Perspective

Parallel Factories for Smart Industrial Operations: From Big AI Models to Field Foundational Models and Scenarios Engineering

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Briefing**:** The rapid advancement of fundamental theories and computing capacity has brought artificial intelligence, internet of things, extended reality, and many other new intelligent technologies into our daily lives. Due to the lack of interpretability and reliability guarantees, it is extremely challenging to apply these technologies directly to real-world industrial systems. Here we present a new paradigm for establishing parallel factories in metaverses to accelerate the deployment of intelligent technologies in real-world industrial systems: *QAII-1.0*. Based on cyber-physical-social systems, *QAII-1.0* incorporates complex social and human factors into the design and analysis of industrial operations and is capable of handling industrial operations involving complex social and human behaviors. In *QAII-1.0*, a field foundational model called *EuArtisan* combined with scenarios engineering is developed to improve the intelligence of industrial systems while ensuring industrial interpretability and reliability. Finally, parallel oil fields in metaverses are established to demonstrate the operating procedure of *QAII-1.0*.

Keywords**:** Cyber-physical-social system (CPSS), Industry 5.0, Metaverses, Parallel factories, Parallel intelligence.

I. INTRODUCTION

OVER the last two centuries, industry has been a major driver of social, livelihood, and economic progress. Industry is both the driving force behind national economic development and the guarantee of our material and cultural needs. Industry 4.0, also known as the Industrial Internet, has integrated information technologies to facilitate industrial development in the past decade. Industry 4.0 is based on cyber-physical systems (CPSs) and is distinguished by networking, which combines products, machines, and resources to create a flexible, personalized, digital, and networked manufacturing mode using information technologies [1]–[3]. The CPS framework, however, ignores an important aspect of real-world industrial systems: Social factor. However, the rapid development of intelligent technologies such as artificial intelligence (AI), internet of things (IoT), and extended reality (XR[1]) today not only increases industrial production efficiency, but also brings social factors and actual industrial production closer together [4], [5]. As a result, CPS, which cannot effectively deal with the complex social and human behaviors in increasingly complex industrial systems, impedes industrial development even further [1], [6]–[8].

So far, we can not help but wonder: "*Should AI, XR, and many other new intelligent technologies be fully integrated to establish a new industrial paradigm that fully flourishes productivity while adequately addressing upcoming challenges?*" To answer this question, Wang launched cyber-physical-social systems (CPSSs) in 2010 [6], and further introduced the concept and framework of Industry 5.0 [1]. CPSS-based Industry 5.0 builds a grand closed-loop control and management paradigm for industry by incorporating complex social and human factors into the design and analysis of industrial systems. Fig. 1 depicts the progression from Industry 1.0 to Industry 5.0.

II. RELATED WORK

This section provides a brief overview of parallel intelligence and big AI models that are key technologies for constructing parallel factories.

A. Parallel Intelligence in Metaverses

It is not difficult to discover that intelligent technologies such as AI, XR, and IoT all highlight a current buzzword: Metaverses. It is now widely recognized that the term "Metaverse" was coined by Neal Stephenson in his science fiction novel *Snow Crash*. Stephenson envisions the metaverse as

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[1]XR denotes technologies that can alter reality by adding digital elements to the user's environment, including virtual reality, augmented reality, and mixed reality.

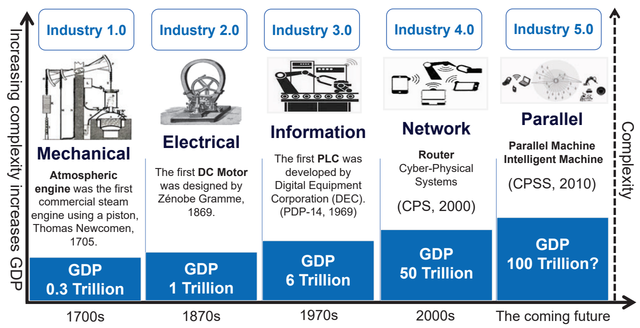


Fig. 1. From Industry 1.0 to Industry 5.0.

