Predictive analytical model for spare parts inventory replenishment

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Abstract — **In today's volatile and turbulent business environment, supply chains face great challenges when making supply and demand decisions. Making optimal inventory replenishment decision became critical for successful supply chain management. Existing traditional inventory management approaches showed as inadequate for these tasks. Current business environment requires new methods that incorporate more intelligent technologies and tools capable to make accurate and reliable predictions. This paper deals with data mining applications for the supply chain inventory management. It describes the use of business intelligence (BI) tools, coupled with a data warehouse to employ data mining technology to provide accurate and up-to-date information for better inventory management decisions and to deliver this information to relevant decision makers in a user-friendly manner. Experiments carried out with the real data set showed very good accuracy of the model which makes it suitable for more informed inventory decision making.**

I. Introduction

The success of many organizations depends on their ability to manage the flow of materials, information, and money into, within, and out of the organization. Such a flow is referred to as a supply chain. Because supply chains may be distributed and complex and may involve many different business partners, there are frequent problems in the operation of the supply chains. These problems may result in delays, in customers' dissatisfaction, in lost sales, and in high expenses of fixing the problems once they occur.

The aim of the integrated supply chain planning and operations management is to combine and evaluate from a systemic perspective the decisions made and the actions undertaken within the various processes which compose the supply chain.

The need to optimize the supply chain, and therefore to have models and computerized tools for medium-term inventory planning and replenishment, is particularly critical in the face of the high complexity of current supply chain systems, which operate in a dynamic, uncertain and truly competitive environment.

It is not enough to know only what happened and what is happening now, but also what will happen in the future and how/why did something happen. Due to the complex interactions occurring between the different components of a supply chain, traditional methods and tools intended to support the inventory management activities seem today inadequate. Thus, predictive analytics and data mining became indispensable and valuable tool for making more intelligent decisions.

On the other hand, predictive models themselves are not enough. Information and knowledge derived from these analytical models needs to be delivered to all parties involved in supply chain inventory management. As a result, collaboration through dedicated web-based workspaces became essential for more efficient and effective coordination and decision making [1].

This paper presents a predictive inventory management approach and describes corresponding data mining models for making out-of-stock prediction of the automotive spare parts. The models are designed on top of the data warehouse which is loaded with sales data from the retail spare parts stores. Model accuracy is demonstrated through testing and evaluation of the results. Finally, the specialized analytical web portal which provides collaborative, personalized and secure analytical services is presented.

II. Background Research

Inventory control is the activity which organizes the availability of items to the customers. It coordinates the purchasing, manufacturing and distribution functions to meet marketing needs.

Inventory management is one of the most important segment of the supply chain management. Companies face the common challenge of ensuring adequate product/item stock levels across a number of inventory points throughout the supply chain. Additionally, uncertainty of demand, lead time and production schedule, and also the demand information distortion known as the *bullwhip effect* [2], makes it even more difficult to plan and manage inventories.

The basis for decision making should be information about customer demand. Demand information directly influence inventory control, production scheduling, and distribution plans of individual companies in the supply chain [3]. Making decision based on local data leads to inaccurate forecasts, excessive inventory, and less capacity utilization.

Generally, determining the adequate stock levels balances the following competing costs:

- Overstocking costs – these include costs for holding the safety stocks, for occupying additional storage space and transportation.
- Costs of lost sales – these are costs when customer wants to buy a product that is not available in that moment.

Commonly, managers have relied on a combination of ERP, supply chain, and other specialized software packages, as well as their intuition to forecast inventory. However, in today's high uncertain environment and large quantities of disparate data demands new approaches for forecasting inventory across the entire chain. Data mining tools can be used to more accurately forecast particular product to the right location.

The best way to deal with these competing costs is to use data mining techniques to ensure that each inventory point (internal warehouse, work-in-process, distribution center, retail store) has the optimal stock levels.

Forecasting and planning for inventory management has received considerable attention from the scientific community over the last 50 years because of its implications for decision making, both at the strategic level of an organization and at the operational level. Many influential contributions have been made in this area, reflecting different perspectives that have evolved in divergent strands of the literature, namely: system dynamics, control theory and forecasting theory [4].

