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Manufacturing Process Optimization in the Process Industry

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ABSTRACT

This paper introduces a technology, a data-driven optimization model of manufacturing service in intelligent manufacturing process using deep learning algorithm and resource agent (DDR), and a data-driven resource agent that represents available manufacturing resources. Asset agent is an intelligent module of entity production unit, which has powerful functions of data processing and service management. This paper includes the method of designing expert-based processes, the current process realization model, and the key performance indicators (KPI) used to evaluate the optimization work. The model aims to maximize efficiency, reduce the cost of manufacturing resources, improve the production and maintenance efficiency of network resources, and improve the manufacturing service level. Finally, the efficiency and technical feasibility of the model are evaluated through a typical example of industrial product production process.

KEYWORDS

Data-Driven Resource Agent, Deep Learning, Key Performance Indicators, Process Optimization

INTRODUCTION

In the industrial sector, creating profitable and marketable products is crucial (Clancy et al., 2023). To significantly improve production efficiency, machine learning plays an important role in the production process by connecting multiple enterprises and using inexpensive sensors to build models (Yan et al., 2023). However, there are still challenges in reducing costs and improving the quality of manufacturing services. To address these challenges, this study proposes a technical solution—namely, a data-driven process manufacturing service optimization model. This model uses deep learning algorithms and resource proxies to intelligently represent available manufacturing resources and use these resources efficiently to minimize costs. Resource proxy is an intelligent module with powerful data processing and service management capabilities. We designed our model to improve the quality of manufacturing services and reduce manufacturing costs by fully using the output of resources, raw materials, and support networks. We also evaluated the proposed optimization model to measure its performance. By comparing experimental results from multiple perspectives, we have demonstrated the advantages of our approach. The results of this study will provide valuable references for improving production efficiency and reducing costs in the field of industrial manufacturing.

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In this article we cover methods for building expert-based processes, existing models for implementing strategies, and key performance indicators (KPIs) for gauging optimization initiatives. We used a standard industrial manufacturer's production scenario to evaluate the suggested model's performance, economic viability, and feasibility.

LITERATURE REVIEW

In this section we provide an overview of an assessment of current data analytics project modeling techniques and address the methods used by experts to model processes. KPIs were considered a basis for assessing the efficacy of process enhancement strategies. Baardman et al. (2023) proposed design of dynamic experiments, an innovative data-driven experimental design methodology for optimizing industrial crystallization processes (OICP). In this case, the technique was applied to the batch crystallization process to establish the optimum lowering improvement, which when integrated, yielded the optimal temperature profile. For the batch crystallization of potassium nitrate in water, we compared literature on the optimum temperature profile produced using a model-based optimization strategy with the data-driven optimum temperature profile to evaluate the efficacy of the OICP optimization method. This comparison revealed some degree of overlap between the distributions when only the parametric volatility was analyzed (Sun et al., 2023). There was significant overlap when the variation in the design variables and the seed capital distribution parameters were evaluated (Mandl & Minner, 2023).

Bernabei et al. (2023) introduced location-specific allocation problems over time intervals during a disease outbreak, factoring in state data collected at regular intervals from different locations and expanding understanding of transport protocol. The problem was formulated as a dynamic optimization model applied to a system of standard equations describing the transmission patterns of infection in various geographic regions (Liu et al., 2023). The data-driven optimization approach determined the optimal distribution of intervention funds across an indefinite number of communities and periods. The results showed that our data-driven optimization technique helps resolve inter-decision problems with unknown system dynamics.

Finally, we reviewed research on centralized and decentralized resource allocation problems, wherein each patch can impose its interference options with or without awareness of other locations. Jieyang et al. (2023) introduced a comprehensive data-driven paradigm for enhancing the efficiency of combustors. In the first step, create a model of fuel economy and nitrous oxide (NOx) output using a deep belief network (DBN). Then, integrate the predictions based on a DBN, the operational constraints, and the control variable constraints into an inter-optimization model. Two goals were considered during optimization: increasing combustion effectiveness and decreasing NOx emission (Bag et al., 2023). The optimization model was nonlinear and complex; hence, standard exact solution techniques could not be used to solve it. The created optimization model's optimum solutions were obtained using the Jaya algorithm (JAYA), a recently introduced swarm intelligence technology. The results showed that modifying the control parameters of the combustion system could improve combustion efficiency and NOx emission. Zdolsek Draksler et al. (2023) introduced mechanization to digitization using information and communications technology (ICT). In contrast, Industry 4.0 describes production techniques that use modern machinery, materials, and worker movement. It changes the manufacturing process to create an efficient system that lowers prices and enhances customer satisfaction.

Because Industry 4.0 is still a relatively new topic, there is much ambiguity, little information, and few published materials about evaluating and controlling quality and efficiency in this setting (Sarna et al., 2023). Thus, manufacturers are still learning about Industry 4.0. Performance and quality are reviewed and monitored using industry standards. Our research examines the industrial standards used by the manufacturing industry for balanced scorecards and quality control management (Sarna et al., 2023). Digitization explores the existing techniques, industrial standards, KPIs, and case studies used to assess performance evaluation systems in information Industry 4.0.

We also address research constraints and openings in data-driven Industry 4.0 and quality Industry 4.0. Nadim et al. (2023) proposed a complete model for predicting multistep machine speed by presenting current deep-learning experiments in intelligent manufacturing. The model's construction uses a long short-term memory (LSTM) encoder-decoder design. Predicting when machines will reach their maximum pace allows automated systems to flexibly adapt manufacturing processes to changes in the system conditions, increasing productivity while decreasing energy use. Comparisons with province forecasting analytics were made using detailed experimental evaluations of actual data from a metal packaging mill, improving the suggested method's efficacy (Aljarrah et al., 2023). Peng et al. (2023) introduced laser additive manufacturing optimization to enhance their external qualities.

In recent years, engineers have used metal alloys, chromium, copper pyrites, and zinc-based alloys. Zhang et al. (2023) investigated the influence of experimental parameters (scan speed and laser power) on morphology and roughness characteristics, and the results revealed consistent adhesion of coatings to the substrate. The best operating parameters for both metals with genetic flaw structures at a preheating temperature of 400 °C were 1,200–1,600 W at 8–12 mm/s with face-centered cubic (FCC) layers and body-centered cubic (BCC) phases (Erkip, 2023). The settings of the laser altered the strength and durability of the metals. The results indicated that the performance of metals with potential coatings and steel fabrication might be improved by tweaking the laser parameters acquired by heating temperatures (Mu et al., 2023).

