

## **A novel bi-level stochastic programming model for supply chain network design with assembly line balancing under demand uncertainty**

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### **Abstract**

This paper investigates the integration of strategic and tactical decisions in the supply chain network design (SCND) considering assembly line balancing (ALB) under demand uncertainty. Due to the decentralized decisions, a novel bi-level stochastic programming (BLSP) model has been developed in which SCND problem has been considered in the upper-level model, while the lower-level model contains ALB problem as a tactical decision in the assemblers of supply chain network. To deal with demand uncertainty, a scenario generation algorithm has been proposed within the stochastic optimization model that combines time series model, Latin hypercube sampling method and backward scenario reduction technique. In addition based on the special structure of the model, a heuristic-based solution method is proposed to solve the developed BLSP model. Finally, computational experiments on several problem instances are presented to show the performance of the model and its solution method. The comparison between the stochastic and equivalent deterministic model demonstrated that the developed stochastic model mainly performs better than the deterministic model especially in making strategic decisions while the deterministic model works better in making tactical decisions.

**Keywords:** Bi-level stochastic programming, supply chain network design, scenario-based approach, assembly line balancing, uncertain demand

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## 1- Introduction

Supply chain network design (SCND) problem is an important issue in supply chain management (SCM) which has attracted research attention over the last few decades. In general in this problem, the optimal number and configuration of the facilities is determined in addition to the quantities of required raw materials, production, distribution and transportation among the facilities such that the customer demand is satisfied and the supply chain value is optimized (Simchi-Levi et al., 2004).

In SCM, there are three levels of decision-making during the time horizon categorized as strategic level (long-term decisions), tactical level (mid-term decisions) and operational level (short-term decisions) (Vidal and Goetschalckx, 1997). The strategic level commonly relates to the decisions such as the determination of number, location and capacity of the facilities and technology selection (Ghiani et al., 2004). SCND is one of the main strategic decisions that sometimes entitled as strategic supply chain planning (Chopra and Meindl, 2007). In the tactical decisions, production levels at manufacturers/factories, assembly policy, lot sizes and inventory levels are determined. Finally, the operational level deals with the scheduling of material flows based on the decisions made in two upper levels (Schmidt and Wilhelm, 2000).

Recently, several review papers have been published on SCND area. Shen, (2007) presents a survey on the new developments of integrated SCND optimization models, especially nonlinear models. Akyuz and Erkan (2010) provide a review on performance measurement of supply chains. They present the basic research approaches and methodologies, requirements and areas for the performance management of the recent supply chain era. Melo et al., (2009) review facility location models in the SCM context and basic features these models must capture to support decision making in the design of supply chain networks across different industries. Klibi et al., (2010) review the optimization models proposed for the SCND problem under uncertainty. They also investigate related strategic SCND evaluation criteria and their use in the existing models. Very recently, Martínez and Moyano (2014), have evaluated the state-of-the-art researches into the relations between SCM, lean management and sustainability to identify the studied areas and the orienting future research.

Many mathematical models have been developed in the related literature in order to design and optimize the supply chain networks (SCNs) by now. These models can range from simple uncapacitated single-product facility location models (see for example Sung and Song, (2003)) to complex capacitated multi-commodity models (see for example Tsiakis and Papageorgiou (2008)) with different objectives such as total cost minimization or profit maximization. Most of these models concentrate on the transportation/distribution networks with considerations such as facility location, capacity planning, inventory management, vehicle routing and so on (Paksoy and Özceylan, 2012a).

In the recent studies, the SCND problem under uncertainty has received much attention and the literature related to this issue is considerably increasing (Klibi et al., 2010). Many studies have addressed customer demand as the only uncertain parameter. Longinidis and Georgiadis (2011) present a mathematical model as an effective strategic decision tool to integrate SCND decisions with financial statement analysis under demand uncertainty. Hamta et al., (2014) investigate the optimization of strategic and tactical decisions in a SCND problem under demand uncertainty. Furthermore, some studies consider several stochastic parameters simultaneously. In this regard, Pishvae et al.,(2009) develop a stochastic mixed-integer linear programming (SMILP) model for multi-stage logistics network design in which quantity and quality of returned products, demands and variable costs are uncertain parameters. Mohammadi Bidhandi and Mohd Yusuff (2011) state that uncertainty generally finds in tactical decisions because most of the tactical parameters are not totally certain when strategic decisions are made. They consider customer demand, capacity of the facilities and operational costs as uncertain parameters.

The production system is one of the vital factors for the optimization of SCNs. In order to create an efficient SCN involved with assembly activities, two main functions of supply chain such as transportation and assembly line processes must be integrated appropriately (Paksoy et al., 2012b). This integration has two main aspects for a supply chain. Firstly, companies try to obtain maximum value by minimizing the transportation costs at each stage of the supply chain. Secondly, companies attempt to optimize the operations inside the supply chain such as line balancing and the opening costs of workstations. Therefore, there is a relationship between logistics processes and assembly line processes that necessitates the integration between them in the SCN (Paksoy and Özceylan, 2012a). On the other hand, assembly line balancing (ALB) as one of the decisive factors, is the most common

operation in SCNs especially when there are a lot of components. It is worth mention that an assembly line consists of a set of sequential workstations connected by a material handling system. In each workstation, a set of tasks is performed while each task has a certain processing time and there is a pre-defined precedence diagram, which determines the sequence of performing the tasks (Becker and Scholl, 2006). In this regard, the main objective of the ALB problem is to assign a set of tasks to the workstations in such a way that the precedence constraints among tasks are met and some measures, such as number of workstations, cycle time or line efficiency are optimized (Hamta et al., 2013). Since balancing the assembly activities has significant influence on the performance and productivity of systems, optimizing assembly activities affects the SCN performance. Many companies such as automobile companies are confronted with this problem where logistics processes and assembly line activities should be considered concurrently to lead to better performance in terms of customer satisfaction, reliability and agility (Hamta et al., 2014).

The importance of uncertainty modeling in different decision levels of SCND has motivated a number of researchers to use stochastic programming approaches when one or more uncertain parameters or variables exist in the optimization problem (see for example Pishvae et al., (2009) and Santoso et al., (2005)). Schütz et al., (2009) develop a two-stage stochastic program to formulate a multi-commodity SCND problem with a description of operational consequences from the strategic decisions. They address strategic location decisions in the first stage decisions and operational decisions in the second-stage. Hamta et al., (2014) propose a two-stage stochastic programming model in which the first-stage contains strategic location decisions, while in the second-stage the SCND and ALB decisions are made.

Table 1 presents a detailed classification of the recent papers published after 2010 based on some supply chain characteristics and decisions such as objectives, characteristics of product and period, uncertainty in demand, capacity, type of modeling, and the solution method. The characteristics of our problem in this paper have been stated in the last row of Table 1. It is worth mentioning that the papers reviewed in Table 1 have been selected based on the similarity to our work in terms of characteristics such as modeling approach and basic assumptions.

**Table 1.** The supply chain decisions of recent papers in SCND area

Article	Objectives	Product		Period		Demand		Capacity	Modeling				Solution method			
		Single	Multiple	Single	Multiple	Deterministic	Stochastic		LP	MILP	MINLP	SMILP	Exact	Heuristic	Meta heuristic	Hybrid
Ahmadi Javid and Azad (2010)	Total costs	✓		✓			✓	✓				✓	✓	✓		
Costa et al. (2010)	Total costs	✓		✓		✓		✓		✓					✓	
Wang et al. (2011)	Total costs, Total CO <sub>2</sub> emission		✓	✓		✓		✓		✓	✓		✓			
Cardona-Valdés et al. (2011)	Total costs, Total service time	✓		✓			✓	✓				✓				✓
Lin and Wang (2011)	Total expected operating cost		✓	✓			✓	✓	✓				✓			

Table 1. Continued

Article	Objectives	Product		Period		Demand		Capacity	Modeling				Solution method			
		Single	Multiple	Single	Multiple	Deterministic	Stochastic		LP	MILP	MINLP	SMILP	Exact	Heuristic	Meta heuristic	Hybrid
Georgiadis et al. (2011)	Total costs		✓		✓		✓	✓				✓	✓			
Rezapour et al. (2011)	Profit	✓		✓		✓				✓					✓	
Longinidis and Georgiadis (2011)	Economic value added		✓		✓		✓	✓				✓	✓			
Nickel et al. (2012)	Total financial benefit		✓		✓		✓					✓	✓			
Sadjady and Davoudpour (2012)	Total costs		✓	✓		✓		✓		✓				✓		
Tsao and Lu (2012)	Total costs	✓			✓		✓				✓			✓		
Babazadeh et al. (2012)	Total costs		✓	✓		✓		✓		✓			✓			
Melo et al. (2012)	Total costs		✓		✓	✓		✓		✓					✓	
Paksoy et al. (2012c)	Total transportation costs		✓	✓			✓	✓	✓				✓			
Carle et al. (2012)	Net operating profits		✓		✓	✓		✓		✓					✓	
Singh et al. (2013)	Total (expected) costs		✓	✓			✓	✓		✓		✓	✓			
Vahdani et al. (2013)	Total costs		✓	✓			✓	✓				✓				✓
Kristianto et al. (2014)	Inventory and transportation	✓		✓		✓		✓				✓	✓			
Khalili-Damghani (2014)	Total purchasing cost		✓		✓		✓			✓				✓		
Roni et al. (2014)	Total costs	✓		✓		✓				✓			✓			

