Knowledge graph network-driven process reasoning for laser metal additive manufacturing based on relation mining

Article *in* Applied Intelligence · August 2024

DOI: 10.1007/s10489-024-05757-8

5 authors, including:

Changri Xiong
Iowa State University

Jinhua Xiao
Politecnico di Milano

Gang Zhao
Dalian University of Technology

Wenlei Xiao
Beihang University

Applied Intelligence
https://doi.org/10.1007/s10489-024-05757-8

Knowledge graph network-driven process reasoning for laser metal additive manufacturing based on relation mining

Changri Xiong[1] · Jinhua Xiao[2] · Zhuangyu Li[1] · Gang Zhao[1] · Wenlei Xiao[1]

Accepted: 7 August 2024

Abstract
Additive Manufacturing (AM) technology offers remarkable flexibility in fabricating products with intricate geometries, presenting unprecedented advantages in material efficiency and speed. The process planning of AM plays a pivotal role in ensuring overall quality and time-efficiency of printed products. This drives engineers and researchers to explore various approaches to achieve optimal AM process solutions. However, numerous challenges persist, particularly in logical relationship reasoning and information representation for complex manufacturing tasks and design requirements. In this study, a novel AM process reasoning method based on relation mining is proposed, leveraging knowledge graph representation and graph neural networks (GNN). An AM knowledge graph is constructed comprising essential process information, followed by implementing RED-GNN to accomplish graph reasoning tasks for parameter recommendation. We then focus on the process planning scenario of lattice structures, a common geometry used for designing products with weight-relief requirements and high sensitivity to process parameters. A series of lattice structure parts are designed and tested using our proposed method, demonstrating strong performance and unveiling new potentials and opportunities in advancing knowledge-based engineering and intelligent manufacturing.

Keywords Additive manufacturing · 3D printing · Lattice structures · Knowledge graph · Knowledge reasoning · Graph neural networks · Process reasoning

1 Introduction

Additive manufacturing, also known as 3D printing, is emerging as a transformative technology capable of fabricating intricate components or products by layering materials based on diverse design specifications. This approach offers significant advantages such as cost-effectiveness and time efficiency [1, 2]. The process of additive manufacturing encompasses crucial stages including part design, tessellated data integration, creation of 3D models, generation of build files, machine data utilization, fabrication of parts, final product finishing, and validation [3]. In recent years, process planning has become a focal point in the field of additive manufacturing, presenting researchers with challenges and opportunities for enhancing manufacturing efficiency. There is a clear demand for optimizing specific process planning methodologies, reflecting the ongoing efforts of engineers and manufacturers to boost production yield while minimizing post-processing requirements for finished products. Notably, determining the optimal build orientation for printed parts is paramount, especially when producing parts in batches. This decision significantly impacts factors such as the projection area onto the building platform, the amount of required support structures, and the maximum build height. Achieving an optimal build orientation is essential for striking a balance between part quality and cost-effectiveness. Numerous studies have demonstrated that build orientation greatly influences the mechanical performance of printed parts [4–6]. Furthermore, laser energy density plays a critical role in achieving superior surface quality and mechanical properties by influencing the microstructure and performance of parts [7]. The evaluation of energy density should carefully consider the thermal properties of the material to ensure compatibility during process

✉ Wenlei Xiao
xiaowenlei@buaa.edu.cn

1 School of Mechanical Engineering and Automation, Beihang University, Beijing 100191, China

2 Department of Management, Economics and Industrial Engineering, Politecnico di Milano, Piazza Leonardo da Vinci 32, 20133 Milan, Italy

planning. In powder bed-based additive manufacturing, the layer thickness is determined by the height of the powder coating, thereby regulating the final product's fineness. Inappropriate thickness may lead to unfused defects, causing discontinuities between deposited layers [8]. Additionally, the design of support structures is integral to the additive manufacturing process. Determining whether a part requires support structures, as well as their specific locations, is crucial for preventing deformation caused by residual thermal stress. Slicing facilitates the creation of the layered structure as a manufacturing feature, while path planning determines how the desired part will be accomplished [9]. Despite the importance of selecting correct manufacturing parameter for designed parts, determining optimal process for laser metal AM is a very sophisticated task that requires immense experience and understanding on the laser melting mechanisms, material's thermomechanical characteristics, structural/geometric influence and so forth. For years, researchers have been carrying out studies on AM process parameters in perspectives of material properties, product mechanical properties, surface roughness and other essential aspects in both qualitative and quantitative means [10], but a systematic solution on providing clear instructions for AM process planning is yet to be found.

Process planning predominantly revolves around the meticulous selection of requisite manufacturing processes and the delineation of precise operational sequences for conventional subtractive manufacturing, such as CNC machining [11]. Drawing from the principles of conventional manufacturing techniques, numerous scholars have produced exhaustive works on optimizing feature-based process planning [12], knowledge-based process planning [13], and STEP-Compliant process planning [14] to ascertain process parameters in additive manufacturing planning. The endeavor to devise a unified optimization methodology for selecting optimal process parameters is formidable, given the variability of design components and their associated manufacturing processes. Yu et al. [15] developed a strut-based process planning method for the WAAM system for lattice structure manufacturing. Innovative bead modelling and sequence optimization techniques are demonstrated that offer highly automated and efficient process control. Xiong et al. [16] proposed a process planning framework by integrating a WAAM knowledge base with computer-aided tools, which incorporates metalmodels and planning rules for decision-making on process variables by a data-knowledge-service structure. Such approaches are by far dedicated to improving printing quality on specific features that involves limited amount of control variables, which could encounter issues when implementing on manufacturing demands with higher complexity. Haruna et al. [17] developed knowledge reasoning method by constructing Knowledge graph for fused deposition modeling-based DFAM (Design For Additive Manufacturing) and elaborated Transformers model to recognize AM entities and relations. By far, there are a few researchers contributing their efforts on resolving process planning issues with methods related to knowledge-based methods, while focusing on different types of AM technologies with distinct printing mechanisms and parameters. Although their work helps the completion of the overall AM process planning "puzzles", it is still inadequate for developing a general pipeline of interconnection between designs and processes in AM.