RELATED MATERIALS AND METHODS

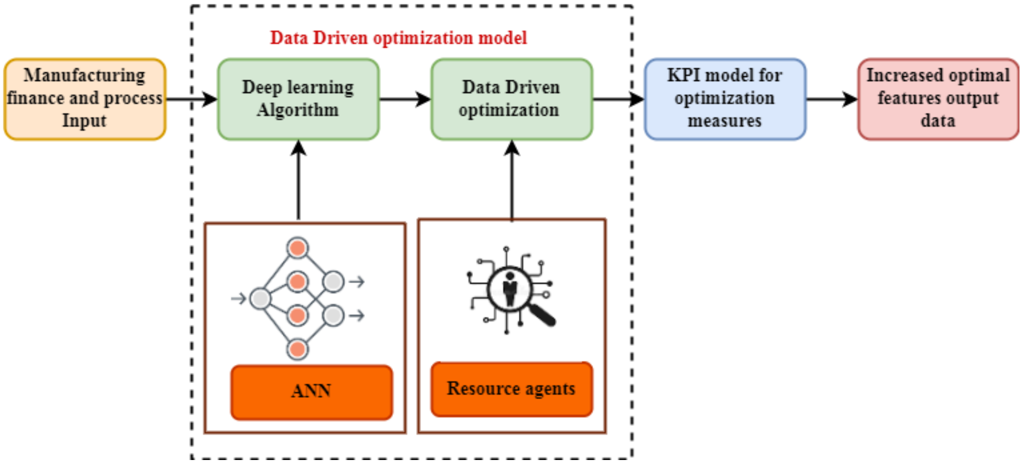
A Data-Driven Optimization Model for the Manufacturing Process

Emerging techniques, such as artificial intelligence (AI), the internet of things (IoT), cloud technology, machine learning, and big data, are driving the fast development of contemporary technological innovation (Sun & Liu, 2023). The fields of science and business are being revolutionized at lightning speed by scientific computing in particular (Hu et al., 2023). Given the prevalence of inter-limited optimization issues in design and production, deep learning is well positioned to benefit the process manufacturing sector (Zhu et al., 2023). For high-dimensional, non-convex, confined, and inter-optimization problems, the best new approaches in machine learning are data-driven optimization techniques that get better with more information.

In this article we discuss the benefits and drawbacks of implementing data-driven research and technology. The primary topic of this study is the requirement for machine learning methods that are easy to interpret, generally applicable and understandable. We discuss issues of paramount importance in the design process, production, testing, affirmation, and service delivery in light of emerging algorithms and technology developments. The capability of a manufacturing system to sift through large datasets and draw forth actionable insights is crucial to the platform's effectiveness. Figure 1 illustrates the structure of the DDR data-driven approach model for the manufacturing process. Data-driven approaches have become popular in this setting because they are simple to deploy and yield helpful information for decision managers. The data-driven methodology can handle various circumstances and adapt to changing objectives, all while uncovering previously unknown patterns within massive databases. Data-driven deep learning algorithms have been proven valuable tools for optimizing industrial processes and allocating scarce resources more effectively. Given the complexity of the manufacturing operation and the enormous number of data involved in geology, geophysics, petrophysics, and design, it appears reasonable that optimizing and predicting manufacturing would be the best way to get ahead of the competition.

The proposed method in manufacturing process optimization uses financial and production data as the data input to the deep learning algorithm, which uses the artificial neural network (ANN). Deep learning is a learning algorithm that uses a very intricate design to evaluate vast

Figure 1. Data-driven optimization model using deep learning resource agents



amounts of information. A vital component of this method is the use of deep neural networks, which are systems of brain cells organized in a way that allows them to analyze and learn a large amount of information and extract relevant abstract aspects from it. As shown in Figure 1, ANNs are a type of technology that draws inspiration from studying the brain and the nervous system. These networks mimic the operation of a neural network while employing only a subset of the ideas behind neural systems. A hidden layer is a processing element that can communicate with other processing components via connections. The hidden layers are frequently arranged in layers or vectors, with the outcome among one layer functioning as the source to the following or subsequent layers. The information flow between network nodes, precisely the electrical impulses of an input layer, is modeled by feeding a neurode with signals of various intensities. A connecting weight compounds the input parameters of a functional block, $w_{nm,}$ to simulate the production enhancement of neural networks. One way that ANNs "learn" is by modifying network "weights," which affect the effects of experience. Compared with more conventional methods for technical indication, using a neural network allows a deliberate choice to be based on a comprehensive study of the requisite data.

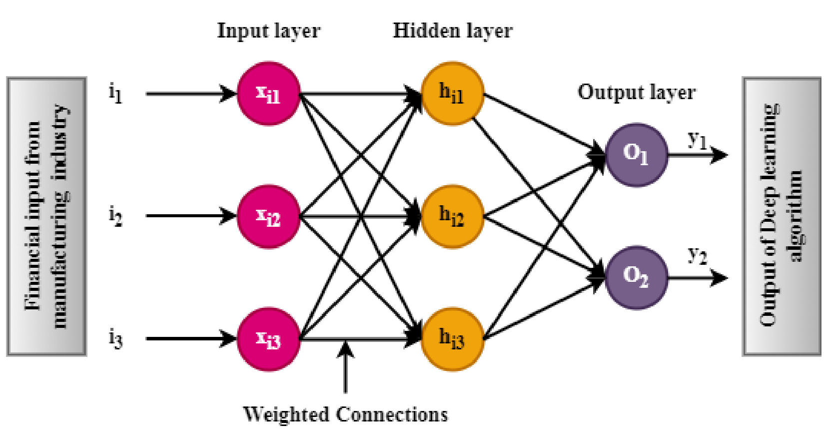
Next, the information is given to the data optimization process, which uses resource agents for the data-driven approach. For this study, we introduced a resource agent system for optimizing services to businesses based on collected data. The company's current components are packaged into a single, cohesive resource agent that leverages malware platform traits. Data analysis is a strength of the agent, and its processing characteristics are packaged as discrete operations. Organizational hierarchies are being replaced by maintenance linkages generated by implementing ideas linkages between production resources. The optimization model optimizes corporate manufacturer operations, automatically organizing complicated production methods by enhancing resource agents' manufacturing capacities and optimizing resource distribution throughout the maintenance network. We discuss KPIs for evaluating optimization strategies in the next section, along with established internet control protocol processes. The approach adopted in this study is geared toward reducing production costs and increasing the likelihood of long-term success in the industry. Although it is not easy to develop an ideal system that can be adaptable and smart, it may be worthwhile to insert sophisticated algorithms into mechanization and production to cut costs and enhance product quality. Life cycle management, design and manufacturing management, economy networking devices, and company strategy are where process automation research primarily focuses its attention.

A Deep Learning Algorithm for Feature Selection

Machine learning and deep learning are two important branches in the field of artificial intelligence (Karaboga et al., 2023). Machine learning algorithms are usually built on statistical and mathematical models, with the goal of identifying and learning patterns through training data to make predictions or decisions (Feng et al., 2023). In contrast, deep learning algorithms use multilayer neural network structures for learning and inference, resulting in higher algorithm complexity. Machine learning algorithms typically require high requirements for feature engineering and data preprocessing, requiring manual extraction and selection of effective features for modeling. Deep learning algorithms can automatically learn feature representations from raw data without the need for manual feature engineering (Gandhi et al., 2023). Machine learning is a relatively simple learning method suitable for small and medium-sized data and tasks, whereas deep learning is a complex learning method suitable for large-scale data and complex pattern recognition tasks. They play important roles in different application scenarios and complement each other.

For this study we designed a feature selection procedure that uses an ANN and resource agents to find the best features to use as inputs for subclassifications. The research creates a method for segmentation using artificial neural networks (the weighted sum methodology). The technique can be used as long as an inquiry is conducted within the context of feature matching, adaptive maximizing, and defect detecting. Growth is possible only via investments in bettering the quality and quantity of the production elements. Tolerance levels in maintenance and design are two characteristics often considered during the feature selection process. The cost of materials, processing capacity needs, and strategies to support this system are all essential considerations. The proposed deep learning system uses a combination of multimodal transportation and an adaptive feature selection technique to acquire data on the relevant variables. The regressive relationship between features can be explored by including an ANN in a framework. Smarter machine learning can provide cheaper monitoring and processing to boost manufacturing performance. There are two ways to look at industrial automation in action. First, manufacturing has emerged as a significant force in the finance sector, and second, the boundary between digital and physical systems is blurring. Thus, industrial modes and methods may consider architectural approaches, such as service-oriented architectures. Implementing those fixes paves the road for massive analysis to reduce costs and increase output. Many processes are involved in creating a functional model, such as information reformatting and data sterilization for discovery. Because information quality affects results, utilizing a method for preparing data is crucial. Figure 2 represents the deep learning algorithm consisting of weighted input neurons, hidden units, and output neurons.

