Alma Mater Studiorum – Università di Bologna

DOTTORATO DI RICERCA IN

Meccanica e Scienze Avanzate dell'Ingegneria

Ciclo XXXII

Settore Concorsuale: 09/B1 – TECNOLOGIE E SISTEMI DI LAVORAZIONE

Settore Scientifico Disciplinare ING-IND/16 - TECNOLOGIE E SISTEMI DI LAVORAZIONE

A METHODOLOGICAL APPROACH TO KNOWLEDGE BASED ENGINEERING SYSTEMS FOR MANUFACTURING

Presentata da: Mattia Mele

Coordinatore Dottorato Prof. Ing. Marco Carricato

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Esame finale anno 2020

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"All knowledge is connected to all other knowledge. The fun is in making the connections. "
Arthur C. Aufderheide

Dedicated to those who share knowledge with others.

Declaration

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

Mattia Mele
February 2020

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Abstract

A survey of implementations of the knowledge-based engineering approach in different technological sectors is presented. The main objectives and techniques of examined applications are pointed out to illustrate the trends and peculiarities for a number of manufacturing field. Existing methods for the development of these engineering systems are then examined in order to identify critical aspects when applied to manufacturing.

A new methodological approach is proposed to overcome some specific limitations that emerged from the above-mentioned survey. The aim is to provide an innovative method for the implementation of knowledge-based engineering applications in the field of industrial production.

As a starting point, the field of application of the system is defined using a spatial representation. The conceptual design phase is carried out with the aid of a matrix structure containing the most relevant elements of the system and their relations. In particular, objectives, descriptors, inputs and actions are defined and qualified using categorical attributes.

The proposed method is then applied to three case studies with different locations in the applicability space. All the relevant elements of the detailed implementation of these systems are described. The relations with assumptions made during the design are highlighted to validate the effectiveness of the proposed method.

The adoption of case studies with notably different applications also reveals the versatility in the application of the method.

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List of Acronyms

Roman Symbols

AA	Actions Array
AI	Artificial Intelligence
AM	Additive Manufacturing
ANN	Artificial Neural Network
ANOVA	Analysis Of Variance
API	Application Programming Interface
AR	Aspect Ratio
BN	Bayesian Network
BNN	Bayesian Neural Network
Bool	Boolean
BUR	Blow Aspect Ratio
C2G	Cradle-to-Gate
CAD	Computer Aided Design
CAFD	Computer Aided Fixture Design
CAM	Computer Aided Manufacturing
CAPP	Computer Aided Process Planning

CAx	Computer Aided x
CBR	Case Based Reasoning
CE	Concurrent Engineering
CM	Cloud Manufacturing
CNC	Computer Numerical Control
CPS	Cyber-Physical Systems
CPT	Conditional Probability Table
Ctgr	Categorical
DA	Descriptors Array
DDM	Design Decision Making
DfAM	Design for Additive Manufacturing
DMS	Data Management System
DOE	Design Of Experiment
Dr	Direct
DWT	Discrete Wavelet Transform
EBM	Extrusion Blow Moulding
EcS	Economic Sustainability
EnS	Environmental Sustainability
ES	Expert System
FCA	Formal Concept Analysis
FE	Finite Element
FEM	Finite Element Method
FL	Fuzzy Logic
FMS	Flexible Manufacturing System

FSA Finite State Automata

G2G Gate-to-Gate

G2Gr Gate-to-Grave

GA Genetic Algorithm

GUI Graphical User Interface

HSM High Speed Machining

IA Inputs Array

IBM Injection Blow Moulding

Indr Indirect

ISO International Organisation for Standardisation

IT Information Technology

KB Knowledge-Based

KBE Knowledge Based Engineering

KBESM Knowledge Based Engineering System for Manufacturing

KBS Knowledge Based System

KM Know-how Matrix

KMS Knowledge Managment System

LCA Life Cycle Assessment

LCI Life Cycle Inventory

LCIA Life Cycle Impact Assessment

MCDM Multiple Criteria Decision Making

MFR Manufacturing Feature Recognition

MLP Multi Layer Perceptron

MOKA Methodology and tools Oriented to Knowledge-based engineering Applications

MOO Multi-Objective Optimisation

Nmr Numeric

Nmrb Numerable

NN Neural Network

NURBS Non-Uniform Rational Basis Spline

OA Objectives Array

OICS Ontology Interface Cloud Service

OOP Object-Oriented Programming

PBF Powder Bed Fusion

PCB Printed Circuit Board

PSL Process Specification Language

QFD Quality Functional Deployment

Qltv Qualitative

RBR Rule Based Reasoning

RM Representativeness Matrix

RMS Reconfigurable Manufacturing Systems

RS Rough-Set

RWD Response Web Design

SBM Stretch Blow Moulding

SL StereoLithography

SLA StereoLithography Apparatus

SLM Selective Laser Melting

SM-API Shared Model Application Program Interface

SMEs Small and Medium Enterprises

SoS	Social Sustainability
TBL	Triple Bottom Line
VR	Virtual Reality

Introduction

The role of digitalisation in process engineering is evolving in accordance to the general trend of science and technology. In particular, the Industry 4.0 paradigm is pushing companies to implement Cyber Physical Systems (CPSs) for the creation of the so called Smart Factories.

In this direction, Information Technology (IT) plays a crucial role by managing the data collected in the company. IT includes the storage, retrieval, transmission, and manipulation of data. In particular, the implementation of smart systems requires the digitalisation of tasks that were previously accomplished by human operators.

Artificial Intelligence (AI) is the set of techniques enabling a software to emulate a human behaviour. Knowledge-Based Systems (KBSs) are a subcategory of AI that aims to capture and reuse the knowledge of the experts of a particular sector. The application of the knowledge-based approach to industrial production goes under the name of Knowledge Based Engineering (KBE). The present work deals with Knowledge Based Engineering Systems for Manufacturing (KBESMs), i.e. applications of KBE that manage the know-how of industrial production.

Hardware systems enabling the collection and transmission of data are nowadays widely diffused in industry, whereas the implementation of KBE is still faltering, especially in the case of Small and Medium Enterprises (SMEs). The main difficulties in this sense derive from the need to implement elements of knowledge that are peculiar of the intended application. In many cases, this specificity does not allow the direct use of pre-existing models of knowledge representation. Furthermore, the operators' know-how often lacks of an explicit formulation, since it descends from the direct experience. KBESs manage this kind of knowledge by means of Machine Learning (ML) and Case Based Reasoning (CBR) techniques.

The rapid introduction of new technologies imposes to shorten the learning time of their features in order to be competitive on the market. For this scope, the computer-aided knowledge management can be an effective support in building and managing process know-how.

Especially in the case of SMEs, the process know-how is often owned by a few persons and does not have a sharp definition. On the contrary, a formal and explicit representation of knowledge eases its sharing among different operators. The rational representation of know-how is also useful in order to point out fuzzy and uncertain aspects that may exist in the knowledge base of companies.

As above-mentioned, the automated reuse of knowledge within the CPS allows the implementation of smart systems acting in real time. Furthermore, this automation can be extended to the design phase of the product and process to reduce the time dedicated to repetitive tasks and enlarging the space of explored solutions.

As a summary, the adoption of KBESM in industry is intended to manage process knowledge by means of one or more of the following actions:

- **Acquire** from the observation of real-world phenomena;
- **Formalise** through a representation that admits reuse in the next phases;
- **Synthesise** by formulating human-readable rules that allow operators to learn by the system;
- **Store** for increasing the knowledge-base of the company;
- **Share** among different human or industrial entities for re-elaboration;
- **Reuse** by human or computer agents in different phases of the industrial chain.

The efforts for the implementation of these systems are often perceived as prohibitive for SMEs due to the lack of necessary expertises. Furthermore, in order to get an effective result on the KBESM, a productive dialogue must be established between the different entities involved. In particular, it is necessary to create a bridge between the several technical experts providing knowledge, the management defining company's strategies and the software experts involved in the implementation.

For this scope, the present work proposes a methodological approach to be used in the very first steps of KBESM development. The approach aims to extend the applicability of this techniques in SMEs and ensure the coherence and effectiveness of the resulting systems. The main requirements of the methodology are identified as follows:

- **Flexibility** to different production scenarios and objectives;
- **Easiness of use** to include in the system the higher number of actors and competencies;
- **Consistency** by preventing the definition of non-coherent elements;
- **Consequentiality** in the determination of techniques that can be used in the implementation phase;

- **Adaptability** to modifications that may occur during the system development.

The thesis is structured as follows:

Chapt. 1 gives a brief overview on the applications of KBESM. The most relevant methodologies for the design of KBS and KBESM are also introduced to point out their main advantages and disadvantages.

Chapt. 2 illustrates the proposed method by giving a description of represented ontologies and procedure to be followed during the conceptual design of a KBESM.

In Chapt. 3, 4 and 5 the method is applied to the development of three systems characterised by different scopes, fields of application and methods. The three case studies report the conceptual and detailed design of KBESMs as well as their implementation. The relations among these phases and the benefits that are achieved through the use of the proposed approach are pointed out. Differences between the investigated systems also allow identifying advantages and disadvantages emerging in applications to dissimilar contexts.

This work aims at giving an overview on the main tasks to be fulfilled by means of KBSEMs in industrial application and on main limits of existing solutions. The methodological approach proposed tries to overcome such limitations addressing targets listed above. The approach here presented is validated through case studies with different features and fields of application in order to prove its validity. The method can be applied to several real cases, promoting the actual implementation of intelligent manufacturing systems in the Industry 4.0 scenario.

Chapter 1

Knowledge-Based Systems in Manufacturing

1.1 The role of Knowledge-Based Systems applied to Manufacturing

During product development, integration and management of manufacturing knowledge play a crucial role in the successful industrial production [134]. Concurrent Engineering (CE) approach expects companies to integrate manufacturing knowledge since the very first phases of design to offer their customers higher-quality products at lower prices and to deliver these products more quickly.

Even more, technological breakthroughs became a significant driver of competitive advantage in both emerging and mature industries [278]. Because of this influence, manufacturing knowledge is considered one of the most valuable resources of a company and requires proper methods for management and application [84]. Therefore, the adoption of Knowledge Based Systems (KBSs) for knowledge management has always been particularly interesting for research and industrial applications in this field [235, 87].

Deep evolutions in Artificial Intelligence (AI) and KBSs in the last decades renewed the interest of researchers in applying such techniques to industrial manufacturing through the application of new rising methods [356, 165, 328].

The role of these systems became even more crucial within the Industry 4.0 paradigm of Cyber Physical System (CPS) and smart factory [296]. In this context, intelligent manufacturing offers a solution to exploit at the best the information of the smart factory to produce and reuse knowledge [360, 338].

1.2 Applications of Knowledge-Based Systems for Manufacturing

1.2.1 Review methods

The present chapter aims to survey the scenario of KBESM in the years between 2007 and 2019.

The applications have been classified for manufacturing field according to [134] using the following categories:

- Machining;
- Casting;
- Plastic Moulding;
- Bulk Forming;
- Sheet Metal Forming;
- Welding;
- Additive Manufacturing.

Additive Manufacturing (AM) was added to the classification proposed by [134] due to its increasing importance in the industrial panorama.

It is worth noticing how many authors, especially in the latest years, prefer to adopt the more general classification of AI instead of KBS; this complicates the challenge of having a complete investigation of the literature scenario. For this purpose, a literature research has been done consulting most relevant scientific search engines by using "Knowledge Based System" and "Artificial Intelligence" as the keyword together with the descriptive terms of the considered manufacturing processes. Articles from both peer reviewed journals and international conferences have been included. Fig. 1.1 shows the number of papers found for each field of application in the examined years.

Observing Fig. 1.1 it is possible to notice a general increasing trend in the number of published papers per year.

Looking at the percentage of publications per field, a leading role of applications in the field of machining can be observed in different years. In fact, the adoption of Computer Aided Manufacturing (CAM) software in this field has a long-time tradition if compared to the other investigated technologies.

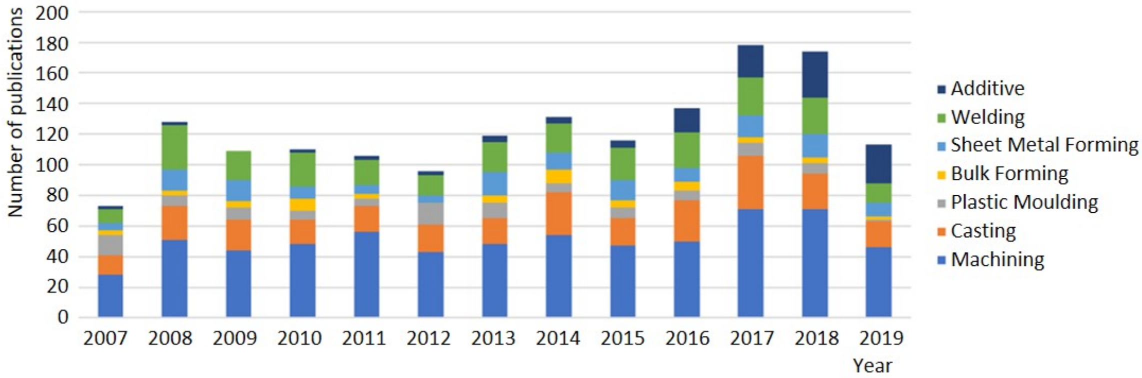

Fig. 1.1 Papers per year applying intelligent systems to manufacturing engineering

In the last years, a considerable increase in the number of publications in AM field can be observed. This corresponds to the general increasing interest of the research for these technologies.

A selection has been operated on the found papers in order to extract the most relevant works for describing the role of KBSs in manufacturing. In the following sections, this batch will be used to provide an overview of the state of art and trend in the different investigated fields. For this scope, reviewed KBSs have been grouped in categories on the basis of their scope. It is worth mentioning since now how this classification is often difficult and incomplete. Nevertheless, this approach allowed getting an overview on the panorama of different analysed technologies. The results are then used in order to give an overview of emerging trends.

Finally, some considerations about the emerging overall scenario are briefly illustrated.

1.2.2 KBSs applied to machining

Machining is the manufacturing field that presents the highest number of applications. It is worth mentioning in this section not only traditional material removal processes (milling, turning, broaching, etc.) are considered but also unconventional ones like for example laser micro-machining or net shape manufacturing by laser and others. In order to display the aim of these KBS implementations, key-topics for a certain group of works have been identified. Even if within a paper these key-topics partially overlap, a category has been assigned to each paper on the basis of its relevance. Six different groups of papers have been identified. They are:

- Decision support systems;
- Process planning;

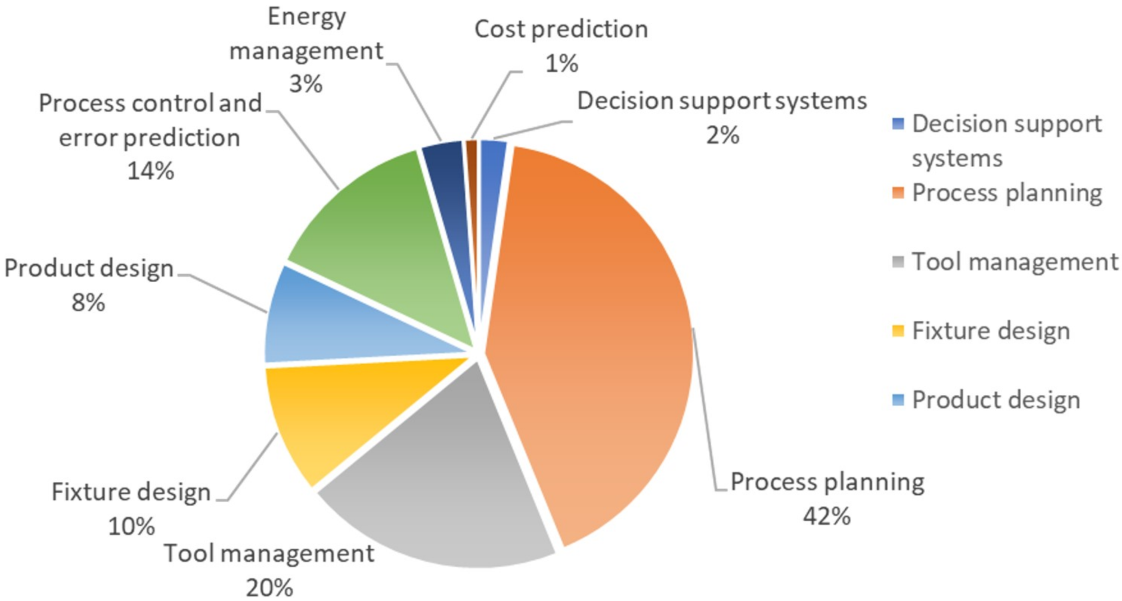

Fig. 1.2 Applications of KBS for machining

- Process monitoring and defect prediction;
- Tool management;
- Fixture design;
- Product design.

Figure 1.2 shows the examined papers that were published during the considered period as a percentage for each mentioned field. Each theme will be discussed in detail within next sessions.

Decision support systems for machining

The main aim of these KBSs is to assist a decision-making process on the basis of previous experiences or stored knowledge.

Methods have been proposed for representing manufacturing process based on ontologies. In these systems, knowledge about machining processes is stored, shared or managed for different purposes [12, 127, 104]. The collection of structured data [244] allows the reuse for sharing [147], rule extraction [217] and reuse [242].

The adoption of web-based Knowledge Management Systems (KMSs) has been proposed and applied in [145, 51, 242].

Some works focused on automatising the selection of machining centres [54, 228] or suppliers [51] by expert systems, while others on tasks or process parameters optimisation [277, 36, 77].

Process Planning for machining

Figure 1.2 shows that most of the examined applications in this manufacturing area aim to Computer Aided Process Planning (CAPP). A manufacturing knowledge representation for this goal is proposed in [59].

A cloud-based system for dynamic production planning is proposed in [96]. Web-based approach is also used in [97] for operation planning. The same task has been fulfilled by using Artificial Neural Networks (ANNs) in [318, 319], graph-based approach in [274] and Rule Based Reasoning (RBR) in [309].

Digitalisation of flexible manufacturing systems has been investigated in [262, 295]. Interaction with user is also adopted for the selection of templates defining the sequence of machining steps in [308].

Process planning involves the analysis of the Computer Aided Design (CAD) model for Manufacturing Feature Recognition (MFR) in several applications ([171, 310, 170, 325, 163, 191]). This kind of approach can also include the representation of intermediate manufacturing states of the machined part, as in [76, 352].

The previously mentioned works aim to be suitable for production planning independently by the product to be processed. In order to better fit specific requirements, some systems have been proposed for specific fields, especially medical and transportation.

In the medical field, a MFR based approach has been proposed by [351], while in [341] process planning is automated for dental restoration. As examples in transportation, in [170] an integrated CAD/Computer Aided Manufacturing (CAM)/CAPP KBS is proposed to store and reuse knowledge in automotive company. [55] adopts a fuzzy evaluation to allocate manufacturing resources allocation during the production of aircraft structural parts. A CAPP for hole-making in marine engines is proposed in [156].

More general optimal hole-making sequence definition for cost minimisation has also been explored by [66] through the application of a modified shuffled frog leaping algorithm.

Figure 1.3 shows the percentage of publications in KBS for machining process planning divided into three main areas, that are: process sequence definition, tool-path optimisation and process parameters selection.

Toolpath optimisation is an important topic that has been mostly faced using STEP-NC representation [169, 363, 342, 337] and Manufacturing Feature Recognition (MFR) on CAD models [197, 320, 108, 91]. A rule-based approach based on calculation of collisions is proposed in [7].

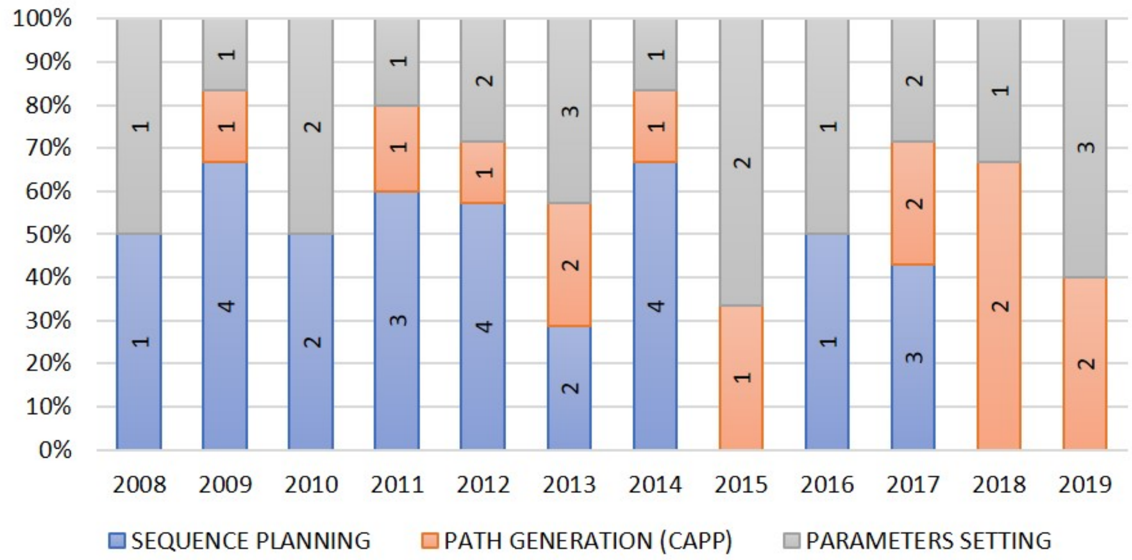

Fig. 1.3 Publications in machining CAPP per area

KBSs to get optimal toolpath basing on process parameters have been presented also for laser cutting processes [8, 58]; in [226] a KBS based on natural language for part program generation in pulsed fibre laser micromachining is proposed.

A specific application to path generation for shoe moulds is presented in [50].
However, as it can be seen in Figure 1.3, the selection of machining parameters, together with sequence planning , covers more than 50% of total publications.

The main objective of the KBSs in this field is to establish relations among machining parameters and final features of the machined parts. As an example, in [162], Bayesian Neural Networks (BNNs) have been used to predict surface finishing on the base of input parameters. In [20] parameters selection is focused onto improving the sustainability of the machining process.

Nevertheless, in most of the cases the parameters optimisation is conducted targeting to several different objectives, leading to a Multi-Objective Optimisation (MOO) problem [241, 252, 252, 22].

An analysis of the geometry is often adopted as a starting point for the definition of optimal cutting parameters; to perform such analysis, STEP-NC representation of the part has been employed in some works [150, 240], while in other cases MFR on CAD models have been preferred [322, 333].

The input parameters that can be included change with the application: as an example, in [8] both cutting and lubricant parameters are considered.

Even in this field, a number of sector-based KBSs have been proposed in order to reach the maximum efficiency. In [105] an automatic NC parameters definition for gear machining is presented. A method for optimal broaching conditions definition using calculation is presented in [138]. An optimisation based onto Genetic Algorithm (GA) is presented in [294] for cement milling; in [277] GA is combined to Fuzzy Logic (FL) and ANN in a soft computing system for the optimisation of High-Speed Milling (HSM).

In [35] ANN has been trained onto the results of a Design of Experiment (DOE) for cost reduction and quality obtaining in laser cutting.

In order to determine optimal conditions for grinding operations, a Web-Based KBS has been proposed in [251], while to determinate grinding wheels dressing parameters for cubic boron nitride a KBS combining Rough-Set (RS) algorithm and Rule Based reasoning (RBR) has been proposed in [330].

Process monitoring and defect prediction for machining

An key-topic of machining oriented KBSs is process monitoring and control or defect predictions during machining under certain conditions. This issue is connected to process planning in order to define proper conditions for achieving a certain product quality [329].

High rates of data acquisition and elaboration in current CNC machines lead researchers to investigate into real-time monitoring systems which can prevent error in-process and represent a complementary way to process simulation by modelling [343]. Different approaches to monitor or predict issues related to machining quality have been proposed including process modelling [303, 304], BN [74], ANN [289] and FL [223]. A RBR based on Decision Trees (DT) has been proposed by [246], while [40] proposed a cloud-based diagnosis system for the elaboration of monitored data. Error compensation can be adopted to improve accuracy of well-established technologies such as milling [160, 354] as well as to facilitate the application of emerging ones [83]. The efficiency of these systems increases when applied to specific operations, as more requirements can be included [174, 154].

Monitoring of tool behaviour is deepen within the next section.

Machine tool and machining tools

The combination between machine tool and machining tools plays a crucial role to determine cost, quality and sustainability of machining process. Therefore, machines and tools selection is a key-activity that is conducted through several different aims, leading in general to a Multi-Criteria Decision Making (MCDM) problem that can be assisted through KBSs. In

[15] a Multi-Attributes Decision Making (MADM) program is developed to select the most suitable high speed machining tool through a Case Based Reasoning (CBR) system.

Numerous KBSs to aid tool selection based on RBR have been proposed as an example by [82, 249, 229, 313, 110].

A soft computing approach using decision trees has been presented in [245]. Examples of cloud-based systems can be found in [177] to choose the best combination of machine and cutters and in [73] for only tool selection. Data acquisition for development of a cloud-based diagnosis system focused on tools condition has also been employed in [41].

A process planning tool aiming to increase tool life has been proposed in [194]; in [34] tool life extension is pursued through data collection in process monitoring. An unsupervised learning based on image analysis is presented for estimation of tool wearing in broaching operations in [292]. A RBR prediction of grinding wheel topography is proposed by [23].

In [339] BNNs have been used to predict thermal behaviour of machine tools.

Finally, an integrated CAD/CAE approach to the design of machine tool is presented in [315].

Fixture design for machining

In tool design, researchers paid a particular interest in automated design of fixtures for machining operations; a review of Computer Aided Fixture Design (CAFD) methods can be found in [32].

KBS designed for this proposal are usually integrated within CAD environment to automate or assist decision-making and modelling activities about fixtures [361, 334, 335].

In [332] a combination of ANN and Finite Element Analysis (FEA) has been proposed for automatic fixture design. A recent trend in this field is to combine RBR and Case Based Reasoning (CBR) within KBSs [13, 221] and to apply in Virtual Reality (VR) [221] [92].

[302] proposes an integration of fixture design optimisation in a wider KBSM for turning based on process simulation.

Product design for machining

According to the general tendency of anticipating manufacturing considerations in the product design process, some KBSs aiming to assist the design of machinable parts have been proposed in the scientific literature. Two examples of frameworks for integrating machining knowledge in design have been outlined and applied in [25] and [4].

In [65] a Web-based Collaborative Design tool integrating a Knowledge-Based Decision System is presented for micro manufacture.

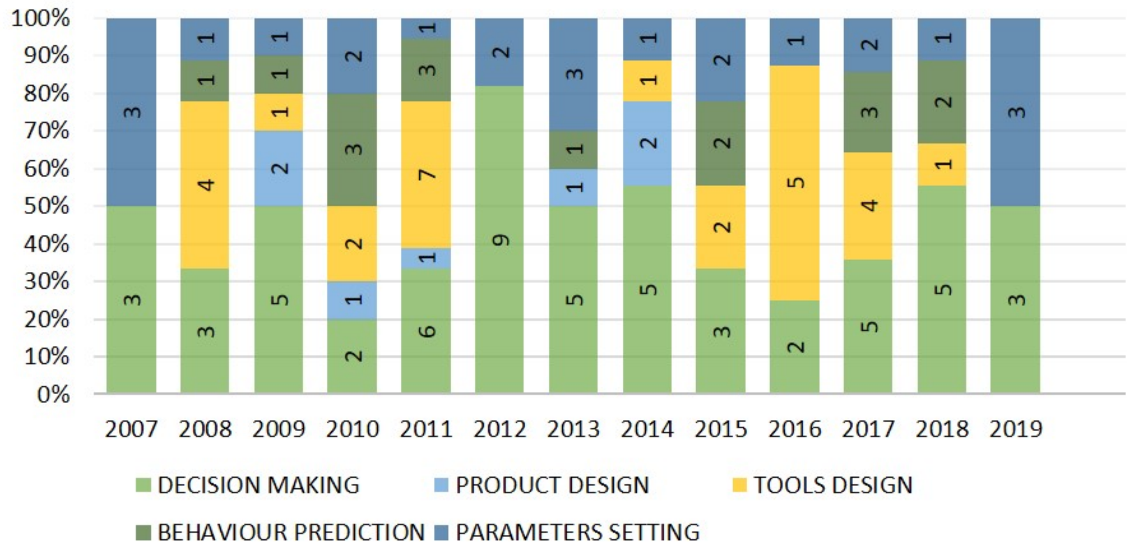

Fig. 1.4 Trends in KBSs for machining

A Design for manufacturing system based on adoption of manufacturable entities has been proposed in [112].

Another interesting application of KBSs to machined parts investigated in recent years is the automatic generation of blank model, as in [331, 178].

Emerged trends for machining and future scenarios

Figure 1.4 presents the percentage of papers published in each of the mentioned fields divided per year.

As it can be observed in Figure 1.4, KBSs for production planning maintains a constant dominant position among publications in this field. Even if RBR systems still have a predominant role in KBSs for CAPP, an increasing number of CBR applications are emerging in order to profitably exploit the large amount of data collected in the production plant.

The development of KBSs for the design of machinable product presents a decreasing number of papers in latest years, while an increase in the number of publications concerning the selection and management of tools used in the machining centres can be observed since 2014. The adoption of RBR seems to be the most adopted approach to this topic. This is applied at different levels of the decision-making process.
Therefore, the future trend in this field seems to be a further enhancement in automation of production planning by including new influential elements (such as machining centres and machining tools) in the digital representation of the production system.

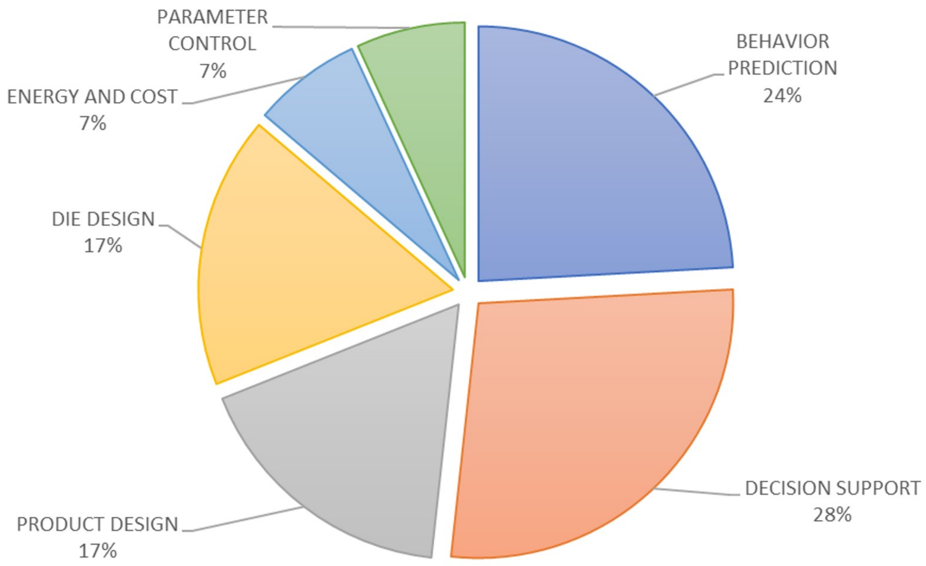

Fig. 1.5 KBSs for casting

1.2.3 KBSs for casting

KBSs find a large use and application for this group of processes thanks to the large amount of available know-how.
Fig. 1.5 provides an overview of reviewed papers on the basis of their field of application. Six main areas, which are listed below, have been recognised:

- Decision support systems;
- Quality prediction;
- Control of process parameters;
- Energy efficiency and cost estimation;
- Product design;
- Die design.

As for the previous section, each area will be described in the next paragraphs and tables will be added in attachment in order to summarise methods and aims of each work.

This overlook allows to underline the main peculiarities of KBSEMs developed for casting technologies. More in detail, it is possible to notice that different techniques and know-how representations are adopted according to the aim of the application.

Decision support systems for casting

Several applications aim to provide advice to the operators of metal casting industries in order to support the decision-making process.
In [238] a semantic approach is adopted to manage and share knowledge about casting of Austempered Ductile Iron (ADI).
Information Technology (IT) to build a platform for knowledge reuse and resource sharing among companies has been applied in [196, 192].
In the approach proposed by [267], rules were extracted by a set of training data and automatically concatenated within the inference engine.
A KBS for material selection in casting has been presented in [161]. The system proposed in [126] for the optimisation of scheduling in steelmaking continuous casting can also be included within this category.
In [347] an application aiming at the development of an intelligent plant for micro-wire casting is presented.

Quality prediction for casting

As it can be seen in Figure 1.5, almost 24% of the KBSs applied to casting deal with the prevision of specific quality characteristics of products realised by means of casting technologies. This is mainly due to the difficulty to properly forecast errors and build predictive model of final product features.

To predict defects that occur in metal parts casting, a CBR approach has been proposed in [326], while an application of the Rough Sets Theory can be found in [143].
A tool for slag detection in continuous casting is presented in [281].
A KBS for data mining from both simulation and experiments has been proposed in [283].
A combination of FL and GA is presented in [276] in order to predict mechanical properties of silica-based resin bonded sand core system.

Control of process parameters for casting

Prediction of behaviour can be adopted in order to optimise process parameters during casting.
In [100] CBR is applied to historical data within a proactive KBS for process parameters control.
In [68] a KBS for squeeze casting parameters optimisation is developed through the application of fuzzy reasoning techniques.

Energy efficiency and cost estimation for casting

Among different objectives of process optimisation, a particular attention is given to cost estimation and energy efficiency, which are two crucial aspects concerning casting processes. In fact, efficient use of energy is a key factor of success for these group of processes that are largely energy consumption dependent. In the same way, in this industrial sector manufacturing enterprises experience hard concurrence and cost prediction for budget estimation is a fundamental business aspect.
In [124] a Multi Agent System (MAS) - a distributed Artificial Intelligence (AI) system that solves problems by social interacting that means by cooperation, coordination and communication among different Knowledge Based Agent (KBA) - is implemented together with Extremal Optimization (EO) method. The aim was the achievement of an artificial intelligent integrated scheduling system for significant economic benefits by increase in hot charge rate in steel-making continuous casting.

In [185] Fuzzy Reasoning (FR) based approach was compared with a more conventional rule based approach for cost estimation of cast metal parts .

Product design for casting

In the previous chapters, a method for the generation of cast blanks for machining processes in [331] has been examined; together with the approach that is described in [59], these two papers can be considered as an example of KBS for the design of castable components.

A knowledge management system to support the design of parts realised through micro-casting and micro-powder injection moulding has been presented in [14].

Recently, in [212] a combination of CAD and FEA is presented for the optimisation of cast metal and injection moulded polymeric parts basing onto micro structure-based material behaviour. In [211] a KB methodology for the design of casting parts including structural and process FE simulation is proposed.

Die design for casting

Researches on assisted design for casting does not deal only with design of parts to be produced in order to be feasible but also concern the manufacturing system and, in particular, die design.

In [136] a CAD integrated KBS for the parametrised modelling and intelligent assembly of 3D die standard parts is proposed for die-casting.

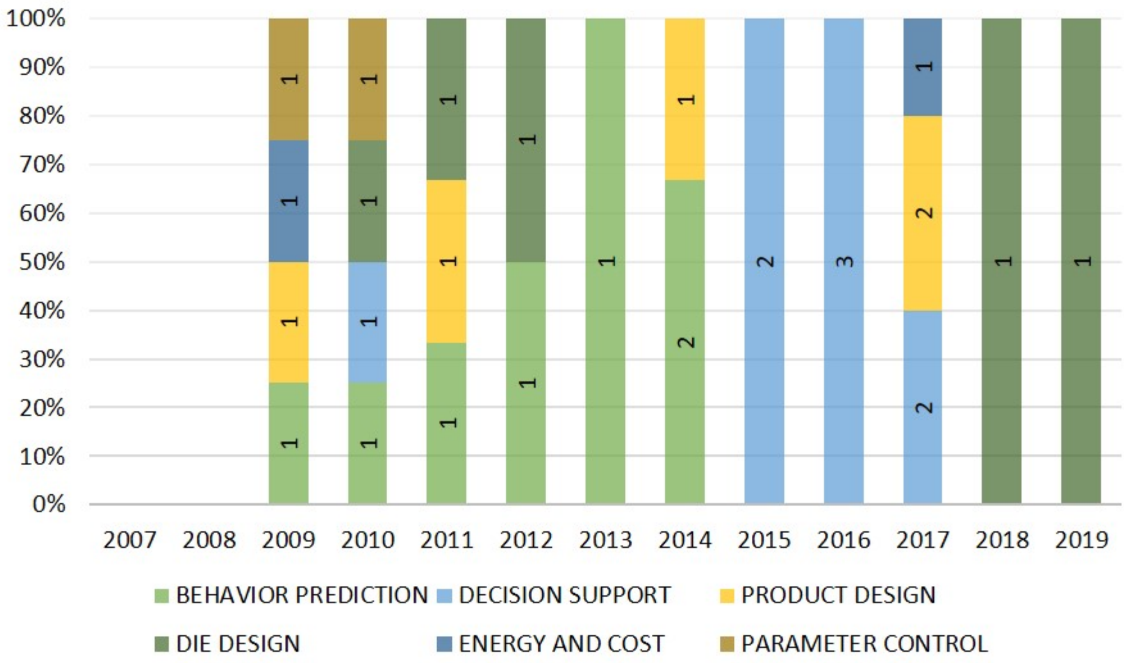

Fig. 1.6 Percentage of publications per year in different fields.

In [151] a MOO CAD integrated KBS for cavity design for die casting is proposed. The method proposed in [125] combines CBR and RBR for the specific design of turbine blades produced through investment casting.

[158] deals with a CBR system for reusing previous design resources in the development of a new product.

[89] describes a Feature Based parametric design for automatising die casting design.

In [316, 253], a KBSM or the design 3D Sand Printed moulds is proposed.

Emerged trends for casting and future scenarios

Figure 1.6 reports the percentage of publications in each of the fields investigated within the time period analysed in this review. As it can be observed, prediction of parts behaviour and, consequently, the parameters management received an increasing interest in the period between 2009 and 2014, while in the most recent years the published works have been mainly focused on more general systems to assist the decision making process in foundries and the design of moulds.

1.2.4 KBSs for plastic moulding

Plastic moulding shows several similar aspects to casting, but at the same time presents important peculiarities affecting all the examined applications of KBSs.
Examined KBSs about this technology have been distinguished according to their objectives as represented in Figure 1.7.
As it will be described in the following part, most of the applications in this field are developed for injection moulding process.

It was possible to distinguish six main areas, that are listed below:

- Decision support systems;
- Product design;
- Die design;
- Process parameters;
- Behaviour prediction.

Decision support systems for plastic moulding

To support the decision making process for injection moulding technology, a semantic web-based KBS has been developed in [133].
A KBS focused on energy saving for injection moulding is proposed in [268].
A recommendation tool for decision making in polymer matrix composite materials processing has been presented in [63].
Finally, in [45] an overview of FORMAT methodology is provided with an application to vacuum forming.

Product design for plastic moulding

Because of the several design constraints related to most of the plastic moulding processes, several KBSs have been developed to assist the design of products to be produced using these technologies. Two examples of such KBS applied to plastic moulding has been already mentioned in the previous chapter [212, 211].
In [247] a representation of product lifecycle to support e-design of injection moulded parts is proposed.
In [362] a web-based KBS to provide designers information about existing and under

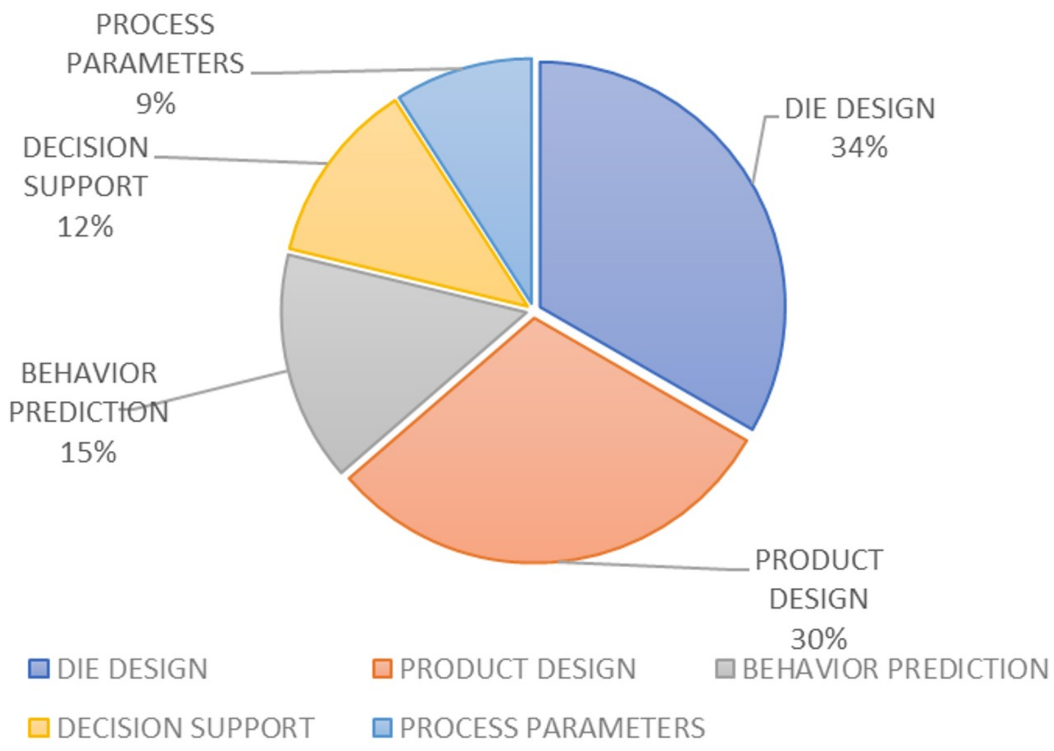

Fig. 1.7 KBSs for plastic moulding

developing products to support injection moulding is presented. A web based approach to assist the design of injection moulded parts is also presented in [132]. A KBS for decision support during the design of injected moulded parts has been outlined in [62] through the usage of both CBR and RBR.
To directly apply design guidelines to CAD models for the manufacturability assessment, a mid-surface representation of the solid part has been adopted in [109]. In [60] an algorithm for the individuation of undercut features in CAD models.
Finally, an interesting family of KBSs in this field is constituted by the ones aiming to evaluate the manufacturability of composite components [60, 285].

Die design for plastic moulding

As in metal casting, the design of manufacturing equipment, and in particular dies, plays a crucial role in injection moulding industry, therefore it is investigated by several KBSs in this field.

In [130] a navigation system to support mould design and reducing time required is presented.
An example of RBR approach to mould design for injection moulding processes is proposed in [250], while CBR approaches can be found in [198] and [103].
In [153] a combination of CAE and DOE is developed to optimise the design of injection moulds in terms of gates and runners. An integration of CAD and CAE has been adopted for the optimisation of mould design and moulding parameters by [190].

A web based KBS for the application of DFM rules during mould design has been presented in [131]; a more specific application to rubber injection moulds can be found in [291].

site materials is proposed in [27].

Finally, some KBSs have been proposed for the design of moulds satisfying specific requirements: in [275] ICT supported system for energy efficient injection moulds design is described, while a KBS for lead time estimation of moulds is presented in [202].

Process parameters for plastic moulding

As mentioned, in [190] not only the design of the mould, but also the design parameters are optimised within the KBS.

In [188, 157] a KB approach to the design of KBSs for the determination of optimal injection moulding parameters was proposed.

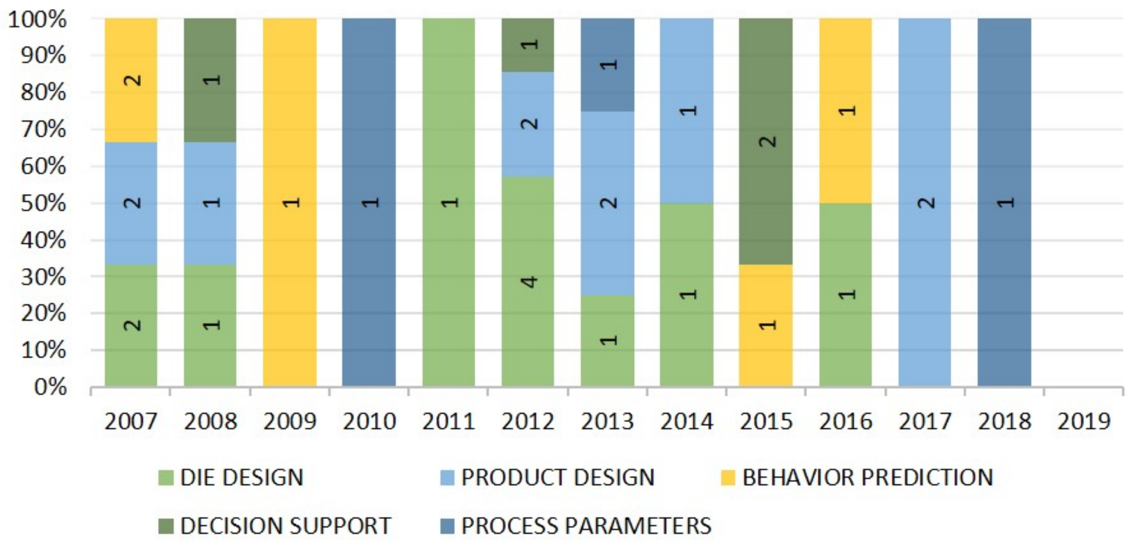

Fig. 1.8 Applications in plastic moulding divided per sector

Back Propagation Neural Networks (BPNNs) have been used in [52] for the determination of the Pareto-optimal solutions for a MOO of injection moulding parameters.

Behaviour prediction for plastic moulding

Specific KBS have been developed to predict behaviours of moulded parts and moulding system under different aspects.

In [144] a KBS for the estimation of defects within injection moulded parts basing onto CAD representation is presented.

A web-based fault-diagnosis system for an injection moulding machine is developed in [297] adopting CBR based onto previous maintenance experience.

A KBS for the prediction of mass fluctuations in injected plastic parts has been developed in [173] through the usage of BPNN.

A Hierarchical Bayesian Network (HBN) approach to estimate the uncertainty in performance prediction of manufacturing processes has been presented in [205] and applied to uncertainty prediction in energy consumption during injection moulding.

Trends for plastic moulding

In Figure 1.8 KBSs for plastic moulding are summarised on the basis of percentage applied to different fields during each year.

