Engineering Applications of Artificial Intelligence 76 (2018) 80–95

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

# Intelligent virtual manufacturing cell formation in cloud-based design and manufacturing

Egon Ostrosi [a,*], Alain-Jérôme Fougères [b]

[a] Université de Bourgogne Franche-Comté, UTBM, ERCOS/ELLIADD, 90010 Belfort, France
[b] ECAM Rennes, Campus de Ker Lann - Bruz, 35091 Rennes, France

ARTICLE INFO

*Keywords:*
Virtual manufacturing cells
Holonic cells
Agents
Holonic agents
Intelligent features

ABSTRACT

Cloud-based design and manufacturing (*CBDM*) can presumably stimulate greater intelligence in cloud-based models. This paper assumes that *cloud-based design for cellular manufacturing* can be referred to as a multiscale, uncertain, and dynamic service-oriented network where a set of CAD parts, modelled by set of features, can be manufactured in intelligent virtual manufacturing cells under certain constraints. Using the concepts of the holon and the attractor, integrating the uncertainty in the modelling of part design and part–manufacturing network, an approach to address intelligent virtual manufacturing cell formation in *CBDM* is proposed. The powerful role of the CAD features is exploited to organize and integrate part design and part–manufacturing engineering knowledge. Intelligent manufacturing features, modelled as fuzzy agents, are recognized in CAD part models and the distributed capabilities of machines in cloud manufacturing are evaluated through mobile intelligent agents. Then, intelligent virtual manufacturing cells, with holonic structure, emerge from the interactions of fuzzy machine holon agents and fuzzy part holon agents with holon agent attractors. The concepts of the holon and the attractor allow multi-scale cell formation with holonic structure: *"intelligent virtual manufacturing cells within an intelligent virtual manufacturing cell"*. These fuzzy cell holons overcome the distinction continuous–discontinuous of traditional cell design formation problem.

## 1. Introduction

Nowadays "cloudify-cations" appears as one of the most popular and mature technological and business environments for engineering (Buyya et al., 2009). A continuously increasing set of cloud-based engineering domains exploit the advanced characteristics of this new paradigm for elasticity, high availability, and performance. The services encapsulation and virtualization are the key technology of cloud-based models (Zhang et al., 2017). Thus, cloud-based design and manufacturing (*CBDM*) has emerged as a new paradigm in networked digital manufacturing and design innovation (Wu et al., 2015). *CBDM* transforms the design, simulation, computing and manufacturing resources, and abilities into design and manufacturing services to form a design and manufacturing cloud, and distributes them to the user on demand (Li et al., 2010). Cloud-based design for configurations (Issa et al., 2017) is another cloud-based engineering process characterized by intensive interaction between customers and distributed actors. In such a socio-technical process, large quantities of information and knowledge are widely distributed across multiple networked actors. New computing and service-oriented cloud-based models, such as materials design, are also developed from existing advanced research models (Sallai et al., 2014).

Investigations on similarities between biological and cloud-based applications (Mohammad et al., 2013) have shown the increasing of "cloudify-cations" in engineering. *This paper addresses the formation of virtual intelligent manufacturing cells in cloud-based design and manufacturing.* Cellular manufacturing is an innovative organizational structure. In a manufacturing cell, a team is usually made of a flexible staff that autonomously executes a subset of well-defined production cycle operations belonging to a family of parts on a restricted group of machines placed physically together in the workshop. From medium and long-term analysis of a production program, the problem can be defined as the part families' recognition of similar process plans, which will be done on independent groups of dissimilar machines. *This is known as the manufacturing cell identification problem.* The main difficulty with the manufacturing cell identification problem is the dynamic of design and manufacturing data. In a cross-disciplinary design team, designers simultaneously select, create, modify, and evaluate design and manufacturing targets and real parameters of a product model

* Corresponding author.
*E-mail address:* egon.ostrosi@utbm.fr (E. Ostrosi).

https://doi.org/10.1016/j.engappai.2018.08.012
Received 2 August 2017; Received in revised form 9 March 2018; Accepted 21 August 2018
Available online 21 September 2018
0952-1976/

(Choulier et al., 2015). Thus, the problem of unexpected grouping typically is present and its occurrence increases in time. If crisis is defined as the inability of a cellular manufacturing system to reproduce its behaviour for which it has been designed, then sustainability is the opposite: the long-term ability of a cellular manufacturing system to reproduce its behaviour. If the models are self-sustaining, then they should be capable of adapting themselves to the new situations. It is an important characteristic of intelligent models. Thus, how a cellular manufacturing system needs to be designed such it is self-sustaining is an important subject of research on emergent behaviour (Valckenaers and Van Brussel, 2005).

This paper assumes that *cloud-based design for cellular manufacturing* can be referred to as a *multiscale*, *uncertain*, and *dynamic* service-oriented network where a set of *CAD* parts, modelled by set of features, can be manufactured in intelligent virtual manufacturing cells under certain constraints.

Features can integrate product data with manufacturing data for cell-formation problems (Mutel and Ostrosi, 2002). A feature is a geometric entity defined by its shape and technological characteristics, typically represented by a set of topologically associated faces. Features play an inevitable role in the modelling and the representation of a *CAD* part. The intelligent reasoning, often implicit, can become explicit while examining the question of inference that features propose and recommend (Ostrosi and Ferney, 2005). Features offer ideas on how to organize and integrate the design and manufacturing engineering knowledge in a way that facilitates inferences. The content of the knowledge that they carry and the way in which this knowledge is represented defines the efficiency of the computing. A feature is also a means of expression and communication. Many methods, using different formalism, such as graph theory (Marefat and Kashyap, 1990; Lockett and Guenov, 2005), knowledge-based system (Henderson, 1994; Marchetta and Forradellas, 2010), volume based decomposition (Kim, 1992; Little et al., 1998), linguistic method (Ostrosi and Ferney, 2005; Gibson et al., 1999; Niua et al., 2015), and neural networks (Han et al., 2000; Sunil and Pande, 2009), have been developed to recognize features in *CAD* parts in order to transform a *CAD* part into intelligent model.

Holonic and intelligent agents are used to create this *multiscale* and *dynamic* service-oriented networked digital design and manufacturing: face–feature–constraint–part–machine–cell. The proposed agents: face, feature, constraint, part, machine, and cell incorporate the functions of observation, decision, and action, as well as possess their own knowledge. Being aware of the geometrical and topological context in a *CAD* environment, the feature agents interact to create a dynamic network between part agents and machine agents. The part agents interact with the machine agents to recognize each other and to form specific sub-communities, called intelligent virtual manufacturing cells, with holonic structure. Intelligent cell holons are thus emerged sub-networks of agents. In their turn, intelligent cell holons are open, distributed, and dynamic objects. Furthermore, in order to capture the dynamic aspects that characterize manufacturing in the cloud, this research introduces the concepts of the attractor of cells. An attractor is a structurally stable part agent or machine agent in *CBDM*. All creation or destruction of intelligent virtual manufacturing cells can be described by the appearance and disappearance of the initial attractors. It is an important property of the dynamic systems.

Cloud-based models also pose challenges such as interoperability, reliability, availability, capability, ability, and adaptability of resources and services across spatial boundaries (Luo et al., 2013; Wang et al., 2017; Chen and Lin, 2017). *The uncertainty is an integral part of the cloud-based models. Cloud-based cellular manufacturing systems can be seen as the result of the evolution and adoption of existing paradigms, such as the agent-based paradigm with increased uncertainty*. The fuzzy set theory (Zadeh, 1965) is particularly suitable for handling uncertain information. Since the introduction of this theory by Zadeh, the theoretical developments (Zimmermann, 1996; Baoding, 2007) have noticed an important increase. Some forms of fuzzy set have also been developed, such as interval valued fuzzy sets (Zadeh, 1973), vague sets (Gau and Buehrer, 1993), rough fuzzy sets (Yang and Hinde, 2010), and intuitionistic fuzzy sets and interval-valued intuitionistic fuzzy sets (Atanassov, 1994). New theoretical and application fields of fuzzy set theory, such as the theory of fuzzy operators (Yager and Kacprzyk, 1997), have also emerged. Many applications (Liao, 2001; Chen and Wang, 2009) have shown the interest of fuzzy set-based modelling.

Introducing the concept of the *attractor*, integrating the *uncertainty* in the modelling of the face–feature–part–constraint–machine–cell network by intelligent agents, this paper proposes an approach to address intelligent virtual manufacturing cell formation in *CBDM*. The paper is organized as following: In the second section, a state of the art on the issues of cellular manufacturing systems is presented. In the third section, the proposed model and the architecture for intelligent virtual manufacturing cell formation in *CBDM* are outlined. The fourth section presents the intelligent virtual manufacturing cell formation approach. In the fifth section, the proposed approach is followed by an illustration with realistic examples of practical application. The conclusions and the perspectives of this research study are finally presented.

## 2. State of the art

The problem of cell formation consists of grouping of machines into cells to process a single part family. The grouping depends on the set of characteristics of machines and the set of characteristics of parts to be manufactured. Many approaches have been developed to deal with the cell formation problem. Research related to the cell formation problem, as a problem of manufacturing system design, concerns two major domains: (1) cell formation problem; (2) artificial intelligence supported manufacturing system design.

### 2.1. Cell formation problem

These approaches can be distinguished according to the importance they attach either to manufacturing process data (process plans, constraints relative to machine capacity, capacity of handling systems, etc.) or product data (global shape, dimensions, surface quality, etc.). The cell formation is also a multi-criteria problem.

The approaches based on manufacturing part process plan approaches use the part–manufacturing plans as a criterion for the formation of manufacturing cells. These approaches identify either sequentially or simultaneously either part families or manufacturing cells.

*Production Flow Analysis* is the earliest approach proposed by Burbidge (1971). Burbidge's (1975) cell formation approach, called "nuclear synthesis", uses one machine to begin cell formation. Ballakur and Steudel (1987) developed a cell-based heuristic, which proposed the machines with the highest workload, called key machines, to be assigned initially to each cell. Wei and Gaither (1990) proposed a capacity constrained multi-objectives cell formation approach, which requires the specification of seed machines. Sundaram and Lian (1990) presented an approach that requires the initial assignment of one part to each cell. Wu et al. (2004) as well as Kim et al. (2005), tackled the cell formation problem with alternative process plans. Mahdavi et al. (2008) developed a heuristic algorithm based on a flow matrix for cell formation and layout design in a simultaneous way using sequence of processing data.

*Cluster analysis* approaches are efficient for working with tables with a large number of data. Cells or part families are formed by clustering machines or parts according to their similarity. McAuley (1972) used a single linkage-clustering algorithm to form machine groups using a binary part–machine matrix. Seifoddini and Wolfe (1986) employed the average linkage-clustering algorithm instead of a single linkage algorithm. Zhang and Wang (1990) applied the single linkage algorithm to a non-binary part–machine matrix, which considered the fuzziness in production flow. Waghodekar and Sahu (1984) presented a heuristic approach based on a similarity coefficient of product type and the total flow of common parts processed by a machine. Wei and Kern (1989) presented a linear clustering procedure based on the calculation of the commonality score between two machines. Tam (1990) developed a method based on the similarity of operations sequences. Gupta and Seifoddini (1990) suggested a cluster analysis method that included relevant production data. Among the cluster analysis approaches, some non-hierarchical ones have been used in the cell formation problem. Non-hierarchical clustering methods are preferred to hierarchical ones because they help natural clusters to emerge from the given data. Lemoine and Mutel (1983) developed a dynamic clustering technique for machine grouping based on the minimization of statistical distances with loads and capacities of machines as statistical weights. Chandrasekharan and Rajagopalan (1986a) used the K-means method on binary data and introduced the concept of "ideal seeds" for grouping parts into families and machines into cells. Chu and Hayya (1987) used the fuzzy K-means clustering algorithm for part family formation. The approach provides the degree of the membership of a part associated with each part family.

*Graph partitioning* and *cross clustering* are also used to formalize the problem of cell formation. Rajagopalan and Batra (1975) developed a graph model and used the similarity coefficients and graph partitioning for grouping machines. Vannelli and Kumar (1986) discussed a method for finding a minimal number of cut-nodes in the partition of the bipartite part–machine graph. Al-Qattan (1990) used the network analysis to form the machine cell and part family. The cross-clustering approaches carry out the decomposition by simultaneously classifying the lines and the columns of the matrix in a way that the crossing of the set of parts and the set of machines should form a diagonal block correspondence. King (1980) developed the rank ordering algorithm (*ROC*). Some improvements and extensions of the *ROC* algorithm have been presented (Chandrasekharan and Rajagopalan, 1986b). McCormick et al. (1972) developed the bond energy analysis (*BEA*), which maximizes the total bond energy. Kusiak and Chow (1987) proposed an efficient cluster identification algorithm that identifies mutually separable clusters and determines their number.

*Mathematical programming* is another formalism used in cell formation problems. Kusiak (1987b) proposed the p-median integer-programming model, which minimizes the total sum of distances between any two parts, for part family formation. Choobineh (1988) formed sequentially part families, using a similarity measure based on the manufacturing operations, and machine cells using an integer-programming model. Purcheck (1985) presented a lattice-theoretic approach and a linear programming technique for machine–part grouping to maximize scheduling flexibility and minimize the total cost of the constituting cells. Gunasingh and Lashkari (1989) proposed a non-linear 0–1 integer programming approach for machine–part grouping based on tooling requirements of the parts, tools available on machines, and processing times. Based on the study of different mathematical programming models, Tsai and Lee (2006) proposed a multi-functional mathematical programming model that incorporates the merits of some cell formation models. Ameli and Arkat (2008) developed a linear integer program model for cell formation considering alternative process routings of part and machine reliability. Recently, Aalaei and Davoudpour (2016) proposed a bi-objective optimization model for dynamic virtual cell formation integrating the supply chain. The all-in-one objective function is often not practical due to computational and implementation complexities. From a real implementation point of view, the solution searched to satisfy an all-in-one objective function does not give practical information on the solutions corresponding to each criterion. The consensual solution by decomposition is more attractive practically for handling a large number of criteria, variables, and constraints (Ostrosi et al., 2010).

Though the manufacturing processes are interesting for the cell formation problem, the majority of manufacturing companies, which apply Group Technology, use more or less the *features of parts* for the implementation of cellular manufacturing systems because one cannot rely only on the manufacturing processes that often become obsolete with the evolution of parts and machines. Similar parts, based on features, are cluster together into families. The types of manufacturing process plans are then defined for each part family. Machines are assigned according to the manufacturing operations to be done for each family. The efficiency of the manufacturing cells is thus mainly dependent on the formation of part families. Xu and Wang (1989) introduced fuzzy cluster analysis, fuzzy classification, and fuzzy equivalence in the process of part-family formation. Ben-Arieh and Triantaphyllou (1992) proposed an approach for dealing with crisp and fuzzy part features based on a revised analytical hierarchy approach. Ben-Arieh et al. (1996) used fuzzy numbers to represent coding information. To integrate the part data with the manufacturing data, Mutel and Ostrosi (2002) developed a fuzzy cell formation approach, which assumes that the product and manufacturing data exist jointly. The product data are described by part features that also determine the manufacturing data.

### *2.2. Artificial intelligence supported manufacturing system design*

Artificial intelligent approaches use the efficient computing techniques from artificial intelligence domain. Many methods and techniques of artificial intelligence applied in the field of manufacturing, from the expert systems (Metaxiotis et al., 2002) to machine learning (Wuest et al., 2016; Jordan and Mitchell, 2015) or deep learning (Chen and Lin, 2014; Bergmann et al., 2014). The *expert system* for the machine–part grouping problem presented by Kusiak (1987a) replicate the human's expertise related to machine capacity, material handling systems capabilities, machine cell dimensions and technological requirements. *Neural networks* are also used to identify part families and machine cells. Malavé and Ramachandaran (1991) used a neural network based on a simple competitive learning algorithm to establish sequentially part families and machine cells. Lee et al. (1992) extended this approach with another competitive learning neural network based on Kohonen's learning rule. Saidi-Mehrabad and Safaei (2007) applied a neural approach for solving a multi-period planning horizon. *Evolutionary algorithms* are used also for cell formation. Mak et al. (2000) proposed an adaptive genetic algorithm for providing the optimal formation of machine cells and part families by sequencing the rows and columns of a machine–part incidence matrix, so as to maximize the bond energy of the incidence matrix. Yasuda et al. (2005) proposed a grouping genetic algorithm for the multiobjective cell formation problem. Chan et al. (2006) proposed a two-stage approach using genetic algorithm for solving the cell formation problem as well as the cell layout problem. Keeling et al. have applied the grouping genetic algorithm to determined machine/part cell formations, which are then simulated to determine their impact on various factory measures (Keeling et al., 2007). With the idea to modify current solutions in a certain direction such that new feasible generated solutions would hopefully improve, or at most, would limit the deterioration of their objective function values, the *metaheuristics* have also been applied to the cell formation problem. Lei and Wu (2006) presented a Pareto-optimality-based tabu search algorithm for machine–part grouping problems with multiple objectives: minimizing the weighted sum of inter-cell and intra-cell moves and minimizing the total cell load variation. Su and Hsu (1998) introduced a modified simulated annealing for the multi-objective machine–part cell formation problem.

