Intelligent Systems for Production Scheduling in High-Mix Low-Volume Manufacturing

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Abstract
Today's globalization drives industries toward increased expectations on quick response to the customers. These expectations have put industries under pressure to become more agile under highly dynamic market conditions in the high-mix low-volume manufacturing systems. Effective production scheduling is a key factor in fulfilling the customer's expectation. It becomes more critical due to dynamics and uncertainty in the manufacturing systems. This research addresses the optimization needs in high mix low volume using genetic algorithm based systems and intelligent simulation for efficient scheduling. The fuzzy dynamics are used to represent dynamics and uncertainty. A reconfigurable simulation model is developed to support optimization model. The simulation model and optimization tool are validated using real-world applications on production scheduling system.

1. Introduction

Production scheduling in manufacturing environments is a complex and challenging task requiring the careful consideration of competing alternative resources coupled with the ability to respond quickly to changing requirements. Many productivity problems in the United States are associated with scheduling operations (Hoitomt 1990). Optimized scheduling is a key factor and is one of the most important planning and operational issues in manufacturing industry for increased productivity. Effective scheduling can improve the customer's expectation on delivery, reduce work-in-process (WIP) inventory and lead-time, and improve machine utilization and reduce bottleneck resources. Unfortunately, the consistency of high quality schedule generations remains a persistent problem in most manufacturing systems despite occasional successes. This problem is becoming more critical for high-mix low-volume manufacturing due to the changing needs in today's supply system (Lee 2003). The challenges is due to the combinatorial nature of highly complicated constraints such as machine dynamics, labor dynamics, operation dynamics, logistics dynamics, and demand dynamics, etc. The diversity of scheduling, the existence of many specific constraints or preferences, and the emergence of efficient scheduling make constraint programming to choose for the resolution of complex industrial problems (Graves 1981). Currently, MRP (Material requirement planning) and ERP (Enterprise Resource Planning) based methods have major difficulties to meet the important goals of on-time delivery and low WIP inventory because of their material centric nature. MRP and simulation is often used for high-level production planning and scheduling (Luh 1999). However, it ignores resource capacities, so the resulting plans or schedules become usually infeasible. ERP is used for enterprise-level scheduling. However, there is major lack for considering optimal solution under the constraints mentioned above.

Traditionally, the manufacturing sectors are in the category of low-product-mix high-volume-mix. Nowadays, the customers' expectation is changing for more customized products, which are transferring manufacturing into high-mix low-volume scenario that puts more dynamics in the manufacturing systems. Competitive advantage in high-mix low-volume manufacturing environments is driven by the organization's ability to effectively plan resource requirements. As the systems are under transformation stage, how to choose an appropriate high-mix manufacturing strategy along with the sound tactical thinking is necessary for the 21st century manufacturing that will confer competitive advantage in cost, quality, delivery, responsiveness, technology and services (William 2002).

In the 21st century high-mix low-volume manufacturing, competitive advantage is required to win the battle for customers in the global marketplace. During the past decade, the manufacturing industry has undergone a dynamic transformation. Recently, traditional manufacturers are inherently subject to high-mix, low volume manufacturing as a business model. Proper planning and scheduling decisions are fundamental to successfully managing a high-mix low-volume manufacturing environment. Mahoney (1998) presented the multiple constraint synchronization scheduling algorithm and a manufacturing operations model to facilitate the management decision-making process in a high-mix low-volume manufacturing environment. Nagano (1999) presented real-time production control for low volume and high product mix manufacturing lot prioritizing algorithm based on factors of lateness and importance. Current trend of information technology as well as automation technology, companies are urging a solution to produce varieties of products with low volume as market demand is fast changing into it. The proposed research provides a scheduling solution in high mix low volume environment. Section 2 provides the proposed scheduling architecture, section 3 shows the production scheduling and section 4 provides the results and discussions.

