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A Description Logic Based Ontology for Knowledge Representation in Process Planning for Laser Powder Bed Fusion

Zuyu Li [1], Meifa Huang [1], Yanru Zhong [2] and Yuchu Qin [1,]*

[1] Guangxi Key Laboratory of Manufacturing System and Advanced Manufacturing Technology, School of Mechanical and Electrical Engineering, Guilin University of Electronic Technology, Guilin 541004, China; zuyu.li@guet.edu.cn (Z.L.); hmhmf@guet.edu.cn (M.H.)

[2] Guangxi Key Laboratory of Intelligent Processing of Computer Images and Graphic, School of Computer Science and Information Security, Guilin University of Electronic Technology, Guilin 541004, China; rosezhong@guet.edu.cn

* Correspondence: yuchu.qin@guet.edu.cn

Abstract: Laser powder bed fusion (LPBF) provides a rapid and cost-effective solution for fabricating metallic parts with near full density and high precision, strength, and stiffness directly from metallic powders. In LPBF, process variables are widely recognised as fundamental factors that have important effect on the quality of the built parts. However, activity of designing process variables for LPBF, i.e., process planning for LPBF, still heavily depends on knowledge from domain experts. This necessitates a knowledge base that enables the capture, representation, inference, and reuse of existing knowledge. In this paper, a description logic (DL) based ontology for knowledge representation in process planning for LPBF is presented. Firstly, a set of top-level DL entities and specific DL entities and semantic web rule language (SWRL) rules for part orientation, support generation, model slicing, and path planning are created to construct the ontology. The application of the ontology is then illustrated via process planning on an LPBF part. Finally, the benefits of the ontology are demonstrated through a few examples. The demonstration results show that the ontology has rigorous computer-interpretable semantics, which provides a semantic enrichment model for LPBF process planning knowledge and enables automatic consistency checking of the ontology, knowledge reasoning on the ontology, and semantic query from the ontology. This would lay solid foundation for development of a process planning tool with autonomous decision-making capability.

Keywords: laser powder bed fusion; process planning; process variable; knowledge representation; description logic; ontology

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1. Introduction

Laser powder bed fusion (LPBF) is an additive manufacturing (AM) process that uses a laser beam to selectively melt metallic powders together to additively manufacture metal parts [1]. The schematic of this process is depicted in Figure 1. An LPBF machine mainly includes a powder bed, a powder delivery apparatus, a build platform, a recoater blade, a rotating mirror, and a laser beam source. The process of using an LPBF machine to fabricate a three-dimensional (3D) part generally consists of the following steps:

- A layer of powder material with specified thickness is spread over the build platform from the powder delivery apparatus by the recoater blade;
- A moving laser beam with certain power selectively scans the layer of powder material with certain speed to create a layer of the 3D part;
- The build platform steps down by one layer thickness and a new layer of powder material is distributed evenly across the build platform;
- The second and third steps are repeated until the 3D part is fully built.

LPBF has advantages in providing high flexibility for geometric design and achieving geometric complexity without additional cost, which are the common advantages of AM technologies over traditional manufacturing technologies. More importantly, LPBF enables rapid fabrication of different metallic parts in a mixed batch with near full density and high precision, strength, and stiffness directly from metallic powders at no extra cost [2]. This feature makes it an attractive technology for producing functional components in a number of key industrial sectors, such as the aerospace, automotive, and biomedical sectors [3].

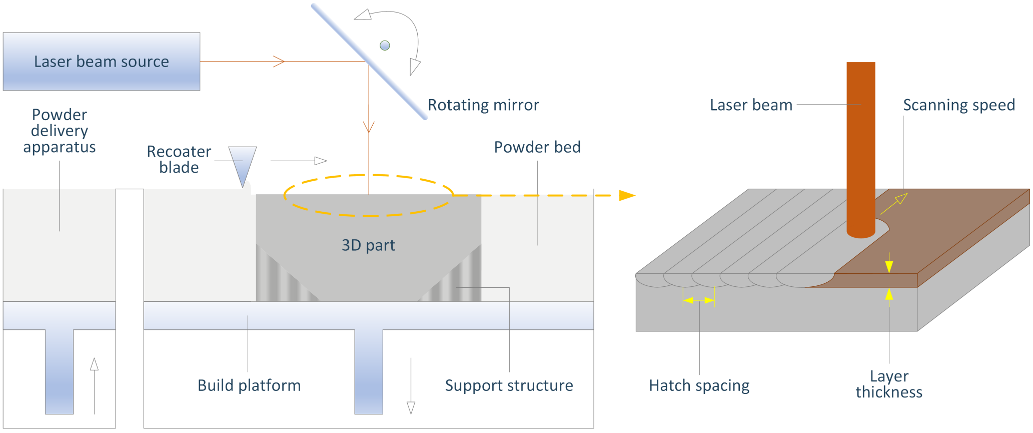


Figure 1. Schematic diagram of the LPBF process.

In general, the process of using LPBF to realise a part meeting certain quality requirements includes a set of activities, where process planning is an important one. In conventional manufacturing, process planning is an activity of determining appropriate sequence of operations and process variables for converting a workpiece from an engineering drawing to its final form. In LPBF, the engineering drawing is replaced by a 3D model. The aim of process planning remains the same, namely to determine appropriate sequence of LPBF operations or process variables to enable efficient and accurate build of an LPBF part from its 3D model. In process planning for LPBF, the process variables to be designed include build orientation, support structure, slices, laser scanning path, and process parameters. These variables are widely recognised as fundamental factors that have important influence on the quality of the built part [4–8]. However, process planning for LPBF is still considered as a challenging activity [9,10] because of the following reasons. Firstly, the physical and chemical processes of LPBF are complex. The lack of a complete understanding of these underlying processes brings great difficulty to the development of optimal process planning methods to build high-quality components [2]. Secondly, most of the existing process planning methods for LPBF focus on specific variables, materials, or structures rather than general strategies. They are difficult to be transferred directly to a build with new variables, materials, or structures. Thirdly, most of the current process planning tools for LPBF are configured by users manually without a standard procedure. There is not yet a tool with autonomous decision-making capability [4–8]. These limitations necessitate a process planning knowledge base that enables the capture, representation, inference, and reuse of existing knowledge about the LPBF process.

In this paper, a description logic (DL) based ontology for knowledge representation in process planning for LPBF is constructed. DLs, a family of formal knowledge representation languages, are well-known for providing rigorous logic-based semantics to support knowledge reasoning [11]. Ontology, a shared, explicit, and formalised specification of concepts, relations, instances, and axioms in an application domain, provides effective means to capture, represent, and reuse domain knowledge [12]. A DL-based ontology is an ontology using a DL as representation language. The most prominent feature of DL-based ontologies is that they can achieve semantic representation and exchange and knowledge discovery and reuse. Although application of DL-based ontologies is rooted in the field of semantic web, it has been extended to many other fields during the past three decades.

In the field of advanced manufacturing, DL-based ontologies have been used to improve the interoperability of industrial information systems [13], achieve knowledge reuse and discovery in product lifecycle management [14], exchange computer-aided design model data [15], and implement intelligent design of tolerance specifications [16]. Through a DL-based ontology, the knowledge in process planning for LPBF can be formalised in DL and semantic web rule language (SWRL) [17] and represented and stored in web ontology language (OWL) [18]. As three benefits of the constructed DL-based ontology, consistency checking, knowledge reasoning, and semantic query can be performed via DL, DL and SWRL, and DL, sparql protocol and rdf query language (SPARQL) [19], and semantic query-enhanced web rule language (SQWRL) [20], respectively.

The remainder of the paper is organised as follows: an overview of related work is provided in Section 2. The details of the constructed DL-based ontology are explained in Section 3. Section 4 documents an application of the ontology and illustrations of the benefits of the ontology. Section 5 ends the paper with a conclusion.

2. Related Work

An ideal model for AM knowledge representation is preferably a standardised model for practical applications [21]. During the past few decades, many standardised models for data representation in AM have been developed [22], but there has not yet been a standardised model for knowledge representation in AM. To fill this gap, many models have been presented within academia, which can be divided into the following categories based on the knowledge representation methods used in them:

- Graph model [23]: this model was presented to formulate the design guidelines for AM. In the model, a set of design guidelines for AM are first defined in a graph form based on relevant literature. Then, the 3D model of a component is decomposed into a group of constitutive features. These features and the relationships between them are identified and represented using graphs. After that, the defined design guidelines are leveraged to revise the offending features to alleviate the manufacturability issue. Finally, the best design for component build is obtained via repeating the first three steps iteratively. The approach can be used by those designers who find it difficult to integrate all the constraints into a unified AM design process. However, it improves the AM design only on the basis of manufacturability. Mechanical strength is not considered in the improvement.
- Finite state automata model [24]: this model was constructed to represent AM design knowledge to support personalised AM. In the model, a formal design process structure combining design for personalisation and design for AM is first established. Then, the artifact-user interactions are formally represented using a finite state automata based on the established structure. Through applying the affordance, effectivity, and preference properties, the artifact properties related to behaviours and preferences of users are systemically linked to design requirements of AM artifacts. The finite state automata model provides a set of formal representations that capture design requirements to improve personalisation level of AM while maintaining the freedom of AM design. However, it can only be applied to the stages of conceptual design and preliminary design and has not yet been included for consideration of process planning.
- Network model [25]: this model was developed to simulate AM processes. In the model, the system of direct material deposition process is taken as an illustrative case study. Networks are first used to visualise the general view of the system functions and the causal relationships between system variables. Then, a set of causal graphs between governing dimensionless products are defined to simplify the causal graphs between system variables. Through the simplification, the causal relationships between system variables are directly extracted before carrying out experiments. The network model provides a feasible way to simulate the direct material deposition process. However, it still needs to be further extended when it is utilised to simulate other AM processes.

