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# Integrated Models and Algorithms for Automotive Supply Chain Optimization

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INTEGRATED MODELS AND ALGORITHMS FOR AUTOMOTIVE SUPPLY CHAIN OPTIMIZATION

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## ABSTRACT

The automotive industry is one of the most important economic sectors, and the efficiency of its supply chain is crucial for ensuring its profitability. Developing and applying techniques to optimize automotive supply chains can lead to favorable economic outcomes and customer satisfaction. In this dissertation, we develop integrated models and algorithms for automotive supply chain optimization. Our objective is to explore methods that can increase the competitiveness of the automotive supply chain via maximizing efficiency and service levels. Based on interactions with an automotive industry supplier, we define an automotive supply chain planning problem at a detailed operational level while taking into account realistic assumptions such as sequence-dependent setups on parallel machines, auxiliary resource assignments, and multiple types of costs. We model the research problem of interest using mixed-integer linear programming.

Given the problem's NP-hard complexity, we develop a hybrid metaheuristic approach, including a constructive heuristic and an effective encoding-decoding strategy, to minimize the total integrated cost of production setups, inventory holding, transportation, and production outsourcing. Furthermore, since there are often conflicting objectives of interest in automotive supply chains, we investigate simultaneously optimizing total cost and customer service level via a multiobjective optimization methodology. Finally, we analyze the impact of adding an additional transportation mode, which offers a cost vs. delivery time option to the manufacturer, on total integrated

cost. Our results demonstrate the promising performance of the proposed solution approaches to analyze the integrated cost minimization problem to near optimality in a timely manner, lowering the cost of the automotive supply chain. The proposed bicriteria, hybrid metaheuristic offers decision makers several options to trade-off cost with service level via identified Pareto-optimal solutions. The effect of the available additional transportation mode's lead time is found to be bigger than its cost on the total integrated cost measure under study.

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# CHAPTER ONE

# INTRODUCTION

## 1.1 Background

The automotive industry is the largest manufacturing sector in the United States (U.S.) in terms of the number of people employed and it also has one of the largest employment multiplier effects in the U.S. economy. Growth or contraction of this sector has a significant impact on the U.S. Gross Domestic Product (Rightmer 2012). Consequently, the competitiveness of the automotive industry is indispensable for achieving prosperity. As automotive companies face intense competition, ever-increasing customer expectations, unpredictable customer loyalty, and little tolerance for poor quality, the industry has developed advanced production systems and excess capacity where possible. Furthermore, due to the nature of this industry, companies operate under tremendous pressure to carry low inventory levels while still meeting acceptable customer service levels (Jacobs *et al.* 2009). The automotive industry has been focusing on its supply chains to increase customer satisfaction with the ultimate aim of generating greater levels of productivity, profitability, and competitiveness (Sezen *et al.* 2012, Singh *et al.* 2005).

A supply chain typically consists of suppliers, manufacturing centers, warehouses, distribution centers, and retail outlets, as well as raw materials, work-in-process inventory, and finished products that flow between the facilities (Figure 1). In practice, it is desirable to be efficient and cost-effective across the entire supply chain rather than simply minimizing transportation costs or minimizing inventories in isolation (Simchi-Levi *et al.* 2008). In addition to being economically important, the automotive industry is one of the most technologically complex industries. Given this high degree of technological sophistication, automotive companies have focused on their core competencies, one of which is preserving high efficiency. As a result, complex automotive supply chain structures have evolved over time. Typically, automotive supply chains revolve around original equipment manufacturers (OEM). Competitive pressures and mergers have reduced the total number of automotive OEMs to fewer than 20 companies throughout the globe. Figure 2 shows a general schematic of a typical automotive supply chain (Chandra and Grabis 2007).

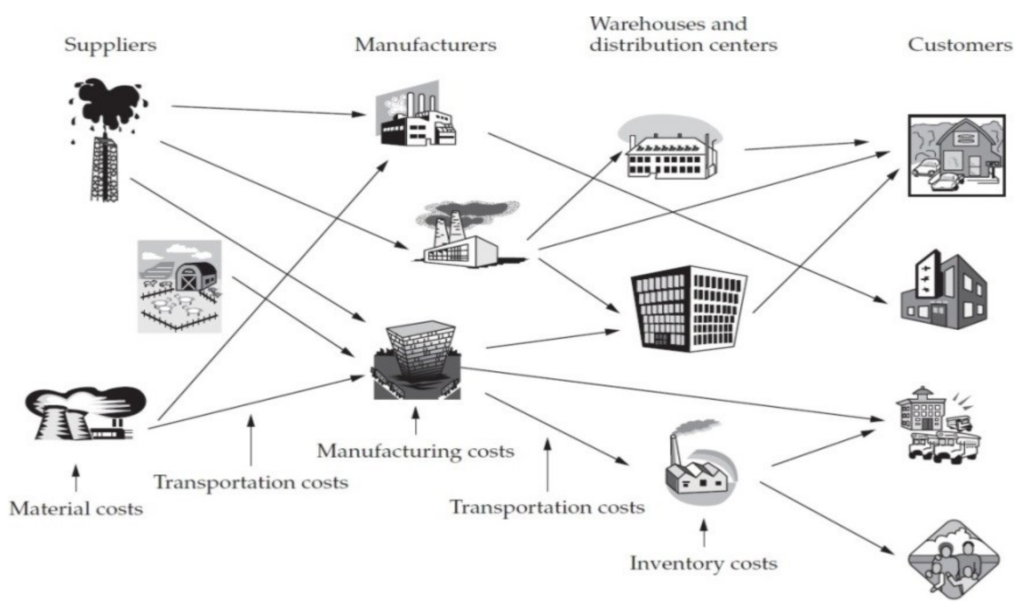


Figure 1. A Typical Supply Chain (Simchi-Levi *et al.* 2008)

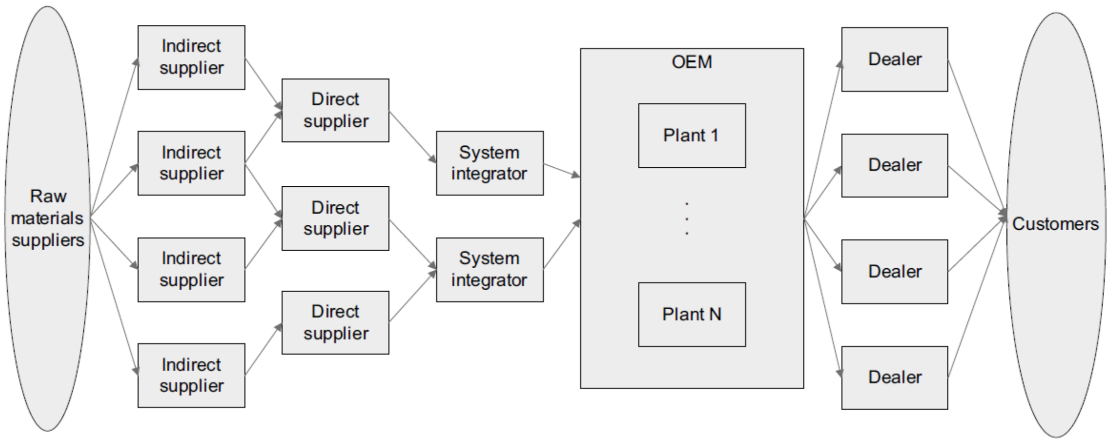


Figure 2. A General Schematic of an Automotive Supply Chain (Chandra and Grabis 2007)

OEMs assemble vehicles and deliver them to dealers. This assembly is performed in a complex network of manufacturing plants. These plants do not merely put together vehicles but form a multi-tier manufacturing system including the manufacturing of such parts as exterior body panels and engines. The majority of product development work is done by OEMs. Consolidation in the automotive industry has also affected the supply chain's supplier tier, which includes the following groups of suppliers:

- indirect suppliers who manufacture parts sold to direct suppliers (e.g., steel)
- direct suppliers who manufacture parts sold directly to system integrators or OEMs (e.g., tire manufacturers)
- system integrators who provide complex and often self-engineered modules directly to OEMs (e.g., dashboard manufacturers)

This classification does not include suppliers of raw materials, which usually are also tightly integrated into automotive supply chains by long-term contracts. However, they differ from other suppliers because raw materials suppliers are less involved in product engineering activities and because many materials can also be purchased in the spot market. Each company can be a member of different supplier groups according to the product in question.

Recently, the system integrator tier has undergone a major change in its role in the automotive supply chain. A few decades ago, OEMs performed many functions currently handled by system integrators. After OEMs outsourced the manufacturing of many parts, system integrators initially maintained strong relationships with their parent company. Currently, despite numerous obstacles, system integrators supply to multiple OEMs. Furthermore, many suppliers for which the automotive industry is not their primary focus have joined automotive supply chains as the variety of options offered to customers has increased. That is especially true of electronics suppliers (Chandra and Grabis 2007).

Although automotive supply chains typically are established around a single OEM, pressure to reduce costs has prompted several major companies to form long term or temporary alliances, such as the alliance between General Motors Corporation and Fiat. These alliances have relatively minor impact on the assembly tier of the supply chain although they can affect suppliers upstream in the supply chain. While the automotive industry traditionally has had a strong focus on engineering and manufacturing, the customer tier has been gaining an ever increasing level of importance. Many automotive companies have found themselves in trouble because of their inability to respond to customer preferences. Achieving flexibility without compromising efficiency is among the industry's top priorities. Lean manufacturing coupled with automated manufacturing systems are among the main approaches employed to follow this priority. The growing focus on the customer tier has also been influenced by mass customization, the pairing of mass production efficiency with customer demand for customized products. Option-based customization dominates the automotive industry as customers can configure vehicles by selecting from a range of available standardized options.

The distribution tier of the automotive supply chain remains comprised of dealerships associated with major automotive manufacturers. OEMs have largely abandoned direct sales plans, although they continue expanding their use of the Internet as a means to better connect with their customers by providing online vehicle configuration capabilities. The European Commission's competition rules have made it possible for dealers to sell products manufactured by multiple companies, although that is yet to have a significant impact on vehicle distribution. Sales to repair shops and other aftermarket consumers also play an important role, and they can occur at any supply chain tier (Chandra and Grabis 2007).

## 1.2 Motivation

In this dissertation, we develop and apply models and algorithms that integrate different supply chain functions in the automotive industry. We explore the application of mixed-integer linear programming and multi-objective optimization methodologies to a realistic, integrated supply chain planning problem. Our overall objective is to investigate methods that ultimately increase the competitiveness of the automotive supply chain via exploring the tradeoff between efficiency and service levels.

The motivation for this research comes from interactions with a Tier-1 automotive supplier to several major automobile manufacturers. The primary application of this research is the production and transportation of bulk interior parts for automotive OEM plants. An injection molding process is used by the supplier to produce dashboards, door panels, and other automotive parts. The finished parts are then transported to several distribution centers via full truck loads for supplying OEM plants. We focus on the integrated production and transportation planning problem while taking into account realistic conditions such as sequence-dependent setups on multiple injection modeling machines operating in parallel, auxiliary resource assignments of overhead cranes, and multiple types of incurred costs. Since unit loads of finished parts are delivered through direct trips from the plant to distribution centers, no vehicle routing is considered in the supply chain system under study.

## 1.3 Research Contributions

The first contribution of this dissertation research is in developing a model for minimizing the total integrated cost of production setups, inventory holding, outsourcing, and transportation in an integrated automotive supply chain. We introduce a model that recommends time-phased production, inventory, and shipping decisions. In addition to a mathematical model, we provide a heuristic-based solution approach for this problem in order to produce solutions for industrial manufacturers in a reasonable amount of time.

The second contribution of this research is that we develop a multi-objective optimization methodology for integrated automotive supply chains. The two objectives of interest in this dissertation are total cost (production set-up, inventory holding, and transportation) and customer service level (i.e., maximum percent outsourced parts per customer). These two objectives reflect the realistic trade-off that is often encountered by automotive industry suppliers. Our goal is to plan for the right levels of production, inventory, shipping, and outsourced quantities over the planning horizon that effectively trade-off these two conflicting objectives.

The third contribution of this dissertation is that it extends our mathematical model to include additional, realistic modes of transportation (e.g. intermodal). This extension will help companies to decide between transportation mode alternatives based on their associated cost impacts. Although the extended model is more difficult to solve, it could ultimately result in or lower cost operations when effective heuristic methods are applied to it.

## 1.4 Research Significance

Very few integrated production and transportation optimization studies have been applied to real-world supply chains (Mula *et al.* 2010). Furthermore, the research studies published to date do not focus on integrated supply chain planning in the automotive industry. Lastly, we also assert that few (if any) previous research studies present multi-criteria optimization methodologies for integrated supply chain planning problems. In total, we claim the following key points differentiate the dissertation research from previously conducted research studies:

- we integrate different supply chain functions (production, warehousing, and transportation) of a Tier-1 automotive supplier at a detailed level to optimize a number of decisions involving multiple part types and multiple customers: production quantities on multiple resources (including parallel machines and auxiliary resources), inventory levels, and shipping quantities
- our research incorporates sequence-dependent setup times in the integrated model
- we apply mixed-integer programming and multi-objective optimization methodologies to the proposed problem to simultaneously address total cost and service level tradeoffs
- we develop suitable algorithms (such as heuristics/metaheuristics) to solve the proposed problem in a timely manner for industry use
- we interact with industry to formulate our models based on realistic assumptions

## 1.5 Literature Review

### *1.5.1 Integrated Production and Transportation Planning*

A review of mathematical programming models for supply chain production and transportation planning is presented by Mula *et al.* (2010). The authors review a total of 44 references over the period from 1989 to 2009. The paper presents a taxonomy framework based on the following elements: decision level, supply chain structure, application, modeling approach, purpose, shared information, limitations, and novelty

(Figure 4). The studies reviewed deal with production planning models that consider transportation as a resource to distribute products and focus on the tactical and/or operational levels of emphasis. However, their possible combinations with aspects of strategic decisions are also discussed. The authors conclude that proposed models in the literature often are validated by numerical examples more than by actual case studies applied to real-world supply chains. While some of the reviewed papers deal with applications, such as glass production, steel production, and the chemical industry, none involve the automotive industry with its technologically complex nature. Timpe and Kallrath (2000) describe a general mixed-integer linear programming model based on a time-indexed formulation for complete supply chain management of a multi-site production network. While the actual application is taken from the chemical industry, the model provides a starting point for many applications in the chemical process industry, food, or consumer goods industries. This model captures aspects of continuous manufacturing and thus does not apply to the discrete manufacturing of highly variable automotive parts.

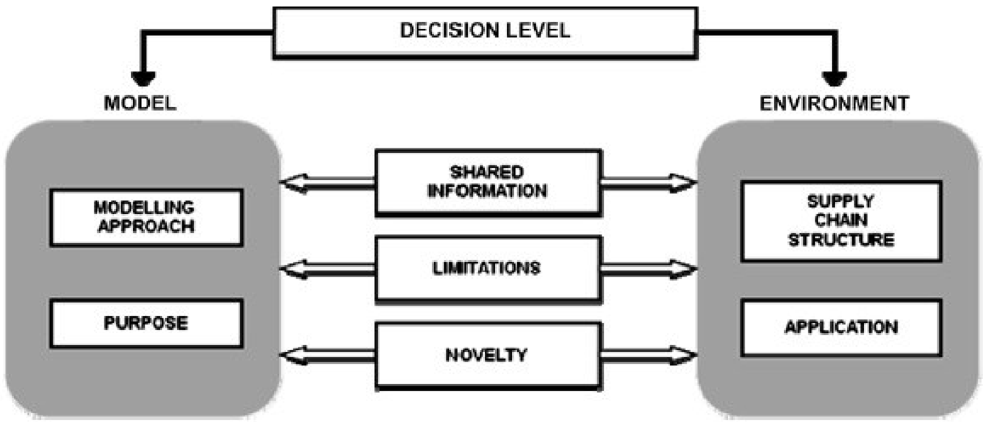


Figure 3. Taxonomy Criteria (Mula *et al.* 2010)

One approach in supply chain planning is to integrate different supply chain functions (e.g. purchasing, production, distribution, and storage) into a single, monolithic model (Park 2005). Rizk *et al.* (2006) examine a multi-item, dynamic production-distribution planning problem between a manufacturing location and a DC. Transportation costs between the manufacturing location and the distribution center offer economies of scale and can be represented by general piecewise linear functions. The production system at the manufacturing location is a serial process with a multiple parallel machine bottleneck stage and divergent finishing stages. A tight mixed-integer programming model of the production process is proposed, as well as three different formulations to represent general piecewise linear functions.

Next, Rizk *et al.* (2008) study the flow synchronization problem between a manufacturing location and multiple destinations. Multiple products can be shipped from the manufacturing location to different locations via multiple transportation modes. These transportation modes may have different transportation lead times. The transportation costs structure of the different transportation modes offer economies of scale and can be represented by general piecewise linear functions. The authors propose a tight mixed-integer programming model for integrated planning of production and distribution in the network. The solution methods proposed are tested experimentally for realistic problems and the advantage of integrated planning over independent but synchronized planning is assessed. The models presented by Rizk *et al.* (2006) and Rizk *et al.* (2008) reflect aspects found in several process industries including divergent finishing stages, such as the pulp and paper industry, the aluminum industry, and the processed food industry. However, such models do not reflect important characteristics of the automotive supply chain industry, such as sequence-dependent setup times and compatibility constraints.

### *1.5.2 Integrated Production and Distribution Scheduling*

Thomas and Griffin (1996) note that there is scarcity in the literature addressing supply chain coordination at an operational level. Chen (2004) confirms that there is a gap of integrated models at the detailed scheduling level, and that there is a need for fast solution algorithms. Chen (2010) reviews existing models that integrate production and outbound distribution scheduling and synthesizes existing results on these models. In practice, decisions at the aggregate planning level and those at the detailed scheduling level often follow a hierarchical relationship.

Aggregate production-distribution plans on product mix, production and transportation capacity availability, and allocation of capacity to products in a given planning horizon (i.e. tactical level) are often used as inputs to generate detailed order-by-order processing and delivery schedules over shorter periods of time (i.e. operational level). The scope of research reviewed includes make-to-order (a.k.a. assemble-to-order, build-to-order) business models in which products are custom-made and delivered to customers within a very short lead time directly from the factory, such as assembly and delivery of personal computers and production and distribution of fashion apparel. Consequently, there is little or no finished product inventory in the supply chain such that production and outbound distribution are very closely linked and must be scheduled jointly to achieve a desired on-time delivery performance at minimum total cost. Other supply chain environments include time-sensitive products, such as perishable products (e.g. ready-mix concrete paste and industrial adhesive materials).

### *1.5.3 Injection Molding Scheduling*

Ghosh Dastidar and Nagi (2005) model an injection molding scheduling problem as a mixed-integer program involving parallel work centers, sequence-dependent setup times and costs, and multiple capacitated resource constraints for a multi-item, multi-class of products in a single stage. The authors collaborate with a healthcare injection molding company. The objective is to meet customer demands while minimizing total inventory holding costs, backlogging costs, and setup costs. The complexity associated with the formulation makes it difficult for standard solvers to address industrial-dimensioned problems in reasonable solution time. The authors propose a two-phase work center-based decomposition scheme, dividing large dimensioned problems into smaller sub-problems. The computational results for different problem sizes demonstrate that this scheme is able to solve industrial-dimensioned problems within reasonable time and accuracy. Our proposed research problem is different from the one presented in this paper as we simultaneously optimize transportation decisions while incorporating crane assignment decisions in the model. Furthermore, we analyze a more extensive experimental problem instance set to reflect realistic conditions in the automotive industry.

### *1.5.4 Automotive Supply Chain Modeling*

Limere *et al.* (2012) introduce a mathematical cost model for evaluating the assignment of parts to one of two possible material supply systems: kitting or line stocking. Case data from an automotive company in Belgium is used to test the model. The results demonstrate that hybrid policies wherein some parts are kitted while others will be stocked in bulk at the line are preferred to the exclusive use of either material delivery system. The factors influencing the preferred delivery method for individual parts are explored. The proposed model is a first attempt to fill a gap in the literature related to kitting. Klug (2011) analyzes critical issues in container demand planning for the product development phase of a new car model before the start of production. Monte Carlo simulation is used to incorporate parameter uncertainty as the study is based on real data from a multi-tier inbound transportation network.

### *1.5.5 Literature Review Summary*

Our review of the available literature reveals that there is a gap in the literature focusing on modeling the automotive supply chain. We could identify only one study that applies mixed-integer linear programming to automotive supply chains. However, this study does not deal with integrated production and transportation planning, which is the subject of our proposed research problem. Although mixed-integer linear programming is applied to the integrated production and transportation planning problem as shown in the reviewed studies, none of these models deals with the automotive industry and thus none focuses on discrete manufacturing aspects or sequence-dependent setup times. A somewhat relevant model to the current research is the one presented by Ghosh Dastidar and Nagi (2005). However, the current research problem is different because it incorporates transportation and auxiliary resource (i.e., crane) decisions. Very few integrated production and transportation optimization studies have been applied to real-world supply chains (Mula *et al.* 2010). Furthermore, the research studies published to date do not focus on integrated supply chain planning in the automotive industry. The current dissertation research attempts to start filling this gap in the related literature.

## 1.6 Dissertation Outline

The rest of this dissertation document is organized as follows. Chapter 2 presents the mathematical model and heuristic solution approaches for minimizing the integrated cost of the two-stage, automotive supply chain. Next, Chapter 3 provides the heuristic solution methodology for the bi-criteria optimization problem of interest, while Chapter 4 analyzes the two-stage automotive supply chain with heterogeneous transportation. Finally, Chapter 5 provides the overall conclusions and future research directions.

# CHAPTER TWO

# INTEGRATED COST OPTIMIZATION IN A TWO-STAGE, AUTOMOTIVE SUPPLY CHAIN

The efficiency of the automotive supply chain is crucial for ensuring the competitiveness of the automotive industry, which represents one of the most significant manufacturing sectors. We model the integrated production and transportation planning problem of a Tier-1 automotive supplier while taking into account realistic conditions such as sequence-dependent setups on multiple injection molding machines operating in parallel, auxiliary resource assignments of overhead cranes, and multiple types of costs. Finished parts go to the integrated supply chain's second stage, transportation, for subsequent delivery by capacitated vehicles to multiple distribution centers for meeting predefined due date requirements. We develop a mixed-integer, linear programming model of the problem, and then present a hybrid simulated annealing algorithm (HSAA), including a constructive heuristic. Our proposed HSAA employs an effective encoding-decoding strategy to approximately solve the NP-hard problem in a timely manner. Computational results demonstrate the promising performance of the proposed solution approach.