Figure 2. A deep learning algorithm for feature selection



Feature selection is an important task in machine learning; it can improve the generalization ability of models, reduce overfitting risks, and accelerate model training speed (Wang et al., 2023). Feature selection-based deep learning algorithms typically include the following steps: (a) extracting useful features from raw data, (b) selecting the features that have a significant impact on the predictive performance of the model from the extracted features, and (c) training deep learning models using filtered features. Each layer's output feeds into the next layer (and maybe others) in the hidden structure, often laid out in a layer or vector arrangement. Information transmission inside the network is modeled by weighted data signals propagating through an intermediary layer. By raising the input data to a processing system by a connecting weight, $w_{nm,}$ the algorithm simulates the strengthening of neural systems. ANNs can mimic learning because of the ability to fine-tune the connection strengths, also known as weights. Replicating network nodes and weights across time enables period ANNs to have their layers' sources become time-shifted representations of the same time information. Still, attempts to improve financial time-series modeling and prediction by adding temporal units to an ANN have typically been met with limited success. A supervised neural network approach results from the numerical value provided by the input data in the training set during learning. A supervised neural network approach also results in the numerical value of the input data in the training set during education. The feed-forward neural network's multilayer perceptron often generates ANNs (MLPs) using the backpropagation algorithm. The network's outputting of approximate goal-calculated values data that are not in the training dataset is the main reason for employing a computational model, but having this capability on its own might be helpful.

The output of the neural network algorithm $y_1, y_{2\ldots} y_n$ is represented as y(x) for the inputs $i_1, i_2 \ldots i_n$ and is described in the nodes as $x_{i1}, x_{i2} \ldots x_{in}$ with the weighted nodes $w_{m,n,}$ which is calculated by equation (1):

$$y\left(x\right) = f\left(\sum_{i=1}^{m} w\left(m,n\right) x\left(n\right)\right) \tag{1}$$

In equation (1), x(n) is the nth element input vector, w(m,n) is the adaptable weights of hidden layer neurons, and f is the neuron threshold function. Because these neurons can detect only the subsequent associations in the training phase, they are categorized as quadratic. Complicated neuron transfer functions, described below in equation (2), are necessary to account for higher-order correlations in the learning algorithm.

$$y\left(x\right) = f[w_0\left(m\right) \sum_{i}^{m} w_1\left(m,n\right) x\left(n\right) + \sum_{i}^{m} \sum_{i}^{n} w_1\left(m,n,i\right) x\left(n,i\right) \tag{2}$$

An ANN can do complex algorithms to provide numerous indications in the industrial sector. Designers can take preventive measures to improve results by using analytics equipped with built-in AI to rapidly integrate and assess massive amounts of data and spot challenges in the initial stages of development. Continuous improvement quality is ensured by constantly tracking the state of all production processes, and the ANN provides more timely, precise forecasting of future projections with its optimization algorithms.

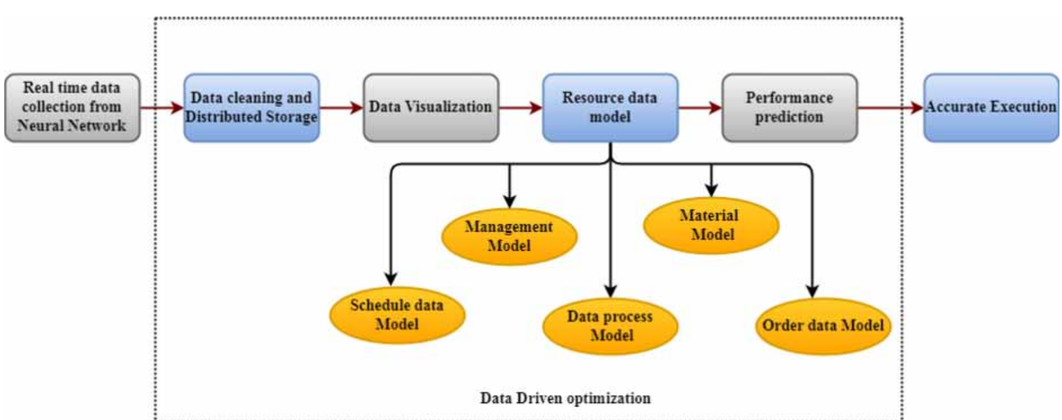
A Data-Driven Optimization Model for Process Manufacturing

Figure 3 shows the resource agents of the data-driven model for the manufacturing process. Automated systems incorporate sophisticated machinery, services, and various industries to produce goods. It is typical for intricate production methods to necessitate coordination between different manufacturing levels. Smart manufacturing studies the issue of maximizing teamwork.

Similarly, industrial data are carried up the hierarchy and transformed into production information, while management data are transmitted down the layers and transformed into control orders. A system based on rankings cannot meet the requirements of modern information processing and a flexible supply network. The facilities at each industry level are incorporated as resource operators with a similar design, with the name resource relating to the four different qualities of complex processes (profound observation, proper analysis, logical outcome, and finding the most effective way). The agents have two parts: financial data and a physical component. The perceptive device's dual roles of collecting proactive instructions from the agent's minimal interaction and obtaining specific facts from the distinct asset or digital world are essential to their operation. The modeling method substantially improves data quality by integrating declarative data of various sorts and forms, extracting and analyzing production data, and merging conceptual aspects to generate communication hubs. The data-driven module combines manufacturing financial and process expertise with a training and inference engine to analyze real-time manufacturing data and arrive at optimal judgments that are both timely and effective. The implementation module carries out the approach and precisely controls the objects to maximize production output and cost reduction. Resource agents use various directive control sets to implement their execution modules in the data-driven approach. The manufactured skills of the agent are packaged as services by the process improvement module, which also handles legitimate service administration and monitoring and integrates seamlessly with those other units to achieve optimal performance. The hardware for data-driven optimization specifies the rules for how agents are to share information, taking into account concerns about privacy and integrity and the need to meet strict time constraints. With immersion, production assets are converted into autonomous, self-learning resource agents continuously exchanging data with data-driven financial entities and physical ones to maximize manufacturing capacities.

The data-driven confined improvement is the essential part of the data-driven idea. Management of this sort enables the resource agent to self-organize and optimize itself. Uniting data and manufacturing agents improves production efficiency and provides the groundwork for maximizing the value of product manufacturing. Although data volumes and categories created by various resource agents may vary, the process for optimizing data-driven capabilities remains constant. Information on the manufacturing network's service sectors, resource beings' interactions, the situation of the upstream industry, and domain-specific resources are all examples of internet-sourced information obtained by resource agents. The commercial industry's information function ensures that information is sent to the appropriate agent. The cognitive tests then save the information in a centralized database after sorting