- Function modelling language model [26]: this model was established to structurally represent the process-related data and knowledge in LPBF using a function modelling language and align them with specific sub-processes of powder bed fusion. It classifies an LPBF product realisation process into six activities, which are product modelling, product model tessellation, process planning, monitoring and control, post process, and quality inspection. On the basis of such classification, the activities process planning and monitoring and control and the data and knowledge associated with them are modelled. The function modelling language model provides a way to understand the organisation of LPBF product realisation process activities and sub-activities and the data flows among them. It also provides a common terminology and new process knowledge for LPBF data management. However, the model is just a conceptual model of the activities. The modelling of specific data and knowledge in each activity is not included.
- Worksheet model [27]: this model was presented to simplify the guidelines of design for AM for novice and intermittent users. In the model, the existing guidelines of AM design are firstly summarised from a certain number of representative research articles. Based on the summarisation, a one-page visual worksheet of the guidelines of design for AM is developed. The effectiveness of the worksheet is demonstrated via several test experiments. The worksheet model can help designers evaluate the potential quality of a component manufactured by AM processes and indirectly recommend feasible methods to redesign it. Its direct benefit is to filter out bad designs before manufacturing, which reduces the time spent on manufacturing and redesign. However, the model is based on the samples provided by a single source, which could limit its potential performance.
- Formal rule model [28]: this model was constructed to represent the design rules with modularity for AM. In the model, the fundamental relations among geometry, process, and material are first decomposed into reusable modules. Then, the modules are described using if-then rules. On the basis of the rules, parts are specialised to represent the process-related parameters for different AM processes. The formal rule model provides consistent and repeatable interpretations of an AM design guideline in different design and process conditions. It can also be used to explain the design principles that are independent of process to those users who are not familiar with AM technologies. Since the core of the model is to reconfigure the existing design rules, rather than to develop new rules, the basic AM principles can be preserved, and meanwhile the customisation and explicit representation of AM design rules can be implemented.
- Bayesian network model [29]: this model was established to fill the knowledge gap between designers and AM technologies. It is hierarchically organised and consists of an overview layer and a detailed information layer. Different types of nodes and their causal relationships in each layer are characterised by Bayesian networks. A knowledge management system for supporting AM was then developed. This system can help designers understand the capabilities of AM processes and form appropriate design solutions at the design stage, which reduces the uncertainty of AM processes to some extent.
- Category theory model [30]: this model was developed to formalise general knowledge in design and process control for powder bed fusion. In the model, a collection of guidelines and rules for these two activities are encapsulated and represented using categorical structures. The category theory model provides a framework to captured, accessed, and interrogated the structured knowledge. However, it has not yet included the representation of specific data in the two activities.

A summarisation of the models above at the aspects of published year, representation method, represented specific AM knowledge, and targeted AM process is provided in Table 1. In addition to these models, the use of ontologies in AM knowledge representation has been gained importance and popularity within academia during the past two decades. Many ontologies [31–52] have been presented in this period. A summarisation of these ontologies at the aspects of published year, representation languages, represented specific AM knowledge, and targeted AM process is provided in Table 2.

Table 1. Overview of existing models for AM knowledge representation.

Ref.	Year	Representation Method	Specific AM Knowledge That Is Represented in the Constructed Model	Process
[23]	2015	Graphs	Design guidelines for AM	AM
[24]	2015	Finite state automata	AM design knowledge for supporting personalised AM	AM
[25]	2016	Networks	Process functions and causal relationships between process variables	DMD
[26]	2017	FML	Process-related data and knowledge in LPBF	LPBF
[27]	2017	Worksheet	Guidelines of design for AM for novice and intermittent users	AM
[28]	2017	Formal rules	Design rules with modularity for AM	AM
[29]	2018	Bayesian networks	Knolwedge in design for AM	AM
[30]	2018	Category theory	General knowledge in design and process control for PBF	PBF

Notes: DMD stands for direct material deposition; FML stands for function modelling language; PBF stands for powder bed fusion.

Table 2. Overview of existing ontologies for AM knowledge representation.

Ref.	Year	Languages	Specific AM Knowledge That Is Represented in the Constructed Ontology	Process
[31]	2007	DL	Design requirements, process plans, and rules that map requirements to plans	AM
[32]	2008	DL	Design requirements, process plans, and rules that map requirements to plans	AM
[33]	2010	DL	Design features and rules for selecting manufacturing variables	AM
[34]	2014	OWL	Knowledge in development for AM processes	LPBF
[35]	2015	OWL, SWRL	Most applicable concepts of AM relevant to process planning applications	AM
[36]	2016	OWL	Laser and thermal metamodels for LPBF	LPBF
[37]	2016	OWL	Information correlating material, design, and manufacturing operations	AM
[38]	2016	OWL	Model fidelity in LPBF	LPBF
[39]	2017	OWL, SWRL	Knowledge in design for AM	AM
[40]	2018	OWL	Design features, manufacturing features, and process parameters	AM
[41]	2018	OWL	Information about innovative uses of AM technologies	AM
[42]	2018	——	Knowledge in process planning for AM	AM
[43]	2019	OWL, SWRL	Knowledge in design for AM	AM
[44]	2019	OWL, SWRL	Data and knowledge in AM value chain	AM
[45]	2019	OWL	Knowledge in AM product lifecycle	AM
[46]	2020	——	Metamodels and planning rules in process planning for wire arc AM	WAAM
[47]	2021	OWL, SWRL	Knowledge for LPBF design rule construction	LPBF
[48]	2021	——	Causal relations between AM parameters and quality assurance requirements	LPBF
[49]	2021	OWL	Process parameters, physical models, thermal models, and build qualities	LPBF
[50]	2021	OWL	Information about the capabilities of LCM process, printers and materials	LCM
[51]	2021	OWL, SWRL	Knowledge for cost estimation in AM	AM
[52]	2021	OWL, SWRL	Knowledge for identifying and prioritising data analytics opportunities in AM	LPBF

Notes: LCM stands for lithography-based ceramic manufacturing; WAAM stands for wire arc additive manufacturing.

As can be seen from Tables 1 and 2, each model/ontology has its specific usage in AM knowledge representation. Some models/ontologies are targeted at general AM processes, while each of other models/ontologies is constructed for one specific AM process, including direct material deposition, LPBF, powder bed fusion, lithography-based ceramic manufacturing, or wire arc additive manufacturing. It can also be seen from the two tables that the models and ontologies related to knowledge representation in process planning for LPBF include the function modelling language model [26], category theory model [30], and ontologies in [31–33,35,37,39,40,42,43,47–49]. However, research gap is evident due to the following reasons: both the function modelling language model [26] and category theory model [30] are conceptual models and do not involve the modelling of specific data and knowledge in process planning for LPBF; the ontologies in [31–33,35,37,39,40,42,43] are targeted at general AM processes and are difficult to be applied to process planning for LPBF directly (need further modifications and extensions); although the ontologies in [47–49] were all developed for the LPBF process, their main purpose is not to represent the knowledge at the process planning stage. To fill the research gap, a DL-based ontology dedicated to knowledge representation in process planning for LPBF is presented in this paper.

3. DL-Based Ontology

A DL-based ontology generally consists of a DL terminology box (TBox), a DL assertion box (ABox), and a set of SWRL rules. The DL TBox is a collection of concepts, relations, and definitions of concepts (terminological axioms). A set of concept assertions, relation assertions, and instance assertions (assertional axioms) constitute the DL ABox. The SWRL rules are used to describe the knowledge that cannot be described by DL. In this section, a DL-based ontology for representation of the LPBF process planning knowledge is developed using Protégé [53] according to standard terminologies for LPBF (ISO/ASTM 52900, 2021), LPBF process planning guidelines (ISO/ASTM 52911-1, 2019; ISO/ASTM 52911-2, 2019), database of LPBF materials [54], database of LPBF machines [54], and existing related research results [4–8]. The schematic diagram of this ontology is shown in Figure 2. Benefiting from the advantages of the developed ontology, the semantics of LPBF process planning data are enriched greatly, and consistency checking, knowledge reasoning, and semantic query, which are not available in current process planning tools for LPBF, can be performed via DL, DL, and SWRL, and DL, SPARQL, and SQWRL, respectively.

In the following subsections, the details of the ontology will be described in a top-down manner. For the sake of clarity, the following labelling convention will be adopted: all entity names are in italics (e.g., *LpbfMachine*, *isBasedOn*, *eosintM270*); the first letters of all DL concept (OWL class) names are in capitalised case (e.g., *Lpbf*, *ProcessPlanning*); all DL relation (OWL property) names have a prefix of 'has' or 'is' (e.g., *hasEnergySource*, *isApplicableFor*); the first letters of all DL instance (OWL individual) names are in lower case (e.g., *ti6Al4V*, *alSi10Mg*).

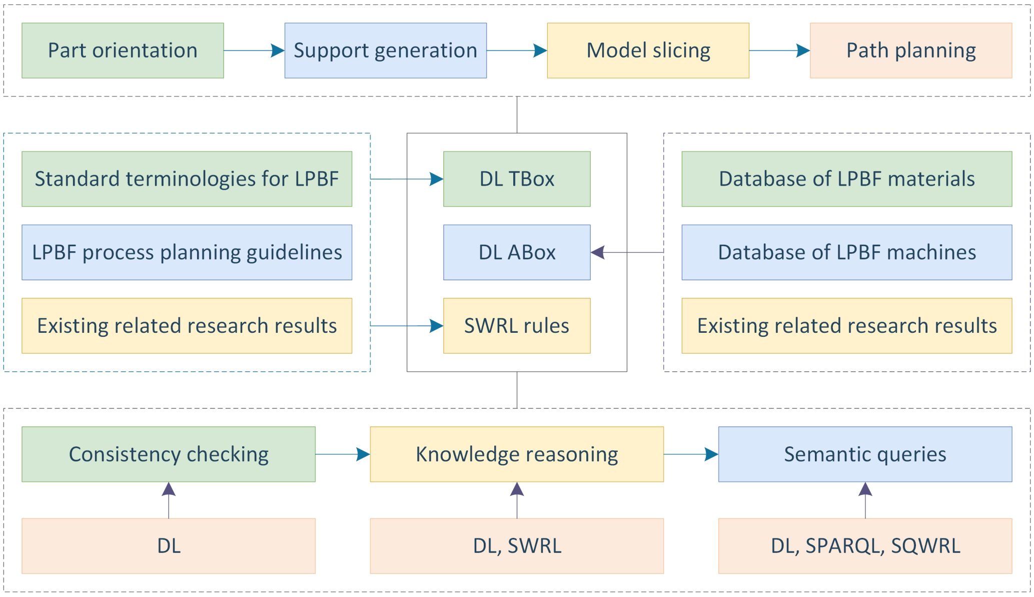

Part orientation
Support generation
Model slicing
Path planning
Standard terminologies for LPBF
LPBF process planning guidelines
Existing related research results
DL TBox
DL ABox
SWRL rules
Database of LPBF materials
Database of LPBF machines
Existing related research results
Consistency checking
Knowledge reasoning
Semantic queries
DL
DL, SWRL
DL, SPARQL, SQWRL

Figure 2. Schematic diagram of the development process of the DL-based ontology.

3.1. Top-Level Entities

LPBF is an AM process whose energy source is a laser beam, build material is a powder material, build platform is a powder bed, and build mechanism is melting. Process planning for LPBF is a product realisation activity that aims to design appropriate process variables to build a part that can satisfy certain build and quality requirements. The main inputs of this activity include a 3D model, an LPBF material, an LPBF machine, and build and quality requirements. The outputs of the activity are a set of process variables, which include build orientation, support structure, slices, laser scanning path, and process parameters.

Process planning consists of four successive tasks that of part orientation, that of support generation, that of model slicing, and that of path planning [55].

