Optimization/simulation modeling of the integrated production-distribution plan: an innovative survey

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Abstract: - Implementation of a supply-chain (SC) system has crucial impacts on a company's financial performance. Overall performance of a SC network is influenced significantly by the decisions taken in its production-distribution plan which integrates the decisions in production, transport and warehousing as well as inventory management. Thus, one key issue in the current research area of performance evaluation of SC network is the optimization of production-distribution plan considering its actual complexity. This paper presents a comprehensive review and analysis on the proposed production-distribution models with special emphasis placed on the optimization and simulation studies. A summary table will be established to describe the main characteristics of the selected models outlining the strengths, weaknesses and the level of complexity for each study. Finally, by providing suggestions for improvements, further works in the area will be addressed.

Key-Words: Supply Chains, Production-Distribution Plan, Demand Uncertainty, Optimization, Simulation

1 Introduction

Supply chain (SC) is the network of organizations, people, activities, information and resources involved in the physical flow of products from supplier to customer [1]. A supply chain network (SCN) can be divided into three major sub-systems:
1. Supply Network (Procurement): the acquisition of raw material and parts from suppliers and their transportation to the manufacturing plants;
2. Production: the transformation and/or assembly of the acquired materials into finished products;
3. Distribution: a network of channeling material to and between plants and delivering products to the end users through the distribution centers.

Production plan concerns the allocation of resources of the company to meet the demand forecast over a certain planning horizon [2] and distribution plans involve the management of warehouse storage assignments, transport routings, and also inventory management [1]. Many studies have investigated problems in production and distribution networks separately, without considering the interactions between activities in different sub-systems. But, in fact, many decisions in production and distribution sub-systems need to be addressed simultaneously, while minimizing production costs, inventory costs, and warehousing and transportation costs. Hence, manufacturing industries need to integrate the activities in production and distribution networks, because for a SC network to function, the coordination among the participating elements is fundamental [3].

A production-distribution plan is influenced by a number of factors. These include the production characteristics at each plant and the distribution features of transporting finished products from the plants to the different end-users through a set of distribution centers [4]. A comprehensive production-distribution model, however, is to be efficient and cost-effective through the entire system of production, warehousing, transportation and inventory management.

Optimization of production-distribution plans concerns the minimization of the total costs, while dealing with a number of constraints, demand uncertainties, production capacity, warehouse capacity, transport routings and facilities' location among others. To do so, in recent studies either analytic or simulation approaches (with their own merits and demerits) have been used.

Total cost in a production-distribution network generally consists of two major cost components: 1). *Production costs*: sum of fixed costs of operating and opening different manufacturing plants and the variable costs associated with production of multiple products at different plans. These variable costs may include regular-time production, overtime production, outsourcing, inventory holding costs and storage costs; 2). *Distribution costs*: sum of fixed costs of opening and operating the distribution centers and variable costs of transporting finished goods from the plants to the end users through the warehouses. The variable costs may include storage costs at warehouses, transportation costs from plants to warehouses and from warehouses to end-users as well as shortage costs of not meeting demand forecasts.

Simulation has been proven to be a powerful performance evaluation and a modeling tool for complex stochastic real-world systems. Growing interest in the use of simulation modeling for the evaluation of SC performance indicates the need for the development of complex simulation models able to answer unsolved questions in production-distribution network. Simulations can be used for two purposes in modeling production-distribution plan: (A) validating the outcomes of the proposed optimization models and (B) developing a flexible simulation package and visualizing the constructed production-distribution plans adaptable to different scenarios in manufacturing environments.

It is obviously impractical trying to plan without considering the prediction of future demand and market challenges. The precision of production and distribution plan is extensively dependent on the demand forecasts. Therefore, the more accurate the forecasts are, the more realistic the associated plans can be. Although several forecasting techniques have been developed in past dealing with uncertainties in the forecasts in different areas, predictions are normally subject to many errors over the planning horizon in uncertain environments. It is, however, generally accepted that (A) the longer the forecast horizon, the worse the forecast and (B) the aggregate and combined forecasts are generally more accurate [1, 2].