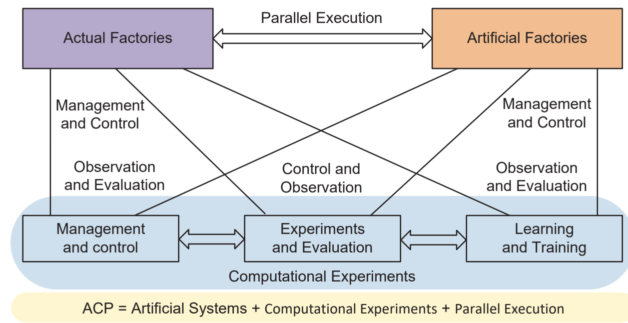


Fig. 2. The basic framework of *QAII-1.0*.

a virtual three-dimensional (3D) space in which everything in the real world is digitally replicated. Based on digital doubles, people interact with other people or software-defined agents for production and consumption. Before metaverses, digital twins (DTs) were regarded as a critical technique for achieving Industry 4.0 [9], [10]. Although both metaverses and DTs attempt to duplicate the genuine physical world and then complete specific tasks, they both have significant flaws when dealing with complex systems, according to the current paradigm. Particularly, the CPS framework serves as the foundation for metaverses and DT in the current paradigm. Therefore, related research disregards the social and human aspects of complex systems. [6]. Furthermore, there is currently no broadly recognized definition of metaverses, despite the fact that it is frequently portrayed by features like interoperability, real-time network access, and immersive 3D user experiences [11]. As a result, the metaverses lack a self-contained scientific theory for control and management of complex systems.

Fortunately, several trailblazers have carried out some significant research that explains and validates the metaverses. Among these studies, parallel intelligence is the scientific theory behind metaverses and DTs [12]–[16]. Parallel intelligence is built on the parallel system theory [17]–[21]. The parallel system theory, proposed by Wang [17], is a scientific research paradigm for modeling, analysis, management, and control of complex systems. The parallel system theory, also known as the ACP theory, involves three main parts: Artificial systems, Computational experiments, and Parallel execution. Artificial systems are utilized to model the real world, which also can be referred to as artificial societies. In computational experiments, numerous intelligent methods can be employed to cope with complex systems. Based on the parallel execution, the feedback from actual and artificial systems is obtained and analyzed to further improve the efficiency of modeling, management, and control of complex systems. Based on the ACP theory, parallel learning, which integrates descriptive learning, predictive learning, and prescriptive learning, was introduced to address complex system issues [22].

B. Big AI Models

The success of big AI models (or foundation models [23]) in natural language processing has received a lot of attention in recent years [23]–[25]. In [26], BERT (Bidirectional Encoder Representations from Transformers) was proposed and achieved then state-of-the-art (SOTA) performance on 11 different natural language processing tests, which initiated the era of big AI models. In [27], the best one in the GPT (Generative Pre-trained Transformer) series so far: GPT-3, which has 175 billion parameters, was put forward to achieve better generality. A large-scale visual language (VL) pre-training model called CLIP (Contrastive Language-Image Pre-training) was proposed in [28], and it is trained by contrastive learning. By predicting whether an image and a text are a match in pre-trained tasks, CLIP may be adapted to a variety of image and language downstream tasks. In [29], PaLM (Pathways Language Model), a Transformer model with 540 billion parameters, was proposed and achieved then SOTA performance in multilingual tasks. Flamingo, a member of the VL models family, was introduced in [30], outperforming other well-tuned large AI models at the time. Inspired by BERT, BEiT (Bidirectional Encoder representation from Image Transformers) was introduced to pre-train vision Transformers using masked image modeling pre-train tasks [31], and it could be quickly and easily applied to downstream vision tasks. Moreover, in the field of VL models, a minimal VL model: ViLT (Vision-and-Language Transformer) was proposed to reduce the dependency on image feature extraction, by simplifying the processing of visual inputs, and ViLT is faster than previous VL models [32]. In [33], to enhance the performance of transferring models in a zero-shot fashion, LiT, namely Locked-image Tuning, was proposed using contrastive-tuning methods. BriVL (Bridging-Vision-and-Language) was proposed in [34] as a method for obtaining multi-cognitive abilities and developing general AI by leveraging weak semantic correlation data. More details about big AI models can be found in [23].

It should be noted that the aforementioned big AI models were created and implemented in ideal and secure settings, making it challenging to directly deploy them to real-world industrial systems [35]–[37].

