Decision-making in the manufacturing environment using a value-risk graph

L. A. Shah · A. Etienne · A. Siadat · F. Vernadat

Abstract A value-risk based decision-making tool is proposed for performance assessment of manufacturing scenarios. For this purpose, values (i.e. qualitative objective statements) and concerns (i.e. qualitative risk statements) of stakeholders in any given manufacturing scenario are first identified and are made explicit via objective and risk modeling. Next, performance and risk measures are derived from the corresponding objective and risk models to evaluate the scenario under study. After that, upper and lower bounds, and target value is defined for each measure in order to determine goals and constraints for the given scenario. Because of the multidimensionality nature of performance, the identified objectives and risks, and so, their corresponding measures are usually numerous and heterogeneous in nature. These measures are therefore consolidated to obtain a global performance indicator of value and global indicator of risk while keeping in views the inter-criteria influences. Finally, the global indicators are employed to develop minimum acceptable value and maximum acceptable risk for the scenario under study and plotted on the VR-Graph to demarcate zones of “highly desirable”, “feasible”, “and risky” as well as the “unacceptable” one. The global scores of the indicators: (value-risk) pair of the actual scenario is then plotted on the defined VR-Graph to facilitate decision-making by rendering the scenarios’ performance more visible and clearer. The proposed decision-making tool is illustrated with an example from manufacturing setup in the process context but it can be extended to product or systems evaluation.

Keywords Value management · Risk analysis · Manufacturing processes simulation · Decision support · MACBETH Methodology · Choquet Integral operator

Introduction

Today’s business environment is more dynamic but also uncertain than ever. The dynamic effect can be attributed to the globalization phenomenon that results in a trend towards global market, global production and global competition. If this trend offers opportunities to companies, it confronts them also with threats because of uncertainties and turbulences in the global market. To avail the opportunities and deal with the threats, companies require a robust decision-support tool for sensible and informed decision-making at strategic, tactical and operational levels.

A typical decision-making process is concerned with identifying and choosing alternatives on the basis of stakeholders’ values and preferences. At the strategic level in the manufacturing context, this process can be applied to the selection of a facility location (Farahani and Asgari 2007;

Malakooti 2011), choosing suppliers (Amid et al. 2009; Ho et al. 2010; Pang and Bai 2013), purchasing pieces of production equipment (Abdi 2009; Wernz and Deshmukh 2012) or designing manufacturing systems (Chan et al. 2000; Li and Huang 2009). Similarly, tactical decisions involve decisions on scheduling (Low et al. 2006), manufacturing process selection and process planning (Shah 2012; Sormaz and Khoshnevis 2003) or assembly line balancing (Özcan and Toklu 2009; Jolai et al. 2009). Regarding operational decisions, they are concerned with deciding order quantities (Demirtas and Üstün 2008), machine/resource allocation (Ertay and Ruan 2005; Taha and Rostam 2012) or material handling (Hao and Shen 2008).

Irrespective of the hierarchical or temporal scale and the application area, values and preferences of stakeholders in addition to their concerns are central to the decision analysis. These values and preferences form the basis for criteria (performance measures or performance criteria in the performance measurement context) by which alternatives are evaluated in a decision problem. However, decision-making techniques often ignore to link systematically the criteria with the values and preferences of the stakeholders. These criteria are often selected based on thinking about the alternatives, rather than thinking about the stakeholders' values (Keeney 1996).

Unlike decision analysis, the performance measures link with global objectives of an organization is well established in the performance measurement (PM) literature (Amoako-Gyampah and Acquaah 2008; Berrah 2002; Dixon et al. 1990; Globerson 1985; Kaplan and Norton 1992, 1996, 2004; Lynch and Cross 1995; Maskell 1991). Here, measures are designed from the stakeholder objectives and used for as diverse purposes as monitoring and control, diagnosis and interaction, communication, learning and improvement and decision-making (Shah 2012). However, the application of performance measures for decision-making is not explicit in the performance measurement literature.

Furthermore, the PM discipline traditionally ignores risk management despite the fact that risk is the sole element that can influence negatively the performance of processes (Vernadat et al. 2013). Also, the importance of risk being part of the performance measurement has been realized recently (Cokins 2012). The purpose is to provide reliable and contextual information as input to decision-making in an integrated manner. Some authors do propose to manage risk for improving process performance (Tuncel and Alpan 2010); however, it is still managed independently of the PM discipline.

In view of the need to develop an integrated solution for evaluating performance and risk in the context of decision-making, the current study integrates performance and risk relevant concepts and couples them with the decision-making process. Furthermore, the study gives a brief explanation, along the way, of the different terms such as performance measures, criteria or performance indicators usually used interchangeably in the same or cross disciplinary field of studies. However, before going to develop the integrated solution; the study reviews some of the theories and practices used in industry and academia alike relating to performance and risk assessment as well as decision-making in order to get insights for better integrated solution development.

Literature review

Since the 1960s, several methodologies have been developed and used for decision-making, performance, and risk assessment. In the context of decision-making, these methodologies can be broadly divided into two categories: graph theory combined with matrix approaches, and multiple criteria methods. The multiple criteria methods can further be classified into mathematical optimization and multiple criteria decision-making (MCDM). Researchers have applied mathematical optimization models to diverse manufacturing problems (Rao 2011). Durand (1993) uses optimization method to assess analytically the performance of product portfolios in a company and its impact on individual product cost using the concept of "shared activity". Nevertheless, optimization models are often employed to find optimal solutions; they are therefore generative methods. For evaluation purpose, multi-criteria decision-making (MCDM) are the popular approaches (Greco 2004).

A decision process in MCDM perspective consists in defining a set of alternatives $\{x^h\}$ where $h = 2$ to m and a set of performance criteria $\{c_i\}$, $i = 1$ to n. The assessor task is to judge the performance of each alternative $\{x^h\}$ under performance criteria c_i and to determine the relative importance of the criteria to arrive at a global judgment. The ideal alternative is the one which outranks all the other ones under each of the performance criterion. That's rarely the case in real scenarios. Instead, we have to make trade-off when selecting between alternatives.

Therefore, a typical decision-making process is some sort of selection process and not a performance measurement process on its own. Even so, some authors have used several MCDM methods to evaluate performance of manufacturing systems. For instance, Tseng et al. (2009) develop a business performance evaluation model for high-tech manufacturing companies in Taiwan using data envelopment analysis, analytical hierarchy process (AHP), and technique for order of preference by similarity to ideal solution (TOPSIS). Similarly, Ertuğrul and Karakaşoğlu (2009) propose a fuzzy model to evaluate the performance of cement industries using financial ratios, AHP, and TOPSIS techniques. Other authors who propose similar approaches include but not limited to (Jablonsky 2007; Pokharel 2008; Yu and Hu 2010; Zolghadri et al. 2008).