## 2.1 Introduction

The automotive industry is the largest manufacturing sector in the United States (U.S.) in terms of the number of people employed and it also has one of the largest employment multiplier effects in the U.S. economy. Growth or contraction of this sector has a significant impact on the U.S. Gross Domestic Product (Rightmer 2012). Consequently, the competitiveness of the automotive industry is important for a higher standard of living. As automotive companies face intense competition, ever-increasing customer expectations, unpredictable customer loyalty, and little tolerance for poor quality, the industry has developed advanced production systems and excess capacity where possible. Furthermore, due to the nature of this industry, companies operate under tremendous pressure to carry low inventory levels while still meeting acceptable customer service levels (Jacobs *et al.* 2009). The automotive industry has been focusing on its supply chains to increase customer satisfaction with the ultimate aim of generating greater levels of productivity, profitability, and competitiveness (Sezen *et al.* 2012, Singh *et al.* 2005).

A supply chain typically consists of suppliers, manufacturing centers, warehouses, distribution centers, and retail outlets, as well as raw materials, work-in-process inventory, and finished products that flow between the facilities. In practice, it is desirable to be efficient and cost-effective across the entire supply chain rather than simply minimizing transportation costs or minimizing inventories in isolation (Simchi-Levi *et al.* 2008). In addition to being economically important, the automotive industry is one of the most technologically complex industries. More information about recent developments in the automotive supply chain is presented by Chandra and Grabis (2007).

The motivation for this research comes from interactions with a Tier-1 automotive supplier to several major automobile manufacturers. The primary application of this research is the production and transportation of bulk interior parts for automotive OEM plants. An injection molding process is used by the supplier to produce dashboards, door panels, and other automotive parts. The finished parts are then transported to several distribution centers for supplying OEM plants. We focus on the integrated production and transportation planning problem while taking into account realistic conditions such as sequence-dependent setups on multiple injection molding machines operating in parallel, auxiliary resource assignments of overhead cranes, and multiple types of incurred costs.

The research problem deals with multi-period planning for production, inventory, and transportation in a two-stage, integrated supply chain system. In the first stage, production, different parts must be scheduled on multiple parallel machines according to part-machine compatibility restrictions—we seek to determine appropriate part production lot sizes. Setups pertaining to tool change vs. color change must be performed to allow an injection molding machine to changeover to a different tool or color. Another limited resource in the production stage is cranes that are required for machine changeovers to a different tool. However, each crane can only serve certain machines due to crane-machine compatibility constraints.

The manufacturing plant's finished parts warehouse has a limited capacity. Finished parts go to the integrated supply chain's second stage, transportation, for subsequent delivery by capacitated vehicles to multiple distribution centers (DCs) to meet predefined due date requirements. Transportation occurs via full truck load (TL) and transportation cost is fixed from the plant to each DC. As the manufacturer typically outsources transportation, we assume that there exist an infinite number of delivery vehicles. Each manufactured part is associated with a customer (i.e., DC) and has its own required cycle time, size (i.e., storage space requirement), and demand schedule (i.e., quantities and due times at a DC). The supply chain only allows direct deliveries without any intermediate stops (i.e., only one customer per trip). Figure 4 shows the supply chain system under study. Our motivating research objective is to minimize total cost, which is comprised of setup costs, inventory (holding) costs, transportation costs, and outsourcing costs.

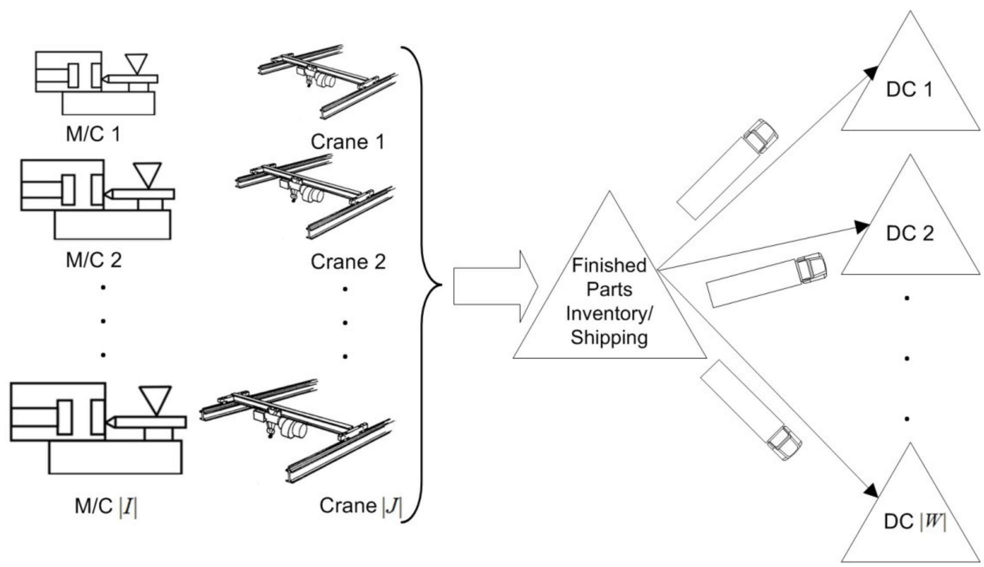


Figure 4. Schematic of the Automotive Supply Chain under Investigation

One approach in supply chain planning is to integrate different supply chain functions (e.g. purchasing, production, distribution, and storage) into a single, integrated model (Park 2005). Thomas and Griffin (1996) note that there is scarcity in the literature addressing supply chain coordination at an operational level. Chen (2004) confirms that there is a gap of integrated models at the detailed scheduling level and that there is a need for fast solution algorithms. Chen (2010) reviews existing models that integrate production and outbound distribution scheduling in make-to-order supply chains with little or no finished product inventory in the supply chain, such as the production and distribution of fashion apparel and the assembly and delivery of personal computers.

Mula *et al.* (2010) indicate that proposed integrated production and transportation planning models in the literature often are validated by numerical examples more than by actual case studies applied to real-world supply chains. Mixed-integer linear programming is applied to the integrated production and transportation planning problem in different contexts, such as continuous manufacturing (Timpe and Kallrath 2000) and process industries (Rizk *et al.* 2006, Rizk *et al.* 2008). We could not identify any paper that models the integrated production and transportation planning problem in the automotive industry at a detailed, operational level, reflecting its technological complexity, discrete manufacturing aspects, sequence-dependent setup times, and compatibility constraints.

Klug (2011) uses Monte Carlo simulation to analyze critical issues in container demand planning for the product development phase of a new car model before the start of production. Limere et al. (2012) introduce a mathematical cost model for evaluating the assignment of automotive parts to one of two possible material supply systems: kitting or line stocking. Zhang *et al.* (2011) study the trade-offs between inventories, production costs, and customer service level in an automobile manufacturing supply chain network, but do not model the details that are included in our proposed research problem. Although a somewhat relevant model to the current research is the one presented by Ghosh Dastidar and Nagi (2005), our proposed research problem is different as we incorporate transportation and auxiliary resource (i.e., crane) decisions. Furthermore, we analyze a more extensive experimental problem instance set to reflect realistic conditions in the automotive industry. The current research aims to start filling the literature gap of integrated automotive supply chain planning at a detailed, operational level.

The rest of this chapter is organized as follows. Section 2.2 formulates a mixed-integer linear programming (MILP) model that captures various pertinent aspects of the problem under study. Due to the problem's complexity and the associated inability to solve large problem instances optimally, a hybrid simulated annealing algorithm is developed for industry application in Section 2.3. Then Section 2.4 describes the experimental study used to evaluate the proposed solution methodologies. Section 2.5 overviews the computational results, and Section 2.6 presents the conclusions and future research directions.

## 2.2 Mixed-Integer Linear Programming Model

We now present a mathematical programming model for minimizing total cost in an integrated, two-stage automotive supply chain. Before presenting the model and its associated notation, we first detail the necessary assumptions made in our research study:

- The number of part types produced by a machine is restricted to one per time period.
- Every machine has a production capacity that cannot be exceeded.
- Parts are shipped directly to customers or held in inventory for shipping in later periods.

- Finished part warehouse at the plant has a holding capacity that cannot be exceeded.
- Every transportation vehicle has a capacity bound that cannot be exceeded.
- A maximum of one machine setup per time period can be performed by a crane.
- Handling times between machines and finished part warehouse at the plant are negligible.
- All machines have been initially set up before the first time period.
- There is no plant finished part inventory at the beginning of the planning horizon.

### 2.2.1 Notation

*Index Sets*

| | |
|---|---|
| $I$ | set of machines, indexed by $i$ |
| $J$ | set of cranes, indexed by $j$ |
| $P$ | set of part types, indexed by $p$ |
| $W$ | set of distribution centers, indexed by $w$ |
| $T$ | set of time periods, indexed by $t$ |

*Parameters*

| | |
|---|---|
| $D_{t,p,w}$ | demand by distribution center $w$ of part type $p$ in time period $t$ (parts) |
| $\mu_p$ | unit production time (cycle time) of part type $p$ (secs) |
| $F$ | length of time period (hours) |
| $S_{i,p,p'}$ | changeover time from part type $p$ to part type $p'$ on machine $i$ (mins) |
| $E_p$ | maximum quantity of parts per unit load of part type $p$ (parts/unit load) |
| $K$ | plant finished part warehouse capacity (unit loads) |
| $G$ | vehicle capacity (unit loads) |
| $H_p$ | unit inventory holding cost of part type $p$ ($/part/period) |
| $L_w$ | cost of a vehicle trip from plant to distribution center $w$ ($/trip) |
| $M_i$ | cost of downtime on machine $i$ ($/min) |
| $N_p$ | cost of outsourcing of part type $p$ ($/part) |
| $A_{i,p}$ | equals one if machine $i$ is compatible with part type $p$, 0 otherwise |
| $B_{j,i}$ | equals one if crane $j$ can serve setup on machine $i$, 0 otherwise |
| $C_{p,p'}$ | equals one if setup from part type $p$ to part type $p'$ requires a crane, 0 otherwise |

*Decision Variables*

| | |
|---|---|
| $\alpha_{t,p,w}$ | quantity of part type *p* transported to distribution center *w* in time period *t* |
| $\beta_{t,w}$ | number of vehicle trips to distribution center *w* in time period *t* |
| $h_{t,p}$ | quantity of finished part inventory of part type *p* in time period *t* |
| $q_{t,i,p}$ | quantity of part type *p* processed on machine *i* in time period *t* |
| $u_{t,p,w}$ | quantity of outsourcing of part type *p* demanded by distribution center *w* in time period *t* |
| $x_{t,i,p}$ | equals one if machine *i* processes part type *p* in time period *t*, 0 otherwise |
| $y_{t,i,p,p'}$ | equals one if machine *i* changes over from part type $p$ to part type $p'$ in time period *t*, 0 otherwise |
| $z_{t,j,i}$ | equals one if crane *j* serves setup on machine *i* in time period *t*, 0 otherwise |

### 2.2.2 Model

$$\begin{aligned} \mathit{minimize} \sum_{t\in T, t\neq 1} \sum_{i\in I} \sum_{p\in P} \sum_{p'\in P, p'\neq p} S_{i,p,p'} M_i y_{t,i,p,p'} + \sum_{t\in T} \sum_{p\in P} H_p h_{t,p} \\ + \sum_{t\in T} \sum_{w\in W} L_w \beta_{t,w} + \sum_{t\in T} \sum_{p\in P} \sum_{w\in W} N_p u_{t,p,w} \end{aligned} \tag{1}$$

*subject to*

$$\beta_{t,w} \geq \frac{1}{G} \sum_{p\in P} \frac{1}{E_p} \alpha_{t,p,w} \qquad \forall t \in T,\ \forall w \in W \tag{2}$$

$$u_{t,p,w} = D_{t,p,w} - \alpha_{t,p,w} \qquad \forall t \in T,\ \forall p \in P,\ \forall w \in W \tag{3}$$

$$\sum_{p\in P} \frac{1}{E_p} h_{t,p} \leq K \qquad \forall t \in T \tag{4}$$

$$h_{t,p} = \sum_{i\in I} q_{t,i,p} - \sum_{w\in W} \alpha_{t,p,w} \qquad t=1,\ \forall p \in P \tag{5}$$

$$h_{t,p} = h_{t-1,p} + \sum_{i\in I} q_{t,i,p} - \sum_{w\in W} \alpha_{t,p,w} \qquad \forall t \in T,\ \forall p \in P, t\neq 1 \tag{6}$$

$$\mu_p q_{t,i,p} \leq F x_{t,i,p} \qquad t=1,\ \forall i \in I,\ \forall p \in P \tag{7}$$

$$\mu_p q_{t,i,p} + \sum_{p' \in P, p' \neq p} S_{i,p,p'} y_{t,i,p,p'} \leq F x_{t,i,p} \qquad \forall t \in T,\ \forall i \in I,\ \forall p \in P,\ t \neq 1 \qquad (8)$$

$$y_{t,i,p,p'} \geq x_{t,i,p} + x_{t-1,i,p'} - 1 \qquad \forall t \in T,\ \forall i \in I,\ \forall p \in P,\ \forall p' \in P,\ t \neq 1, p \neq p' \qquad (9)$$

$$x_{t,i,p} \leq A_{i,p} \qquad \forall t \in T,\ \forall i \in I,\ \forall p \in P \qquad (10)$$

$$\sum_{p \in P} x_{t,i,p} \leq 1 \qquad \forall t \in T,\ \forall\ i \in I \qquad (11)$$

$$\sum_{j \in J} z_{t,j,i} = \sum_{p \in P} \sum_{p' \in P, p' \neq p} y_{t,i,p,p'} C_{p,p'} \qquad \forall t \in T,\ \forall\ i \in I,\ t \neq 1 \qquad (12)$$

$$z_{t,j,i} \leq B_{j,i} \qquad \forall t \in T,\ \forall\ j \in J,\ \forall\ i \in I,\ t \neq 1 \qquad (13)$$

$$\sum_{i \in I} z_{t,j,i} \leq 1 \qquad \forall t \in T,\ \forall j \in J,\ t \neq 1 \qquad (14)$$

$$\sum_{j \in J} z_{t,j,i} \leq 1 \qquad \forall t \in T,\ \forall i \in I,\ t \neq 1 \qquad (15)$$

$$\alpha_{t,p,w}, \beta_{t,w}, h_{t,p}, q_{t,i,p}, u_{t,p,w} \geq 0 \text{ and integer} \qquad \forall i \in I,\ \forall\ j \in J,\ \forall p \in P,\ \forall w \in W,\ \forall t \in T \qquad (16)$$

$$x_{t,i,p}, y_{t,i,p,p'}, z_{t,j,i} \in \{0, 1\} \qquad \forall i \in I,\ \forall j \in J,\ \forall p \in P,\ \forall p' \in P,\ \forall t \in T, p' \neq p \qquad (17)$$

The model's objective function (1) minimizes total cost, which is composed of setup, inventory holding, transportation, and outsourcing cost. Constraint set (2) calculates the number of vehicle trips to every distribution center at every time period based on truck capacity and unit load volumes, while constraint set (3) computes the quantities of outsourcing of every part type demanded by each DC in every time period. Next, constraint set (4) ensures the capacity of plant finished part warehouse is not exceeded. Constraint sets (5) and (6) conserve the flow of every part type inventory during the first time period and after the first time period, respectively. Next, constraint sets (7) and (8) ensure the available capacity of every machine cannot be exceeded during the first time period and after the first time period, respectively.

Constraint set (9) dictates that if a machine changes to a different part type after the first time period, a setup is required. Constraint set (10) ensures that every machine respects machine-part type matching restrictions. Constraint set (11) limits the number of part types produced by a machine to one per time period. Next, constraint set (12) enforces that a machine setup requiring a crane (i.e., a tooling changeover) occurs if and only if a crane serves the setup. Constraint set (13) dictates that every crane respects crane-machine compatibility restrictions. Next, constraint sets (14) and (15) limit the number of machine setups per time period to a maximum of one per crane and one per machine, respectively. Finally, constraint sets (16) and (17) are non-negativity integer and binary value constraints, respectively.

A number of small problem instances were created and solved to optimality using Gurobi to verify the accuracy of the proposed model. For example, one such small problem consisted of five machines, three cranes, five part types, four time periods, and a single DC. The optimal objective function value obtained by Gurobi version 5.1 was the same as that which was produced by manual calculations and therefore, the model was deemed to be accurate and valid.

### *2.2.3 Complexity*

The current integrated supply chain problem of interest subsumes another known-to-be NP hard problem, the capacitated lot sizing problem (Florian *et al.* 1980). The classical capacitated lot sizing problem consists of determining the amount and timing of production over a planning horizon. Capacity restrictions constrain the production quantity in each period. A fixed setup cost and a linear production cost are specified, and there is also an inventory holding cost proportional to the inventory amount and time carried. The proposed integrated research problem subsumes the classical capacitated lot-sizing problem because the former involves additional constraints, such as sequence-dependent setup times and transportation constraints.

To illustrate, consider a special case of our research problem, where there is only one distribution center that is located in the same plant facility, so there is no transportation. Also, the cost of outsourcing is relatively very large, and there is enough production capacity to satisfy all of the demand, so the optimal solution to the problem dictates that there is no outsourcing (i.e. all demand is satisfied from in-house production). At the same time, all setups require no cranes (i.e. all part types need only one tooling) and are not sequence dependent (i.e. setup times are determined only by the current part type and are not affected by the previous part type on the same machine). Furthermore, there are no compatibility restrictions between machines and part types. In this special case of our problem, the objective function (1) consists of only two components, which are production setup cost and inventory holding cost. Constraint sets (2), (9), (10), (12), (13), (14), and (15) are omitted due to the described conditions. Furthermore, $u_{t,p,w}$is removed from (3) and (16), and $\alpha_{t,p,w}$ is taken out of (5), (6), and (16). Finally, $y_{t,i,p,p'}$, and $z_{t,j,i}$ are removed from (17). Then the remaining model reflecting this special case is the capacitated lot sizing problem, which is NP-hard. Since the capacitated lot sizing problem is a special case of our research problem, no algorithm exists that can solve the current research problem of interest to optimality in polynomial time. Therefore, we propose a heuristic algorithm for achieving near-optimal solutions in a timely manner, especially for large problem instances.

## 2.3 Hybrid Simulated Annealing Algorithm

The first use of simulated annealing (SA) to solve combinatorial optimization problems was introduced by Kirkpatrick *et al.* (1983). SA is known for its flexibility and ability to handle large and complex problems (Jans and Degraeve 2007), and it is a memoryless algorithm in that the algorithm does not use any information gathered during the search prior to the current iteration. In addition to the current solution, the best solution found since the beginning of the search is stored (Talbi 2009). There are four components of the proposed hybrid simulated annealing algorithm (HSAA): encoding-decoding strategy, constructive heuristic starting solution, perturbation schemes, and algorithm parameters. We now detail additional required notation and equations, and then describe the proposed HSAA for integrated automotive supply chain planning.

### *2.3.1 Required HSAA Notation and Equations*

| | |
|---|---|
| $\gamma_p$ | grand total demand per part type |
| $\delta_p$ | upper bound of number of machine runs required to satisfy grand total demand per part type |
| $\theta$ | upper bound of number of machine runs |
| $\pi_{t,p}$ | lower bound of number of machines needed to satisfy part type time period demand |
| $\sigma_p$ | part type "fortune" (number of machines compatible with the part type ) |
| $\tau$ | matrix of priority lists of part type machine runs over planning horizon |

| | |
|---|---|
| $iter$ | HSAA iteration counter |
| $f_{best}$ | minimum total cost achieved throughout the search (corresponding to $\tau_{best}$) |
| $\tau_{best}$ | $\tau$ resulting in the least total cost achieved throughout the search (corresponding to $f_{best}$) |
| $\tilde{t}_{iter}$ | HSAA temperature parameter at iteration $iter$ (e.g. $iter$=1, 2, 3…etc.) |
| $\tilde{\alpha}$ | HSAA parameter used in the cooling schedule |
| $pr$ | probability of accepting proposed solution $\tau_{proposed}$ and $f_{proposed}$ |
| $rand$ | a random number between 0 and 1 generated from uniform distribution |
| $\overline{iter}$ | maximum number of iterations in HSAA (stopping criterion) |

Equation sets (18)-(22) define the first five parameters mentioned above in the notation listing. The ceiling operator $\lceil\blacksquare\rceil$ produces the smallest integer not less than $\blacksquare$. The definitions of the remaining parameters are discussed in the following sections.

$$\gamma_p = \sum_{t\in T}\sum_{w\in W} D_{t,p,w}\,, \qquad \forall p \in P \qquad (18)$$

$$\delta_p = \left\lceil \frac{\gamma_p \mu_p}{F - \max_{i\in I, p\in P, p'\in P, p'\neq p}(S_{i,p,p'})} \right\rceil, \qquad \forall p \in P \qquad (19)$$

$$\theta = \sum_{p\in P} \min\left(\delta_p, \sum_{i\in I} A_{i,p}\right) \qquad (20)$$

$$\pi_{t,p} = \left\lceil \frac{\mu_p \sum_{w\in W} D_{t,p,w}}{F} \right\rceil, \qquad \forall t \in T, \forall p \in P \qquad (21)$$

$$\sigma_p = \sum_{i\in I} A_{i,p} \qquad \forall p \in P \qquad (22)$$

### *2.3.2 Encoding-Decoding Strategy*

While most steps of the proposed HSAA, including the constructive heuristic, work in the encoding space, the decoding step is responsible for generating the values of all decision variables and objective function (i.e. total integrated cost) related to a specific encoding. We present an effective, indirect encoding method that is motivated by the need to capture all practically possible assignments of part types to machine and crane setups flexibly, yet efficiently. The proposed encoding method avoids generating any infeasible solutions from perturbation schemes, and it also aims to reduce the search space as much as possible. These aspects contribute to the ultimate objective of improving the algorithm's performance. The encoding for the proposed HSAA consists of the matrix $\tau$ that has $|T|$ rows and $|I| + \theta$columns. Each row in $\tau$ represents a single time period and consists of an active tuple of size $|I|$ and an inactive tuple of size $\theta$. The active tuple reflects a priority list. Considering an active tuple, every entry in that active tuple represents either a possible part type run or a forced machine idling. A part type run or machine idling in the active tuple's first entry (column) has a higher priority than the second entry, and so on. Since every entire row in $\tau$ is generated to consist of all possible part type runs and machine idle periods that could be required to satisfy the total demand over the planning horizon, the goal is to activate the best tuple of entries of part types and machine idlings in every time period to arrive at the lowest total integrated cost.

This approach also efficiently prioritizes setups to allow the most effective assignment of cranes. Depending on the parameters $\delta_p$ and $\theta$, an example of the matrix $\tau$ for a small problem instance with $|I| = 3; |P| = 3; and\ |T| = 2$ could be like the one shown in Figure 5. In this small instance, there are two runs for part type one, three runs for part type two, and one run for part type three. For example, the active tuple in the first row (i.e., first time period) prioritizes first a part type two run, then a part type one run. Next, a machine is left idle. The inactive tuple has no effect on the decision variable and objective function values resulting from the decoding step in a current HSAA iteration.

