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Machine Learning Applications in Demand Forecasting and Order Fulfillment for Smart Manufacturing OSS

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Abstract: ***The demand-driven paradigm of the modern market environment imposes enormous challenges on enterprise production and logistics. Smart manufacturing based on cloud edge collaboration is changing the traditional manufacturing mode into on-demand order manufacturing mode, which requires enterprises to have a perfect demand forecasting model. Current cloud-edge architecture just focuses on how to guarantee system stability and computing resource composition, but seldom studies how to make full use of multi-source heterogeneous cloud-edge resources to provide competitive service level agreements for smart manufacturing. Therefore, in smart manufacturing, the supply chain sensing layer needs to build a multi-source heterogeneous time series forecasting mechanism. Among these tasks, demand forecasting based on time series has attracted widespread attention due to its wide application scenarios and challenging characteristics. Demand forecasting is a key business in a supply chain, and a variety of intelligent demand forecasting methods have been developed. In production management, forecasting the processing time of a specific job input is essential for dynamic scheduling in job shop systems. The scheduling model comprising the manufacturing attributes and characteristics of the order processing is built to forecast order completion date. This forecast mechanism plays a key role in order management and scheduling decision-making. Currently, the existing cloud-edge management systems are seldom designed for smart manufacturing and hardly predict multi-source heterogeneous time series. Therefore, the corresponding modeling methodology should be proposed to comprehensively consider diverse data characteristics (complexity, completeness, frequency, sampling rate, etc.). With the rapid development of the industrial internet, various types of demanding data are heavily accumulating in cloud-edge environments. However, how to effectively select and utilize such multi-source heterogeneous data to improve edge computing is still a challenging problem in future smart manufacturing. The cloud-edge collaborative computing architecture and technologies place strict requirements on the performance of multi-source heterogeneous data selection and processing methods. State-of-the-art cloud-edge computing methods often ignore the existence of diverse multi-source heterogeneous data. Hence, the key techniques regarding how to model the selection and processing of multi-source heterogeneous supply chain data should be studied, which may significantly change the cloud-edge resource management and scheduling algorithms.***

Keywords: ML for Demand Forecasting, Smart Manufacturing OSS, Predictive Order Fulfillment, AI-Driven Supply Chain Optimization, Machine Learning in Production Planning, Demand Sensing Algorithms, Real-Time Inventory Forecasting, Intelligent Order Management, Data-Driven Manufacturing Decisions, Adaptive Forecasting Models, AI-Powered Supply Chain Analytics, ML-Based Inventory Optimization, Operational Support Systems in Manufacturing, Predictive Analytics for Manufacturing, Automated Demand Planning

1. Introduction

With the continuous development of the market economy and advancement of science and technology, consumers expect ordered products to be delivered within a shorter cycle. The increasingly market-centric order production method puts extremely strict requirements on corporate capacity and timely completion. To cope with the volatility of customer order demand, enterprises need to effectively control the ordered tasks in the manufacturing job-shop and formulate a reasonable production plan based on customer demand. In the manufacturing industry, order management runs through the entire production cycle. The accurate prediction of the product completion period is the main factor affecting the decision of order management and control. This paper explores the order management and completion date prediction of manufacturing job-shops based on deep learning.

Forecasting is the crux of retail supply chain management and the key to better supply chain performance. Several retailers are using models to provide forecast guidance in applications such as Cognitive Demand Forecasting and Demand Integrated Product Flow. The recent disruptions have made it critical for supply chains to have the resiliency to handle unexpected events. The biggest challenge lies in matching supply with demand. Reinforcement Learning is being increasingly adopted in supply chain management to improve forecast accuracy and solve supply chain optimization challenges. Companies have developed algorithms to keep up with rising consumer delivery expectations. This paper explores the application of Reinforcement Learning in supply chain forecasting and describes how to build suitable models and algorithms.

1.1. Background and Significance

Smart Manufacturing has become more connected and secured than before owing to the Industry 4.0 revolution. However, a very important accessory of the Industry 4.0 revolution is the analysis of huge data generated in the SM context. Modern SM sensing devices like Robots, AR glasses, Cameras, and Sensors generate a huge amount of data (both structured and unstructured) in the Form of Video, Image, Text, and Captions. Several organizations in the Smart Manufacturing context are facing difficulty in identifying, analyzing, and processing the data. There exist some applications that use Machine Learning algorithms to recognize certain tasks but a very few OSS have been built that analyze and process a spectrum of SM data. Hence, the researchers wanted to develop such OSS. Researchers selected the Demand Forecasting and Order Fulfilment as the applications in the context of the Smart Manufacturing services.

Figure 1: Machine Learning for Product Demand Forecasting

Manufacturers can revolutionize their order fulfilment processes by implementing robust AI demand forecasting systems in conjunction with AM/AIS. AI-based demand forecasting systems can lessen delays, minimize misallocations, mitigate excess inventory, and improve customer experience. Many manufacturers face a complex set of AI barriers when trying to take advantage of innovative forecasting solutions. AM/AIS is imperative to design and implement effective AI forecasting systems. On the analytics side, AM/AIS enables manufacturers to generate the level of forecasting accuracy, forecast horizon, and forecast volatility required for a business. On the IT side, AM/AIS ensures that the pool of prediction models can be easily interoperable, that forecasting systems can be efficiently developed, and that business users can easily tactically adjust the system to meet rapidly changing demand conditions. AI-based forecasting systems can ease the forecast process, modelling, evaluation, and implementation tasks. In this paper, the researchers claimed that demand forecasting is the key to better supply chain performance across the planning, execution, and business components of a retail supply chain. This paper discusses ways that AI/ML models such as ensembles and deep learning are being used by retailers to improve forecasting in applications such as Cognitive Demand Forecasting, Demand Integrated Item Flow, and Forecast Performance Improvement.

2. Overview of Smart Manufacturing

With the continuous development of the market economy and the advancement of science and technology, consumers expect ordered products to be delivered within a shorter cycle. The increasingly market-centric order production method puts forward extremely strict requirements on the corporate capacity of production and timely completion. To cope with the volatility of customer order demand, enterprises need to effectively control the ordered tasks in the manufacturing job-shop and to formulate a reasonable production plan based on customer demand for the completion period and their current manufacturing capacity. In the manufacturing industry, order management runs through the entire production cycle. The accurate prediction of the product completion period is the main factor affecting the decision of order management and control.

The operation of a manufacturing job-shop is difficult to manage, owing to the heterogeneity of raw materials, complex transformation process, and varied production flows. The completion time of ordered products can be predicted well by combining data mining with the analysis of the discrete data in the manufacturing industry, which are featured by scattered distribution, large volume, and poor authenticity. However, the existing studies have not fully considered the complex processing procedures, the features of manufacturing attributes, and the repetitive orders of stable consumers. To solve these problems, this paper explores the order management and completion date prediction of manufacturing job-shops based on deep learning. The proposed model was proved effective through experiments.

The smart manufacturing application domain poses certain technical challenges for the use of ML-based models for anomaly detection. First, in the smart manufacturing domain, there are multiple types of sensors concurrently generating data about the same events. These sensors are of varying capabilities and costs. The sensor data characteristics change with the operating point of the machines. The inference and the anomaly detection processes therefore have to be calibrated for the operating point. Thus, we need case studies of anomaly detection deployments on such systems. Most of the existing work has relied on classical models for anomaly detection and failure detection in such systems, while there is a rich literature on anomaly detection in many IoT-based systems. There are few existing works that document the use of ML models for anomaly detection in smart manufacturing systems. In particular, most of the existing work is focused on categorizing anomalies in the semiconductor industry, windmill monitoring, and laser-based manufacturing. The data from these sensors can be analyzed in a real-time manner to fill a critical role in predictive maintenance tasks, through the anomaly detection process. Thus, we propose our anomaly detection technique for smart manufacturing systems. In this paper, we study the maintenance problem of smart manufacturing systems by detecting failures and anomalies that would have an impact on the reliability and safety of these systems.