2. Proposed Scheduling Architecture

This research addresses these issues by tackling the optimization of production scheduling problem using genetic algorithm which include the capacity constraints, machine dynamics, operational (labor) dynamics and logistics dynamics, etc. The fuzzy systems are used to represent those dynamics. Figure 1 illustrates the proposed approach of production scheduling system. Acceptable combinations for each demand type of product are needed to be determined in accordance with the material available and demand specifications. Among the acceptable combination of components, the best ones that can make the best use of material and best use of resources will be obtained. A report will be generated and indicate how many demands can be fulfilled and how the materials are chosen and effective use of resources. The intelligent modeling and simulation will provide necessary capacity constraints on the real-time shop floor. It figures out the bottleneck and optimizes the system using scenario analysis.

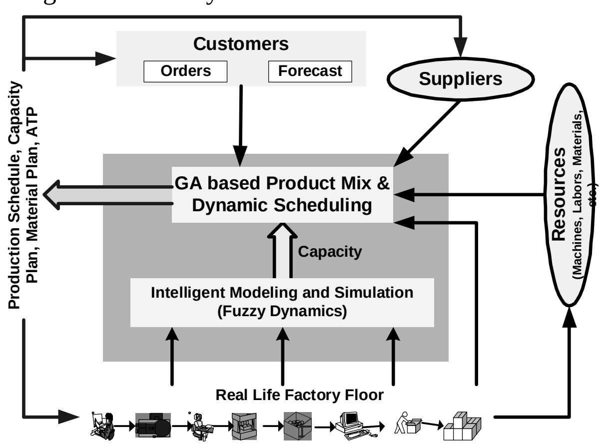

Fig 1: Product mix and dynamic scheduling architecture

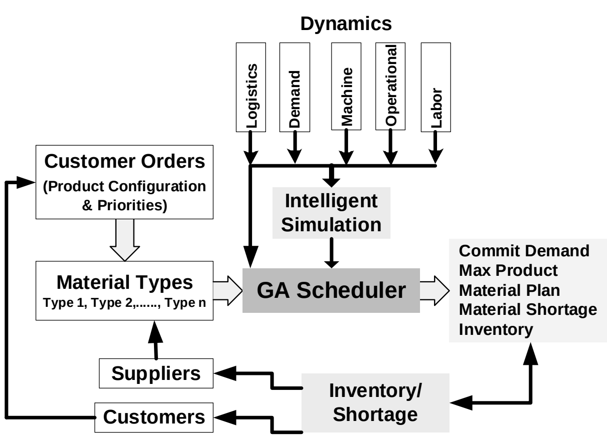

Fig. 2: GA scheduler for production scheduling

Figure 2 illustrates the proposed approach of genetic algorithm (GA) scheduling system. A generated report can be used to alert the manufacturer to the possible material shortage early; it can also indicate how much time is available to recover from the material shortage as well as find the alternatives to get the target product by overtime or by redesigning the assembly line if problems happen frequently. Moreover, the inventory report will provide managers with information on how much inventory will be needed before the next material procurement.

3. Production Scheduling

The variation within the systems, and within the operations exists in manufacturing environment. Some variations are dependent and some are independent. The dependent variations are more critical to manage, as they depend on various factors or sub-systems. The following dynamics are considered for proposed systems: machine dynamics, labor dynamics and logistics dynamics (Ali 2003). Analogous to a real world machine and labor dynamics can be constructed into two components. One component is in charge of processing (manufacturing, transporting, storing, testing, and so on) entities (parts); it is named as body while the other is concerned with controlling the activity and performance of the body; this is named as brain. The brain accommodates the integrated mapping knowledge about the mapping field and the integrated inference mechanism to use the knowledge. The body encompasses an entity processing mechanism, feature set, and attribute set of the real-life element. The behavior of the body is controlled by the brain via feature set, while the brain uses the mapping knowledge to drive the feature value on the basis of attribute set from the body.

3.1 Constraints

Various types of constraints are considered in production scheduling: capacity constraints, component supply constraints, demand constraints, material constraints, product configuration constraints (material-to-product constraints, material-to-material constraints), priority constraints, and routing constraint.

3.2. Genetic approach

Chromosomal Representation

In GAs, typically, string representation is used where chromosomes have either binary or symbolic gene values. In this scenario, the production is represented, as strings for every period and satisfied constraints will be used for legal candidate solutions. In order to ensure that the chromosome is feasible, every chromosome attained in reproduction, crossover, and mutation operations must be checked.

