Leveraging LLM and KG for Knowledge Transfer in Traditional Material Manufacturing Industry: Experience and Challenges

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Abstract
Traditional manufacturing sectors, particularly aluminium casting, face growing pressure to improve knowledge transfer to new generations and customers. The complexity and volume of production information often make conventional methods inefficient. While Large Language Models (LLMs) and Knowledge Graphs (KGs) show promise in knowledge management, applying them to domain-specific contexts like aluminium casting processes presents persistent challenges. This paper draws on practical implementation experience to highlight key obstacles encountered in deploying an LLM-KG system for knowledge transfer in this setting.

Keywords
Material manufacturing, Knowledge graph, Large language model application, Knowledge transfer, Smart manufacturing

1. Introduction

Traditional manufacturing industries, including those that produce aluminium casting, rolling, forging, and stamping, form the backbone of global industrial supply chains, producing critical components for sectors ranging from aerospace to consumer electronics. Decades of operational expertise have endowed these industries with invaluable knowledge that directly impacts product quality, process efficiency, and innovation capacity. However, traditional methods of knowledge transfer and dissemination are often limited and result in critical know-how being confined within specific individuals or departments.

This creates several challenges. First, companies face significant costs—both in time and resources—to train employees to an expert level [1]. Second, when experienced personnels leave, they frequently take valuable knowledge with them, including knowledge they have reported, but often lack effective management of that reported knowledge, making it difficult to preserve or share with newcomers [2, 3]. Furthermore, transferring manufacturing expertise across departments or to customers remains problematic. Understanding production processes often requires hands-on experience and contextual knowledge that are not easily documented or communicated [4]. For customers, even comprehensive on-site training programs may fail to ensure effective knowledge transfer, particularly when introducing new manufacturing techniques [5]. These challenges are pervasive across material manufacturing domains and highlight the need for more systematic and scalable knowledge management solutions.

Advances in large language models (LLMs) offer powerful capabilities for knowledge extraction and dissemination, while Knowledge Graphs (KGs) provide graph-based representations that contextualise and interlink domain-specific knowledge. Their integration enables more intelligent knowledge management by bridging unstructured textual content with structured semantic representations. Together, these two technologies have shown promising results in various domains in enhancing the accessibility and transfer of domain expertise across organisational boundaries and also system faulse detection

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[6, 7, 8, 9, 10, 11]. However, the application of KGs and LLMs in the material manufacturing sector remains limited. Further development, validation, and testing are still needed. Effective deployment also requires substantial domain-specific knowledge and close collaboration with experts. In this industrial statement paper, we share our experience utilizing KGs and LLMs in the light metal manufacturing sector. Specifically, we describe our initial efforts to leverage these state-of-the-art methods to manage extensive technical documentation and facilitate knowledge transfer processes within and beyond the organization.

2. Use Case Description

This project applies LLMs and KGs to (1) manage historical casting documents, (2) enhance knowledge sharing, (3) streamline training for employees and customers, and (4) structure the data repository. A dedicated ontology [12] and prototype domain-specific LLM [13, 14] have been developed, with domain experts guiding data preparation and evaluation. LLM outputs are evaluated by using F1 score, precision, and expert review. The initial development results indicate strong potential to support these objectives.

3. Lessons Learned and Areas Needing Further Work

Through our efforts to implement LLM- and KG-based knowledge transfer solutions in manufacturing, we have gained several insights and identified areas needing further progress.

First, while many organizations have extensive documentation, much of it is unstructured and inconsistently managed. Converting this information into usable formats requires considerable time and effort. Establishing standardized documentation practices and clear data governance remains essential. Second, the domain-specific nature of production data makes expert involvement both critical and challenging. Limited expert availability for data preparation, validation, and knowledge review has significantly slowed progress. Developing workflows and tools that reduce their time burden and help scale their input is an ongoing need. Third, key knowledge about defects, mistakes, and practical experience is often tacit and informally retained. Employees may be unwilling or unable to share this information, and some knowledge is difficult to articulate. Raising awareness of the importance of capturing and sharing such insights requires sustained cultural change. Finally, building trust in new systems is vital. Gaining acceptance across the organization takes time and depends on clear communication and demonstrable benefits. In order to tackle the above-mentioned difficulty, we are currently working on several projects that leverage LLMs to assist in ontology and knowledge graph construction within the metallurgy domain, and around 15 papers and 4 books were used. We also welcome collaborations to accelerate these efforts.

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Declaration on Generative AI

During the preparation of this work, the author(s) used ChatGPT-4o and Grammarly in order to: grammar, wording, and spelling checking. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and took full responsibility for the publication's content.

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