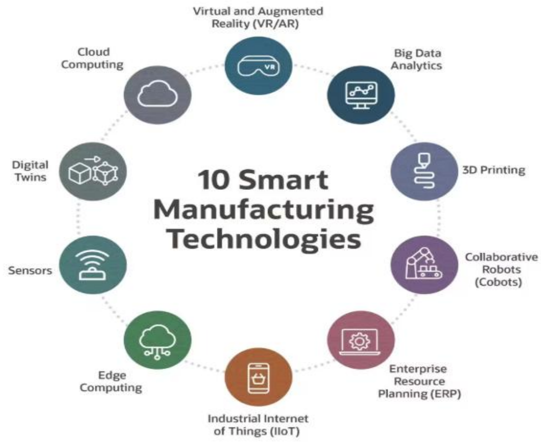

Figure 2: Smart Manufacturing

2.1. Definition and Key Features

Smart manufacturing is the integration of industry 4.0 technologies - Industrial Internet of Things, Big Data Analytics, Artificial Intelligence - for optimal scheduling of resources across the entire supply chain using real-time and reliable information. Demand forecasting is the first task of supply chain planning - whether it is a single enterprise, a network of manufacturing systems or a logistics system. Inconsistency of demands changes the order fulfilment of production systems. The following discussion looks at the specific sub-tasks demand forecasting and order fulfilment problems in the smart manufacturing industry and how machine learning can contribute to more accurate analysis of demand and control of order fulfilment.

Demand forecasting is the process of estimating future customer demand for a product or service. It's a vital part of business planning that can help a business avoid stockouts and overstock situations. There are six key features of intelligent demand forecasting processes: multi-channel data processing, hierarchical forecasting, hybrid forecasting, explainable forecasting, collaborative forecasting, and multi-scenario forecasting. Machine learning methods are mainly used in three areas of demand forecasting tasks: data preprocessing, demand forecasting modeling, and forecasting accuracy evaluation. Data preprocessing includes using outlier detection methods for data anomalies and missing values. Demand forecasting modeling, which is the critical process of building forecasting models, encompasses machine learning, deep learning, and mixed-model models. Positional similarity and empirical probability methods widely used in statistical methods are conventional approaches to forecasting accuracy evaluation, but with the development of new models, this heavily relies on post-evaluation methods with great difficulties.

Order fulfilment is the often-filled process of obtaining, packing, and delivering goods. It involves how purchase orders are filled. Shop-floor planning refers to the order release, shop scheduling and shop control for the entire manufacturing operation. It is indispensable for constructions in a smart manufacturing shop. With the wide application of Internet of Things technologies in the shop-floor environment, improving the completeness of data collection in smart manufacturing while ensuring data availability are both challenges for understanding data beyond the qualified data types. How to re-evaluate the level of metric validity and estimate the value of non-collectable metrics from the perspective of knowledge graph becomes the focus of the task of shop-floor planning knowledge graph construction. There are three key technologies, including discrete-event simulation, semantic modelling, and knowledge graph reasoning, to intelligently combine machine learning technologies in the post-evaluation function.

2.2. Importance of Smart Manufacturing

The continuous innovation of science and technology and the promotion of industrial information drive the deep integration of manufacturing and the Internet. The Internet of Things, big data, cloud computing, artificial intelligence, and other new generation technologies continue to be widely used in manufacturing, which gives birth to the new generation of manufacturing mode: smart manufacturing. In the era of big data, science and technology, products, plants, and operations management in smart manufacturing are becoming more complex. On the one hand, the continuous increase in product variety leads to difficulties in production planning and scheduling, which need to be optimized from minimizing the production time and making the full use of equipment. On the other hand, machines, factories, and other smart manufacturing elements scattered in different environments will generate a large amount of multi-source data. Reasonable analysis or mining of multi-source data such as production process data and product data can better improve the efficiency of production and operation scheduling and product quality.

Machine learning has become one of the important components of data mining. The major application areas include demand forecasting, product segmentation, and balance analysis among markets, production, and supplies. Demand forecasting involves time series-based ML engines to predict sales for a new product, holiday sales, and price promotion using event-based predictors. It usually includes predictive process chain and hybrid approaches. The time series-based ML engines include auto-regressive, ARIMA, Holt-Winters method, granular time series modeling, and clustering-based multivariate time series prediction. The event-based predictors involve week type, price promotion, retailer type, and holiday events, where ML techniques in product/market segmentation and lag clients using project segmentation and clustering algorithms are applied to balance production management and scheduling in metal-forming manufacturing streams.

Equ 1: Demand Forecasting via Time Series Prediction (LSTM/ARIMA base).

$$\hat{D}_{t+1} = f(D_t, D_{t-1}, \ldots, D_{t-n})$$

- $\hat{D}_{t+1}$ = predicted demand at time $t+1$
- f = time series model (e.g., LSTM, ARIMA)
- D_t = observed demand at time t

  → Core model for anticipating future demand based on historical consumption.

3. Demand Forecasting

With the continuous growth of the market economy and the improvement of science and technology, consumers from various industries keep raising their demands and expectations for product quality and delivery time. To meet consumers' needs, manufacturers would continuously adjust and change their production for delivering the right products to the right place without oversupply or undersupply based on the experience and rudimentary equipment, which usually leads to a product ordering–production–provision chain consisting of multiple stages in manufacture. As the product complexity level increases, the product ordering cycle becomes more and more longer, which leads to agents at different stages producing, allocating, selling, and delivering simultaneously.

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Hence, the conflicts of interest among agents in procurement supplier and manufacturer, stock keeping unit-price specification and storage planning, and capacity planning and sequencing lead to introducing the concept of multi-entity Collaborative Supply Chain (CSC) which meets common targets of social functions and ecological functions like energy conservation and emission reduction, and makes green supplier chain management possible among agents. As the success of electronics products development, continuous bulk supply staircase products with complicated structure and configuration become the major demand in wholesale markets, followed by drastically increased selection complexity and accuracy concerns in sourcing activities.

Essentially, the SCM is a large biconvex optimization problem. Due to the complexity and privacy of manufacturing knowledge, the biconvex problem is usually solved through multi-party communication, which consumes enormous labor and leads to less-than-optimality. To alleviate the difficulties, proposed a consensus-based and privacy-preserving Scalability-oriented Coordinative Agreement (SCA) mechanism although the optimistic correctness of the proposed SCA algorithm is not guaranteed. In this uncertain forecasting environment, numerous Machine Learning (ML) or Analytic Hierarchy Process (AHP)-based methods were proposed. However, the reliability and applicability of such models remained vague. Unlike previous conventions, which mainly focused on quantifying the mechanisms, some other conceptualistic research works modeled target market price fluctuations by displaying retrospective pricing. Nevertheless, such methodology usually relied on complex assumptions and suffered from the end-uselessness problem while unifying all market agents including manufacturers, suppliers, retailers, and consumers into simulation.

3.1 Role of Demand Forecasting in Manufacturing

Demand uncertainty is a common characteristic of many industries and directly affects businesses. The process of recognizing and estimating future demand is critical to business, but obtaining accurate forecasts is not simple. Demand forecasting (DF) aims to estimate and predict observable future demand values based on historical information of the demand or activity. DF is an increasingly important element of productivity and competitiveness that greatly impacts the business performance of manufacturers. Inaccurate estimates in DF can lead to missed sales opportunities, reduced margins, unnecessary cost growth, or even bankruptcy.

