A novel method of material demand forecasting for power supply chains in industrial applications

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Abstract
Based on research on big data, data mining and other relevant technical theories, a power material demand analysis system is designed and implemented based on big data technology. The main aim of the study is to forecast material demand and provide data support for decision-makers. The system includes a data centre subsystem and an application subsystem. At the same time, two kinds of collaborative transmission process models of supply chain information are established, and simulation analysis is carried out on the two models by the Monte Carlo method to verify the effect of collaborative transmission of information flow in supply chains within big data environments. The major contribution of the work is the design of a supply chain model with the help of big data. The impacts of the Internet of Things with empirical studies and limited models are the focuses of the study. It can be seen from the simulation results that there will be a minimum $R$ to minimise the cost $C$ under the two supply chain information-transfer process models. The manufacturing cost of the big data platform is about 50% lower than that of the traditional supply chain, and increased delay costs accordingly lead to increased costs for manufacturers in both supply chains.

1 | INTRODUCTION

Electric power enterprises are the basic pillar of industry and national economies. The healthy development of electric power is a premise of the healthy development of national economies [1]. With the development of science and technology, air-conditioners, smartphones, computers and other devices that use electricity can be seen everywhere around us. Electricity has a great influence on people’s lifestyles, and many things are hard to imagine without electricity. Therefore, demand for electricity continues to increase year over year [2]. During the 13th five-year plan period, it has been necessary to forge ahead towards the goal of building a moderately prosperous society in every respect. The realization of this goal cannot be achieved without the support of electricity. It is predicted that power demand will continue to grow; therefore, it is necessary to speed up construction of distribution networks. In 2015, the National Energy Administration (NEA) issued an action plan on power distribution network construction and reconstruction. This plan pointed out that investment in power distribution network should be accelerated. Investment in power distribution network construction and reconstruction during the 13th five-year plan period should be at least 1.7 trillion yuan [3].

Power supply is the basic guarantee in the process of power grid construction. In recent years, with rapid growth in the scale of China’s power grid construction, the importance of material management in detailed enterprise operations is becoming increasingly significant. Since 2009, power enterprises have continuously deepened their degrees of material management. Material management has changed from the original loose and extensive single procurement mode to a centralised and lean supply chain management mode, and an efficient material management system has gradually taken shape [4]. Material demand management of electric power enterprises is an important ability that is growing and gaining importance. Big challenges faced by the provincial power companies are to project material demand accurately in order to accurately secure power supply. Demand forecasting is the key to solve this problem and also help reduce inventory backlogs [5].

At present, the material demand management of provincial power companies mainly comes from the demand planning of
grass-roots units in various cities. This depends on the work experience of the programme manager. In making a statistical forecast, the head of each supply department makes an estimate of material demand for the next quarter or year in the area in which he/she is responsible, and then the demand estimates are combined and summarised to make a forecast of the company's material demand for the next quarter or year. However, this method is vulnerable to individual subjective factors, and even when a few very experienced persons can make a more accurate estimate of the material needs of their area of responsibility, this method cannot be effectively transplanted to other areas.

Under the trend of data fusion in the existing system by the Internet of Everything (IBM minicomputers, EMC storage devices, Oracle databases), the limitation of system architecture is unable to complete distributed data fusion and analyse demand using huge amounts of data. Therefore, power grid enterprises must embrace the development opportunity of the era of big data. Big data machine learning tools have been sufficiently able to provide the scientific theory for material demand forecasting and planning in power grids [6]. Material demand forecasting is an important tool to improve power grid operating capacity. Accurate and reasonable material demand forecast results can lay a good foundation for material procurement, effectively improve forward-looking enterprise material management, and create favourable conditions for the enterprise to coordinate resources in advance. Therefore, on the basis of full import data, this paper regularly imports the newly added data into HDFS (incremental import) to keep the data in sync with the database and USES the combination of HDFS and MySQL to realize the storage of power supply data so as to improve reliability, data storage capacity and data processing speed. At the same time, the system provides a cron expression parser for the user according to the prompt of a different time field ‘fool type’ tick configuration. The process of data analysis of each link into a job, a power supply demand analysis system for maintaining data collection, analytics and other operations are composed of the task pool. Finally, the practicability of the big data system model is verified by comparing the minimum cost curve of the big data system and the traditional supply chain under different delay costs.

Continuing, Section 2 represents current research trends in the power supply chain. In Section 3, we present the research method with the proposed design of the system. In Section 4, we present the testing and simulation process of the proposed model. Finally, Section 5 concludes with a discussion of various aspects of the completed research.