Based on the description above, twenty-eight top-level concepts were created and depicted in Figure 3. Among them, *Lpbf*, *LpbfPart*, *LpbfMaterial*, *LpbfMachine*, *ProcessPlanning*, *PartOrientation*, *SupportGeneration*, *ModelSlicing*, and *PathPlanning* are composite concepts (concepts that need to be defined by other concepts), while the remaining concepts are atomic concepts (concepts that cannot be defined by other concepts). The DL definitions of the nine composite concepts are given by the following terminological axioms:

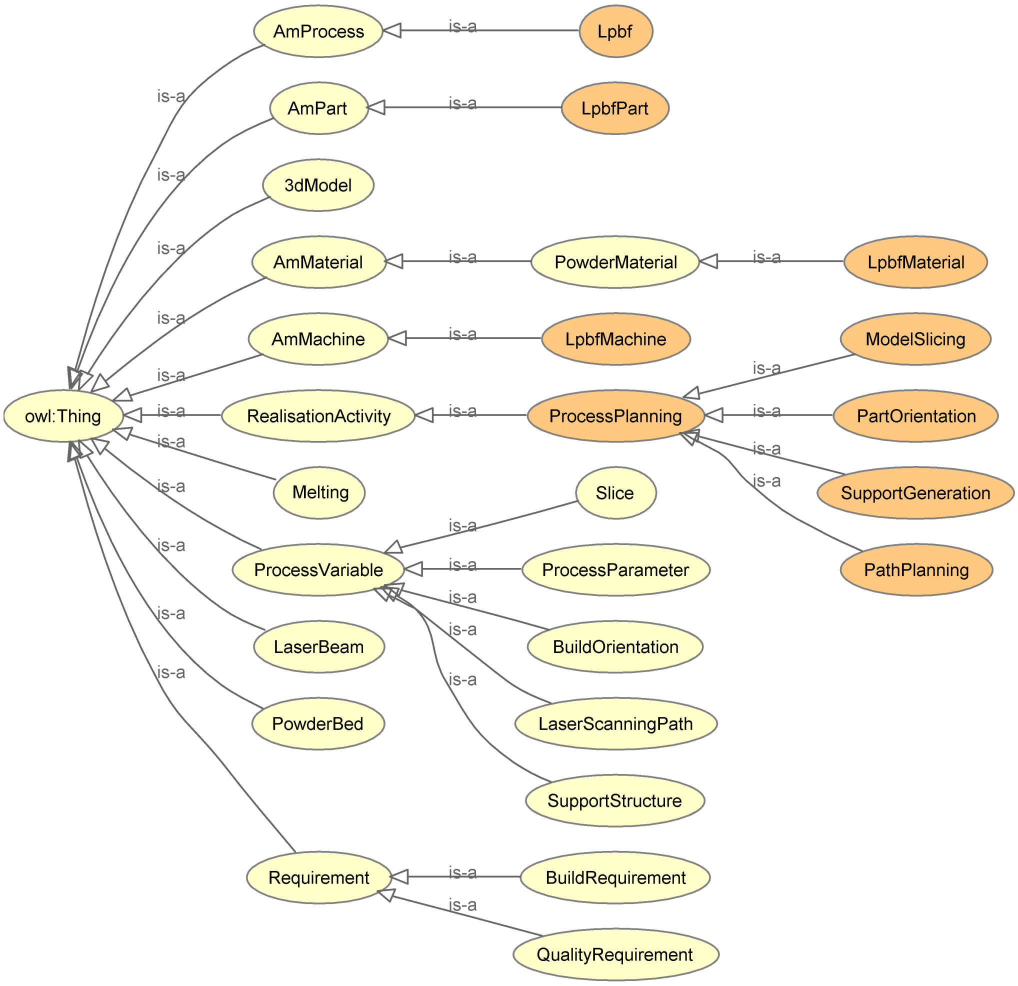


Figure 3. Graphical representation of top-level concepts and their hierarchies.

$$Lpbf \equiv AmProcess \sqcap \exists hasEnergySource.LaserBeam \sqcap \exists hasBuildMaterial.PowderMaterial \\ \sqcap \exists hasBuildPlatform.PowderBed \sqcap \exists hasBuildMechanism.Melting \tag{1}$$

$$LpbfPart \equiv AmPart \sqcap \exists isManufacturedUsing.Lpbf \tag{2}$$

$$LpbfMaterial \equiv PowderMaterial \sqcap \exists isApplicableFor.Lpbf \tag{3}$$

$$LpbfMachine \equiv AmMachine \sqcap \exists isBasedOn.Lpbf \tag{4}$$

$$ProcessPlanning \equiv RealisationActivity \sqcap \exists hasAimOfDesigning.ProcessVariable \tag{5}$$

$$PartOrientation \equiv ProcessPlanning \sqcap \exists hasAimOfDesigning.BuildOrientation \tag{6}$$

$$SupportGeneration \equiv ProcessPlanning \sqcap \exists hasAimOfDesigning.SupportStructure \tag{7}$$

$$ModelSlicing \equiv ProcessPlanning \sqcap \exists hasAimOfDesigning.Slice \tag{8}$$

$$PathPlanning \equiv ProcessPlanning \sqcap \exists hasAimOfDesigning.LaserScanningPath \sqcap \exists hasAimOfDesigning.ProcessParameter \tag{9}$$

where ≡ is the concept definition symbol in DLs which is used to define a concept, ∃ is the existential restriction symbol in DLs which is used to denote that there are one or more instances of a concept that have a specific relation, ⊓ is the concept conjunction symbol in DLs which is used to obtain the intersection of instances of two concepts, and *hasEnergySource*, *hasBuildMaterial*, *hasBuildPlatform*, *hasBuildMechanism*, *hasAimOfDesigning*, *isManufacturedUsing*, *isApplicableFor*, and *isBasedOn* are object relations whose domain, range, and meaning are listed in Table 3.

Table 3. Domain, range, and meaning of eight top-level object relations.

Object Relation	Domain	Range	Meaning
hasEnergySource	*AmProcess*	*LaserBeam*	An AM process that has energy source of
hasBuildMaterial	*AmProcess*	*PowderMaterial*	An AM process that has build material of
hasBuildPlatform	*AmProcess*	*PowderBed*	An AM process that has build platform of
hasBuildMechanism	*AmProcess*	*Melting*	An AM process that has build mechanism of
hasAimOfDesigning	*RealisationActivity*	*ProcessVariable*	A realisation activity that has aim of designing
isManufacturedUsing	*AmPart*	*Lpbf*	An AM part that is manufactured using
isApplicableFor	*PowderMaterial*	*Lpbf*	A powder material that is applicable for
isBasedOn	*AmMachine*	*Lpbf*	An AM machine that is based on

The build and quality requirements are specified by process planners based on certain indicators. Indicators for describing the build requirements of an LPBF part mainly include support volume, build time, and build cost, while indicators for specifying the quality requirements of an LPBF part mainly contain dimensional error, geometric error, volumetric error, surface roughness, density, hardness, yield strength, tensile strength, elongation, residual stress, and fatigue strength. In the process of planning for LPBF, the values of these indicators for an LPBF part to be built are usually predicted via certain prediction models. To describe indicator values, fourteen top-level data relations named *hasSupportVolume-mm3*, *hasBuildTime-h*, *hasBuildCost-GBP*, *hasDimensionalError-mm*, *hasGeometricError-mm*, *hasVolumetricError-mm3*, *hasSurfaceRoughness-µm*, *hasDensity-g/cm3*, *hasHardness-HV*, *hasYieldStrength-MPa*, *hasTensileStrength-MPa*, *hasElongation-Pct*, *hasResidualStress-MPa*, and *hasFatigueStrength-MPa* were created. The domain and range of each data relation are respectively *LpbfPart* and xsd:double. This means that an LPBF part has predicted indicator value of xsd:double.

The widely known LPBF materials include Ti6Al4V, AlSi10Mg, stainless steel, and tool steel. Recently, several other types of LPBF materials, such as tungsten, zinc alloy, magnesium alloy, and metal matrix composite, have been developed [56]. Therefore, eight assertional axioms were created as follows: *LpbfMaterial*(*ti6Al4V*); *LpbfMaterial*(*alSi10Mg*); *LpbfMaterial*(*stainlessSteel*); *LpbfMaterial*(*toolSteel*); *LpbfMaterial*(*tungsten*); *LpbfMaterial*(*zincAlloy*); *LpbfMaterial*(*magnesiumAlloy*); *LpbfMaterial*(*metalMatrixComposite*). According to the Senvol Database [54], there have been two hundred and thirty-six LPBF machines available in the market to date. The names of these LPBF machines were used to instantiate the concept *LpbfMachine* to create two hundred and thirty-six assertional axioms. For example, in the database, EOSINT M270 is an LPBF machine. An assertional axiom *LpbfMachine*(*eosintM270*) was created to make this assertion.

3.2. Entities for Part Orientation

Part orientation is a process planning task that aims to design a build orientation that best meets the build and quality requirements to build a part [4]. The main inputs of this task include a 3D model of a part to be built and specific build and quality requirements on the part. Its output is a 3D model in a build orientation. The 3D model is the results of the design activity and generally encoded in a specific format [22], such as the STL (standard tessellation language) format, 3MF (3D manufacturing file) format, and AMF (additive manufacturing file) format.

Existing methods for part orientation can be classified into search-based methods and rule-based methods [4]. Search-based methods take the part orientation problem as a multi-objective optimisation problem. They usually adopts specific search algorithms, such as the random search algorithm [57], genetic algorithm [58], particle swarm algorithm [59], and iterative tabu search algorithm [60], to search an orientation that can optimise multiple objectives at the same time from infinite possible orientations. In search-based methods, a build orientation is generally expressed via an angle pair (α, β), where the build orientation lines up along the +z axis after rotating the 3D model α ($0 \leq \alpha \leq 360$) degrees around the x axis and β ($0 \leq \beta \leq 360$) degrees around the y axis. Search-based methods usually have relatively high accuracy and relatively low efficiency. They are generally applied to free-form surface models.

Rule-based methods take the part orientation problem as a multi-objective decision-making problem. It first generates a certain number of alternative orientations from infinite possible orientations via performing shape feature recognition [61,62] or triangular facet clustering [63–65] on the 3D model and carrying out rule-based reasoning according to the recognition or clustering results. Then, a multi-objective decision-making method is used to select an orientation from the alternative orientations that can satisfy multiple objectives at the same time. In rule-based methods, a build orientation is generally represented by a unit vector (x, y, z). Rule-based methods are relatively efficient, since they do not spend time on many meaningless calculations. However, they are difficult to achieve desired accuracy on free-form surface models. They are more suitable for regular surface models.

Based on the analysis above, it is recommended to use a rule-based method for part orientation when the input 3D model is a regular surface model and to use a search-based method on a free-form surface model.