So far many reviews of literature on the proposed strategic production-distribution models have been developed [5-15]. However our survey indicates that there is no specific review conducted on visualizing the actual capabilities of the proposed models. The rest of this paper is organized as follows: In section two, the previously developed production-distribution models will be introduced and the strengths and weaknesses of each study will be discussed. Section three introduces the attempts in accommodating uncertainties in demand forecasts. In conclusion, section four of this paper addresses the need for further works in the area and suggestions for improvements will be made.

2 Production-distribution models

The literature in the area of SC modeling indicates that the optimization and simulation of the production-distribution plan has been an active research area over the last decades and many solutions have been made to solve complex problems. Linear programming and mixed-integer programming have been generally used for mathematically modeling of the problems from various scales and optimization methods, such as Artificial Intelligent (AI) tools, Lagrangean relaxation, simulation techniques, or even combination of two have been applied to achieve near-optimum solutions. In this section, we indicate the previously developed models concerning the optimization and/or simulation of production-distribution problem and discuss the strengths and weaknesses of each study.

Cohen & Lee presented a strategic modeling framework and a hierarchical decomposition approach to analyze the interactions between functions in a SCN [16]. They consider four sub-modules each representing a part of the overall SC: material control, production control, finished goods stockpile, and distribution network control. In a hierarchical decomposition, each sub-module is heuristically optimized and the output of a sub-module solution is used as the input data to all other sub-problems. Besides not taking into account a number of features of a complex SC, their model relies on the non-tested approximations to characterize and solve the random variables describing the linkages between most locations [17].

In 1994, Chandra and Fisher considered a simple scenario comprising a single plant that produces a number of products and maintains an inventory of finished goods at the plant [18]. The customer demand is known; hence, the uncertainties in demand forecasts were ignored. They compared two approaches for managing this operation: in the first scenario the production scheduling and vehicle routing problems were solved separately, and in the other set-up an integrated model was developed to evaluate the impacts of cooperation. The two approaches were applied to test cases and the reduction in total operating cost obtained through the coordination reported to be from 3% to 20%.

Pyke and Cohen developed a model of an integrated production-distribution system which comprise of a single work station at a factory, a stockpile of finished goods, and a single retailer [19]. They proposed the approximations for the distributions of random variables that were then used to compute operating characteristics for the system and an algorithm for finding near-optimal values of the decision variables was developed. A year before they had also analyzed the performance characteristics of the batch sizing in an integrated, three-location, single-product production-distribution network presenting a Markov chain mode and illustrated the key tradeoffs of interest [17]. Apparently, their model also did not consider many characteristics of a complex SCN.

In 1997, Alfieri and Brandimarte used MODSIM, an object-oriented simulation language, to outline the simulation modeling of a multi-echelon inventory management system [20]. However, since a very simplified case study was considered and the problem was not a real-world scenario, they did not consider a dynamic modeling and ignored many characteristics and features which come into consideration in reality.

Dobrila Petrovic et al. proposed a fuzzy model of a production SC including inventories and production facilities between them operating in an uncertain environment [21, 22]. Customer demand, supply deliveries along the SC and external/market supply, which were considered 3 sources of uncertainties, were represented by fuzzy sets. It was demonstrated that uncertain customer demand and uncertain supply delivery along the SC have great impact on SC behavior. Although simulation models were carried out to assess some effects of uncertain external supply on the SC service level and the approaches were analyzed for improving the SC performance in an uncertain environment, the study particularly focused on uncertainty issues and does not consider the actual scope of the variables and constraints in a today's SCN.

Barbarosoglu and Ozgur presented a mixed integer mathematical model and used the method of Lagrangian relaxation for a production-distribution problem functioning in a 2-echelon system [23]. The designed Lagrangian heuristic was indicated to provide good solutions though, the study concerns a SCN consisting of a single manufacturing plant working under known demand forecasts with no uncertainty involved.

Young Hae and Sook Han proposed a specific problem solving procedure using a hybrid approach by combining analytic and simulation methods [24]. They studied an integrated multi period, multi product, and multi shops satisfying the retailer's demand while keeping inventories as low as possible. They used a linear program for the formulation of the problem, GAMS (General Algebraic Modeling System) to implement the formulation; and also ARENA as the simulation tool. The study does not investigate a multi-plant and multi-stack buffer scenario and also ignores the environmental uncertainties.

