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Integrated Production and Distribution Scheduling with Multiple Objectives

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Eray Cakici
Transplace
Lowell, AR

Mary E. Kurz
Department of Industrial Engineering, Clemson University
Clemson, SC

Scott J. Mason
Department of Industrial Engineering, University of Arkansas
Fayetteville, AR

Abstract

We study the problem of minimizing total weighted tardiness and total distribution costs in an integrated production and distribution environment. Orders (jobs) are processed on a single production line and delivered to customers by capacitated vehicles. Each order is associated with a customer and has a weight (priority), processing time, due date, and size. A mathematical model is developed in which a number of weighted linear combinations of the objectives are used as a single objective. Because even the single objective problem is NP-hard, different heuristics based on a genetic algorithm (GA) are developed to further approximate the Pareto optimal set of solutions.

Keywords
Supply chain scheduling, multi-objective optimization, heuristics, and genetic algorithms

1. Introduction

Scheduling problems often require an analysis that includes multiple objectives. Many problems faced by decision makers involve making a selection from different alternative solutions while satisfying several criteria that are usually in conflict with each other (for example, the cost and service level). Industries—such as aircraft, electronics, semiconductors manufacturing, etc.—have tradeoffs in their scheduling problems in which multiple objectives are considered in the process of optimizing the overall performance of the system [1]. A schedule minimizing one objective can lead to a poorly satisfied objective elsewhere. Therefore, any methodology applied in such multi-objective scheduling problems has to find a compromise between these conflicting objectives. The aim is to achieve a "best-compromise" solution of all of the objectives. Generally no such single solution exists, and the decision maker's preference affects the selection of the best compromise among the set of efficient solutions. Such solutions are also called Pareto optimal solutions; for those non-dominated solutions, no feasible solution exists that can better satisfy one objective without negatively affecting at least one other criterion. Therefore, many multi-objective methods try to reduce the solution space to the set of efficient solutions [2].

Costs and service levels are two main objectives of interest in a typical supply chain. Both objectives can be better optimized by collaborative decision-making models. Lack of integration yields to substantial inefficiencies and, consequently, poor total system performance. Especially in make-to-order industries, lead times are short and limited inventory is held in the supply chain. Therefore, coordinating production and distribution operations becomes more crucial for satisfying on-time delivery requirements without intermediate storage. In such a situation, delivery times to meet service considerations and consolidation opportunities to reduce transportation costs are highly affected by production schedules. Motivated by the fact that an increasing number of companies are now adopting make-to-order business models, we study the problem of optimizing customer service levels and total distribution costs in an integrated production and distribution environment. Because generally there is very little or no inventory and production costs are typically independent of the processing sequence, transportation costs are the main driver for minimizing total system cost. Customer service levels are measured by weighted tardiness, where tardiness is the positive difference between a job's delivery time and due date. Orders are received by a manufacturer, processed on a single production line, and delivered directly to customers by capacitated vehicles without visiting any other locations. Customers are in different locations and a fixed customer-dependent transportation cost is incurred for each delivery. Every order (job) is associated with a customer and has a weight (priority), processing time, due date, and size (storage space required in the transportation unit). A mathematical model is presented in which weighted linear combinations of the objectives are used to aggregate objectives into a single objective. Because even the single objective problem is NP-hard, several GA-based approaches are developed to further approximate a Pareto optimal set of solutions without aggregating objectives for this multi-objective problem.

The rest of this paper is organized as follows. In the next section, we review the previous work on multi-objective supply chain scheduling. In Section 3, we briefly discuss mixed-integer programming formulation of the problem under study. Section 4 describes different heuristic algorithms to further approximate the Pareto optimal set of solutions. Section 5 presents the results of computational experiments. We conclude the paper with a summary and suggestions for future research directions in section 6.

