Towards Industrial Foundation Models: Framework, Key Issues and Potential Applications

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***Abstract*—Foundation models have demonstrated remarkable capabilities in various tasks such as natural language processing, content generation, and complex reasoning and have the potential to spark new technology and application revolutions in the industrial domain. However, Industrial Foundation Models (IFMs) remain almost unexplored, and the industrial sector has domain-specific issues and challenges to address when harnessing the capabilities of foundation models. Therefore, we introduce the concept and construction paradigm of IFMs and propose a 5-dimensional general framework of the IFMs. Moreover, we present the key research issues and technologies of IFMs and discuss some advanced and potential industrial applications. We hope this paper can serve as a useful resource for researchers seeking to innovate within the domain of IFMs.**

Keywords- deep learning; foundation models; industrial foundation models

I. INTRODUCTION

Foundation models (FMs) are trained on massive, diverse, and unlabeled datasets, typically through self-supervised learning, and can be applied to numerous downstream tasks [1]–[4]. Unlike task-specific Deep Learning Models (DLMs), FMs often contain billions, even trillions of model parameters, offering previously unseen capabilities such as in-context learning, multimodal processing, enhanced generation, and fine-grained feature learning. These extensive capabilities of FMs position them with significant potential in the industrial domain, including cleaning and integrating industrial big data, industrial content generation, multimodal inputs and outputs, human-centered flexible interactions, and industrial domain knowledge and decision support.

Although there have been early efforts [5], [6] to develop Industrial Foundation Models (IFMs) or apply the Large Language Model (LLM) to the industrial fields, this industrial Artificial Intelligence (AI) paradigm is still in its infancy. This is due to the challenges associated with accessing large and high-quality industrial datasets, as well as the diversity, high knowledge density, high reliability and interpretability required in the industrial domain. Further efforts and technological innovation are needed to promote the development of IFMs. Some survey papers [2]–[4] on the general-purpose FMs can be referenced, while the industrial sector has domain-specific issues to be addressed when harnessing the capabilities of FMs. Therefore, this paper aims to provide an overview of IFMs and discuss key research issues and potential applications of IFMs. Also, it should be noted that the research issues discussed are representative rather than complete.

The contributions of this paper are as follows.

- We analyze the distinctive characteristics of IFMs in comparison to traditional industrial DLMs and outline the construction paradigm of IFMs.
- We propose a 5-dimensional general framework for IFMs, encompassing aspects of data, model, computation, industrial characteristics, and industrial applications.
- We provide the key research issues and potential key technologies associated with IFMs, and present advanced and potential industrial application scenarios of IFMs.

The rest of this paper is organized as follows. Section II introduces the concept and category of IFMs, and proposes a 5-dimensional general framework of IFMs. Section III summarizes the key research issues and opportunities of IFMs. Section IV introduces advanced and potential industrial applications of IFMs, and Section V concludes the paper.

II. INDUSTRIAL FOUNDATION MODEL

A. *Concept of Industrial Foundation Model*

IFMs are large pre-trained deep learning models that are trained on massive amounts of data, especially on industrial-specific data, which can learn the generic data patterns and representations and can be adapted to a wide range of downstream industrial tasks. Compared to traditional industrial DLMs, pre-trained IFMs have several notable characteristics as follows.

Large scale. Large-scale training datasets, abundant computational resources, and large amount of model parameters are three main characteristics of IFM compared to traditional industrial DLMs.

Controlled generation. Unlike data driven DLMs in non-industrial areas, IFMs are subject to much stricter requirements for reliability and explainability, especially in industrial generation applications such as Research and Development (R&D) and design, process generation, code generation, and Question and Answering (Q&A). It is particularly important to ensure that the model's outputs are not solely data-driven but also conform to the fundamental principles and logic of real-world industrial processes and systems.

Generalizability and adaptability. Traditional DLMs typically rely on task-specific training with labeled datasets, potentially limiting their adaptability to various other tasks. IFMs, in contrast, are usually pre-trained using large-scale industrial data to learn generic data representation that can be adapted to diverse industrial scenarios through transfer learning and fine-tuning.

Emergence. An ability is emergence if it is not present in smaller DLMs but is present in larger foundation models [7]. For example, LLMs have demonstrated excellent in-context learning and knowledge reasoning capabilities. IFMs that built through LLMs will inherit this capability.