Jayaraman & Pirkul studied an integrated logistics model for locating production and distribution facilities in a multi-echelon environment [4]. They presented a mixed-integer programming to an integrated, multi-commodity production and distribution problem and Lagrangian relaxation scheme was then applied to the model. To solve the dual problem arising in the approach they used a sub-gradient optimization method. Later on, in 2003, Jayaraman and Ross proposed a heuristic approach based on simulated annealing only for designing of the distribution network in SC environment; hence, not dealing with production plants and manufacturing costs [25]. However, both studies consider constant demand that preclude the application of the model in many environments and also do not considering the details of the major production cost components.

In 2002, Jang, Jang, Chang, and Park presented a combined model of network design and production/distribution planning for a SCN. They used a Lagrangian heuristic for the design of SCN and proposed a Genetic Algorithm (GA) for integrated production-distribution planning problem [26]. However, their model not also ignores the dynamic environment in which the demand forecasts amend over the time, but also the model is not tightly integrated as they have proposed separate models for 3 sub-networks (inbound sub-network comprising suppliers and manufacturing plants, distribution sub-network from plants to warehouses as well as outbound sub-network consisting of distribution canters and final customers).

Using mixed integer linear programming, Syarif, Yun & Gen modeled a logistic chain network problem [27]. Based on Prufer numbers, the authors developed a spanning tree-based GA approach for the optimization of the multi-source, single-product, multi-stage SC design problem. The implemented algorithm, however, was shown to give better heuristic solutions only for the medium-sized problems as Prufer-coding performs poor as the problem instances become larger [28]. Also, in 2005, Yah proposed a revised mathematical model (using mixed integer programming) and developed a heuristic algorithm using a greedy method (GM) improved through a hybrid local search method, combing linear programming with three local improvement procedures [28].

Also, the year after, Yeh proposed a memetic algorithm (a combination of GA, greedy heuristic, and local search methods) for the same problem [29]. The author investigated the performance of the model on the randomly generated problems. From the computational experiments it was indicated that the proposed MA is efficient and effective in solving the problem with high quality and more exact solutions, less relative error in fewer numbers of generations. There are, however, a number of characteristics of a complex SCN having not been considered in either of the proposed models by Syarif et al in 2002 and Yeh in 2005 and 2006 (like multiple products in multiple periods as well as considering demand uncertainty).

Two heuristic methodologies based on Lagrangian relaxation and simulated annealing were developed and compared through a computational experiment by Syam for a location-consolidation problem [30]. He indicated that in terms of both computational time and solution quality, the Lagrangian methodology outperforms the annealing procedure for medium-sized and large problems, while annealing procedure provided better solutions for small problems. However, the comparison does not take into consideration the variables and constrains associated with the inherent demand uncertainties in a dynamic environment and ignores the actual production and assembly costs in manufacturing plants appearing in reality.

Aimed to maximizing the corporation's profit based on total revenue, Bhutta et al. presented a mixed-integer linear formulation focusing on multinational corporation facility location decisions [31]. Many scenarios are considered in this work based on various facility configurations and levels of exchange and tariff rates. However, the multiplicity of the distribution canters, production/assembly alternatives and forecasting uncertainties were ignored in the cost-effective modeling and also the study does not attempt to optimize the proposed model.

Chan, Chung, and Wadhwa developed a combined Hybrid Genetic Algorithm and AHP method for production and distribution problems in multi-factory SC [32]. Analytic hierarchy process (AHP) was used for organizing and weighting the decision-making criteria and Hybrid Genetic Algorithm was applied to determine the job allocation for each plant. In this model, a single product type, multi-factory SC is considered and the products are transported from the manufacturers directly to the customers (no warehouse). There are also a lot of simplifications in production processes and scheduling.

In 2005, Gen and Syarif proposed a new approach called spanning tree-based hybrid genetic algorithm (hst-GA) to solve the multi-time period production/distribution and inventory problem [33]. Their model integrated facility location decisions, distribution costs, and inventory management for multi-products and multi-time periods. In order to improve the efficiency of GA, a Fuzzy logic controller (FLC) was also hybridized to the evolutionary process for making auto-tuning of the GA parameters. However, alike previous models, in this study also customer demand is assumed to be always known and the system works in an uncertain environment. Also, the detailed cost components in the production and distribution networks have been simplified and not taken into consideration.