2. Literature Review

A recent review of the integrated production and distribution scheduling models in the literature can be found in Chen [3] In this paper, optimizing the tradeoff between total weighted tardiness and transportation costs is studied. Relatively few papers exist in the literature studying integrated decisions at a detailed scheduling level in which multiple objectives involve tardiness and transportation costs. Synchronization of assembly operations with air transportation is investigated in Li *et al.* [4] for a make-to-order-based computer manufacturer. The objective is to minimize overall total cost including total delivery tardiness cost. The problem is divided into two sub-problems. The air transportation allocation is formulated and solved as an integer linear program, and two heuristic approaches are presented for the assembly-scheduling problem. Pundoor and Chen [5] study minimizing the total distribution costs plus maximum tardiness. A set of orders with equal sizes is received at the beginning of the planning horizon, processed by the supplier, and delivered to the customers by capacitated vehicles. Both single and multiple customer cases are studied along with a special case. Either an efficient algorithm or proof of intractability is proposed for different cases of the problem. A heuristic approach incorporating a dynamic programming algorithm is developed for the general case. The authors show that an integrated approach yields significantly better results when compared with a sequential approach in which scheduling decisions are first made for order processing then followed by delivery scheduling decisions. In our study, we assume order sizes are unequal, which is more difficult to solve than problems with equal sizes [3]. The batching problem in the distribution part involves bin packing, and that problem itself is strongly NP-hard [6]. Hall and Potts [7] consider different integrated production and distribution problems. The objective is to minimize the sum of total transportation costs and total scheduling cost involving total weighted completion time, the maximum lateness, total weighted number of late jobs, and the total tardiness. The production side is modeled as either single or parallel machine environment. A fixed transportation cost is incurred for each delivery and vehicles have an infinite capacity. Several algorithms and intractability results are presented. Chen and Hall [8] examine various supply chain configurations in which suppliers provide parts to a manufacturer. Conflict issues are discussed when each party has its own objective, such as minimizing total completion times for suppliers and minimizing maximum lateness for the manufacturer. Cooperation opportunities and ways to resolve conflicts are also shown under various assumptions of relative bargaining powers of suppliers and the manufacturer. In summary, generally the objective function examining the tradeoff between the tardiness-related objective and transportation cost is defined as $\alpha T + (1-\alpha)C$, where T represents the total weighted tardiness and C represents the total distribution cost. To our knowledge, there is no previous research in the supply chain scheduling literature applying multi-objective analysis in which a set of non-dominated solutions are generated instead of a single solution.

3. Mathematical Formulation

This problem can be formulated as a mixed integer programming (see Cakici *et al.* [9]). Due to size limitations of this paper, the model is not presented here. In the model, both objectives are aggregated into a single objective by summing up the weighted objectives in which well-suited weights for different objectives are required to obtain useful non-dominated points on the Pareto front. Considering the production stage alone by assuming transportation time and costs are equal to 0, our reduced problem of minimizing weighted tardiness on a single machine is NP-hard in the strong sense [10]. Due to the higher complexity of our problem, heuristic approaches are needed to produce good solutions. A mathematical model can be used for assessing heuristic solution quality for small-sized instances. In this work, we focus on different GA-based approaches to solve our challenging, practically-motivated multi-objective problem.

4. Heuristics

GAs have been shown as a promising technique by many researchers for solving multi-objective optimization problems [11]. A GA is applied to the distribution part of our problem in which infinite number of capacitated vehicles exists and only direct deliveries (one customer per trip) are allowed. To decode trip assignments, each job is associated with a random trip number in which a maximum number of delivery trips is equal to the number of jobs. Trips that are eligible to deliver jobs of each customer are pre-defined in order to overcome the infeasibility issues caused by direct delivery restrictions (when jobs of different customers are randomly assigned to the same trip), and trip assignments are performed by randomly selecting a trip from the set of pre-determined trips of the associated customer. In the crossover phase, two parent chromosomes and a crossover point are selected randomly. A one-point crossover is applied with a probability of p_c such that a random number is drawn from U(0,1) and crossover is applied if the number is less than crossover probability. Job assignments before the crossover point are copied from the first parent; the rest is copied from the second parent. If the crossover is not applied to the parent chromosomes, they are copied directly to the offspring. Mutation is applied in each chromosome of the offspring according to a pre-defined mutation probability, p_m, where a job is randomly selected and assigned to a random trip (batch) of the associated customer. Each infeasible solution is penalized by multiplying an objective value with an exponential function of the number of infeasible trips (deliveries in which capacity is exceeded) to maintain feasibility in the next generations. For example, if a particular solution i has a total weighted tardiness of TWT_i and includes two infeasible trips, then updated total weighted tardiness is $TWT_i \times e^2$.

