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ORIGINAL PAPER

A new method for the design of knowledge-based engineering systems for manufacturing

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Abstract
Knowledge-based engineering systems for manufacturing are used to digitalise the process know-how and reuse this knowledge within the design and production phases. Their adoption allows the establishment of beneficial interactions between human experts and intelligent systems. An initial implementation of these systems can be confusing and infeasible, especially for small and medium enterprises which have not had sufficient previous experiences in applying these approaches. The main reason for this is the wide range of different scenarios that occur in real industrial cases. Existing methods that were proposed for the design of knowledge-based engineering systems fail to fulfil the needs of process engineering because they do not include certain fundamental aspects of the product design and manufacturing. This article presents a new systematic approach to design and develop knowledge-based engineering systems for manufacturing surpassing these limitations. This approach includes graphic representations that depict and organise all the relevant elements of the system. First of all, the method is described detailing the operations which have to be performed to design a new system. Finally, a real case to highlight the association between the preliminary design phase and the features of the implemented knowledge-based engineering systems for manufacturing is presented. The method is demonstrated to be a flexible approach to the systematic implementation of intelligent systems for manufacturing. Being user-friendly, its use will increase the number of potential users in small and medium enterprises.

Keywords Knowledge-based engineering · Manufacturing · Method · Intelligent systems · Intelligent manufacturing

List of Abbreviations

AA	Actions array
AI	Artificial intelligence
AM	Additive manufacturing
BNN	Bayesian neural network
Bool	Boolean
C2G	Cradle-to-gate
CBR	Case-based reasoning
CE	Concurrent engineering
CPS	Cyber-physical system
Ctgr	Categorical
DA	Descriptors array
Dr	Direct
EcS	Economic sustainability
G2G	Gate-to-gate
G2Gr	Gate-to-grave
IA	Inputs array
IE	Interactive engineering
Indr	Indirect
KBE	Knowledge-based engineering
KBES	Knowledge-based engineering system
KBESM	Knowledge-based engineering system for manufacturing
KBS	Knowledge-based system
KM	Know-how matrix
KNOMAD	Knowledge nurture for optimal multidisciplinary analysis and design
LC	Life cycle
MODIA	Matrix of objectives, descriptors, inputs and actions
MOKA	Methodology and tools oriented to knowledge-based ebgineering applications
MOO	Multi-objective optimisation
Nmr	Numeric
Nmrb	Numerable
OA	Objectives array

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RBR	Rule-based reasoning
RM	Representativeness matrix
Qltv	Qualitative
SF	Smart factory
SMEs	Small and medium enterprises
TBL	Triple bottom line

1 Introduction

1.1 Motivation of the study

The management of manufacturing knowledge plays a crucial role in determining the success of any industrial production [1]. In order to offer high quality products to their customers in a timely manner, while at the same time maintaining low costs, Concurrent Engineering (CE) encourages companies to integrate production know-how from the design phase onwards [2,3]. Appropriate management of process expertise from the earliest stages of product development can lead to significant benefits for both emerging and mature industries [4,5].

As a result, production know-how is one of a company's most valuable resources and needs appropriate processes to ensure that is managed and reused properly [6,7].

The application of Knowledge-Based Engineering Systems (KBESs) is therefore a key topic for both industry and research [8,9]. These systems can be applied to all the phases of knowledge management from its acquisition [10] to its reuse within the production [11].

Extensive advances in Artificial Intelligence (AI) and KBSs in recent decades have renewed great interest in research bodies applying these techniques in the field of industrial production [12–14].

The role of these systems becomes even more crucial within the Industry 4.0 paradigm of Cyber-Physical Systems (CPS) and Smart Factory (SF) [15,16]. In this context, intelligent manufacturing offers an efficient way to exploit the information coming from the SF to generate reusable knowledge [17,18].

To demonstrate this importance, Fig. 1 shows the number of publications per year on the topic knowledge-based and intelligent systems applied to the field of industrial manufacturing. Below, these applications will be referred to as Knowledge-Based Engineering Systems for Manufacturing (KBESMs).

Applications are classified by process field according to the categorisation proposed by Kalpakjian and Schmid [1]. Additive Manufacturing (AM) is included because of the importance of this group of processes in the modern industry [19]. Figure 1 shows that the number of publications is constantly increasing. Moreover, it is possible to observe that these applications are distributed in all the process fields.

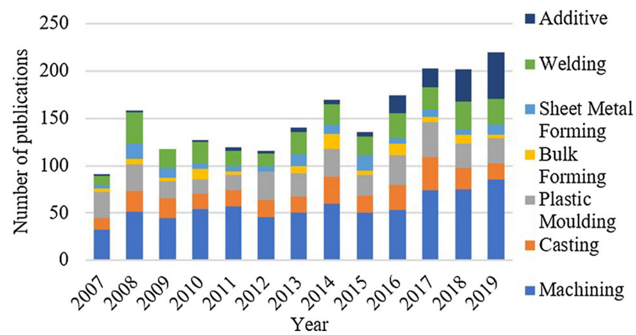

Fig. 1 Publications per year proposing knowledge-based and intelligent systems for manufacturing

Section 1.2 underlines the role of KBESMs in Interactive Engineering (IE).

1.2 Knowledge-based engineering systems for manufacturing in interactive engineering

IE comprises several virtual tools to support engineers in decision making during the development of new products. The research in this area deals with capturing and reusing the knowledge of product design and manufacturing [20]. Knowledge based modelling is fundamental in this field to formalise relations between elements of the system and highlight potential incoherences [21].

