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A survey of feature modeling methods: historical evolution and new development

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Abstract

Initially developed for geometric representation, feature modeling has been applied in product design and manufacturing with great success. With the growth of computer-aided engineering (CAE), computer-aided process planning (CAPP), computer-aided manufacturing (CAM), and other applications for product engineering, the definitions of features have been mostly application-driven. This survey briefly reviews feature modeling historical evolution first. Subsequently, various approaches to resolving the interoperability issues during product lifecycle management are reviewed. In view of the recent progress of emerging technologies, such as Internet of Things (IoT), big data, social manufacturing, and additive manufacturing (AM), the focus of this survey is on the state of the art application of features in the emerging research fields. The interactions among these trending techniques constitute the socio-cyber-physical system (SCPS)-based manufacturing which demands for feature interoperability across heterogeneous domains. Future efforts required to extend feature capability in SCPS-based manufacturing system modeling are discussed at the end of this survey.

Keywords

Feature modeling, Feature ontology, Feature interoperability, Engineering informatics, Socio-cyber-physical system

1. Introduction

Feature-based modeling has been extensively applied in various engineering fields including design, product lifecycle modeling, semantic modeling, process control, and system integration [1]. In the past, there have been several papers that reviewed the development of features. They focused more on the applications of features in modeling geometry and product lifecycles. This survey briefly covers that part as the historical evolution but lays more emphasis on the new development of features in recent years. Especially, the tremendous advancement in Internet of Things (IoT), big data, new manufacturing paradigms and methodologies poses higher requirements for feature interoperability and information consistency. We propose that features should not be restricted to the modeling of a single product. To meet the new challenges raised by industry upgrading, features should be capable of the modeling of advanced manufacturing system consisted of cyber, social, and physical dimensions. This evolution process is demonstrated in Fig.1, based on which this survey is composed.

Specifically, the rest of this review is expanded as follows: Section 2 starts the survey with features' original application in geometry representation and then extends to feature-based modeling of various product lifecycle stages. The interoperability issue emerges in this evolvement process, which brings about relevant modeling approaches reviewed in Section 3. Section 4 introduces the new development of feature modeling methods due to the shifting of informatics and manufacturing schemes in recent years. A discussion of the bottlenecks and future research directions is carried out in Section 5 based on the literature reviewed. The conclusions of this survey come at last.

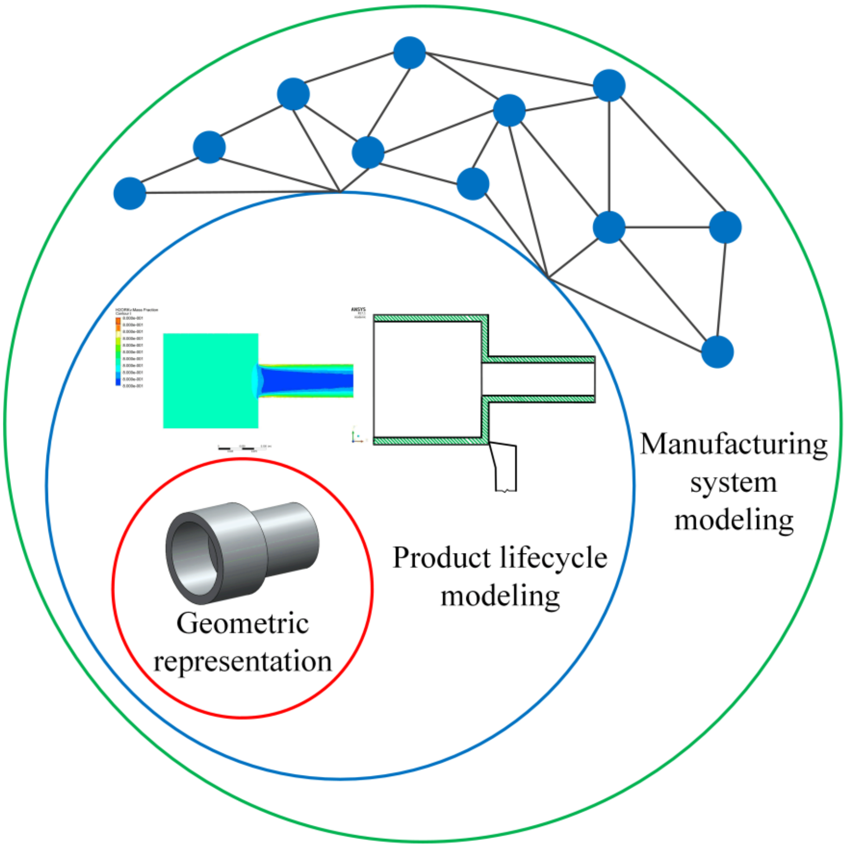

Fig. 1. Development and evolution of feature modeling methods.

2. Evolution of feature definitions

2.1. Geometry representation

In the background of product engineering, features were initially referred to as form features which are generic shapes for product development purposes [2]. Examples can be a hole, slot, pocket, and chamfer in a product model [3]. To represent geometric shapes, constructive solid geometry (CSG) is commonly applied, which represents a geometry at the implicit level [4]. The other widely used method is boundary representation (B-rep), which explicitly represents an object by its boundary like faces, edges, and vertices [5]. Comparing to B-rep, CSG is preferred for computational geometric modeling due to its insensitivity to topological changes [6,7]. Other than geometric representation, feature concepts were further developed to model non-geometric product properties which are essential in different stages of the whole product lifecycle. However, this usually makes feature definitions driven by a specific application in product development [8]. These heterogeneous feature definitions are briefly explored in the following sub-sections.

2.2. Functional features in conceptual design

In the conceptual design stage, the design intent is embedded in a customer's requirement for functions represented as a set of geometric and functional rules satisfied by the final product [9]. Functional modeling serves as a means of linking different levels of product or system design, which is conceptual. However, there is a huge challenge to unify different definitions and representations of functions from literature [10]. In design research specifically, it is widely accepted that a function is a relationship between input and output of energy, material, and information [11]. Schulte et al. [12] argued that, if features in the design process contain information related to functions, they would be more useful to support a design engineer. They defined the functional feature as "a set of functional faces, which embody the active surface of a physical effect to meet the requirements of a certain design (sub-) function". Based on this concept, they tried to restore or construct the detailed geometry from the functional faces they defined. One of the important applications of functional features is the 3D layout design before the embodiment or detailing begins [13]. For example, Li et al. [14] employed the functional feature tree modeling approach which integrates functional modeling and geometric modeling for engineering layout problem with complex design requests.

2.3. CAE features in design analysis and improvement

In the analysis stage supported by computer-aided engineering (CAE), CAE features are applied to represent engineering analysis knowledge [8]. In most real industrial applications, CAE simulation is computationally expensive and time-consuming [15]. It is a common practice that the product modeled by computer-aided design (CAD) should be simplified before simulation to enhance the efficiency of CAE [16]. Therefore, idealization features were proposed to remove the details and reduce the dimension of a CAD model [17]. In a similar work reported by Hamri et al. [18], simplification features are defined to remove certain form features in a CAD model. There were other works focused on the geometry conversion from CAD domain to CAE analysis. For instance, Deng et al. [19] put forward CAD-CAE features to transform the features of a CAD model into features of a CAE model. Xia et al. [20] developed a CAD/CAE incorporate software framework in which CAE features are composed of geometry entities and analysis attributes including boundary conditions feature, material feature, mesh feature, rendering feature, etc.

2.4. Machining features in manufacture

In the manufacturing stage, a machining feature (MF) can be defined from a geometric perspective as a shape that represents volumes to be removed [21]. Machining features have a wide application in computer-aided process planning (CAPP) and computer-aided manufacturing (CAM) [22]. To further distinguish machining features from design features. Yan et al. [23] defined a machining feature as an object with geometric and topological characteristics which are associated with a set of machining operations. Machining feature also extends its functionalities in many other applications. For instance, Wang et al. [24] presented an enriched machining feature (EMF) concept that extends a traditional machining feature with intermediate machining volume information. In this way, EMF can be applied in machining process sequencing for distributed process planning. Li et al. [25] raised the concept of dynamics features that contain the machining effects, such as cutting allowance left, over-cut, surface quality and accuracy, to assist manufacturing decision making. To improve the manufacturability of the topologically optimized product, Liu and Ma [26] introduced 2.5D machining features into the optimization process, which was further extended to design for hybrid manufacturing [27].

2.5. Assembly features

In the product assembly stage, features are applied in assembly modeling and assembly planning [28]. Assembly modeling enables the computerized representation of assemblies of discrete parts through specifying assembly features [29] while assembly planning involves stability analysis, grip planning, motion planning, and sequence planning based on assembly features [28]. Generally, an assembly feature is defined as a generic way to mate the components by relationships [30,31]. Specifically, the relationships are composed of face connections, constraints, parameters, kinematic relations, and structural relations [32]. The product architectures that constrain the modular design of assembly geometry can be further defined by associative assembly design features which model geometric or non-geometric associations [33].

3. Feature interoperability and information consistency

The interoperability issue arises after the definition of features becomes application-driven because the semantics is drastically affected by different product development stages in which features are modeled and interpreted [34]. Various approaches have been investigated to resolve the interoperability issue, which will be reviewed in this section.

3.1. An ontological approach to feature definitions and product lifecycle management

Ontologies are widely employed in the transparent modeling of human knowledge and reliable data sharing [8] because ontologies provide a common vocabulary with a shared semantics [35]. Especially, ontologies have an extensive application in software engineering for domain modeling, in which a feature model is a hierarchy of features with variability [36].