Manufacturers typically respond to demand fluctuations by managing and adjusting capacity and inventory. DF is an important precursor of capacity and inventory decision-making and is a key factor influencing businesses' performance. In summary, DF has the following roles in a manufacturing system: Dependency information and demand signals are collected. These signals are processed and modeled to obtain a set of demand innovations. The innovations are combined with the dependency information to generate an expected demand profile. The expected demand profile is used to find capacity/inventory solutions.
There are multiple well-known models for performing DF. Popular methods include Naïve, Moving Average, Exponential Smoothing, Box-Jenkins and Croston for univariate time series data. While supervised learning-based approaches including regression analysis, neural networks, and Bayesian data analysis are popular for multivariate data with specific cross-sectional data. These methods provide different solution spaces and the corresponding forecast performances largely depend on the features of the demand pattern. DF with completely new data can be easily adjusted to each model domain. Meanwhile industry needs to have an adaptive choice framework for any data characteristics.

3.2. Traditional Methods vs. Machine Learning Approaches

Accurate demand forecasting is imperative for optimum resource management, efficiency improvement, and increasing productivity in smart manufacturing OSS. Conversely, if demand isn't accurately predicted, it could lead to inefficiencies in resource utilization and inaccurate production planning. Consequently, production efficiency will be reduced, and the fulfillment-to-order cycle will be lengthened. Therefore, demand forecasting, a methodology of estimating the future demand of a product or service executing datetime and quantities, is especially important for smart manufacturing OSS. It can also provide companies with insights into future performance. Companies can use machine learning algorithms to forecast demand for their services or products as they have the feature of processing large sets of data and analyzing them without human involvement.

The smart manufacturing OSS system can collect the events and status of the job through IoT devices. These events are time-stamped log information, such as create, start, end, and terminate. Time-stamped log information can automatically be used for the future predictive task without any data cleaning and preprocessing. The smart supervision system also offers real-time data to ensure the tasks proposed in an open scheduling approach are still applicable even in dynamic environments. This real-time data varies from scheduling data, machine settings, job's events, and task numbers to completion time, and can impact the job completion time. Accurate order fulfillment time estimation helps the smart scheduling OSS system propose strategies with respect to estimated time.

The open scheduling framework should estimate order fulfillment time and schedule jobs to minimize tardiness in a smart manufacturing OSS. The open smart scheduling approach can ensure the plans still hold under a new job, machine breakdown, repair, maintenance, and rework tasks. The smart manufacturing OSS requires quick replies for the order fulfillment estimation. With the multi-view representation, the deep learning-based completion date forecasting can be effectively performed in smart manufacturing OSS. The smart manufacturing OSS system routinely collects the task sequence information and status log messages that can be used among the deep learning model and schematically performed classification helper for task-to-machine mapping.

3.3 Data Requirements for Effective Forecasting

The critical bottlenecks of a smart manufacturing OSS are examined, including demand forecasting, allocation of supplier production resources in order fulfillment, and scheduling of production resources at the considered supplier in Plan for Every Part (PFEP) process. Two Machine Learning methods including forecasting with LSTM and completion time prediction with Deep Learning are studied and employed to address the decisions of smart manufacturing OSS about demand forecasting and order fulfillment. A self-attention mechanism is incorporated into the deep learning network to capture the high-order and long term correlation. Experimental results demonstrate the effectiveness of the proposed data-driven methods in demand forecasting and order fulfillment for smart manufacturing OSS.

Demand forecasting has become the primary and critical decision for inventory management. It affects the whole chain of procurement, production, and sale. Accurate demand forecasts can help manufacturers significantly optimize inventory management and thus minimize costs, such as transportation, warehousing, and stockouts, while improving customer satisfaction. In contrast, inaccurate demand forecasts can result in overstocking and waste rate of perishables, which cause huge potential loss, i.e., 1% increase in demand forecasting accuracy can lead to a cost decrease of 5% to 8%. Demand forecasting is essential for all industries including fast-moving-consumer-goods, high-technology, and high-value-per-unit goods, i.e., motorcycles.

Due to the slow dynamic diffusion of the COVID-19 pandemic, exponential growth demands are surged for two-wheelers worldwide. The inconsistent and unanticipated demands hurt the motorcycle component supply chain seriously. To minimize shortage cost, the motorcycle component suppliers must predict deliveries with high accuracy. In practice, their widely-used forecasting methods cannot properly handle the estimating process since the low fitting performance leads to huge loss. Potential insights in better forecasting methods are thus studied that combine curve analysis with machine learning. Curves are first fitted with chosen mathematical forms, which transform the forecasting problem into remaining parameters estimation. Subsequently, the sophisticated machine learning algorithm is applied to learn and predict parameters. Accurate parameter forecasting can improve the forecast accuracy of models.

4. Machine Learning Techniques for Demand Forecasting

Demand forecasting and order management have gained more attention since the supply chain backbone is shifting to smart, autonomous supply chains (SASC) with smart manufacturing (SM) OSS. Accurate forecasting leads to an effective decision on management and control, safety stock level, logistics and transportation arrangement, supply and inventory management mechanisms, and control of actual run time. An integrated demand forecasting and order management model is constructed to assist the demand planning department translate the business plan into the forecast of demand during the forecasting period, and then assist the scheduling and priority planning department manage the orders received during the fulfillment period.

AI techniques, including ML algorithms fed by demand histories and events and LSTM for time-series sequence learning, are leveraged to predict customer order arrivals or demand events in a given time duration. The whole proposed model is effective and suitable for a complex combined product with multiple market sectors, hence reducing the necessity of human-based and experience-based management which is incapable for today's volatile market. Traditional legacy demand forecasting methods such as intelligent agents (IA), fuzzy neural network (FNN), and ARIMA based on time series exist inaccuracy due to data limitation, difficult modelling of seasonality, confidence interval over/under estimation which would not be acceptable for e-tail outlet strategies. Data mining based methods adopted on new product development forecasting have limitations of knowledge starving and knowledge representation. Some classic algorithms, such as SARIMA, Holt-Winters, ANNs, and SVMs, to time series forecasting face scalability problems with large input data. Besides, methods based on heuristics are usually specific to a certain type of problem and prohibit transferability to others. Thus this paper models accurately and precisely the order management with efficiency of computing through a non-handcrafted approach.

	Traditional forecasting	Machine learning forecasting
Ability to consider numerous variables and data sources	Adding extra variables and sources requires substantial effort	Multiple variables and sources can be smoothly incorporated thanks to the high level of automation
Volume of manual work	High	Low
Amount of data required	Small	Large
Maintenance complexity	Low	High
Technology requirements	Low	High
Best fit	Mid / long-term planning Established products Stable demand	Short / mid-term planning New products Volatile demand scenarios

Figure 3: Demand Forecasting Methods: Using Machine Learning

4.1 Supervised Learning Algorithms

As one of the artificial intelligence technologies, supervised learning has been widely used and studied because of its strong learning and fault tolerance ability. After K-product data get into the respective models, K-product completion time data were generated. Each of the models was then retrained several times. In all prediction models, the training set and test set ratio is 80/20 in this study. The MAE, RMSE, and R-Squared are used as the performance evaluation indicators. In the prediction model framework, the fitting performance of random forest regression models, ANN regression models, LSTM regression models, and SVR regression models are selected to compare the degree of deviation between the predicted and real values. First, the value ranges of random forest regression models and 50 hyperparameter settings are narrowed down based on Grid Search. After that, the subsequent fitting performance is tested based on the narrowed hyperparameter values. The complete networks contain multiple hidden layers in which the numbers of the neurons are set as (30, 25) and the activation functions are ReLu and softplus functions. The last layer output is 1. The fitting performance of the 20 hyperparameter settings is tested and shown in this study. The parameters values, activation functions, and optimizers of the winning ANN prediction model are listed. A short-term memory network is used to preserve the time series information. The predicted and real values are employed to calculate the mid-performance indicators which are used to compare the fitting performance of the prediction models. The settings of SVR prediction models are not illustrated in this study. Without further narrowing down of hyperparameters, the SVR prediction model is directly applied to predict completion time and compared with other regression models, as the fittings performance result show its poor performance.

