Expert Systems With Applications 60 (2016) 16–26

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

A decision support system for real-time order management in a heterogeneous production environment

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ARTICLE INFO

Article history:
Received 29 August 2015
Revised 25 April 2016
Accepted 27 April 2016
Available online 29 April 2016

Keywords:
Order management
Order prioritization
Multi-criteria decision making
Fuzzy logic
Risk mitigation
Heterogeneous production environments

ABSTRACT

In today's competitive market, many companies are morphing from the traditional new build, single brand, and silo environments to facilities accommodating diverse business missions. The later are called heterogeneous production environments in which the different business channels share their final production stage (shipping) to enable competitive advantages. In these production environments, at the operational level, the critical success factors are customer satisfaction, on-time delivery, product complexities, supply allocation, and resource utilization. At the strategic level, the success factors are revenue, customer urgency, and sales impact. This study proposes an End-to-End Customer Order Management System (E2E COMS) focusing on effective utilization of individual and shared resources to support real-time order management and mitigate risk of managing diverse missions. The proposed system consists of three integrated tools: Order Prioritization Tool (OPT) to assess and prioritize customer orders for each business channel, Order Fulfillment Progress Projection Tool (OFPPT) to predict the expected remaining order completion time considering inventory and resource capacity constraints, and risk mitigation tool to assess the risk of missing an order shipment due to shipping constraints. A real-time dashboard is developed to visualize the prioritized customer orders, expected time to arrive at the shipping area, shipping instructions, and two-dimensional risk assessment charts. The proposed system can effectively be used for shipping capacity management as well as prompt decision making.

1. Introduction

A typical Supply Chain (SC) spans numerous different entities, and involves the flow of significant volume and types of products in a systematic and timely manner. Supply Chain Management (SCM) encompasses the planning and management of activities involved in sourcing and procurement, conversion, and logistics related management activities. SCM integrates supply and demand management within and across companies (Aqlan, 2016). For example, a manufacturing operation may include numerous business channels (also referred to herein as "channels"). SCM also includes coordination and collaboration with customers as well as channel partners. Channel partners can be suppliers, intermediaries, third-party providers, and other collaborating manufacturers. Delivery management functions in SCM include, among other functions, preparing orders for delivery and managing the logistics of delivery operations (Leernders, Fearon, Flynn, & Johnson, 2002). For example, orders arrive at a shipping dock or location for shipment to various customers. Operations, which range from receiving the orders to shipping, and up to their delivery at the final destination, are within the purview of delivery management functions.

Order management in manufacturing systems is an integral part of a company's logistics. In many industrial applications, the degree of orders' priority is not the same. Some orders are very urgent, while others are less urgent. Orders with the highest priority must be processed first, and the delivery due dates must be met for all the orders (Sel et al., 2012). In complex manufacturing environments, managing and prioritizing customer orders can be a difficult task due to order complexity and the number of controllable and uncontrollable factors that affect order priority.

This research proposes a framework for order management in heterogeneous production environments. The framework considers various factors from strategic and operational levels in production channels to prioritize the orders and predict their cycle times. Furthermore, a risk assessment approach is proposed to support the decision-making process. An expert system utilizes multi-criteria decision making methods, heuristic algorithms, and artificial intelligence techniques for managing and prioritizing customer orders.

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http://dx.doi.org/10.1016/j.eswa.2016.04.035
0957-4174/

The expert system assists the decision makers in making dynamic and real-time decisions while considering uncertainty and risk.

The rest of this paper is organized as follows: Section 2 discusses related literature on order prioritization, cycle time calculation, and risk mitigation; Section 3 details the proposed order management system for heterogeneous production environments; Section 4 depicts the experimental results of the order management system; and Section 5 addresses the conclusions and future directions of the research.

2. Related literature

Production scheduling and customer order prioritization are considered important issues in international supply networks. Scheduling is the assignment of jobs (or orders) into stations to minimize delay and meet the due date. The degree of priority of the orders is not the same in most industrial applications. Some orders are very urgent, some are generally urgent, and others are general orders. Highest priority orders must be processed first and the due date must be met for all the orders. In most manufacturing environments, customer orders have different priorities. Order prioritization can be based on several factors, such as customer value and order size (Pardoe & Stone, 2005), makespan (Krishna, Mahesh, Dulluri, & Rao, 2010), tardiness cost (Vepsalainen & Morton, 1987), and shipping date. Several studies discussed job prioritization in job shops and flow shops, which is considered a typical scheduling problem (Sels, Gheysen, & Vanhoucke, 2012; Vepsalainen & Morton, 1987).