However, borrowed from philosophy, the meaning of ontology is ambiguous and not intuitive in the background of feature modeling, which needs deep investigation. Computer scientists inherit "ontology" from metaphysics and apply it to represent formal descriptions of objects in the world, including their properties and correlations, so that they can be classified and related to one another [37]. Gruber [38] defined ontology as "an explicit specification of conceptualization". From this definition, ontology represents the semantics of concepts and their relationships by using description languages. For instance, Dartigues et al. [35] applied the US National Institute of Standards and Technology (NIST) CORE product model, which offers a generic product representation scheme for the entire product development activity [39], to build the ontology that represents the common concepts between CAD and CAPP by

Unified Modeling Language (UML). Tessier and Wang [40] combined Ontology Web Language (OWL) and Semantic Web Rule Language (SWRL) to represent feature classes in the form of ontologies. Generally, one of the main components of ontologies, i.e., concepts, can be defined by a UML class diagram shown in Fig. 2.

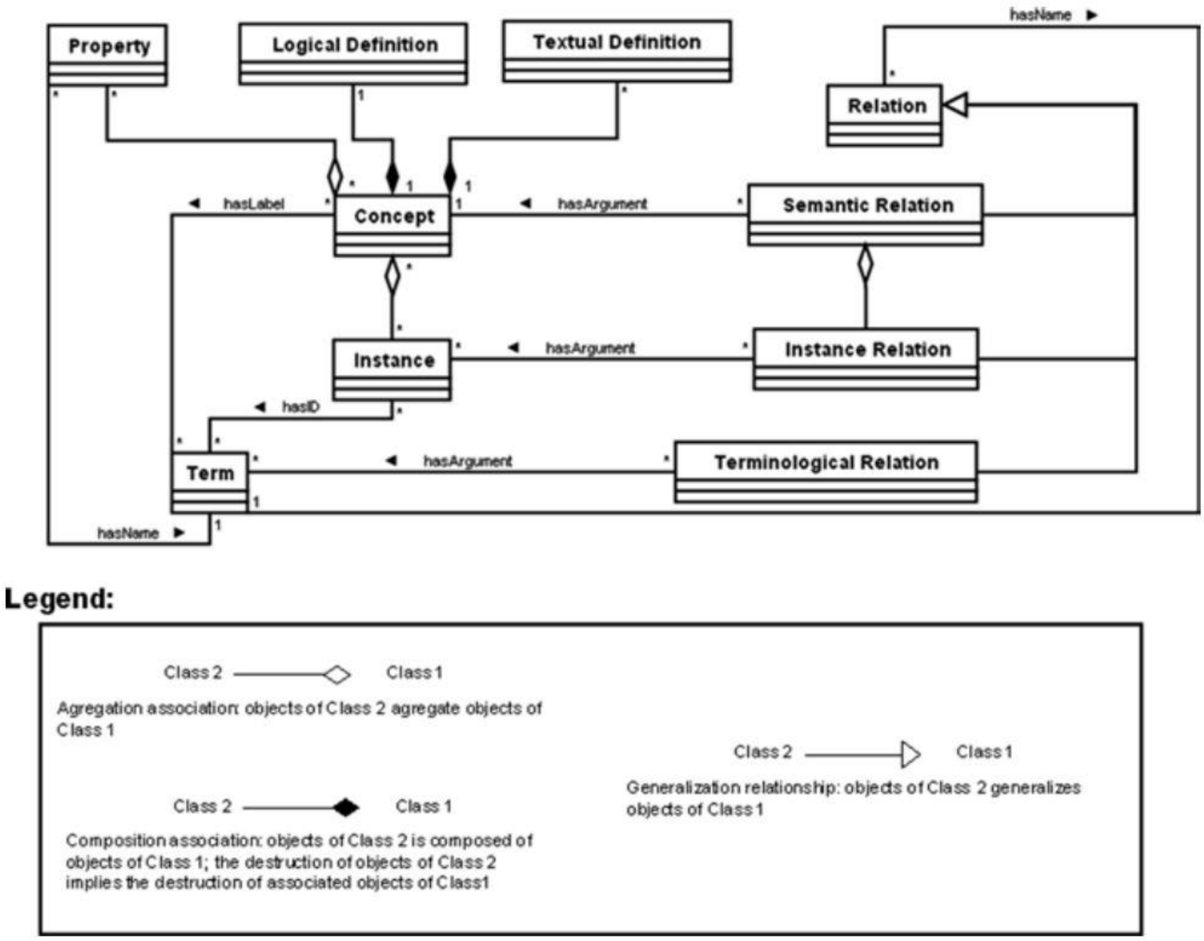

Fig. 2. UML class diagram of ontology components and their relationships [41].

Products nowadays are becoming more and more complex, which is one of the reasons why various stages are needed in product development. This situation promotes the emergence of product lifecycle management (PLM) which provides a knowledge management platform to streamline the information of a product and related stages throughout the product's lifecycle [42]. Efforts have been dedicated to building PLM by the ontological method. Sudarsan et al. [43] developed a product information modeling framework for PLM in which the product information modeling architecture is composed of product ontology and interoperability standards. To implement ontology and features into PLM, Matsokis and Kiritsis [44] proposed an ontology model of product data and Knowledge Management Semantic Object Model, which supports multi-levels of interoperability.

3.2. Multiple-view feature modeling

Throughout the lifecycle of a product, each activity has its own view on the product model [45]. The information consistency can be maintained through view updating in multiple-view feature modeling [46]. Technically, multiple feature views are based on design by features, feature recognition [47], and feature conversion [48]. For example, in simulation-based design, the analysis view [49] needs to be associated with CAD models from the design view in a multiple-view product development environment. Cunningham and Dixon [50] applied design by features to create the feature model for the design view and used feature conversion to establish the finite-element model for the analysis view [46]. For molding products, Lee [51] proposed that the design view is composed of form features and moldability features, while the manufacture view is focused on the design of the mold. The conversion from the design view to the manufacture view is achieved by the geometric relationships between the product and the mold. The structural optimization view of the product was proposed by Liu et al. [52] based on the associative optimization feature concept. Recently, Li et al. [53] presented multiple-view feature modeling for design-for-additive manufacturing in which the design view, manufacturing view, and analysis view are incorporated as shown in Fig. 3.

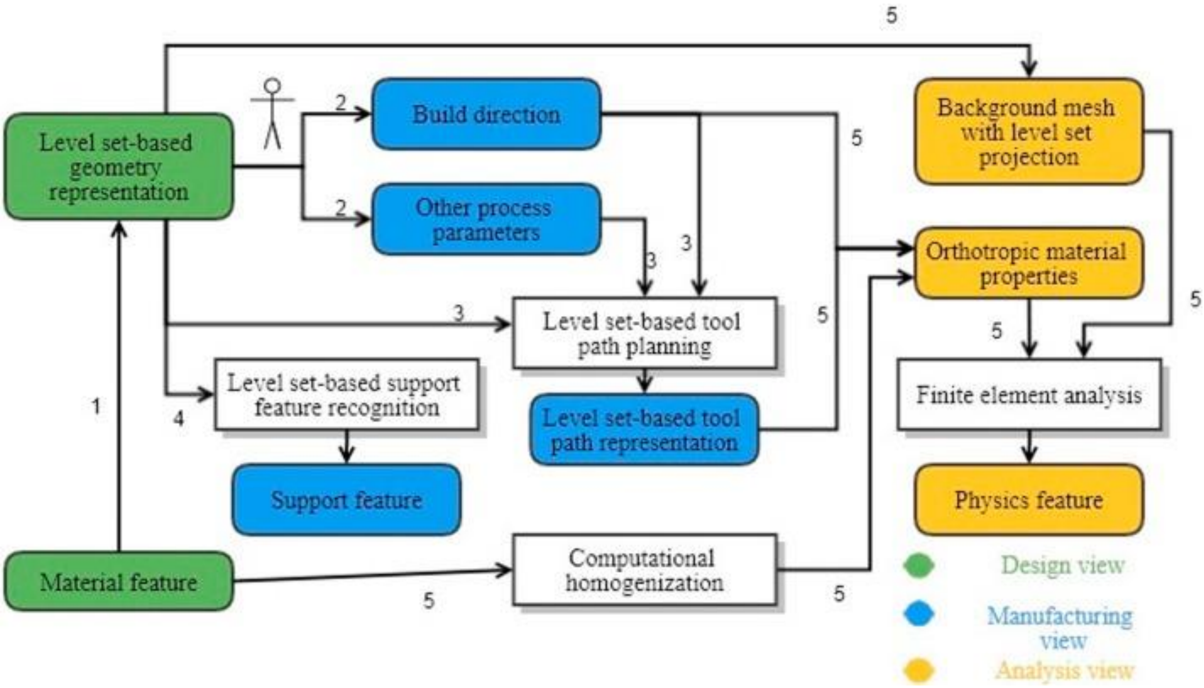

Fig. 3. Multiple-view feature modeling framework for design-for-additive manufacturing [53].

The feature conversion in the aforementioned approaches is usually one-way starting from the original design view [54]. To achieve multi-way feature conversion [55], Hoffmann and Joan-Arinyo [56] created a master model that has domain-specific clients who have their own view on the product model. As problems related to tolerances appear in several stages of a product lifecycle [57], the master model coordinates the CAD view, geometric dimensioning and tolerancing view, manufacturing process planning view and other downstream views under the control of the change protocol. In order to enable a designer to specify the product model from an arbitrary view, Bronsvoort and Noort [46] introduced conceptual design view, assembly design view, part detail design view, and part manufacturing planning view in a multiple-view feature modeling scheme. All the phases of product development are supported regardless of the order of appearance, and the information consistency is kept by automatic checking and recovering algorithms. For product development involving CAE, Smit and Bronsvoort [49] proposed that the analysis view should be a part of the multiple-view feature modeling paradigm that propagates the changes in a multi-directional manner. In the proposed paradigm, knowledge plays an essential role in integrating analysis view with other views in product development.