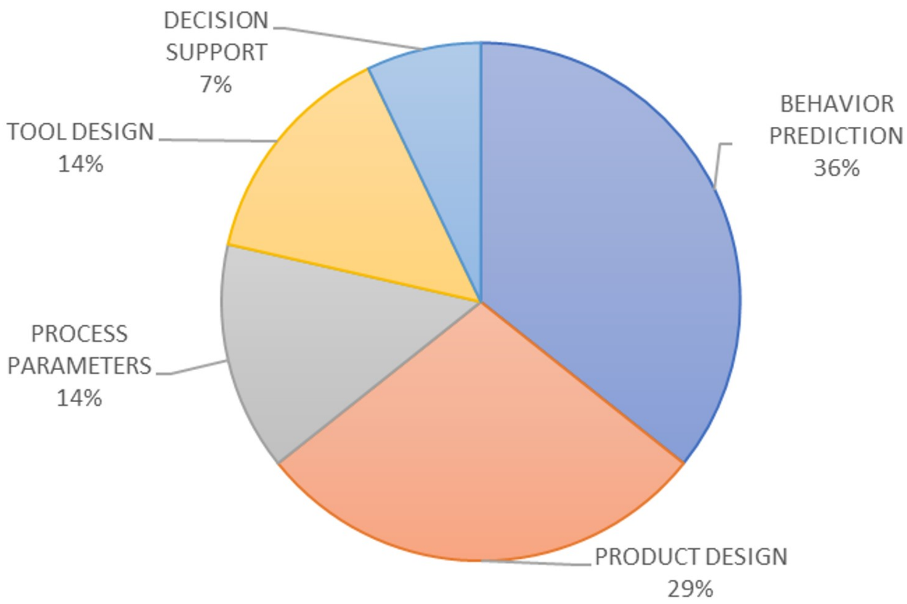

Fig. 1.9 KBSs in bulk deformation divided for application

As it can be observed, there is not a well-defined trend in the development of these systems, being the percentage of applications randomly distributed with a stable predominance of product and die design assistants.

1.2.5 Bulk metal forming

Despite its wide applications in engineering production, bulk forming its quite a niche for developing of KBSs, as it can be observed in Fig. 1.1.

It was possible to distinguish six main areas in this field, that are listed below:

- Behaviour prediction;
- Process parameters;
- Product design;
- Tool design;
- Decision support systems;

In Figure 1.9 the percentage of KBSs reviewed in this field are divided in categories as made for previous processes.

Behaviour prediction for bulk metal forming

As it can be observed in Figure 1.9, most of the KBSs applied to bulk forming aim to predict some behaviours of the manufactured product on the basis of process parameters. An overview of relevant effects for most of the technological processes in this field is provided in [287].

In [46] a FE approach is adopted to model actual welding occurring in extrusion of complex profiles.

An ANN based approach to estimation of flow stresses in plastic deformation is proposed in [119].

A SVM based approach has been developed in [5] to classify defects occurring in hot bar rolling of steels monitored during inspection.

Recently, a cloud-based KB adopting FEA for predicting limiting dome height and failure mode during hot stamping process has been presented in [312].

Process parameters for bulk metal forming

Deeply connected with the previous activity, also in the field of bulk deformation some applications have been developed to find out the optimal set of process parameters.

In [2] a combination of FL and GA is proposed for the optimisation of hot-rolling process parameters.

GA are instead combined to FEA to optimise tube bending parameters in [167].

Product design for bulk metal forming

In [16] a CAD integrated KBS including DFM rules for the design of manufacturable bent pipes has been proposed.

DFM is combined to axiomatic design approach within a KBS considering both process properties and execution variables for forging process in [86].

In [168] a KBS for the determination of tube bending limits has been proposed using analytical and FE methods and experimental data.

A KBS for manufacturability assessment of tube hydroforming is proposed in [209] through reduction of 3D CAD data to a 1D skeleton graph.

Tool design for bulk metal forming

A KBS to assist the design of tools for bulk metal forming can be observed in [39] with an application of ANN to the design of aluminium extrusion dies.

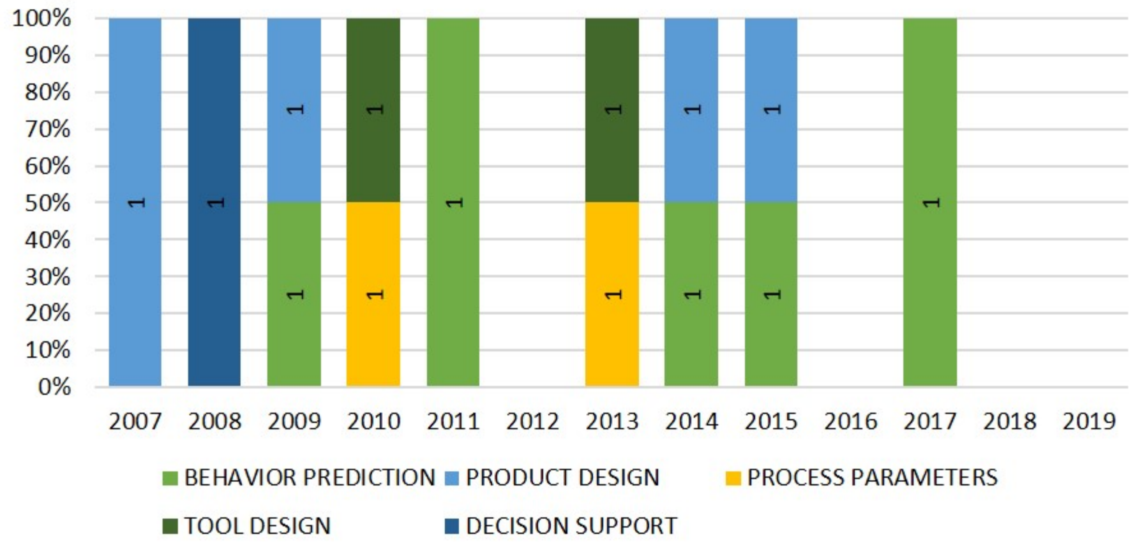

Fig. 1.10 Publications per year in bulk metal forming

In [166] an integration of CAD and FEA is adopted to assist selection and design of tools for metal tube bending.

Decision support for bulk metal forming

An example of decision support KBS for bulk forming can be found in [350], where Rough-Set theory is applied for knowledge acquisition and reuse in cold extrusion.

Trends for bulk metal forming

Figure 1.10 reports the percentage of papers in each of the mentioned field published each year.

As it can be seen, the prediction of characteristics of the product and its design are the fields of most interest for the development of KBSs in the field of bulk manufacturing in the recent years.

1.2.6 Sheet metal forming

In metal forming, a distinction is made between bulk forming and sheet metal forming for the different methods and equipment employed.

A survey of KBSs for sheet metal stamping has been published in 2014 [231]; the overview is here extended to more recent works and different sheet metal forming techniques.

It was possible to distinguish six main areas, that are listed below:

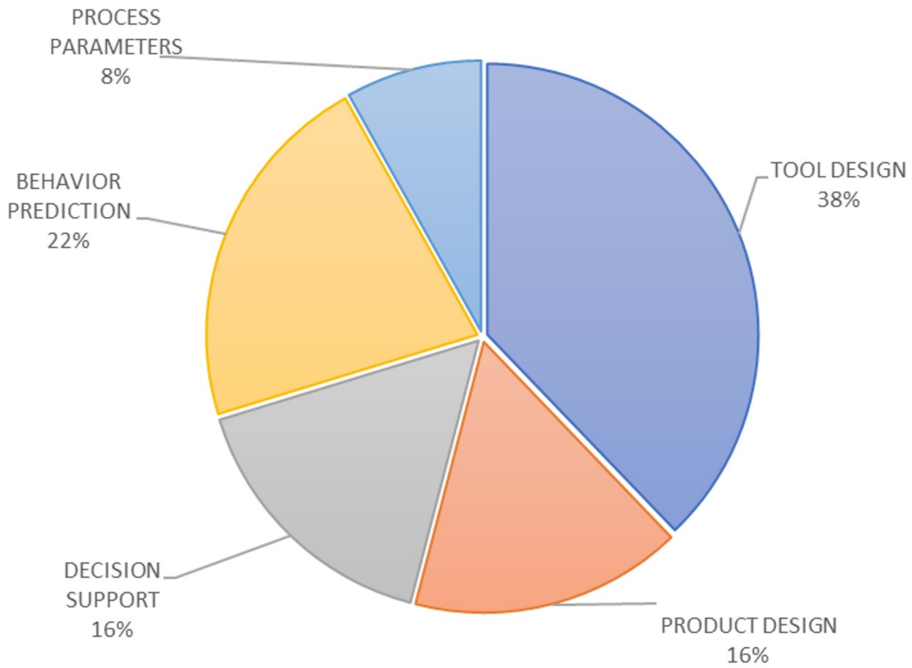

Fig. 1.11 Publications in sheet metal forming divided per scope

- Part design;
- Tool design;
- Behaviour prediction;
- Process parameters;
- Decision support.

Figure 1.11 shows the amount as percentages of the scientific publications about sheet metal forming divided per scope.

As it can be seen, most of the applications of KBSs in this field aim to support the design of formed parts and production tools.

Part design for sheet metal forming

The design of sheet metal formed parts involves several considerations in order to ensure the transformation of the blank sheet metal into the final product. Therefore DFM rules plays a crucial role in this field and have been the basis for development of many KBSs [231].
In [207] an intelligent assistant is developed to provide recommendations for strip-layout design of sheet metal parts produced on progressive deep drawing dies. Blank layout and

strip-layout are then automatically modelled through in CAD environment.
A KBS for assisting the design of incremental is developed in [213] through the use of ANNs.
A CAD integrated KBS for bend-allowance estimation of air-bended sheet metal parts is presented in [152], while in [327] a system to assist preform design for shell nosing products through a combination of CAD and CAE has been presented.
A sector application of these systems can be observed in [114] where a KBS has been developed to speed up the design process of formed sheet parts for automotive field.

Tool design for sheet metal forming

Due to the huge influence of process equipment onto quality and convenience of forming processes, the development of KBSs to aid their proper design is the field of research with the highest number of publications.
In [1] a CAPP KBS for axisymmetrical deep drawing part is presented. The output of the system consists of the set of optimal parameters and the CAD model of the tool adopted for the process.
More recently another CAD integrated KBS for the design of deep drawing die components and assembly has been proposed in [206].
An expert system for die design and process planning of sheet metal forming operations is presented for blanking operations in [272]. The task of automating blanking die design to shorten development time is also covered by [175, 273, 149]. A CAD integrated KBS to support the design of cutting dies components and assembly is developed by [301].
In [176] an integrated CAD/CAM/CAE KBS has been developed to assist the automated modelling of stamping dies for the automotive field.

Behaviour prediction for sheet metal forming

The necessity to estimate the behaviour of components during the manufacturing process led to the generation of KBSs for the prediction of specific product features affected by the forming process. GAs have been employed together with ANN and FEA in [38] for prediction of spring-back angles in sheet metal formed parts.
A predictive system for cost estimation of sheet metal parts has been proposed by [21].

In [311, 317] cloud-based KBS is coupled with FE simulation for the MOO of sheet metal forming.

Process parameters for sheet metal forming

As in other fields, prediction of product features related to manufacturing process is often used to adjust process parameters according to the intended result.

So in [214] a KBS for deviations prediction in incremental formed sheet metal parts is used for control of driving machines' process.

A self-adapting KBS for the control of incremental press bending on the integral wing-skin panels has been developed in [344].

In [75] a Cloud-Based KBS based on the use of FE methods has been developed to predict the outcome of sheet metal forming processes.

Decision support for sheet metal forming

Some KBSs developed for sheet metal forming aim to combine different aspects of the aforementioned applications in order to assist the manufacturing at different levels; examples obtained through the combination of different CAx environments can be found in [219, 101, 111].
An assistant tool for evaluation and forecasting of the in-plane bending process is described in [284].
More specific tools are then designed for sector applications.

For example, an application of KBS to aircraft panel forming is presented in [56], while a neuro-fuzzy inference system for rule extraction in asymmetric single point incremental forming is presented in [288].

Trends for sheet metal forming

Figure 1.12 summarises the percentage of KBSs presented per year divided according to their application.

It is possible to notice how the design of products and production tools are the most covered areas in this field with a stable trend. This is even truer if we consider that, in many cases, the more general decision supporting tools include this task among other modules.

1.2.7 Welding

The applications of KBSs to manufacturing includes also joining techniques. In particular, welding is a prolific field due to the broad use and the need of know-how of these group of processes. A large number of different heat sources are available and, typically, a rele-

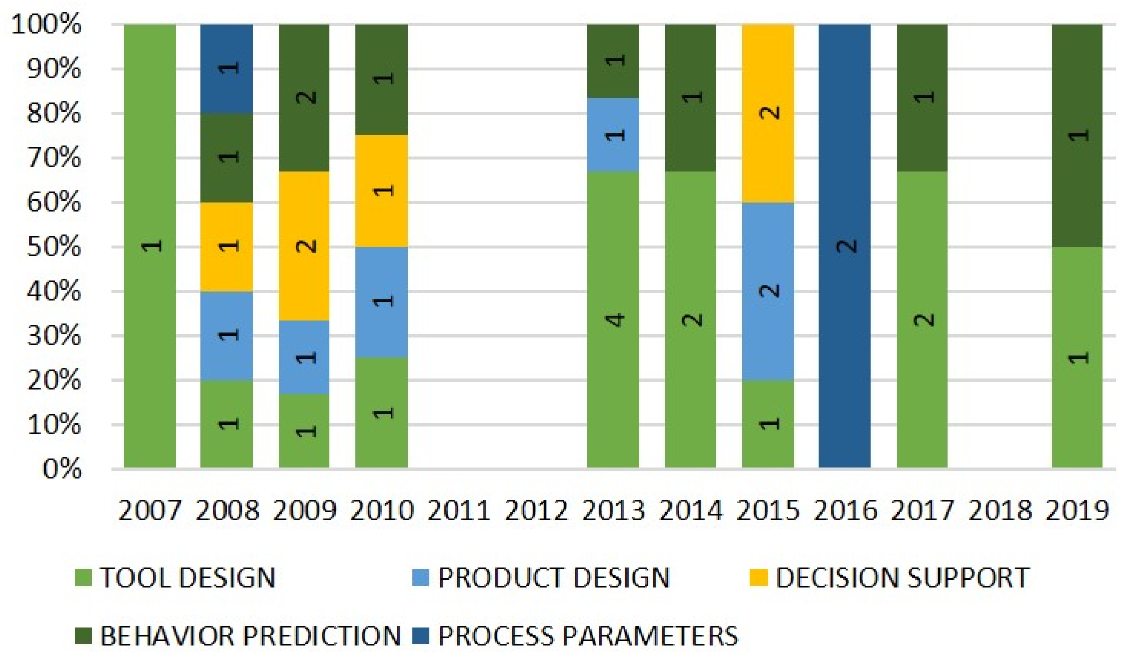

Fig. 1.12 Publications per field in sheet metal forming

vant number of process parameters must be controlled also if material properties are not considered.

An overview of examined systems is provided in Figure 1.13.It was possible to distinguish six main areas, that are listed below:

- Decision support systems;
- Behaviour prediction;
- Defects management and control
- Process parameters
- Product and tool design

Defects management and control has been separated from general behaviour prediction to underline the relevance of these features in this manufacturing field.

Decision support systems for welding

The selection of a proper welding technique is a significant problem due to the mentioned available large number of heat sources but also depends on processed materials and product

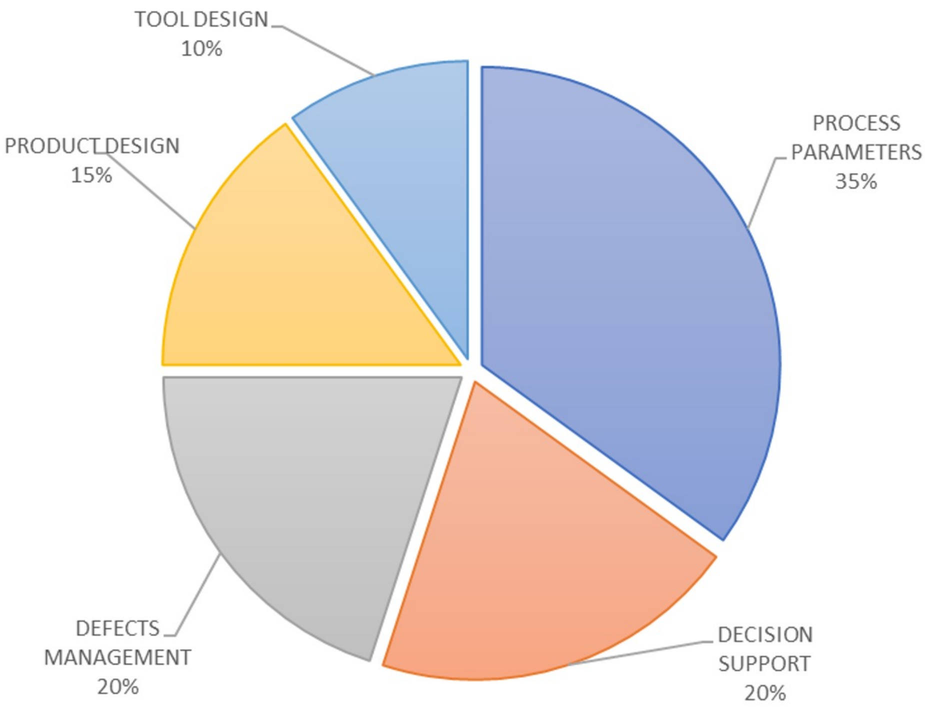

Fig. 1.13 KBS applications for welding

design. As a consequence, a huge number of factors must be taken into account. KBSs can be precious in this choice as assistants of experienced or inexperienced process engineers and managers to realise decision making systems.

Fuzzy-based KBSs to assist welding process selection have been proposed in [195] for repairing nodular cast iron engine block and in [120] for high pressure vessel manufacturing. Fuzzy techniques are also adopted in [139] to develop a Design Decision Making (DDM) assistant for assembly and joining that has been tested on real welded structures.
Arc-welding knowledge is also included within the web-based management system [51] already mentioned in 1.2.2.

In[299] a KBS for Reconfigurable Manufacturing Systems (RMS) is presented with an application to spot- welding.

Behaviour prediction for welding

As in previously analysed manufacturing fields, the decision making activity is deeply related to the prediction of product features on the basis of adopted technological and process parameters.

The prediction of physical phenomena during welding process is an important field of research. A KBS basing on Finite Element Method (FEM) is adopted in [264] to predict heat behaviour for back control in Gas Tungsten Arc Welding (GTAW) of stainless steel. A KBS has been applied to electric welding with a direct observation of bead geometry through an optic camera in [243].

By using different strategies, ANNs have been trained during online testing analysis for online prediction about process output. [122] proposed a KBS using ANNs that could solve both the problems of forward and reverse process mapping in case of the electron beam welding process of reactive materials.

A fuzzy based KBS for rules extraction and inference has been proposed in [85] and applied to prediction of welding distortion in marine engines.
Among different features, cost plays, of course, a crucial role for industrial competitiveness. KBSs for cost-modelling of welding processes are proposed in [324] for spot welding and in [6] for remote laser welding.

Defects management and control for welding

Quality analysis and inspection of products for defects identification is probably the characteristic of processes that needs the highest level of knowledge. This problem is typically faced by a forward process modelling.
In [346] an Adaptive Network-based Fuzzy Inference (ANFI) system has been applied to recognise and classify welding defects by radiographic images. Rough Set Theory (RST) has also been applied to intelligent defects recognition and welding quality classification in [286].
A system for the analysis, diagnosis and correction of defects in aluminium welding has been developed in [298].
In [293] a fuzzy rule extraction and inference system is proposed and applied to welding fault diagnosis.

Process parameter optimisation for welding

As a consequence of features prediction and defects diagnosis, several applications of KBSs aim to the individuation of optimal set of welding parameters. This problem is typically faced by a reverse process modelling.
In [234] the robust design approach has been applied for the individuation of optimal parameters in super duplex stainless steel arc welding.
A input-output model for submerged arc welding parameters has been developed in [70] by using Taguchi's Design Of Experiment (DOE) and optimised by Genetic Algorithm (GA) and Particle Swarm Optimization Algorithm (PSOA). A different model for submerged arc

welding based on ANNs has been used in [141] for a two wire processing of High Strength Low Alloy (HSLA) steels.
A combination of fuzzy logic and GA has been applied in [255] to find out the optimal set of parameters for ultrasonic welding.
In [49] an adaptive system has been developed for robotic speed control welding of moderate-thick plate with variable groove. A KBS for robotic welding is also developed in [259] for the automated control of current and wire feed rate in Gas Tungsten Arc Welding (GTAW).

Product and tool design for welding

For KBS development, the design of welded products and tools for welding is a niche of research due to the standardisation of most of the equipment and for certain groups of objects like for example welded vessels that have a large diffusion for different uses. Interesting researches have been published in this field and are worth to be mentioned.

In [359] a KBS for the design of welding vessels has been proposed. A Multi Objective (MO) KBS for weldability assessment for aerospace application is developed in [218] by using the Howtomation© suite.

In[28] an automated NC programming system for locators is presented and applied to an automobile welding line. In [314] a CBR KBS is proposed in order to assist the design of fixtures for welding process.

Trends for welding

Figure 1.14 reports the percentage of publications of KBSs for welding in each of the aforementioned areas during the investigated period.

It is possible to observe that in the latest year the general trend is to move from KBSs for the prediction of welding features basing on process parameters optimisation to more complex systems, which are able to optimise such parameters automatically to fulfil a set of requirements.
This is a natural evolution of KBS applications, not only for welding, in the direction of a fully automated process.

1.2.8 Additive Manufacturing

The definition of Additive Manufacturing (AM) includes a number of technologies with deep differences in terms of materials, architectures and fields of application [237, 95]. Nevertheless, some peculiar aspects of these technologies (such as the layer-based construction

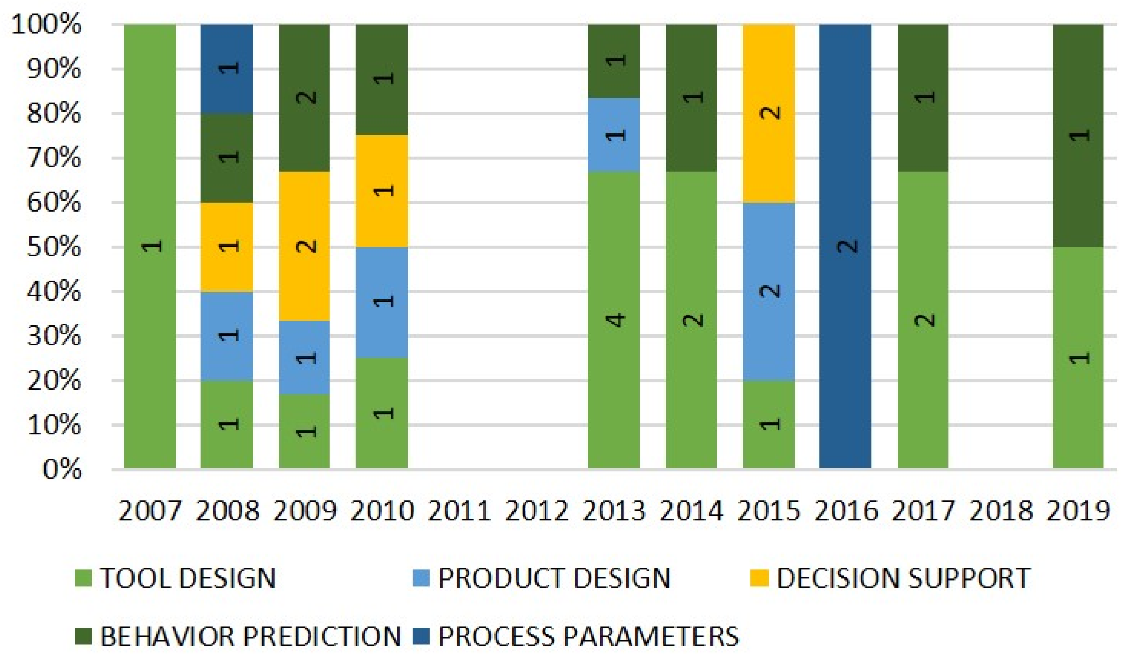

Fig. 1.14 Publications per year in welding fields

strategy) can be recognised. Accordingly, KBSM applied to AM technologies are analysed as a group in this section.

The applications in literature have been classified according to the scope three main categories, that are:

- Decision support systems;
- Behaviour prediction;
- Product design.

Figure 1.15 shows the percentage composition of papers reviewed in this field.

It can be immediately noticed how most of the KBSM applications in the fields are focused on Design for Additive Manufacturing (DfAM), i.e. on the inclusion in product design of constraints and opportunities deriving from the adoption of AM.

As these technologies are quite recent if compared to the other categories discussed above, the formalisation and reuse of knowledge for decision making is a very important research challenge.

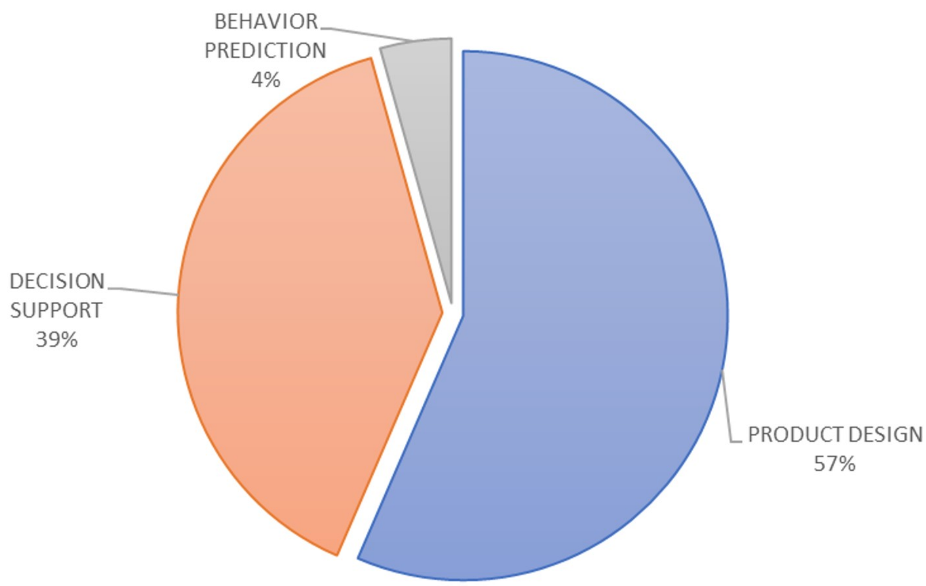

Fig. 1.15 Publications applying KBS to AM divided per scope

Part Design

As shown in Fig. 1.15, most of the applications of KBS in AM are oriented to part design. These applications include the manufacturing-oriented mass customisation of products [348], the verification of DfAM rules on digital mock-ups of parts [140] and the compensation of manufacturing-induced defects [256].

An ontology-based representation of parts is proposed by several authors in order to apply design guidelines of the specific AM technology [9, 72]. The adoption of ontologies and RBR is particularly charming in this field as it enables the reuse of the codified manufacturing know-how [323].

CBR has been also efficiently applied to identify relevant manufacturing features [179] for the specific AM process. [317] proposed BN for the organisation and reuse of DfAM knowledge.

In [186] a KBS for knowledge extraction from text and reuse in CAD environment was proposed. The integration of KBS in parametric CAD graphic environment has been deepen by [48].

According to the principle of mass customisation mentioned above, several KBSM are designed to assist the design and production of specific components. The applications include medical [263, 307], aeronautical [146] and various customisable parts [137, 47].

Assisted Decision Making

The general lack of knowledge in AM technology makes the use of KBSM profitable for different decision-making problems.

A study on the role of knowledge-based information sharing in AM has been presented by [248]. [204] outlined a method for the selection of KB ANN to fill the gaps of knowledge in the field of AM production.

At the highest level, KBSMs have been applied to assist the selection of the proper AM technology for given objectives [266, 265, 203, 358]. In [321] a KB approach to MCDM is presented and applied to the selection of AM process and inspection system. Technology selection has also been investigated by [254] in a wider ontology based approach aiming to include several aspects of the process, such as manufacturability assessment.

In [172] ontology based representation has been used in the development of a KB CAPP system for AM technologies. A KB multi-objective CAPP for these processes can also be found in [355, 9].

The KB approach has been also applied to the selection of optimal part orientation [357] and tool-path [10] according to part geometry. A KBSM for the adaptive slicing of AMed parts was proposed by [233].

Behaviour Prediction

An example of KBSM for the prediction of physical behaviout can be found in [98], where a KBS for prevision and control microstructure in as-deposited metal additive manufacturing is presented.

In [364] a KB approach to thermal field is obtained by superposing local solutions according to laser path in SLM.

Trends in KBS for Additive Manufacturing

Figure 1.16 reports the percentage of publications of KBSs for AM per year.

1.2.9 General considerations on the outlined panorama

Objectives of examined KBSs are strictly connected to peculiarities that are proper of considered manufacturing fields. Nevertheless, it was possible to recognise five main areas that are in common. They are:

- Decision support systems development to assist decisional processes (e.g. process or equipment selection).

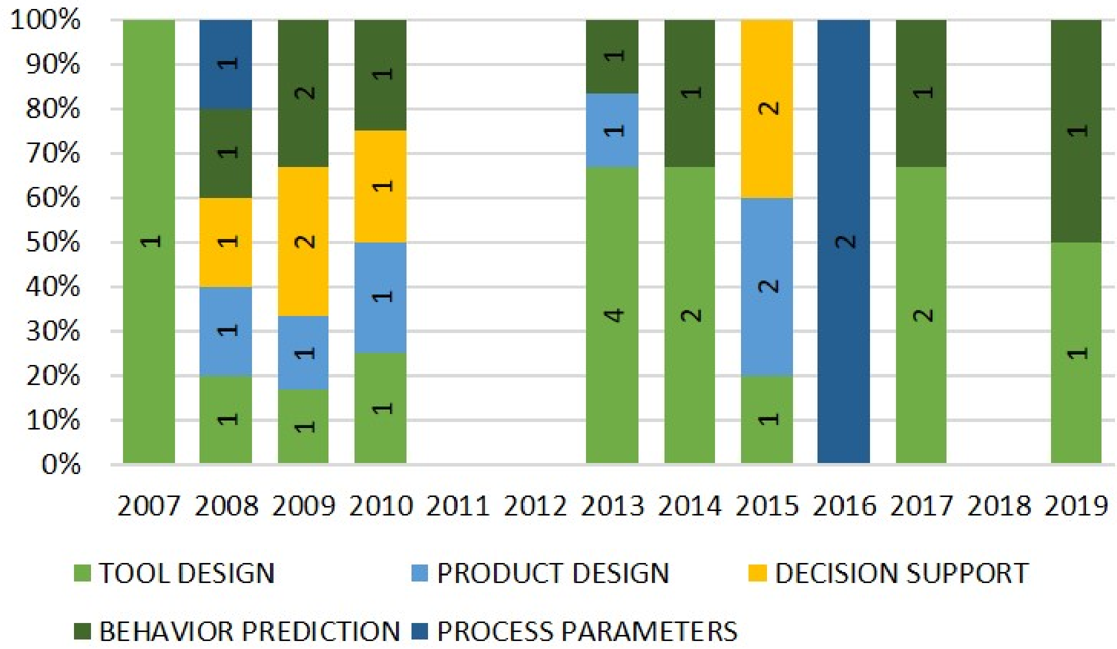

Fig. 1.16 Publications per year in welding fields

- Product design for rules application to ensure or enhance manufacturability.
- Tool design to assist the design of equipments for production purposes.
- Prediction of product features for estimation of relevant or crucial features of the final product, which depend on manufacturing conditions.
- Process parameters optimisation by the use of previously mentioned estimations to determinate the optimal set of parameters to obtain a defined result.

Figure 1.17 maps the percentage of KBSs in each of the examined manufacturing fields and grouped into the identified five main areas.

By the presented scenario, different trends have been observed for KBS applications depending on the analysed processes.

It is worth noticing how the huge number of researches concerning the development of KBSs for decision making assistance in processes such as machining and casting, which have a large history, are founded on a relevant amount of knowledge and a solid tradition in digitalisation of manufacturing information. In this case, the aim is clearly the automation of decisional processes that are critical to success and that are still nowadays carried out by humans. In these cases, CBR systems are mainly used to automate know-how and working experiences in order to assist human apprenticeships.

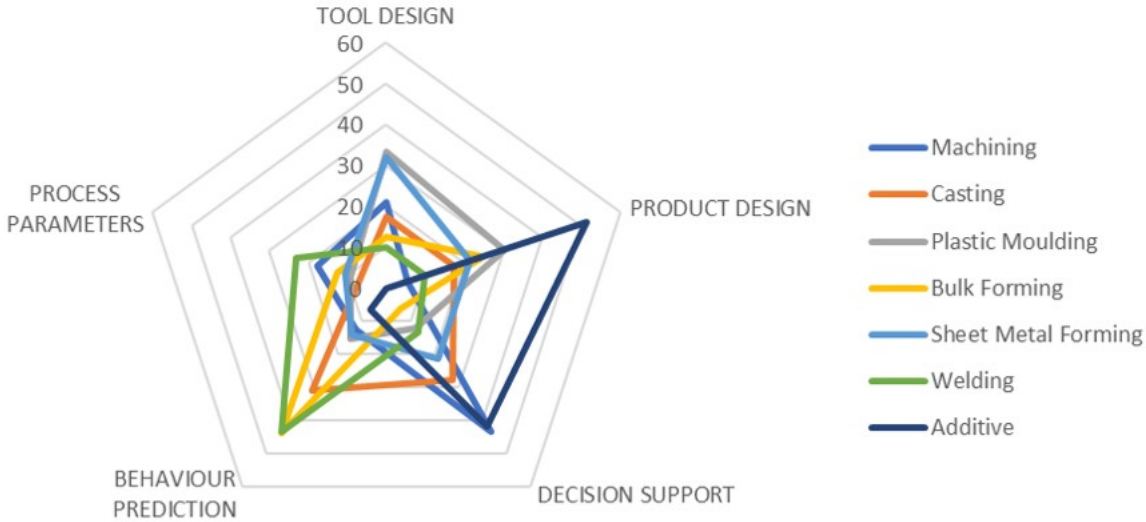

Fig. 1.17 Maps of KBSs objectives in different manufacturing fields

On the other hand, decision-making systems in AM are used to compensate for the lack of knowledge in the field and the adoption of these technologies by non-expert users. Also in this case, the deep digitalisation of these technologies plays a fundamental role in enabling the automation of decision-making at different stages of the process development.

Instead, a major interest in prediction of product features is mainly present for manufacturing processes with higher uncertainties. In particular, a huge attention is paid in welding processes to defect categorisation, diagnosis and failure predictions in order to reduce the amount of scraps in highly or fully automated process. This interest is directly reflected on the will to assist the selection of proper and optimal process parameters and to avoid defect occurrence.

The great influence of the equipment on the product quality and process costs in plastic moulding and sheet metal forming processes lead researches to focus on the KBSs to assist tool design in order to reduce the time-to-market and guarantee higher product quality.
For all the considered manufacturing processes, KBSs that aid the product design since the very first steps of development resulted key-tools to guarantee manufacturability in the following production steps. This aspect underlines the importance of DFM rules and leads to the development of RBR systems.

To summarise, the general trend shows an increasing use of integrated systems, which connect different areas of the production plant, moves towards the same direction of the Industry 4.0 by horizontal and vertical integration of numerous engineering activities.

It is worth to mention that depending on the manufacturing sector, a prevalence of Case Based Reasoning (CBR) or Rule Based Reasoning (RBR) systems can be observed. In particular, the former type have been encountered mainly in machining, casting and welding, while the latter ones have been mainly met in remaining fields. However, in general, if all the manufacturing application are considered, a balanced number of applications of the two approaches have been examined.

Concerning KBSs development, the integration of RBR with CBR systems seems to be the frontier. This approach aims to exploit the high amount of data captured in modern production plant and it is simultaneously able to produce a human-understandable knowledge.

The analysis of literature points out the huge variety of applications of KBSM at different steps of the process development. Despite these differences, peculiar features characterising these systems from general KBSs can be recognised. In Chapt. 2 a systematisation of these aspects and a methodological approach to KBSMs will be proposed.

1.3 Methods for the design of Knowledge-based systems

Several methods can be found in literature for the development of Knowledge-Based Engineering (KBE) systems. As these systems are intended for also including manufacturing requirements, the relevance to the present work is evident.

In the following, the most popular and relevant methods are briefly described in order to point out to the reader their most peculiar features and limitations for the application to manufacturing engineering.

A more extensive review of the period 1982-2002 can be found in [227].

1.3.1 CommonKADS

CommonKADS (Methodology and tools Oriented to Knowledge-based engineering Applications (MOKA)) is one of the first and most popular methodologies proposed for the development of KBSs in engineering. This method is the result of a series of international research projects on knowledge engineering carried out starting from European Esprit program in 1983 [258]. Even if details on the implementation are out of the scope of this chapter,the method is founded on the use of predefined models [257]:

- **Organization model** The organization model supports the analysis of the major features of an organization, in order to discover problems and opportunities for knowledge systems, establish their feasibility, and assess the impacts on the organization of intended knowledge actions.

- **Task model** Tasks are the relevant subparts of a business process. The task model analyses the global task layout, its inputs and outputs, preconditions and performance criteria, as well as needed resources and competences.

- **Agent model** Agents are executors of a task. An agent can be human, an information system, or any other entity capable of carrying out a task. The agent model describes the characteristics of agents.

- **Knowledge model** The purpose of the knowledge model is to explicate in detail the types and structures of the knowledge used in performing a task. It provides an implementation-independent description of the role that different knowledge components play in problem-solving, in a way that is understandable for humans.

- **Communication model** The communication model aims to represent the communicative transactions between the agents involved. The communication model is conceptual and implementation-independent.

- **Design model** Based on requirements defined by previous models, the design model gives the technical system specification in terms of architecture, implementation platform, software modules, representational constructs, and computational mechanisms needed to implement the functions laid down in the knowledge and communication models.

The adoption of these models allowed the application of the method to several different fields [257, 279].

As outlined by [183], the main limitation of this methodology is in the complexity of the model that requires a quite long training and effort for implementations. Such aspects become a limit in the actual implementability of the method. Furthermore, the model-based framework of CommonKADS limits is mainly intended for rule-based reasoning in the form *"if...then"*; the extension of the methodology to modern Deep Learning techniques can thus result tricky and uncertain.

1.3.2 MOKA

Methodology and tools oriented to Knowledge-based engineering Applications (MOKA) is a method is the result of the Advanced Information Technology (AIT) pilot phase ESPRIT Project 7704 [210].

The MOKA distinguished between two main types of model, i.e. :

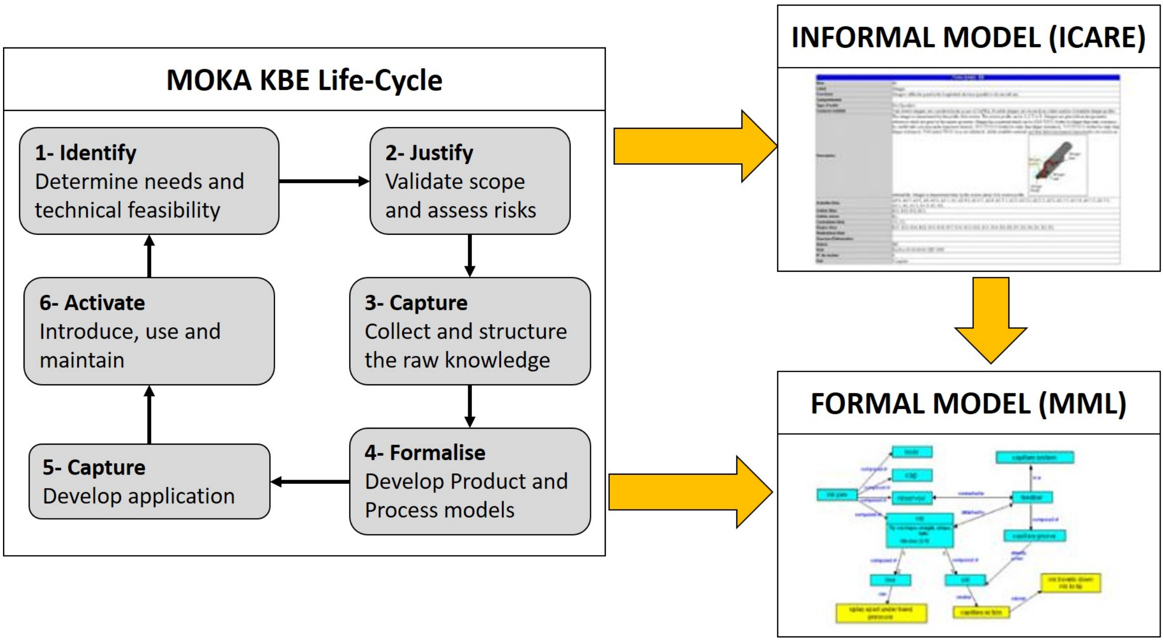

Fig. 1.18 MOKA methodology [64]

- **Informal Model** A structured, natural language representation of engineering knowledge using pre-defined forms.

- **Formal Model** An object-oriented map of the knowledge elements and their relations that can be directly implemented in a OOP.

The method represents as ontologies the design descriptors and requirements, establishing relations of derivation, consistency and fulfilment among these two sets [142]. This concept is further extended within the proposed method in Chapt. 2.

MOKA also introduced an iterative concept in the design of KBE applications, as schematically represented in Fig. 1.18 [64]. Also this circularity of the method is reused in the method proposed in the following.

[142] discussed the suitability of MOKA in including CBR knowledge, unlike previous methods.

As pointed out by [64] the main limitation of MOKA is that it does not provide any information on the way the KBE applications are actually integrated in the design process. In fact, no information on the implementation stage are given. The limitation of requirements to the design field also restrict the range of variables that can be used for satisfying the project requirements.

1.3.3 KNOMAD

As MOKA is intended for general applicability, it lacks of useful details for particular disciplines. In particular, fields as manufacturing would need to deep the *use* step of the MOKA methodology to allow the effective implementation of manufacturing considerations within the design process. Starting from these considerations, researchers from TU Delft University proposed the KNOMAD methodology [64]. The acronym KNOMAD summarises the steps followed by the method, listed below:

- **Knowledge capture** Declaration of the scope, objective(s) and assumptions of the concerned project or use-case Identification of knowledge explicit and tacit sources. Documentation of the captured knowledge for reuse in the following steps of the method

- **Normalisation** Quality control of the knowledge captured in the previous step. Normalisation of the acquired knowledge (according to method's criteria) for reuse in the next steps.

- **Organisation** The normalised knowledge is converted in ontologies for an object-oriented representation of information. The aim of this phase is to allow the retrieval of knowledge by different experts and its reuse in the following steps of KBS development.

- **Modeling** In this step, a model of products and processes is built. The Multi-Model Generator approach proposed by [155, 306]. In this approach he product models are generated combining the model parameters with knowledge formalised in previous steps. Authors underline the extensibility of this step to process parameters (unlike previous methods).

- **Analysis** The analysis modules are intended to calculate the effects induced by a design decision on a specific field. As an example, a manufacturing analysis module may calculate manufacturing costs, manufacturability estimates and manufacturing logistics. The integration of MOO in this step can also be obtained by introducing iterative modification of design parameters.

- **Delivery** The accepted design solutions outcoming from previous phases are delivered and implications are evaluated.

The KNOMAD methodology allows overcoming many of the limitations deriving from the use of previous methods. In particular, the inclusion of MOO admits the modelling of more realistic industrial problems. The representation of process-related parameters as ontologies also allows efficiently including the constraints and opportunities deriving from the production phase.

Despite this benefits, the linear structure of KNOMAD make it rigid to changes during product development. The actual match of aims outlined in the knowledge capture phase with benefits outlined in the delivery one is not ensured by the method's structure. The representation of elements does not provide indications on the techniques to be used for the final implementation of the KBS, which is let to operator's experience. The high level of details used for ontologies poses some constraints to the implementation of the solution, that may need to be modified in order to make it feasible.

1.3.4 Manufacturing-oriented methodologies

According to considerations exposed above, the general methods for KBS development lack to address important peculiar aspects related to production engineering. Therefore, specific studies on methods for developing Knowledge Based Systems for Manufacturing (KBSM) have been proposed.

Even if a wide literature on Agent-Based and Intelligent Systems in manufacturing can be found [200, 360], few methodological works have been proposed. In the last years (i.e. during the development of the present research) some approaches to the description of manufacturing ontologies and the analysis of system failure have been proposed.

More in detail, an analysis of the semantic representation of manufacturing systems have been proposed by [208], pointing out the benefits and limitations of different languages when applied to the modelling of manufacturing ontologies. This work also defined some basic requirements in the representation of manufacturing ontologies.

An ontology-based failure analysis in manufacturing field has been proposed by [53]. The method stands on representing entities and their connections in a web-based system that can be later investigated by human experts to find out the possible causes of failure and proposing solutions.

In [37] a method for diagnosis of manufacturing-induces defects is presented; the approach is based on organising process ontologies within a BNN representing the manufacturing flow. The main difficulty in the implementation of this approach derives from the need of a database for training of the system and network configuration.

An architecture for agent-based manufacturing systems named CASOA has been recently presented in [282]. This architecture manage organisational aspects of the production by means of four types of agents, that are

- **Product Agents** representing the product to be manufactured; this agent is connected to others by means of communication tools.
- **Machining Agents** perform machining and storing of operations, referring to machine tools, testing equipments and others.
- **Conveying agents** The conveying agents can transport the product agent from current location to the destination, referring to conveyor belts, auto guided vehicles or other transportation equipment.
- **Suggestion Agents** The suggestion agent represents the software component on the cloud which is responsible for processing orders and generating scheduling suggestions.

A cloud-assisted knowledge-base is used to manage relations among these agents.

1.4 Conclusions

The present chapter provides an overview on the scenario of KBES applied to manufacturing. The analysis deeps each technological field in order to point out the goals and methods of the corresponding KBESMs.

It emerges that both CBR and RBR are widely applied to the most various problems. The overview also shows the influence of specific requirements on features of the solution. This variety makes impossible to find a structure or method common to investigated systems.

In the last part of the chapter, the main methodologies for the design and implementation of KBES are summarised. The rigidity of these approaches seems to not match the peculiar problems faced by systems in the literature review.