The fast and elitist Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is used to obtain widely distributed Pareto optimal solutions. Deb *et al.* [12] show that in many problems, NSGA-II is able to perform better than other multi-objective evolutionary algorithms with respect to fitness (quality) and spread (diversity) of the solutions (see Deb *et al.* [12] for more detailed information about NSGA-II). To further improve the convergence to the Pareto optimal front and diversify the solution space, we introduce immigration and propose two variants of NSGA. (NSGA-II without immigration is NSGA-II-Type0.) Instead of copying all *N* sorted solutions, we add new randomly generated chromosomes into the next mating pool through immigration. In the first variant, NSGA-II-Type1, a constant percentage of the next generation is created by immigration in which 10% is chosen in this study. The second variant, NSGA-II-Type2, transfers only the solutions that are non-dominated over all solutions in the mating pool. The remaining solutions are generated through immigration. GAs used to form delivery trips are incorporated with dispatching rules to schedule jobs on the production side. Given delivery trips of orders, an optimal schedule exists to minimize TWT in which there is no idle time in processing of orders at the manufacturer, and orders delivered together are also processed consecutively [5]. Therefore, once the delivery trips are formed via GA, the problem reduces to a single machine scheduling problem with the objective of minimizing total weighted tardiness in which each batch can be viewed as a single job while sequencing the batches. Because every order will be delivered immediately after the corresponding batch completes its processing, a modified due date d'_j is introduced such that $d'_j = d_j - t_j$ for job $j \in J$. A composite dispatching rule, ATC [13], is applied to sort the batches in two ways. In the first way, BSR1, batches are sorted in non-increasing order of $I_j(t) = \frac{w_j}{p_j}\exp\left(\frac{-\max(d'_j - p_j - t, 0)}{k\bar{p}}\right)$ in which k is the look-ahead parameter and $\bar{p}$ is the average processing time of all jobs. Every time any machine becomes idle at time t, the batch with the highest index is chosen. In the other way, BSR2, a batch sorting index $BI_b(t) = \frac{W_b}{P_b}\exp\left(\frac{-\max(D_b - P_b - t, 0)}{k\bar{P}}\right)$ is used to select the batch for processing in which an aggregated batch due date $D_b = \sum_{j:y_{jb}=1}^{n} w_j d'_j \Big/ \sum_{j:y_{jb}=1}^{n} w_j$, weight $W_b = \sum_{j:y_{jb}=1}^{n} w_j$, and processing time $P_b = \sum_{j:y_{jb}=1}^{n} p_j$ are calculated for each batch. Instead of the average processing times of jobs, the average of batch processing times ($\overline{P}$) is considered.

We employ both sequencing rules combined with three variants of NSGA-II discussed above. As a result, we examine six different heuristics approaches for our multi-objective supply chain scheduling problem:

Table 1. Heuristic Descriptions

Heuristic	Trip Assignment (Distribution)	Batch Sequencing (Production)
MO1	NSGA-II-Type0	BSR1
MO2	NSGA-II-Type0	BSR2
MO3	NSGA-II-Type1	BSR1
MO4	NSGA-II-Type1	BSR2
MO5	NSGA-II-Type2	BSR1
MO6	NSGA-II-Type2	BSR2