3.3. Multi-disciplinary and multi-application integration

3.3.1. Functional and physical feature modeling

The essence of engineering design is to map a specific function onto a reliable physical artefact. The design intent conveyed by functional features should be consistently adhered to throughout different stages in product development. However, the original definition of functional feature proposed by Schulte [12] is too restricted and provides no detailed information on how to incorporate with CAD and the subsequent applications. In order to overcome the defects, Cheng and Ma proposed a new functional feature modeling scheme as shown in Fig. 4. Specifically, the functional feature [58,59] is defined to incorporate functional design considerations into CAD modeling. Functional decomposition [60] is applied to break down an overly abstract function into several more detailed primitive functions, which are usually called sub-functions. A function structure is the compatible combination of sub-functions into an overall function [60]. Since functional concepts are not concrete and in order to attach them into geometric entities of the product, a new form of geometry, namely abstract geometry, is introduced to provide an intermediate between abstract functions and concrete geometries [58,59]. Abstract geometries are used to capture the fundamental geometric elements of the design functionals and are associated with downstream CAD geometric entities.

Further, physics feature, in the form of named variables and a set of mathematical equations describing the physics phenomena, is proposed to model the behavior of the design artifact [59]. It contains information related to the physics/phenomena context involved in the design, for example, a mathematical model that describes a physical phenomenon, engineering properties that affect the design choice, etc. Note that one mathematical model could be applied to model different physical phenomena.

There are engineering tools available for physics-related behavior modeling, the result of which can be transferred to physics feature and further utilized by downstream design activities. For example, Modelica [61] models the dynamic behaviors of the technical systems consisting of components like mechanical, electrical, fluid, thermal, hydraulic, control, etc., which are described by simple differential, algebraic, and discrete equations. Some behaviors are described by more complex partial differential equations, which require advanced methods, for example, CAE, mostly solved with finite element method (FEM) and Computational Fluid dynamics (CFD), mostly solved with Finite Volume Method (FVM). Advanced engineering tools are also available for modeling such behaviors, such as ANSYS, Abaqus, OpenFOAM, deal.II, etc. The implementation of functional features and physics features will be demonstrated in the following subsections.

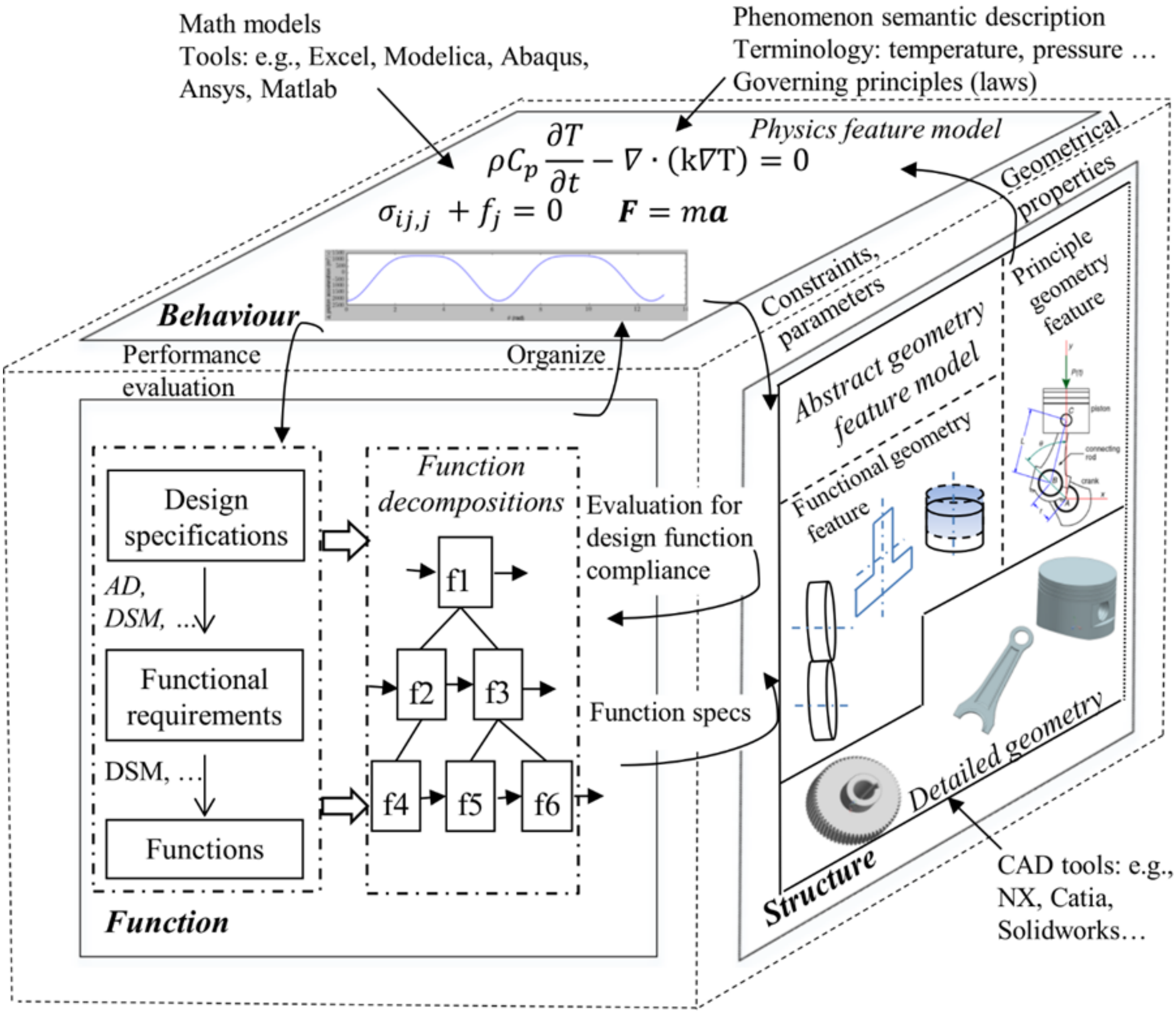

Fig. 4. Functional feature modeling cube [59].

3.3.2. Functional features implementation in multi-disciplinary associations

Just like the aforementioned research into product and process integration in mechanical engineering domain, extensive research has been conducted in chemical engineering field as well. For computer-aided process engineering (CAPE), CAPE open standards have been established to address the interoperability among various applications, which adopts an object-oriented approach to model individual process components as separate objects with middleware handling communications among those objects [62–64]. Also, formal ontology in CAPE domain was developed and further applied to model the semantic associations among heterogeneous data from conceptual all the way through to detailed engineering phase [65,66].

Despite all these efforts, the research on product and process integration is still domain-specific [34,66–69]. In order to deal with the interoperability problem across mechanical and chemical engineering domains, Xie and Ma proposed the inter-domain functional feature, shown in Fig. 5, to associate chemical process features and mechanical design features, and therefore the design intent in chemical engineering can be expressed more explicitly in a tangible object form [70]. In this scheme, design knowledge, such as design codes, expert rules, and numerical laws, is abstracted into the constraint models, which formalize the dependency and references among features across domains. The establishment of such flexible associative relationships among interdisciplinary features provides precise contextual information as well as convenient updates of functional mapping. Also, the explicit representation of engineering constraints can offer quantitative evaluation capability rather than just qualitatively registering the dependencies among detailed engineering model entities.

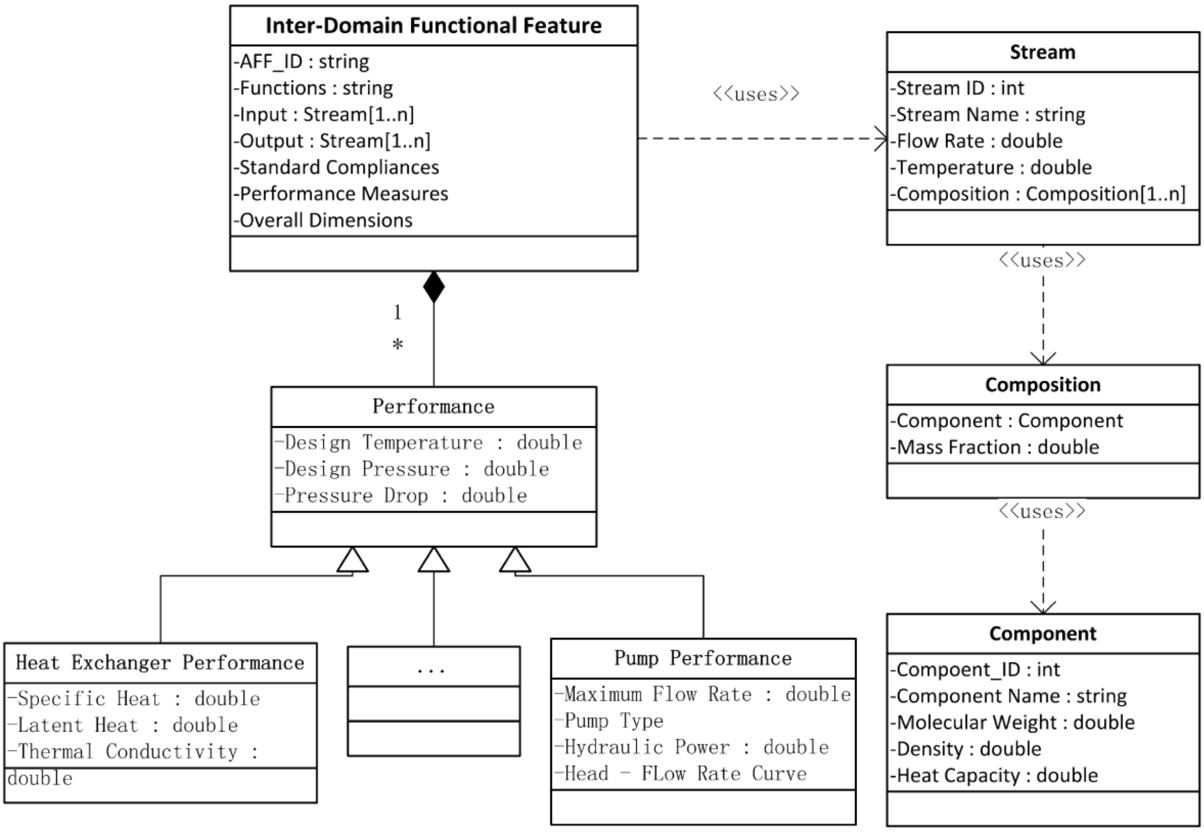

Fig. 5. Inter-domain functional feature definition [70].