Main benefits and limits of existing methodologies are underlined. These pros and cons will be taken into account within the next chapter during the design of a flexible methodology that aims to fit needs of KBESM design.

Chapter 2

A method for the design of Knowledge-Based Systems for Manufacturing

2.1 Introduction

Observing the literature review in 1.2 it is possible to notice how the definition of KBESM includes a number of applications with different scopes, users and methodologies. The features of a knowledge-based systems depend on several different factors, including:

- The field of application;
- The expected user;
- The desired level of automation;
- The resources available for programming the system (in terms of time, money and operators);
- The available equipment;
- The expected lifespan of the system.

All these factors contributes to determine the details of system implementation, that have thus to be defined according to the specific case. Nevertheless, the implementation of KBSs for industrial manufacturing is characterised by specific requirements that are transversal to different applications.

As described in 1.3, general methods for the design of KBSs show some limitations when applied to the manufacturing field as they do not take into account the characteristic requirements of this field. On the other hand, a general approach to developing KBESMs must allow including the wide range of techniques and applications emerging in 1. To efficiently aid the development, the method has also to include information useful to the detailed design and implementation phases of the system.

Furthermore, it has been discussed how the adoption of complicated methodologies may require an excessive effort by the company, thus precluding the use by Small and Medium Enterprises (SMEs).

The requirements to be satisfied during the definition of a general approach can be summarised as follows:

- Applicability to different scopes;
- Applicability to different manufacturing technologies;
- Possibility to include different rule-based and case-based techniques;
- Guidelines about implementation phase;
- Easiness of use.

In the present chapter, an approach to the development of KBMSs is proposed. Conceptual tools to be used since the very first stage of the KBESM development are given in order to ensure coherence of the outlined framework. The presented method is intended to be used also by low-experienced users, enlarging the collaboration among experts and, as a consequence, the batch of knowledge that can be included in the system.

The high-level definition of entities in the system makes it suitable for the application to deeply different technologies and techniques. Nevertheless, the definition of attributes for different entities allows assisting the implementation phase by defining the set of suitable techniques. A loop structure of the method is adopted in order to allow iterative refinement, modification and rethinking of the elements and their relations.

The method is divided in three steps, that are:

- **Applicability definition**, where the boundaries of the system are defined at the highest level. The assumptions made in this phase lay the foundations for next development and must not be modified.
- **Conceptual design** This phase is the core of the method and aims to collect all the relevant aspects of the KBESM development. During this phase the ontologies of the

system are defined and characterized according to the application. Relation among entities are also clarified and organised.

- **Design refinement** The Conceptual design emerging from the previous phase is optimised iteratively to include new considerations and solve emerging issues. This phase can be continued during the detailed design of the KBESM .

In the following, these phases will be described in order to provide methodological guidelines for the development of KBMSs. The proposed method will be then applied in following chapters for the design of different systems, in order to point out its makings.

2.2 Mapping applicability of Knowledge Based Systems for Manufacturing

The first step for the design of a KBESM is the definition of the expected applicability of the system. In particular, the systems are classified basing on the intended function and the level of knowledge of the expected user.

2.2.1 Process-Product plane

The manufacturing of a product is the combination of two main fields, i.e. the design of the product and the technologies adopted for its transformation. Therefore,in order to reach a certain feature of the final product, the expert has to operate on its design specification and/or the processing conditions. In real-case scenarios, the expert is usually not allowed freely modifying all the aspects of the design and process.
For example, the KBESM s presented in Chapt. 1 act on a fixed number of variables (input level) in order to reach a given aim in the product (or production) features (output level). These variables can be found in the design of the product or in the design of the process.
In particular, it is possible to distinguish between systems used for the optimisation of a specific product and others that can be applied to different families of products. Moreover, some KBESM are designed to allow the selection of the technological process between different options, while others are restricted to a specific technology. Accordingly, the applicability plane is defined as in Fig. 2.1.

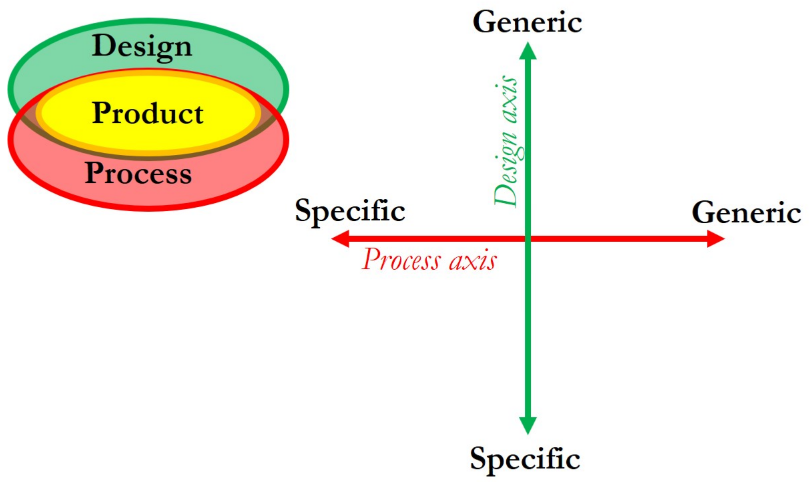

Fig. 2.1 Process-product plane

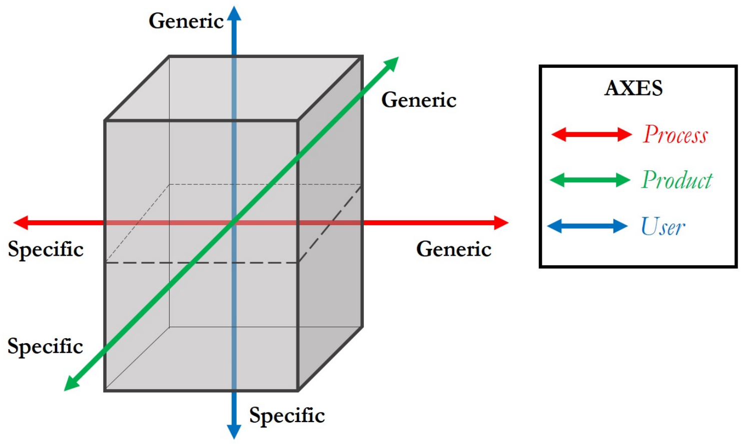

Fig. 2.2 KBMS space

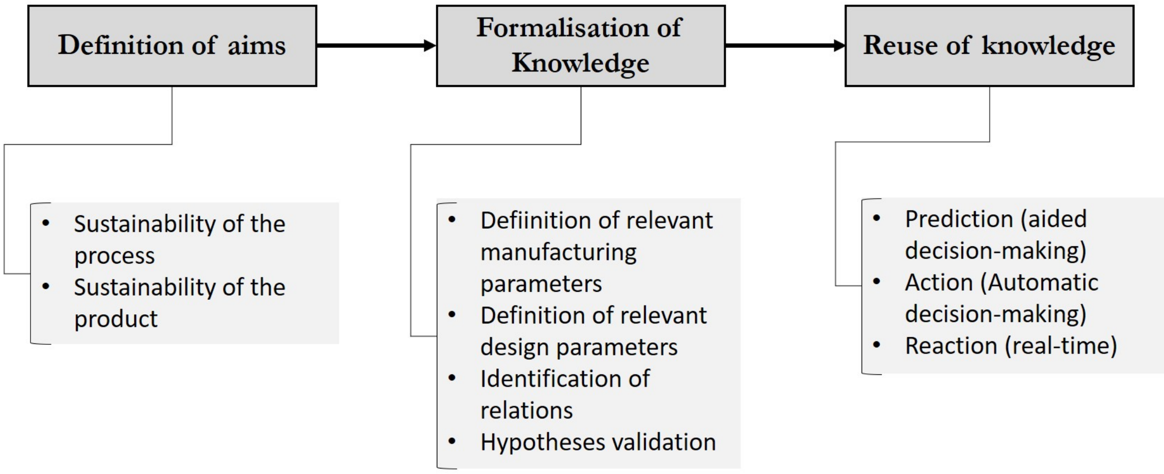

Fig. 2.3 Logical sequence for the design of KBMS

2.2.2 User axis

KBMSs are intended to aid humans in extracting, collecting, organising and reusing knowledge related to industrial production. Therefore, each system has a user, which can be more or less evident depending on the degree of automation of the KBS.

The definition of the expected user is thus fundamental since the very first step of the KBESM design. In particular, the level of knowledge of the human user interacting with the system must be clear during the whole design process. In fact, looking to the application in Chapt. 1, it can be observed how the users of the introduced systems can differ in terms of expertise, role and responsibility in the process chain. Higher is the amount of requirements on the user, lower is the applicability of the system and vice versa. Therefore, the map of KBESM applicability is completed by means of the user axis, as represented in Fig. 2.2.

2.3 Design flow

Once the field of applicability has been defined, the design phase of the KBMS begins. Fig.2.3 summarises the main phases in the design of an intelligent system for manufacturing.

The starting point is the definition of aims, i.e. the objective to be addressed by using the KBMS. These aims must be searched in two main areas: the quality of the product and the sustainability of the process. The quality of the product deals with the features of the result of the production cycle and is directly related to the satisfaction of the user. The sustainability of the process concerns the economic, environmental and societal impact related to the transformation stage. As it will be described in the following, also the quality of the product can be considered as a sustainability aim in the usage phase.

Once the goals to be achieved have been defined, it is necessary to clarify, formalise and organise the relevant knowledge, i.e. all the information that can be used to achieve the imposed aims. More in detail, it is necessary to highlight which parameters of the manufacturing process and/or product design are significant for the scope and whether they can be directly or indirectly modified within the KBESM .
The connection between such parameters and the predefined objectives must be clearly pointed out. Furthermore, it is necessary to identify the relations occurring among the selected parameters. In this phase some hypotheses about the role and relations of different parameters can be made; these relations must be then tested and validated before of developing the system.
As it will be evident in the following, the formalisation of knowledge is the most important and demanding task in the design of KBMS. In the following, an analytical method is proposed to support this phase.
Finally, the knowledge extracted and organised has to be reused to aid the production. According to this scope, the methods for the application of the KB system must be defined and implemented. This can be made in different ways, basing on the level of automation and the responsive time of the system. In particular, the knowledge can be used to make some predictions about the fulfilment of imposed aims; this advices can be then used by a human user to formulate decisions on the process and product variables. This case will be referred in the following as *Aided Decision Making*. The reuse of this information can be also automated by means of an intelligent system, that completes the decision-making process providing a final solution to the end user. This case will be named *Automatic Decision Making* . When the automatic decision making is based on live acquired data and performed within the cycle time of the process, the system will be indicated as *real time*. These systems usually integrate some actuators to modify parameters the production without the need of human interaction.

In the following section, a systematic approach to these phases will be proposed.

2.4 Matrix Objective-Descriptors-Inputs-Actions

In the present section, a systematic approach to the design of KBESM is proposed. The methodological framework is inspired by methods for the design of industrial products such as [94] and Quality Function Deployment (QFD) [44, 11]. Some aspects of knowledge management proposed by works in Chapt. 1.3 have also been included. In particular, the extension to MOO problems (characteristic of manufacturing field) is guaranteed. Furthermore, a loop structure of the method is used to allow the iterative refinement of the system.

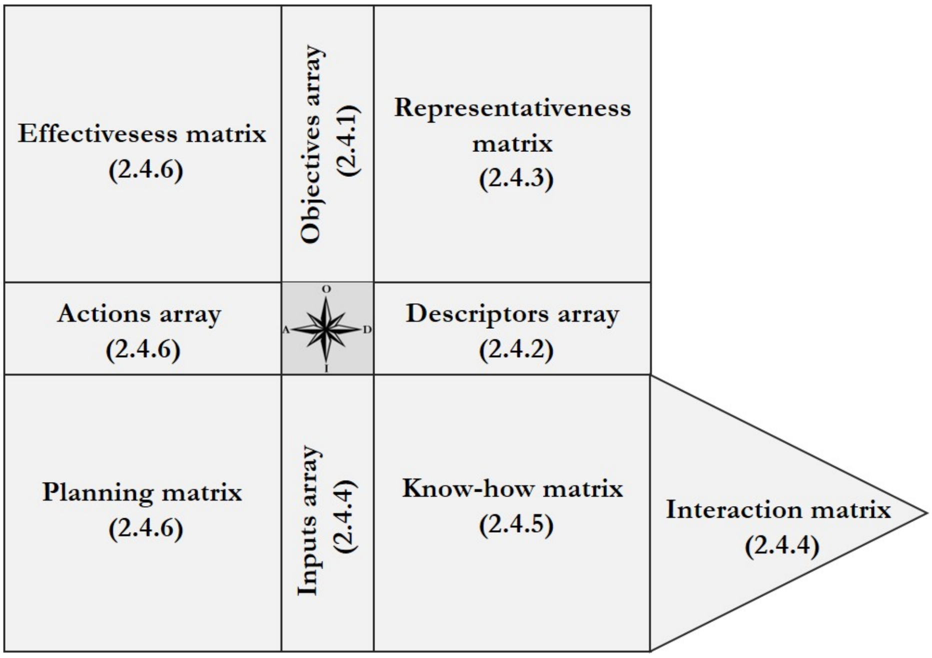

Fig. 2.4 Schematical representation of the Matrix Objective-Descriptors-Inputs-Actions (MODIA)

The central element of the proposed approach is the Matrix Objective-Descriptors-Inputs-Actions (MODIA), schematically represented in Fig. 2.4.

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

In the following, the process of creating the MODIA during design of KBESM will be presented and the different part of the matrix will be described. In the actual design of a KBESM, several modifications to the previous steps may be iteratively performed to refine the design of the system.

2.4.1 Objectives array

According to what exposed in 2.3, the first step in the design of a KBESM is the definition of objectives, i.e. of the aims to be fulfilled by means of the system. The Objective Array (OA) is a list of the objectives together with their most important features

The aims of the production have to be searched in two main fields, that are the sustainability of the process and the sustainability of the product. More in detail, sustainability of the process concerns every stage preceding the delivery of the final product, while the sustainability of the product refers to the rest of the Life Cycle (LC). Fig. 2.5 provides a schematic

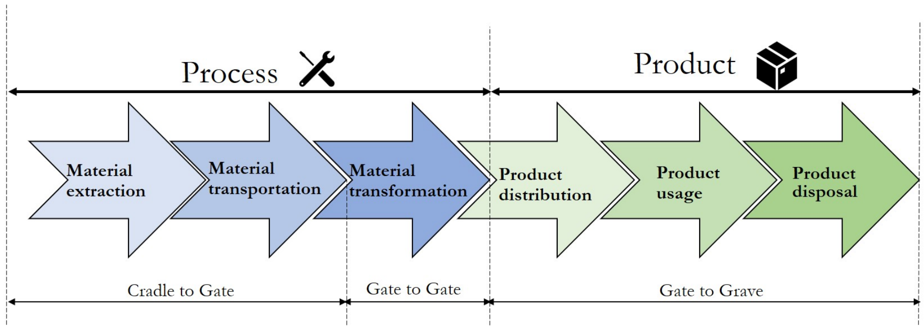

Fig. 2.5 Process and project phases in the product Life Cycle

representation on the timeline of the product. Fig. 2.5 also points out the correspondence with the Cradle-to-Gate (C2G), Gate-to-Gate (G2G) and Gate-to-Grave (G2Gr) phases of the LC as defined in ISO 14040:2006 and 104044:2018 [215, 216].

Nowadays, the Triple Bottom Line (TBL) [128] is commonly accepted for the classification of sustainability aspects. According to this theory, sustainability can be divided in three main branches, i.e.:

- Economic Sustainability (EcS);
- Environmental Sustainability (EnS);
- Social Sustainability (SoS).

Fig. 2.6 gives a schematic representation of the TBL. To reach the actual sustainability of the process or product, satisfactory results must be achieved in all the three areas. Nevertheless, each of the objectives can be focused on one or more of these fields. It is worth noticing how all the objective 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 in which stage (or stages) of the LC and in which field (or fields) of sustainability it is expected to give benefits. These information are reported next to the name of the objective in the OA, as shown in Fig 2.7. As an example, the Objective 1 in Fig. 2.7 is expected to give benefits on both Environmental and Economic sustainability of the product, i.e. in the Cradle-to-Gate phases of the LC.

It is also possible, during this phase, to assign a weight to each objective, representing its relative importance for the system. This has to be done by taking into account the attributes defined above (i.e. stages and fields of improvement).

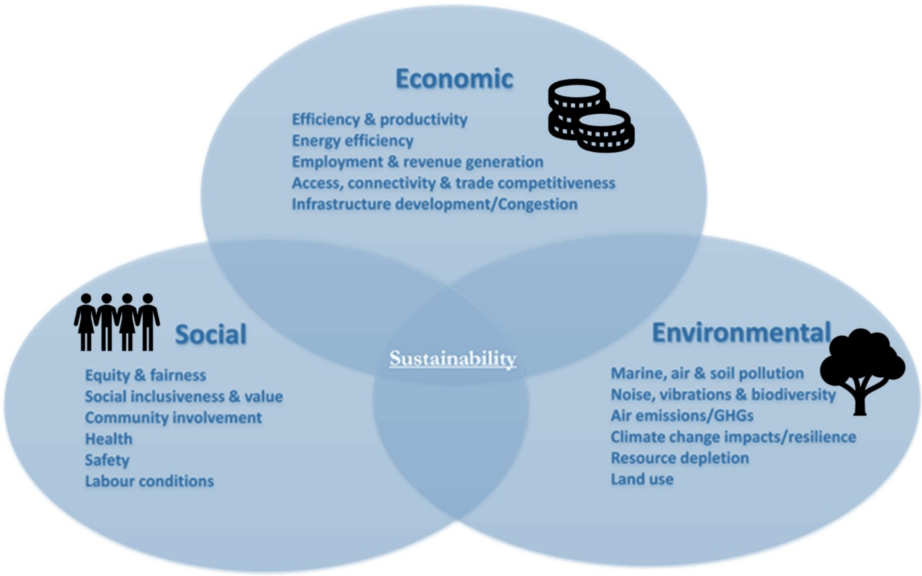

Fig. 2.6 Schematisation of the Triple Bottom Line (TBL)

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

Fig. 2.7 Example of Objectives Array (OA)

2.4.2 Descriptors array

To verify the effectiveness of the KBESM , at least one descriptor must be defined for each aim. A descriptor is thus here defined as an attribute able to provide information on the fulfilment of one or more objectives of the KBESM .
Descriptors are here described using four classifications, i.e.:

- Type;
- Source;
- Measurement;
- Tangibility.

As different kind of attributes can be used as descriptors, the type attribute distinguish their nature as one of the following:

- *Numeric (Nmr)*;
- *Numerable (Nmrb)* ;
- *Boolean (Bool)*;
- *Categorical (Ctgr)*;
- *Qualitative (Qltv)*.

A *numeric* descriptor is an attribute expressed by means of a natural, integer, rational, real or complex number. A *numerable* attribute is not intrinsically numeric, but can be converted to a number by means of a correspondence (as an example using marks). *Boolean* refers to logic attribute whose value can be true or false. When an attribute is defined by means of univocal labels, it is classified as *categorical*. The *qualitative* type is used for categories which are not sharply defined and admit intersection of sets; FL is usually adopted to deal with this kind of attributes.
The way these values are obtained leads to the definition of measurement technique, that can be:

- *Direct (Dr)*, when the attribute is directly observable and measurable;
- *Indirect (Indr)*, when the value is derived from the observation of related attributes.

This distinction is particularly relevant because, in the case of an Indr descriptor, it is necessary to ensure that all the related Dr attributes necessary to its evaluation are included in the set of descriptors.

A further classification of is made considering the source of descriptors. In particular,two type of sources are distinguished, i.e.:

- *Virtual (Vr)*, when the attribute is measured in a digital representation of the process or product
- *Physical (Phy)*, when the attribute is obtained by measuring on ore more physical quantities.

It is worth mentioning how these classifications can, in general, coexist when it is possible to derive the same attribute in the virtual or physical environment. Nevertheless, as the techniques for measuring the attribute in the two fields are deeply different, it is appropriate to make a sharp distinction during the design of KBESM .
Finally, it is possible to distinguish between:

- *Tangible (Tg)*
- *Intangible (Intg)*

descriptors. Different sub-classifications of intangible attributes and methods for their measurement can be found in literature [57, 102].

Once all the four classifications of each descriptor have been made, the Descriptors Array (DA) can be built; an example is shown in Fig. 2.8.

Descriptor 1				Descriptor 2				Descriptor 3				Descriptor 4				Descriptor 5				..			
Ctgr	Phy	Indr	Tgb	Ctgr	Phy	Dr	Tgb	Qltv	Vr	Indr	Intg	Nmr	Vr	Dr	Tgb	Nmr	Phy	Dr	Tgb				

Fig. 2.8 Example of Descriptors Array (DA)

2.4.3 Representativeness Matrix

As exposed in 2.4.2, each descriptor represents the fulfilment of at least one aim. However, more in general, a number of connections can exist between imposed aim and descriptors identified 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

Objective 1	G2Gr	EnS, EcS	8			5	
Objective 2	G2G	SoS					3
Objective 3	C2G, G2Gr	EnS, EcS, SoS	2		7		
Objective 4	G2Gr	EnS		8			1
Objective 5	G2G	EcS	6				
			Descriptor 1	**Descriptor 2**	**Descriptor 3**	**Descriptor 4**	**Descriptor 5**
			Ctgr, Phy, Indr, Tgb	Ctgr, Phy, Dr, Tgb	Qltv, Vr, Indr, Intg	Nmr, Vr, Dr, Tgb	Nmr, Phy, Dr, Tgb

Fig. 2.9 Example of Representativeness Matrix (RM)

$RM_{i,j}$ of the matrix is defined as the importance effectiveness of the j-th descriptor in determing the fulfilment of the i-th objective. An example is shown in Fig. 2.9.

The values in the RM have to be assigned by the designer of the system on the basis of previous knowledge and specific considerations. It is also possible to consult different experts for a more accurate determination of these values. In any case, a redefinition of RM elements can be operated in the next phases of the KBESM design on the basis of direct observation.

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

2.4.4 Inputs Array and Interaction Matrix

Inputs Array (IA) is a collection of the parameters affecting descriptors pointed out in 2.4.2. As in the case of descriptors, they are classified, according to the type, in numeric, numerable, boolean, categorical and qualitative.
As discussed in 2.3, the parameters of a KBESM have to be searched in the the process or product design. Accordingly, input parameters are classified as

- *Process (Proc)* parameters;
- *Design (Des)* parameters.

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 during its design.

Another fundamental distinction can be made basing on the chance to set inputs' values. 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)*, if it is possible to set the parameter at fixed intervals during the production (e.g. at the end of a cycle);
- *Steady (Std)*, when the value can be modified only before the whole production take place;
- *Read Only (RdOn)*, when the value of the parameters can not be modified directly, but only observed during the process .

As in the previous cases, the inputs parameters are collected in the IA together with their classifiers, as exemplified in Fig. 2.10.

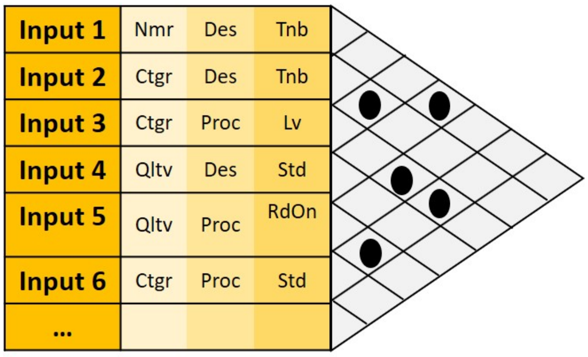

Fig. 2.10 Example of Inputs Array (IA) and Interaction Matrix (IM)

In the most general case, not all the parameters in Inputs Array are independent. Therefore, it is necessary to highlight which are the reciprocal influences between the inputs parameters. For this scope, a triangular matrix named Interaction Matrix (IM) is used. As shown in Fig. 2.10, a dot is used to mark non-independent pairs of input parameters.

2.4.5 Know-how Matrix

The Know-how Matrix (KM) is designed using descriptors from 2.4.2 as columns and inputs from 2.4.4 as rows. The generic cell $KM_{i,j}$ is then used to point out eventual correlation between the *i*-th input parameter and the *j*-th descriptor. In particular, three different kind of relations are distinguished, i.e.:

- Knowledge (Knw);
- Experience (Exp);
- Hypothesis (Hpt).

				Descriptor 1	Descriptor 2	Descriptor 3	Descriptor 4	Descriptor 5
				Ctgr, Phy, Indr, Tgb	Ctgr, Phy, Dr, Tgb	Qltv, Vr, Indr, Intg	Nmr, Vr, Dr, Tgb	Nmr, Phy, Dr, Tgb
Input 1	Nmr	Des	Tnb				Knw	
Input 2	Ctgr	Des	Tnb		Exp			
Input 3	Ctgr	Proc	Lv			Exp		Hpt
Input 4	Qltv	Des	Std		Hpt		Knw	
Input 5	Qltv	Proc	RdOn	Exp				
Input 6	Ctgr	Proc	Std					

Fig. 2.11 Example of Know-how Matrix (KM)

A relation is based on knowledge when it is defined by an explicit rule coming from a reliable source; demonstrated physical rules are an example of Knw relation. 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 a conjecture about the correlation between input and descriptor, the relation is defined as Hpt.
It is worth mentioning how the type of relations in the KM might be modified during the developing of the KBESM with a formalisation of the know-how. As an example, if an hypothesis is tested by means of 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. Fig. 2.11 shows an example of KM built using IA form 2.4.4 and DA from 2.4.2.

2.4.6 Actions Array, Planning Matrix and Effectiveness Matrix

At this point of the MODIA design, it is possible to define actions to be performed in order to fulfil the imposed aims. Actions are primarily classified basing on the agent, i.e. on the subject that performs the action. Such a classification distinguishes:

- Human (Hmn)
- Software (Sfw)
- Hybrid (Hbr)

Hmn actions are performed by the user of the KBESM or another human agent basing onto the information given by the KBESM . This kind of actions belong to the field of Aided Decision Making outlined in 2.3. The elaboration of information includes in the KBESM may also be performed by a software on the basis of specific rules and criteria: this is the

case of both Automatic Decision-Making and Real Time systems defined in 2.3. It is also possible to have actions performed conjunctively by a human and a software agent (Hbr). This is the case of interactive systems, in which a dialogue between the user and the software is established in order to reach the final solution.
As for the inputs in 2.4.4, a classifier is used to describe the response time of the action. The attributes adopted in 2.4.4 (with the only exception of *read-only*) are thus reused with analogous meanings:

- *Live (Lv)*, an action that can be performed and have an effect at any istant of the production;
- *Tunable (Tnb)*, an action that can be effectively performed at fixed moments of the production;
- *Steady (Std)*, if the action can be performed only before the production takes place.

The definition of actions is a fundamental aspect of the design of the KBESM , and it involves all the elements of the MODIA. For this reason, the remaining elements of the matrix, i.e. the Planning Matrix (PM) and the Effectiveness Matrix (EM), will be described in this section.

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 2.12. Inside the primary objective, one or more descriptors to be used as evaluators of the action must be defined. In the example of Fig. 2.12, Descr 2 is chosen as only descriptor for Act 1. The correspondent cell of the EM reports 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 semi colon is used to separate values in 2.12.

The columns of the KM corresponding to the selected descriptors are then explored to find cells, with non-empty values, i.e. inputs having a correlation with such descriptors; the same rows of the PM are filled with a "S" in correspondence with the column of the designed action. This notation means that such inputs are significant for the action. As an example, in Fig. 2.12 Inp 2 and Inp 4 are found to be significant for Act 1.

The "S" used in Fig. 2.12 is a temporary notation. In fact, the role of each input for the action must be defined. In particular, for a certain action, an input can be a

- *Variable (Var)*, when it can be modified by the action to change the fulfil the aim
- *Parameter (Par)*, when it can not be directly modified by the action.

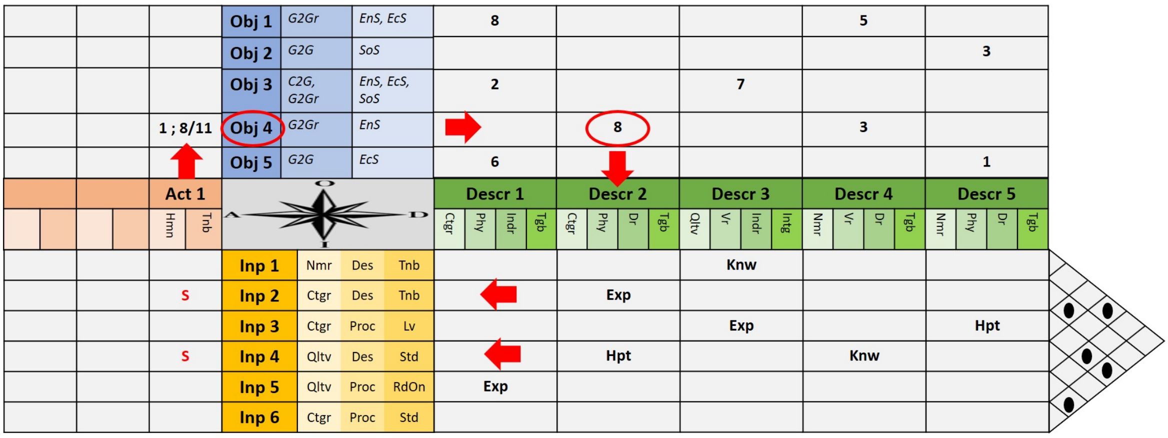

Fig. 2.12 Example of Action definition (part 1)

The role of each input has to be defined by the designer of the KBESM . During this phase, at least one significant input must be converted to Var.

The definition of variables and parameters is subject to some constraints deriving from 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 that Tnb inputs can not be used as variables of Lv actions, while Std inputs cannot be used for both Tnb and Lv ones.

When the role of significant parameters has been defined, it is necessary to enter in the interaction matrix (2.4.4) at each input marked as variable and assign an "S" in the PM to every interacting input. As an example, in Fig. 2.13 the Inp 4 has the role of variable for the Act 1. The interaction matrix shows points out a relation between this input and Inp 1, therefore an S is placed in the PM in correspondence to Act 1 and Inp 1. These phases have to be repeated iteratively until the role of Var or Par has been assigned to all the significant inputs of the action.

The adoption of IM in this phase is fundamental to ensure that no relevant parameters are omitted by the action. When input variables of the action are modified, further descriptors (and thus objectives) will be affected. To take into account this effect, the KM and RM must be used in order to properly modify the EM. An example is shown in Fig. 2.14: as 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, indicating 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. It is worth noticing how the influence of Inp 4 on Descr 4 leads to address both the descriptors (2;11/11) of the main Objective (Obj 4). Therefore, it

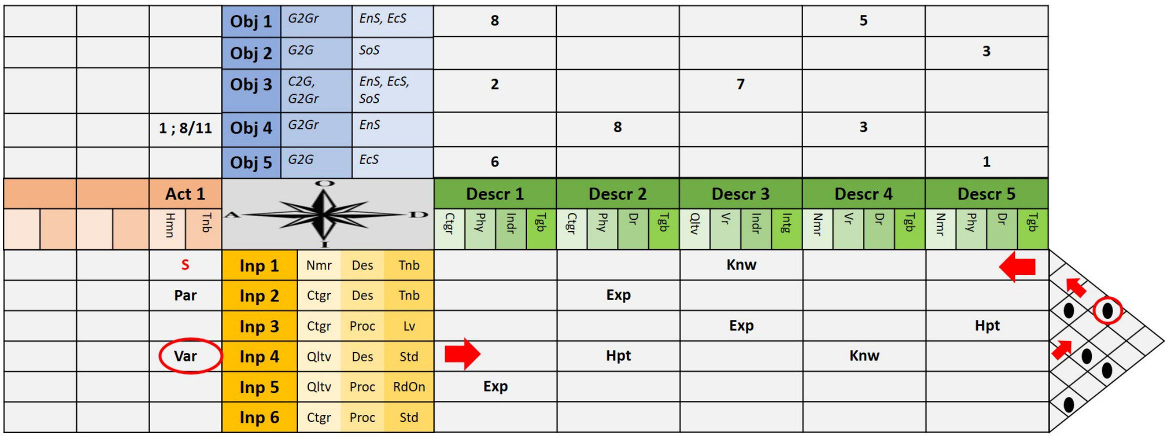

Fig. 2.13 Example of Action definition (part 2)

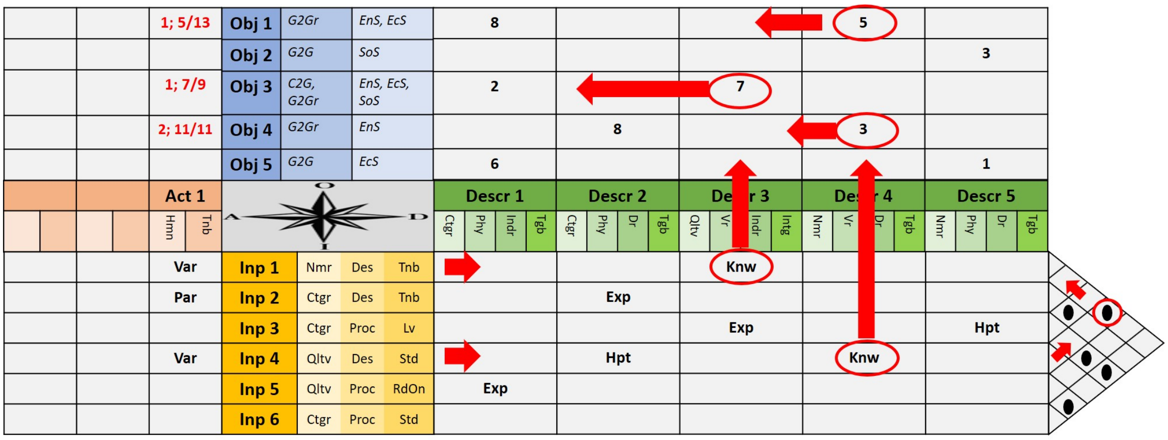

Fig. 2.14 Example of Action definition (part 3)

is convenient to choose the minimum number of descriptors for the main objective when starting to define an action; further descriptors can be eventually added in the following if the values in EM show a non-effective fulfilment of the aim.

2.4.7 Analysis of the matrix

After the design has been completed, a matrix as the one in Fig. 2.15 is obtained. The MODIA provides an overview on the design of the KBESM and can be used to point out several peculiar features. As mentioned above, this analysis can also be performed on an existing system.

A first analysis on the KBESM 's trend can be made observing the OA. In fact, the stages of the LC at which objectives aim tell how much the system is oriented to the process or to the product. In the same way, it is possible to understand which of the aspects of the TBL

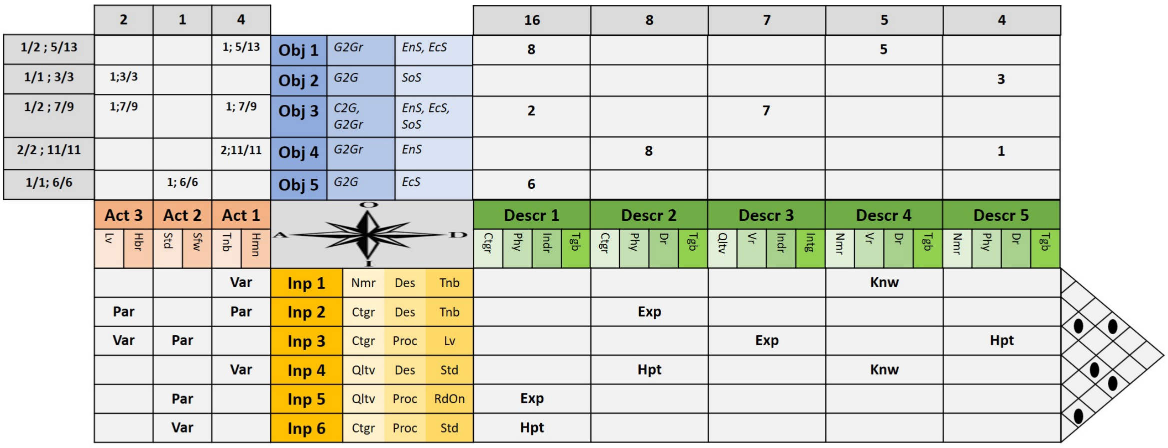

Fig. 2.15 Example of complete MODIA

are more addressed by the system. This analysis is fundamental in order to determine if the KBESM is actually in line with the mission behind its design.

The RM also offers an immediate glance on the role of the descriptors. In fact, the sum of values in each column (reported in Fig. 2.15) quantifies the influence of each descriptor on the entire KBESM .

The analysis of DA allows pointing out the percentage of descriptors that can be obtained in a virtual representation of the product. At the same time, the splitting between tangible and 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; this can be made 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 the input parameter in the decision-making. 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 have thus to be performed before than Tnb and Lv ones. A further order can be defined among actions with the same respone attribute by sorting columns of the AA (the PM and EM must be rearranged accordingly).

The distribution of Hmn, Sfw and Hbr attributes defines the degree of automation in the KBESM ; this information, together with the ordering of action, determine if and in which stages a human agent has to be present.

The sum of rows in the EM (shown in Fig. 2.15) allows understanding how much the proposed objectives can be satisfied in the designed system configuration. The sum must omit repetitions of the same descriptor in different actions.

The sum of the descriptors for each action, (i.e. of columns in EM, see Fig. 2.15) immediately distinguish 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 by means of the KM. As an example, when an action is carried out by human, one or more predictive models must be realised to aid the decision-making. Looking to the type of the 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 (readable in the IA) and the kind of knowledge (in the KM) aid to restrict the field of possible methods. For example, if a relation based on experience is given between one or more numerical inputs and a categorical descriptor, ANN and SVM are good candidates; if the descriptor is a Bool, also Logistic Regression (LR) can be considered.

Actions accomplished by software needs to pair at the prediction of descriptor a strategy to find optimal set of inputs. Also in this case, the KM can be used to restrict the field of methods. As an example, if the column of a certain descriptor in the KM has all Knw values, a RBR 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 iteratively modified several times during both the preliminary and detailed design of the system. While the design of the KBESM proceeds, further information can be added in the matrix (e.g. the methods adopted in different actions).

Several variants of the MODIA as presented here may be introduced. For example, a weight can be assigned to different objectives to distinguish their importance, or further classifications may be added to attributes. Nevertheless, the opportunity of having a complete overview on the KBESM offered by the method still remains valid.

Chapter 3

Plastic bottle moulding

3.1 Applicability definition

The KBESM presented in this chapter aims to aid the design and production of plastic bottles. The system is intended to be used in a preliminary phase of the product development in order to integrate in the design of the product manufacturing and usage requirements. The family of products is thus well-defined, nevertheless several product within this family will be managed by the system.

Different combinations of materials and processes will be investigated by the system in order to find out the optimal solution under a given set of requirements. In particular, the system has to manage the principal 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). These processes will be combined with industrial materials used for this family of products. Even if the details of the material will be provided by the user, the following families will have to be considered:

- Polyethylene (PE);
- Polyethylene Terephthalate (PET);
- Low Density Polyethylene (LDPE);
- High Density Polyethylene (HDPE);
- Polycarbonate (PC);
- Polypropylene (PP).

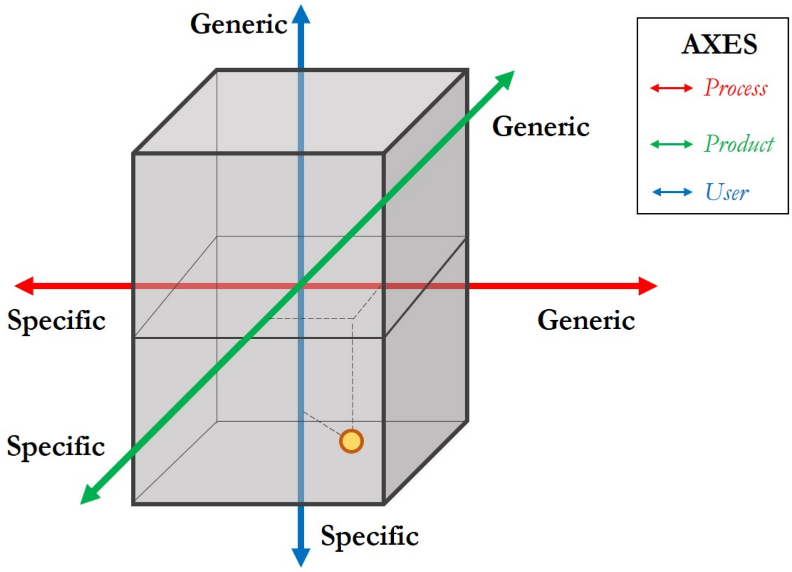

Fig. 3.1 Location in the applicability space of the KBESM for bottle moulding

The system is intended to aid the design phase of the product that precedes its industrial production. Accordingly, the user is supposed to be an industrial designer working in the field. This implies that a specific know-how is owned by the user.

The location of the KBESM in the applicability space can thus the represented as in Fig.3.1.

3.2 Conceptual design

As mentioned above, the mission of the present KBESM is to include in the design stage of plastic bottle the know-how related to both the process and usage of the product. This is made in order to automate repetitive tasks carried out by the designer and reduce the eventual issues in the manufacturing stage. Furthermore, the system intends to provide some considerations about the environmental impacts of the product, that is a key topic in the field of plastic bottles.

According to these general vision, six objectives are defined for the system, i.e.:

- *Aesthetic*, i.e. the look of the product. This objective focuses on the usage phase (G2Gr) and aims to make the product more appealing for the customer; this improves the satisfaction of the customer (SoS) and the market of the product (EcS);

- *Manufacturability*. This objective focuses on making the product easy to produce by means of blow moulding technique. This aspect is related in particular to EcS in the G2G phase;
- *Liquid transportation*, that is the main objective of the product in the usage phase (G2Gr). This deals with the amount of liquid contained by the bottle and its easiness of use. This objective aims to all the three elements of the TBL;
- *Ecology*. The ecology of the product is determined basing on its environmental impact, thus it deals with EnS in all the phases of the LC (cradle-to-grave) according to the criteria given by [215]. This objective is particularly sensitive for plastic packaging;
- *Transportability* That is the easiness of transportation of the product during its distribution phase (G2Gr). This reflects directly on EnS and EcS. Furthermore, as the last transportation is made by customers, SoS is also included;
- *Resistance*, i.e. the mechanical strength of the bottle when external forces are applied. This aspect affects the SoS and EcS of the product in the G2Gr phase, as it defines its possible usage.

In order to measure the relevant features of the system, the following descriptors can be identified:

- *Curvature of the surfaces*;
- *Height of the bottle* ;
- *Capability of the bottle* ;
- *Mass of the bottle* ;
- *Life Cycle Impact Assessment (LCIA) indicators*;
- *Bounding Box*, i.e. the dimensions of the minimum rectangular parallelepiped containing the bottle;
- *Maximum diameter* ;
- *Wall thickness*;
- *Projected area* in the opening direction of the mould.

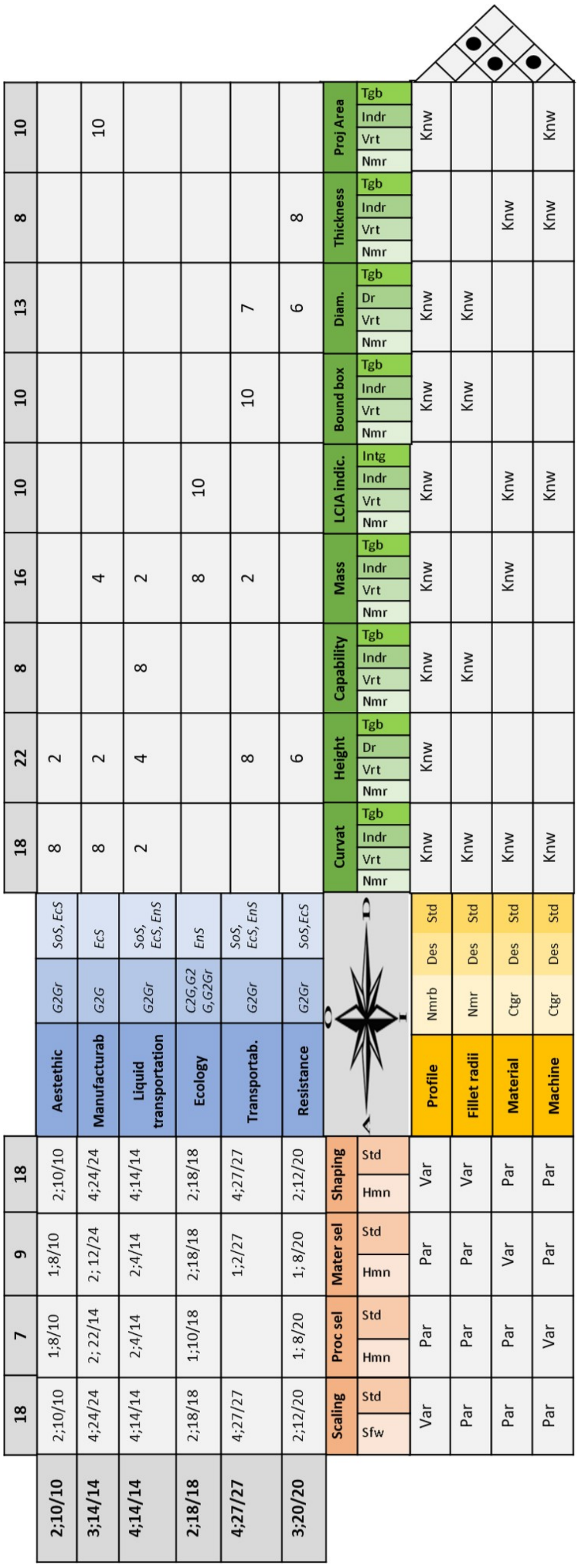

Fig. 3.2 MODIA of the KBESM for plastic bottles' moulding

The RM of MODIA in Fig. 3.2 summarises how this 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. 3.2 also shows the attributes of descriptors.

The designed inputs of the KBESM are:

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

In Fig. 3.2, the attributes of these inputs are given. As in can be noticed in the KM, all the relations are based on knowledge; this suggests how a RBR approach will be suitable in the detailed design phase.

The first designed action is the definition of the bottle shape. This activity will be performed by the user of the system, i.e. the product designer, basing on his own skills and know-how. This action takes as variables the profile of the bottle and the radii of the fillets; the material and machine used for the production are parameters that defines the constraints of the shape design. As it can be seen in the EM, this action influences a number of 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. It is worth mentioning how these are the solutions proposed in the design phase, that might be slightly different from the actual ones due to emerging aspects in te detailed design of the product.