To represent the knowledge in part orientation, seven concepts named *Objective*, *Method*, *SearchBasedMethod*, *RuleBasedMethod*, *AnglePair*, *UnitVector*, and *Form*, sixteen relations listed in Table 4, four instances named *methodInRef57*, *methodInRef58*, *methodInRef59*, and *methodInRef60* (instances of *SearchBasedMethod*), and five instances named *methodInRef61*, *methodInRef62*, *methodInRef63*, *methodInRef64*, and *methodInRef65* (instances of *RuleBasedMethod*) were created. Based on these entities, an ontological view of part orientation for LPBF is delineated in Figure 4, and two SWRL rules for recommending a part orientation method for an input 3D model were developed as follows:

$$\begin{aligned} &PartOrientation(?x1) \wedge 3dModel(?x2) \wedge SearchBasedMethod(?x3) \wedge hasInput(?x1, ?x2) \wedge \\ &hasGeometricForm(?x2, freeForm) \rightarrow hasRecommendedMethod(?x1, ?x3) \end{aligned} \quad (10)$$

$$\begin{aligned} &PartOrientation(?x1) \wedge 3dModel(?x2) \wedge RuleBasedMethod(?x3) \wedge hasInput(?x1, ?x2) \wedge \\ &hasGeometricForm(?x2, regularForm) \rightarrow hasRecommendedMethod(?x1, ?x3) \end{aligned} \quad (11)$$

where the statements on the left and right of → are respectively the antecedent and consequent of an SWRL rule, *antecedent* → *consequent* denotes that if the antecedent holds then the consequent holds, $C_i(?x_j)$ (C_i is a DL concept) or $R_i(?x_j, ?x_k)$ (R_i is a DL relation) is an atom in an SWRL rule which is used to describe a condition, $\wedge$ is the atom conjunction symbol in an SWRL rule which denotes 'and', each variable is marked using a question mark as its prefix, and *freeForm* and *regularForm* are instances of *Form*.

3.3. Entities for Support Generation

Support generation is a process planning task that aims to generate the minimum amount of support structure that best meets the build and quality requirements to build a part [5]. The main inputs of this task include a 3D model in a build orientation for a part to be built and specific build and quality requirements on the part. Its output is a 3D model with support structure in a build orientation.

Table 4. Domain, range, and meaning of sixteen relations in part orientation.

Data Relation	Domain	Range	Meaning
hasInput	*ProcessPlanning*	owl:Thing	A process planning task that has input of
hasOutput	*ProcessPlanning*	owl:Thing	A process planning task that has output of
hasSearchAlgorithm	*SearchBasedMethod*	xsd:string	A search based method that has search algorithm of
hasGenerationApproach	*RuleBasedMethod*	xsd:string	A rule-based method that has generation approach of
hasSelectionApproach	*RuleBasedMethod*	xsd:string	A rule-based method that has selection approach of
hasObjective	*ProcessPlanning*	*Objective*	A process planning task that has objective of
hasEncodedFormat	*3dModel*	xsd:string	A 3D model that has encoded format of
	Slice	xsd:string	A slice that has encoded format of
hasAngleAlpha-deg	*AnglePair*	xsd:double	An angle pair that has rotation angle α of
hasAngleBeta-deg	*AnglePair*	xsd:double	An angle pair that has rotation angle β of
hasCoordinateX	*UnitVector*	xsd:double	A unit vector that has x coordinate of
hasCoordinateY	*UnitVector*	xsd:double	A unit vector that has y coordinate of
hasCoordinateZ	*UnitVector*	xsd:double	A unit vector that has z coordinate of
hasGeometricForm	*3dModel*	*Form*	A 3D model that has geometric form of
hasRecommendedMethod	*PartOrientation*	*Method*	An orientation task that has recommended method of
hasOrientation	*3dModel*	*BO*	A 3D model that has build orientation of
isDescribedBy	*BuildOrientation*	*AnglePair*	A build orientation that is described by an angle pair of
	BuildOrientation	*UnitVector*	A build orientation that is described by a unit vector of

Note: *BO* stands for *BuildOrientation*.

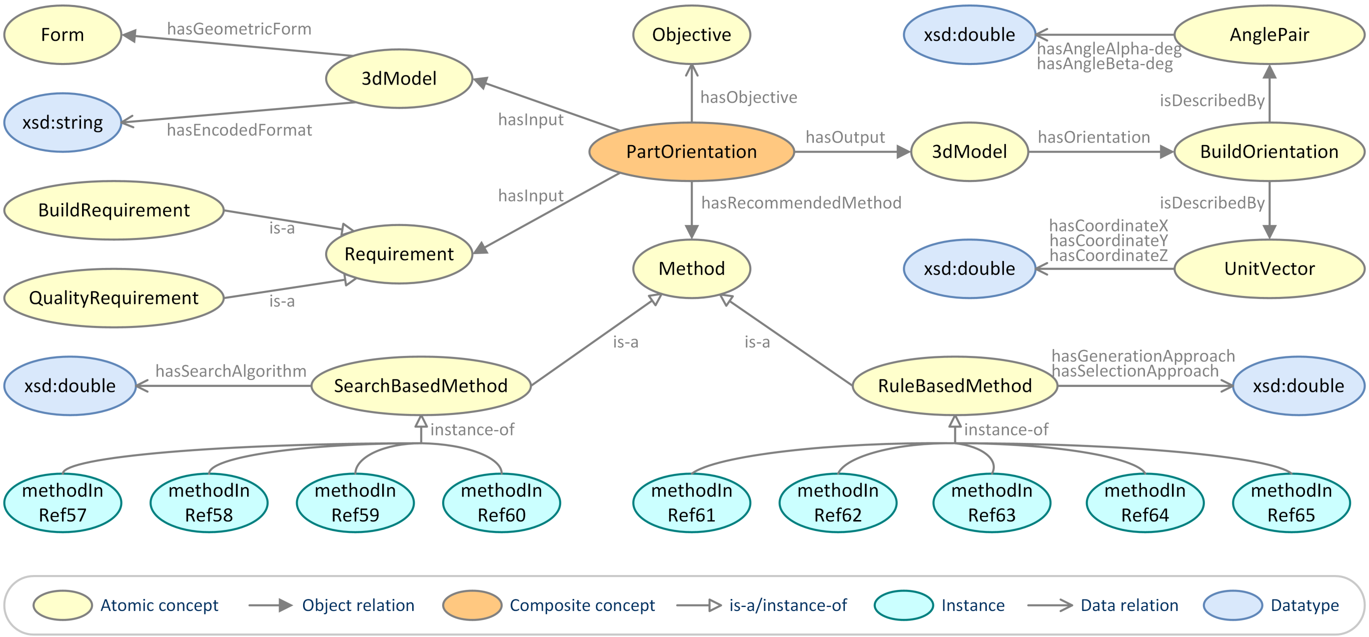


Figure 4. An ontological view of part orientation for LPBF.

To generate the support structure for a 3D model in a given build orientation, the first step is to detect the overhang area on the model that needs to be supported. In existing support generation methods, this detection is generally carried out using the angles between the normal vectors of triangular facets and the build orientation. When the angle corresponding to a triangular facet is greater than a certain value, the area corresponding to the triangular facet is considered to be the overhang area that needs to be supported [5].

After detecting the supported overhang area, a specific shape of support structure will be generated for it. So far, a number of different shapes of support structures for AM part build have been developed [5]. The support structures suitable for LPBF part build mainly include lattice support structure [66], cellular support structure [67], unit cell support structure [68], pin support structure [69], Y support structure [69], IY support structure [69], and tree support structure [70]. In practice, which shape of support structure to use is usually determined by the used process planning tool, since each process planning tool provides its specific shapes of support structures.

Support generation is usually coupled with optimising the selected shape of support structure to minimise its total volume and improve part quality. To date, many optimisation methods have ben presented within academia. For example, a lattice support structure optimisation method based on Taguchi experiment was presented in [71]; a lattice support structure optimisation framework based on genetic algorithm was established in [72]; in [59], a topology optimisation method was used to optimise lattice support structure to prevent residual stress induced build failure; in [73], the topology of lattice support structure is optimised to maximise its thermal conductivity and to mitigate the effect of thermal stress on the dimensional and geometric accuracy of an LPBF part; a method for optimising the topology of lattice support structure is presented in [74]; a hybrid optimisation framework for topology, build orientation, and support structure is established in [75]. These methods provide practical tools for optimisation of the support structure of an LPBF part. They can be selected according to specific optimisation objects and objectives.

To represent the knowledge in support generation, a concept named *SupportedArea*, five relations listed in Table 5, and seven instances named *latticeStructure*, *cellularStructure*, *unitCellStructure*, *pinStructure*, *yStructure*, *iyStructure*, and *treeStructure* (instances of *SupportStructure*) were created. Using these entities, an ontological view of support generation for LPBF is delineated in Figure 5.

Table 5. Domain, range, and meaning of five relations in support generation.

Data Relation	Domain	Range	Meaning
hasSupportedArea	*3dModel*	*SupportedArea*	A 3D model that has supported area of
hasDetectionMethod	*SupportedArea*	xsd:string	A supported area that has detection method of
hasSupport	*3dModel*	*SupportStructure*	A 3D model that has support structure of
hasGenerationTool	*SupportGeneration*	xsd:string	A support generation task having generation tool of
hasOptimisationMethod	*SupportStructure*	xsd:string	A support structure having optimisation method of

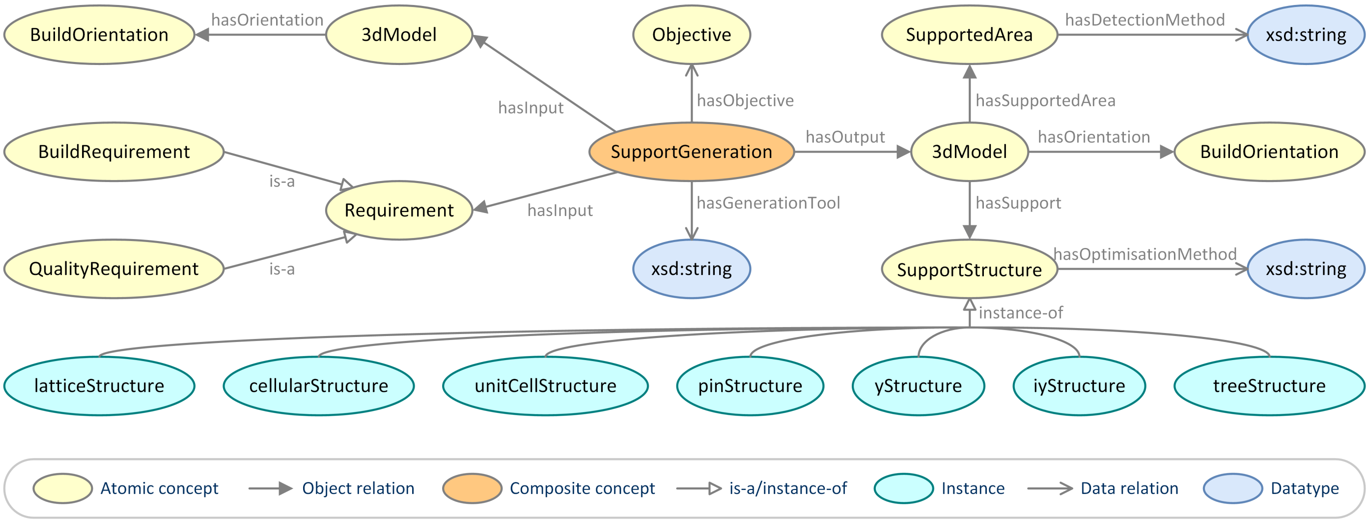


Figure 5. An ontological view of support generation for LPBF.

