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Research Article

An Ontology-Enabled Case-Based Reasoning Decision Support System for Manufacturing Process Selection

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In nowadays industry 4.0 and changeable manufacturing context, designers and manufacturing engineers struggle to determine appropriate quick, accurate (with flawless quality), and cost-effective processes to design highly customized products to meet customer requirements. To determine manufacturing processes, the matching between product features, material characteristics, and process capabilities needs to be optimized. Finding such an optimized matching is usually referred to as manufacturing process selection (MPS), which is not an easy task because of the infinite combinations of product features, numerous material characteristics, and various manufacturing processes. Although problems associated with MPS have received considerable attention, semantic web technologies are still underexplored and their potential is still uncovered. Almost no previous study has considered combining case-based reasoning (CBR) with ontologies, a famous and powerful semantic web enabler, to achieve MPS. In this study, we developed a decision support system (DSS) for MPS based on ontology-enabled CBR. By applying automatic reasoning and similarity retrieving on an industrial case study, we show that ontologies enable process selection by determining competitive matching between product features, material characteristics, and process capabilities and by endorsing effective case retrieval.

1. Introduction

In the era of the fourth industrial revolution (I4.0) [1] and amongst the changeable manufacturing [2], product design and development have to cope with tough challenges, such as mass customization, improved quality, reduced costs, and short lead times. To meet customer requirements, designers have to develop new designs or have to reengineer existing ones, rapidly, effectively, and efficiently [3]. Unfortunately, the materials and processes that shaped previous designs are either obsolete, not necessarily well suited, or no longer competitive enough to adapt existing designs or form new ones. Therefore, manufacturing material and process selection and/or adaptation need to be considered to bridge the gap between customer requirements, design specifications, material characteristics, and process capabilities [4]. Since a high percentage of production cost is determined at a design stage, material and processes need to be selected and adapted in a manner to keep design and development costs under control [5]. Therefore, decision support systems (DSS) are required to assist designers with material and process selection and adaptation [6].

Empowered by recent discoveries and new technologies, material engineering has contributed to the creation of new materials and composites. Material selection has gained immense attention recently, and numerous powerful digital tools have been developed to facilitate it [7]. For example, the MatWeb [8] library contains more than 120,000 types of materials, including metals, plastics, ceramics, and composites. Indeed, manufacturing process engineering has evolved to accommodate new materials. Ashby et al. [9] estimated that more than 1000 processes exist to shape materials. However, as we will explain in Section 2, developing DSS to assist manufacturing process selection (MPS) has not gained sufficient attention in recent studies. In fact, process selection is more complex and difficult than material selection for the following reasons [10]:

(i) Processes do not share the same characteristics. For example, the characteristics of welding processes are different from those of casting processes. Furthermore, standards such as the European EN ISO 4063 or the reference codes of the American Welding Society provide different characteristics for different categories of welding processes.

(ii) Each type of manufacturing process is restricted to certain materials. For example, casting processes are only suitable for metals and cannot be used with plastics.

(iii) The number of product features and attributes that should be considered in process selection is more important than in material selection.

(iv) Transferring product shape features to process characteristics can be a very complex task.

In small and medium enterprises and for product designs of small-to-medium complexity [11], the experience and expertise of designers and manufacturing engineers can be sufficient and reliable to determine the processes that can shape particular product designs. However, with the increasing complexity of customer requirements, material variety, product designs, and process capabilities, on the one hand, and due to the aging, retirement, and unavailability of manufacturing experts [12], on the other hand, the management of manufacturing and manufacturability knowledge is becoming increasingly difficult and challenging.

Since the early 1990s, artificial intelligence (AI) has been considered to assist or relieve human experts from dealing with some kinds of manufacturing design/engineering tasks. Several tools such as expert systems and case-based reasoning (CBR) systems have been developed to assist manufacturing engineering experts, especially for process selection [13]. However, such systems usually rely exclusively on either rules or cases to capture only part of the required manufacturing knowledge. Although they provide reasoning and inferencing capabilities, they usually fail to capture the underlying structure of manufacturing knowledge (e.g., relations, extensions, and specializations) [14]. Ontologies and the semantic web have recently emerged as technologies for knowledge representation [15]. These technologies tend to be adopted in the manufacturing domain to deal with and facilitate knowledge capture, structure, sharing, reasoning, and reuse [16]. However, semantic web technologies are still underexplored, and tools are still underdeveloped to match product features and material characteristics with process capabilities and to capture expert MPS knowledge. As it will be shown and assessed through a detailed literature review in Section 2, few studies have considered CBR, and almost none have considered combining CBR with ontologies to achieve MPS.

With respect to this gap, in this study, we developed an ontology-enabled CBR DSS for MPS. We aim to combine ontologies with CBR to achieve MPS through reasoning and inferencing based on rules for completely new product designs and similarity retrieval with existing previously stored design cases whenever a case base of designs is available. Therefore, the remainder of the study is organized as follows. Section 2 reviews related works about MPS. Section 3 introduces the suggested DSS architecture. Section 4 presents the conceptual model and details the description of the underlying ontology model along with knowledge instances and rules used to enable inferencing. Section 5 illustrates cases representation and product similarity calculations along with the retrieval algorithm. Section 6 elaborates a case study to show the usage and potential of the proposed system. Section 7 draws some conclusions and highlights some possible future works.

2. Related Works

MPS deals with the automatic allocation of manufacturing resources to achieve optimized matching between part features, material characteristics, and process capabilities based on input information including part geometry (geometric features and part dimensions) and constraints (quality, mechanical, and economical) [17]. For subtractive manufacturing, the process can be selected via a geometric analysis of features and then by matching these features with the appropriate machining processes [18]. For additive manufacturing, process selection can be done based on material choice, part size, and build quality [6]. This variation in the criteria for process selection makes it difficult to create generic allocators [17]. Therefore, several different MPS approaches exist:

(i) *Multicriteria decision-making approaches* (MCDM) rank available candidate processes based on a set of weighted criteria. Such approaches were suggested in [6, 19, 20].

(ii) *Systematic approaches* develop step-by-step procedures to facilitate the selection of materials and/or processes. A review of such approaches can be found in [9].

(iii) *Analytical methods*, such as those based on cost estimation, help designers evaluate and select the best capable processes [21].

(iv) *Optimization-based approaches* develop algorithms to determine processes based on the optimization of one or multiple criteria. Such approaches can be found in [22, 23].

It is worth noting that the applicability of these approaches is usually limited to a set of particular processes, and these approaches suffer from genericity shortcomings. For example, the approach by Kek and Vinodh [19] is dedicated only to injection molding and laser sintering, while the approach by D'Ans and Degrez [22] is confined to surface treatment technology processes. Therefore, more generic approaches are needed, and knowledge-based approaches can contribute to this end.

2.1. Knowledge-Based MPS. The matching between design specifications, material characteristics, and process capabilities needs to be preceded by the knowledge of several types of attributes, some of which can be expressed as numbers, like density or thermal conductivity; some are Boolean, such as the ability to be recycled; some, like resistance to corrosion, can be expressed only as a ranking (poor, adequate, and good, for instance); and some can only be captured in text and images [9]. The best suitable process for a particular combination of the work material and shape feature is generally selected by a domain expert on the basis of various factors, such as workpiece material, shape feature to be generated, material removal rate, surface finish, surface damage, corner radii, tolerance, cost, safety, and power requirements [24]. Process selection involves knowledge not only about the capabilities of individual resources and global processes but in some cases also about inabilities and shortcomings of resources and processes or about risks associated with the use of some technologies instead of others. Knowledge about strengths, weaknesses, history of use, and future potential of already made process selection decisions can also be of valuable help and support.

Thus, manufacturing engineers must have a vast and in-depth knowledge about the characteristics and capabilities of different available processes. Unfortunately, most of the manufacturing engineers lack exhaustive domain knowledge, and availability of experts is also sometimes constrained [24]. Therefore, several AI tools have been developed to assist manufacturing engineering experts with product design, material and process selection, and process planning tasks [13]. However, such systems usually rely on either rules or (in the exclusive sense) cases to capture only part of the required manufacturing knowledge. Although these methods provide reasoning and inferencing capabilities, they usually fail to capture the underlying structure of manufacturing knowledge (e.g., relations, extensions, and specializations) [14]. This more exhaustive knowledge capture is better achieved by recent emerging semantic web technologies [25].