Finally, the style geometry defined by the designer needs to be refined in order to meet requirements imposed by the objectives. This action is delegated at the software, that will use as variable the shape defined by the designer. Therefore, this action must follow the previous ones and its column is the EM is similar to the one of shaping.

All the inputs (and consequently actions) are Std: this means that the KBESM will be usable only before the production takes place. Furthermore, it is possible to notice how the system will be design-driven, as all the input variables are in the design of the product (Des). This is in line with the initially declared expected user.

The KBESM is oriented to both the production and design, presenting objectives in all the phases of the LC. The sum of rows in the EM points out how the designed configuration of the system enables to efficiently act on all the descriptors and address the initial objective.

3.3 Detailed design

The KBESM is designed as an High Level Computer Aided Design template (HLCAD). The main features of this kind of systems are:

- Automate the routine tasks, thus reducing the modelling time;
- Include requirements on the product features;
- Analyse the model and provide reports to be used during decision-making.

For these scopes, a plug-in for a commercial CAD software (i.e. PTC Creo) has been developed. This approach aims to integrate process and functional requirements in the usual working environment of the product designer. A Graphical User Interface (GUI) will be thus added to the CAD environment to allow the input of product and process parameters. For this scope, Visual Basic (VB) language and Creo's Application Program Interface (API) were used.

The actions designed in 3.2 will be implemented in the following order:

- Input of design requirements and sketch of the profiles;
- Adapting the solution to the design requirements;
- Analyse the solutions for different combinations of materials and machines;
- Choose the optimal solution basing on the information provided by the system.

The first and last point will be carried out by the designer, while the remaining two will be automated within the KBSM.

3.3.1 Representation of the product

A huge number of different shapes can be used to design a bottle for the market; accordingly, several different strategies may be used for CAD representation of the product [182]. In order to describe the model through a list of parameters (according to the idea of Nmrb input), a preliminary restriction has to be done, defining the sequence of features of the general model.

A basic axisymmetric geometry can be obtained through the rotation of shape in Fig. 3.3. This is a simplification of the shapes commonly adopted; further details on part geometries can be easily integrated in the proposed framework.

In this very first model a flat base is adopted; a bottom straight part (B) is joined to it using a circular fillet (A). The rotational shape of the bottle is then defined using a Non-Uniform

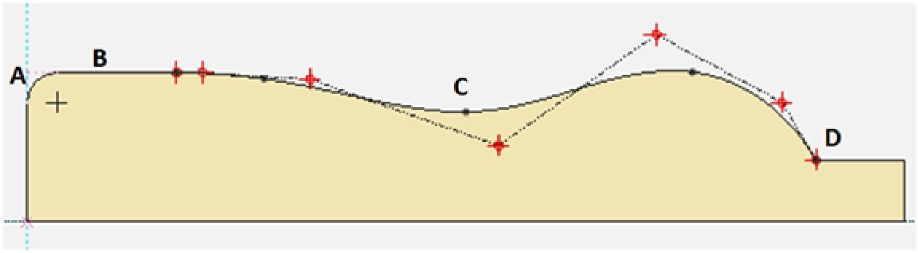

Fig. 3.3 Basic revolving profile used for modeling of bottle

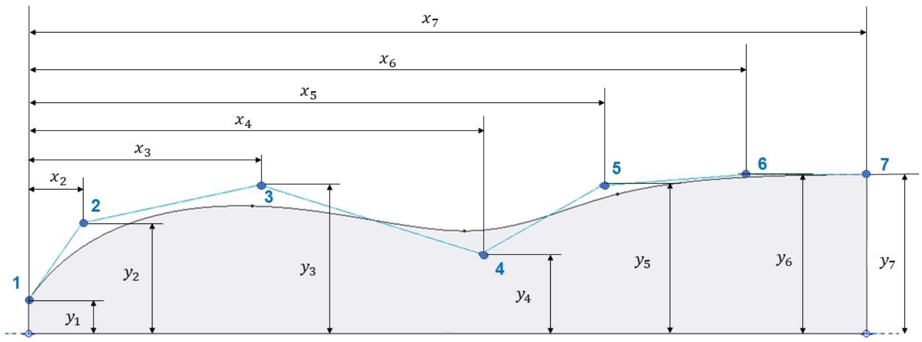

Fig. 3.4 NURBS curve used for the bottle modelling

Rational Basis Spline (NURBS) curve [C], constrained to be tangent to the straight line (B) in its left part (with reference to Fig. 3.3). Neck is also represented as a straight line (D) in this first draft.

A circular fillet is adopted to round the conjunction between the neck and the spline. Once the diameter is defined, the detailed features of the neck (e.g. the geometry of threads) are determined by using standards related to bottle closures and preforms [33].

In this very basic configuration, the user-defined parameters for the shape are limited to the neck diameter, the spline shape, the height of the bottom part and the radii of top and bottom fillets.

The diameter of the neck is a very important functional requirement; once the pre-form has been chosen, all the geometrical parameters of the neck are assigned according to the standard employed. In the basic sample in Fig. 3.3, the NURBS curve has been modelled using 5 knots and 7 control points and it is tangent to the bottom cylindrical part of the bottle. It can be noticed how this very simple general model allows representing a huge range of existing bottles. The NURBS, once the knots array has been defined, can be described through the coordinates x_i ,y_i of its N control points (N=7 in the example) with reference to a datum coordinates system. Fig. 3.4 shows the parametric representation of the NURBS curve.

In order to describe the shape of the NURBS independently from absolute dimensions of the curve (that will be managed by the automated system), the coordinates of the control points can be normalised using the abscissa of the bottom point, leading to the adimensional coordinates a_i' and b_i' in Eq. 3.1 and 3.2.

$$a_i' = \frac{x_i}{x_N} \tag{3.1}$$

$$b_i' = \frac{y_i}{x_N} \tag{3.2}$$

As definition, a_N and b_N' will be equal to one. Furthermore, in order to ensure the tangency of the NURBS to the cylindrical bottom part, y_{N-1} must be equal to y_N, that is to say b_{N-1}' is equal to b_N' .

Finally, according to the profile in Fig. 3.3, the y coordinate of the first point is defined as in Eq. 3.3

$$y_1 = \frac{D_n k}{2} \tag{3.3}$$

where $D_n k$ is the neck diameter imposed by the designer. The value b_i' in Eq. 3.2 is thus replaced by b_i as defined in Eq. 3.4. The a_i coefficient is unchanged and equal to a_i' .

$$b_i = \frac{y_i - y_1}{x_N} \tag{3.4}$$

Using a multiplication factor on relative parameters a_i and b_i, it is possible to scale the NURBS profile maintaining the shape. As shaping is a Hmn action (see Fig. 4.2), the definition of the NURBS is made by the user by dragging the control points in Fig. 3.4 within the GUI. According to the mentioned constraints, the point 1 in Fig. 3.4 will be anchored, while only one between 6 and 7 will me movable in y-direction.

Within the GUI, the designer will also define the height of the bottom part (B in Fig. 3.3), the diameter neck D_{nk} and the radii of the bottom and top fillets.

To obtain the bottle shape, the revolution of shape in Fig. 3.3 must be shelled with a certain thickness. This parameter is not directly set by the user, but it is assigned by the KBESM basing on RBR, as it will be clear in the following. It is also worth mentioning how the actual value of the bottle thickness can differ from the nominal one depending on manufacturing conditions [135].

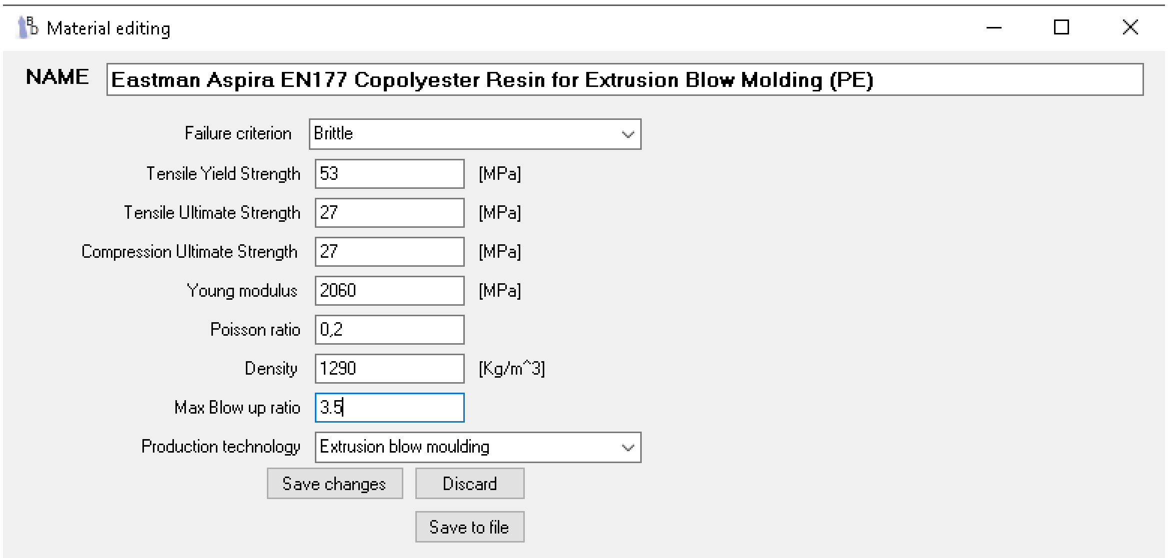

Fig. 3.5 Graphical User Interface for the definition of plastic materials

3.3.2 Representation of the material

In order to efficiently evaluate the manufacturing-induced constraints of the design, an Object Oriented Programing (OOP) representation of the material is needed.

To make the application usable in a real industrial design, the opportunity to set the characteristics of a commercial material is given to the user by means of the GUI shown in Fig. 3.5.

The commercial name of the material is given in the textbox at the top of the form. The family of the polymer reported in parenthesis at the end of the string (PE in the example of Fig. 3.5) is read as an attribute by the KBSM.

The user is also allowed setting the failure criterion to be used for the resistance verification of the material; in particular, this attribute can be:

- Brittle
- Ductile
- Unspecified

In the case of unspecified failure criterion, the more conservative calculation of the two will be used by the system for the calculation.

The nominal mechanical properties of the material are assigned by typing in the values (in MPa) of yield tensile strength, ultimate tensile strength, ultimate compression strength and the modulus of elasticity. The value of Poisson ratio by default is set to 0.2 (that is a

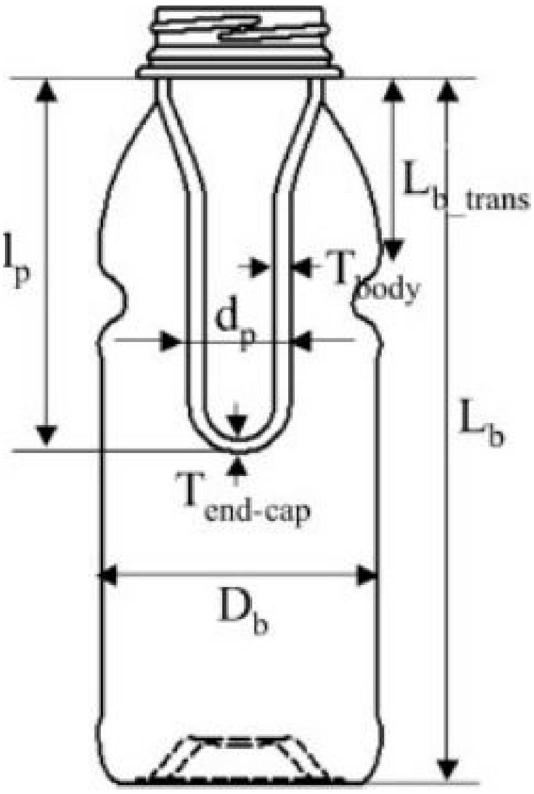

Fig. 3.6 Schematically representation of some characteristic dimensions of the preform and product [290]

characteristic value for the investigated families of polymers) and can be modified by the user if more accurate data are available. This values will be used by the KBESM for the calculation and verification of product's resistance.

The density of the material is also required in order to enable the calculation of mass properties of the product.

In blow moulding processes the final geometry is obtained by stretching an initial using pressured air. Fig. 3.6 [290] shows the example of stretch blow moulding, where the initial shape is an injection moulded preform.

The hoop ratio (λ_h) is defined as the ratio between the outsider diameter of the product (D_b) and the outside diameter of the preform (d_p). The axial ratio (λ_{ax}) is defined as the ratio of the bottle height diameter of the product (L_b) to the height of the preform (L_p). The product of hoop and axial ratios goes under the name of Blow Up Ratio (BUR) and is a characteristic measure of the total stretched ratio undergone by the material during the blowing process [290]. The BUR can be thus calculated as in 3.5

$$BUR = \lambda_h \lambda_{ax} = \frac{D_b}{D_p}\frac{L_b}{L_p} \tag{3.5}$$

Analogous calculation can be applied in the case of injection blow moulding and extrusion blow moulding by considering the initial shape blown used for blowing.

The BUR is a fundamental parameter for blowing processes as it determines the orientation of material molecules and, in turn, the physical and mechanical properties of the final product. To avoid the polymer over-stretching and delamination, the BUR can not exceed a given maximum value [290, 159]. Therefore, the GUI of Fig. 3.5 allows defining the maximum admissible BUR for the material. As it will be clear in the following, this value will be used, together with other inputs of the system, to determine the actual maximum BUR of the product.

Finally, the user is allowed defining whether the polymer must be used only for a specific blow moulding process (injection, stretch or extrusion blow moulding) due to its supplying state. If not specified, the material is considered to be suitable for all the three variants of the process.

3.3.3 Representation of the machine

As in the case of the material, the machine must be represented in the OOP to include its specifics in the KBSM. Fig. 3.7 shows the GUI used for equipment definition.

The machine is defined by the name of the producer and model. According to its technical limitations and/or to the choices of the company, the usage of the machine can be limited to a certain family of polymers. Accordingly, the user has to specify which families are suitable for usage on the equipment, as shown in Fig. 3.7.

The clamping force is defined as the maximum force that can be operated by the machine on the mould to balance the internal pressure and prevent opening [159]. This is a peculiar feature of the equipment that has to be defined by the user; ton is adopted as unit of measure according to industrial normal practice in this field.

The average power consumption (in kW) and the maximum working pressure (in bar) are characteristic technical data reported in the technical data sheet of the machine and have to be included in its definition. This information will be used for following evaluation of the performance of the production.

The minimum and maximum processable diameter and volume define the range of applicability of the equipment.

The bottom part of the GUI is different according to the blowing process adopted. In Fig. 3.7, an example of injection blow moulding equipment is shown. Different configurations

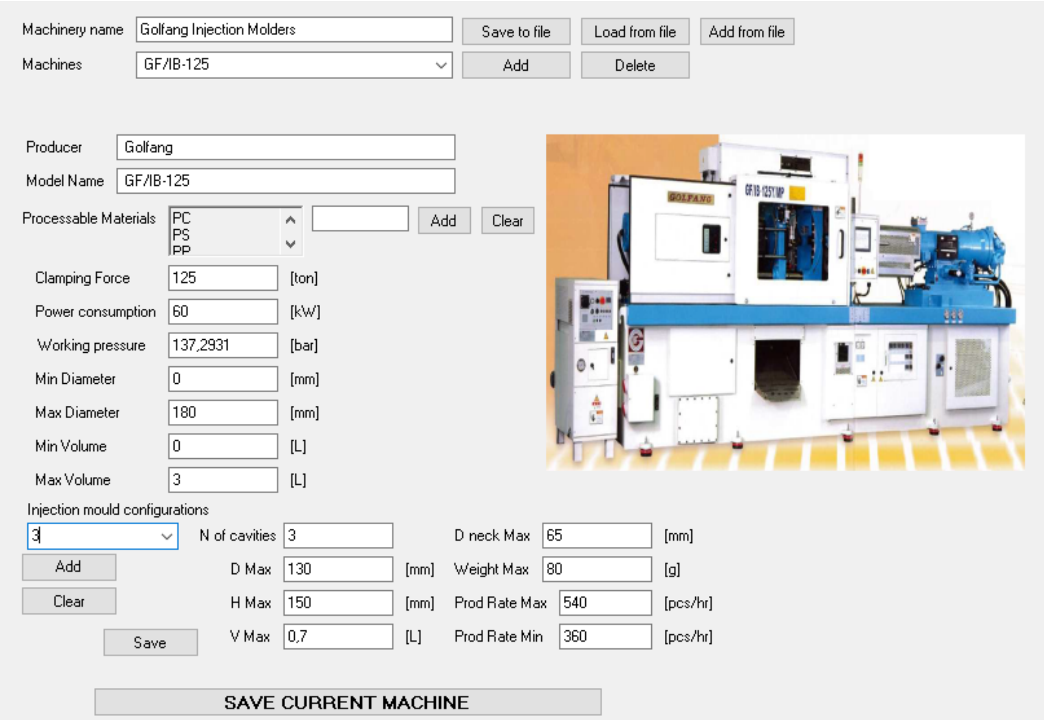

Fig. 3.7 Graphical User Interface for the definition of injection blow moulding equipment

of the mould can be set for the same machine, as shown in Fig. 3.7. In particular, moulds with a different number of cavities can be adopted. For each configuration, the maximum admissible diameter of the neck has to be defined. As well, the limit value of the product diameter and height are set in the panel. The definition of the manufacturing constraints also includes the maximum weight of material that can be injectes in the mould and the maximum volume of air that can be blown to maintain an adequate pressure. Even if these values may slightly vary according to the specific geometry of cavities, preliminary indications are usually provided by the producer.

Finally, the minimum and maximum production rates (expressed in parts per hour) are important data provided in the technical data sheet that determine the productivity of the machine under the given configuration.

Analogous information is used to define configurations of extrusion blow moulding and stretch blow moulding machines, as shown in Fig. 3.8 and 3.9, respectively.

As can be seen in Fig. 3.8, the definition of equipment for extrusion blow moulding requires an additional information, that is the maximum extrusion rate of material in kg/hr. The D1 and D2 diameters refer to the maximum dimensions in the opening direction of the mould and in the orthogonal one.

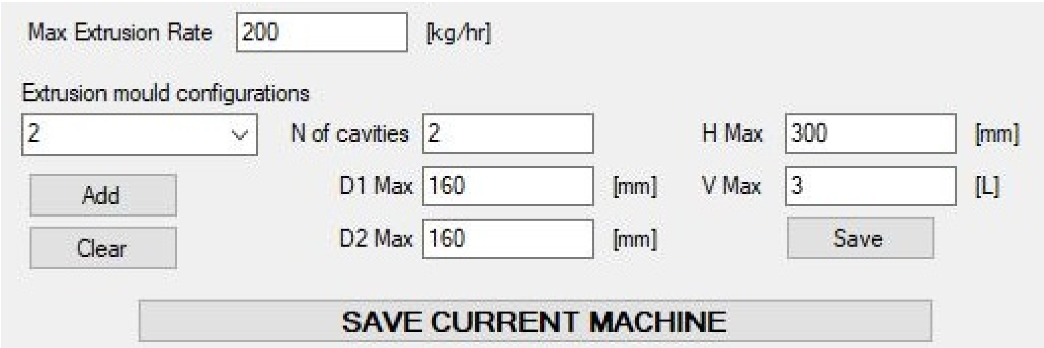

Fig. 3.8 Detail of Graphical User Interface for the definition of extrusion blow moulding equipment

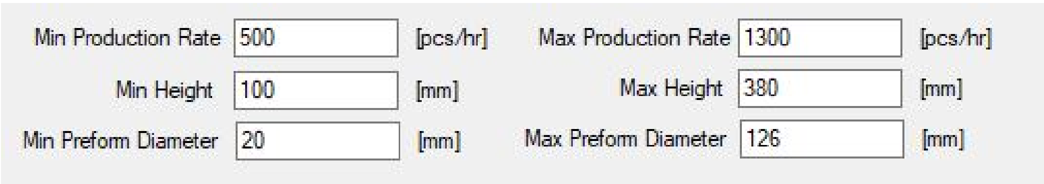

Fig. 3.9 Detail of Graphical User Interface for the definition of stretch blow moulding equipment

In the panel of Fig. 3.9 the minimum and maximum diameter of the preform are included, as they are constrained by the features of the stretch blow moulding apparatus. This information will be used by the KBESM to check if it is possible to find a preform that does not exceed the maximum BUR defined above.

The machines can be collected in a machinery (see upper part of Fig. 3.7), i.e. a set of equipment that can be used for the production. This allows easily defining the field of possible manufacturing solutions for the product by giving a more accurate description of real resources allocated by the company for the production.

3.3.4 Design requirements

The definition of design requirements is fundamental in order to feed the KBESM with criteria to be satisfied in the automatic adaptation of the design. The basic parameters of these criteria must be given by the user directly (in the GUI) or indirectly (e.g. through material and machine parameters defined above).

The limits on product dimensions defined for machines in 3.3.3 and the BUR in 3.3.2 are examples of constraints induced by the process.

Another crucial parameter for the manufacturability of the product is the Aspect Ratio (A_R), defined as in eq. 3.6

$$A_R = \frac{L_b}{D_b} \tag{3.6}$$

Where L_b and D_b are, respectively, the total height of the bottle and its maximum diameter, as represented in Fig. 3.6. The aspect ratio has to be limited between a minimum and a maximum value based on the experience of the manufacturer. These boundaries can be set by the user for the specific combination of material and machine.

The nominal thickness of the product has a lower boundary necessary to avoid the tearing of the material during inflation. Also in this case, the limit value depends on the combination of material and machine and has to be defined by the expert.

The risk of tearing becomes higher in regions with narrow curvatures; furthermore, the filling of this regions may be not uniform, resulting in a poor quality of the product and a high deviation from nominal thickness. Therefore, shallow curvatures are usually preferable for the design of moulds [159]. A maximum value of the surface curvature is thus defined for the product. For the NURBS curve in Fig. 3.4, the curvature k_{NURBS} in each point can be expressed as in Eq. 3.7 [220]

$$k_{NURBS}(x,y) = \frac{\dot{x}\ddot{y} - \ddot{x}\dot{y}}{(\dot{x}^2 + \dot{y}^2)^{3/2}} \tag{3.7}$$

For circular fillets, the curvature is given by the inverse of the radius. The Gaussian curvature of the surface [220] can be obtained by multiplying these planar curvatures by the radius of revolution, i.e. the opposite of y coordinate in Fig. 3.4. As the KBESM is implemented as a plug in for a CAD software, the built-in function for the computation of Gaussian curvature in a generic point can also be adopted.

The first functional requirement of a bottle is the volume of liquid (V_L) to be contained. This very simple requirement is not easy to satisfy in the concept design, as the internal volume has to be numerically calculated in the case of complex geometries. Therefore, the target volume is a requirement imposed by the user through the GUI; the KBESM will resize the whole design in order to fulfil this aim.

Under the point of view of mechanical resistance, plastic bottle are usually subject to two verifications, i.e. the maximum top load (TL_{max}) and the maximum internal pressure (p_{max}).

The top load analysis is intended to verify the resistance of the bottle under the weight of similar packagings during transportation and stocking. Therefore, the GUI user allows defining the maximum number of layers during stocking ($N_{L,max}$). The maximum top load TL_{max} can be thus calculated as in Eq.

$$TL_{max} = N_{L,max} g (w_b + V_L \rho_L) S_F \tag{3.8}$$

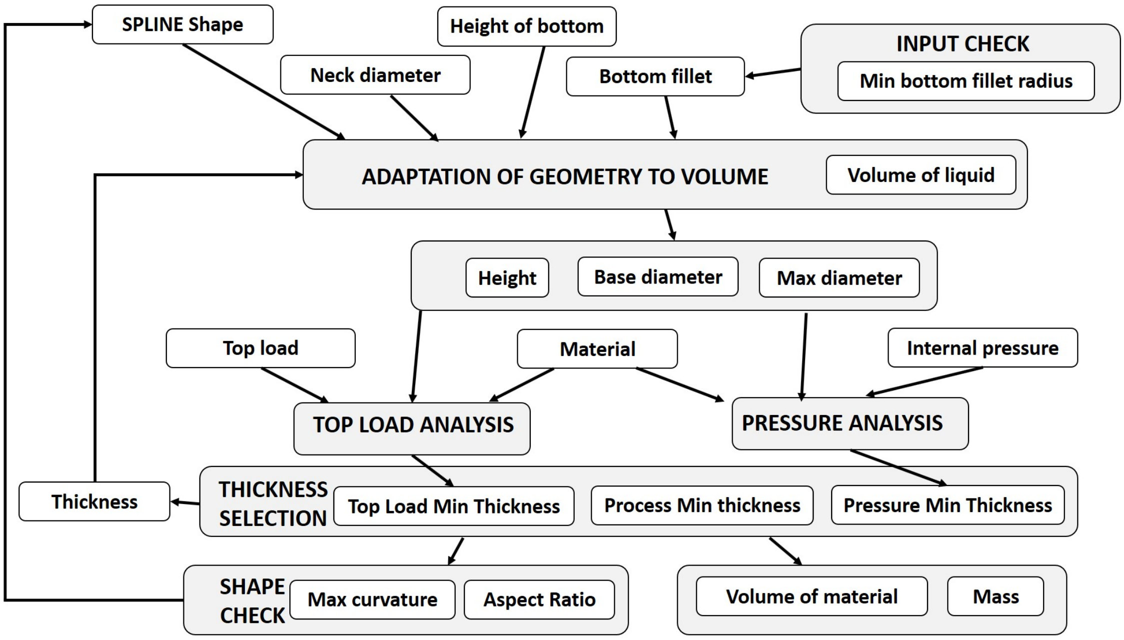

Fig. 3.10 Flow chart of geometry adapting process

where g is the gravity acceleration, w_b is the weight of the bottle, ρ_L is the density of the liquid and S_F is a safety factor. This limit value will be used to determine the minimum thickness. The value of maximum internal pressure (p_{max}) is set by the user in the GUI; also this criterium leads to the definition of a minimum wall thickness.

It is worth noticing that several definitions of the minimum thickness have been given according to different criteria; the actual nominal thickness of the product will be thus determined as the intersection of these.

3.3.5 Adaptation of the geometry

As mentioned, the sketch of the designer has to be resized by the system in order to meet the criteria above. Fig. 3.10 summarises the flow of operations used for the adaptation of bottle geometry in the KBESM.

The geometry specifications given by the user are received as an input from the GUI. The input profile of the NURBS (defined as in Fig. 3.4 by points x_i, inp and y_i, inp) is thus rescaled to match the Volume of liquid V_L required by the user.

The rescaled shape of the bottle allows extracting some relevant parameters such as the total height and the different diameters. These data are combined with the ones of the material for the calculation of minimum thickness basing on mechanical resistance. The values of TL_{max} and p_{max} provided in the GUI are used for this scope. The nominal thickness is then chose as the maximum limit values deriving from mechanical calculation and the one defined by the process as in 3.3.4. The rescaling procedure is repeated using this value of thickness for the calculation. The iterative procedure terminates when the difference between thickness calculated at two consecutive iterations is under a fixed threshold value.

Scaling of the shape

The scaling procedure is operated iteratively. As a value of thickness is necessary to calculate the internal volume, an arbitrary plausible value is set for the first iteration.

The steps adopted for the iterative scaling procedure are reported in the following. The index j is used for counting iterations. The algorithm terminates when the difference between internal volume of the bottle at two consecutive iterations is less than a fixed threshold value ε_V.

1. The initial scale factor sf_{nk} is calculated as in Eq. 3.9

$$sf_nk = \frac{D_{ne}}{2y_{1,inp}} \tag{3.9}$$

2. The profile is rescaled by means of sf_{nk} to meet the requirement on the bottle neck. The rescaled coordinates x_0 and y_0 are calculated as in Eq. 3.10 and Eq. 3.11, respectively.

$$\forall i \in [1;N] x_{i,0} = x_{i,inp} sf_{nk} \tag{3.10}$$

$$\forall i \in [1;N] y_{i,0} = y_{i,inp} sf_{nk} \tag{3.11}$$

3. The internal volume of the product after rescaling (V_0) is computed and the initial scaling factor sf_0 is obtained as in eq. 3.12.

$$sf_0 = \sqrt[3]{\frac{V_0}{V_L}} \tag{3.12}$$

4. The parameters $a_{i,j}$ and $b_{i,j}$ are calculated from $x_{i,j}$ and $y_{i,j}$ as in Eq. 3.1 and Eq. 3.4, respectively.

5. The rescaled $x_{i,j+1}$ and $y_{i,j+1}$ coordinates are calculated as in Eq. 3.13 and Eq. 3.14, respectively.

$$\forall i \in [1;N] \;\; x_{i,j+1} = a_{i,j}\, sf_j\, x_{N,j} \tag{3.13}$$

$$\forall i \in [2;N] \;\; y_{i,j+1} = y_{i,j} + b_{i,j}\, sf_j\, x_{N,j} \tag{3.14}$$

6. The internal volume of the bottle after rescaling (V_{j+1}) is calculated.
7. If $|V_{j+1} - V_j| \leq \varepsilon_V$, the algorithm stops.

   Elsewhere, the scaling factor is corrected as in Eq. 3.15 and the algorithm is repeated from point 4

$$sf_{j+1} = sf_j + w_s \frac{|V_{j+1} - V_j|}{|V_{j+1} + V_j|} \tag{3.15}$$

The value w_s in Eq. 3.15 is a corrective weight used for search. The value of w_s must be sufficiently low to prevent the method from diverging. On the other hand, too small values of w_s may lead to long calculation times.

Thickness calculation

The mechanical resistance of the bottle may be calculated through Finite Element (FE) simulation, giving the boundary conditions defined by the user [67, 280]. To reduce the calculation time, thus enabling a higher number of iterations, a simplified model is adopted here to calculate the internal pressure and top load resistance analytically.

The simplest model to approach the internal pressure analysis is to consider the bottle as a pressurized cylinder. The external radius of the equivalent cylinder $r_{e,av}$ is assumed equal to the average value of y on the spline of Fig. 3.4.

According to [260], assuming that only the internal pressure p_i is present, the tangential stress σ_t and radial stresses σ_r at the generic radial coordinate r can be calculated as in Eq. 3.16 and 3.17, respectively.

$$\sigma_t = \frac{r_{i,p}^2 p_i}{r_{e,av}^2 - r_{i,p}^2}\left(1 + \frac{r_{i,p}^2}{r^2}\right) \tag{3.16}$$

$$\sigma_r = \frac{r_{i,p}^2 p_i}{r_{e,av}^2 - r_{i,p}^2}\left(1 - \frac{r_{i,p}^2}{r^2}\right) \tag{3.17}$$

Where $r_{i,p}$ is the internal radius of the bottle.

The maximum shear stress according to Tresca's criterion is located at the inner radius. In order to find the minimum allowable thickness, the maximum shear stress is set equal to the maximum allowable stress for the material σ_{lim}, i.e. the ultimate tensile stress for brittle materials and yield strength for ductile ones. A safety factor $S_{F,p}$ is used, as shown in Eq. 3.18.

$$|\sigma_t - \sigma_r| = \frac{\sigma_{lim}}{S_{F,p}} \tag{3.18}$$

Substituting the Eq. 3.16 and 3.17 in Eq. 3.18, the maximum admissible internal radius $R_{i,max,p}$ can be calculated as in Eq. 3.19

$$R_{i,max,p} = \sqrt{\frac{1}{\sigma_{lim}} - 2S_{F,p}} \tag{3.19}$$

Therefore, the minimum thickness $t_{min,p}$ to resist the nominal internal pressure is given by Eq. 3.20

$$t_{min,p} = r_{e,av}(1 - \sqrt{\frac{1}{\sigma_{lim}} - 2S_{F,p}}) \tag{3.20}$$

To verify the resistance to top load for ductile materials, a simplified model of buckling is used. The bottle is modelled as a cylinder with radius equal to $r_{e,av}$ as defined above and height L_b. This is a conservative model, as the actual shape of the profile increases the resistance to buckling of the bottle. According to Eulero's and Johnson's formulas [260], the critical buckling stress σ_{Eul} can be calculated, depending on the value of σ_{Eul} as in Eq. 3.21 and 3.22

$$\sigma_{Eul} = \frac{E\,\pi^2\,J_z}{L_B^2\,A_t} \quad if\ \sigma_{Eul} \leq S_y/2 \tag{3.21}$$

$$\sigma_{Johnson} = S_y - \frac{L_B^2\,S_y^2}{J_z\,E\,4\pi^2} \quad if\ \sigma_{Johnson} \geq S_y/2 \tag{3.22}$$

Where E is the Young's modulus of the material and S_y its Yield strength. A_t is the area of the transversal section and J_z its moment of inertia, calculated as in Eq. 3.23 and Eq.3.24 ,respectively.

$$A_t = \pi(R_{e,av}^2 - R_{i,b}^2) \tag{3.23}$$

$$J_z = \frac{\pi(R_{e,av}^4 - R_{i,b}^4)}{4} \tag{3.24}$$

Where $R_{i,b}$ is the internal radius of the cylinder. Using a safety coefficient $S_{F,b}$, the maximum value of $R_{i,b}$ can be calculated as in Eq. 3.25 if 3.21 is used for $sigma_{Eul}$ or 3.26 if $\sigma_{Eul} \geq S_y/2$

$$R_{i,b,max} = \sqrt[4]{R_{e,av}^4 - \frac{4TL_{max}L_B^2}{\pi^3 E}} \tag{3.25}$$

$$R_{i,b,max} = \sqrt{\frac{\frac{L_B^2}{\pi^2 E} - \frac{TL_{max}}{S_y \pi} \frac{\sqrt{(TL_{max}E\pi - L_B^2 S_y)^2 - 4E\pi^2 S_y R_{e,av}^2 (TL_{max}E\pi + L_B^2 S_y + E\pi^2 R_{e,av}^2 S_y)}}{S_y \pi^2 E}}{2}} \tag{3.26}$$

Once the value of maximum internal radius has been calculated, the Eulero critical buckling stress must be computed again to verify if the right criterium has been adopted and, eventually, repeat the calculation. The minimum allowable thickness resulting from buckling analysis ($t_{b,min}$) can be thus obtained as in Eq. 3.27:

$$t_{min,b} = R_{e,av} - R_{i,b,max} \tag{3.27}$$

In case the material has a brittle behaviour, the maximum internal radius can be calculated as in Eq. 3.28

$$R_{i,b,max} = \sqrt{R_{e,av} - \frac{TL_{max}S_{F,b}}{\pi S_C}} \tag{3.28}$$

where S_C is the ultimate compression strength of the material. The value of $t_{min,b}$ is obtained also in this case using Eq. 3.27.

The nominal thickness t_n is thus obtained as in Eq. 3.29

$$t_n = min(t_{min,b}, t_{min,p}, t_{min,m}) \tag{3.29}$$

Where $t_{min,m}$ is the minimum thickness allowed by manufacturing constraints, as defined in 3.3.4.

3.3.6 Product analysis

After the product design modification, a verification of all the constraints listed in 3.3.4 must be performed. This verification allows pointing out non-feasible solution; during this phase, the result of each analysis is stored for following reports

For this scope, the maximum diameter of the bottle (D_B) is computed to calculate BUR and AR as in Eq. 3.5 and 3.6, respectively. The projected area (A_p) of the bottle surface on a plane containing the axis of rotation is also extracted by the CAD environment. This area will be multiplied by the air pressure p_a and the number of cavities of the mould (N_c). The resulting value (multiplied by a safety factor $S_{f,c}$) has to be less or equal than the clamping force of the mould F_C, as in Eq. 3.30

$$A_p \ N_C \ p_a \ S_{f,c} \leq F_C \tag{3.30}$$

All the remaining manufacturing constraints are given as geometrical parameters, so they can be easily get by an analysis of the CAD model.

The design adaptation and the verification of constraints already imply the calculation of several descriptors described in 3.2. In particular, the curvature of surfaces, the height and capability of the bottle and the maximum diameter have been calculated on the geometry. The mass of the bottle is obtained by a simple multiplication of the product volume (V_p) by the density of the polymer (this value has to be calculated for the verification of manufacturing constraints in case of injection blow moulding, as shown in Fig. 3.7).

The bounding box is defined as the minimum parallelepiped inscribing the geometry of the product; its volume (V_BB) can be calculated as in Eq.

$$V_{BB} = D_B^2 * (LB + h_{nk}) \tag{3.31}$$

where h_{nk} is the height of the bottle's neck. The packaging efficiency η_p can be thus calculated as in Eq. 3.32

$$\eta_p = \frac{V_p + V_L}{V_{BB}} \tag{3.32}$$

This parameter allows getting an immediate information about the transportation efficiency of the designed geometry.

To compute the LCIA of the product according to criteria in [215], all the phases and contributions of the product LC should be included. However, the present application of the LCA is intended for a comparative study among different design solution; this allows omitting all the contributions that are not affected by design choices, as they are supposed to be invariant.

The boundaries of the LCIA are cradle-to-gate. The study is based on simplified hypotheses. As an example, the transportation, in terms of ways and distances, of the raw materials are assumed the same for each material selected. Therefore, the impact of transportation is not included in the Life Cycle Inventory (LCI) computation. The KBESM allows the user to include LCI data imported from a number of sources, as well as custom data coming from providers.

In the present implementation, LCI data from the European Life Cycle Database (ELCD) [236] are integrated into the application. The LCI flow for the production of the raw material are selected by the KBESM basing on the family of the plastic material. The analysis refers to the unity of product; accordingly, the weight of the bottle is used as reference for the material flow.

By means of the information about the equipment given in 3.3.3, the production rate (p_R, in items/hour) and the power consumption of the production system (E_c, in kW) are given. This information allows calculating the energy consumption (e_s, in MJ/item) for the production of a single bottle, as in Eq. 3.33

$$e_s = 3.6 \;\; E_c \;\; p_R \tag{3.33}$$

This quantity is used as a reference flow for the determination of impacts related to electricity consumption according to ELCD data. More detailed systems for LCA can be easily integrated within this framework.

Once all the LCI data have been collected for the unit of product, the calculation of LCIA indicators can be performed. In the presented implementation, the ILCD 2011 MidPoint method [78, 79] for the calculation of LCIA has been used. Accordingly, the following indices are calculated

- Climate change
- Ozone depletion
- Cancer human health effects
- Non-cancer human health effects
- Ionizing radiation - human health
- Ionizing radiation - ecosystem
- Photochemical ozone - human health
- Acidification terrestrial
- Eutrophication terrestrial
- Eutrophication freshwater

- Eutrophication marine
- Ecotoxicity freshwater
- Land use
- Resource depletion - water
- Resource depletion- mineral, fossils and renewables

All these indicators are thus included in the reports to quantify the LC impact of the product.

3.3.7 Report of the solutions

The material and process selection (see 3.2) has to be performed by the user on the basis of information extracted by the system. For this scope, a report of the possible solutions has to be provided by the system to support the decision-making process.

In the input phase, the user has to define the available set of machines and materials that may be eventually used for the production. The space of possible solutions is defined by matching the compatibility between materials and machines as defined in 3.3.2 and 3.3.3.

For each possible combination of process and material, the adjusting procedure described in Fig. 3.10 and 3.3.5 is performed. At the end of this phase, the adapted design is analysed and a report is generated for the solution. All the reports are then collected and managed to enable comparison. Fig. 3.11 shows the report of a solution in the GUI.

The report shows the combination of material and process, and tells if the solution is valid. In case of non-valid solutions, the list of checks that have not been satisfied is reported to provide information that can be used by the designer to overcome this limits if necessary.

After the results of validation checks, a list of the solution's attribute is given. In particular, this list contains all the descriptors in 3.3, thus allowing the evaluation of the solution by the user.

To support the decision making, a graphical mapping of solutions is also provided.

It is evident how exploring the possible combinations for several materials and machines, a very large set of possible solutions can be generated.

Different levels of automation may be used for the solution of the MOO problem [17, 189]. According to the conceptual design in 3.2, the solution here is delegated to designer; the role of the KBESM is thus to support the user in Multiple Criteria Decision Making (MCDM) [187]. In this context, a graphical representation of the several different solutions is a very immediate way to facilitate the understanding of alternatives purposed by the KBSM.

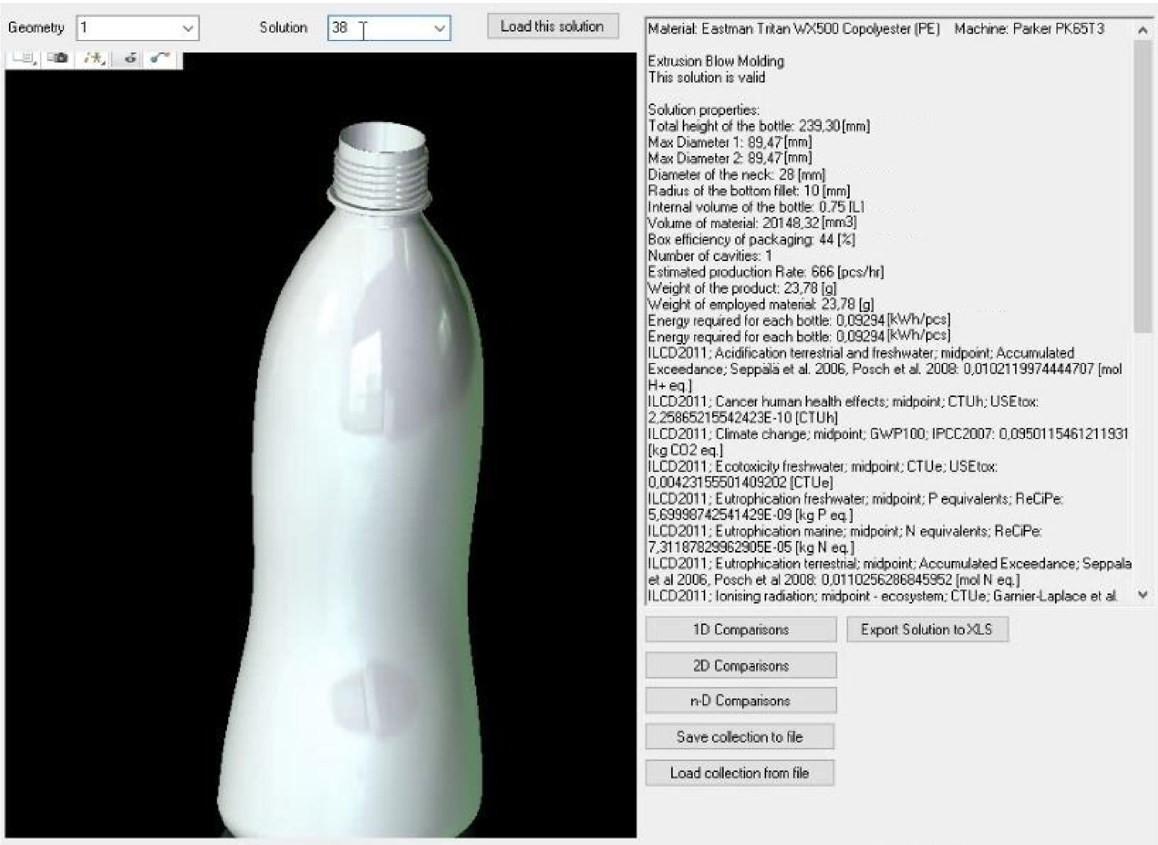

Fig. 3.11 Solution report form

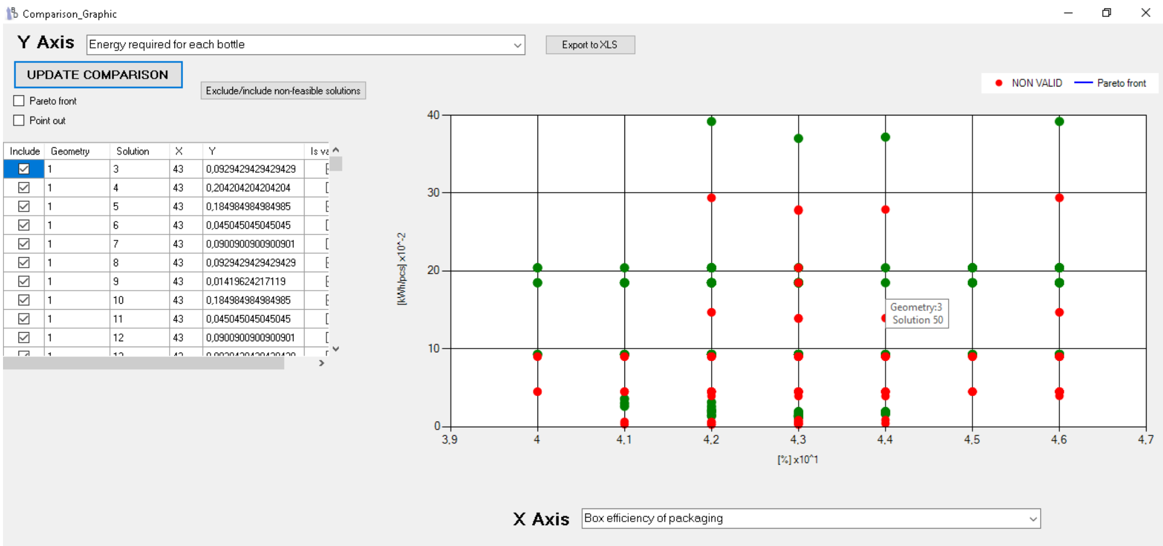

Fig. 3.12 2D map of solutions on the basis of packaging efficiency and energy consumption

To efficiently get a quick mapping of solutions on the base of a generic couple of attributes selected by the user, a scattered plot can be adopted. Fig. 3.12 displays the GUI of the KBESM analysed as an example of this approach using Box efficiency of packaging η_p as X-axis and Energy required for the production of each bottle as Y-axis. When the user move the cursor onto a point, the number of the solution is displayed.

This method allows efficiently pointing out the best set of solution for a generic pair of attributes.

In general, the comparison of solutions within the KBESM is a MOO of the general set S_{opt} of m functions, as represented in equation 3.34:

$$S_{opt} = \{f_1(X), f_2(X)...f_m(X)\} \;\; with \, X = \{x_1, x_2...x_n\} \tag{3.34}$$

The array of variables X in this case is defined by the inputs of the design, while the functions representing the set S_{opt} are the descriptors provided by the KBSM.

