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# Big data driven decision-making for batch-based production systems

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**Abstract**

The era of big data has brought new challenges to chemical enterprises. In order to maximize the benefits, enterprises are considering to implement intelligent service technology into traditional production systems to improve the level of intelligence in business. This paper proposes a service framework based on big data driven prediction, which includes information perception layer, information application layer and big data service layer. In this paper, the composition of big data service layer is described in detail, and a sales predicting method based on neural network is introduced. The salability of products is divided, and the qualitative economic production volume mechanism is finally given. Based on the framework, an intelligent service system for enterprises with the characteristics of mass production is implemented. Experimental results show that the big data service framework can support chemical enterprises to make decisions to reduce costs, and provides an effective method for Smart Product Service System (PSS).


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*Keywords:* Big data; Smart Product-Service System; Sales predict; Economic batch quantity; production plan;

## 1. Introduction

In recent years, the development of the IoT makes big data collecting in manufacturing has become no longer difficult [1]. The production mode of enterprises is rapidly developing to the multi-variety and small-batch fashion, and has produced customized production activities driven by personalized needs in specific industries or specific links of product production [2], As a result, the big data of manufacturing industry, which is more complex in structure, diverse in type, huge in volume and fast in updating speed, has been identified [3]. How to excavate the economic value hidden under big data has become increasingly urgent for enterprises. In the face of a large amount of historical sales data, how to use big data method to predict product sales volume and guide the economic batch selection and production plan of enterprises have become a key to the success of enterprises.

With the increasing diversity of products, it becomes more meaningful to study the formulation of economic production batch of products. As a typical mode of production, mass production is widely used in industry, for example, paint and food enterprises. Features of mass production include: (1) high flexible machines, mostly fixed capacity machines; (2) multiple varieties and small batch customer orders; (3) semi-continuous production process. When making production plans, many enterprises do not have big data to support the process of making production plans, and only rely on the experience of managers to decide the production tasks. This method of abandoning sales predict will have the following disadvantages: (1) the artificially assigned production plan is too subjective,

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which may easily lead to disastrous consequences such as capital occupation and inventory overstock, or increase the cost of delay; (2) lack of scientific big data analysis methods, managers' decisions lack of foresight, and it is difficult to support the long-term development of enterprises. This paper thus takes the typical chemical enterprises as the research background to investigate the production decision-making. The big data method is used to predict the salability of products and economic batch selection. A neural network method is introduced to predict the sales volume, a hierarchical method of product salability and a qualitative economic batch selection mechanism are provided for production planning faced by chemical enterprises.

## 2. Literature Review

In this paper, the relevant literature was reviewed from the perspective of economic batch problem and the application of big data in manufacturing industry.

In terms of economic batch quantity problem, Lu et al. [4] studied the economic production quantity model considering equipment failure, and solved the optimal equipment inspection strategy while obtaining the economic production quantity. Lu et al. [5] studied the mass production plan of steel rolling under various flexible conditions and established the hybrid nonlinear programming model for flexible optimization. Nobil et al. [6] proposed a multi-machine multi-product economic batch quantity problem for an imperfect manufacturing system, and proposed a hybrid genetic algorithm to solve the model. However, few scholars have studied the application of big data to solve the economic batch quantity problem.

Big data is an emerging field, referring to a set of large and complex data sets that are difficult to process with existing tools or traditional data processing programs. Researchers generally believe that big data modeling, including monitoring and prediction optimization and risk control, plays a crucial role in the development of manufacturing industry. In recent years, with the wide use of the IoT and Internet access digital products, big data has been integrated into our daily life [7]. The manufacturing industry also faces the problem of being swallowed up by big data due to the introduction of sensor electronic equipment and digital machines into production lines, workshops and factories [8]. Hence the enthusiasm for big data in manufacturing, Zhong, et al. [9] proposed challenges and opportunities faced before and prospects for the future by introducing big data processing technology and big data decision model. Although manufacturing industry is loaded with massive data, compared with financial, IT and other fields, the research and application of big data in manufacturing industry is still in the primary stage [10].

The limitation of the above research lies in that few scholars have studied how to use big data to solve the economic production quantity problem. In the economy production quantity model, more attention is paid to inventory capacity and equipment status, ignoring the importance of product salability for economy batch selection. Therefore, based on the existing research, this paper discusses how to use big data sales predict to guide the economic batch selection and production planning of chemical production process.