However, due to applied perturbation schemes, some of the current inactive tuple entries can belong to active tuples in future iterations and are then decoded accordingly.

In the proposed HSAA, the decoding step is first responsible for mapping the $\tau$ matrix to the corresponding values of all binary decision variables. Our decoding strategy divides the original problem into several sub-problems by working on one $\tau$ matrix entry at a time in priority order (i.e., in order of the columns in the $\tau$ matrix). Given a single entry, four machine-part type assignment rules (Figure 6) are applied sequentially that attempt to assign the current part type run to a compatible machine at the lowest possible cost. This is achieved by trying to minimize the setup cost for both the current part type and any remaining part types to be assigned to machines. The values of all binary variables are calculated in this step. Since each set of binary variable values relate to a set of optimal values for the continuous and integer variables, this optimal set is found by solving a reduced MILP model, which is the original MILP model problem with the binary variables fixed. Solving the resulting reduced MILP also computes the corresponding objective function value (i.e., total integrated cost). The details of decoding and objective function evaluation are depicted in Figure 6.

### *2.3.3 Constructive Heuristic Starting Solution*

We develop a constructive heuristic to allow the HSAA search process to start from a point that is as close as possible to an optimal solution, thus maximizing the efficiency of the algorithm. The heuristic is based on the idea of minimizing inventory holding costs by attempting to produce the demand of any given time period within the same time period (i.e., not too early). A flow chart describing the constructive heuristic for generating the initial $\tau$ matrix is shown in Figure 7. An example of the constructive heuristic and decoding is presented in Appendix A.

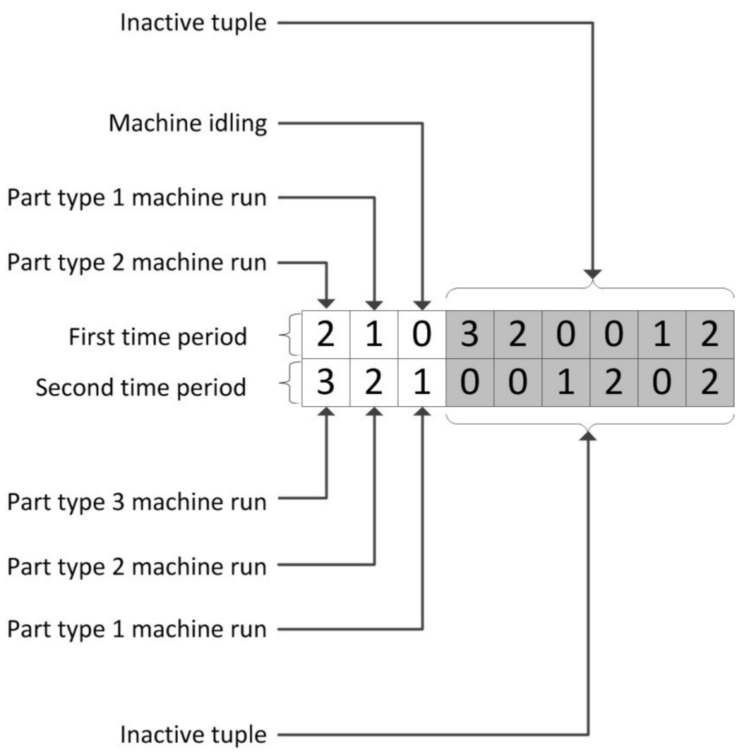


Figure 5. An Example Encoding (Matrix of Priority Lists $\tau$) for a Small Instance

### *2.3.4 Perturbation Schemes*

At every iteration of the proposed HSAA, the algorithm first generates six different neighbors to the current $\tau$ matrix, and then evaluates all six neighbors to select the neighbor with the least corresponding total integrated cost as the proposed neighbor. This approach, termed the "best move" strategy, provides the advantage of freeing the HSAA's performance from its possible dependence on the cooling schedule, with the objective of avoiding problems with both converging to a near optimal solution and escaping traps of locally optimal solutions (Ishibuchi *et al.* 1995). The six perturbation schemes (PS) employed are described in Table 1, and an example of PS1 is depicted in Figure 8.

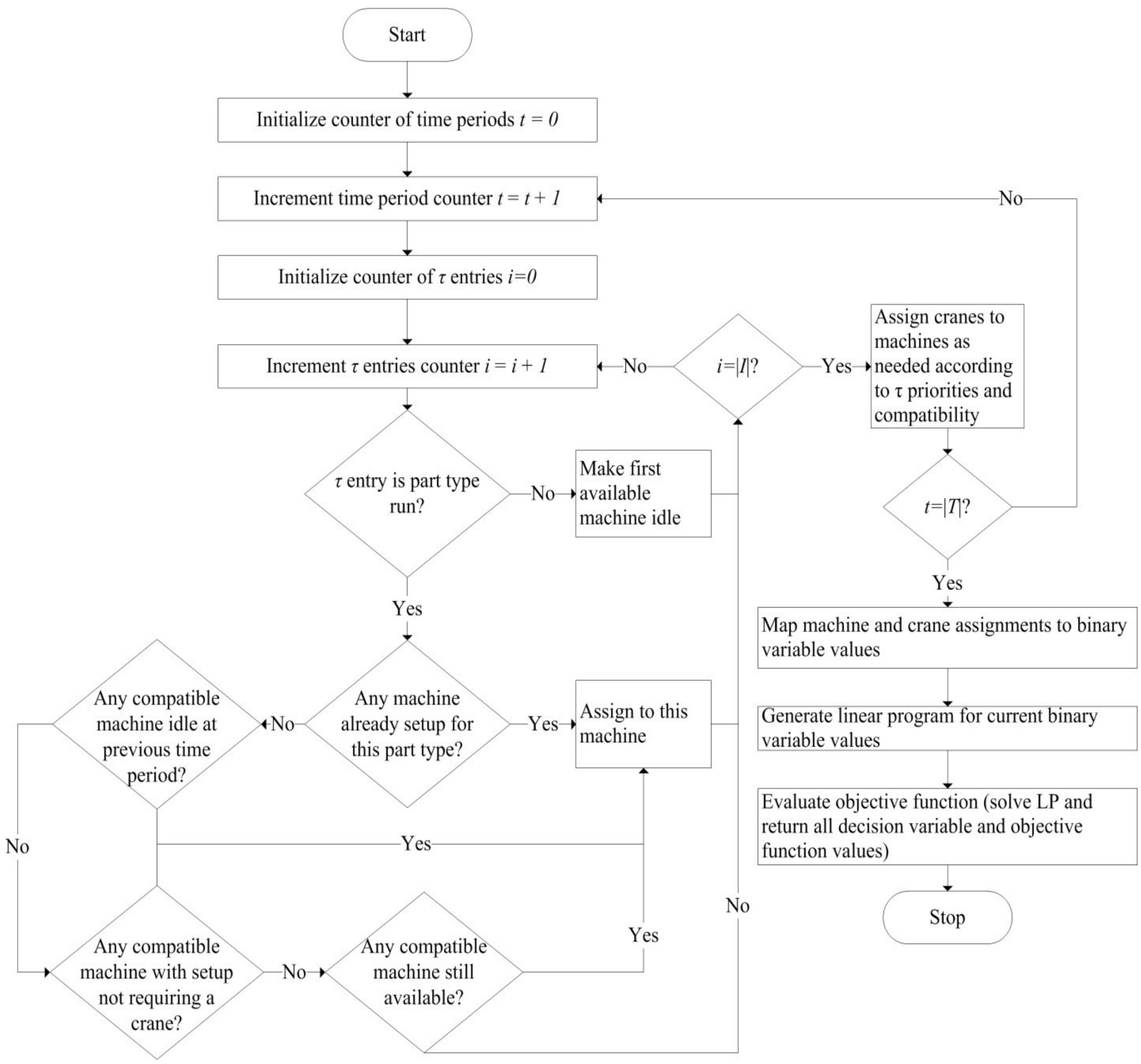


Figure 6. Flow Chart of Decoding and Objective Function Evaluation

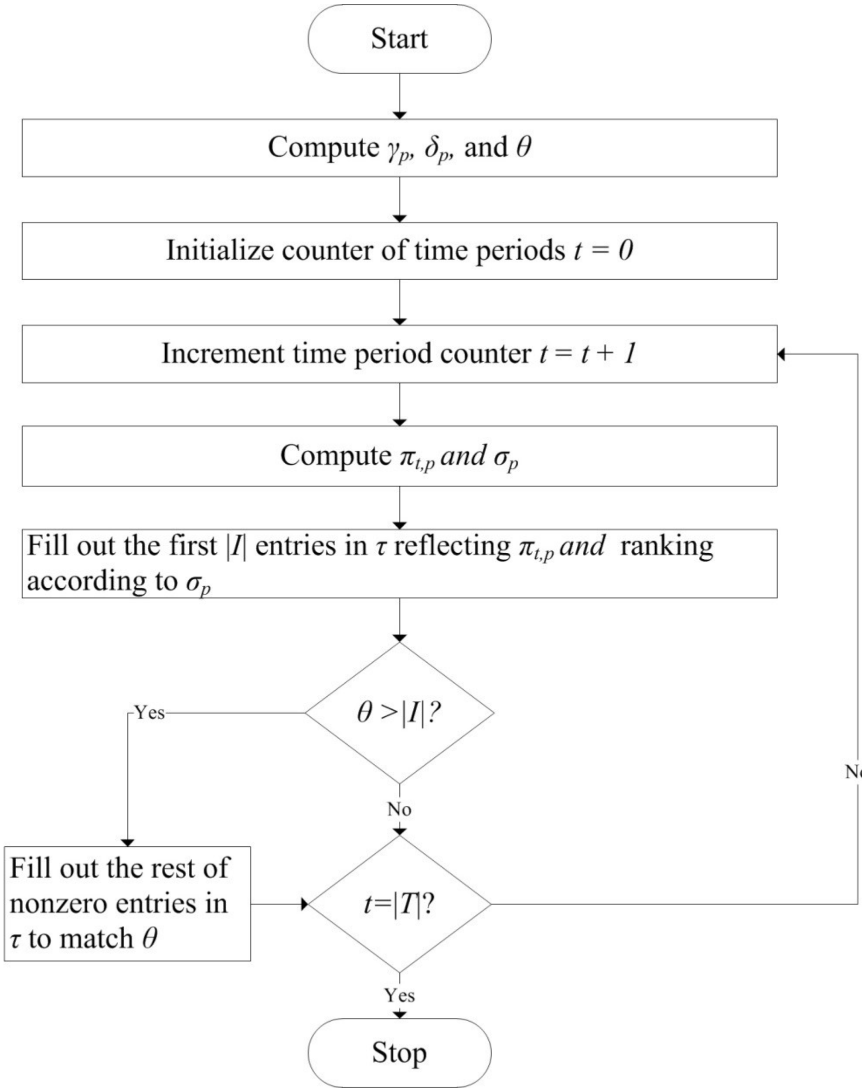


Figure 7. Flow Chart of Generating Starting Matrix of Priority Lists (Initial $\tau$)

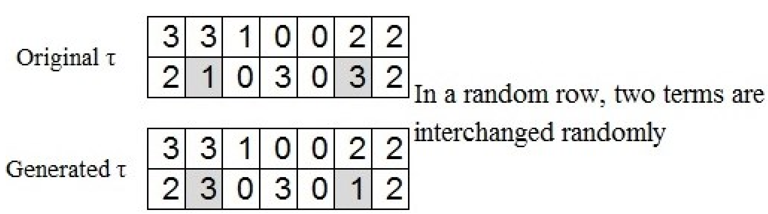


Figure 8. An Example of Perturbation Scheme 1

Table 1. Perturbation Schemes used in HSAA

| Perturbation Scheme | Description |
|---|---|
| PS1 | In a random row of $\tau$ (encoding), two terms (values) are randomly interchanged (swapped). |
| PS2 | In a random row of $\tau$ (encoding), a single term (value) is randomly moved (inserted). |
| PS3 | In a random row of $\tau$ (encoding), a string of terms (values) is randomly moved (inserted). |
| PS4 | In a random row of $\tau$ (encoding), a string of terms (values) is randomly reversed. |
| PS5 | In a random row of $\tau$ (encoding), a string of terms (values) is randomly reversed and moved (inserted). |
| PS6 | In all rows of $\tau$ (encoding), two random columns of terms (values) are interchanged (swapped). |

### *2.3.5 Algorithm Parameters*

Three important parameters in the proposed HSAA are starting temperature, cooling schedule (i.e., the rule that defines the temperature at every iteration), and stopping criterion. In every iteration of the HSAA, given a current solution (matrix $\tau$), a proposed solution is identified from the best of the solutions generated by the six perturbation schemes. If the proposed solution has a corresponding lower total cost than the current solution, then the proposed solution becomes the current solution in the next iteration. Otherwise, a worse solution is accepted with a certain probability, thereby allowing the HSAA to escape local optima. This probability depends on how far the search process has progressed and how bad the proposed solution is.

Following the recommended values in the literature and based on some pilot test runs, the starting temperature is selected to be 500 and the number of iterations is set equal to 500. Since the objective function is evaluated six times in each iteration, the total number of objective function evaluations is 3,000. The cooling schedule is adopted from the one presented by Negenman (2001) and forces the probability of accepting a worse solution to decrease with each iteration (Equation 23). In this way, as the number of iterations increases, the gained proximity to the optimum is not lost. The cooling schedule parameter $\tilde{\alpha}$ should be between 0 and 1 and is selected here to be 0.99 to give the algorithm more freedom for escaping local optima. The probability of accepting a move with worse objective function (i.e., a higher total cost) is computed according to Equation 24. A summary of the proposed HSAA is depicted in Figure 9.

$$\tilde{t}_{iter} = \tilde{\alpha}^{iter}\tilde{t}_1 \tag{23}$$

$$pr = e^{\frac{-(f_{proposed} - f_{current})}{\tilde{t}_{iter}}} \tag{24}$$

## 2.4 Experimental Study

An extensive set of problem instances is generated for testing the proposed mixed-integer linear programming model and HSAA solution approaches. The problem instance set is generated primarily based on data obtained from a leading automotive supplier. Furthermore, the experimental factors reflect a wide range of parameter combinations that can be encountered by automotive suppliers. We seek to investigate the solution approaches' performance in terms of both solution quality and computation time with respect to a variety of realistic factors. Six experimental factors are investigated at a number of levels, resulting in 96 different factor combinations (Table 2). For every combination of experimental factors, 10 problem instances are generated, resulting in a total of 960 instances. The numbers of each type of crane (i.e., small, medium, and large) are generated to ensure that every machine is compatible with at least one crane and, if applicable, to be in proportion to the numbers of each type of machine. The details of generating the problem instances are depicted in Tables 2 through 6.

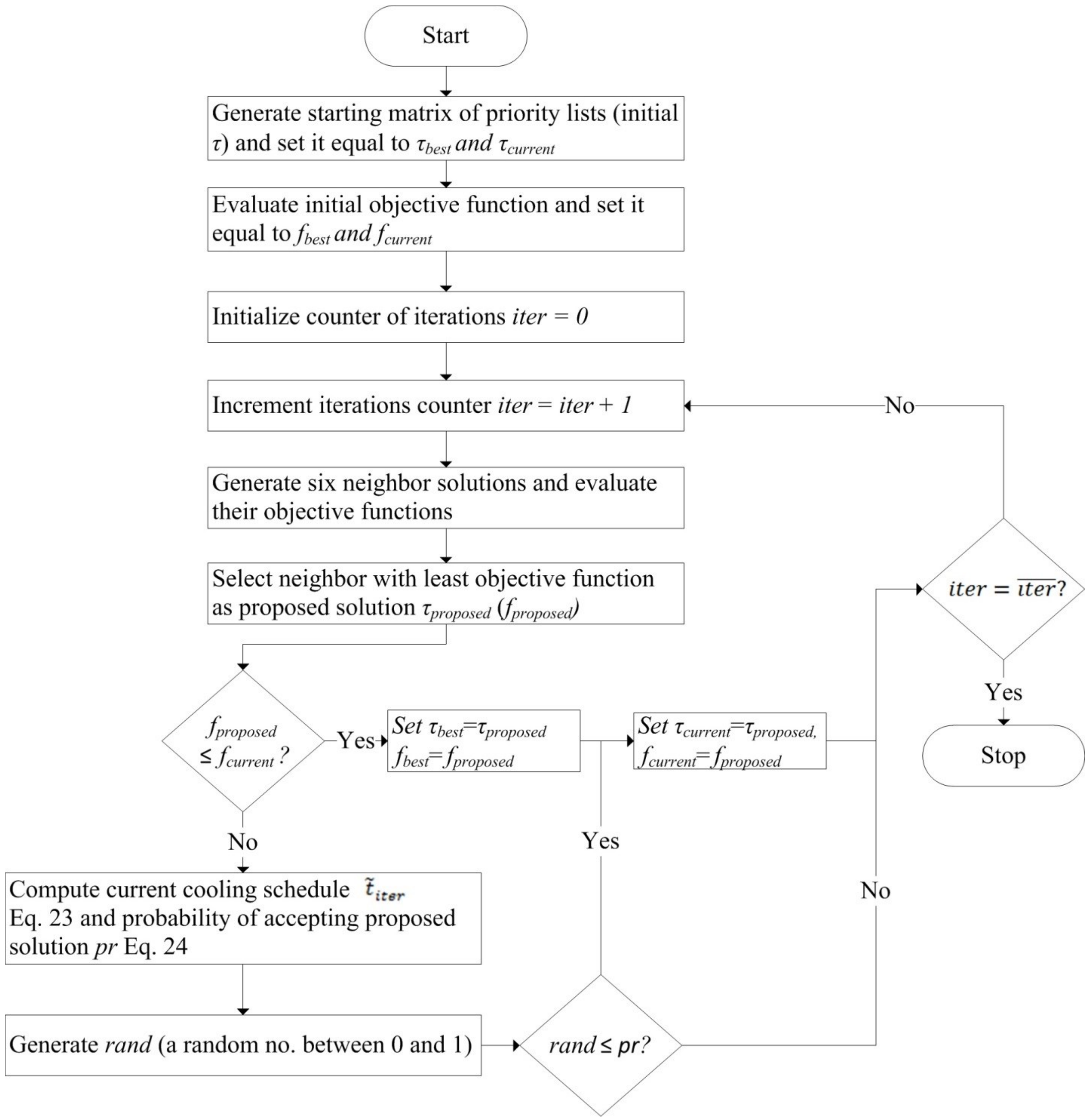


Figure 9. Flow Chart of the Proposed Hybrid Simulated Annealing Algorithm (HSAA)

Table 2. Description of Experimental Design

| Factors | Number of Levels | Level Description |
|---|---|---|
| Part type (machine) mix | 3 | 0, 1, 2 |
| Number of machines ($\lvert I \rvert$) | 2 | 5, 10 |
| Number of cranes ($\lvert J \rvert$) | 2 | 3, 5 |
| Number of part types ($\lvert P \rvert$) | 2 | 5, 25 |
| Number of DCs ($\lvert W \rvert$) | 2 | 1, 3 |
| Number of time periods ($\lvert T \rvert$) | 2 | 4, 16 |
| **Total Combinations** | **96** | |

Table 3. Constituents of Part Type and Machine Mixes

| Part type (machine) mix | Small (%) | Medium (%) | Large (%) |
|---|---|---|---|
| Mix 0 | 60 | 20 | 20 |
| Mix 1 | 20 | 60 | 20 |
| Mix 2 | 20 | 20 | 60 |

Table 4. Other Experimental Parameter Values

| Parameters | Values |
|---|---|
| $S_{i,p,p'}$ | 15, 30, 40, 45, 55 |
| $\mu_p$ | Small: DU[10,45], Medium: DU[46,80], Large: DU[81,120] |
| $N_p$ | Small: DU[10, 40], Medium: DU[41,70], Large: DU[71, 100] |
| $H_p$ | Small: DU[1,4], Medium: DU[5,7], Large: DU[8, 10] |
| $E_p$ | Small: DU[201, 5000], Medium: DU[51, 200], Large: DU[10,50] |
| $M_i$ | Small: DU[10, 40], Medium: DU[41,70], Large: DU[71, 100] |
| $K$ | $7\lvert I \rvert$ |
| $G$ | 10 |
| $L_w$ | DC1: 100, DC2: 300, DC3: 500 |
| $F$ | 6 |

Table 5. Experimental Setup Time Values

| $S$ (mins) | Tool Change | Color Change |
|---|---|---|
| Small machine | 40 | 15 |
| Medium machine | 45 | 30 |
| Large machine | 55 | 45 |

Table 6. Details for Generating Experimental Parameters *D, A, B,* and *C*

| Parameter | Assumptions |
|---|---|
| $D_{t,p,w}$ | • DU[65%, 95%] estimated capacity<br>• 80% chance there is strictly positive demand at a specific time period, of a specific part type, by a specific DC<br>• Estimated small machine capacity = $\frac{F\lvert I_{small}\rvert}{\max_{p\in P_{small}}(\mu_p)}$ ,<br>$\lvert I_{small}\rvert$= number of small machines, $\lvert P_{small}\rvert$= number of small part types<br>• Estimated medium machine capacity =$\frac{F\lvert I_{medium}\rvert}{\max_{p\in P_{medium}}(\mu_p)}$,<br>$\lvert I_{medium}\rvert$= number of medium machines, $\lvert P_{medium}\rvert$= number of medium part types<br>• Estimated large machine capacity = $\frac{F\lvert I_{large}\rvert}{\max_{p\in P_{large}}(\mu_p)}$,<br>$\lvert I_{large}\rvert$= number of large machines, $\lvert P_{large}\rvert$= number of large part types |
| $A_{i,p}$ | • 70% chance that a small, medium, or large machine can process a specific small part type<br>• 70% chance a medium or large machine can process a medium part type<br>• 70% chance a large machine can process a large part type<br>• Every part type can be processed by at least one machine |
| $B_{j,i}$ | • Small cranes are compatible with small machines<br>• Medium cranes are compatible with medium machines<br>• Large cranes are compatible with large machines |
| $C_{p,p'}$ | • 10% chance that two part types of the same size group (i.e., both are small, medium, or large) are the same part type but only different color |

## 2.5 Results and Discussion

### *2.5.1 Mixed-integer Linear Programming Model*

The mathematical model is coded in AMPL and all 960 generated problem instances are analyzed by Gurobi version 5.1 on an Intel Core i7, 3.4GHz processor, 32 GB of RAM, 64-bit, Windows 7 workstation. Given the problem's complexity, a time limit is set for running every problem instance. At first, all instances are run with a time limit of 20 minutes. Then, the instances that achieved an optimality gap of less than or equal to 10% in 20 minutes are run again with a one hour time limit. Of the 960 instances, 478 (49.8%) are solved to optimality using the proposed mathematical model.