KBESMs integrate the production knowledge in the very first steps of the product design, providing designers with information on the constraints and impacts of the production [22,23]. This approach allows different experts to exchange information through a common interface in order to achieve a common goal, namely the product quality [24]. As an example, Pellicciari et al. [25] presented a method for the design of adaptive manufacturing systems which combines the knowledge of mechanical and software engineers.

In addition to manufacturing rules and constraints, the design must consider several aspects, such as aesthetic properties of manufactured parts, which can be included in a KBESM [26,27].

KBESs can be used to aid the design and development of several different products [28–30]. The specific features of these systems depend on the processes, the product and the objectives. For this reason, the initial implementation of a KBESM may seem out of reach for businesses with no previous experience in this field.

In order to aid the implementation of knowledge-based solutions, different systematic approaches have been proposed. These methods are reviewed in Sect. 1.3 discussing their main critical issues when applied to the design of KBESM. A new method addressing these limitations is presented in Sect. 2.

1.3 State-of-the-art

Several methods to foster the implementation of general KBESs have been proposed in the body of literature [31].

The CommonKADS is a popular method based on the use of some predefined models to describe ontologies [32,33]. This method has been successfully applied in several different fields [33,34]. As pointed out by Lovett et al. [35], the main drawback of this methodology derives from the complexity of the model, which limits its effective implementation in Small and Medium Enterprises (SMEs). Furthermore, the model-based framework of CommonKADS is mainly intended for Rule-Based Reasoning (RBR), i.e. the application of rules in the form *"if...then"*.

The Methodology and tools Oriented to Knowledge-based engineering Applications (MOKA) is another widely used approach [36].

The MOKA distinguishes between informal and formal models for the development of KBESs. The method represents design descriptors and requirements as ontologies and establishes relations of derivation, consistency and fulfilment among elements of these two sets [37]. Among its several innovations, the MOKA introduced an iterative approach to design KBE applications [38].

Klein [37] showed that, unlike previous methods, the MOKA allows the inclusion of Case-Based Reasoning (CBR) knowledge.

As pointed out by Curran et al. [38] the main limitation of MOKA is that it does not provide any guidelines to integrate the KBE applications in the design process. Indeed, no information about the implementation stage is given. Also, the method only allows defining objectives and requirements concerning the design of the product. This is a further limitation to its application in the field of manufacturing.

Since the MOKA is intended for general use, it lacks details about the field of application. In order to effectively implement the process know-how in the design phase, it is necessary to explore the *use* step of the MOKA methodology in more depth. The Knowledge Nurture for Optimal Multidisciplinary Analysis and Design (KNOMAD) methodology was proposed in order to overcome these issues [38]. This method allows us to model Multi-Objective Optimisation (MOO) problems to fit a larger number of real cases. The process-related parameters are included as ontologies to consider the constraints and the opportunities that come from the production phase.

Despite these benefits, the linear structure of KNOMAD and the high level of detail used to represent ontologies make this method resistant to changes during the product development. Also, the structure of the method does not ensure the matching between the aims outlined in the knowledge capture phase and the benefits obtained in the delivery one. Finally, the representation of the elements does not provide any indication of which techniques should be used for the final implementation of the KBES.

As the general methods for the development of KBS fail to address important aspects particular to production engineering, a number of specific methods for the development of KBESM have been proposed [17,39].

An analysis of the semantic representation of manufacturing systems was made by Negri et al. [40], which pointed out the benefits and the limitations of different languages when applied to the modelling of manufacturing ontologies.

An ontology-based failure analysis in the manufacturing field was proposed by Chhim et al. [41]. The method consists of representing entities and their connections in a web-based system, which is investigated by human experts.

In [42] a method for the diagnosis of manufacturing-induced defects is presented. This approach organises the process ontologies within a Bayesian Neural Network (BNN) representing the manufacturing flow. The main difficulty in implementing this approach stems from the need for a database for system training and network configuration.

An architecture for agent-based manufacturing systems named CASOA has been recently presented by Tang et al. [43]. This architecture manages the organisational aspects of the production using four types of agents, whose links are managed through a cloud-assisted knowledge base.

Despite their advantages, these methods require an experienced user for their implementation. Moreover, their ontologies must be often modified to adapt to real manufacturing scenarios.

To overcome these limitations, this present work sets out a new method to aid the design and the development of KBESMs. The proposed approach aims to be flexible while including the special needs of industrial manufacturing applications. Ease of use is maintained to increase the number of potential users among SMEs.

2 Method

The presented method aims to provide a simple way to build conceptual frameworks of KBESMs which can be applied to the widest range of manufacturing scenarios. On one hand, this approach must guarantee the consistency of the system during all the phases of its development. On the other hand, flexibility is one of the most important requirements, as mentioned in Sect. 1. It consists of three consecutive phases:

- *Applicability definition*, where the boundaries of the system are defined at the highest level;
- *Conceptual design*, the core phase where all the relevant aspects of the KBESM are made explicit;
- *Analyses and refinement*, where the conceptual design is investigated and eventually improved.