General artificial intelligence. IFMs accumulate a broad understanding of industrial processes and contexts during pre-training and may move toward industrial general artificial intelligence by applying instruction adaptation techniques such as reinforcement learning from human feedback, prompt tuning, and chain-of-thought.

B. *Construction Paradigm*

Build IFMs based on general-purpose FMs. It aims to integrate the general capabilities of the existing general-purpose FMs, such as Q&A, content generation, image description, visual understanding, etc., to achieve industrial domain adaptation. One approach is to use the general-purpose FMs as a black box, and achieve industrial adaptation through plug-in industrial knowledge or expert bases, tuning-free prompting, large and small model collaboration, etc. This does not require industrial domain training or fine-tuning of the general-purpose FMs. For example, Myriad [5] is a large multi-modal model based on MiniGPT-4, which applies vision experts for industrial anomaly detection. Another approach is to perform local parameter training or tuning based on general-purpose FMs through fine-tuning such as prompt tuning, adapter tuning, low-rank adaptation etc. to focus on industrial subdivisions. For example, Authentise uses a dataset of 12,000 journals and standards related to the additive manufacturing industry to fine-tune the general LLM and launch 3DGPT for additive manufacturing technology Q&A.

The advantage of this paradigm is that it can transfer knowledge between source and target tasks and help to fully exploit the performance of general-purpose FM. For the small size of fine-tuning dataset compared to the pre-training dataset, this process can enable low-cost domain adaptation based on the general-purpose FMs with the stored knowledge. However, the IFM in this paradigm may not be trained on entirely industrial domain data, and as a result, the model parameters often perform sub-optimally on few-shot or zero-shot tasks.

Build IFMs from scratch. It refers to directly using all or a certain proportion of industrial domain datasets to pre-train IFMs from scratch, enabling the model to acquire industrial domain knowledge. For example, BloombergGPT [8] is a 50-billion parameters language model that is trained on a wide range of financial data. The advantage of this paradigm is its higher industrial expertise, enabling a better understanding and performance in handling downstream industrial tasks without concept drift. Additionally, it excels in capturing specific patterns and regularities within the industrial domain. However, this paradigm requires collecting a large amount of industrial data, data cleaning, and pre-training the model with abundant computational resources, which incurs high costs. Moreover, pre-training on domain-specific data may lead to overfitting issues, resulting in suboptimal performance when dealing with downstream tasks.

C. *Framework of Industrial Foundation Model*

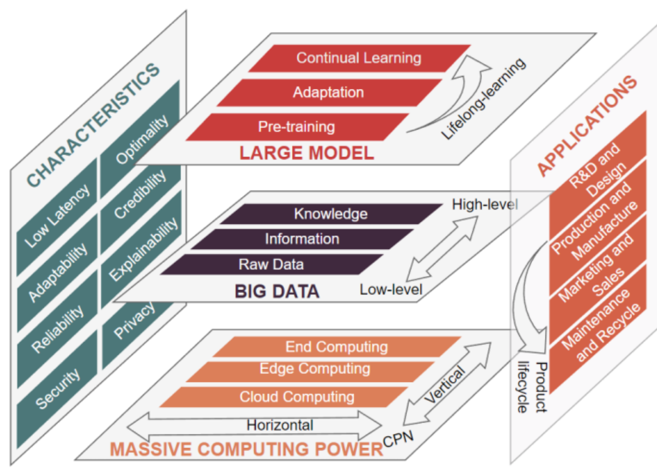

Figure 1. 5-Dimensional general framework of IFM.

To make the IFM concept clear, we proposed a novel and general framework of IFM (as shown in Figure 1) with multiple views. Commencing with the authentic requisites of the industrial domain, we systematically scrutinize and proffer the pivotal characteristics of IFM, including low latency, optimality, adaptability, credibility, reliability, explainability, security, and privacy. Subsequently, we deliberate upon the triad of computation, data, and model, which are the three fundamental constituents employed in the training and adaptation of IFMs for industrial product lifecycle applications, including R&D and design, production and manufacture, marketing and sales, and maintenance and recycle. This holistic consideration serves to substantiate the application of IFMs within the industrial domain. Centered around this framework of IFM, Section III extensively explores the key issues and challenges of IFM, along with potential research directions.