2.2. Semantic Web Technologies for MPS. According to Ramos [16], an ontology is a method for knowledge representation that enables reasoning on asserted knowledge to infer new knowledge. Semantic web technologies are considered a way to design ontologies available for networks of computers. Ontologies are an enabler of knowledge-based systems that allow the following [26, 27]:

(i) Structuring knowledge about a specific domain based on taxonomies and class (also called concept) hierarchies
(ii) Defining a standardized and common vocabulary for users and software
(iii) Instantiating data, facts, and knowledge elements through class/concept instances, also called individuals
(iv) Capturing complex relations between knowledge elements through properties, restrictions (also called class/concept membership criteria), and rules
(v) Reasoning about facts and inferring new ones, particularly through automatic classification

Manufacturing engineering involves research related to the ontology of CAD [28] and some ontologies of manufacturing [29, 30]. Urwin and Young [31] introduced an ontology to capture machining knowledge to facilitate the design of complex products in aerospace manufacturing. An ontology that focuses on supporting the interoperability between manufacturing enterprises is suggested by Palmer et al. [25]. El Kadiri and Kiritsis [27] reviewed the use of ontologies for product lifecycle management. Sanfilippo and Borgo [32] presented a state of the art of the feature-based product modeling approach and proposed a high-level ontology-based perspective to harmonize the feature definitions. Later, Sanfilippo [33] suggested a modular ontological architecture and a general framework where features are contextualized within a larger system for product knowledge representation.

A few studies have considered ontologies to primarily help with the material selection task and its relation to, interactions with, and influence on process selection [14]. In the particular case of the process selection task, some effort has been dedicated to structure the knowledge on materials and processes [34]. Some ontology-based approaches have been developed for specific processes, such as additive manufacturing [35], and therefore suffer from genericity considerations. Some studies have developed semantic approaches to the automatic recognition of machining features [18].

As stated and thoroughly discussed by Ramos [16] and Sanfilippo et al. [36], to date, generally accepted manufacturing ontologies are lacking; there is no standard ontology for materials, products, resources, processes, or manufacturing systems. Moreover, ontology languages have different levels of expressivity, making careful process of evaluation for each use case necessary [37].

Although here we do not claim to address all shortfalls raised by Ramos [16] and Sanfilippo et al. [36], we develop an ontology that is compatible with existing ones and that primarily focuses on recommending manufacturing processes for candidate product features and material characteristics under consideration. The suggested ontology-based system contributes to bridging the gap between product engineering, material engineering, and process engineering.

2.3. CBR for MPS. CBR is an AI paradigm that brings together reasoning and machine-learning techniques to solve problems based on past experiences, called cases [38]. One of the greatest assets of CBR is its eagerness to continuous learning. Main et al. [39] provided a step-by-step tutorial on development of a CBR system. Richter and Weber [40] detailed the methods, techniques, and tools used to design a

CBR system. Bergmann et al. [41] and Biswas et al. (2014) provided an overview of CBR applications in various domains, including engineering, medicine, law, and economy.

With respect to MPS, some researchers have developed CBR approaches to select manufacturing process equipment [43, 44]. These studies considered a specific type of process and tried to select the best equipment to improve the output of the process. CBR approaches have also been suggested for process parameter identification, selection, and set up [45–47]. Xia and Rao [48] suggested a CBR approach to help in operating the manufacturing process. In these studies, the process type is already known in advance. Boral and Chakraborty [24] developed a CBR approach for MPS. This approach is specific to nontraditional machining processes and therefore suffers from genericity considerations.

To the best of our knowledge, no study has combined ontologies with CBR to achieve MPS. In the following text, we show that such hybridization is appealing because it combines ontology and CBR features, as shown in Table 1.

3. System Architecture

The architecture of the suggested DSS is depicted in Figure 1 in terms of components (ontology and graphical user interface (GUI)), functions (specify, search, and select processes based on similarity, select processes based on rules, adapt processes and store cases), and interactions with decision makers (DMs).

The DSS is designed to achieve the following main functions:

(i) *Specify product features and attributes*. when a new product is under consideration for process selection, a new instance is created in the ontology to specify its features and attributes (cf. Section 6.1). This information will be used to recommend processes based on matching the product features and attributes to predefined process capabilities using rules and cases.

(ii) *Search for similar product(s)*. at this step, the ontology is searched for product(s) that share similarities with the new design under consideration. A similarity algorithm evaluates the proximity between designs in terms of common features and close attribute scores (cf. Section 5).

(iii) *Select processes based on similarity*. to manufacture the new product under consideration, DMs are given the possibility to select those processes that were used to manufacture similar products stored as cases in the ontology.

(iv) *Select processes based on rules*. in case the similarity algorithm does not find any similar products stored in the ontology, automatic reasoning and inferencing recommend process(es) based on SWRL rules (cf. Section 4.4). To manufacture the new product under consideration, the DM is given the possibility to select the most convenient processes from the set of recommended ones.

(v) *Adapt selected processes*. DM can then adapt the recommended processes (i.e., add, remove, and change).

(vi) *Adapt selected processes*. finally, the case (a new product under consideration and the selected/adapted processes) is stored in the ontology to enable the future similarity-based retrieval.

4. Ontology Design

The suggested ontology is compatible with the existing reference manufacturing system ontologies, such as ontologies in [29, 30, 49, 50]. Protégé [51] is used as the construction tool. The process selection knowledge involves three main concepts: manufacturing process concept, engineering material concept, and engineering product concept. This selection knowledge is structured and represented in a unified modeling language (UML) class diagram, as shown in Figure 2.

4.1. Manufacturing Processes.

Manufacturing processes involve science and technology by which a material is given its final shape, satisfying the necessary structure and properties of its intended use [52]. Formation of the desired shape is a major part of processing, which could be a simple, one-step operation or a combination of various processes, depending on the part design and material specification. The *MfgProcess* class captures the knowledge about manufacturing processes in terms of taxonomy and the capabilities of the manufacturing processes.

4.1.1. Taxonomy of Manufacturing Processes.

The *MfgProcess* class is specialized/extended into as many subclasses as required to span the range of the existing manufacturing processes. For instance, the suggest taxonomy is compatible with the one by Swift and Booker [52]:

(i) The *Casting* subclass captures knowledge about casting processes (i.e., sand casting, die casting, and investment casting), where a molten metal is poured in a mold cavity to give the desired shape

(ii) The *Molding* subclass captures knowledge about molding processes (i.e., plastic and composite processing, powder metallurgy, and foaming), where a liquid or pliable raw material is shaped in a mold

(iii) The *Forming* subclass captures knowledge about the forming processes (i.e., forging, sheet metal, and extrusion), which make use of suitable stresses (compression, tension, shear, or combination of stresses) to cause plastic deformation

(iv) The *Machining* subclass captures knowledge about both traditional (i.e., milling, turning, and drilling) and nontraditional (i.e., electrical discharge machining, electrochemical machining, electron beam machining, laser beam machining, chemical machining, ultrasonic machining, and abrasive jet machining)

Table 1: Appealing features of ontology and CBR combination.

Features	CBR	Ontology	Ontology-enabled CBR
Complex representation of knowledge through the concepts and relations of object-oriented modeling and design (classes, instances, relations, properties and attributes, and inheritance)		✓	✓
Knowledge representation of past experiences and outcomes	✓		✓
Inferencing and reasoning based on similarity	✓		✓
Inferencing, reasoning, and automatic classification based on restrictions and rules		✓	✓

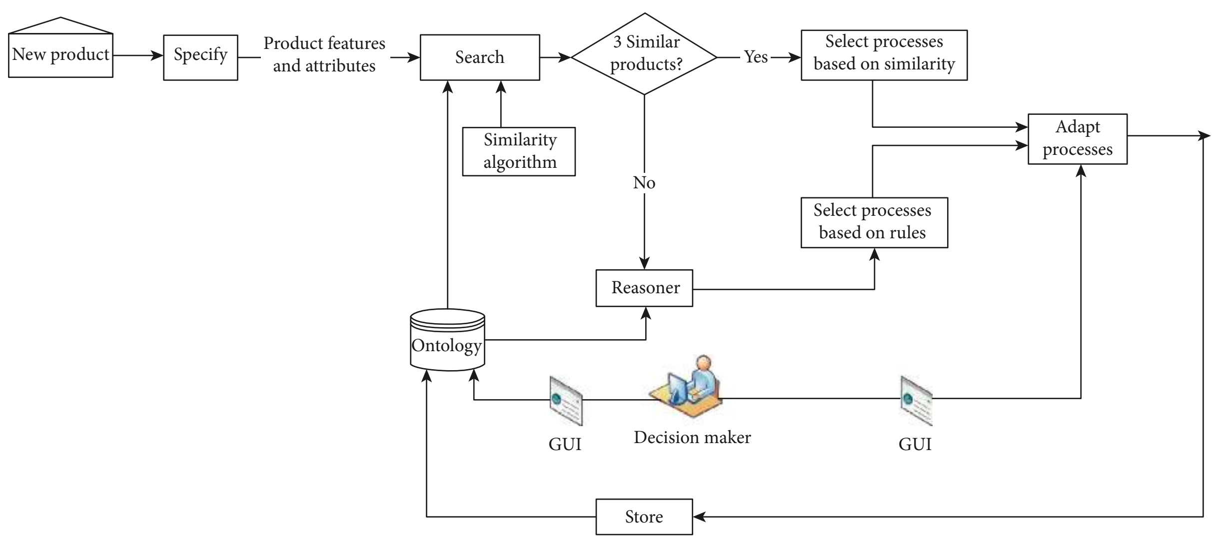


Figure 1: Architecture of the suggested DSS for MPS.