III. QAII-1.0: PARALLEL FACTORIES IN METAVERSES

To address the aforementioned issues, we present a new smart factory paradigm in industrial metaverses: *QAII-1.0*[2]. Figs. 2 and 3 depict the basic framework and the operating

[2]Qingdao Academy of Intelligent Industries (QAII) is rooted in independent innovations and promotes the commercialization of scientific and technological achievements. *QAII-1.0* is the first generation of parallel factories in metaverses proposed by QAII for Industry 5.0.

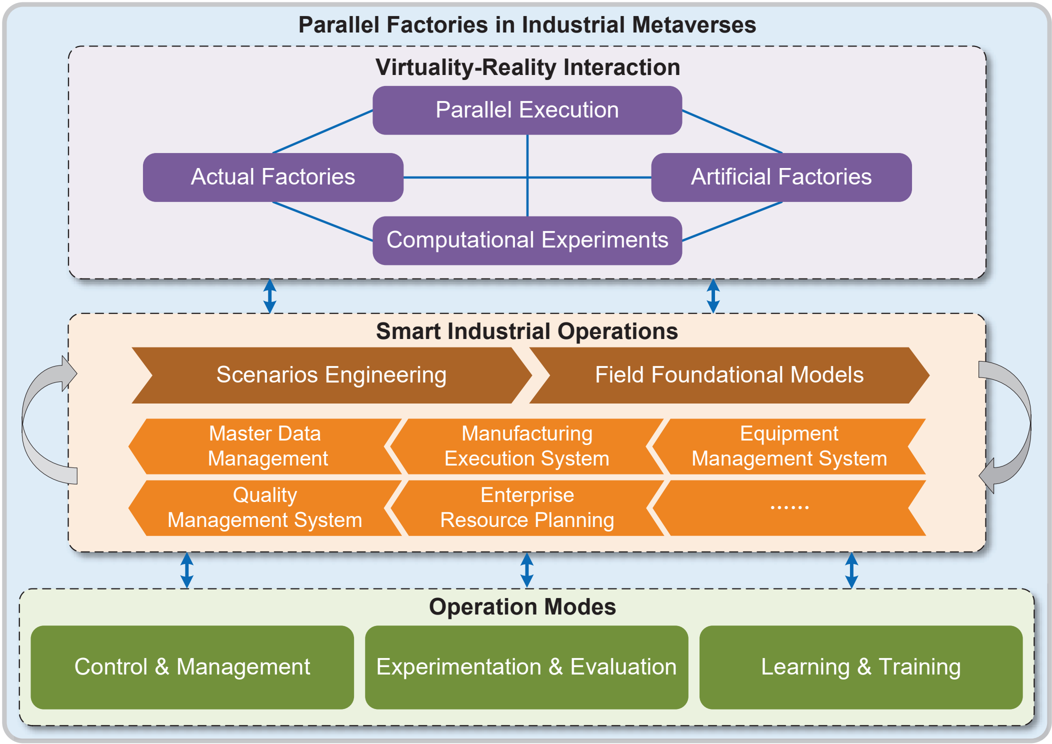


Fig. 3. The operating framework of *QAII-1.0*.

framework of *QAII-1.0*, which is designed based on the ACP theory and the decentralized autonomous organization (DAO) principle. The main goal of *QAII-1.0* is, under the condition of human-machine collaboration, to direct intelligent industrial equipment to accomplish various scenarios-oriented tasks through the cooperation of actual and virtual factories. Specifically, *QAII-1.0* includes the following three steps: 1) *Artificial systems*: To get around problems like non-reproducibility, expensive physical tests, and difficulty assuring safety for actual factories, construct artificial factories; 2) *Computational experiments*: Conduct computational experiments based on artificial and actual factories for analyses, evaluation, and prediction; 3) *Parallel execution*: Through parallel execution, artificial and real factories are intimately interwoven to achieve guidance, management, and control of actual factories.

To enhance the intelligence of industrial systems, we propose a scenarios engineering (SE) + field foundational models (FFMs) approach. Traditional feature engineering-based AI methods have attained SOTA performance on some specific tasks, but without the in-depth consideration of issues such as interpretability, security, and sustainability [36], [37]. Therefore, it is difficult to apply these SOTA methods to actual industrial systems directly. In parallel factories, SE can be viewed as the integration of industrial scenarios and operations within a certain temporal and spatial range, where suitable AI methods are to complete the design, certification, and verification. The design, validation, and calibration for industrial operations will be supported by intelligence & index (I&I), calibration & certification (C&C), and verification & validation (V&V) under the framework of SE, and *QAII-1.0* can then achieve the 6S (safety, security, sustainability, sensitivity, service, and smartness) goal [36].