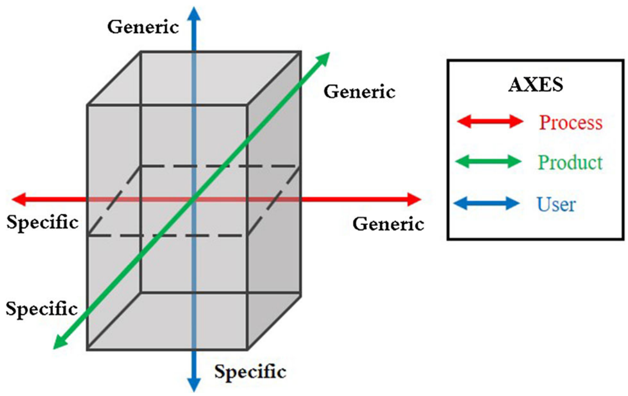

Fig. 2 Graphical representation of the applicability space

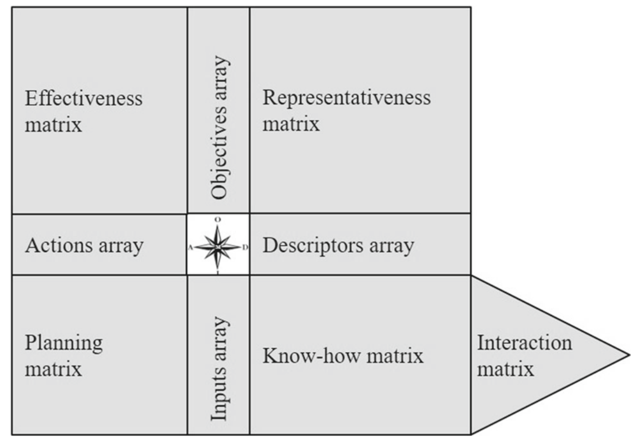

Fig. 3 Structures of the Matrix of Objectives-Descriptors-Inputs-Actions (MODIA)

These phases are described below to provide a step-by-step guide to the development of KBESMs.

2.1 Applicability definition

This phase defines the system application boundaries. It includes the most relevant elements of a KBESM, namely:

- Product;
- Process;
- User.

For each element, it is necessary to declare if we have a specific or a generic target.

As an example, when developing a system for a specific product, we can include specific functional requirements and features. However, if the product is not defined, a feature extraction might be necessary to feed the system with information about its geometry.

As well, KBESMs are also designed for a specific technology and allow the consideration of particular process parameters. When the process is partially defined, it is only possible to include a small part of this knowledge.

Finally, the definition of the expected user plays a crucial role while developing a KBESM. When we know the user in advance, it is possible to plan an intense interaction between this user and the system. This definition makes it possible to efficiently combine the know-how possessed by a person with the one incorporated in the software. If "a priori" assumptions about the human agent are not made, this collaboration must be partially transferred to a number of potential users.

The three fundamental elements listed above are used as axes of the 3D space. A spatial representation of the applicability space is shown in Fig. 2.

As a first step, it is thus necessary to define the position of the KBSEM on the space in Fig. 2. Subsequent decisions made during conceptual design must be consistent with this initial assumption.

2.2 Conceptual design

A systematic approach to the design of KBESM is proposed. The methodological framework is inspired by methods for the design of industrial products [44] and Quality Function Deployment (QFD) [45,46]. Some aspects of knowledge management proposed by works mentioned in Sect. 1 have also been included, such as the circularity of MODIA or the extension to MOO problems of KNOMAD.

The central element of the proposed approach is the Matrix of Objectives-Descriptors-Inputs-Actions (MODIA), schematically represented in Fig. 3.

The MODIA is intended to summarise all the relevant aspects of a KBESM and aid the design of the system. Nonetheless, this tool can also be adopted for the analysis of an existing system.

In the following paragraphs, the process of compiling the MODIA during the design of a KBESM will be presented and the different parts of its structure will be described.

2.2.1 Objectives array

The first step into the design of a KBESM is the definition of the aims to be achieved by using the system. The Objective Array (OA) is a list of the objectives with their most relevant features.

The objectives of production must be sought in two main fields, which are process sustainability and product sustainability. More specifically, the sustainability of the process refers to the Cradle-to-Gate (C2G) and Gate-to-Gate (G2G) phases, while the sustainability of the product relates to the Gate-to-Grave (G2Gr) phase of the LC as defined in ISO 14040:2006 and 104044:2018 [47,48].

The Triple Bottom Line (TBL) [49] is commonly accepted for the classification of sustainability aspects. According to this theory, sustainability can be divided into Economic Sus-

Obj. 1	G2Gr	EnS, EcS
Obj. 2	G2G	SoS
Obj. 3	C2G, G2Gr	EnS, EcS, SoS
Obj. 4	G2Gr	EnS
Obj. 5	G2G	EcS
...	...	...

Fig. 4 Example of Objectives Array (OA)

Table 1 Classifiers of descriptors

Type	Measurement	Source	Tangibility
Numeric	Virtual	Direct	Tangible
Numerable	Physical	Indirect	Intangible
Boolean			
Categorical			
Qualitative			

tainability (EcS), Environmental Sustainability (EnS) and Social Sustainability (SoS). All the objectives concerning the quality of the process and product can be classified according to these sustainability criteria.

When defining an objective, it is necessary to specify at which stage (or stages) of the LC, and in which field (or fields) of the sustainability framework benefits are expected. This information is reported next to the name of the objective in the OA, as shown in Fig. 4.

