	97	98,8	104,25	111,75	3	3	5
CR3	57	60	63	65	105,5	110,75	116,4	120	4	4	7
CR4	55	57	58	59	101,75	105,25	107,05	108,85	4	5	8
CR5	64	66	67,5	70	118,25	121,75	124,5	129	3	4	6
CR6	68	70	72	75	121	129	132,8	138,5	4	5	8
CR7	53	54	57	58	98	100,55	106	107,75	3	3	5
CR8	49	54	58	63	91	100	107,5	117	4	4	7
CR9	60	61	64	67,5	111,25	113	118,5	125,25	3	4	6
CR10	64	65,7	68	72	118	121,15	125,45	133	3	3	5
CR11	50	52	54,6	61	93	96,5	101,4	112,75	3	4	6
CR12	66	68,5	73	81	122	126,75	135,5	151	3	3	5

Table 8. The twelve technical bid solutions (S).

	Duration(Weeks)				Cost(K$)				OCS	OCP
S	a	b	c	d	a	b	c	d	[1–9]	[1–9]
S1	63	65	74	83	180,5	189,25	212,25	238,5	6	6
S2	52	53	56	60	160	166,8	181,25	193,75	5	5
S3	57	60	63	65	172,5	182,75	193,4	205	6	7
S4	55	57	58	59	173,75	181,75	188,05	194,85	8	8
S5	64	66	67,5	70	197,25	205,75	211,5	219	7	6
S6	68	70	72	75	185	197	207,8	219,5	6	8
S7	53	54	57	58	175	184,55	194	199,75	5	5
S8	49	54	58	63	159	171,5	187,5	202	8	7
S9	60	61	64	67,5	178,25	184,5	193,5	207,5	8	6
S10	64	65,7	68	72	194	201,65	209,45	221	5	5
S11	50	52	54,6	61	175	184	192,4	206,75	7	6
S12	66	68,5	73	81	194	202,75	214,5	234	7	5

pair (S_i, S_j) and for each criterion k. As some examples of possibility distributions are presented in Section 3.2 (Figure 2), we have not presented this result in this section.

The vectors ($D^k_{Si\prec Sj}$ and $D^k_{Sj\prec Si}$) are further exploited to compute the mono-CDR between the potential solutions using Algorithm 2, presented in Section 3.4. The result is shown in Figure 4. The matrix at the upper level represents the possibilistic dominance of solution S_i over solution S_j with respect to the cost. The matrix at the lower level represents the possibilistic dominance of solution S_i over solution S_j with respect to the duration. For instance, solution S_{11} certainly dominates (CD) solution S_1 with respect to the duration. Then, mono-CDR$^{Duration}(S_{11}, S_1)$ is equal to CD. However, with respect to the cost, S_{11} dominates S_1, not certainly, but with a weak possibility (WPD). Then, mono-CDR$^{Cost}(S_{11}, S_1)$ is equal to WPD. Consequently, S_1 is dominated by S_{11} with respect to the two decision criteria. That is why mono-CDR$^{Duration}(S_1, S_{11})$ and mono-CDR$^{Cost}(S_1, S_{11})$ are equal to NA (Not Applicable). As the dominance of a solution over itself is not relevant, it is not shown in Figure 4.

In the next section, these two matrices are used to construct the Pareto-front.

4.2.2. The Pareto-dominance and the Pareto-front

The twelve potential solutions are represented in Figure 5. Each solution is represented by two lines. The horizontal line represents the duration of the solution whereas the vertical line represents the cost of the solution. For each line, the solid part represents the interval of the estimation values (EV) which are the most possible values (possibility = 1). The dotted parts of the line (at the two sides of the solid line) represent the values that are outside the interval EV. At both sides, the possibility of these values is equal to the parameter e which is computed using Equation (2), and represented on one side of the dotted lines in Figure 5.