With the associations and cross references among different domain features systematically managed as engineering constraints at a fine granularity, a feature parameter association map can be dynamically constructed as needed, which always reflects the most updated dependency information. The map generated in this procedure provides engineers graphical visualization of association information, which evolves along the lifecycle of engineering projects. Also, snapshots of the feature association map can be used for tracing engineering changes and referenced in the future. Further, change propagation algorithm can be developed with a solid context to evaluate engineering change impacts and provide intelligent advice on change propagation solutions [71]. Fig. 6 demonstrates how the change propagation is controlled in a multilayer manner aided by the association map.

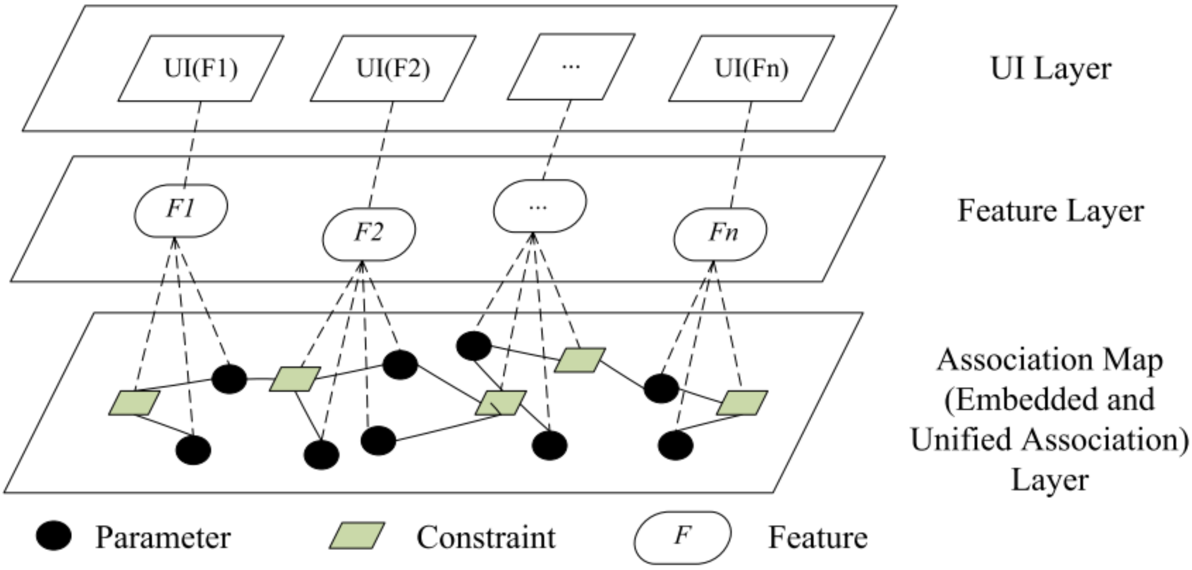

Fig. 6. Multilayer change scope control [71].

3.3.3. Functional features and physics features implementation in CAD/CFD integration

In CAD/CAE integration, besides the efforts in synchronizing the CAD and CAE models and interpreting the CAE results introduced in Section 2, the CAE model setup should be highlighted as a vital component which affects the simulation accuracy greatly. However, the question of how to create a correct CAE model automatically poses another barrier for seamless CAD/CAE integration. This situation becomes even worse when CFD is needed to analyze the flow field because the CFD model requires strong background knowledge and rich experience to deal with the nonlinearity.

To assist the CFD solver setup, an effective approach is to establish a system in which the relevant knowledge is represented as rules and coded into the system. Known as expert systems, the rule-based systems are the simplest form of artificial intelligence [72]. Research works have been dedicated to CFD expert systems when CFD solvers were still in-house codes [73–75]. The recent development of CFD makes it more user-friendly, which in turn requires more interactions with CAD. CAD/CFD integration happens to serve this purpose, which is supposed to extract the design information from CAD and convert it into the robust CFD simulation model which finally derives accurate results.

Li et al. [76] proposed a CAD/CFD integration system based on feature concepts shown in Fig. 7. Based on the new functional feature concept [59], the fluid functional feature is composed of design parameters, functional descriptions, and functional geometry. The functional geometry can be further decomposed into inlet, outlet, inner faces, and symmetry plane if there is any. The CFD boundary features establish the link between the CAD design model and the CFD fluid domain including fluid attributes, boundary conditions, and mesh. According to the fluid attributes and boundary conditions, the equations in fluid physics features help to evaluate the flow regime. Subsequently, suitable physics models are selected for the CFD solver based on the rules embedded in the fluid physics features. After the simulation is completed, the convergence status and the analysis model are recorded as parts of the dynamic physics features which further facilitate the generation of the robust simulation model. The intelligent functions of the fluid physics features and dynamic physics features are fulfilled by a Python 3 code which invokes ANSYS Workbench and executes different scripts [77]. One important application of the CAD/CFD integration system is to optimize fluid flow product design based on metamodeling [78]. In order to conduct metamodeling, a series of designs need to be analyzed. The proposed system is capable of configuring the solver according to various designs and generating accurate results which are the input of metamodeling. By extracting the sensitivity information, CFD effect features are obtained, which can be employed to improve the design.

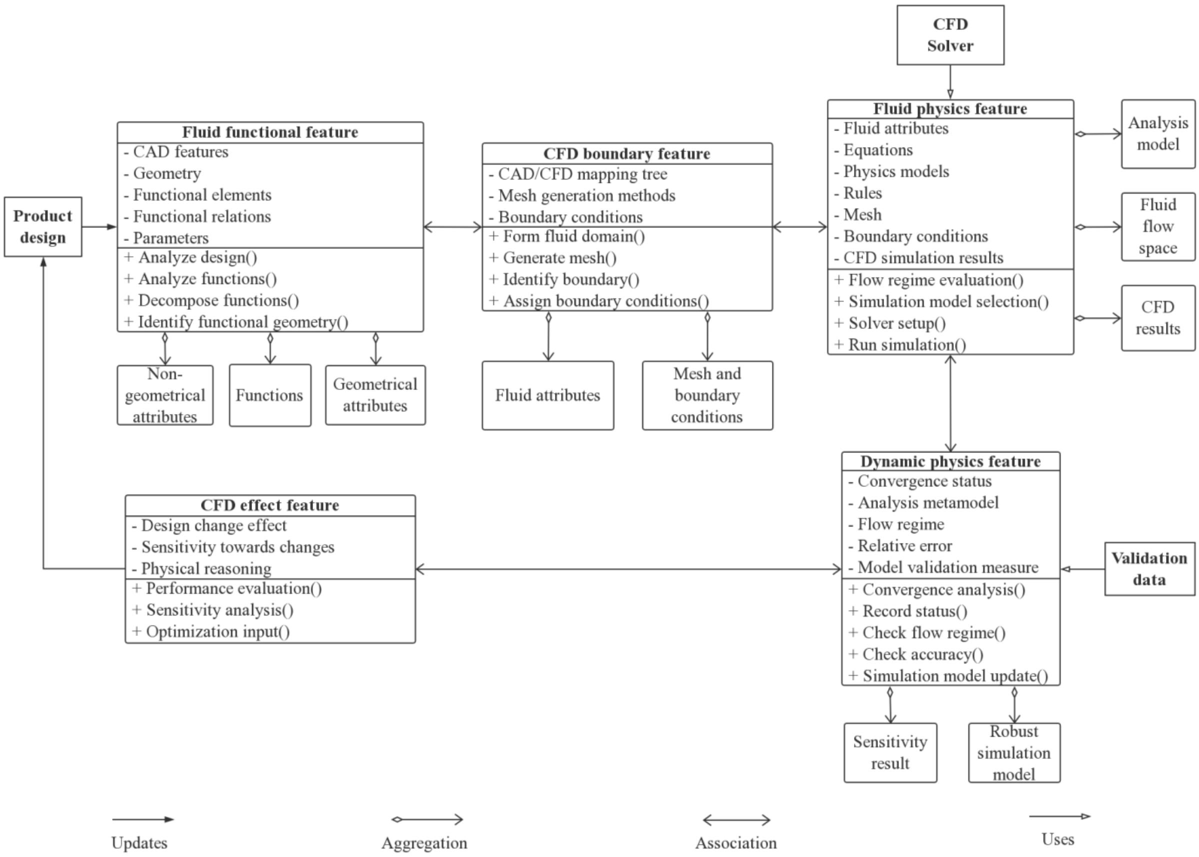

Fig. 7. UML diagram representing inter-feature associations.