Lim, Jeong, Kim, and Park, presented probably one of the most comprehensive mathematical models to determine the capacities of facilities in a production-distribution network [34]. They developed a simulation model to analyze a production-distribution plan for higher customer satisfaction and lower total relevant costs, while taking replenishment policies into consideration. The developed mathematical and a simulation model was then applied to a simple example test problem. However, the paper does not attend the uncertainties in demand forecasts, the possibility of considering different production alternative and elements of the total production-distribution costs in details.

Nishi, Konishi, and Ago, in 2007, proposed a distributed decision making system for the integrated optimization of production scheduling and distribution for an aluminum rolling processing line [35]. An integrated optimization model was formulated using commercial MILP solvers that was decomposed into production scheduling and warehouse planning sub-problems using an augmented Lagrangian approach. The study formulated a single production process with no end-user involved. It ignores the detailed cost elements in the production stage, transportation alternatives from plants to warehouses, and also the inherent uncertainty in demand forecast.

Aliev et al developed a fuzzy integrated multi-period and multi-product production and distribution model in 2007 [36]. The model was formulated in terms of fuzzy programming and the solution was provided using Genetic Algorithm. The primary objective of the optimization was to maximize the overall profit (the return from sales less production, transportation, and storage and maintenance expenses) and not the minimization of the total cost. It is, however, assumed that at any time, fuzzy demand forecasts for future time periods were available; hence, the system works under no demand uncertainty. The selected case study is a simplified model with only two plants, DCs, customer zones and no production alternatives offered.

Altiparmak, Gen, Lin and Karaoglan proposed a steady-state genetic algorithm for the single-source multi-product, multi-stage SCN design problem [37]. The problem was basically to work out the choice of plants and distribution canters to be opened and the distribution network design to satisfy the customer demand at minimum cost. The effectiveness of the proposed model was investigated comparing the obtained results with those achieved through CPLEX, Lagrangian heuristic, hybrid GA and simulated annealing on a set of SCN design problems in terms of average CPU time. Experimental study showed that the steady-state genetic algorithm found better heuristic solutions than the other heuristic approaches. However, the problem can be still built on more realistic scenarios considering the dynamism of the environment (uncertainties in demand forecasts) as well as taking into consideration the detailed production cost elements from microscopic view.

Appendix 1 summarizes and compares the major characteristics of the proposed models. However, wide range of real-time variables and constraints and the inherent environmental uncertainties may preclude the previously developed models from functioning effectively in many of today's manufacturing environments.

3 Accommodating uncertainties in demand forecasts

Almost any forecasting procedure can be classified into one of the four categories of: judgment approach, market research approach, time-series approach and casual approach [1]. Time-series methods project the past history into future [38] and have received more attention in demand forecasting in manufacturing areas due to many privileges comparing to other techniques. Time-series approaches include moving average and exponential smoothing methods [1, 39]: (A) Moving average is a simple method of forecasting, based on the average value of the variables over the specific preceding periods and bring it into the future forecast, while minimizing the irregularities in the data. This is generally done on MS Excel sheets. (B) Exponential smoothing is the weighted average of the previous forecast and the last demand point, where the more recent points receive more weight. Exponential smoothing works well in situations with no seasonal pattern and no trend. Methods such as Regression Analysis are more useful if there is a trend in data and also Seasonal Decomposition methods consider seasonal changes in demand. A more complex version of exponential smoothing method is Holt-Winters procedure where trends and seasonality are taken into account [40]. Although over the last years a variety of other complex methods have been proposed, due to the limitations in time and resources, complex differentiated methods with many parameters involved are more difficult to develop in practice.

There are many reasons why to apply the appropriate forecasting method and why to improve the quality of demand forecasts: Yenradee et al. compared Winter's, decomposition, and Auto-Regressive Integrated Moving Average (ARIMA) approaches in forecasting the market demands as an entry to the production plan [41]. The results indicated that although the ARIMA model provided more reliable demand forecasts, it was more complicated to apply. It was also indicated that the total production costs can be reduced by 13.2% when the appropriate forecasting models were applied. Jeunet assessed the impact of demand forecast errors on the cost performance of several lot-sizing techniques in a multi-level context [42]. She found that decreasing the level of error has a non-linear relationship to the improvements in the performance of all techniques. She concluded that it is always worth decreasing the error magnitude, since bigger cost reductions are obtained when moderate error decrease is achieved.