Table 1. Continued

Article	Objectives	Product		Period		Demand		Capacity	Modeling				Solution method			
		Single	Multiple	Single	Multiple	Deterministic	Stochastic		LP	MILP	MINLP	SMILP	Exact	Heuristic	Meta heuristic	Hybrid
The present paper	Total costs, number of workstations	✓			✓		✓	✓		✓	✓			✓		

LP: Linear Programming; MILP: Mixed-Integer Linear Programming; MINLP: Mixed-Integer Nonlinear NLP: Non Linear Programming

Although SCND problem has been investigated widely, but little attention has been given to use bi-level programming (BLP) as the modeling approach. SCND problem can be considered as a Leader-Follower where top managers are the leaders, and the assemblers are the followers who make decisions about their activities considering top-level decisions Hamta et al., (2015). Roghanian et al., (2007) propose a probabilistic multi-objective BLP problem and its application in enterprise-wide supply chain planning where some parameters are random variables. Sun et al. (2008) developed a BLP model to obtain the optimal location of distribution centers where the upper-level model determines the optimal location, and the lower-level model gives an equilibrium demand distribution.

The main contribution of this paper is to develop a bi-level stochastic programming (BLSP) for a SCND problem considering ALB and demand uncertainty. To the best of authors' knowledge, this problem which is applicable to many real-world situations, is novel and has not been addressed in the related literature. The most similar study to our work belongs to Paksoy et al., (2012b). They developed an MINLP model to integrate SCND and ALB problems. However, they did not pay attention to the bi-level nature of the problem. In addition, since the variations in customers' demands change the products shipped between layers of the SCN in each period, demand uncertainty has significant effects on the flows inside the SCN. This issue also affects the assignment of tasks and layout of the workstations. The main objective of the developed BLSP model in this paper is to optimize the performance of the considered SCN under demand uncertainty. A scenario-based algorithm is proposed to deal with demand uncertainty in which time series model and Latin hypercube sampling (LHS) (Iman, 2008) are employed. Finally, the BLSP model performance is evaluated under generated scenarios.

The remainder of this paper is structured as follows. Section 0 introduces problem description and mathematical formulation of the BLSP model under study. Section 0 explains how to deal with demand uncertainty that serve as input to developed BLSP model. Section 0 describes the solution method. The computational experiments over several problem instances and the comparison with the deterministic model are presented in Section 0. Finally, Section 0 leads to the concluding remarks and guidelines for future research.

## 2- Problem statement and formulation

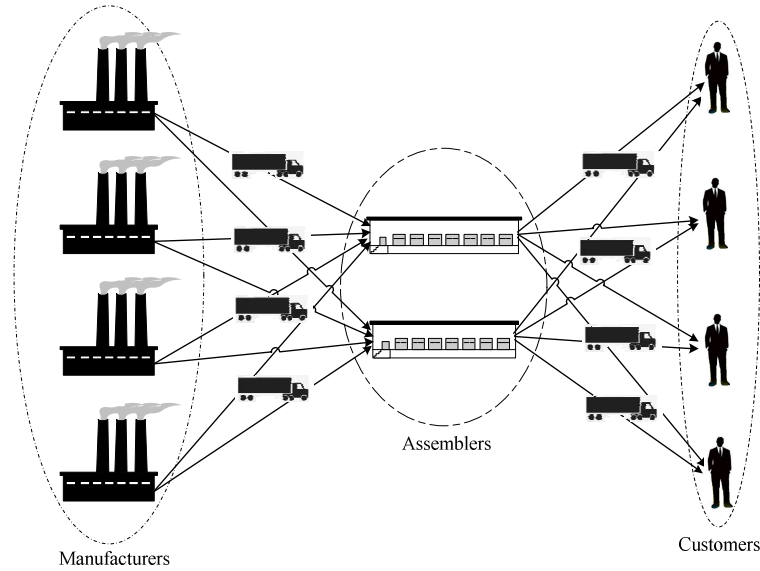
In this section, the problem statement, notations and the mathematical formulation of problem under study are presented.

### 2-1- Problem statement

This paper considers the simultaneous optimization of strategic and tactical decisions in the SCN to design and optimize an SCN. Figure 1 shows the structure of considered SCN including manufacturers, assemblers and customers. An SCND problem is addressed as a strategic decision and ALB problem is tackled as a tactical decision. In the assemblers, single-product and straight assembly lines are concerned with the aim of minimizing the number of workstations for a certain cycle time.

The main purpose of this paper is to model and solve an SCND problem considering ALB using stochastic BLP. BLP is a tool to model decentralized decisions which contains the objective(s) of the leader at the first level and that of the follower at the second level (Colson, 2005). Since the problem

under study involves two different decision-makers including supply chain managers and the assemblers' decision makers who make connected decisions with interactions on each other, BLP is adapted to describe the problem appropriately (Hamta et al., 2015). Considering demand uncertainty, the problem is formulated as a BLSP model in which SCND problem as a strategic decision is considered in the upper-level model, while the lower-level model contains the ALB as a tactical decision. The main decision variables obtain after solving the model are the amount of flows between two sequential echelons, assemblers' cycle times, and tasks assignment to the workstations in the assemblers.



**Figure 1.** The structure of considered SCN

The basic assumptions behind the studied problem are common assumptions for SCND and ALB problems (see for example Hamta et al., (2014)). In this paper, it is assumed the maximum capacity of manufacturers and assemblers is given. In addition, the upper bound of the number of potential workstations at each period is determined via dividing total task times by average initial cycle times.

## 2-2- Mathematical model

This subsection presents the BLSP formulation of the problem. The scenario-based stochastic approach has been used in the BLSP model for capturing the customers' demands in both levels of the model to find the best decisions. The proposed scenario-based approach will be explained in Section 0 in detail.

### 2-2-1-Basic model of BLSP

A BLP model is applied for a problem with two different decision-makers, which make decentralized decisions successively (Colson, 2005). In this paper, supply chain network decisions such as flows of products and cycle times are made by top-level managers, and then determined decisions are employed in assemblers to balance the assembly lines. Since we concern uncertainty in customers' demands, a stochastic version of BLP has been used in the paper. BLSP method allows applying concepts of stochastic programming directly to bi-level structure. In other words, BLSP completes relationship between the actors to deal with bi-level structure and uncertainty simultaneously. The stochastic programming framework seems more flexible and investigations connected with the bi-level structure can be incorporated more efficiently into the stochastic programming context (Werner, 2005). Therefore, the BLSP approach can treat the implications of the bi-level features adequately.

In terms of BLSP, a general stochastic programming problem with bi-level structure can be formulated as follows where the uncertainty environment is expressed by a random variable  $\omega \in \Omega$ . In

addition  $x$  and  $y$  are the decision variables of upper-level and lower-level problems, respectively (Werner, 2005):

$$\begin{aligned} \text{(U) Min}_{x} & F(x, y^*, \omega) \\ \text{s.t.} & G(x, y^*, \omega) \leq 0, \end{aligned} \quad (1)$$

where  $y^*$  is an optimal solution of the leader's perception of the follower's decision process.

$$\begin{aligned} \text{(L) Min}_{y} & f(x, y, \omega) \\ \text{s.t.} & g(x, y, \omega) \leq 0 \end{aligned} \quad (2)$$

The BLSP model consists of two sub-problems: (U) is an upper-level problem with variables  $x \in R^{n_1}$  and (L) is a lower-level problem with the decision vector of the lower-level decision-makers  $y \in R^{n_2}$ . Function  $F : R^{n_1} \times R^{n_2} \times \Omega \rightarrow R$  is the objective function of upper-level decision-makers or top-level managers, and the vector-valued function  $G : R^{n_1} \times R^{n_2} \times \Omega \rightarrow R^{m_1}$  is the constraint set of the upper-level decision vector. Similarly, function  $f : R^{n_1} \times R^{n_2} \times \Omega \rightarrow R$  is the objective function of lower-level decision-makers, and  $g : R^{n_1} \times R^{n_2} \times \Omega \rightarrow R^{m_2}$  is the constraint set of the lower-level decision vector. All of the constraints and objective functions may be linear, quadratic, nonlinear, fractional, etc.