5. Computational Study

An extensive set of problem instances is used to test our proposed approaches' performances. We consider three different sets of jobs (8, 20, and 50). The weights of jobs are randomly generated integer values on [1, 5] and [1, 10]. Two different levels of job sizes are generated from a discrete uniform distribution in ranges [1, 25] and [1, 50] in which vehicle capacity is 50. The number of customers, job due dates, processing times, transportation times, and transportation costs are generated similar to Pundoor and Chen [5]. We examine two levels for the number of customers, 2 and 4. Transportation times required to travel to each customer are discrete random numbers between 10 and 100. Transportation costs are equal to transportation times. A random integer is generated on [1, 10] for each job's processing time. Job due dates are generated from a discrete uniform distribution DU $\left[p_{\min} + t_{\min}, \lambda/2\left(\left(p_{\min} + p_{\max}\right)n + \left(t_{\min} + t_{\max}\right)\right)\right]$, in which $p_{\min}$ and $p_{\max}$ are minimum and maximum processing times, and likewise $t_{\min}$ and $t_{\max}$ are minimum and maximum transportation times. Three different levels of due date tightness factor λ are investigated (0.5, 1, and 1.5). Due dates are also characterized by processing and transportation times. For each of the 72 test combinations (3 x 2 x 2 x 2 x 3), 10 random instances are generated. Therefore, a total of 720 problem instances are used to examine the performance of our proposed algorithms.

The optimization model is implemented in AMPL and solved by CPLEX 11.1 for generating Pareto optimal solutions in small-sized (8-jobs) problems. Both objectives are aggregated into a single objective by summing up the weighted objectives. A non-negative scaling parameter α is used to assign different weights to objectives such that α for TC and $(1-\alpha)$ for TWT. Because it is not possible to investigate every combination in a reasonable time (within 2 hours), we employ α in declines of 0.1, starting from 1, and resulting in 11 different objective functions for the same problem instance. For 8-job instances, these 11 points may not be representative of the entire solution space. Therefore, optimal solutions for the given objectives are placed in the set of partial Pareto optimal solutions, PPO, and compared against the non-dominated solutions found by each heuristic. Our heuristic algorithms are implemented in Visual Basic for Applications (Excel 2007). All tests are performed on a PC, Intel Pentium Dual-Core Processor (3.39 GHz CPU speed) with 3GB RAM. The look-ahead parameter, k, is selected as 1.5 in batch sequencing rules.The population size is set as 100, and 100 generations are created. The crossover probability, p_c, is defined as 0.8, and 0.1 is used for mutation probability, p_m. We combine all Pareto front solutions achieved from different heuristics in a new set of non-dominated solutions, Pareto best front (PBF_MO1-6). We define the performance of heuristics based on the number of Pareto front solutions that has been contributed to the set of solutions in PBF_MO1-6. Let $ND(H)$ be the solutions in PBF_MO1-6 that are obtained by heuristic H and $ND(B)$ be the total number of solutions in PBF_MO1-6. The performance ratio of a particular heuristic H, $PR(H) = \frac{ND(H)}{ND(B)}$, is computed to assess the solution quality of heuristics over all problem instances (Table 2). Heuristics employing BSR2—an aggregated batch due dates, processing times, and weights are utilized for the jobs of the same trip—outperform the heuristics with BSR1. (An index is computed for each job and total index of a particular trip's jobs is considered for sequencing.) The best two heuristics are highly competitive. On average, 56.8% of PBF_MO1-6 is obtained by MO4 (10% of next generation is created by immigration and BSR2 is used as the batch sequencing rule) whereas 55.3% of PBF_MO1-6 is obtained by MO2 (BSR2 is applied with no immigration). As the number of jobs increases, heuristics without immigration perform better. MO2 produces the most Pareto best front solutions when the number of job sizes are high, due dates are tight, job sizes are small, and more customers are positioned in the supply chain. There is also a slight increase in solution times when immigration is employed. (For example, in 50-job instances MO2 takes 121 seconds on average whereas MO4 averages 130 seconds.)

Table 2. Heuristic Results

	Level	MO1	MO2	MO3	MO4	MO5	MO6
# of Jobs	8	40.9%	85.7%	42.6%	90.4%	42.2%	88.5%
	20	8.0%	34.9%	6.7%	40.9%	4.6%	29.0%
	50	17.9%	47.6%	11.5%	38.1%	2.8%	5.9%
# of Customers	2	22.6%	49.8%	20.6%	53.4%	16.5%	37.4%
	4	20.9%	61.5%	19.5%	60.4%	17.3%	52.1%
Job Due Date Tightness Factor	0.5	34.2%	53.7%	32.0%	51.9%	28.1%	40.6%
	1	15.3%	54.8%	14.4%	59.8%	11.2%	45.0%
	1.5	15.8%	57.4%	13.6%	58.6%	11.1%	46.6%
Job Sizes	DU[1,25]	21.6%	51.9%	20.9%	51.3%	17.0%	40.9%
	DU[1,50]	22.0%	58.8%	19.2%	62.4%	16.7%	47.3%
Job Weights	DU[1,5]	21.4%	55.1%	19.5%	57.0%	16.3%	44.3%
	DU[1,10]	22.2%	55.5%	20.6%	56.6%	17.4%	43.8%
Averages		**21.8%**	**55.3%**	**20.1%**	**56.8%**	**16.8%**	**44.0%**