In order not to deviate from the practical application of the prediction model framework study, a K-product data set is formed from a real-world job-shop scheduling problem. Batch modes have advantages in order management comparison and demand forecasting and can be converted into Job-shop shading. More data sources can be added to the models. However, these data sources must be cautious. Data pre-processing on the original job done time input data was bypassed, as all original data were normalized as predicted inputs into the prediction models. The completion time prediction and order management early study focus on the classical Hand-made HA method and the topic data source usage are tested. Observational data dimensions, arrival rate, and raw order instruction are considered as input characteristics. The completion time prediction model development focuses on classic regression algorithms and the robustness test of predicted instructions.

4.2 Unsupervised Learning Techniques

An unsupervised analysis is performed to mine potential types of users and behavior patterns in the order fulfillment database. Leveraging appropriate AI technologies can provide accurate prediction services and better user experience for the intelligent production order and fulfillment services.

The popularity of the companies' communal production services provides an opportunity for batch production of light and small parts. Digital technologies enable better order processing and shop floor management. Smart systems can further match user needs with proper manufacturing facilities to facilitate customized production with high quality and efficiency. However, many challenges still remain for the intelligent fulfillment of the product orders. Traditional rule-based approaches are unable to take full advantage of large volumes of production log data. Data-driven methods can be developed to tackle the complexity and uncertainty involved in the fulfillment process.

There is much room to improve the throughput of already fulfilled orders with better management policies. A smart system can be developed to optimize the fulfillment performance of the product orders, including manufacturing task assignment, process plan generation, schedule configuration, production control, and capacity expansion. Due to the volatility of user demands, user commercialization, technical barriers, and high costs, some of these practices may be impossible to implement in other places. Nevertheless, if the services are commoditized, these applications will become widely adopted by other places.

4.3. Time Series Analysis with Machine Learning

Time series data have been investigated for nearly 40 years in forecasting, but supply chain applications are still relative newcomers. An extensive literature on supply chain forecasting has been written but few truly integrate machine learning into either the forecasting or the decision-making processes. Every forecasting application is also a decision-making application. In forecasting and planning, there are often multiple decisions to be made, among them data perspective, accuracy emphasis, cost tolerance, forecast aggregation, and interpretation of the forecast. Organization and process aspects are equally important. For example, the forecasting process should be transparent for the business user, who must trust and understand it. Organization aspects include integration of all relevant departments, decision hierarchy, responsibilities, and data integrity, as well as protection against creative manipulation to suit individual agendas.

Evolutionary game theory, a field in mathematics that studies competition between strategic agents, models the core-choice process of data perspectives, and considers agents' intentions and the discovery of better choices. A data perspective is the aggregate of ones from all levels in the hierarchy, with the topmost level maximal. Errors and costs or rewards also accumulate towards the top. On the contrary, accuracy of a given forecast declines fast as its aggregation level increases. An open and sell perspective are shown to outperform all others in a strategic competition. Time series forecasts with these perspectives and based on machine learning are found to provide unmatched accuracy in a case study on store-item classes in a large retail chain.

Considering planning and forecasting as two fundamentally coupled but distinct processes, separate but mutually informed models can improve performance. Machine-learning support vector regression improves forecast accuracy in both processes, but with resource dependency. Three models are shown in a case study on planning areas of truck arrivals at a food retailer, which operates stores, where these models significantly improve prediction accuracy. However, the need for real-time prediction remains and deeper models, such as recurrent neural networks, which can learn the temporal structure of time series data, are needed. With the rapid increase in retailing e-commerce, new questions are raised, for example, how to forecast sales of new items with no past data available, and how to design a model ensemble framework to combine the outputs of various forecasting models.

5. Case Studies in Demand Forecasting

Forecasted demand is vital in production planning and inventory control. However, managing complex product structures with valid, reliable, and consistent forecasted demand is challenging. The emerging Internet of Things and sensor technology enables manufacturers to monitor the state and attributes of their products in real-time along the manufacturing value stream, allowing acquiring demand forecastability and self-fulfilling forecasted demand for time windows. Customizing rule-based demand forecasting based on demand forecastability can greatly enhance forecast accuracy. Reasoning about forecasted demand fulfillment capability is enabled by simulating smart manufacturing execution. Production plans are generated by analyzing the discrepancies between the state and attributes of the products with the forecasted demand data. In many organizations, the marketing/sales business unit often comes up with sales targets as a function of historic seasonality and new launches/releases of products.

Top-down targets from marketing to commercial teams usually require a further appropriate allocation onto specific sales entities, types of products and time periods. Nonetheless, this allocation needs to consider, first of all, the potential at each sales entity and product level. Such potential is often captured by earlier sales/consumption information, therefore the forecast is inferred with information from the sell-through perspective. The sales force rarely has prior estimation information concerning the time period or product model level. Demand forecasting for new products is statistically problematic because extensive historical records on them are usually lacking. Moreover, new products are sometimes in new functional categories or launched in overseas markets, making aggregation or analogy difficult.
The assigned principal understands that daily sales forecast targets can be fulfilled with allowed deviations in the short run, while routinely investigating the cause of excessive errors and/or stockouts. Uncertainty in market-driven demand is often transferred to and subsequently amplified in manufacturing planning, MRP and materials replenishment planning. Nevertheless, smart manufacturing can sense the state and attributes of products at any point in time and exquisite model-based reasoning combined with first principles can analyze the dynamics causing the deviation, in turn enabling corrective actions to cope with such potential issues. Demand forecasting targets often are time series structured by varying aggregation resolutions. First, a time series can be transformed into a predetermined stationary model and its parameters can be statistically trained, e.g. in terms of one-step-ahead forecast. Subsequently, a statistical model is estimated to reproduce actual and incomputable time series into forecasted ones on a predefined future time period, e.g. one-step-ahead forecast. The forecasting reliability and structural correctness of the model can be statistically verified and validated by applying appropriate goodness-of-fit tests, while the forecast out-of-sample errors can be assessed in several dimensions.

5.1 Case Study 1: Retail Sector

The retail sector is an enabler of modern economies and society. Supply chain management (SCM) involves controlling the material flow from suppliers to manufacturers, distribution centers (DC), retailers, consumers, and reverse Cascades. SCM affects the whole life cycle of a product and involves many activities such as demand forecasting, supply inventory and replenishment planning, production planning and scheduling, transportation routing or departure time route selection, and order allocation. Demand forecasting is a critical problem and has been extensively researched across multiple disciplines. Accurately forecasting future demand guides order fulfillment to optimize available resources and capacities. It controls inventory and prevents over/under-stocking. An accurate forecast avoids product or service shortage.

The retail sector is a profit-oriented trading sector. Retailers place orders to manufacturers to receive a certain product type and volume of items to satisfy future demand in retail stores or e-commerce. Unless the product is made to order, it usually takes time for a manufacturer to fulfill the order. The order fulfillment time can be critical for retailers. Except for the trade price, the critical attribute of an order is the completion date the retailer expects to receive the ordered items. The order completion date is computed based on a forecast of the future retail demand. When the solid order completion date estimates are not provided to retailers, excess orders will be placed, and order prices will be increased. Thus, the time aspect of order management is even more critical for better supply chain performance in the retail sector.

Although deep learning networks have been successfully used to predict manufacturing job-shop order completion date or order delivery time, few works in the literature were targeted explicitly at forecasting the date by which the order fulfillment is guaranteed. This paper focuses on order completion date prediction (OCDP). Order management is essential to the order fulfillment process. Order completion date prediction is the crucial part of order management and control.

5.2 Case Study 2: Manufacturing Sector

Hitherto, the massive amounts of data collected in the smart manufacturing systems' operational environment remain underused, mainly due to the difficulties in modeling domain-specific experts' prior knowledge of the systems, which controls the manufacturing systems' operations over time. Recently, Opportunity-Exploration (OE) systems have emerged as the new paradigm leveraging the power of statistical learning methods.