Algorithm 2 is used to determine the set of non-dominated solutions (Pareto front). At this stage, the person in charge of the elaboration of the technical bid solution (bidder or decision maker) provides the Required Level of Dominance (RLD^k) for each decision criterion k. As two decision criteria are considered, fifteen combinations of RLD^k are allowed (see the left part of Figure 6). However, we consider only three combinations in this example. They are shown in the right part of Figure 6 and correspond to the three scenarios which are presented and discussed in the following (CD-CD, SPD-SPD, and WPD-WPD).

Si \ Sj	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1		NA	NA	NA	IND	IND	NA	NA	NA	IND	NA	WPD
S2	SPD		SPD	WPD	CD	SPD	SPD	WPD	SPD	CD	WPD	CD
S3	WPD	NA		NA	SPD	SPD	WPD	NA	IND	SPD	IND	SPD
S4	SPD	NA	WPD		CD	SPD	WPD	NA	WPD	SPD	WPD	SPD
S5	IND	NA	NA	NA		NA	NA	NA	NA	NA	NA	IND
S6	IND	NA	NA	NA	WPD		NA	NA	NA	WPD	NA	WPD
S7	WPD	NA	NA	NA	SPD	SPD		NA	IND	SPD	NA	SPD
S8	SPD	NA	WPD	WPD	SPD	SPD	WPD		WPD	SPD	WPD	SPD
S9	WPD	NA	IND	NA	SPD	SPD	IND	NA		SPD	NA	SPD
S10	IND	NA	NA	NA	WPD	NA	NA	NA	NA		NA	WPD
S11	WPD	NA	IND	NA	SPD	SPD	WPD	NA	WPD	**SPD**		SPD
S12	NA	NA	NA	NA	IND	NA	NA	NA	NA	NA	NA	

Mono-criterion dominance relations for the cost

Si \ Sj	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12
S1		NA	NA	NA	IND	IND	NA	NA	NA	IND	NA	IND
S2	CD		SPD	WPD	CD	CD	IND	IND	SPD	CD	NA	CD
S3	SPD	NA		NA	SPD	CD	NA	NA	WPD	SPD	NA	CD
S4	CD	NA	SPD		CD	CD	NA	IND	CD	CD	NA	CD
S5	IND	NA	NA	NA		SPD	NA	NA	NA	WPD	NA	SPD
S6	IND	NA	NA	NA	NA		NA	NA	NA	NA	NA	IND
S7	CD	IND	SPD	WPD	CD	CD		WPD	CD	CD	NA	CD
S8	SPD	IND	SPD	IND	CD	CD	NA		SPD	CD	NA	CD
S9	SPD	NA	NA	NA	SPD	CD	NA	NA		SPD	NA	SPD
S10	IND	NA	NA	NA	NA	SPD	NA	NA	NA		NA	SPD
S11	CD	WPD	SPD	SPD	CD	CD	WPD	WPD	SPD	CD		CD
S12	IND	NA	NA	NA	NA	IND	NA	NA	NA	NA	NA	

Mono-criterion dominance relations for the duration

Figure 4. The possibilistic mono-criterion dominance relations.