### 2-2-2- Model notations

The sets, indices, constants, parameters and decision variables employed in the mathematical model are defined as follows:

#### Sets and indices:

$M$	set of manufacturers, indexed by $m \in M$
$A$	set of assemblers, indexed by $a \in A$
$C$	set of customers, indexed by $c \in C$
$J$	set of potential workstations with estimated number of potential workstations, indexed by $j \in J$
$N$	set of tasks, indexed by $i \in N$
$r, q$	index of tasks
$P$	set of couples of tasks $(r, q)$ in which task $r$ is the immediate predecessor of task $q$
$K$	set of components, indexed by $k \in K$
$T$	set of periods in planning horizon, indexed by $t \in T$
$S$	set of scenarios, indexed by $s \in S$

#### Constants and parameters:

$TC_{ma}^{MA}$	transportation cost from manufacturer $m$ to assembler $a$ at period $t$
$TC_{act}^{AC}$	transportation cost from assembler $a$ to customer $c$ at period $t$
$Dc_{ma}^{MA}$	distance between manufacturer $m$ and assembler $a$
$Dc_{ac}^{AC}$	distance between assembler $a$ and customer $c$
$Cap_{mkt}^M$	capacity of manufacturer $m$ for component $k$ at period $t$
$Cap_{at}^A$	capacity of assembler $a$ at period $t$
$D_{cts}$	demand of customer $c$ at period $t$ in scenario $s$
$t_i$	task time of task $i$
$Pr_{ts}$	occurrence probability of scenarios at period $t$
$WT_t$	total working time at period $t$

**Decision variables:**

- $Y_{maktst}^{MA}$  Quantity of component  $k$  shipped from manufacturer  $m$  to assembler  $a$  at period  $t$  in scenario  $s$
- $Y_{actst}^{AC}$  quantity of product shipped from assembler  $a$  to customer  $c$  at period  $t$  in scenario  $s$
- $V_{ajts} = \begin{cases} 1 & \text{if task } i \text{ is assigned to workstation } j \text{ for assembler } a \text{ at period } t \text{ in scenario } s, \\ 0 & \text{otherwise} \end{cases}$
- $Z_{ajts} = \begin{cases} 1 & \text{if at least one task is assigned to workstation } j \text{ for assembler } a \text{ at period } t \text{ in scenario } s, \\ 0 & \text{otherwise} \end{cases}$
- $CT_{ats}$  cycle time for assembler  $a$  at period  $t$  in scenario  $s$

**2-2-3- Upper-level model**

In the upper-level of our developed BLSP model, the considered SCND decisions are made including the amount of flows between two sequential echelons and assemblers' cycle times under demand uncertainty.

$$\text{Min } Z_U = \sum_{t \in T} \sum_{s \in S} Pr_{ts} \times \left( \sum_{m \in M} \sum_{a \in A} \sum_{k \in K} TC_{mat}^{MA} \times Dc_{ma}^{MA} \times Y_{maktst}^{MA} + \sum_{a \in A} \sum_{c \in C} TC_{act}^{AC} \times Dc_{ac}^{AC} \times Y_{actst}^{AC} \right) \quad (3)$$

$$\sum_{a \in A} Y_{maktst}^{MA} \leq Cap_{mkt}^M \quad \forall m \in M, \forall k \in K, \forall t \in T, \forall s \in S \quad (4)$$

$$\sum_{c \in C} Y_{actst}^{AC} \leq Cap_{at}^A \quad \forall a \in A, \forall t \in T, \forall s \in S \quad (5)$$

$$\sum_{a \in A} Y_{actst}^{AC} \geq D_{cts} \quad \forall c \in C, \forall t \in T, \forall s \in S \quad (6)$$

$$\sum_{m \in M} Y_{maktst}^{MA} - \sum_{c \in C} Y_{actst}^{AC} = 0 \quad \forall a \in A, \forall k \in K, \forall t \in T, \forall s \in S \quad (7)$$

$$CT_{ats} \leq WT_t / \sum_{c \in C} Y_{actst}^{AC} \quad \forall a \in A, \forall t \in T, \forall s \in S \quad (8)$$

$$Y_{maktst}^{MA}, Y_{actst}^{AC}, CT_{ats} \geq 0 \quad \forall m \in M, \forall a \in A, \forall k \in K, \forall t \in T, \forall c \in C, \forall s \in S \quad (9)$$

The objective function of upper-level model, i.e. Relation (3), minimizes the expected transportation costs between two sequential echelons. Constraints (4) and (5) assure the total quantity of components shipped from each manufacturer to the assemblers, and the total amount of products shipped from each assembler to the customers should not exceed the capacity of that manufacturer and assembler at each period in each scenario, respectively. Constraint (6) guarantees the satisfaction of customer demand for all products at each period in each scenario. Relation (7) shows the total component amount shipped from manufacturers to the assembler equals to the total shipped product amount from that assembler to customers to satisfy the demand at each period in each scenario. Constraint (8) states that cycle time of all assemblers at each period in each scenario must be lower than or equal to the working time in all periods divided by the total product amount shipped from each assembler to customers. Constraint (9) denotes the non-negativity restriction of upper-level decision variables, i.e.

$Y_{maktst}^{MA}$ ,  $Y_{actst}^{AC}$  and  $CT_{ats}$ .



### 2-2-4-Lower-level model

The lower-level of our developed BLSP model represents the assignment of tasks to the workstations in the assemblers, which is the objective of ALB problem. It should be noted that the simple assembly line balancing problem (SALBP) is categorized into two main groups: SALBP-I and SALBP-II. SALBP-I intends to assign tasks to the workstations in such a way that the number of workstations is minimized for a given cycle time, while SALBP-II tries to minimize the cycle time for a given number of workstations (Hamta et al., 2011). Since SALBP-I generally happens when the organization intends to design new assembly lines, we select this type which is more compatible with the considered problem in the lower-level model.

$$\text{Min } Z_L = \sum_{t \in T} \sum_{s \in S} Pr_{ts} \times \left( \sum_{a \in A} \sum_{j \in J} \sum_{t \in T} Z_{ajts} \right) \quad (10)$$

$$\sum_{j \in J} V_{ajts} = 1 \quad \forall a \in A, \forall i \in N, \forall t \in T, \forall s \in S \quad (11)$$

$$\sum_{j \in J} j \times V_{arjts} - \sum_{j \in J} j \times V_{aqjts} \leq 0 \quad \forall a \in A, \forall (r, q) \in P, \forall t \in T, \forall s \in S \quad (12)$$

$$\sum_{i \in N} t_i \times V_{ajits} \leq CT_{ats} \quad \forall a \in A, \forall j \in J, \forall t \in T, \forall s \in S \quad (13)$$

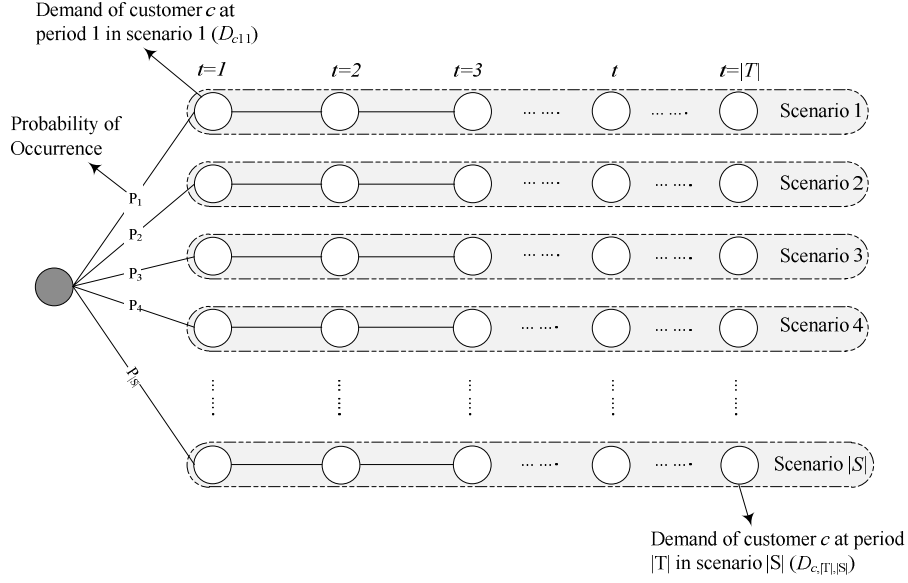
$$\sum_{i \in N} V_{ajits} \leq M \times Z_{ajts} \quad \forall a \in A, \forall j \in J, \forall t \in T, \forall s \in S \quad (14)$$

$$V_{ajts}, Z_{ajts} \in \{0,1\} \quad \forall a \in A, \forall i \in N, \forall j \in J, \forall t \in T, \forall s \in S \quad (15)$$