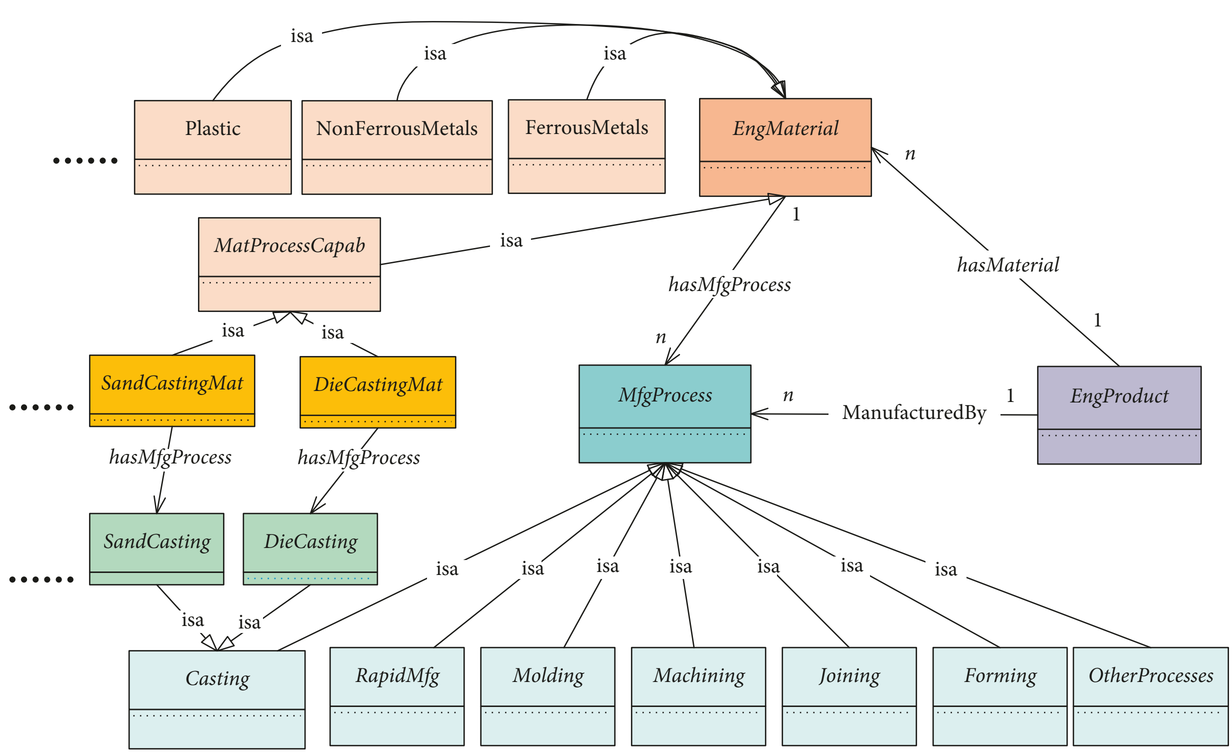


Figure 2: Process selection knowledge model.

machining processes, where a piece of material is cut into a desired final shape and size by a controlled material removal process

(v) The *Joining* subclass captures knowledge about joining processes (i.e., assembly, welding, screwing, and press fitting), where two or more parts are connected at their contacting surfaces

(vi) The *RapidMfg* subclass captures knowledge about rapid manufacturing processes (i.e., 3D printing, selective laser sintering, and lamination), where a solid object is manufactured by sequential delivery of energy and or material to the specified point in space

(vii) The *OtherProcesses* subclass captures knowledge about other function processes, such as lapping, morticing, and blasting

Notably, the *MfgProcess* class can be extended with other new classes to accommodate advances in manufacturing science.

4.1.2. Capabilities of Manufacturing Processes. Each manufacturing process has different capabilities in terms of product features and attributes it can realize.

(i) Product features are related to structural properties of product shape, such as depression, uniform wall, axis of rotation, and regular cross section. Shape generation capabilities describe the requirements of product features a process can meet.

(ii) Product attributes are related to dimensioning properties of product design, such as size, thickness, weight, tolerance, and surface finish. Range capabilities describe the product attribute requirements a process can meet.

Consequently, MPS is based on matching product features and attributes to shape generation and range capabilities.

(1) Shape Generation Capabilities. These describe the requirements of product structural properties (i.e., a form of product or its external and internal boundaries or surfaces) that can be met by a process. This study relies on the same description as Boothroyd et al. [5] to structure these capabilities, which involves the following.

(i) Depression in a single direction: it is the ability to form a groove or recess in the surface of the part in a single direction of tooling motion. An example of the tooling motion direction is the direction of mold opening in injection molding and the direction of the extruded product in an extrusion process. This capability is described in the ontology using *hasDepressSingleDirec* data property.

(ii) Depression in a double direction: it is the ability to form a groove or recess in the surface of the part in a double direction of the tooling motion. This capability can be described in the ontology using the *hasDepressDoubleDirec* data property.

(iii) Uniform wall: it refers to the thickness of part walls. Any nonuniformity arising from the natural tendency of the process, such as material stretching or buildup behind projections in centrifugal processes, is ignored, and the wall is still considered uniform. This capability is described in the ontology using *hasUniWall* data property.

(iv) Uniform cross section: it refers to parts where any cross sections normal to the axis of a part are identical, excluding a draft (slight taper) in the axial direction for die or mold release. This capability is described in the ontology using a *hasUniSect* data property.

(v) Axis of rotation: it refers to parts whose shapes can be generated by rotation around a single axis. This capability is described in the ontology using the *hasAxisRot* data property.

(vi) Regular cross section: cross sections normal to the axis of the part contain a regular pattern (i.e., a splined shaft or hexagonal pattern). Changes in shape that maintain a regular pattern are permissible (i.e., a splined shaft with a hexagonal head). This capability is described in the ontology using the *hasRegXSec* data property.

(vii) Captured cavity: it is the ability to form cavities with reentrant surfaces (i.e., a bottle). This capability is described in the ontology using the *hasCaptCav* data property.

(viii) Enclosed: it refers to parts that are hollow and completely enclosed. This capability is described in the ontology using the *hasEnclosed* data property.

(xi) Draft-free surface: it refers to production of constant cross sections in the direction of the tooling motion. Many processes can approach this capability when less than ideal draft allowances are specified, but this designation is reserved for processes where this capability is a basic characteristic and no draft can be obtained without cost penalty. This capability is described in the ontology using the *hasNoDraft* data property.

(2) Range Capabilities. These describe which requirements of product dimensioning properties a process can meet.

(i) Tolerance: it refers to the permissible limit(s) of variation in a physical dimension of a product in millimeters. This capability is described in the ontology using the *hasTolerance* data property and can be measured using *hasToleranceUnit* in mm.

(ii) Surface finish: it refers to the measurement of the surface texture or topography in millimeters. This capability is described in the ontology using the *hasSurfaceFinish* data property. The measurement unit is described using the *hasSurfaceFinishUnit* property and is measured in mm.

(iii) Part weight: it refers to the measurement of product weight in kilograms. This capability is described in the ontology using the *hasPartWeight* data property. The measurement unit is described using the *hasWeightUnit* property and is measured in kg.

(vi) Max (and min) wall thickness: it refers to the measurement of the maximum (and minimum) wall thickness in millimeters. This capability is described in the ontology using the *hasMaxWallThickness* (and *hasMinWallThickness*) data property. The measurement unit is described using the *hasThicknessUnit* property and is measured in mm.

(v) Material capability: it refers to the ability of the manufacturing process to shape a set of materials so that each engineering material can be shaped by a set of processes. This capability is described in the ontology using the *hasMfgProcess* object property.

(vi) Required quantity: it refers to the economic lot size (minimum number of pieces) to be produced using a process. In practice, each manufacturing process is recommended to produce a range of quantities because of cost considerations. For example, sand casting and die casting processes have the capability to manufacture the same product, but the selection between the two processes is based on the quantity of production. On account of the mold and equipment costs, sand casting is costly for low quantities, while die casting is costly for high quantities. Therefore, the required quantity has to be considered as a range capability. This capability is described in the ontology using the *hasReqQuantity* data property. The measurement unit is described using the *hasQuantityUnit* property and is measured in *Pcs.*

Figure 3 shows the definition of these capabilities in the suggested ontology.