2.2.2 Descriptors array

At least one descriptor must be chosen to verify the effectiveness of the KBESM for each aim. A descriptor is thus defined here as an attribute able to provide information on the fulfilment of one or more objectives of the KBESM. Descriptors are here classified using four categories, as summarized in Table 1

The type of attribute distinguishes the shape of information. A Numeric (Nmr) descriptor is an attribute expressed using a natural, integer, rational, real or complex number. A Numerable (Nmrb) attribute is not intrinsically numeric but can be converted to a number through correspondence (for example, using marks). Boolean (Bool) refers to a logic attribute whose value can be true or false. When an attribute is defined using univocal labels, it is classified as Categorical (Ctgr). The Qualitative (Qltv) type is used for categories,

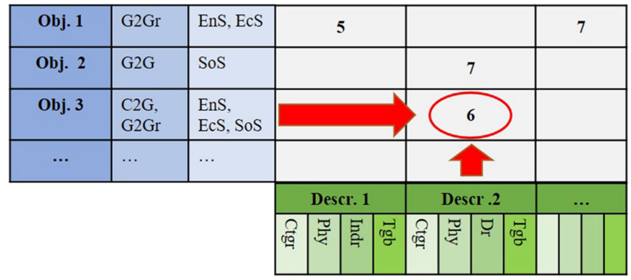

Fig. 5 Example of Representativeness Matrix

which are not clearly defined and allows for the intersection of sets; Fuzzy Logic (FL) is usually used to deal with this kind of attributes [50].

The way these values are obtained leads to the definition of the measurement technique, which can be Direct (Dr) when the attribute is measured directly, or Indirect (Indr) when the value is derived from the observation of related attributes.

A further classification can be made by considering the source of descriptors. In particular, Virtual (Vr) and Physical (Phy) measurements are distinguished. These classes can both be acceptable when it is possible to derive the same attribute in the virtual or physical environment. Nevertheless, as the techniques for measuring are deeply different, it is necessary to make a clear distinction during the design of the KBESM.

Finally, it is possible to distinguish between Tangible (Tg) and Intangible (Intg) descriptors. Different subclassifications of intangible attributes and methods for their measurement can be found in the literature [51,52].

Finally, the Descriptors Array (DA) is built by collecting descriptors together with their classifiers, as has been described for the OA (Fig. 5).

2.2.3 Representativeness matrix

Each descriptor represents the fulfilment of at least one aim. In general, several connections can exist between imposed aims and descriptors used for their evaluation. To clarify these connections, the Representativeness Matrix (RM) is built using the elements of OA as rows and DA as columns. The generic element $RM_{i,j}$ of the matrix is defined as the efficacy of the j-th descriptor in determining the fulfilment of the i-th objective. An example is shown in Fig. 5.

Values in the RM have to be assigned after debate among technical experts. In any case, a redefinition of the RM scores can be made at any time during the KBESM project based on direct observation.

According to the definition of descriptors, the sum of elements in each row and each column of the RM has to be higher than zero.

Table 2 Classifiers of inputs

Type	Phase	Changes
Numeric	Process	Live
Numerable	Design	Tunable
Boolean		Steady
Categorical		Read-Only
Qualitative		

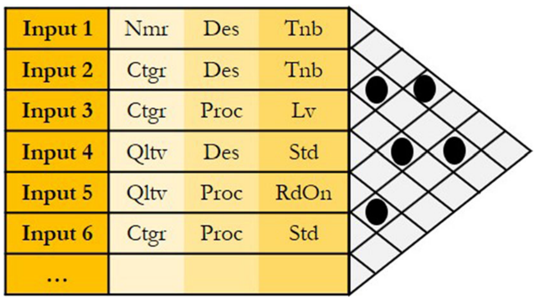

Fig. 6 Example of input array and interaction matrix

2.2.4 Inputs array and interaction matrix

Inputs Array (IA) is a collection of the parameters affecting descriptors. Classifiers of inputs are summarised in Table 2.

Inputs are classified according to their type in the same manner as descriptors.

As already mentioned, KBESM parameters should be searched for in the fields of Process (Proc) or Product Design (Des). More accurately, Proc parameters are the ones describing specific features of the adopted technological process, while Des parameters concern the nominal characteristics of the product defined in its design.

Another fundamental distinction can be made based on the possibility of setting values of Inputs. In particular, parameters will be classified as Live (Lv) when the value can be modified in real-time at any moment of the production, Tunable (Tnb) when it is possible to set the input at fixed intervals during the production (e.g. at the end of a cycle), Steady (Std) when it can be modified only before the whole production takes place and Read-Only (RdOn) when values cannot be modified directly.

As in the previous cases, input parameters are collected in the IA together with their classifiers, as exemplified in Fig. 6.

In general, not all the parameters in the Inputs Array are independent. Therefore, it is necessary to highlight which the reciprocal influences between the input parameters are. For this purpose, a triangular matrix named Interaction Matrix (IM) is included. As shown in Fig. 6, a dot is used to mark non-independent pairs of input parameters.