Although, these methodologies claim to tackle performance by selecting a set of criteria, next determining their weights using AHP technique and finally ranking them using TOPSIS or any other ranking method, there are some disadvantages and pitfalls. For example, the criteria, meant to measure the degree to which an objective is met in a decision analysis in much the same way as performance measures do in the performance measurement field, are not often derived from the strategies in the decision methodologies; they may or may not reflect the values of the stakeholders. Secondly, most of the MCDM methods employed to evaluate performance use an additive model for the aggregation purpose. The choice of an additive model implicitly assumes difference independence (Kirkwood and Sarin 1980). For instance, this would mean that increasing in performance level of one measure does not influence other measure(s), that is to say, there exists no performance criteria interaction (Beliakov et al. 2010). Unfortunately, this is not often the case in the real life examples (quality versus cost optimization is the usual example).

In addition, the use of MCDM methods for performance evaluation is not in in-agreement with the established PM process where performance measures are designed in line with the objectives; they are then measured, analyzed and actions are next planned accordingly (Santos et al. 2002). This line of thinking has led to the development of a range of PM frameworks, namely balanced scorecard (Kaplan and Norton 1992, 1996), performance prism (Neely et al. 2002), SMART (Lynch and Cross 1992), and ECOGRAI (Bitton 1990; Ducq and Vallespir 2005). These frameworks have their respective strengths and weaknesses (Shah 2012). In the decision-making context, only ECOGRAI has built-in decision-making capability; however, it is not in the realm of MCDM. Moreover, no framework has the provision for quantitative consolidation of non-additive performance measures of the different dimensions they present.

To deal with risk in the decision analysis, a common approach is the application of utility theory (Keeney and Raïffa 1993). Utility theory, in addition to developing preference function over set of alternatives for measures/criteria, captures risk associated with the outcome of a decision and models individual behavior towards risk; that is, whether the decision-maker is risk averse, risk neutral or risk seeking. But, in the PM context, the risk factors and the associated risks likely to affect process performance can be identified in advance using tools and techniques such as failure mode and effect analysis (FMEA), cause and effect analysis, SWIFT and assessed using FMEA, fault tree analysis and event tree analysis (ISO/IEC31010 2009). In addition to these analytical techniques, the Monte Carlo simulation method also provides a statistical approach towards risk assessment among others (Mun 2006).

However, these risk assessment techniques have certain limitations. The major one is that they model and analyze risks from a subsystem perspective. A system is reduced to subsystems or component parts and then each part is considered independently. Nevertheless, a failure may not happen because of one risk event, but a combination of mutually inclusive risk events which may lead to system/process failure. To address this issue, one way is to approach the risk assessment problem via process simulation. However, it requires an activity-based approach to risk modeling and assessment. Larson and Kusiak's risk assessment approach (Larson and Kusiak 1996a,b) is relevant here because it is capable to deal with reliability and risk concepts in the process environment. However, the approach takes all risks and their relationship with activities for granted and proposes no mechanism to identify and associate them with the activities.

To conclude this overall discussion on theories and practices of PM, risk assessment and decision analysis, we believe that there exists a commonality in these theories and approaches; they all are developed to maximize *value* (i.e. objectives satisfaction) for their stakeholders. However, they continue to work independently. Thus, in the next section, a conceptual framework is proposed to unify the relevant concepts and provide a foundation for the integrated solution.

Unifying performance measurement and risk assessment with decision-making

To unify the fundamental concepts of different domains into one framework, a common element (also called link element) and a common representation mechanism for the link element are required (Neiger et al. 2008). In the case of performance measurement and risk assessment, the *link element* is value, which represents the degree of stakeholders' satisfaction with regard to defined objectives. Since performance measurement practices are *in fine* designed to evaluate value (encompassing efficiency, effectiveness and customer satisfaction); risk assessment practices, on the other hand, are aimed to preserve the value, i.e. to secure the chance for success (Sienou 2009).

Concerning the *representation mechanism*, activity modeling is the right choice because activity is the federating unit relating objectives with value and risk. For example, the value of any business process or activity based entity can be expressed in terms of objectives, and realized by activities via objectives realization. However, the activities are subject to risk, which ultimately affect the objective realization, and negatively influence the value creation process. The relationship of these elements, where activity occupies a central role, is expressed in the form of a tetrahedral framework and

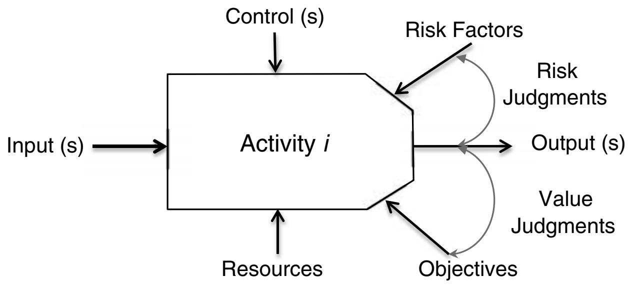

Fig. 1 Conceptual value-risk model

presented in the literature (Vernadat et al. 2013). Therefore, an activity model (modified IDEF0) is chosen as the primary model to combine, host and represent the elements related to value and risk. Moreover, the activity model using IDEF0 formalism is appropriate to model the control elements, which are often ignored in process modeling methodologies. The resulting model named conceptual value-risk model is shown in Fig. 1.

The model describes that an activity i consumes resources (including cost and time) to produce deliverables (outputs) whose magnitude (in the broader sense) is controlled by controls including allocation models (which can be ABC cost model or scheduling model) and operating policies as well as the quality level expected and the provided inputs. The deliverables in the context of manufacturing can be a change in the morphology of an unfinished or finished workpiece or information creation from inspection activities (Etienne 2007). However, the activity can be exposed to diverse risk factors RF_i. It is likely that these risk factors trigger risk events R_i which in turn can influence negatively the value creation process.