(3) Example. In an ontology-based semantic representation, an instance (individual) is a specific realization of an ontology class. Knowledge of each manufacturing process, engineering material, and product is captured as instances. To capture realistic knowledge about the capabilities of a set of manufacturing processes, the ontology is instantiated with data obtained from the CustomPart [53] library. For example, *Casting* class is a pool of manufacturing process instances such as *SandCasting*, *DieCasting*, and *InvestmentCasting*. To define the *SandCasting* instance, the shape generation and range capabilities are defined, as shown in Table 2.

4.2. Engineering Materials. Knowledge about materials is captured in the *EngMaterial* class and classified into two subclasses: knowledge about material types is stored in the *MatTypes* subclass, while that related to the manufacturability is stored in the *MatProcessCapability* subclass.

(i) In the *MatTypes* subclass, knowledge regarding engineering materials is classified based on the atomic bonding force of the particular material and can be divided into three classes: *MetalsMat*, *PolymericMat*, and *CeramicsMat.* Additionally, materials can be combined to create a forth class *CompositesMat* (cf. Figure 4(a)).

(ii) In the *MatProcessCapability* subclass, knowledge regarding engineering materials is classified into subclasses based on the capability of the manufacturing processes to shape these materials (cf. Figure 4(b)). For example, *SandCastingMat* class includes materials that can be shaped using sand casting processes, which are mostly metals such as aluminum, copper, lead, magnesium, tin, and zinc [53].

4.3. Engineering Products. Knowledge about products to be engineered is captured in the *EngProduct* class. The product can be a single part or a constituent of a product. *EngProduct* class is classified into subclasses based on the application of the product, such as *ApplianceProducts*, *PumpProducts*, *AutomobileProducts*, and *EngineProducts* (cf. Figure 4(c)). Knowledge of engineering products is defined using the features and attributes of the product (cf. Figure 3). Product-related knowledge is provided by experts and increases gradually as the ontology is used to select processes.

4.4. Rules and Inference. The hierarchal classification of process selection knowledge alone is not sufficient to capture causal relationships. Semantic web rule language (SWRL) is an effective method to represent causal relations and has been widely applied in knowledge systems [37]. SWRL rules need to be considered to enable deductive reasoning and knowledge retrieval. In this work, SWRL rules are used to define manufacturing processes and engineering products to match product features and attributes with process characteristics and capabilities.

SWRL rules are expressed in the following form: antecedents $\longrightarrow$ consequence. Antecedent and consequence parts can be expressed as the conjunctive formula of atoms $a_1 \wedge a_2 \wedge, \ldots, \wedge a_n$ and $b_1 \wedge b_2 \wedge, \ldots, \wedge b_m$, respectively. Atom a_i and b_j ($1 \leq i \leq n$, $1 \leq j \leq m$) can be in either of the forms $C(?x)$ or $P(?x, ?y)$, in which if x is an instance of class C, then $C(?x)$ holds; if x is related to y by property P, then $P(?x, ?y)$ holds. To explain usage of SWRL rules, the definition of the *SandCasting* instance is explained in "Example" in Section 4.1.2. The SWRL rule shown in Table 3 defines the shape generating capability and range capability of the sand casting process shown in Table 2. This rule means that if any engineering product satisfies this antecedent (shape generating capability and range capability), the sand-casting process will be recommended to shape this product.

Rule completeness is verified for parts that are known in advance. Five types of local industries are visited (automobile spare parts, pumps, engines, appliance, and electric parts), and hundreds of engineering products/parts are selected. The selected products are diversified as much as possible to cover a wide range of manufacturing process

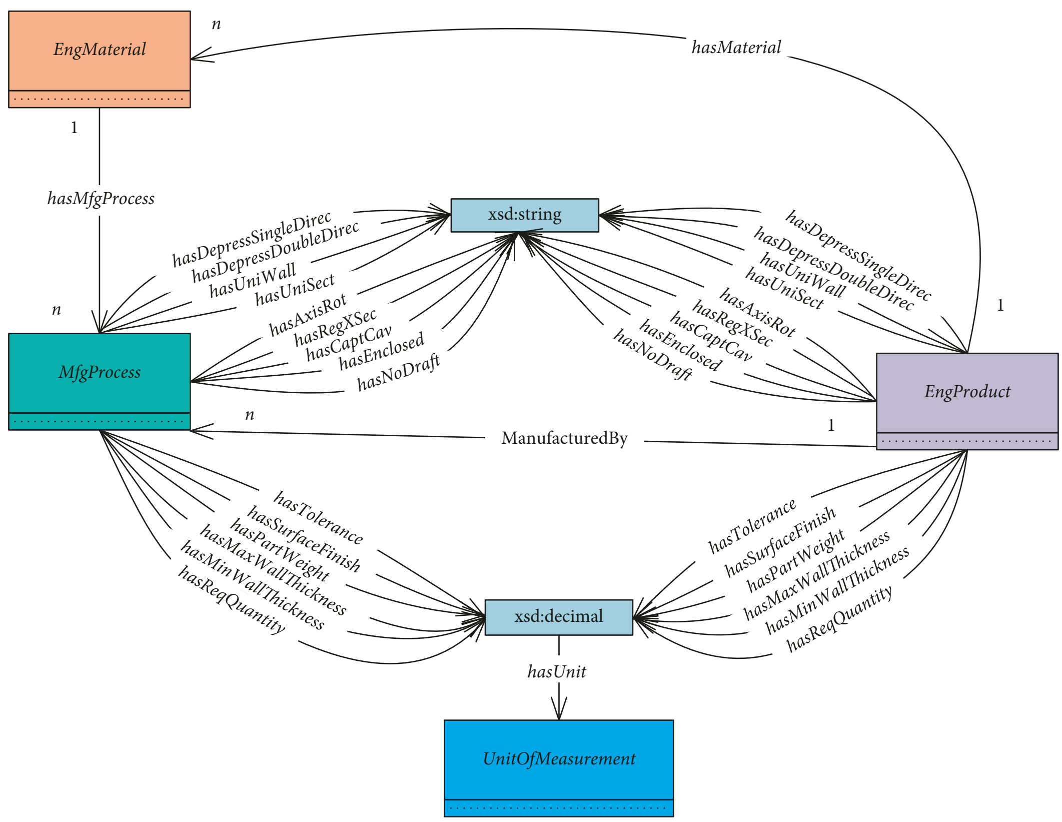


Figure 3: Definition of the manufacturing process class.

Table 2: Shape generation and range capabilities of the sand casting process.

Shape generation capabilities		Range of capabilities		
Features	Capability	Attributes	Range	Unit
Depression in a single direction	*Y*	Tolerance	>0.381	mm
Depression in a double direction	*Y*	Surface finish	>0.003175	mm
Uniform wall	*Y_*	Part weight	(0.0907, 450,000)	kg
Uniform cross section	*Y*	Max wall thickness	<1016	mm
Axis of rotation	*Y*	Min wall thickness	>3.175	mm
Regular cross section	*Y*	Required quantity	(11,000)	Pcs
Captured cavity	*Y*	Material capability	Aluminium, copper, lead, magnesium, metals, tin, zinc	
Enclosed	*N*			
Draft-free surface	*N*			

Y: process is capable of producing parts with this characteristic; *N*: process is not capable of producing parts with this characteristic; *M*: parts produced with this process must have this characteristic; *Y_*: parts using this process are easier to form with this characteristic.

types. Rules and inferencing are crucial to match product features and attributes to process characteristics and capabilities, especially in case the product is new and no similar product is stored in the ontology, and to build the ontology knowledge and enable case-based selection of processes based on product similarity retrieval when there are similar product(s) stored in the ontology.

5. CBR

CBR comprises a few core parts: case representation, case retrieval, similarity measures, and case adaptation. In the suggested approach, the adaptation is carried out by the DM (Section 3). The remaining parts of the developed CBR are described in this section.