3.4. Entities for Model Slicing

Model slicing is a process planning task that aims to truncate the build model (i.e., a 3D model with support structure) into a set of thin slices that best meet the build and quality requirements to build a part [6]. The main inputs of this task include an LPBF machine, a 3D model with support structure in a build orientation for a part to be built, and specific build and quality requirements on the part. Its outputs are a set of thin slices. A slice corresponds to a layer of the part to be built. The main attributes of a slice are its contour and thickness. This thickness is usually called layer thickness, which is one of the critical LPBF process parameters. The output slice information is generally encoded in a proprietary format [22], such as the CLI (common layer interface), SLC (stereo lithography contour), and HPGL (Hewlett-Packard graphics language) format.

The simplest model slicing strategy is uniform slicing in single direction, which truncates the build model into a set of slices with equal thickness along the direction perpendicular to the build orientation. It is the first model slicing strategy in AM and is the most widely used strategy in industry [6]. The biggest advantage of the uniform slicing in single direction is that it is simple, efficient, and robust. However, this strategy would lead to a loss of control over the part accuracy, since it neglects the actual geometry of the build model [55].

In the past few years, a number of improvement strategies were developed [76–78], where representative ones are uniform slicing in multiple directions, variable slicing in single direction, and variable slicing in multiple directions. Each strategy has its specific characteristics. Generally, a slicing strategy is selected based on actual objectives [6]:

- if the objectives of model slicing are normal accuracy and high efficiency, then uniform slicing in single direction (ussd) is recommended;
- if the objectives of model slicing are normal accuracy, reduced support, and alleviated anisotropy, then uniform slicing in multiple directions (usmd) is recommended;
- if the objective of model slicing is high accuracy, then variable slicing in single direction (vssd) is recommended;
- if the objectives of model slicing are high accuracy, free of support, and alleviated anisotropy, then variable slicing in multiple directions (vsmd) is recommended.

To represent the knowledge in model slicing, two concepts named *SliceContour* and *SlicingStrategy*, three relations listed in Table 6, and four instances named *ussd*, *usmd*, *vssd*, and *vsmd* (instances of *SlicingStrategy*) were created. Based on these entities, an ontological view of model slicing for LPBF is delineated in Figure 6, and four SWRL rules for recommending a model slicing strategy were developed as follows:

$$ModelSlicing(?x1) \wedge hasObjective(?x1, normalAccuracy) \wedge hasObjective(?x1, highEfficiency) \rightarrow hasRecommendedStrategy(?x1, ussd) \tag{12}$$

$$ModelSlicing(?x1) \wedge hasObjective(?x1, normalAccuracy) \wedge hasObjective(?x1, reducedSupport) \wedge hasObjective(?x1, alleviatedAnisotropy) \rightarrow hasRecommendedStrategy(?x1, usmd) \tag{13}$$

$$ModelSlicing(?x1) \wedge hasObjective(?x1, highAccuracy) \rightarrow hasRecommendedStrategy(?x1, vssd) \tag{14}$$

$$ModelSlicing(?x1) \wedge hasObjective(?x1, highAccuracy) \wedge hasObjective(?x1, freeOfSupport) \wedge hasObjective(?x1, alleviatedAnisotropy) \rightarrow hasRecommendedStrategy(?x1, vsmd) \tag{15}$$

where *normalAccuracy*, *highEfficiency*, *reducedSupport*, *alleviatedAnisotropy*, *highAccuracy*, and *freeOfSupport* are instances of *Objective*.

Table 6. Domain, range, and meaning of three relations in model slicing.

Data Relation	Domain	Range	Meaning
hasContour	*Slice*	*SliceContour*	A slice that has contour of
hasThickness-mm	*Slice*	*xsd:double*	A slice that has thickness of
hasRecommendedStrategy	*ModelSlicing*	*SlicingStrategy*	A model slicing task that has recommended strategy of

3.5. Entities for Path Planning

Path planning is a process planning task that aims to design a laser scanning path and a set of process parameters that best meets the build and quality requirements to build a part [6,7]. The main inputs of this task include an LPBF material, an LPBF machine, a set of slices for a part to be built, and specific build and quality requirements on the part. Its outputs are a laser scanning path and a set of process parameters.

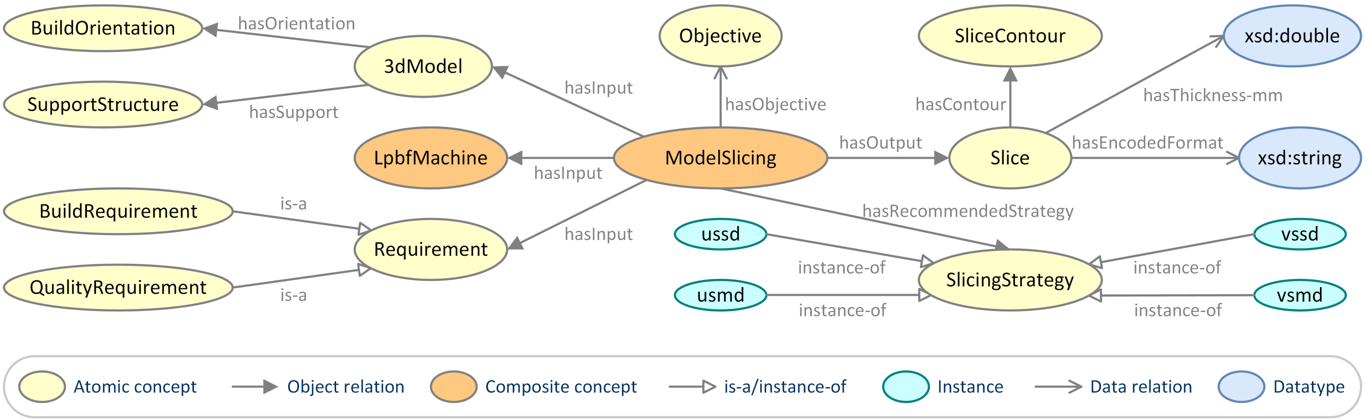


Figure 6. An ontological view of model slicing for LPBF.

An important step in path planning is to select or develop a proper laser scanning path. This step is affected by the adopted model slicing strategy. If a planar slicing strategy is adopted, alternative path patterns mainly include raster, zigzag, multi-direction, grid, spiral, contour, and hybrid paths. Each path has its specific strengths and shortcomings. In general, the path patterns are selected according to specific objectives [6]:

- If the objective of path planning is high build efficiency, then raster path is recommended;
- If the objectives of path planning are high build efficiency and high mechanical performance, then zigzag path or grid path is recommended;
- If the objectives of path planning are high geometric accuracy and high mechanical performance, then multi-direction path or contour path is recommended;
- If the objectives of path planning are high geometric accuracy, less path passes, less path elements, and high mechanical performance, then spiral path is recommended;
- If the objectives of path planning are high build efficiency and high geometric accuracy, then hybrid path is recommended.

Another important step in path planning is to design a set of optimal process parameters. According to the study in [79], controllable process parameters include layer thickness, laser power, scanning speed, hatch spacing, recoating time, recoating speed, dosing per layer, bulk temperature, oxygen level, chamber pressure, gas flow speed, and ambient temperature. Among them, layer thickness, laser power, scanning speed, and hatch spacing are four critical process parameters. The volumetric energy density calculated from them is an important indicator to measure the effect of process parameters on part quality [80]. For design of process parameters, most of existing methods first generate a set of combinations of process parameters, then predict certain part quality indicators under each combination, and finally determine the optimal process parameters on the basis of the prediction results [8].

To represent the knowledge in path planning, an object relation named *hasRecommendedPath*, thirteen data relations named *hasLayerThickness-mm*, *hasLaserPower-W*, *hasScanningSpeed-mm/s*, *hasHatchSpacing-mm*, *hasLaserSpotDiameter-mm*, *hasRecoatingTime-s*, *hasRecoatingSpeed-mm/s*, *hasDosingPerLayer-Pct*, *hasBulkTemperature-DegC*, *hasOxygenLevel-Pct*, *hasChamberPressure-kPa*, *hasGasFlowSpeed-m3/s*, and *hasAmbientTemperature-DegC*, and seven instances named *rasterPath*, *zigzagPath*, *multiDirectionPath*, *gridPath*, *spiralPath*, *contourPath*, and *hybridPath* (instances of *LaserScanningPath*) were created. The domain and range of the object relation are respectively *PathPlanning* and *ScanningPath*. This means that a path planning task has designed laser scanning path of (a specific scanning path). The domain and range of each data relation are respectively *PathPlanning* and xsd:double. This means that a path planning task has designed process parameter value of xsd:double. Based on the crated entities, an ontological view of path planning for LPBF is delineated in

Figure 7, and seven SWRL rules for recommending a laser scanning path were developed as follows:

$$\begin{gathered} PathPlanning(?x1) \wedge hasObjective(?x1, highBuildEfficiency) \rightarrow \\ hasRecommendedPath(?x1, rasterPath) \end{gathered} \tag{16}$$

$$\begin{gathered} PathPlanning(?x1) \wedge hasObjective(?x1, highBuildEfficiency) \wedge \\ hasObjective(?x1, highMechanicalPerformance) \rightarrow hasRecommendedPath(?x1, zigzagPath) \end{gathered} \tag{17}$$

$$\begin{gathered} PathPlanning(?x1) \wedge hasObjective(?x1, highGeometricAccuracy) \wedge \\ hasObjective(?x1, highMechanicalPerformance) \rightarrow hasRecommendedPath(?x1, multiDirectionPath) \end{gathered} \tag{18}$$

$$\begin{gathered} PathPlanning(?x1) \wedge hasObjective(?x1, highBuildEfficiency) \wedge \\ hasObjective(?x1, highMechanicalPerformance) \rightarrow hasRecommendedPath(?x1, gridPath) \end{gathered} \tag{19}$$

$$\begin{gathered} PathPlanning(?x1) \wedge hasObjective(?x1, highGeometricAccuracy) \wedge \\ hasObjective(?x1, lessPathPasses) \wedge hasObjective(?x1, lessPathElements) \wedge \\ hasObjective(?x1, highMechanicalPerformance) \rightarrow hasRecommendedPath(?x1, spiralPath) \end{gathered} \tag{20}$$

$$\begin{gathered} PathPlanning(?x1) \wedge hasObjective(?x1, highGeometricAccuracy) \wedge \\ hasObjective(?x1, highMechanicalPerformance) \rightarrow hasRecommendedPath(?x1, contourPath) \end{gathered} \tag{21}$$

$$\begin{gathered} PathPlanning(?x1) \wedge hasObjective(?x1, highBuildEfficiency) \wedge \\ hasObjective(?x1, highGeometricAccuracy) \rightarrow hasRecommendedPath(?x1, hybridPath) \end{gathered} \tag{22}$$

where *highBuildEfficiency*, *highMechanicalPerformance*, *highGeometricAccuracy*, *lessPathPasses*, and *lessPathElements* are instances of *Objective*.