Big AI models are crucial to achieving parallel factories. However, as stated previously, the existing big AI models are designed based on feature engineering and are therefore difficult to straightforwardly apply to actual industrial operations. Fortunately, with the help of SE, we can establish actual industrial operations as scenarios-oriented models based on the industrial data and knowledge to accurately describe industrial production. Then, we construct an FFM to support smart industrial operations using I&I, C&C, and V&V. The term "FFM" refers to this type of big model that is built on SE and targeted towards a particular field. More details on the combination of SE and FFM in *QAII-1.0* will be illustrated in the next section.

Meanwhile, *QAII-1.0* has the following three operation modes: 1) Control & management: In this mode, artificial and actual factories interact in real-time, and achieve sensing, prediction, management, and control through parallel execution; 2) Experimentation & evaluation: In this mode, analyses, evaluations, and optimization of various scenarios, planning, and management schemes are carried out; 3) Learning & training: In this mode, learning and training are conducted mainly for managers, planners, and workers in factories.

Based on the operating framework, Fig. 4 further illustrates the architecture of *QAII-1.0*. This architecture includes the following five layers: the support layer, the data interaction layer, the FFM layer, the digital operation layer, and the application layer, and each layer is coupled with the other from the bottom up. Based on the high-performance computing platform, web 3.0, and DAO principle, *QAII-1.0* integrates IoT, big data, 5G, edge computing, cloud computing, and XR

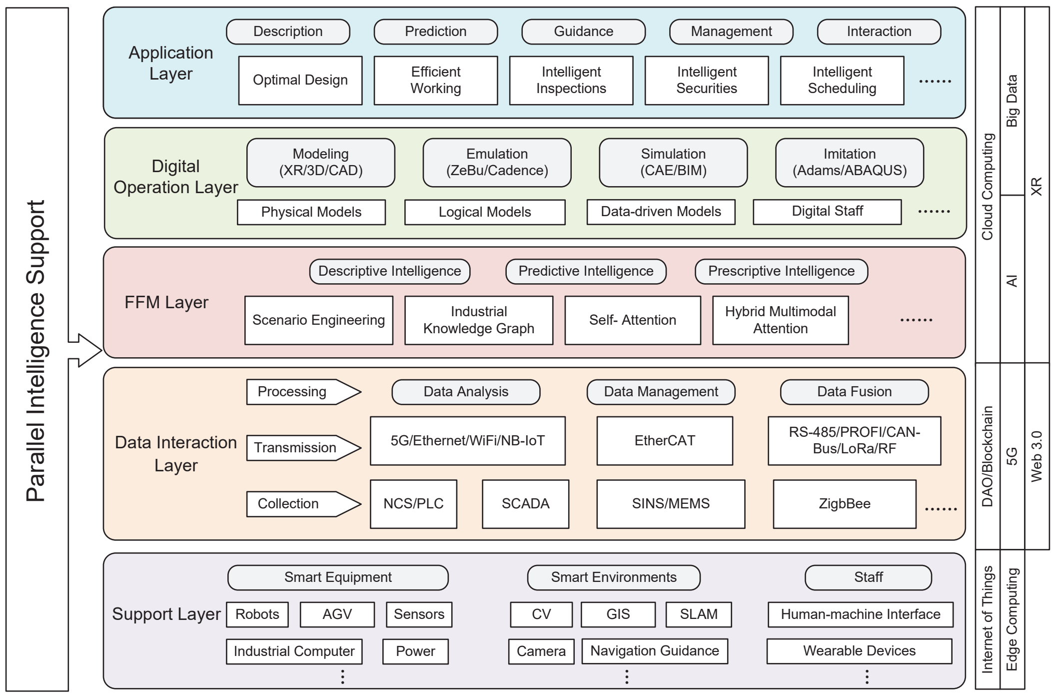


Fig. 4. The basic architecture of *QAII-1.0*.

technologies to realize X2X[3].

Support layer: The support layer provides big data foundation support for the establishment of *QAII-1.0*. Under the framework of CPSS, many intelligent technologies, including IoT and edge computing, can be employed to acquire and perceive data from intelligent devices.