5.1. Case Representation. Two main types of case representations exist to capture the case knowledge: traditional and semantic methods. Traditional case representations are simple methods such as feature vector frame-based, object-oriented, textual, hierarchal, and predicate-based methods. Semantic methods such as ontologies and semantic rules are known as knowledge-intensive methods, which are more intelligent ways, and in addition to case representation, can enhance the whole CBR process including retrieval, storage, and adaptation. El-Sappagh and Elmogy

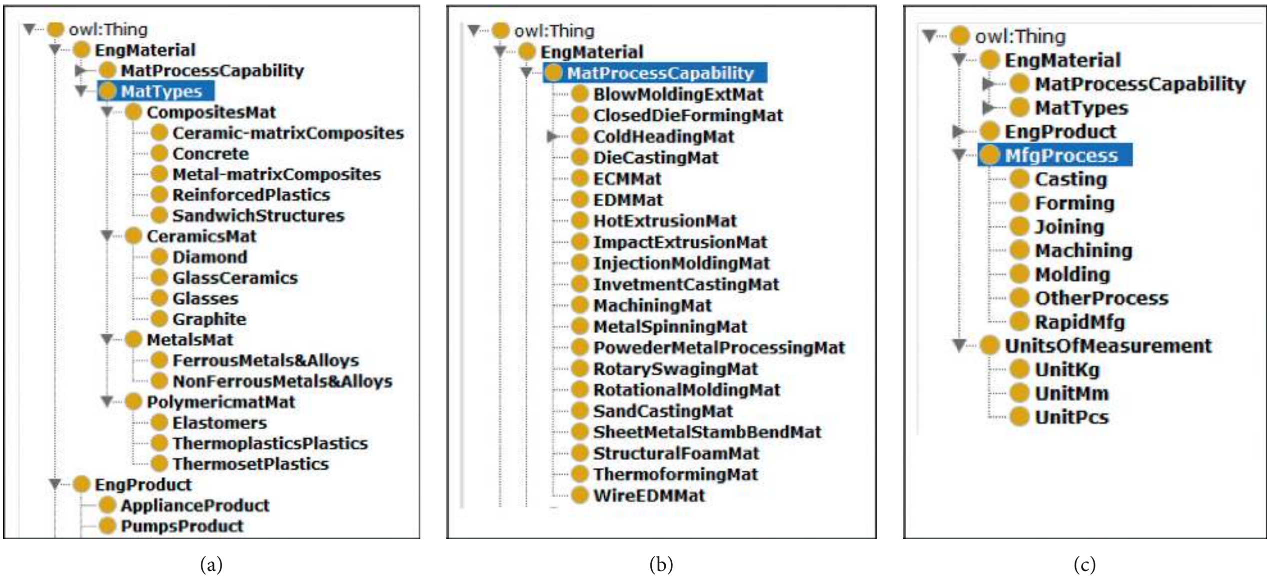


Figure 4: Taxonomy of (a) materials, (b) capabilities, and (c) manufacturing processes.

Table 3: SWRL rule for the defining sand casting process.

Antecedent	Consequence
EngProduct(?x) ^ hasMaterial(?x, ?y) ^ SandCastingMat(?y) ^ hasDepressSingleDirec(?x, ?DSValue) ^ swrlb: startsWith(?DSValue, "Y") ^ hasDepressDoubleDirec(?x, ?DDValue) ^ swrlb:startsWith(?DDValue, "Y") ^ hasUniWall (?x, ?UWValue) ^ swrlb:startsWith (?UWValue, "Y") ^ hasUniSect(?x, ?USValue) ^ swrlb:startsWith(?USValue, "Y") ^ hasAxisRot(?x, ?ARValue) ^ swrlb:startsWith(?ARValue, "Y") ^ hasRegXSec(?x, ?RXSValue) ^ swrlb:startsWith(?RXSValue, "Y") ^ hasCaptCav(?x, ?CCValue) ^ swrlb: startsWith(?CCValue, "Y") ^ hasEnclosed(?x, ?EnValue) ^ swrlb:startsWith(?EnValue, "N") ^ hasNoDraft(? x, ?NDValue) ^ swrlb:startsWith(?NDValue, "N") ^ hasPartWeight(?x, ?PWvalue) ^ swrlb:greaterThan(? PWvalue, 0.0907) ^ swrlb:lessThan(?PWvalue, 450000) ^ hasUnit(?x, ?PWUnValue) ^ Unitkg(? PWUnValue) ^ hasMinWallThickness(?x, ?MWTValue) ^ swrlb:greaterThan(?MWTValue, 3.175) ^ hasMaxWallThickness(?x, ?MxWTValue) ^ swrlb:lessThan(?MxWTValue, 1016) ^ hasThicknessUnit(?x, ? ThUnValue) ^ UnitMm(?ThUnValue)^ hasTolerance(?x, ?TValue) ^ swrlb:greaterThan(?TValue, 0.381) ^ hasToleranceUnit(?x, ?TUnValue) ^ UnitMm(?TUnValue) ^ hasSurfaceFinish(?x, ?SFValue) ^ swrlb: greaterThan(?SFValue, 0.003175) ^ hasSurfaceFinishUnit(?x, ?SFUnValue) ^ UnitMm(?SFUnValue) ^ hasReqQuantity(?x, ?RQNumber) ^ swrlb:greaterThan(?RQNumber, 1) ^ swrlb:lessThan(?RQNumber, 1000)hasQuantityUnit(?x, ?QUnValue) ^ UnitPcs(?QUnValue)	SameAs(SandCasting, ?x)

[54] investigated the effectiveness of the two representation methods and found that semantic representation overweighs the traditional methods, which are considered to be knowledge-poor representations. They do not describe constrains and relations between cases features. However, such methods can be used for simple cases with relatively few features. This study developed a semantic representation for the knowledge related to product features that determine the selection of manufacturing processes. The suggested ontology (cf. Section 4) is used as a formal platform to represent the cases.

Cases of MPS comprise the new product as the problem and the manufacturing process as a solution. The structure of the case is shown in Table 4. The case contains features of the product and manufacturing process that determine the capability of the manufacturing processes to shape the product. The case contents are product shape features and attributes and process-related capabilities (cf. Section 4.1.2). Each case stored in the ontology has a product linked to one manufacturing process by the *hasMfgProcess* object property (cf. Figure 3). Many products can be manufactured by the same manufacturing process, a fact on which the retrieval process is built. The algorithm retrieves any stored product(s) similar to the new product to investigate the possibility of using the same process used to manufacture the former to manufacture the latter. A representation of a new product is captured when a new product or change in the design of an existing product is introduced, while a representation of the new manufacturing process occurs less frequently when a new process is invented to accommodate the rapid changes of products and the synthesis of new materials.

5.2. Product Similarity. The objective of similarity evaluation and product retrieval is to search the ontology for product(s) that are similar to a new product under consideration and to

Table 4: An overview of case representation.

	Case part	Content	Update frequency
Problem description	New product	Product shape features Product attributes	(i) Introduction of the new product (ii) Design change for the existing product
Solution	Manufacturing process	Shape generation capabilities Range capabilities	(i) Invention of new process

sort them from the most similar to the least similar. Similarity measures quantify the degree of resemblance between a new product and existing products and play a very important role in ontology retrieval. In previous studies, numerous similarity measures have been proposed, including numeric, syntactic, and semantic evaluations [55, 56].

Existing semantic similarity measures, such as those developed by Akmal et al. [55], Lin [57], and Palmer [58], are based on data and object properties of the products, focusing mainly on properties inherited from the upper classes. Such measures are not effective for MPS, where similarity based on the inherited properties of two products does not mean they can be manufactured using the same process. For example, a metal base and a handle of an electric kettle inherit the same properties of the electric kettle. However, they are manufactured using two different processes. The metal base is manufactured by the sheet metal forming processes, while the handle is manufactured by injection molding.

Some approaches, such as the one used by Fradi et al. [59], identify similar products based on shape features. Coding approaches such as Optiz, KK-3, MICCLASS, and DCLASS focus on selecting a set of products to form a group technology, in which similar parts are manufactured in one location using a set of machines named a manufacturing cell. Such approaches are not pertinent for MPS because they neglect most of the nine shape features listed in “Shape Generation Capabilities” in Section 4.1.2, which are critical for determination of processes capabilities.

To retrieve similar products, a similarity measure should be designed based on product shape features and attributes, which determine the capability of the manufacturing process(es) (cf. Section 4.1.2). In this approach, a new semantic similarity retrieval method is designed to measure the mutual product shape features and attributes by calculating the value of object and data properties in the ontology, which quantify these connections. So the developed measure focused only on these objects and data properties and not on all inherited properties such as the existing semantic similarity measures. Designing the similarity measure depends on problem characteristics and the measuring scale (nominal, interval, or ratio) of these characteristics. Product shape features and attributes are measured in two different scales. For these reasons, two similarity methods are developed for convenience for the two-measurement scales. In the following text, the two similarity measures and their weighting methods are explained.

5.2.1. Weight of Product Features and Attributes. Assigning weights to criteria is a difficult task, especially for DMs who are not familiar with the intricacies or subtleties of MCDM techniques. Simos [60, 61] proposed a technique based on a pack of cards that allow any DM (not necessarily familiarized with MCDM) to think about and express the way in which the DM wishes to prioritize the different criteria. This procedure also aims to communicate to MCDM specialists the information needed to assign a numerical value to the weights. The original SIMOS procedure was later revised to overcome some of its limitations [62] and robustness issues [63]. The revised SIMOS procedure is used to assign weights to the product features and attributes separately. To avoid bias, three experts from three different industries are involved individually in the revised SIMOS procedure. Thus, the average weight is considered for similarity calculation.