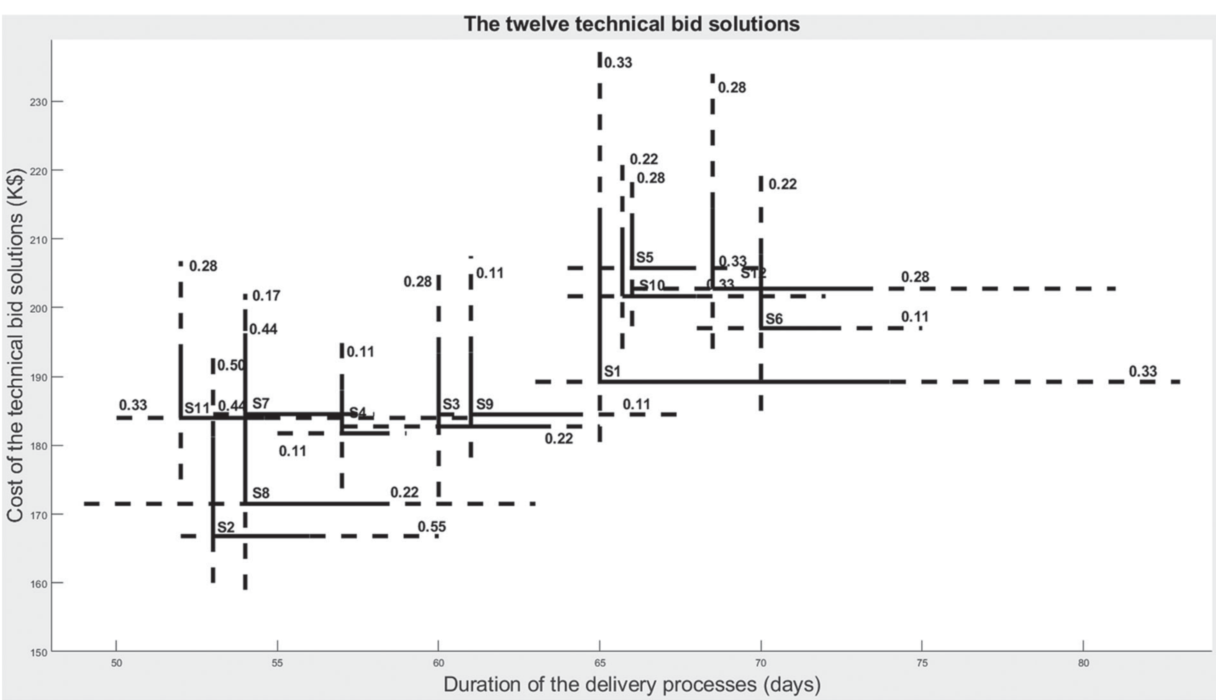

Figure 5. The twelve potential technical bid solutions.

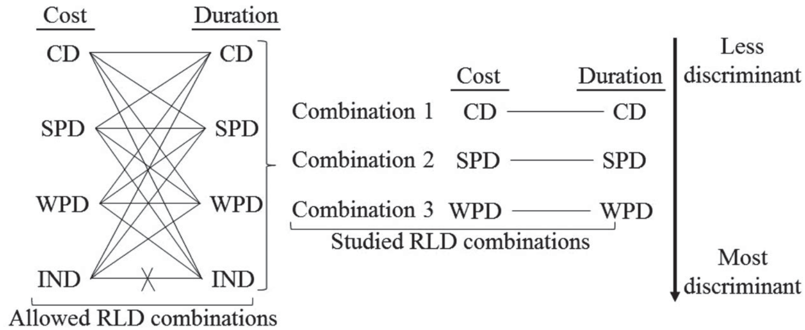

Figure 6. Allowed and studied combinations of RLD.

1. Combination 1 (CD-CD). In this scenario, the decision maker has defined the Certain Dominance relation (CD) as the RLD for each decision criterion (cost and duration). This RLD combination is the less discriminating one. In order that a solution S_i Pareto-dominates another solution S_j, for each decision criterion, the dominance relation of S_i over S_j must be certain CD. From Figure 4, it can be seen that the dominated solutions with respect to this RLD combination are S_5, S_{10} and S_{12}. They are shown in red colour in Figure 7.

With this RLDs combination (CD-CD), the obtained non-dominated solutions (S_1, S_2, S_3, S_4, S_6, S_7, S_8, S_9, and S_{11}) are, with certainty, the most interesting ones. However, the number of potential solutions is still too large (nine solutions). In order to reduce the number of solutions in the Pareto-front, the decision maker has to reduce the RLD on the decision criteria.