Job shop scheduling has generated a great deal of research. The objective of job shop scheduling is to arrange the jobs in such a way that optimizes certain criteria (e.g., minimize makespan, maximize machine utilization, etc. subject to a set of constraints such as job priority, number of machines, availability of raw materials, among others). Several studies discussed job prioritization on the shop floor, which is considered a typical scheduling problem. The methods used for solving such scheduling problems include genetic algorithms, neural networks, fuzzy logic, simulation, and analytics. For example, Vinod and Sridharan (2011) used simulation modeling to study the due-date assignment problems and scheduling decision rules in a system that consisted of non-identical machines in series. Golenko-Ginzburg, Kesler, & Landsman, (1995) used a problem-specific heuristic approach to analyze random operations and different priorities in a system that consisted of non-identical machines in series. Zhang, Yan, and Chang (1991) used neural networks for job shop scheduling with priority in a general job shop. Tavana, Zarook, and Santos-Arteaga (2015) used Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for scheduling unrelated machines with aging effect and multi-maintenance activities. Michalos, Makris, and Mourtzis (2011) proposed a web-enabled tool based on an intelligent algorithm that used multiple criteria to recommend rotation schedules for truck assembly lines. The tool considered criteria related to operators' characteristics, such as competence, repetitiveness, travel distance, and skill level to ensure employee satisfaction. Other studies utilized data visualization and analytics for production and order management (e.g., Aqlan, Lam, & Ramakrishnan, 2014).

Every sector of an industry or organization generates large amounts of data. This data can be of various types: continuous, categorical, nominal, ordinal, strings, etc. Visual analytics, which combines various automated analysis techniques, can assist managers and business leaders to understand, reason, and base decisions on large and complex data sets (Keim, Kohlhammer, Ellis, & Mannsmann, 2010). Visual analytics is a multi-disciplinary approach that incorporates knowledge from various inter-related research areas, such as data mining, data management, data fusion, statistics, artificial intelligence, visualization, and cognition science (Keim and Shang, 2011). Their research emphasized the development of a foundation and infrastructure of visual analytics, conducting interdisciplinary research, and integrating visual analytics with real-world applications.

The development of Decision Support Systems (DSSs) for production scheduling has been discussed in the literature. For example, Suh, Lee, Le, and Ko (1998) developed a reactive scheduling procedure based on a constrained satisfaction approach for hot-rolling schedules at steelworks. Schniederjans and Carpenter (1996) developed a heuristic job scheduling support system for a manufacturing environment. Pillutla and Nag (1996) constructed an object-oriented model for production scheduling decisions. Mourtzis, Doukas, & Psarommatis, (2012) used a multi-criteria approach to evaluation production performance in a highly customer-driven environment. Multiple conflicting criteria were considered including: lead time, final product cost, flexibility, annual production volume, and environmental impact.

Previously, researchers took initiatives to prioritize orders within a business channel by using various scheduling, optimization, discrete-event simulation, agent-based simulation, and artificial intelligence techniques to optimize certain criteria (e.g., revenue, cost, cycle time) (Aqlan & Lam, 2016; Carvalho, Barroso, Machado, Azevedo, & Cruz-Machado, 2012; Giannakis & Louis, 2011). While proposing optimal solutions, most researchers failed to consider both strategic and operational decision criteria and quantify their impacts into the decision making process due to the existing complexity and variability in managing shared stages that cater to multiple business channels (Aqlan & Lam, 2016). Therefore, rather than proposing an optimal solution, a two-dimensional risk matrix can be helpful in understanding the risk likelihood from the strategic and operation levels' perspective. The risk matrix would assist decision makers for customer order management by considering production phase and business requirement. To achieve the goal, this study proposes a framework that incorporates a multi-criteria decision making method, an artificial intelligence technique, and a heuristic algorithm to ensure effective utilization of individual and shared resources. An expert system for End-to-End (E2E) Customer Order Management System (COMS) is developed. The COMS expert system identifies the attributes and their importance to prioritize orders, predict order completion time, and quantify strategic and operational levels risk indices for a capacity constrained supply chain stage.

3. Research methodology

3.1. System description

This study considers a fabrication-fulfillment production system in a high-end server manufacturing company. Typical characteristics of a server manufacturing company are aggressive new product introduction cycles, continuous quality improvement, seasonal demand patterns, high penalty cost from end-product order fulfillment, small profit margins, and a large number of parts and features (Aqlan et al., 2014; Cao, Xi, & Smith, 2003; Efendigil, Onut, & Kahraman, 2009; Ramakrishnan et al., 2008). With a high variety of product types, the company experiences a high volume of customer orders toward the end of each month or quarter due to skewed demand pattern. Traditionally, the decision makers in the company have focused on developing their expertise on streamlining an individual business channel. Currently, the company is facilitating four diverse business channels; namely new brand, used brand, cross brand solutions, and customer solutions (Saha, 2015).

All business channels have their own dedicated SC network that processes their respective variety of customer orders by maintaining order types and product fulfillment criteria (Saha, 2015). These