Data interaction layer: The data interaction layer offers real-time dynamic data interaction support for *QAII-1.0*. Based on 5G and other advanced transmission technologies, on-site industrial data are collected through programmable logic controllers (PLCs), numerical control systems (NCSs) and intelligent sensors, and then transmitted to the cloud platform by industrial Ethernet, 5G networks, bus interfaces, EtherCAT, etc. Finally, based on DAO and web 3.0, feedback, interaction, and collaboration between actual and artificial factories are achieved utilizing deep learning and multimodal data analysis and fusion technologies.

FFM layer: The intellectual foundation of *QAII-1.0* is the FFM layer, which creates descriptive, predictive, and prescriptive intelligence based on the parallel system theory.

Digital operation layer: The digital operation layer establishes digital models for components in *QAII-1.0*. By using cloud computing, big data, AI, and XR technologies, digital models are used to demonstrate the appearance, geometry, motion mechanism, geometric association and coupling relationship, and other attributes of actual factories and the components inside, and finally establish multi-scale and multi-dimensional digital virtual models of actual factories. In the meantime, the digital operation layer provides experimental platform for computational experiments.

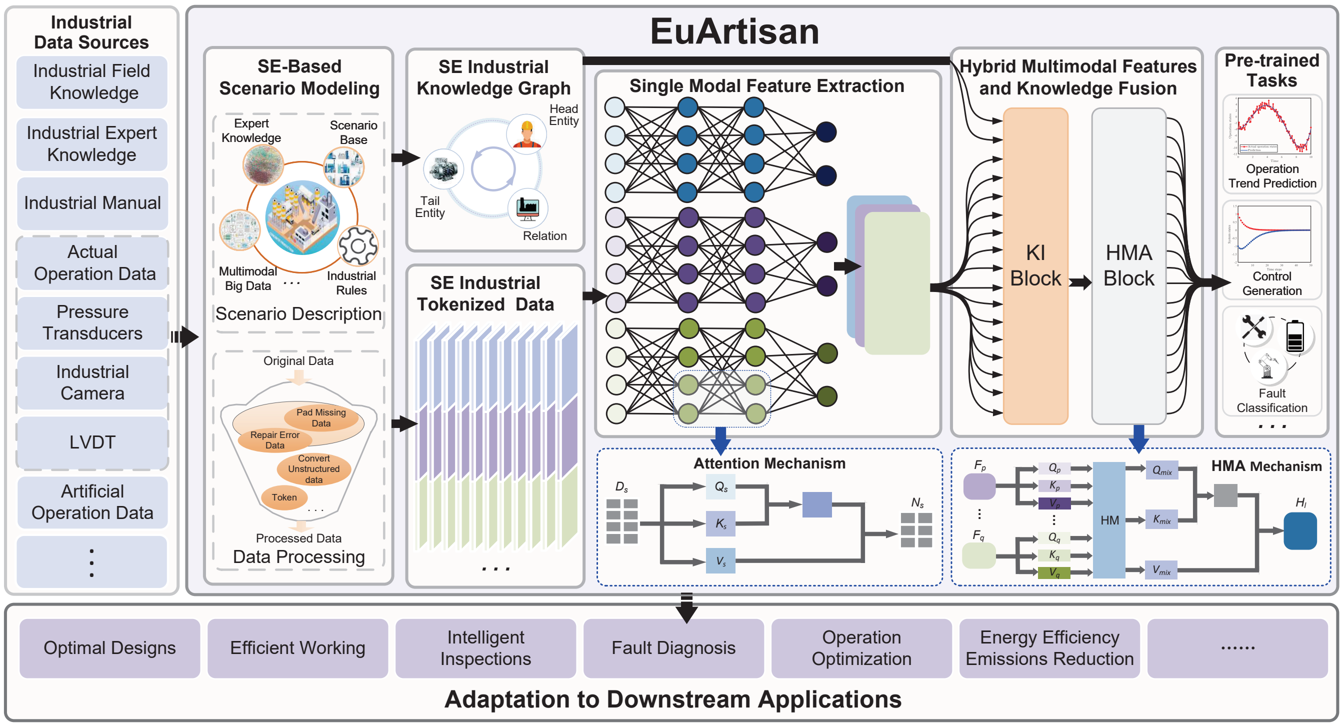
[3]X2X refers to virtuality-virtuality, virtuality-reality, reality-virtuality, reality-reality

Application layer: The application layer provides application ecology for *QAII-1.0*. This layer offers application tasks like precise description, diagnosis, prediction, control, and decision-making for smart industrial operations based on the interoperability of the preceding layers.