The breakdown of the MILP model's solution performance for every factor level is given in Table 7. The most significant factor affecting the performance of the MILP model is the number of part types. As the number of part types increases, it becomes much more difficult to solve the problem to optimality using the proposed model. The lowest average optimality gap (1.1%) is realized at the low level of the number of part types factor, while the highest average optimality gap (37.2%) is observed at the high level of the same factor.

Table 7. Optimality Gap and Percentages of Instances Solved Optimally with the Proposed MILP Model

| Factor | Level | Average Optimality Gap% | Min Optimality Gap% | Max Optimality Gap% | % Frequency of Achieving Optimum |
|---|---|---|---|---|---|
| Part type (machine) mix | Mix0 | 15.1% | 0.0% | 64.0% | 55.6% |
| | Mix1 | 19.6% | 0.0% | 79.0% | 48.1% |
| | Mix2 | 22.7% | 0.0% | 84.2% | 45.6% |
| Number of machines ($\|I\|$) | 5 | 15.4% | 0.0% | 62.9% | 51.9% |
| | 10 | 22.9% | 0.0% | 84.2% | 47.7% |
| Number of cranes ($\|J\|$) | 3 | 19.3% | 0.0% | 78.7% | 49.2% |
| | 5 | 19.0% | 0.0% | 84.2% | 50.4% |
| Number of part types ($\|P\|$) | 5 | **1.1%** | 0.0% | 41.7% | 94.8% |
| | 25 | 37.2% | 0.0% | 84.2% | 4.8% |
| Number of DCs ($\|W\|$) | 1 | 18.4% | 0.0% | 84.2% | 51.7% |
| | 3 | 19.9% | 0.0% | 80.5% | 47.9% |
| Number of time periods ($\|T\|$) | 4 | 7.9% | 0.0% | 41.4% | 54.8% |
| | 16 | 30.4% | 0.0% | 84.2% | 44.8% |
| | **Overall** | **19.1%** | **0.0%** | **84.2%** | **49.8%** |

### 2.5.2 *Hybrid Simulated Annealing Algorithm*

The proposed HSAA is coded in MATLAB 7.9, and all 960 problem instances are solved three times independently, resulting in a total of 2880 instance runs. Every instance run is set to run until either reaching the optimal solution (if it was known from solving the same instance by the mathematical model) or for 500 iterations (i.e., 3000 objective function evaluations), whichever occurs first. For an example problem instance run, the proposed HSAA's objective function convergence over 477 iterations and the total costs obtained by PS1-6 at every iteration as well as the optimum solution are shown in Figure 10.

We compute a performance ratio (Equation 25) to assess the performance of the HSAA for problem instances with known optimal solutions from the MILP model (1434 instance runs). A summary of the performance ratio values produced by the proposed HSAA are listed in Table 8. Regarding the remaining 1446 instance runs with unknown optimal solutions, we compute the heuristic ratio (Equation 26) to assess the HSAA performance (Table 9). It is observed that as the number of part types increases from 5 to 25, the average heuristic ratio decreases from 1.270 to 1.119, implying the improving performance of the HSAA against the MILP model. A summary of the proposed HSAA's required solution times for 960 instance runs on an Intel Core i7, 3.4GHz processor, 8GB of RAM, 64-bit, Windows 7 workstation is shown in Table 10. In practice, if implemented, the HSAA will be run frequently to optimize the daily operations of an automotive supplier. Therefore the algorithm's solution time is required to be reasonable (e.g., not more than three hours, according to a local supplier). On average, the algorithm takes only 2444 seconds (41 minutes) to solve an instance. Since the longest solution time among all 960 instances equals 9622 seconds (2 hours 40 minutes), we consider the HSAA solution times to be acceptable. Furthermore the six HSAA perturbation schemes could be run in parallel, thus reducing the solution time significantly.

$$Performance\ Ratio = \frac{HSAA\ solution}{MILP\ Optmal\ solution} \tag{25}$$

$$Heuristic\ Ratio = \frac{HSAA\ solution}{MILP\ Time\ Limited\ solution} \tag{26}$$

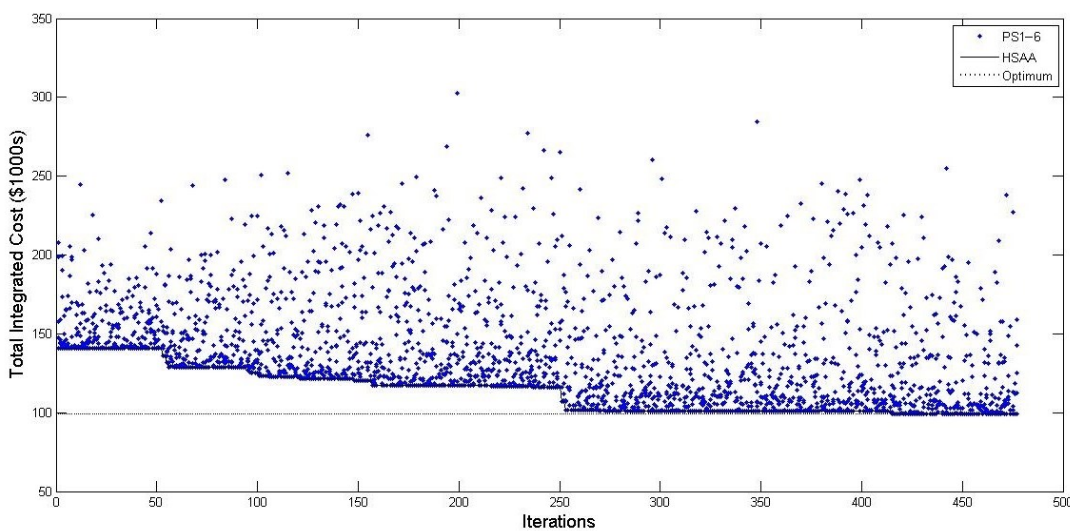


Figure 10. HSAA Objective Function Improvement over Time for an Example Problem Instance

Table 8. Performance Ratio and % Frequency of Achieving Optimum by HSAA

| Factor | Level | Average PR | Min PR | Max PR | % Frequency of Achieving Optimum |
|---|---|---|---|---|---|
| Part type (machine) mix | Mix0 | 1.026 | 1.000 | 1.943 | 69.9 |
| | Mix1 | 1.054 | 1.000 | 2.765 | 71.2 |
| | Mix2 | 1.129 | 1.000 | 2.681 | 53.0 |
| Number of machines ($\|I\|$) | 5 | 1.023 | 1.000 | 2.526 | 69.7 |
| | 10 | 1.113 | 1.000 | 2.765 | 60.1 |
| Number of cranes ($\|J\|$) | 3 | 1.065 | 1.000 | 2.526 | 68.1 |
| | 5 | 1.068 | 1.000 | 2.765 | 62.3 |
| Number of part types ($\|P\|$) | 5 | 1.067 | 1.000 | 2.765 | 68.4 |
| | 25 | 1.063 | 1.000 | 1.427 | 0.0 |
| Number of DCs ($\|W\|$) | 1 | 1.093 | 1.000 | 2.765 | 60.5 |
| | 3 | 1.038 | 1.000 | 1.677 | 70.1 |
| Number of time periods ($\|T\|$) | 4 | 1.029 | 1.000 | 2.440 | 74.1 |
| | 16 | 1.112 | 1.000 | 2.765 | 54.1 |
| | **Overall** | **1.066** | **1** | **2.765** | **65.1** |

Table 9. Heuristic Ratio Summary

| Factor | Level | Average HR | Min HR | Max HR | % Frequency of Meeting or Beating MILP |
|---|---|---|---|---|---|
| Part type (machine) mix | Mix0 | 1.162 | 0.994 | 1.547 | 0.2 |
| | Mix1 | 1.109 | 0.398 | 1.540 | 2.2 |
| | Mix2 | 1.115 | 0.637 | 2.133 | 7.9 |
| Number of machines ($\|I\|$) | 5 | 1.078 | 0.966 | 1.584 | 1.3 |
| | 10 | 1.172 | 0.398 | 2.133 | 5.8 |
| Number of cranes ($\|J\|$) | 3 | 1.121 | 0.762 | 1.683 | 3.6 |
| | 5 | 1.133 | 0.398 | 2.133 | 3.8 |
| Number of part types ($\|P\|$) | 5 | 1.270 | 1.005 | 2.133 | 0.0 |
| | 25 | 1.119 | 0.398 | 1.584 | 3.9 |
| Number of DCs ($\|W\|$) | 1 | 1.152 | 0.637 | 1.683 | 1.0 |
| | 3 | 1.103 | 0.398 | 2.133 | 6.1 |
| Number of time periods ($\|T\|$) | 4 | 1.096 | 0.994 | 1.305 | 0.2 |
| | 16 | 1.153 | 0.398 | 2.133 | 6.5 |
| | **Overall** | **1.127** | **0.398** | **2.133** | **3.7** |

Table 10. Summary of HSAA Solution Times

| Factor | Level | Average Solution Time (secs) | Min Solution Time (secs) | Max Solution Time (secs) |
|---|---|---|---|---|
| Part type (machine) mix | Mix0 | 2406 | 1 | 8945 |
| | Mix1 | 2427 | 1 | 9208 |
| | Mix2 | 2498 | 1 | 9622 |
| Number of machines ($\|I\|$) | 5 | 1790 | 1 | 5298 |
| | 10 | 3098 | 1 | 9622 |
| Number of cranes ($\|J\|$) | 3 | 2431 | 1 | 9622 |
| | 5 | 2456 | 1 | 9445 |
| Number of part types ($\|P\|$) | 5 | 258 | 1 | 914 |
| | 25 | 4630 | 1 | 9622 |
| Number of DCs ($\|W\|$) | 1 | 2445 | 1 | 9208 |
| | 3 | 2443 | 1 | 9622 |
| Number of time periods ($\|T\|$) | 4 | 1219 | 1 | 2978 |
| | 16 | 3669 | 1 | 9622 |
| | **Overall** | **2444** | **1** | **9622** |

The HSAA results show promise of providing optimal or near-optimal integrated supply chain plans for a Tier-1 automotive supplier. In practice, the supply chain planning process occurs over a rolling planning horizon of several days, such as one week. Given the frequency of required decision making in practice, the viability of the proposed solution method stems from the attractive solution times of 2444 seconds on average, which can be improved further by running the six perturbation schemes in parallel. It is estimated that this approach will reduce the HSAA solution time by at least five times, accounting for the time needed for non-decoding/objective function evaluation steps in HSAA. . The developed solution approach can also be embedded in other models for other longer-term applications, such as calculations of required production capacity, needed finished part warehouse capacity, auxiliary resource capacity, and safety stock inventory levels.

## 2.6 Conclusions and Future Research

In this chapter, we developed a mixed-integer linear programming model to optimize the total cost of an integrated production and transportation planning problem from the automotive industry. A hybrid simulated annealing algorithm employing a constructive heuristic and an effective encoding-decoding strategy was proposed to solve the same problem to near optimality in a timely manner suitable for implementation in industry. Computational results demonstrate the promising performance of the proposed solution approaches. The most significant factor affecting the MILP model's performance is the number of part types—as the number of part types increases, so does the model's required computation time. In contrast with the MILP model, the proposed HSAA's relative performance improves as the number of part types increases. In HSAA, the six perturbation schemes can be configured to run in parallel, thus increasing the algorithm's speed and potential effectiveness. Applying HSAA in practice will make approximate optimization of realistic problem instances with large numbers of part types possible in a timely manner. The developed solution algorithm can be embedded in models for other longer-term applications, such as calculations of required capacities.

In the future, we will develop a multi-objective optimization methodology for integrated automotive supply chains. Another research direction is to extend the current mathematical model to include multiple modes of transportation in the automotive supply chain's second stage.

# CHAPTER THREE

# A BI-CRITERIA HYBRID METAHEURISTIC FOR ANALYZING AN INTEGRATED AUTOMOTIVE SUPPLY CHAIN

The automotive industry is one of the most important manufacturing sectors in the world due to several factors, such as its economic impact and technological complexities. While supply chain performance can have a dramatic impact on the automotive industry, there are multiple, often conflicting objectives that typically are used to optimize performance. We model the tradeoff between cost and service level and present a bi-criteria heuristic optimization methodology for a two-stage, integrated automotive supply chain. Our problem contains sequence-dependent setups on parallel machines and auxiliary resource assignments. We minimize the total cost of setups, inventory holding, and transportation costs, and the maximum percentage of outsourced parts per customer, simultaneously. We use our proposed method to solve a set of problem instances that are based on industrial data. Our proposed method generates approximate Pareto (efficient) solutions in a timely manner for use in practice.

## 3.1 Introduction

The importance of the automotive industry and its supply chain cannot be underestimated due to its economic impact and technological complexities (Chandra and Grabis 2007, Jacobs *et al.* 2009, Rightmer 2012, Sezen *et al.* 2012, Singh *et al.* 2005). Furthermore, in short-term automotive part order planning, both monetary and nonmonetary objectives should be incorporated in the assessment of relevant problems

(Volling and Spengler 2011, Volling *et al.* 2013). This research study is motivated by a real-world problem faced by a Tier-1 automotive supplier. As shown in Figure 11, the supply chain system under study is focused on the production and transportation of bulk automotive plastic parts. Injection molding machines produce center consoles, dashboards, door panels, and other automotive parts. In the production stage, one of two different types of setups, tool change or color change, is needed to change production to a different tool or color, and a crane is used to perform a tool change. There are compatibility constraints that relate both cranes to machines and part types to machines. In the transportation stage, unit loads of finished parts are transported via full truck loads to multiple distribution centers (DCs).

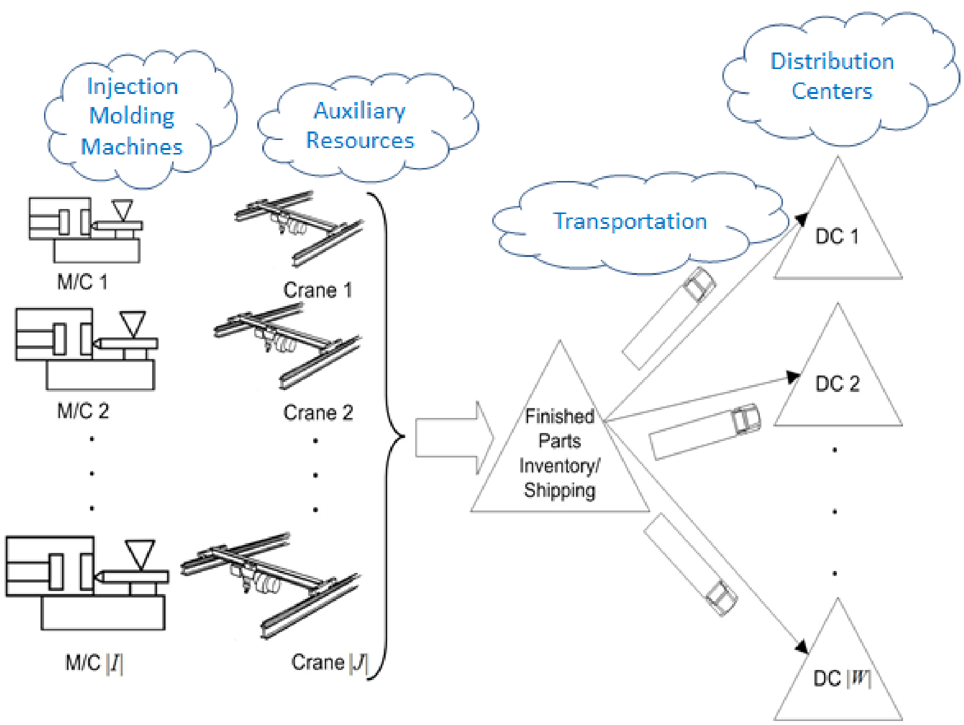


Figure 11. Two-Stage, Automotive Supply Chain System

In our previous research, the problem was modeled as a single-objective optimization problem, but this current study extends the problem to analyze a bi-objective optimization problem. We directly model the tradeoff between two objective functions: cost (i.e., the summation of production setup costs, inventory holding costs, and transportation costs) and service level as measured by the maximum percent of outsourced parts per customer. Minimizing the maximum percent outsourced parts per customer emulates maximizing customer service levels, which are best met by in-house production to ensure the consistency in finished parts quality. These two objectives are conflicting as maximizing service level can lead to additional production setups, inventory, and/or transportation costs, thereby increasing cost. Applying a multi-objective optimization methodology can shed light on the realistic trade-off between these two conflicting objectives encountered by automotive suppliers. The goal of this research study is to help decision makers plan for the right production, inventory, shipping, and outsourcing quantities over their planning horizon via an effective trade-off analysis.

Multiobjective optimization is an established research field, and one of the ways to classify this research is based on the role of the decision maker in the optimization process. There are interactive and non-interactive methods. In interactive methods, the decision maker is involved during the optimization process by supplying their preferences in real-time. The disadvantage of this approach is that it could be time-consuming to the decision maker, and it could also stretch the time needed for the optimization process. On the other hand, in non-interactive methods, the decision maker does not interfere during the optimization process. Once the optimization process is complete, the decision maker gets a set of solutions describing the various possibilities, and they choose one of these solutions based on their preferences and the surrounding circumstances. In this research, we employ a non-interactive multiobjective optimization approach to present the decision maker with a set of options and also to speed up the optimization process.

The rest of this chapter is organized as follows. Section 3.2 reviews the literature on multi-objective optimization of mixed-integer linear programming models and multi-objective metaheuristics. Section 3.3 provides our bi-criteria mathematical model that captures the details of the research problem under study. The description of a proposed bi-criteria hybrid metaheuristic is outlined in Section 3.4. Finally, Section 3.5 presents our experiment results while Section 3.6 presents our conclusions and offers directions for future research.

## 3.2 Literature Review

### *3.2.1 Multi-objective Mixed-Integer Linear Programming*

First, we define the following terminology for a minimization problem as it is used extensively in the research problem under study:

> *A feasible solution $\hat{x} \in X$ (feasible set in decision space) is called efficient or Pareto-optimal if there is no other $x \in X$ such that $f(x) \leq f(\hat{x})$ . If $\hat{x}$ is efficient, $f(\hat{x})$ is called a nondominated point. If $x^1, x^2 \in X$ and $f(x^1) \leq f(x^2)$, then $x^1$ dominates $x^2$ and $f(x^1)$ dominates$f(x^2)$. The set of all efficient solutions $\hat{x} \in X$ is denoted $X_E$ and called the efficient set. The set of all non-dominated points $\hat{y} = f(\hat{x}) \in Y$ (feasible set in criterion space), where $\hat{x} \in X_E$, is denoted $Y_N$ and called the non-dominated set (Ehrgott 2005).*

It is important to distinguish between two types of efficient solutions. In the criterion space, supported Pareto points lie on the boundary of the convex hull of feasible set $Y$, while non-supported Pareto points are in the interior of the convex hull of feasible set $Y$. Supported efficient solutions are optimal solutions of the parameterized single objective problem. Non-supported efficient solutions cannot be found by solving the parameterized single objective problem. As the number of decision variables increases, the number of non-supported efficient solutions grows very quickly as shown in Figure 12 (Visée *et al.* 1998).

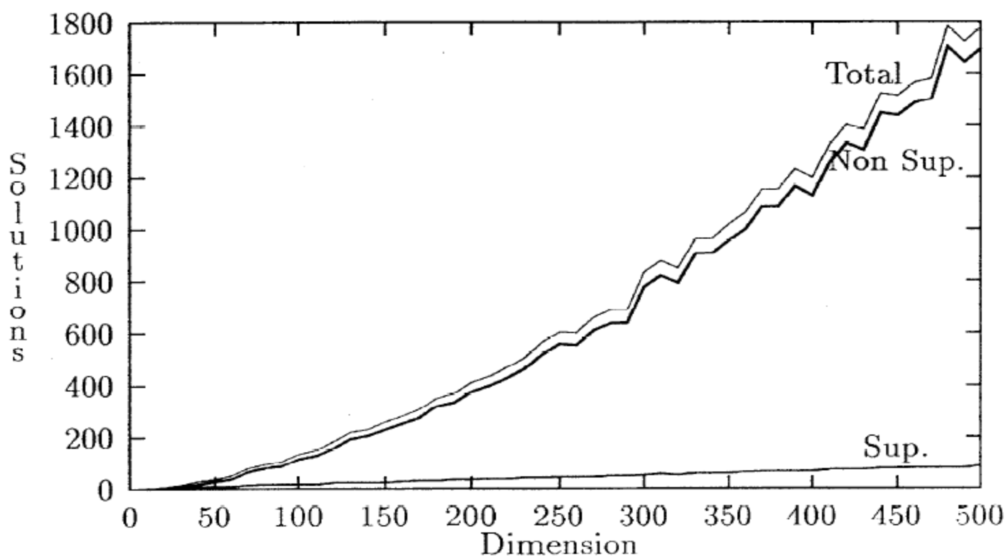


Figure 12. Number of Supported and Non-Supported Efficient Solutions (Visée *et al.* 1998)

In multi-objective optimization, a single solution optimizing all objectives simultaneously does not exist, in general. Instead, a search is conducted for feasible solutions within a set of efficient (Pareto-optimal, non-dominated) solutions. The identification of a best compromise solution requires the preferences expressed by the decision maker to be taken into account. The existence of multiple objectives add to the difficulty of combinatorial optimization problems so that multi-objective combinatorial optimization problems are very hard to solve exactly, even if they are derived from easy single objective optimization problems (Alves and Clímaco 2007, Ehrgott and Gandibleux 2004).

It is worth noting that scalarization with weighted sums of objective function components does not identify all efficient solutions of a multi-objective discrete optimization problem because these types of problems are non-convex. The unconstrained multi-objective combinatorial optimization problem is NP complete (Ehrgott 2005). In the $\varepsilon$-constraint method, constraints on objective values usually make the problem NP-hard (Ehrgott 2005). For instance, many bi-criteria scheduling problems are NP-hard, making it impossible to find all efficient solutions in polynomial time for medium or large sized problems (Nagar *et al.* 1995). It follows that an active research area is developing heuristics and metaheuristics to find efficient solutions of larger bi-criteria (multi-objective) mixed-integer linear programming problems (Ehrgott and Gandibleux 2004).

### *3.2.2 Multi-objective Metaheuristics*

The theory behind and application of multi-objective metaheuristics are reviewed by Jones *et al.* (2002). Multi-objective metaheuristics can benefit several application areas, such as engineering, operations research, finance, and medicine. Multi-objective metaheuristics' strengths include suitability to integer variable problems and overall flexibility. Their disadvantages include an inability to guarantee an exact optimal solution and the need for the modeler to set a large set of parameters. However, in many real-world, complex problems, there is no conventional method that is guaranteed to find the optimal solution. Therefore multi-objective metaheuristics often are considered in this case.