4. Features in the emerging informatics and manufacturing scheme

4.1. Internet of Things

Firstly introduced in 1999, the concept of IoT was defined by Kevin Ashton as uniquely identifiable interoperable connected objects with radio-frequency identification (RFID) [79]. In recent years, the rapid development of the Internet provides a global platform for machines and smart objects to communicate, dialogue, compute and coordinate [80]. As a result, the concept of "Things" is not restricted to RFID objects anymore. Instead, it has been expanded to any real or physical objects, such as sensors, actuators, and smart items [81]. Correspondingly, the wide applications of IoT have been witnessed in some fields including smart industry, smart home, smart energy, smart transport, and smart health [82]. In this evolution process, different visions have been developed towards IoT because of the heterogeneous interests of the people involved. Despite all the differences, the visions can be summarized as "Things oriented", "Internet oriented", and "Semantic oriented" [83]. Among those visions, features in the IoT scenario are originated from the characteristic properties and behaviors of the "Things" [84].

Feature modeling is significant to the management of common and variable features in IoT [85]. To be specific, the common features are mandatory features for all products while variable features are used according to the required specifications of a product [86]. Based on this scheme, Abbas et al. [85] established the detailed IoT-based feature model for the “Things”. Based on the presented modeling method, a temperature sensor module in IoT can be represented by a feature model shown in Fig. 8. As indicated by the legend, the temperature sensor is the root node which has four child nodes. The unit, ZigBee, and connectivity are mandatory, which can be categorized as common features. The screen is optional, which is a variable feature. The values and options of unit, screen, and connectivity are all variable features according to the aforementioned method.

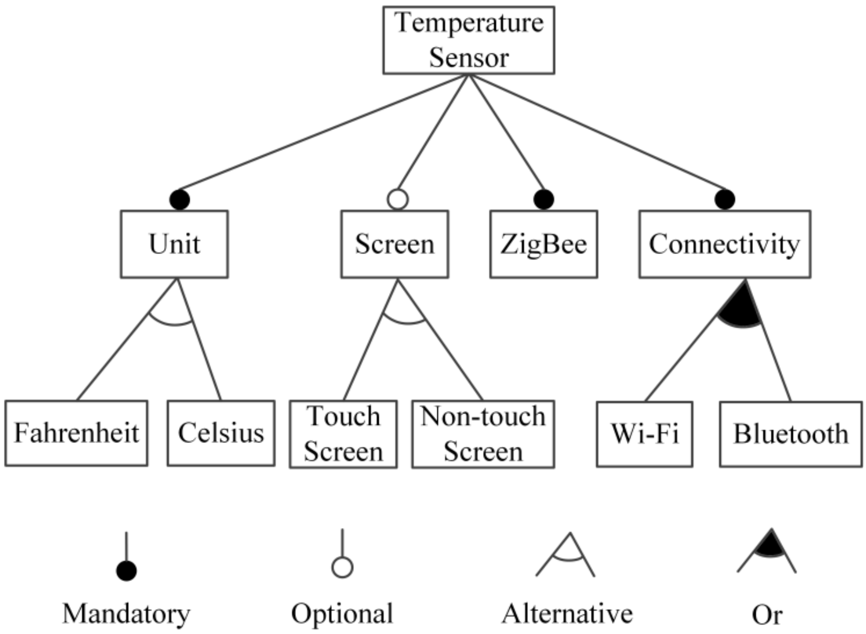

Fig. 8. Feature model of a temperature sensor in IoT.

Because heterogeneous things that belong to different platforms are applied in IoT [87], the semantic interoperability is critical for the “Things” to communicate with each other through the Internet [88]. Many research works have been done to conquer the interoperability issue caused by the diversity of protocols and technologies utilized in the IoT environment. For example, Kiljander et al. [89] proposed a novel semantic level interoperability architecture in which the information and capabilities of devices are characterized by semantic web knowledge representation. Further efforts still need to be made to enhance the semantic interoperability in IoT feature modeling.

4.2. Big data

Through IoT, information acquisition platforms, and ERP systems within enterprises, big data can be collected [90]. These data acquisition approaches make the datasets increase at an exponential rate, which requires advanced techniques to process within limited run times [91]. In the context of big data, features refer to data attributes which are the keys to the accuracy and efficiency of data mining algorithms [92]. Aided by feature modeling, the semantic-based big data analysis helps to extract the manufacturing relationships [93]. For instance, based on the unstructured text data obtained from cross-enterprise social interaction media, Leng and Jiang [94] proposed Word Features (WF) and Position Features (PF) to formulate the sentence level features that represent the manufacturing relationships. As shown in Fig. 9, each word is represented as $[WF_i, PF_i]^T$. Through combinations, the whole sentence can be denoted as $\boldsymbol{x} = \{[WF_0, PF_0]^T, [WF_1, PF_1]^T, \ldots, [WF_4, PF_4]^T\}$. Further, to extract manufacturing relationships among various named entities (e.g., enterprises, products, demands, and capabilities) from the text-based context, a deep learning model based on an improved stacked denoising auto-encoder for sentence-level features is proposed instead of exploiting man-made features that elaborately optimized for the relationship extraction task [95]. For big data in the form of images, Li et al. [96] proposed a deep convolutional computation model which extends the convolutional neural network from the vector space to the tensor space to learn hierarchical features embedded in the data obtained from IoT. Big data also contributes to the intelligent diagnosis of machine operation conditions. Lei et al. [97] proposed a two-stage learning method to extract features that represent diverse fault symptoms [98] from mechanical big data. In their method, features are firstly extracted from vibration signals by sparse filtering. Then, based on the resulted features, health conditions are then classified by a "softmax" regression. Seen from the above literature, it can be observed that data mining, machine learning, and signal processing are commonly used methods to efficiently extract features from large-scale coarse data.

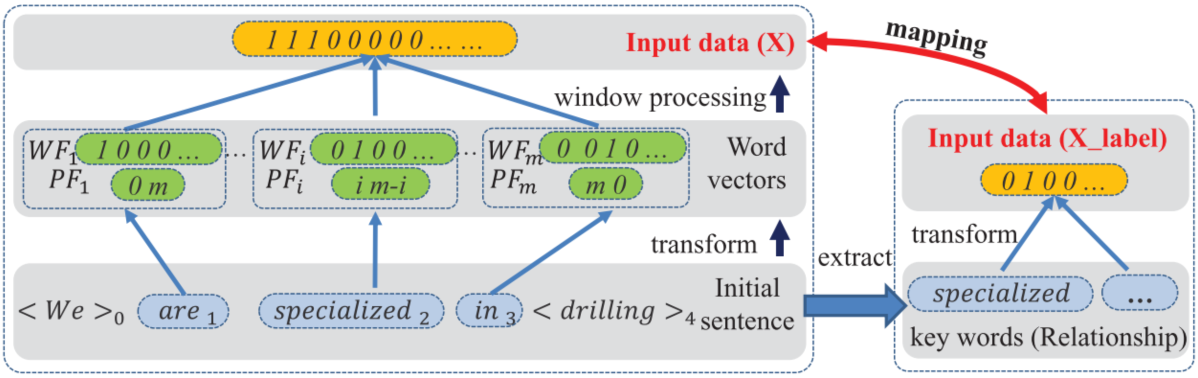

Fig. 9. Sentence level input data formulation based on WF and PF [94].

After feature extraction, feature selection plays a key role in reducing the high-dimensionality of the derived features so that learning algorithms can be conducted more efficiently. Commonly, feature selection strategies are classified as filter, wrapper, embedded, and ensemble techniques [99]. Further, Wang et al. treated feature selection as a combinatorial optimization problem and categorized the feature selection methods into exhaustive search, heuristic search, and hybrid methods [92]. The suitability of using feature selection has been demonstrated in a variety of applications that require the processing of huge amount of data [100]. For example, Lin et al. performed an improved cat swarm optimization algorithm to select features in a text classification experiment for big data [101]. Fong et al. proposed a novel lightweight feature selection method for mining streaming data by using accelerated particle swarm optimization (APSO) type of swarm search [102].

Implementing feature modeling in big data is critical for improving system performance and efficiency since big data is always characterized by its high sparsity, unbalanced, and large-scale nature. By incorporating advanced granular computing methods [103] and hybrid learning models [104], the automatic feature modeling, extraction, and selection techniques need to be developed to handle complex data sets.

4.3. Social manufacturing

Social manufacturing is a novel manufacturing paradigm which is based on the rapid development of the Internet and social media [105,106]. Specifically, it is a dynamically changeable socio-technical system which covers all the stages of a product lifecycle including requirement/demand generation, product design, production, marketing, services, and so on [107]. Facilitated by the internet-based connections and communications in business, socialized manufacturing resources (SMRs) are self-organized into resource communities and then further into a social manufacturing network. The implementation of social manufacturing is based on the product-order-driven runtime logic which is in the form of outsourcing and crowdsourcing mode, as well as product service systems [108].