Random Variable Generation

During constraint checking and objective value calculating, computer simulation can be used to generate random variable, which is normally distributed in the model. The procedure of generating a random variable is as follows:

Step 1. Generate the random variable.

Logistics Constraint

Step 1. Set initial cost.
Step 2. Generate random variable.
Step 3. Find alternatives and use fuzzy dynamics.
Step 4. Repeat steps 2 and 3.
Step 5. Set logistics.

Shortage Constraint

Step 1. Set.
Step 2. Generate random variable.
Step 3. Calculate for material shortage.
Step 4. Repeat steps 2 and 3.
Step 5. Return.

Capacity Constraint

Step 1. Initialize.
Step 2. Check with factory floor constraints.
Step 3. Check material availability.
Step 4. Set optimal capacity.

Objective Functions

Step 1. Generate random variable and initialize.
Step 2. Apply mathematical model for objective values.
Step 3. Compare values.
Step 4. Set new values.
Step 5. Return.

Population Initialization

A GA typically starts from a randomly generated population of candidate solutions. The schedules are initialized by randomly assigning production to every product item and period, and simultaneously checking the constraints. Finally, population size chromosomes can be obtained. The procedure is as follows:

Step 1. Set selection area.
Step 2. Generate random variable.
Step 3. Check the constraints' feasibility.
Step 4. If all constraints are feasible, then continue to the next step. Otherwise, repeat steps 1-3.
Step 5. Repeat steps 1 through 4 by population size.
Step 6. Calculate the objective values.
Step 7. Sort the chromosomes by objective values.
Step 8. Set as the best chromosome.

Fitness Function

The fitness function (the difference square between the customer demand and the committed demand) is set for maximum production throughput. The genetic planner assigns the fitness function evaluation to an individual chromosome.

Selection

The population selection operation involves selecting random chromosomes based on fitness by total population size and thus getting a new generation. The procedure is as follows:

Step 1. Calculate every chromosome' s possibility.
Step 2. Generate a random variable.
Step 3 Select the chromosome.
Step 4. Repeat steps 2 and 3 by total population size.

Crossover Operation

Much of the power of a GA arises from recombination and population crossover is the main recombination method. It generates two offspring from two parent strings by first randomly selecting a given number of crossing sites and then exchanging alternate pairs of equally positioned sections between the strings. The procedure is as follows:

Step 1. Set crossover possibility operation.
Step 2. Generate a random variable to choose the chromosome as a parent string.
Step 3. Group randomly the parents.
Step 4. Generate a random variable for the offspring
Step 5. Generate the offspring.
Step 6. Checking the offspring's feasibility.
Step 7. Repeat step 4 until every group.
Step 8. Calculate objective values.

Mutation Operation

Population mutation operation is another recombination method to increase the variability and convergence; generates an offspring from a parent string. The mutation operation procedure is as follows:

Step 1. Set the mutation possibility
Step 2. Generate a random variable to choose the chromosome as a parent string.
Step 3. Generate a random direction.
Step 4. Generate offspring.
Step 5. Check the offspring's feasibility. If feasible, return to step 7; otherwise, go to step 6.
Step 6. Generate a random variable and repeat step 5.
Step 7. Repeat steps 2 through 5 by population size.
Step 8. Find objective value as an optimal solution.

Decision-making problems often encounter uncertain factors such as machine dynamics, systems dynamics, or logistics dynamics as a form of random or fuzzy variables, or some combination of these. The genetic algorithm based system is developed and validated with real case studies, which will be interdependent. Randomness and fuzzy learning are used for proposed system, which could provide better decision making for industry practitioners.