IV. EuArtisan: Toward SE and FFM for Smart Industrial Operations

As mentioned earlier, improving the intelligence of current industrial systems is necessary to achieve *QAII-1.0*. To this end, we present *EuArtisan*, a SE-based FFM for intelligent industrial operations. The basic framework of *EuArtisan* is depicted in Fig. 5, and it consists of the following blocks: SE-based scenario modeling block, single modal feature extraction, hybrid multimodal features and knowledge fusion block, pre-trained tasks block, and adaptation to downstream applications block. In the following, we will give details of these blocks.

SE-based scenario modeling block. Big AI models require enormous amounts of data to train, and their application in industry can be even more challenging. In the case of industrial scenarios, the data to be processed will be more complex, and we frequently have to deal with multimodal data, unstructured data, and incomplete data. Another issue is that it is difficult to model a wide variety of industrial systems in an analytical way. To address the aforementioned issues, we propose a SE-based scenario modeling approach. According to SE, we establish a scenario base, which includes industrial rules, expert knowledge, and multimodal data, to precisely describe industrial operations. Then, based on the I&I, C&C, and V&V framework, we design *EuArtisan* to support smart industrial operations. Then, to effectively train *EuArtisan*, we



• KI: Knowledge Integration; HM: Hybrid multimodal; HMA: HM attention; LVDT: Linear variable displacement transducer.

Fig. 5. The basic framework of *EuArtisan*.

need to pre-process data, including padding of missing data, structuring structured data, and tokenization of data. Finally, we can obtain the SE-based industrial knowledge graph and tokenized data.

Single modal feature extraction block and **hybrid multimodal features and knowledge fusion block**. Since *EuArtisan* needs to handle big multimodal data, two blocks are designed for feature extraction. In the single modal feature extraction block, we use the self-attention mechanism to initially extract features from single modal data. All industrial operations in a factory should be highly connected given that they all eventually go toward the same objective, and thus features and knowledge behind operations should be strongly correlated. Therefore, it is not enough to do feature extraction only for single modal data. On the other hand, since different tasks require different data, it is not necessary to fuse all the features in one task, which can result in computational redundancy. To further extract features in multimodal data and attain hybrid multimodal features, we propose a hybrid multimodal attention (HMA). In HMA, whether or not a specific feature is involved in the feature fusion is decided by an HM module. Moreover, the SE industrial knowledge graph is included to improve *EuArtisan*'s performance for particular industrial tasks, a process known as knowledge integration.

Pre-trained task block. Pre-trained task design is a critical step to achieving big AI models, and *EuArtisan* is no exception. First, pre-training tasks should be relevant to downstream tasks to ensure the effectiveness of the feature extraction. Second, it is challenging to manually label data because the training of big models requires vast amounts of data. For example, in [26], two pre-trained tasks are proposed for BERT using self-supervised learning: Masked-language modeling and next sentence prediction. Based on the above analyses, we can design the following pre-training tasks: Operation trend prediction, control generation, fault classification, and tasks in virtual space.

In actual factories, various intelligent sensors generate a vast amount of operational data, and we can predict operation trends using self-supervised learning. It is worth noting that, in standard industrial system modeling, a neural network is usually utilized to predict the next state based on the current state and action, i.e., predicting a Markov decision process. The goal is to train a neural network to satisfy a certain mapping, and the mathematical expression is as follows:

$$f : (s, a) \to s' \tag{1}$$

where s and a denote the current state and action of an industrial system, respectively, and s' denotes the next step state. The proposed operation trend prediction is far different from this way. Assuming we have two motors, each with a different set of parameters, if we follow (1) to train a neural network, the same (s, a) may correspond to different s'. The case of the same data corresponding to different labels may lead to unsatisfactory training results. Therefore, we construct the following mathematical expression in the operation trend prediction:

$$\bar{f} : (\bar{s}, \bar{a}) \to \bar{s}' \tag{2}$$

where $\bar{s}$ and $\bar{a}$ denote the sequence of current states and actions of an industrial system, respectively, and $\bar{s}'$ denotes the sequence of next period states. Our goal is to extract more features contained in systems by using a period of runtime data. Furthermore, by substituting (s, a) with two similar devices, we can forecast the dynamics of another different class of related devices by mining features of the two associated devices mentioned above.