Figure 3. Data-driven optimization module



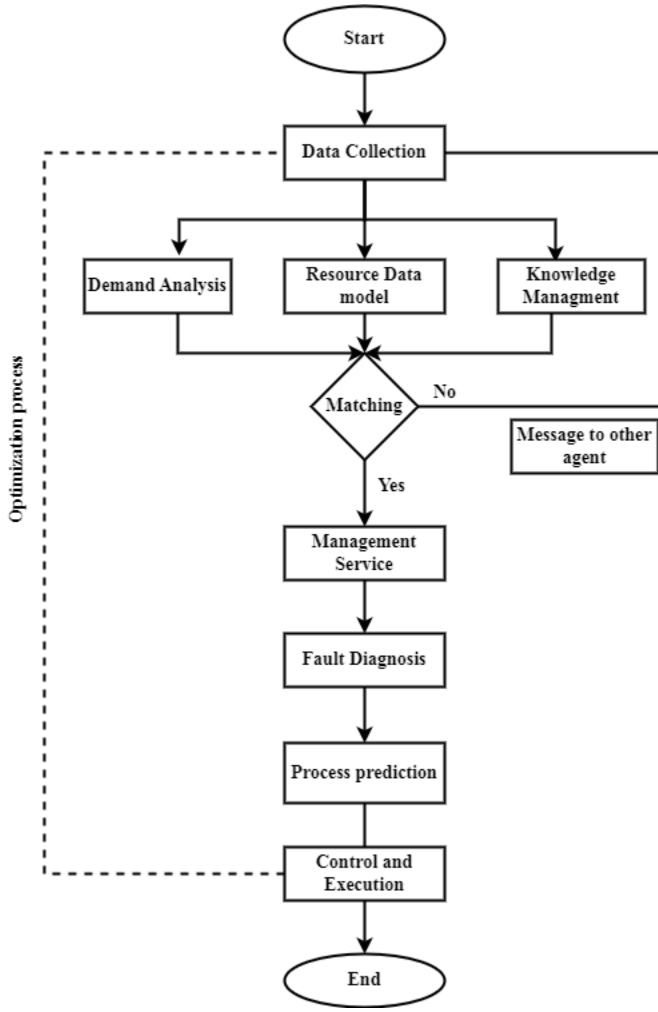
it into actual field measurements. Various data models are made available via data modeling. The resource data model not only stores the literal state and spatial computational methods of production resources but also uses vivid domain descriptions to document the production capabilities owned by the physical entity. In DDR, technical specifications for customer requests are recorded in the order data model. The agent can also refer to the process, scheduling, and management models, all of which explain the production mechanism and information, to help optimize its decisions.

As an alternative, the company's many production methods are bundled into a decentralized subnetwork. Each device may process information, manage resources, and interact with information independently. In a data-driven processing pattern, a considerable amount of complicated, decentralized commercial data will be transmitted successfully between processes following the evaluation and decision-making needs of the agent. In addition, the service management module encapsulates the agent's industrial capacity conventionally by taking the characteristics abstracted from the resource data model. Manufacturing processes of varying scales and granularity can be completed with resources at varying levels. During encapsulation, the agent conceals information about the physical entity's controls. Industrial services are organized the same way as other production methods are when they are called. Therefore, breaking down large-scale manufacturing into smaller, more acceptable steps is the same as breaking down massive services to businesses into more refined, more manageable steps. The synchronicity of a similar production process is the everyday use of manufacturing excellence at the exact resolution. All contributions to the quality of the organization entity are comparable to the collection of shared service interactions produced between all production resources. As a result, once the industrial activity recorded in the data-driven portal is active, a communication network will be formed among the agents involved. The agent initially recorded the manufacturing service as responsible for delivering the service, while all agents on the resource model collaborated to complete the unique manufacturing activities. The optimization of productivity leads naturally to the efficiency of the use of resources.

Figure 4 shows the industry's overall manufacturing process optimization based on a data-driven approach. At first, the data is collected in the database, which includes process information and financial data. In the demand analysis, the data-driven manufacturing model simplifies allocating and arranging factory assets to meet fluctuating demand. However, the performance of product creation cannot be enhanced compared with the conventional manufacturing model because the difficulty of optimizing the complex and variable production system has not been tackled. However, two approaches can be taken to maximize production efficiency after converting the business into a decentralized network of resource agents.

The resource data model proactively identifies production systems by mining the database for information and combining it with the expertise of the producing process to make the best possible decision about how to balance supply with demand. The associated manufacturing service is automatically created and added to the database if the agent possesses production skills. Alternatively, it sends the demand information to the agents responsible for the relevant resources. In the producing service, the resource agent will use the defect diagnostic and efficiency help to determine if the service agents can work together to carry out the production customizations. If some manufacturing resources fall short of the required assistance, a new resource agent is identified, and overall productivity is evaluated correctly to diagnose the fault. In the end, the improved data-driven model is implemented more methodically in the form of manufacturing choices. A unique industrial data management technology has been integrated into a dispersed storage and computation environment. After the quality of each machine has been verified, the operation's data are sent to the performance analysis module, which thoroughly analyzes the current state and predicts critical performance indicators at each stage of the process. If the requirements of the request are satisfied, the precise control and execution module will transform the associated data into a workable manufacturing and distribution management plan.

Figure 4. Manufacturing optimization process based on data-driven model in industry



KPIs are used to assess the effectiveness of various methods for enhancing the production process and reducing costs. Historically, the financial sector has been the primary user of KPI systems. KPIs give teams goals to work toward, checkpoints to evaluate their success, and information that anybody in the company can use to make smarter choices. Later, KPIs were expanded to incorporate nonmonetary systems and quality measures. The suggested hierarchical structure for KPIs makes it possible to see how they are connected. Many other KPI systems are available today, each catering to a narrower subset of the industrial sector or offering a more general model without domain-specific KPIs. We provide a unique modeling approach for manufacturing data-driven projects by merging process variables with a KPI model to assess optimization methods. This approach corrects the flaws of prior methods. The system was developed to be implemented in current production setups. The KPI model has mathematical relationships that can be analyzed, whereas the links between the process parameters and the foundational KPIs are calculated using a learning method. Here, we use the dates and timestamps on data about operating parameters to connect them to characteristics of the core KPIs that determine how efficient our equipment is as a whole.

Consequently, the business's product information is being used appropriately and effectively by the industrial assets. The precision of manufacturing excellence is elevated by the enhanced processing capabilities made possible by the data-driven managed service optimization method. The capacity for real-time scheduling, achieved by integrating the actual production rate of the sector with the current system of the devices, enables data-driven optimization of the allocation of resources.

RESULTS AND ANALYSIS

Analysis of Experimental Results

Performance Evaluation

In the Udemy course Deep Learning A-Z - ANN Dataset: Hands-On Artificial Neural Networks, given by Kirill Eremenko (data scientist and foreign exchange systems expert) and Hadelin de Ponteves, students analyze industrial data used for process optimization using an ANN . The dataset is excellent for beginners in machine learning because it offers a safe space to experiment with different methods. The total number of views is 38,318, and downloads are 3,715. For more information go to https://www.kaggle.com/datasets/filippoo/deep-learning-az-ann

Accuracy, efficiency, transaction cost, and latency time are all measurements of the system's performance when using resource agents, as are the performance ratio on employing the deep learning approach and optimizing financial data on the data-driven model.

Initially, the throughput time displayed the maximum number of transactions that could occur in a given time. The integrated system's outputs display similar behavior, albeit somewhat different outcomes. When contrasting this study's experimental setting with others, we think it's important to note that we used a publicly available application here, whereas previous research has been restricted to internal testing environments.

Equation (3) measures the accuracy and precision of the confusion matrix, which is used to assess the effectiveness of the suggested framework for extensive data analysis.

$$Accuracy = \frac{Tp + Tn}{Tp + Fn + Tn + Fp} \tag{3}$$

In equation (3), Tp represents the typical profiles that were accurately identified, and the actual negative rate, Tn, is the number of anomaly files that have been accurately labeled. False positives (Fp) are the total number of abnormal profiles that were improperly tagged as usual (Fn) in the past.