Provided that different forecasts obtained through diverse methods can be combined, new complex methods with higher accuracy are normally resulted. Over the last decade, a large literature has evolved on achieving more accurate results through combined forecasts (see [39, 43-47] for some of the most effective studies).

2.1 Models for demand forecast updates

So far a number of straightforward forecasting techniques have been developed, each with its own applications in minimizing the forecast error variance. However, demand predictions are generally subject to many errors over the planning horizon in uncertain environments. The idea is to achieve more accurate forecasting outcomes for the sake of periodic production-distribution planning through updating demand forecast. The general framework for the forecast updating is as follows: the initial forecasts can be computed using historical data from previous seasons using one of the generalized approaches (exponential smoothing method, for instance). As new information from the current periods becomes available, the forecast values are revised periodically to improve the quality of production-distribution plan.

Some researchers analyze the previous studies attempted to generate demand forecast updates for various purposes (See [48-51]). We summarize some of the achievements obtained in the recent research projects addressing the application, value and performance evaluation of demand forecast updates. However, according to Cattani and Hausmanemand it might be an unrealistic expectation for manufacturers that forecast accuracy always improves as forecasts are updated in the final periods before the demand event [52].

Sethi et al. formulated a non-standard optimization model which allows for forecast updates for any number of future demands at some forecasting cost [53]. They consider a general, discrete-time, stochastic dynamic optimization scenario in which the decision maker has the possibility to obtain information on the uncertain future at given cost.

Fisher and Raman modeled and analyzed production commitment decisions for a fashion skiwear manufacturer [54]. The manufacturer was able to arrange the production of a family of products in two runs, one occurring before the selling season and the other after the observation of early sales and updating the available data. Applying the procedure in a selected firm resulted in up to 60% increase in profits. Similar scenario was in Iyer and Bergan's quick response analysis in manufacturer-retailer channel [55]. Information obtained in the first stage was used to update the parameters in the demand distribution function using the Bayesian approach, and the decision of how much to produce was made in the second stage.

Several research papers in literature deal with the problem of inventory management and/or optimal ordering quantities, incorporating demand information updates. Eppen and Iyer analyzed a quick response program in a fashion buying problem and developed a heuristic that combines the newsvendor model and the Bayesian model to update a distribution [56]. Lovejoy also studied the ordering policies for some inventory problems with uncertain demand distributions [57]. He modeled the demand process as an integrated autoregressive moving average process and showed the optimality of myopic policies under certain conditions. Gurnani and Tang developed a model to determine the optimal ordering policy for a retailer having the option to order a single product at two instants before a single selling season [58]. While demand and the retailer's purchasing cost for the second period is uncertain, the retailer gathers market information between two instances to better describe the demand distribution considering the trade-off between a more accurate forecast and a potentially higher unit cost at the second instant.

Modeling the SC performance over a single selling season, Ferguson illustrated the tradeoffs associated with the timing selection of the firm's order quantity commitment in a multilevel supply chain with uncertain end-product demand [49]. At the same time, Yan, Liu and Hsu showed how demand forecast updates can effect the ordering of raw materials in a dual-supplier system [59]. They considered the ordering of raw material from two suppliers, one fast and expensive and other slow but cheep. They assumed demand forecasts' information is updated by improving the inaccuracy in forecasts over the time.

Huang et al. studied a purchase contract with a demand forecast update by formulating a two-stage dynamic programming problem [60]. The purchase contract provides the buyer an opportunity to adjust the initial commitment based on an updated demand forecast obtained at a later stage.

Heath & Jackson evaluated demand forecasts with application to safety stock analysis in production/distribution systems [61]. Authors created a model for quantifying the effects of forecast error on production and distribution costs. They evaluated the economical safety stock factor for each product at each DC for each month under different forecasting methods and concluded that (A) safety stock factor can be reduced using the statistical forecast method resulting in significant cost savings, (B) reducing safety stock factor using the traditional forecast method does not show much benefit and (C) Increasing forecast accuracy is more beneficial than extending the available capacity.