To calculate the interim value μ_i (for the individual activity i) of a process using the proposed model, the outputs (or deliverables) of the activity appraised by performance measures are compared and judged, in the decision context, with reference to assigned objectives of the activity using utility theory. As a result, interim value functions are designed for each performance measure at an activity level. For instance, the output of an activity is appraised using performance measure, and compared with the corresponding objective to ascertain the level of satisfaction (Berrah 2002). However, decision to determine how much level of satisfaction is important for that particular measure with regard to ideal and neutral points (reference points representing goals and constraints) in a given context requires value judgment. This judgment is quantified in terms of value function when modeling preferences and strength of preferences via value elicitation technique (Shah 2012). The overall value of a process is then obtained by aggregating the interim values of all its activities using an aggregation operator F as shown by Eq. 1

$$Global\ Value, \mathcal{V} = \mathrm{F}(\mu_{1,}\mu_2, \ldots, \mu_n) \quad (1)$$

Similarly, the outputs of activity i are compared and judged using risk measures to develop the interim risk function r_i. The global risk of the process is then obtained by aggregating the interim risks, first at the activity level and then all along the process by means of an aggregation operator F as shown by Eq. 2.

$$Global\ Risk, \mathcal{R} = \mathrm{F}(r_1, r_2, \ldots, r_m) \quad (2)$$

The global indicators of value and risk are then used to evaluate process alternatives in the decision context. The following section elaborates on how to quantitatively calculate value and risk for a process.

Development of global value and risk indicators

Performance indicators, as opposed to performance criteria, "indicate" or "interpret" the level of performance regarding a performance dimension but do not claim to measure it. In the current study, *Value* as a performance indicator is an appropriate balance (aggregation) of different performance measures used to appraise quantitatively stakeholders' satisfaction. Similarly, the *Risk* indicator is an appropriate balance of different risk measures used to appraise stakeholders' concerns. To compute the performance and risk indicators, a qualitative as well as quantitative value and risk models are proposed. The proposed models formalize the expectations (i.e. values) and concerns (i.e. risks) of stakeholders and transform them into global value and risk indicators using the concept introduced in the conceptual value-risk model (cf. Fig. 1).

Qualitative value model

Values of stakeholders are qualitative objective statements reflecting their expectations. Qualitative value modeling is therefore required to identify these objectives $O_i(i = 1, \ldots, n)$ appropriate for the process considered and to define performance measures $M_j(j = 1, \ldots, m)$ in order to assess the degree to which these objectives are met. For this purpose, the value model inspired by the value-focused thinking framework (VFT) of Keeney (1996) is applied.

Value-focused thinking framework (VFT) provides a structured approach to elicit fundamental objectives from stakeholder values. To begin with, the overall fundamental objective is determined. In the words of Keeney (1996), it defines "the breadth of concern". For instance, in a supply chain context, a high level fundamental objective can be "To satisfy each customer order". Next, this objective is broken down to identify more specific objectives while asking a simple guiding question "What do you mean by that". For instance, the customer order satisfaction means "on-time delivery", "minimum cost" and "high quality". This process

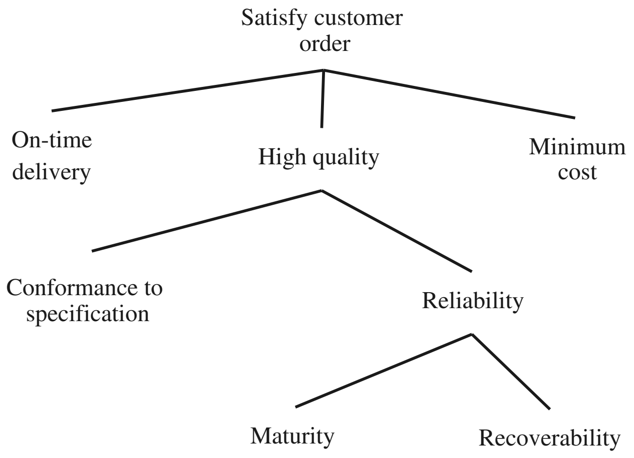

Fig. 2 Fundamental objectives hierarchy

of objective decomposition continues until the upper level objective cannot be further broken down. The identified fundamental objectives are then organized in the form of hierarchy as shown in Fig. 2.

The sub-objectives on the lower level of the hierarchical structure are quantifiable and, hence, performance measures can be defined for each of them. For instance, for the refined objectives of maturity and recoverability, "the number of process errors occurred" and the mean time between failures (MTBF) can be defined as performance measures/criteria, respectively. These measures are then used to evaluate alternative solutions, which are identified and then modeled using activity modeling methodologies.

Activity modeling

Process modeling is the identification and representation of a sequence of activities needed to support (directly or not) the realization of some objectives (Curtis et al. 1992). In the manufacturing context, activities are identified from the need to produce product features (Sormaz and Khoshnevis 2003). In the supply chain context, they can be identified from the generic business process pattern (level-3) of the supply chain operations reference model (SCOR 2012). Once identified, they are then arranged in sequence defining the logical dependencies and constraints between them. For this purpose, the IDEF3 method adapted with a modified UOB construct based on the activity construct of our conceptual value-risk model (see Fig. 1) is used. It can easily model, besides objectives and risks, the logical and temporal dependencies existing within the process activities as shown in Fig. 3.

Next, the identified objectives of the value model are related to the activities of the model. Let's suppose, an activity "Turn feature i" whose objective (O_i) is to realize the feature with specification i can be modeled as shown in Fig. 4.

So, O_i represents the functional objective i associated with the activity "Turn feature i". Other non-functional objectives relevant to time and cost can also be associated to the activity. It is relevant to mention that core activities (in the value chain) are determined only for functional objectives and evaluated against both functional and non-functional objectives.

However, the activity is subject to uncertainties in the form of risk factors that may affect its value creation capability. Therefore, a risk model is included to account for the risks.

Risk modeling

In a process perspective, risk stems from the uncertainty regarding the ability of the process to deliver "the value proposition"—and the consequences thereof. To account for the uncertainty and its consequences on the value proposition, risk factors residing externally to the activity are first identified through an objective-driven approach and then analyzed via a process-based approach.

Objective-driven approach to risk identification

Since risk factors are likely to obstruct objectives attainment while triggering risk event (cf. Fig. 5), it is therefore logical to identify risks with regard to the objectives.