To reduce the task to the minimization of a set of functions, even when the target is the maximization or the achievement of a predefined value (which can be obtained by calculations in the KBSM), the m objective functions representing the set S_{opt} in equation 3.34 can be obtained from the descriptors $d_i(X)$ as in Eq. 3.35

$$f_i(X) = \begin{cases} d_i(X) & \text{if } d_i(X) \text{ has to be minimised} \\ -\,d_i(X) & \text{if } d_i(X) \text{ has to be maximised} \\ |d_i(X) - t_i| & \text{if } d_i(X) \text{ points to the target value } t_i \end{cases} \tag{3.35}$$

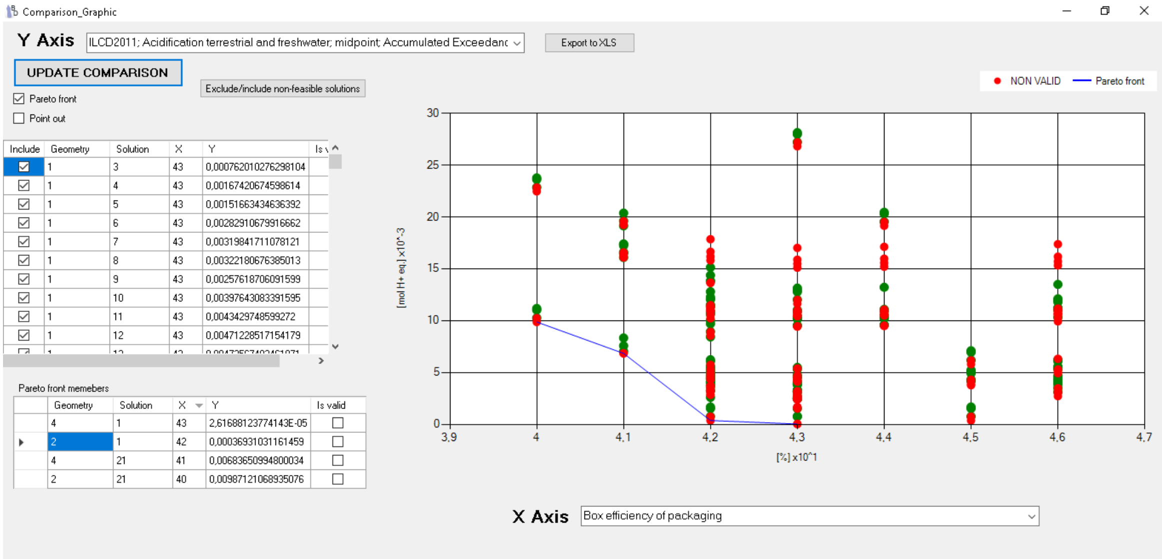

Fig. 3.13 Highlighting of Pareto front on 2D maps

Indicating as S_u and S_v the generic u-th and v-th solutions belonging to the collection of solutions C^s produced by the KBESM and defined by the input sets X_u and X_v, the solution S_v is said to dominate S_u if the condition in Eq. 3.36 is met:

$$S_u \prec S_v \iff \{f_i X_v \leq f_i(X_v) \forall i \in [1,m]\} \wedge \{\exists i^* \in [1,m] | f_{i^*}(X_u) < f_{i^*}(X_v) \tag{3.36}$$

Using this definition, the Pareto Front of non-dominated solutions (P_F) [17] can be built through the condition in Eq. 3.37

$$S_u \in P_F \iff \nexists v \in [1,m] | S_v \prec S_u \tag{3.37}$$

The Pareto front is pointed out by means of a blue line on the 2D map, as shown in Fig. 3.13

According to the definitions in Eq. 3.36 and Eq. 3.37, the Pareto front can be calculated for a generic number of objective functions. When moving from two to N-dimension, it becomes difficult to provide an efficient graphical representation of the Pareto front [29]. In the present implementation of the KBSM, a generic number of attributes can be used for the calculation of P_F, resulting in a list of non-dominated solutions.

The maps of Fig. 3.12 and Fig. 3.13 include both the feasible and non-feasible solutions, marked with green and red colour, respectively. If a non-feasible solution appears to be particularly interesting due to the values of its descriptors, the designer can investigated

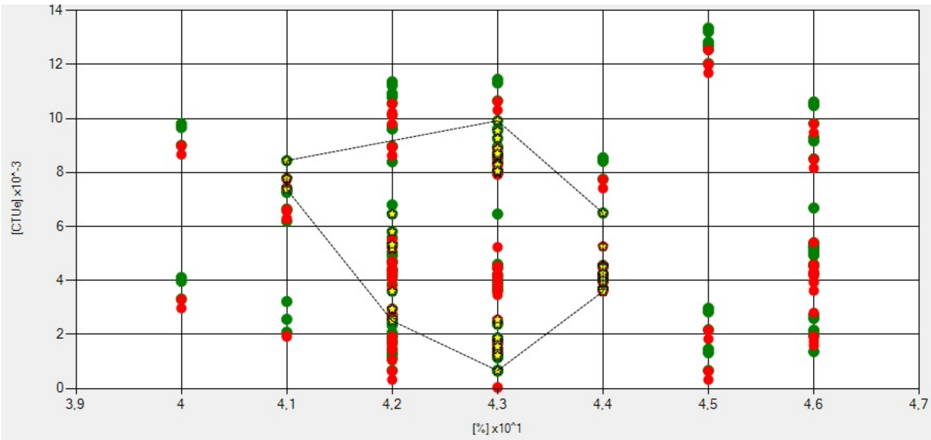

Fig. 3.14 Highlighting of a subset sharing an input parameter

more in detail the reason of non-feasibility (with the aid of the report) to overcome these limitations.

In order to give to the designer a more accurate understanding about the effects of input variables on the descriptors, it is possible to highlight in 2D maps solutions sharing a common attribute. Solutions belonging to selected subsets are marked with a special marker (i.e. a yellow star) as in Fig. 3.14.

To immediately point out the region of maps where investigated solutions stand, the convex-hull of the subset in the space of the graphic is drawn using Graham's algorithm [99]. This approach follows the one proposed by [18] for material selection in mechanical design, allowing getting a visualisation of the the region of plane in which the subset of solutions stands.

3.4 Conclusions

The present chapter demonstrated the opportunity to apply the methodology exposed in Chapter 2 to the design of a KBESM for assisting design of plastic blow moulded bottles.

The definition of applicability defined the system as applicable to the design of a specific product with different technologies. Furthermore, a well-defined user (i.e. a designer of bottles) has been chosen.

The choice of a specific product allowed including, in the conceptual design phase, a number of objectives connected to the usage phase of the product (i.e. gate-to-grave phase of the LC).

All the descriptors used by the KBESM can be obtained by the virtual representation of the process; this allows having a completely virtual implementation of the system that enables Std actions by the designer.

According to the allocation in the applicability space, a generic manufacturing process has to be managed; therefore, all the inputs of the system have been chosen in the field of the product design. This is also coherent with the expected user of the system. As all the relations within the KM of Fig. 3.2 are based on knowledge, a completely RBR approach has been used for the implementation.

The high-level experience of the user also led to design most of the actions as human-based. Automation was used only for the automation of repetitive design tasks, allowing the exploration of a high number of possibilities in a reduce timespan. The main role of the KBESM is thus to aid the MCDM by the user, providing forecasts on product feature and giving the widest overview on the design opportunities. For this scope, the adoption of reports and maps of the explored opportunities was fundamental. In particular, the transparency of RBR to the user allows pointing out the eventual issues found during manufacturability assessment, allowing further investigations in an iterative design process.

The main limitation of the presented system derives from the restricted number of processable geometries. In fact, even if the proposed architecture can still be applied, its extension to more complex geometries leads to a dramatic increase in the time required for programming. Therefore, in order to extend the system to a higher number geometries (i.e. moving on the product axis of applicability system) a redefinition of ontologies must be adopted to preserve the fulfilment of objectives while containing the time necessary for system implementation.

Chapter 4

Manufacturability Assessment in Stereolithography

4.1 Applicability definition

In this chapter, the development of a KBSM for manufacturability assessment in Stereolithography (SL) is presented.

The definition of Stereolithography Apparatus (SLA) includes a wide range of machines with notable differences in terms of size, energy consumption and supply chain [24]. Therefore, the field of application of the KBSM developed in this chapter is further restricted to bottom-up desktop SLA; the peculiar features of this type of machine [237] will be thus taken into account during the development of the system.

As the price of this kind of machine makes them affordable for private usage, no limitations will be given to the user of the system. Accordingly, all the process know-how necessary to ensure manufacturability has to be included within the KBSM.

Finally, as SL can be used for the fabrication of parts with different geometries and few number of components, no limitations are applied to the product. As a consequence, it will not be possible to include specific knowledge related to product function within the KBSM.

Fig. 4.1 shows the location of the KBSM in the applicability space according to the proposals described above.

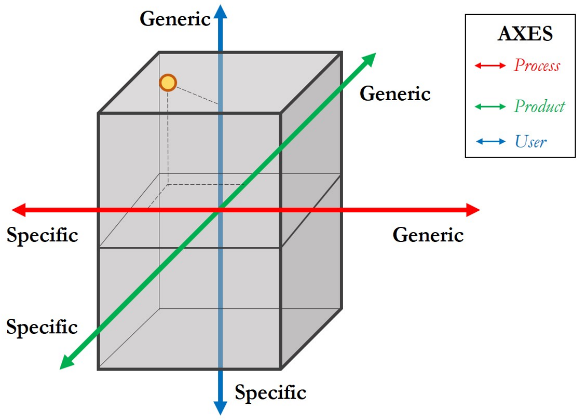

Fig. 4.1 Location in the applicability space of the KBSM for SL manufacturability assessment

4.2 Concept Design

As already mentioned above, the KBSM has to assess the manufacturability of the parts to be manufactured by means of SL. For this scope, the geometries have to be investigated in order to point out eventual critical issues and solutions.

The main objectives to be satisfied by the system are accuracy, definition and cleanability.

The term *accuracy* refers to the correspondence between manufactured part and virtual model, i.e. to the avoidance of dimensional and geometrical errors on the product. A severe loss of accuracy may require sequent operations or the repetition of the process, resulting in economic and environmental impacts. Less severe deformations of the part may still allow its usage, but with malfunctioning or aesthetic defects leading to user's dissatisfaction. Accordingly, part accuracy aims to improve all the three pillars of the TBL.

Definition means that all the features of the model are present on the final product, independently by their accuracy; as it will be described in the following, this aspect is particularly critical for small details (both embossed and engraved). The same considerations made for accuracy can be applied, leading to classify this aim as EnS, EcS and SoS.

Finally, at the end of the SL process, the part must be divided by the non transformed material (i.e. liquid resin). For this scope, all the internal end external surfaces of the part must be reached by a solvent to remove the non polymerised material. IsoPropyl Alcohol (IPA) is generally used for washing being a solvent of the most common photopolymers used in SL (i.e. epoxy and methacrylate resins). The exceeding material can corrupt the proper functioning of the product, leading to economic impacts. Furthermore, the liquid resin is a contaminant agent that risks to be released during the usage phase. Therefore, *cleanability* refers to the possibility to reach all the surfaces so to remove the exceeding resin from the part.

These aims are reported in the MODIA of Fig. 4.2.

The main causes of distortion in parts by SL are the internal stresses arising from density change during the layer-by-layer photo-polymerisation of the material [95]. This stresses can result in deformation where the thickness of the part does not allow a sufficient resistance.

As an example, Fig. 4.3 shows the distortion of two vertical walls with different thickness. Another example of geometries affected by this defect are vertical pins with high aspect ratio (i.e. length/diameter).

As the material is not supported during construction, deformation may also occur due to part own weight under the action of gravity. This effect is in particular critical in the case of overhang geometries with angles not allowing the material self-supporting.

The minimum width of the polymerised material depends on the laser spot size, power, speed and on the interaction between material and laser [95]. This imposes a limit to the minimum feature (both embossed and engraved) that can be realised by means of SL. In bottom-up SLA, the shear forces required to detach the part from the tank at the end of each layer lead to a further limitation in minimum manufacturable features [237]. In case of engraved details (including holes) the minimum dimension also has to take into account the capillarity effect that does not allow the cleaning of exceeding resin.

More in general, in order to remove the non-transformed resin from cavities, the part requires holes of a sufficient size to allow material flowing.

The descriptors and inputs of the MODIA are compiled accordingly, as it can be observed in Fig. 4.2.

All the relations in the KM are defined as Knw, since sharp design rules can be given in a preliminary approximation: as the KBSM is intended to be used for a specific SLA (cfr. 4.1), the dependencies of design rules by the specific machine is not included in the MODIA.

The actions consist in the assessment of design rules through part verification. As a generic user is considered, all the actions have to be managed by software. In Fig. 4.2 it can be observed how the definition of actions leads to seven mono-objective problems. The software will have both the role of verifying the respect of design rules and proposing solutions for their overcoming.

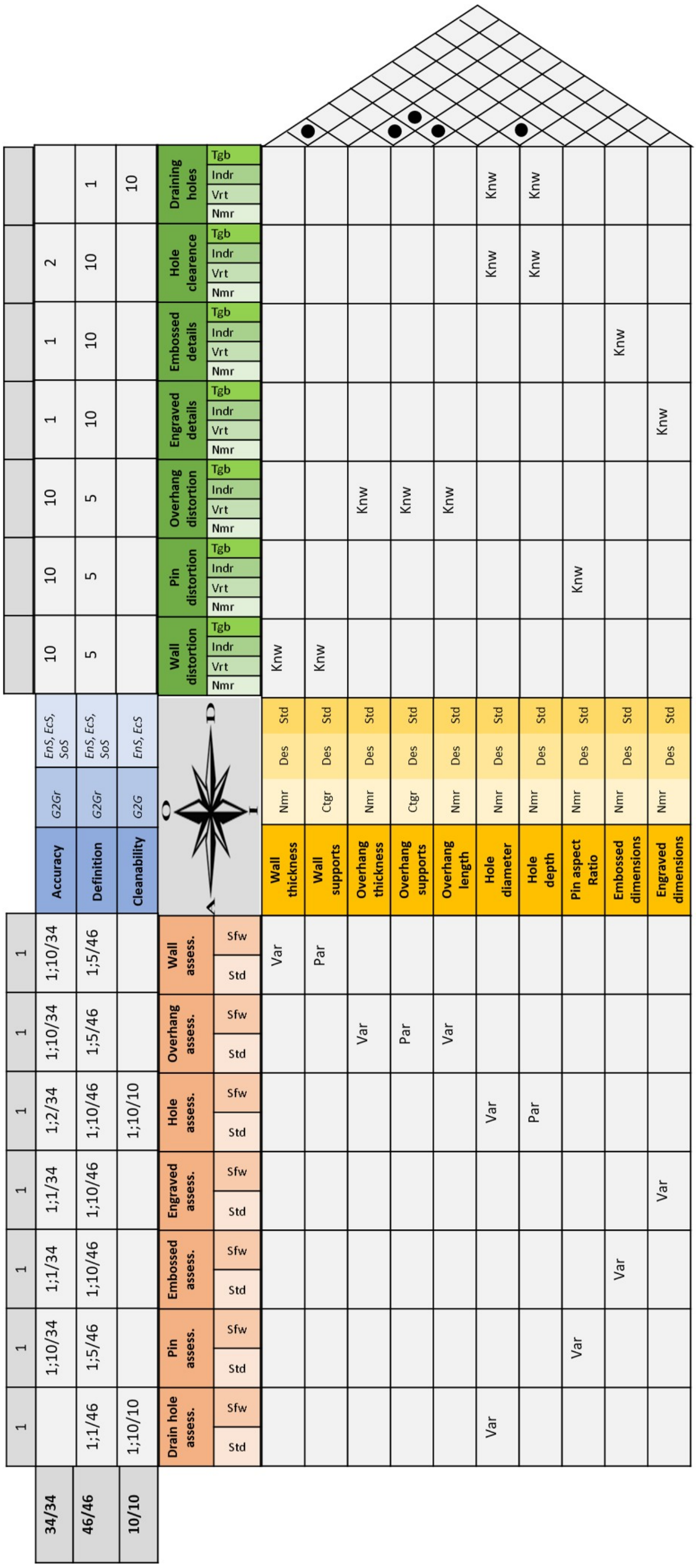

Fig. 4.2 MODIA of the KBSM for SL manufacturability assessment

a) b)

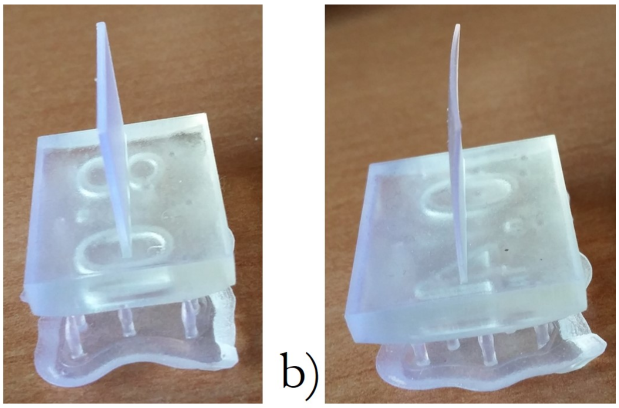

Fig. 4.3 Vertical walls with thickness a) = 0.8 mm, b) = 0.4mm

4.3 Detailed Design

4.3.1 Manufacturing Feature Recognition

As no specifications about the product are given in the KBSM, the design rules have to be expressed in terms of geometrical features; in order to enable the recognition of these relevant features on a generic geometry, a Manufacturing Feature Recognition (MFR) strategy is implemented.

Among the several approaches that can be used for feature recognition [106, 19], graph-based approach revealed to be particularly suitable in application to recognition of manufacturing features. As an example, [181] proposed a mid-surface approach to injection moulding; this approach has been extended to the field of machining by [353].

In [180] an application of the graph-based method to Case Based Reasoning (CBR) for identifying relevant features in AM products is proposed; sub-graphs have been isolated and compared to relevant graph representations within the case base through the usage of a similarity index that has been proposed by the authors. In [232] a distinction is operated between functional and non-functional features; the part is then represented as a graph having functional features as nodes and non-functional features as connections between them. This kind of representation allows the authors to apply DfM rules by pointing out manufacturing issues related to a particular feature or a relation among different ones.

The methodology here proposed is based on the interpretation of the B-Rep of examined parts and does not depend on the modelling sequence. Furthermore, it is not required the transformation of the geometry such as in mid-surface approach, thus reducing the computational complexity and enabling the detailed analysis of actual geometry. In order

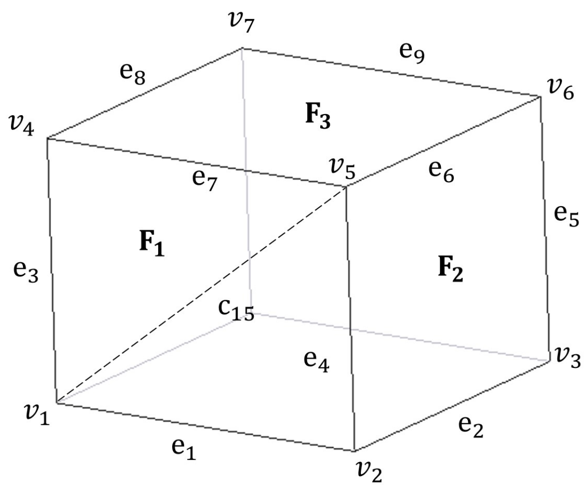

Fig. 4.4 Examples of edges, vertices, faces and connectors on a simple part

to overcome the limits of traditional methods, which rise from the direct interpretation of geometrical entities, new and original composed geometrical entities are defined in 4.3.2 and then adopted for graph-based representation of the model.

In the proposed approach, Design for Additive Manufacturing (DfAM) rules are statically defined, according to the criteria exposed in 4.1 and 4.2. Nevertheless, the limit values of rules can be dynamically tuned by the user to fit the specific combination amongst materials, machine characteristics and product structure, whether he owns these information. The completely rule-based approach is intended to avoid uncertainties proper of CBR systems, eliminate the necessity of a training base and allow direct control of MFR and DfAM rules.

4.3.2 Manufacturing Geometrical Entities

Relations among basic entities

The proposed method employs conventional definitions of vertices, edges and faces to define elements that are then used for the MFR. These elements and their relations with fundamental entities have been defined in the next lines. Then connectors, border edges, chains, bricks,islands and blocks are introduced. If an edge e_i is bounded by a vertex v_j, we say that the vertex belongs to the edge, as written in Eq. 4.1.

As an example, in Fig. 4.4 it is possible to observe that $v_2 \in e_1$, $v_2 \in e_2$. A vertex can belong to different edges at the same moment.

$$v_j \in e_i \tag{4.1}$$

In the same way, if a face F_k is bounded by an edge e_i, then the edge belongs to the face, as it is shown in Eq. 4.1.

$$v_j \in e_i \tag{4.2}$$

As an example, in Fig. 4.4 $e_1 \in F_1$ and $e_2 \in F_2$. Each edge belongs to two different faced simoultaneously (e.g. $e_4 \in F_1 \ \wedge \ e_4 \in F_2$). Then, a relation between vertices and faces can be defined as in Eq. 4.3

$$(v_j \in e_i) \wedge (e_i \in F_k) \rightarrow v_j \in F_k \tag{4.3}$$

As obvious, a vertex can belong to several faces (in any case more than two).

Connectors

A connector is assumed to be a virtual edge that connects two vertices. Connectors allow for connecting vertices, which do not share an edge. They play the same role and own same properties such as edges. This assumption allows extending the use of the searching algorithm to recognise relevant geometric features within the model.As an example, in Fig. 4.4, the connector $c_{1,5}$ is displayed; $c_{1,5}$ connects v_1 with v_5. It is thus possible to write: $v_1 \in c_{1,5} \wedge v_5 \in c_{1,5}$. Obviously, connectors belong only to a face

Border edges and their features

The definition of border edges has been adopted when an edge e_i is also a border for a face F_k , then the notation in Eq. 4.4 is used:

$$e_i \subset F_k \tag{4.4}$$

A border edge is defined when the conditions in Eq. 4.5 and 4.6 are simultaneously satisfied.

$$\{e_i, e_j\} \subset F_k \rightarrow e_i \in F_k \wedge e_i j \in F_k | (v_l \in e_i \wedge v_l \in e_j) \tag{4.5}$$

$$\exists \varepsilon \in \mathbb{R} | \bar{PO} \leq \varepsilon \rightarrow e_i, e_j \subset F_k \tag{4.6}$$

To explain the meaning of the vector $\bar{PO}$, it is necessary to define a pair of vectors $\vec{s_i}$ and $\vec{s_j}$ as in the Eq. 4.7:

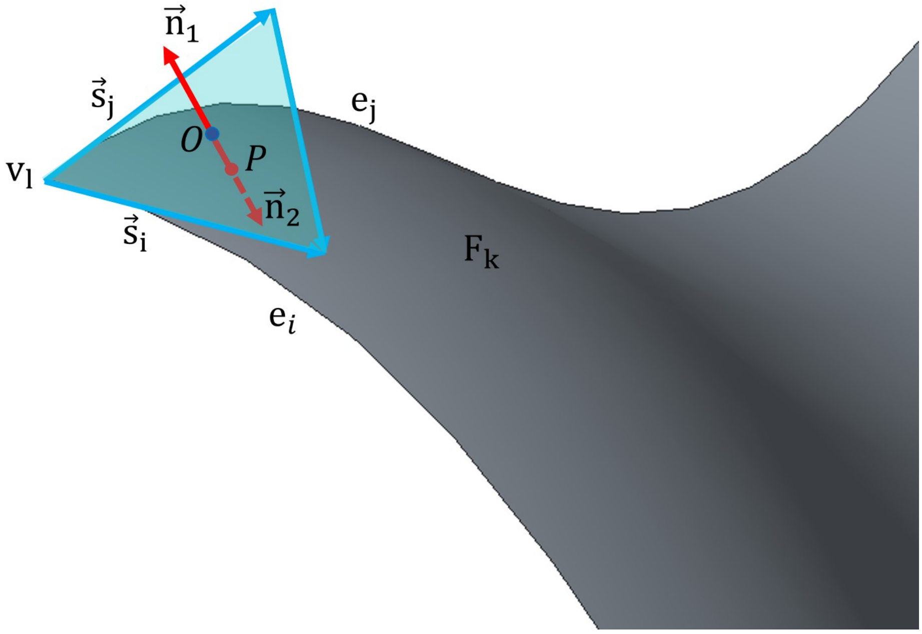

Fig. 4.5 Graphical representation of the procedure for determination of border edges

$$\begin{cases} \vec{s_i} = \varepsilon \bar{t_i} \\ \vec{s_j} = \varepsilon \bar{t_j} \end{cases} \tag{4.7}$$

where $\varepsilon \in \mathbb{R}$, t_i and t_j represent tangents to e_i and e_j centred in the vertex vl, respectively (Fig. 4.5. A triangle defined by the vectors $\vec{s_i}$ and $\vec{s_j}$ can be drawn.

Two normal vector $\vec{n_1}$ and $\vec{n_2}$ can be drawn and centred on the centre O. The intersection point P of one of them with the surface F_k can be found. Finally, the edges ei and ej are border edges for the surface F_k if exists $\varepsilon \in \mathbb{R}$ small enough that the distance $\overline{OP}$ between the centre O and the intersection point P is minor or equal to ε.

Chains, loop chains and border chains

A set of edges $C = \{e_1, e_2...e_n\}$ is a chain if each edge satisfies the condition described in Eq. 4.8:

$$(\forall v_j \in e_i) \wedge (\forall e_i \in C) \exists e_k \in C | (v_j \in e_k) \wedge (k \neq i) \tag{4.8}$$

In Fig. 4.6 is represented a simple part. A number of chains can be seen, as: $C_2 = \{e_9, e_{11}, e_{13}, e_{15}, e_{14}, e_{10}\}$ and $C_3 = \{e_9, e_{11}, e_{13}, e_{16}, e_{18}, e_{17}, e_{14}, e_{10}\}$.

If all the edges of a chain lay on the same face, then the chain is a loop chain of a face or simply a loop (Eq. 9):

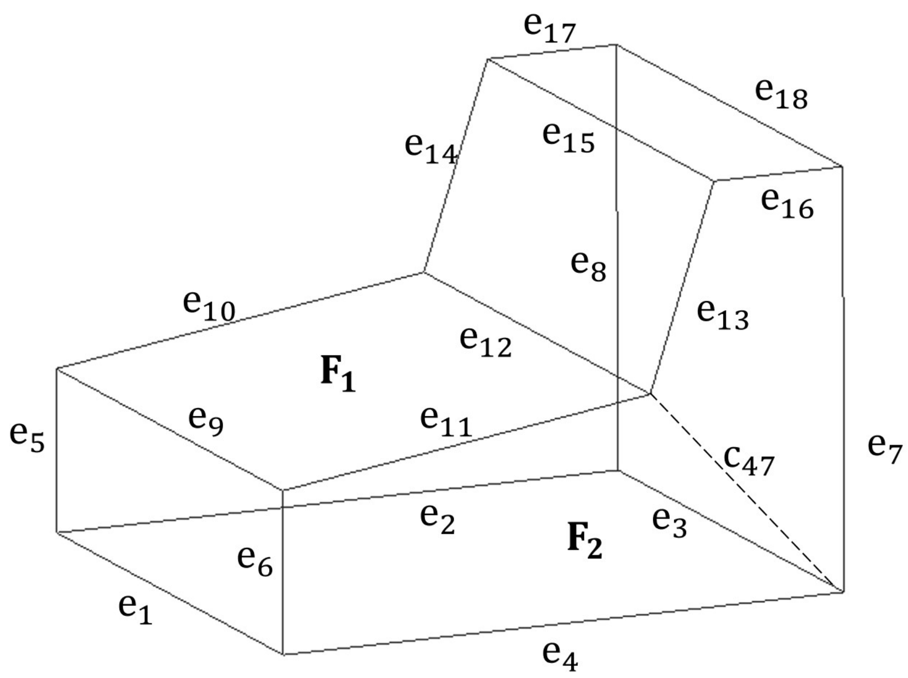

Fig. 4.6 Example for chain recognition

$$C_k \; is\; a\; loop\; if\; \forall e_i \in C_k \rightarrow e_i \in F_j \tag{4.9}$$

As an example, chains $C4 = \{e_1, e_2, e_3, e_4\}$ and $C_5 = \{e_9, e_{10}, e_{11}, e_{12}\}$ in Fig. 4.6 can be classified as loop chains or loops. The definition of chain remains in case one or more edges are substituted by connectors (i.e. virtual edges): as an example, in Fig. 4.6 we can define the chain $C6 = \{e_4, e_6, e_{11}, c47\}$. A border chain for a face is that chain which contains two border edges for the same face (Eq. 4.6):

$$C_k \subset F_j \iff \exists e_n, e_m \in C_k | \{e_n, e_m\} \subset F_j \tag{4.10}$$

As an example, in Fig. 4.6, C_2 and C_3 are border chains for face F_1; C_6 is a border chain for F_2.

Bricks and their features

A brick B_0 is a set of connected chains $\{C_1, C_2, ...C_n\}$ for whom is Eq. 4.11:

$$\forall C_i \in B_0 : \exists e_k \in C_i \land \exists C_j \in B_0 | C_j \neq C_i \land e_k \in C_j \tag{4.11}$$

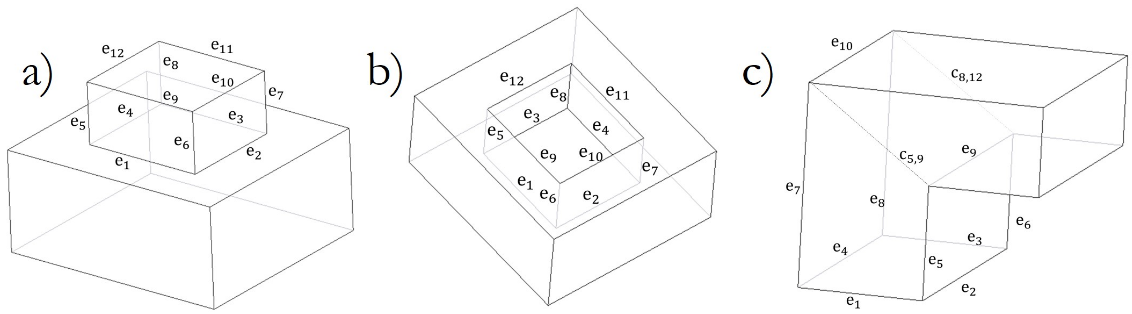

Fig. 4.7 Samples of a) embossed brick, b) engraved brick and c) brick defined by the use of connectors

As an example, in Fig. 4.7 a) and b) the set of chains containing edges $e_1,...,e_{12}$ constitutes an embossed brick or an engraved brick, respectively.

In Fig. 4.7 c), the chain that includes edges $\{e_1,...,e_{10}$ and connectors $c_{5,9},...,c_{8,12}$ represents a brick, which was defined by the use of connectors.

A face F_k belongs to a brick B_o ($F_k \in B_o$) if a chain C_i inside B_o borders F_k, i.e. as in Eq. 4.12:

$$F_k \in B_o \iff \exists C_i \in B_o | C_i \subset F_k \tag{4.12}$$

A brick Bo is defined filled brick when its surfaces bound a volume. The notation $B_o\otimes$ is used in order to express this condition. The notation $B_o\oslash$ is used to express the opposite condition also referred as *empty brick*. To check this condition, firstly a gravity centre g of the n faces $\{S_1,...,S_n\}$ is calculated as the gravity centre of nodes obtained after meshing each generic face by dividing its boundary edges in m nodes along its u and v parameters as it is shown in Eq. 4.13:

$$\begin{cases} g_X = \frac{\sum_{i=0}^{n-1}\sum_{i=0}^{n-1}\sum_{i=0}^{n-1} X_{i,u,v}}{n \times m^2} \\ g_Y = \frac{\sum_{i=0}^{n-1}\sum_{i=0}^{n-1}\sum_{i=0}^{n-1} Y_{i,u,v}}{n \times m^2} \\ g_Z = \frac{\sum_{i=0}^{n-1}\sum_{i=0}^{n-1}\sum_{i=0}^{n-1} Z_{i,u,v}}{n \times m^2} \end{cases} \tag{4.13}$$

Then, it is possible to define the central point Pc0 of the first face S1 in the brick set — i.e. $(X_{0,m/2,m/2}, Y_{0,m/2,m/2}, Z_{0,m/2,m/2})$ — and thus the direction of vector d_{g0} that is connecting the gravity centre g to the central point P_{c0} is determined as in Eq. 4.14:

$$\vec{d_{g0}} = \frac{\vec{P_{c0}} - g}{|\vec{P_{c0}}| - g} \tag{4.14}$$

After that, a ray-tracing algorithm (e.g. [107]) is implemented to find the q intersection points $\{P_1,...,P_q\}$ with the mentioned $\{S_1,...,S_q\}$ surfaces, where $q < leqn$.

If q is an even integer number, it is possible to define a point P_m as the middle point between P_1 and P_2; on the contrary, if q is an odd integer number, then $P_m = g$. Eq. 4.15 summarises these assumptions

$$\begin{cases} q \; mod \; 2 = 1 \rightarrow P_m = g \\ q \; mod \; 2 = 0 \rightarrow P_m = P_1 + \frac{P_2 - P_1}{2} \end{cases} \tag{4.15}$$

where mod indicated the modulus operator, that returns the reminder of the Euclidean division of q by 2.

Finally, the problem of determining whether the brick B is filled or not is reduced to determining if point P_m is internal or external to the considered part. This can be done using a ray casting algorithm along a generic direction starting from the point P_m and considering all the faces of the model thus obtaining the set of intersection points $\{P_1,...,P_r\}$. This criterium is shown in Eq. 4.16:

$$\begin{cases} r \; mod \; 2 = 1 \rightarrow B\otimes \\ r \; mod \; 2 = 0 \rightarrow B\oslash \end{cases} \tag{4.16}$$

Figure 4.8 a) and b) graphically represent the procedure described above for bricks, which are coloured in red. In both cases bricks are empty (corresponding to the first and second line of Eq. 4.15, respectively)

Islands, blocks and their features

We define an island Iw as a set of bricks $\{B_1,...,B_n\}$ that does not share edges with other bricks in the model, Eq. (17):

$$\forall B_i \in I_W : \nexists e_j \in B_i | e_j \in B_k \wedge B_k \notin I \tag{4.17}$$

This defines an isolated part of the model that can consist of one or more brick sharing edges or connectors. As an example, red bricks in Fig. 4.9 are islands. All the membership relations will be extended from elements previously defined to the island: a face belongs to an island if it belongs to a brick of the island, etc.

A chain Ci is an external chain of an island Iw if it shares all edges with a face that does not belong to such an island. The used symbol is $\frac{C_i}{I_w}$, defined as in Eq. 4.18 :

$$\frac{C_i}{I_w} \iff \forall e_k \in C_i : \exists F_j | e_k \in F_j \wedge F_j \notin I_w \tag{4.18}$$

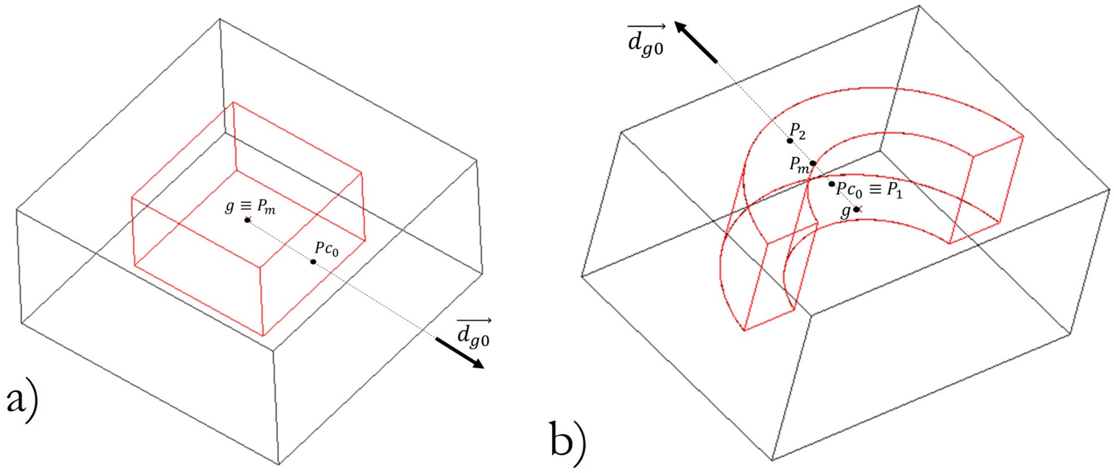

Fig. 4.8 Procedure to determinate whether a brick is filled or empty depending on the position of the gravity centre g. a) An empty brick with $g = P_m$ inside the brick. b) An empty brick with g outside the brick and Pm as the middle point between P_1 and P_2

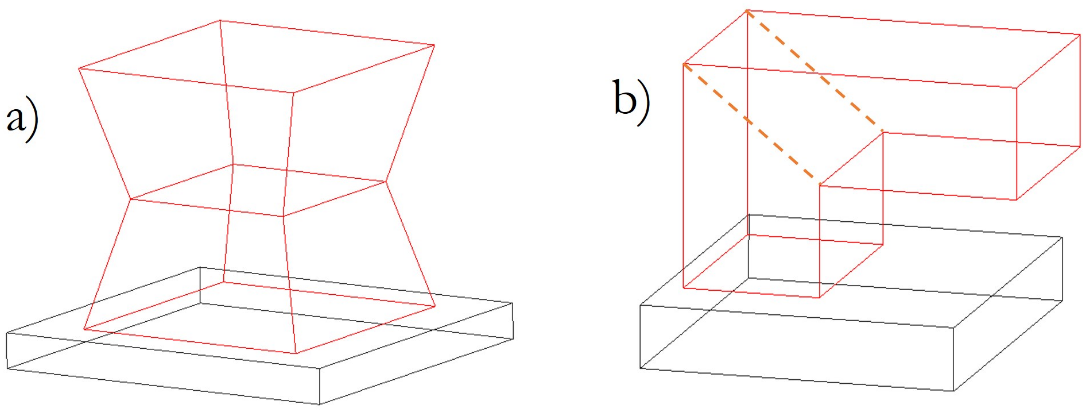

Fig. 4.9 Samples of islands which are formed by two bricks

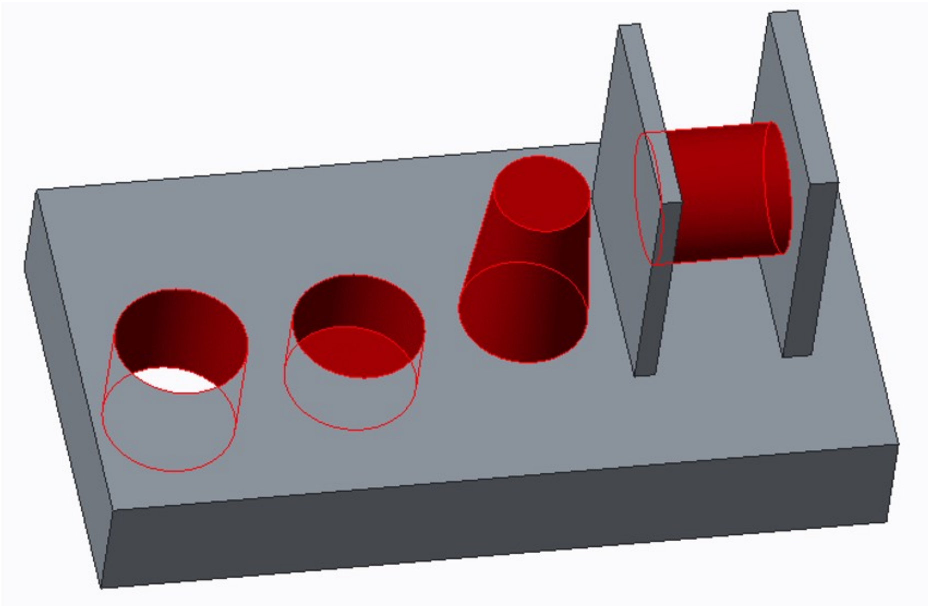

Fig. 4.10 Examples of four smooth islands (geometries in red colour)

In case an island does not have any external chain, it is referred to with the name of block. It is worth to mention that an external chain is always a loop chain or a loop because of the definition.

Smooth loops and smooth islands

In case a face is connected to only two edges, one exception arises: such a condition can be verified only if the two mentioned vertices are classified as closed loops. This particular and singular case will be identified with the name of smooth island: the singular surface and both the two connected loops belong to the smooth island, which includes possible surfaces enclosed by this closed loop. Smooth islands are represented in the Fig. 4.10 below (highlighted in red colour) to exemplify this definition.

4.3.3 Identification of Manufacturing Geometrical Entities

As stated above, a B-Rep of the model to be produced (in its final orientation) is used as a basis for verification of DfAM rules. For this propose, it is necessary to identify the entities defined in 4.3.2 on the geometry. After identification has been fulfilled, the set of geometrical entities constituting the CAD model is compared with DfAM rules (expressed in term of mentioned entities) to provide feedback to the designer about eventual critical issues that are in a relationship with the geometry manufacturability.

In the following sub-sections adopted rules and their use within a general algorithm-based system for CAD analysis and geometrical entities recognition are discussed. Being not possible to present a general algorithmic approach to manufacturing knowledge translation in terms of geometrical entities, this aspect is deepened within the next section with some examples from the specific implementation.

Island detection

A graph-based representation of the model, which considers edges as elements and vertices as connectors, easily allows identifying islands (in term of edges) as they are nonconnected sub-graphs. Once the edges of an island have been defined, it is possible to recognise loops, which are formed by those edges that belong to the island. Faces, which belong to the island, can be identified as the ones that are bordered by those loops that belong to the mentioned island. Finally, by knowing island's faces, it is also allowed determining whether an island is filled or empty. Therefore, the rest of the proposed MFR algorithm is to split these islands into a set of bricks that can be adopted for the application of DfM rules in AM. This development is discussed in the next sub-paragraph

Brick-by-loop search procedure

To perform this task, we associate to every new island a set of edges named Assigned Edges and a set of chains named Queue Chains, by stating that an edge is assigned if it belongs to this set and that a chain is in the queue if it belongs to this set, respectively. By starting from a chain C_i, which belongs to an island I_k, we define a set of edges named branches of the chain, which are Non-Assigned Edges that belongs to I_k and share at least one vertex with an edge that belongs to C_i, as in Eq. 4.19 :

$$e_j\ is\ a\ branch\ of\ C_i \in I_k \iff e_j\ is\ Non-assigned \wedge e_j \in I_k \wedge \exists v_l | ((v_l \in e_j) \wedge (v_j \in C_i)) \tag{4.19}$$

A vertex, which belongs to a branch but does not belong to the chain C_i, will be referred in the following sentences as an opened vertex of the branch. Furthermore, we state that two branches e_j and e_k of the chain C_i are Related Branches — expressed in term of the notation $e_j \asymp ek$ - if it exists an edge of the chain that shares a vertex with each of them, as expressed in Eq. 4.20.

$$e_j \asymp e_k \iff \exists e_l \in C_i \wedge \exists (v_g, v_h) \in e_l | e_j \wedge v_h \in e_k \tag{4.20}$$

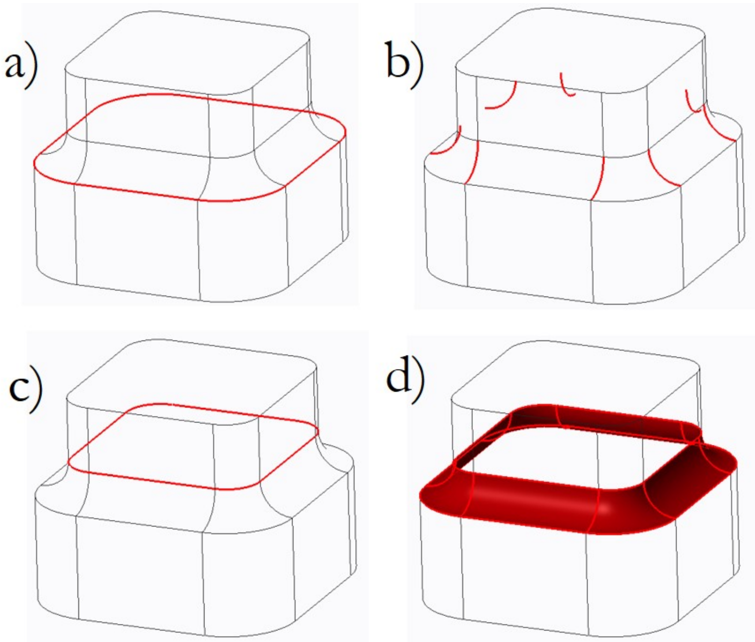

Fig. 4.11 Schematization of brick-by-loop procedure: a) The starting chain C_i. b) Branches of C_i. c) The corresponding chain of C_i. d) The resulting brick

If two branches of a chain have a common vertex belonging to the chain, thus they will be named *twin branches*. On the base of these statements, we are going to expose how to compose the chain C_j, named *Corresponding Chain* of C_i and indicated as $C_j = Corr(C_i)$. As a first step, we search for edges, which belong to island, that connect open vertices of branches. These edges are added to the new chain. Then, we close the chain by adding new connectors between open vertices of related branches in case an edge has not yet been assigned between those branches; in case there is more than one combination between opened vertices (that is in the case of twin branches), the connector has to be placed between those vertices with minor distance. The procedure stops when two edges (or connectors) in the open chain are assigned to every opened vertex of branches. The brick is formed by chains $C_i, C_j = Corr(C_i)$ and all the side chains, which are obtained by using an element (edge or connector) of C_i, one of C_j and two branches. The steps of the procedure here described are summarised in Fig. 4.11

Model Analysis

The sequence of steps that are necessary to identify different regions of the model in terms of islands and bricks can be summarised as follows:

1. *Smooth island detection* Find smooth islands through model surfaces, cf. 4.3.3

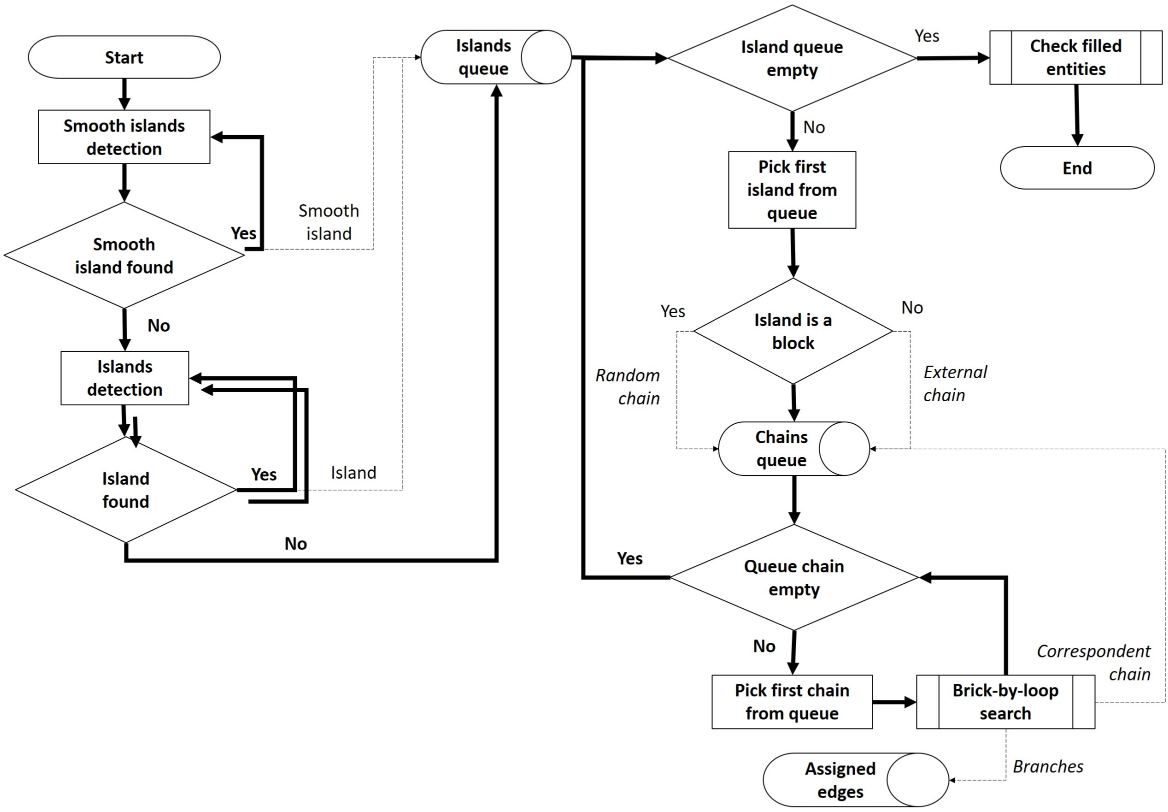

Fig. 4.12 Flowchart of the algorithm dedicated to geometry analysis

2. *Smooth island detection* Isolate islands form a graph-based representation of models as in cf. 4.3.3

3. *Analysis of islands* If the island is a block, add a random chain to Queue Chains else add all the external chains to Queue Chains according to 4.3.2

4. *Queue Chain analysis* Apply the brick-by-loop search procedure in 4.3.3 to each Queue Chains by substituting original chains with correspondent chains in Queue Chains list and by adding branches to assigned edges list.