III. Key Research Issues and Opportunities of Industrial Foundation Model

A. *Industrial Large-scale Dataset*

With the evolution of industrial Internet of Things (IoT) technologies, the industrial domain has amassed a significant volume of data. However, when leveraging these data to build large IFMs, the following challenges still need to be addressed.

Unbalanced sample and incomplete data. (i) Industrial systems are typically designed with high reliability and strict control, ensuring stable operation for most of the time. Although the industrial data from these systems is voluminous, a majority of it consists of fixed repetitive period data and there exists a scarcity of valuable abnormal operating condition data that can be used for model learning purposes. (ii) Industrial equipment, sensors, processes, and environments undergo constant changes over time, leading to alterations in the distribution of historical data and its validity. (iii) Incomplete data poses another challenge as many external variables in industrial systems lack comprehensive records such as operation time or intervention actions. (iv) Furthermore, the data continuity and integrity persistently always fall short of satisfactory levels. Solving these problems not only requires innovation and empowerment of technologies such as data enhancement, zero-shot learning, and data generation but also requires collaboration in data management such as long-term data maintenance and data quality management.

Data collection and sharing. Pre-training data for FMs in general natural language processing and computer vision fields can be obtained on a large scale from the Internet, while industrial datasets are always owned by equipment operators and enterprises, and are often very precious and confidential. This greatly limits the sharing and use of these industry data. For this issue, Federated Learning (FL) is a potential solution. FL is a distributed machine learning framework that allows decentralized clients to learn collaboratively without sharing their private data. Some studies have conducted preliminary explorations. For example, Tan et al. [9] proposed a lightweight FL framework where clients jointly learn to fuse the representations generated by multiple fixed pre-trained models. Guo et al. [10] proposed a PromptFL framework that replaces the federated model training with the federated prompt learning.

B. *Model Architecture and Pre-training for Time-series Data*

The data in the industrial domain is generally time-series data that collected by various IoT sensors, such as vibration signals and sound signals, etc. In the expansive realm of FMs, Transformer stands prominently as architectural marvels. While transformers are effective in text-to-text or text-to-image models, there are challenges when applying transformers to industrial time series data. Specifically, the data of time series is formally presented in a numerical form, arranged in chronological order, similar to natural language. However, the semantic information of time series data does not exist in isolated data points but rather resides in trends and periodic variations, which is different from natural language or images. While the Transformer model excels in handling natural language and utilizes attention mechanisms to capture dependencies between contextual elements, it cannot capture continuous temporal relationships and understand the periodicity and trends in time series data. Although some Transformer-based models can integrate temporal information through positional encoding, they does not directly account for temporal dynamics. Therefore, the traditional Transformer architecture cannot directly applied to industrial time series that vary in lengths, period, and granularity.

To address this challenge, one approach involves exploring methods to adapt the Transformer architecture for industrial time series. For example, employing dynamic encoding method which is more flexible compared to fixed-window encoding. Kazemi et al. [11] proposed representing time in the form of vector embeddings, akin to vocabulary embeddings. Toknekaboni et al. [12] introduced a self-supervised method for learning generalized representations of non-stationary time series, and experimental results indicate that the model's learned universal representations can be directly applied to downstream tasks. Exploring novel model architectures tailored for industrial time series is another investigation. The key distinction of time series from natural language and image lies in its inherent temporal structure, which requires these novel model architectures to not only understand patterns within the data but also how these patterns evolve over time.

C. *Reliability*

The reliability of IFMs represents that models can operate stably and produce reliable inference results. On the one hand, industrial environments can contain a variety of changes and anomalies such as noise, outliers and differently distributed data. A reliable IFM should be able to handle these situations while maintaining prediction accuracy and stability. On the other hand, IFM must produce decisions or content (e.g. industrial code generation, knowledge Q&A, and resource scheduling) that are intelligible and user-friendly, aligning seamlessly with real-world industrial conditions, environments, and knowledge. However, owing to the hallucination issue, IFMs may generate outputs that appear logically sound but deviate from real-world facts or user inputs, which poses a significant threat to the reliability of IFMs.