A neural network forms the basis of the proposed feature selection technique, and tolerance levels for maintenance and design are common factors to consider when deciding which features to implement. Important factors include the price of resources, the required processing power, and the operations that need to be supported. Our data-driven approach uses a multilayer perceptron to calculate optimal financial data information by evaluating different feature subsets. When deciding on a starting population density, account for storage capacity, features count, and response rate. Employ trial and error to discover how many neurons to use. Note that we used the neural network to generate a cost function, with the primary purpose being to minimize that function. After several repetitive calculations, the algorithm reaches the optimal features, starting with the initial solutions. Finally, after looking at some classification models, we settled on the best one. Comparisons have been made between ANN and other classification models, such as the Gaussian support vector machine (SVM), the random forest (RF), and the convolutional neural network (CNN). Classification accuracies serve as the primary metrics by which classifiers are ranked. Each technique's success rate in determining the correct class is quantified and presented as a percentage. Table 1 includes some statistical findings (such as the proportion of accurate forecasts). We also used different feature extraction approaches and evaluated their performance compared with our suggested strategy.

We used typical approaches to reduce the dimensions of our data collection and then compared the outcomes. The chosen categorization is supplied with the retrieved features to achieve a higher performance ratio. The experimental findings (Table 2) suggest that our proposed method effectively achieves the conventional ones. The table shows the accuracy of the trained and test data on which the proposed model's average accuracy is 95%. The performance accuracy of the DDR model using the ANN of the deep learning method is flexible for feature selection purposes, and it is calculated using equation (3).

Analysis of the Accuracy of Feature Selection

The graph produced to determine the accuracy using equation (3) of the highly adaptable deep learning approach on financial data to evaluate the cost of production is shown in Figure 5. Decision tree (DT), Gaussian SVM, and CNN are only a few mining techniques used to create the data-driven optimization model strategy described in this work's pervasive environment. The graph represents the accuracy rate of the ANN in the deep learning method, which has higher accuracy than the other algorithms. Specifically, we employed a flexible plan for selecting features in our approach comprising various channels for disseminating data about critical criteria for identifying malfunctions. As a result, we added ANN into our model to further investigate the irregular correlation between characteristics. The production's precision level can be improved with the help of deep learning. The graph shows that the proposed model's accuracy is higher than that of RF, SVM, and CNN.

Analysis of Optimization Model Efficiency

In Figure 6 the graph is plotted to calculate the efficiency ratio of the suggested data-driven model on resource agents using deep learning with neural networks. The proposed solution boosted productivity

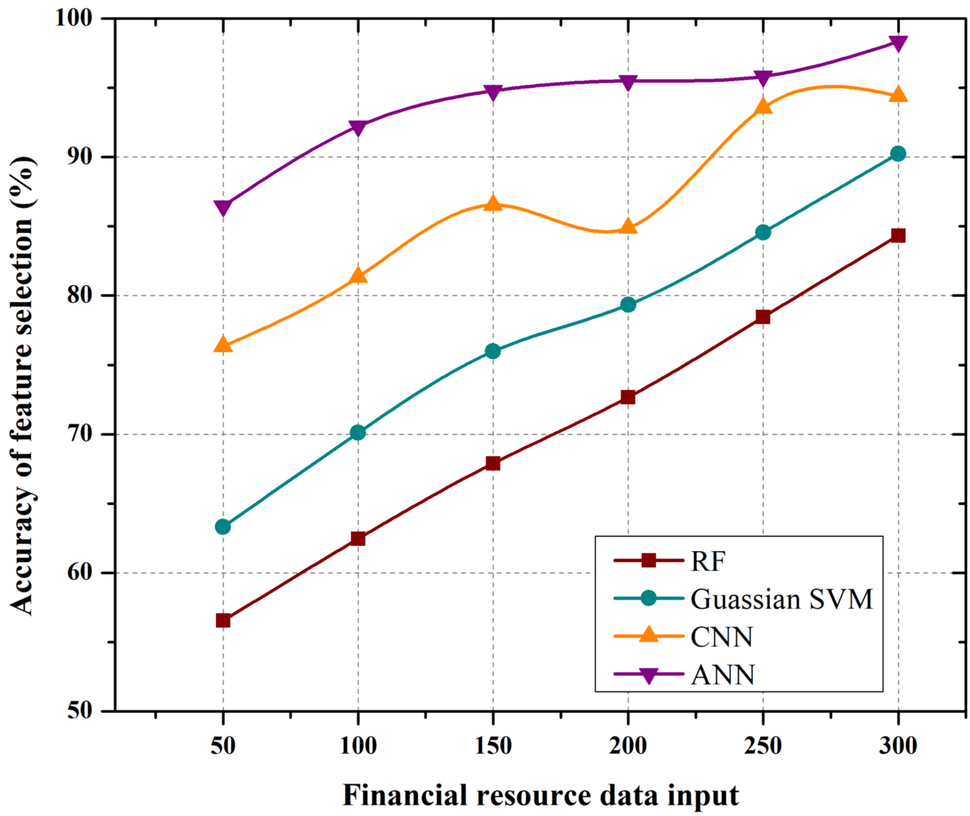
Table 1. Different classifications of machine learning algorithms

Classification Method	The Success Rate of Feature Selection (%)	The Failure Rate of Feature Selection (%)
Random forest	73	27
Linear discriminant	62	36
Guassian SVM	80	17
Convolutional neural network	85	14
ANN (proposed method)	93	5

Table 2. Examining the relative effectiveness of several feature extraction techniques

Feature Extraction Method	Accuracy of Train Data (%)	Accuracy of Test Data (%)
Correlation-based feature selection	78.34	73.65
Sequential forward selection	67.87	61.27
Sequential backward selection	82.39	80.18
Lasso regression	79.72	70.37
Filtration selection model	80.34	79.45
Feature selection modal using a deep learning method	95.46	92.45

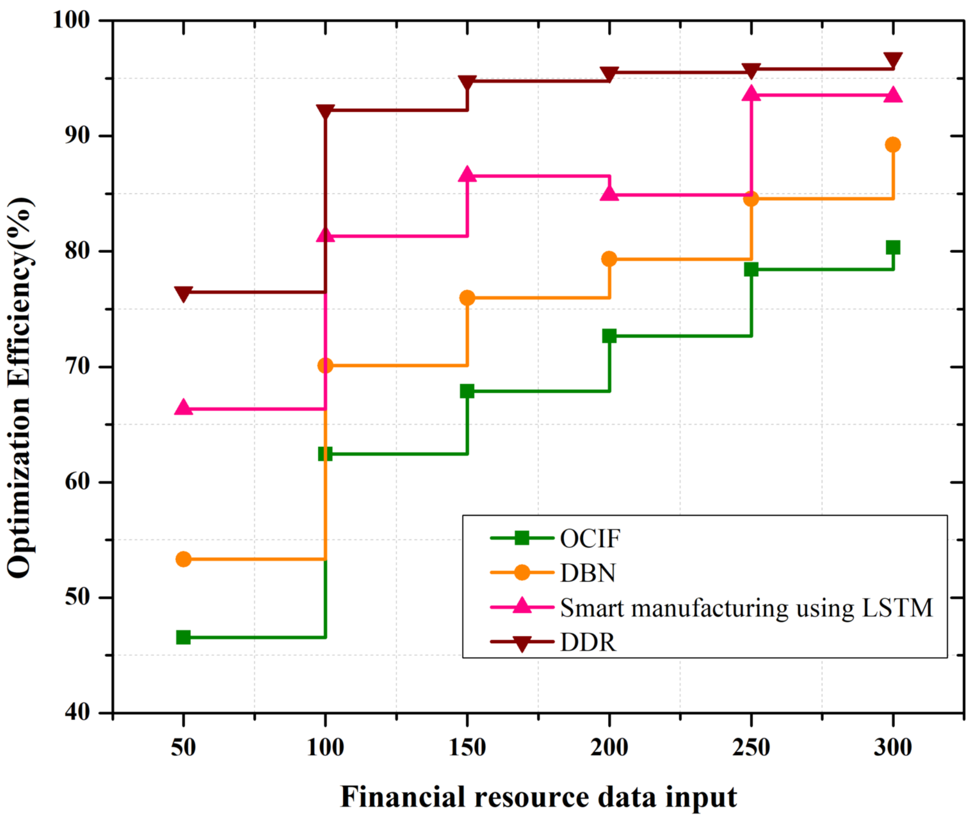
Figure 5. The accuracy rate of deep learning methods in the manufacturing process