Table 5 shows the result for product features weight (WF_i). The three experts agreed that the enclosed and draft-free surfaces are the two most important features for determining the manufacturing process. Although they have different views regarding the importance of depression in the double and single directions, there is, to some extent, a consensus on the other four shape features.

The same process is repeated for eliciting the weight of product attributes (WA_i). Table 6 shows this result. By far, tolerance is the dominant attribute for processes selection. The three SIMOS applications for the three experts assigned more than 30% of weight for this attribute. Both max wall thickness and min wall thickness are assigned around 40% of the weight combined. The remaining 30% is divided between the other three attributes: around half for surface finish and half for both part weight and part quantity.

5.2.2. Similarity of Product Features. The nine product features listed in the first column of Table 2 are considered to calculate product feature similarity ($\mathrm{FSim}(x, y)$) as a percentage. As product features are measured in a nominal scale (i.e., only one value among the set {Y, N, M, and $Y\_$} is assigned to each feature, as illustrated in Table 2), determining an exact match between each feature value for two different products to be compared is possible. First, the value of similarity ($\mathrm{Sim}(x_i, y_i)$) of two products x and y is calculated for each feature i, $i = 1, \ldots, 9$, using the following equation [56]:

$$\mathrm{Sim}(x_i, y_i) = \begin{cases} 1, & x_i = y_i, \\ 0, & x_i \neq y_i, \end{cases} \quad (1)$$

where x_i is the value of feature i for product x. Next, the following equation is developed to calculate $\mathrm{FSim}(x, y)$:

Table 5: Product feature weight.

Product features	Expert #1	Expert #2	Expert #3	Average (WF_i)
Regular cross section	0.046	0.059	0.046	0.05
Axis of rotation	0.046	0.059	0.046	0.05
Uniform cross section	0.072	0.073	0.063	0.07
Uniform wall	0.072	0.073	0.08	0.07
Depression in a double direction	0.097	0.133	0.12	0.12
Depression in a single direction	0.097	0.088	0.127	0.11
Draft-free surface	0.174	0.162	0.159	0.16
Enclosed	0.198	0.176	0.174	0.18
Captured cavity	0.198	0.176	0.176	0.19
				$\sum \mathrm{WF}_i = 1$

Table 6: Product attributes weight.

Product attributes	Expert #1	Expert #2	Expert #3	Average (WA_i)
Required quantity	0.113	0.074	0.045	0.05
Part weight	0.134	0.074	0.073	0.09
Surface finish	0.175	0.148	0.153	0.15
Maximum wall thickness	0.195	0.185	0.18	0.18
Minimum wall thickness	0.195	0.185	0.207	0.19
Tolerance	0.3	0.334	0.341	0.32
				$\sum \mathrm{WF}_i = 1$

$$\mathrm{FSim}(x, y) = \frac{\sum_{i=1}^{9} \mathrm{WF}_i \times \mathrm{Sim}(x_i, y_i)}{9} \times 100. \qquad (2)$$

5.2.3. Similarity of Product Attributes. Six product attributes are used to calculate the similarity score between products x and y, namely, tolerance, surface finish, part weight, required quantity, and maximum and minimum wall thickness. As the attributes are measured as a ratio, the similarity can be calculated as a percentage. The similarity percentage (ASim) of attribute j between two products x and y can be calculated as follows:

$$\mathrm{ASim}(x_j, y_j) = \frac{\min(x_j, y_j)}{\max(x_j, y_j)} \times 100, \qquad (3)$$

where x_j is the value of attribute j of product x and $j = 1, \ldots, 6$. The two values of attributes x_j and y_j should be measured with the same measurement scale explained in "Range Capabilities" in Section 4.1.2. Then, the similarity score $(\mathrm{Score}(x, y))$ of the six attributes is calculated as follows:

$$\mathrm{SScore}(x, y) = \frac{\sum_{j=1}^{6} \mathrm{WA}_i \times \mathrm{ASim}(x_j, y_j)}{6}. \qquad (4)$$

As a result, the feature and attribute similarity percentages can be used for product retrieval, as will be explained in the following section.

5.3. Product Retrieval. A semantic retrieval algorithm is developed to fetch through existing products stored in the ontology and list the products that are similar to the new product under consideration. In the beginning, to calculate an overall product similarity percentage, the average value of similarity product features and attributes is used to retrieve products from the ontology. Unexpectedly, in some cases, the similarity algorithm results in products manufactured by a process that are not capable to shape the new product. Such misleading results, in majority of the cases, are caused by the high similarity of product attributes and low similarity of features. Almost, all products with high similarity values of shape features can be manufactured with the same process or at least by the same family of processes. For example, sand casting, die casting, and gravity casting are from the casting process family, which can shape the same product features with some differences in product attributes such as surface finish and tolerance.

Table 7: Threshold of product features similarity.

$\mathrm{FSim}(x, y)$	Number of irrelevant processes	%
0.3	28	28
0.4	18	18
0.5	13	13
0.6	4	4
0.7	2	2
0.8	1	1
0.9	0	0

To overcome this issue, a threshold feature is designed, according to which the stored product(s) should have some common features with the new product to be selected. The threshold is a value of the $\mathrm{FSim}(x, y)$ score, which represents a cutoff value of similarity shape features out of one that product should have to be selected. One hundred products are selected to run the experiment for seven percentage values. Table 7 shows the result of the experiments and how many irrelevant product processes are retrieved corresponding to threshold values. The experiment begins with an $\mathrm{FSim}(x, y)$ value of 0.3, where less than 0.3 feature similarity usually

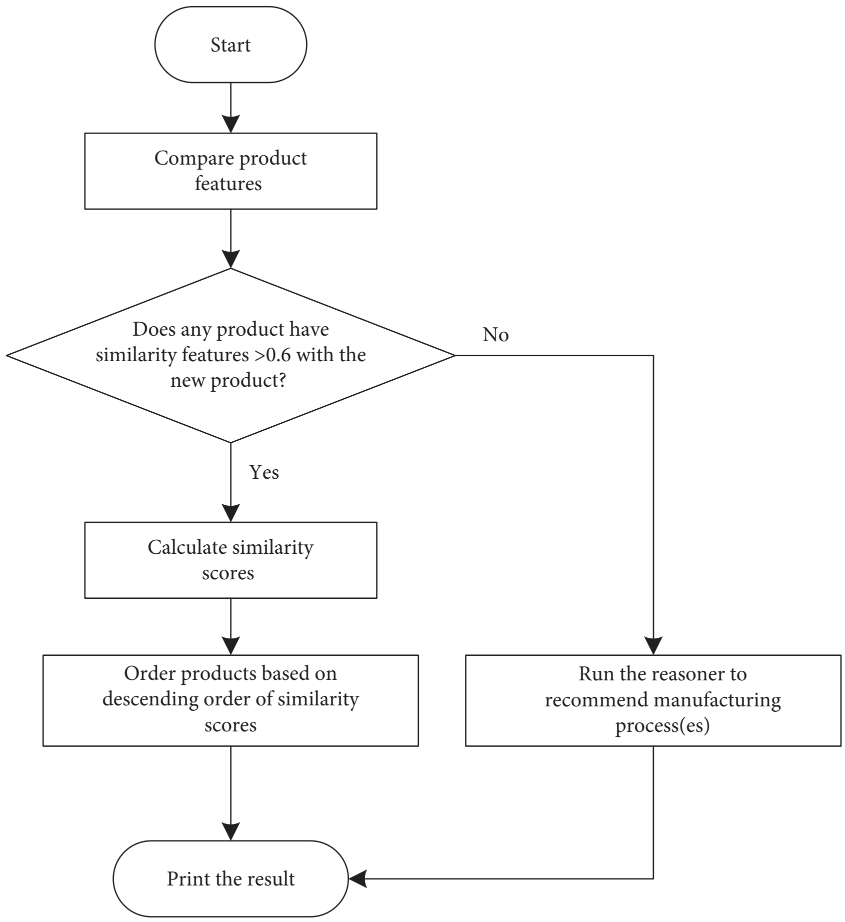


Figure 5: Flow chart of the retrieval algorithm.

retrieves misleading products. In addition, finding 0.7 or more feature similarity between two products is very rare, unless the two products are identical with different sizes. From Table 7, it can be seen that as the value of $\mathrm{FSim}(x, y)$ increases, the number of retrieved irrelevant product processes decreased sharply. With a 0.6 value, the algorithm retrieved only 4% of cases with irrelevant product processes. These products are listed in the bottom of the overall similarity product list. In such cases, the DM can find the appropriate process from products ranked on the top of the list, so the value of 0.6 is selected to be the threshold.

Figure 5 shows the flow chart of the retrieval algorithm. The algorithm works according to the following steps (Algorithm 1).