A number of research projects have demonstrated that the efficiency of inventory systems does not relate directly to demand forecasting performance, as measured by standard forecasting accuracy measures. When a forecasting method is used as an input to an inventory system, it should therefore always be evaluated with respect to its consequences for stock control through accuracy implications metrics, in addition to its performance on the standard accuracy measures [5].

Chandra and Gabris used simulation modeling to investigate the impact of the forecasting method selection on the bullwhip effect and inventory performance for the most downstream supply chain unit [6]. The study showed that application of autoregressive models compares favorably to other forecasting methods considered according to both the bullwhip effect and inventory performance criteria.

Liang and Huang employed multi-agents to simulate a supply chain [7]. Agents are coordinated to control inventory and minimize the total cost of a SC by sharing information and forecasting knowledge. The demand is forecasted with a genetic algorithm (GA). The results show that total cost decreases and the ordering variation curve becomes smooth.

Spare parts are very common in many industries and forecasting their requirements is an important operational issue. In recent years, there have been advances in forecasting methods for spare parts, demand information sharing strategies and the design of forecast support systems. Boylan and Syntetos give thorough review on these developments and provides avenues for further research are explored [8].

Accurate demand forecasting is of vital importance in inventory management of spare parts in process industries, while the intermittent nature makes demand forecasting for spare parts especially difficult. Hua et al. proposed an approach that provides a mechanism to integrate the demand autocorrelated process and the relationship between explanatory variables and the nonzero demand of spare parts during forecasting occurrences of nonzero demands over lead times [9]. The results show that this method produces more accurate forecasts of lead time demands than do exponential smoothing, Croston's method and Markov bootstrapping method.

Bala proposed an inventory forecasting model which use of purchase driven information instead of customers' demographic profile or other personal data for developing the decision tree for forecasting [10]. The methodology combines neural networks, ARIMA and decision trees.

Dhond et al [11] used neural-network based techniques for the inventory optimization in a medical distribution network which resulted in 50% lower stock levels. Symeonidis et al [12] applied data mining technology in combination with the autonomous agent to forecast the price of the winning bid in a given order.

Even though, forecasting is seen as a crucial segment of effective inventory management and supply, there are no many reports from the industry which demonstrate successful application of the prediction models and solutions. This is especially true when it comes to automotive spare parts supply management that is characterized by high uncertainty of demand and thousands of different parts. Most of the existing research is focused on specific segments of the analytical solutions (i.e. only predictions). Data mining models and analytical cubes are designed in such a way to accommodate specificity of the automotive spare parts management in terms of products, stores, inventory, and time dimensions. Since every prediction model is unique (in terms of products, demand, etc.) and related to specific data set, it is not possible to make concrete comparative analysis. However, the proposed predictive models provide top-level accuracy (even up to 99% in certain cases). Also, in contrast to existing research methods, the approach presented in this paper introduces the complete business intelligence model which combines specialized data warehouse, the two-phase data mining modeling approach, and analytical web portal for information delivery.

III. INVENTORY FORECASTING MODEL

This section describes the business intelligence solution for the real automotive supply chain, which utilizes data warehouse and data mining technology to provide timely information for spare parts inventory management decisions. The presented methodology is designed to provide out-of-stock predictions at the location/product level. For a particular product, data mining model is built that makes out-of-stock predictions for each store in the chain. This approach enables more effective balance between the competing costs related with stocking.

A. Data Warehouse Design

In order to gather data from many distributed sources, we needed to extract, clean, transform and load data into the data warehouse that summarize sales data from 36 retail stores and for more than three thousands of different spare parts. These data are distributed among multiple heterogeneous data sources and in different formats (relational databases, spreadsheets, flat files and web services).

We have used the Unified Dimensional Model (UDM) technology to provide a bridge between the user/developer and the data sources [13]. A UDM is constructed over many physical data sources, allowing us to issue queries against the UDM using one of a variety of client tools and programming technologies. The main advantages are a simpler, more readily understood model of the data, isolation from heterogeneous backend data sources, and improved performance for summary type queries.