For this purpose, an assertion that obstructs the objective attainment is sufficient to identify the relevant risk events. For instance, for the global objective of the running exam-

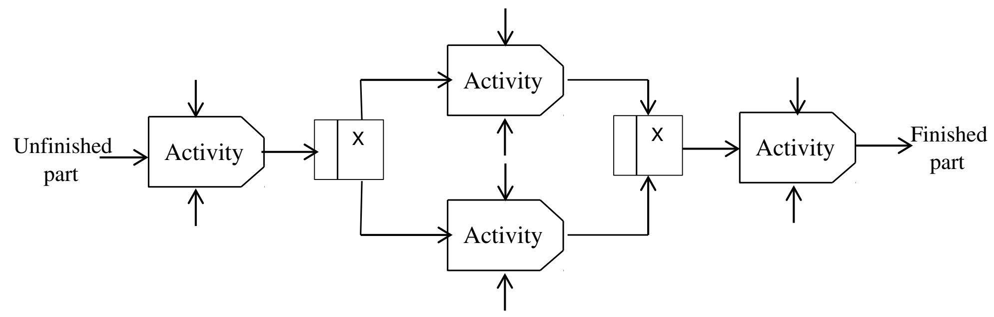

Fig. 3 Modified IDEF3-based process model

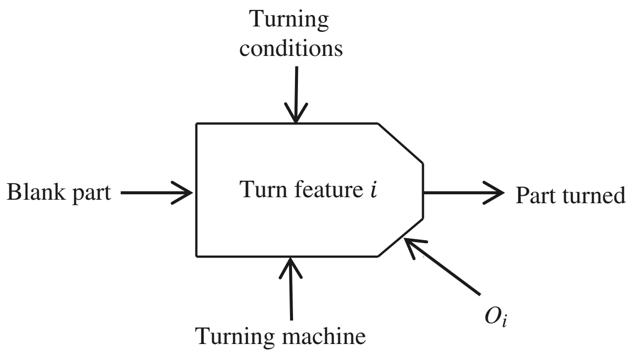

Fig. 4 One step of an objective-oriented process model

Fig. 5 Risk factor, risk event and objective relationships

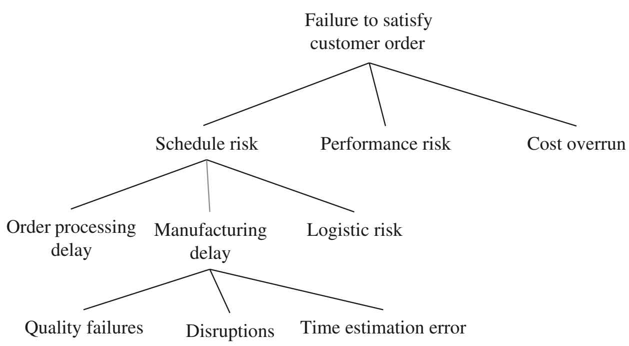

Fig. 6 Objective-driven risk identification

ple, "failure to satisfy the order" can be a global risk since it asserts the downside of the global objective in question. From the global risk event, lower level risks are then identified similar to objective decomposition. Figure 6 shows the identified risks detailed for schedule risk and organized into the risk hierarchy.

Next, the identified risks are assessed qualitatively using the process failure and effect analysis (PFMEA) technique and prioritized for further quantitative assessment in the process simulation environment.

Process-based risk assessment approach

The identified risks cannot be assessed as long as the contextual information is not available. Because the process model contains sufficient information regarding the execution of the activities, and the environment thereof; they are therefore consulted when analyzing a particular risk. To this end, the risk events are first related to the activities by developing an activity/risk matrix as shown in Table 1, which applies to the manufacturing of a part such as the one illustrated in Fig. 11 and detailed in Shah (2012).

Table 1 Excerpt of the activity/risk matrix (Shah 2012)

Risks			
Activities	Failure to adjust in the modular fixture	Axel/body assembly failure	Duration estimation error
Turn F4_B	×		×
Turn (F6, F6')_C		×	×
Part F8_A			

For instance, the risk event "Failure to adjust in the modular fixture" can originate if the operation Turn F4_B meaning "Turn Feature F4-Body" of the part Body is not carried out per specification requirement. Similarly, all risk events are linked to the activities which are then assessed qualitatively in the process FMEA table.

Qualitative risk assessment Since in manufacturing processes the activity execution environment (i.e. operating conditions, operator or machine/tool) is known through the part process plan model, it is therefore reasonable to estimate the likelihood and detection parameters for the identified risk events (cf. Table 1) and then assess them using FMEA as shown in Table 2.

The critical risks in terms of RPN in the FMEA table are then incorporated in the process model as shown in Fig. 7.

The risks incorporated into the process model are next analyzed quantitatively.

Quantitative risk assessment, a process orientation The underlying assumption for an activity-based risk assessment is that each activity in a process is exposed to risk factors RF_i, $(i = 1, \ldots, n)$ and thus can trigger one to many risk events, which in turn can affect the achievement of process objectives (as illustrated in Fig. 5).

To quantitatively assess the identified risks in the process environment, the only relevant methodology is that of Larson and Kusiak's Risk Assessment (Larson and Kusiak 1996a,b). This approach parameterizes risk using Kaplan and Garrick (1981) definition of risk, as expressed by Eq. 3

$$R = (S, P, C) \tag{3}$$

where R, S, P and C represent the estimated risk, risk scenario, likelihood and consequence, respectively.

To calculate the global risk for an individual activity, all risks of diverse nature are identified and modeled separately as expressed by Eq. 4.

$$\begin{aligned} \textit{Individual risk in activity} &= \mathrm{P}_{ij}\left(\mathrm{C}^{q}_{\mathrm{ij}} + \mathrm{C}^{c}_{\mathrm{ij}} + \mathrm{C}^{t}_{\mathrm{ij}} + \cdots\right) \\ &= P_{ij} C_{ij} \end{aligned} \tag{4}$$

Table 2 Excerpt of the process FMEA table

Process	Failure mode	Causes (risk factors)	Effects	P	C	D	RPN
Activity *i*	Duration estimation error	Unavailable information Wrong information Incomplete information Wrong belief	Uncertain lead time	5	7	6	210

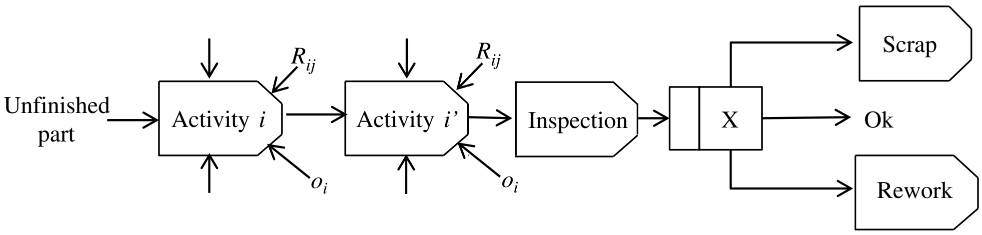

Fig. 7 Objective-oriented risk aware process model

where, P_{ij}, probability of a risk event j on activity i; $\mathrm{C}^{q}_{\mathrm{ij}}, \mathrm{C}^{c}_{\mathrm{ij}}, \mathrm{C}^{t}_{\mathrm{ij}}$, impact on quality, cost and time objectives, respectively.

Therefore, the global risk for an individual activity i subject to risk events j is given by Eq. 5.

$$\mathrm{R_i} = \sum_{\mathrm{j=1}}^{\mathrm{J}} d_{ij}(\mathrm{P_{ij}} \times \mathrm{C_{ij}}) \quad (5)$$

where d_{ij}, the importance of risk j on activity i; $\mathrm{C_{ij}}$, the impact of risk j on activity i.