Regarding the origins of hallucination, the mainstream view is the boundary of knowledge that is the knowledge learned by IFMs has a clear time boundary and will become obsolete with time if it lacks continuous updating. At present, model editing [13] is an effective approach to mitigate hallucinations. For example, Shuster et al. [14] used the retrieval augmented generation method to modify the non-parametric knowledge of the model to reduce hallucination in conversation. However, many model editing methods tend to neglect potential side effects on the general abilities of models such as LLMs [15]. Therefore, addressing the phenomenon of hallucination while ensuring the overall performance of the IFMs is unaffected remains an area requiring further investigation.

Furthermore, the integration of IFMs with knowledge graphs represents a viable approach to enhance the reliability of

IFMs. For example, within the realm of industrial Q&A, leveraging large language models like Generative Pre-trained Transformer (GPT) for robust natural language understanding, coupled with the contextual information and entity relationships provided by knowledge graphs, can provide reliable and interpretable professional results and effectively mitigate the occurrence of hallucinations.

D. Explainability

Explainability means that the decisions and outputs of the IFMs can be interpreted and understood, and the internal structure and functioning of the IFM can be understood by humans. It is a prerequisite for building trust and adoption AI systems in industrial domains, such as nuclear energy and aerospace, that require reliability as well as safety-critical. However, with the development of pre-trained FMs, the inner workings and operating mechanisms of these models become more challenging to explain and understand, as FMs often have hundreds of millions of parameters, a large number of non-linear transformations, and complex hierarchies. Additionally, FMs can capture unpredictable data relationships and advanced abstractions and features, which are incomprehensible.

Some studies [16] have focused on explainable LLMs to help researchers and practitioners better trust and understand models at scale and training paradigms, which provide useful references. However, it is crucial to note that the industry operates within a highly technical domain characterized by robust mechanisms and dense knowledge. Industrial data merely offers partial representations of meticulously designed systems, and their interrelationships can be explained through mechanistic models. In contrast to statistical models, mechanistic models emphasize the explicit representation of the intrinsic mechanisms governing a system, rather than solely relying on observational data. They provide a deeper level of understanding by directly incorporating the structure and operational principles of the system. Furthermore, domain expertise contributes numerous valuable characteristic variables, such as the frequency domain characteristics of bearing vibration data. Therefore, exploring the fusion method of the mechanistic model, industrial domain expertise and IFMs are supportive of the explainability of the model.

E. Continual Learning

As the production environment changes, the data distribution also undergoes alterations in industrial production, especially customized and personalized production, which is known as out-of-distribution. FMs have shown promising progress in few-shot and zero-shot tasks, but they may exhibit relatively diminished generalization performance when confronted with novel data distributions and environmental shifts. This necessitates the continuous iterative upgrading of IFMs during runtime to adapt to shifts in data distribution, ensuring the sustained capacity of the model to generate accurate and reliable results in actual industrial production.

The most straightforward approach is to periodically re-train the IFMs from scratch with the latest data to keep them consistent with current industry knowledge. However, re-training is expensive and environmentally unfriendly, and risks degenerating valuable pre-trained knowledge irrelevant to the update in the model. Continual learning aims to enable a model to learn from a continuous data stream across time while reducing catastrophic forgetting of previously acquired knowledge. With continual learning, a deployed IFM has the potential to dynamically adapt to the evolving industrial landscape without resource-intensive re-training from scratch.

At present, one continual learning approach for FMs such as LLMs is continual pre-training [17], where the data corpus is usually unsupervised and the traditional continual learning methods such as regularization, replay, and representation are introduced to alleviate catastrophic forgetting. Another emerging approach is continual knowledge editing. Knowledge editing aims to precisely modify FMs to incorporate specific knowledge, without negatively influencing other irrelevant knowledge [18]. Although there have been some early attempts at both approaches, they are still in their infancy, efficient and continuously updated approaches to IFM knowledge require further exploration. Furthermore, federated continuous learning, as an approach designed to combine federated learning and continuous learning, can also be applied in the domain adaptation and model continual updating of IFMs.

F. Computing Power Network

The convergence of IFMs and end-edge-cloud Computing Power Network (CPN) [19] has become a novel and inevitable paradigm after the convergence of AI and edge computing [20], [21]. On the one hand, IFMs require large computing power as support, while CPN can seamlessly adapt the computing and communication needs of IFMs to the multi-level computing service capabilities of end-edge-cloud devices at anytime and anywhere. On the other hand, in the industrial Internet, there are a large number of scenarios (such as quality inspection, predictive maintenance and diagnostics) that require real-time processing on the end or edge devices. The edge sinking of IFMs will become a trend, making intelligent decision-making more real-time and more efficient.