5. *Check Phase* If all the edges of the island have been assigned, move to next island, otherwise iterate from point 4.

6. Volume detection Check whether islands, blocks and bricks are filled or not using procedures in 4.3.2.

The algorithm is also summarised in 4.12

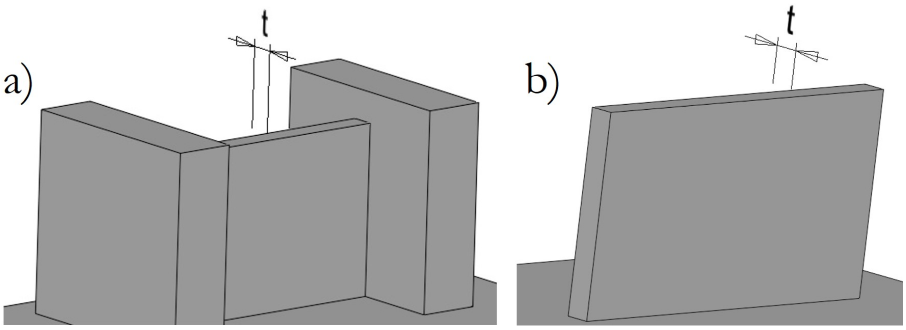

Fig. 4.13 Examples of a) supported and b) non-supported walls

4.3.4 Design for Additive Manufacturing rules

The design rules exposed in 4.2 are her translated in terms of geometrical features. The correspondence between these features and the entities is exposed in the next sections. These rules are derived from literature [88] and direct observation.

Walls

As already discussed in 4.2, thin walls are particularly prone to distortions induced by internal stresses. It is necessary to distinguish the case of supported walls (i.e. walls connected on sides) from non-supported ones, as the second are more vulnerable to deformations. The two cases are reported in Fig. 4.13 a) and Fig. 4.13 b), respectively.

In order to avoid wall distortion, the thickness of the wall t in Fig. 4.13 has to be higher than a minimum value t_{min}.

If B_i is a brick of the model, $n_s(B_i)$ is the number of faces belonging to B_i and $n_c(B_i)$ is the number of chains belonging to B_i, then conditions in Eq. 4.21 and Eq. 4.22 can be used to recognise supported and non-supported walls, respectively:

$$If\ n_s(B_i) < n_c(B_i) - 2 \wedge B_i \otimes \ \rightarrow\ B_i\ is\ a\ supported\ wall \tag{4.21}$$

$$If\ n_s(B_i) < n_c(B_i) - 1 \wedge B_i \otimes \ \rightarrow\ B_i\ is\ a\ non-supported\ wall \tag{4.22}$$

In both cases, critical dimension t corresponds to the minimum non-zero distance between two surfaces belonging to B_i and has to be compared to the minimum value t_{min}.

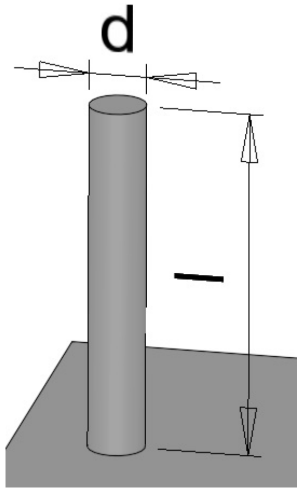

Fig. 4.14 Example of vertical pin

Vertical Pins

Vertical pins are defined as elongated geometries oriented according to Z-Axis. An example of vertical pin is shown in Fig. 4.14

As stated in 4.2, these geometries are particularly prone to deformations due to internal stresses. In order to limit these deformations, the aspect ratio $ar_p = l/d$ (where l and d are, respectively, the length and diameter of the pin as in Fig. 4.14) has to less or equal to a given maximum value $ar_{p,max}$.

If I_k is a smooth island of the model and $n_s(I_k)$ is the number of faces belonging to I_k , naming as $\hat{n}(S_l)$ the normal vector of the generic l-th surface (S_l), a vertical pin is identified when the condition in Eq.4.23 is met:

$$If\ I_k \otimes \wedge n_s(I_k) = 2 \wedge \exists S_l \in I_k | \hat{n}(S_l) \equiv \hat{Z} \rightarrow\ B_i\ is\ a\ vertical\ pin \tag{4.23}$$

The distance l can thus be measured as the maximum distance between the two loops of the island, while d is the minimum size of the bounding box enclosing the feature.

Horizontal overhangs

As already mentioned in 4.2, another cause of distortion in parts by SLA is the effect of weight on non-supported geometries. As an example, Fig. 4.15 shows an horizontal non-supported overhang.

If B_i is a brick of the model, $n_s(B_i)$ is the number of faces belonging to B_i and $n_c(B_i)$ is the number of chains belonging to B_i $\hat{n}(S_l)$ the normal vector of the generic l-th surface (S_l), an overhang is recognised when the condition in Eq. 4.24 is satisfied.

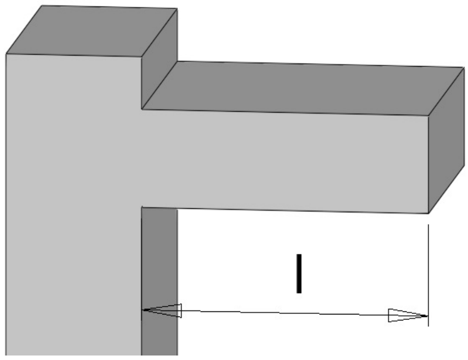

Fig. 4.15 Example of horizontal overhang

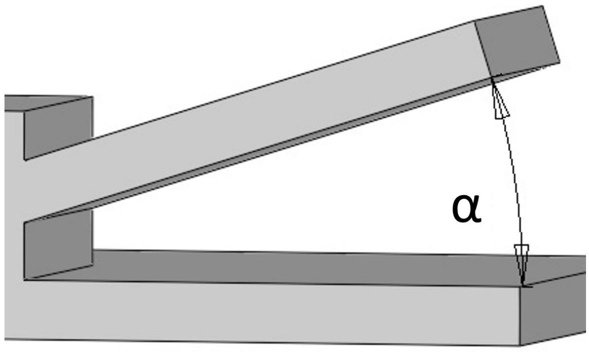

Fig. 4.16 Example of sloped overhang

$$If\ B_i \otimes \wedge If\ n_s(B_i) < n_c(B_i) - 1 \wedge \exists S_l \in B_i | \hat{n}(S_l) \equiv \hat{Z} \rightarrow\ B_i\ is\ a\ horizontal\ overhang \quad (4.24)$$

The length of the horizontal overhang l must not exceed a given limit value l_{max} in order to avoid part distortion. The distance l can be computed as the maximum distance between the only empty loop chain and the remaining surfaces of the brick.

Sloped overhangs

When the value of overhang length as defined above exceeds l_{max}, it is necessary to distinguish between horizontal and sloped overhang as the one represented in Fig. 4.16.

In particular, when the angle α (as represented in Fig. 4.16) is less than a given minimum value α_{min}, the overhang can not be built without inducing excessive distortions (if support structures are not built).

A sloped overhang can be recognised by removing the condition of surface normal to Z in Eq. 4.24, i.e. as in Eq. 4.25.

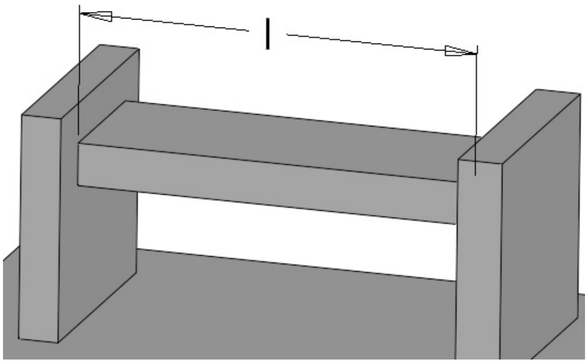

Fig. 4.17 Example of bridge

$$If\ B_i \otimes \wedge If\ n_s(B_i) < n_c(B_i) - 1 \rightarrow\ B_i\ is\ a\ horizontal\ overhang \tag{4.25}$$

The verification of rules is made by checking the normal vectors of all the surfaces belonging to B_i.

Bridges

As in the case of walls, a difference has to be made on overhangs if two supporting geometries are present; in this case, the geometry takes the name of *bridge*. An example of bridge is shown in Fig. 4.17.

The recognition of a bridge can be made by using the conditions in 4.26.

$$If\ B_i \otimes \wedge If\ n_s(B_i) < n_c(B_i) - 2 \wedge \exists S_l \in B_i | \hat{n}(S_l) \equiv \hat{Z} \rightarrow\ B_i\ is\ a\ bridge \tag{4.26}$$

To prevent bridge warping,the maximum length between empty loop chains (l in Fig. 4.17) must be less or equal than a given value l_{max}. In [88] the value of l_{max} is suggested for a given transversal section of the bridge; interpolation on experimental observation may be used to extend this result to other dimensions.

Embossed and engraved details

In section 4.2 the limitations on minimum embossed and engraved details have been introduced. Fig. 4.18 a) and 4.18 b) report examples of embossed and engraved details, respectively.

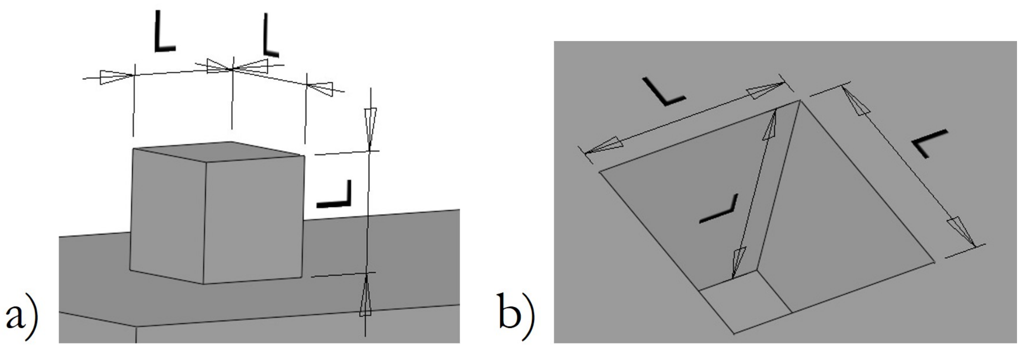

Fig. 4.18 Example of a) embossed and b) engraved details

Each filled brick can be considered as an embossed detail, while each non-filled brick can be considered as an engraved detail. The check on the generic brick B_i can be thus made as in Eq. 4.27.

$$\begin{cases} B_i \otimes \rightarrow B_i \; is\ a\ embossed; detail \\ B_i \oslash \rightarrow B_i \; is\ an\ engraved; detail \end{cases} \tag{4.27}$$

To ensure the proper manufacturing of details, each dimension (L in Fig. 4.18) must be higher than a fixed minimum value L_{min}. Different values of L_{min} are used for embossed ($L_{min,em}$) and engraved ($L_{min,en}$) features.

The minimum non null distance between surfaces of the brick is thus compared to L_{min} for the validation of the DfAM rule.

Minimum hole diameter

As already discussed, the machine accuracy also reflects on the minimum diameter of manufacturable holes. This constraint includes both through and blind holes. In a first approximation, the minimum diameter ($d_m in$) is given as a constant value, i.e. the effect of hole length and orientation is ignored.

Every empty smooth island with less than 4 surfaces can be recognised as an hole.The diameter is then computed as the minimum size of the bounding box enclosing the feature.

Minimum Drain Hole Diameter

In order to avoid liquid entrapment, a draining hole as the one in Fig. 4.19.

The condition has to be verified on every empty block of the model . In particular, it is necessary to verify if exists an empty surface (S_l) belonging to the brick (Br_i) and,

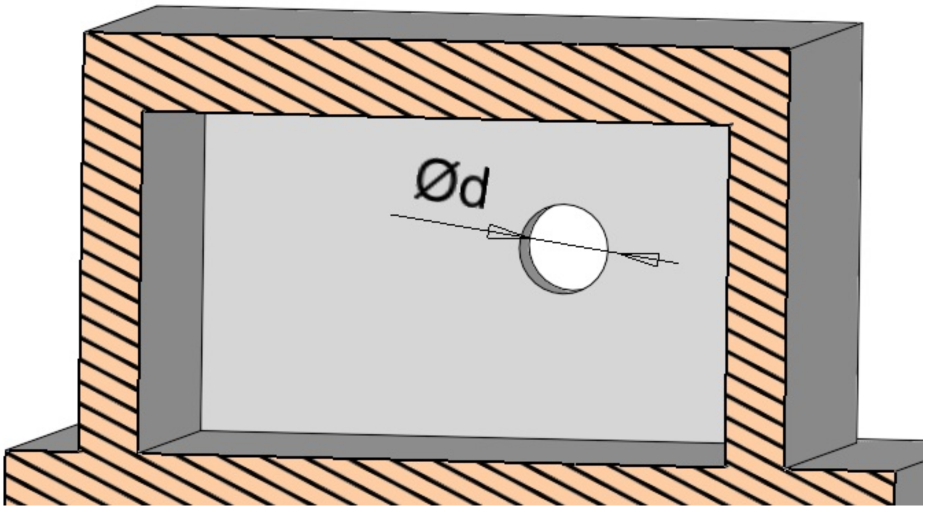

Fig. 4.19 Example of draining hole

simultaneously, to an empty smooth island with one surface; this condition is expressed in Eq. 4.28

$$\exists Br_i | Br_i \oslash \wedge \exists S_l \in Br_i | S_l / \wedge S_l \in I_{s,k} \tag{4.28}$$

Where $I_{s,k}$ is a smooth island with two empty loops (i.e. a through hole). The diameter of the hole is then compared to the minimum diameter allowing the flow of liquid resin.

4.3.5 Implementation

The described system has been implemented as a plug in for the CAD software CimatronE 12 by 3D Systems. C# programming language has been used for accessing the software of the CAD through its Application Programming Interface (API).

The first step in the usage of the system is to define the orientation of the part to the coordinate system of the machine, as it defined many of the features described in 4.3.2.

Fig. 4.20 provides a graphical representation of the OOP representation of entities described in 4.3.2.

The DfAM rules described in 4.3.4 are implemented in the KBSM. The GUI in Fig. 4.21 allows defining which checks have to be performed on the model to assess manufacturability.

The limit values are assigned for a specific combination of machine and material. In the first implementation, the values given by [88] for a Formlabs Form2 using Clear 04 resin (i.e. a mix of Methacrylate and Diphenyl phosphine oxide) have been used. Nevertheless, when more accurate information are given, the user has the opportunity to modify these values using the GUI in Fig. 4.21.

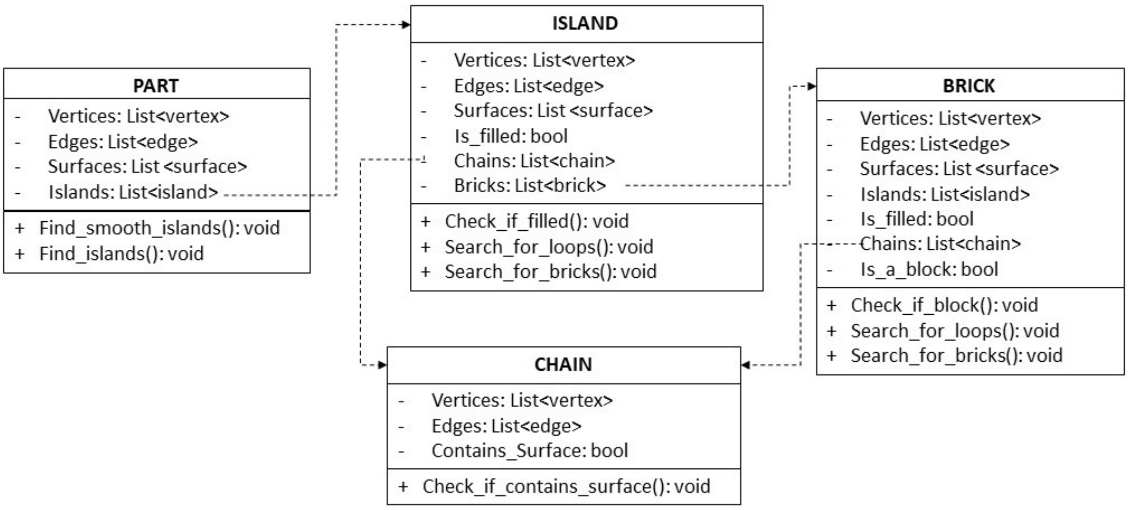

Fig. 4.20 Graph representation of manufacturing relevant geometrical entities in OOP

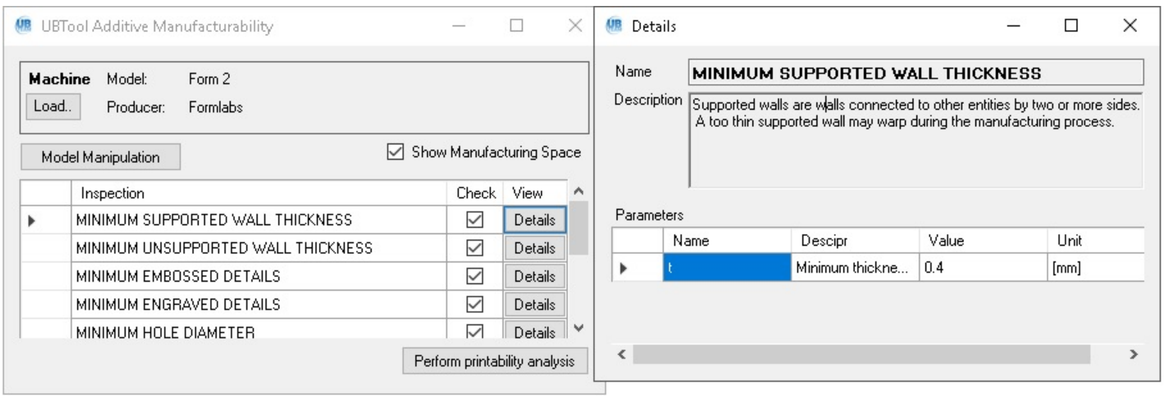

Fig. 4.21 Interface for rule selection and tuning of parameters

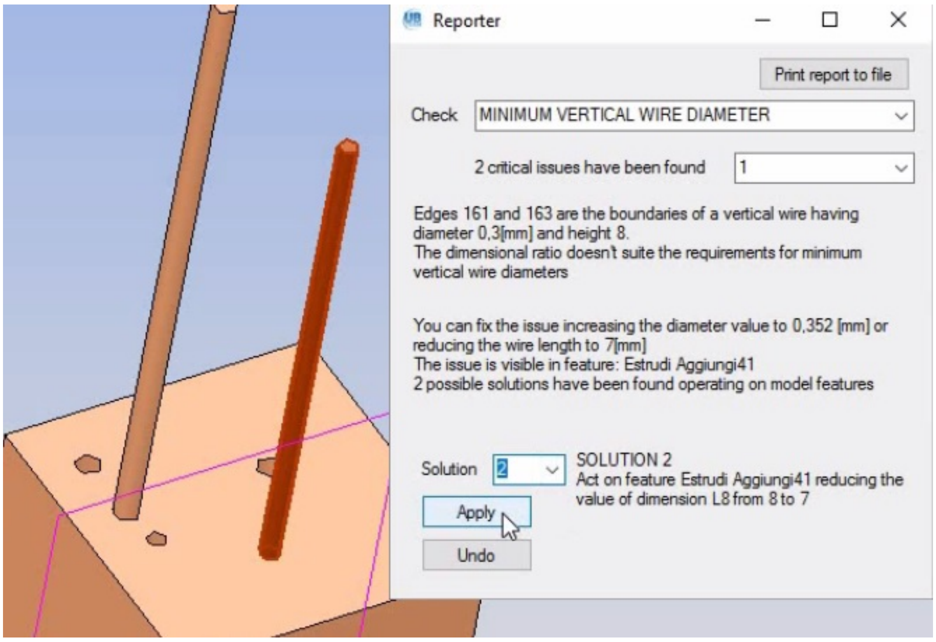

Fig. 4.22 Interface for rule selection and tuning of parameters

Once the manufacturability check has been completed, a report of critical issues is provided to the user. An example of such an output is shown in Fig. 4.22. The report includes a description of the critical geometries (in terms of surfaces and edges); these entities are also highlighted in the three-dimensional environment for a better understanding.

A textual description of the possible solutions is included. When a native geometry (i.e. moedeled within the same CAD environment) is analysed, these solutions can be also executed automatically by the KBSM. For some of the DfAM described in 4.3.4 more than one solution can be adopted. As an example, when the aspect ratio of a vertical pin is exceeded (as in Fig. 4.22), an increase of diameter d or a shortening of length l are equally suitable to overcome the problem. In this case, the user has to choose which solution has to be applied on the model.

4.4 Conclusions

The application of the proposed methodology to a well-defined technology allows a clear and sharp definition of the manufacturing-induced defects. The manufacturing know-how has been synthesised in DfAM rules about product geometry. The limit values of these rules can be varied in order to take into account the specific characteristics of the combinations of machine and material adopted for the production.

As the KBSM is designed to be applied for a generic product, no information about the geometry are given during the design of the KBSM. As a consequence, the DfAM have to be translated in terms of local features. As relevant features are usually different from the ones used for modelling, a definition of ad hoc entities was necessary. The geometrical entities have been defined (starting from elementary elements) so to efficiently address DfAM criteria. As a consequence, the study of the manufacturing rules have to be performed at the beginning of the system development.

In 4.2 a generic user has been chosen. Therefore, the highest possible knowledge content has to be given to the KBSM, leaving to the user only that choices that do not compromise the success of actions. In this direction, the adoption of rule-based knowledge allows giving precise indications on the possible solutions to identified critical issues.

The applicability to a generic geometry allows aiding the production of very different components. On the other hand, this approach does not allow including, next to process-based considerations, requirements related to the usage phase of the product.

As in the case of Chapter 3, the KBSM has been developed starting from the dimension of the applicability space with the highest specificity (in this case, the process).

Implementation allowed verifying the efficiency of the designed system on geometries produced by SL. The simplicity of KBSM actually enables its use by non-expert operators. Future developments could easily integrate formulas, instead of constants, for the calculation of limit values.

Chapter 5

Build Job preparation in Powder Bed Fusion

5.1 Applicability definition

The example discussed in this chapter deals with the design of a KBESM for the preparation of build jobs in Powder Bed Fusion (PBF). In particular, the KBESM is aims to assist the preparation of the build job once the design of the part has been completed and the parts have been converted to STL files.

The system has thus to be applied to a specific process, which is PBF. On the other, hand, no specifications about the part to be processed are given; in other words, the system has to be applicable to a generic product.

As PBF is mainly used for the production of high-level mechanical and biomedical parts [340], the user is expected to have information about the requirements to be met by the production. In particular, the quality level to be reached in terms of dimensional accuracy and surface roughness has to be clear. Furthermore, as PBF machines are only adopted at industrial level (i.e. no desktop solutions are on the market) a general knowledge of the PBF process is expected.

The KBESM can be thus schematically represented in the space of applicability as shown in Fig. 5.1.

5.2 Conceptual design

As mentioned above, the system is supposed to aid the user during the preparation of parts for the PBF process. In particular, the following objectives have to be met:

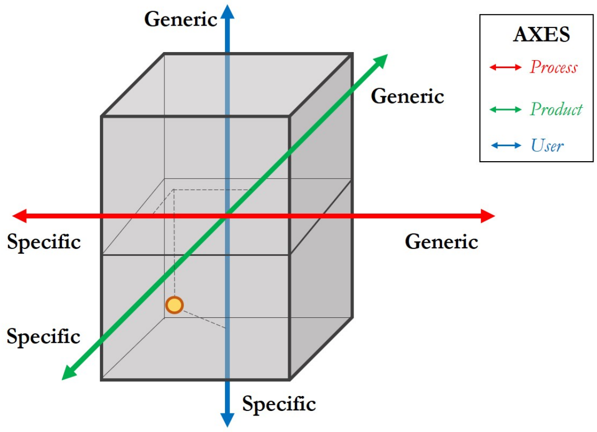

Fig. 5.1 Location in the applicability space of the KBESM for PBF preparation

- *Accuracy*, i.e. the respect of dimensional and geometrical design specifications
- *Roughness*, i.e. the fulfilment of surface roughness constraints imposed by the application
- *Build time* necessary to the fabrication of the part
- *Material consumption*, which varies according to the amount of supporting structures that are necessary to the fabrication of part
- *Cleanability*, i.e. easiness of removing the non-transformed powder at the end of the process.

These objectives are summarised in the MODIA of Fig. 5.2.

The accuracy of the product is one of the fundamental concerns in PBF production as the part is strongly affected by internal residual stresses at the end of the process [42, 230]. The satisfaction of dimensional requirements affects the proper functionality of the part, with a direct impact on SoS of the gate-to-grave life step. When the design requirements are not met by the PBF, further processes (when possible) may be adopted; this directly affects the economical and environmental sustainability of the product's LC in the gate-to-gate phase. Analogous considerations can be made for the surficial quality (i.e. roughness) of the produced part.

The build time is one of the most influential factors in determining the costs related to PBF [239]. For this reason, the reduction of processing time allows significantly improving the economic sustainability of the gate-to-gate LC phase. Furthermore, the electrical demand of the process is one of the most influential factors on most of the LCIA indicators, as

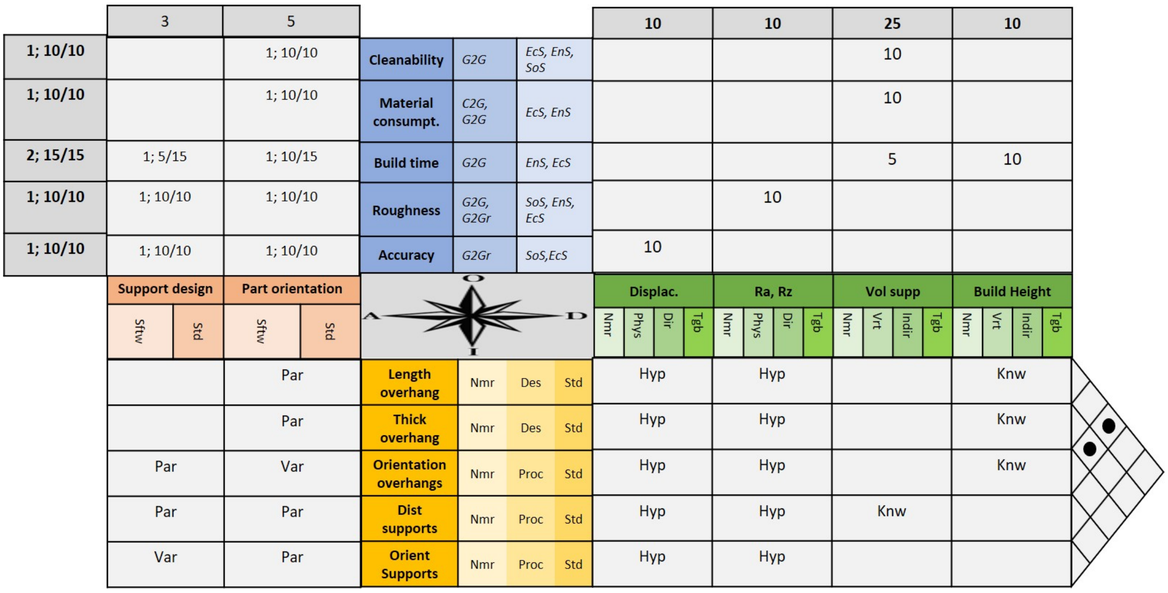

Fig. 5.2 MODIA of the KBESM for PBF build preparation

demonstrated by [81]; the same work also pointed out how the importance of the processing phase on the total energy consumption. Therefore, reducing the time necessary to material transformation is one extremely effective strategy to improve the environmental sustainability of the production in the gate-to-gate step [222].

Given a certain part design, the amount of material that is actually transformed depends onto the amount of support structures necessary to part fabrication. The production of powder (usually by means of gas atomisation) and its transportation have in turn a significant impact on the economic and environmental sustainability of the production [184]. Furthermore, the support structures needs to be removed at the end of the process and disposed as a waste, since this material can not be recycled in next productions; this results in a further environmental and economic impact in gate-to-gate LC phase of the product. For these reasons, a reduction of the supporting structures' volume is a key strategy to improve economic and environmental sustainability of the process.

At the end of the process, non-transformed powder must be accurately cleaned from parts in order to avoid its diffusion during following manufacturing steps and product utilisation. As fine metal powder represent a direct risk for human health [31, 113], the complete removal of exceeding material is fundamental in order to avoid environmental and societal impacts in both the gate-to-gate and gate-to-grave LC phases.

In order to verify the dimensional and geometrical accuracy of the part, the displacement of reference points from their nominal position can be used. The measurement of displacement has to be done on the manufactured part; aligning techniques and reference points are chosen according to the requirements to be met.

For the evaluation of roughness, the parameters and procedures defined by the International Organisation for Standardisation (ISO) (and, in particular, Ra and Rz parameters) are commonly adopted [115, 116, 118]. These descriptors have been already adopted in literature in order to investigate the roughness of parts by PBF [270].

Once the support structures of the part have been designed, their volume can be easily extracted by the virtual environment. Analogously, the build height of the part is calculated as the Z-dimension of the bounding box that contains the part with its supporting structures.

The RM in Fig. 5.2 shows how these descriptors are supposed to represent the objectives previously outlined.

In particular, the displacement and R-parametes are direct measures of accuracy and roughness, respectively. According to the description given, the material consumption is directly related to the amount (i.e. volume) of processed support structures. The volume of support structures also determines the easiness of removing powder from the manufactured part; as it will be detailed in the following, also the design of supports has a fundamental influence on the cleanability of the part at the end of the process.

The building time is affected by a number of factors including both part geometry and process parameters (in particular scanning strategy and feed rate); several models for the estimation of the build time in the design stage have been proposed in literature [225, 239]. A first estimation can be made neglecting the difference in scanning speed between contours and hatching, i.e. considering a constant volumetric transformation rate. This approach is adopted by most of commercial software for initial estimations; more accurate predictions may be obtained by self-learning using a higher number of geometrical and process parameters [71].

Under the hypothesis of constant volumetric building rate, the volume of supporting structures and the height of the part can be considered as only descriptors for building time; in particular, a higher influence is assigned to the height, as the re-coating time usually is usually more influential if compared to the scanning time of supports.

Overhangs, i.e. geometries that have to be built on non-melted powder, are subject to localised deformations due to gravity and internal stresses during part fabrication. For such geometries, support structures play a double role by balancing internal stresses and aiding the heat dissipation that causes them [121, 95, 349]. The amount of internal stresses to be avoided is in turn affected by the geometry of overhangs, in particular in terms of thickness and length [230, 261, 345]. The inclination of overhangs to the building direction is the most influential factor, that leads to determine whether support structures have to be used during build preparation [121, 164]. The orientation is also fundamental for the determination of the surface roughness, due to the staircase effect on sloped part surfaces [271]. Accordingly, these factors are used as inputs of the KBESM in Fig. 5.2.

According to what exposed above, the design of supports plays a fundamental role on the obtainable part quality. Several approaches have been proposed in literature to enhance the part quality by means of support design [123, 90, 93]. In the present work, supports consisting in a single-scan line are considered [30, 269]. This structures are widely used in industrial applications due to their fast building and easy removing at the end of the process. Under this restriction, the orientation of scanning line and their relative distance are the most influential design parameters.

As direct models of the correlation between these parameters and the part quality (in terms of accuracy and roughness) are lacking, the corresponding relations of the KM in Fig. 5.2 have been marked as Hyp. An experimental campaign (described in 5.3) was run to deepen these relations and refine the KM. The remaining connections in Fig. 5.2 are based on explicit geometrical rules.

Two main actions are designed for the system, i.e. part orientation and support design. Both these actions have to be performed by the software, resulting in a highly automated KBSM.

The part orientation deals with the determination of optimal relative angles between the machine and model coordinate systems. The orientation of scanning lines is chosen as variable for the support design (i.e. the distance between lines is used as a parameter).

The analysis of MODIA in Fig. 5.2 points out how the KBESM is completely process-driven, since no variables have been assigned to design inputs. As well, the number of objectives in the gate-to-gate LC phase shows how the system is mainly process-oriented.

All the actions are delegated to a software agent, i.e. an automated decision making strategy is adopted. Observing the sum of columns in EM, it is also possible to notice how both the actions will deal with MCDM problems.

5.3 Experimental analysis of relations

5.3.1 Design of experiment

In order to explicit the relations of the overhang and support geometrical parameters with the accuracy and roughness of parts, an experimental campaign was performed.

According to what exposed in the previous sections, the levels of the experiment are:

- Length of the overhang (L_{oh})
- Thickness of the overhang (t_{oh})

- Inclination of the overhang (α_{oh})
- Distance between support lines (d_{sl})

The benchmark part of Fig. 5.3 was used for testing.

The part is designed to allow the measurement of the roughness and displacements of the 20 mm plate, as it will be clear in the following. In order to investigate the effect of support design, linear supporting structures are built under the overhang, as shown in Fig. 5.4. The supports are connected to the part using teeth with height 1.5 and width 0.8 mm to ease the removal. The software Magics from Materialise has been used for support design.

Preliminary tests pointed out the insufficient resistance of one-directional walls; in fact, these structures led to the uncontrolled deformations during construction as shown in Fig.5.5, with consequent interruption of the build job.

For this reason, the design of supports has been modified adding reinforcements orthogonal to the line direction; Fig. 5.6. shows these reinforcements (in red colour) and their dimensions (as a function of d_{sl}).

The levels used for each factor are summarised in Tab. 5.1

Table 5.1 Levels of experimental factors

Factor	N. levels	Values	Unit of Measure
L_{oh}	3	$20, 40, 60$	mm
t_{oh}	3	$2, 4, 8$	mm
α_{oh}	5	$10, 20, 30, 40, 50$	$\circ$
d_{sl}	3	$1, 1.5, 2$	mm

A full-factorial Design of Experiment (DOE) [201] would lead to the fabrication of 135 specimens. In order to reduce the number of tests a D-Optimal DOE has been adopted [61, 129]. The D-Optimality has been reached by means of Coordinate-Exchange algorithm [193], leading to the selection of specimens in Tab. 5.2. The specimens 13, 14, 15 and 18 have been used for repetitions (marked with letter *a*).

5.3.2 Manufacturing of the specimens

A SLM 250HL machine by SLM Solution was used for the experiment. The specifications of the machine are reported in Tab. 5.3 [300].

The focus of the laser was shifted in order to compensate the effect of thermally induced effects on optical system [80]. A value of 3 mm was chosen according to the findings by [26].

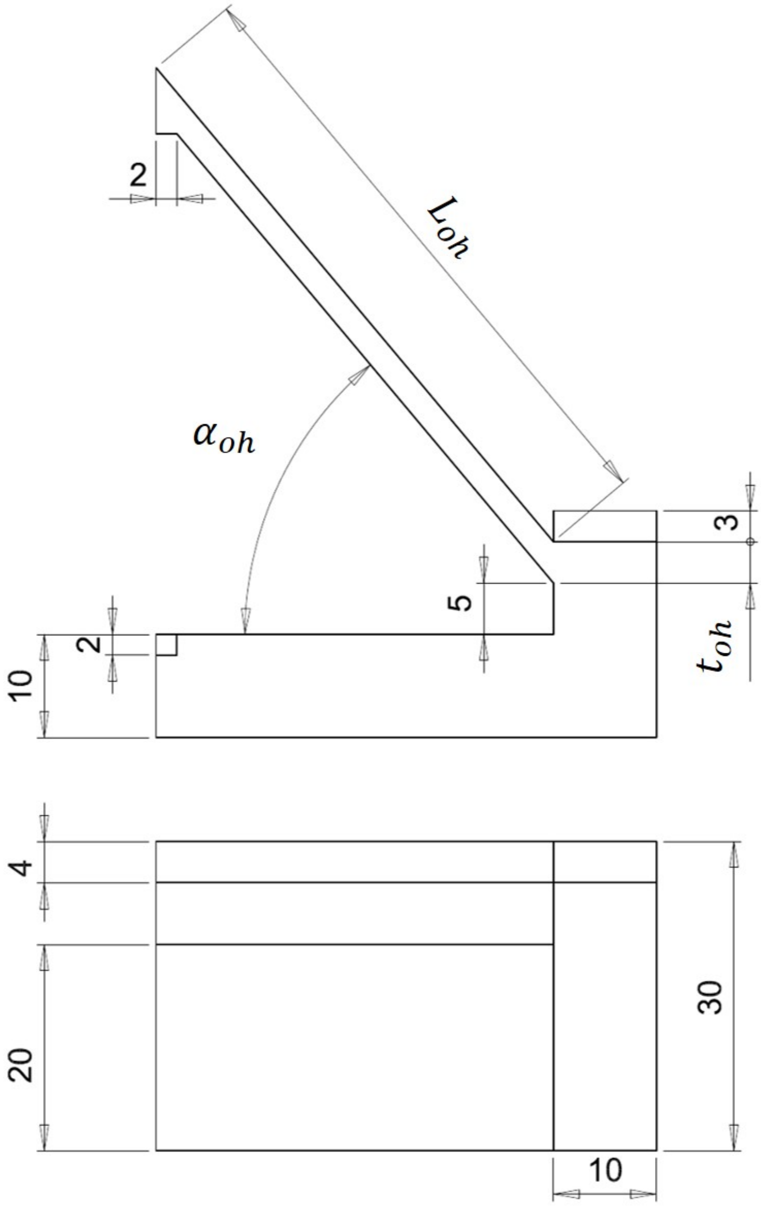

Fig. 5.3 Benchmark part used for the experimental campaign

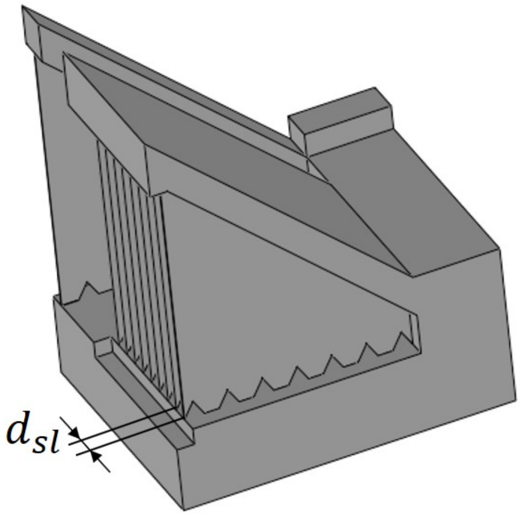

Fig. 5.4 Supported benchmark part

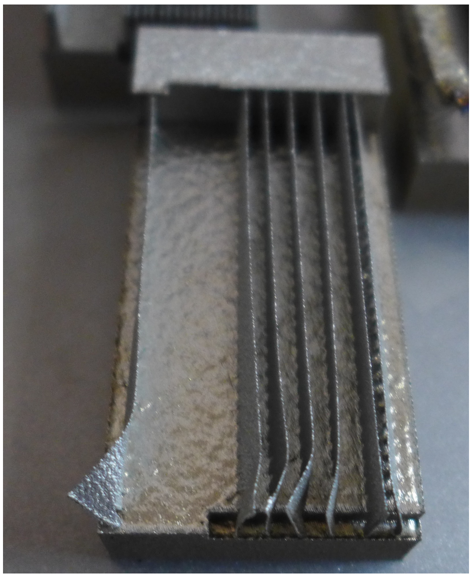

Fig. 5.5 Failure of build process due to support wall deformation

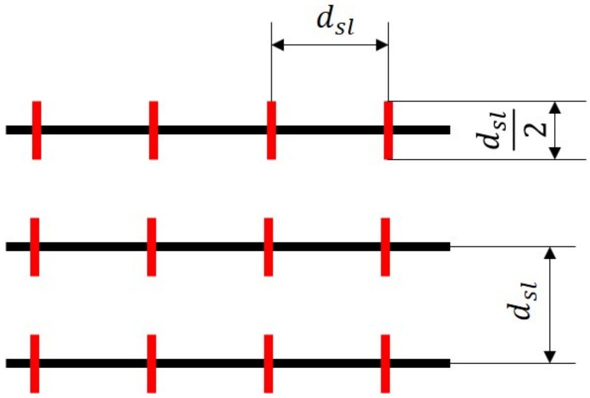

Fig. 5.6 Orthogonal reinforcements (in red) to prevent distortion of wall supports (in black)

316L stainless steel powder by SLM Solution AG has been used as feedstock material. According to the datasheet provided by the manufacturer, the material has a density of 7.95 $\frac{g}{cm^3}$ and a thermal conductivity of 15 $\frac{W}{m^2K}$. The chemical composition of the alloy is reported in Tab. 5.4. The particles have a spherical shape with diameter ranging from 10 to 45μm.

The specimens have been manufactured with a layer height (h_L) of 0.05 mm. Argon was used as assistance gas for the process. Four build jobs have been used to produce all the benchmark parts. Tab. 5.2 reports the build job of each specimen.

The process parameters used for the manufacturing of specimens are summarised in Tab.5.5.

5.3.3 Experimental procedure

The displacement and roughness of the overhang have been measured by means of both mechanical and optical measuring systems.

For the mechanical measurement of the displacement, a Vernier caliper with accuracy $\pm 0.05mm$ has been used. The distance between the parallel steps of the specimens (see Fig. 5.3) has been measured as in Fig. 5.7. The measure has been repeated in ten different positions and compared to the nominal value (h_n) as calculated in Eq. 5.1.

$$h_n = \lfloor \frac{2+5+L_{oh}sin(\alpha_{oh})-2tan(\alpha_{oh})}{h_L} \rceil h_L \tag{5.1}$$

The average value and the standard deviation of differences between h_n and measured values has been recorded and used for analysis.

The optical measurement of displacement was made using a Keyence VHX 5000 digital microscope. A frontal image of each specimen has been acquired using a a 100X magnification ; a sample image is shown in Fig. 5.8. The distance between edges in the front part

Table 5.2 Specimens used for the experimental activity

Run	L_{oh} [mm]	t_{oh} [mm]	α_{oh} [°]	d_{sl} [mm]	Build Job
1	60	6	50	2	2
2	60	6	10	2	1
3	20	2	10	2	3
4	40	6	10	1	1
5	20	6	50	2	4
6	60	6	30	1	1
7	20	4	10	1	4
8	20	6	10	2	4
9	60	2	10	1	1
10	20	2	50	2	4
11	20	6	50	1	4
12	60	4	50	1	3
13	40	2	10	1.5	1
13a	40	2	10	1.5	2
14	20	4	50	1.5	3
14a	20	4	50	1.5	4
15	20	6	20	1.5	3
15a	20	6	20	1.5	4
16	60	2	10	2	2
17	60	2	50	2	2
18	40	4	30	2	3
18a	40	4	30	2	4
19	20	2	30	1	4
20	40	2	50	1	3

has been measured using an image analysis software (i.e. GIMP, GNU Image Manipulation Program). Ten measures in different positions of the edges have been acquired also in this case, so to investigate the average value and standard deviation of the displacement.

It is worth mentioning since now how, even if the nominal value measured by the two methods is the same, they correspond to different geometrical descriptors. In fact, in the case of caliper, the measured height is the distance between the highest peak of the bottom surface and the lowest point of the upper surface. On the other hand, the optical measure corresponds to the distance between the intersection points of the step with the front face (i.e. the one where the microscope is focused). This difference is schematically represented in Fig. 5.9. These two quantities have been considered in the study as they are both relevant in order to determine the accuracy of the process.