A two-stage, multi-population genetic algorithm (MPGA) is presented by Cochran *et al.*(2003). The MPGA aims to solve parallel machine scheduling problems with multiple objectives. In the first stage of the MPGA, the multiple objectives are combined into a single objective so that the algorithm can converge quickly to good solutions with respect to all objectives. Solutions of the first stage are then divided into several sub-populations, which become the initial populations of the second stage. The solutions for each objective are improved within the individual sub-populations while another sub-population contains solutions satisfying the combined objective. Computational results show that the two-stage MPGA outperforms a benchmark method, the multi-objective genetic algorithm, in most test problems with two and three objectives.

The bi-criteria problem of minimizing the total weighted tardiness and total distribution costs in an integrated production and distribution environment is studied by Cakici *et al.* (2012). Orders are received by a manufacturer, processed on a single production line, and delivered to customers by capacitated vehicles. Each order (job) is associated with a customer, weight (priority), processing time, due time, and size (volume or storage space required in the transportation unit). The authors develop both a mathematical model and several genetic algorithm-based heuristics with dispatching rules to approximate a Pareto-optimal set of solutions. Both the mathematical modeling and heuristic solution approaches produce a significant number of non-dominated solutions. Typically, a significant fraction of the Pareto super front is composed of new solutions produced by heuristics.

A new multi-objective production planning model of a real world problem which is proved to be NP-Complete is presented in (Karimi-Nasab and Konstantaras 2012). The problem involves a single product with dynamic, deterministic demand. The authors provide a heuristic to explore the feasible solution space and find Pareto-optimal solutions in a reasonable amount of time. The performance of the proposed problem-specific heuristic is verified by comparing it against a multi-objective genetic algorithm on a set of randomly generated test instances. As the algorithm is completely adapted to the specific problem structure under study, it performs better than the multi-objective genetic algorithm, especially for small- and medium-sized instances.

An innovative multi-objective, evolutionary algorithm (MOEA) to solve a very complex network design problem variation, the multi-commodity capacitated network design problem (MCNDP), is presented in (Kleeman *et al.* 2012). The non-dominated sorting genetic algorithm (NSGA-II) is selected as the MOEA framework which is modified and parallelized to solve the generic MCNDP. A novel initialization procedure and mutation method are integrated which result in a reduced search space. Empirical results indicate that effective topological Pareto solutions are generated for use in highly constrained, communication-based network design. The authors also show that with parallelization, better non-dominated Pareto front solutions can be found more often using the M-NSGAII parallel island implementation with restricted migration.

The gaps in decision-making support based on multi-objective optimization (MOO) for build-to-order supply chain management (BTO-SCM) are identified in (Afshin Mansouri *et al.* 2012). Only four of the BTO-SC optimization contributions identified use MOO techniques while 17 papers do not use MOO techniques. Recommended future research directions include: reformulation of existing optimization models from an MOO perspective, developing of scenarios around service-based objectives, development of efficient solution tools, considering the interests of each supply chain party as a separate objective to account for fair treatment of their requirements, and applying the existing methodologies on real-life data sets. Considering the computational complexity of the decision models for real-life applications, further research is essential to develop efficient algorithms and metaheuristics capable of providing good approximations of Pareto-optimal solutions in a short amount of time. The authors recommend industrial collaboration to provide the research community with real data sets upon which efficient MOO tools can be developed.

One of the powerful metaheuristic methods is simulated annealing. A comprehensive review of simulated annealing-based, single- and multi-objective optimization algorithms is presented by Suman and Kumar (2006). The key in simulated annealing is probability calculation, which involves building the annealing schedule. Computational results and suggestions to improve the performance of simulated annealing-based multi-objective algorithms are presented. It is suggested that the performance of SA-based multi-objective algorithms can be improved by combining simulated annealing with another algorithm. The contribution of our current research focuses on a bi-criteria metaheuristic solution approach for a problem faced by a Tier-1 automotive supplier. The bi-criteria problem under study reflects a set of realistic assumptions, and it has not been solved in the literature to date.

## 3.3 Mathematical Model

We now present a model for the bi-criteria optimization problem of interest as motivated by the automotive supply chain. Assumptions and pertinent notation are outlined, followed by the model and a discussion of its constituent parts.

### *3.3.1 Assumptions*

First, we make the following assumptions in our research analysis:

- The number of part types produced by any machine is restricted to one per time period.
- Every machine has a production capacity that cannot be exceeded.
- Parts are shipped directly to customers or held in inventory for shipping in later periods.
- The finished part warehouse at the plant has a holding capacity that cannot be exceeded.
- Every transportation vehicle has a capacity that cannot be exceeded.
- A maximum of one machine setup per time period can be performed by a crane.
- Handling times between machines and finished part warehouse at the plant are negligible.
- All machines have been initially set up before the first time period.
- There is no plant finished part inventory at the beginning of the planning horizon.
- Outsourcing is used to complement in-house production in order to completely satisfy demand.

### 3.3.2 Notation

*Objective Functions*

| | |
|---|---|
| $f^1$ | the first objective function, summation of production setup cost, inventory holding cost, and transportation cost |
| $f^2$ | the second objective function, maximum percent outsourced parts per customer |

*Index Sets*

| | |
|---|---|
| $I$ | set of machines, indexed by $i$ |
| $J$ | set of cranes, indexed by $j$ |
| $P$ | set of part types, indexed by $p$ |
| $W$ | set of distribution centers, indexed by $w$ |
| $T$ | set of time periods, indexed by $t$ |

*Parameters*

| | |
|---|---|
| $D_{t,p,w}$ | demand at distribution center $w$ of part type $p$ in time period $t$ (parts) |
| $\mu_p$ | unit production time (cycle time) of part type $p$ (secs) |
| $F$ | length of time period (hours) |
| $S_{i,p,p'}$ | changeover time from part type $p$ to part type $p'$ on machine $i$ (mins) |
| $E_p$ | quantity of part type $p$ per unit load (parts/unit load) |
| $K$ | plant finished part warehouse capacity (unit loads) |
| $G$ | vehicle capacity (unit loads) |
| $H_p$ | unit inventory holding cost of part type $p$ ($/part/period) |
| $L_w$ | cost of a vehicle trip from plant to distribution center $w$ ($/trip) |
| $M_i$ | cost of downtime on machine $i$ ($/min) |
| $A_{i,p}$ | 1 if machine $i$ is compatible with part type $p$, 0 otherwise |
| $B_{j,i}$ | 1 if crane $j$ can serve setup on machine $i$, 0 otherwise |
| $C_{p,p'}$ | 1 if setup from part type $p$ to part type $p'$ requires a crane, 0 otherwise |

*Decision Variables*

| | |
|---|---|
| $\alpha_{t,p,w}$ | quantity of part type $p$ transported to distribution center $w$ in time period $t$ |
| $\beta_{t,w}$ | number of vehicle trips to distribution center $w$ in time period $t$ |
| $h_{t,p}$ | quantity of finished part inventory of part type $p$ in time period $t$ |
| $q_{t,i,p}$ | quantity of part type $p$ processed on machine $i$ in time period $t$ |
| $u_{t,p,w}$ | quantity of outsourcing of part type $p$ demanded by distribution center $w$ in time period $t$ |
| $u_{max}$ | maximum percent outsourced parts per customer |

| | |
|---|---|
| $x_{t,i,p}$ | equals one if machine $i$ processes part type $p$ in time period $t$, 0 otherwise |
| $y_{t,i,p,p'}$ | equals one if machine $i$ changes over from part type $p$ to part type $p'$ in time period $t$, 0 otherwise |
| $z_{t,j,i}$ | equals one if crane $j$ serves setup on machine $i$ in time period $t$, 0 otherwise |

### *3.3.3 Model*

$$minimize\ f^1 = \sum_{t\in T, t\neq 1}\sum_{i\in I}\sum_{p\in P}\sum_{p'\in P, p'\neq p} S_{i,p,p'} M_i y_{t,i,p,p'} + \sum_{t\in T}\sum_{p\in P} H_p h_{t,p} + \sum_{t\in T}\sum_{w\in W} L_w \beta_{t,w} \qquad (27)$$

$$minimize\ f^2 = u_{max} \qquad (28)$$

*subject to*

$$u_{max} \geq \frac{\sum_{t\in T}\sum_{p\in P} u_{t,p,w}}{\sum_{t\in T}\sum_{p\in P} D_{t,p,w}} \qquad \forall w\in W \qquad (29)$$

$$\beta_{t,w} \geq \frac{1}{G}\sum_{p\in P}\frac{1}{E_p}\alpha_{t,p,w} \qquad \forall t\in T, \forall w\in W \qquad (30)$$

$$u_{t,p,w} = D_{t,p,w} - \alpha_{t,p,w} \qquad \forall t\in T, \forall p\in P, \forall w\in W \qquad (31)$$

$$\sum_{p\in P}\frac{1}{E_p} h_{t,p} \leq K \qquad \forall t\in T \qquad (32)$$

$$h_{t,p} = \sum_{i\in I} q_{t,i,p} - \sum_{w\in W}\alpha_{t,p,w} \qquad t=1, \forall p\in P \qquad (33)$$

$$h_{t,p} = h_{t-1,p} + \sum_{i\in I} q_{t,i,p} - \sum_{w\in W}\alpha_{t,p,w} \qquad \forall t\in T, \forall p\in P, t\neq 1 \qquad (34)$$

$$\mu_p q_{t,i,p} \leq F x_{t,i,p} \qquad t=1, \forall i\in I, \forall p\in P \qquad (35)$$

$$\mu_p q_{t,i,p} + \sum_{p'\in P, p'\neq p} S_{i,p,p'} y_{t,i,p,p'} \leq F x_{t,i,p} \qquad \forall t\in T, \forall i\in I, \forall p\in P, t\neq 1 \qquad (36)$$

$$y_{t,i,p,p'} \geq x_{t,i,p} + x_{t-1,i,p'} - 1 \qquad \forall t\in T, \forall i\in I, \forall p\in P, \forall p'\in P, t\neq 1, p\neq p' \qquad (37)$$

$$x_{t,i,p} \leq A_{i,p} \qquad \forall t \in T, \forall i \in I, \forall p \in P \qquad (38)$$

$$\sum_{p \in P} x_{t,i,p} \leq 1 \qquad \forall t \in T, \forall i \in I \qquad (39)$$

$$\sum_{j \in J} z_{t,j,i} = \sum_{p \in P} \sum_{p' \in P, p' \neq p} y_{t,i,p,p'} C_{p,p'} \qquad \forall t \in T, \forall i \in I, t \neq 1 \qquad (40)$$

$$z_{t,j,i} \leq B_{j,i} \qquad \forall t \in T, \forall j \in J, \forall i \in I, t \neq 1 \qquad (41)$$

$$\sum_{i \in I} z_{t,j,i} \leq 1 \qquad \forall t \in T, \forall j \in J, t \neq 1 \qquad (42)$$

$$\sum_{j \in J} z_{t,j,i} \leq 1 \qquad \forall t \in T, \forall i \in I, t \neq 1 \qquad (43)$$

$$h_{t,p}, u_{max} \geq 0 \qquad \forall p \in P, \forall t \in T \qquad (44)$$

$$\alpha_{t,p,w}, \beta_{t,w}, q_{t,i,p}, u_{t,p,w} \geq 0 \text{ and integer} \qquad \forall i \in I, \forall p \in P, \forall w \in W, \forall t \in T \qquad (45)$$

$$x_{t,i,p}, y_{t,i,p,p'}, z_{t,j,i} \in \{0,1\} \qquad \forall i \in I, \forall j \in J, \forall p \in P, \forall p' \in P, \forall t \in T, p' \neq p \qquad (46)$$

Objective function (27) minimizes the total cost of production setup, inventory holding, and transportation, while objective function (28) minimizes the maximum percent outsourced parts per customer. Constraint set (29) calculates the value of objective function (28). Constraint set (30) computes the number of vehicle trips to every distribution center at every time period, while constraint set (31) calculates the quantities of every part type outsourced by every DC in every time period. Next, constraint set (32) ensures the capacity of the plant finished part warehouse is not exceeded. Constraint sets (33) and (34) conserve the flow of every part type in inventory during the first time period, and for all subsequent time periods, respectively. Next, constraint sets (35) and

(36) ensure the available capacity of every machine cannot be exceeded during the first time period, and after the first time period, respectively.

Constraint set (37) dictates that if a machine changes over to a different part type after the first time period, a setup is required. Constraint set (38) ensures that every machine respects machine-part type matching restrictions. Constraint set (39) restricts the number of part types produced by any machine to one per time period. Next, constraint set (40) enforces that a machine setup requiring a crane (i.e., a tooling changeover) occurs if and only if a crane serves the setup. Constraint set (41) dictates that every crane respects crane-machine compatibility restrictions. Next, constraint sets (42) and (43) limit the number of machine setups per time period to a maximum of one per crane and one per machine, respectively. Finally, constraint sets (44), (45), and (46) are non-negativity, positive integer, and binary variable type constraints, respectively.

### *3.3.4 Problem Complexity*

The problem under study includes the classical capacitated lot sizing problem, which is NP-hard, in addition to sequence-dependent setup times, compatibility, and transportation constraints. Furthermore, the multiple objectives add to the difficulty of the problem. Since there is no algorithm that can solve the current problem to optimality in polynomial time, we propose a heuristic optimization methodology for identifying approximate Pareto-optimal solutions in a reasonable amount of time.

## 3.4 Bi-criteria Hybrid Metaheuristic

For the problem under study, we propose a multi-objective hybrid simulated annealing algorithm (MOHSAA) which extends the single-criterion metaheuristic presented in Chapter 2.

*Required MOHSAA Notation and Equations*

| | |
|---|---|
| $\gamma_p$ | grand total demand per part type (47) |
| $\delta_p$ | upper bound of number of machine runs required to satisfy grand total demand per part type (48) |
| $\theta$ | upper bound of number of machine runs (49) |
| $\pi_{t,p}$ | lower bound of number of machines needed to satisfy part type time period demand (50) |
| $\sigma_p$ | part type "fortune", number of machines compatible with the part type (51) |
| $\tau$ | matrix of priority lists of part type machine runs over the planning horizon |
| *iter* | MOHSAA iteration counter |
| $F_N$ | List of nondominated solutions in the objective space achieved throughout the search (corresponding to $\tau_E$) |
| $\tau_E$ | List of efficient solutions in the decision space achieved throughout the search (corresponding to $F_N$) |
| $\tilde{t}_{iter}$ | MOHSAA temperature parameter at iteration *iter* (e.g. *iter*=1, 2, 3…etc.) |
| $\tilde{\alpha}$ | MOHSAA parameter used in the cooling schedule |
| *pr* | probability of accepting proposed solution $\tau_{proposed}$ and $f_{proposed}$ |
| *rand* | a random number between 0 and 1 generated from uniform distribution |
| $\overline{\imath ter}$ | maximum number of iterations in MOHSAA (stopping criterion) |

$$\gamma_p = \sum_{t \in T} \sum_{w \in W} D_{t,p,w}\,, \qquad \forall p \in P \qquad (47)$$

$$\delta_p = \left\lceil \frac{\gamma_p \mu_p}{F - \max_{i \in I, p \in P, p' \in P, p' \neq p}(S_{i,p,p'})} \right\rceil, \qquad \forall p \in P \qquad (48)$$

$$\theta = \sum_{p \in P} \min\left(\delta_p, \sum_{i \in I} A_{i,p}\right) \qquad (49)$$

$$\pi_{t,p} = \left\lceil \frac{\mu_p \sum_{w \in W} D_{t,p,w}}{F} \right\rceil, \qquad \forall t \in T, \forall p \in P \qquad (50)$$

$$\sigma_p = \sum_{i \in I} A_{i,p} \qquad \forall p \in P \qquad (51)$$

The ceiling operator $\lceil \blacksquare \rceil$ produces the smallest integer not less than $\blacksquare$. An overview of MOHSAA is depicted in Figure 13. The pertinent components of the proposed MOHSAA are encoding, decoding, constructive heuristic starting solution, perturbation scheme, and algorithm parameters. The constructive heuristic starting solution is the same as the one presented in Chapter 2 (Figure 14). We employ an effective, indirect encoding-decoding strategy to avoid generating any infeasible solutions during the algorithm's search, while keeping a relatively small search space. The MOHSAA encoding is the matrix $\tau$ that has $|T|$ rows and $\theta + |I|$ columns. Each row in $\tau$ represents a single time period and consists of an active tuple (i.e. a priority list) of size $|I|$ and an inactive tuple of size $\theta$. Every entry in an active tuple represents either a possible part type run or a forced machine idling. The search goal is to activate the right tuples of entries of part types and machine idlings in every time period to find new efficient solutions. Activating the best tuple in every row also leads to deactivating $\theta$ entries in the same row. The activation-deactivation process is achieved by applying the algorithm's perturbation scheme over iterations. Setups (i.e. crane assignments as needed) are also prioritized according to the active tuples in $\tau$. Depending on the parameters $\delta_p$ and $\theta$, an example of the matrix $\tau$ for a small problem instance with $|I| = 2; |P| = 4; and\ |T| = 3$ could be like the one shown in Figure 15.

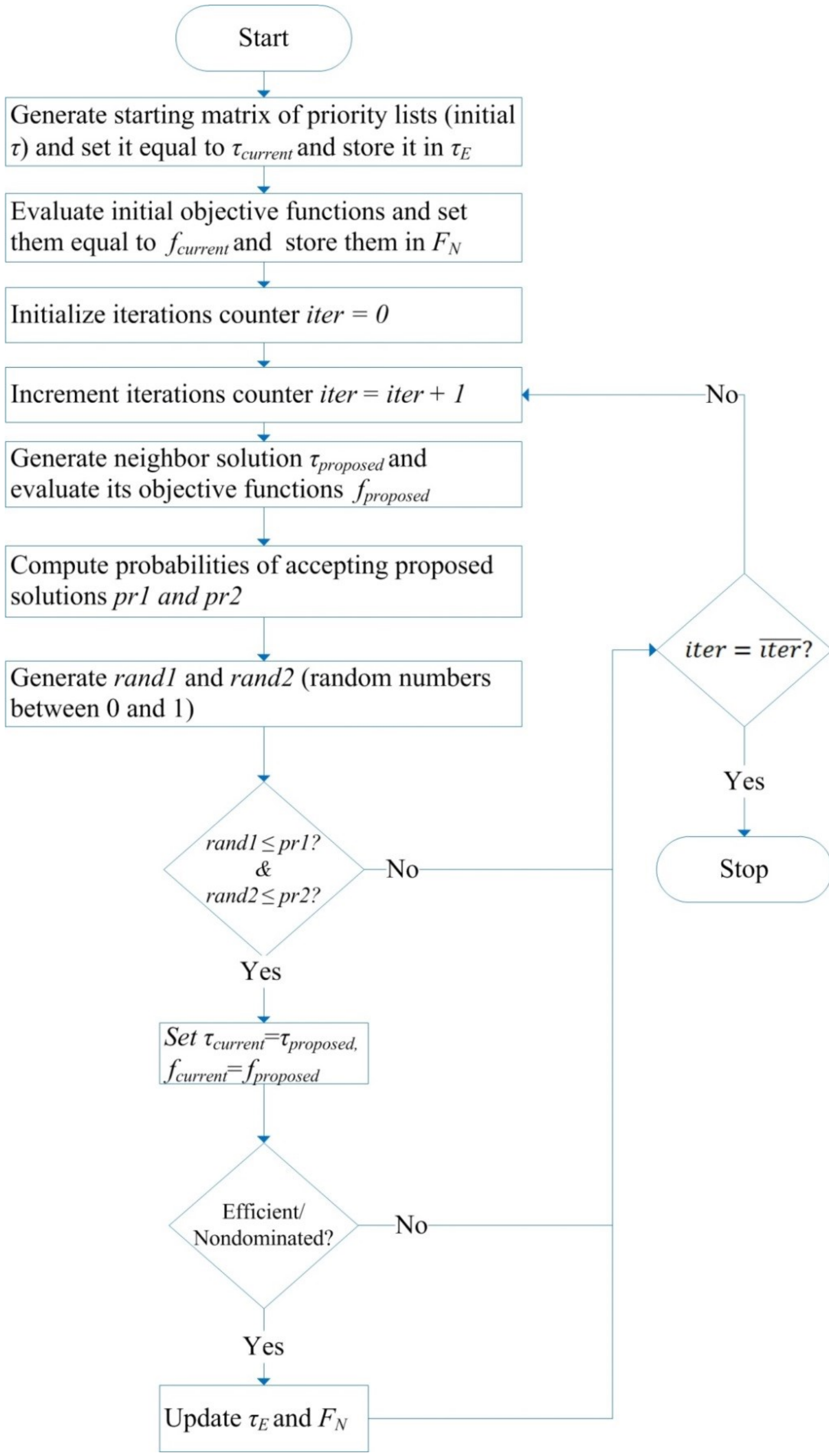


Figure 13. Overview of the Proposed Metaheuristic (MOHSAA)

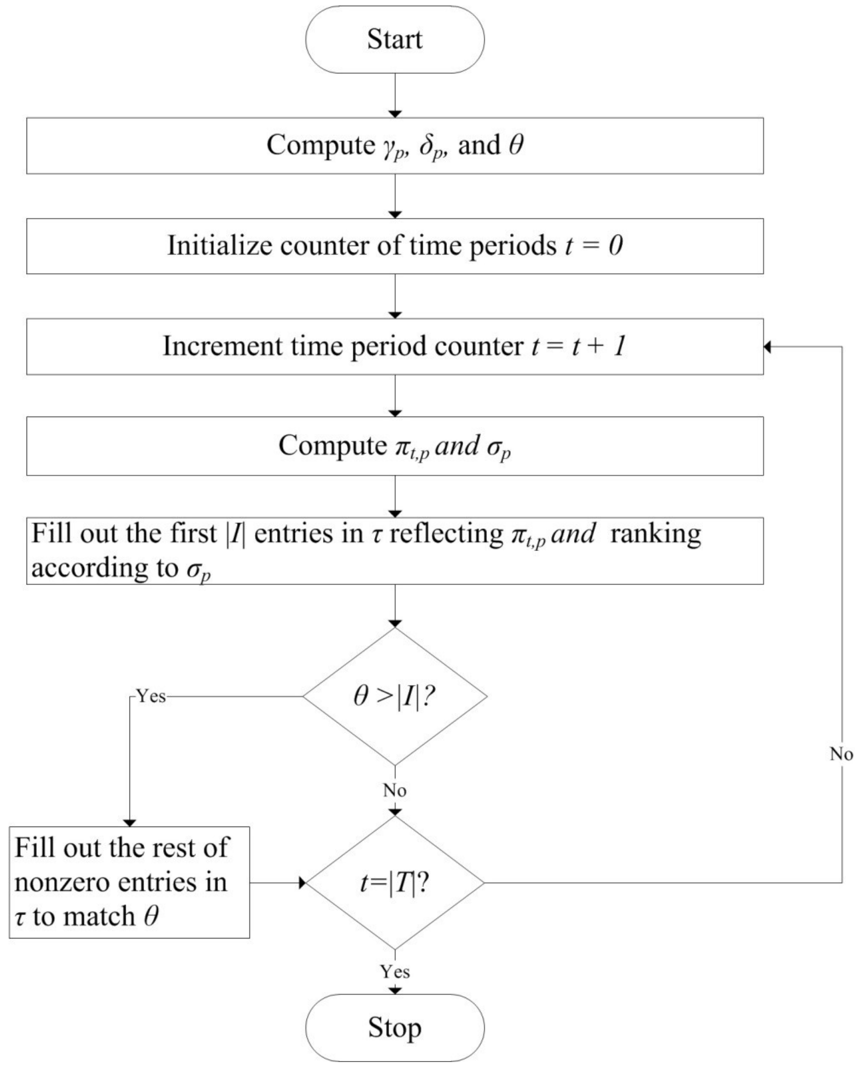


Figure 14. Constructive Heuristic for Generating Initial $\tau$

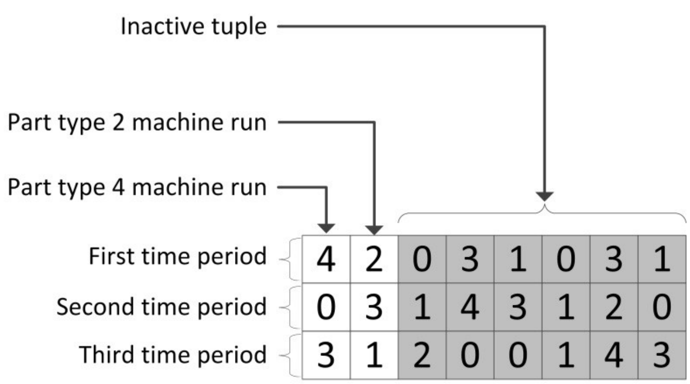


Figure 15. A Small Example of $\tau$

Decoding and objective function evaluation occur such that the two objective function values are decoded from a given matrix of priority lists ($\tau$). In the proposed MOHSAA, the decoding step is responsible for mapping the matrix to the corresponding values of all binary decision variables. The strategy behind the decoding step is to divide the problem into several sub-problems by working on one matrix entry at a time, in priority order (i.e., in order of the columns in the matrix). Given a single entry, four machine-part type assignment rules are applied sequentially that attempt to assign the current part type run to a compatible machine at the lowest possible cost (Figure 16). This is achieved by minimizing the setup cost for both the current part type and any remaining part types to be assigned to machines. The values of all binary variables are calculated in this step.