One of the most important aspects of social manufacturing is its service-oriented character in which the term “service” generally indicates a series of activities. For instance, service providers offer services requested by consumers; consumers accept the services and give feedback to the service providers through social media [109,110]. Under this circumstance, the geographically distributed, cross-disciplinary service providers and service accepters have to establish unified service features to define, communicate, and locate their tangible and intangible service demands and capabilities. With the recent development of social manufacturing, there are researchers who applied feature modeling techniques to represent the capability information. For example, Leng et al. proposed the concept of manufacturing feature, which takes advantage of the ontology method to define and classify manufacturing resource for integrated decision making and reasoning [108]. Liu et al. established a similar ontology based manufacturing feature model to represent the processing capability and production capability of manufacturing service providers for outsourcing decision making [111,112]. Cao et al. constructed a more detailed machining service capability model using ontology and semantic web methods to represent the machining features that can be offered by a service provider for the purpose of cross-enterprise collaborations [113].

As aforementioned, SMRs are usually self-organized into virtual communities to provide manufacturing resource as a whole. This is especially significant for small and medium enterprises to enhance their competitiveness against other large enterprises, which is another benefit and characteristic of social manufacturing [114]. Therefore, several researchers investigated the application of features in the formation of social manufacturing communities. For instance, Ding et al. studied how to classify the manufacturing resource providers into communities according to their similar manufacturing service features based on a topology model [115]. Leng et al. defined the manufacturing relationship features in the context of cross-enterprise collaborations, and developed a deep learning approach to extract these features for manufacturing demand-capability matchmaking [94]. According to the design ability features of the members in a designer community, Yang and Jiang found a way to represent the design resources of designer communities in social manufacturing [93]. Fig. 10 represents the basic operation mechanisms of social manufacturing and how the aforementioned feature concepts function in this advanced manufacturing system.

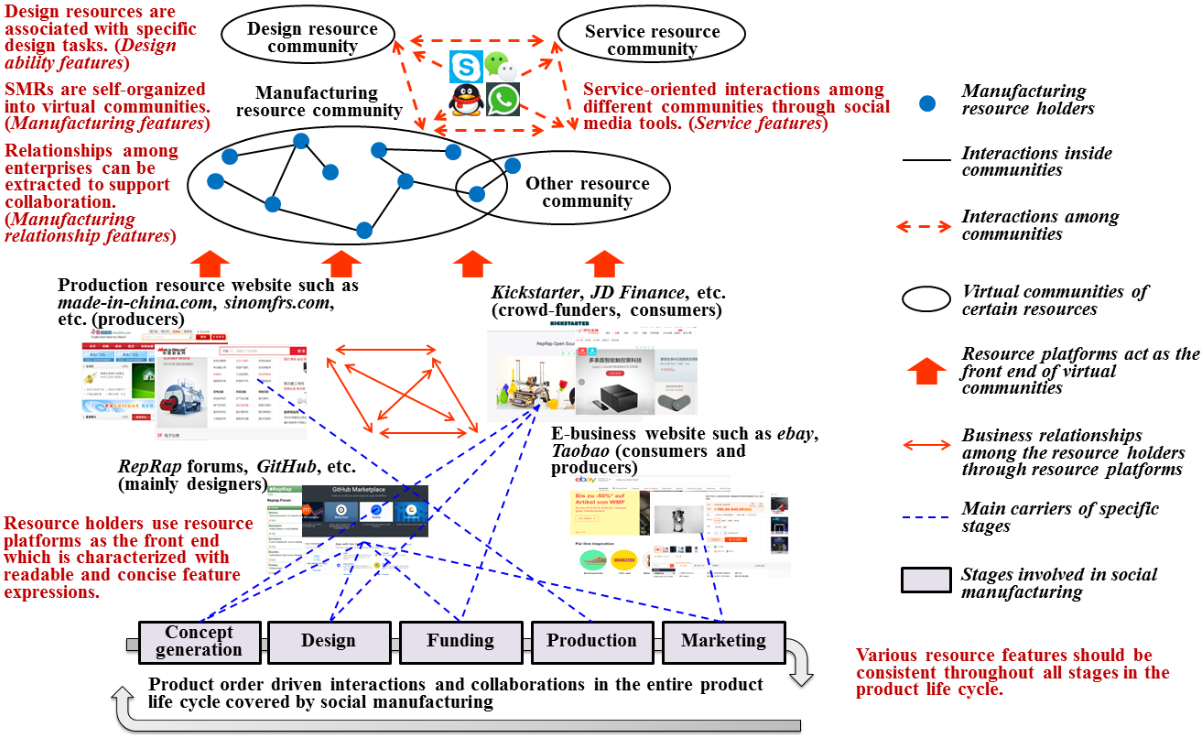

Fig. 10. The operation mechanism of social manufacturing and the involved feature concepts.

In addition to the two characteristics mentioned above, social manufacturing is a sophisticated paradigm which also features with the virus-like organizational structure propagation, SMR capabilities sharing, dynamically distributive infrastructure, big-data driven decision-making, and various industrial software applications [93]. These entire characteristics request for more in-depth studies on the unified, pellucid, convenient feature identification, representation, and interoperation in the social manufacturing scheme involving inter and intra enterprise communications, multiple production steps collaborations, and multi-disciplinary interactions.

4.4. Additive and hybrid manufacturing

The initial concept of social manufacturing was put forward with the focus on additive manufacturing (AM) because the owner of each 3D printer is theoretically a producer and a node in socialized manufacturing. The application of feature modeling techniques in AM is significant in the design of structures [116].

4.4.1. Tools and steps in conducting additive manufacturing

As shown in Fig. 11, an AM process generally involves serval steps ranging from a 3D model to a physical object. It is important to notice that the information flow preserves the approximate geometric information regarding the original input model. A 3D CAD model that fully describes the geometric information is required to initiate an AM process. The 3D model can be either created by a CAD software or constructed from a physical object through reverse engineering [117,118]. For products manufactured by conventional methods, the primary scheme of most commercial CAD/CAM software is CSG or B-rep. When it comes to AM, B-rep or CSG methods are faced with the problem of numerical robustness [119]. Back to 1987, 3D system Inc. created Standard Tessellation Language (STL) to transfer the information embedded in 3D CAD models to AM machines. In this way, a CAD file can be converted to header and water-tight triangular meshes [119,120]. However, STL representation may cause problems because of the numerical errors (i.e. non-manifold facets, cracks, incorrect normals, overlapping facets [121]) induced during surface creation. The errors can be reduced by selectively and locally increasing the density of STL file facets without unnecessary increase of the file size by Vertex translation algorithm (VTA) [122] or Surface-based Modification Algorithm (SMA) [123]. Currently, STL is the mainstream standard in AM process, but there are still some other types of representations. For example, voxel-representation is adopted in medical applications using AM, because it can be directly obtained from images of computed tomography (CT) or magnetic resonance imaging (MRI) [124]. Hiller and Lipson [125] proposed a new Additive Manufacturing file format as STL2.0 which supports multi-material and surface properties. The ISO/ASTM 52915:2016(E): Standard Specification for Additive Manufacturing file Version 1.2[1] describes an interchange format to support producing geometries in full color with functionally-defined gradations of materials and microstructures [126].

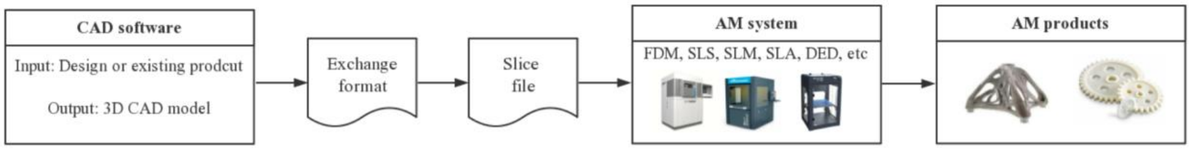

Fig. 11. Information flow in AM.

4.4.2. Features in additive manufacturing

To print the material layer by layer using a 3D printing machine, the exchange format is transferred to the slice file which contains the information for each layer. The slice file carries the information of printing orientation, layer thickness and tool path in each layer. Due to the layer by layer nature, a typical staircase error is caused when the shape does not align with the printing orientation, which is demonstrated in Fig. 12. The staircase error can be reduced by using thinner slices at the cost of more printing layers and building time. Another common issue in AM is the loss of peak features in a printed part, which is presented in Fig.13. To address the problem, a variety of adaptive slice methods have been developed to use slices of varying thickness according to the part geometry [127–131]. In a study reported by [128], the authors identified the peak features and employed a selective hatching strategy on a non-uniform rational B-spline (NURBS) surface to reduce the overall building time, while maintaining the desired surface quality.

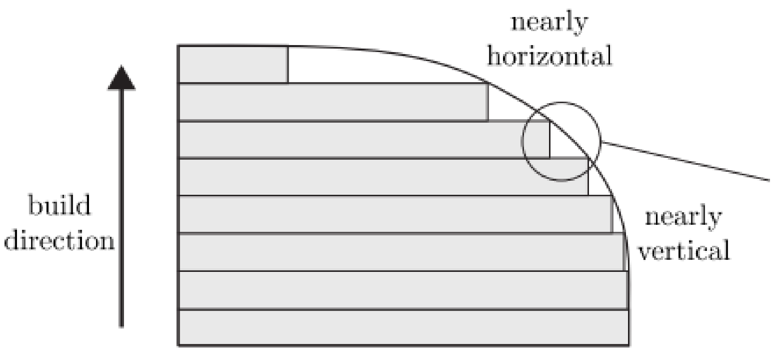

Fig. 12. Staircase error in AM [132].