Graph structures are among the most intuitive ways to represent data and concepts along with their interrelationships. In the real world, graphs are highly useful for depicting point cloud data, traffic and urban infrastructure systems, social networks, molecular structures, and more. Knowledge Graphs (KG) are a typical example of graph-structured ontology representation, ideally suited for representing additive manufacturing (AM) parameters from design to production. By formalizing experiential information and manufacturing parameters into structured knowledge networks, decision-making and optimization in the AM process become significantly more efficient. Furthermore, the integration of intelligent techniques, such as machine learning and neural networks, becomes more feasible. Since the early 2000s, the graph neural network (GNN) model has been applied across numerous scientific and engineering fields, proving to be highly practical. GNNs can process most types of graph-structured data in multi-dimensional space and show promising results for knowledge modeling. Wu et al. [18] and Zhou et al. [19] gave comprehensive overviews on GNNs with illustrations of the taxonomy and applications. In general, GNNs can be categorized in four main types: (1) RecGNN(recurrent GNN), for learning node representations using recurrent neural architectures; (2) ConvGNN(convolutional GNN), a generalization of convolution from grid to graph, stacking graph convolutional layers to extract high-level node representations; (3) GAE(graph autoencoders), for learning network embeddings and graph generative distributions by reconstructing graphical structure information; (4)STGNN(spatial–temporal GNN), for discovering latent patterns from spatial–temporal graphs. As illustrated, current Graph Neural Networks (GNNs) are designed to generate outputs for various analytical tasks: node-level tasks, edge-level tasks, and graph-level tasks. Node-level tasks focus on node regression and node classification, aiming to learn and predict node properties and values. Edge-level tasks involve uncovering hidden representations for the links between nodes. Graph-level tasks require obtaining compact representations of entire graphs. Researchers exploring the potential of GNNs in manufacturing have been applying GNN-based approaches across various aspects of the field. With increasing demand of near-zero-defect manufacturing, Leonhardt et al. [20] proposed the Process Estimator neural Network (PEN) that blends a single graph convolution layer with two fully-connected layers for root cause analysis in multistage manufacturing. In their work, GCNN had shown superb capability on processing 3D mesh data, which can be interpreted as undirected graphs. But struggles may be imposed when the mesh data become larger and more complex. Zhang et al. [21] focused on multiple machines in multistage manufacturing process and developed a path enhanced bidirectional graph attention network (PGAT) to model dependencies among machines directed graphs. The target-specific attention decoder made prediction of the measurement values from stages, yet still faces issues involving computational complexities in real-time applications. Mozaffar et al. [22] focused on thermal modeling in AM processes, especially for complex unstructured geometries. A physics-aware data-driven model was proposed to gain high predictive ability and computational efficiency with AI assisted analysis model. The spatiotemporal dependencies in AM processes can be captured using GNN, such that the AM thermal responses can be predicted and reproduced. However, this approach is highly dependent on data quality. Huang et al. [23] conducted optimization of production yield in machine process systems with integrated control framework using graph attention network (GAT) and multi-agent reinforcement learning (MARL). Real-time information across levels of machine, process and system in general manufacturing systems can be analyzed by GAT as node features to generate node embeddings, along with material flows as links in graph. Wang et al. [24] had sought a solution for performance improvement of manufacturing feature recognition, and a hybrid learning framework is proposed that combines graph-based, rule-based, and GNN methods altogether to accomplish feature extraction, classification and decomposition tasks. This hybrid framework shows good efficiency and robustness for recognizing both isolated and interacting features, but could also encounter integration challenges combining different methodologies. Lai et al. [25] considered the bottleneck issues in production system and addressed the challenges in future bottleneck prediction. To identify future manufacturing systems, an interpretable modeling framework based on GAT is proposed to transform topology features of complex manufacturing into graph representations and model relations between stations. The future bottleneck can be found by capturing temporal trends and station interactions and analyzing predicted blockage and starvation, yet still lack of capabilities in dynamic production environments.

The adoption of knowledge-driven process reasoning offers a promising approach to unravel the intricate interplay between specific printed parts and process planning in additive manufacturing (AM). Given the limited understanding of AM process control mechanisms and the challenges of incorporating analytical procedures into process planning, a method independent of physical and numerical analysis appears practical. Consequently, a GNN-based reasoning method has been developed to explore intelligent decision-making for process parameters in AM planning. This method leverages graphical representation to understand the internal relationships among parameters and reasons through the related AM knowledge from part design to manufacturing stages. Our main contributions are summarized as follow:

- The concept of a knowledge base for additive manufacturing (AM) and the construction of a relational knowledge graph are proposed.
- A GNN-based reasoning method is proposed to leverage the graph-structured AM knowledge, enhancing parameter recommendation capabilities within the AM process reasoning framework.
- An AM knowledge graph for periodic lattice parts is constructed using actual parameters and tested with the proposed method.

The remainder of this paper is structured as follows: Section 2 illustrates the methodology in detail. A case study is demonstrated in Section 3 with implementation of a RED-GNN approach for AM parameter deducing and process planning. Section 4 and 5 discuss and conclude the presented work.

2 Knowledge reasoning based on GNN

Knowledge-based engineering for additive manufacturing (AM) leverages theoretical information and expert experience to solve reasoning problems through a knowledge base. In practical applications, knowledge reasoning deduces complex relationships from user-provided information combined with existing knowledge and data. AM process planning focuses primarily on selecting the appropriate manufacturing technology, raw materials, process parameters, processing equipment and its parameters, workspace planning, and determining printing orientations and paths. As AM technology continuously evolves, intelligent decision-making in AM process planning becomes crucial, significantly impacting downstream manufacturing processes by determining the optimal manufacturing approach. To thoroughly explore knowledge reasoning in AM process planning decisions, leveraging extensive experience and data libraries, it is essential to propose an overarching framework that illustrates AM knowledge interoperability and reasoning methods. This includes knowledge representation, application implementation, and reasoning mechanisms. AM knowledge representation and reasoning are crucial in determining final decisions about part design and the manufacturing process. Consequently, the AM knowledge base must encompass all relevant knowledge content, providing data, information, and experiential insights, such as rule libraries, material libraries, feature libraries, and information on AM equipment and planning. Additionally, deep relationships among various knowledge layers should be represented through ontology-based knowledge models. This paper will only focus on the mechanism of knowledge reasoning based on application implementation in specific manufacturing cases.