However, as existing edge and end devices cannot generally execute complete IFMs, which poses a significant challenge to implement the deployment of such large models without compromising their performance. One approach is the convergence of Deep Learning-as-a-Service (DLaaS) and CPN since DLaaS disassembles IFMs into independent services or microservices and each focusing on a specific task or function. This modular nature makes IFMs easier to manage, compute, and personalize to support different downstream applications and the endless end-edge-cloud intelligent collaboration paradigms (e.g. progressive inference [22] and model splitting). Another approach is to explore efficient terminal adaptive technologies while preserving IFMs’ performance, including lightweight, compression and pruning, and optimization of network topology.

G. Security and Privacy

The application of IFMs relies on industrial end-edge-cloud computing facilities and communication networks, so it also faces the security and privacy issues of the industrial Internet, including device security (e.g. side-channel attacks, backdoor leaks, hardware Trojans, etc.) and network security (e.g. distributed denial of service, communication protocol security, identity access security, etc.). In addition, IFMs themselves also face a variety of security and privacy threats that undermine the CIA (Confidentiality, Integrity, and Availability) triad.

Confidentiality of IFM. Maintaining confidentiality means that sensitive information (e.g. training and inference data, model parameter) can only be accessed by authorized individuals or systems. IFM systems should protect confidentiality against inference and reconstruction attacks (e.g. model inversion attacks) and model stealing attacks (e.g. model extraction attacks, and side-channel Attacks).

Integrity of IFM. The goal of integrity is to protect information from unauthorized modifications, ensuring the accuracy and consistency of data. Adversarial attacks, adversarial prompts, data poisoning, and backdoor attacks can all compromise the integrity of IFMs. Meanwhile, adversarial prompts represent a novel threat in FMs, introducing undesirable model behavior through the crafting of adversarial prompt inputs which are typically categorized into prompt injection attacks and jailbreaking.

Availability of IFM. Availability focuses on the continuous operation of IFM, and ensures the accessibility of the service. Resource exhaustion attacks and denial of service attacks can pose threats to the availability of IFM.

When designing and deploying IFMs, it is crucial to thoroughly consider the aforementioned attacks, and establish corresponding protection mechanisms and methods to elevate the security and privacy protection level of the IFM system.

IV. ADVANCED AND POTENTIAL APPLICATIONS OF INDUSTRIAL FOUNDATION MODEL

A. *Customized and Personalized R&D and Design*

Mass personalized production is emerging as a predominant manufacturing model, necessitating customer engagement not only in the design and manufacturing phases but throughout the entire product life cycle [23], [24]. IFM can serve as an efficient tool platform for customers, R&D teams, designers, and manufacturers, facilitating the active involvement of non-expert customers throughout the entire process of product R&D, design, and manufacturing. Specifically, customers can leverage the platform offered by IFMs to articulate and refine their ideas and present them to the R&D team, designers, and manufacturers in a professional language, which substantially mitigates communication costs. Based on the personalized requirements of customers, the R&D team can leverage IFMs to analyze the structural data of products, delve into the configuration and mechanisms of the products, and harness the emergent capabilities of IFMs to generate product prototypes that closely align with the customers' needs. According to the product prototype, IFMs can provide a simulation test environment for industrial product performance simulation and safety assessment. Additionally, IFMs can assist in documenting the complete lifecycle of a product, enabling the R&D team and designers to iterate on products based on historical information, further reducing R&D and design cycles, and lowering manufacturing costs.

B. *Intelligent Production and Manufacture*

Industrial multimodal content intelligent generation. IFMs can generate high-quality and professional industrial content, including text, Q&A, and code. (i) IFMs possess the capability to generate diverse industrial documents, including production preparation records, equipment inspection records, production reports, etc. This ability holds significant value in terms of information recording and communication within the industrial domain. (ii) IFMs can provide accurate and professional answers to a variety of complex domain questions, encompassing equipment maintenance queries, fault diagnosis, quality inspection, safety production regulations, and industrial standards. This enhances decision-making efficiency and knowledge management levels. (iii) The industrial code generation capability of IFMs extends beyond SQL code generation, programmable logic controller code generation, and industrial protocol integration to encompass production equipment control and zero-code industrial application development, which offers efficient and customizable solutions for industrial production.