by automating corporate activities, evaluating data, connecting with customers and staff, and providing good financial improvement: specifically, managing relationships, investments, and obligations using the profitability ratio to maximize earnings using machine learning. The efficiency of the machine learning output is calculated by the input given to the optimization system. The proposed DRR model efficiency is higher when the graph is compared with the traditional approach, such as OICP, DBN, and intelligent manufacturing using the LSTM model. Industrial efficiency can be represented as a percentage by dividing the desired outputs by the actual performance. There is a wide range of production speeds because of the machines and procedures used. Generally speaking, slower rates lead to lower profitability as speeds fluctuate, whereas faster speeds impact quality management. Increasing productivity, or operational efficiencies, pinpoints the conditions under which products can be manufactured at the least potential per-unit cost. Production performance, and consequently profits, can be expanded by making the most of existing funds and cutting down on unnecessary trash. However, it has a low degree of accuracy and cooperation in its financial planning, making it impossible to meet modern group organizations' more complicated economic control requirements. Efficiency is calculated as shown in equation (4):

$$Production\,efficiency = \frac{Actual\,output\,rate}{standard\,output\,rate} * 100 \tag{4}$$

Figure 6. The efficiency of a data-driven model



Analysis of Average Transaction Rate Cost

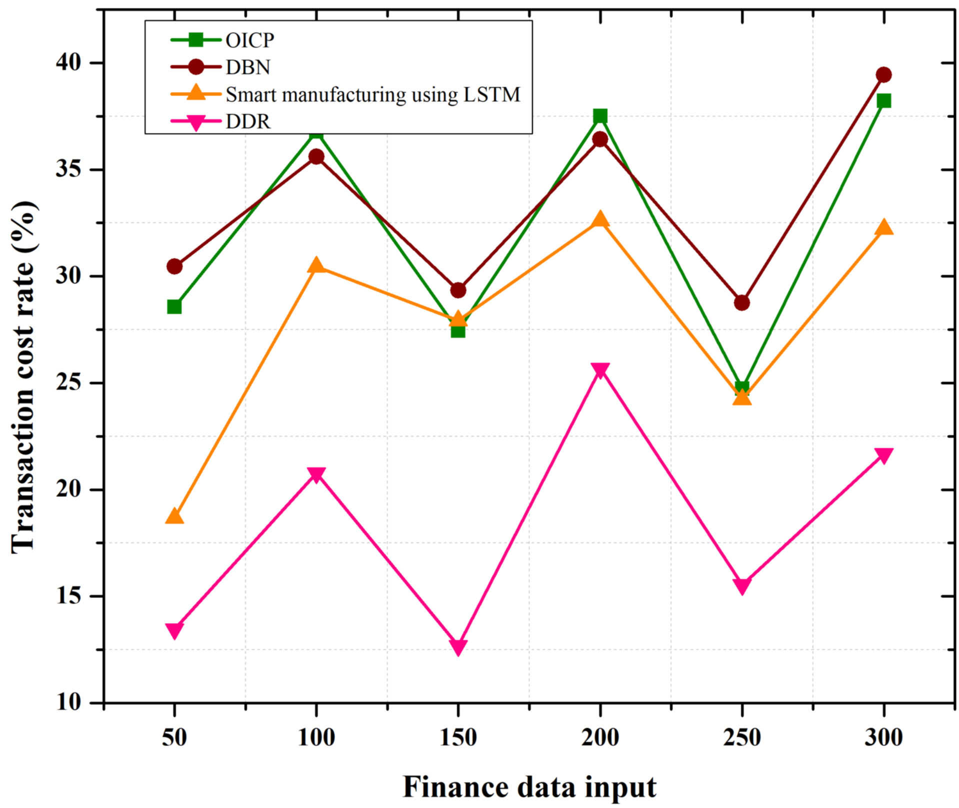
Figure 7 shows that fluctuation in the process optimization transaction cost increases the likelihood of application failures in proportion to response flow throughput. As device density fluctuates, the transaction rate and compute units must manage a greater volume of requests. The resource agents report the number of inquiries processed to the infrastructure nodes. A transaction cost is a premium incurred when participating in any exchange process. The prices of a company's economic system are referred to as transaction costs. Decision-makers develop firm strategies by analyzing transaction and production costs instead of only production costs. The transaction rate cost formula is shown in equation (5):

$$T_R = F_H + X_c \quad (5)$$

In equation (5), T_R is the transaction rate, F_H denotes the fixed overhead of the process manufacturing, and X_C is the operating costs. Fixed costs equal charges plus taxes; operating costs equal implementation costs plus potential costs.

The graph plotted in Figure 7 is compared with the traditional approaches, such as OICP, DBN, and intelligent manufacturing using the LSTM model. The proposed data-driven model using deep learning and resource agents (DDR) transaction cost is lower.

Figure 7. Average transaction rate cost for process manufacturing



Analysis of Average Delay in Processes

Optimization of financial and process data driven by input retention data takes time to be successfully implemented. Figure 8 shows the average delay (in milliseconds) as a function of the total number of records in deep learning. The deep learning algorithm uses agent-based resources to calculate the delay based on the number of inputs. Delays introduced by the storage and retrieval of data packets are called data delays. The time required for a manufacturing process to obtain source data from a data warehouse is in milliseconds; this required time is called information delay in the industry. The ability of an organization to quickly adapt to changing market trends depends on minimizing transmission delays and enabling business users to access operational information in near real time. Delay is a measurable key statistic expressed in seconds or milliseconds in round trip time (RTT); that is, the accumulated time required for data to appear at the required location from its starting point. In the case of delay, as more and more users experience substandard performance, the average delay will also increase. RTT is calculated using the formula shown in equation (6) and taking Tp as the propagation delay.