## 3. Problem description

### 3.1. Production planning processes in chemical enterprises

The information source for chemical production enterprises to make production plans mainly comes from sales orders received by customer service as follows. First of all, customer service get all orders, according to the product type of order split and merge, and based on personal experience to judge the popularity of products. Then combined with limited inventory, the capacity of production equipment in the workshop was linked; finally, based on the above information, the production planning decision is made. The production planning process is shown in Fig.1.

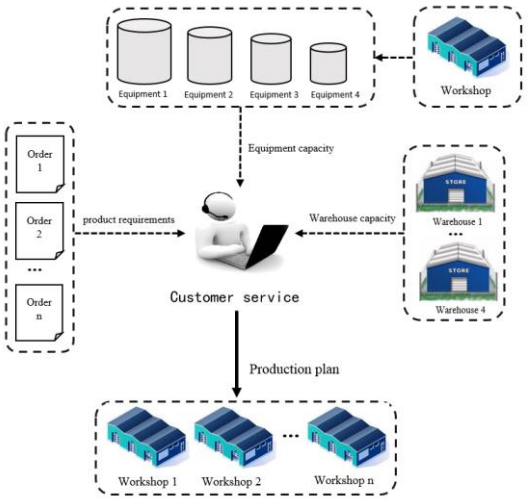


Fig.1. Chemical enterprises formulate production planning process

### 3.2. Problem identification

Through the analysis of the above operation process, it can be seen that the production equipment capacity of chemical enterprises is mostly fixed, but the demand of each product is dynamic. So there is a great risk of decision-making based on past experiences manually. The traditional model only considers the production batch formulation of a single product, but in the actual production processes, product demand are different. At the same time, in a batch production process, when the production batch is large, the equipment adjustment cost can be saved, but at this time the WIP inventory will increase, so the WIP cost increases correspondingly, and causes the capital occupation and other hazards. On the contrary, the production volume hours, although the cost of work in process is low, but at this time the cost of equipment adjustment will increase. Because of the lack of goods caused by the loss of orders delayed delivery staff overtime, and even caused the loss of corporate reputation and other problems, it is necessary to study how to determine the batch size of multi-product economic production. This paper presents a method to predict the trend of product sales and to formulate economic production batch based on inventory status. Some problems are identified as follows:

- **Existing chemical enterprise production system and big data method have a low degree of integration:**

chemical enterprises have gradually acquired big data with '4V' characteristics, but have not formed a complete set of information architecture. The integration degree of big data method and existing production system of chemical enterprises is not high. And the interaction degree between data knowledge and decision-making in each information transmission link is low.

- **Existing methods cannot support the decision-making of production planners:** the classical EPQ (Economic Production Quantity) model could not take into account the influence of product saleability. But the big data approach can help people make decisions, this method can predict the future product saleability, by taking this factor as the model input, obtains the model output, helps the policy-maker to make the correct decision.

## 4. Proposed methodology

### *4.1. Architecture based on big data service*

The architecture of the proposed approach is shown in Fig.2 :

- **Information perception layer:** this layer can collect, transmit and process the information in the operation of manufacturing equipment and system, including the information generated in the operation of products and manufacturing equipment and manufacturing software in the acquisition system, and conduct unified integration and preprocessing of the collected information. This layer provides complete data for information application layer and big data service layer.
- **Information application layer:** this layer acquires all kinds of signals transmitted by the information perception layer and provides information services for applications including system configuration process scheduling load control. This layer is the decision control center in the architecture, where a large amount of data needs to be transferred to the big data service layer for processing.
- **Big data service layer:** this layer is a key support to promote production system running, and its main function is integrate multi-time, multi-dimensional industrial Internet information, multi-dimensional data visualization based on real-time, multi-dimensional information intelligent decision-making services, such as detected fault, predict the outcome, optimized decision, prevent risks and so on, to provide data for intelligent decision making and knowledge.

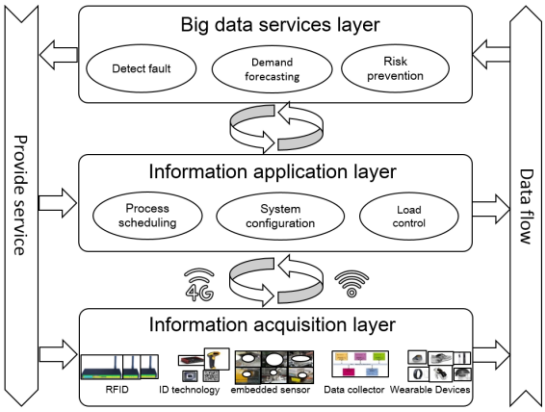


Fig.2. Architecture based on big data service

### *4.2. Sales predict method*

#### *4.21. Data processing*

The core of the big data service layer is to build a data warehouse [11], which is a strategic set providing all types of data support for the formulation process at all levels of an enterprise. Data processing process includes: determining the direction of enterprise decision-making, integration can fully describe the data involved in the analysis object and the correlation; the extracted data are processed through cleaning, compression, feature selection and other data processing operations. The organized data warehouse can be used to provide data visualization, sales predict, fault analysis and so on, and the data processing process is shown in Fig.3.