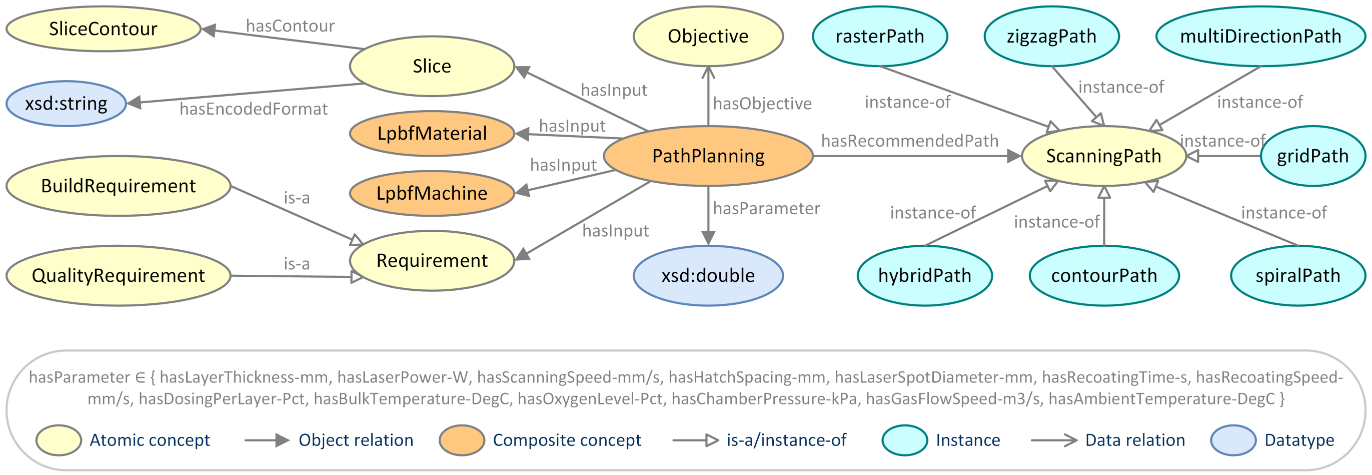
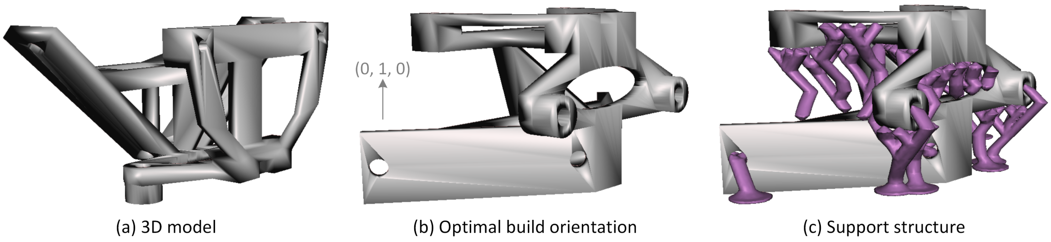


Figure 7. An ontological view of path planning for LPBF.

4. Application and Illustrations

4.1. Application of the Ontology

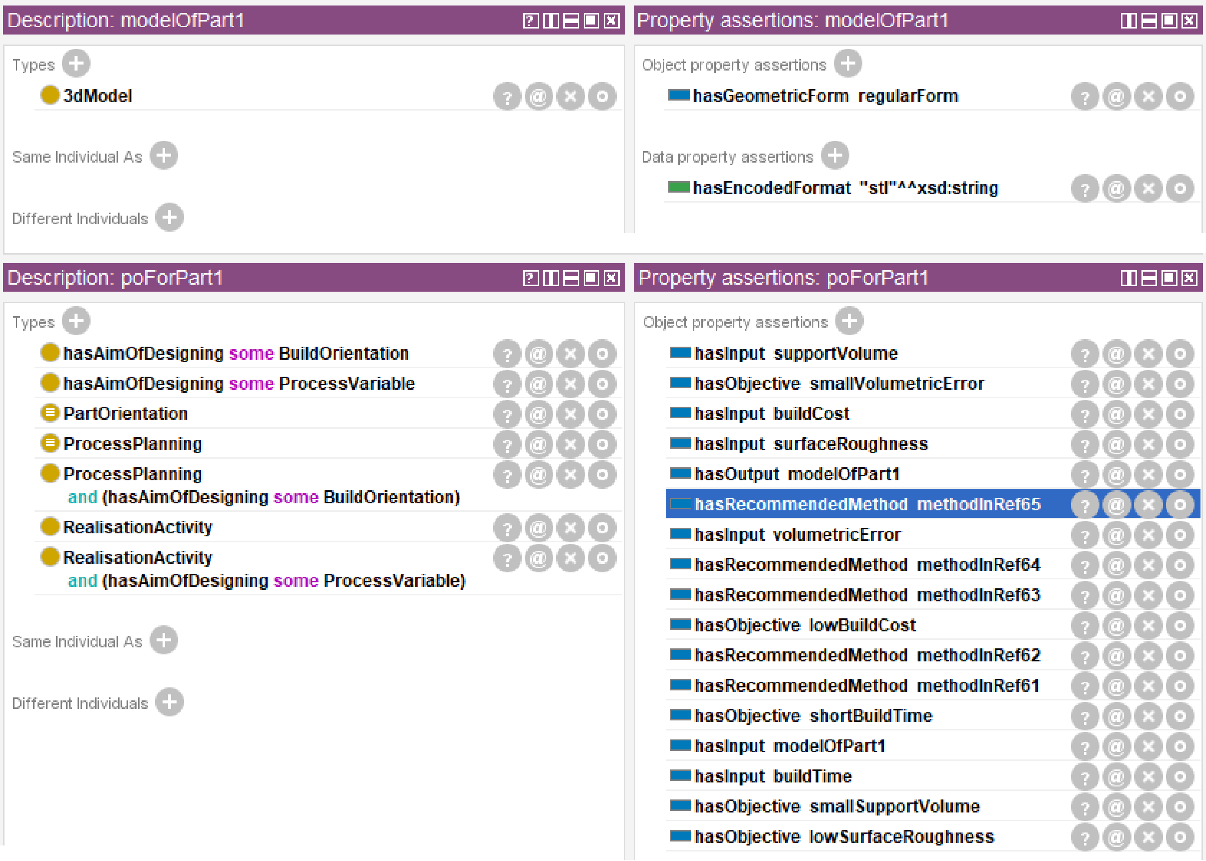
Process planning on an LPBF part is carried out to illustrate the application of the developed DL-based ontology. The 3D model of the part is encoded in the STL format and shown in Figure 8. This model is a regular form model, which was developed in [61]. It has 1181 vertices, 2426 triangular facets, total surface area of 9137.33 mm^2, and total volume of 9603.15 mm^3. The bounding box of the model has a length of 74.09 mm, a width of 33.75 mm, and a height of 34.34 mm. It is assumed that the part will be built using the LPBF material Ti6Al4V and the LPBF machine EOSINT M270. Before starting the actual part build, four process planning tasks on the part, part orientation, support generation, model slicing, and path planning, are needed to be completed successively. The objectives of part orientation are small support volume, short build time, low build cost, small volumetric error, and low surface roughness. The used support generation tool is Meshmixer. The objectives of model slicing are normal accuracy and high efficiency. The objective of path planning is high build efficiency.



(a) 3D model (b) Optimal build orientation (c) Support structure

Figure 8. 3D model, optimal build orientation, and support structure of an LPBF part.

The first task to be completed is part orientation. Based on the information above, two concept assertions *3dModel*(*modelOfPart1*) and *PartOrientation*(*poForPart1*) and thirteen relation assertions for *modelOfPart1* and *poForPart1* shown in Figure 9 were first created. Then, five relation assertions for recommending a part orientation method, which are also shown in Figure 9, were generated after performing OWL/SWRL reasoning using the Drools reasoning engine. According to the reasoning results, the rule-based methods in [61–65] are recommended to perform part orientation. Here the rule-based method in [65] was used and the determined optimal build orientation under the five objectives is depicted in Figure 8. Based on this, two concept assertions *BuildOrientation*(*oboForPart1*) and *UnitVector*(*unitVector1*), a new relation assertion for *poForPart1*, and five relation assertions for *modelOfPart1*, *oboForPart1*, and *unitVector1* shown in Figure 10 were generated in the ontology.



Description: modelOfPart1

Types
3dModel

Same Individual As

Different Individuals

Property assertions: modelOfPart1

Object property assertions
hasGeometricForm regularForm

Data property assertions
hasEncodedFormat "stl"^^xsd:string

Description: poForPart1

Types
hasAimOfDesigning some BuildOrientation
hasAimOfDesigning some ProcessVariable
PartOrientation
ProcessPlanning
ProcessPlanning and (hasAimOfDesigning some BuildOrientation)
RealisationActivity
RealisationActivity and (hasAimOfDesigning some ProcessVariable)

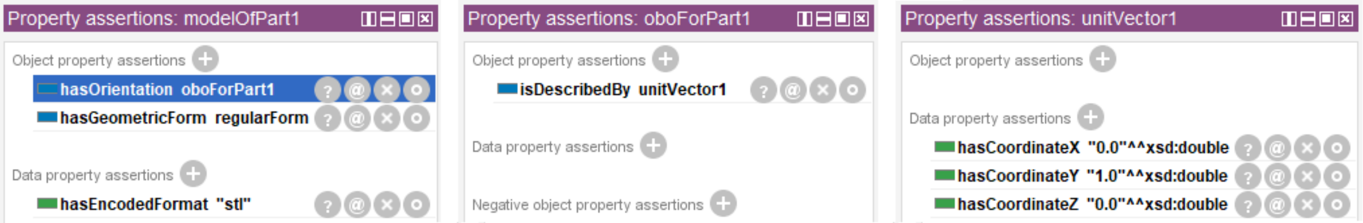
Same Individual As

Different Individuals

Property assertions: poForPart1

Object property assertions
hasInput supportVolume
hasObjective smallVolumetricError
hasInput buildCost
hasInput surfaceRoughness
hasOutput modelOfPart1
hasRecommendedMethod methodInRef65
hasInput volumetricError
hasRecommendedMethod methodInRef64
hasRecommendedMethod methodInRef63
hasObjective lowBuildCost
hasRecommendedMethod methodInRef62
hasRecommendedMethod methodInRef61
hasObjective shortBuildTime
hasInput modelOfPart1
hasInput buildTime
hasObjective smallSupportVolume
hasObjective lowSurfaceRoughness

Figure 9. Assertions and reasoning results of part orientation for the LPBF part.