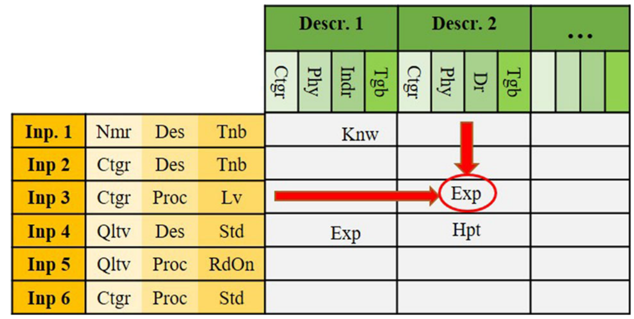

Fig. 7 Example of Know-how matrix (KM)

Table 3 Classifiers of actions

Actor	Changes
Human	Live
Software	Tunable
Hybrid	Steady

2.2.5 Know-how matrix

The Know-how Matrix (KM) is designed using descriptors as columns and inputs as rows. The generic cell $KM_{i,j}$ establishes an eventual correlation between the i-th input and the j-th descriptor. In particular, we distinguish between relations based on Knowledge (Knw), Experience (Exp) or Hypothesis (Hpt).

A relation is based on knowledge when it is defined by an explicit rule coming from a reliable source. Physical laws are an example of linkages through Knw. Exp relations occur when a correlation between inputs and descriptors has been observed in previous cases, but no explicit formulation is given. In case there is no evidence, but only conjecture about the correlation between input and descriptor, the relation is marked as Hpt.

The type of relations in the KM might be modified during the developing of the KBESM when a modification of the know-how occurs. As an example, if a hypothesis is tested through experimental activity, it is possible to shift from Hpt to Exp relation. In the same manner, if a reliable regression model is built, the Exp relation can be converted to Knw level.

The type of relation between input and descriptor is reported in the corresponding intersection cell. Figure 7 shows an example of KM.

2.2.6 Actions array, planning matrix and effectiveness matrix

At this point, it is possible to define actions to be performed to fulfil the predetermined aims. Classifications of actions are summarised in Table 3.

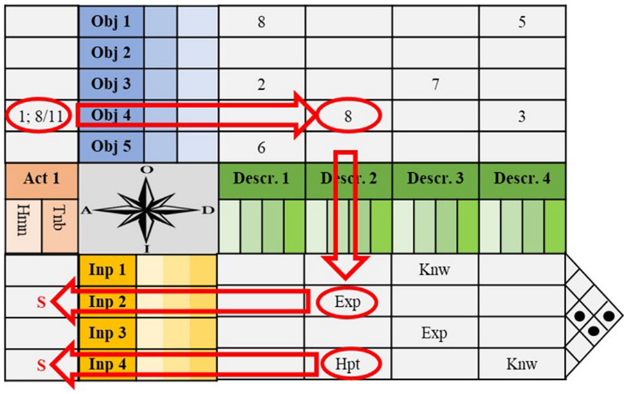

Fig. 8 Example of action definition (part 1)

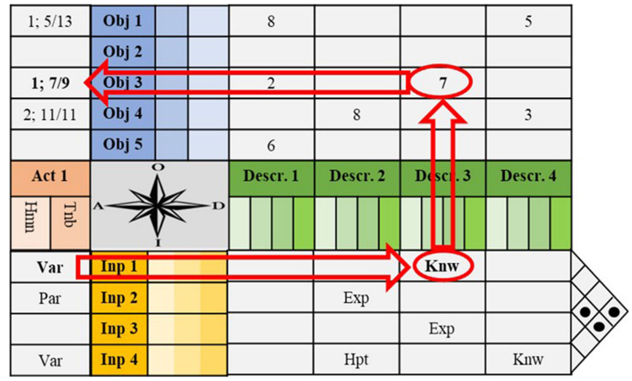

Fig. 9 Example of action definition (part 2)

Actions are primarily classified based on the agent, i.e. on the subject performing the action. This can be the Human (Hmn) user, the Software (Sfw) or an Hybrid (Hbr) of these two.

As in the case of inputs, a classifier is used to describe the response time of the action. Naturally, the label Read-Only is excluded in this case, since the action always needs to modify some inputs.

The definition of actions is a fundamental aspect of the design of the KBESM and it involves all the entities of the MODIA. The remaining elements of the matrix, namely the Planning Matrix (PM) and the Effectiveness Matrix (EM), are compiled during the definition of actions.

When designing a new action, a primary objective has to be defined. As an example, Obj 4 is the primary objective of Act 1 in Fig. 8.

One descriptor of the objective must be selected as an evaluator for the action. In the example of Fig. 8, Descr 2 is chosen for Act 1.

The correspondent cell of the EM reports the number of descriptors considered by the *j*-th action (column) and the sum of their representativeness for the *i*-th objective (row) divided by the sum of all the values in the *i*-th row of RM. A semicolon is used to separate values in Fig. 8.

The column of the KM corresponding to the selected descriptor is then explored to find cells, with non-empty values. These rows correspond to inputs that correlate with that descriptor. Corresponding rows of the PM are filled with an "S" in the column of the designed action. This notation means that the inputs are significant for the action. As an example, in Fig. 8, Inp 2 and Inp 4 are found to be significant for Act 1.

The "S" used in Fig. 8 is a temporary notation. The role of each input for the action must be defined. More specifically, an input can be a Variable (Var) if it can be modified by the action, or a Parameter (Par) when its value cannot be directly modified by the action.

The role of each significant input within the action must be defined before continuing. During this phase, at least one significant input must be selected as Var. In the example of Fig. 8, we define Inp 2 as Par and Inp 4 as Var.

The definition of variables and parameters is subject to some constraints due to the nature of inputs summarised in the IA. Firstly, read-only (RdOn) inputs cannot be used as variables as they are not modifiable by the user. Furthermore, the response time of the input parameter must be less or equal than the one of the action: this means, for example, that Tnb inputs cannot be used as variables of Lv actions, while Std inputs cannot be used for either Tnb and Lv ones.