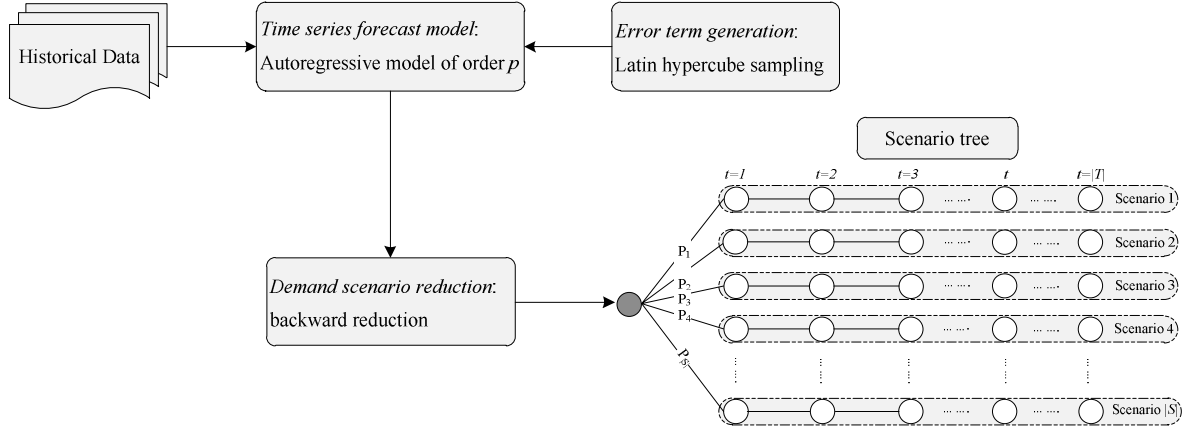
The objective function of lower-level model minimizes the expected total number of opened workstations in all assemblers. Constraint (11) guarantees that each task must be assigned to one workstation in all assemblers at each period in each scenario. Constraint (12) ensures the precedence relations between the tasks by assigning task  $r$  as an immediate predecessor of task  $q$  in all assemblers at each period in each scenario. Constraint (13) expresses that total task times in each workstation should not exceed the corresponding cycle time in all assemblers at each period in each scenario. Constraint (14) guarantees that workstation  $j$  is opened, i.e.  $Z_{ajts} = 1$ , if at least one task is assigned to it in all assemblers at each period in each scenario. Constraint (15) denotes the binary nature of variables  $V_{ajts}$  and  $Z_{ajts}$ .

### 3- Dealing with Demand uncertainty

To deal with demand uncertainty, this paper presents a scenario-based approach to generate demand scenarios in the BLSP model by approximating the stochastic demand process fitted from historical data. It is worth mentioning that a scenario is a description of a future state with a probability assigned to it that indicates the importance of that scenario in uncertain environment (Birge and Louveaux, 2011). A scenario tree is employed to represent demand uncertainty with a given probability for each scenario (Figure 2). Each scenario determines the customer's demand for a certain product in planning horizon. Several demand scenarios are generated from the particular distribution through scenario generation algorithm presented in this section. This algorithm includes three steps, namely time series forecast modeling, LHS method to generate error term in the forecast model, and demand scenario reduction to build the scenario tree from historical data. Details of each step are explained in the following subsections. **Figure 3** demonstrates the outline of the proposed scenario generation algorithm to deal with demand uncertainty in the considered problem.



**Figure 2.** A scenario tree for a customer ( $c$ ) with discrete demand scenarios



**Figure 3.** The outline of proposed algorithm for dealing with demand uncertainty and scenario generations

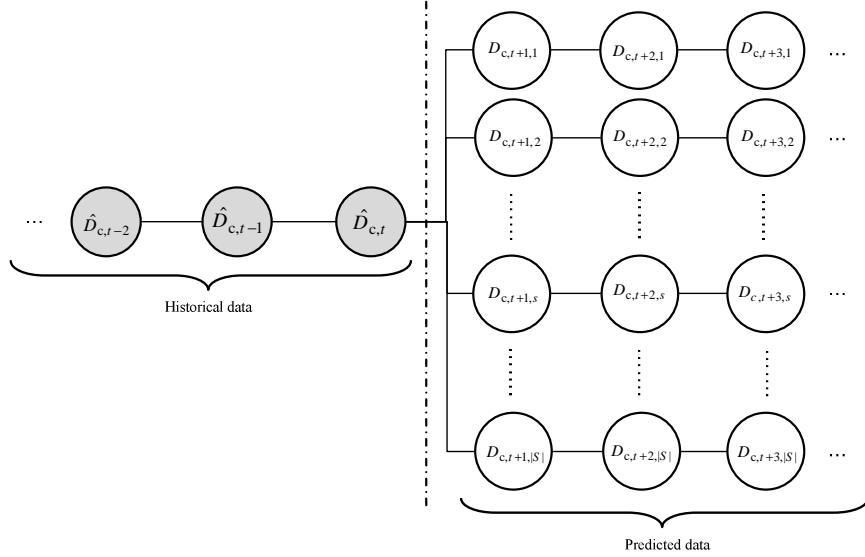
### 3-1- Time series forecast model

In order to deal with uncertainty, a suitable time series model can be utilized to consider time dependencies of demand in multiple periods in each scenario. We employ an autoregressive (AR) process of  $P$  th order to model demand uncertainty (see for example [22]). In our case, the predicted demand at period  $t + 1$  and scenario  $s$  denoted by  $D_{c,t+1,s}$  considering the error term  $\varepsilon_{c,t+1,s}$  is given by the following relation:

$$D_{c,t+1,s} = \alpha + \sum_{i=1}^P \beta_i \hat{D}_{c,t+1-i} + \varepsilon_{c,t+1,s} \quad \forall c \in C, \forall t \in T, \forall s \in S \quad (16)$$

where  $\alpha$  is a constant,  $\beta_i$  is AR parameters,  $\hat{D}_{c,t+1-i}$  is the historical demand of customer  $c$  at  $(t+1-i)$  period, and  $\varepsilon_{c,t+1,s}$  is the error term at  $(t+1)$  th period and  $s$  th scenario. Then, the following formulation is employed to generate scenarios at subsequent periods:

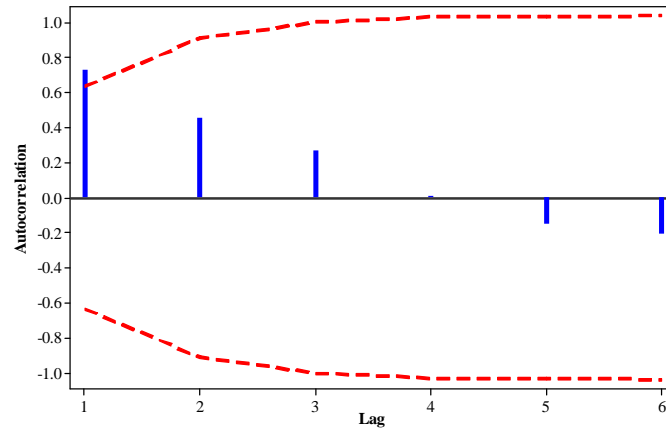
$$D_{c,t+j,s} = \begin{cases} \alpha + \sum_{i=1}^P \beta_i \hat{D}_{c,t+j-i} + \varepsilon_{c,t+1,s}, & j=1 \\ \alpha + \sum_{i=1}^{j-1} \beta_i D_{c,t+j-i,s} + \sum_{i=j}^P \beta_i \hat{D}_{c,t+j-i} + \varepsilon_{c,t+j,s}, & 1 < j \leq P \\ \alpha + \sum_{i=1}^P \beta_i D_{c,t+j-i,s} + \varepsilon_{c,t+j,s}, & j > P \end{cases} \quad (17)$$



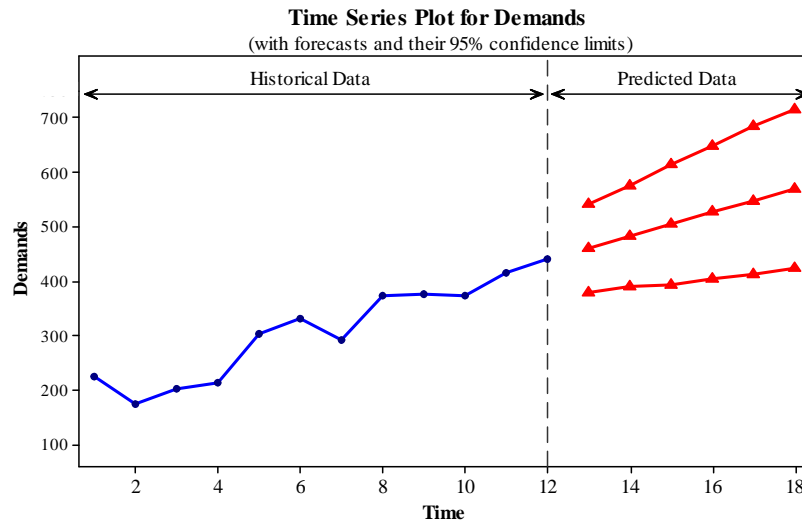
**Figure 4.** Demand generation method for customer  $c$