Neural network and genetic algorithms embodies powerful general principle for processing information. However, they do not process *knowledge* and do not always provide *knowledge* that can be exploited by a human expert. For an expert human, the network often remains a black box that provides an answer, but the network does not provide*explication and easy justification for interpretation*. Besides knowledge, another important issue in cellular manufacturing systems is how various distributed design and manufacturing data *cooperate well within an uncertain* networked digital manufacturing and design to form manufacturing cells. *Holons* (Valckenaers and Van Brussel,

2005) *and multi-agent systems* (Weiss, 1999) *are among the most complex artifacts emanating from deliberate human design and development activities.* Agents in a network have their own level of knowledge, can share the knowledge or can communicate their knowledge (Chira et al., 2006; Fougères, 2011). The knowledge and information can be fuzzy (Wang et al., 2010). Agents, being reactive and autonomous, can update and follow the fuzzy information evolution coming from their environment and the other agents (Ghasem-Aghaee and Ören, 2003). Agents interact within a multi-agents system. If they can interpret the fuzzy information that they either receive or perceive, then the agent can also interact in a fuzzy way. Indeed, the agents can discriminate a fuzzy value of interaction, for instance, a degree of affinity with another agent. Agents are reactive to their environment, they interact between them, they permanently adjust their behaviour, and they co-evolve with their environment and the other agents. Their evolution can be fuzzy, when they can be designed to interpret fuzzy information and to adopt a fuzzy behaviour (Ghasem-Aghaee and Ören, 2003). *Thus from manufacturing process and product points of view, cellular manufacturing design can be assisted by agents using fuzzy logic*. Distribution and decentralization of agents permit the system to be flexible (Ming Chao et al., 2002; Marik and McFarlane, 2005). Multi-agent systems are thus well adapted to respond to the heterogeneity of some organizations (Nahm and Ishikawa, 2005). Indeed, agents are able to self-discriminate because they can be designed to belong to different communities. Multi-agent systems are well adapted to simulate the behaviour of organizations (Leitão, 2009). They offer a major interest for the management of phenomena, such as self-organization and emergence (van Aart, 2005). The idea to use the paradigm agent to design complex and interactive systems either distributed or cooperative is not a new one (Weiss, 1999). Many agent-based systems have been proposed in many industrial fields (Trentesaux et al., 2000; Cutkosky and Englemore, 1993; Parunak et al., 1999; Monostori et al., 2006; Moon et al., 2009; Valckenaers et al., 2003). Adding that the development of multi-agent system begins to be well controlled (Wagner, 2003; Cernuzzi et al., 2005; Biswas, 2008).

Holon defines a whole that is part of a vaster whole, and that at the same time contains elements, or sub-parts, of which it is composed and which provide its structural and functional meaning (Koestler, 1967). Thus, the "holon" represents a very interesting concept to overcome the dichotomy between parts and wholes, and to account for the integrative tendencies of design. The fact of double-headed implies that holons must be necessarily included in a typical vertical arrangement, with progressive accumulation and forming a nested hierarchical order called a holarchy. Fundamental insights into Holonic Systems Design, augmented with some research results on complex adaptive systems and with some implications for the design of Holonic Multi-Agent Systems, have shown the potential of holon based engineering (Valckenaers and Van Brussel, 2005; Esmaeili et al., 2016; Mella, 2009). One of the most important properties of a holon is that it exchanges information, material, or resources with other holons via its interfaces through negotiation and cooperation preserving the nested vertical order and horizontal flexibility. Many applications have been proposed using the notion of the holon and holonic multi-agent systems. Holonic design (Issa et al., 2017), holonic manufacturing systems (Giret and Botti, 2009; Valckenaers et al., 1998; Van Brussel et al., 1998; Hsieh, 2010), holonic control (Blanc et al., 2008; Wang, 2001; Balasubramanian et al., 2001; Leitao and Restivo, 2008), control of the customer–supplier relationships (Ounnar et al., 2009), design of complex systems (Honma et al., 1998; Valckenaers and Van Brussel, 2005), assembly systems (Arai et al., 2001), and intelligent transportation systems modelling (Abdoos et al., 2013) have shown the potential advantages of this concept for supporting intelligent applications. The application of holonic concepts to manufacturing (Van Brussel et al., 1998; Hsieh, 2010) was initially motivated by the inadequacy of existing manufacturing systems to deal with the evolution of products within an existing production facility, and to maintain a satisfactory performance outside of normal operating conditions. Holon based manufacturing scheduling distributes scheduling functions to several entities, combining their calculation power and local optimization capability (Leitao and Restivo, 2008). Modelling of the mechanism for the reconfiguration design of holonic manufacturing systems also have been studied (Hsieh, 2010). Holonic assembly is designed to accommodate sudden changes and breakdowns of assembly devices (Arai et al., 2001). Holon networks has been used successfully for the identification of large-scale nonlinear dynamical systems. A holonic modelling has been applied for complex adaptive systems (Honma et al., 1998). The holonic modelling is thus considered to bring a new paradigm of engineering.

### 2.3. Discussion

From Burbidge's cells to those nowadays', the problem of cell formation has been evolved. Initially formed to respond to a stable and robust demand, cells have been evolved to dynamic ones to respond to an unstable and flexible demand. However, the dynamic cells have found difficulties in real implementation due to the lack of intelligent technologies. It is the concept of virtual cells, initially introduced by McLean et al. (1982), that allows exploiting the processing of part families into machines grouped virtually. The concept of virtual cells is also innovative in intelligent cloud based design and manufacturing. Holonic and intelligent agents can be used to create a dynamic service-oriented networked digital design and manufacturing, from *CAD* parts to virtual intelligent cells formation. This issue is developed in this paper.

## 3. Modelling and architecture

### 3.1. Notations

The following notations and concepts are used in the proposed modelling:

$F = \{f_i\}$ is the universal set of faces of a *CAD* part, $i \in I_F$, $I_F = \{1, 2, \dots, n_F\}$;

$X = \{x_i\}$ is the universal set of manufacturing features, $i \in I_X$, $I_X = \{1, 2, \dots, n_X\}$;

$X_{ij} = \{x_{ij}\}$ is the universal set of operational features of the manufacturing feature $x_i$, $i \in I_X$, $I_X = \{1, 2, \dots, n_X\}$; $J_X = \{1, 2, \dots, n_{X'}\}$;

$P = \{p_i\}$ is the universal set of parts $i \in I_P$, $I_P = \{1, 2, \dots, n_P\}$;

$M = \{m_i\}$ is the universal set of machines $i \in I_M$, $I_M = \{1, 2, \dots, n_M\}$;

$C = \{c_l\}$ is the universal set of constraints $l \in I_C$, $I_C = \{1, 2, \dots, n_C\}$;

$\tilde{F} = \{(f_i, \mu_{\tilde{R}}(f_i))\}$ over $F$ is the fuzzy set of faces, $\mu_{\tilde{R}}(f_i)$ is the membership function of the faces $f_i$ in the fuzzy set $\tilde{F}$;

$\tilde{X} = \{(x_i, \mu_{\tilde{X}}(x_i))\}$ over $X$ is the fuzzy set of manufacturing features, $\mu_{\tilde{X}}(x_i)$ is the membership function of the feature $x_i$ in the fuzzy set $\tilde{X}$;

$\tilde{C} = \{(c_l, \mu_{\tilde{C}}(c_l))\}$ over $C$ is the fuzzy set of constraints for the manufacturing view, $\mu_{\tilde{C}}(c_l)$ is the membership function of the constraint $c_l$ in the fuzzy set $\tilde{C}$;

$\tilde{P} = \{(p_i, \mu_{\tilde{P}}(p_i))\}$ over $P$ is the fuzzy set of parts, $\mu_{\tilde{P}}(p_i)$ is the membership function of the part $p_i$ in the fuzzy set $\tilde{P}$;

$\tilde{M} = \{(m_i, \mu_{\tilde{M}}(m_i))\}$ over $M$ is the fuzzy set of parts, $\mu_{\tilde{M}}(m_i)$ is the membership function of the part $m_i$ in the fuzzy set $\tilde{M}$;

$\tilde{\mathfrak{R}}_1 = (F, X)$ is the fuzzy relationship between the universal set of faces $F$ and the universal set of manufacturing features $X$;

$\tilde{\mathfrak{R}}_2 = (F, C)$ is the fuzzy relationship between the universal set of faces $F$ and the universal set of constraints $C$;

$\tilde{\mathfrak{R}}_3 = (P, X)$ is the fuzzy relationship between the universal set of parts $P$ and the universal set of manufacturing features $X$;

$\tilde{\mathfrak{R}}_4 = (P, C)$ is the fuzzy relationship between the universal set of parts $P$ and the universal set of constraints $C$;

$\tilde{\mathfrak{R}}_5 = (X, M)$ is the fuzzy relationship between the universal set of manufacturing features $X$ and the universal set of machines $M$;

$\tilde{\mathfrak{R}}_6 = (C, M)$ is the fuzzy relationship between the universal set of constraints $C$ and the universal set of machines $M$;

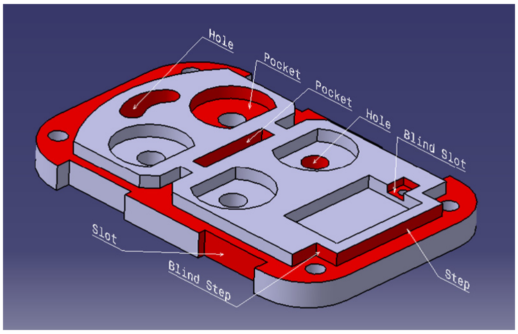



**Fig. 1.** *CAD* part with some manufacturing features.

$\tilde{\Re}_7 = (P, M)$ is the fuzzy relationship between the universal set of parts $P$ and the universal set of machines $M$;
$\tilde{A} = \{\tilde{\alpha}_i\}$ is the fuzzy set of agents $i \in I_{\tilde{A}}$, $I_{\tilde{A}} = \{1, 2, \ldots, m_A\}$;
$\tilde{A}_F = \{\tilde{f}_i\}$ is the fuzzy set of face agents $i \in I_{\tilde{A}_F}$, $I_{\tilde{A}_F} = \{1, 2, \ldots, m_F\}$;
$\tilde{A}_X = \{\tilde{x}_i\}$ is the fuzzy set of feature agents $i \in I_{\tilde{A}_X}$, $I_{\tilde{A}_X} = \{1, 2, \ldots, m_X\}$;
$\tilde{A}_P = \{\tilde{p}_i\}$ is the fuzzy set of part agents $i \in I_{\tilde{A}_P}$, $I_{\tilde{A}_P} = \{1, 2, \ldots, m_P\}$;
$\tilde{A}_M = \{\tilde{m}_i\}$ is the fuzzy set of machine agents $i \in I_{\tilde{A}_M}$, $I_{\tilde{A}_M} = \{1, 2, \ldots, m_M\}$;
$\tilde{A}_C = \{\tilde{c}_i\}$ is the fuzzy set of cell agents $i \in I_{\tilde{A}_C}$, $I_{\tilde{A}_C} = \{1, 2, \ldots, m_C\}$;
$\tilde{H}_P = \left\{\tilde{P}_j^i\right\}$ is the fuzzy set of part holon agents $i \in I_{\tilde{H}_P}$, $I_{\tilde{H}_P} = \{1, 2, \ldots, h_P\}$, $j \in J_{\tilde{H}_P}$, $J_{\tilde{H}_P} = \{1, 2, \ldots, h_P\}$, where $\tilde{P}_j^0 \in \tilde{A}_P$ *and* $\tilde{P}_j^{i>1} = \{\tilde{P}_1^0, \tilde{P}_2^0, \ldots, \tilde{P}_1^{i-1}, \tilde{P}_2^{i-1}, \ldots\}$;
$\tilde{H}_M = \left\{\tilde{M}_j^i\right\}$ is the fuzzy set of machine holon agents $i \in I_{\tilde{H}_M}$, $I_{\tilde{H}_M} = \{1, 2, \ldots, h_M\}$, $j \in J_{\tilde{H}_M}$, $J_{\tilde{H}_M} = \{1, 2, \ldots, h_M\}$, where $\tilde{M}_j^0 \in \tilde{A}_M$ *and* $\tilde{M}_j^{i>1} = \{\tilde{M}_1^0, \tilde{M}_2^0, \ldots, \tilde{M}_1^{i-1}, \tilde{M}_2^{i-1}, \ldots\}$;
$\tilde{H}_C = \left\{\tilde{C}_j^i\right\}$ is the fuzzy set of cell holon agents $i \in I_{\tilde{H}_C}$, $I_{\tilde{H}_C} = \{1, 2, \ldots, h_C\}$, $j \in J_{\tilde{H}_C}$, $J_{\tilde{H}_C} = \{1, 2, \ldots, h_C\}$, where $\tilde{C}_j^0 \in \tilde{A}_C$, $\tilde{C}_j^i = \left\langle \tilde{M}_j^i, \tilde{P}_j^i, \tilde{R}_j^i \right\rangle$, $\tilde{M}_j^i \subset \tilde{H}_m$, $\tilde{P}_j^i \subset \tilde{H}_p$, *and* $\tilde{R}_j^i : \tilde{M}_j^i \leftrightarrow \tilde{P}_j^i$;

### *3.2. Face–feature–constraint–part–machine network modelling*

This paper considers intelligent features, with their local behaviour, efficiently to integrate computer-aided part data with computer-aided manufacturing data in the problem of intelligent virtual manufacturing cell formation. In *CAD* modelling, features are generic or specific forms to which engineers associate certain attributes and engineering knowledge used in the different phases of part design and manufacturing. For instance, Fig. 1 shows a CAD part with some manufacturing features.

The manufacturing of a feature goes through different intermediate states, where each state defines an intermediate feature, called an *operational feature*. A *CAD* part can therefore be represented by its operational features. The manufacture of the part involves the machine's ability to produce operational features that is their forms and technological characteristics.

A face–feature–constraint–part–machine network (Fig. 2) is created by taking into account the modelling of parts in design and manufacturing. The network and uses the design and manufacturing relationships among the sets of faces, features, constraints, parts and machines. For instance, Fig. 3a and b show respectively the part–feature subnetwork and feature–machine subnetwork, which are extracted from face–feature–constraint–part–machine network (Fig. 2). Then, the following fuzzy sets and relationships are defined from this network:

- **Fuzzy set of faces**. During feature interaction, a face can be virtually extended. As a result, there is an uncertainty. Thus, a fuzzy set $\tilde{F} = \{(f_i, \mu_{\tilde{R}}(f_i))\}$ over $F$ can be defined.

