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Supply Chain Management Optimization and Prediction Model Based on Projected Stochastic Gradient

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Abstract: Supply chain management (SCM) is considered at the forefront of many organizations in the delivery of their products. Various optimization methods are applied in the SCM to improve the efficiency of the process. In this research, the projected stochastic gradient (PSG) method was proposed to increase the efficiency of the SCM analysis. The key objective of an efficient supply chain is to find the best flow patterns for the best products in order to select the suppliers to different customers. Hence, the focus of this research is on developing an efficient multi-echelon supply chain using factors such as cost, time, and risk. In the convex case, the proposed method has the advantage of a weakly convergent sequence of iterates to a point in the set of minimizers with probability one. The developed method achieves strong sequence convergence to the unique optimum, with probability one. The SCM dataset was utilized to assess the proposed method's performance. The proposed PSG method has the advantage of considering the holding cost in the profit analysis of the company. The results of the developed PSG method are analyzed according to the product's profit, stock, and demand. The proposed PSG method also provides the prediction of demand to increase profit.

Keywords: holding cost; optimization method; prediction; projected stochastic gradient; supply chain management

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1. Introduction

Firms consider economic, social, and environmental outcomes for internal and supplier operations. In the past two decades, sustainable supply chain management (SSCM) has begun integrating economic, social, and environmental goals in a firm's supply chain process to increase stable outcomes of supply chains [1]. Optimizing supply decisions helps to achieve smaller supply investments with high production performance. Supply networks have a complex structure, and the task of optimizing configuration parameters and supply decisions is complex [2]. Several new technologies, such as additive manufacturing and the implementation of Industry 4.0, are creating new supply chain management (SCM) challenges [3,4]. Supply chain planning (SCP) is considered to be at the forefront of business function from raw materials to the fulfillment of customer demands. SCP is categorized into operational, tactical, and strategic decisions based on the time horizon. A business environment with a complex structure is characterized by great variability, frequent disruption, and high uncertainty. Therefore, many companies face a major challenge in maintaining a viable and efficient supply chain [5]. In such a hostile environment, the supply chain process must cope with planning parameters such as supply, demand, and cost that show uncertainty [6,7]. Multiple problems exist, such as low overall efficiency, high logistic cost, backward logistic technology, long transportation time, large cargo damage, and difficulty in guaranteeing quality, which is difficult to adapt to current demand [8].

The supply chain is made up of complex network entities, from upstream to downstream, such as customers, retailers, warehouses, transporters, manufacturers, and suppliers. SCM involves information flow management, service, and product that each play a role in customer satisfaction and the success of the company [9]. In a dynamic marketplace, SCM decision makers encounter issues at all levels of the supply chain, including transportation, distribution planning, production, supplier selection, inventory management, and facility location [10,11]. An optimal supply chain plan defines the amount of material transported between facilities at any given time period within the planning horizon. The inventory level of storage facilities must also be simultaneously determined to regulate these flows due to inventory balance constraints in multi-period planning models [12]. The uncertainty in demand must also be addressed to prevent stockouts. Demand uncertainty must also be considered in order to avoid stockouts, and for uncertainty, safety stocks, or the stochastic programming model, is considered. However, the stochastic optimization problem is still challenging to solve, which is addressed in limitation [13]. There are many different types of SCM issues, each with its own set of uncertainties and challenges. Most of the factors in the supply chain are dynamic in nature, hence making the SCM problem an NP-hard problem. Therefore, researchers utilize various optimization techniques such as metaheuristics, gradient based methods, the simulation approach, and recently, machine learning methods. Therefore, the objective of this research work is to solve a multi-echelon supply chain problem using a modified gradient method. In this research, the projected stochastic gradient (PSG) method is applied to increase the efficiency of the analysis of the SCM method, which will be explained in Section 3. The SCM data is used to evaluate the PSG method's performance and to compare its performance in different scenarios, as discussed in Section 4. Finally, the conclusions deduced from the research work are presented in Section 5.

2. Research Background and Literature Review

The dynamic features of supply chain management make it challenging to increase availability and network connectivity. In this section, recent research in supply chain management is reviewed for its advantages and limitations. Various techniques are applied by researchers for supply chain management optimization. Currently, machine learning techniques are also becoming popular in several applications [14–18].

To improve supply chain resilience, Xia et al. [19] examined the multi-layer nature of supply chain networks. From a topological perspective, the supply chain connectedness was analyzed, and the t-core approach was applied to break down the network into several layers and to distinguish the network layer based on node impact. A layer-based rewiring strategy was used to restore the network once it had been disrupted. The analysis shows that this method increases the resilience for targeted disruption. This method increases the resilience of the supply chain network using the consideration of a multi-layer network. The optimization method was required to optimize the probability of the rewiring operation to achieve a better tradeoff between network efficiency and network connectivity.