To implement knowledge reasoning for additive manufacturing (AM) design and process planning, it is crucial to collect and structure manufacturing attributes and parameters. These elements often present complex characteristics and correlations in various forms, necessitating their organization into a more accessible ontology for the knowledge reasoning system to process and operate efficiently. A knowledge graph (KG) serves as an exemplary method for representing and storing information and instances as feature entities with triple form (subject-relation-object) interactions within a graph-structured ontology. One significant advantage of KGs is their capacity to link an unlimited number of entity nodes with diverse relational edges, aggregating into a directional graph. This capability provides substantial freedom to represent sophisticated multi-scaled ontologies. As a practical demonstration, an AM knowledge graph (AMKG) that encompasses the ontology of lattice structure design and selective laser melting (SLM)-based 3D printing processes is constructed, as illustrated in Fig. 1. Generally, entities in the AMKG can be classified into two categories: part design entities and manufacturing entities. Part design entities encompass the geometric features of the lattice model, while manufacturing entities define the AM process parameters for fabricating the designed part, contingent on the capabilities of the AM machine. Note that the entities in AM knowledge graph can vary in their own data type. For instance, *strut_diameter*, *strut_length* and *downskin_angle* entities are attributes of *unit_cell_type* entity, which will be constructed as three triplets: (*unit_cell_type*, *isComposedOf*, *strut_diameter*), (*unit_cell_type*, *isComposedOf*, *strut_length*), (*unit_cell_type*, *isComposedOf*, *downskin_angle*). Meanwhile *strut_diameter*, *strut_length* and *downskin_angle* will also have specific numerical values assigned for each one of them.

Based on the graphical mechanism of the AM knowledge graph (AMKG), a Graph Neural Network (GNN)-based method is proposed to learn the knowledge structures and develop reasoning strategies. This approach aims to deduce missing information from incomplete AM process and recommend plausible process parameters to achieve optimal as-built quality. In our framework, RED-GNN (Relational-Directed-Graph-based Graph Neural Network), developed and proven by Zhang and Yao [26], is used as the core approach for its efficiency and effectiveness for both inductive and transductive reasoning tasks, which is an essential performance demanded by potential complex decision-making assignments in AM. Considering a graph G consists of nodes N, to represents objects or concepts and edges E with relations between N, a GNN's major task is to transform G into a learnable network $\mathcal{G}$ that combines information contained in N along with the relationship contained in E into embeddings while preserving the fundamental logic or topology of G. Such that, by iteratively aggregating messages in the nodes and their local neighborhood, $\mathcal{G}$ is empowered to fulfill predictions of unlabeled or missing nodes and links, and many other inferential jobs using the information within the embeddings. Such process is known as message passing in learning procedures, and can be mathematically expressed as the following message passing update and aggregation function [26]:

$$\boldsymbol{h}_u^{k+1} = UPDATE^k(\boldsymbol{h}_u^k, AGGREGATE^k(\{\boldsymbol{h}_v^k, \forall v \in \mathcal{N}(u)\}))$$

where v represents the neighboring nodes of node u in local neighborhood $\mathcal{N}(u)$. In every iteration, the current state $\boldsymbol{h}_u^k$ is combined with the aggregation of neighborhood state

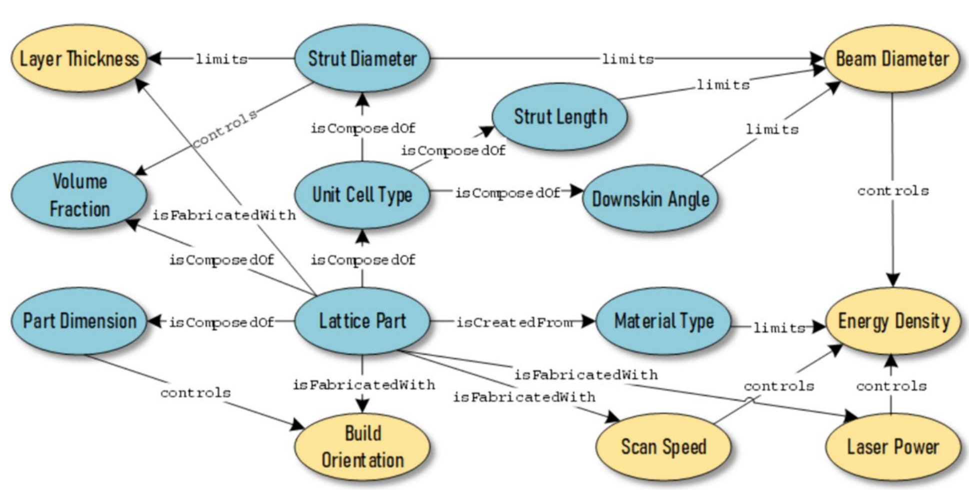


Fig. 1 Knowledge graph for AM specifications

$\boldsymbol{h}_v^k$ at time step k and update to the next $k+1$ state $\boldsymbol{h}_u^{k+1}$. This general framework lays the foundation of the GNN implementation. Note that the way of aggregation can be customized to fit the specific needs of the GNN algorithm, which leads to the blooming of the development of GNN variants. For the applications in KG, the message passing mechanism can be adapted to [26].

$$\boldsymbol{h}_{e_o}^l = \delta\left(W^l \bullet \sum\nolimits_{(e_s,r,e_o)\in\mathcal{F}} \phi\left(\boldsymbol{h}_{e_s}^{l-1}(e_q, r_q), \boldsymbol{h}_r^l\right)\right)$$

where $\boldsymbol{h}$ is the encoded layer representation, l is the layer index number, $\mathcal{F}$ represents the sets of the fact triples which is originally from KG, δ is the activation function, $\phi(*,*)$ is the message on the l-hop neighbor edges $(e_s, r, e_o) \in F$ of entity e_o with dimension d, and W^l is a weighting matrix within span of $d \times d$. After aggregation of all layers, local structures of all entities are captured and jointly work with a decoder scoring function to quantitatively analyze the KG triples. However, such representations are lacking clarity and interpretability of local evidence for some queries due to the independency of aggregated information.