The following data sets are used for the out-of-stock predictive modeling:

- Sales data that is aggregated at the store, product (part), and day level. Daily sales are stored for each product that is sold, for each store in the retailer's chain.
- Inventory data that is aggregated at the store, product (part), and day level. This is the number of days that the product has been in stock, for each product, for each day, and for each store.
- Product (part) information such as product code, name, description, price, and product category.
- Store information such as store description, store classification, store division, store region, store district, city, zip code, space capacity, and other store information.

- Date information that maps fact-level date identifiers to appropriate fiscal weeks, months, quarters, and years.

The data warehouse is the basis for all business intelligence applications and particularly for data mining tasks. Data warehouse allows us to define data mining models based on the constructed data warehouse to discover trends and predict outcomes.

B. Data Mining Methodology

In order to increase the quality and accuracy of the forecasts, we have applied a two-phase modeling process. Phase I of the modeling process consists of clustering stores in the supply chain based upon aggregate sales patterns. After store-cluster models have been constructed, in phase II, these clusters are used to more accurately make out-of-stock predictions at the store/product level [14].

The general data mining process is shown in Figure 1. The process begins analyzing the data, choosing the right algorithm in order to build the model. The next step is model training over the sampled data. After that, model is tested, and if satisfactory, the prediction is performed.

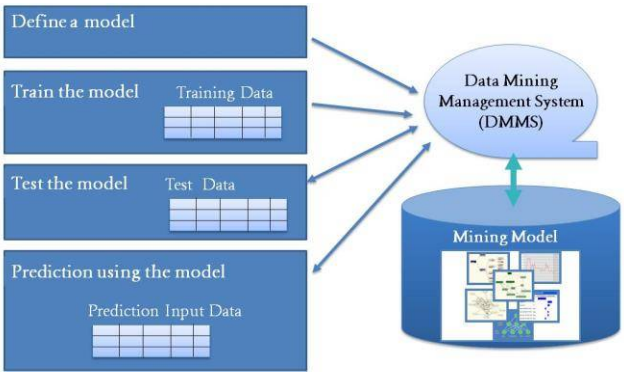


Figure 1. Data mining process

C. Inventory Predictive Modeling Process

Phase I consists of grouping together those stores that have similar aggregate sales patterns across the chain. Store clustering is accomplished by using the data mining Clustering algorithm. Dataset holds aggregate sales patterns and Clustering algorithm groups together stores into clusters. The modeling dataset is based on aggregate sales data that is derived from the data warehouse. The measure that is used to group together stores is computed over this aggregate sales data.

In phase II, cluster models were used to build more accurate out-of-stock forecasting models. This allows predictive algorithms such as Decision Trees and neural Networks to use the results of the clustering process to improve forecasting quality. In essence, to make the predictions for a given spare part p in a given store s, the forecasting algorithms use the fact that the sales for the same spare part p in a similar store s may produce better results when determining whether or not a particular part will be out of stock in a particular store.

Modeling process consists of the following high-level steps:

1. Use the spare part hierarchy in the product information (dimension) portion of the data warehouse to determine the spare part category c(p) for part *p*. We assume that spare parts within the same category have similar aggregate sales patterns across the chain of stores, and the product hierarchy is used to identify the set of similar products c(p) for a given product *p*. Alternatively, a product clustering approach could be used to determine a data-driven grouping of spare parts similar to *p* by clustering parts based upon their sales across the chain of stores.
2. Prepare modeling dataset $D_{cluster}$ for store clustering to capture store-level properties and sales for category c(p).
3. Apply the Clustering algorithm to the dataset $D_{cluster}$ to obtain k clusters (groups) of those stores that are similar across store-level properties and sales for category c(p).
4. For each cluster l = 1,…,k obtained in previous step:
    a. Let S(l) be the set of stores that belong to cluster l. These stores have similar category-level aggregate sales, for the category c(p).
    b. Create a dataset $D_{inventory}$(p,S(l)) consisting of historic and current weekly sales aggregates, and changes in weekly sales aggregates, for each store s in S(l). In addition, include Boolean flags indicating whether or not product p was in stock or out of stock one week into the future and two weeks into the future.
    c. Apply the predictive modeling algorithms (in this case Decision Trees and Neural Networks) to the dataset $D_{inventory}$(p,S(l)). Use the historic and current weekly sales aggregates as input attributes and the one- and two-week out-of-stock Boolean flags as output or predict-only attributes. This instructs data mining engine to generate a model that takes as its input the historic and current weekly sales, along with changes in weekly sales, and then make a prediction of the Boolean flags that indicate whether or not spare part p will be out of stock one and two weeks into the future.