2. Combination 2 (SPD-SPD). In this scenario, the decision maker has reduced the RLD combination to SPD-SPD. This second combination is more discriminating than the first one. Indeed, in order that a solution S_i Pareto-dominates another solution S_j, for each decision criterion, the dominance relation of S_i over S_j must be certain (CD) or uncertain but with a strong possibility (SPD). Consequently, four additional solutions (S_1, S_3, S_6 and S_9) are dominated with respect to this RLD combination. They are shown in cyan colour in Figure 7.

Compared to the first scenario, in this second scenario, the number of non-dominated solutions has decreased. Even if the resulting set of non-dominated solutions is not certain with the defined RLDs, the decision maker knows that it is most plausible that the five non-dominated solutions (S_2, S_4, S_7, S_8 and S_{11}) are the five most interesting ones. The decision maker can further reduce the RLD on the decision criteria in order to discriminate more solutions.

3. Combination 3 (WPD-WPD). The decision maker has further reduced the RLDs. At present, the RLD combination is WPD-WPD which is more discriminating than the previous ones. In order that a solution S_i Pareto-dominates another solution S_j, for each decision criterion, the dominance of S_i over S_j must be either: certain (CD) or uncertain but with a strong possibility (SPD) or uncertain with a weak possibility (WPD). As shown in Figure 4, two additional solutions (S_4 and S_7) are dominated with respect to this RLD combination. They are shown in blue colour in Figure 7. Only three solutions S_2, S_8 and S_{11}, shown in green colour, are non-dominated. Even if it is not certain that these solutions S_2, S_8 and S_{11} are the best ones, with this RLD combination, the decision maker knows that it is most plausible that these three solutions are the most interesting ones.

4.2.3. Exploiting the Pareto front for decision making

In situations where only one solution remain in the Pareto front, the decision maker just selects this solution for the commercial offer. However, most of the time, more than one solution remain in the Pareto front. In this example, with the last combination (WPD-WPD), three potential solutions S_2, S_8 and S_{11} remain in the Pareto front. They are indifferent to each other with respect to all the decision criteria. Therefore, in order to choose one solution, it is necessary to give more importance or priority to one decision criterion. Two different approaches can be adopted depending on the availability of additional information about the prioritisation of the decision criteria.

In some cases there is no additional information about the prioritisation of the decision criteria or the decision maker cannot explicitly formalise it. In such a case, the decision maker selects the most interesting solution according to her/his preferences regarding the decision criteria even if she/he is not able to explicitly provide these preferences. In Figure 4, one can see that solution S_{11} dominates solution S_2 with a weak possibility with respect to the duration ($S_{11} \prec_{WPD}^{duration} S_2$). Solution S_2 dominates solution S_{11} with a weak possibility with respect to the cost ($S_2 \prec_{WPD}^{cost} S_{11}$). Solution S_8, in