2 | LITERATURE REVIEW

Demand forecasting is very important for supply chain management material planning. Existing domestic and foreign research has presented many theories and methods for material forecasting. Sheinbaum-Pardo, C. [7] has proposed a model based on historical demand data using a linear regression model, a moving average method and an exponential smoothing method. Using these models, mean square error has been calculated to measure prediction accuracy, taking the prediction result with the least mean square error in each model as the final demand prediction. Yongjie, Q. I. [8] constructed a test model based on similarity analysis coefficient to test and predict, on the basis of a linear regression model, the material delivery data of a power system. Xie, Y. [9] has applied the least square linear regression analysis to develop the material plan of the Urumqi railway bureau by improving the efficiency of demand plan management. However, the aforementioned literature only studies demand management of the supply chain and does not mention much about collaborative transmission of supply chain information.

Big data is a collection of data large enough to be complex in storage management and analysis. Also, this big volume of data is far beyond the processing range of traditional technologies and software tools. The characteristics of rapid growth, a variety of data types and low value density are known as the ‘4 v’. To keep up with the trend of global big data technology development, science in China is also highly concerned about the field of big data for all walks of life. Since 2012, domestic Internet operators have taken the lead in launching the research, development and applications of big data technology—these include Sina, TaoBao, Baidu, China mobile, China Unicom and jdCities and other enterprises to promote the applications of big data. Alibaba group's ‘Rubik's cube of TaoBao data’ platform analyzes and mines massive transactional records and commodity browsing records to realize commodities. The intelligent recommendation greatly enhances the shopping experience of buyers. In the aspect of nonlinear prediction, authors applied support vector machine algorithm to the material demand prediction of the power industry and transformed the demand prediction into a classification problem, providing the basis for the audit of material purchase data quantity and types. Song bin analysed the demand characteristics of power grid materials and used the network algorithm of BP goods to predict materials demand. In recent years, natural disasters have occurred frequently around the world, and the prediction of emergency power supply has become a hot topic. With the Hanchuan earthquake as the background, the authors conducted demand predictions of disaster emergency supplies based on the normalized European algorithm. Chourasia, S. [10] constructed a supply chain competition model in which manufacturers, retailers and third-party logistics participate in competition in the context of big data, and introduced the key variable of private information acquisition cost. Through the analysis of the model, it is concluded that supply chain stability is related to the leakage of private information, and the profit of competitors depends on the cost of information acquisition. Recent changes to China's energy policymaking gadget are the latest in a series of recognized modifications intended at refining energy governance. In March 2008, the NPC permitted two new embellishments, the National Energy Commission and NEA [11,12].

Researching the field of material forecasting at home, abroad, and in the field of research on big data technology, this paper discusses the importance and significance of power
supply demand forecasting. Also, this paper points out the deficiencies of existing methods and finds research gaps using literature on data fusion and big data management of power supply demand. With the help of the task scheduling management, automation of the data analysis process is realized. Users only need a small amount of configuration, and the system can run automatically and periodically according to the configuration. The analysis concludes that the government should adopt different strategies to regulate the competitive relationship among the member enterprises of the supply chain when guiding and supervising competition between the public product and free competition markets.

3 | RESEARCH METHODS

3.1 | Design of power material demand analysis system

The power supply demand analysis system studied in this paper is based on Hadoop [13]. The architecture design of the system adopts the idea of layering. The power material demand analysis system mainly includes data acquisition, data storage, data analysis, task scheduling and application layers. By adopting a pluggable modular design, users can independently use the functions of each layer and interact with each module in the form of an interface.

3.1.1 | Data acquisition (migration) layer design

The data of the power material demand analysis system mainly come from the relational database distributed in provinces and cities. The data acquisition module should realize the two-way data migration between HDFS (Hadoop distributed file system) and relational databases (including Oracle, SQL Server, MySQL etc.). Automatic data acquisition and processing can be carried out according to task configuration [14,15].

The data collection work is divided into two types, and the system just launched needs all the historical data in the database as a one-time import into HDFS (full amount import), after system online, because of the large amount of source data, the use of the full import quantity each time to update the data both in time and efficiency is not feasible, so we are going forward on the basis of the full amount of import on a regular basis to import new data into the HDFS (incremental import). In this way, the data of the data warehouse can be synchronized with the database, which also reflects the time-varying characteristics of the data warehouse [16]. Figure 1 is a flow chart of Sqoop-imported data.