The implementation of RED-GNN relies on the construction of r-digraphs, which generalize relational paths in knowledge graphs (KG). This approach combines the interpretability and transferability of path-based methods with the structure-preserving properties of subgraphs. An r-digraph is defined as a directed graph with multiple interconnected layers. With the integration of GNN, r-digraphs can be encoded and learned with exceptional efficiency. The encoding process generally involves three steps: (1) Identify and extract the neighboring entities for both the query entity e_q and the answer entity e_a; (2) Build the subgraph based on the intersection of these neighboring entities; (3) Execute message passing on the subgraph to obtain the graph-level representation, which serves as the final encoding. Figure 2 is a graphical demonstration of r-digraph encoding process. Detailed algorithmic specifics are beyond the scope of this discussion and can be referenced in the original article by Zhang and Yao.

The knowledge-based engineering framework in this work integrates both the RED-GNN and the AM knowledge base (container of AMKG). As demonstrated in Fig. 3, the design specifications of a lattice structure part are sampled to create an AMKG, which is then processed by the RED-GNN. In summary, the AM knowledge base provides experience-based information on parameter combinations and structured ontologies, while the GNN focuses on conducting evidence exploration for reasoning and logical deduction. Knowledge relationships and feature-behavior correlations are established as prerequisite knowledge based on experiential data collection and organization within the AM knowledge base, which is used to generate the AMKG. Meanwhile, the RED-GNN infers process parameters from part design

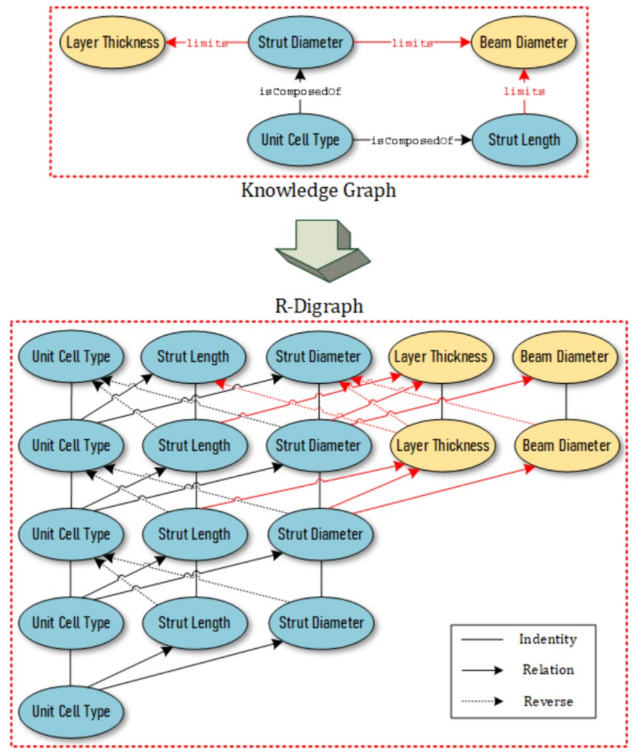


Fig. 2 R-digraph encoding of AMKG

features by learning the graph structure and mining deep relationships. It then complements the missing relational paths in the AMKG, thereby providing a complete process plan for AM production tasks.

3 Case study

Lattice structures are a unique yet critical aspect of additive manufacturing, widely used in aerospace and biomedical industries for their exceptional weight-relieving, energy-absorbing abilities, and high specific strength. Formed by interconnected thin struts or walls in periodic or irregular patterns, lattice structures often serve as the hollow infill of solid body parts. Their complexity makes them unsuitable for fabrication methods other than AM. This geometric uniqueness presents significant challenges in ensuring overall printing quality through conventional AM process planning. Specifically, considering strut-based lattice structures using laser powder bed AM processes, the lattice cells are typically very small, and the struts have varying inclination angles based on the build orientation, leading to complex formation mechanisms. For example, improper hatch spacing can induce undesired pores inside the struts. Inappropriate laser power and scanning speed can result in inconsistencies in strut thickness and poor surface roughness, causing defects and potentially leading to mechanical

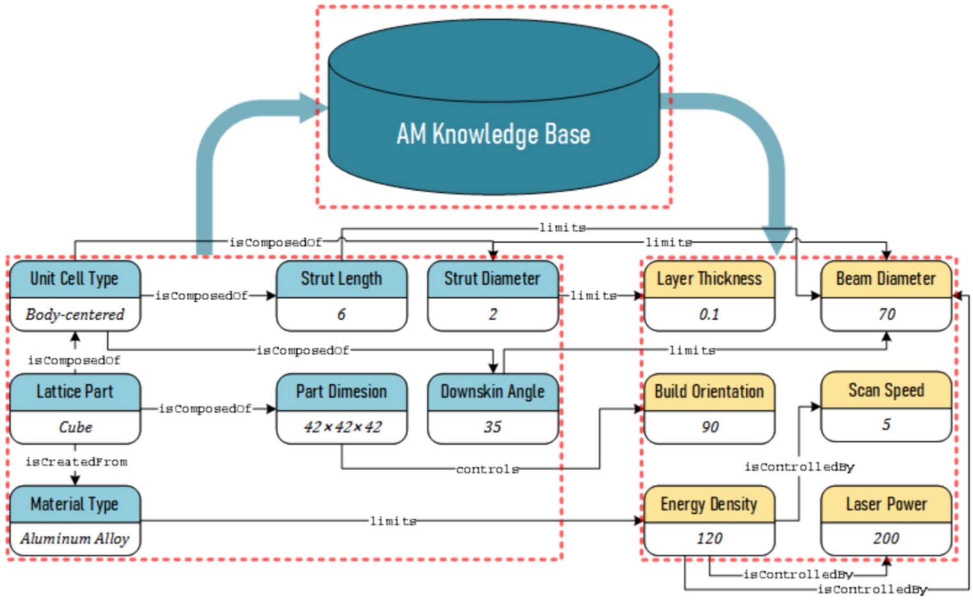


Fig. 3 Graphical demonstration of AM knowledge reasoning

failures. Additionally, surface polishing and other post-processing techniques are usually not feasible for lattice structures due to the inaccessibility of the internal areas for machine tools. Therefore, it is evident that lattice structures are highly sensitive to process parameters, and the quality of the process plan critically affects the performance of lattice structure products.