6. Case Study

The objective of process selection is to select the most suitable processes from a set of available processes to shape a given product to meet design requirements and material specifications. To use the suggested DSS, first, the new product has to be defined in the ontology. Section 6.1 demonstrates this definition. Next, the DSS selects processes according to two possible paths:

(i) In case the part under consideration is new and cannot be compared to any part stored in the ontology, the DSS will start the reasoner and run the sematic rules in the Protégé to match product features and attributes to some predefined process capabilities and copy the recommended process(es) from the classified ontology result to the GUI screen. Section 6.2 illustrates this usage.

(ii) In case similarities with existing parts are found, the DSS will retrieve similar product(s) stored in the ontology and select processes based on previous decisions made for these products. Section 6.3 illustrates this usage.

The result of the first step is stored in the ontology to build the knowledge that enables the second step.

To demonstrate the capability of the suggested ontology to select manufacturing processes, let us consider Figure 6, which shows the 3D CAD model for a cylinder head of a gasoline engine. The required quantity of this part is 2000 Pcs.

6.1. Defining Product Features and Attributes. Features and attributes of the product are shown in Table 8. Features are defined according to the description made in "Shape Generation Capabilities" in Section 4.1.2. Tolerance and surface finish are not critical for parts of ±0.5 mm and less than 0.01 mm, respectively. Part weight is approximated from the volume of the product and suggested materials. As

(i) Start. The ontology knowledge base is loaded to access product instances.
(ii) *Step 1*. Compare the features of the new product with those of the stored products and calculate product feature similarity percentage $\mathrm{FSim}(x, y)$ according to equation (2).
(iii) *Step 2*. Select the products that have a minimum threshold of shape features equal to 0.6 of the $\mathrm{FSim}(x, y)$ score. Two cases may occur.
(iv) No product has an $\mathrm{FSim}(x, y) > 0.6$. In this case, the algorithm runs the reasoner to recommend the capable process.
(v) *Step 2.1*. Run the reasoner to match product features and attributes to predefined process characteristics and capabilities (cf. Section 6.2) and print the list of capable process(es).
(vi) There are product(s) that have $\mathrm{FSim}(x, y) > 0.6$. In this case, the algorithm selects these products to calculate product attribute similarity.
(vii) *Step 2.2*. Compare the attributes of the new product to the attributes of the stored products and calculate product attribute similarity percentage $\mathrm{SScore}(x, y)$ according to equation (4).
(viii) *Step 2.3*. Sort retrieved products in the descending order of $\mathrm{SScore}(x, y)$ and print the list of these products.
(ix) End

Algorithm 1

Figure 6: Case study one on the 3D CAD model.

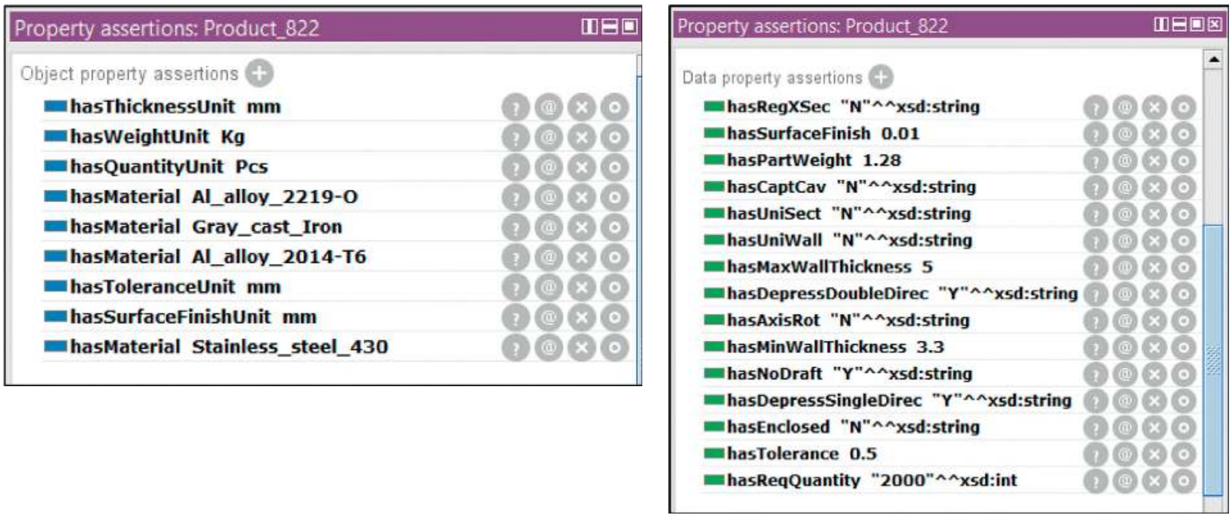
Table 8: Product shape features and attributes.

Features	Capability	Attributes	Value	Unit
Depression in a single direction	*Y*	Tolerance	±0.5	mm
Depression in a double direction	*Y*	Surface finish	<0.01	mm
Uniform wall	*N*	Part weight	1.28	kg
Uniform cross section	*N*	Maximum wall thickness	5	mm
Axis of rotation	*N*	Minimum wall thickness	3.3	mm
Regular cross section	*N*	Required quantity	2000	Pcs
Captured cavity	*N*	Recommended material	Gray cast iron, aluminum alloy 2014-T6, stainless steel 430	
Enclosed	*N*			
Draft-free surface	*Y*			

shown in Figure 6, the maximum and minimum wall thickness of the part is 5 and 3.3 mm. Three materials are recommended for this product: gray cast iron, aluminum alloy 2014-T6, and stainless steel 430. The recommendation of the material is based on transferring product functions to material properties. These properties are used in the MatWeb [8] digital tool to recommend the set of materials.

An instance named Product_822 is created in the *EngProduct* class to capture the product features and attributes according to data in Table 8. Object and data properties will be defined, as shown in Figure 7. Object properties define the recommended materials and the measurement units (cf. Figure 7(a)). Data properties define shape features and attribute values (cf. Figure 7(b)).

6.2. Selecting Manufacturing Processes Based on Rules. To use the DSS, the ontology should be open to enable the retrieval and reasoner to fetch within the stored knowledge for possible case or recommending processes. Using the same name of the

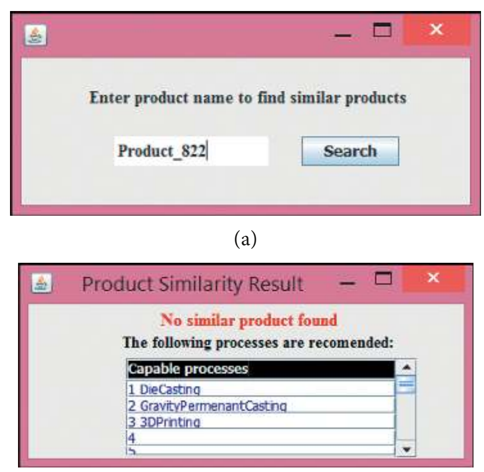


(a) (b)

FIGURE 7: Definition of the case study in the ontology: (a) object properties; (b) data properties.

instance (Product_822) created for the cylinder head (cf. Section 6.1), the search is carried out as shown in Figure 8(a). Unfortunately, the DSS did not find any similar products stored in the ontology. Automatically, the DSS runs the SWRL rule for process selection. A reasoner (also called classifier) is an AI piece of software used in association with the ontology to infer logical consequences from a set of asserted facts or axioms. For reasoning, Pellet 3.0 is used because it has some required capabilities (such as complex data-type reasoning and support of SWRL rules) that are not present in other reasoners [64].

Figure 8(b) shows the result of reasoning along with the result of the retrieval algorithm displayed in red font. The reasoner retrieved three manufacturing processes to shape the product: die casting, gravity permanent casting, and 3D printing. The DM has to select one of these three recommended processes. Whatever the DM selects, the selection will be captured in Product_822 instance as a new case to enable future case retrieval for similar products.



(a)

(b)

FIGURE 8: DSS result for reasoner and rule matching: (a) entering product name; (b) search result.

6.3. Selecting Manufacturing Processes Based on Similarity. To demonstrate the capability of the suggested DSS to select manufacturing processes based on similarity with existing products, let us consider Figure 9, which shows the 3D CAD model for a casing of the sewage electrosubmersible pump to be manufactured.

Similar to the definition of the product Product_822 in Section 6.1, an instance named Product_91 is created in the *EngProduct* class to capture the product features and attributes according to the data shown in Table 9.

Figure 10 shows the result of the execution of the retrieval algorithm. The algorithm inferred five products similar to Product_91. Product_54 is the most similar with the similarity score percentage SScore(Product_91, Product_54) = 94%.