Industrial robots with embodied intelligence. Embodied intelligence refers to the capacity of a system or entity to exhibit intelligent behavior through interaction, perception, and motion in its environment. However, classical robotic planning and control methods typically require meticulous modeling of the world, and when circumstances change, rebuilding the models becomes necessary, making them less effective in supporting future flexible and reconfigurable production environments. Although deep or reinforcement learning methods contribute to mitigating these issues, they still face challenges related to distribution shifts and reduced generalization capabilities. While the combination of IFMs and robots can create more powerful and comprehensive intelligent systems. Large IFMs contribute powerful cognitive and decision-making capabilities, while the physical embodiment of robots allows the application of these capabilities in the real world. For example, by utilizing the perceptual and understanding capabilities of IFMs, industrial robots can achieve more intelligent autonomous navigation, object manipulation, and environmental perception. Leveraging the natural language processing and comprehension abilities of large IFMs, industrial robots can collaborate and interact with humans in a more effective and human-centric manner.

Industrial domain knowledge and decision support. IFM demonstrates robust feature extraction and reasoning capabilities, which have found applications in diverse industrial domains, including quality inspection, prognostics and health management, and production safety inspection. As IFM continues to develop and industrial intelligence deepens, its application scope will expand to areas such as supply chain optimization, energy management, and environmental monitoring, providing the industrial sector with smarter, more efficient and sustainable solutions.

C. *Interactive Marketing and Sales*

Leveraging the powerful capabilities of IFMs in text generation, data analysis, and automation, these models provide innovative and efficient solutions in areas such as creative advertising, market research, personalized recommendations, social media management, marketing automation, sentiment analysis, and market forecasting. For example, these models can analyze market data, identify potential trends, predict market changes, and provide businesses with more accurate market strategies and sales plans, and based on market research, IFMs can generate advertising copies and product descriptions that better align with market demands, assisting businesses in effectively promoting their products. In addition, the Q&A capabilities of IFMs help businesses better interact with customers, enhancing marketing and sales effectiveness.

D. *Efficient Maintenance and Recycle*

IFMs also have potential in product maintenance and recycling. Leveraging the domain-specific knowledge acquired from upstream tasks, IFMs can generate maintenance guides and operation manuals, providing detailed steps and recommendations to maintenance personnel, effectively improving efficiency and reducing the occurrence of human errors. Moreover, IFMs can offer professional guidance, enabling individuals without specialized knowledge to acquire basic maintenance skills. Additionally, by analyzing the material composition and performance of equipment, these models can instruct on the safe disassembly and recycling of devices, maximizing the utilization of renewable resources in end-of-life equipment. In summary, IFMs can enhance equipment reliability, lower maintenance costs, and promote sustainable development.

V. Conclusions

In this paper, we introduce the concept and construction paradigm of IFMs, and propose a 5-dimensional general framework of the IFMs from data, model, computation, characteristic, and application. Around this framework, we point out potential key research issues and technologies that can be further explored. Moreover, we present the advanced and potential industrial applications of IFMs, providing insightful considerations for stakeholders and practitioners. In the future, we will further analyze and explore pre-training and domain-adaptation technologies for IFMs. We expect that this paper can provide valuable guidance for future research in this field.

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References

[1] R. Bommasani et al., "On the opportunities and risks of foundation models," 2021, [Online]. Available: http://arxiv.org/abs/2108.07258

[2] C. Zhou et al., "A comprehensive survey on pretrained foundation models: A history from BERT to ChatGPT," 2023. [Online] Available: https://doi.org/10.48550/arXiv.2302.09419

[3] Z. Ji et al., "Survey of hallucination in natural language generation," ACM Comput. Surv., vol. 55, no. 12, pp. 1–38, 2023.

[4] J. Gu et al., "A systematic survey of prompt engineering on vision-language foundation models," 2023. [Online] Available: https://doi.org/10.48550/arXiv.2307.12980

[5] Y. Li et al., "Myriad: Large multimodal model by applying vision experts for industrial anomaly detection," 2023. [Online] Available: https://doi.org/10.48550/arXiv.2310.19070

[6] Y.-F. Li, H. Wang, and M. Sun, "Chatgpt-like large-scale foundation models for prognostics and health management: A survey and roadmaps," Reliab. Eng. & Syst. Saf., p. 109850, 2023.