In this study, lattice parts manufactured by SLM with good overall quality are chosen to construct AMKG and function as dataset that trains and tests the GNN-based reasoning method. The selected lattice structure parts are all designed with periodically aligned unit cells. Such arrangement is aimed at simplify the data structure and thus has the potential to improve the performance of knowledge reasoning, since the geometric characteristics of the lattice part are heavily dependent on the unit cell. Some of the parts with the design and process information are shown in following table.

In the AMKG designated for lattice structures, design entities are derived from the design specifications of a lattice part model. A periodic lattice-structured part usually comprises four main properties: unit cell specifications, part dimensions, material data, and mechanical behaviors. The unit cell specifications include *edge_length*, cross-sectional diameter of struts (*strut_diameter*), *strut_angle* that relative to the horizontal plane, and the *volume_fraction*, which is determined by both *unit_cell* specs and *part_dimensions*. For manufacturing entities, critical parameters include *laser_power*, *energy_density* and diameter of the laser beam (*beam_diameter*), *layer_thickness*, *build_orientation*, *scan_pattern* and *scan_speed*. *energy_density* is determined by *beam_diameter*, *laser_power* and *scan_speed*, and is highly correlated with the material type used for manufacturing of the lattice part. Appropriate *laser_power* and *scan_speed* need to be determined according to material's thermal conductivity and reflectivity, while proper *beam_diameter* is usually proportional to the size and slant angle of struts (*strut_length*, *strut_diameter*, *downskin_angle*). *Scan_pattern* and *build_orientation* significantly influence the mechanical performance of the lattice part, affecting the anisotropy and consistency of printed layers. *build_orientation* is also correlated to the dimensions of the lattice part, where minimal vertical height or optimal support generation are key considerations. *layer_thickness* is often set to balance the best overall build quality and minimum printing time, with *strut_diameter* being an additional condition for determining *layer_thickness*. Five fundamental relationships between entities are used to establish the relationships among design and process parameters. Geometry specifications and process parameters are linked with *isComposeOf*, *limits*, and *controls* relations to express dependencies. Essential process parameters are directly connected to the entities representing the lattice part by *isFabricatedWith* relation.

After constructing the knowledge graph, RED-GNN is employed to efficiently aggregate the node representations of the proposed graph into a more interpretable structure for AM knowledge reasoning. From the query entity to any entity on the graph, the network is encoded layer-wise, with edges representing relations that connect neighboring entities between layers. In each iteration of the recursive process, the neighboring entities of each entity in the previous layer are identified and added to the next layer along with the current ones. The inter-layer edges of relations are linked both forwardly and reversely to facilitate message passing until the final entity (answer entity) is reached. The relations are encoded into attention weights to control the significance of different types of edges, ensuring that the correct path with strong correlations is searched and followed for the query Fig. 4.

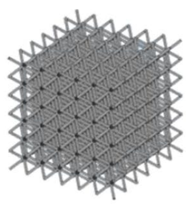
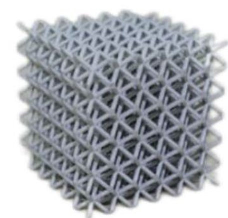
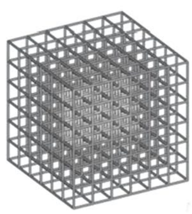
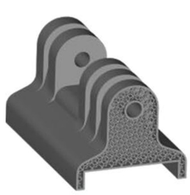
A test is performed with the constructed sample AMKG to accomplish an inductive reasoning task. This task simulates the scenario where a new part is being designed and introduced to the system, requiring parameter prediction based on experiential process knowledge. Implementation of the GNN reasoning method took reference from [26], with similar dataset and hyperparameter setup as well. 3/4 of the graph data is used as training dataset for GNN and the rest is set to be the queries to test and validate that trained model.

Table 1 demonstrates that the performance of the RED-GNN method on AMKG reasoning is comparable to, and even outperforms, other baseline datasets on certain performance indicators. In Table 2, the ranking of process parameter reasoning results for some example parts is listed. The ranking indicates where the original (correct) query-answer pairs are positioned among all possible triplets combined with the query (e_q, r_q) and answer entities $e_a \in V$. It can be observed that most parameters are ranked relatively high, although several do not achieve an ideal score. This suggests that local evidence is not mined effectively to support the reasoning, likely due to insufficient data for the GNN to propagate a well-encoded result. Nevertheless, the results are sufficient to provide manufacturing parameter recommendations for achieving acceptable as-built part quality at the early stage of designing for AM.

4 Discussion

Considering the challenges of implementing knowledge reasoning for AM process parameters of lattice structures, we presented a novel approach based on AM knowledge graph representation encoded by RED-GNN. This approach

Table 1 Examples of lattice parts with corresponding design and process parameters

Lattice Model	Design Parameters	Process Parameters	Printed Sample
 Lattice Cube 1	Cell type: Body-centered Strut diameter: 2 mm Strut length: 6 mm Downskin angle: 35° Material: AISI630	Laser power: 150 W Scan speed: 700 mm/s Hatch distance: 0.105 mm Layer thickness: 0.025 mm Beam diameter: 0.15 mm	
 Lattice Cube 2	Cell type: Cubic Strut diameter: 1 mm Strut length: 8 mm Downskin angle: 0°, 90° Material: AISI630	Laser power: 180 W Scan speed: 1165 mm/s Hatch distance: 0.105 mm Layer thickness: 0.025 mm Beam diameter: 0.15 mm	
 Tilt Component	Cell type: Dodecahedron Strut diameter: 1.2 mm Strut length: 3 mm Downskin angle: 35° Material: AlSi10Mg	Laser power: 350 W Scan speed: 1800 mm/s Hatch distance: 0.09 mm Layer thickness: 0.035 mm Beam diameter: 0.08 mm	
 Bearing Support (Cross-section)	Cell type: Rhombic-Dode Strut diameter: 1.2 mm Strut length: 3 mm Downskin angle: 35° Material: AlSi10Mg	Laser power: 370 W Scan speed: 1700 mm/s Hatch distance: 0.12 mm Layer thickness: 0.04 mm Beam diameter: 0.11 mm	