**Table 1**
Topological and geometric attributes.

| Topology | | Geometry | | |
|---|---|---|---|---|
| Relative positions | Type of face | Angle | Type of adjacency | Type of face |
| $a_1^{tpl}$ | $a_2^{tpl}$ | $a_1^{geo}$ | $a_2^{geo}$ | $a_3^{geo}$ |

**Table 2**
Topological and geometric domains.

| Attributes | Domains and corresponding codes | | | |
|---|---|---|---|---|
| | 0 | 1 | 2 | 3 |
| $a_1^{tpl}$ | Adjacent | Non-adjacent | Parallel | Virtual adjacent |
| $a_2^{tpl}$ | Base | Side | Frontal | |
| $a_1^{geo}$ | Concave | Convex | Flat | Other |
| $a_2^{geo}$ | Line | Non-straight line | Other | |
| $a_3^{geo}$ | Plane | Non-plane | | |

- **Fuzzy set of constraints**. A fuzzy set of constraints $\tilde{C} = \{(c_l, \mu_{\tilde{C}}(c_l))\}$ over $C$ can be defined for design and manufacturing. For instance, the value of profile roughness parameter *Ra* of a face is a constraint, which has an impact on the selection of the manufacturing process. The main dimension (for example, the maximum diameter for a rotational part) and the ratio of dimensions (for example, Maximum Length/Maximum Diameter) are also constraints associated to the manufacturing of a part.
- **Fuzzy set of manufacturing features**. The fuzzy set $\tilde{X} = \{(x_i, \mu_{\tilde{X}}(x_i))\}$ over $X$ defines the degree of membership of feature to the fuzzy set $\tilde{X}$. It is the result of the interaction among features, the virtualization of extension of faces, and different alternatives to define the interacted features.
- **Fuzzy set of parts**. The fuzzy set $\tilde{P} = \{(p_i, \mu_{\tilde{P}}(p_i))\}$ over $P$ defines the degree of membership of each part to the fuzzy set $\tilde{P}$. It is an evident corollary of the fuzzy set of manufacturing features composing a fuzzy part.
- **Fuzzy set of machines**. The set of machines is not crisply defined, due to machines' ability to manufacture the set a features, to satisfy the set of constraints, and therefore to manufacture the set of parts. The fuzzy set $\tilde{M} = \{(m_i, \mu_{\tilde{M}}(m_i))\}$ over $M$ is the fuzzy set of machines that defines the degree of membership of each machine to the fuzzy set $\tilde{M}$.
  **Fuzzy relationship face–part**. A part is a morphological entity represented by a set of topologically associated faces. In Boundary Representation (B. Rep), a part is explicitly represented by a set of faces. Thus, every part $X_i$ can be characterized by a set of faces $F = \{f_1, f_2 \cdots f_i \cdots f_m\}$ that satisfies a set of topological and geometric relations. These relations are defined for domains corresponding to the set of topological and geometric attributes, respectively. Table 1 shows typical cases of those attributes and Table 2 shows their respective domains. However, some attributes of faces, such as geometric attributes, can be vaguely defined. Indeed, during part design a face can have different alternative geometries. Thus, a fuzzy relationship $\tilde{\Re}_0 = (F, P)$, characterized by the membership function $\mu_{\tilde{\Re}_0}(f, p)$, can be defined between these two sets. The membership function, defined in [0..1], indicates the degree of vagueness of attributed face in a part.

- **Fuzzy relationship face-manufacturing feature**. A manufacturing feature is a morphological entity represented by a set of topologically associated faces, and characterized by its form, dimensions, and tolerances. Manufacturing features represent the manufacturing view of the part. It is the local point of view of the part. Thus, the universal set of faces $F = \{f_i\}$ and the universal set of manufacturing features $X = \{x_i\}$ are related in the *CAD* part modelling. In the case of interacted manufacturing features, a fuzzy relationship $\tilde{\Re}_1 = (F, X)$, characterized by the

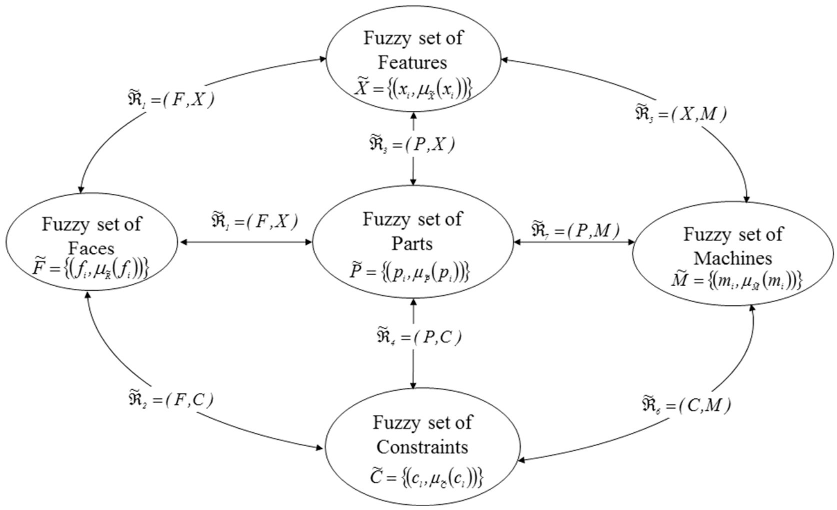



**Fig. 2.** Face–feature–constraint–part–machine network.

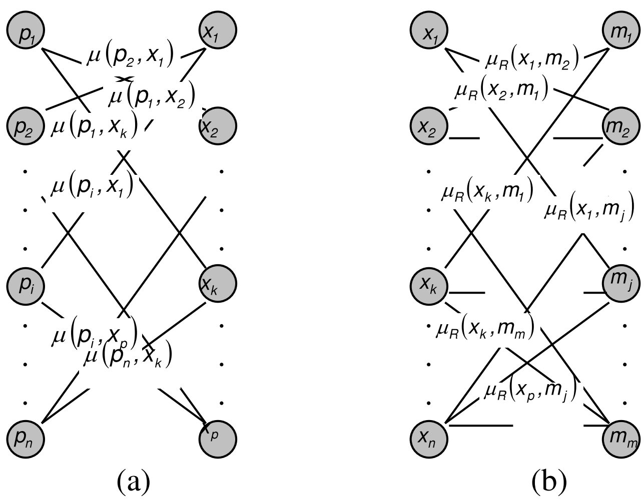



**Fig. 3.** (a) Part–feature subnetwork and (b) Feature–machine subnetwork.

membership function $\mu_{\tilde{\mathfrak{R}}_1}(f,\ x)$, can be defined between these two sets. The membership function, defined in [0..1], indicates to what degree a face participates in a recognized feature.

- **Fuzzy relationship part–manufacturing feature**. A fuzzy relationship $\tilde{\mathfrak{R}}_3 = (P, X)$, characterized by the membership function $\mu_{\tilde{\mathfrak{R}}_3}(p,\ x)$, can be defined between the universal set of parts $P$ and the universal set of features $X$. The membership function $\mu_{\tilde{\mathfrak{R}}_3}(p,\ x)$ defined in [0..1], indicates to what degree a part is composed by the set of manufacturing features.
- **Fuzzy relationship manufacturing feature–machine**. A fuzzy relationship $\tilde{\mathfrak{R}}_5 = (X, M)$, characterized by the membership function $\mu_{\tilde{\mathfrak{R}}_5}(x,\ m)$, can be defined between the universal set of manufacturing features $X$ and the universal set of machines $M$. The membership function, defined in [0..1], indicates to what degree a manufacturing feature can be manufactured in a machine.
- **Fuzzy relationship face–constraint**. Different constraints, such as material or global dimensions, are represented in *CAD* parts. Thus, the universal set of faces $F = \{f_i\}$ and the universal set of universal constraints $C(v_t)$ are related in the *CAD* part modelling. A fuzzy relationship $\tilde{\mathfrak{R}}_2 = (F, C)$, characterized by the membership function $\mu_{\tilde{\mathfrak{R}}_2}(f,\ c)$, can be defined between these two sets. The membership function, defined in [0..1], indicates to what degree a face is related to a constraint.
- **Fuzzy relationship part-constraint**. Manufacturing has its own view on the product. It imposes its own universal set of constraints $C(v_t)$ on a part. A fuzzy relationship $\tilde{\mathfrak{R}}_4 = (P, C)$, characterized by the membership function $\mu_{\tilde{\mathfrak{R}}_4}(p,\ c)$, can be defined between the universal set of parts $P$ and the universal set of constraints $C$. The membership function, defined in [0..1], indicates to what degree a part satisfies the universal set of constraints $C$.
- **Fuzzy relationship machine-constraint**. Manufacturing also imposes its own universal set of constraints $C(v_t)$ on machines. A fuzzy relationship $\tilde{\mathfrak{R}}_6 = (C, M)$, characterized by the membership function $\mu_{\tilde{\mathfrak{R}}_6}(c,\ m)$, can be defined between the universal set of constraints $C$ and the universal set of machines $M$. The membership function, defined in [0..1], indicates to what degree a machine satisfies the universal set of constraints $C$.

### 3.3. Architecture modelling for intelligent virtual manufacturing cell formation

The network building (Fig. 2) goes through, firstly, intelligent recognition of operational features, and, secondly, distributed capabilities of machines recognition in networked digital manufacturing and design. Holonic manufacturing cells emerge from the interaction of parts and machines in the face–feature–constraint–part–machine network (Fig. 4).

The proposed approach for intelligent virtual manufacturing cell formation includes the following distributed and concurrent phases:

- Phase 1: ***Intelligent features recognition***. This phase consists of intelligent recognition of manufacturing features in *CBDM*.
- Phase 2: ***Distributed capabilities of machines evaluation in CBDM.*** In this phase, the mobile intelligent agents recognize the ability of machines to manufacture parts.
- Phase 3: ***Cell holon formation.***In this phase, the virtual and fuzzy cell holons are formed in *CBDM*.

### 3.4. Fuzzy agent model for intelligent virtual manufacturing cell formation

The previous section has proposed face–feature–constraint–part–machine network modelling, so this section can now present the

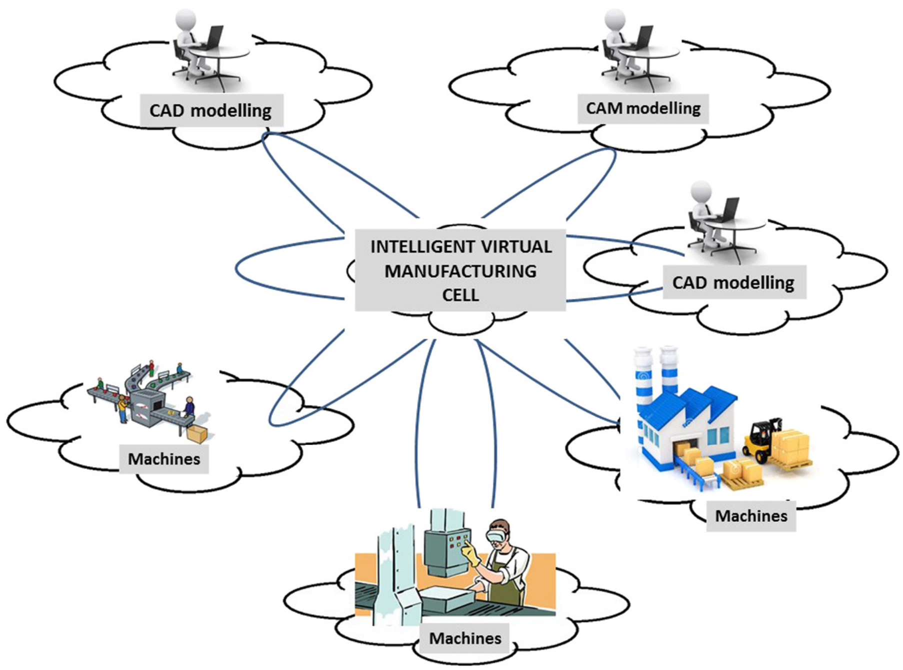



**Fig. 4.** Intelligent virtual manufacturing cell formation in cloud based design and manufacturing.

fuzzy agentification of architecture and elements of this network. A fuzzy agent-based system $\tilde{M}_\alpha$ is defined a 5-tuple (1):

$$\tilde{M}_{\tilde{\alpha}} = \langle \tilde{A}, \tilde{I}, \tilde{P}, \tilde{O}, \Phi_A \rangle \tag{1}$$

where $\tilde{A}, \tilde{I}, \tilde{P}$ and $\tilde{O}$, are respectively a fuzzy set of agents $\{\tilde{\alpha}_i\}$, a fuzzy set of interactions between fuzzy agents, a fuzzy set of roles that fuzzy agents can perform, a fuzzy set of fuzzy organizations (*i.e.* communities of fuzzy agents) defined for fuzzy agents of $\tilde{\alpha}_i \in \tilde{A}$, and $\Phi_A$ is a set of functions of fuzzy agents' generation defined by the following Eq. (2):

$$\varphi : \tilde{A}^n \rightarrow \tilde{A}^m \quad \varphi(\tilde{\alpha}_i, \tilde{\alpha}_j) \Rightarrow \tilde{A}' = \tilde{A} + \left\{\tilde{\alpha}_j\right\} \tag{2}$$

Agents, interactions, roles, organizations are thus fuzzy. The behaviour of a fuzzy agent $\tilde{\alpha}_i \in \tilde{A}$ is also fuzzy. It is inspired by the basic cycle: *perceive, decide,* and then *act* (Fougères, 2013; Ostrosi et al., 2012). Observations, decisions, actions and knowledge of a fuzzy agent are also fuzzy (Fougères and Ostrosi, 2013). Thus, a fuzzy agent is described by the following 4-tuple (3):

$$\tilde{\alpha}_i = \left\langle \tilde{\Phi}_{\tilde{\Pi}(\tilde{\alpha}_i)}, \tilde{\Phi}_{\tilde{\Delta}(\tilde{\alpha}_i)}, \tilde{\Phi}_{\tilde{\Gamma}(\tilde{\alpha}_i)}, \tilde{K}_{\tilde{\alpha}_i} \right\rangle \tag{3}$$

where $\tilde{\Phi}_{\tilde{\Pi}(\tilde{\alpha}_i)}$, $\tilde{\Phi}_{\tilde{\Delta}(\tilde{\alpha}_i)}\tilde{\Phi}_{\tilde{\Gamma}(\tilde{\alpha}_i)}$ and $\tilde{K}_{\tilde{\alpha}_i}$ are respectively fuzzy functions of observation (4), decision (5), action (6) of the fuzzy agent $\tilde{\alpha}_i$, and fuzzy set of knowledge (7).

$$\tilde{\Phi}_{\tilde{\Pi}(\tilde{\alpha}_i)} : (\tilde{E}_{\tilde{\alpha}_i} \cup \tilde{I}_{\tilde{\alpha}_i}) \times \tilde{\Sigma}_{\tilde{\alpha}_i} \rightarrow \tilde{\Pi}_{\tilde{\alpha}_i} \tag{4}$$

$$\tilde{\Phi}_{\tilde{\Delta}(\tilde{\alpha}_i)} : \tilde{\Pi}_{\tilde{\alpha}_i} \times \tilde{\Sigma}_{\tilde{\alpha}_i} \rightarrow \tilde{\Delta}_{\tilde{\alpha}_i} \tag{5}$$

$$\tilde{\Phi}_{\tilde{\Gamma}(\tilde{\alpha}_i)} : \tilde{\Delta}_{\tilde{\alpha}_i} \times \tilde{\Sigma}_{\tilde{M}_{\tilde{\alpha}_i}} \rightarrow \tilde{\Gamma}_{\tilde{\alpha}_i} \tag{6}$$

$$\tilde{K}_{\tilde{\alpha}_i} = \tilde{P}_{\tilde{\alpha}_i} \cup \tilde{\Sigma}_{\tilde{\alpha}_i} \cup \tilde{\Delta}_{\tilde{\alpha}_i} \tag{7}$$

where $\tilde{E}_{\tilde{\alpha}_i}, \tilde{I}_{\tilde{\alpha}_i}, \tilde{\Sigma}_{\tilde{\alpha}_i}, \tilde{\Pi}_{\tilde{\alpha}_i}, \tilde{\Delta}_{\tilde{\alpha}_i}$ and $\Gamma_{\tilde{\alpha}_i}$ are respectively the finite fuzzy sets of observed events, interactions, states, perceptions, decisions, and actions of the fuzzy agent $\tilde{\alpha}_i$; and where $\tilde{\Sigma}_{\tilde{M}_{\tilde{\alpha}_i}}$ is the state of the fuzzy agent-based system $\tilde{M}_{\tilde{\alpha}}$. Fuzzy decision rules, objects and characteristics of the domain with their fuzzy values of the domain (for instance, the geometric and topological attributes), the acquaintances in the form of a network of affinities, and dynamic knowledge (observed fuzzy events, fuzzy internal states) are included in fuzzy set of knowledge.

An fuzzy interaction $\tilde{\imath}_i \in \tilde{I}$ between two fuzzy agents is defined by the following tuple (8):

$$\tilde{\imath}_i = \langle \tilde{\lambda}_c, \tilde{\alpha}_s, \tilde{\alpha}_r, \tilde{\eta}_i \rangle \tag{8}$$

where $\tilde{\lambda}_c \in \tilde{\Lambda}$ is a fuzzy cooperative act defined between the fuzzy agent source $\tilde{\alpha}_s$ and the fuzzy agent(s) destination $\tilde{\alpha}_r \left| \left\{\tilde{\alpha}_r\right\}\right.$ during fuzzy interaction $\tilde{\imath}_i \in \tilde{I}$; $\tilde{\Lambda} = \{$*inform, diffuse, ask, reply, confirm*$\}$ is a fuzzy set of cooperative acts that are sufficient to enable fuzzy agents to perceive the intention of cooperation associated with the content of the fuzzy message $\tilde{\eta}_i$. Furthermore, the fuzzy agent cooperation protocol requires a response message for each interaction between fuzzy agents (*inform* ⇒ *confirm; diffuse* ⇒ *confirm; ask* ⇒ *accept* | *refuse*).