Figure 4 demonstrates a schematic view of generating different scenarios for customer  $c$ . The scenarios are generated based on the error terms, which follows normal distribution with mean zero and variance  $\sigma_{\varepsilon}^2$ . In our case, the error terms are generated at each period for all customers based on the method will explain in Subsection 0. As a practical example of implementing the considered time series model, the demand of a special type of civil aircrafts is concerned. Since the historical data has a non-constant mean and variance, therefore the ARIMA model is the most suitable to describe the behavior of demands (Chen and Lu, 2012). For this purpose, first the autocorrelation between data should be checked to help determine a likely model. We performed that and found there is a single large spike of 0.7 at lag 1, which is typical of an autoregressive process of order one (Figure 5). Figure 6 shows the historical data from 2002, i.e. period 1 in the abscissa of Figure 6, to 2013, i.e. period 12 in the abscissa of Figure 6, used to predict the future demands, including the average and 95% confidence intervals of demand values in next 6 months (from period 13 to period 18). Consequently, the estimated ARIMA parameters and the results of related hypothesis test for this product are as follows:

Type	Coef.	SE	Coef.	T	P
AR 1	-0.4482	0.2923	-1.53	0.080	
Constant	31.35	12.44	2.52	0.033	



**Figure 5.** Autocorrelation Function for demands with 5% significance limits.



**Figure 6.** Historical and predicted demand quantities of the considered product.

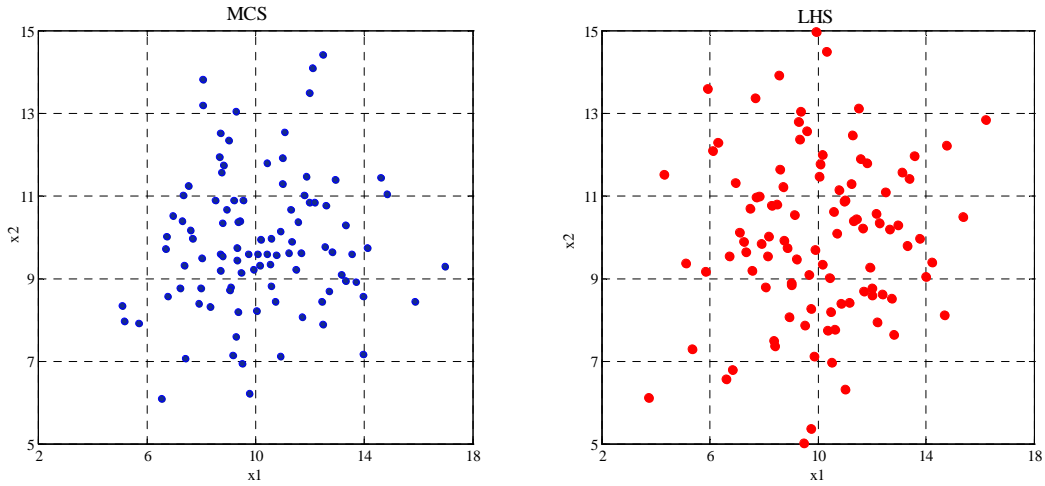
It should be noted that the coefficients of the fitted ARIMA model are estimated by maximum likelihood estimation (MLE) via Minitab statistical software. The mean demand and 95% confidence limits (CL) of the considered product based on the fitted model are reported in Table 2 for 6 future periods.

**Table 2.** The mean demand and 95% confidence limits of the product for 6 periods.

Period	13	14	15	16	17	18
Mean Demand	460.145	482.466	503.812	525.595	547.182	568.857
95% Lower CL	379.259	390.081	393.17	402.652	411.725	422.508
95% Upper CL	541.032	574.852	614.454	648.538	682.639	715.205

### 3-2- Error term generation using LHS method

Most of former works have used Monte Carlo simulation (MCS) to generate error term ( $\epsilon$ ) and consequently different scenarios (See for example Chen and Lu (2012)). In this paper, LHS method is employed to cover more domain space of stochastic parameters rather than MCS. LHS is recommended as a method to improve the efficiency of sampling method (Iman, 2008). Figure 7 compares the performance of MCS and LHS methods for an example with two variables  $x_1$  and  $x_2$  following normal distribution ( $x_1 \sim N(10, \sqrt{5}^2)$  and  $x_2 \sim N(10, 2^2)$ ).



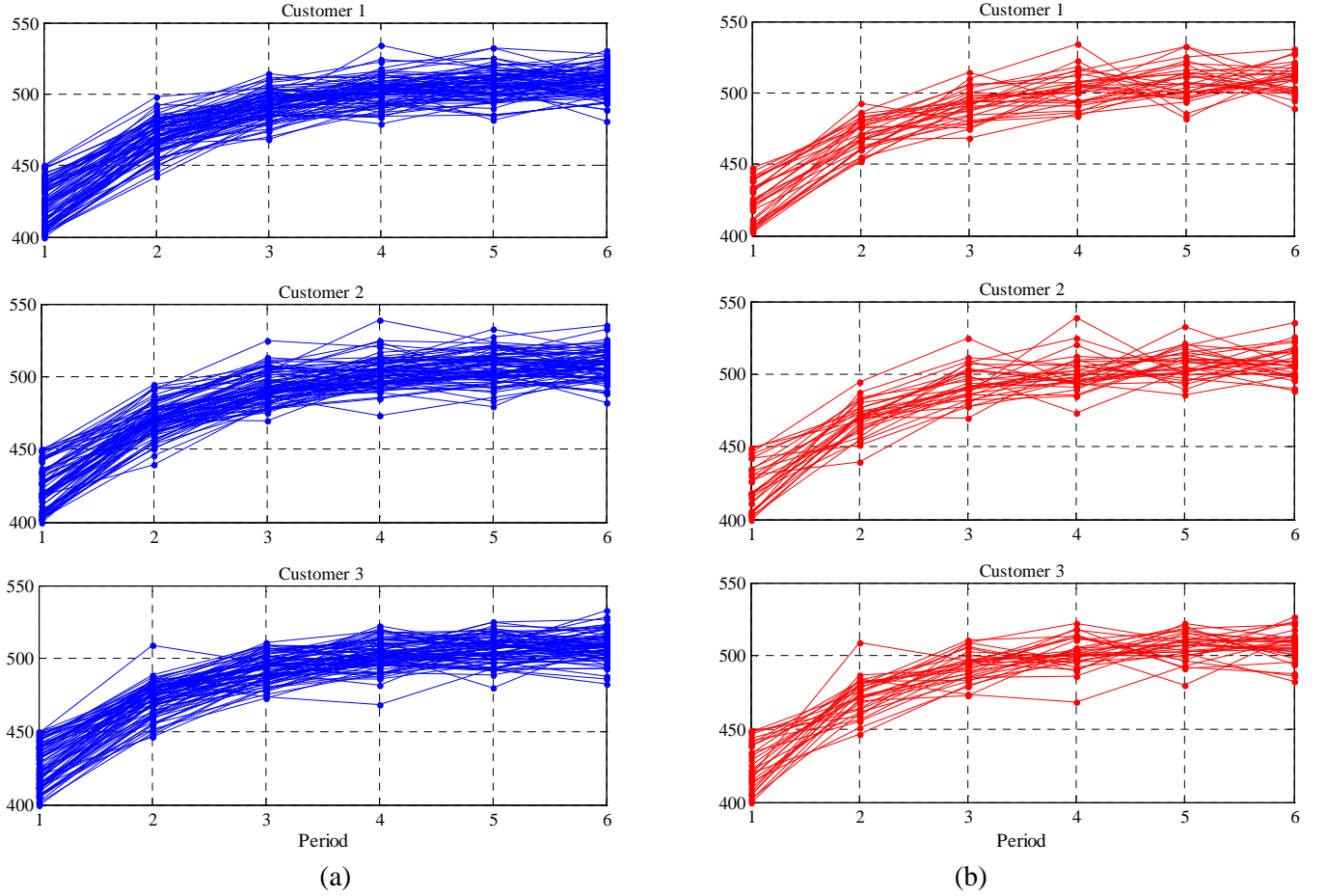
**Figure 7.** Comparison between LHS and MCS methods.

To construct scenario tree, suppose we have  $/T/$  periods. In each period, the error terms are generated using a normal distribution as mentioned before. Since error terms are period-independent, the new terms are generated at the next period by the same way. This procedure is continued until the last period. The steps of LHS method employed to generate error terms are explained in pseudo-code of proposed scenario generation algorithm presented at the end of this section.

### 3-3- Scenario reduction

As it is clear, large number of scenarios makes the optimization model cumbersome to be solved, especially in large scale problems. In order to reduce the number of scenarios efficiently, a scenario reduction technique should be used. In the literature, two scenario reduction methods exist: backward and forward (Dupačová et al., 2003). For simplicity, we employ backward reduction technique. The algorithmic framework of backward technique is described in Step 3 of scenario generation algorithm.

In the civil aircraft case, the backward reduction algorithm has been used to reduce 80 generated scenarios to 30 reduced set for 3customers in 6 future periods (Figure 8). As shown in the reduction results, the shape and characteristics of generated scenarios are retained and the reduced scenarios can be used to predict appropriately.



**Figure 8.**(a) 80 generated scenarios for three customers in six future periods (b) 30 demand scenarios obtained by reduction method from 80 generated scenarios in (a).