The power material demand analysis system provides the user with a configurable data acquisition function. The acquisition layer architecture is completed by the acquisition task analysis engine in collaboration with the task configuration. The user needs to pre-configure information about the data source and schedule time information. First, the acquisition task parsing engine is responsible for parsing and reading the basic information of the data source configured by the user, generating the task that can be scheduled, putting the task into the task pool and waiting to be scheduled. Then, the task scheduling engine determines whether the data collection task needs to be performed at the current time point according to the task time configuration of the user. Due to the large amount of data collected, the execution time of data collection task should be reasonably planned according to the hardware performance and use time of the source database server, and the peak period should be staggered as far as possible to avoid substantial performance degradation of the system using the data source in the process of data collection.

The purpose of the data acquisition is to enable the data analysis layer of the power material demand analysis system to use data other than the HDFS as the data source. In today's software systems, valuable data is stored in relational databases, and our power supply data is no exception, so we need a tool to collect (migrate) it from relational databases to HDFS. It is important to note that the data collection work is to be divided into two types, the system has just launched, and all historical data in the database is a one-time import into HDFS (full amount import), after system online, because of the large amount of source data, so a full import quantity each time to update the data both in time and efficiency is not feasible, so on the basis of the full amount of import, we regularly add new data into the HDFS (incremental import). In this way, the data in the data warehouse can be kept in sync with the database, which also reflects the time-varying characteristics of the data warehouse.

3.1.2 | Data storage layer design

This system uses a combination of HDFS and MySQL to achieve electric power supply data storage, so it can make full use of HDFS with high reliability, high scalability of data storage capacity and at the same time use Map Reduce for efficient data processing. This can leverage the advantage of the relational database to add and delete data, and quickly show multidimensional results over a period of time for supplied data and predicted results [17]. HDFS is responsible for storing the original data of power supply and the files processed by Map Reduce at the analysis layer. For the analysis layer, with the passage of time, the rapid development of the state grid, and the demand for data fusion of various networks and provincial companies, data storage capacity cannot be borne by a single file system, so a distributed file system with high expansion and high availability must be adopted for storage [18,19]. HDFS arises at a historic moment in the face of the need for mass data storage. In addition, HDFS for hardware demand is low, it can run on cheap commercial servers or even personal computers, and data uploaded to the HDFS system will be in the Name under the control of the Node to store different data Node, to avoid the single-point-of-failure problem of storage systems with increased amounts of data that HDFS can easily scale. Therefore, HDFS is suitable as the storage solution for the power supply demand analysis system.
MySQL is used to build the application subsystem of the material demand analysis system. The data generated by the analysis layer are located on HDFS, and these result data will be imported into MySQL periodically for use by the application layer. Similar to the data migration layer, we can do secondary development on the basis of Sqoop to realize the migration of HDFS data to the MySQL database [20].

3.1.3 Data analysis layer design

The data analysis layer is responsible for data analysis and mining, and the mining results are used by the application layer. Data mining is the process of discovering hidden value from large amounts of data stored in databases, data warehouses, or other sources. Power supply data was obtained from the acquisition layer have duplicate records, do not have a unified format, cannot be directly used; the data are mined to collect electricity supply data before preprocessing, making it ‘clean, reliable data’. Data quality directly affects the accuracy of the data mining results.

Data analysis and prediction is the core module of power material demand analysis system. This paper introduces the design and implementation of the data analysis and prediction algorithm as a separate chapter. The fifth chapter introduces the selection and design of the prediction algorithm in detail and its implementation using R language. R is a data analysis language, as well as an open source free software, mainly used for statistical analysis and an excellent tool for data analysis and mining [21]. In the release of the project, using R to implement data statistics, the mining algorithm is implemented, and R provides an executable R Script file. Exe is used to run R script, so it can be invoked by writing Java code RScript. Exe to perform R script in this way allows the R materials forecast algorithm to be integrated into material demand analysis [22].

3.2 Quantitative model of information flow collaborative control of the supply chain

Taking the total cost of supply chain as the objective function, this paper analyzes the synergy effect of information flow mechanism of supply chain under the big data environment.