Next, objective function evaluation is achieved by solving the resulting mixed-integer linear program (MILP) from the decoding step to compute the values of the decision variables and the corresponding two objective function values. The MILP has a single objective, which is to minimize the maximum percent outsourced parts per customer (28), and the resulting total cost ($f^1$) is calculated from the identified decision variable values accordingly. We model this MILP in AMPL and solve it using CPLEX. An absolute MIP gap of 1% is set to speed the solution of the MILP since some variables are non-binary, nonnegative integer. To explore the search space, the applied perturbation scheme dictates that in a random row of $\tau$ (encoding), two terms (values) are randomly interchanged (swapped), noting that each of these two terms can belong to any column in $\tau$, and could originally be in any of the active and inactive tuples.

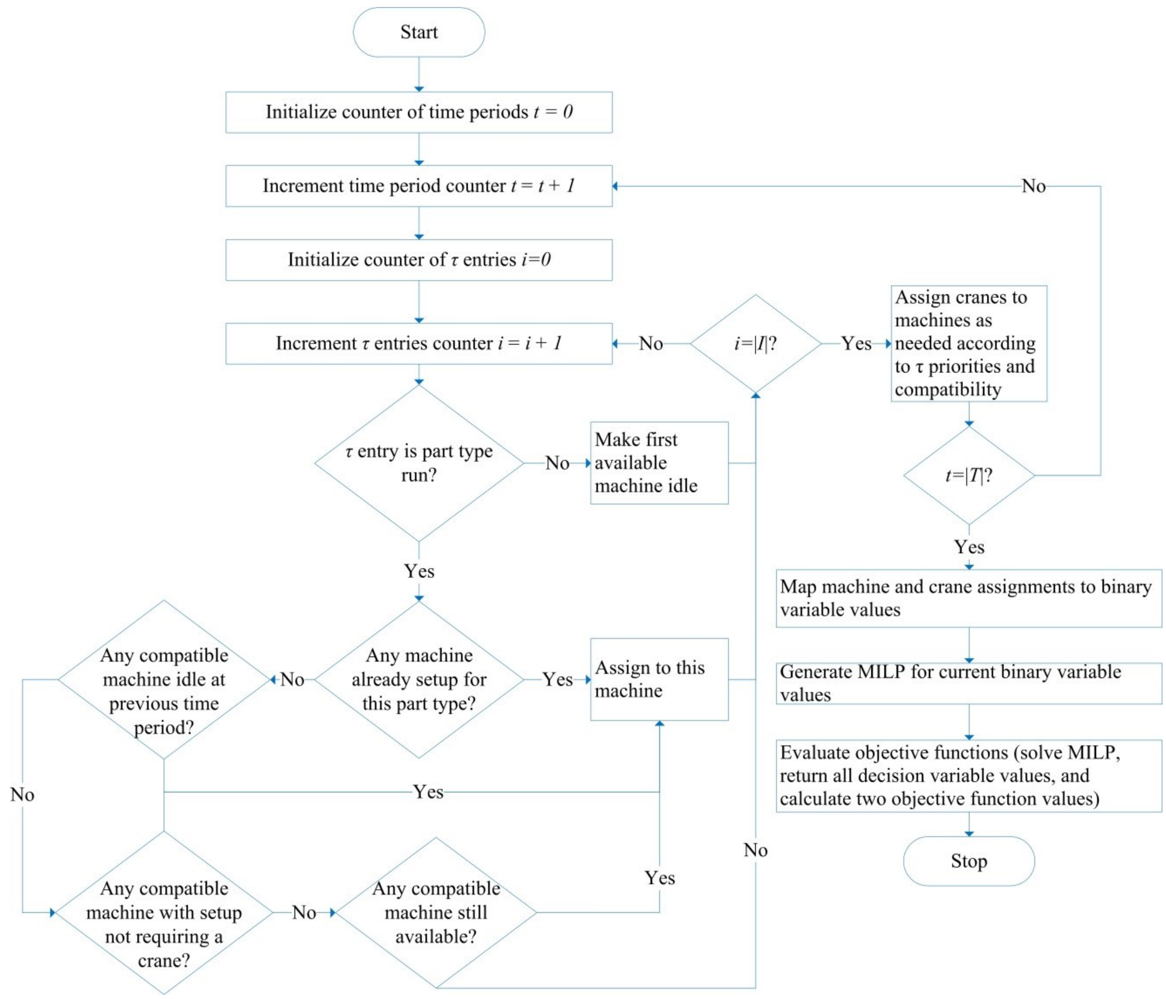


Figure 16. Decoding and Bi-objective Evaluation

Following the recommended values in the literature, we conduct some pilot testing runs. From these efforts, the starting temperature in the MOHSAA is set to 5000 and the number of iterations is set equal to 3000. The cooling schedule equation is the same as in Chapter 2, but in the current study the cooling schedule parameter ($\tilde{\alpha}$) is set to equal 0.9. Unlike The algorithm in Chapter 2, here there are two separate temperature calculations at every iteration, one for each objective function. In order to accept a move in the proposed MOHSAA, both acceptance conditions must be satisfied simultaneously as shown in Figure 13.

In the objective space, given the current point $(f^1_{current}, f^2_{current})$ in the current iteration of the algorithm's search process, a proposed point $(f^1_{proposed}, f^2_{proposed})$ is generated via applying the algorithm's perturbation scheme. Then comparisons are made between the two current objectives and the two proposed objectives. If the proposed solution either dominates or is not dominated by the current solution, both probabilities are set to one. If the proposed solution is dominated by the current solution, each probability is calculated based on how far the algorithm is in the search process (*iter* value) and how much higher the proposed objective function is. Finally, if the proposed point is the same as the current point in the objective space, both probabilities are set to one. The details of calculating the two probabilities of accepting a move to update the current solutions are depicted in Figure 17.

### 3.5 Results and Discussion

Six experimental factors are investigated at a number of levels, resulting in 96 different factor combinations (Table 11). For every combination of experimental factors, 10 problem instances are generated, and every instance is independently solved three times, resulting in a total of 2880 instance runs. The numbers of each type of crane (i.e., small, medium, and large) are generated to ensure that every machine is compatible with at least one crane and, if applicable, to be in proportion to the numbers of machine types. The details of generating the 960 test instances are in accordance with conditions presented in Chapter 2.

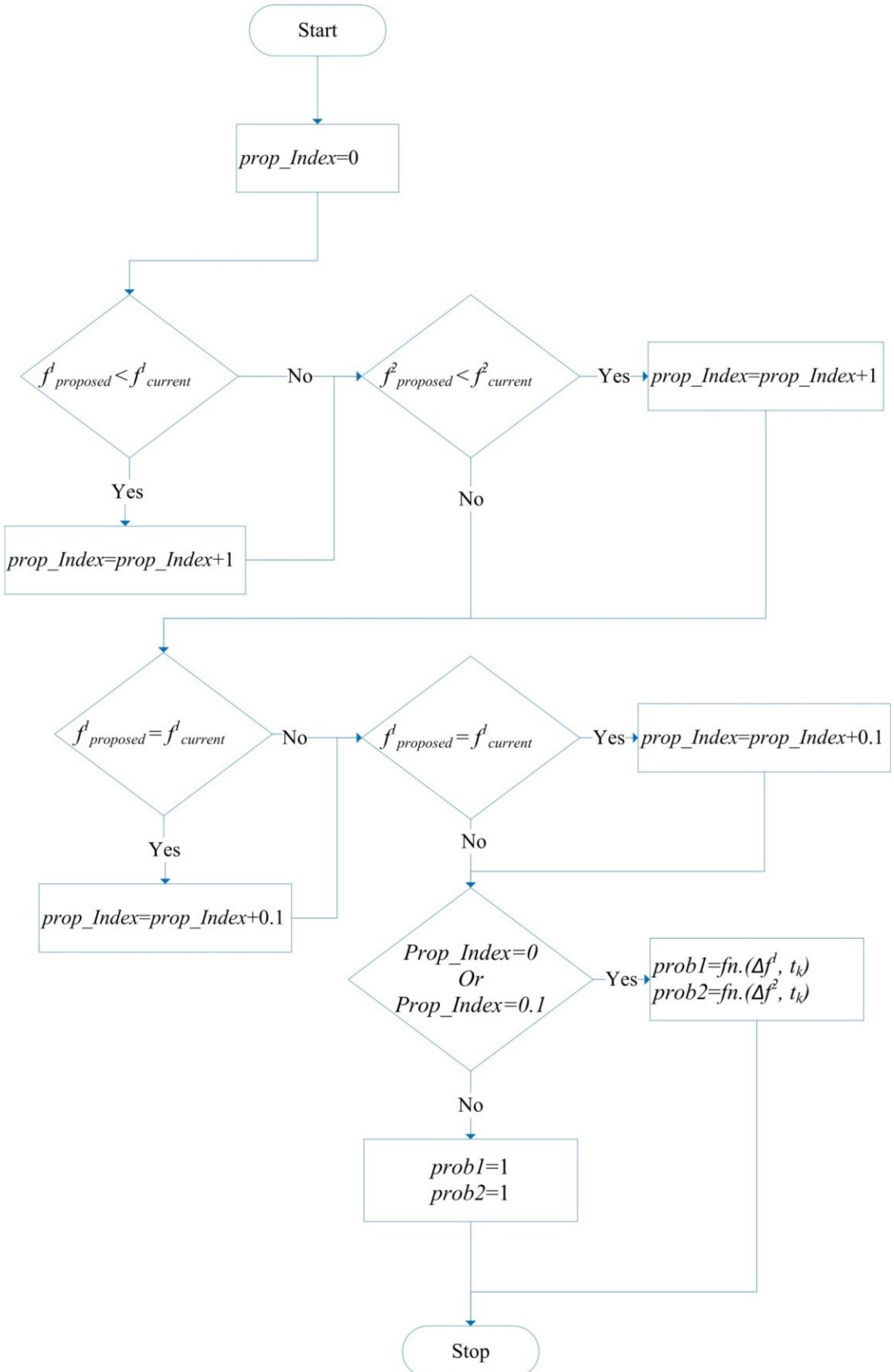


Figure 17. Calculation of Two Probabilities of Accepting a Move to Update the Current Solution

Table 11. Description of Experimental Design

| Factors | Number of Levels | Level Description |
|---|---|---|
| Part type (machine) mix | 3 | 0, 1, 2 |
| Number of machines ($\|I\|$) | 2 | 5, 10 |
| Number of cranes ($\|J\|$) | 2 | 3, 5 |
| Number of part types ($\|P\|$) | 2 | 5, 25 |
| Number of DCs ($\|W\|$) | 2 | 1, 3 |
| Number of time periods ($\|T\|$) | 2 | 4, 16 |
| **Total Combinations** | **96** | |

The proposed MOHSAA is coded in MATLAB 8.1 and AMPL (CPLEX 11.2), and all 2880 problem instance runs are run on a number of workstations, including an Intel Core i7, 3.4GHz processor with 8GB of RAM on a 64-bit, Windows 7 workstation. Every instance is set to run for 3000 iterations (i.e., 3000 objective function evaluations). Two examples of the feasible and Pareto points obtained for a small and a large instance are shown in Figures 18 and 19, respectively. Although the feasible points in Figure 19 appear more condensed than those in Figure 18, the scale of the x-axis, total cost, in Figure 19 is more compact (i.e., in 100,000s). A summary of the results of all 2880 instance runs analyzed is provided in Tables 12 through 15. From these results, the most important experimental factor appears to be the number of part types, which is in line with the finding of the single-criterion model of Chapter 2.

The numbers of efficient (nondominated) solutions obtained by the MOHSAA are listed in Table 12, and the solution times (seconds) are listed in Table 13. As the number of part types increases, so does the solution time and number of efficient (nondominated) points. This finding is also in line with Section 3.2 (Figure 12), which gives confidence that the proposed MOHSAA generates both supported and non-supported efficient solutions. In Table 12, it is noted that the measures of the factors Part Type (Machine) Mix, Number of Machines, and Number of Cranes are close at their different levels, indicating the insignificant effects of these three factors on the number of Pareto-optimal points obtained. On average, the proposed MOHSAA takes 1855 seconds (~31 minutes) to solve a single instance run, and among all of the 2880 instance runs solved, the longest solution time is 8793 seconds (~2 hours, 27 minutes). According to our conversations with an automotive industry supplier, the proposed method would be run daily to optimize the operations in a planning horizon of several days. Since the results show the proposed algorithm's solution time to be less than three hours in the worst case, it is considered suitable for industry use. We are currently in discussions with the supplier to deploy our proposed MOHSAA.

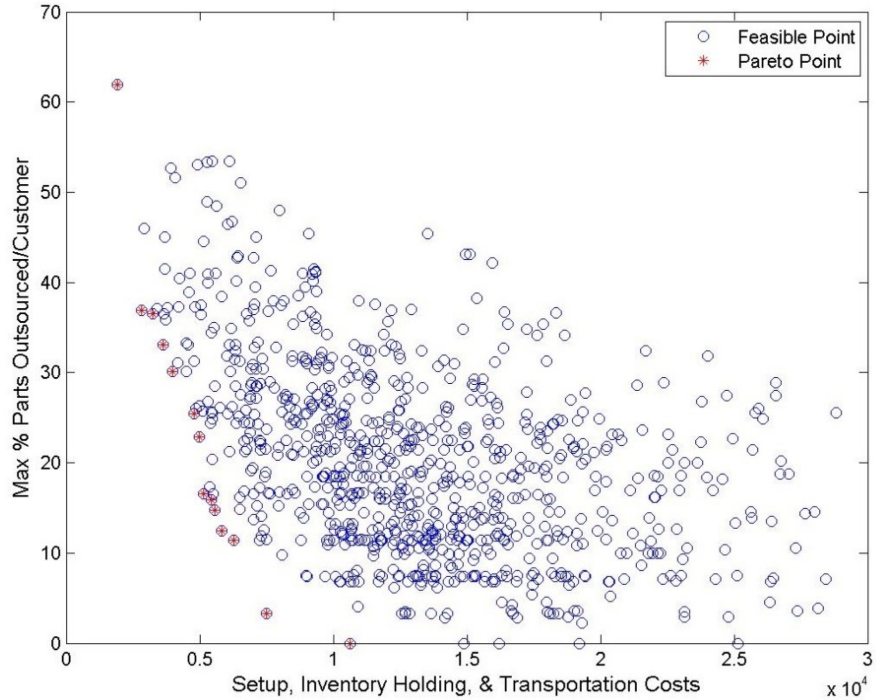


Figure 18. Feasible and Efficient (Nondominated) Points of a Small Instance

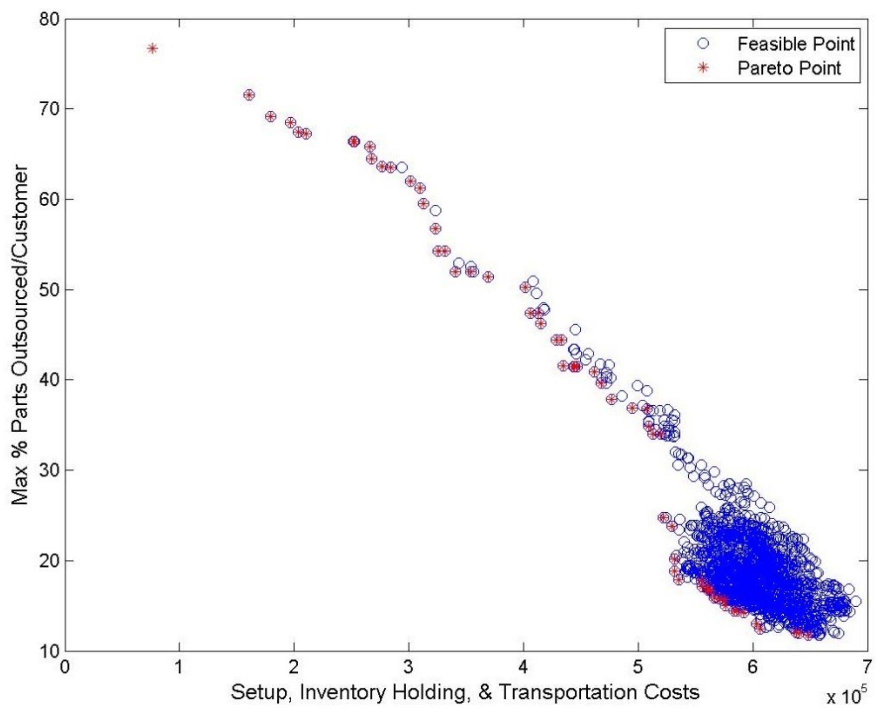


Figure 19. Feasible and Efficient (Nondominated) Points of a Large Instance

Table 12. Number of Efficient (Nondominated) Solutions by MOHSAA

| Factor | Level | Mean | Median | Min | Max |
|---|---|---|---|---|---|
| Part type (machine) mix | Mix0 | 16.1 | 14 | 1 | 52 |
| | Mix1 | 17.8 | 14 | 1 | 63 |
| | Mix2 | 18.5 | 14 | 1 | 69 |
| Number of part types ($\|P\|$) | 5 | 7.2 | 7 | 1 | 23 |
| | 25 | 27.8 | 25 | 5 | 69 |
| Number of machines ($\|I\|$) | 5 | 17.3 | 14 | 1 | 62 |
| | 10 | 17.7 | 14 | 1 | 69 |
| Number of cranes ($\|J\|$) | 3 | 17.4 | 14 | 1 | 62 |
| | 5 | 17.5 | 14 | 1 | 69 |
| Number of time periods ($\|T\|$) | 4 | 13.3 | 13 | 1 | 32 |
| | 16 | 21.6 | 18 | 1 | 69 |
| Number of DCs ($\|W\|$) | 1 | 16.7 | 14 | 1 | 57 |
| | 3 | 18.3 | 14 | 1 | 69 |
| | **Overall** | **17.5** | **14** | **1** | **69** |

Table 13. MOHSAA Solution Times (Seconds)

| Factor | Level | Mean | Median | Min | Max |
|---|---|---|---|---|---|
| Part type (machine) mix | Mix0 | 1853 | 955 | 299 | 8793 |
| | Mix1 | 1853 | 927 | 306 | 8226 |
| | Mix2 | 1858 | 955 | 312 | 8146 |
| Number of part types ($\|P\|$) | 5 | 494 | 455 | 299 | 1026 |
| | 25 | 3215 | 2608 | 942 | 8793 |
| Number of machines ($\|I\|$) | 5 | 1424 | 909 | 299 | 6488 |
| | 10 | 2285 | 1234 | 335 | 8793 |
| Number of cranes ($\|J\|$) | 3 | 1850 | 956 | 303 | 8206 |
| | 5 | 1860 | 950 | 299 | 8793 |
| Number of time periods ($\|T\|$) | 4 | 1038 | 794 | 299 | 2810 |
| | 16 | 2672 | 1736 | 377 | 8793 |
| Number of DCs ($\|W\|$) | 1 | 1841 | 913 | 299 | 8156 |
| | 3 | 1868 | 962 | 308 | 8793 |
| | **Overall** | **1855** | **953** | **299** | **8793** |