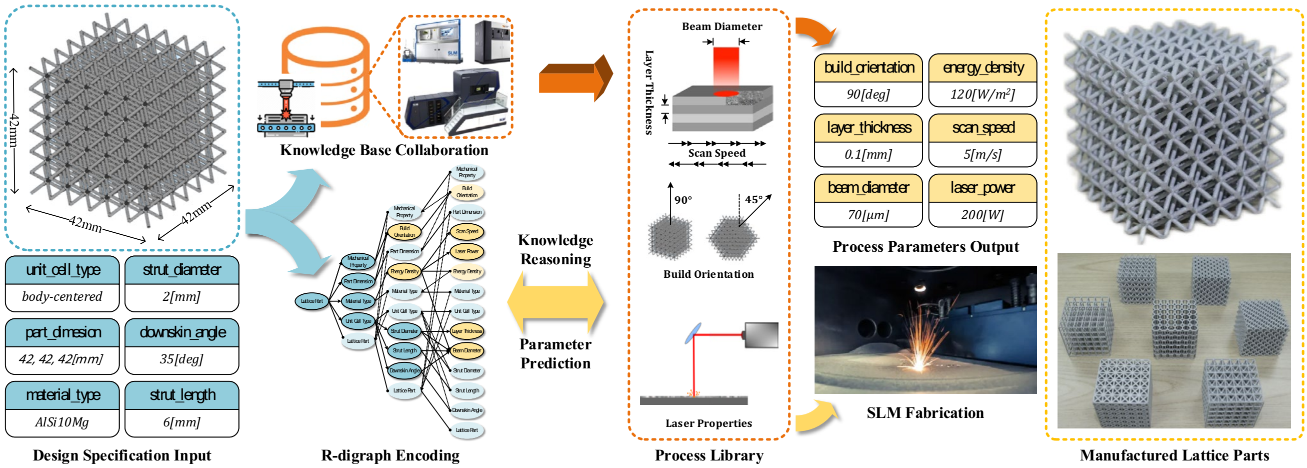


Fig. 4 Scenerio of the proposed GNN-based AM knowledge reasoning method

collaborates with a knowledge base containing data and libraries of design and manufacturing. The innovations are presented as followed:

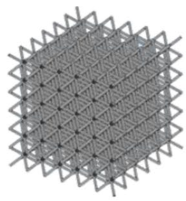
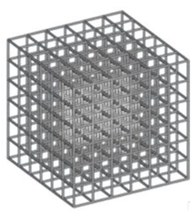
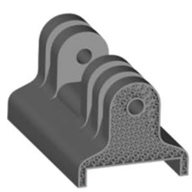
- The concept of a knowledge base for additive manufacturing (AM) and the construction of a relational knowledge graph are proposed. Essential information in AM design and processes is organized into relational graphs for process-oriented knowledge representation, providing potential for further relation mining and knowledge reasoning.
- A GNN-based reasoning method is proposed to leverage the graph-structured AM knowledge, enhancing parameter recommendation capabilities within the AM process reasoning framework. RED-GNN is utilized for parameter prediction due to its inductive reasoning ability on subgraphs, as AM knowledge can be viewed as an aggregation of multiple subgraphs, each representing a part's process information. This approach allows for more effective extraction of local evidence, thereby improving the reliability of the reasoning process.
- Process reasoning for lattice structure parts is presented as a typical AM process planning case. An AM knowledge graph for periodic lattice parts is constructed using actual parameters and tested with the proposed method. This simulates a real-world process reasoning scenario, demonstrating the effectiveness of the GNN-based reasoning method for such tasks.

The work presented in this paper is still in its early stages and requires further development. The following sections discuss perspectives and recommendations for future work:

- High product quality and printing stability in additive manufacturing (AM) depend significantly on accurate process parameters guided by expert engineering knowledge. This often necessitates extensive experimentation with test parts, which can result in numerous printing failures. These trials, while tedious and resource-intensive, help process designers and engineers accumulate valuable experience and refine process parameters for specific products.Here, the AM knowledge base proves essential by aggregating real-world experiential knowledge, engineering data, and physical mechanisms into categorized libraries that form comprehensive ontologies. These ontologies support knowledge graph induction and parameter optimization tasks. The AM knowledge base should be the primary source of prior information related to part design features and manufacturing parameters, aiding decision-making in process planning. In the proposed framework, the AM knowledge base is crucial for the quantitative aspect of knowledge reasoning. While manufacturing process planning generally involves various databases for organizing and extracting process information, the AM knowledge base functions as a dynamic encyclopedia rather than just a collection of clustered data.

Future work should focus on incorporating a broader range of AM process data to enhance the AM knowledge base's functionality. For selective laser melting (SLM), this includes differentiating powder material properties such as particle shape, size, distribution, chemical composition, thermal conductivity, and melting point. Additionally, factors like the laser beam's entry angle, frequency, and pulse duration, as well as parameters of the printing environment like protection gas properties and base plate temperature, should be considered. Enriching the AM knowledge base with this information will significantly improve its capability

Table 2 AMKG prediction ranking of selected test parts

Queried Example Part	Predicted Parameter	Ranking
 Lattice Cube 1	Layer thickness:0.025mm	1
	Hatch distance: 0.105 mm	1
	Beam diameter: 0.15 mm	3
	Laser power: 150 W	5
	Scan speed: 700 mm/s	5
 Lattice Cube 2	Layer thickness: 0.025 mm	1
	Hatch distance: 0.105 m	1
	Beam diameter: 0.15 mm	3
	Scan speed: 1165 mm/s	5
	Laser power: 180 W	6
 Tilt Component	Layer thickness: 0.035 mm	7
	Hatch distance: 0.09 mm	10
	Scan speed: 1800 mm/s	10
	Laser power: 350 W	11
	Beam diameter: 0.08 mm	30
 Bearing Support	Laser power: 370 W	7
	Hatch distance: 0.12 mm	11
	Layer thickness: 0.04 mm	11
	Scan speed: 1700 mm/s	12
	Beam diameter: 0.11 mm	37

to enhance printing quality and reduce costs, addressing more complex and diverse AM demands.