Suppose that in a supply network, there are two downstream suppliers in the core enterprise to provide materials, and the two raw materials can be produced after they arrive at the same time. The production input ratio is 1:1:1. In the traditional supply chain, the total cost of the core enterprise includes delay costs, out of stock costs, holding costs of two kinds of raw materials, residual inventory costs of two kinds of raw materials, and production costs. The holding costs of two raw materials refers to the fact that the information cannot be shared and the information flow between suppliers is not...
transparent, resulting in the delivery of raw materials from the two suppliers. The surplus inventory costs of the two raw materials are caused by asymmetric information. In order to avoid the risk of material shortage from the supplier, the manufacturer orders more than the actual demand [23,24]. Suppliers can supply in the same quantity at the same time without carrying cost of a particular raw material. The surplus material inventory cost, with combined information and transparency of the two suppliers' supplies the material. The supplier that supplies vendor's supply in the same amount as the core enterprise supply, is equivalent to the sum of two kinds of raw materials. The raw material comprises of unit holding costs and products of the remnant material [25].

Symbols in the model are described as follows:

\[ R_1, R_2 \] Manufacturer's actual demand and order quantity
\[ S_1, S_2 \] Actual supply from the two suppliers
\[ t_1, t_2 \] Supplier delays in delivery time
\[ c_1, c_2 \] Unit carrying costs of the two materials
\[ a_1, a_2 \] Unit price of the two materials
\[ n \] Unit cost of delay in construction by the manufacturer
\[ P \] Fixed production costs
\[ C \] Total manufacturer cost

Therefore, the total cost of core enterprises in the traditional supply chain is

\[
C_1 = n \cdot \max(t_1 + t_2) + n[R_1 - \min(S_1 - S_2)] + [t_1 - t_2] \cdot (c_1S_1 + c_2S_2) + c_1[S_1 - \min(S_1, S_2, R_1)] + c_2[S_2 - \min(S_1, S_2, R_1)] + R_1(a_1 + a_2) + p
\]  \( (1) \)

The total cost of core enterprises in the supply chain under the big data platform is

\[
C_1 = n \cdot \max(t_1 + t_2) + n[R_1 - \min(S_1 - S_2)] + (c_1 + c_2)[\min(S_1, S_2) - R_1] + R_1(a_1 + a_2) + p
\]  \( (2) \)

4 | SYSTEM TEST AND SIMULATION ANALYSIS

4.1 | Power material demand analysis system test

The data analysis module periodically performs time-consuming offline analysis and prediction, and the data prediction module is responsible for presenting the prediction results in a friendly manner. First, various constraints are selected. If the project unit chooses Liaoning province, the data source analysed will be the summary of material demand data of various cities in Liaoning province. Material categories can be selected as key material categories such as steel core aluminium strand, transformer, iron tower and combined electrical appliances. Time granularity can be summarised on a monthly or annual basis. You can select the voltage level and summarise the data source for the voltage level for that data source. A condition must be selected for each drop-down selection box. After all conditions are selected, click on query, and then the system reads out the offline analysis results which meets the selected conditions. The system requirements are imported from MySQL database, and display them in the form of line graph, as shown in Figure 2. When the prediction results are presented, the average relative error rate is given to measure the prediction accuracy for the reference of users. The results are acceptable for the average relative error rate which is less than 10%. If the average relative error rate of prediction results is less than 10%, and the prediction results have a large deviation from the inventory, the email or SMS interface of the calling system will send out a warning to relevant personnel that a standard has been exceeded.

In this paper, each link in the process of data analysis is abstracted into a job. The power material demand analysis system maintains a task pool composed of multiple jobs such as data collection and analysis. Most of these tasks are offline and run in the background without interaction with users.

The system provides a cron expression parser, and users can automatically generate corresponding cron expressions in real time by checking ‘tool’ configuration according to the prompts of different time fields, which reduces the difficulty of starting the system and shortens the time for users to accept the system.

![Figure 2](image-url) Query of forecast results of material demand
4.2 Example analysis of supply chain cooperation model

Make \( n = 1, r = 50, m = 10, s = 5.17, k = 8.0 \), BG went from 12.5 to 37.5, let's think about what happens to \( \alpha \) and \( \beta \). When market demand is stable and the technical level and use cost of big data service providers remain certain, the price \( G_B \) of raw materials purchased by suppliers will have a certain impact on the big data cost shared by suppliers and manufacturers and the total profit of the supply chain, as shown in Table 1.

By analysing the changes of big data cost sharing coefficient of suppliers and manufacturers, as shown in Figure 3, when making decentralised decisions, as the price of raw materials purchased by suppliers increases, the cost of big data borne by suppliers decreases gradually, while the cost of big data borne by manufacturers increases gradually, the price of raw materials when suppliers purchase them \( G_B \in (17.5, 22.5) \) between big data cost sharing coefficients of suppliers and manufacturers will reach a balance and achieve synergy. In order to ensure their own profits, suppliers will choose to bear a small amount of big data technology costs. At this point, if suppliers and manufacturers cannot agree on the way to allocate the cost of big data, the supply chain can seek appropriate raw material prices to enable suppliers and manufacturers to share the cost of using big data technology equally.