D. Phase I: Store clustering

The goal of store clustering is to obtain groups of stores that have similar sales patterns, focused on sales over the spare parts in the category to which part *p* belongs *c*(*p*). Phase I begins with constructing the dataset that will be used for store clustering.

The dataset used for store clustering consisted of store-level aggregate sales over the time period of four years. Typically, the dataset consists of a single table with the unique key (StoreID) that identifies each item (store in the chain). The creation of this table can be automated by designing the appropriate ETL package. However, we decided to take advantage of the UDM and defined the data source view against it. This way, denormalized data source view is created over normalized set of fact and dimension data and without worrying about underlying data sources.

The store clustering task is to group together stores based upon similarity of aggregate sales patterns. Firstly, we had to identify a set of aggregate sales attributes relevant for this project. Attributes were aggregated over the fact data in the data warehouse. These attributes are category-specific (*total_sale_quantity*, *total_sale_amount*, *quantity_on_order*, *discount_amount*, etc.) and store-specific (*total_sales*, *total_weekly_on_hand*, *total_weekly_on_order*, etc.).

After initial business understanding phase, data cleaning and transformation, data warehouse construction and loading, the next step is clustering mining model construction.

Cases (i.e. stores) within the same group have more or less similar attribute values. The mining structure defines the column structure that will be used to construct the store-clustering model. All attributes are selected as *input* attributes except the *Category_Fraction_Sales* (fraction of total non-discount sales coming from parts in category *c*(*p*) in the given store) and *Category_Total_Sales_Quantity* (total quantity of spare parts in category *c*(*p*) that were sold during the non-discount period) attributes that are selected as *predict*.

Two clustering algorithm parameters were tuned in order to get better outcome. *Cluster_Count* parameter specifies the maximum number of clusters to search for in the source data. In order to produce distinct clusters that sufficiently capture the correlations in store properties and aggregate sales/inventory values, the *Cluster_Count* parameter was altered and tested with different values to obtain desired results. The other parameter *Minimum_Support* instruct clustering algorithm to identify only those clusters that have given value or more cases (stores in our case) in them. After setting the parameters for the Clustering algorithm, the mining structure is processed, thereby creating and populating the mining model. Figure 2 shows store clustering mining structure and algorithm parameters.

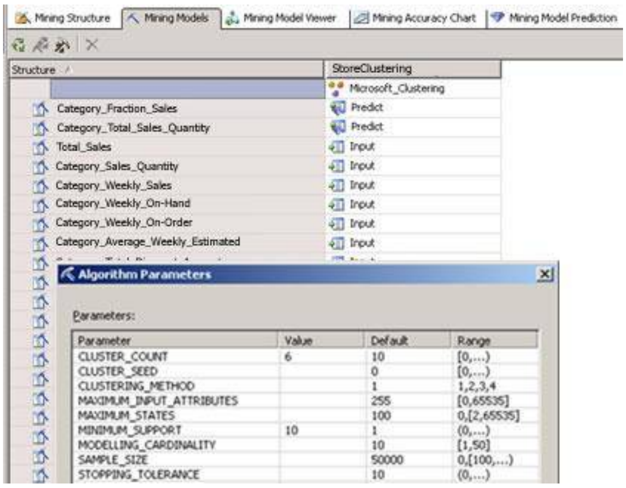


Figure 2. Store-clustering mining structure

In the model-building stage, we build a set of models using different algorithms and parameter settings. After the store-clustering models have been constructed, they are evaluated by using the Cluster Browser to determine if the clusters are distinguished by category sales patterns.

The store clusters tend to be discriminated primarily by the *total_sales*, *category_sales_quantity*, *category_weekly_sales*, *category_weekly_on-hand*, and *on-order* values. Figure 3 shows the derived store clusters shaded with the different density consistent with the population values, and also the link density relationships.