As for the control generation and fault classification, we can get labels from the scenario base and expert knowledge. Regarding the tasks in virtual space, the training data and labels are generally coupled together at the time of data generation and no further manual labels are required.

Adaptation to downstream applications block. Once our model has been pre-trained, we may fine-tune it to meet particular downstream applications and keep it constantly learning. Besides, the fine-tuned model will be applied to digital virtual models concurrently, and the cloud system will continuously track and analyze the performance of both the actual system and the digital virtual models. When the performance is not as expected, the model and the digital virtual models will be further updated simultaneously. It is not difficult to find out that the implementation of *EuArtisan* adheres to the rule of "Local simple remote complex".

V. Application: Parallel Oil Fields in Metaverses

This section introduces a specific application of parallel factories: Parallel oil fields. Parallel oil fields, as depicted in Fig. 6, primarily consist of actual oil fields, artificial oil fields, *EuArtisan*, and high performance computing environments. Throughout the life cycle, parallel oil fields support industrial operations such as geological survey, seismic exploration, drilling, mud logging, well logging, casing & cementing, completion, oil extraction, enhanced oil recovery (EOR), transportation, and oil-refinery. Parallel oil fields aim to optimize the efficiency of operations, save energy, reduce worker engagement in the actual oil production, achieve an increase in oil production, and develop intelligent oil fields while ensuring safety and reliability.

Parallel oil fields also involve the following three steps: 1) Artificial oil fields: Establish multi-scale and multi-dimensional digital virtual models of actual oil fields, such as reservoir geological model, drilling model, digital staff model, and sucker rod pumping system (SRPS) model, and provide the fundamental components for simulations and computational experiments; 2) Computational experiments: For geological survey, mud logging, oil extraction, EOR, etc., computational experiments provide the experimental platform employing digital virtual models and assist in optimizing industrial operations; 3) Parallel execution: We optimize artificial oil fields and computational experiment results through parallel execution.

In parallel oil fields, *EuArtisan* is utilized to offer intellectual support. First, *EuArtisan* gathers operational data and knowledge from artificial and actual oil fields. An oil field is a typical case of big data and multimodal data, data including seismic images, SEG-Y, downhole videos, drilling daily reports (DDRs), and PVT (pressure, volume, and temperature). Data formats include temporal series, videos, two-dimensional (2D)/3D images, natural language, and expert knowledge. To ensure secure and effective data usage, SE must be employed. In order to adequately depict oil field operations, we establish the oil scenario basis based on SE, which includes industrial rules, expert knowledge, and multimodal data. We also get tokenized data and the knowledge graph for the oil industry at the same time. Additionally, we develop appropriate pre-trained tasks to extract features from multimodal data in oil fields in accordance with downstream tasks. Furthermore, a high-performance computing environment is required for engineering applications.

Next, we will give a brief description of two operations: well logging and oil extraction. Well logging, also called borehole logging, is a process of measuring geophysical parameters using the geophysical properties of rock formations such as electrochemical properties, electrical conductivity, acoustic properties, and radioactivity. In short, well logging is the measurement of physical parameters of stratigraphic rocks. In oil extraction, the underground crude oil is extracted to the surface according to requirements of oil field development. It is not difficult to find out that well logging and oil extraction are related. The properties of reservoir rocks, for example, might determine the method of oil extraction, such as flowing oil production and artificial lift. The mechanical and kinematic parameters of lift devices used in artificial lift methods are also closely related to the properties of the rock formation.

In the following, we illustrate the above operations in parallel oil fields. In artificial oil fields, we establish virtual reservoir well models which describe reservoir properties and virtual artificial lift devices. In computational experiments, these virtual models offer simulation conditions and can also produce virtual data to make up for the absence of actual data from oil fields. As mentioned above, the two operations are related, and from the perspective of machine learning, the features required for the two operations can be shared. The training process involves feeding *EuArtisan* data from both operations, such as γ-ray, spontaneous potential, and motor driving torque in SPRS. *EuArtisan* is then trained using elaborate pre-trained tasks. Recalling that pre-trained tasks should be relevant to downstream tasks and should be self-supervised, prediction tasks, tasks in the expert knowledge base, and tasks in virtual space are appropriate. For example, 2D/3D image-based permeability prediction, porosity prediction, prediction of SPRS motion characteristics, indicator diagram-based fault classification in fault knowledge base, and tasks in virtual space. Once *EuArtisan* has received adequate training, we can fine-tune it to fit the downstream tasks in well logging and oil extraction. Besides, the fine-tuned *EuArtisan* is applied to artificial and actual oil fields concurrently, and the cloud system will continuously track, analyze, and improve the performance of both the actual and artificial oil fields.