Gallego and Ã–zer [62] established the form of optimal policies for a model with advance demand information (customers place orders in advance of their needs). They modeled the problem of finding effective inventory control policies (replenishment decisions) under advance demand information and found that the policy parameters depend on the observed demands beyond the protection period (e. g. the lead-time plus a review period).

So and Zheng used a simple two-level SC model (a retailer and a supplier) to analyze how the supplier's lead-time performance and the retailer's forecast demand updating can affect the order fluctuations of the retailer [63]. It was assumed that the external demands faced by the retailer are correlated between two successive time periods and the retailers uses the latest demand information to update its future demand forecasts. The authors indicated that demand correlation can increase the variability of the order quantity and the increase in the order quantity variability is higher when the demand correlation is higher.

In 2003, Sethi et al. looked into extending the results for classical single-mode inventory problems to allow for two consecutive delivery modes [64]. A model comprising a periodic review inventory system with fast and slow delivery modes, fixed ordering cost, and regular demand forecast updates at the beginning of each period was analyzed. They considered forecast updates based on signal observations and showed that the optimal policy levels depend on the observed signal values.

Feng et al. also consider a discrete-time, periodic-review inventory system with three consecutive delivery modes (fast, medium, and slow) and demand forecast updates [48]. At the beginning of each period, the inventory level and demand information are updated and decisions on how much to order based on the three delivery modes are made. They found that the optimal inventory replenishment policy for the fast and medium modes is a base-stock policy, while the slow mode does not follow a base-stock policy in general.

4 Conclusions and suggestions for further improvements

The review on the literature indicates that the area of optimization/simulation of production-distribution plan in SC has been an active research area over the last years. Many studies have attempted to solve multi-facility, multi-product and multi-period production-distribution problems. However, so far there is no research carried out on the optimization of production-distribution network that accommodates inherent market demand uncertainty and considers production cost elements in details. This is particularly due to the associate complexities with the modeling of the actual SCN. Therefore, to fulfill these needs there is a need to develop an integrated optimization model which includes all the elements of production and distribution cost and considers periodic updates in demand forecasts (See Appendix2 for the realistic scope of a comprehensive production-distribution network).

Appendix2 illustrates the comprehensive production-distribution model which incorporates multi-products, multi-plants, multi-warehouses, multi-end users and multi-time periods. It also takes demand uncertainties into consideration by applying periodic updates when additional demand data becomes available from the previous periods. The model needs to consider all the production and distribution cost components in details to develop a flexible optimization model able to be adapted to various scenarios. Production costs are including fixed costs of operating and opening different manufacturing plants and variable costs of regular-time and overtime production costs, outsourcing costs, WIP Inventory holding costs and storage costs at stack buffers. Distribution costs comprise transportation costs form manufacturing plant to warehouses, transportation costs form warehouses to end users, storage costs at the warehouses: inventory holding costs of finished goods as well as shortage costs of not meeting demand forecasts at customer zones.

Further to this research, to fulfill the current needs in the area, following comprehensive problem in a production-distribution network is being studied by the authors (Appendix2): *i* types of products, each consists of n parts, are produced in *p* different manufacturing plants with various capacities over *t* time-periods. Products are distributed to *e* end-users through *w* warehouses of different capacities; hence, *y* transport routings are to be considered. According to the model, each product visits at least one plant, one warehouse and one customer zone in its travel from the plants to the end users. The whole system operates in an uncertain environment, under demand fluctuations; hence, periodic updates in demand forecasts are applied once additional demand data becomes available from the previous periods. It also comprises all the production and distribution cost components in details.

Artificial intelligent tools, GAs in particular, are used for the optimization of this problem according to their following advantages:

- GA is capable of handling large search spaces
- GA is generally straightforward to apply
- GA conducts a search through the space of solutions by exploiting a population of points in parallel rather than a single point
- GA creates a number of optimal solutions allowing the user to make the final decision
- GA is effectively applicable for continuous and discrete problems
- GA has great flexibility in defining the constraints and the quality measures

To validate the outcomes of the proposed optimization model and develop a flexible simulation package, AutoMod and Arena are used for the simulation of the production-distribution network. AutoMod and Arena are two well-known simulation packages widely used to construct highly accurate simulations for planning and design, particularly building manufacturing models for analyzing operations and controlling development testings. AutoMod is capable of combining three-dimensional graphics with the most comprehensive set of templates and objects for modeling purposes almost in any area of manufacturing and material handling [65]. It has been widely used for many applications in manufacturing industries, such as automated material handling systems, warehousing and distribution networks and many other applications in automotive industries [66].