Pseudo-code of the proposed scenario generation algorithm is represented as follows:

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**Nomenclature:**

- $|S|$  number of generating scenarios at each period
  - $|S|_{target}$  desired number of reduced scenarios
  - $|C|$  number of customers
  - $Sc_t$  set of scenarios at period  $t$
  - $Pr_{t,j}$  probability of constructed scenario  $j$  at period  $t$
  - $DSc_t$  set of scenarios that to be deleted at period  $t$
  - $Dis_{ijt}$  Euclidean distance between scenario  $i$  and  $j$  at period  $t$
- 

**Begin**

**For each**  $t \in T$

**Step 1.** Generate  $\varepsilon_{cts}$  ( $c = 1, 2, \dots, |C|$ ;  $s = 1, 2, \dots, |S|$ ) using LHS as follows[52]:

- i.  $M$  is a  $|C| \times |S|$  matrix in which rows are random permutation of  $1, \dots, |S|$ .
- ii.  $M'$  is a  $|C| \times |S|$  matrix randomly generated using uniform (0,1) distribution.
- iii.  $G = \frac{1}{|S|}(M - M')$ .
- iv.  $\hat{\varepsilon}_{ij} = F_{\varepsilon}^{-1}(G_{ij})$  ( $i = 1, 2, \dots, |C|$ ;  $j = 1, 2, \dots, |S|$ ), where  $F_{\varepsilon}^{-1}()$  is inverse cumulative distribution

function of  $\varepsilon$ .

**Step 2.**Construct demand scenarios

**If** ( $t > 1$ ) **then**

a. Construct set  $Sc_t$  by  $|S| \times |S|_{target}$  Scenarios using Relation (17) using

$$\varepsilon_{cts} (c = 1, 2, \dots, |C|; s = 1, 2, \dots, |S|).$$

b.  $Pr_{t,j} = \frac{1}{|S|},$

**Else**

a. Construct  $|S|$  demand scenarios for period 1 using Relation (16).

b.  $Pr_{1,j} = \frac{1}{|S|}, j = 1, \dots, |S|$

**End if**

**Step 3.**Backward scenario reduction

i. Define  $Sc_t$  as a set of all initial scenarios at period  $t$  and  $DSc_t$  is a null set.

ii. **While** ( $|Sc_t| > |S|_{target}$ )

a.  $Dis_{ijt} = \sqrt{\left( \sum_{r=1}^{|C|} \sum_{p=1}^t (D_{rpi} - D_{rpi})^2 \right)}, i = 1, \dots, |Sc_t|; j = 1, \dots, |Sc_t|$

b.  $MDis_{st} = \min_{s'=1, \dots, |Sc_t|} \{Dis_{ss't}\} \quad \forall s = 1, \dots, |Sc_t|, \forall t \in T$ , find the scenario index  $f$  that has the minimum distance with scenario  $s$ .

c. Calculate  $PS_{st} = Pr_s \times MDis_{st} \quad \forall s = 1, \dots, |Sc_t|, \forall t \in T$

d. Find the scenario index  $d$  such that  $PS_{dt} = \min PS_{st} \quad \forall s = 1, \dots, |Sc_t|, \forall t \in T$

e.  $Sc_t = Sc_t - \text{scenario}(d), DSc_t = DSc_t + \text{scenario}(d), Pr_{t,f} = Pr_{t,f} + Pr_{t,d}$

**End while**

**End for**

**End**

**4- Solution method**

It is generally difficult to solve the BLP problem. One reason is that BLP even in its simplest version is an NP-hard problem (Ben-Ayed et al., 1988). Even if both upper and lower-level problems are convex, the whole BLP problem can be non-convex. Therefore, even if we obtain the solution of BLP, it is generally local optimum not global. Finding the response or reaction relation is the key point to solve the BLP. Response relation determines the relationship between upper and lower variables in a BLP model[44]. In the special formulation of this paper, finding relationship between upper-level variables and lower ones is simple. Constraint (13) represents explicitly the relationship between binary lower-level variables and continuous upper-level variables.

Our proposed solution method is a heuristic algorithm based on Constraint (13) by considering the generated demand scenarios using the algorithm presented in Section 0. It should be mentioned that the proposed solution method is a hybrid method in which exact methods have been employed through a heuristic approach. Exact methods such as branch and bound have been implemented by GAMS solvers. In this method, cycle time ( $CT_{ats}$ ) is a given parameter in the lower-level model. After solving the lower-level model and obtaining the value of variable  $V_{aijts}$ , Constraint (13) should be added to the upper-level model. Then for the fixed  $V_{aijts}$  obtained from lower-level model, upper-level problem is solved to find new  $CT_{ats}$ . This iterative process is continued until the stopping criterion is established and convergence to the optimal solution of the original BLSP model. The stopping criterion is that difference between two sequential objective function values of upper-level model should be lower than a small positive number ( $\varepsilon$ ). Following the proposed solution method for the developed BLSP model is presented:

**Step 1.** Generate demand scenarios using the proposed algorithm in Section 0;

**Step 2.** Determine an initial set for  $CT^0$ ;

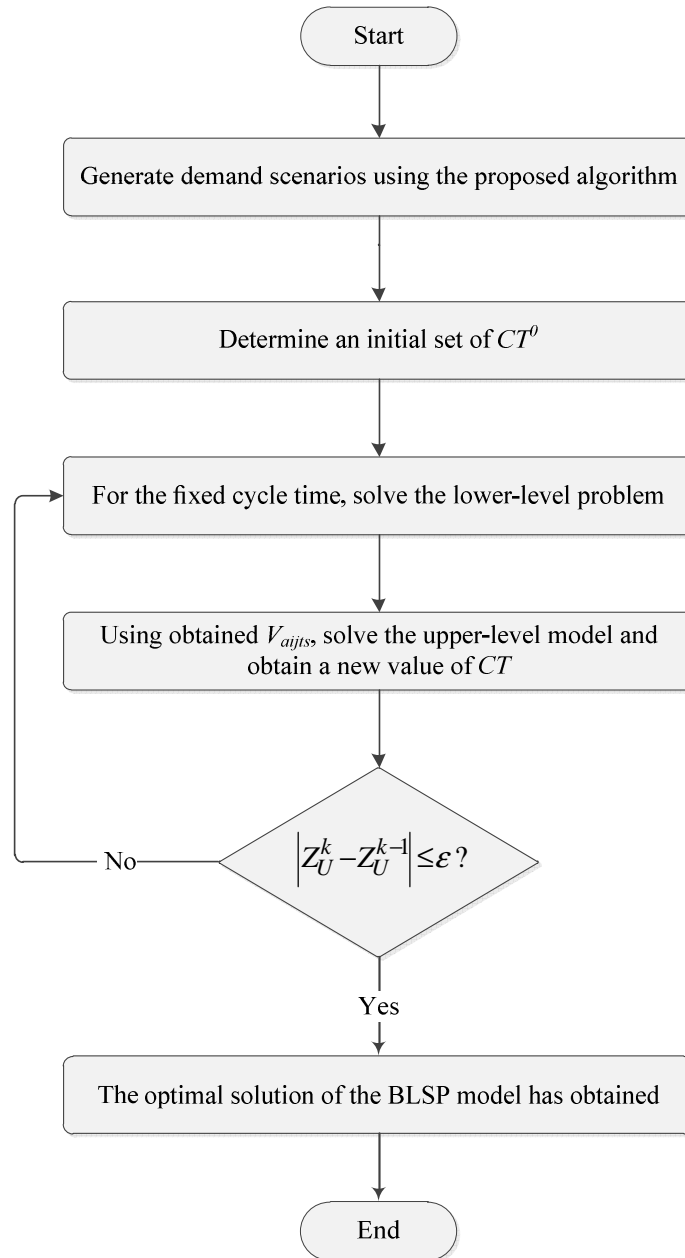
**Step 3.** For the fixed  $CT_{ats}^k$ , solve the lower-level model and obtain  $V_{ajts}^k$ ;

**Step 4.** Using obtained  $V_{ajts}^k$  from Step 3, solve the upper-level model and find a new value for  $CT$ ;

**Step 5.** If  $|Z_U^k - Z_U^{k-1}| \leq \varepsilon$  stop, where  $\varepsilon$  is the convergence tolerance; otherwise, set  $k=k + 1$  and go back to Step 3.

Figure 9 shows the steps of the proposed algorithm to solve the considered BLSP model. It should be noted that since upper-level model is an MINLP problem, an appropriate solution method should be employed in iterations such as branch-and-bound method or outer approximation algorithm. Sometimes an inner penalty function method can be utilized to relax nonlinear constraints, and then the upper-level model can be solved by the solution methods of linear convex optimization problems (Roghalian et al., 2007). On the other hand, the MILP solution methods can be employed to solve the lower-level model. In this regard, GAMS/ Cplex as a well-known GAMS solver is used in the lower-level model to obtain optimal solution. Since our proposed solution method is a heuristic method, it is hard to test its convergence. For this purpose, different initial points can be considered to solve the problem and if all results are the same, it shows that the algorithm converges (In this regard, see for example Hamta et al. (2015) and Sun et al. (2008)).