E. Phase II: Inventory predictive modeling

The dataset used for the inventory predictive model task takes into account weekly sales data for a given spare part across all stores in the supply chain. We used a *sliding window* strategy to create the dataset used for predictive modeling. The sliding window strategy typically is a good data preparation strategy when the data has a temporal nature (for example, when predictions are made into the future) and the type of the predictable quantity is discrete (such as Boolean out-of-stock indicators). If there is sufficient temporal data and the predictable quantity is inherently numeric, time-series modeling may be a preferred strategy.

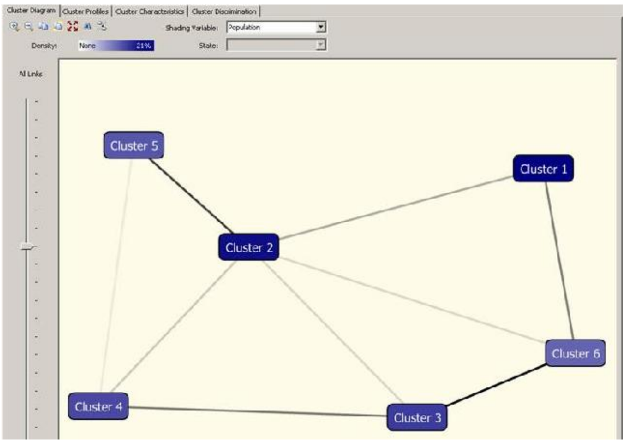


Figure 3. Store clusters

Typically, there are very few out-of-stock events that occur for a single store and single product. To obtain accurate predictive models, the training data needs to include a sufficient number of out-of-stock events and in-stock events to identify trends differentiating the two. The following data preparation strategy was aimed at achieving a sufficient number of out-of-stock events and in-stock events by considering a given product *p* over the entire chain of stores. We included the store cluster label (derived from the store-cluster model) to allow the predictive modeling algorithms to identify trends in out-of-stock behavior that might be different between different store clusters.

For each store *s* in the retail chain a unique key (store/week identifier) is generated. Some of the attributes which describe the entity are: *current_week_on_hand*, *one_weeks_back_on_hand*, *one_week_back_sales*, *current_week_sales*, *cluster_label* (from the store-clustering model), *four_weeks_back_sales*, *five_weeks_back_on_hand*, *two_weeks_back_sales*, *first_week_sales_change*, *one_week_oos_boolean*, *two_week_oos_boolean*, etc.

The data mining algorithms will attempt to identify the pertinent correlations for making accurate predictions. Since the pertinent correlations are not known, we have included all possible attributes in the training dataset. Attributes first/second/third week sales change help to approximate the change in sales week over week. Typically, these types of attributes can be very useful in improving a model's predictive accuracy.

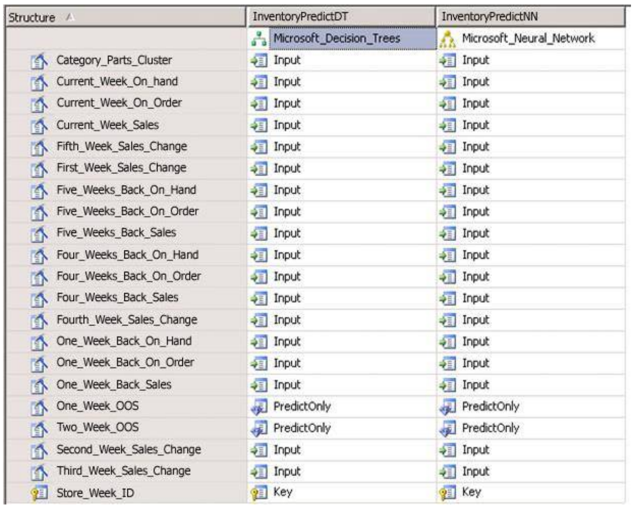
To more objectively evaluate the predictive accuracy of the models, it is common practice to hold out a subset of data and call this the *testing set*. The remainder of the dataset is called the *training dataset.* The data mining models are constructed using the training dataset. Predictions from the model are then compared with the actual values over the testing set.

First a data source is created that specify the database server instance that stores the training and test tables for the spare parts under consideration.