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Appendix1. Summary table: the characteristics considered in the proposed production-distribution models

Reference	**Author(s) Year**	**Type of work: M = Mathematical modeling O = Optimization S = Simulation modeling**	**TC = Total cost minimization P = Profit maximization**	**Optimum transport routings**	**Multiple periods**	**Multiple plants**	**Multiple products**	**Multiple warehouses / DCs**	**Multiple end-users**	**Methods Applied**
[16]	Cohen & Lee 1988	M & O	TC	X	---	X	X	X	---	Generating a series of linked, approximate sub-models and Introducing a heuristic optimization procedure
[18]	Chandra & Fisher 1994	M	TC	X	---	---	X	X	---	Comparing two approaches in managing production and distribution networks in terms of the reduction in operating costs
[17, 18]	Pyke & Cohen 1993 & 1994	M & O	TC	X	---	---	X	---	---	SSD Approximation (approximate steady state distribution) to compute associated costs and find near-optimal values for decision variables
[20]	Alfieri & Brandimarte 1997	M & S	TC	X	---	X	---	---	X	Developing a simplistic object-oriented simulation model using MODSIM II
[23]	Barbarosoglu & Ozgur 1999	M & O	TC	X	X	---	X	X	X	Using mixed integer mathematical modeling and the Lagrangean relaxation method to provide optimum solutions

[24]	Young Hae & Sook Han 2000	Hybrid: Analytic + Simulation	TC	X	X	---	X	X	X	Modeling/formulation: linear program (LP) + GAMS (General Algebraic Modeling System) Simulation: ARENA simulation package
[4]	Jayaraman & Pirkul 2001	M & O	TC	X	X	X	X	X	X	Using mixed-integer programming formulation and Lagrangian relaxation scheme - Proposing a heuristic solution to evaluate the model performance
[27]	Syarif, Yun & Gen 2002	M & O	TC	X	---	X	---	X	X	Using mixed integer linear programming for mathematical modeling and developing spanning tree-based GA approach (based on Prufer numbers) for the problem optimization.
[30]	Syam 2002	M & O	TC	X	---	X	X	X	X	Developing and comparing two methodologies based on Lagrangian relaxation and simulated annealing
[31]	Bhutta et al. 2003	M	P	X	X	X	X	---	X	Using a mixed integer linear formulation
[32]	Chan et al. 2005	M &O	TC	X	---	X	---	---	X	Using AHP for the criteria weighting and Genetic Algorithms to determine the job allocations
[33]	Gen and Syarif 2005	M & O	TC	X	X	X	X	---	X	Using spanning tree-based hybrid genetic algorithms and Fuzzy Logic Controller (FLC) for auto-tuning GA parameters

[28]	Yeh 2005	M & O	TC	X	---	X	---	X	X	Using mixed integer programming for mathematical modeling and developing a hybrid heuristic algorithm using a greedy method improved through a hybrid local search method
[29]	Yeh 2006	M & O	TC	X	---	X	---	X	X	Proposing a memetic algorithm (MA), combining GA, greedy heuristic, and local search methods
[34]	Lim et al. 2006	M & S	TC	X	X	X	X	X	X	Microsoft Excel premium Solver for mathematical modeling and IBM SC Analyzer as the simulation optimizer tool
[35]	Nishi et al. 2007	M & O	TC	---	X	---	X	X	---	Using a commercial MILP - Lagrangian decomposing to decompose the problem into three optimization sub-problems
[36]	Aliev et al. 2007	M & O	P	X	X	X	X	X	X	Using fuzzy programming for the formulation of the model and Genetic Algorithms to find the optimum solution
[37]	Altiparmak et al. 2007	M & O	TC	X	X	X	X	X	X	Proposing a steady-state genetic algorithm and comparing the achieved results with those obtained through CPLEX, Lagrangian heuristic, hybrid GA and simulated annealing

Appendix2. The realistic scope of a comprehensive production-distribution network