A fuzzy set $\tilde{H}$ of holonic fuzzy agents (*i.e.* fuzzy holons) is defined recursively as follows (Hsieh, 2010):

- given a fuzzy agent-based system $\tilde{M}_\alpha$, each fuzzy agent $\widetilde{\alpha_i} \in \tilde{A}$ formed an atomic holonic fuzzy agent $\widetilde{h_i}$, $\widetilde{h_i} = \left(\left\{\widetilde{\alpha_i}\right\}, \ \left\{\widetilde{\alpha_i}\right\}, \emptyset\right) \in \tilde{H}$, then
- higher level holonic fuzzy agent $\widetilde{h_i}$ are formed: $\widetilde{h_i} = \left(\tilde{H}_0, \ \tilde{H}', \tilde{R}\right) \in \tilde{H}$, where $\tilde{H}' \subseteq \tilde{H}$ is the set of holonic fuzzy agents that participate in $\widetilde{h_i}$; $\tilde{H}_0 \subseteq \tilde{H}'$ is the non-empty set of holonic fuzzy agents that represent $\widetilde{h_i}$ to the environment and is responsible for coordinating the actions inside $\widetilde{h_i}$; $\tilde{R}$ defines a fuzzy relationship inside $\widetilde{h_i}$ (*i.e.* $\tilde{R}$ specifies the holonic fuzzy agent organization).

This holonic fuzzy agent model can now be applied to the specific problem of intelligent virtual manufacturing cell formation. First, the sets of faces, features, parts, machines, and cells are fuzzy agentified (9):

$$Agentification: \ F, X, P, M, C \rightarrow \tilde{A}_F, \tilde{A}_X, \tilde{A}_P, \tilde{A}_M, \tilde{A}_C \tag{9}$$

Each face of the set $F = \left\{F_1, F_2, \dots, F_m\right\}$ is transformed into a fuzzy agent $\tilde{F}_{[1..m]} \in \tilde{A}_F$; each recognized feature of the set $X = \left\{X_1, X_2, \dots, X_n\right\}$ is transformed into a fuzzy agent $\tilde{X}_{[1..n]} \in \tilde{A}_X$; each parts of the set $P = \left\{P_1, P_2, \dots, P_o\right\}$ is transformed into a fuzzy agent

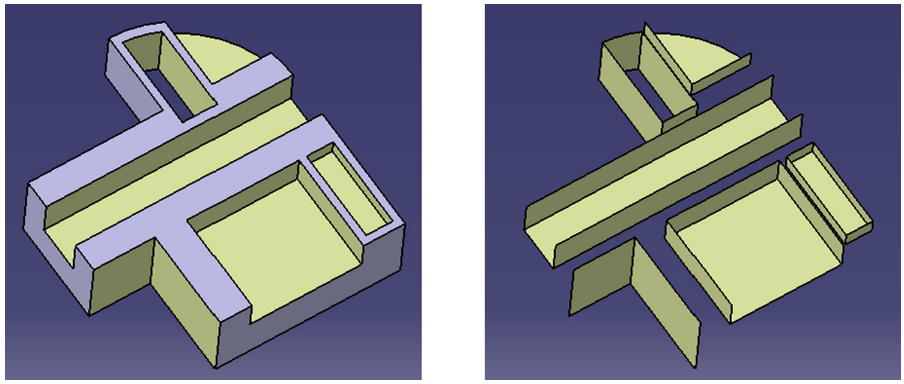


**Fig. 5.** Manufacturing features as a set of faces.

| | $\tilde{p}_1$ | $\tilde{p}_2$ | $\tilde{p}_3$ | $\tilde{p}_4$ | $\tilde{p}_5$ | $\tilde{p}_6$ | $\tilde{m}_1$ | $\tilde{m}_2$ | $\tilde{m}_3$ | $\tilde{m}_4$ | $\tilde{m}_5$ | $\tilde{m}_6$ | $\tilde{m}_7$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\tilde{x}_{11}$ | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0.3 | 0 | 0.2 | 0 | 0.2 |
| $\tilde{x}_{12}$ | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| $\tilde{x}_{21}$ | 0 | 0 | 0.8 | 0.9 | 0.9 | 0 | 0 | 0 | 0.4 | 0 | 0.8 | 0 | 0.8 |
| $\tilde{x}_{22}$ | 0 | 0 | 0.8 | 0.9 | 0.9 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 | 0 |
| $\tilde{x}_{31}$ | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0.5 | 0 | 0.3 | 0 | 0.3 |
| $\tilde{x}_{41}$ | 0 | 0.8 | 0 | 0 | 0 | 0 | 0.8 | 1 | 0.2 | 0 | 0.2 | 0 | 0.2 |
| $\tilde{x}_{51}$ | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0.5 | 0 | 0.3 | 0 | 0.3 |
| $\tilde{x}_{61}$ | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0.4 | 0 | 0.8 | 0 | 0.8 |
| $\tilde{x}_{71}$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8 | 0 | 0.7 | 0 | 0.7 |
| $\tilde{x}_{81}$ | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0.3 | 0 | 0.3 | 0 | 0.3 |
| $\tilde{x}_{82}$ | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0.9 | 0 | 0.3 | 0 |
| $\tilde{x}_{91}$ | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0.3 | 0 | 0.3 | 0 | 0.3 |

**Fig. 6.** Fuzzy relationships between fuzzy operational feature agents and fuzzy part agents as well as fuzzy operational feature agents and fuzzy machine agents.

$\tilde{P}_{[1..o]} \in \tilde{A}_P$; each machine of the set $M = \{M_1, M_2, \ldots, M_p\}$ is transformed into a fuzzy agent $\tilde{M}_{[1..p]} \in \tilde{A}_M$ ; each formed cell of the set $C = \{C_1, C_2, \ldots, Cq\}$ is transformed into a fuzzy agent $\tilde{c}_{[1..q]} \in \tilde{A}_C$.

Then, from fuzzy agent's part, machine and cell, holonic fuzzy agents are generated (10):

$$Holonisation:\ \tilde{A}_F, \tilde{A}_X, \tilde{A}_P, \tilde{A}_M, \tilde{A}_C \rightarrow \tilde{H}_F, \tilde{H}_X, \tilde{H}_P, \tilde{H}_M, \tilde{H}_C \quad (10)$$

where $\tilde{F}_j^i \in \tilde{H}_F$ with $\tilde{F}_j^0 \in \tilde{A}_F$ and $\tilde{F}_j^{i>1} = \{\tilde{F}_1^0, \tilde{F}_2^0, \ldots, \tilde{F}_1^i, \ldots, \tilde{F}_m^i\}$; $\tilde{X}_j^i \in \tilde{H}_X$ with $\tilde{X}_j^0 \in \tilde{A}_X$ and $\tilde{X}_j^{i>1} = \{\tilde{X}_1^0, \tilde{X}_2^0, \ldots, \tilde{X}_1^i, \ldots, \tilde{X}_n^i\}$; $\tilde{P}_j^i \in \tilde{H}_P$, with $\tilde{P}_j^0 \in \tilde{A}_P$ and $\tilde{P}_j^{i>1} = \{\tilde{P}_1^0, \tilde{P}_2^0, \ldots, \tilde{P}_1^i, \ldots, \tilde{P}_o^i\}$; $\tilde{M}_j^i \in \tilde{H}_M$ with $\tilde{M}_j^0 \in \tilde{A}_M$ and $\tilde{M}_j^{i>1} = \left\{\tilde{M}_1^0, \tilde{M}_2^0, \ldots, \tilde{M}_1^i, \ldots, \tilde{M}_p^i\right\}$; $\tilde{C}_j^0 \in \tilde{A}_C$, $\tilde{C}_j^i = \left\langle \tilde{M}_j^i, \tilde{P}_j^i, \tilde{R}_j^i \right\rangle$ with $\tilde{M}_j^i \subset \tilde{H}_m, \tilde{P}_j^i \subset \tilde{H}_p, and\, \tilde{R}_j^i :\ \tilde{M}_j^i \leftrightarrow \tilde{P}_j^i$.

## 4. Intelligent virtual manufacturing cell formation

This section presents the intelligent virtual manufacturing cell formation using agents.

### 4.1. Intelligent manufacturing features recognition

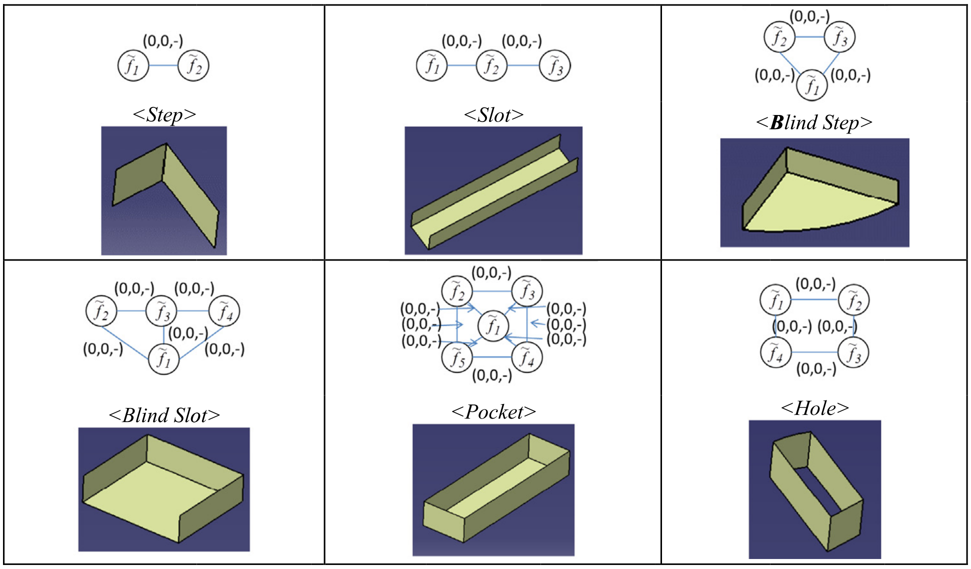
Any manufacturing feature $x_i \in X$ can be characterized by a set of faces $F_{X_i} = \{ f_1, f_2 \cdots f_j \cdots f_m\}$ that satisfy a set of topologic and geometric relations (*cf.* Table 1). Each face $f_i \in F_{X_i}$ is transformed into a fuzzy face agent $\tilde{f}_i \in \tilde{A}_F$. For instance, Table 3 shows the agentification of the six manufacturing features presented in Fig. 5.

Each fuzzy face agent $\tilde{f}_i \in \tilde{A}_F$ possesses a fuzzy set of knowledge (9), including:

- the topologic and geometric relation $e_i^* = (a_2^{tpl}, a_3^{geo})$ of the face $f_i$ (*cf.* Table 1);
- a set of triplets $e_{ij} = \left(a_1^{tpl}, a_1^{geo}, a_2^{geo}\right)$ corresponding to the topologic and geometric relations between a pair of faces $\left(f_i, f_j\right)$ (*cf.* Table 1);
- a graph $G_{\tilde{f}_i}$ corresponding to the generational history of the face agent;
- a set of fuzzy face agents' networks $\tilde{f}_X$, corresponding to the known features, recognized or associated;
- a set of decision rules $\tilde{A}_{\tilde{f}_i}$ and the set of grammar rules $\{P_0, \ldots, P_n\}$ (Ostrosi and Ferney, 2005).

To illustrate the fuzzy feature agent knowledge modelling, Table 4 describes a simple feature and knowledge of the four fuzzy face agents $\tilde{f}_1$, $\tilde{f}_2$, $\tilde{f}_3$, and $\tilde{f}_4$ representing it. Using their knowledge, the four fuzzy face agents identify a slot feature (Table 4.a), then a step feature (Table 4.b).

**Table 3**
Fuzzy face agent's network modelling of manufacturing features.




Each fuzzy feature agent $\tilde{x}_i$ possesses a fuzzy set of knowledge (9), including:

- a graph $G_{\tilde{X}_i} = \left\langle \tilde{A}_{F_{\tilde{X}_i}}, \tilde{R} \right\rangle$, where $\tilde{A}_{F_{\tilde{X}_i}}$ is the set of fuzzy face agents making up the fuzzy feature agent $\tilde{x}_i$, and $\tilde{R}$ is the fuzzy set of relationship between fuzzy face agents;
- the set of fuzzy part agents $\tilde{A}'_P \subset \tilde{A}_P$ including the fuzzy feature agent $\tilde{x}_i$;
- a set of fuzzy agent' feature-specific decision rules $\tilde{\Delta}_{\tilde{x}_i}$.

In the case of the mechanical design, a finite set of manufacturing features can produce an unlimited number of configurations of manufacturing features in interaction. Let us consider the feature presented in Table 4.a. By interaction, the three fuzzy face agents $\tilde{f}_1$, $\tilde{f}_2$, $\tilde{f}_3$ communicate their geometric and topological characteristics. Therefore, they can collectively identify the features they represent together by activating the grammar rules memorized in their knowledge base. For instance, considering graph (b) in Table 3:

(1) the three fuzzy face agents $\tilde{f}_1$, $\tilde{f}_2$, $\tilde{f}_3$ exchange their topologic and geometric characteristics (*inform*($\tilde{f}_1, \{\tilde{f}_2, \tilde{f}_3\}, e_1$, *1, 0*), *inform*($\tilde{f}_2, \{\tilde{f}_1, \tilde{f}_3\}, e_2$, *0, 0*), and *inform*($\tilde{f}_3, \{\tilde{f}_1, \tilde{f}_2\}, e_3$, *1, 0*));

(2) with this new information, the fuzzy face agent $\tilde{f}_2$ recognizes a slot formed by fuzzy face agents $\tilde{f}_1$, $\tilde{f}_2$, $\tilde{f}_3$;

(3) then, the fuzzy face agent $\tilde{f}_2$ informs the two other fuzzy agents that they form together a slot (*inform*($\tilde{f}_2, \{\tilde{f}_1, \tilde{f}_3\}$, *slot*, $[\tilde{f}_1, \tilde{f}_2, \tilde{f}_3]$)); after this recognition, a fuzzy feature agent $\tilde{x}_1$ is generated.

Thus, a relationship $\mathfrak{R}_3 = (P, X)$, characterized by the membership function $\mu_{\mathfrak{R}_3}(p, x)$, can be defined between the universal set of *CAD* parts $P$ and the universal set of manufacturing features $X$. If a manufacturing feature $x$ is recognized to belong to a part $p$ then the membership function is: $\mu_{\mathfrak{R}_3}(p, x) = 1$, otherwise $\mu_{\mathfrak{R}_3}(p, x) = 0$. In the case of feature interaction, because of the loss of topological information, the manufacturing feature membership to a part implies an uncertainty. This uncertainty means the existence of a fuzzy relationship $\tilde{\mathfrak{R}}_3 = (P, X)$ between the set of parts $P$ and the set of manufacturing features $X$. This fuzzy relationship is a subset of the Cartesian product $P \times X$, with the membership function $\mu_{\tilde{\mathfrak{R}}_3}(p, x) \in [0, 1]$.

### 4.2. Distributed capabilities of machines evaluation in CBDM

During manufacturing, a manufacturing feature goes through different intermediate manufacturing states, as the result of manufacturing operations. Each intermediate state is characterized in its turn by form, dimensions, and tolerances. Thus, each intermediate state defines some intermediate features called the operational features $x_{ij}$. It yields that the manufacturing feature $x_i$ is the last operational feature $x_{ij}$, the result of the ultimate manufacturing operation.