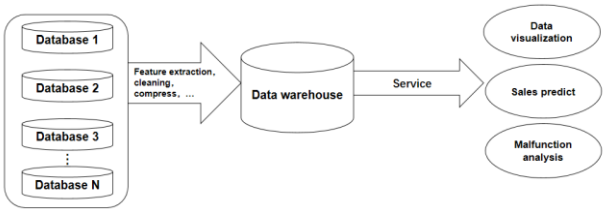


Fig.3. Data processing flow chart

#### *4.22. Product salability predict*

- *Neural network prediction method*

Artificial neural network is a dynamic system with a directed graph topology established manually, which makes state response to continuous or intermittent input [12]. Neural network analysis is a nonparametric estimation method, which constitutes the interpretation scheme that can best fit the historical data of the analysis target, its characteristics are: can be fully approximate arbitrary complex nonlinear relations; all the quantitative or qualitative information is stored in the neurons of the network with equal potential distribution, which has strong robustness and fault tolerance. Moreover, parallel partial processing method can be adopted, and rapid operation can be carried out under the condition of big data. As shown in Fig.4, it is a three-layer neural network structure schematic diagram, including input layer hidden layer and output layer.

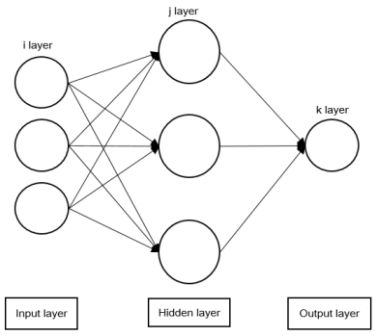


Fig.4. Schematic diagram of neural network structure

- *Product salability stratified processing method*

First, build a statistical table of product sales, as shown in table 1, then the product sales predict results for all categories are read from their respective storage nodes and grouped by the field name 'Production_ID', 'OrderDate'. Ultimately corresponding to the field name 'MonthQuantity' in Table 1, the predicted monthly sales are sorted by the numerical size.

Table 1. Statistical table structure

| Production_ID | OrderDate | DayQuantity | MonthQuantity | Salability |
|---|---|---|---|---|

As shown in Fig.5, according to the sorted monthly sales volume, the saleability was divided into 4 grades, which were marked as 'Extremely unpopular', 'Unpopular', and 'Popular', 'Extremely popular'. The higher the marked grade was, the higher the salability of the corresponding product was [13], and the results were recorded in the 'Salability' in Table 1.

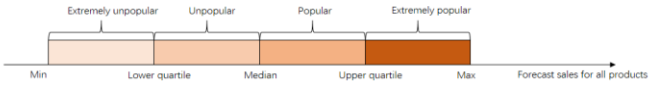


Fig. 5 Hierarchical diagram of product salability

- *Qualitative economic production volume mechanism*

According to the prediction method of product salability in the previous section, the product has the characteristics of salability. The salability of products has a deep impact on the production plan, which largely determines the long-term planning and short-term planning of the enterprise, prevents the overstock and out of stock, and ensures the balance between sales in the production management process. Therefore, according to the future salability of the product and the existing inventory of the product, this paper sets up a qualitative economic batch quantity selection mechanism, as shown in Fig.6.

(1) The product through the predictions in the extremely popular/ popular phase, it indicates that the future market demand is huge, and it is preferred to use large-capacity equipment for full-load production. In a short time, the surplus finished products will not cause inventory overstock because of its high salability, and the overall inventory cost is lower than the equipment adjustment cost, so we can do more inventory to reduce the delay cost.

(2) The product is in the stage of extremely unpopular/ unpopular, then, the production plan of the product is more dependent on the size of the inventory at this time. If the inventory is relatively large, a quantitative production plan (quantity demanded - inventory) is developed to reduce the capital and inventory occupation of the product.