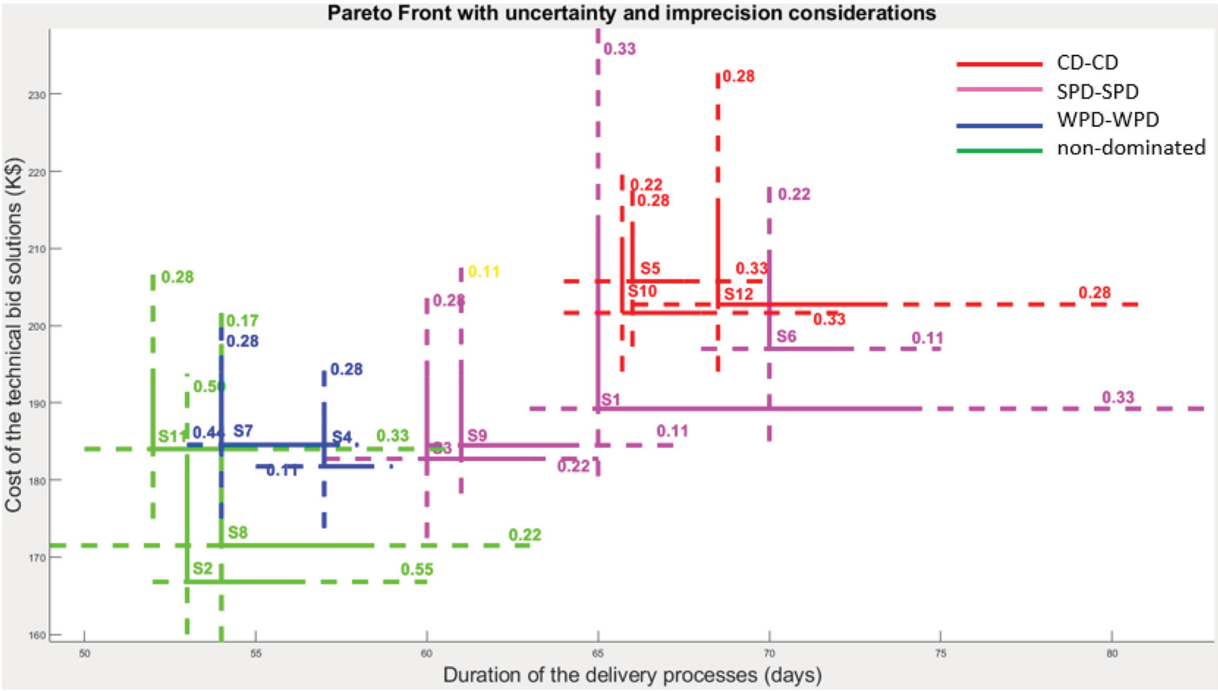

Figure 7. Pareto front – Dominated solutions following each RLD combination.

turn, dominates solution S_{11} with a weak possibility with respect to the cost ($S_8 \prec^{cost}_{WPD} S_{11}$). solution S_{11} dominates solution S_8 with a weak possibility with respect to the duration ($S_{11} \prec^{duration}_{WPD} S_8$). Finally, solution S_2 dominates solution S_8 with a weak possibility with respect to the cost ($S_2 \prec^{cost}_{WPD} S_8$). The two solutions S_2 and S_8 are indifferent to each other with respect to duration (S_2 IND^{duration} S_8). If the decision maker has a strong preference for the criterion *Cost*, she/he would choose the technical bid solution S_2, as it dominates the other solutions with a weak possibility with respect to the cost.

In the contrary, in some other cases, some additional information about the prioritisation of the decision criteria are available and the decision maker is able to formalise it as a weight (or a relative importance) for each decision criterion. In such a case, some well-known outranking methods as PROMETHEE or ELECTRE (Renzi, Leali, and Di Angelo 2017; Behzadian et al. 2010) can be used to rank the solutions remaining in the Pareto front. As this article focuses on situations where the decision maker does not have additional information about the prioritisation of the decision criteria, for seek of clarity, this case is not developed here. It should be considered for future research. First ideas have been reported in Sylla et al. (2019a).

One can observe that the Required Levels of Dominance (RLDs) are very useful in the decision making process. By setting them at the higher level (CD-CD), they enables the bidder to make the choice of the most interesting technical bid solution from a Pareto front which is certainly the set of the best solutions. Indeed, as the dominance relations are required to be certain, any solution that remains in the Pareto front is certainly better than any other solution that has been removed. They also allow the bidder, by reducing the RLDs (WPD-WPD for instance), to make the choice of the most interesting solution from a smaller Pareto front while having the knowledge about the level of certainty or possibility that this solution is the most interesting one.

It is important to mention that, by modelling all the possible values that may occur for a decision criterion with their possibility level, this approach allows to take into account the changeability of the values of the decision criteria in the decision process. Therefore, the proposed approach provides a robust Pareto front with regards to changes in parameters (inputs) values.