The manufacturability of a part is evaluated in terms of capabilities of available machines to manufacture the operational features $x_{ij}$, taking into account the characteristics of *form*, *dimensions*, and *tolerances*. In this way, there is a relationship among the set of operational features $X$ and the set of machines *M*, which indicates the ability of machines to manufacture these operational features. This relationship, noted by $\mathfrak{R}_5 = (X, M)$, can be represented by the membership function $\mu_{\mathfrak{R}_5}(x, m)$ defined on the Cartesian product $X \times M$, with $\mu_{\mathfrak{R}_5}(x, m) = 1$ if an operational feature $x$ can be manufactured in a machine $m$, and $\mu_{\mathfrak{R}_5}(x, m) = 0$ otherwise. However, the expert knowledge on machines is expressed in natural language and it is introduced by the subjective descriptions. In addition, the nature of knowledge, on the ability of a machine to manufacture an operational feature set, is gradual. The expert does not always reason by 0 or 1. Therefore, a fuzzy relationship $\tilde{\mathfrak{R}}_5 = (X, M)$, characterized by the membership function $\mu_{\tilde{\mathfrak{R}}_5}(x, m)$, can be defined by softening the definition of the classic characteristic function. The membership function, defined in [0..1], indicates in what degree an operational feature can be manufactured in a machine.
Thus, to describe the ability of machines to manufacture the operational features, the following fuzzy relationships can be built:

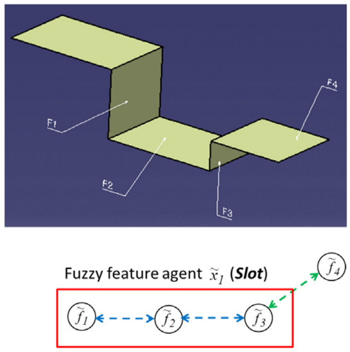
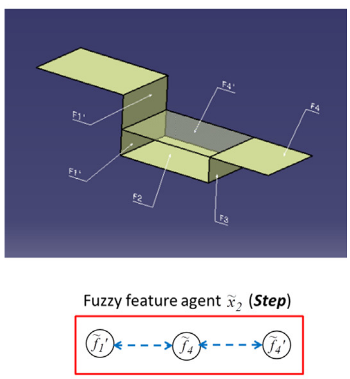
- *form-machine*, noted $\tilde{R}_{form}$ defined by the membership function $\mu\left(form, m_j\right)$ and associated to the property "*machine $m_j$ able to manufacture the specified form*";
- *dimension-machine*, noted $\tilde{R}_{dimension}$, defined by the membership function $\mu\left(dimension, m_j\right)$ and associated to the property "*machine able to manufacture the dimension*";
- *tolerance-machine*, noted $\tilde{R}_{tolerance}$, defined by the membership function $\mu\left(tolerance, m_j\right)$ and associated to the property "*machine able to manufacture the tolerance*";

The simultaneous satisfaction of these properties corresponds to the property "*machine able to manufacture the operational feature*". From these degrees of membership, by using the minimum operator, the membership function $\mu_{\tilde{\mathfrak{R}}_5} \in [0..1]$ is computed from the following Eq. (11):

$$\mu\left(x_k, m_j\right) = \min\left[\mu\left(form, m_j\right), \mu\left(dimension, m_j\right), \mu\left(tolerance, m_j\right)\right] \quad (11)$$

In the case of interacted features, a manufacturing feature can be recognized in part with a certain degree (*cf.* 4.1). Therefore, the

**Table 4**
Block of "Initial and acquired" knowledge of fuzzy face agents.

| *Graphical representation* | *Feature agent's knowledge* | |
|---|---|---|
|   (a) | $\tilde{f}_1 : \{\langle P_0, ..., P_n \rangle,$ | // initial knowledge |
| | $\langle e_1^*, 1, 0\rangle, \ \langle e_{1,2}, 0, 1, 0\rangle,$ | // informed by designer |
| | $\langle e_2^*, 0, 0\rangle,$ | // informed by $\tilde{f}_2$ |
| | $G_{\tilde{f}_1} = [\tilde{f}_1],$ | // generated by $\tilde{f}_1$ |
| | $\langle slot, 1, [\tilde{f}_3, \tilde{f}_2, \tilde{f}_1]\rangle,$ | // informed by $\tilde{f}_2$ |
| | $G_{\tilde{f}_1} = [\tilde{f}_1', \tilde{f}_1''],$ | // generated by $\tilde{f}_1$ |
| | $\langle step, 2, [\tilde{f}_1', \tilde{f}_4, \tilde{f}_4']\rangle, ... \}$ | // informed by $\tilde{f}_4$ |
| | $\tilde{f}_2 : \{\langle P_0, ..., P_n \rangle,$ | // initial knowledge |
| | $\langle e_2^*, 0, 0\rangle, \ \langle e_{2,1}, 0, 1, 0\rangle,$ | // informed by designer |
| | $\langle e_{2,3}, 0, 1, 0\rangle,$ | // informed by designer |
| | $\langle e_1^*, 1, 0\rangle, \ \langle e_3^*, 1, 0\rangle,$ | // informed by $\tilde{f}_1$ and $\tilde{f}_3$ |
| | $G_{\tilde{f}_2} = [\tilde{f}_2],$ | // generated by $\tilde{f}_2$ |
| | $\langle slot, 1, [\tilde{f}_3, \tilde{f}_2, \tilde{f}_1]\rangle, ... \}$ | ***// identified feature*** |
|   (b) | $\tilde{f}_3 : \{\langle P_0, ..., P_n \rangle,$ | // initial knowledge |
| | $\langle e_3^*, 1, 0\rangle, \ \langle e_{3,2}, 0, 1, 0\rangle,$ | // informed by designer |
| | $\langle e_{3,4}, 3, 1, 0\rangle,$ | // informed by designer |
| | $\langle e_2^*, 0, 0\rangle, \ \langle e_4^*, 0, 0\rangle,$ | // informed by $\tilde{f}_2$ and $\tilde{f}_4$ |
| | $G_{\tilde{f}_3} = [\tilde{f}_3],$ | // generated by $\tilde{f}_3$ |
| | $\langle slot, 1, [\tilde{f}_3, \tilde{f}_2, \tilde{f}_1]\rangle, ... \}$ | // informed by $\tilde{f}_2$ |
| | $\tilde{f}_4 : \{\langle P_0, ..., P_n \rangle,$ | // initial knowledge |
| | $\langle e_4^*, 0, 0\rangle, \ \langle e_{4,3}, 3, 1, 0\rangle,$ | // informed by designer |
| | $\langle e_3^*, 1, 0\rangle,$ | // informed by $\tilde{f}_3$ |
| | $G_{\tilde{f}_4} = [\tilde{f}_4],$ | // generated by $\tilde{f}_4$ |
| | $G_{\tilde{f}_4} = [\tilde{f}_4, \tilde{f}_4'],$ | // generated by $\tilde{f}_4$ |
| | $\langle step, 2, [\tilde{f}_1', \tilde{f}_4, \tilde{f}_4']\rangle, ... \}$ | ***// identified feature*** |

composed relationship $\tilde{\mathfrak{R}}_7 = (P, M)$ between the universal set of parts and the universal set of machines is a fuzzy one. The max–min composition between the fuzzy relationship $\tilde{\mathfrak{R}}_3 = (P, X)$ and the fuzzy relationship $\tilde{\mathfrak{R}}_5 = (X, M)$ is the fuzzy set $\tilde{\mathfrak{R}}_7 = (P, M)$. The membership function is then defined as following (12):

$$\mu_{\tilde{\mathfrak{R}}_7}(p, m) = \mu_{\tilde{\mathfrak{R}}_3 \circ \tilde{\mathfrak{R}}_5}(p, m) = \max_x \ \min\ [\mu(p, x), \mu(x, m)], \quad \forall\ p\ \in\ P, \forall\ m\ \in\ M \tag{12}$$

Fuzzy relationships between machines and parts must satisfy simultaneously the manufacturing features requirements as well as the constraints of manufacturing view and is defined as (13):

$$\mu_{\tilde{\mathfrak{R}}_8}(p, m) = \mu_{\tilde{\mathfrak{R}}_4 \circ \tilde{\mathfrak{R}}_6}(p, m) = \max_x \ \min\ [\mu(p, c), \mu(c, m)], \quad \forall\ p\ \in\ P, \forall\ m\ \in\ M \tag{13}$$

Thus, a consensus can be introduced between the fuzzy relationship (12) and (13). Then, the membership function $\mu_{\tilde{\mathfrak{R}}_9}(p, m)$ of the fuzzy set of consensual fuzzy relationship between parts and machines can be defined as (14):

$$\mu_{\tilde{\mathfrak{R}}_9}(p, m) = \min\left[\mu_{\tilde{\mathfrak{R}}_7}(p, m), \mu_{\tilde{\mathfrak{R}}_8}(p, m)\right], \forall\ p\ \in\ P, \forall\ m\ \in\ M \tag{14}$$

From agent point of view, each fuzzy machine agent $\tilde{m}_i$ possesses knowledge on the fuzzy set of operational feature agents $\tilde{A}'_X \subset \tilde{A}_X$

| | $\tilde{m}_1$ | $\tilde{m}_2$ | $\tilde{m}_3$ | $\tilde{m}_4$ | $\tilde{m}_5$ | $\tilde{m}_6$ | $\tilde{m}_7$ |
|---|---|---|---|---|---|---|---|
| $\tilde{p}_1$ | 1 | 1 | 0.5 | 1 | 0.3 | 0 | 0.3 |
| $\tilde{p}_2$ | 0.8 | 0.8 | 0.2 | 0 | 0.2 | 0 | 0.2 |
| $\tilde{p}_3$ | 0 | 0 | 0.4 | 0 | 0.8 | 0.8 | 0.8 |
| $\tilde{p}_4$ | 0 | 0 | 0.4 | 0 | 0.9 | 0.9 | 0.9 |
| $\tilde{p}_5$ | 0 | 0 | 0.4 | 0 | 0.9 | 0.9 | 0.9 |
| $\tilde{p}_6$ | 1 | 1 | 0.5 | 0.9 | 0.3 | 0.3 | 0.3 |

**Fig. 7.** Fuzzy relationship between fuzzy part agents and fuzzy machine agents.

that it can manufacture (based on Eq. (11)). In addition, each fuzzy part agent $\tilde{p}_i$ possesses knowledge on its recognized operational fuzzy feature agents $\tilde{A}'_X \subset \tilde{A}_X$. Thus, through interaction between fuzzy part agents, fuzzy operational feature agents, fuzzy machine agents and fuzzy manufacturing constraints emerge the consensual fuzzy relationship between fuzzy part agents and fuzzy machine agents (based on Eqs. (12), (13), (14)). Then, each fuzzy part agent $\tilde{P}_i$ possesses knowledge on the set of fuzzy machine agents $\tilde{A}'_M \subset \tilde{A}_M$, which are able to manufacture

**Table 5**
Algorithm of virtual fuzzy cell holon formation using part holon attractor.

***Type of messages exchanged during this distributed algorithm***

| | | | | |
|---|---|---|---|---|
| $//Exchange\_1(\tilde{P}_i^x, \tilde{P}_j^x)$: | $(P_i^x) - ask\left(\tilde{P}_i^x, \tilde{P}_j^x, X(\tilde{P}_j^x)\right)$ | $\rightarrow (\widetilde{P}_j^x)$ | then | $(\tilde{P}_i^x) \leftarrow reply\left(\tilde{P}_j^x, \tilde{P}_i^x, X(\tilde{P}_j^x)\right) - (\tilde{P}_j^x)$ |
| $//Exchange\_2(\tilde{P}_i^x, \tilde{M}_j^x)$:: | $(P_i^x) - ask\left(\tilde{P}_i^x, \tilde{M}_j^x, P(\tilde{M}_j^x)\right)$ | $\rightarrow (\tilde{M}_j^x)$ | then | $(\widetilde{P}_i^x) \leftarrow reply(\tilde{M}_j^x, \tilde{P}_i^x, P(\tilde{M}_j^x)) - (\tilde{M}_j^x)$ |
| $//Exchange\_3(\tilde{P}_i^x, \tilde{P}_j^x)$: | $(P_i^x) - ask\left(\tilde{P}_i^x, \tilde{P}_j^x, CAF(\tilde{P}_j^x)\right)$ | $\rightarrow (P_j^x)$ | then | $(\tilde{P}_i^x) \leftarrow reply\left(\tilde{P}_j^x, \tilde{P}_i^x, CAF(\tilde{P}_j^x)\right) - (\tilde{P}_j^x)$ |

| ***Algorithm*** | ***Meaning*** |
|---|---|
| **(S0)** Given an initial set of p fuzzy part holons $\{\tilde{P}_1^0, \dots, \tilde{P}_p^0\} \in \widetilde{H}_P$; | //initial conditions (Eq. 10) |
| Given an initial set of m fuzzy machine holons $\{\tilde{M}_1^0, \dots, \tilde{M}_m^0\} \in \widetilde{H}_M$; | //initial conditions (Eq. 10) |
| Given an initial set of c fuzzy cell holons $\{\tilde{C}_1^0, \dots, \tilde{C}_c^0\} \in \widetilde{H}_C$; | //initial conditions (Eq. 10) |
| $EACH\ part\ holon\ agent\ \tilde{P}_i^x\ DO$ { | |
| **(S1)** $CAF \leftarrow 1$ | //current CAF = 1.0 |
| $\tilde{X}_i^x \subseteq \tilde{A}_X$ | //set of features that compose the part holon $\tilde{P}_i^x$ |
| $\widetilde{M}_i^x \subseteq \tilde{A}_M$ | //set of machines that manufacture the part holon $\tilde{P}_i^x$ |
| $\_h \leftarrow false$ | //$\tilde{P}_i^x$ is not included in a part holon of higher level |
| **(S2)** $WHILE\ (\_h == false)$ { | //while $P_i^x$ is not included in a part holon of higher level |
| $FOR\ j\ in\ 1..Card(F^x)$ | //loop to know how much features compose $\tilde{P}_i^x$ |
| $nbX_i^x\ [j] \leftarrow Exchange\_1(\tilde{P}_i^x, \tilde{P}_j^x)$ | |
| **(S3)** $IF\ \left(\max(Card(\tilde{X}_i^x), nbX_i^x)\right)\ THEN$ | //$\tilde{P}_i^x$ is composed by the greatest number of features |
| $A_i \leftarrow \tilde{P}_i^x$ | //$\tilde{P}_i^x$ is an attractor of part holons |
| **(S4)** $generate(\tilde{P}_i^{x+1})$ | //generation of a new part holon $\tilde{P}_i^{x+1} \leftarrow \tilde{P}_i^x$ |
| $generate(\widetilde{M}_i^{x+1})$ | //generation of a new machine holon $\widetilde{M}_i^{x+1} \leftarrow \widetilde{M}_i^x$ |
| **(S5)** $calculate(CAF_i, \widetilde{M}_i^x, \widetilde{M}_i^{x+1})$ | //calculation of $CAF_i \leftarrow Card(\widetilde{M}_i^{x+1})/Card(\widetilde{M}_i^x)$ |
| $FOR\ k\ in\ 1..Card(\widetilde{M}_i^x)$ | //loop to get the list of families manufactured by the |
| $F_m \leftarrow Exchange\_2(\tilde{P}_i^x, \widetilde{M}_k^x)$ | //machine holons that manufacture $\tilde{P}_i^x$ |
| **(S6)** $FOR\ l\ in\ 1..Card(F_m)$ | //loop for each family manufactures by the machines of $\widetilde{M}_i^x$ |
| $CAF_i.[\tilde{P}_l^x] \leftarrow Exchange\_3(\tilde{P}_i^x, \tilde{P}_l^x, \widetilde{M}_i^{x+1})$ | //exchange to get the CAF of $\tilde{P}_l^x$ |
| $IF\ \left(CAF_i.[\tilde{P}_l^x] \geq CAFencours\right)\ THEN$ | //$\tilde{P}_i^x$ is an attractor for the part holon $\tilde{P}_l^x$ |
| $\tilde{P}_i^{x+1} \leftarrow \tilde{P}_l^x$ | //$\tilde{P}_l^x$ is included in the new part holon $\tilde{P}_i^{x+1}$ |
| $inform(\tilde{P}_i^x, \tilde{P}_l^x, \tilde{P}_i^{x+1})$ | //$\tilde{P}_l^x$ is informed of inclusion in the part holon $\tilde{P}_i^{x+1}$ |
| $ELSE\ \ inform(\tilde{P}_i^x, \tilde{P}_l^x, !\,\tilde{P}_i^{x+1})$ | //$\tilde{P}_l^x$ is informed of not inclusion in the part holon $\tilde{P}_i^{x+1}$ |
| **(S7)** $generate(\tilde{C}_i^{x+1}, A_i, \tilde{P}_i^{x+1}, \widetilde{M}_i^{x+1})$ | //generation of the new cell holon $\tilde{C}_i^{x+1}$ |
| $ELSE$ | //$\tilde{P}_i^x$ is not composed by the greatest number of features |
| $wait(inform(\tilde{P}_j^x, \tilde{P}_i^x, a))$ | //$\tilde{P}_i^x$ is waiting information of possible attraction |
| $IF(a ==\ \tilde{P}_i^{x+1})\ THEN$ | //$\tilde{P}_i^x$ is attracted by the part holon $\tilde{P}_y^x$ |
| $\_h \leftarrow true$ | //$\tilde{P}_i^x$ is included in a part holon of higher level |
| **(S6')** $A_i \leftarrow \tilde{P}_j^x$ | //attractor of $\tilde{P}_i^x$ is the part holon $\tilde{P}_j^x$ |
| $ELSE\ \ \_h \leftarrow false$ | //$\tilde{P}_i^x$ is always not included in a part holon of higher level |
| **(S8)** $lower(CAF)$ | //lower the current CAF (for instance CAF = CAF – 0,1) |
| **(S9)** } $END\ WHILE$ | |
| } $END\ D0$ | |