Product_162 is the next product in the similarity list with a similarity score of 58%. Figure 11 shows the 3D CAD

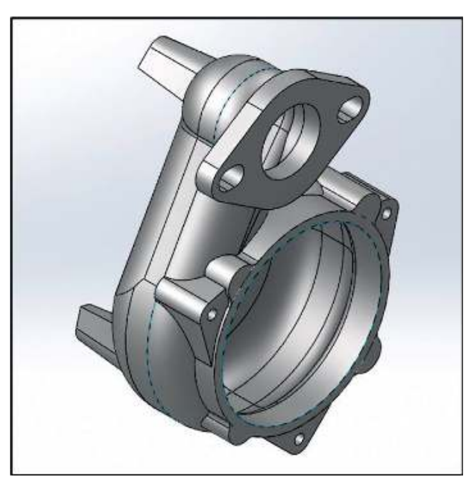
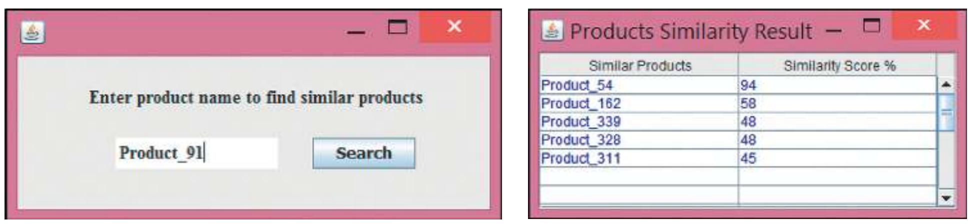


FIGURE 9: Case study two on the 3D CAD model.

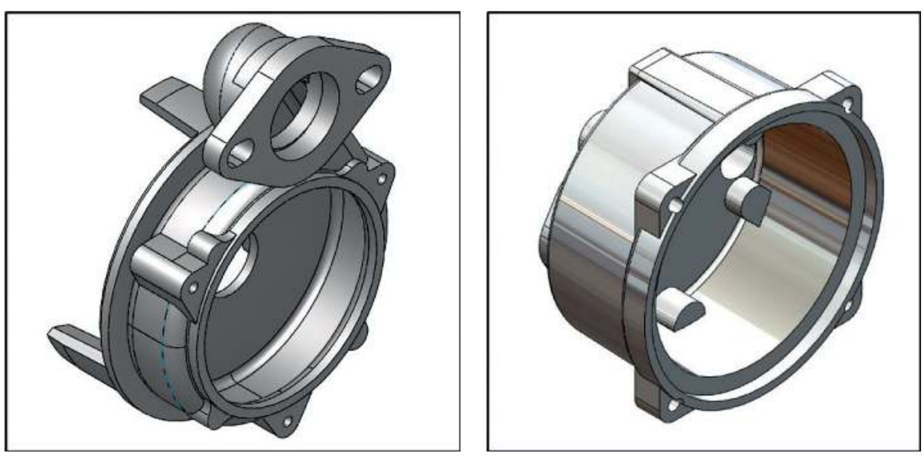
Table 9: Product shape features and attributes.

Features	Capability	Attributes	Value	Unit
Depression in a single direction	*Y*	Tolerance	±0.3	mm
Depression in a double direction	*Y*	Surface finish	<0.02	mm
Uniform wall	*N*	Part weight	3.42	kg
Uniform cross section	*N*	Maximum wall thickness	25	mm
Axis of rotation	*N*	Minimum wall thickness	6	mm
Regular cross section	*N*	Required quantity	250	Pcs
Captured cavity	*Y*			
Enclosed	*Y*	Recommended material	Gray cast iron, 314/316 stainless steel	
Draft-free surface	*N*			



(a) (b)

Figure 10: DSS result for similar product retrieval: (a) entering product name and search; (b) result.



(a) (b)

Figure 11: 3D CAD model: (a) Product_54; (b) Product_162.

models of Product_162 and Product_54. As depicted in Figure 11(a), Product_54 is a casing of a drainage electric-submersible pump.

Now, if the DM clicks on any of the listed products, the manufacturing processes used to manufacture these products will be visible and the suitability of these processes for the new part can be decided by the DM. In the case the processes used to manufacture these products are not suitable for the new Product_91, the DM has given the possibility to adapt the solution by recommending processes that are more suitable to the new product or can use the reasoner to infer another process(es), as explained in Section 6.2. Whatever the DM selects, the solution will be stored in the Product_91 instance to enable future similarity retrieval for similar products.

7. Conclusion and Future Works

In this study, we investigated semantic web technologies to achieve MPS and developed an interactive DSS for MPS based on ontology-enabled CBR. We showed that ontologies are an effective tool for capturing and structuring designer knowledge about product features, material characteristics, and process capabilities. By applying two types of automatic retrieval and reasoning on a case study, namely, rule-based reasoning using SWRL and similarity retrieval, we showed that ontologies enable process selection by determining competitive matching between product features, material characteristics, and process capabilities and by product similarity retrieval.

The suggested approach can be extended in a number of ways. As manufacturing processes require different types of machines, tools, and equipment, the suggested approach can be extended to aid in selection. In this work, the assignment of weight for shape features and attributes relied on a group of DMs; however, the developed similarity algorithm can be extended by considering fuzzy measures to enhance product retrieval. Multicriteria decision-making could be considered to prioritize process selection in case many processes are available. An ontology plug-in could be designed to capture 3D product shape features and attributes from 3D CAD models directly. As customer requirements and product specifications are subject to frequent changes and quick evolution, capturing the knowledge about change and its impact on requirements and specifications is worth considering to prepare design and manufacturing capabilities to meet such changes.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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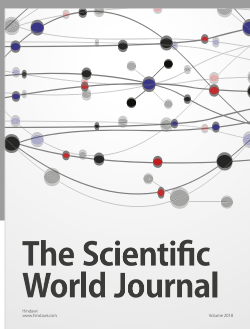
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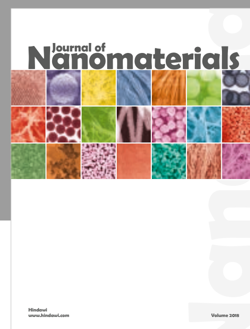
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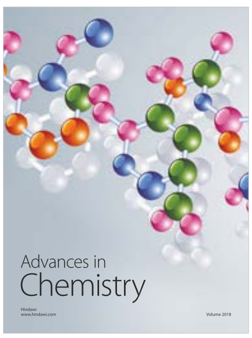
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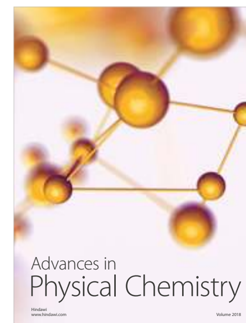
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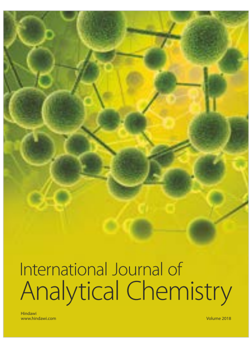
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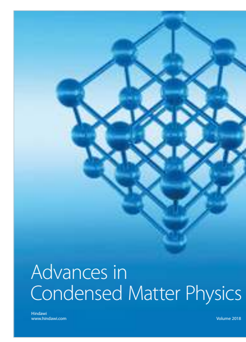
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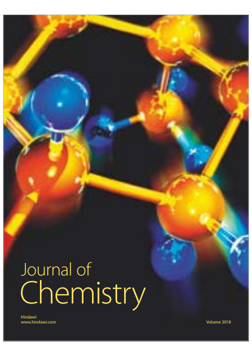
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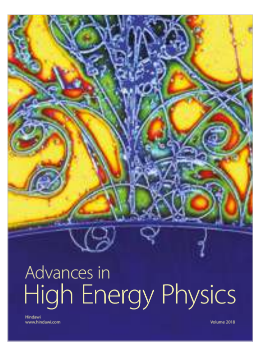
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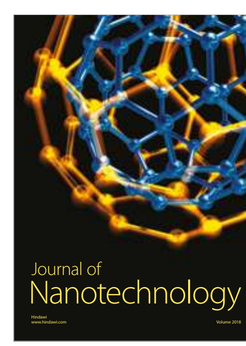
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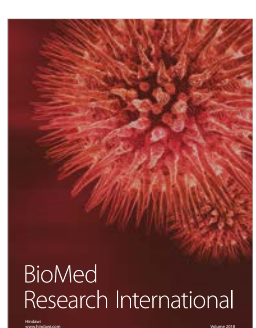
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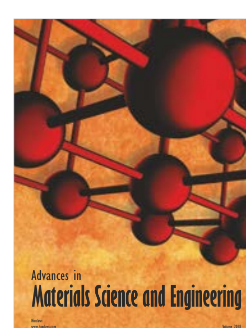
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