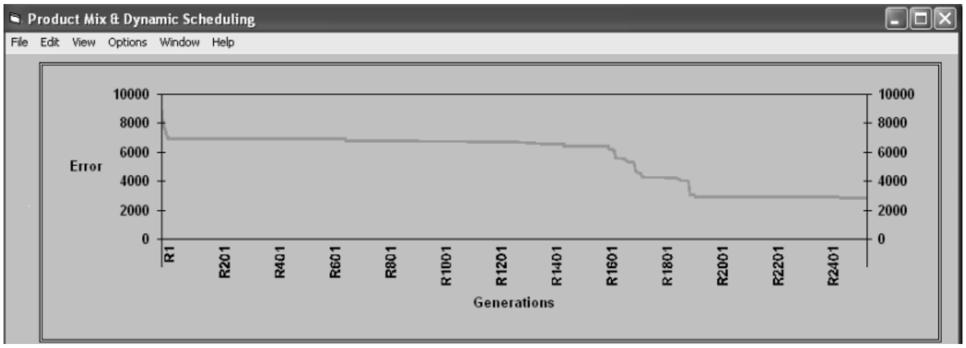

Fig. 3: Fitness function error

4. Results and Discussions

A genetic algorithm is developed using Visual Basic to solve the specified problems. The product demand data, constraint of materials, and product information are received from the database. After running the experiment, the commit demands, material allocations, and demand errors are sent back to the database. The stopping criterion should be such that sufficient generations are allowed so as to obtain a near-optimal solution. The number of generations also varies markedly with the randomly generated initial solution. The error - the difference between actual demand and available to promise - is represented in the user interface. The different run scenarios are considered in order to get an optimal production scheduling. As we would get realistic information from the intelligent simulation modeling for capacity constraints, the information will be dynamically updated and set into the production schedule. The error is depicted in Figure 3. The error initially reduces sharply, however, the decreasing rate of demand error for more generation is not so high. Demand error becomes constant after certain generations. Figure shows the demand error improvement is not very efficient with the number of generations, as it has been chosen random generation and checked only valid chromosomes. The demand error reduction is much higher when only valid chromosomes are produced after crossover and mutation. Thus, producing valid chromosomes during crossover and mutation is better than generating random chromosomes and checking for validation. Moreover, we can say that the initial generations are playing a big role in getting an optimal solution more quickly. As the system is interacting with the database, it is taking too much computational time. The variation in a single product and single week is not much; however, when multiple products and multiple time periods are considered, the variations are too high due to the dynamics involved in the manufacturing systems with different time periods.

5. Conclusions

A systematic approach is proposed for production scheduling, which is used to decide which type and how much product will be produced and the corresponding quantity of the product for an optimal market potential. The proposed product genetic algorithm system deals with the close balance between customer demand and commit demand and provides optimal resource allocation to the factory floor. It is integrated with the database, and directed to send a report to the database. The reconfigured/redesigned model was developed to include stochastic variability. The approach presented herein has been implemented in a real-life application, which will be a learning tool for industry practitioners.

6. References

A. Ali, “Multi-constraint based intelligent scheduling of manufacturing systems”, Ph.D. Dissertation, University of Wisconsin-Milwaukee, 2003.

S.C. Graves, “A review of production scheduling”, Operations Research, vol. 18, pp. 841-852, 1981.

D. Hoitomt, P. Luh, E. Max, K. Pattipati, “Scheduling jobs with simple precedence constraints on parallel machines”, IEEE Control System Mag., p. 34-40, 1990.

J. Lee, “E-manufacturing – fundamental, tools and transformation”, Int. Journal of Robotics and Computer-integrated manufacturing, v. 9. no. 6, pp. 501-507, 2003.

P.B. Luh, D. Chen, and L.S. Thakur, “An effective approach for job-shop scheduling with uncertain processing requirements”, IEEE Transactions on Robotics and Automation, vol. 15, no. 2, 1999.

R.M. Mahoney, “Multiple constraint synchronization in a high-mix, low-volume manufacturing environment”, Annual Int. Conf. Proc. - APICS, Oct 26-29, Washington DC, pp. 363-367, 1998.

S. Nagano, “Real-time production control for low volume & high product mix manufacturing lot prioritizing algorithm based on factors of lateness and importance”, IEEE Int. Symp. Semiconductor Mfg. Conf. Proc., Santa Clara, CA, pp. 333-336, 1999.

T.W. William, “Low volume, high mix supply chains”, APICS Educational & Research Foundation 2001 Academic/Practitioner Summer Workshop Proc., 2002.