Table 14. Lowest (Highest) Cost Nondominated Solutions in $1000s

| Factor | Level | Mean | | Median | | Min | | Max | |
|---|---|---|---|---|---|---|---|---|---|
| Part type (machine) mix | Mix0 | 41.7 | (176.1) | 23.9 | (123.6) | 0.4 | (0.6) | 273.2 | (647.4) |
| | Mix1 | 40.7 | (179.0) | 22.7 | (115.2) | 0.5 | (2.5) | 213.8 | (633.4) |
| | Mix2 | 36.0 | (191.1) | 14.7 | (98.1) | 0.5 | (3.3) | 175.4 | (736.1) |
| Number of part types (\|$P$\|) | 5 | 37.3 | (92.2) | 16.0 | (48.3) | 0.4 | (0.6) | 213.8 | (612.8) |
| | 25 | 41.7 | (271.8) | 22.9 | (227.4) | 0.6 | (47.9) | 273.2 | (736.1) |
| Number of machines (\|$I$\|) | 5 | 26.8 | (135.3) | 16.9 | (84.1) | 0.4 | (0.6) | 122.5 | (424.3) |
| | 10 | 52.2 | (228.7) | 30.9 | (141.0) | 0.9 | (2.8) | 273.2 | (736.1) |
| Number of cranes (\|$J$\|) | 3 | 38.8 | (180.7) | 22.2 | (111.2) | 0.4 | (0.6) | 213.8 | (716.6) |
| | 5 | 40.1 | (183.3) | 20.9 | (114.0) | 0.5 | (2.8) | 273.2 | (736.1) |
| Number of time periods (\|$T$\|) | 4 | 7.1 | (65.8) | 5.6 | (62.0) | 0.4 | (0.6) | 66.3 | (229.2) |
| | 16 | 71.9 | (298.3) | 61.0 | (282.3) | 8.6 | (21.4) | 273.2 | (736.1) |
| Number of DCs (\|$W$\|) | 1 | 44.4 | (176.1) | 20.7 | (107.6) | 0.4 | (0.6) | 273.2 | (736.1) |
| | 3 | 34.6 | (187.9) | 22.0 | (117.6) | 3.4 | (3.6) | 213.8 | (716.6) |
| | **Overall** | **39.5** | **(182.0)** | **21.8** | **(113.1)** | **0.4** | **(0.6)** | **273.2** | **(736.1)** |

Table 15. Lowest (Highest) Maximum Percent Outsourced Parts per Customer Nondominated Solutions

| Factor | Level | Mean | | Median | | Min | | Max | |
|---|---|---|---|---|---|---|---|---|---|
| Part type (machine) mix | Mix0 | 14.9 | (53.5) | 8.8 | (62.5) | 0.0 | (0.0) | 57.1 | (98.4) |
| | Mix1 | 14.6 | (48.6) | 8.9 | (57.9) | 0.0 | (0.0) | 55.3 | (98.2) |
| | Mix2 | 14.0 | (49.6) | 8.4 | (63.5) | 0.0 | (0.0) | 56.0 | (97.6) |
| Number of part types (\|$P$\|) | 5 | 1.7 | (19.0) | 0.3 | (12.3) | 0.0 | (0.0) | 14.8 | (88.0) |
| | 25 | 27.2 | (82.2) | 24.8 | (85.2) | 6.2 | (52.8) | 57.1 | (98.4) |
| Number of machines (\|$I$\|) | 5 | 18.6 | (58.2) | 13.7 | (73.8) | 0.0 | (0.0) | 57.1 | (98.4) |
| | 10 | 10.3 | (43.0) | 7.6 | (52.8) | 0.0 | (0.0) | 34.6 | (93.1) |
| Number of cranes (\|$J$\|) | 3 | 14.5 | (50.5) | 9.0 | (61.3) | 0.0 | (0.0) | 56.5 | (98.2) |
| | 5 | 14.4 | (50.6) | 8.5 | (61.2) | 0.0 | (0.0) | 57.1 | (98.4) |
| Number of time periods (\|$T$\|) | 4 | 19.7 | (56.6) | 13.4 | (65.0) | 0.0 | (0.0) | 57.1 | (98.4) |
| | 16 | 9.2 | (44.6) | 8.1 | (54.6) | 0.0 | (0.0) | 32.5 | (98.2) |
| Number of DCs (\|$W$\|) | 1 | 14.0 | (48.9) | 8.8 | (59.6) | 0.0 | (0.0) | 57.1 | (98.4) |
| | 3 | 14.9 | (52.3) | 8.8 | (67.3) | 0.0 | (0.0) | 56.5 | (98.2) |
| | **Overall** | **14.5** | **(50.6)** | **8.8** | **(61.2)** | **0** | **(0.0)** | **57.1** | **(98.4)** |

Unlike using the single objective optimization approach, here in every instance the different Pareto solutions generated by the proposed MOHSAA offer the supply chain planner options to trade-off total cost with service level, which are two conflicting objectives. The range of such options increases as problem size increases (Tables 14 and 15). Furthermore, the widest range occurs with increased number of part types. In practice, the best solution would be selected from the identified Pareto solutions based on the specific circumstances surrounding the decision maker, such as company outsourcing policies, contractual agreements with customers, and downtime maintenance plans. In addition to the operational, daily use of the proposed MOHSAA, it can also be used as a building block for a long-term planning approach. Such long-term applications can deal with calculations related to the addition of new resources (e.g. machines) to the plant and the determination of safety stock inventory levels.

Compared to other methods, our proposed bicriteria hybrid metaheuristic employs an effective approach to find a wide range of approximate Pareto-optimal solutions in a reasonable amount of time. Our approach avoids the disadvantages of Weighted Sums and $\varepsilon$-constraint scalarization techniques. The Weighted Sums method combines the different objectives into a single objective and vary the weights of the two objectives several times. The resulting problems are solved to obtain Pareto-optimal solutions. However, this process is time consuming. Furthermore, it is not practical to add two functions with different scales and/or units of measure (e.g. $1000s and %) into a single function because the function with the larger magnitude will overshadow the other function.

This approach finds only supported Pareto-optimal solutions, which is just a small percentage of the Pareto-optimal set. The $\varepsilon$-constraint method requires setting a grid with different right hand side values on the inequality constraint expressing one of the two objective functions, while optimizing the other (primary) objective. Setting good values for the right hand side of the constraint reflecting the secondary objective function presents a difficulty for this method. For example, if a limit of 10% is set on the maximum percent of outsourced parts per customer, a specific total cost value can be obtained by solving this single objective problem. However, there could a much lower total cost solution with maximum percent of outsourced parts per customer of 10.1% and this solution will not be identified because of the inequality constraint. Additional difficulties with $\varepsilon$-constraint method is that it is time consuming to solve the problem repeatedly to cover the grid of all values of the right hand side of the constraint for the secondary objective. Our proposed MOHSAA avoids the shortcomings of these methods.

### 3.6 Conclusions and Future Research

Utilizing optimization for planning orders in the automotive supply chain can have a positive economic impact for companies. Multi-criteria optimization involves more than one objective function to be optimized simultaneously. We model a two-stage automotive supply chain involving production at a Tier-1 automotive supplier and transportation to distribution centers (customers) at a detailed, operational level using a bi-criteria, mixed-integer linear programming model. The model examines two conflicting objectives: 1) the summation of setup, inventory holding and transportation costs and 2) the maximum percent outsourced parts per customer. The model prescribes key decision variables, including production, inventory, shipping, and outsourcing quantities over the planning horizon.

Given the problem's complexity, we develop a hybrid metaheuristic as a first attempt to solve this problem. Our solution approach avoids the disadvantages of other multiobjective optimization techniques, such as the need to solve the problem several times and the inability to find non-supported Pareto-optimal solutions. Experimental results reveal that the proposed MOHSAA is suitable for industry use and offers the decision maker (e.g. supply chain planner) options to tradeoff cost and service level. Furthermore, as the problem size in terms of the number of part types increases, so do the solution time as well as the number and range of efficient (nondominated) solutions. Possible directions for future research include extending the current problem to include multiple plants in the production stage and investigating different objectives, in addition to cost and service level, such as an objective related to sustainability (e.g. $CO_2$ emissions minimization). More hybrid metaheuristic solution approaches will be required to solve such extended problems. Another direction of future research is comparing the performance of the proposed MOHSAA to other metaheuristic optimization techniques, such as the Nondominated Sorting Genetic Algorithm II (NSGA-II).

# CHAPTER FOUR

# OPTIMIZING INTEGRATED COST IN A TWO-STAGE, AUTOMOTIVE SUPPLY CHAIN WITH MULTIPLE TRANSPORTATION MODES

As the automotive industry has been striving to increase its efficiency and competitiveness, great focus often is placed on opportunities for improving its supply chain operations. We study the effect of introducing multiple modes of transportation in an industry-motivated production and transportation problem involving short-term automotive supply chain planning. We consider multiple, heterogeneous modes of transportation that offer a cost vs. delivery time option to the manufacturer. We present a mixed-integer linear programming model that captures the availability of multiple transportation modes. We then provide a solution approach based on a hybrid simulated annealing algorithm that we use to analyze the problem. Computational results demonstrate the efficacy of the proposed metaheuristic-based solution approach, given the problem's NP-hard computational complexity. Experimental results demonstrate the effect of additional transportation mode lead times compared to cost in the integrated supply chain.

## 4.1 Introduction

This research study extends Chapter 2 and deals with optimizing an integrated, two-stage automotive supply chain. We study total integrated cost minimization in a real-world production and transportation planning problem of a Tier-1 automotive supplier dealing with short-term automotive part order planning. In previous research on the integrated supply chain's first stage, production, we model several realistic conditions such as sequence-dependent setups on multiple injection molding machines operating in parallel, auxiliary resource assignments of overhead cranes, and multiple types of costs. The integrated supply chain's second stage, transportation, consists of capacitated vehicles that deliver finished parts to multiple distribution centers (DCs) for meeting customers' predefined due date requirements. Our earlier study assumed transportation occurs via full truck load (TL) and that transportation cost is fixed from the plant to each DC. The supply chain only allows direct deliveries without any intermediate stops (i.e., only one customer per trip) via an unlimited (i.e. infinite) transportation fleet.

Now, we extend the previous model by allowing multiple modes of transportation in the second stage of the integrated supply chain system (Figure 20). An additional mode of transportation can be intermodal, which is a combination of two or more transportation modes. In our research problem, intermodal can be: plant-truck-rail-truck-distribution center. Rail transportation has several advantages as it is fuel efficient and thus environmental friendly; it contributes to reducing traffic congestion in the road network by reducing the number of trucks on the road and thus preserving the road conditions for longer times; and it is also cost competitive.

While all modes of transportation deliver to the same destinations (DCs), their costs and lead times vary. Adding this aspect to the modeled problem helps decision makers decide between different transportation alternatives based on their impact on the objective function (i.e. total integrated cost). The goal of this research study is to help decision makers plan for the right production, inventory, transportation, and outsourcing quantities over the planning horizon by considering the multiple modes of transportation simultaneously.

The rest of this chapter is organized as follows. Section 4.2 reviews some of the related literature. Section 4.3 provides a mixed-integer linear programming model that captures the details of the current research problem as well as a metaheuristic solution method. Section 4.4 presents the numerical experiment results, including a comparison of the results from different transportation mode cost and lead time multiples. Conclusions and directions for future research are outlined in Section 4.5.

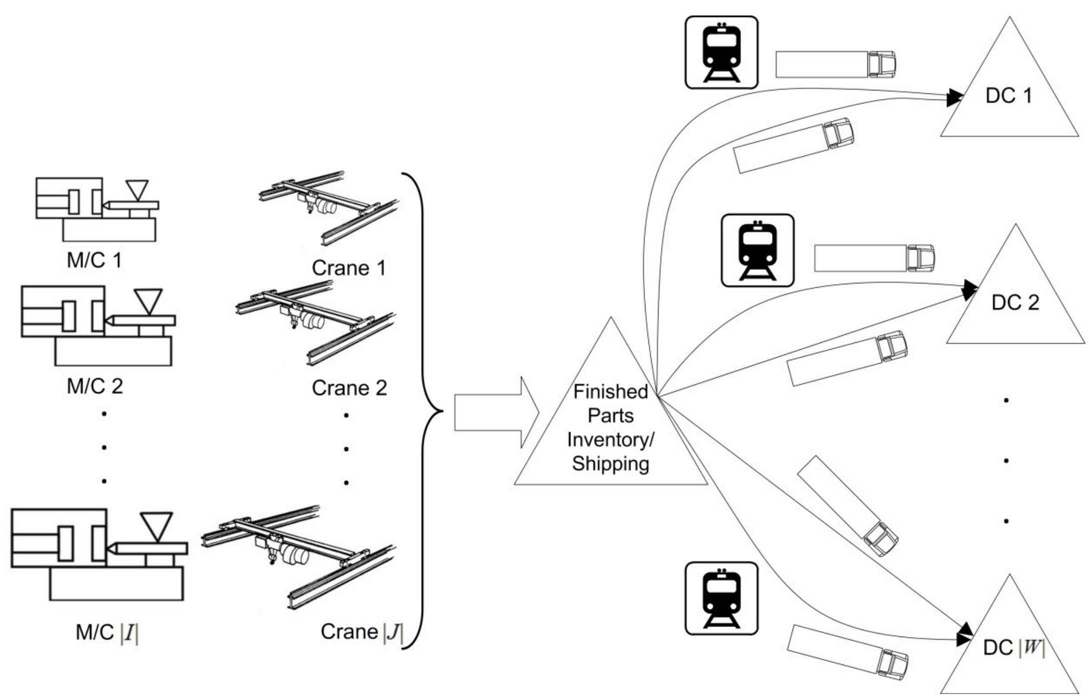


Figure 20. The Two-Stage Automotive Supply Chain System with Heterogeneous Transportation

## 4.2 Literature Review

Production and inter-facility transportation scheduling for process industries is studied by de Matta and Miller (2004). The authors develop a dynamic production and transportation decision model to simultaneously determine the cost minimizing quantities of products an intermediate plant must produce and ship to a finishing plant using different transportation modes. Furthermore, the model simultaneously determines the cost minimizing quantities of products that the finishing plant must produce to meet its customer demands on-time. One of the several benefits of coordinating production and transportation decisions is that it helps control the use of expedited transportation options through timely shipments of sufficient intermediate product quantities via the normal, "less" expensive mode to meet the input requirements of the finishing plant. This approach also decreases intermediate product inventory holding costs.

A general two-stage logistics scheduling with batching and transportation problem is presented by Chen and Lee (2008). The problem involves jobs of different importance being processed by one first-stage processor and then, in the second stage, the completed jobs must be batch-delivered to various pre-specified destinations in one of a number of available transportation modes. The objective is to minimize the sum of weighted-job delivery time and total transportation cost. The paper provides an overall picture of the problem complexity for various cases and problem parameters and gives polynomial algorithms for solvable cases. On the other hand, for the most general case, an approximation algorithm of performance guarantee is presented.

Minimizing the total cost of logistics and carbon emissions in intermodal transportation is studied by Zhang *et al.* (2011). The authors propose an integer programming model to illustrate the impact of considering carbon emissions on intermodal transportation decisions. The concept of transportation-oriented scheduling in the automotive industry is investigated by Florian *et al.* (2011) who present a simulation model using real scheduling data to demonstrate the potential savings realized by means of smoothing and bundling demands in scheduling. The planning approach increases utilization and reduces $CO_2$ emissions.

Integrated optimization of customer and supplier logistics at a leading automotive supplier is studied by Yildiz *et al.* (2010). The authors identify the opportunity for cost savings by using a mixed-integer programming model that matches opposite flows from and to customers and suppliers. It is assumed that the automotive supplier makes all transportation arrangements for its customers and suppliers. The automotive supplier utilizes the unused capacity of return trips from their customers by identifying a subset of promising customer routes that can be combined with its existing supplier routes through cross-docking, to save overall system costs.

We introduce a model that recommends time-phased production, inventory, and shipping decisions. Although some research on optimization models involving production scheduling, transportation, and the automotive supplier industry exist in the literature, none focus on minimizing the total integrated cost in a two-stage, automotive supply chain with heterogeneous transportation at a detailed, operational level. This is the subject of our current research as we seek to fill this gap in the literature that is of practical importance to industry.

## 4.3 Methodology

### *4.3.1 Mixed-integer Linear Programming Model*

The mixed-integer linear programming (MILP) model presented in Chapter 2 is extended here to capture the availability of multiple transportation modes. In order to develop this extension, some changes in the original model's index sets, parameters, variables, and constraint sets are necessary. The whole MILP model for multiple transportation modes is as follows.

*Index Sets*

| | |
|---|---|
| $I$ | set of machines, indexed by $i$ |
| $J$ | set of cranes, indexed by $j$ |
| $P$ | set of part types, indexed by $p$ |
| $W$ | set of distribution centers, indexed by $w$ |
| $T$ | set of time periods, indexed by $t$ |
| $R$ | set of transportation modes, indexed by $r$ |

*Parameters*

| | |
|---|---|
| $D_{t,p,w}$ | demand by distribution center $w$ of part type $p$ in time period $t$ (parts) |
| $\mu_p$ | unit production time (cycle time) of part type $p$ (secs) |
| $F$ | length of time period (hours) |
| $S_{i,p,p'}$ | changeover time from part type $p$ to part type $p'$ on machine $i$ (mins) |
| $E_p$ | maximum quantity of parts per unit load of part type $p$ (parts/unit load) |
| $K$ | plant finished part warehouse capacity (unit loads) |
| $G$ | vehicle capacity (unit loads) |
| $H_p$ | unit inventory holding cost of part type $p$ ($/part/period) |
| $L_{r,w}$ | cost of one trip from plant to distribution center $w$ via transportation mode $r$ ($/trip) |
| $M_i$ | cost of downtime on machine $i$ ($/min) |
| $N_p$ | cost of outsourcing of part type $p$ ($/part) |

| | |
|---|---|
| $A_{i,p}$ | equals one if machine $i$ is compatible with part type $p$, 0 otherwise |
| $B_{j,i}$ | equals one if crane $j$ can serve setup on machine $i$, 0 otherwise |
| $C_{p,p'}$ | equals one if setup from part type $p$ to part type $p'$ requires a crane, 0 otherwise |
| $\varepsilon_{r,w}$ | duration (time periods) of trip to distribution center $w$ via transportation mode $r$ |

*Decision Variables*

| | |
|---|---|
| $\alpha_{t,p,r,w}$ | quantity of part type $p$ transported to distribution center $w$ in time period $t$ via transportation mode $r$ |
| $\beta_{t,r,w}$ | number of trips to distribution center $w$ via transportation mode $r$ in time period $t$ |
| $h_{t,p}$ | quantity of finished part inventory of part type $p$ in time period $t$ |
| $q_{t,i,p}$ | quantity of part type $p$ processed on machine $i$ in time period $t$ |
| $u_{t,p,w}$ | quantity of outsourcing of part type $p$ demanded by distribution center $w$ in time period $t$ |
| $x_{t,i,p}$ | equals one if machine $i$ processes part type $p$ in time period $t$, 0 otherwise |
| $y_{t,i,p,p'}$ | equals one if machine $i$ changes over from part type $p$ to part type $p'$ in time period $t$, 0 otherwise |
| $z_{t,j,i}$ | equals one if crane $j$ serves setup on machine $i$ in time period $t$, 0 otherwise |

$$\begin{aligned} minimize \sum_{t\in T, t\neq 1} \sum_{i\in I} \sum_{p\in P} \sum_{p'\in P, p'\neq p} S_{i,p,p'} M_i y_{t,i,p,p'} + \sum_{t\in T} \sum_{p\in P} H_p h_{t,p} \\ + \sum_{t\in T} \sum_{r\in R} \sum_{w\in W} L_{r,w}\, \beta_{t,r,w} + \sum_{t\in T} \sum_{p\in P} \sum_{w\in W} N_p u_{t,p,w} \end{aligned} \tag{52}$$

*subject to*

$$\beta_{t,r,w} \geq \frac{1}{G} \sum_{p\in P} \frac{1}{E_p} \alpha_{t,p,r,w} \qquad \forall t \in T, \forall r \in R, \forall w \in W \tag{53}$$

$$u_{t,p,w} = D_{t,p,w} - \alpha_{t,p,r,w} \qquad t=1..\varepsilon_{r,w}-1, \forall p \in P, r=1, \forall w \in W \tag{54}$$

$$u_{t,p,w} = D_{t,p,w} \sum_{r\in R} \alpha_{t-\varepsilon_{r,w}+1,p,r,w} \qquad t=\varepsilon_{r,w}..|T|, \forall p \in P, \forall w \in W \tag{55}$$

$$\sum_{p\in P} \frac{1}{E_p} h_{t,p} \leq K \qquad \forall t \in T \tag{56}$$

$$h_{t,p} = \sum_{i \in I} q_{t,i,p} - \sum_{r \in R} \sum_{w \in W} \alpha_{t,p,r,w} \qquad t=1,\ \forall p \in P \tag{57}$$

$$h_{t,p} = h_{t-1,p} + \sum_{i \in I} q_{t,i,p} - \sum_{r \in R} \sum_{w \in W} \alpha_{t,p,r,w} \qquad \forall t \in T,\ \forall p \in P, t \neq 1 \tag{58}$$

$$\mu_p q_{t,i,p} \leq F x_{t,i,p} \qquad t=1,\ \forall i \in I,\ \forall p \in P \tag{59}$$

$$\mu_p q_{t,i,p} + \sum_{p' \in P, p' \neq p} S_{i,p,p'} y_{t,i,p,p'} \leq F x_{t,i,p} \qquad \forall t \in T,\ \forall i \in I,\ \forall p \in P,\ t \neq 1 \tag{60}$$

$$y_{t,i,p,p'} \geq x_{t,i,p} + x_{t-1,i,p'} - 1 \qquad \forall t \in T,\ \ \forall i \in I,\ \ \forall p \in P,\ \ \forall p' \in P,\ t \neq 1, p \neq p' \tag{61}$$

$$x_{t,i,p} \leq A_{i,p} \qquad \forall t \in T,\ \forall i \in I,\ \forall p \in P \tag{62}$$

$$\sum_{p \in P} x_{t,i,p} \leq 1 \qquad \forall t \in T,\ \forall\ i \in I \tag{63}$$

$$\sum_{j \in J} z_{t,j,i} = \sum_{p \in P} \sum_{p' \in P, p' \neq p} y_{t,i,p,p'} C_{p,p'} \qquad \forall t \in T,\ \forall\ i \in I,\ t \neq 1 \tag{64}$$

$$z_{t,j,i} \leq B_{j,i} \qquad \forall t \in T,\ \forall\ j \in J,\ \forall\ i \in I,\ t \neq 1 \tag{65}$$

$$\sum_{i \in I} z_{t,j,i} \leq 1 \qquad \forall t \in T,\ \forall j \in J,\ t \neq 1 \tag{66}$$

$$\sum_{j \in J} z_{t,j,i} \leq 1 \qquad \forall t \in T,\ \forall i \in I,\ t \neq 1 \tag{67}$$

$$\alpha_{t,p,r,w}, \beta_{t,r,w}, h_{t,p}, q_{t,i,p}, u_{t,p,w} \ \geq 0 \textit{ and integer} \qquad \forall i \in I,\ \forall\ j \in J,\ \forall p \in P,\ \forall w \in W,\ \forall t \in T \tag{68}$$

$$x_{t,i,p}, y_{t,i,p,p'}, z_{t,j,i} \in \{0, 1\} \qquad \forall i \in I,\ \forall j \in J,\ \forall p \in P,\ \forall p' \in P,\ \forall t \in T, p \neq p' \tag{69}$$

The model's objective function (52) minimizes total integrated cost, which is composed of setup, inventory holding, transportation, and outsourcing cost. Constraint set (53) calculates the number of trips to every distribution center at every time period via every transportation mode based on transportation capacity and unit load volumes.