After the data source view is added, a new mining structure is created for the inventory predictive modeling process.

Decision Trees and Neural Network models are built to determine which algorithm produces the most accurate models (as measured by comparing predictions with actual values over the testing set). After an initial mining structure and mining model is built (specifying the input and predictable attributes), other mining models can be added.

In Figure 4 the part of the mining structure and mining algorithms are shown. Input indicates that the attribute value will be used as an input into the predictive model. PredictOnly indicates that these values should be predicted by the data mining model. Key indicates the column that uniquely identifies the case of interest



Structure	InventoryPredictDT	InventoryPredictNN
	Microsoft_Decision_Trees	Microsoft_Neural_Network
Category_Parts_Cluster	Input	Input
Current_Week_On_hand	Input	Input
Current_Week_On_Order	Input	Input
Current_Week_Sales	Input	Input
Fifth_Week_Sales_Change	Input	Input
First_Week_Sales_Change	Input	Input
Five_Weeks_Back_On_Hand	Input	Input
Five_Weeks_Back_On_Order	Input	Input
Five_Weeks_Back_Sales	Input	Input
Four_Weeks_Back_On_Hand	Input	Input
Four_Weeks_Back_On_Order	Input	Input
Four_Weeks_Back_Sales	Input	Input
Fourth_Week_Sales_Change	Input	Input
One_Week_Back_On_Hand	Input	Input
One_Week_Back_On_Order	Input	Input
One_Week_Back_Sales	Input	Input
One_Week_OOS	PredictOnly	PredictOnly
Two_Week_OOS	PredictOnly	PredictOnly
Second_Week_Sales_Change	Input	Input
Third_Week_Sales_Change	Input	Input
Store_Week_ID	Key	Key

Figure 4. Out-of-stock mining structure with mining models

F. *Predictive Modeling Results*

The predictive accuracy of mining models were evaluated by examining them over the testing set. There are a few popular tools to evaluate the quality of a model. The most well-known one is the lift chart. It uses a trained model to predict the values of the testing dataset. Based on the predicted value and probability, it graphically displays the model in a chart. The lift chart compares the predictive performance of the mining model with an ideal model and a random model. Figure 5 shows the lift chart for Boolean two-week out-of-stock predictions for the front bulb spare part. The task is to predict a true/false value as to whether the part will be in stock or out of stock two weeks into the future at any store in the chain. The overall predictive accuracy of this model is close to the ideal model.

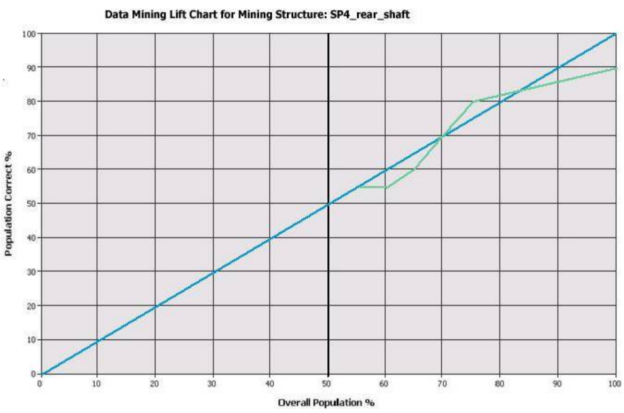


Figure 5. Lift chart for two-week out-of-stock predictions

Table 1 summarizes the predictive accuracies for the five products that were considered in this task. On average, the data mining models can predict whether or not a product will be out of stock one week into the future with 98.52% accuracy. Predictions on whether or not the product will be out of stock two weeks into the future are, on average, 86.45% accurate.

TABLE I.

OUT-OF-STOCK PREDICTIVE ACCURACIES FOR FOUR SPARE PARTS

	Out-of-Stock	
PRODUCT	Week 1	Week 2
Product 1	98.26%	93.31%
Product 2	99.10%	94.12%
Product 3	97.65%	89.48%
Product 4	99.70%	92.93%
AVG ACCURACY	**98.68%**	**92.46%**

Sales opportunity

By using the developed data mining predictive models we can analyze sales opportunities. The method for calculating the lost sales opportunity for each spare part was computed by multiplying the number of out-of-stock total store weeks by the two-week Boolean predicted value. Multiplying the out-of-stock predicted values by the percentage of actual sales for the year by the respective retail sale price generates the total sales opportunity. Sales opportunity formula:

Yearly increase in sales =
(# of total OOS weeks for all stores) x (2-week Boolean predicted accuracy)
X (% of actual sales across all stores) x (retail price)

Additionally, it is possible to generate profit charts which use input parameters such as: population, fixed cost, individual cost and revenue per individual.