**Table 6**
*CAD* part and recognized fuzzy manufacturing features.

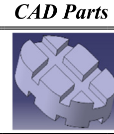
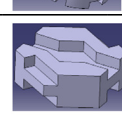
| | *CAD Parts* | *Fuzzy manufacturing features* | | *CAD Parts* | *Fuzzy manufacturing features* |
|---|---|---|---|---|---|
| $p_1$: |  | $\tilde{x}_1$ : (Through hole, 1, 1)<br>$\tilde{x}_3$ : (Pocket, 2, 1)<br>$\tilde{x}_5$ : (Blind slot,2 1) | $p_4$: |  | $\tilde{x}_2$ : (Slot, 2, 0,9)<br>$\tilde{x}_2$ : (Slot, 4, 0,9) |
| $p_2$: |  | $\tilde{x}_4$ : (Opened hole, 8, 0.8) | $p_5$: |  | $\tilde{x}_2$ : (Slot, 2, 0.9)<br>$\tilde{x}_6$ : (Blind step, 4, 1)<br>$\tilde{x}_6$ : (Blind step, 4, 1) |
| $p_3$: |  | $\tilde{x}_2$ : (Slot,2, 0.9)<br>$\tilde{x}_2$ : (Slot, 2, 1) | $p_6$: |  | $\tilde{x}_3$ : (Pocket, 1, 1)<br>$\tilde{x}_5$ : (Blind slot, 2, 1)<br>$\tilde{x}_7$ : (Step, 2, 1)<br>$\tilde{x}_8$ : (Hole, 2, 1)<br>$\tilde{x}_9$ : (Counter-bored-hole, 2, 1) |

**Table 7**
Fuzzy manufacturing features agents and their fuzzy operational features agents.

| Fuzzy manufacturing features | Fuzzy operational features |
|---|---|
| Through hole ($\tilde{x}_1$) | Through hole drilling ($\tilde{x}_{11}$); through hole grinding ($\tilde{x}_{12}$) |
| Slot ($\tilde{x}_2$) | Slot milling ($\tilde{x}_{21}$); slot grinding ($\tilde{x}_{22}$) |
| Pocket ($\tilde{x}_3$) | Pocket milling( $\tilde{x}_{31}$) |
| Opened hole ($\tilde{x}_4$) | Opened hole milling ($\tilde{x}_{41}$) |
| Blind slot ($\tilde{x}_5$) | Blind slot milling ($\tilde{x}_{51}$) |
| Blind step ($\tilde{x}_6$) | Blind step milling ($\tilde{x}_{61}$) |
| Step ($\tilde{x}_7$) | Step milling ($\tilde{x}_{71}$) |
| Hole ($\tilde{x}_8$) | Blind hole drilling ($\tilde{x}_{81}$); blind hole grinding ($\tilde{x}_{82}$) |
| Counter-bored-hole ($\tilde{x}_9$) | Counter-bored-hole drilling ($\tilde{x}_{91}$) |

**Table 8**
The different steps of formation of intelligent virtual manufacturing cells by agents.

<table>
<tr><th>Agents</th><th>Matrices</th><th>CAF</th></tr>
<tr>
<td>$\tilde{A}_P = \{\tilde{p}_1, \tilde{p}_2 \dots \tilde{p}_6\}$<br>$\tilde{A}_M = \{\tilde{m}_1, \tilde{m}_2 \dots \tilde{m}_7\}$<br>$Holon: \tilde{p}_i \rightarrow \tilde{P}_i^0$<br>$Holon: \tilde{m}_j \rightarrow \tilde{M}_j^0$<br>$\widetilde{H}_p = \{\tilde{P}_1^0, \tilde{P}_2^0 \ \dots, \tilde{P}_6^0\}$<br>$\widetilde{H}_m = \{\widetilde{M}_1^0, \widetilde{M}_2^0 \dots \widetilde{M}_7^0\}$<br>$\widetilde{H}_c = \{\tilde{C}_1^0, \tilde{C}_2^0, \tilde{C}_3^0, \tilde{C}_4^0\}$</td>
<td>$\begin{array}{ccccccc} \text{Card(Xi)} & 4 & 1 & 2 & 2 & 3 & \underline{5} \\ & \tilde{p}_1 & \tilde{p}_2 & \tilde{p}_3 & \tilde{p}_4 & \tilde{p}_5 & \tilde{p}_6 \\ \tilde{m}_1 & \mathbf{1} & 0.8 & 0 & 0 & 0 & \mathbf{1} \\ \tilde{m}_2 & \mathbf{1} & 0.8 & 0 & 0 & 0 & \mathbf{1} \\ \tilde{m}_3 & 0.5 & 0.2 & 0.4 & 0.4 & 0.4 & 0.5 \\ \tilde{m}_4 & \mathbf{1} & 0 & 0 & 0 & 0 & \mathbf{0.9} \\ \tilde{m}_5 & 0.3 & 0.2 & 0.8 & 0.9 & 0.9 & 0.3 \\ \tilde{m}_6 & 0 & 0 & 0.8 & 0.9 & 0.9 & 0.3 \\ \tilde{m}_7 & 0.3 & 0.2 & 0.8 & 0.9 & 0.9 & 0.3 \end{array}$</td>
<td>CAF = [0.9 .. 1]<br>**CAF1( $\tilde{p}_6$ ) = 2.9/3**<br>**CAF1( $\tilde{p}_1$ ) = 3/3**<br>~~CAF1( $\tilde{p}_2$ ) = 1,6/3<1~~<br>CAF2( $\tilde{p}_5$ ) = 2.7/3→1<br>CAF2( $\tilde{p}_4$ ) = 2.7/3→1<br>~~CAF2( $\tilde{p}_3$ ) = 2.4/3<1~~<br>~~CAF2( $\tilde{p}_2$ ) = 0.4/3<1~~</td>
</tr>
<tr>
<td>$\widetilde{H}_p = \{\tilde{P}_1^0 \dots \tilde{P}_6^0, \tilde{P}_1^1 \ \dots \tilde{P}_4^1\}$<br>$\widetilde{H}_m = \{\widetilde{M}_1^0 \dots \widetilde{M}_7^0, \widetilde{M}_1^1 \dots \widetilde{M}_4^1\}$<br>$\widetilde{H}_c = \{\tilde{C}_1^0 \dots \tilde{C}_4^0, \tilde{C}_1^1, \tilde{C}_2^1\}$</td>
<td>$\begin{array}{ccccc} \text{Card(Xi)} & \underline{9} & 5 & 1 & 2 \\ & \tilde{P}_1^1 & \tilde{P}_2^1 & \tilde{P}_3^1 & \tilde{P}_4^1 \\ \widetilde{M}_1^1 & \mathbf{1} & 0 & \mathbf{0.6} & 0 \\ \widetilde{M}_2^1 & 0.3 & 0.9 & 0.2 & 0.8 \\ \widetilde{M}_3^1 & \mathbf{0.5} & 0.4 & 0.2 & 0.4 \end{array}$</td>
<td>CAF = [0.6 .. 0.8]<br>**CAF1( $\tilde{P}_1^1$ ) = 1.5/2**<br>**CAF1 ( $\tilde{P}_3^1$ ) = 0.6/1**<br>CAF2( $\tilde{P}_2^1$ ) = 0.9/1<br>CAF2( $\tilde{P}_4^1$ ) = 0.8/1</td>
</tr>
<tr>
<td>$\widetilde{H}_p = \{\tilde{P}_1^0 \dots \tilde{P}_6^0, \tilde{P}_1^1 \ \dots \tilde{P}_4^1, \tilde{P}_1^2, \tilde{P}_2^2\}$<br>$\widetilde{H}_m = \{\widetilde{M}_1^0 \dots \widetilde{M}_7^0, \widetilde{M}_1^1 \dots \widetilde{M}_4^1, \widetilde{M}_1^2, \widetilde{M}_2^2\}$<br>$\widetilde{H}_c = \{\tilde{C}_1^0 \dots \tilde{C}_4^0, \tilde{C}_1^1, \tilde{C}_2^1, \tilde{C}_1^2, \tilde{C}_2^2\}$</td>
<td>$\begin{array}{ccc} \text{Card(Xi)} & \underline{10} & 7 \\ & \tilde{P}_1^2 & \tilde{P}_2^2 \\ \widetilde{M}_1^2 & \mathbf{0.6} & 0.3 \\ \widetilde{M}_2^2 & \mathbf{0.3} & 0.8 \end{array}$</td>
<td>CAF = [0.4 .. 0.5]<br>**CAF1( $\tilde{P}_1^2$ ) = 0.9/2**<br>**CAF1( $\tilde{P}_2^2$ ) = 1.1/2**</td>
</tr>
<tr>
<td>$\widetilde{H}_p = \{\tilde{P}_1^0 \dots \tilde{P}_6^0, \tilde{P}_1^1 \ \dots \tilde{P}_4^1, \tilde{P}_1^2, \tilde{P}_2^2, \tilde{P}_1^3\}$<br>$\widetilde{H}_m = \{\widetilde{M}_1^0 \dots \widetilde{M}_7^0, \widetilde{M}_1^1 \dots \widetilde{M}_4^1, \widetilde{M}_1^2, \widetilde{M}_2^2, \widetilde{M}_1^3\}$<br>$\widetilde{H}_c = \{\tilde{C}_1^0 \dots \tilde{C}_4^0, \tilde{C}_1^1, \tilde{C}_2^1, \tilde{C}_1^2, \tilde{C}_2^2, \tilde{C}_1^3\}$</td>
<td>$\begin{array}{cc} \text{Card(Xi)} & \underline{17} \\ & \tilde{P}_1^3 \\ \widetilde{M}_1^3 & \mathbf{0.5} \end{array}$</td>
<td>CAF = 0.4<br>**CAF1(, $\tilde{P}_1^3$) = 0.5/1**</td>
</tr>
</table>

its fuzzy feature agents. Also, each fuzzy machine agent $\tilde{m}_i$ possesses knowledge on the fuzzy set of part agents $\tilde{A}'_P \subset \tilde{A}_P$ that it is able to manufacture. The emerged fuzzy relationship between fuzzy part agents and fuzzy machine agents will is used for cell holon formation.

### 4.3. Cell Holon formation

The architecture of holons shows "horizontal" and "vertical" self-similarity. Horizontal self-similarity relates to self-similarity across different specializations on one level of aggregation. Vertical self-similarity refers to self-similarity across different levels of aggregation: higher-level holons work similarly to lower-level holons. Thus, the verticality is characterized by various levels of self-similarity. The first hypothesis of our work postulates that the intelligent virtual manufacturing cell should have the structure of the holon. That means creating "*intelligent virtual manufacturing cells within an intelligent virtual manufacturing cell.*"

The second hypothesis of our work postulates that intelligent virtual manufacturing holons tend to evolve toward some particular physical elements: parts or machines. These are called *attractors*. An attractor is thus a structurally stable element, part or machine, in *CBDM*.

An algorithm, which draws its inspiration from the holon structure generation based on these hypotheses, is adopted for creating "*fuzzy cells within a fuzzy cell*" (Ostrosi et al., 2003). A fuzzy cell holon is defined through two basic coupled elements: *fuzzy part holon* and *fuzzy machine holon*. Thus, fuzzy cell holons formation is achieved via the following steps:

- Step 0: ***Initial conditions***. Every fuzzy part and every fuzzy machine is a holon. Thus a new relationship between the *fuzzy part holon* and *fuzzy machine holon* is defined. The level of verticality of fuzzy cell holon is equal to zero.

- Step 1: ***Coefficient of Attraction Force***. The contribution of a *fuzzy part holon j* to a *fuzzy cell holon* must be greater than or equal to an acceptable value of the *attraction force*, noted as *Coefficient of Attraction Force (CAF)*. Higher the value of CAF is, higher is the force of attraction between parts in a cell. CAF varies from 1 to 0.
  - Step 2: ***Vertical "self-similarity"***. A new level of verticality of fuzzy cell holons is defined. It defines the current level. The new relationship between the *fuzzy part holon* and *fuzzy machine holon*will be used for fuzzy cell holons formation for the considered level.
    - Step 3: ***Fuzzy Attractor Identification***. Identifying the *fuzzy part holon j* as an attractor creates a *new fuzzy cell holon*. An attractor is a structurally stable part toward which a cell tends dynamically to be formed. For instance, a particular part with the maximum number of features can be considered as attractor.
    - Step 4: ***Attraction of fuzzy machine holons***. A *fuzzy part holon j* exerts a force of attraction on *fuzzy machine holons*. All the *fuzzy machines holons i* required by the *fuzzy part holon* attractor *j* are searched for coupling.
    - Step 5: ***Attraction of fuzzy part holons***. All the *fuzzy parts holons j* required by the *fuzzy machine holons i* in the *fuzzy cell holon* are considered for coupling. The contribution of a *fuzzy part holon j* to the *fuzzy cell holon* must be greater than or equal to value of the *Coefficient of Attraction Force (CAF)*. If fuzzy part holon *j* verifies this condition of attraction, then fuzzy part holon *j* is assigned to the fuzzy cell holon. Otherwise, it is rejected.
    - Step 6: ***Equivalent fuzzy cell holons and Transfer***. A fuzzy machine holon can contribute in an equal way to several fuzzy cell holons. These fuzzy cell holons are called equivalent fuzzy cell holons. The contribution of a fuzzy machine holon *i* assigned to a fuzzy cell holon must be greater than its contribution to all the other concurrent fuzzy cell holons. If fuzzy machine holon *i* is transferred from an old fuzzy cell holon to the new fuzzy cell holon, then the old fuzzy cell holon is discarded. All the fuzzy machine holons *i* and all the fuzzy part holons *j* in the old cell become eligible to participate in the creation of a new fuzzy cell holon.
    - Step 7: ***New fuzzy cell holon***. If a fuzzy part holon *j* is found in step 3, then steps 4–6 are repeated. Otherwise, the formation of the fuzzy cell holons for this level is finished.
  - Step 8: ***Fuzzy cells within a fuzzy cell***. If fuzzy cell holons of the current level are different from fuzzy cell holons of previous level, then the fuzzy part holons are aggregated into a *whole fuzzy part holon*, and the fuzzy machine holons are aggregated into a *whole fuzzy machine holon*. A new relationship is defined between the *fuzzy part holon* and *fuzzy machine holon.* The steps 2–7 are repeated.
- Step 9: If a new lower value of CAF is defined in step 1, then steps 2–6 are repeated. Otherwise, the formation of the fuzzy cell holons is finished.

Step 0 assume that every fuzzy part and every fuzzy machine is a holon. Steps 1 and 9 insure the variation of Coefficient of Attraction Force. The force of attraction of *fuzzy part holons* and *fuzzy* machine holons can vary from strong to poor. Steps 2 and 8 insure the "vertical" self-similarity of fuzzy cell holons for a given Coefficient of Attraction Force. Steps 3 to 7 insure "horizontal" self-similarity of fuzzy cell holons for a given Coefficient of Attraction Force.

The distributed algorithm of virtual cells formation executed by each fuzzy part holon agent $P_i^x$ (from fuzzy part holons $P_j^0$ generated in Step 0) is presented in Table 5. The steps of original algorithm (Step 0–9) are identified by the indices **S0** to **S9**.