They analyze collected data in a real-time manner to uncover and exploit latent states of the systems to improve performance. Nevertheless, the extensive use of operability, productivity, flexibility, and safety of the manufacturing systems in time-sensitive applications largely remains unexplored. This work bridges this research gap by presenting a new OE approach for the safe and productive orchestrating of complex smart manufacturing systems in real-time using state-space parameterized Markov decision process models (w-MDP), where w is a set of time-varying weights parameterizing the system's optimal state transition costs.

Smart Manufacturing (SM) refers to a maintenance paradigm auguring a new era of cost-effective and efficient operations of manufacturing systems (MS). Over the last decades, complex adaptive MS have been holistically transformed into smart manufacturing systems (SMS) with massively rich Engineering Cyber Physical Systems (ECPS) that seamlessly integrate on-floor cyber-actors and cyber-infrastructure, generating huge amounts of diverse data describing the systems' states and functioning in their operating environment in real time. Collectively, these unprecedented Data-Driven opportunities (DDOs) pave the way for new paradigms and harvesting methods to uncover the systems' unobserved states, latent knowledge, and unveiling better rules in real-time.

The specific context necessitates an exploration of opportunities in automatically alerting about evolving system state transitions that may trigger switching the proposed models, for instance between safe, reliable, flexible, and productive regimes. Intelligent rejected job completion date (JCD) predictions are targeted by mining job attribute features from multiple data sources on modern industrial job-shop systems. It is challenging to predict JCD for rejected jobs since both of their JCD and attributes are unavailable when they are raised. To address this challenge, a new method, monitoring-replay-network (MRN), is proposed to predict the JCD of rejected jobs based on modeling the auto-encoding of loss data via a homeostatic mechanism. The MRN consists of a monitoring network to gather sequential execution features of jobs and a replay network to recover the attributes of finished jobs via forecasting the execution features of loss jobs.

Equ 2: Forecasting Accuracy: Mean Absolute Percentage Error (MAPE).

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left| \frac{D_t - \hat{D}_t}{D_t} \right|$$

- D_t = actual demand
- $\hat{D}_t$ = forecasted demand

→ Common metric to evaluate ML model accuracy in forecasting.

6. Order Fulfillment in Smart Manufacturing

To facilitate intelligent order fulfillment, manufacturing jobs that need to be planned based on orders are assigned. Production scheduling with cost control and guaranteed delivery would then be generated based on the input jobs. Delivery dates would also be predicted based on similar jobs that have already been produced. The focused usage of big data in any smart manufacturing OSS software also provides a basis for intelligent order fulfillment. Machine Learning (ML) based on historical data has been implemented instead of hand-crafted rules, which are expensive to tune and maintain. Intelligent routine compliance checking (RCC) and action recommendation tasks on concurrent workflows are explored.

Powered by historical data of workflows and their actions, a new ML model is proposed, RL-Graph, aiming to 1) robustly encode both workflows and sent-action via graph networks; and 2) extract the concurrent action representation via attention mechanism. Routine compliance checking is formulated as an outlier detection task and tackled via the fast-flow method. Action recommendation on concurrent workflows is addressed via efficient and robust candidate action evaluation, employing the semantic-aware graph network framework. It innovatively exploits the high efficiency and robust performance of ensemble learning, enabling time-sensitive compliance checking with even a large number of actions. Real-world event logs from actual deployed workflows in a major company are utilized to evaluate the suitability and effectiveness of the proposed architecture.

6.1. Understanding Order Fulfillment Processes

The manufacturing industry is one of the industries with the most vigorous development in vintage and history. It takes in the methods and means of industrial technology to manufacture products with accordance with demand and plans. It owns factories and uses machines, lorries, etc., to carry out mass productions. Various manufacturing processes and procedures are widely and deeply involved, and comprehensive data are produced, as a result, studies of either basic theories or advanced applications based on data mining and machine learning in this area are rare. However, smart equipment with internet facilities were attained, and open-source technologies of the Internet and data mining were also developed quickly as the dramatic growth of the Internet economy.

It is anticipated that new and broader applications can be envisioned. With the quick and deep penetration of internet and mobile commerce technologies, information is almost instantaneously provided and shared. Online shopping and purchasing, hand-held mobile trading systems, etc. are becoming part of life with the fast development and improvement of smart personal gadgets, mobile hardware facilities and datacasting tools. Meanwhile, the rapid development of high-speed communication technologies puts forward extremely strict requirements for the electronics manufacture. As a result, the manufacture of electronics components and materials must be very quick and highly capable to meet the increasingly multi-level and multi-brand manufacture processes of personal gadgets, electric gadgets, photosystem, etc. to satisfy the quickly rising consumer needs.

Special and generic procedures and processes are generally involved in the manufacture of electronics components and materials. Such complicated manufacturing processes are heterogeneous among orders, extremely easy to be interchanged with each other during processing, and thus difficult to manage completely. An electronic components and materials manufacturing factory contains various types of machines and fulfill the orders normally by batch processing mode. These processes take days, weeks, or more, thus making it very difficult to schedule on-time. With more and more product models and brands to be manufactured, the interchanged processes in heterogeneous production will be even more complicated. From a technique perspective, nearly all current predictive analysis studies only focus on either upstream data or downstream scheduling or optimization. Little attempts combined data mining and scheduling or controlling within the same framework. This paper intends to provide a brief introduction and overview on the order management system of a smart electronics components and materials manufacturing factory and presents the architecture and basic techniques for handling the order management, order fulfillment, and scheduling problems.

6.2. Challenges in Order Fulfillment

Observing exceptions is an essential part of intelligent order fulfillment. These are orders or order items that cannot be satisfied when they are due for fulfillment. Orders can be late, i.e., delivered too late when excluded from the hold and re-plan. Some orders are unfulfillable because lots are too late or unassignable as there are no suitable lots. Orders that cannot be assigned for other reasons, i.e., orders that have been re-planned or held. Observing and classifying lots or orders is an important task before orders are scheduled and assigned.
To observe failures or exceptions, data preprocessing is performed. A long and sticky cascade of vins (variation, incident, and ick) means that an order is becoming or trying to be late. This increasing x is a good candidate failure observation. A long x that is negative means that the order is likely becoming or trying to be unfulfillable. Attributes such as WoStart, WoHold, and WoTime can be encoded as a flag in observations, i.e., zeroing either WoIsDue or WoRSt. Classifications of these observations according to categories of failures to be observed. Focus on the preparation of data for further decision procedure.

Custom props for observation view, which are boilerplate attributes defined in all our observations but overridden with our desired values in each observation. Data preparation for unsupervised modeling, which complements data preprocessing with adding new attributes to the table of Wo. New attributes are added to characterize the state of a lot for each scheduled order or observation granularity. It's a collection of new attributes grouped by their names, which starts with prop, and can be summaries on the observed at the end of the cascade if needed.

Each of these prop attributes is added into Wo's designated table as an observation property and observed on attributes of lots. New observation view specs (observations/views for scheduled orders), each of them is a pipe of views selected and copied from the original table but merged with corresponding props for description and observation view specs.