- To enable intelligent logic reasoning of AM specifications and features, the framework integrates graph representation of AM knowledge with the RED-GNN method. The knowledge graph has proven to be highly flexible and effective in structuring design and process information, with extensive applications in social network analysis and literature classification. Given the complexity of AM process parameters and design requirements, graph representation is a convenient approach for creating an AM knowledge graph. RED-GNN has demonstrated high efficiency in learning from graph-structured data and mining relationships, particularly for knowledge graph reasoning in both inductive and transductive tasks, thanks to its relational digraph mechanism.

However, the current scale of the AM knowledge presented in this work does not fully showcase GNN's capabilities in handling graph data. Generally, as the size of the knowledge graph increases and the complexity of entity correlations grows, the advantages of GNN become more pronounced. Future research should involve expanding the knowledge graph to a larger database to further validate the effectiveness and complexity tolerance of the framework. Additional experiments are needed to test this knowledge-driven methodology on more complex design-for-AM

(DfAM) products. Furthermore, extending the tasks to other levels of graph inference could enhance the framework's ability to process a variety of design and manufacturing cases in the future.

- Lattice structures are a typical design feature for additive manufacturing (AM), as they are not efficiently produced using conventional fabrication methods. With the advancement of AM technology and the increasing demand for lightweight structures and metamaterials in industries such as aerospace and biomedical science, lattice structure designs are gaining significant attention. A case study is presented to demonstrate the process planning and parameter reasoning for a strut-based periodic lattice structure part. Periodic lattice structures, with their relatively simple topology, are suitable for research at the current stage of technological progress.

In practice, various engineering objectives—such as heat exchange, acoustical performance, and impact reduction—require different types of lattice structures. These structures can be designed for arbitrary geometric domains, particularly those with topology-optimized designs. Future research could explore additional lattice types, such as shell-based cellular structures, stochastic open-cell porous structures, and triply periodic minimal surface (TPMS) structures. Each of these lattice types offers opportunities for further studies on knowledge representation and feature-behavior relationships, contributing to the progressive development of the proposed methodology. Stochastic lattice structures, in particular, present significant challenges due to their highly irregular and almost uncontrollable nature. Their representation may fit into the current framework but requires careful design and adaptation to be effectively integrated.

5 Conclusion

To address the challenges of process reasoning in additive manufacturing, a novel approach is proposed for AM process planning that leverages knowledge representation learning methodologies and employs the state-of-the-art GNN variant known as RED-GNN. The AM knowledge graph-driven process reasoning method integrates the AM knowledge base with RED-GNN to tackle the process reasoning task from complementary perspectives. This method benefits from the flexibility of graph representation and the efficiency and robustness of RED-GNN, offering significant potential for providing superior autonomous guidance for AM processes. The goal is to enhance the performance of AM systems, achieving optimal product quality and cost savings. Further development is necessary to improve the prediction accuracy of the reasoning model. This includes expanding the data scale and increasing the complexity of the knowledge graph ontology to better adapt to diverse production environments and demands. Future improvements should also focus on integrating the proposed method into AM expert systems for validation in practical applications.

Authors contribution Conceptualization: Jinhua Xiao, Changri Xiong; Methodology: Changri Xiong, Jinhua Xiao; Formal analysis and investigation: Changri Xiong, Zhuangyu Li; Writing—original draft preparation: Changri Xiong, Jinhua Xiao; Writing—review and editing: Jinhua Xiao, Wenlei Xiao; Resources: Changri Xiong, Jinhua Xiao, Zhuangyu Li; Supervision: Wenlei Xiao, Gang Zhao.

Funding This research is supported by National Natural Science Foundation of China, No. 52305551.

Data availability The sample data used for constructing AM knowledge graph as well as generating test results of proposed method is publicly available and can be found in Github repository: https://github.com/changrixiong/AMKG-data-demo.git.

Declarations

Competing interests We declare that we have no financial or personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be constructed as influencing the position presented in, or the review of, the manuscript entitled.

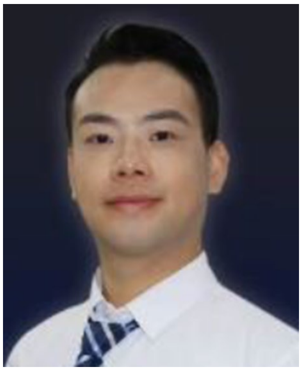
Ethical and informed consent for data used Not applicable.

References

1. Gibson I, Rosen DW, Stucker B (2010) Additive Manufacturing Technologies. Addit Manufact Technol p 17–40 https://doi.org/10.1007/978-1-4419-1120-9
2. Campbell I, Bourell D, Gibson I (2012) Additive manufacturing: rapid prototyping comes of age. Rapid Prototyp J 18(4):255–258. https://doi.org/10.1108/13552541211231563
3. Kim DB, Witherell P, Lipman R, Feng SC (2015) Streamlining the additive manufacturing digital spectrum: A systems approach. Addit Manuf 5(2):20–30. https://doi.org/10.1016/j.addma.2014.10.004