Once the role of the significant parameters has been defined, the interaction matrix at each input marked as variable is entered and an "S" in the PM is assigned to each input that interacts. These inputs must in turn be set as Var or Par. In the example of Fig. 8, Inp 1 is related to Inp 4. It means that significant for Act 1. The role of Var is assigned to Inp 1.

This procedure must be repeated iteratively until the role of Var or Par has been assigned to each significant input of the action. The adoption of IM in this phase is fundamental to ensure that any relevant parameter is omitted by the action.

When input variables of the action are modified, further descriptors (and thus objectives) will be influenced. To take into account this effect, the KM and RM must be used to properly modify the EM.

An example is shown in Fig. 9. Since Inp 1 is set as Var, the corresponding row of the KM is scanned, finding the relation of this parameter with Descr 3 (Knw). As a consequence, all the objectives that are represented by Descr 3 (in this case only Obj 3), are affected by Act 1. The EM is modified accordingly, reporting that Act 1 affects one descriptor (Descr 3) of Obj 3, i.e. the 7/9 of the representative descriptors. The same is made for Inp 4 (effects on EM are already reported in Fig. 9).

It is worth underlying that the influence of Inp 4 on Descr 4 leads both the descriptors (2;11/11) of the main Objective

(Obj 4) to be addressed. This suggests that it is appropriate to choose the minimum number of descriptors for the main objective when starting to define an action. Eventually, more descriptors can be added if the values in EM show a non-effective fulfilment of aims.

2.3 Analysis of the system

When the MODIA is completed, an analysis of the designed system is necessary. This phase allows us to highlight eventual critical aspects and refine the design of the system. This kind of analysis can also be performed on existing systems to find their weak points or possible improvements.

Figure 10 shows an example of a complete MODIA.

A first analysis on the KBESM can be made by observing the OA. The stages of the LC of the objectives indicate how much the system is oriented to the process or the product. In addition, it is possible to understand which aspects of TBL are best addressed by the system. This analysis is fundamental to determine whether KBESM is actually in line with the underlying purpose of its design.

The RM also offers an immediate glance at the role of descriptors. The sum of values in each column (reported in Fig. 10) quantifies the influence of each descriptor on the entire KBESM.

The analysis of DA highlights the percentage of descriptors that can be measured in a virtual representation of the product. At the same time, the composition in terms of tangible versus intangible assets can be obtained.

As in the case of OA, the IA can be used to verify how much the KBESM is design-driven or process-driven, by considering the percentage of Des and Proc inputs that are used as variables in the different actions.

The number of Var values in each row of the PM gives information about the importance of that input in the decision-making. However, the number of both Var and Par values shows the influence of changes in the parameter value on the whole KBESM.

The response time of actions in AA is also useful to define their order. As an example, Std actions precede the production and thus have to be performed before Tnb and Lv ones.

The distribution of Hmn, Sfw and Hbr attributes defines the degree of automation in the KBESM. This must be consistent with the assumption concerning the expected user that was defined in the applicability space. If an inexperienced or general user is expected, the amount of Hmn actions must be limited accordingly.

The comparison between agents and time attributes also tells us if and in which stages of the production a human agent has to be present.

The sum of rows in the EM (shown in Fig. 10) allows us to understand how much the proposed objectives can be satisfied by the KBESM. The sum must omit repetitions of the same descriptor in different actions.

The sum of descriptors for each action, (i.e. of columns in EM, see Fig. 10) immediately distinguishes actions dealing with a single objective from MOO problems. This distinction is particularly important when moving to the detailed design of the KBESM.

During the detailed design of the system, the MODIA provides a map to determine the best methods for each action, in particular using the KM. As an example, when an action is carried out by a human, one or more predictive models must be implemented to aid the decision-making. Looking at the type of descriptors, it is immediately clear if regression, classification or fuzzy models have to be adopted. If the descriptors have different types, then more than one predictive tool will be necessary for the same action.

The type of inputs (in the IA) and the kind of knowledge (in the KM) help to restrict the field of possible methods. For example, if a relationship based on experience is given between one or more numerical inputs and a categorical descriptor, Artificial Neural Networks (ANN) and Support Vector Machines (SVM) are suitable candidates. If the descriptor is a Bool, Logistic Regression (LR) can also be considered.

Besides the prediction, actions accomplished by the software must also include a strategy to find an optimal set of inputs. Once again, the KM can be used to restrict the field of methods. On one hand, if the column of a certain descriptor in the KM has all Knw values, a rule-based strategy can be adopted to set inputs. On the other hand, when a correlation based on experience exists between a Qltv input and a Nmr descriptor, a combination of FL and GA is a possible solution.

As mentioned in the previous paragraphs, the MODIA may be repeatedly modified during the preliminary or the detailed design and analysis of the system.

3 Example of application

Although the complete development of a real system cannot be included here, applicability space and MODIA used for the development of a real KBESM are presented. The most characteristic elements are described to illustrate their connection to the application.

Details about the implementation of this system can be found in previously published papers cited in the following pages.

3.1 Applicability space

This section presents a KBSEM to aid the design and production of plastic bottles.