**Figure 9.** The steps of the proposed algorithm to solve the developed BLSP model

## 5- Computational experiments

In order to evaluate the performance of the developed BLSP model and the solution method, numerical experiments over some randomly generated problem instances are used. These instances have been generated in different sizes (small, medium and large) to evaluate the model performance for all sizes of problems. The model and its proposed solution method were implemented in GAMS in linkage with MATLAB.

### 5-1-Data generation and settings

The required data for the problem instances can be characterized into four groups: transportation costs and distances, two types of maximum capacities, customers' demands and time data. The sources of random generation and fixed values of parameters used in the problem instances are listed in Table 3. The data for ALB, i.e. task times and precedence constraints, are obtained from homepage for assembly line optimization research ([www.assembly-line-balancing.de](http://www.assembly-line-balancing.de)). Afterward, using the generated parameters, 15 problem instances with different sizes are constructed.

**Table 3.**Parameters values used in the problem instances

Category	Parameter	Corresponding range and distribution function
Transportation costs and distances	$TC_{mat}^{MA}, TC_{act}^{AC}$	$\sim$ Uniform(1,5)
	$Dc_{ma}^{MA}$	$\sim$ Uniform(200,400)
	$Dc_{\alpha}^{AC}$	$\sim$ Uniform(400,600)
Capacities	$Cap_{mkt}^M$	$\sim$ Uniform(6000,7500)
	$Cap_{at}^A$	$\sim$ Uniform(4500,6000)
Customers' demands	$D_{cts}$	$AR(1): D_{cts} = \alpha + \beta \hat{D}_{c,t-1,s} + \epsilon_{cts}$
		$\alpha \sim$ Uniform (20, 40)
		$\beta \sim$ Uniform (0.15, 0.2)
		$\epsilon_{cts} \sim$ N(0, Uniform (20, 35))
		$\hat{D}_{c,t-1,s} \sim$ Uniform (30, 50)
Time data	$t_i$	From homepage for assembly line optimization research
	Initial $CT_{ats}$	$\sim$ Uniform( $\sum t_i /  J , \sum t_i / ( J  - f)$ ), where $f$ is a constant selected based on the size of problem
	$WT_t$	28800

### 5-2- Problem instances generation

Several problem instances are randomly generated considering assumptions that reflect the real-world situation. Sizes of these problem instances are chosen based on the range of test problems presented in the literature (see for example Pishvae et al.,( 2010)).Table 4 reports the characteristics of 15 problem instances used in this section. The size of a problem instance is determined by characteristics shown in the first row of **Table 4**.

**Table 4.** The characteristics of the problems instances.

Problem instance	Number of manufacturers ( $M$ )	Number of assemblers ( $A$ )	Number of customers ( $C$ )	Number of potential workstations ( $J$ )	Number of tasks ( $N$ )	Number of components ( $K$ )	Number of periods ( $T$ )	Number of scenarios ( $S$ )	Number of scenarios after reduction
1	4	2	4	4	9	7	2	60	20
2	4	2	4	4	9	7	2	100	40
3	4	6	6	4	9	7	4	60	20
4	4	6	8	4	11	7	4	100	40
5	8	10	10	4	9	7	2	60	20
6	8	10	12	4	11	7	4	100	40
7	10	13	13	7	21	8	2	60	20
8	10	13	15	8	25	8	4	60	20
9	15	18	18	7	21	8	2	100	30
10	15	18	20	8	25	8	4	60	20
11	20	22	22	9	28	10	2	60	20
12	20	23	24	10	29	10	4	60	20
13	20	22	25	10	30	10	2	60	20
14	21	24	25	10	30	10	4	80	30
15	22	24	25	12	35	11	2	80	30

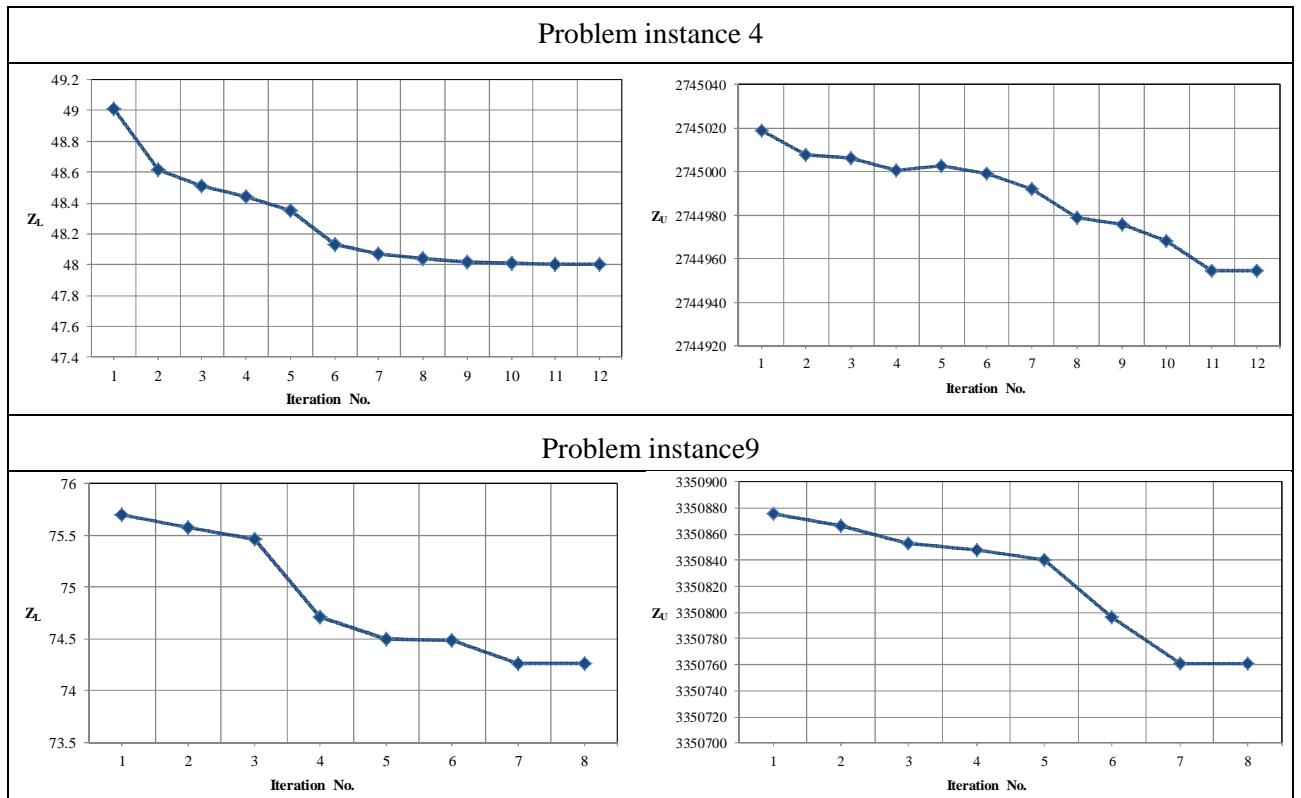
### 5-3- Computational results

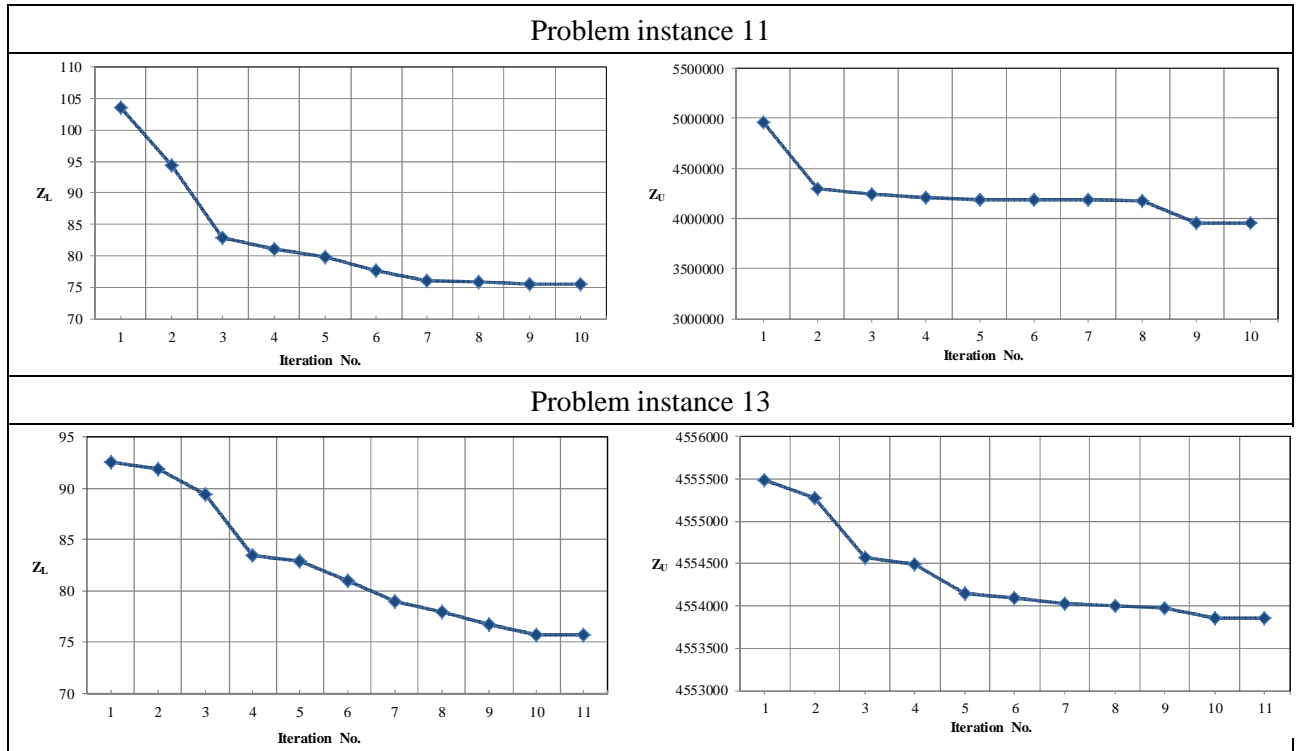
This subsection presents iteration number in which the iterative process stops, the best lower and upper objective values and the CPU time for the pre-defined problems instances. It should be noted that the stopping criterion is based on step 5 of solution method presented in section 0. The proposed solution method was coded in MATLAB 7.1 where the lower-level and upper-level models were formulated in GAMS 23.5. All experiments were run with an Intel Pentium IV dual core 2.1 GHz CPU PC at 3 GB RAM under a Microsoft Windows 7 environment.