VI. Conclusion

Going back to the question at the beginning of this paper, our answer is self-evident: "*Yes!*". To this end, based on SE and FFM, we present a new paradigm for parallel factories in metaverses: *QAII-1.0*, which offers a secure and reliable guarantee for the application of AI, XR, DAO, web 3.0, blockchain, and many other new intelligent technologies in

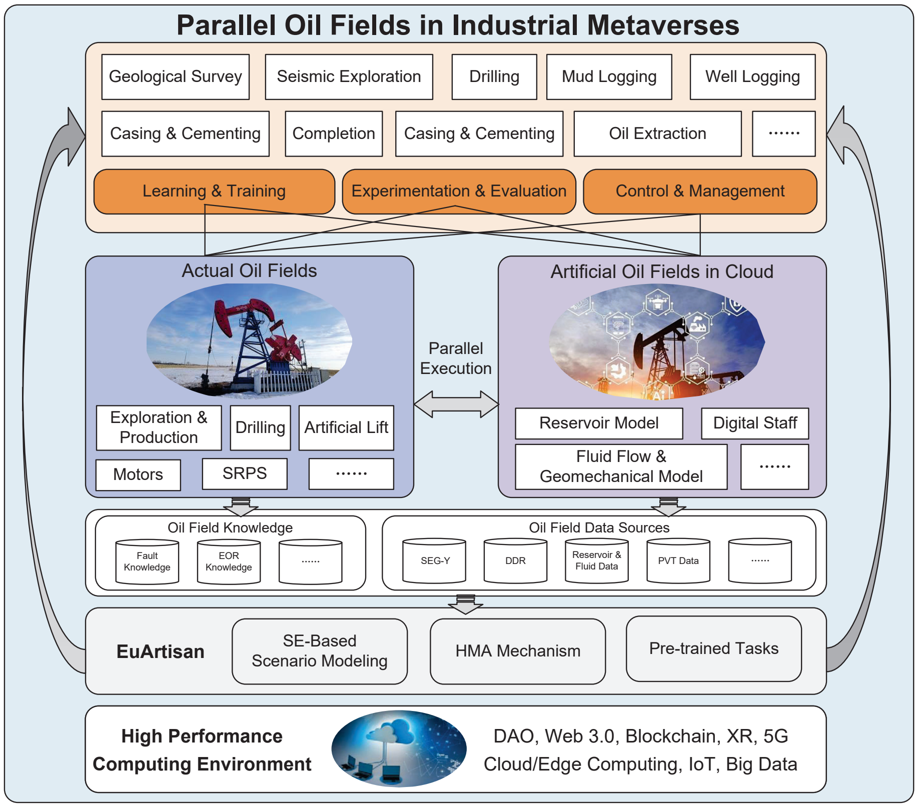


Fig. 6. The framework of parallel oil fields in metaverses.

real-world industrial scenarios. Then, an FFM called *EuArtisan* is introduced in *QAII-1.0* to achieve high-level machine intelligence for industrial systems. The design, certification, and verification for *EuArtisan* are implemented based on SE, and adhere to the DAO principle. Finally, parallel oil fields are given to demonstrate the operating procedure of *QAII-1.0*. We believe the combination of *QAII-1.0* and *EuArtisan* is the key to achieving smart industrial operations in Industry 5.0.

Acknowledgment

The idea of parallel factories was first proposed by Prof. Fei-Yue Wang in the early 2000s. After 20 years of development, it has been practiced and applied in many fields, such as parallel ethylene plants, parallel nuclear power plants, and parallel thermal power stations. In this work, we further integrate the idea of FFM and SE, which are also proposed by Prof. Fei-Yue Wang, into parallel factories, developing and expanding the idea with new concepts and technologies. Since the idea is proposed, several symposiums, workshops, and seminars have been organized to explore the architecture, key technologies, and applications of parallel factories, and *QAII-1.0* and *EuArtisan* were gradually formed. We would like to thank Prof. Fei-Yue Wang, for leaving no stone unturned to share his perspective and knowledge with us, which greatly improved this work.

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