Let us define a process path P_k in a process P to be a valid sequence of activities in P, i.e. there exist a path in P that goes from the start activity to the end activity of path P_k.

The global risk $\mathrm{R(p_k)}$ of the process path P_k in a process P is calculated by aggregating global risks of activities in path P_k using Eq. 6.

$$\mathrm{R(p_k)} = \sum_{\forall \mathrm{i} \in \mathrm{p_k}} \mathrm{R_i} = \sum_{\forall \mathrm{i} \in \mathrm{p_k}} \sum_{\mathrm{j=1}}^{\mathrm{J}} d_{ij}(\mathrm{P_{ij}} \times \mathrm{C_{ij}}) \quad (6)$$

And the probabilities $P_r(P_k)$ of the path set (or scenario) must verify Eq. 7.

$$\sum_{\mathrm{k=1}}^{\mathrm{K}} P_r(P_k) = 1 \quad (7)$$

So, the expected risk of the process P made of K path sets is given by Eq. 8.

$$E(R_p) = \sum_{\mathrm{k=1}}^{K} P_r(P_k) \left(\sum_{\forall \mathrm{i} \in \mathrm{p_k}} \sum_{\mathrm{j=1}}^{\mathrm{J}} d_{ij}(\mathrm{P_{ij}} \times \mathrm{C_{ij}}) \right) \quad (8)$$

Equation 8 calculates the expected risk of the whole process P.

Quantitative value-risk model for decision-making

In the a priori context, discrete event simulation seems to be an appropriate method since it offers a great potential in analyzing processes (Bosilj-Vuksic et al. 2007). For this purpose, alternatives are developed and modeled using process methodologies. In addition to the process models, further data, i.e. experimental factors (inputs) and responses (outputs) are required to make the model executable. For detail about the data requirements for simulation, see Robinson et al. (2010). Once defined, the measures of interests (outputs) are collected by performing simulation experimentations.

However, the performance and risk measures issued out of simulation experiments are usually large in numbers and heterogeneous in nature, and hence provide little insight about the global performance and risk of a process. Therefore, a quantitative value-risk model, based on the principles of MCDM, is constructed, which allows us to determine how well process alternatives perform to attain the stakeholders' expectations in the presence of risk.

The model develops value and risk functions for both performance and risk measures, respectively. A value function (or utility function) converts a process alternative score on a measure to a standard unit in the range of [0, 1]. Next, the scores are aggregated to form global indicators for both value and risk independently using Eq. 9.

$$\mathcal{V}(\mathrm{C}) = \mathrm{F}\left(\nu(\mathrm{c_1}), \nu(\mathrm{c_2}), \ldots, \nu(\mathrm{c}_n)\right) \quad (9)$$

$c \in C$, represents a performance measure of set C; $\nu(c)$, is a value function of a performance measure c; $\mathcal{V}(C)$, is a global value function (consolidated expression) for the set C; F, is an aggregation operator (or aggregation function).

To develop value function $\nu(c)$ for a measure c, the current study employs the MACBETH method. The value functions

$\nu(c)$ (henceforth value expression x_i), are then consolidated using the 2-additive Choquet Integral (CI) as the aggregation operator. The choice of MACBETH over other MCDM techniques for value expression construction is because the latter can be extended (through generalization) to the Choquet Integral operator (Labreuche and Grabisch 2003).

MACBETH

Measuring Attractiveness by a Categorical Based Evaluation TecHnique (MACBETH) is a multi-criteria decision analysis approach used to determine commensurate measures (value and risk expressions) as well as aggregated ones while comparing different alternatives (Bana e Costa et al. 2012; Bana et al. 2005). Two alternatives at a time are compared pair-wise for a performance measure and thus ordinal information is obtained. Next, ordinal information is transformed into cardinal one by means of the concept of "difference of attractiveness", which is quite natural to decision-makers who usually rely on verbal levels of attractiveness such as {null, very weak, weak, moderate, strong, very strong, extreme}.

The MACBETH procedure starts by defining a set of alternatives $A = \{a_{1,}a_2 \ldots a_m\}$ and performance criteria $C = \{c_{1,}c_2 \ldots c_n\}$, and associate each c_i of C with a_i of A via its value elicitation mechanism to determine a profile $x_i^a = (x_{c_1}^a, x_{c_2}^a \ldots x_{c_n}^a)$ where $x_{c_i}^a$ represents a value or risk expression of measure c_i in alternative a_i on a scale of [0, 1]. For the inter-criteria commensurability issue, two reference alternatives namely good and neutral with the performance value of 1 and 0, respectively, are defined.

MACBETH relies on the additive aggregation model for the aggregation of expressions $x_{c_i}^a$. However, this is not often the case in real-life where criteria may interact with each other. Therefore, the 2-additive Choquet Integral, a special case of the Choquet integral is chosen where pair-wise interactions among performance criteria are considered. It can handle interdependencies among different expressions by means of Choquet capacities.

2-Additive Choquet integral

The mathematical model of the 2-additive Choquet Integral is defined by Eq. 10 (Grabisch and Labreuche 2010).

$$\mathcal{V}(x) = \sum_{i=1}^{n} v_i x_i - \frac{1}{2} \sum_{\{i,j\} \subseteq C} I_{ij} |x_i - x_j| \tag{10}$$

where, $\mathcal{V}(x)$ models vectors of value and risk expressions x_i and x_j (known from MACBETH), v_i denotes a Shapley index (with $\sum_{i=1}^{n} v_i = 1$) that represents the importance of criterion *i* relative to all other criteria and I_{ij} represents interaction between criteria/expressions (c_i, c_j), ranging in $[-1, 1]$, where -1 means strong negative synergy, 0 means no influence and +1 means strong positive synergy.

The performance and risk expressions x_i and x_j are defined using the MACBETH procedure. To calculate the Shapley indices v_i as well as the interaction criteria I_{ij}, the approach needs to solve systems of equations having v_i and I_{ij} as variables. For this purpose, a set of equations can be used. These equations are based on the principles of MACBETH for weight determination where MACBETH proposes to consider some fictive situations for each value and risk expression (Clivillé et al. 2007). In such fictive situations, the alternatives satisfy one or two value or risk expression simultaneously. A preference ranking of these situations along with the strength of preference will give a system of equations whose solution determines the CI parameters.