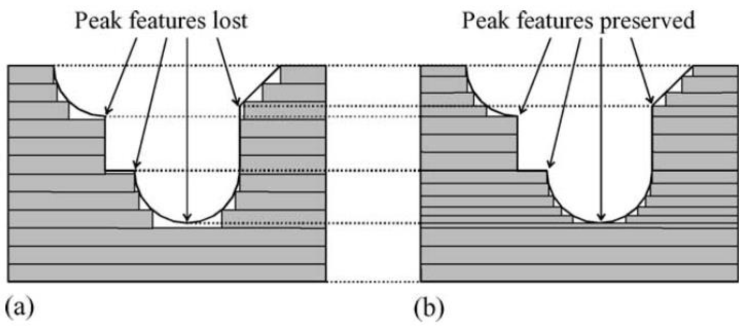

Fig. 13. (a) Peak features lost in uniform thickness layer deposition; (b) peak feature preserved in adaptive thickness layer deposition [128].

In addition to the layer thickness, the printing orientation is another critical factor for AM [133]. For some complex parts, it is difficult to achieve the quality requirement by printing the entire body in the same direction with planar slicing. Zhao et al. [134] developed a featured-based five-axis path planning method for AM. Specifically, an AM feature is defined as an abstract class of all features that comprise the basic attributes of id (the identifier of the feature), part_id (the id of the part that the feature belongs to) and support_structure (the support structure for the suspended features). Further, AM features are categorized into two5D AM features and freeform features which represent the features grow from a plane and features accumulate on a curved surface, respectively. Based on the proposed AM features, the fidelity of printing is improved by implementing different slicing and printing orientations. Ding et al. [135] developed a feature-based algorithm to slice a CAD model in multi-directions for satisfying the support-less and collision-free deposition purpose. In their research, as illustrated in Fig. 14, a CAD model is decomposed into sub-volumes using a curvature-based volume decomposition method, and the sub-volumes are regrouped by a depth-tree structure approach with the same slicing directions. Some similar feature-based studies on multi-direction slicing strategies can be found in literature as well, such as silhouette edges projection [136], transition wall [137], centroid axis extraction [138], marching algorithm [139], offset slicing [140], skeleton method [141], and modular boundary decomposition [142].

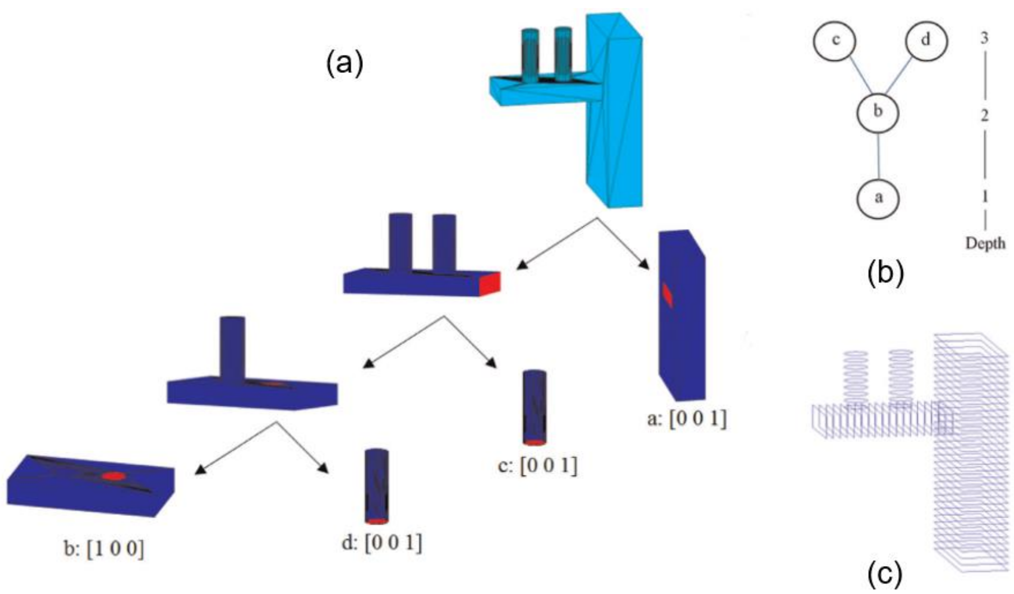

Fig. 14. (a) Decomposition of a CAD model into sub-volumes with their build directions; (b) regrouping of sub-volumes by a depth-tree structure approach; (c) result of sliced CAD model with minimal support structures [135].

One important characteristic of AM is that support structures are employed to prop the overhang features that incline beyond a certain degree to avoid collapsing during fabrication [143]. Therefore, the support feature should be included as a subclass of AM features. It should be noted that support features vary with different printing parameters for the same printed part [53]. For instance, the volume of support features can be minimized by optimizing the build direction [144–146]. As a result, support features are strongly dependent on the geometric and related technological attributes of the parent AM feature class. The relationships between the support features and the parent AM features can be potentially managed by the associative feature [147] regime.

4.4.3. Features in hybrid manufacturing

Even though AM is capable of building parts with high geometric and material complexities, it is difficult to control the surface finish quality and dimensional accuracy [148]. Therefore, hybrid manufacturing (HM) which combines AM and subtractive manufacturing (SM) has drawn great attention in recent years [149]. HM leverages AM's advantages in design freedom, supply chain reduction [150], environmental impact reduction [151], and SM's strength in high fabrication precision and surface finishing quality. To define the precedence constraints for HM process planning, the AM and SM features need to be defined and extracted. Because SM produces a part by removing materials in essence, the definition of SM features coincides with the conventional MFs. In an HM based remanufacturing context, Le et al. [152] defined the AM features (AMFs) as a geometrical shape and the associated attributes including geometrical form and dimensions, build directions, starting surface, material, and tolerance. Further, manufacturing rules were applied to associate MFs and AMFs to generate the process planning for HM, which is illustrated in Fig. 15. Obviously, AM and SM features should be distinguished to improve the manufacturability. Kerbrat et al. [153] developed a hybrid and modular approach to achieve the explicit separation, which is demonstrated in Fig. 16. On top of that, the cost model [154] and environmental impact model [151] were also investigated to enrich AM and SM features in HM.

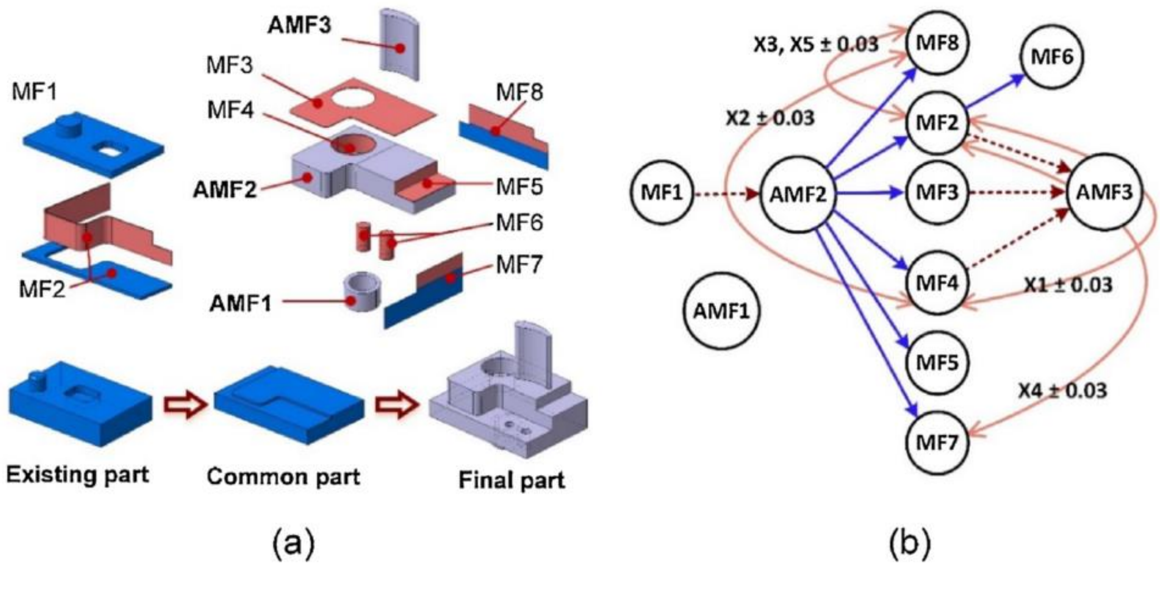

Fig. 15. Process planning for HM by SM and AM feature-based method: (a) MFs and AMFs extraction; (b) associations between MFs and AMFs [152].

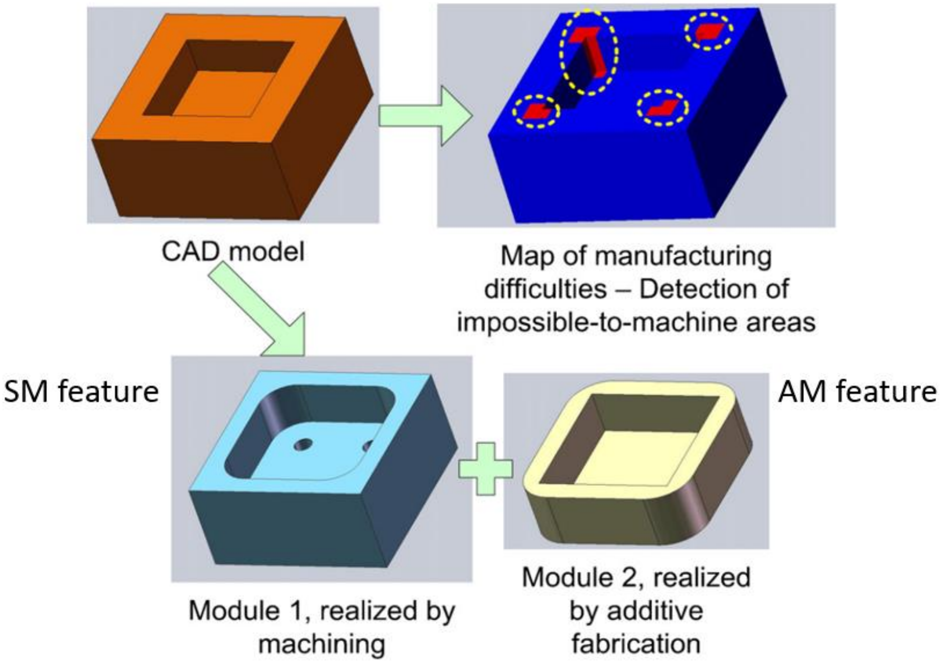

Fig. 16. Explicit separation of SM and AM features in reducing manufacturing difficulties [153].