$$RTT = 2 * T_p \tag{6}$$

$$Average\,Latency = P_d + Q_d + T_d + RTT \tag{7}$$

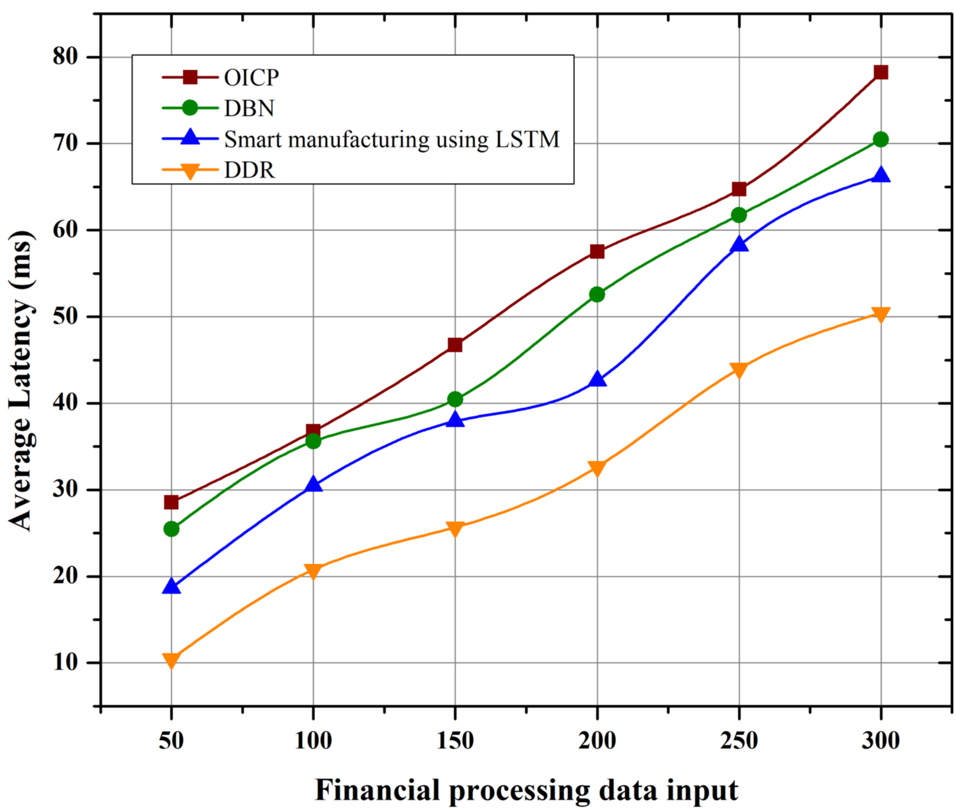
Average waiting time is calculated according to equation (7), where P_d represents the processing delay, Q_d represents queuing delay, T_d is the transmission delay, and RTT is round-trip time. When the number of users trying to use a service exceeds the number of resources supporting them, the delay will increase regardless of the user's feeling about the quality of experience. See Figure 8 to see how the proposed solution improves the status quo regarding average latency. Note that the gap between modes widens with the increase of the number of users, which shows the superiority of the proposed method under serious network restrictions.

In intelligent factories, it is always a key challenge to effectively use data to organize complex operations and provide higher production services. This study presents a strategy for optimizing services for businesses that use data collected from the real world to boost manufacturing capability. In addition, in a traditional organization, the production relationship of each manufacturing unit is replaced by the interactions of operation concepts between raw materials and resources. The model can improve the production efficiency by adjusting the agents that constitute material recovery and improving the resource production capacity.

Analysis of Real-World Applications

With the development of manufacturing and continuous technological progress, the modern industrial production environment has become increasingly complex. To reduce costs, as well as improve

Figure 8. Average latency (ms) of process manufacturing on data-driven optimization



production efficiency and quality, many manufacturing enterprises have adopted various optimization methods and technologies. However, in practice, there are still some challenges, such as how to fully use available resources, how to ensure the quality of manufacturing services, and how to cope with complex manufacturing processes. These challenges require more intelligent methods and technologies to address. Therefore, in this article we explore the application of data-driven process manufacturing service optimization models in the industrial field to improve production efficiency, reduce costs, and improve the quality of manufacturing services. This study has a wide range of practical applications, especially in the industrial field.

Manufacturing Service Optimization

Through data-driven process manufacturing service optimization models, enterprises can maximize the reduction of manufacturing costs and improve the quality of manufacturing services. This model uses deep learning algorithms and resource proxies (DDR) to intelligently represent and manage available manufacturing resources, thereby optimizing production processes, reducing scrap rates, and improving production efficiency.

Productivity Improvement

Machine learning plays an important role in the production process. Connecting multiple enterprises and using inexpensive sensors to build models can significantly improve production efficiency. By using data-driven methods, enterprises can monitor and analyze the production process, promptly identify problems, and take corresponding measures, thereby improving production efficiency and reducing production downtime.

Resource Optimization Management

A data-driven process manufacturing service optimization model can intelligently manage and allocate available manufacturing resources. By fully using the output of resources, raw materials, and support networks, enterprises can better plan and manage the use of resources, thereby reducing costs and improving resource utilization.

Expert Strategy Assistance

The methods introduced in this article also include construction methods based on expert strategies. This means that enterprises can use expert knowledge and experience to guide the production process and optimize it in conjunction with data-driven models. This combination can improve the accuracy and efficiency of decision-making, helping enterprises better cope with complex manufacturing environments.

Cost Reduction and Profit Enhancement

By optimizing manufacturing services and resource management, enterprises can reduce manufacturing costs and improve production efficiency. This process will directly affect the profits of the enterprise and enhance its advantage in market competition. By using the data-driven process manufacturing service optimization model proposed in this article, enterprises can maintain competitiveness in a constantly changing market environment.

In summary, the research methods and models proposed in this article have broad practical application potential in the industrial field. By optimizing manufacturing services, improving production efficiency, optimizing resource management, and combining expert strategies, enterprises can reduce costs, increase profits, and gain an advantage in market competition. These applications will bring significant economic benefits and sustainable development to industrial enterprises.

The data-driven process manufacturing service optimization model discussed in this article has certain limitations in its application in the industrial field. By taking corresponding measures, we can overcome the limitations of data-driven process manufacturing service optimization models in industrial applications, thereby improving production efficiency, reducing costs, and improving the quality of manufacturing services.

Data Collection and Processing

This model requires a large amount of production data and related information to train and optimize the model. However, in certain production environments, data collection and processing may be limited owing to the lack or unreliability of sensors and other data collection devices. Therefore, enterprises can increase data collection equipment and sensors, and they can also adopt other methods, such as simulation and model prediction, to collect and process necessary data.

Model Accuracy

Although data-driven models have been widely used in the production process, different production environments and conditions can have an impact on the accuracy of the model. Therefore, in different production scenarios, adjusting and optimizing the model to improve its accuracy and adaptability are necessary steps. Enterprises can regularly evaluate and adjust their models to ensure their accuracy and adaptability. In addition, the performance of the model can be improved by collaborating with other enterprises and experts to share experience and best practices.

Personnel Skills and Training

The data-driven process manufacturing service optimization model requires professional knowledge and skills to be effectively used and maintained. Therefore, it is necessary to train and educate production personnel to improve their understanding and application ability of the model. Enterprises can provide relevant training and education for production personnel to enhance their understanding and application ability of data-driven process manufacturing service optimization models and provide them with necessary skills and knowledge.

CONCLUSION

In the industrial sector, creating profitable and marketable products is crucial. To significantly improve production efficiency, machine learning plays an important role in the production process by connecting multiple enterprises and using inexpensive sensors to build models. To reduce costs, we proposed a technical solution, which is a data-driven process manufacturing service optimization model. This model uses deep learning algorithms and resource proxies (DDR) to intelligently represent available manufacturing resources to minimize costs. Resource proxy is an intelligent module with powerful data processing and service management capabilities. In this paper, we also introduced KPIs for evaluating optimization work, as well as other methods for implementing processes and building expert strategies. The purpose of our model is to improve the quality of manufacturing services and reduce manufacturing costs by fully using resources, raw materials, and support networks. Finally, we evaluated the effectiveness and practicality of the proposed model through an actual industrial manufacturing process scenario. We compared the experimental results from multiple perspectives and demonstrated the advantages of our solution. Although we discussed the advantages of using Resource Proxy (DDR) in our paper, the implementation of this method may require additional costs and resources, which is also a limitation. In the future, we can consider exploring more cost-effective data processing and service management technologies to reduce the additional costs and resources required for implementing this method. In addition, alternative methods, such as advantage-based algorithms, can be explored in the future to address the challenges faced by problem optimization and ensure continuous improvement of feature extraction and optimization strategies.