7. Machine Learning Applications in Order Fulfillment

Prediction of product completion dates in manufacturing shops is one of the critical times and social issues. In job shops, a set of orders containing various products will be given to the manufacturing shop for processing, while for customers, the completion date (due date) of products is the main factor affecting satisfaction. Therefore, it is essential to predict the completion date of every order before order processing. However, this has a high degree of complexity due to a great number of exogenous factors, uncertainty in processes, and dynamics in manufacturing jobs. Nowadays, deep learning-based methods have been widely adopted to predict the completion date because of their ability to extract high-level representative features of the time series data. With the development of deep learning, many improved prediction models have been proposed. To better extract the variables generated by the processing condition and influential factors of process prediction, some customized deep learning models, such as LSTM and ensemble learning, were employed to predict the processing completion time. The order management and completion date prediction of a manufacturing job shop faced in this paper are newly updated based on machine-learning demand forecasting. Order management refers to controlling and processing orders to satisfy customer demand within the promised completion date (due date) and to maximize profit. The order completion date is the time that every ordered product is completely manufactured after all processes or operations. Order management and completion date prediction are two interconnected problems. The former provides a dynamic schedule for every order to be processed by balancing the flow rate and work in process to meet various delivery dates, while the latter predicts the completion dates of given orders based on the current order and resource status.

7.1 Predictive Analytics for Order Management

With the continuous development of the market economy and the advancement of science and technology, consumers expect ordered products to be delivered within a shorter cycle. The increasingly market-centric order production method puts forward extremely strict requirements on the corporate capacity of production and timely completion. To cope with the volatility of customer order demand, enterprises need to effectively control the ordered tasks in the manufacturing job-shop and to formulate a reasonable production plan based on customer demand for the completion period and their current manufacturing capacity. In the manufacturing industry, order management runs through the entire production cycle. The accurate prediction of the product completion period is the main factor affecting the decision of order management and control. The completion time of ordered products can be predicted well by combining data mining with the analysis of the discrete data in the manufacturing industry. However, the existing studies have not fully considered the complex processing procedures, the features of manufacturing attributes, and the repetitive orders of stable consumers. To solve these problems, this paper explores the order management and completion date prediction of manufacturing job-shops based on deep learning.

Forecasting is the crux of retail supply chain management (SCM) and the key to better supply chain performance. Several retailers are using AI/ML models to gather datasets and provide forecast guidance in applications such as Cognitive Demand Forecasting and Demand Integrated Product Flow. The biggest challenge lies in matching supply with demand. Reinforcement Learning (RL) is being increasingly adopted in SCM to improve forecast accuracy and solve supply chain optimization challenges. Companies like UPS and Amazon have developed RL algorithms to define winning AI strategies. This white paper explores the application of RL in supply chain forecasting and describes how to build suitable RL models.

7.2 Optimization Algorithms for Inventory Management

Agile supply chains with think-act-sense technology offer value, speed, and resiliency. Forecasting future component demands enables an enterprise to establish a proper strategy for buying raw materials and fulfill orders in an appropriate quantity and date. Recent advances in machine learning contribute to precise estimation of future demand based on previous time series data. This work presents a smart manufacturing and operative support system (OSS) composed of three sub-systems: a cloud supply-chain OSS forecasting component, a multi-agent order fulfillment OSS planner, and an AR-powered smart factory OSS. The research illustrates the system's structure and algorithms by displaying a practical smart factory case.

Despite the widespread use of machine learning in supply chains, few works investigate its use in demand forecasting at the supply chain level and order fulfillment strategies. There is great value in estimating demand at the supply chain level, as procurement plans based on this demand can be broadly implemented. Furthermore, order fulfillment is essential as incorrectly fulfilling an order can affect subsequent orders from a company. Meanwhile, failures in order fulfillment can impact revenue during upturns in demand. In the smart manufacturing and operative support system (OSS), there are two major services offered to an enterprise: supply chain OSS and smart factory OSS. This work advances input understanding of OSS. Although a few works investigate the application of machine learning for demand or order fulfillment alone, there are no works on the simultaneous discussion of both applications at the supply chain and manufacturing levels. This problem is challenging due to the complexity of the problems of estimating demand forecasting and order fulfillment agents.

Machine-learning estimation models are studied based on time series applications. The forecasted demand for the supply chain is fed to the order fulfillment agents. The agents determine the selling prices of products and optimize orders sent to manufacturers. The allocation of orders distributes the optimal quantity of products to each factory. To reduce optimization time, a two-stage optimization approach is presented, where a large optimization problem is decomposed into small problems. A hybrid of meta-heuristic and approximation algorithms is also introduced for the upper-level optimization problem.

8. Integration of Demand Forecasting and Order Fulfillment

In recent years, smart manufacturing OSS has been an emerging area of scholarly interest attracted by vast industry opportunities and challenges. However, few studies have been conducted on time-sensitive OSS with transaction volume forecasting and order fulfillment, which are core concerns of STM service providers. In response, a model is developed to forecast the transaction volume of smart manufacturing OSS, with good performance under production breakdown scenarios. Furthermore, based on models and multi-granularity historical demand data, a bi-objective order fulfillment model for STM OSS with a batch of candidate orders is established and solved by a hybrid algorithm. Results show the effectiveness of bi-objective optimization on the reduction of missed quota requests, doctrines, and jobs under realistic scenarios.

Although research on OSS for smart manufacturing and on-demand service systems has been emerging, comprehensive studies are still limited. Inspired by OSS from platforms such as online car-hailing and hotel booking, efforts are made to forecast transaction volume based on influence factors, model spatiotemporal data, and fulfill qualified orders and admit requester matching. OSS involving service providers and requests, which arise in many industries, were classified into on-demand service systems. Investigation of an OSS model and design algorithms to study competitive/contrasted OSS environments is proposed, focusing on time-sensitive on-demand smart manufacturing OSS dissemination service systems characterized by temporal service requests and geographic service providers and quantifying service delivery time modeling.

Future research of order acceptance considering workload, setup, and completion time of jobs should be studied in advancing technology platforms, with resonant training of data visualization models of photos, words, and sounds handled by modules to design and dispatch chatbots for effective interaction through multiple modalities. Moreover, OSS matching and optimizing may be extended in mobility-smart manufacturing scenarios, such as industrial collaborative robots or portable tooling machines for edge processing to serve real-time needs.

8.1 Synergies Between Forecasting and Fulfillment

The recent developments of machine learning (ML) methods for order fulfilment in the context of smart manufacturing opens doors to new areas for future research and development in the subject area. Most importantly, it is necessary to analyse how accurate forecasts can aid in task assignments and production scheduling where performance metrics such as on-time delivery (OTD) or due date adherence (DDA) are optimised. To date, the majority of studies in the area of machine learning for order fulfilment in smart manufacturing have only considered current information, disregarding future forecasts. There also exists a body of research in the area of forecasting, but interaction between forecasting and order fulfilment has not yet been studied in the context of smart manufacturing.

By using a simulation study, forecasting of future workloads is shown to be useful for better assignment of tasks to production resources. First numerical experiments demonstrate that forecasting is indeed helpful in combination with more sophisticated rescheduling approaches. These results can pave the way for future research into new dynamic task assignment and production scheduling methods that also take future forecasts into consideration. Additionally, many ML methods rely on black-box representations, which imposes limitations for users that intend to better understand performance behaviour or obtain actionable insights.

It is necessary to explore the viability of hybrid approaches, fusing black box ML methods with white box-based meta heuristic algorithms to obtain explainable models that still perform well. To combine the strengths, it is favourable to use

ML methods to inform and guide population-based algorithms' behaviour during the search process. Another emerging line of research is to employ and applied deep reinforcement learning (DRL)-based policies for the manufacturing processes. DRL models are able to learn and self-improve continuously through interactions with the environment and obtain actionable insights on process improvement.