Property assertions: modelOfPart1

Object property assertions
- hasOrientation oboForPart1
- hasGeometricForm regularForm

Data property assertions
- hasEncodedFormat "stl"

Property assertions: oboForPart1

Object property assertions
- isDescribedBy unitVector1

Data property assertions

Negative object property assertions

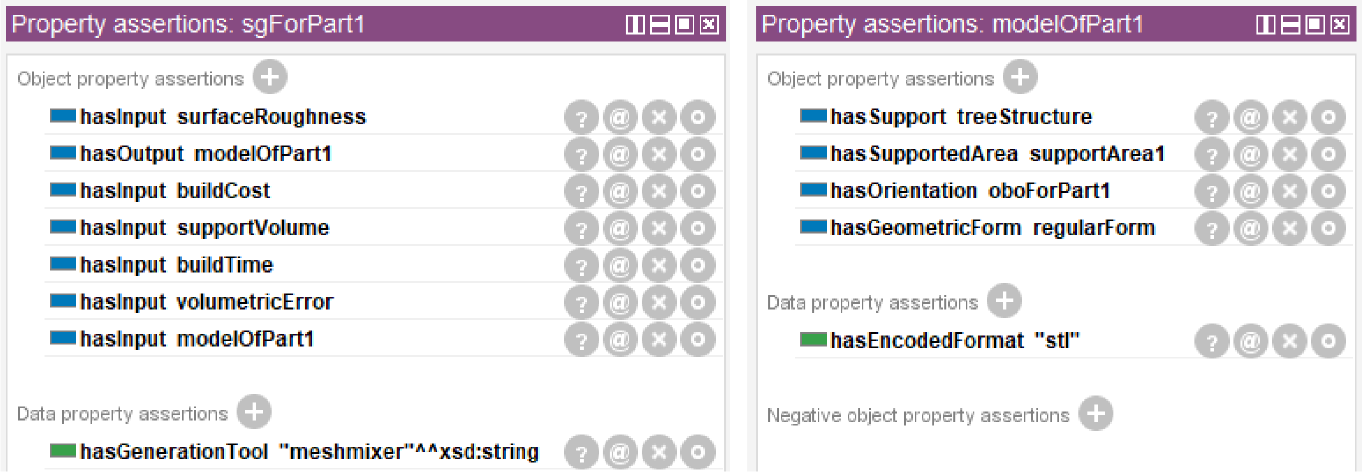
Property assertions: unitVector1

Object property assertions

Data property assertions
- hasCoordinateX "0.0"^^xsd:double
- hasCoordinateY "1.0"^^xsd:double
- hasCoordinateZ "0.0"^^xsd:double

Figure 10. Results of part orientation for the LPBF part in the ontology.

The second task to be completed is support generation. In this task, a concept assertion *SupportGeneration*(*sgForPart1*) and seven relation assertions shown in Figure 11 were first created. Then, support generation was carried out using Meshmixer and the generated support structure is depicted in Figure 8. Based on this, two new relation assertions for *modelOfPart1* shown in Figure 11 were generated in the ontology.



Property assertions: sgForPart1

Object property assertions
- hasInput surfaceRoughness
- hasOutput modelOfPart1
- hasInput buildCost
- hasInput supportVolume
- hasInput buildTime
- hasInput volumetricError
- hasInput modelOfPart1

Data property assertions
- hasGenerationTool "meshmixer"^^xsd:string

Property assertions: modelOfPart1

Object property assertions
- hasSupport treeStructure
- hasSupportedArea supportArea1
- hasOrientation oboForPart1
- hasGeometricForm regularForm

Data property assertions
- hasEncodedFormat "stl"

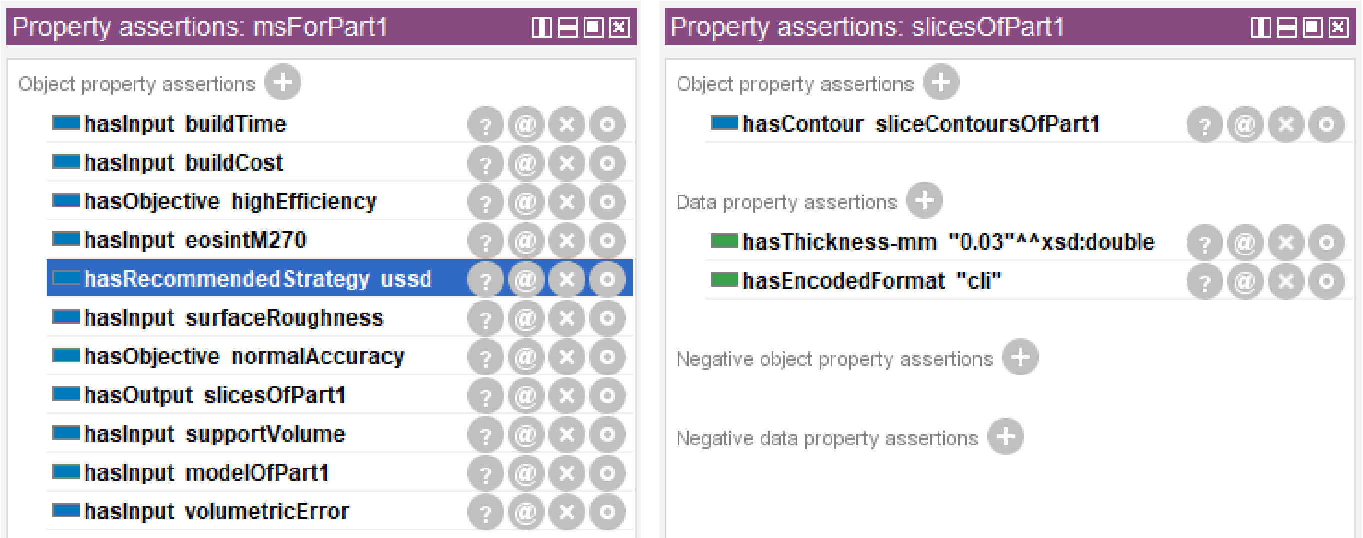
Negative object property assertions

Figure 11. Results of support generation for the LPBF part in the ontology.

The third task to be completed is model slicing. Firstly, a concept assertion *ModelSlicing*(*msForPart1*) and nine relation assertions shown in Figure 12 were created. Then, a relation assertion for recommending a model slicing strategy, which is also shown in Figure 12, was generated after performing OWL/SWRL reasoning using the Drools reasoning engine. According to the reasoning results, ussd (uniform slicing in single direction) can be selected to slice the build model with a thickness of 0.03 mm. Based on this, a new relation assertion for *msForPart1* and three relation assertions for *slicesOfPart1* shown in Figure 12 were generated in the ontology.

The last task to be completed is path planning. Firstly, a concept assertion *PathPlanning*(*ppForPart1*) and nine relation assertions shown in Figure 13 were created. Then, a relation assertion for recommending a laser scanning path, which is also shown in Figure 13, was generated after performing OWL/SWRL reasoning using the Drools reasoning engine. According to the reasoning results, raster path is selected to build the part under the following process parameters: layer thickness is 0.03 mm; laser power is 150 W; scanning speed is 1250 mm/s; hatch spacing is 0.07 mm; recoating time is 20 s; each of the remaining controllable process parameters takes its default value. Based on this, five new relation assertions for *ppForPart1* shown in Figure 13 were generated in the ontology.

Based on all designed process variables above, the total support volume, total build time, total build cost, total volumetric error, and average surface roughness of the LPBF part were predicted using the prediction models in [81]: total support volume is 4587.15 mm^3; total build time is 7.75 h; total build cost is 360.37 GBP; total volumetric error is 78.85 mm^3; average surface roughness is 10.61 µm. Based on this, five new relation assertions for *part1* shown in Figure 13 were generated in the ontology.



Property assertions: msForPart1

Object property assertions

- hasInput buildTime
- hasInput buildCost
- hasObjective highEfficiency
- hasInput eosintM270
- hasRecommendedStrategy ussd
- hasInput surfaceRoughness
- hasObjective normalAccuracy
- hasOutput slicesOfPart1
- hasInput supportVolume
- hasInput modelOfPart1
- hasInput volumetricError

Property assertions: slicesOfPart1

Object property assertions

- hasContour sliceContoursOfPart1

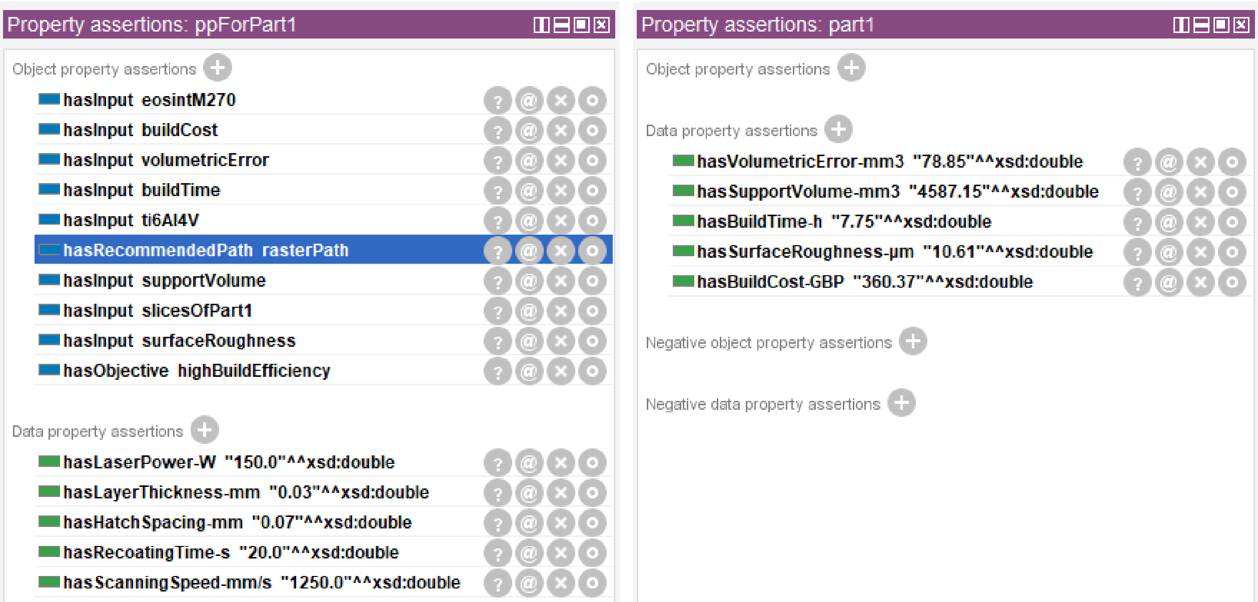
Data property assertions

- hasThickness-mm "0.03"^^xsd:double
- hasEncodedFormat "cli"

Negative object property assertions

Negative data property assertions

Figure 12. Results of model slicing for the LPBF part in the ontology.