The fictive situations are such that only one $x_i = 1$ and all others are equal to zero, thus the aggregated performance is given by Eq. 11 (Clivillé et al. 2007):

$$\mathcal{V}^i = v_i - \frac{1}{2} \sum_{j=1, j \neq i}^{n} I_{ij} \tag{11}$$

The aggregated performance of the situations where one $P_i = 0$ and all other equals to one will be as follows in Eq. 12:

$$\mathcal{V}^i = 1 - v_i - \frac{1}{2} \sum_{j=1, j \neq i}^{n} I_{ij} \tag{12}$$

Situations where only two value or risk expressions are equal to $x_i = 0$ and $x_j = 0$ and all other are equal to zero are given by Eq. 13:

$$\mathcal{V}^{i,j} = v_i + v_j - \frac{1}{2} \left(\sum_{k \in \aleph_{1,n}} I_{ik} + \sum_{k \in \aleph_{1,n}} I_{jk} \right) \tag{13}$$

By determining v_i and I_{ij} using Eqs. 11, 12 and 13, global value and risk indicators are calculated with the mathematical model of the 2-additive CI (cf. Eq. 10) for each alternative of the problem understudy.

Construction of the value-risk graph

The decision-making process will be more convenient if zones of aversion, acceptability and desirability are determined and graphically visualized both for value and risk. For this purpose, a two dimensional graph of value $\mathcal{V}$ and risk $\mathcal{R}$ in the range of [0, 1] on the x-axis and y-axis are defined, respectively.

Determining the ranges of value and risk

To define value on the x-axis, the latter is divided in three ranges:

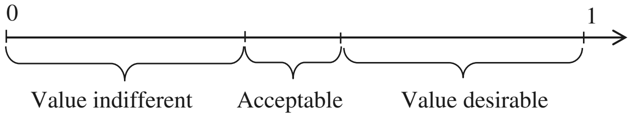

Fig. 8 Range of values on x-axis

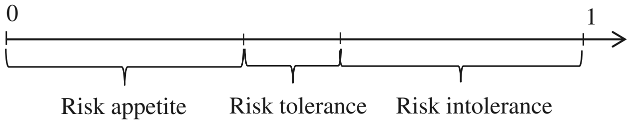

Fig. 9 Range of risks on y-axis

Value aversion/indifference The value indifference refers to the range of value which is not significant and for which a company will avoid pursuing the process.

Value tolerance/acceptable The value tolerance or acceptable range remains between the upper bound of the value indifference until the point where the value starts becoming desirable. In this range, the company may pursue the process.

Value desirable Beyond the acceptable range is the desirable range, i.e. the company is willing to pursue the process.

These ranges are drawn on the x-axis line as shown in Fig. 8.

In a similar way, the y-axis is divided into:

Risk appetite The risk appetite refers to the risk which an organization is willing to accept in pursuit of process objectives.

Risk tolerance The risk tolerance specifies the maximum risk the organization is willing to take in pursuit of the process objectives.

Risk intolerance The risk intolerance range corresponds to the risk level which is not acceptable.

The risk ranges have been drawn on Fig. 9.

Additionally, it is proposed to develop a value-to-risk curve to model the acceptability of a process when the value progresses with regard to risk. In reality, organizations may take risk beyond the risk tolerance in pursuit of value creation for their stakeholders. For this purpose, a value/risk ratio can be defined that will be restricted within a minimum acceptable value and a point of risk beyond which an organization cannot afford to pursue its objectives in any respect. The aim of the value/risk ratio is to determine the upper bound for the acceptability of a process in pursuit of objectives fulfillment. However, its determination is still subjective and depends on the company's attitude towards pursuing its objectives (value creation) and risk taking.

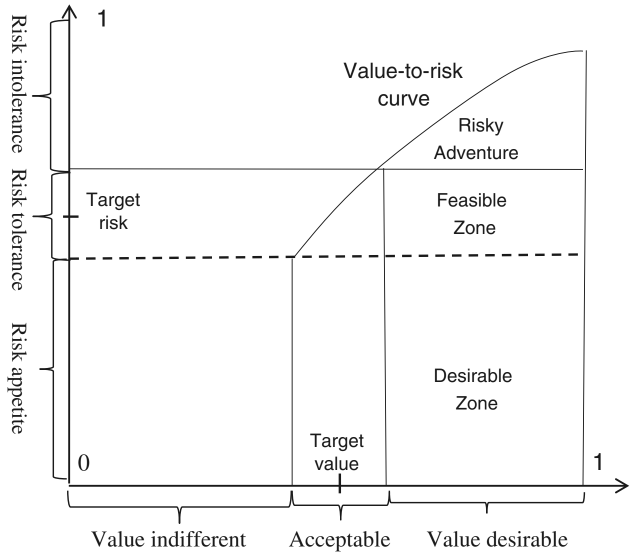

Fig. 10 Value-risk graph for decision-making

By defining the ranges for both value and risk measures and value/risk ratio, a value-risk graph is developed as illustrated in Fig. 10.

Calculating the ranges quantitatively

To determine the value and risk ranges quantitatively, a target, a lower bound and an upper bound for each performance and risk measures are defined. For instance, a process cost in the range of 10, 12 and 16 units will have a lower bound of 10, a target of 12 and an upper bound of 16 units, respectively. In this context, the lower bound is the ideal scenario while the upper bound is the worst case. Once the ranges for each measure have been defined, they are then normalized in the range of [0, 1] using the value elicitation technique and aggregated to obtain global indicators (Shah 2012).

Application

The proposed methodology is illustrated on a case study about a manufacturing company that designs and fabricates product on make-to-order (MTO) basis.

Reference product

In this case study, the company produces mechanical locators as a reference product. This is a work holding device that is placed in a modular fixture to locate a work-piece during machining process. Figure 11 shows the mechanical locator in loaded and unloaded configurations.

To validate the proposed methodology for value and risk assessment of manufacturing processes under different sets of demands, different manufacturing scenarios have been

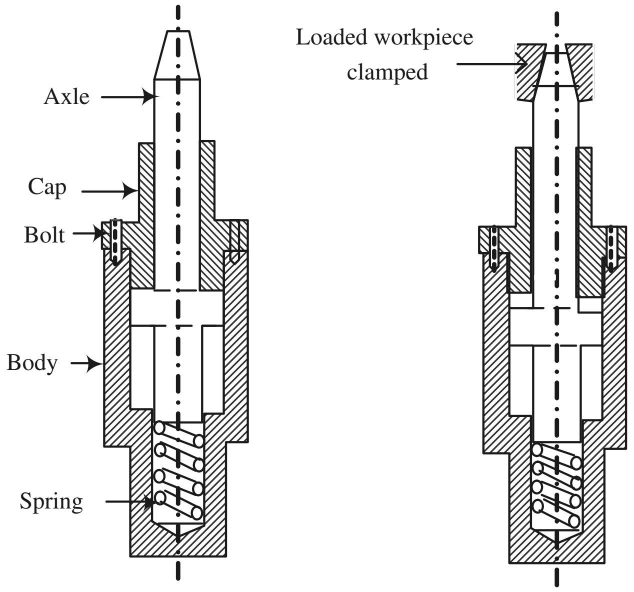

Fig. 11 Mechanical locator configurations: free (*left*) and loaded (*right*)

developed and illustrated (Shah 2012). However, this paper only presents one manufacturing scenario in the case of process design and selection of the best alternative.