8.2 Impact on Supply Chain Efficiency

With the continuous development of the market economy and the advancement of science and technology, the demand for production by consumers is growing exponentially. The market competition is becoming increasingly fierce, and consumers expect ordered products to be delivered within a shorter cycle. The increasingly market-centric order production method puts forward extremely strict requirements on the corporate capacity of production and timely completion. To cope with the volatility of customer order demand, enterprises need to effectively control the ordered tasks in the manufacturing job-shop and to formulate a reasonable production plan based on customer demand for the completion period and their current manufacturing capacity. In today's rapidly changing, homogeneous, uncertain and customer-oriented market competition, order management, like the lifeblood of manufacturing enterprises, runs through the entire production cycle. Thereby affecting the overall performance. The accurate prediction of the completion period of the ordered product is the main factor affecting the decision of order management and control. This task aims to predict the completion time of the product based on internal discrete production data involving multiple machines, processes, and semi finished products in the manufacturing industry. The completion time of the ordered product can be predicted well with the development of data mining by in-depth extracting the historical order information and production operation status occurring in the job-shop. However, due to the scattered distribution, large volume, and poor authenticity of data, it is challenging for the manufacturing industry to conduct a good prediction. The manual selection and extraction is difficult for the data preprocessing stage with a long cycle. Moreover, the local approach ignores the complex correlations among the orders and is not scalable on large instances. By proposing a processes-based prediction model, the high dimensional original feature space is automatically constructed. The selection, filtering, and visualization of relevant features are achieved by aggregating similar features to reduce the redundant extraction features in the feature selection stage. With the auxiliary information of completion date, a novel hybrid deep learning architecture integrated with the variational autoencoder is introduced to improve the prediction accuracy. With the development of the digital economy, enterprises are collecting more and more data. Data-driven AI techniques are attractive methods to mine data and improve the accuracy of order management. However, big data usually leads to the curse of dimensionality wherein the predictive performance is severely deteriorated.

Equ 3: Order Fulfillment Efficiency Score (OFE).

$$OFE = \frac{O_{on\_time}}{O_{total}} \cdot A_{alloc}$$

- O_{on_time} = orders delivered on time
- O_{total} = total orders
- A_{alloc} = accuracy of inventory allocation (0–1 scale)
  → Reflects the effectiveness of ML-driven order fulfillment.

9. Technological Frameworks Supporting Machine Learning

Some modern technological frameworks support the implementation of the discussed machine learning applications for demand forecasting and order fulfillment. Forecasting is the crux of retail supply chain management (SCM) and the key to better supply chain performance. All retailers are looking at implementing AI/ML models for Cognitive Demand Forecasting, Product End-of-Life Forecasting, and Demand Integrated Product Flow. Demand Forecasting is a categorical problem with a lesser number of classes, while Product End-of-Life Forecasting is a time-series problem to differentiate between end-of-life and active products. Cognitive Demand Forecasting calls for predicting a greater number of potential future demand units based on historical demand data and overall demand seasonality. Addressing these challenges also aligns with the overall goals of improving forecast accuracy, minimizing stock-outs based on past forecasting inaccuracies, and optimizing inventory holding costs.

At the same time, RL is an area of AI that is in vogue and is being increasingly adopted in SCM. Several companies have already developed multiple RL algorithms in-house for better data due diligence, to define winning AI strategies for higher revenue, optimizing warehouse space utilization, and reducing outbound freight rates for its trucking business. Furthermore, frameworks in the form of problem solvers, such as the integration of RL models for demand forecasting in the cloud-based retail supply chain, are evolving as a priority strategy for retailers. In addition, to create a footprint of the scaling complexity of the RL algorithms, frameworks like the OpenAI Gym toolkit are becoming the preferred choice for building RL algorithms for supply chain use cases. This excessive growth of OpenAI Gym in the supply chain ecosystem is overwhelmingly obvious as it is delivered as easily accessible code that requires minimal effort and time to set up.

Another technological framework supporting the implementation of the discussed machine learning applications is Keras. In manufacturing, conceiving ideas for a product and developing an optimal design is crucial. Some local optimum that helps reach Pareto-optimal designs. It can accurately predict the completion time of an ordered product or job in a job-shop environment, and adjust production plans according to that prediction, so that requirements for customers can be satisfied.

9.1 Software Solutions for Smart Manufacturing

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With the continuous development of the market economy and the advancement of science and technology, consumers expect ordered products to be delivered within a shorter cycle. The increasingly market-centric order production method puts forward extremely strict requirements on production capacity and timely completion. To cope with the volatility of customer order demand, enterprises need to effectively control the ordered tasks in the manufacturing job-shop and to formulate a reasonable production plan based on customer demand and their current manufacturing capacity. In the manufacturing industry, order management runs through the entire production cycle. The accurate prediction of the product completion period is the main factor affecting order management and control. Existing research mainly focuses on the prediction of the completion time of the whole product. The completion time of these two ordered products is expected to be in the third and fourth weeks, respectively. For the above-mentioned orders that need to compete for completion, although the completion time of the two jobs has been reasonably predicted, it is not enough. Customers need to know which job can be completed earlier. This paper aims to predict the completion time of multiple products without inputting a specific scheduling scheme.

Figure 4: Software Solutions for Smart Manufacturing

As an important part of the smart factory, manufacturing OSS has been put into large-scale application. However, with the continuous increase of service platform nodes and manufacturing tasks, industrial OSS faces a thorny problem of service matching. It is hard to match service demands and service providers efficiently. Traditional service matching methods, however, may cause some problems. For example, service expression formalization in knowledge-layer is difficult and heterogeneous service description forms are hard to understand. Existing rule/formula-based matchers are not exact and time-consuming. In order to improve the matching performance and ensure the real-time implementation demand, the hybrid-DNN-based matching model and its service-layer representation model are proposed by a two-layer matching mechanism. The experiments on benchmark datasets demonstrate the effectiveness of hybrid-DNN methods. In addition, the thread for further study is put forward.

9.2 Data Infrastructure and Cloud Computing

In order to achieve the goal of global intelligent manufacturing, it is necessary to integrate Internet of Things (IoT), big data technology, and other technologies to establish a data-driven intelligent production mode, and execute the formulation and optimization of the production plan, procurement plan, and supply chain management and optimization by the full use of data mining and machine learning (ML) techniques.

During the modeling and design of the planned mechanism, the substantial data quantity of smart manufacturing enterprise directly decides consistency and efficiency of production process and model; thus, the consideration of this data must be fully involved in and a data ecosystem, where information and knowhow are freely shared and effectively used, be constructed. The workflow of smart manufacturing OSS including the product design, production logistics and process optimization is presented as a comprehensive overview based on various control and planning models such as ontology-based planning information model, multi-layer production planning model, discrete event control model, etc. This work is expected to highlight the prediction, process traceability, and reengineering of the complex process regarding how to fulfill customer orders production planning in a cloud-based smart manufacturing environment. With the rapid development of the industry and the increasingly fierce competition among enterprises, how to win the market and obtain greater profits has become a huge challenge for manufacturing enterprises. According to the strategic development plan “Made in China 2025”, the competition among manufacturing enterprises has tended to be the competition of the manufacturing production service system. The production service system is a set of planning, control and logistics flow which manage resources including machines, materials and manpower to ensure the execution of manufacturing orders under the constraints of complex environments; meanwhile, the production service system involves a sequence of decision-making problems including planning, scheduling, dispatching and the execution. The increasing order volume and diversity will make the production planning problem researched numerously by researchers. These traditional models are too difficult to be generalized given the dynamism, uncertainty and large scale of the smart manufacturing system.

10. Future Trends in Machine Learning for Manufacturing

The applications of machine learning in demand forecasting and order fulfillment will achieve maximum usage of artificial intelligence and deep learning technologies together with enabling energies. The smart manufacturing excellence in order fulfillment for manufacturing job shops will be developed. The industrial environments could discover their ability of adjusting adaptive characteristics of machine learning algorithms, especially deep learning.

After good algorithms, settings, structures, and parameters for demand forecasting tasks are adopted and fine-tuned, there would be very limited spaces for further improvements using refined data sets. The attention risk notice and consideration for anomalous observations and features in the social recommendation task will be discussed and studied because those abnormal conditions were patiently persistent but invisible in the whole feed-forward recommendation mechanism. With instruments and sensors getting smarter and smarter, vast amounts of manufacturing data would be continuously collected, stored, and made available. Several ongoing projects that focus on enabling open, extensible, and affordable cyber-physical solutions to broaden widespread adoptions, and ensuring seamless multi-level integration between existing machines to the cloud will be presented. Advanced smart manufacturing business use cases with good AI implementations towards a more sustainable future will also be presented.