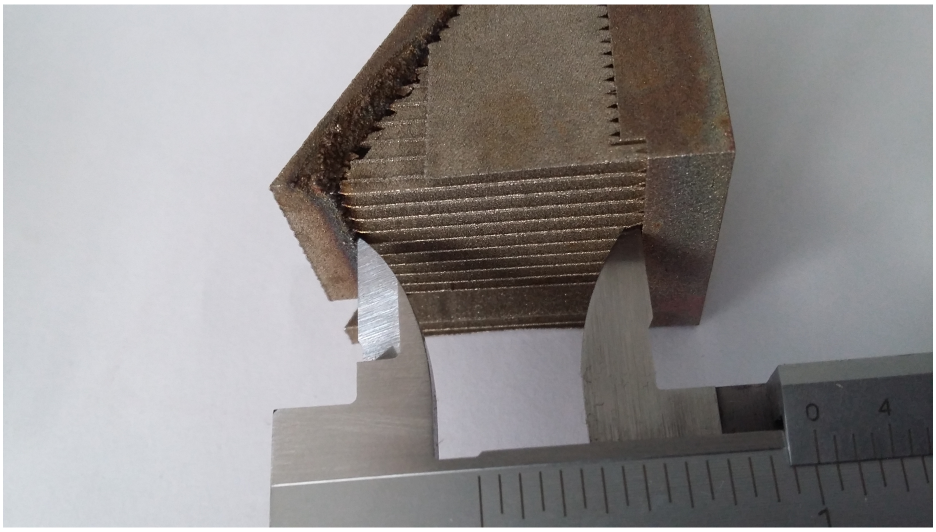

Fig. 5.7 Measurement of the displacement by means of caliper

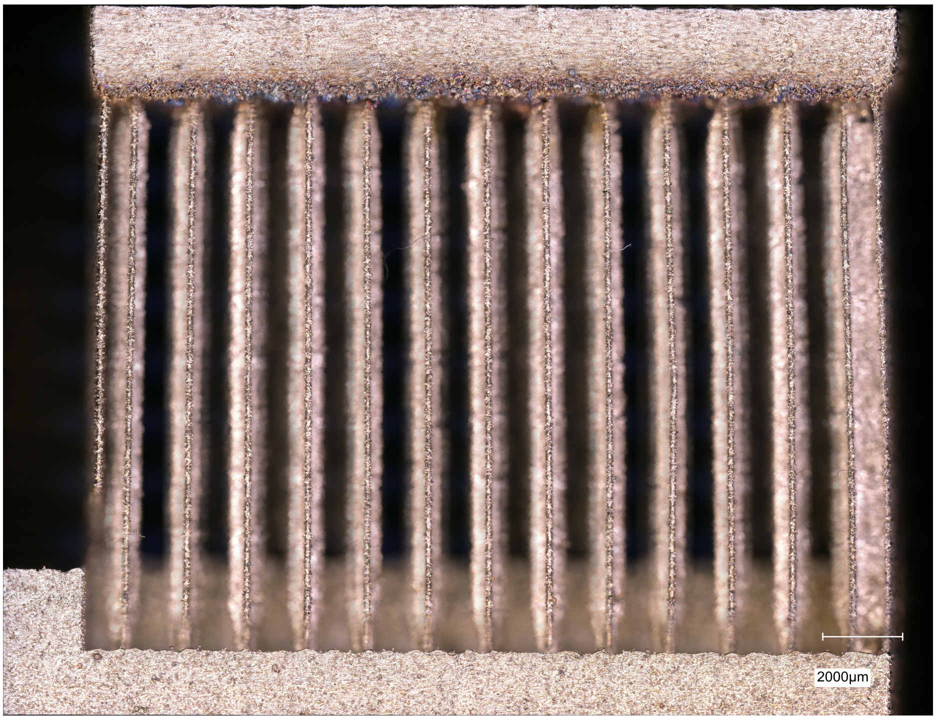

Fig. 5.8 Frontal image of the specimen acquired by means of Keyence VHX 5000 digital microscope

Table 5.3 Technical specifications of *SLM* 250^{HL} machine[300]

Building space	250 x 250 x 350	mm
Laser(cw)	400	W
Focal point diameter	70...300	μm
Layer thickness	20...100	μm
Particle size	10...65	μm
Building speed	5...20	$\frac{cm^3}{h}$
Tolerance (XYZ directions)	$\pm$50	μm
Focus distance	3	mm

Table 5.4 Chemical composition of 316L feedstock powder

Element	Fe	Cr	Ni	Mo	Mn	Si	P	S	C	N
Min (%)	Balance	16	10	2						
Max(%)	Balance	18	14	3	2	1	0.045	0.03	0.03	0.1

The measurement of roughness was made considering the upper face of the overhang as a periodic surface; the distance between stairs (*Rsm*) is considered as period, as shown in Fig.5.10 . The calculation of Rsm is made as in Eq. 5.2 leading to the results in Tab. 5.6.

$$Rsm = \frac{h_L}{sin(\alpha_{oh})} \tag{5.2}$$

The values of roughness sampling length l_r and evaluation length l_n given by [115] are summarised in Tab. 5.7

Comparing Tab. 5.6 and Tab. 5.7 it is possible to notice how different values of l_r and l_n are recommended for specimens with different inclinations. In order to adopt the same sampling and filtering conditions, the values of l_r and l_n have been set equal to 0.8 and 4 mm, respectively, for all the tests.

The physical measurement of surface roughness was made using a HOMMEL-ETAMIC Nanoscan 855 contact system. According to the indication given in [117], a probe with radius $r_{tip} = 5\mu m$ was used for measurements, being the expected average roughness R_a far higher than 0.5 μm. The profile has been measured along three different lines, calculating both R_a and R_Z roughness parameters [118]. Average values of both the descriptors have been used for regression.

For optical measurement of roughness, the optical surface measuring system Infinitefocus 3.5 by Alicona Imaging GmbH has been used. A 4x1 mm area has been acquired for each specimen using a step of 5 μm in the XY plane and a vertical step of 200 *nm*. Also in this case, R_a and R_Z measurements of three parallel profiles have been averaged and used to build a regression model.

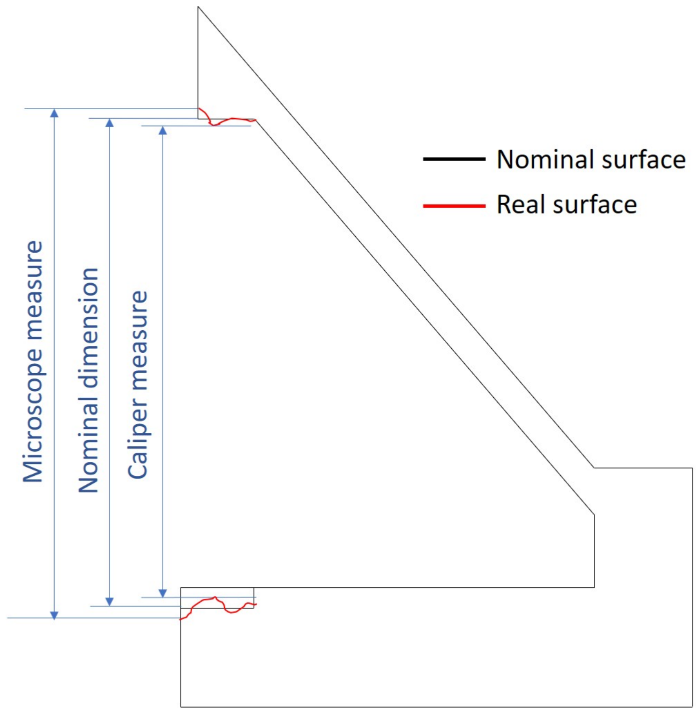

Fig. 5.9 Differences in displacements measured by means of different techniques

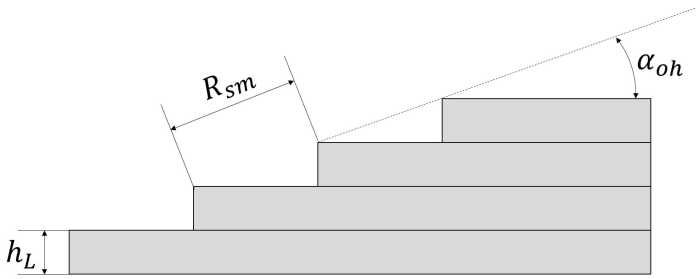

Fig. 5.10 Rsm evaluation on the basis of nominal dimensions

Table 5.5 Process parameters used for the manufacturing of specimens

Parameter	Value	Unit of measure
Focal point diameter	160	μm
Focus Position	3	mm
Contour laser power	100	W
Contour laser speed	440	$\frac{mm}{s}$
Hatching laser power	275	W
Hatching laser speed	760	$\frac{mm}{s}$
Hatch distance	120	μm
Hatching angle increment	90	$^{\circ}$
Support scanning laser power	150	W
Support scanning laser speed	700	$\frac{mm}{s}$

Table 5.6 Rsm values for manufactured specimens

Angle [°]	10	20	30	50
Rsm [mm]	0.28	0.15	0.1	0.07

5.3.4 Results and discussion

Physical Measurement of displacement

The results of vertical displacements measured by means of caliper (Δh_c) are summarised in Tab. 5.8. The average value of distortion ($\Delta h_{c,aver}$) varies between - 0.48 and 0.43 mm, while standard deviation ($\Delta h_{c,std}$) is in the range [0.05;0.18] mm. Uncertainty evaluation shows a good repeatability of average values, with a maximum difference of 0.08 mm between specimens 13 and 13a.

The Analysis Of Variance (ANOVA) of average values leads to the results summarised in Tab.5.9. The analysis points out the the leading role of interaction between overhang thickness and inclination in determining the distortion of the part; also the two stand-alone factors (α_{oh} and t_{oh}) reveals to be significant, with a p-value of 0.01 and 0.047, respectively. This trend is coherent with the influence of thickness and inclination on the residual stresses that determine the part deformation [69, 305]. It is worth noticing how, in the range of dimensions used for the experiment, the length of the overhang does not have a significant influence on the displacement. The interaction of t_{oh} with d_{sl} also shows a p-value < 0.05, pointing out the influence of support spacing on displacements for high values of overhang thickness.

The linear regression fitting the average values of $\Delta_{h,c}$ is reported in Eq. 5.3. This regression has $R^2 = 94.61\%$ and $R^2_{adj} = 90.47\%$. Fig. 5.11 shows the residuals plots of the regression.

Table 5.7 Recommended values of roughness sampling length and evaluation length [115]

R_{sm} mm	l_r mm	l_n mm
$0.013 \leq R_{sm} \leq 0.04$	0.08	0.4
$0.04 \leq R_{sm} \leq 0.13$	0.25	1.25
$0.13 \leq R_{sm} \leq 0.4$	0.8	4
$0.4 \leq R_{sm} \leq 1.3$	2.5	12.5
$1.3 \leq R_{sm} \leq 4$	8	40

Table 5.8 Measurements of vertical displacement obtained by means of caliper

Run	L_{oh} [mm]	t_{oh} [mm]	α_{oh} [°]	d_{sl} [mm]	Build Job	$\Delta h_{c,aver}$ [mm]	$(\Delta h_{c,std})$ [mm]
1	60	6	50	2	2	-0.48	0.09
2	60	6	10	2	1	0.43	0.14
3	20	2	10	2	3	-0.23	0.18
4	40	6	10	1	1	0.23	0.12
5	20	6	50	2	4	-0.39	0.09
6	60	6	30	1	1	-0.34	0.16
7	20	4	10	1	4	-0.07	0.07
8	20	6	10	2	4	0.36	0.09
9	60	2	10	1	1	-0.15	0.10
10	20	2	50	2	4	-0.32	0.10
11	20	6	50	1	4	-0.31	0.10
12	60	4	50	1	3	-0.43	0.13
13	40	2	10	1.5	1	-0.11	0.11
14	20	4	50	1.5	3	-0.35	0.14
15	20	6	20	1.5	3	0.19	0.15
16	60	2	10	2	2	-0.31	0.18
17	60	2	50	2	2	-0.45	0.08
18	40	4	30	2	3	-0.21	0.17
19	20	2	30	1	4	-0.26	0.06
20	40	2	50	1	3	-0.22	0.06
13a	40	2	10	1.5	2	-0.19	0.12
14a	20	4	50	1.5	4	-0.37	0.05
15a	20	6	20	1.5	4	0.13	0.05
18a	40	4	30	2	4	-0.26	0.13

Table 5.9 ANOVA of average error measured by means of caliper

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	10.00	1.41	1.41×10^{-1}	22.83	0.00×10^{0}
L_{oh}	1.00	7.50×10^{-4}	7.54×10^{-4}	1.20×10^{-1}	7.32×10^{-1}
t_{oh}	1.00	2.98×10^{-2}	2.98×10^{-2}	4.82	4.70×10^{-2}
α_{oh}	1.00	5.61×10^{-2}	5.61×10^{-2}	9.07	1.00×10^{-2}
d_{sl}	1.00	9.39×10^{-3}	9.39×10^{-3}	1.52	2.40×10^{-1}
$L_{oh}t_{oh}$	1.00	6.10×10^{-3}	6.10×10^{-3}	9.90×10^{-1}	3.38×10^{-1}
$L_{oh}\alpha_{oh}$	1.00	1.74×10^{-2}	1.74×10^{-2}	2.82	1.17×10^{-1}
$L_{oh}d_{sl}$	1.00	1.34×10^{-3}	1.34×10^{-3}	2.20×10^{-1}	6.50×10^{-1}
$t_{oh}\alpha_{oh}$	1.00	3.34×10^{-1}	3.34×10^{-1}	54.08	0.00×10^{0}
$t_{oh}d_{sl}$	1.00	4.98×10^{-2}	4.98×10^{-2}	8.06	1.40×10^{-2}
a*d	1.00	1.59×10^{-2}	1.59×10^{-2}	2.57	1.33×10^{-1}
Error	13.00	8.03×10^{-2}	6.18×10^{-3}		
Lack-of-Fit	9.00	7.36×10^{-2}	8.18×10^{-3}	4.89	7.00×10^{-2}
Pure Error	4.00	6.69×10^{-3}	1.67×10^{-3}		
Total	23.00	1.49			

$$\begin{aligned}\Delta h_{c,aver} = -3.68\times10^{-1} + 1.54\times10^{-3}L_{oh} + 9.33\times10^{-2}t_{oh} + 1.38\times10^{-2}\alpha_{oh} + \\ -1.73\times10^{-1}d_{sl} - 5.37\times10^{-4}L_{oh}*t_{oh} - 9\times10^{-5}L_{oh}*a_{oh} + 9.9\times10^{-4}L_{oh}*d_{sl} + \\ -3.96\times10^{-3}t_{oh}*\alpha + 6.02\times10^{-2}t_{oh}*d_{sl} - 3.39\times10^{-3}\alpha_{oh}*d_{sl}\end{aligned} \tag{5.3}$$

An analogous analysis was performed using the values of standard deviations ($\Delta h_{c,std}$). The results of ANOVA are reported in Tab. 5.10. It is possible to notice the significance of d_{sl} on the standard deviation of values. This effect demonstrates the role of supports in mitigating the differences between lateral and central regions of the plane; the interaction of d_{sl} with t_{oh} points out that these differences are due to the amount of molten material above the measuring plane.

The linear regression of data lead to $R^2 = 68.770\%$ and $R^2_{adj} = 44.63\%$, that is to say linear regression can not be used to model the variation of measured values.

Optical Measurement of displacement

The average values ($\Delta h_{m,aver}$) and standard deviations ($\Delta h_{m,std}$) of vertical displacements calculated on microscopic pictures are reported in Tab. 5.11. It is possible to notice how all

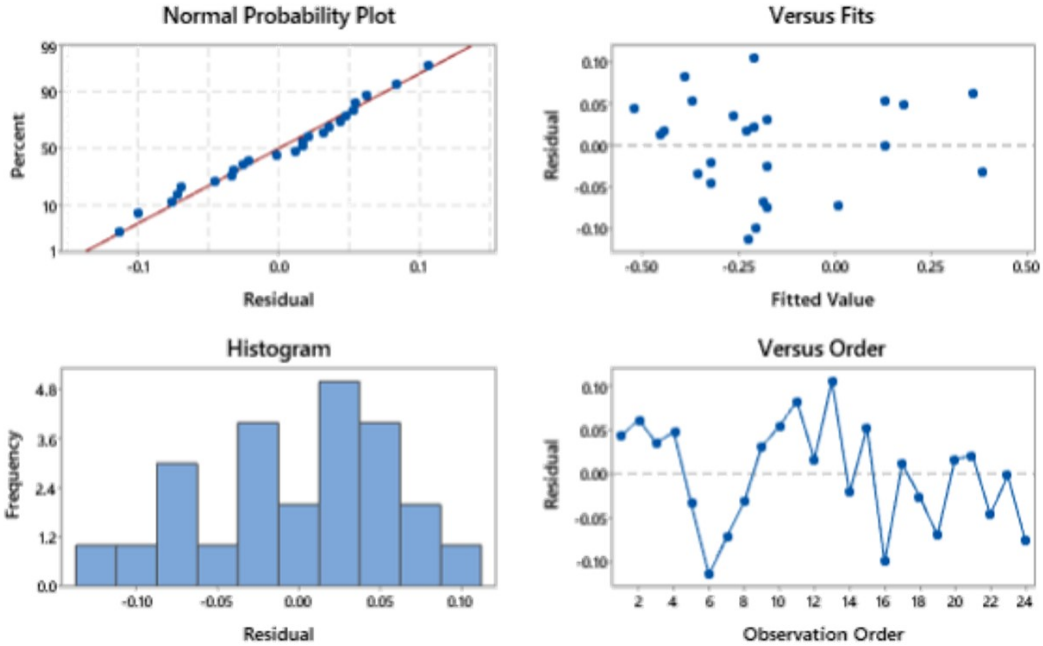

Fig. 5.11 Residual plots for regression of average $\Delta h_{c,aver}$ as in Eq. 5.3

Table 5.10 ANOVA of standard deviation of error measured by means of caliper

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	10.00	2.52×10^{-2}	2.52×10^{-3}	2.85	4.00×10^{-2}
L_{oh}	1.00	1.28×10^{-3}	1.28×10^{-3}	1.45	2.50×10^{-1}
t_{oh}	1.00	1.27×10^{-3}	1.27×10^{-3}	1.43	2.53×10^{-1}
α_{oh}	1.00	4.28×10^{-4}	4.28×10^{-4}	4.80×10^{-1}	4.99×10^{-1}
d_{sl}	1.00	1.37×10^{-2}	1.37×10^{-2}	15.46	2.00×10^{-3}
$L_{oh}t_{oh}$	1.00	1.12×10^{-3}	1.12×10^{-3}	1.27	2.80×10^{-1}
$L_{oh}\alpha_{oh}$	1.00	4.51×10^{-4}	4.51×10^{-4}	5.10×10^{-1}	4.88×10^{-1}
$L_{oh}d_{sl}$	1.00	1.93×10^{-3}	1.93×10^{-3}	2.18	1.64×10^{-1}
$t_{oh}\alpha_{oh}$	1.00	1.67×10^{-3}	1.67×10^{-3}	1.89	1.92×10^{-1}
$t_{oh}d_{sl}$	1.00	6.51×10^{-3}	6.51×10^{-3}	7.37	1.80×10^{-2}
$\alpha_{oh}d_{sl}$	1.00	3.36×10^{-3}	3.36×10^{-3}	3.80	7.30×10^{-2}
Error	13.00	1.15×10^{-2}	8.84×10^{-4}		
Lack-of-Fit	9.00	2.76×10^{-3}	3.06×10^{-4}	1.40×10^{-1}	9.93×10^{-1}
Pure Error	4.00	8.74×10^{-3}	2.18×10^{-3}		
Total	23.00	3.67×10^{-2}			

Table 5.11 Measurements of vertical displacement obtained by means of Keyence microscope

Run	L_{oh} [mm]	t_{oh} [mm]	α_{oh} [°]	d_{sl} [mm]	Build Job	$\Delta h_{m,aver}$ [mm]	$\Delta h_{m,std}$ [mm]
1	60	6	50	2	2	2.16	0.07
2	60	6	10	2	1	0.99	0.19
3	20	2	10	2	3	-0.02	0.11
4	40	6	10	1	1	0.58	0.06
5	20	6	50	2	4	0.63	0.19
6	60	6	30	1	1	1.67	0.07
7	20	4	10	1	4	0.35	0.05
8	20	6	10	2	4	0.92	0.09
9	60	2	10	1	1	0.32	0.07
10	20	2	50	2	4	0.50	0.07
11	20	6	50	1	4	0.34	0.08
12	60	4	50	1	3	3.12	0.13
13	40	2	10	1.5	1	0.28	0.05
14	20	4	50	1.5	3	0.49	0.06
15	20	6	20	1.5	3	0.65	0.17
16	60	2	10	2	2	0.32	0.13
17	60	2	50	2	2	3.56	0.14
18	40	4	30	2	3	0.99	0.14
19	20	2	30	1	4	1.29	0.09
20	40	2	50	1	3	1.80	0.14
13a	40	2	10	1.5	2	0.42	0.05
14a	20	4	50	1.5	4	0.93	0.10
15a	20	6	20	1.5	4	0.91	0.09
18a	40	4	30	2	4	0.66	0.14

the average displacements are positive, with the only exception of specimen 3 with $\Delta h_{m,aver}$ equal to -0.02 mm. The range of measured average values is far higher than the one in Tab. 5.8, with a maximum value of 3.56 mm. These behaviour can be explained if considering the difference between real and nominal shape of the edge remarked in Fig. 5.9. The range of standard deviations on measurements is coherent with the one observed for caliper.

Tab. 5.12 reports the ANOVA results for average values $\Delta h_{m,aver}$ in Tab. 5.11. The p-value shows the influence of the interaction between overhang inclination and thickness on measured displacements, in accordance with the results observed for caliper measurements. Nevertheless, in the case of microscope measurements, the interaction between overhang inclination and length appears to be the most influential factor on the measured values. A possible explanation derives from considering how these factors affect the height in the building platform where the edge is located and, in turn, its capability of disposing heat.

Table 5.12 ANOVA of average displacements measured by means of Keyence microscope

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	10.00	16.82	1.68	14.99	0.00
L_{oh}	1.00	3.42×10^{-2}	3.42×10^{-2}	3.00×10^{-1}	5.90×10^{-1}
t_{oh}	1.00	9.77×10^{-2}	9.77×10^{-2}	8.70×10^{-1}	3.68×10^{-1}
α_{oh}	1.00	4.95×10^{-2}	4.95×10^{-2}	4.40×10^{-1}	5.18×10^{-1}
d_{sl}	1.00	9.76×10^{-2}	9.76×10^{-2}	8.70×10^{-1}	3.68×10^{-1}
$L_{oh}t_{oh}$	1.00	1.43×10^{-1}	1.43×10^{-1}	1.28	2.79×10^{-1}
$L_{oh}\alpha_{oh}$	1.00	3.98	3.98	35.44	0.00
$L_{oh}d_{sl}$	1.00	3.95×10^{-2}	3.95×10^{-2}	3.50×10^{-1}	5.63×10^{-1}
$t_{oh}\alpha_{oh}$	1.00	1.19	1.19	10.63	6.00×10^{-3}
$t_{oh}d_{sl}$	1.00	1.09×10^{-1}	1.09×10^{-1}	9.70×10^{-1}	3.42×10^{-1}
a*d	1.00	2.48×10^{-2}	2.48×10^{-2}	2.20×10^{-1}	6.46×10^{-1}
Error	13.00	1.46	1.12×10^{-1}		
Lack-of-Fit	9.00	1.26	1.40×10^{-1}	2.85	1.63×10^{-1}
Pure Error	4.00	1.97×10^{-1}	4.93×10^{-2}		
Total	23.00	18.28			

Eq. 5.4 fits the measured average error values with $R^2 = 92.02\%$ and $R^2_{adj} = 85.88\%$. The graph of residual of the regression model are reported in Fig. 5.12. The graph points out the presence of unusual observation with high residuals, compared to the case of caliper. This can be explained by the local errors that can occur on the edge of the parts.

$$
\begin{aligned}
\Delta h_{m,aver} = 0.35 - 1.04\times10^{-2}L_{oh} + 1.69\times10^{-1}t_{oh} + 1.30\times10^{-2}\alpha_{oh} + \\
-5.59\times10^{-1}d_{sl} - 2.60\times10^{-3}L_{oh}t_{oh} + 1.36\times10^{-3}L_{oh}\alpha_{oh} + \\
+5.36\times10^{-3}L_{oh}d_{sl} - 7.49\times10^{-3}t_{oh}\alpha_{oh} + 8.91\times10^{-2}t_{oh}d_{sl} - 4.24\times10^{-3}
\end{aligned}
\tag{5.4}
$$

In this case, no correlation between input variables and standard deviation can be observed performing ANOVA. Accordingly, no regression can be made on the values of $\Delta h_{m,std}$ by using a linear model.

Contact measurement of roughness

Tab. 5.13 summarises the results of roughness measurements by means of Nanoscan contact system. In particular, average and standard values of Ra and Rz parameters are reported with obvious notation.

Table 5.13 Measurements of roughness by means of Nanoscan contact machine

Run Run	L_{oh} [mm]	t_{oh} [mm]	α_{oh} [°]	d_{sl} [mm]	Build Job	$Ra_{av,n}$ $[\mu m]$	$Ra_{std,n}$ $[\mu m]$	$Rz_{av,n}$ $[\mu m]$	$Rz_{std,n}$ $[\mu m]$
1	60	6	50	2	2	11.26	0.94	55.17	3.44
2	60	6	10	2	1	17.88	2.64	82.35	3.43
3	20	2	10	2	3	18.49	2.36	86.72	3.33
4	40	6	10	1	1	17.87	0.95	82.07	7.63
5	20	6	50	2	4	9.75	0.85	49.04	6.27
6	60	6	30	1	1	14.40	2.86	63.56	14.70
7	20	4	10	1	4	17.93	1.11	82.11	6.35
8	20	6	10	2	4	15.57	1.95	73.33	5.02
9	60	2	10	1	1	14.69	3.67	66.64	20.95
10	20	2	50	2	4	9.00	1.04	44.09	5.35
11	20	6	50	1	4	8.31	1.20	38.69	6.04
12	60	4	50	1	3	10.71	2.56	49.58	1.67
13	40	2	10	1.5	1	19.76	2.20	84.95	5.64
14	20	4	50	1.5	3	11.26	2.87	54.48	14.93
15	20	6	20	1.5	3	15.83	3.73	75.66	16.06
16	60	2	10	2	2	19.86	2.05	90.37	10.02
17	60	2	50	2	2	11.02	1.38	55.50	7.89
18	40	4	30	2	3	12.43	3.14	61.41	16.83
19	20	2	30	1	4	11.97	1.78	54.97	5.51
20	40	2	50	1	3	9.02	1.09	47.00	2.78
13a	40	2	10	1.5	2	16.06	0.59	80.58	3.32
14a	20	4	50	1.5	4	8.73	2.14	50.66	10.77
15a	20	6	20	1.5	4	14.15	0.55	67.25	3.87
18a	40	4	30	2	4	13.06	0.47	64.31	4.73

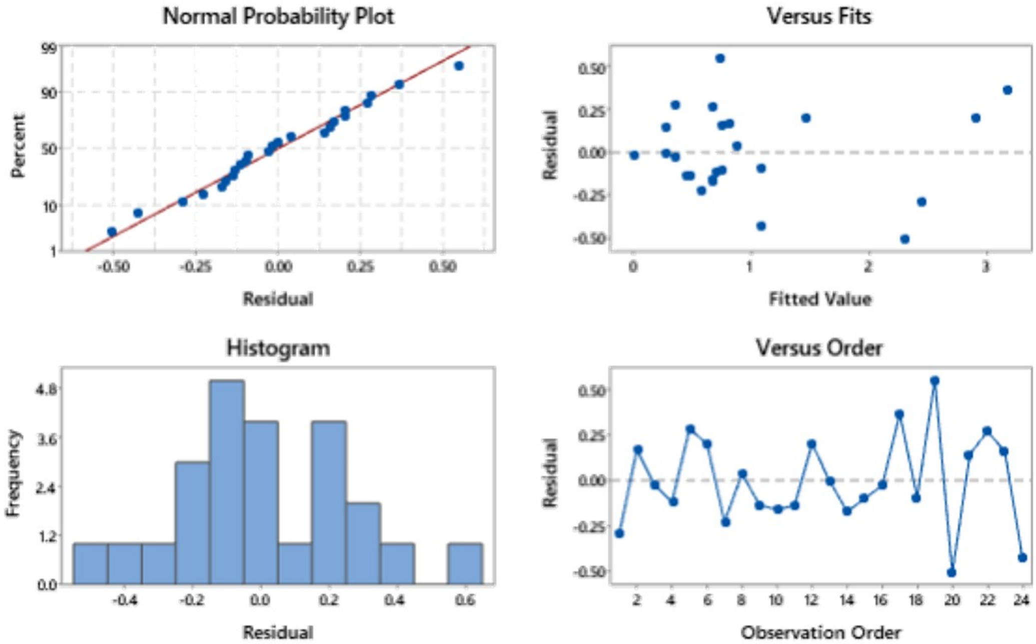

Fig. 5.12 Residual plots for regression of average $\Delta h_{m,aver}$ as in Eq. 5.4

As it can be observed, the average values of $Ra_{av,n}$ range between 8.31 and 19.86 μm, thus confirming the initial hypothesis of Ra>0.05 μm that led to the choice of the probe diameter. The high values of standard deviation on the measures point out the non-homogeneity of the surface; in particular, this effect can be observed on $Rz_{std,n}$ due to the higher influence of localised defects on Rz parameter. The variability of feedstock powder

The results of ANOVA on $Ra_{av,n}$ are summarised in Tab. 5.14. It can be immediately noticed how the inclination of the overhang is the only relevant factor for the prediction of roughness. This behaviour has been observed using both Ra and Rz. This result is also confirmed by the ANOVA of Rz parameter, reported in Tab. 5.15. In particular, the result shows how (in the range of the experiment) the thermal role of the supporting structures in disposing heat [349] is negligible compared to the staircase effect in the determination of surface roughness.

The regression models of $Ra_{av,n}$ is given in Eq. 5.5. The regression has $R^2 = 91.58\%$ and $R^2_{adj} = 85.11\%$; the graphs of residuals are shown in Fig.5.13.

$$\begin{aligned} Ra_{av,n} = 18.05 - 8.28\times10^{-2}L_{oh} + 4.96\times10^{-1}t_{oh} - 2.42\times10^{-1}\alpha_{oh} + 2.10d_{sl} + \\ +7.41\times10^{-3}L_{oh}t_{oh} + 8.15\times10^{-4}L_{oh}\alpha_{oh} + 3.38\times10^{-2}L_{oh}d_{sl} + \\ +8.03\times10^{-3}t_{oh}\alpha_{oh} - 6.47\times10^{-1}t_{oh}d_{sl} - 6.10\times10^{-3} \end{aligned} \tag{5.5}$$

Table 5.14 ANOVA of average Ra measured by Nanoscan

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	10.00	285.77	28.58	14.14	0.00
L_{oh}	1.00	2.17	2.17	1.08	3.19×10^{-1}
t_{oh}	1.00	8.43×10^{-1}	8.43×10^{-1}	4.20×10^{-1}	5.30×10^{-1}
α_{oh}	1.00	17.25	17.25	8.54	1.20×10^{-2}
d_{sl}	1.00	1.38	1.38	6.80×10^{-1}	4.23×10^{-1}
$L_{oh}t_{oh}$	1.00	1.16	1.16	5.80×10^{-1}	4.62×10^{-1}
$L_{oh}\alpha_{oh}$	1.00	1.43	1.43	7.10×10^{-1}	4.15×10^{-1}
$L_{oh}d_{sl}$	1.00	1.57	1.57	7.80×10^{-1}	3.93×10^{-1}
$t_{oh}\alpha_{oh}$	1.00	1.37	1.37	6.80×10^{-1}	4.25×10^{-1}
$t_{oh}d_{sl}$	1.00	5.76	5.76	2.85	1.15×10^{-1}
a*d	1.00	5.10×10^{-2}	5.14×10^{-2}	3.00×10^{-2}	8.76×10^{-1}
Error	13.00	26.27	2.02		
Lack-of-Fit	9.00	14.63	1.63	5.60×10^{-1}	7.85×10^{-1}
Pure Error	4.00	11.64	2.91		
Total	23.00	312.04			

Table 5.15 ANOVA of average Rz measured by Nanoscan

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	10.00	4940.23	494.02	14.06	0.00×10^{0}
L_{oh}	1.00	51.45	51.45	1.46	2.48×10^{-1}
t_{oh}	1.00	14.27	14.27	4.10×10^{-1}	5.35×10^{-1}
α_{oh}	1.00	291.60	291.60	8.30	1.30×10^{-2}
d_{sl}	1.00	22.42	22.42	6.40×10^{-1}	4.39×10^{-1}
$L_{oh}t_{oh}$	1.00	9.40	9.40	2.70×10^{-1}	6.14×10^{-1}
$L_{oh}\alpha_{oh}$	1.00	35.27	35.27	1.00	3.35×10^{-1}
$L_{oh}d_{sl}$	1.00	39.99	39.99	1.14	3.06×10^{-1}
$t_{oh}\alpha_{oh}$	1.00	10.18	10.18	2.90×10^{-1}	6.00×10^{-1}
$t_{oh}d_{sl}$	1.00	74.93	74.93	2.13	1.68×10^{-1}
a*d	1.00	4.50×10^{-1}	4.46×10^{-1}	1.00×10^{-2}	9.12×10^{-1}
Error	13.00	456.93	35.15		
Lack-of-Fit	9.00	400.57	44.51	3.16	1.40×10^{-1}
Pure Error	4.00	56.36	14.09		
Total	23.00	5397.15			

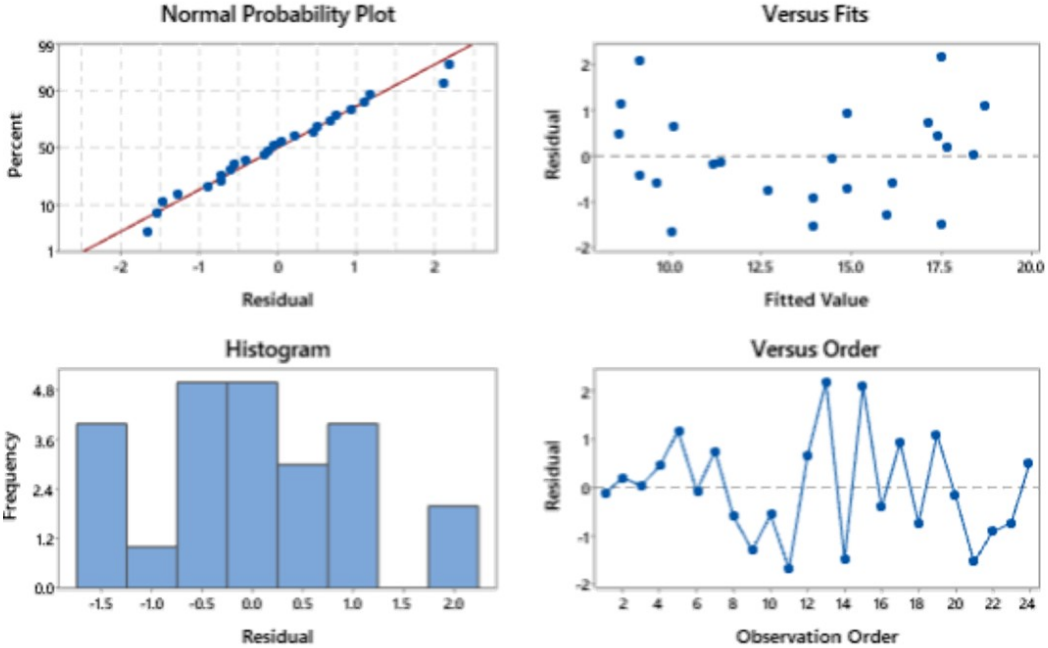

Fig. 5.13 Residual plots for regression of average $Ra_{av,n}$ as in Eq. 5.5

Similar results can be found for the regression of $Rz_{av,n}$ as in Eq. 5.6, where $R^2 = 91.53\%$ and $R^2_{adj} = 85.02\%$ were observed. The corresponding graphs of residuals are shown in Fig.5.14.

$$\begin{aligned} Rz_{av,n} = 83.3 - 4.03 \times 10^{-1} L_{oh} + 2.04 t_{oh} - 9.95 \times 10^{-1} \alpha_{oh} + 8.50 d_{sl} + \\ + 2.11 \times 10^{-2} L_{oh} t_{oh} + 4.04 \times 10^{-3} L_{oh} \alpha_{oh} + 1.70 \times 10^{-1} L_{oh} d_{sl} + \\ + 2.19 \times 10^{-2} t_{oh} \alpha_{oh} - 2.33 t_{oh} d_{sl} - 1.80 \times 10^{-2} \end{aligned} \tag{5.6}$$

The ANOVA of standard deviations didn't reveal any relevant factors for neither $Ra_{std,n}$ nor $Rz_{std,n}$; as a consequence, no regression model can be built for the standard deviation.

Optical measurement of roughness

The values of Ra and Rz measured using Alicona optical system are reported in Tab. 5.16. It is immediately clear how the values of roughness measured by means of this systems are higher than the one registered with Nanoscan and reported in the previous section; as an average, a difference of +31.7% in Ra and +32.08% in Rz was registered. This can be explained considering the geometrical limitations of the spherical probe tip in reaching the

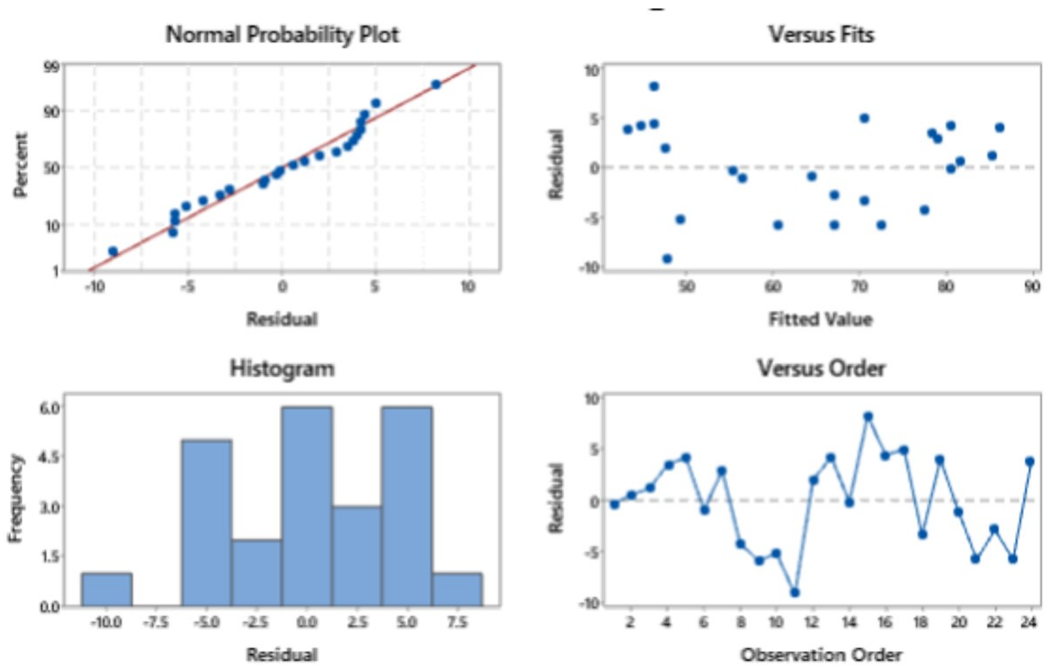

Fig. 5.14 Residual plots for regression of average $Rz_{av,n}$ as in Eq. 5.6

narrowest valleys of the profile (these is even more significant due to the fact that a probe with $r_{tip} = 5\mu m$ was used for measuring).

Tab. 5.17 and Tab. 5.18 report the results of ANOVA on $Ra_{av,a}$ and $Rz_{av,a}$ values, respectively. How it can be noticed, the inclination of the overhang α_{oh} is, also in this case, the only significant factor for both Ra and Rz average measured roughness. This result confirms the trend observes by the analysis of contact measurements.

Eq. 5.7 shows the regression equation used for Ra average values; this model fits the data with an $R^2 = 88.20\%$ and $R^2_{adj} = 79.12\%$; the residual plots are shown in Fig. 5.15.

The regression model of $Rz_{av,a}$ is given in Eq. 5.8, while the correspondent residuals are plotted in Fig. 5.16; the regression has $R^2 = 81.60\%$ and $R^2_{adj} = 67.45\%$.

The low values of R^2_{adj} and the residual plots show how the regression models here presented are less effective in fitting measured data than in the case of contact measurements. This can be explained with the higher sensitiveness of this measuring system to localised irregularities of the surface, as exposed above. This is more evident in the measure of Rz, as localised deep valleys are more influential in the calculation of this parameter, if compared with Ra.

Table 5.16 Measurements of roughness by means of Alicona optical system

Run Run	L_{oh} [mm]	t_{oh} [mm]	α_{oh} [°]	d_{sl} [mm]	Build Job	$Ra_{av,a}$ $[\mu m]$	$Ra_{std,a}$ $[\mu m]$	$Rz_{av,a}$ $[\mu m]$	$Rz_{std,a}$ $[\mu m]$
1	60	6	50	2	2	12.18	1.82	60.52	5.09
2	60	6	10	2	1	21.06	1.46	89.5	7.47
3	20	2	10	2	3	35.58	3.69	148	20.82
4	40	6	10	1	1	30.86	5.29	139.09	27.23
5	20	6	50	2	4	10.74	1.18	53.13	7.79
6	60	6	30	1	1	16.33	1.85	77.2	6.24
7	20	4	10	1	4	26.32	2.69	109.75	17.27
8	20	6	10	2	4	23.12	2.44	90.91	2.81
9	60	2	10	1	1	22.99	3.33	91.48	13.81
10	20	2	50	2	4	10.85	1.17	61.6	2.22
11	20	6	50	1	4	9.62	0.41	48.4	6.37
12	60	4	50	1	3	9.61	1.57	49.04	1.08
13	40	2	10	1.5	1	22.29	1.34	97.68	10.26
13a	40	2	10	1.5	2	20.14	3.33	86.81	11.67
14	20	4	50	1.5	3	11.09	0.31	60.21	6.7
14a	20	4	50	1.5	4	12.24	3.03	64.97	8.03
15	20	6	20	1.5	3	24.04	2.64	116.08	35.63
15a	20	6	20	1.5	4	24.04	2.23	121.98	15.83
16	60	2	10	2	2	25.4	4.23	108.77	11.21
17	60	2	50	2	2	11.88	1.07	69.76	11.98
18	40	4	30	2	3	18.52	3.69	90.94	9.08
18a	40	4	30	2	4	15.45	2.47	87.33	21.46
19	20	2	30	1	4	16.69	2.48	87.26	12.39
20	40	2	50	1	3	11.45	3.85	64.88	18.25

Table 5.17 ANOVA of average Ra measured by Alicona

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	26.40	11.00	2.40	3.20×10^{-2}	
L_{oh}	-1.63×10^{-1}	1.85×10^{-1}	-8.80×10^{-1}	3.96×10^{-1}	21.85
t_{oh}	1.98	1.79	1.11	2.88×10^{-1}	21.05
α_{oh}	-5.59×10^{-1}	1.92×10^{-1}	-2.90×10^{0}	1.20×10^{-2}	25.07
d_{sl}	7.11	5.91	1.20	2.50×10^{-1}	14.28
$L_{oh}t_{oh}$	9.90×10^{-3}	2.27×10^{-2}	4.30×10^{-1}	6.71×10^{-1}	10.41
$L_{oh}\alpha_{oh}$	3.42×10^{-3}	2.25×10^{-3}	1.52	1.52×10^{-1}	8.36
$L_{oh}d_{sl}$	-2.62×10^{-2}	8.90×10^{-2}	-2.90×10^{-1}	7.73×10^{-1}	18.70
$t_{oh}\alpha_{oh}$	4.10×10^{-3}	2.26×10^{-2}	1.80×10^{-1}	8.60×10^{-1}	9.03
$t_{oh}d_{sl}$	-1.61×10^{0}	8.90×10^{-1}	-1.81×10^{0}	9.30×10^{-2}	18.84
a*d	3.11×10^{-2}	8.90×10^{-2}	3.50×10^{-1}	7.32×10^{-1}	16.92

Table 5.18 ANOVA of average Rz measured by Alicona

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	10.00	14011.00	1401.10	5.77	2.00×10^{-3}
L_{oh}	1.00	370.30	370.27	1.52	2.39×10^{-1}
t_{oh}	1.00	559.70	559.72	2.30	1.53×10^{-1}
α_{oh}	1.00	1157.10	1157.12	4.76	4.80×10^{-2}
d_{sl}	1.00	172.20	172.19	7.10×10^{-1}	4.15×10^{-1}
$L_{oh}t_{oh}$	1.00	31.50	31.48	1.30×10^{-1}	7.25×10^{-1}
$L_{oh}\alpha_{oh}$	1.00	504.20	504.17	2.07	1.73×10^{-1}
$L_{oh}d_{sl}$	1.00	15.60	15.60	6.00×10^{-2}	8.04×10^{-1}
$t_{oh}\alpha_{oh}$	1.00	99.90	99.88	4.10×10^{-1}	5.33×10^{-1}
$t_{oh}d_{sl}$	1.00	927.90	927.93	3.82	7.30×10^{-2}
a*d	1.00	91.80	91.77	3.80×10^{-1}	5.49×10^{-1}
Error	13.00	3158.70	242.98		
Lack-of-Fit	9.00	3064.30	340.48	14.43	1.00×10^{-2}
Pure Error	4.00	94.40	23.60		
Total	23.00	17169.60			

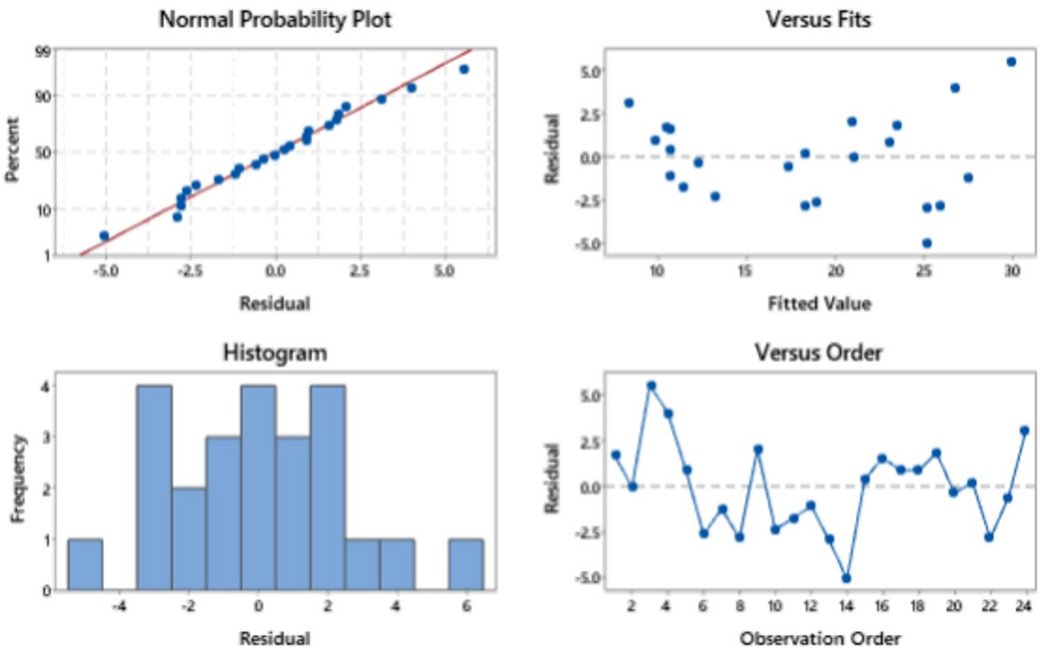

Fig. 5.15 Residual plots for regression of average $Ra_{av,a}$ as in Eq. 5.7

$$
\begin{aligned}
Ra_{av,a} = 26.4 - 1.63 \times 10^{-1} L_{oh} + 1.98 t_{oh} - 5.59 \times 10^{-1} \alpha_{oh} + 7.11 d_{sl} + \\
+9.90 \times 10^{-3} L_{oh} t_{oh} + 3.42 \times 10^{-3} L_{oh} \alpha_{oh} - 2.62 \times 10^{-2} L_{oh} d_{sl} + \\
+4.10 \times 10^{-3} t_{oh} \alpha_{oh} - 1.61 t_{oh} d_{sl} + 3.11 \times 10^{-2}
\end{aligned} \tag{5.7}
$$

$$
\begin{aligned}
Rz_{av,a} = 116.0 - 1.08 L_{oh} + 12.79 t_{oh} - 1.98 \alpha_{oh} + 23.50 d_{sl} + \\
+3.90 \times 10^{-2} L_{oh} t_{oh} + 1.53 \times 10^{-2} L_{oh} \alpha_{oh} 1.06 \times 10^{-1} L_{oh} d_{sl} + \\
-6.90 \times 10^{-2} t_{oh} \alpha_{oh} - 8.21 t_{oh} d_{sl} + 2.58 \times 10^{-1}
\end{aligned} \tag{5.8}
$$

5.3.5 Correlation models and redefinition of the Know-how Matrix

Section 5.3.4 points out clear trends of the displacement and roughness while varying the part design parameters. Nevertheless, the non-homogeneity of the part and the influence of adopted measuring system make difficult to have accurate prediction of exact values . As the KBESM will be used to make comparisons between alternative solutions, normalised models of distortion and roughness are then preferred to the absolute ones presented in 5.3.4.