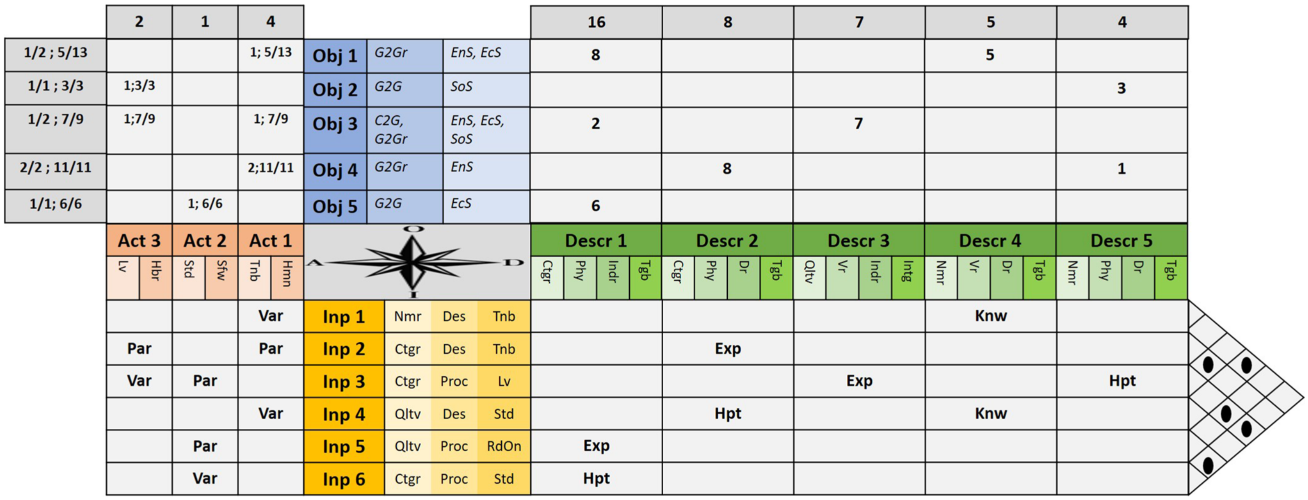

Fig. 10 Example of a complete MODIA

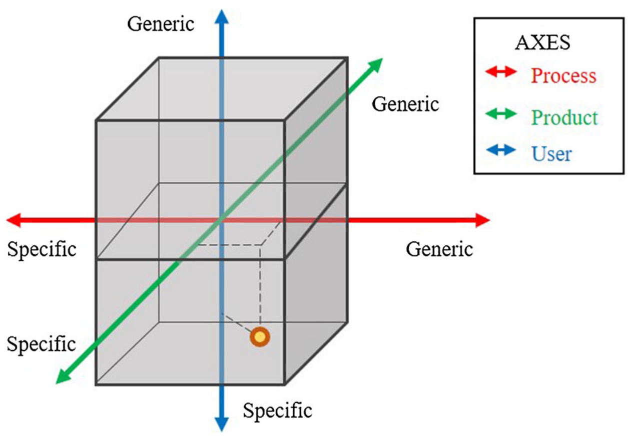

Fig. 11 Location in the applicability space of the KBESM for bottle moulding

The system is intended to be used in the preliminary phase to integrate elements of both manufacturing know-how and the product design.

First of all, since the product to be managed by the KBSEM is well-defined, this system is located in the specific direction of the green axis within product space, as shown in Fig. 11.

Different combinations of materials and processes will be investigated by the system to identify the optimal solution under a given set of requirements. In particular, the system has to manage the main blow moulding processes used in the industrial field for the production of plastic bottles, i.e. Stretch Blow Moulding (SBM), Injection Blow Moulding (IBM) and Extrusion Blow Moulding (EBM). Several polymers that fit this scope must be capable of being precessed. As a consequence, we can consider the process as rather generic (Fig. 11).

Finally, the system is intended to aid the design phase of the product. Accordingly, the user is supposed to be an industrial designer working in the field. This is a highly specific user, who possesses expert knowledge of know-how that can be made use of in the interaction with KBESM.

The defined location of the KBESM in the applicability space is shown in Fig. 11.

3.2 Matrix of objectives, descriptors, inputs and actions

As mentioned above, the purpose of the present KBESM is to include in the design stage the know-how related to both the process and usage of plastic bottles. In addition, the system aims to provide an insight into the environmental impact of the product, which is a key issue in the field of plastic bottles.

Figure 12 shows the MODIA used for developing this system.

According to this broad perspective, six objectives have been established for the system, i.e.:

- *Aesthetic*, i.e. the look of the product.
- *Manufacturability*. This objective focuses on making the product easy to produce through blow moulding technique.
- *Liquid transportation* This deals with the amount of liquid contained by the bottle and its ease of use.
- *Ecology*. The ecology of the product is determined by its environmental impact, so it deals with EnS in all phases of the Life Cycle (LC).
- *Transportability* This is how easy it is to transport the product during the distribution phase.
- *Resistance*, i.e. the mechanical strength of the bottle when external loads are applied.