4. Jawade SA, Joshi RS, Desai SB (2019) Comparative study of mechanical properties of additively manufactured aluminum alloy, in Materials Today: Proceedings, Elsevier Ltd, p 9270–9274. https://doi.org/10.1016/j.matpr.2020.02.096
5. Hitzler L, Schoch N, Heine B, Merkel M, Hall W, Öchsner A (2018) Compressive behaviour of additively manufactured AlSi10Mg. Materwiss Werksttech 49(5):683–688. https://doi.org/10.1002/mawe.201700239
6. Xu Z, Liu A, Wang X (2021) Fatigue performance and crack propagation behavior of selective laser melted AlSi10Mg in 0°, 15°, 45° and 90° building directions. Mater Sci Eng A 812. https://doi.org/10.1016/j.msea.2021.141141
7. Chen J, Hou W, Wang X, Chu S, Yang Z (2020) Microstructure, porosity and mechanical properties of selective laser melted AlSi10Mg. Chinese J Aeronautics https://doi.org/10.1016/j.cja.2019.08.017
8. Wu H, Li J, Wei Z, Wei P (2020) Effect of processing parameters on forming defects during selective laser melting of AlSi10Mg powder. Rapid Prototyp J 26(5):871–879. https://doi.org/10.1108/RPJ-07-2018-0184
9. Zhang Y, Bernard A (2014) AM feature and knowledge based process planning for additive manufacturing in multiple parts production context, 25th Annual International Solid Freeform Fabrication Symposium & #65533. An Additive Manufacturing Conference, SFF 2014(August):1259–1276
10. Nandhakumar R, Venkatesan K (2023) A process parameters review on selective laser melting-based additive manufacturing of single and multi-material: Microstructure, physical properties, tribological, and surface roughness. Mater Today Commun 35:105538. https://doi.org/10.1016/J.MTCOMM.2023.105538
11. Ren L, Sparks T, Ruan J, Liou F (2010) Integrated Process Planning for a Multiaxis Hybrid Manufacturing System. J Manuf Sci Eng 132(2):021006. https://doi.org/10.1115/1.4001122
12. KingslyJebaSingh D, Jebaraj C (2005) Feature-based design for process planning of machining processes with optimization using genetic algorithms. Int J Prod Res 43(18):3855–3887. https://doi.org/10.1080/00207540500032160
13. Park SC (2003) Knowledge capturing methodology in process planning. CAD Computer Aided Design 35(12):1109–1117. https://doi.org/10.1016/S0010-4485(02)00182-3
14. Um J, Rauch M, Hascoët JY, Stroud I (2016) STEP-NC compliant process planning of additive manufacturing: remanufacturing. Int J Adv Manufact Technol May:1–16. https://doi.org/10.1007/s00170-016-8791-1
15. Yu Z, Ding D, Pan Z, Li H, Lu Q, Fang X (2021) A strut-based process planning method for wire arc additive manufacturing of lattice structures. J Manuf Process 65:283–298. https://doi.org/10.1016/J.JMAPRO.2021.03.038
16. Xiong Y, Dharmawan AG, Tang Y, Foong S, Soh GS, Rosen DW (2020) A knowledge-based process planning framework for wire arc additive manufacturing. Adv Eng Inform 45:101135. https://doi.org/10.1016/J.AEI.2020.101135
17. Haruna A, Yang M, Jiang P, Ren H (2024) Collaborative task of entity and relation recognition for developing a knowledge graph to support knowledge reasoning for design for additive manufacturing. Adv Eng Inform 60:102364. https://doi.org/10.1016/J.AEI.2024.102364
18. Wu Z, Pan S, Chen F, Long G, Zhang C, Yu PS (2021) A Comprehensive Survey on Graph Neural Networks. IEEE Trans Neural Netw Learn Syst 32(1):4–24. https://doi.org/10.1109/TNNLS.2020.2978386
19. Zhou Y, Zheng H, Huang X, Hao S, Li D, Zhao J (2022) Graph Neural Networks: Taxonomy, Advances, and Trends. Assoc Comput Mach. https://doi.org/10.1145/3495161
20. Leonhardt V, Claus F, Garth C (2022) PEN: Process Estimator neural Network for root cause analysis using graph convolution. J Manuf Syst 62:886–902. https://doi.org/10.1016/j.jmsy.2021.11.008
21. Zhang D, Liu Z, Jia W, Liu H, Tan J (2022) Path Enhanced Bidirectional Graph Attention Network for Quality Prediction in Multistage Manufacturing Process. IEEE Trans Industr Inform 18(2):1018–1027. https://doi.org/10.1109/TII.2021.3076803
22. Mozaffar M, Liao S, Lin H, Ehmann K, Cao J (2021) Geometry-agnostic data-driven thermal modeling of additive manufacturing processes using graph neural networks. Addit Manuf 48. https://doi.org/10.1016/j.addma.2021.102449
23. Huang J, Su J, Chang Q (2022) Graph neural network and multi-agent reinforcement learning for machine-process-system integrated control to optimize production yield. J Manuf Syst 64:81–93. https://doi.org/10.1016/j.jmsy.2022.05.018
24. Wang PY, Yang WA, You YP (2023) A hybrid learning framework for manufacturing feature recognition using graph neural networks. J Manuf Process 85:387–404. https://doi.org/10.1016/j.jmapro.2022.10.075
25. Lai X, Qiu T, Shui H, Ding D, Ni J (2023) Predicting future production system bottlenecks with a graph neural network approach. J Manuf Syst 67:201–212. https://doi.org/10.1016/j.jmsy.2023.01.010
26. Zhang Y, Yao Q (2022) Knowledge Graph Reasoning with Relational Digraph, in WWW 2022 - Proceedings of the ACM Web Conference 2022, Association for Computing Machinery, Inc, p 912–924. https://doi.org/10.1145/3485447.3512008

Changri Xiong is a Ph.D candidate in the School of Mechanical Engineering & Automation, Beihang University, Beijing, China. His main research interests include metamaterial design and applications, CAD for additive manufacturing, and intelligent manufacturing.



Jinhua Xiao received his PhD (2019) and joint PhD (2019) in Department of Mechanical Engineering from University of Technology of Compiegne, Compiegne, France, and in the Automated Production Research Laboratory (LURPA) from ENS Paris-Saclay, Paris, France, respectively. He is currently an assistant professor of Department of Management, Economics and Industrial Engineering at Polytechnic University of Milan, Milan, Italy. His main research interests include machining learning, smart manufacturing informatics, smart process planning, automated disassembly, optimization and decision-makings, prediction and evaluation, and knowledge-driven product/process.

Zhuangyu Li is a Ph.D. candidate at the School of Mechanical Engineering & Automation, Beihang University, Beijing, China. His research focuses on geometric modeling of lattice structures, design for additive manufacturing, and topology optimization.

Gang Zhao is a professor in the School of Mechanical Engineering & Automation at Beihang University, Beijing, China. He received his Ph.D. degree from Beihang University. His research interests include new geometric modeling methods for curves and surfaces, CAD / CAM, intelligent NC programming technology, and distributed network NC technology.

Wenlei Xiao is currently an associate professor in the School of Mechanical Engineering & Automation at Beihang University, China. He received his Ph.D degree from Beihang University in 2012, and was a postdoc at Peking University from 2012 to 2014. His research interests include intelligent CNC, CAD/CAM and digital twin.