IV. BUSINESS INTELLIGENCE WEB PORTAL

Capability to deliver analytical information to the end-user via standard Web technologies, as well as enabling decision-makers to access these information in a unified way, become a critical factor for the success of data warehousing and data mining initiatives. Enterprise information portal serve as a virtual desktop providing transparent access to the information objects (reports, cubes, spreadsheets, etc.) as described in [15].

In order to provide better user experience we have designed the business intelligence (BI) Web portal as an integrated, Web-based online analytical processing (OLAP) solution that enables employees throughout the entire supply chain to create and share reports, charts and pivot tables, based on online OLAP services, cube files, relational database and web services.

BI applications often require specialized propriety client tools and the process of maintenance and modification is time-consuming and difficult. The designed BI Web portal offers the standard user interface to easily create centralized place for business analytics. The portal is modular (made of many web parts) and enables up to four data views in different formats. The main modules are the BI Tree web part which organizes content using a tree structure, the BI Viewer web part for creating views on data, and the BI Data Analysis web part to further analyze or manage the data displayed in a view. Figure 6 shows BI portal with two data views that present two reports for presenting data mining results. The reports are stored in a separate report server and integrated in the portal using standard XML web service technologies.

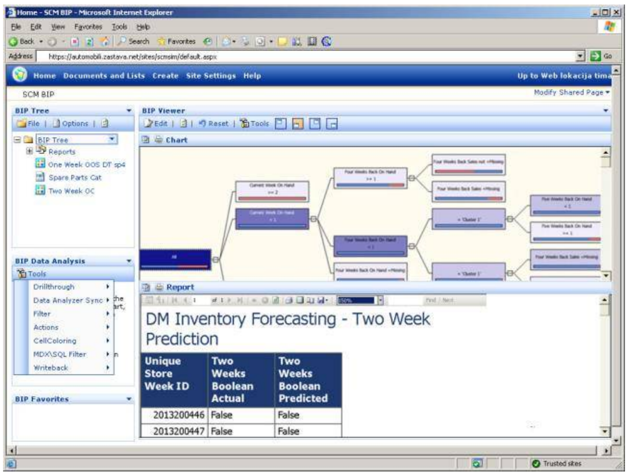


Figure 6. Business Intelligence Web Portal

The portal can be saved as a template and implemented with out-of-the-box functionality in many locations. The security is enforced through SSL encryption together with the authentication and authorization. User roles (reader, contributor, and administrator) are also supported. These security mechanisms are especially important in the context of the supply chain where many different companies cooperate.

By implementing the presented BI portal it is possible to deliver data mining results to the right person, any time, via any browser and in a secure manner. Personalization and filtering capabilities enable end users to access information relevant to them. All this features allow supply chain partners to bring more informed decision collaboratively.

V. CONCLUSION

The goals of modern SCM are to reduce uncertainty and risks in the supply chain, thereby positively affecting inventory control, planning, replenishment and customer service. All these benefits contribute to increased profitability and competitiveness.

In practice, organizations face many challenges regarding the inventory management that include uncertainty, data isolation, problems with data sharing and local decision making.

In this paper, we propose a unified supply chain intelligence model to integrate and consolidate all inventory relevant data and to use business intelligence (BI) tools like data warehousing and data mining, to perform accurate forecasts and finally to deliver derived knowledge to the business users via web portal.

An approach with data warehouse enables data extraction from different sources and design of integrated data storage optimized for analytical tasks such as data mining.

The presented out-of-stock prediction model is tested with real automotive data set and demonstrated excellent accuracy for one week and two week forecasting. This information can be very useful when making inventory planning and replenishment decisions which can ultimately result in more sales, decreased costs and improved customer service level.

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