Manufacturing scenario

The company understudy receives an order of N mechanical locators of high quality with a lead-time of T weeks. The high (HQ) and low quality (LQ) of a product can be measured by the satisfaction index (q) detailed in the literature (Anselmetti 2008). In addition, the price P is fixed for each mechanical locator for the defined quality level.

To fabricate and deliver the product, the company purchases springs and bolts from the market while the three other parts, namely axle, body and cap, are machined at the facility. All the purchased parts are assumed to be available whenever needed.

In the case of non-delivery at agreed upon lead-time and with required specifications (quality level), the company can ask for due date tolerance, already defined in the contract. If the due date passes, then the company is subject to penalty cost of \$2 per unit time tardy up to 5 days (required to calculate risk impact). Failing to provide the product in time and with the desired quality level will lead to cancellation of the customer order with a backlog cost of \$10 for N mechanical parts.

Application of the methodology to the manufacturing scenario

Having defined the scenario, the proposed methodology is applied to define the pair of global value and risk indicators.

Table 3 Minimum and maximum acceptable performance and risk measures

Measures							
Levels	C_1	C_2	C_3	C_4	R_1	R_2	R_3
Upper bound	24	18	100	100	4	5	1
Target level	20	14	80	75	2	2	0.3
Lower bound	18	12	75	60	1	1	0.2

So, a qualitative value model is developed for the scenario. From the global objective “satisfaction of customer order”, lower level objectives are determined using the qualitative value model principles. Since quality is the critical objective, requirements specifications (functional objectives) for the high quality mechanical locator in addition to time and cost objectives are determined more rigorously. Besides the economic focus, the company considers its employees satisfaction as a facet of the global objective.

Once defined, all the objectives are then organized in a hierarchy similar to the one of Fig. 2. Next, performance measures are derived from each lower level objective in the hierarchy. For the sake of simplicity, the current study only focuses on few critical dimensions such as cost, time, technical performance and employee satisfaction and considers the following measures: manufacturing cycle time (C_1), manufacturing total cost (C_2), technical performance (C_3) and employee satisfaction (C_4) as performance criteria for the scenario understudy.

To model the risk of the manufacturing scenario, the objective-oriented risk model is used to identify the major risk events relevant to time, cost and quality dimensions that correspond to schedule risk (R_1), cost overrun (R_2) and performance risk (R_3), respectively. Next, evaluation methods are determined in the next step for both the performance and risk measures (Vernadat et al. 2013). In the current study, the uncertainty and so the risk related to demand or supply is not modeled. The evaluation can be extended to include supply risk if upstream supply chain business processes are modeled; however, the demand type uncertainty is independent of the activities performed in a supply chain; it cannot be, therefore, modeled with the current proposed methodology.

To calculate the minimum performance and maximum risk acceptable for the scenario, the decision-maker defines the target, upper bound and lower bound for the measures as presented in Table 3.

The minimum acceptable value and maximum acceptable risk expressions are calculated by means of the MACBETH method. The upper and lower bounds for each measure act as two reference points: good and neutral in the value elicitation process. The normalized measures are then tabulated in the Table 4.

Table 4 Acceptable performance and risk expressions

Measures	C_1	C_2	C_3	C_4	R_1	R_2	R_3
Performance and risk expressions	0.33	0.4	0.43	0.48	0.57	0.67	0.55

Table 5 Simulation results for three process plan models

Measures							
Process plans	C_1	C_2	C_3	C_4	R_1	R_2	R_3
Process Plan 1 (PP1)	20.5	16.6	0.87	0.94	0.715	5.57	3.96
Process Plan 2 (PP2)	20.4	13.8	0.90	0.91	0.28	2.46	4.12
Process Plan 3 (PP3)	22.4	12.4	0.78	0.74	3.6	0.415	3.94

To determine the Shapley indices v_i and the interaction parameters I_{ij} for the purpose of aggregation, the evaluator is first asked to provide the preference modeling for the measures pair-wise as well as individual ones as shown below:

$$= C_3\&C_1 >^3 C_3\&C_2 >^3 C_2\&C_1 >^4 C_3\&C_4 >^3 C_1\&C_4 >^2 C_2\&C_4 >^2 C_3 >^3 C_1 >^2 C_2 >^4 C_4 >^4 \text{“0”}$$

The preference modeling is then transformed into systems of equations using Eqs. 11, 12 and 13, the solution of which provides the Shapley indices and interaction criteria as further presented in Table 7. These parameters are then put into the Eq. 10 to obtain the acceptable global minimum value and maximum risk for the manufacturing scenario:

- Global minimum acceptable value level $=$ **0.39**
- Global maximum acceptable risk level $=$ **0.59**

These global values will be used as points of reference to appraise the actual scenario understudy.

To realize the objectives of the value model, alternative process plans (candidate solutions) are generated using the Sormaz and Khoshnevis (2003) approach. This approach breaks down the product part into geometrical features. Next, for each feature, process candidates are selected using inquiries to the appropriate knowledge base of the manufacturing processes and sequenced while considering the geometrical, economical and technological constraints. The result is a network of process plans for the part in question.

Once the process plans network is generated, the next step is the selection of the process plan to be used for the product manufacturing based on value and risk indicators. For this purpose, the process plans are modeled using the modified IDEF3 method (cf. Fig. 7) and evaluated against the identified performance and risk measures in the simulation environment using the Rockwell ARENA 13.5 discrete event simulation software. The results of the simulation experiments are obtained and tabulated in Table 5.