Feature modeling techniques have demonstrated advantages in facilitating the process planning in HM. However, only the geometric information embedded in AM and SM features are not sufficient for process planning. Besides the manufacturing rules, the economic model and dynamic attributes also need to be further investigated for AM and SM features in an HM process.

5. Bottlenecks and future outlook of feature modeling methods

As can be seen from the literature reviewed in Section 4, feature modeling techniques have already been adopted in research fields like IoT, big data, social manufacturing, and AM. Though different, these domains are inter-related. To name a few, IoT can control and monitor the data-driven AM processes through specific applications [155]; based on the mining of big data, demands from customers can be extracted and matched with the capability of the SMRs in social manufacturing [156]. Facilitated by IoT and big data, manufacturing becomes smart. Combining smart manufacturing and AM, the socio-cyber-physical system (SCPS)-based manufacturing is established by adding a social “dimension” [157] to the cyber-physical system (CPS) [158]. This is a revolutionary manufacturing paradigm which achieves mass customization and mass personalization. However, the intricate associations in this system pose higher requirements for feature modeling methods.

5.1. Feature interoperability and information consistency across domains

In a review presented by Ma et al. [34] in 2008, feature interoperability is clearly pointed out as an issue which needs to be solved in a new feature modeling paradigm. After years of development in feature modeling techniques, the interoperability is still recognized as a problem in a review offered by Sanfilippo and Borgo [8] in 2016. They argue that the interoperability issue is due to the lack of a general theory to support the analysis and representation of the domain-specific information. This situation becomes more obvious in the new era for manufacturing in which heterogeneous data, devices, and standards are actively involved. The multifarious feature definitions in product development not only induce the interoperability issue but also present a threat to the consistency maintenance which is supposed to validate engineering intent [34]. As a result, engineering intent is difficult to maintain and easy to lose in an interdisciplinary situation.

5.2. New challenges in socio-cyber-physical system-based manufacturing

The interoperability and consistency issues occur after features shift from pure geometric modeling to product modeling in different stages of the product lifecycle. Nowadays, due to the rapid development of IoT, the services within the manufacturing environment become increasingly integrated [159]. Actually, the industrial IoT is the premise for industry 4.0 in which all kinds of equipment should interact effectively to complete the assigned tasks in a collaborative manner [160]. In SCPS-based manufacturing, the Internet, customers, social media, equipment, and producers interact intensively, which requires features should not be restricted to the modeling of a single product and its lifecycle. Instead, the functionalities of features should be extended to the modeling of the new manufacturing system. Besides the interoperability issue across different domains in SCPS-based manufacturing, the data-intensive applications involved in the system also challenge the application of feature modeling. Therefore, more investigation of feature modeling methods needs to be conducted in the future to resolve these challenges.

5.3. Future research directions

Inspired by the idea of feature-oriented domain analysis, the complex SCPS-based manufacturing system can be divided into various domains based on the features illustrated in Section 4. Definitely, the knowledge and techniques involved are domain-specific, which demands elaborate treatment to avoid the interoperability and consistency issue. However, defining a feature that models the whole system including heterogeneous domains is almost impossible and not necessary. Thus, generic features [161] are proposed to represent the common features in different domains, while associative features [147] should be applied to model the relationships among generic features in each domain. In this way, the feature based multidisciplinary manufacturing system can be established in a consistent and systematic way. As ontology based modeling is the major approach for product development in both software product line and manufacturing, the generic features and associative features should be formalized in an ontological manner. As demonstrated in Fig. 17, the detailed research directions of feature modeling methods, in the background of SCPS-based manufacturing, are suggested as follows.

1. Standardization is a potential solution to systematic interoperability [162]. For instance, STEP (Standard for the Exchange of Product data) by the International Organization for Standardization (ISO) [163] has been developed to describe the entire product data throughout the product lifecycle. To provide a unified feature definition within the scope of the concerned domain, standards should be established and provide a collection of glossaries. The messaging automation among the features in different domains can be achieved by features in the form of protocols.

2. Scalability is the ability of the storage to process increasing amounts of data in an appropriate manner [164], which is critical in this “big data” era. In SCPS-based manufacturing, the cloud database needs to be capable of managing the socio and

manufacturing data that change dynamically. Therefore, features have to be designed in flexible structures to meet the scalable requirement.

3. Security of social data sharing across enterprises is one of the factors that hinder the application of social manufacturing [105,165]. The secure communication of features attributed as private needs to be guaranteed. An example would be the feature information embedded in orders and transactions which are of business values in the highly competitive market. On the other hand, features of SMRs should be able to be managed by trending technologies like blockchain [166]. Thus, the security can be enhanced in the form of trustiness supported by a credit keeping mechanism.

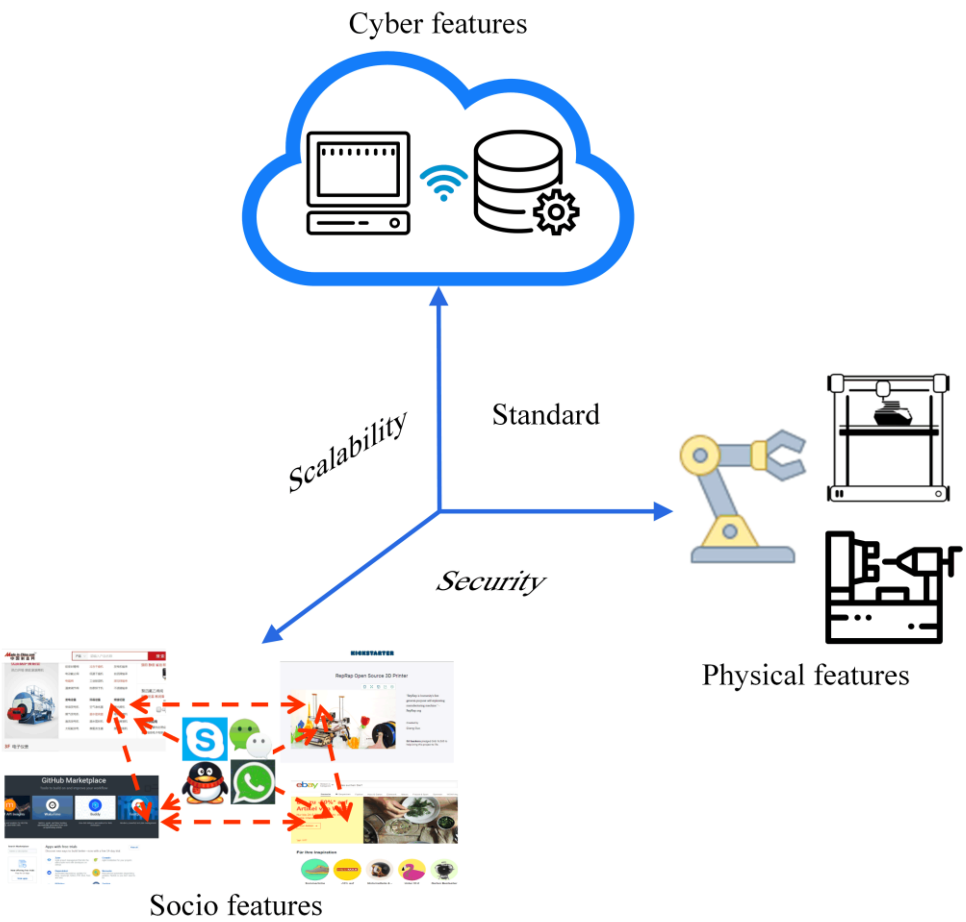

Fig. 17. Features and key components in SCPS-based manufacturing.

6. Conclusions

This paper briefly reviews features' initial application in geometry representation and extends the introduction of feature applications to product development stages like conceptual design, design analysis and improvement, manufacture, and assembling. Feature interoperability has become a trending research topic since the definition of features become application-driven. Correspondingly, efforts have been made in ontological feature modeling, multiple-view feature modeling, functional and physical feature modeling to resolve the interoperability issue. The emphasis of this paper is on the advanced feature modeling methods that have been proposed recently by researchers, who extended their efforts to the emerging techniques including IoT, big data, social manufacturing, and AM. Most features in these fields behave differently from the classical feature concepts, which distinguishes this survey from the other review papers on feature modeling methods.

The fusion of these emerging techniques promotes SCPS-based manufacturing. It is imperative to enrich the capability of features to the modeling of this new manufacturing paradigm beyond the application-oriented modeling of a single product. It has been revealed that the interoperability and data-intensive applications are the challenges in implementing feature modeling in SCPS-based manufacturing. For future development, it is proposed that the common features in each domain are represented by generic features while the correlations among the domains are established by associative features supported by the standardization of the concerned domain and protocols. Besides, features should be scalable to accommodate the data-intensive applications. The secure storage and sharing of features are also suggested to be further investigated.

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