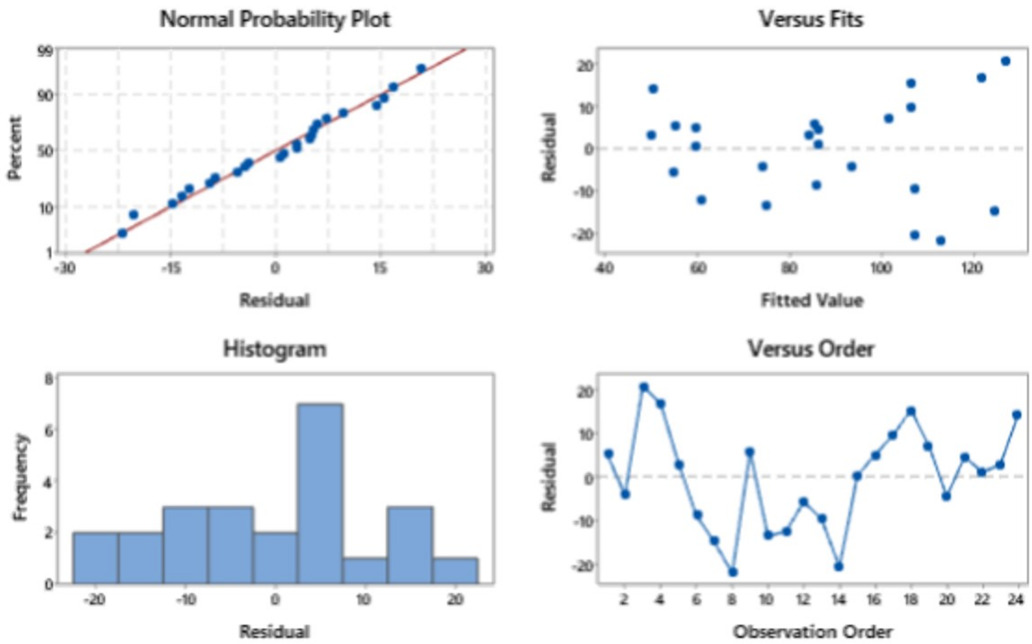

Fig. 5.16 Residual plots for regression of average $Rz_{av,a}$ as in Eq. 5.8

The two analyses of the vertical displacement pointed out how all the investigated parameters are influential for part distortion measured by means of different techniques.

The measurement made by means of contact system revealed to be less influenced by random defects, allowing reaching an higher fitness of the regression. Accordingly, the model of Eq. 5.3 will be used for correlation. The normalised output values of vertical displacement d_{vn} are resized to the range [-1;1], leading to Eq. 5.9. As obvious, this model has the same R^2 and R^2_{adj} of the one in Eq. 5.3; residual plots in Fig. 5.11 also remain valid.

$$\begin{aligned} d_{vn} = -0.368 + 1.54\times10^{-3}L_{oh} + 9.33\times10^{-2}t_{oh} + 1.38\times10^{-2}\alpha_{oh} + \\ -1.73\times10^{-1}d_{sl} - 5.37\times10^{-4}L_{oh}t_{oh} - 9.00\times10^{-5}L_{oh}\alpha_{oh} + 9.90\times10^{-4}L_{oh}d_{sl} + \\ -3.96\times10^{-3}t_{oh}\alpha_{oh} + 6.02\times10^{-2}t_{oh}d_{sl} - 3.39\times10^{-3} \end{aligned} \quad (5.9)$$

The analysis of roughness data highlighted the overhang inclination as only influential factor; accordingly, α_{oh} is adopted as only variable of the normalised model. The Ra data from contact measurement ($Ra_{av,n}$) revealed to be the less influenced by localised random defects. Therefore, these data will be used as a basis for the development of the normalised model. The output values r_{an} are normalised within the range [0;1]; Eq.

$$r_{an} = 9.49\times10^{-1} - \alpha_{oh}\times1.65\times10^{-2} \quad (5.10)$$

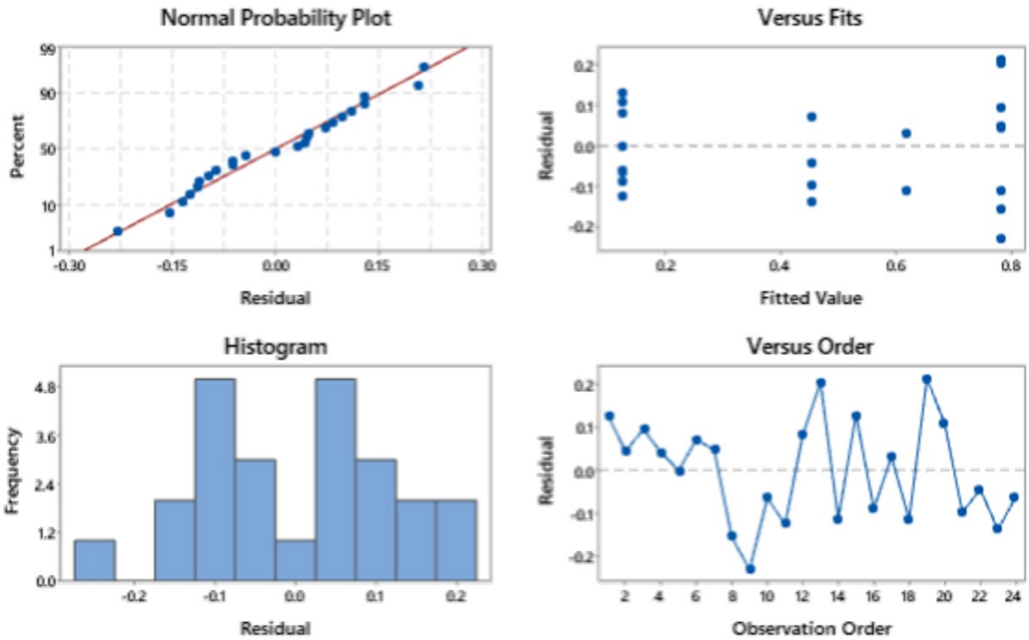

Fig. 5.17 Residual plots for regression of normalised roughness values according to in Eq. 5.10

This model has $R^2 = 85.89\%$ and $R^2_{adj} = 85.25\%$; it can be observed how R^2_{adj} is slightly higher than the ones calculated in the case of Eq. 5.5 due to the absence of several non-influential variables in the model. Fig. 5.17.

The results of experimentation presented in 5.3.4 allowed defining the relations between inputs and descriptors that were marked as Hyp in 5.2. In particular, the ANOVA allowed pointing out the non-empty cells of the KM, i.e. the input that are significant to descriptors.

The equation derived above explicit these relations, providing correlations between inputs and descriptors. Therefore, according to the descriptions of KM given in 2.4.5, the correlation moved from Hyp to Knw. The KM of MODIA in Fig. 5.2 is thus redesigned as in Fig. 5.18.

5.4 Detailed design of the system

The implementation of the system will be made through the following steps:

- Import of the part geometry
- Definition of support parameters
- Definition of the design requirements
- Optimisation of the orientation

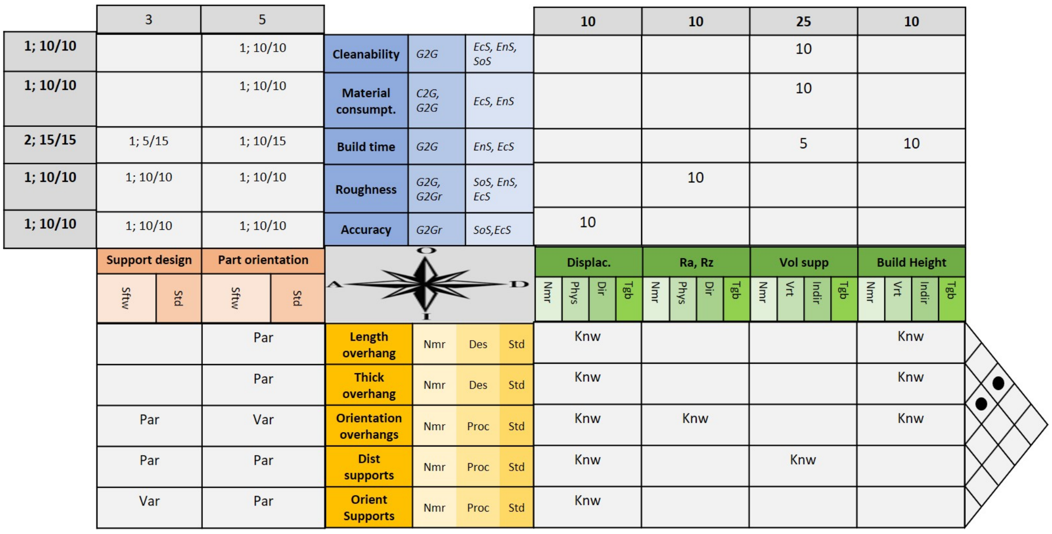

Fig. 5.18 MODIA of the KBESM for PBF build preparation redesigned after the experimental campaign

- Verification of the proposed solution

According to the concept design of the system presented in 5.2, the KBESM has to fulfil two main tasks, that are the orientation of the part and the design of support structures. The design of supports can be made only once the part has been oriented, therefore these actions have to be performed sequentially. To allow an optimisation of predefined aims, an iterative loop will be adopted.

The KBESM was implemented as a stand-alone software using C# language. OpenGL library has been adopted for graphical tasks. In the following sections, the main aspects of the implemented system are described.

5.4.1 Analysis of the geometrical model

The model is imported in the software as an STL triangular mesh. In this codification, each triangle is represented by means of 12 floating point values, i.e.:

- The Cartesian coordinates of the three vertices $\{v_{1,x}, v_{1,y}, v_{1,z}, v_{2,x}, v_{2,y}, v_{2,z}, v_{3,x}, v_{3,y}, v_{3,z}\}$
- The normal vector of the surface $\hat{N} = \{n_x, n_y, n_z\}$

The normal vector can be directly used in order to verify if the surface requires supports. In fact, defining as α_{lim} the minimum inclination to the horizontal that allows self-supporting of the material (as in Fig. 5.19), the need of supports S_b can be evaluated as in Eq. 5.11

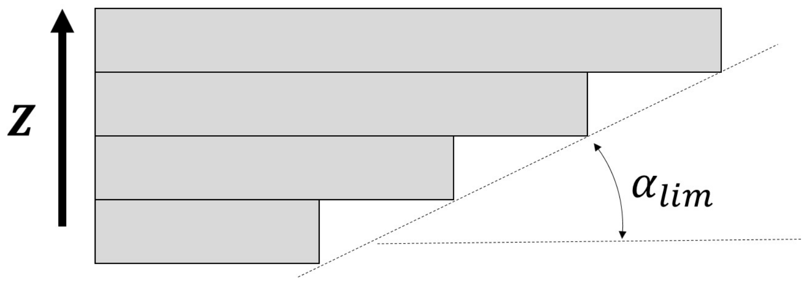

Fig. 5.19 α_{lim} for material self-supporting

$$S_b(X) = \begin{cases} 1 & if n_z \leq -cos(\alpha_{lim}) \\ 0 & \text{elsewhere} \end{cases} \tag{5.11}$$

A region-based approach is used for the design of supporting structures. For this scope, the bounding box of the model, i.e.the minimum parallelepiped enclosing the part, is calculated; the dimensions of the bounding box along the three axial directions are calculated as in Eq. 5.12, 5.13 and 5.14, respectively. Basing on these definitions, the diagonal of the bounding box (d_{BB}) can be calculated as in Eq. 5.15.

$$BB_X = v_{x,max} - v_{x,min} \tag{5.12}$$

$$BB_Y = v_{y,max} - v_{y,min} \tag{5.13}$$

$$BB_Z = v_{z,max} - v_{z,min} \tag{5.14}$$

$$d_{BB} = \sqrt{BB_X^2 + BB_Y^2 + BB_Z^2} \tag{5.15}$$

The XY projection of the bounding box is meshed by means of a grid with side step s_g as shown in Fig. 5.20.

Vertical rays are sent from the centre of each grid element (represented by a circle in Fig. 5.20). For the generic element of the grid with position (i,j), the central grid element coordinates (x_i, y_j) can be calculated as in Eq. 5.16 and Eq. 5.17

$$x_i = \begin{cases} \frac{1}{2}(BB_x - s_g \lfloor \frac{BB_x}{s_g} \rceil) & if\ i = 1 \\ BB_x - x_{1,j} & if\ i = \lceil \frac{BB_x}{s_g} \rceil \\ x_{1,j} + (i-1)s_g & \text{elsewhere} \end{cases} \tag{5.16}$$

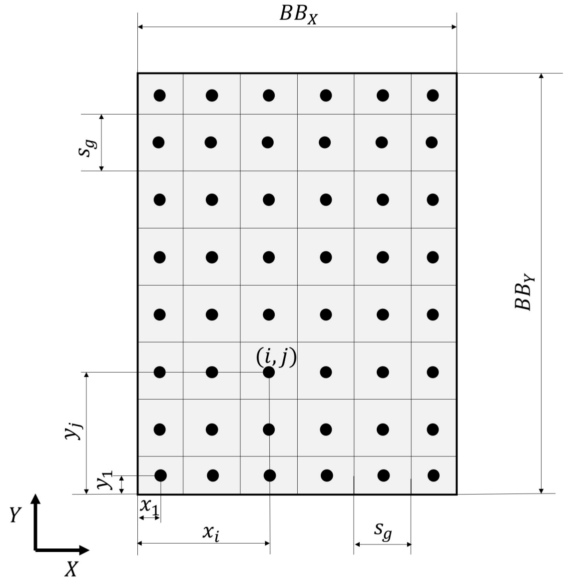

Fig. 5.20 Planar grid of the part bounding box in XY

$$y_j = \begin{cases} \frac{1}{2}(BB_y - s_g \lfloor \frac{BB_y}{s_g} \rceil) & if\ j = 1 \\ BB_y - y_{1,j} & if\ j = \lceil \frac{BB_y}{s_g} \rceil \\ y_{1,j} + (i-1)s_g & \text{elsewhere} \end{cases} \tag{5.17}$$

A vector $\vec{d_{i,j}}$ with origin $(x_i, y_j, v_{z,min})$ and direction (0,0,1) is defined for every element (i,j) of the grid. A ray-casting algorithm [199] is used to check the intersection points $P_{i,j,k}$ of $\vec{d_{i,j}}$ with the part, as shown in Fig. 5.21.

As the part must satisfy the manifold condition, the intersection point $P_{i,j,k}$ lays on a triangle with negative n_z if k is odd and on a triangle with positive n_z if k is even. The manifold condition also implies that the total number of intersections $P_{i,j,k}$ is even for every pair *(i,j)*. The maximum number of intersections observed on the grid (i.e. the higher value reached of k) will be indicated as $N_{max,int}$.

It is then possible to define two three-dimensional matrices of dimensions $[\lceil \frac{BB_x}{s_g} \rceil, \lceil \frac{BB_y}{s_g} \rceil, N_{max,int}]$ named H_s and T_s, whose generic elements are defined as in Eq.5.18 and Eq. 5.19 , respectively.

$$H_s(i,j,k) = \begin{cases} P_{i,j,2k-1} - P_{i,j,2(k-1)} & if\ \exists P_{i,j,2k} \\ 0 & if\ \nexists P_{i,j,2k} \end{cases} \tag{5.18}$$

$$T_s(i,j,k) = \begin{cases} P_{i,j,2k} - P_{i,j,2k-1} & if\ \exists P_{i,j,2k} \\ 0 & if\ \nexists P_{i,j,2k} \end{cases} \tag{5.19}$$

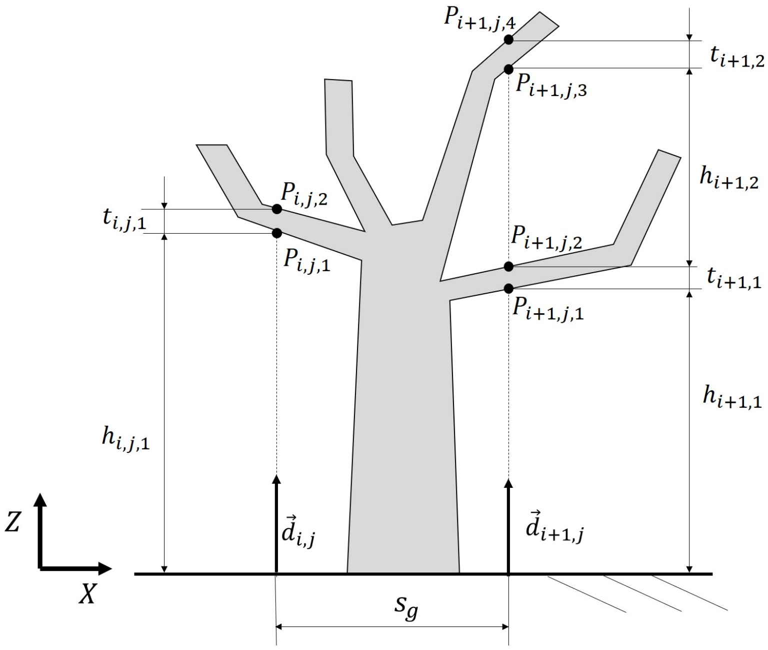

Fig. 5.21 Intersections of ray casting with the mesh

It is worth mentioning how the matrices H_s and T_s varies (both in terms of sizes and values) according to the orientation of the investigated geometry.

5.4.2 Design of support structures

The design of the supports is made using reinforced vertical walls as the ones represented in Fig. 5.6. As one single scan line is used for support construction, the actual thickness of the vertical wall depends on a number of parameters, including[3, 336]:

- The scanning speed
- The laser power
- The reflectivity of the powder
- The grain size of the powder

For each element of a grid as the one represented in Fig. 5.20, the necessity of support structures is determined by using Eq. 5.11. As it can be observed in Fig. 5.18, reducing the volume of support structures is fundamental in order to reduce the wasted material and building time and enhance the cleanability of the model. Accordingly, the orientation of supporting walls is chosen in order to minimise the distortion of the part while limiting the amount of transformed material.

0	0	0	33	27	29	0
0	54	56	35	12	16	22
0	25	36	47	80	0	0
0	0	0	0	0	0	0
0	0	0	0	0	0	0
0	11	0	13	0	0	0
28	25	10	10	14	0	0
0	26	22	24	16	0	0
0	0	0	0	0	0	0

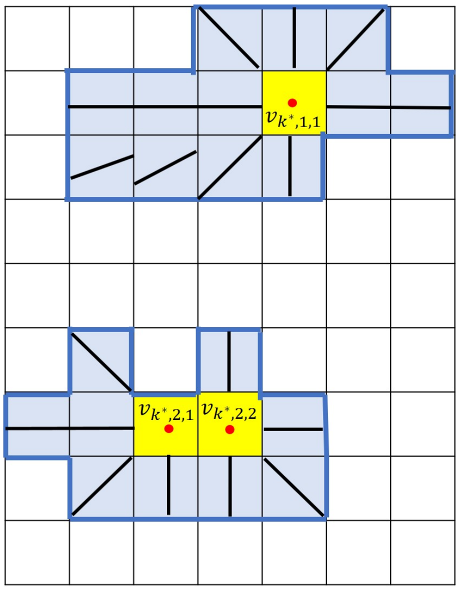

Fig. 5.22 Example of pivot determination for a given intersection level k^*

Indicating as $Tr(P_{i,j,k})$ the triangle on which the intersection point $P_{i,j,k}$ lays, it is possible to define the matrix H_{cp} of dimensions $[\lceil \frac{BB_x}{s_g} \rceil, \lceil \frac{BB_y}{s_g} \rceil, N_{max,int}]$; the generic element $H_{cp}(i,j,k)$ is then calculated as in Eq. 5.20.

$$H_{cp}(i,j,k) = S_b(Tr(P_{i,j,2k-1})) \sum_{l=1}^{k} (T_s(i,j,l) + H_s(i,j,l)) \tag{5.20}$$

According to Eq. 5.20, elements of H_{cp} are equal to zero if the region does not require support and equal to the height of the intersection point from the bottom plane in any other case. Therefore, at a certain value k^* (referred in the following as *intersection level*), the two dimensional matrix $H_{cp}(i,j,k^*)$ is like shown in Fig. 5.22. In the matrix $H_{cp}(i,j,k^*)$, it is possible to distinguish the cluster of supported elements, represented in blue in Fig. 5.22. For each cluster h, the minimum values of $H_{cp}(i,j,k^*)$ (highlighted in yellow in Fig. 5.22) are identified; the corresponding centres of the grid (in red in Fig. 5.22) will be referred as *pivotal points* and indicated as $[v_{k^*,h,1},\ v_{k^*,h,1},\ \ldots]$.

For each element (i,j) of the grid, the supporting wall is oriented as the vector connecting the centre of the element (x_i,y_j) with the projection on the XY-plane of the nearest pivotal point $v_{k^*,h,m} = (x_{v*}, y_{v*}, z_{v*})$. The direction vector $\hat{d}_{i,j,k}$ can thus be calculated as in Eq. 5.21.

$$\hat{d}_{i,j,k} = \left(\frac{x_{v*} - x_i}{\sqrt{(x_{v*} - x_i)^2 + (y_{v*} - y_i)^2}}, \frac{y_{v*} - y_i}{\sqrt{(x_{v*} - x_i)^2 + (y_{v*} - y_i)^2}}, 0\right) \tag{5.21}$$

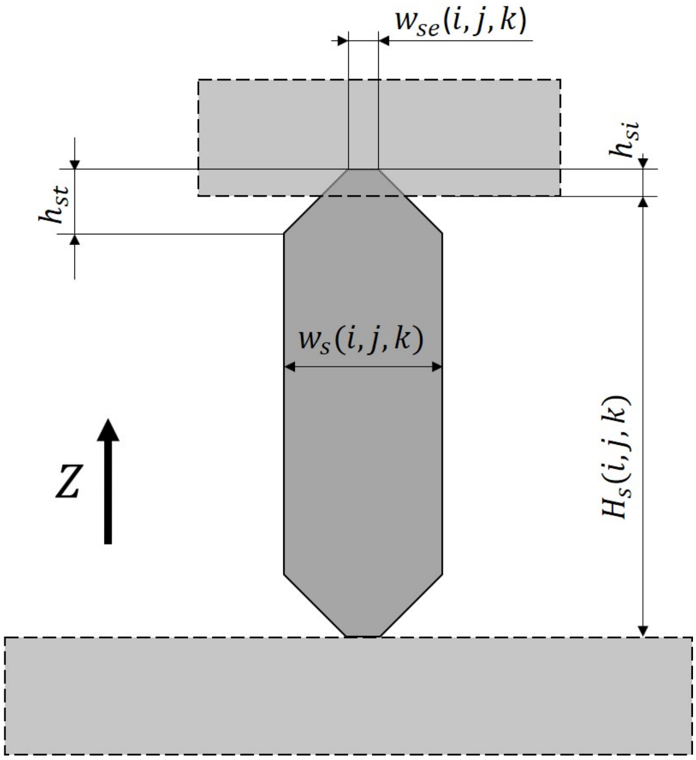

Fig. 5.23 Schematisation of support wall and connection teeth

The support is designed to pass through the point of coordinates (x_i,y_j) and remain inside the grid element,as shown in Fig. 5.22. The actual width of the support structure w_S is thus calculated as in Eq. 5.22, where $\hat{X} = \{1,0,0\}$ and $\hat{Y} = \{0,1,0\}$.

$$w_S(i,j,k) = max(\frac{s_g}{|\hat{d}_{i,j,k}.\hat{X}|}, \frac{s_g}{|\hat{d}_{i,j,k}.\hat{Y}|}) \tag{5.22}$$

This width is reduced in the connection between supports and part in order to ease the removing of the supporting structures during the post processing. The transitions between supports and part are referred to as *teeth* and present the typical shape shown in Fig. 5.23. The height of the support tooth h_{st} and the aspect ratio α_{ws} between the width of the support and the final width of the tooth (as in Eq. 5.23) are used to define the geometry of the teeth.

$$\alpha_{ws} = \frac{w_{se}(i,j,k)}{w_s(i,j,k)} \tag{5.23}$$

The height of the support in Z direction can be obtained by the matrix H_s calculated in Eq. 5.18. It is worth noticing how the actual coordinates of the connection to the part may vary according to the slope of the surface: ray-casting approach exposed above can be extended to solve this issue.

An intersection of height h_{sl} between the support and the part is used to enhance the resistance of the structure, as shown in Fig.5.23. The value of h_{si} needs to be compared to the values of thicknesses in the matrix T_s of Eq. 5.19 in order to prevent part piercing.

A difference between top and bottom teeth may be operated according to different levels; as an example, the bottom teeth of the first level (i.e. the connection of the part to the build platform) is often avoided (i.e. $\alpha_{ws} = 1$) to improve the resistance, as this does not affect the surface quality of the part.

Transversal ribs as the ones described in 5.3 are included using the dimensions in Fig. 5.6; similar criteria as above are adopted for teeth.

5.4.3 Evaluation of the solution

In order to evaluate the suitability of possible solutions, different models are built for the product features. This models, as already mentioned in the previous sections, have to be applied in a comparative analyses of the solutions. In order to aggregate different attributes, the scores assigned to properties are normalised in the following.

As an example, the methods defined in 5.4.2 lead to the definition of the geometry of the support structures. A score P_{supp} is assigned to the volume of supports as defined in Eq. 5.24.

$$P_{supp} = \frac{\sum_{i=1}^{\lceil BB_x/s_g \rceil} \sum_{j=1}^{\lceil BB_y/s_g \rceil} \sum_{k=1}^{N_{max,int}} S_b(Tr(P_{i,j,2k-1})H_{cp}(i,j,k)s_g^2}{BB_x BB_y BB_z} \tag{5.24}$$

Eq. 5.24 compares the space where support structures are located to the whole space of the model bounding-box (in its own coordinate system). It is worth noticing how this calculation does not consider the effect of change in support width due to orientation in grid (Eq. 5.22) as it is considered negligible on the overall volume of supports. Furthermore, the thickness of the support wall and the geometry of teeth are not considered for the study, as these parameters do not vary with the orientation of the part (as it can be seen in the IM of Fig. 5.18). Therefore, the reduction of volume of supporting structures corresponds to the minimisation of P_{supp}.

According to Rickenbacher et al. [239], the building time T_{Build} of the part (considering one single unit per build job) can be estimated as in Eq. 5.25:

$$T_{Build} = a_0 + a_1 \times N_L + a_2 \times V_P + a_3 \times S_{Supp} + a_4 S_{Tot} \tag{5.25}$$

Where:

- N_L is the number of layers

Table 5.19 ANOVA of average Rz measured by Nanoscan

Regression coefficient	Value	Unit
a_0	-1.29	h
a_1	4.53×10^{-3}	h
a_2	1.80×10^{-4}	h/mm^3
a_3	1.59×10^{-4}	h/mm^2
a_4	-1.33×10^{-4}	h/mm^2

- V_P is the volume of the part (mm^3)
- S_{Supp} is the total surface area of the support structures (mm^2)
- S_{Tot} is the total surface area of the part (mm^2)
- a_0, a_1, a_2, a_3, a_4, are the regression coefficients

The values proposed by [239] for regression coefficients, together with their unit of measurement, are summarised in Tab. 5.19

As the orientation does not affect the volume of the part, the contribution of $a_2 \times V_P$ does not affect the comparative analysis. In a preliminar analysis, the building height is assumed to be affected only by the number of layers N_L, i.e. by the maximum height of the oriented part ($v^*_{z,max}$). Accordingly, to evaluate the efficiency of orientation in building time, a comparison between $v^*_{z,max}$ and the diagonal of the bounding box in the model coordinate system (d_{BB}) is used. The penalty factor for part height (P_{height}) is thus calculated as in Eq. 5.26.

$$P_{height} = \frac{v^*_{z,max}}{d_{BB}} \tag{5.26}$$

Considering the results exposed in 5.3.5, the normalised values of roughness can be calculated as in 5.10. The normal direction $\hat{N}$ of the facet element can be used to determine the angle for estimation: accordingly, Eq. 5.10 is modified as in Eq. 5.27 in order to calculate the roughness penalty factor P_{rough}.

$$P_{rough} = 9.49 \times 10^{-1} - arcsin(|n_z|) \times 1.65 \times 10^{-2} \tag{5.27}$$

The calculation of Eq. 5.27 assumes the same roughness for downward and upward facing element, i.e. neglects the compensation of stair stepping effect that occurs before surfaces solidification on downward facing elements according to [271].

In order to build a predictive model for distortion, a grid-based approach similar to the one described in 5.4.1 and 5.4.2 is adopted; a grid with element size $s_{g,d}$ is adopted for the scope. This approach allows investigating the local distortion independently by the size of triangular elements used for meshing.

Using a notation similar to 5.4.2, the pivotal point of the intersection point $P_{i,j,k} = (x_P(i,j,k), y_P(i,j,k), z_P(i,j,k))$ will be indicated as $v*(i,j,k) = (x_{v*}(i,j,k), y_{v*}(i,j,k), z_{v*}(i,j,k))$.

Using this notation, the equivalent overhang length of the intersection points are thus collected in the matrix L_{OH} of size $[\lceil\frac{BB_x}{s_g}\rceil, \lceil\frac{BB_y}{s_g}\rceil, N_{max,int}]$, whose generic element $L_{OH}(i,j,k)$ can be defined as in Eq. 5.28.

$$L_{OH}(i,j,k) = \begin{cases} \sqrt{(x_P - x_{v*})^2 + (y_P - y_{v*})^2 + (z_P - z_{v*})^2} & if\ \exists P_{i,j,2k} \\ 0 & if\ \nexists P_{i,j,2k} \end{cases} \tag{5.28}$$

Analogously, it is possible to define the matrix α_{OH} of the equivalent overhang inclinations; the generic element can be calculated as in Eq. 5.29

$$\alpha_{OH}(i,j,k) = \begin{cases} arcsin(\frac{\sqrt{(x_P - x_{v*})^2 + (y_P - y_{v*})^2}}{\sqrt{(x_P - x_{v*})^2 + (y_P - y_{v*})^2 + (z_P - z_{v*})^2}}) & if\ \exists P_{i,j,2k} \\ 0 & if\ \nexists P_{i,j,2k} \end{cases} \tag{5.29}$$

The distance between supports in Eq. 5.9 is replaced with the size of the grid used for support generation (s_g) that is the actual distance between parallel adjacent support walls.

Accordingly, the penalty distortion function is written as a matrix P_{dist} of size $[\lceil\frac{BB_x}{s_g}\rceil, \lceil\frac{BB_y}{s_g}\rceil, N_{max,int}]$, whose generic element $P_{dist}(i,j,k)$ can be calculated as in Eq. 5.30 if $\exists P_{i,j,2k}$ (while it is equal to zero in other cases).

$$\begin{aligned} P_{dist}(i,j,k) = -0.368 + 1.54\times10^{-3}L_{OH}(i,j,k) + 9.33\times10^{-2}T_S(i,j,k) \\ +1.38\times10^{-2}\alpha_{OH}(i,j,k) - 1.73\times10^{-1}s_g + \\ -5.37\times10^{-4}L_{OH}(i,j,k)T_S(i,j,k) - 9.00\times10^{-5}L_{OH}(i,j,k)\alpha_{OH}(i,j,k) + \\ +9.90\times10^{-4}L_{OH}(i,j,k)s_g - 3.96\times10^{-3}T_S(i,j,k)\alpha_{OH}(i,j,k) + \\ +6.02\times10^{-2}T_S(i,j,k)s_g - 3.39\times10^{-3} \end{aligned} \tag{5.30}$$

It is worth mentioning how the penalty functions described in Eq. 5.27 and 5.30 may lead to values out of the range [0;1] for values of the input parameters out of the space of the DOE described in 5.3.3. Furthermore, outside of this range the model works in extrapolation, thus the reliability far from the explored range can not be guaranteed. In particular, the behaviour of the model for angles approaching zero should be investigated by means of

Table 5.20 General and local requirements for the build orientation optimisation

General requirements	Local requirements
Building time	No-support regions
Average roughness	Local roughness
Average distortion	
Maximum distortion	
Support volume	

further experimentations. Nevertheless, the trend of the model is assumed to be suitable for comparative studies.

In order to allow the optimisation of part orientation and support design, an evaluation criteria of the solutions must be defined. For this propose, a fitness function F_{fit} of the part in a given orientation is here defined. As the actual aims of the production are strictly related to the specific features of the product, an ad-hoc definition of the requirements is needed. According to Fig. 5.1, the system has to be developed for a generic product, so no a priori definitions of the requirements can be made. On the other hand, the user of the system is supposed to own a specific knowledge about the product; therefore, the definition of the optimisation aims is delegated to the user. As the requirements of the part may vary on the different regions of the geometry, a split between general and local requirements is made, as summarised in Tab. 5.20 .

The know-how of the user is exploited in order to define the requirements.

The local requirements are defined for each element of the mesh by means of weight coefficients. As a default, the weight of each factor is set equal to 1 and can be modified according to user preferences. In the implementation of the solution, the user is allowed defining specific regions of the mesh where the weights of requirements are different from the rest of the mesh.

Therefore, each triangular element T_i is characterised by a penalty factor for the presence of supports ($w_{p,s}(i)$) and a penalty factor for surface roughness ($w_{p,r}(i)$). Indicating as N_T the total number of triangular elements, the overall penalty for supports and regions (P_s) and for local roughness (P_r) can then be calculated as in Eq. 5.31 and Eq. 5.32, respectively:

$$P_s = \frac{1}{N_T} \sum_{i=1}^{N_T} S_b(T_i) w_{p,s}(i) \tag{5.31}$$

$$P_r = \frac{1}{N_T} \sum_{i=1}^{N_T} w_{p,r}(i) P_{rough}(T_i) \tag{5.32}$$

Where $P_{rough}(T_i)$ is the penalty given to roughness of the i-th triangle, calculated as in 5.27.

Also the general requirements of the part are defined by the user giving a penalty weight to each of the criteria listed in Tab. 5.20. In particular, the following notation is used for penalty factors:

- $w_{p,bt}$ Penalty factor for the building time
- $w_{p,ar}$ Penalty factor for the average roughness
- $w_{p,ad}$ Penalty factor for the average distortion
- $w_{p,md}$ Penalty factor for the maximum distortion
- $w_{p,sv}$ Penalty factor for the support volume

The Fitness function (F_f) for the part in a given orientation and with a defined support design can be expressed as in Eq. 5.33

$$\begin{aligned} F_f = P_s + P_r + w_{p,bt}P_{height} + w_{p,md}max(P_{dist}(i,j,k)) + w_{p,sv}P_{supp} + \\ + \frac{1}{N_T}\sum_{i=1}^{N_T} P_{rough}(T_i) + w_{p,ad}\frac{\sum_{i=1}^{\lceil BB_x/s_g \rceil}\sum_{j=1}^{\lceil BB_y/s_g \rceil}\sum_{k=1}^{N_{max,int}} P_{dist}(i,j,k)}{\lceil BB_x/s_g \rceil \times \lceil BB_y/s_g \rceil \times N_{max,int}} \end{aligned} \tag{5.33}$$

The MOO is thus reduced to a single objective optimisation (the minimisation of F_f) as defined in Eq. 5.33.

5.4.4 Optimisation of the part orientation

As mentioned above, a GA-based approach to part orientation is adopted to find the optimal part orientation.

For this scope, the orientation of the part in the build chamber is described by means of the three rotation angles θ_x, θ_y and θ_z (Euler angles) of the part coordinate system of the model on the coordinate system of the machine.

Using Euler angles, the coordinates of the rotated model $V^* = [v_x^* v_y^* v_z^*]^T$ are thus obtained multiplying the internal coordinates of the generic point $V = [v_x v_y v_z]^T$ by the rotational matrix shown in Eq. 5.34, where $c\theta$ and $s\theta$ are the cosine and sine of the angle θ.

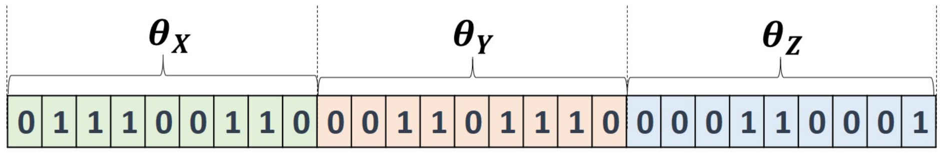

Fig. 5.24 Chromosome representing the rotational angles in 8-bit codification

Table 5.21 General and local requirements for the build orientation optimisation

Parameter	Default value
n_{st}	20
$n_{min,pop}$	100
$n_{max,pop}$	200
$n_{max,pop}$	0.3

$$\begin{bmatrix} v_x^* \\ v_y^* \\ v_z^* \end{bmatrix} = \begin{bmatrix} c\theta_y c\theta_z & -c\theta_y s\theta_z & s\theta_y \\ s\theta_x s\theta_y c\theta_z + c\theta_x s\theta_z & -s\theta_x s\theta_y s\theta_z + c\theta_x c\theta_z & -s\theta_x c\theta_y \\ -c\theta_x s\theta_y c\theta_z + s\theta_x s\theta_z & c\theta_x s\theta_y s\theta_z + s\theta_x c\theta_z & \theta_x c\theta_y \end{bmatrix} \begin{bmatrix} v_x \\ v_y \\ v_z \end{bmatrix} \tag{5.34}$$

Using the support design strategy described in 5.4.2, each set of angles (θ_x, θ_y, θ_z) corresponds to a value of the fitness function ($F_f(\theta_x, \theta_y, \theta_z)$) calculated as in Eq. 5.33.

The values of rotation angles are then converted in binary codification and composed to obtain the chromosome genotype [43, 224]. Fig. 5.24 shows an example in which the values of angles (in degrees) are represented using a 9-bit codification (thus allowing to span the range of integers [0-360]).

A two-point crossover strategy with splitting points between angles (i.e. in the points highlighted in Fig. 5.24). A mutation strategy is introduced to prevent the GA from converging to a local optimum instead of finding the global one. A flip-bit mutation is adopted in the present approach, i.e. each chromosome of the offspring generation has a given mutation probability (p_{mut}) to invert the bit of a gene (from 0 to 1 and vice versa). The population at each iteration is limited between a minimum ($n_{min,pop}$) and a maximum ($n_{max,pop}$) number of chromosomes [148].

At each iteration h, the fitness function of each chromosome is calculated and the best fitness value ($F_{f,min}(h)$) is found. A stagnation termination strategy is adopted, i.e. the algorithm ends when no improvements in the minimum observed fitness function are observed after a certain number n_{st} of consecutive iterations.

The default values adopted in the implementation are summarised in Tab. 5.21.

These values can be varied by the user in case he has previous expertise with the calculation method and prefers to adjust the values according to the specific case.

5.5 Conclusions

The present chapter demonstrated the opportunity to apply the methodology exposed in Chapter 2 to the design of a KBESM for assisting the build job preparation in PBF.

In applicability space, the system was defined as applicable to the design of a generic product with a specific combination of technology and material. Furthermore, the user has been supposed to be an expert of the process and to gain elements of knowledge about product requirements.

The adoption of a generic product required the use of local regions (triangular and grid elements) as objects of the analysis. The limitation to a specific process allowed implementing in the solution ad-hoc models obtained by means of experimental activity. The know-how of the user has been exploited for the definition of requirements, allowing introduction of the peculiar needs of the manufactured part.

Fig. 5.18 points out how the actions of the system have to be managed by software; accordingly, a sequence between the two actions has been defined and an iterative approach was used for optimisation.

This approach allowed shifting the time dedicated by the user from the trial and error and repetition of automatic tasks to the analysis and definition of the optimisation objectives. Interaction is thus performed by redefining the aims if satisfying solution is not reached.

The main limitation of the presented approach derives from the specificity of the models obtained through experimentation and implemented in the system. To overcome this limit, a more general rule-based approach able to take into account machine and material features may be developed.

Conclusions

The analysis of the literature on KBESMs allowed pointing out the main common features of these systems. A wide range of objectives, processes, methods and solutions has been found in the scientific literature. A-priori guidelines about the implementation of KBESM can not be defined, as they would over-constrain the representation and reuse of the real manufacturing know-how.

The main methodologies proposed in literature for the development of KBSs and KBESMs have been analysed. It has been noticed that the general methodologies does not allow an efficient application to industrial process engineering if not with laborious modifications, as they do not include by default the specific ontologies of manufacturing know-how. On the other hand, the methods for knowledge representation in manufacturing tend to limit representable entities and relations. Furthermore, these methods do not provide any guideline about the techniques that must be adopted during the low-level implementation of the KBESM.

To overcome these limitations, a new approach to the conceptual design of KBESMs has been proposed in Chapt. 2. The method starts from the definition of the applicability field to be covered by the KBESM. This important information was missing in the previous methods and allows us to achieve a sharp view of the outlined system. The consequences of applicability definition on the next decisional steps of KBESM design have also been pointed out.

Next, the MODIA was presented by detailing its ontologies and relations between them. The structured definition of entities prevents the inclusion of elements that are not coherent among each other or with the intended applicability field of the application. The explicit formulation of the relations also clarifies the kind of know-how owned by the company and the potential benefits resulting from the adoption of the KBESM. This enables an early decision-making according to intended strategies. The graphical representation of the MODIA also provides a continuous overview of KBESM during its design, easing the modification or redefinition of its aspects. The closed-loop structure of the matrices ensures that all the entities affected by a certain modification are adjusted to preserve the overall consistency of the system. Attributes of ontologies and relations limit the set of techniques that can be used for the fulfilment of tasks of the system, thus providing a guideline for the detailed design and implementation of the KBESM.

In the application to the design of an industrial product the opportunity to include manufacturing know-how in a design-driven system was demonstrated. The peculiarities of the system descending from its location in the applicability matrix have been discussed. The opportunity to use knowledge deriving from the expert user has been exploited in the implementation of the system, leading to a collaborative aided-decision making system. The implementation demonstrated that the automation of repetitive tasks allowed to reducing the time required for modelling. Besides, the comparison and test of a large number of solutions was enabled.

On the other hand, in the case of SL, a system for inexperienced users was designed. For this scope, all the process knowledge has been implemented in the system by means of a RBR approach. This case also showed that the applicability to a general product does not permit the inclusion of functional requirements. Furthermore, this condition obliges to define local geometrical entities for the verification of the manufacturability conditions.

In the last case study, the knowledge about the product was integrated by the user, since the system is located in the lower region of the applicability space. The interaction between the user and software has been thus moved from the decision-making phase (as in the first case study) to the definition of aims. This implementation also demonstrated the application of a completely software based action, by integrating the decision-making within the KBESM.

As a conclusion, the proposed approach demonstrated its suitability to the design of KBESMs applied to different fields of the process engineering and with dissimilar scopes and applicabilities. The applications also pointed out the correlation among attributes of the ontologies and the techniques used for the implementation. The simplicity of the method allows a fast learning as well as the immediate understanding of the main important elements of the KBESM.

For these reasons, the proposed approach seems to be an inclusive path to extend the parterre of users of KBESMs in the Industry 4.0 scenario.

MODIA methodology has been proved to overcome the main limitations deriving from existing methods for the design of KBESMs mentioned in Chapt. 1. The present work can be thus considered as a step forward in the state of art on methods for design of KBESMs.

A future development of this work will integrate the framework presented in Chapt. 2 within a software application, so to further ease the implementation of MODIA framework extending the batch of users. Moreover, a next direction of the present research will aim at including decisional maps to guide the user to the choice of best RBR and CBR methodologies on the basis of the attributes defined in the MODIA.

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