[7] J. Wei et al., "Emergent abilities of large language models," 2022, [Online]. Available: http://arxiv.org/abs/2206.07682

[8] S. Wu et al., "Bloomberggpt: A large language model for finance," 2023. [Online] Available: https://doi.org/10.48550/arXiv.2303.17564

[9] Y. Tan, G. Long, J. Ma, L. Liu, T. Zhou, and J. Jiang, "Federated learning from pre-trained models: A contrastive learning approach," Adv. Neural Inf. Process. Syst., vol. 35, pp. 19332–19344, 2022.

[10] T. Guo, S. Guo, J. Wang, X. Tang, and W. Xu, "PromptFL: Let federated participants cooperatively learn prompts instead of models-federated learning in age of foundation model," IEEE Trans. Mob. Comput., 2023.

[11] S. M. Kazemi et al., "Time2Vec: Learning a vector representation of time," 2019, [Online] Available: http://arxiv.org/abs/1907.05321

[12] S. Tonekaboni, D. Eytan, and A. Goldengerg, "Unsupervised representation learning for time series with temporal neighborhood coding," in 9th Int. Conf. Learn. Represent. (ICLR), 2021.

[13] Y. Yao et al., "Editing large language models: Problems, methods, and opportunities," in Proceedings of Conf. Empir. Methods Nat. Lang. Process. (EMNLP), 2023, pp. 10222-10240.

[14] K. Shuster, S. Poff, M. Chen, D. Kiela, and J. Weston, "Retrieval augmentation reduces hallucination in conversation," in Proceedings of Conf. Empir. Methods Nat. Lang. Process. (EMNLP), 2021, pp. 3784-3803.

[15] J.-C. Gu et al., "Model editing can hurt general abilities of large language models," 2024. [Online] Available: https://doi.org/10.48550/arXiv.2401.04700

[16] H. Zhao et al., "Explainability for large language models: A survey," ACM Trans. Intell. Syst. Technol., 2023.

[17] Z. Zhang, M. Fang, L. Chen, M.-R. Namazi-Rad, and J. Wang, "How do large language models capture the ever-changing world knowledge? A review of recent advances," in Proceedings of Conf. Empir. Methods Nat. Lang. Process. (EMNLP), 2023, pp. 8289-8311.

[18] S. Wang, Y. Zhu, H. Liu, Z. Zheng, C. Chen, and others, "Knowledge editing for large language models: A survey," 2023, [Online] Available: https://doi.org/10.48550/arXiv.2310.16218

[19] X. Tang et al., "Computing power network: The architecture of convergence of computing and networking towards 6G requirement," China Commun., vol. 18, no. 2, pp. 175–185, 2021.

[20] C. Yang, Y. Wang, S. Lan, L. Wang, W. Shen, and G. Q. Huang, "Cloud-edge-device collaboration mechanisms of deep learning models for smart robots in mass personalization," Robot. Comput. Integr. Manuf., vol. 77, p. 102351, 2022.

[21] C. Yang et al., "Cloud-edge-device collaboration mechanisms of cloud manufacturing for customized and personalized products," in 2022 IEEE 25th Int. Conf. Comput. Support. Coop. Work Des. (CSCWD), 2022, pp. 1517–1522.

[22] C. Yang, Z. Lai, Y. Wang, S. Lan, L. Wang, and L. Zhu, "A novel bearing fault diagnosis method based on stacked autoencoder and end-edge collaboration," in 2023 IEEE 25th Int. Conf. Comput. Support. Coop. Work Des. (CSCWD), 2023, pp. 393–398.

[23] C. Yang, S. Lan, W. Shen, G. Q. Huang, X. Wang, and T. Lin, "Towards product customization and personalization in IoT-enabled cloud manufacturing," Cluster Comput., vol. 20, no. 2, pp. 1717–1730, 2017.

[24] C. Yang, Y. Wang, Y. Jiang, S. Lan, and L. Wang, "Metaverse: Architecture, technologies, and industrial applications," in 2023 IEEE 19th Int. Conf. Autom. Sci. Eng. (CASE), 2023, pp. 1–6.