To measure the relevant features of the system, the following descriptors can be identified:

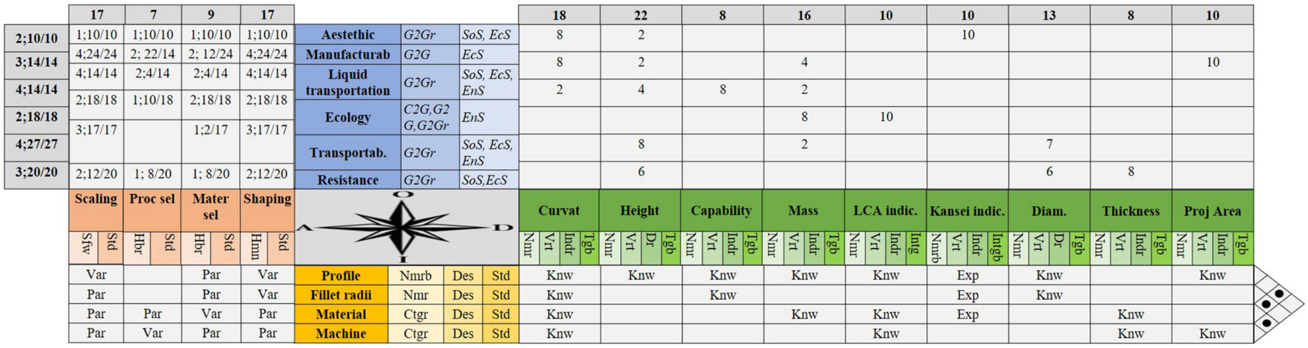

Fig. 12 MODIA of the KBESM for bottle design

- *Curvature of the surfaces*;
- *Height of the bottle*;
- *Capacity of the bottle*;
- *Mass of the bottle*;
- *Life Cycle Impact Assessment (LCIA) indicators*;
- *Kansei indices*, i.e. the descriptors of user perception of the product;
- *Maximum diameter*;
- *Wall thickness*;
- *Projected area* in the opening direction of the mould.

The RM of MODIA in Fig. 12 summarises how these descriptors are supposed to be representative of the above-mentioned objectives. The marks are given on a scale from 1 to 10. The DA in Fig. 12 also summarises the attributes of descriptors.

The designed inputs of the KBESM are:

- *Profile*, which is the curve that defines the shape of the bottle through an axial revolution;
- *Fillet radii*, the bottom and top radii of the bottle;
- *Material*, i.e. the specific plastics used for production;
- *Machine*, which defines both the specific equipment and its parameters.

In Fig. 12, the attributes of these inputs are given.

As will be noticed in the KM, most of the relations are based on knowledge. In greater detail, 85.7% of the total know-how is based on explicit relations. This suggests how a Rule-Based Reasoning (RBR) approach will be suitable in the detailed design phase. Details of the implementation can be found in [53].

The only relations based on experience (Exp) are the ones relating geometrical and material inputs to the Kansei descriptors of the user perception. Firstly, these relations were surveyed with a questionnaire. Then, ANNs were trained on the acquired data and used to predict the kansei engineering features of a bottle digital mock-up. The details on this implementation were presented by the authors in a previous publication [54].

The first activity is the definition of the bottle shape. This will be performed by the user of the system, i.e. the product designer, based on their skills and know-how. This takes the profile of the bottle and the radii of the fillets as variables. The material and machine used for the production are parameters that define the constraints of the shape design. As can be seen in the EM, this assumption influences several descriptors, affecting all the objectives of the KBSM.

The designer will be also in charge of choosing the right combination of material and machine for the manufacturing of the product. The solution is selected by the user in a set proposed by the system. This set is calculated by taking into account manufacturing constraints and performances of different solutions, [53]. As a consequence, these are hybrid actions.

Finally, the shape defined by the designer needs to be refined to meet all the requirements imposed by the objectives. This step is delegated to the software, which will use the shape defined by the designer as a starting point. Therefore, this operation must follow the previous ones and its column in the EM is similar to the one of shaping.

All the inputs (and consequently actions) are Std, which means that the KBESM will be usable only before the production takes place. Furthermore, it is possible to highlight how the system will be design-driven, as all the input variables belong to the design phase of the product (Des). This reflects the location of the system in the applicability space. Since we have a specific product, it is possible to define input variables within its design in advance. However, the inclusion of different processes does not allow the use of process parameters, as these vary from one technology to another.

The KBESM is oriented to both the production and usage phases, as it presents objectives in all the phases of the LC. The sum of rows in the EM indicates that the designed configuration of the system allows to act on all the descriptors and address the predetermined objectives.

All the actions aim to achieve more than one objective. As a consequence, a MOO approach is adopted for aided decision-making using Pareto front of non-dominated solutions [53].

4 Conclusions

This article presents an innovative method for the development of knowledge-based engineering systems for manufacturing.

The applicability space, defined in Sect. 2.1, ensures consistency between the intended use scenario and the characteristics of the system.

The MODIA, introduced in Sect. 2.2, clarifies the relations between the main aspects of the KBESM and the existing know-how. Moreover, the structure of the MODIA allows the automatic calculation of the potential benefits achievable through the system implementation.

The adoption of a graphical representation allows an overview of all the relevant elements of the system during every phase of its development. The loop structure allows the automatic update of all the matrices when changes are made.

Above all, the adoption of these tools ensures the consistency among all the elements of the system during each phase of its development.

The applicability space and MODIA used in the development of a real KBESM were presented. This case highlights the relationships between the conceptual design phase and the implementation which follows.

In general, the method offers a simple and flexible approach to high-level design and development of knowledge-based engineering systems for various manufacturing applications. Its introduction can therefore be seen as a significant step forward in expanding the number of SMEs that will embrace the Industry 4.0 paradigm.

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Declarations

Conflict of interest All authors declare that they have no conflict of interest.

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