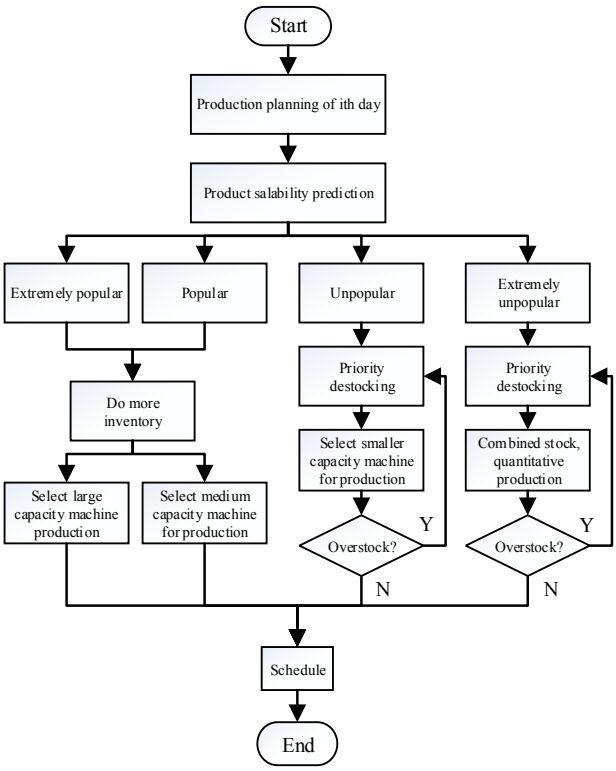


Fig.6. Economic batch quantity selection mechanism

## 5. An illustrative example

The research of this paper comes from a fine chemical enterprise. The enterprise is equipped with production equipment with capacity of 1T, 3T, 5T, 8T, 13T and so on, produces 5,032 kinds of chemical products and creates millions of pieces of sales data every year. This paper uses historical sales data to predict the salability of products to guide enterprises to select economic batches and make production plans.

### *5.1. Product salability predict*

In this paper, the data source from the CRM and ERP system of this enterprise, which can obtain the sales and related data of all product categories of the enterprise in the past ten years. Each product has a unique ID (Production_ID) in the corresponding database, and the product ID can be used to correlate historical sales data for that product. Firstly, the data set is preprocessed to remove the dirty data with outliers, duplicates, or missing values. Finally, more than 1000 sales records were sorted out as research data. According to the

collected data set and the neural network prediction method [14], the sales volume of product A in July is predicted to be 379613Kg, and the actual order quantity is 381070Kg, with an error of 0.38%, as shown in Fig.7. Then, the monthly sales volume of all the products of this enterprise in the future is predicted and saved in Table 1.

As shown in Table 2, according to the division of product salability, the monthly sales volume of product A will be above the upper quartile of the monthly sales volume of all products, which means it will be extremely popular in the next month.

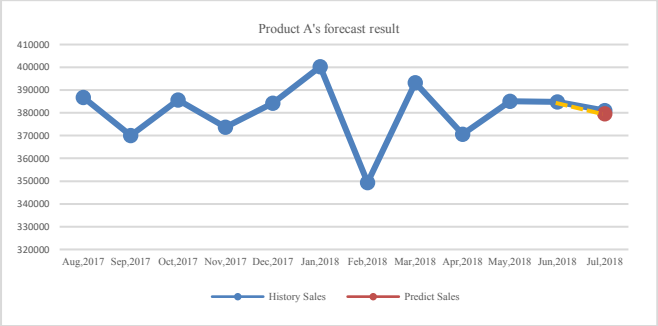


Fig.7. Monthly sales predict chart of product A

Table 2. Products monthly sales predict statistical table

| Statistic | Value | Measurement unit |
|---|---|---|
| Min | 62451 | Kg |
| Lower quartile | 128364 | Kg |
| Median | 241975 | Kg |
| Upper quartile | 334587 | Kg |
| Max | 413640 | Kg |

### *5.2. Economic batch selection and production planning*

According to the qualitative economic production volume mechanism of this paper, the production plan of product A should give priority to the use of 13T large-capacity equipment, so as to meet customer demand and reduce production cost. The result is shown in Table 3.

Table 3. Product A production planning

| Product_ name | Order_quantity | Equipment_capacity | Production _date | Delivery_ date | Inventory | Unit |
|---|---|---|---|---|---|---|
| A | 10.3 | 13 | 2018.7.1 | 2018.7.3 | 1.3 | T |

## 6. Conclusion

In this paper, based on the economic batch of chemical enterprises, the production plan is considered as the background to study the application of production data in complex environment. By building a set of production system based on big data prediction service information architecture, this paper provides a neural network prediction model, product salability division method and the qualitative economic batch quantity select mechanism to guide chemical enterprises in production decision-making.

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