Property assertions: ppForPart1

Object property assertions

- hasInput eosintM270
- hasInput buildCost
- hasInput volumetricError
- hasInput buildTime
- hasInput ti6Al4V
- hasRecommendedPath rasterPath
- hasInput supportVolume
- hasInput slicesOfPart1
- hasInput surfaceRoughness
- hasObjective highBuildEfficiency

Data property assertions

- hasLaserPower-W "150.0"^^xsd:double
- hasLayerThickness-mm "0.03"^^xsd:double
- hasHatchSpacing-mm "0.07"^^xsd:double
- hasRecoatingTime-s "20.0"^^xsd:double
- hasScanningSpeed-mm/s "1250.0"^^xsd:double

Property assertions: part1

Object property assertions

Data property assertions

- hasVolumetricError-mm3 "78.85"^^xsd:double
- hasSupportVolume-mm3 "4587.15"^^xsd:double
- hasBuildTime-h "7.75"^^xsd:double
- hasSurfaceRoughness-μm "10.61"^^xsd:double
- hasBuildCost-GBP "360.37"^^xsd:double

Negative object property assertions

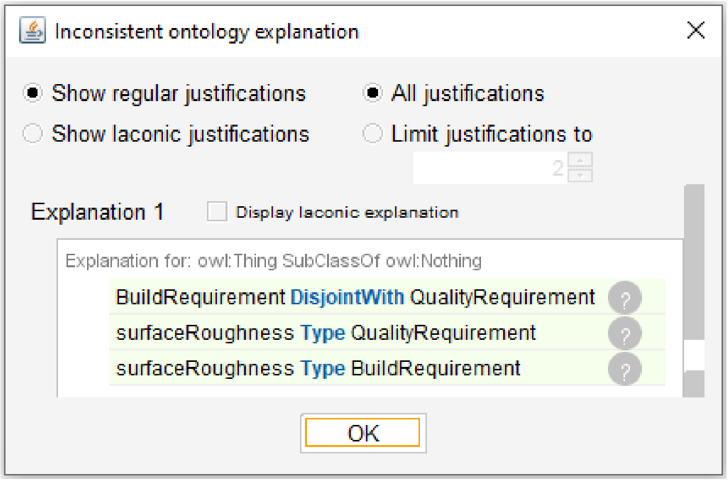
Negative data property assertions

Figure 13. Results of path planning for the LPBF part in the ontology.

4.2. Illustrations of the Benefits

OWL DL can provide the strongest expressive capability under the premise of computational completeness and computational decidability, which enables reasoning mechanisms like consistency checking of the OWL DL ontology, knowledge reasoning on the ontology and semantic query from the ontology.

Consistency checking is performed to determine whether an instantiation of a concept satisfies the definition of the concept or would create an inconsistency. Using the HermiT reasoner in Protégé, the consistency of the developed ontology for LPBF process planning can be checked automatically. For example, if *surfaceRoughness* is further asserted as an instance of *BuildRequirement* in the ontology, then an inconsistency will be detected automatically, as shown in Figure 14, because *BuildRequirement* has been defined to be disjoint with *QualityRequirement* and the instance *surfaceRoughness* does not satisfy this definition. Once there are no inconsistencies in the developed ontology, knowledge reasoning can be performed on it.



Inconsistent ontology explanation

● Show regular justifications ● All justifications

○ Show laconic justifications ○ Limit justifications to 2

Explanation 1 □ Display laconic explanation

Explanation for: owl:Thing SubClassOf owl:Nothing

BuildRequirement DisjointWith QualityRequirement

surfaceRoughness Type QualityRequirement

surfaceRoughness Type BuildRequirement

Figure 14. Example of consistency checking of the ontology.

Knowledge reasoning is carried out to reach new conclusions in a context based on the explicit knowledge in this context. In a DL-based ontology with SWRL rules, new knowledge can be inferred via either a DL reasoner or an SWRL reasoner. For example, the previous subsection has described the details of using the Drools reasoner (an SWRL reasoner integrated in Protégé) to reason out a recommended part orientation method, a recommended model slicing strategy, and a recommended laser scanning path in the developed ontology for LPBF process planning. After performing knowledge reasoning on the ontology, its an enriched version will become available for semantic query.

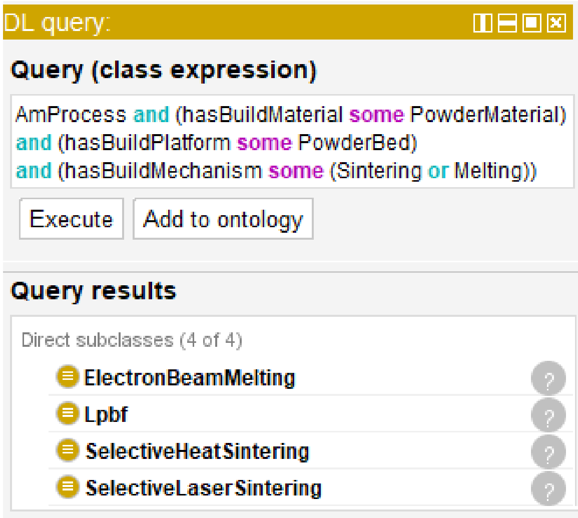
Semantic query is performed to search specific knowledge from an ontology. Three commonly used semantic query techniques for an OWL DL ontology with SWRL rules are DL query, SPARQL query, and SQWRL query, which respectively uses the reasoning mechanism of DL, SPARQL, and SQWRL to implement semantic query. For example, assume the following terminological axioms are defined in the developed ontology:

$$\begin{aligned} SelectiveLaserSintering \equiv AmProcess &\sqcap \exists hasEnergySource.LaserBeam \\ &\sqcap \exists hasBuildMaterial.PowderMaterial \\ &\sqcap \exists hasBuildPlatform.PowderBed \\ &\sqcap \exists hasBuildMechanism.Sintering \end{aligned} \tag{23}$$

$$\begin{aligned} SelectiveHeatSintering \equiv AmProcess &\sqcap \exists hasEnergySource.ThermalEnergy \\ &\sqcap \exists hasBuildMaterial.PowderMaterial \\ &\sqcap \exists hasBuildPlatform.PowderBed \\ &\sqcap \exists hasBuildMechanism.Sintering \end{aligned} \tag{24}$$

$$\begin{aligned} ElectronBeamMelting \equiv AmProcess &\sqcap \exists hasEnergySource.ElectronBeam \\ &\sqcap \exists hasBuildMaterial.PowderMaterial \\ &\sqcap \exists hasBuildPlatform.PowderBed \\ &\sqcap \exists hasBuildMechanism.Melting \end{aligned} \tag{25}$$

There is an AM process whose build material is a powder material, build platform is a powder bed, and build mechanism is sintering or melting. Someone needs to determine which specific AM processes it might belong to. If a common text search is adopted, no results will be obtained. However, if a DL query is carried out, the situation will be completely different. As shown in Figure 15, the description of the AM process is taken as the input of a DL query, and it can be inferred from the query results that the process might belong to selective laser sintering, selective heat sintering, electron beam melting, or LPBF.



```
AmProcess and (hasBuildMaterial some PowderMaterial)
and (hasBuildPlatform some PowderBed)
and (hasBuildMechanism some (Sintering or Melting))
```

Direct subclasses (4 of 4)

- ElectronBeamMelting
- Lpbf
- SelectiveHeatSintering
- SelectiveLaserSintering

Figure 15. Example of a DL query from the ontology.

5. Conclusions

In this paper, a DL-based ontology with SWRL rules for knowledge representation in process planning for LPBF is developed. Firstly, a set of top-level DL concepts, DL relations, DL instances, and DL axioms are created to represent the knowledge in general process planning activity. Then, specific DL concepts, DL relations, DL instances, and SWRL rules are respectively developed to describe the knowledge in part orientation, support generation, model slicing, and path planning. After that, the application of the developed ontology is demonstrated via process planning on an LPBF part. Finally, the benefits of the ontology are outlined and illustrated using examples. The illustration results show that the ontology has rigorous computer-interpretable semantics, which would lay solid basis for development of an LPBF process planning tool with autonomous decision-making capability.

Each of existing LPBF process planning tool has its specific knowledge representation method. Although ontology-based method has advantages in automatic consistency checking, knowledge reasoning, and semantic query and is gaining importance and popularity in AM knowledge representation, it should not be considered as a complete replacement of the methods used in existing tools, but more as an alternative method to improve them in some aspects. At present, existing ontologies for knowledge representation in LPBF are not yet mature. More powerful ontologies and related tools that can realise autonomous decision-making need to be further investigated.

Future work will aim especially at improving the developed DL-based ontology to overcome a main limitation: knowledge representation in process planning for multi-part production is not considered. An important feature of LPBF is that it enables rapid fabrication of multiple different parts in a mixed batch [60]. The developed ontology focuses on knowledge representation in process planning for production of one single part, it cannot be applied to the situation where multiple parts in the same build need to be planned simultaneously. From the perspective of application, it is of necessity and importance to improve the ontology to handle this situation. Further, the conventional LPBF process planning pipeline is somewhat complex and a simpler pipeline has been presented in [82]. It would be interesting to develop a DL-based ontology for this simpler pipeline.

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Abbreviations

ABox	Assertion Box
AM	Additive Manufacturing
AMF	Additive Manufacturing File
CLI	Common Layer Interface
DL	Description Logic
HPGL	Hewlett-Packard Graphics Language
LPBF	Laser Powder Bed Fusion
OWL	Web Ontology Language
SLC	Stereo Lithography Contour
SPARQL	Sparql Protocol And Rdf Query Language
SQWRL	Semantic Query-enhanced Web Rule Language
STL	Standard Tessellation Language
SWRL	Semantic Web Rule Language
TBox	Terminology Box
3D	Three-Dimensional
3MF	3D Manufacturing File
usmd	uniform slicing in multiple directions
ussd	uniform slicing in single direction
vsmd	variable slicing in multiple directions
vssd	variable slicing in single direction

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