Through the analysis of the change of total profit of the supply chain, as shown in Figure 4, the total profit of the supply chain shows a decreasing trend as the price of raw materials purchased by supplier's increases. The \( R^2 \) value of the fitting curve of the total profit change of the supply chain is close to 1, indicating that the change trend is highly reliable. Therefore, when considering the investment in big data technology, the supply chain should consider the total cost of the supply chain. Blind investment in big data technology will erode the profit of the supply chain, making it difficult to achieve supply chain coordination.

4.3 Simulation analysis of information flow coordination in supply chain

Suppose \( t_1 \) and \( t_2 \) obey uniform distribution \( U(0, 0.4) \); \( a_1 \) and \( a_2 \) follow uniform distribution \( U(0, 0.5) \). \( S_1 \) and \( S_2 \) are uniformly distributed \( U(0.6, 1) \). Make \( c_1 = 20, c_2 = 35, R_1 = 1500, n \) has a step size of 20, between 100 and 200, generate 1000 groups of random variables of \( t_1, t_2, a_1, a_2, S_1 \) and \( S_2 \), and conduct simulation by MATLAB to obtain the relationship between the total cost \( C \) of core enterprises and their actual demand \( R_1 \) in the information flow transfer process models of two supply chains. The simulation results are shown in Figure 5 and Figure 6.

Based on the simulation results, two groups of data are analysed to obtain the minimum cost curves of the two supply chains under different delay costs, as shown in Figure 7.

It can be seen from the simulation results that there will be a minimum \( R \) to minimise the cost \( C \) under the two supply chain information transfer process models. The manufacturing cost of big data platform is about 50% lower than that of traditional supply chain, and with the increase of delay cost, the cost of manufacturers in both supply chains will increase accordingly.

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**TABLE 1** Numerical analysis of supply chain cooperation model

| \( G_B \) | \( Q \) | \( T \) | \( P \) | \( \Phi \) | \( A \) | \( \beta \) |
|---|---|---|---|---|---|---|
| 12.5 | 10.8 | 30 | 5 | -9.3025 | 0.414 | 0.586 |
| 17.5 | 10.8 | 35 | 0 | -42.9025 | 0.464 | 0.536 |
| 22.5 | 10.8 | 40 | -5 | -101.0025 | 0.514 | 0.486 |
| 27.5 | 10.8 | 45 | -10 | -183.6025 | 0.564 | 0.436 |
| 32.5 | 10.8 | 50 | -15 | -290.7025 | 0.614 | 0.386 |
| 37.5 | 10.8 | 55 | -20 | -422.3025 | 0.664 | 0.336 |

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**FIGURE 3** Variation of cost sharing coefficient of big data

**FIGURE 4** Total profit trend of supply chain
this paper establishes the cost allocation equation and conducts simulation analysis on the model based on numerical analysis and the Monte Carlo method. In terms of research content, the main conclusions are as follows:

(1) The design of the data centre subsystem is a blend of big data technology using the Hadoop-distributed file system and provides a transparent, reliable, scalable data storage capacity, that lays a solid foundation for analysing huge amounts of data. It then uses the graph programming model for efficiently preprocessing huge amounts of data, and with the help of Hive data warehouse tools to simplify the difficulty of program development.

(2) The subsystem of the data centre is designed according to the idea of stratification. According to the different links of data processing, it can be divided into data acquisition, data storage, data preprocessing and analysis layers. In addition, a task scheduling management layer is specially designed. With the help of task scheduling management, automation of the data analysis process is realized.

(3) In terms of tactical coordination, no matter which party bears the use costs of big data technology, suppliers and manufacturers make decisions together and choose a reasonable cost allocation and benefit distribution mechanism that is conducive to the stability of supply chain operation and the realization of coordination at the tactical level.

The study found that at present, relevant studies mainly rely on qualitative research methods to analyse the management problems of big data in the supply chain and lack corresponding quantitative analysis and empirical research. This paper adopts the research method of ‘qualitative and quantitative’ to elaborate the coordination problem of big data system. However, in the research process, this paper takes a two-level supply chain as an example, which has certain limitations. Based on contract theory, the coordination problem of a multi-stage supply chain may be considered for future directions. The
real-time regulation methods of uncoordinated problems in the supply chain and system dynamics of big data may also be analysed in future work.

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