**Table 9**
Holon agents formed during the formation of intelligent virtual manufacturing cells.

| Set of holon agents | Formed holon agents | |
|---|---|---|
| Part holon agents | $\tilde{P}_1^1=(\tilde{p}_6,\{\tilde{p}_1,\tilde{p}_6\},\emptyset)$<br>$\tilde{P}_3^1=(\tilde{p}_2,\{\tilde{p}_2\},\emptyset)$<br>$\tilde{P}_1^2=(\tilde{P}_1^1,\{\tilde{P}_1^1,\tilde{P}_3^1\},\emptyset)$<br>$\tilde{P}_1^3=(\tilde{P}_1^2,\{\tilde{P}_1^2,\tilde{P}_2^2\},\emptyset)$ | $\tilde{P}_2^1=(\tilde{p}_5,\{\tilde{p}_4,\tilde{p}_5\},\emptyset)$<br>$\tilde{P}_4^1=(\tilde{p}_3,\{\tilde{p}_3\},\emptyset)$<br>$\tilde{P}_2^2=(\tilde{P}_2^1,\{\tilde{P}_2^1,\tilde{P}_4^1\},\emptyset)$ |
| Machine holon agents | $\tilde{M}_1^1=(\tilde{m}_1,\{\tilde{m}_1,\tilde{m}_2,\tilde{m}_4\},\emptyset)$<br>$\tilde{M}_3^1=(\tilde{m}_3,\{\tilde{m}_3\},\emptyset)$<br>$\tilde{M}_1^2=(\tilde{M}_1^1,\{\tilde{M}_1^1,\tilde{M}_3^1\},\emptyset)$<br>$\tilde{M}_1^3=(\tilde{M}_1^2,\{\tilde{M}_1^2,\ \tilde{M}_2^2\},\emptyset)$ | $\tilde{M}_2^1=(\tilde{m}_5,\{\tilde{m}_5,\tilde{m}_6,\tilde{m}_7\},\emptyset)$<br>$\tilde{M}_2^2=(\tilde{M}_2^1,\{\tilde{M}_2^1\},\emptyset)$ |
| Cell holon agents | $\tilde{C}_1^1=(\tilde{P}_1^1,\tilde{M}_1^1,\tilde{R}_1^1)$<br>$\tilde{C}_3^1=(\tilde{P}_3^1,\emptyset,\emptyset)$<br>$\tilde{C}_1^2=(\tilde{P}_1^2,\tilde{M}_1^2,\tilde{R}_1^2)$<br>$\tilde{C}_1^3=(\tilde{P}_1^3,\tilde{M}_1^3,\tilde{R}_1^3)$ | $\tilde{C}_2^1=(\tilde{P}_2^1,\tilde{M}_2^1,\tilde{R}_2^1)$<br>$\tilde{C}_4^1=(\emptyset,\tilde{M}_3^1,\emptyset)$<br>$\tilde{C}_2^2=(\tilde{P}_2^2,\tilde{M}_2^2,\tilde{R}_2^2)$ |

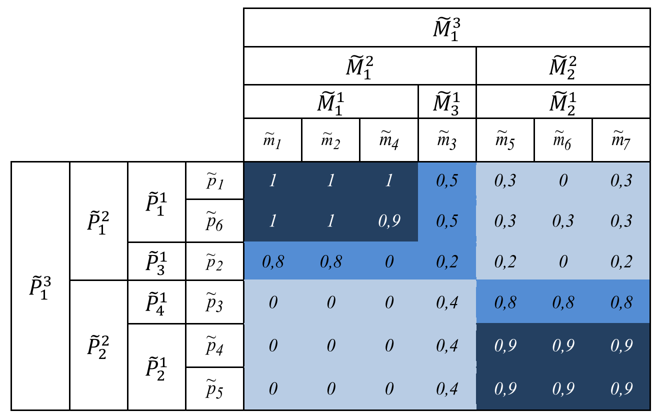



**Fig. 8.** "*Fuzzy cells within fuzzy cell*": matrix representation of fuzzy cell holons.

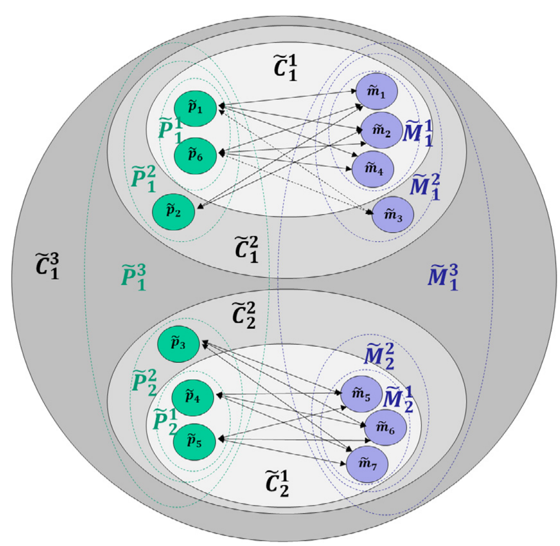



**Fig. 9.** "*Fuzzy cells within fuzzy cell*": graph representation of fuzzy cell holons.

**Table 10**
Comparison between the proposed approach and main groups of approaches.

| Cell formation approaches | Attributes for cell formation | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Type of data | | | Part family and cell formation procedure | | Implementation | | Intelligence based on | | Organization | | | Architecture | |
| | Part attributes | Manufacturing | Part and manufacturing | Sequential | Simultaneous | Physical | Virtual | Knowledge | Network | Autonomy | Cooperation | Distribution | One-scale: Cell | Multiscale: Cell-in-Cell |
| Production flow analysis | | √ | | | √ | √ | | | | | | | √ | |
| Cluster analysis | √ | √ | √ | √ | | √ | | | | | | | √ | |
| Cross clustering | | √ | | | √ | √ | | | | | | | √ | |
| Graph theory | √ | √ | √ | √ | √ | √ | | | | | | | √ | |
| Mathematical programming | | √ | | √ | √ | √ | √ | | | | | | √ | |
| Expert systems | | √ | | | √ | √ | | √ | | | | | √ | |
| Neural network | | √ | | √ | √ | √ | | | √ | √ | | √ | √ | |
| Genetic algorithms | | √ | | | √ | √ | | | √ | √ | | √ | √ | |
| Metaheuristics | | √ | | | √ | √ | | | | | | | √ | |
| **Proposed approach** | √ | √ | √ | | √ | | √ | √ | √ | √ | √ | √ | | √ |

## 5. Application

A *SME* design and manufacture is a variety of new innovative products. The *SME* is strongly concerned with protection of its proprietary information. It has limited funds on investing in expensive manufacturing equipment. Therefore, it cooperates with other *SMEs* on cloud so that to be competitive in manufacturing of its innovative products. Table 6 shows some designed parts for a new product. Intelligent manufacturing features agents are recognized in *CAD* parts (*cf.* 4.1). For instance, the part $p_1$ has three manufacturing features *Through hole*, *Pocket*, and *Blind slot*. For the feature, *Through hole*, its number of instances is equal to 1 and the membership of this feature to the part $p_1$ is equal to 1.

Table 7 shows the *fuzzy manufacturing feature agents* and their corresponding *fuzzy operational feature agents* (*cf.* 4.2). For instance, *Slot milling,*noted $\tilde{x}_{21}$, is a *fuzzy operational feature agent* and results from milling operations.

Fuzzy relationships between fuzzy operational feature agents and fuzzy part agents as well as fuzzy operational feature agents and fuzzy machine agents are given in Fig. 6. Fuzzy relationship between fuzzy part agents and fuzzy machine agents has emerged from the interactions between fuzzy operational feature agents, fuzzy part agents and fuzzy machine agents Fig. 7.

This fuzzy relationship $\tilde{\Re}_8 = (P, M)$ between fuzzy part agents and fuzzy machine agents is consensual because it does not change from the composition with the other fuzzy relationship $\tilde{\Re}_9 = (P, M)$. Then, from the attractor agent recognition, the fuzzy part agents and fuzzy machine agents interact to form the fuzzy cell holon agents (*cf.* 4.3). Different steps for the formation of intelligent virtual manufacturing cells by agents are shown in Table 8.

There are three levels of fuzzy holon agent cells formed during the formation of intelligent virtual manufacturing cells. For instance, in the second level, two fuzzy cell holon agents are recognized: $\tilde{C}_1^2 = \left(\tilde{P}_1^2, \tilde{M}_1^2, \tilde{R}_1^2\right)$ and $\tilde{C}_2^2 = \left(\tilde{P}_2^2, \tilde{M}_2^2, \tilde{R}_2^2\right)$. The first fuzzy cell holon agent $\tilde{C}_1^2$ is composed by fuzzy part holon agent $\tilde{P}_1^2$ and the fuzzy machine holon agent $\tilde{M}_1^2$, related by the fuzzy sub-relationship $\tilde{R}_1^2$ (Table 9).

The structured matrix in diagonal blocks (Fig. 8) and the network of fuzzy holonic agent (Fig. 9) show the holonic structure (holarchy) of cellular system. Thus, intelligent virtual manufacturing cells are emerged sub-networks of fuzzy holonic agents. Thus, these emerged fuzzy cell holons are open, distributed, and dynamic objects. These cell holons overcome the distinction continuous–discontinuous of traditional cell design formation problem.

The creation or destruction of intelligent virtual manufacturing cells can be described by the appearance or disappearance of the initial attractors. However, the knowledge of these attractors can only partially allow knowing what will emerge during virtual cell formation. From the holonic structure of intelligent virtual manufacturing cells, the group of manufacturing feature agents to be manufactured in each cell holon agent can be inferred. Consequently, each new part agent involving these feature agents can easily find the corresponding cell holon agent.

## 6. Discussion and conclusions

The concept of virtual cells is innovative in intelligent *CBDM*. Virtual cell formation is not an orderly and well-behaved design problem. Sudden transformations and unpredictable changes characterize virtual cell formation problem. Therefore, the formation of intelligent virtual manufacturing cells is an important subject of *CBDM*.

The comparison between the proposed approach and the existing approaches is shown in Table 10. In the proposed approach, the concepts of the holon and the attractor are proposed to model the intelligent virtual manufacturing cells in *CBDM*. The concepts of the holon and the attractor allow multi-scale cell formation. It means formation of cell holons with holonic structure: *"intelligent virtual manufacturing cells within an intelligent virtual manufacturing cell"*. Furthermore, the proposed cell holon formation model is driven by the integrative tendencies of cell formation: *the part design knowledge and part–manufacturing knowledge*. The model presents an evolution comparing to the existing approaches. The proposed approach forms cell in the face–feature–constraint–part–machine network. Parts, machines and cells communicate through manufacturing features. The virtual cells with holon structure are formed dynamically and simultaneously based on the distributed intelligence of autonomous fuzzy agents in the network. Each element of the network has its own knowledge.

Holonic and intelligent agents are modelled to create the dynamic service-oriented networked digital design and manufacturing, from CAD parts to virtual intelligent cells formation. The powerful role of the CAD features, modelled as fuzzy agents, is exploited to organize and integrate the part design and part–manufacturing engineering knowledge in a way that a set of CAD parts, modelled by set of features, can be manufactured in intelligent virtual manufacturing cells. The dynamic network between fuzzy part agents and fuzzy machine agents emerge from the fuzzy feature agents' interaction. The proposed model shows that intelligent virtual manufacturing cells, with holonic structure, emerge from the interaction of fuzzy machine agents and the fuzzy part agents with fuzzy agent attractors. Intelligent virtual manufacturing cells are emerged fuzzy holonic sub-networks of fuzzy machine and fuzzy parts agents.

Thus, these emerged fuzzy cell holons are open, distributed, and dynamic objects. These fuzzy cell holons also overcome the distinction continuous–discontinuous of traditional cell design formation problem.

The model shows that uncertainty of the content of the design and manufacturing knowledge that agent features carry as well as the dynamic service-oriented networked digital design and manufacturing: face–feature–constraint–part–machine–cell, explains the dynamic formation of the intelligent virtual manufacturing cells. Though the creation or destruction of intelligent virtual manufacturing cells can be described by the appearance or disappearance of the initial attractors, the knowledge of these attractors can only partially allow knowing what will emerge during virtual cell formation.

The proposed approach provides a new framework to integrate CAD part modelling and cellular manufacturing in *CBDM*. Intelligent virtual manufacturing cells have the long-term ability to reproduce their behaviour. However, the intelligent virtual cell formation problem is a discontinuous phenomenon. Describing the evolution of cells structure, in those situations where gradually changing forces lead to abrupt changes in behaviour, would be a challenging endeavour.

## References


Aalaei, A., Davoudpour, H., 2016. Revised multi-choice goal programming for incorporated dynamic virtual cellular manufacturing into supply chain management: A case study. Eng. Appl. Artif. Intell. 47, 3–15.

van Aart, C., 2005. Organizational Principles for Multiagent Architectures. Birkhauser Verlag, Basel.

Abdoos, M., Mozayani, N., Bazzan, A.L.C., 2013. Holonic multi-agent system for traffic signals control. Eng. Appl. Artif. Intell. 26, 1575–1587.

Al-Qattan, I., 1990. Designing flexible manufacturing cells using a branch and bound method. Int. J. Prod. Res. 28 (2), 325–336.

Ameli, M.S.J., Arkat, J., 2008. Cell formation with alternative process routings and machine reliability consideration. Int. J. Adv. Manuf. Technol. 35 (7–8), 761–768.

Arai, T., Aiyama, Y., Sugi, M., Ota, J., 2001. Holonic assembly system with Plug and Produce. Comput. Ind. 46, 289–299.

Atanassov, K., 1994. Operators over interval-valued intuitionistic fuzzy sets. Fuzzy Sets and Systems 64, 159–174.

Balasubramanian, S., Brennan, R.W., Norrie, D.H., 2001. An architecture for metamorphic control of holonic manufacturing systems. Comput. Ind. 46, 13–31.

Ballakur, A., Steudel, H.J., 1987. A within-cell utilisation based heuristic for designing cellular manufacturing systems. Int. J. Prod. Res. 25 (5), 639–665.

Baoding, L., 2007. Uncertainty Theory. Springer, Berlin.

Ben-Arieh, D., Lee, S.E., Chang, P.T., 1996. Theory and methodology: Fuzzy part coding for group technology. Eur. J. Oper Res. 92, 637–648.

Ben-Arieh, D., Triantaphyllou, E., 1992. Quantifying data for group technology with weighted fuzzy features. Int. J. Prod. Res. 30 (6), 1285–1299.

Bergmann, S., Stelzer, S., Strassburger, S., 2014. On the use of artificial neural networks in simulation-based manufacturing control. J. Simul. 8 (1), 76–90.

Biswas, P.K., 2008. Towards an agent-oriented approach to conceptualization. Appl. Soft Comput. 8 (1), 127–139.

Blanc, P., Demongodin, I., Castagna, P., 2008. A holonic approach for manufacturing execution system design: An industrial application. Eng. Appl. Artif. Intell. 21, 315–330.

Burbidge, J., 1971. Production flow analysis. Prod. Eng. 50, 139–152.

Burbidge, J., 1975. The Introduction of Group Technology. Heinemann, London.

Buyya, R., Yeo, C.S., Venugopal, S., Broberg, J., Brandic, I., 2009. Cloud computing and emerging it platforms: Vision, hype, and reality for delivering computing as the 5th utility. Future Gener. Comput. Syst. 25, 599–616.

Cernuzzi, L., Cossentino, M., Zambonelli, F., 2005. Process models for agent-based development. Engi. Appl. Artif. Intell. 18 (2), 205–222.

Chan, F.T.S., Lau, K.W., Chan, P.L.Y., Choy, K.L., 2006. Two-stage approach for machine-part grouping and cell layout problems. Robot. Comput.-Integr. Manuf. 22 (3), 217–238.

Chandrasekharan, M.P., Rajagopalan, R., 1986a. An ideal seed non-hierarchical clustering algorithm for cellular manufacturing. Int. J. Prod. Res. 24 (2), 451–464.

Chandrasekharan, M.P., Rajagopalan, R., 1986b. MODROC: an extension of rank order clustering for group technology. Int. J. Prod. Res. 24 (5), 1221–1233.

Chen, X.W., Lin, X., 2014. Big data deep learning: challenges and perspectives. IEEE Access 2, 514–525.

Chen, T., Lin, C.W., 2017. Estimating the simulation workload for factory simulation as a cloud service. J. Intell. Manuf. 28 (5), 1139–1157.

Chen, T., Wang, Y.C., 2009. A fuzzy set approach for evaluating and enhancing the mid-term competitiveness of a semiconductor factory. Fuzzy Sets and Systems 160, 569–585.

Chira, O., Chira, C., Roche, T., Tormey, D., Brennan, A., 2006. An agent-based approach to knowledge management in distributed design. J. Intell. Manuf. 17 (6), 737–750.

Choobineh, F., 1988. A framework for the design of cellular manufacturing systems. Int. J. Prod. Res. 26 (7), 1161–1172.

Choulier, D., Fougères, A.J., Ostrosi, E., 2015. Developing multiagent systems for design activity analysis. Comput.-Aided Des. 59, 201–213.

Chu, C.H., Hayya, J.C., 1987. A fuzzy clustering approach to manufacturing cell formation. Int. J. Prod. Res. 25 (4), 561–569.

Cutkosky, M., Englemore, R., 1993. PACT: an experiment in integrated concurrent engineering systems. IEEE Comput. 26 (1), 28–37.

Esmaeili, A., Mozayani, N., Jahed Motlagh, M.R., Matson, E.T., 2016. The impact of diversity on performance of holonic multi-agent systems. Eng. Appl. Artif. Intell. 55, 186–201.