However, compared to the wide applications in other fields, the utilization of machine learning in intelligent manufacturing systems has been relatively slow. Several technical hurdles and challenges, such as lack of understanding of the data and system dynamic, data conceptualization, process modeling, uniqueness of the data, security, and high configuration of ML devices, hinder the application of ML techniques in this domain.

The need for better understanding of the progress of the ML technology in the intelligent manufacturing field is brought forth. Commonly used ML techniques and innovations developed and proposed for smart manufacturing applications in process monitoring, diagnostic, and control are presented. The performance of ML techniques are compared with classical methods and among architectures. Finally, the possible future trends and research focus in this domain are discussed.

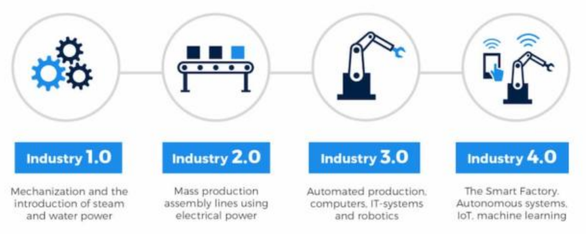

Figure 5: Future Trends in Machine Learning for Manufacturing

10.1 Emerging Technologies and Innovations

The emergence of AI technologies, with applications ranging from robotics and connected devices to cloud/multi-cloud/edge computing, has played a critical role in the development of the 4th Industrial Revolution, or Industry 4.0. These technologies transform manufacturing operations into smart manufacturing. They are also leading to disruptive innovations in value networks across industries for smart manufacturing. Machine learning, a subfield under AI, is the body of knowledge that deals with algorithms that learn from historical data and make predictions about the future. These prediction results can then be used to improve upon processes such as Demand Forecasting and Order Fulfillment for Smart Manufacturing OSS.

Demand Forecasting for OSS in Smart Manufacturing. With ever-changing customer order patterns and preferences, accurately forecasting the demand in the OSS must be handled with care. This would require the infrastructure, systems and processes to enable real time data collection of relevant context features around OSS, as well as accurate and timely prediction of demand. Machine Learning models and techniques can greatly help in this process using data from existing OSS running in factories.

One example of machine learning techniques used is the Long Short-Term Memory (LSTM). They are a Recurrent Neural Network (RNN) architecture that could discover the interaction between current demand and past demand, which is essential for order demand forecasting. They can learn what to remember or forget on their own, and train the dependency across time steps. The LSTM model design developed in this proposal uses features more relevant to the OSS process of the job and order information, environment, factory configuration, product specifications, etc.

Following feature engineering, hyper-parameter tuning is performed based on the EarlyStopping and ReduceLRonPlateau techniques to tune epochs to train on and the optimizers. Then, a final evaluation of the performance of the optimal ML model using previously unseen test datasets is performed. Evaluations include the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) metrics, and comparison to the best AutoRegressive Integrated Moving Average model. With a robust Demand Forecasting engine developed and tested, engineering teams can make faster data-driven decisions with minimum business disruptions by generating early warning alerts about unusual demand or rare scenarios not captured in simulation tools.

10.2 The Role of AI in Future Manufacturing

With the rapid development of intelligent technology, artificial intelligence (AI) is widely applied in all walks of life, especially in intelligent manufacturing. The competitiveness of manufacturing mainly depends on technological advancement. In five areas, AI has strong application prospects in future manufacturing. First, AI is widely used in the modeling of manufacturing systems. The models obtained through AI represent the mapping relationship that intelligence learns from the data of complex manufacturing systems.

New intelligent modeling methods, such as deep learning and reservoir computing, help to establish superior models of the manufacturing systems. In addition to deep networks, the use of novel learning structures such as neural Turing machines should be encouraged in modeling. Second, AI is used for interpreting complex manufacturing models. AI analyzes the knowledge and working principles of manufacturing systems from the models constructed by existing data-driven methods as a black box. As a knowledge extraction tool, AI analyzes the results of black-box or gray-box models and interprets the knowledge of manufacturing systems, so that manufacturers can better understand systems.

Third, integrating numerous knowledge from multi-domain and multi-level systems is becoming a new tendency of manufacturing design. Surrogates with interpretability can be used to interpret the construction results and underlying knowledge of numerical surrogates of manufacturing systems. Moreover, knowledge graphs are powerful tools to represent the relative relationship of knowledge in different domains. By organizing important knowledge with different types, AI helps identify the potential knowledge in the graph and mediates the transfer of knowledge across domains and levels. Fourth, the prediction of manufacturing system performance with uncertainty is increasingly important for decision-making.

AI simulates the discrepancies between computed performance with uncertain input statistics and ground truth. The software used in the industry is gradually developing into commercial codes with the embedded ability of deep learning. The uncertainty quantification methods with deep learning can provide prediction algorithms to identify the unpredicted performances. Fifth, AI plays a key role in the self-evolution of modeling and interpreting technology. The theory can be enriched with explaining historical models and knowledge. The evolutionary modeling and interpretation systems automatically construct models or explain existing models with knowledge transfer and data sharing.

11. Conclusion

This report presents insights about key machine learning applications in demand forecasting and order handling optimization called order fulfillment in the context of a smart manufacturing platform.

The chaotic reality of demand is always a major challenge for organizations in delivery and service-oriented industries. For optimal satisfaction of demand on time and cost, demand-intensive industries such as smart manufacturing cannot just utilize highly developed capacities. Considerable, intelligent, and better combined use of capacities is paramount. Machine learning-based solutions that forecast demand and optimize order handling based on the forecasted demand conquer this challenge. In this study about machine learning applications in demand forecasting and order handling, it is clearly demonstrated that smart manufacturing shall adopt a concept to develop and service applications in the cloud.

In addition, cloud manufacturing software or other software is an inherently very good basis for and topic in intelligent and evolving service-oriented manufacturing. On-demand capacities and services modelled independently through technology can be easily integrated for creating solutions and combined with each other in/on derivatives of the smart manufacturing. Common to demand-oriented is that the key production and service parameters: demand, delivery, and price that complicate capacity assignment give rise to unique challenges for manufacturing and service efficiency. A breakthrough is foreseen in widespread cloud-based demand forecast, integration or order handling software whose conceptual utility idea is supported theoretically or empirically.

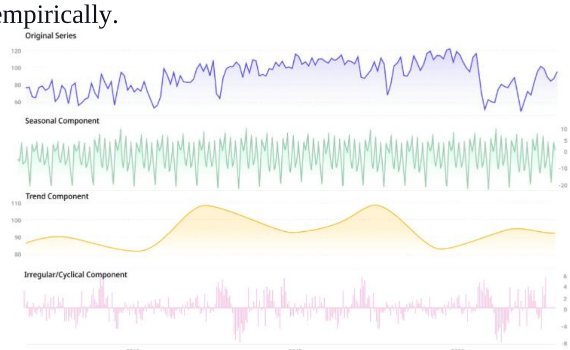

Figure 6: Machine learning applications in demand forecasting for smart manufacturing oss

With cloud-based applications for demand forecasting and order handling optimization on a smart manufacturing platform, new research questions arise. Research is needed into offering the hybrid combining of both forecasted and realised batches and developing intelligent applications that learn the usage and enhance robustness and validity of all delivery processes. The latter is of equal interest because a breakthrough would enable companies to optimise all mass-capacity intensive delivery processes ultimately including the entire service and/or production re-assembling and mass-ready process, and with it be sustainable competitive. Such software applied on a smart manufacturing platform would lead to an intelligence that would be established as the most competitive and valuable economic space envisioned originally as the cloud.

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