5. Conclusion and further research

In this article, we have studied the elaboration of a technical bid solution in an Engineer-To-Order (ETO) bidding process. In such a context, when selecting the most interesting technical bid solution to propose to a customer, a bidder faces the problem of the feasibility of the potential solutions. In fact, the lack of relevant information generates uncertainty and risks regarding her/his future ability to provide the proposed solution once the offer is accepted by the customer.

Therefore, in this article, a Multi-Criteria Decision Making (MCDM) support approach has been proposed in order to help bidders to select the most attractive and feasible solution during an ETO bidding process. An attractive and feasible solution has good values for the evaluation criteria and low uncertainty (or high confidence) about the future ability of the bidder to provide the solution according to these values. The proposed MCDM support approach is based on the Pareto-dominance principle and possibility theory. It brings together three main stages supported by new methods and algorithms which are the key contributions of this article. The first stage is the modelling of the values of the decision criteria. It is supported by a new method which uses the bidder's confidence in the technical bid solutions to automatically model the uncertain and imprecise values of the decision criteria by possibility distributions. Thus, it enables this confidence in the selection process to be taken into account. The second stage is the pairwise comparison of the potential solutions with respect to a single decision criterion. Four new generic possibilistic mono-criterion dominance relations (Certain Dominance (CD), Strong Possibility of Dominance (SPD), Weak Possibility of Dominance (WPD) and Indifference (IND)) and an algorithm have been developed. They make it possible to compute the relevant mono-criterion dominance relation between two solutions and to know the level of certainty of the dominance. The third stage is the interactive construction of the Pareto front which is the set of the most interesting solutions. It is supported by a method and an algorithm which allow comparison of the potential solutions with respect to all the decision criteria and thus determine the restricted set of the most interesting ones (Pareto front) while taking into account the level of certainty of dominance between solutions.

Using the proposed approach, the decision maker will have a restricted set of best solutions. This bring more flexibility to the selection process. Thus, based on her/his feeling or some additional information, she/he can decide which is the most interesting solution to propose to the customer. In an ETO bidding process or, more generally, in any engineering design process, when selecting the most interesting solutions, this approach can be very useful for the designer or the decision maker, especially in the early phases of the design process, which is characterised by imprecision, uncertainty and confidence issues.

The case of the design of a technical bid solution of a crane presented in Section 4 has shown that this approach is applicable and effective. It is important to mention that in situations where many possible configurations (systems) are relevant to customers' requirements, many potential technical bid solutions have to be considered in the decision making process. First, each solution should be evaluated with regards to the decision criteria (cost and duration) but also in terms of confidence indicators (OCS and OCP). This can be done using a configuration software which implements appropriate evaluation methods (Sylla et al. 2017, 2019b). Then, the proposed multi-criteria decision support approach can be applied for the selection of the most interesting solution. The algorithms proposed in this article allow to automate and facilitate the whole decision making process even in such situations.

With the proposed MCDM support approach, the decision maker has to interact with the decision support tool to define different combinations of Required Levels of Dominance (RLDs) for the decision criteria in order to determine the most interesting technical bid solutions. In situations where the number of decision criteria is large (greater than five, for instance), this may be time consuming. Moreover, in this article, the focus has been placed on situations where the decision maker cannot explicitly provide the relative importance of each decision criterion. However, in some situations, the decision maker may have this knowledge. In such a context, it is necessary to consider the relative importance of each decision criterion when comparing the potential solutions with respect to all the criteria. Therefore, future research should consider extending the proposed approach to such situations. A method could be developed to integrate the possibilistic mono-CDR with a relevant outranking method (PROMETHEE or ELECTRE) in order to rank the potential solutions. In addition, in this article, we consider one decision-maker's (a bidder) point of view. However, in some practical situations several decision makers are involved in the decision process. Therefore, extending the proposed approach to the case of group decision making should also be considered as future research. It could be achieved by identifying relevant aggregation methods that allow to aggregate the preferences of multiple decision makers. The last aspect of possible future research is to perform a benchmark with competing approaches in the literature.

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No potential conflict of interest was reported by the author(s).

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