Fougères, A.-J., 2011. Modelling and simulation of complex systems: an approach based on multi-level agents. Int. J. Comput. Sci. Issues 8 (6), 8–17.

Fougères, A.-J., 2013. A modelling approach based on fuzzy agents. Int. J. Comput. Sci. Issues 9 (6), 19–28.

Fougères, A.-J., Ostrosi, E., 2013. Fuzzy agent-based approach for consensual design synthesis in product configuration. Integr. Comput.-Aided Eng. 20, 259–274.

Gau, W.L., Buehrer, D.J., 1993. Vague sets. IEEE Trans. Syst. Man Cybern. 23, 610–614.

Ghasem-Aghaee, N., Ören, T.I., 2003. Towards Fuzzy Agents with Dynamic Personality for Human Behavior Simulation. In Proceedings of SCSC 2003, Montreal, Canada, pp. 3–10.

Gibson, P., Ismail, H., Sabin, M., 1999. Optimisation approaches in feature recognition. Int. J. Mach. Tools Manuf. 39 (5), 805–821.

Giret, A., Botti, V., 2009. Engineering Holonic Manufacturing Systems. Comput. Ind. 60 (6), 428–440.

Gunasingh, K.R., Lashkari, R.S., 1989. The cell formation problem in cellular manufacturing systems - a sequential modelling approach. Comput. Ind. Eng. 16 (4), 469–476.

Gupta, T., Seifoddini, H., 1990. , Production data based similarity coefficient for machine-component grouping decisions in the design of cellular manufacturing system. Int. J. Prod. Res. 28 (7), 1247–1269.

Han, J., Pratt, M., Regli, W.C., 2000. Manufacturing feature recognition from solid models: a status report. IEEE Trans. Robot Automat. 16 (6), 782–796.

Henderson, M.R., 1994. Manufacturing Feature Identification. Artificial Neural Networks for Intelligent Manufacturing. London: Chapman & Hall, pp. 229–264.

Honma, N., Abe, K., Sato, M., Takeda, H., 1998. Adaptive evolution of holon networks by an autonomous decentralized method. Appl. Math. Comput. 91, 43–61.

Hsieh, F.S., 2010. Design of reconfiguration mechanism for holonic manufacturing systems based on formal models. Engi. Appl. Artif. Intell. 23 (7), 1187–1199.

Issa, H., Ostrosi, E., Lenczner, M., Habib, R., 2017. Fuzzy holons for intelligent multi-scale design in cloud-based design for configurations. J. Intell. Manuf. 28 (5), 1219–1247.

Jordan, M.I., Mitchell, T.M., 2015. Machine learning: Trends, perspectives, and prospects. Science 349 (6245), 255–260.

Keeling, K.B., Brown, E.C., James, T.L., 2007. Grouping efficiency measures and their impact on factory measures for the machine-part cell formation problem: A simulation study. Eng. Appl. Artif. Intell. 20 (1), 63–78.

Kim, Y.S., 1992. Recognition of form features using convex decomposition. Computer-Aided Design. 24 (9), 461–476.

Kim, C.O., Baek, J.G., Jun, J., 2005. A machine cell formation algorithm for simultaneously minimising machine workload imbalances and inter-cell part movements. Int. J. Adv. Manuf. Technol. 26 (3), 268–275.

King, J.R., 1980. Machine-component grouping in production flow analysis: an approach using a rank order clustering algorithm. Int. J. Prod. Res. 18 (2), 213–232.

Koestler, A., 1967. The Ghost in the Machine. Arkana Books, London.

Kusiak, A., 1987a. EXGT-S: A knowledge based system for group technology. Int. J. Prod. Res. 26 (5), 887–904.

Kusiak, A., 1987b. The generalised group technology concept. Int. J. Prod. Res. 25 (4), 561–569.

Kusiak, A., Chow, W.S., 1987. Efficient solving of the group technology problem. J. Manuf. Syst. 6 (2), 117–124.

Lee, H., Malavé, C.O., Ramachandran, S., 1992. A self-organizing neural network approach for the design of cellular manufacturing systems. J. Intell. Manuf. 3, 352–32.

Lei, D., Wu, Z., 2006. Tabu search for multiple-criteria manufacturing cell design. Int. J. Adv. Manuf. Technol. 28, 950–956.

Leitão, P., 2009. Agent-based distributed manufacturing control: A state-of-the-art survey. Eng. Appl. Artif. Intell. 22, 979–991.

Leitao, P., Restivo, F., 2008. A holonic approach to dynamic manufacturing scheduling. Robot. Comput.-Integr. Manuf. 24, 625–634.

Lemoine, Y., Mutel, B., 1983. Automatic recognition of production cells and part families. In: Ellis, T.M.R., Semenkov, O.I. (Eds.), Advances in CAD/CAM. North-Holland Publishing Company, Amsterdam, pp. 239–249.

Li, B.H., Zhang, L., Wang, S.L., Tao, F., Cao, J.W., Jiang, X.D., Song, X., Chai, X.D., 2010. Cloud manufacturing: a new service-oriented networked manufacturing model. Comput. Integr. Manuf. Syst. 16 (1), 1–16.

Liao, T.W., 2001. Classification and coding approaches to part family formation under a fuzzy environment. Fuzzy Sets and Systems 122, 425–441.

Little, G., Clark, D.E., Corney, J.R., Tuttle, J.R., 1998. Delta-volume decomposition for multi-sided components. Comput.-Aided Des. 30 (9), 695–705.

Lockett, H.L., Guenov, M.D., 2005. Graph-based feature recognition for injection moulding based on a mid-surface approach. Comput.-Aided Des. 37 (2), 251–262.

Luo, Y., Zhang, L., Tao, F., Ren, L., Liu, Y., Zhang, Z., 2013. A modeling and description method of multidimensional information for manufacturing capability in cloud manufacturing system. Int. J. Adv. Manuf. Technol. 69, 961–975.

Mahdavi, I., Shirazi, B., Paydar, M.M., 2008. A flow matrix-based heuristic algorithm for cell formation and layout design in cellular manufacturing system. Int. J. Adv. Manuf. Technol. 39 (9–10), 943–953.

Mak, K.L., Wong, Y.S., Wang, X.X., 2000. An adaptive genetic algorithm for manufacturing cell formation. Int. J. Adv. Manuf. Technol. 16 (7), 491–497.

Malavé, C.O., Ramachandaran, S., 1991. Neural network-based design of cellular manufacturing systems. J. Intell. Manuf. 2, 305–314.

Marchetta, M.G., Forradellas, R.Q., 2010. An artificial intelligence planning approach to manufacturing feature recognition. Computer-Aided Design. 42 (3), 248–256.

Marefat, M., Kashyap, R., 1990. Geometric reasoning for recognition of three dimensional object features. In: Trans. of 8th Army Conf. on Applied Mathematics and Computing, pp. 705–731.

Marik, V., McFarlane, D., 2005. Industrial adoption of agent-based technologies. IEEE Intell. Syst. 20 (1), 27–35.

McAuley, J., 1972. Machine grouping for efficient production. Prod. Eng. 51 (2), 53–57.

McCormick, W.T., Schweitzer, P., White, T.W., 1972. Problem decomposition and data reorganization by a clustering technique. Oper. Res. 20, 993–1009.

McLean, C.R., Bloom, H.M., Hopp, T.H., 1982. The virtual manufacturing cell. In: Proc. of the 4th IFAC/IFIP Conf. on Information Control Problems in Manufacturing Technology, Gaithersburg, MD, pp. 105–111.

Mella, P., 2009. The Holonic Revolution: Holons, Holarchies and Holonic Networks: The Ghost in the Production Machine. Pavia University Press, Pavia, Italy.

Metaxiotis, K.S., Askounis, D., Psarras, J., 2002. Expert systems in production planning and scheduling: A state-of-the-art survey. J. Intell. Manuf. 13 (4), 253–260.

Ming Chao, K., Norman, P., Anane, R., James, A., 2002. An agent-based approach to engineering design. Comput. Ind. 48 (1), 17–27.

Mohammad, A.F., Dargham, J., Mcheick, H., Noor, A.T., 2013. Software evolution as SaaS: Evolution of intelligent design in cloud. Procedia Comput. Sci. 19, 486–493.

Monostori, L., Vancza, J., Kumara, S.R.T., 2006. Agent-based systems for manufacturing. Ann. CIRP. 55 (2), 697–720.

Moon, S.K., Simpson, T.W., Kumara, S.R.T., 2009. An agent-based recommender system for developing customized families of products. J. Intell. Manuf. 20 (6), 649–659.

Mutel, B., Ostrosi, E., 2002. Feature-based manufacturing cell formation using a fuzzy-set approach. Int. J. Comp. Integr. Manuf. 15 (2), 152–167.

Nahm, Y.E., Ishikawa, H., 2005. A hybrid multiagent system architecture for enterprise integration using computer networks. Robot. Comput.-Integr. Manuf. 21 (3), 217–234.

Niua, Z., Martin, R.R., Langbein, F.B., Sabin, M.A., 2015. Rapidly finding CAD features using database optimization. Comput.-Aided Des. 69, 35–50.

Ostrosi, E., Ferney, M., 2005. Feature modeling using a grammar representation approach. Int. J. Artif. Intell. Eng. Des. Anal. Manuf. 19 (4), 245–259.

Ostrosi, E., Ferney, M., Garro, O., 2003. A fractal approach for concurrent engineering. Int. J. Concurr. Eng.: Res. Appl. 11 (4), 249–265.

Ostrosi, E., Fougères, A.-J., Ferney, M., 2012. Fuzzy agents for product configuration in collaborative and distributed design process. Appl. Soft Comput. 8 (12), 2091–2105.

Ostrosi, E., Tautrim, J., Fukuda, S., 2010. Consensual cell searching in cellular manufacturing design. Int. J. Adv. Manuf. Technol. 51, 769–788.

Ounnar, F., Pujo, P., Mekaouche, L., Giambiasi, N., 2009. Integration of a flat holonic form in an HLA environment. J. Intell. Manuf. 20 (1), 91–111.

Parunak, H., Sauter, J., Fleisher, M., 1999. The RAPPID Project: symbiosis between industrial requirements and MAS research. Auton. Agents Multiagent Syst. 2, 111–140.

Purcheck, G.F.K., 1985. Machine-component group formation: an heuristic method for flexible production cells and flexible manufacturing systems. Int. J. Prod. Res. 23, 911–943.

Rajagopalan, R., Batra, J.L., 1975. Design of cellular production systems: a graph-theoretic approach. Int. J. Prod. Res. 13 (6), 567–579.

Saidi-Mehrabad, M., Safaei, N., 2007. A new model of dynamic cell formation by a neural approach. Int. J. Adv. Manuf. Technol. 33 (9–10), 1001–1009.

Sallai, J., Varga, G., Toth, S., Iacovella, C., Klein, C., McCabe, C., Ledeczi, A., Cummings, P.T., 2014. Web- and cloud-based software infrastructure for materials design. Procedia Comput. Sci. 29, 2034–2044.

Seifoddini, H., Wolfe, P.M., 1986. Application of the similarity coefficient method in group technology. IIE Trans. 18 (3), 271–277.

Su, C.-T., Hsu, C.-M., 1998. Multi-objective machine-part cell formation through parallel simulated annealing. Int. J. Prod. Res. 36, 2185–2207.

Sundaram, R.M., Lian, W.S., 1990. An approach for cellular manufacturing systems. Manuf. Rev. 3 (2), 91–97.

Sunil, V., Pande, S., 2009. Automatic recognition of machining features using artificial neural networks. Int J. Adv. Manuf. Technol. 41 (9–10), 932–947.

Tam, K.Y., 1990. An operation sequence based similarity coefficient for part families formations. J. Manuf. Syst. 9 (1), 55–68.

Trentesaux, D., Pesin, P., Tahon, C., 2000. Distributed artificial intelligence for FMS scheduling, control and design support. J. Intell. Manuf. 11 (6), 573–589.

Tsai, C.C., Lee, C.Y., 2006. Optimization of manufacturing cell formation with a multi-functional mathematical programming model. Int. J. Adv. Manuf. Technol. 30 (3–4), 309–318.

Valckenaers, P., Van Brussel, H., 2005. Fundamental insights into holonic systems design. In: Lecture Notes in Computer Science: Holonic and Multi-Agent Systems for Manufacturing, Vol. 3593. pp. 11–22.

Valckenaers, P., Van Brussel, H., Hadeli, , Bochmann, O., SaintGermain, B., Zamfirescu, C., 2003. On the design of emergent systems: an investigation of integration and interoperability issues. Eng. Appl. Artif. Intell. 16 (4), 377–393.

Valckenaers, P., Van Brussel, H., Wyns, J., Bongaerts, L., Peeters, P., 1998. Designing holonic manufacturing systems. Robot. Comput.-Integr. Manuf. 14, 455–464.

Van Brussel, H., Wyns, J., Valckenaers, P., Bongaerts, L., Peeters, P., 1998. Reference architecture for holonic manufacturing systems: PROSA. Comput. Ind. 37, 255–274.

Vannelli, A., Kumar, K.R., 1986. A method for finding minimal bottle-neck cells for grouping part-machines families. Int. J. Prod. Res. 24 (2), 387–400.

Waghodekar, P.H., Sahu, S., 1984. Machine-component cell formation in group technology: MACE. Int. J. Prod. Res. 22 (6), 937–948.

Wagner, G., 2003. The agent–object-relationship metamodel: towards a unified view of state and behaviour. Inf. Syst. 28 (5), 475–504.

Wang, L., 2001. Integrated design-to-control approach for holonic manufacturing systems. Robot. Comput.-Integr. Manuf. 17, 159–167.

Wang, X., Wong, T.N., Wang, G., 2010. Service-oriented architecture for ontologies supporting multi-agent system negotiations in virtual enterprise. J. Intell. Manuf. 23 (4), 1331–1349.

Wang, J., Zhang, L., Duan, L., Gao, R.X., 2017. A new paradigm of cloud-based predictive maintenance for intelligent manufacturing. J. Intell. Manuf. 28 (5), 1125–1137.

Wei, J.C., Gaither, N., 1990. A capacity constrained multiobjective cell formation method. J. Manuf. Syst. 9 (3), 222–232.

Wei, J.C., Kern, G.M., 1989. Commonality analysis: a linear cell clustering algorithm for group technology. Int. J. Prod. Res. 27 (12), 2053–2062.

Weiss, G., 1999. Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence. The MIT Press.

Wu, T.H., Chen, J.F., Yeh, J.Y., 2004. A decomposition approach to the cell formation problem with alternative process plans. Int. J. Adv. Manuf. Technol. 24 (11–12), 834–840.

Wu, D., Rosen, D.W., Wang, L., Schaefer, D., 2015. Cloud-based design and manufacturing: A new paradigm in digital manufacturing and design innovation. Comput-Aided Des. 59, 1–14.

Wuest, T., Weimer, D., Irgens, C., Thoben, K.D., 2016. Machine learning in manufacturing: advantages, challenges, and applications. Prod. Manuf. Res. 4 (1), 23–45.

Xu, H., Wang, H.P., 1989. Part family formation for GT applications based on fuzzy mathematics. Int. J. Prod. Res. 27 (9), 1637–1651.

Yager, R.R., Kacprzyk, J., 1997. The Ordered Weighted Averaging Operators: Theory and Applications. Kluwer, Norwell, MA.

Yang, Y.J., Hinde, C., 2010. A new extension of fuzzy sets using rough sets: R-fuzzy sets. Inform. Sci. 180, 354–365.

Yasuda, K., Hu, L., Yin, Y., 2005. A grouping genetic algorithm for the multiobjective cell formation problem. Int. J. Prod. Res. 43 (4), 829–853.

Zadeh, L.A., 1965. Fuzzy sets. Inf. Control 8 (3), 338–353.

Zadeh, L.A., 1973. Outline of a new approach to the analysis of complex systems and decision processes interval- valued fuzzy sets. IEEE Trans. Syst. Man Cybern. SMC-3, 28–44.

Zhang, C., Wang, H.P., 1990. Concurrent formation of part families and machine cells based on the fuzzy set theory. J. Manuf. Syst. 11 (1), 61–67.

Zhang, Y., Zhang, G., Liu, Y., Hu, D., 2017. Research on services encapsulation and virtualization access model of machine for cloud manufacturing. J. Intell. Manuf. 28 (5), 1109–1123.

Zimmermann, H.J., 1996. Fuzzy Set Theory and its Applications, third ed.. Kluwer Academics Publishers, Boston.