All problem instances were solved using the proposed heuristics solution algorithm. The results for each problem instance are reported in Table 5. In addition, Figure 10 shows the convergence of the upper-level and lower-level models' objective values ( $Z_U$  and  $Z_L$ ) for problem instances 4, 9, 11 and 13 until the stopping criteria is met. The obtained results show that the proposed solution algorithm is efficient in solving the developed model and so this algorithm can be employed in finding the optimal solutions of problem instances with different sizes in reasonable computational time.

**Table 5.**Theobtained results fromthe proposed solution method for the defined problems instances

Problem instance	Iteration number (to stop the iterative process)	$Z_U$	$Z_L$	CPU time
1	6	1169178	12.67	26 s
2	5	1007695	13.1	96 s
3	9	2979740	72.3	2245 s
4	12	2744954	48	3975 s
5	6	1614678	61.07	965 s
6	7	5031525	90.78	7124 s
7	10	2513249	90.28	3981 s
8	9	5902075	100.65	3788 s
9	8	3350761	74.26	8584 s
10	7	5240030	145.72	8419 s
11	10	3952291	75.57	> 3 hours
12	17	8609533	114.57	> 3 hours
13	11	4553853	75.73	7539 s
14	21	8370290	196	> 3 hours
15	25	5116175	148.02	> 3 hours

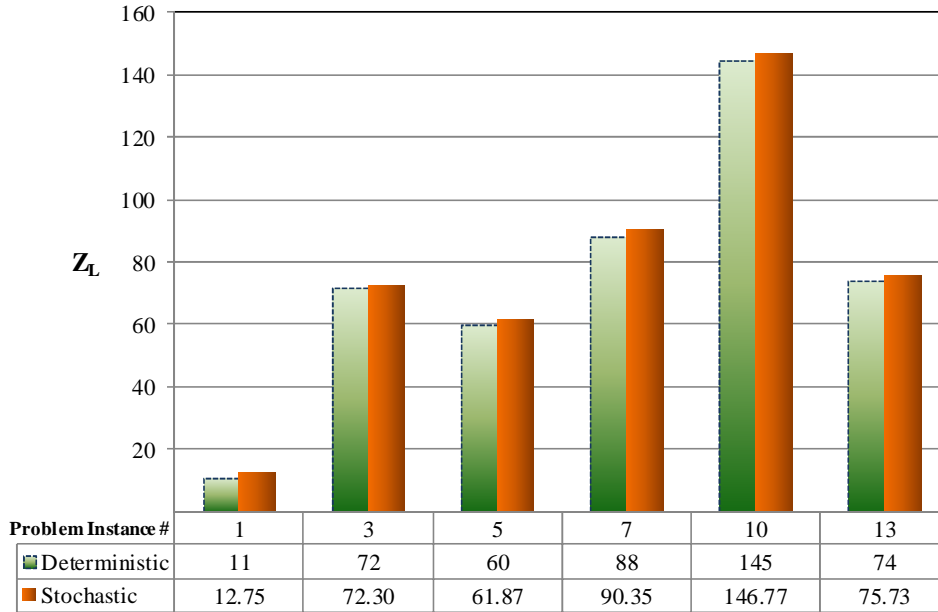




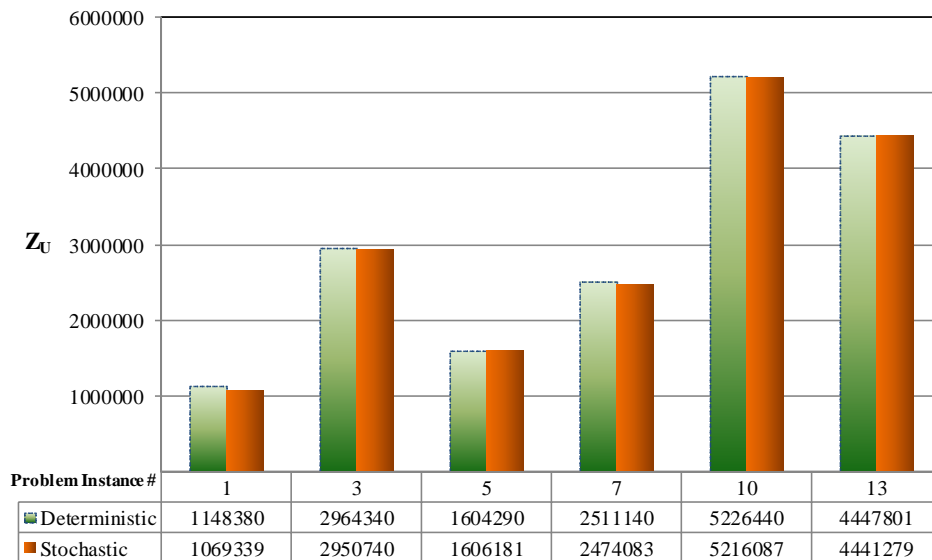
**Figure 10.** The convergence of  $Z_L$  and  $Z_U$  for several problem instances

#### 5-4- Comparison between stochastic and deterministic models

In this subsection, the performance comparison between the developed stochastic model and its equivalent deterministic version is made. In the deterministic model, the scenario indices and the corresponding probabilities ( $Pr_{ts}$ ) are removed from the model. In addition due to meaningful comparison between deterministic and stochastic models, in the deterministic model, one of the generated scenarios is selected randomly for cycle time, i.e.  $CT_{ats}$ , and customer demand ( $D_{cts}$ ) at each period. For this purpose, several problem instances with different sizes are selected from Table 4. Figure 11 and Figure 12 demonstrate the performance of the stochastic and deterministic models in terms of  $Z_L$  and  $Z_U$  for several problem instances defined in Subsection 0. As Figure 11 shows, the deterministic model has obtained better  $Z_L$  in all problem instances. On the other hand, Figure 12 illustrates that the stochastic model obtains better  $Z_U$  in comparison with deterministic model in most of problem instances. To conclude, the developed stochastic model mainly performs better than the equivalent deterministic model in making strategic decisions while the deterministic model works better in making tactical decisions, i.e. ALB decisions.



**Figure 11.** Comparison between stochastic and deterministic models in terms of  $Z_L$  for several problem instances



**Figure 12.** Comparison between stochastic and deterministic models in terms of  $Z_U$  for several problem instances

## 6- Conclusions and future research

This paper addresses an important issue concerning the integration of strategic and tactical decisions in supply chain management. The main objective of this paper is to introduce and characterize the problem of integrating supply chain network design and assembly line balancing problems under demand uncertainty. A special case of supply chain networks is considered in which assembly activities are a main stage of the supply chain in the uncertain environment. A novel bi-level stochastic programming model is developed to design and optimize the considered supply chain including manufacturers, assemblers and customers. In order to deal with demand uncertainty, a three-step algorithm is proposed to generate different demand scenarios. Moreover, a heuristic method is proposed to solve the developed model. Finally, computational experiments over several problem instances show that the developed model is valid and capable to be employed in practical cases. The comparison between the stochastic and equivalent deterministic model is also made.

Future research can investigate multiple products, U-shaped or two-sided assembly lines and equipment selection. Considering location, routing or inventory decisions in supply chain network

design problem is also a valuable future work. In addition, since CPU time increases significantly when problem size and the number of scenarios increase, developing meta-heuristic algorithms or exact solution methods (such as branch-and-bound method) to solve large-scale problems is of interest for future studies.

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