DATA AVAILABILITY

The figures and tables used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

We declare that we have no conflicts of interest.

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REFERENCES

Aljarrah, O., Li, J., Heryudono, A., Huang, W., & Bi, J. (2023). Predicting part distortion field in additive manufacturing: A data-driven framework. *Journal of Intelligent Manufacturing*, *34*(4), 1975–1993. doi:10.1007/s10845-021-01902-z

Baardman, L., Cristian, R., Perakis, G., Singhvi, D., Skali Lami, O., & Thayaparan, L. (2023). The role of optimization in some recent advances in data-driven decision-making. *Mathematical Programming*, *200*(1), 1–35. doi:10.1007/s10107-022-01874-9

Bag, S., Kilbourn, P., & Pisa, N. (2023). Guest editorial: Data-driven quality management systems for improving supply chain management performance. *The TQM Journal*, *35*(1), 1–4. doi:10.1108/TQM-11-2021-315

Bernabei, M., Eugeni, M., Gaudenzi, P., & Costantino, F. (2023). Assessment of smart transformation in the manufacturing process of aerospace components through a data-driven approach. *Global Journal of Flexible Systems Managment*, *24*(1), 67–86. doi:10.1007/s40171-022-00328-7

Clancy, R., O'Sullivan, D., & Bruton, K. (2023). Data-driven quality improvement approach to reducing waste in manufacturing. *The TQM Journal*, *35*(1), 51–72. doi:10.1108/TQM-02-2021-0061

Erkip, N. K. (2023). Can accessing much data reshape the theory? Inventory theory under the challenge of data-driven systems. *European Journal of Operational Research*, *308*(3), 949–959. doi:10.1016/j.ejor.2022.08.024

Feng, L., Peng, J., & Huang, Z. (2023). A data-driven prediction model of blast furnace gas generation based on spectrum decomposition. *Journal of Advanced Computational Intelligence and Intelligent Informatics*, *27*(2), 304–313. doi:10.20965/jaciii.2023.p0304

Gandhi, S., Kiwelekar, A., Netak, L., & Shahare, S. (2023). A blockchain-based data-driven trustworthy approval process system. *International Journal of Information Management Data Insights*, *3*(1), 100162. doi:10.1016/j.jjimei.2023.100162

Hu, Y., Li, X., Song, Y., & Huang, C. (2023). Data-driven evaluation framework for the effectiveness of rural vitalization in China: An empirical case study of Hubei Province. *Environmental Science and Pollution Research International*, *30*(8), 20235–20254. doi:10.1007/s11356-022-23393-y PMID:36251194

Jieyang, P., Kimmig, A., Dongkun, W., Niu, Z., Zhi, F., Jiahai, W., Liu, X., & Ovtcharova, J. (2023). A systematic review of data-driven approaches to fault diagnosis and early warning. *Journal of Intelligent Manufacturing*, *34*(8), 3277–3304. doi:10.1007/s10845-022-02020-0

Karaboga, T., Zehir, C., Tatoglu, E., Karaboga, H. A., & Bouguerra, A. (2023). Big data analytics management capability and firm performance: The mediating role of data-driven culture. *Review of Managerial Science*, *17*(8), 2655–2684. doi:10.1007/s11846-022-00596-8

Liu, F., Zhang, C., Zhang, Y., & Liu, H. (2023). A data-driven approach for the measurement and improvement of regional industrial ecological efficiency for carbon peaking and carbon neutralization. *Environmental Science and Pollution Research International*, *30*(3), 7655–7670. doi:10.1007/s11356-022-22699-1 PMID:36044133

Mandl, C., & Minner, S. (2023). Data-driven optimization for commodity procurement under price uncertainty. *Manufacturing & Service Operations Management*, *25*(2), 371–390. doi:10.1287/msom.2020.0890

Mu, W., Xie, J., Ding, H., & Gao, W. (2023). Data-driven evaluation of the synergistic development of economic-social-environmental benefits for the logistics industry. *Processes (Basel, Switzerland)*, *11*(3), 913. doi:10.3390/pr11030913

Nadim, K., Ragab, A., & Ouali, M.-S. (2023). Data-driven dynamic causality analysis of industrial systems using interpretable machine learning and process mining. *Journal of Intelligent Manufacturing*, *34*(1), 57–83. doi:10.1007/s10845-021-01903-y

Peng, Y., Ahmad, S. F., Irshad, M., Al-Razgan, M., Ali, Y. A., & Awwad, E. M. (2023). Impact of digitalization on process optimization and decision-making towards sustainability: The moderating role of environmental regulation. *Sustainability (Basel)*, *15*(20), 15156. doi:10.3390/su152015156

Sarna, S., Patel, N., Corbett, B., McCready, C., & Mhaskar, P. (2023). Process-aware data-driven modelling and model predictive control of bioreactor for the production of monoclonal antibodies. *Canadian Journal of Chemical Engineering*, *101*(5), 2677–2692. doi:10.1002/cjce.24752

Sun, S., & Liu, Y. (2023). Data-driven eco-efficiency analysis and improvement in the logistics industry in Anhui. *International Journal of Environmental Research and Public Health*, *20*(6), 4810. doi:10.3390/ijerph20064810 PMID:36981718

Sun, W., Zhou, Z., Ma, F., Wang, J., & Ji, C. (2023). Industrial application of data-driven process monitoring with an automatic selection strategy for modeling data. *Processes (Basel, Switzerland)*, *11*(2), 402. doi:10.3390/pr11020402

Wang, Y., Wu, C., Zhao, S., Guo, Z., Han, M., Zhao, T., Zu, B., Du, Q., Ni, M., & Jiao, K. (2023). Boosting the performance and durability of heterogeneous electrodes for solid oxide electrochemical cells utilizing a data-driven powder-to-power framework. *Science Bulletin*, *68*(5), 516–527. doi:10.1016/j.scib.2023.02.019 PMID:36841731

Xu, Z., & Dang, Y. (2023). Data-driven causal knowledge graph construction for root cause analysis in quality problem solving. *International Journal of Production Research*, *61*(10), 3227–3245. doi:10.1080/00207543.2022.2078748

Yan, F., Zhang, X., Yang, C., Hu, B., Qian, W., & Song, Z. (2023). Data-driven modelling methods in sintering process: Current research status and perspectives. *Canadian Journal of Chemical Engineering*, *101*(8), 4506–4522. doi:10.1002/cjce.24790

Zdolsek Draksler, T., Cimperman, M., & Obrecht, M. (2023). Data-driven supply chain operations—The pilot case of postal logistics and the cross-border optimization potential. *Sensors (Basel)*, *23*(3), 1624. doi:10.3390/s23031624 PMID:36772664

Zhang, M., Yang, D., Du, J., Sun, H., Li, L., Wang, L., & Wang, K. (2023). A review of SOH prediction of Li-Ion batteries based on data-driven algorithms. *Energies*, *16*(7), 3167. doi:10.3390/en16073167

Zhu, Z., Xiang, Y., Zhao, M., & Shi, Y. (2023). Data-driven remanufacturing planning with parameter uncertainty. *European Journal of Operational Research*, *309*(1), 102–116. doi:10.1016/j.ejor.2023.01.031

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