To have a better understanding of the solution qualities, Pareto super front (PSF) is formed by combining PPO and PBF_MO1-6. The quality of solutions in PBF_MO1-6 and PPO are evaluated by the number of solutions contributed to PSF. For example, the performance ratio of PBF_MO1-6, $PR(H^*)$, is $ND(H^*)/ND(S)$ in which the number of Pareto front solutions achieved by heuristics that are also non-dominated in PSF is defined as $ND(H^*)$, and $ND(S)$ is the total number of non-dominated solutions in PSF. Table 3 shows the results for each level of the experimental design factors in 8-job instances. Both approaches produce a significant number of non-dominated solutions for PSF. Heuristics are able to find new non-dominated solutions when compared to solutions of the mathematical modeling approach. On average, 16.6% of the PSF is new solutions produced by heuristics in addition to the ones obtained from the optimization model by using different objective functions. On the other hand, heuristics can produce solutions much faster; on average, GAs run in 24 seconds whereas mathematical models take over 1.5 hours to achieve solutions for each 8-job instance.

Table 3. Mathematical Models vs. Heuristics

		PPO	PBF_MO1-6
# of Customers	2	82.9%	55.5%
	4	83.9%	45.3%
Job Due Date Tightness Factor	0.5	76.0%	56.7%
	1	84.2%	38.5%
	1.5	90.0%	56.0%
Job Sizes	DU[1,25]	77.0%	56.7%
	DU[1,50]	89.8%	44.1%
Job Weights	DU[1,5]	81.4%	58.4%
	DU[1,10]	85.4%	42.5%
Averages		**83.4%**	**50.4%**

6. Conclusions and Future Research

In this paper, we investigate integrated production and distribution planning decisions in a supply chain at a detailed scheduling level. Our problem involves multiple objectives: minimizing weighted tardiness and minimizing total distribution costs. We develop different GAs combined with dispatching rules to handle both objectives of our supply chain scheduling problem and find an approximation of the Pareto optimal set. Solutions obtained by each heuristic are compared with Pareto best front, a combination of Pareto front solutions from all heuristics. To further assess the solution quality of heuristics, another set of solutions for each small-sized instance is generated by using different objective functions in the proposed mathematical model.

Algorithms employing the BSR2 in the production side (an aggregated batch due dates, processing times, and weights are utilized for the jobs of the same trip) produce more Pareto best front solutions than the ones with BSR1 (where an index is computed for each job and a total index of a particular trip's jobs is considered for sequencing). Heuristics also find more Pareto best front solutions without immigration in large-sized problem instances. Computational tests have shown that both mathematical modeling and heuristics approaches are competitive and can produce significant number of non-dominated solutions for the Pareto super front. Heuristics are able to find new non-dominated solutions. On average, significant fraction of the Pareto super front is composed of new solutions produced by heuristics in addition to the ones obtained from the optimization model by using different objective functions for small-sized instances. These results indicate that heuristics are not only able to produce the same Pareto front solutions, but also new solutions, because it is not practical to run the mathematical model for every combination of weighted objectives.

To our knowledge, this research is the first study tackling a multi-objective supply chain scheduling problem by generating an approximate set of Pareto optimal solutions. There is still a vast area of research problems in which multi-objective evolutionary algorithms can be applied. The problem studied in this paper can be extended by considering multiple machines in the production stage and involving routing decisions in order deliveries. Another interesting research topic would be examining different chromosome encodings for NSGA-II in which production schedules can also be involved along with more replications.

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