Table 6 Value and risk functions for the manufacturing scenario

Expressions							
Process plans	x_1	x_2	x_3	x_4	r_1	r_2	r_3
Process Plan 1 (PP1)	0.63	0.1	0.5	0.14	0.12	0.98	0.66
Process Plan 2 (PP2)	0.83	0.5	0.6	0.20	0.38	0.57	0.78
Process Plan 3 (PP3)	0.18	0.7	0.11	1.0	0.88	0.14	0.56

To obtain the value and risk expressions, the process plans are ranked on the basis of desirability as well as strengths of preference for each criterion as follows:

$$C_1 \Rightarrow Good >^1 PP2 >^2 PP1 >^4 PP3 >^1 Neutral$$
$$C_2 \Rightarrow Good >^2 PP3 >^1 PP2 >^2 PP1 >^1 Neutral$$
$$C_3 \Rightarrow Good >^1 PP2 >^1 PP1 >^2 PP3 >^3 Neutral$$
$$C_4 \Rightarrow Good >^0 PP3 >^4 PP2 >^1 PP1 >^1 Neutral$$

In the same way, information is provided on alternatives for each risk measure. This ordinal preference modeling is then transformed into normalized value and risk expressions with MACBETH. The resulting value and risk expressions are then populated in Table 6.

To consolidate the expressions, the Shapley indices v_i and the interaction parameters I_{ij} have already been determined in the calculation of global minimum value and maximum risk and presented in Table 7. The 2-additive Choquet integral model (Eq. 10) is then employed to aggregate the value and risk expressions as presented in Table 7.

From Table 7, it can be seen that the quality dimension with a Shapley index of 0.3 is the most attractive because of the customer interest in high quality products. In addition to that, the company takes into consideration the satisfaction of its employees ($v_4 = 0.18$), particularly of the shop floor operators. However, employee satisfaction has the least Shapley index value of all the performance criteria. Concerning the interaction parameters I_{ij}, in the risk aggregation, the schedule risk $R1$ and quality risk $R3$ interaction have a synergistic effects on the overall global risk ($I_{13} = 0.13$).

The aggregated score, the global value and the global risk for the three manufacturing process plans are plotted on the value-risk graph as shown by Fig. 12.

From the value-risk graph (cf. Fig. 12), it is clear that only process plan PP1 falls in the desirable region for the scenario understudy. Therefore, the process plan PP1 is chosen to manufacture the product, while the other two scenarios PP2 and PP3 are dropped.

Conclusion and future work

The work reported in this paper introduced a framework and methodology for decision-making in the manufacturing envi-

Malakooti 2011), choosing suppliers (Amid et al. 2009; Ho et al. 2010; Pang and Bai 2013), purchasing pieces of production equipment (Abdi 2009; Wernz and Deshmukh 2012) or designing manufacturing systems (Chan et al. 2000; Li and Huang 2009). Similarly, tactical decisions involve decisions on scheduling (Low et al. 2006), manufacturing process selection and process planning (Shah 2012; Sormaz and Khoshnevis 2003) or assembly line balancing (Özcan and Toklu 2009; Jolai et al. 2009). Regarding operational decisions, they are concerned with deciding order quantities (Demirtas and Üstün 2008), machine/resource allocation (Ertay and Ruan 2005; Taha and Rostam 2012) or material handling (Hao and Shen 2008).

Irrespective of the hierarchical or temporal scale and the application area, values and preferences of stakeholders in addition to their concerns are central to the decision analysis. These values and preferences form the basis for criteria (performance measures or performance criteria in the performance measurement context) by which alternatives are evaluated in a decision problem. However, decision-making techniques often ignore to link systematically the criteria with the values and preferences of the stakeholders. These criteria are often selected based on thinking about the alternatives, rather than thinking about the stakeholders' values (Keeney 1996).

Unlike decision analysis, the performance measures link with global objectives of an organization is well established in the performance measurement (PM) literature (Amoako-Gyampah and Acquaah 2008; Berrah 2002; Dixon et al. 1990; Globerson 1985; Kaplan and Norton 1992, 1996, 2004; Lynch and Cross 1995; Maskell 1991). Here, measures are designed from the stakeholder objectives and used for as diverse purposes as monitoring and control, diagnosis and interaction, communication, learning and improvement and decision-making (Shah 2012). However, the application of performance measures for decision-making is not explicit in the performance measurement literature.

Furthermore, the PM discipline traditionally ignores risk management despite the fact that risk is the sole element that can influence negatively the performance of processes (Vernadat et al. 2013). Also, the importance of risk being part of the performance measurement has been realized recently (Cokins 2012). The purpose is to provide reliable and contextual information as input to decision-making in an integrated manner. Some authors do propose to manage risk for improving process performance (Tuncel and Alpan 2010); however, it is still managed independently of the PM discipline.

In view of the need to develop an integrated solution for evaluating performance and risk in the context of decision-making, the current study integrates performance and risk relevant concepts and couples them with the decision-making process. Furthermore, the study gives a brief explanation, along the way, of the different terms such as performance measures, criteria or performance indicators usually used interchangeably in the same or cross disciplinary field of studies. However, before going to develop the integrated solution; the study reviews some of the theories and practices used in industry and academia alike relating to performance and risk assessment as well as decision-making in order to get insights for better integrated solution development.

Literature review

Since the 1960s, several methodologies have been developed and used for decision-making, performance, and risk assessment. In the context of decision-making, these methodologies can be broadly divided into two categories: graph theory combined with matrix approaches, and multiple criteria methods. The multiple criteria methods can further be classified into mathematical optimization and multiple criteria decision-making (MCDM). Researchers have applied mathematical optimization models to diverse manufacturing problems (Rao 2011). Durand (1993) uses optimization method to assess analytically the performance of product portfolios in a company and its impact on individual product cost using the concept of "shared activity". Nevertheless, optimization models are often employed to find optimal solutions; they are therefore generative methods. For evaluation purpose, multi-criteria decision-making (MCDM) are the popular approaches (Greco 2004).

A decision process in MCDM perspective consists in defining a set of alternatives $\{x^h\}$ where $h = 2$ to m and a set of performance criteria $\{c_i\}$, $i = 1$ to n. The assessor task is to judge the performance of each alternative $\{x^h\}$ under performance criteria c_i and to determine the relative importance of the criteria to arrive at a global judgment. The ideal alternative is the one which outranks all the other ones under each of the performance criterion. That's rarely the case in real scenarios. Instead, we have to make trade-off when selecting between alternatives.

Therefore, a typical decision-making process is some sort of selection process and not a performance measurement process on its own. Even so, some authors have used several MCDM methods to evaluate performance of manufacturing systems. For instance, Tseng et al. (2009) develop a business performance evaluation model for high-tech manufacturing companies in Taiwan using data envelopment analysis, analytical hierarchy process (AHP), and technique for order of preference by similarity to ideal solution (TOPSIS). Similarly, Ertuğrul and Karakaşoğlu (2009) propose a fuzzy model to evaluate the performance of cement industries using financial ratios, AHP, and TOPSIS techniques. Other authors who propose similar approaches include but not limited to (Jablonsky 2007; Pokharel 2008; Yu and Hu 2010; Zolghadri et al. 2008).

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