Constraint sets (54) and (55) compute the quantities of outsourcing required for every part type at each DC in the first and all subsequent time periods, respectively. Next, constraint set (56) ensures the capacity of the plant's finished part inventory storage is not exceeded. Constraint sets (57) and (58) conserve the flow of every part type during the first and subsequent periods, respectively. Next, constraint sets (59) and (60) ensure the available capacity of every machine cannot be exceeded during any time period.

Constraint set (61) dictates that if a machine changes to a different part type after the first time period, a setup is required. Constraint set (62) ensures that every machine respects machine-part type matching restrictions. Constraint set (63) limits the number of part types produced by a machine to one per time period, while constraint set (64) enforces that a machine setup requiring a crane (i.e., a tooling changeover) occurs if and only if a crane serves the setup. Constraint set (65) dictates that every crane respects crane-machine compatibility restrictions, while constraint sets (66) and (67) limit the number of machine setups per time period to a maximum of one per crane and one per machine, respectively. Finally, constraint sets (68) and (69) are non-negativity, integer, and binary value constraints, respectively. To verify the accuracy of the developed extended model, a number of problem instances were solved using the original and extended models, while keeping the cost and lead time of the second transportation mode the same in both models. The two models resulted in the same objective function values, verifying the accuracy of the developed model extension.

Similar to the original MILP model, there is no existing algorithm that can solve the current research problem to optimality in polynomial time. Therefore, we propose a hybrid metaheuristic algorithm for achieving near-optimal solutions in a timely manner in the next section.

### 4.3.2 Hybrid Simulated Annealing Algorithm

The hybrid simulated annealing algorithm (HSAA) presented in Chapter 2 is adapted to solve the extended MILP model outlined in Section 4.3.1. The original encoding-decoding strategy is used in the current study, but a necessary decoding modification is made to accommodate the multiple modes of transportation. Once the matrix of priority lists $(\tau)$ is decoded into machine-part type and crane-machine assignments, the values of all binary variables become fixed, producing a reduced mixed-integer linear program (MILP) with the original binary variables becoming input parameters in the reduced model.

The next step is to solve the reduced MILP to finish the decoding and objective function evaluation procedure, including solving for the shipping quantities via each transportation mode. However, since even the reduced MILP can sometimes need a significant amount of time to solve to optimality, we set a time limit of five seconds to speed up the algorithm performance. This time limit, multiplied by the number of iterations the proposed HSAA search performs, sets an upper bound on the overall algorithm's run time. Nevertheless, the five-second time limit is not reached in most cases, and therefore the HSAA often solves single instances quite quickly.

Moreover, since the required modification involves the decoding stage only and the constructive heuristic starting solution works in the encoding space, the latter is used here without any changes. Again, the HSAA is coded in MATLAB, while the reduced

MILP model is coded in AMPL and solved using CPLEX. According to preliminary results from some pilot test runs, the number of iterations is set to equal 3000, and the starting temperature equals 5000. Only one perturbation scheme is used: the one resulting in the best results in our previous research. This perturbation scheme swaps two terms randomly in a random row of the encoding matrix of priority lists. Finally, the cooling schedule parameter is set to equal 0.9.

### *4.3.3 Experimentation Strategy*

In Chapter 2, we demonstrated the promising performance of the proposed HSAA to solve the original problem. Moreover, in contrast with the original MILP model, the proposed HSAA's relative performance improves as the problem size grows. Building on previous research findings, we shift our focus in the current study to analyze the effect of availability of multiple transportation modes in the two-stage, automotive supply chain system. Three problem instance sets of three sizes that we term "small," "medium," and "large" are the subject of analysis in the current study. These three problem test instance sets are outlined in Table 16. Further details on the generation of test instance data are in accordance with the instances analyzed in Chapter 2 to reflect realistic conditions in the automotive supply chain. The combinations of five cost and seven lead time multiples result in 35 instances per every instance set, and the proposed, adapted HSAA is used to solve all instances. The cost and time multiples reflect the different possible longer lead times and lower costs of the additional transportation mode (intermodal).

Table 16. Description of Problem Test Instance Sets

| Instance Set | Part type (machine) mix | Number of part types ($\|P\|$) | Number of machines ($\|I\|$) | Number of cranes ($\|J\|$) | Number of time periods ($\|T\|$) | Number of DCs ($\|W\|$) |
|---|---|---|---|---|---|---|
| 1 (large) | 2 | 25 | 10 | 5 | 16 | 3 |
| 2 (small) | 1 | 5 | 5 | 5 | 16 | 3 |
| 3 (medium) | 0 | 25 | 5 | 3 | 16 | 1 |

## 4.4 Results and Discussion

Every problem instance is solved using the proposed HSAA five times independently, resulting in a total of 525 problem instance runs. Given the problem's NP-hard computational complexity, the proposed HSAA can find approximate solutions in a timely manner for industry use (3828 seconds, on average). The resulting total integrated costs (averages over five runs per instance) are listed in Tables 17 through 19. Figures 21 through 23 show the variation of total integrated costs across the different cost and lead time multiples of the additional transportation mode.

Table 17. Total Integrated Costs for the Large Test Instance Set in $1000s

| Cost Multiples | Time Multiples | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 0.1 | 562.5 | 468.3 | 427.6 | 415.1 | 418.0 | 431.9 | 450.9 |
| 0.3 | 566.5 | 470.8 | 428.7 | 417.8 | 419.9 | 434.8 | 460.1 |
| 0.5 | 572.1 | 474.3 | 431.2 | 419.8 | 421.3 | 434.9 | 461.7 |
| 0.7 | 575.2 | 475.7 | 433.8 | 422.8 | 422.8 | 438.4 | 463.5 |
| 0.9 | 579.4 | 478.3 | 440.6 | 428.1 | 423.9 | 448.1 | 465.3 |

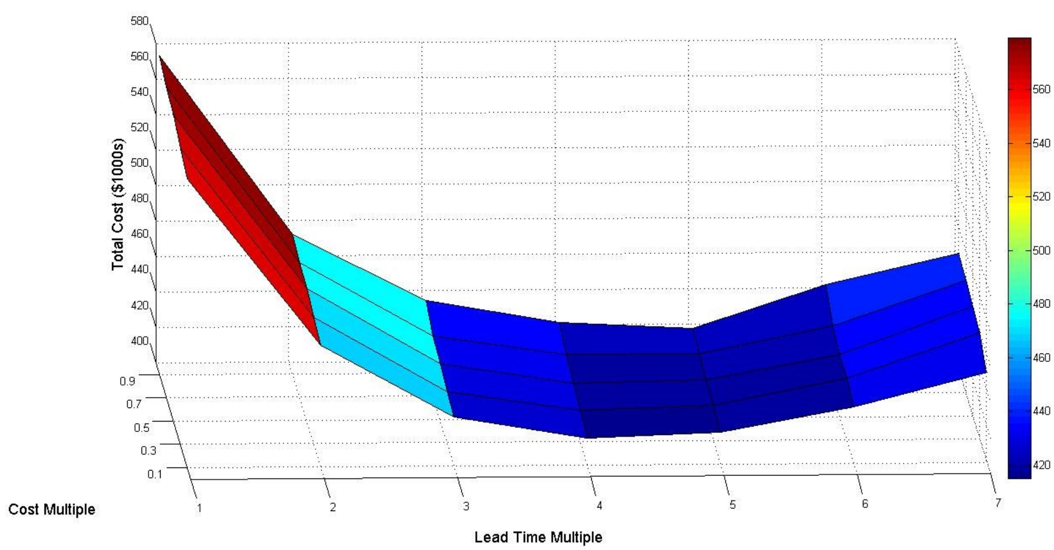


Figure 21. Results for the Large Instance Set

Table 18. Total Integrated Costs for the Small Test Instance Set in $1000s

| Cost Multiples | Time Multiples | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 0.1 | 81.1 | 61.3 | 54.9 | 54.2 | 59.1 | 63.4 | 70.2 |
| 0.3 | 84.0 | 64.3 | 56.3 | 56.5 | 61.5 | 66.0 | 70.3 |
| 0.5 | 86.9 | 65.9 | 58.4 | 60.3 | 62.6 | 66.8 | 70.4 |
| 0.7 | 89.8 | 69.7 | 58.9 | 61.5 | 66.3 | 68.7 | 71.1 |
| 0.9 | 92.7 | 72.5 | 62.5 | 62.6 | 68.3 | 70.5 | 71.4 |

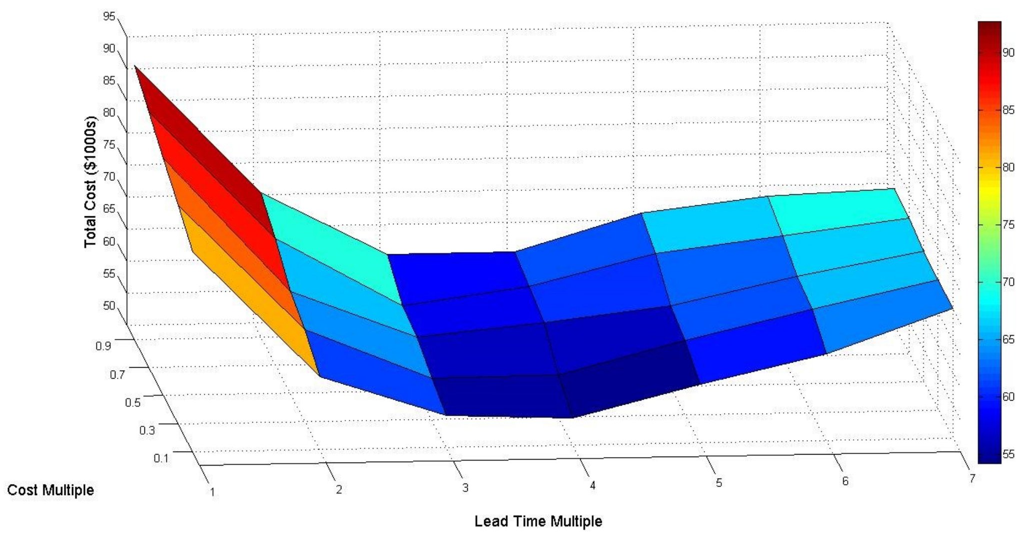


Figure 22. Results for the Small Instance Set

Table 19. Total Integrated Costs for the Medium Test Instance Set in \$1000s

| Cost Multiples | Time Multiples | | | | | | |
|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 0.1 | 296.4 | 254.9 | 234.4 | 227.3 | 226.6 | 231.9 | 239.8 |
| 0.3 | 296.7 | 255.2 | 234.7 | 227.5 | 226.9 | 232.1 | 240.0 |
| 0.5 | 297.1 | 255.5 | 235.0 | 227.8 | 227.1 | 232.4 | 240.2 |
| 0.7 | 297.4 | 255.8 | 235.3 | 228.1 | 227.4 | 232.8 | 240.4 |
| 0.9 | 297.7 | 256.1 | 235.5 | 228.3 | 227.6 | 232.8 | 240.6 |

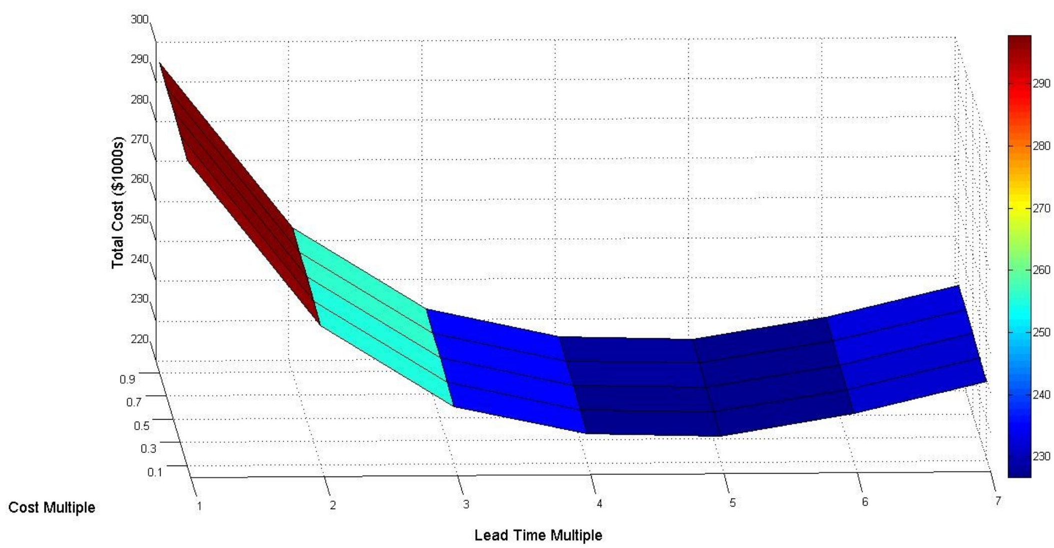


Figure 23. Results for the Medium Instance Set

From Figures 21 through 23, it is evident that introducing an additional transportation mode with a cheaper transportation cost but a longer lead time can have a dramatic effect on the total integrated cost. Also, further increasing the lead time multiple reduces the total integrated cost, especially in the large and medium-sized problem instance sets. As the lead time multiple increases, there is a larger opportunity for cost saving through reducing the more expensive transportation mode as well as storage costs. Moreover, as the cost multiple increases, so does the total integrated cost. This is expected since increasing the cost multiple has a direct effect on increasing the total integrated cost. However, the effect of the lead time multiple is much higher than that of the cost multiple.

Using the low-cost, longer lead-time transportation mode cuts some of the cost of the higher-cost transportation mode and also saves some production setup and storage costs. The slower mode of transportation allows early production of some part type quantities that are demanded at later periods, which saves production setup cost. Furthermore, once these parts are produced they are shipped via the slower transportation mode and thus the company saves the cost for storing these parts. These cost savings are possible because of the synergies identified by applying our proposed solution method to minimize the total integrated cost.

In the case of small-sized instance set (Figure 22), beyond a lead time multiple of two, the effect is not as large as in the cases of medium and large-sized sets. Also in all instance sets, as the second transportation mode lead time multiple increases beyond four or five, the total integrated cost increases. This is explained by the fact that when the lead time multiple is so long, there is less opportunity for making use of the less expensive second transportation mode over the planning horizon. In other words, although the quality (potential inventory holding cost savings per time period) increases, the quantity (how many times these savings can be realized) decreases, and the resulting total integrated cost actually increases. Overall, our results indicate that as the problem size increases, so does the opportunity for higher cost savings through an additional transportation mode with longer lead time. These insights can be used in practice by automotive supply chain decision makers towards decreasing the total integrated cost.

## 4.5 Conclusions and Future Research

We present a mixed-integer linear programming model that captures the details of a total integrated cost minimization problem in a two-stage, automotive supply chain under different transportation options. The multiple transportation options offer different lead times at varying costs. The proposed solution approach demonstrates the different effects the cost and lead time of an additional transportation mode have on the total integrated cost. The insights gained from this research highlight the impact of the additional transportation mode lead time on reducing the total integrated cost by reducing the inventory holding and transportation costs over the single transportation mode case. In future research, the problem can be extended to include additional aspects, such as the environmental effects due to $CO_2$ emissions from transportation.

# CHAPTER FIVE

# CONCLUSIONS AND FUTURE RESEARCH

In this dissertation, we introduce a two-stage automotive supply chain optimization problem involving production at a Tier-1 automotive supplier and transportation to distribution centers (customers) at a detailed, operational level. The problem has not been studied in the literature to date. Our research contributes towards higher efficiency and service levels in the automotive supply chain, which can have a favorable economic outcome for the automotive industry. We develop three mixed-integer linear programming models to capture the realistic details of our problem, and our interactions with a Tier-1 automotive supplier company help to assess the validity of our models.

The first mathematical model reflects the details of the two-stage automotive supply chain system under study including its multiple machines, auxiliary resources, limited capacities, machine-part type and machine-crane compatibilities, sequence-dependent setups, production decisions, inventory decisions, and transportation decisions via full truck loads. While the objective of the first model is to minimize the total integrated cost of production setup, inventory holding, transportation, and outsourcing, the second mathematical model has two conflicting objectives instead of just one. The first objective is to minimize the total cost of production setup, inventory holding, and transportation, and the second objective is to minimize the maximum percent of outsourced parts per customer. Finally, the third mathematical model extends the first model by adding the capability of utilizing additional transportation modes in the supply chain system's second stage. The model's objective function becomes minimizing total integrated cost of production setup, inventory holding, outsourcing and transportation cost of all transportation modes. The model extension also necessitates modifications of capacity and conservation of flow constraints in addition to some decision variables.

After showing that the first MILP model we develop to analyze the research problem under study is NP-hard, we develop a hybrid metaheuristic approach, including a constructive heuristic and an effective encoding-decoding strategy, to find near-optimal solutions in an acceptable amount of time. Computational results demonstrate the promising performance of the proposed solution approaches. The most significant factor affecting the MILP model's performance is the number of part types—as the number of part types increases, so does the model's required computation time. In contrast with the MILP model, the proposed HSAA's relative performance improves as the number of part types increases. In HSAA, the six perturbation schemes can be configured to run in parallel, thus increasing the algorithm's speed and potential effectiveness. The best performing perturbation schemes are identified, and this insight can be used in the future for further performance improvement of HSAA.

Next, to address the existence of multiple optimization objectives, we develop a bi-criteria, mixed-integer linear programming model. The model examines two conflicting objectives: 1) the summation of setup, inventory holding and transportation costs and 2) the maximum percent outsourced parts per customer. The model prescribes key decision variables, including production, inventory, shipping, and outsourcing quantities over the planning horizon. Given the problem's complexity, we develop a hybrid metaheuristic as a first attempt to solve this problem. Experimental results reveal that the proposed MOHSAA is suitable for industry use and offers the decision maker (e.g. supply chain planner) options to tradeoff cost and service level. Furthermore, as the problem size in terms of the number of part types increases, so do the solution time as well as the number and range of efficient (nondominated) solutions.

Finally, we provide a mixed-integer linear programming model that captures the details of a total integrated cost minimization problem in a two-stage, automotive supply chain under different transportation options. The multiple transportation options offer different lead times at varying costs. The proposed hybrid metaheuristic solution approach is used to analyze the different effects that the cost and lead time of the additional transportation mode have on the total integrated cost. The insights gained from this research highlight the impact of the additional transportation mode lead time on reducing the total integrated cost by reducing the production setup, inventory holding and transportation costs over the single transportation mode case.

There are a number of possible future research directions to extend the models and algorithms presented in this dissertation. On the models side, possible directions for future research include extending the current problem to include multiple plants in the production stage and investigating different objectives, in addition to cost and service level, such as an objective related to sustainability (e.g. $CO_2$ emissions minimization). Another direction for future research is utilizing the current models as building blocks towards investigating longer-term applications, such as capacity and safety stock level decision making. On the algorithms side, more hybrid metaheuristic solution approaches will be required to solve the extended models. Future research can develop and apply other heuristic optimization methodologies to solve the problems under investigation.

# APPENDIX A

# AN EXAMPLE OF THE CONSTRUCTIVE HEURISTIC AND DECODING

*Inputs*

$|I| = 5, |P| = 5, |W| = 1, |T| = 4$

Tables 20 and 21 list two key input parameters for the example.

Table 20. Demand of Part Types Over the Planning Horizon, *D*

| **Time Periods** | **Part Types** | | | | |
|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** |
| **1** | 0 | 409 | 431 | 292 | 135 |
| **2** | 0 | 0 | 457 | 0 | 0 |
| **3** | 356 | 372 | 0 | 250 | 170 |
| **4** | 0 | 417 | 414 | 259 | 164 |

Table 21. Machine-Part Type Compatibility, *A*

| **Machines** | **Part Types** | | | | |
|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** |
| **1** | 1 | 0 | 1 | 0 | 0 |
| **2** | 0 | 1 | 0 | 0 | 0 |
| **3** | 1 | 1 | 1 | 0 | 0 |
| **4** | 1 | 1 | 1 | 1 | 0 |
| **5** | 0 | 1 | 0 | 1 | 1 |

*Constructive Heuristic Calculations (Tables 22 through26):*

Table 22. Grand Total Demand per Part Type, $\gamma_p$

| **Part Types** | | | | |
|---|---|---|---|---|
| **1** | **2** | **3** | **4** | **5** |
| 356 | 1198 | 1302 | 801 | 469 |

Table 23. Upper Bound of Number of Machine Runs Required to Satisfy Grand Total Demand per Part Type, $\delta_p$

| **Part Types** | | | | |
|---|---|---|---|---|
| **1** | **2** | **3** | **4** | **5** |
| 1 | 3 | 4 | 3 | 3 |

$\theta = 10$

Table 24. Lower Bound of Number of Machines Needed to Satisfy Part Type Time Period Demand, $\pi_{t,p}$

| **Time Periods** | **Part Types** | | | | |
|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** |
| 1 | 0 | 1 | 1 | 1 | 1 |
| 2 | 0 | 0 | 1 | 0 | 0 |
| 3 | 1 | 1 | 0 | 1 | 1 |
| 4 | 0 | 1 | 1 | 1 | 1 |

Table 25. An Example of Part Type "Fortune" (Number of Machines Compatible with Each Part Type), $\sigma_p$

| **Part Types** | | | | |
|---|---|---|---|---|
| **1** | **2** | **3** | **4** | **5** |
| 3 | 4 | 3 | 2 | 1 |

Table 26. Matrix of Priority Lists, $\tau$, Resulting From Constructive Heuristic Starting Solution

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | 4 | 3 | 2 | 0 | 1 | 2 | 2 | 3 | 3 | 4 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 1 | 2 | 2 | 2 | 3 | 3 | 4 | 4 | 5 | 0 |
| 5 | 4 | 1 | 2 | 0 | 2 | 2 | 3 | 3 | 3 | 4 | 0 | 0 | 0 | 0 |
| 5 | 4 | 3 | 2 | 0 | 1 | 2 | 2 | 3 | 3 | 4 | 0 | 0 | 0 | 0 |

*Decoding (Table 27):*

Table 27. Decoded Assignments of Machines to Part Types

| | | **Machines** | | | | |
|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** |
| **Time Periods** | **1** | 3 | 2 | 0 | 4 | 5 |
| | **2** | 3 | 0 | 0 | 0 | 0 |
| | **3** | 0 | 2 | 1 | 4 | 5 |
| | **4** | 3 | 2 | 0 | 4 | 5 |

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