Goldbeck et al. [20] proposed a multi-stage stochastic model to optimize the pre-disruption investment decision, the post-disruption dynamic adjustment of the supply chain, and the repair of resource allocation. For optimization, the model took into account three types of decisions: capacity planning, operational adjustment, and recovery strategy. The proposed model analyzed the importance of trade-offs between investing in production capacity and repair capabilities. The research took into account the general formulation of two forms of dependence relations: failure propagation and functional dependency. This process helps to analyze the interdependency effects such as assets failure, unavailability production, and repair resources.

In a general acyclic supply network, Grahl et al. [21] provided a method for representing the safety stock allocation decision and stock levels for various service periods. For 38 generic instances, a basic genetic algorithm and problem-adjusted simulated annealing were presented. The investigation revealed that increasing the service time reduces the network's holding costs and results in higher performance compared to other metaheuristic algorithms when it comes to solution quality and speed. However, the optimization method had lower efficiency in the SCM.

Cai, et al. [22] applied the back propagation neural network (BPNN) for the risk evaluation of supply chain management. The BPNN method analyzes the existing risk factor in SCM to build a risk evaluation factor. The analysis showed that the BPNN method solves the problem of a risk evaluation system. The BPNN method effectively determined the supply chain risk and helped in the decision-making process for risk management. The accuracy of the model was low, and important features of SCM are required to be applied to increase the efficiency. Kannan et al. [23] utilized the genetic algorithm (GA) and particle swarm optimization (PSO) for optimizing the integrated forward logistics multi-echelon distribution inventory supply chain model with a closed loop. The results revealed that GA provided better optimum solutions, i.e., minimum total cost compared to the PSO. Pourhejazy and Kwon [24] presented a review about contemporary operation research methods in SCM and reported that simulation-based optimization techniques dominate in the research. Merkuryeva et al. [25] employed a simulation-optimization-based approach to analyze and evaluate the efficiency of a certain planning policy across the whole multi-echelon supply chain for automatic switching from non-cyclic to cyclic planning and to optimize the cyclic planning policy for mature products. Multi-objective GA and response surface-based local search methods were applied. Apart from the simulation-based optimization approaches, several metaheuristics based techniques (GA, simulated annealing, tabu search, etc.) have been applied by researchers in analyzing and solving supply chain optimization problems such as vehicle routing, production, vehicle fleet size, vehicle scheduling, resource allocation, forecasting, inventory management, vendor selection, etc. [26].

Mixed integer linear programming (MILP) was used by Santander et al. [27] to present a local closed loop supply chain (CLSC). A case study of university 3D printing trash from schools in northeastern France was used to test the model. The sensitive analysis took into account market fluctuations, as well as the amount of plastic garbage generated by the school. The investigation revealed that using this novel method of plastic recycling has both economic and environmental benefits. The optimization method is required to increase the efficiency of the supply chain.

Using a vendor managed inventory (VMI) strategy, Amiri et al. [28] created a model to calculate the ideal sales volume of perishable products in a two-echelon supply chain. In this study, a two-tier supply chain for perishable goods with a single buyer was assessed. One vendor and many buyers were used to evaluate the proposed model. The model optimized the sales profit using metaheuristics methods based on buyers' requests in various periods. The metaheuristics techniques such as GA, PSO, and co-evolutionary PSO (CPSO) were used for optimization. The analysis showed that VMI on the two-echelon supply chain method has better performance to optimize the probability of the supply chain. The efficacy of the optimization was lower and needed to be increased. However, while several optimization techniques have been applied by researchers in SCM, there remains a lack of research literature on gradient based methods, which can provide fast convergence to suboptimal value.

Problem Description and Proposed Solution

The existing research in SCM involves analyzing the factors and providing efficient decisions to improve the company's profit. An integrated network of facilities and transportation alternatives for the supply, manufacture, storage, and distribution of resources and goods can be classified as a supply chain. Supply chains differ greatly in size, complexity, and scale from one industry to the next [29]. Most of the studies consider only one product producer and manufacturing center, but in real life application, the supply chain has multiple parts; hence, in this research, a multi-echelon supply chain is considered, with different producers and customers. Multi-echelon supply chain management optimization is considered to be a complex problem [30]. Therefore, the model must optimize various producers, manufacturing units, and customers with trade-offs to cost and lead time. An SCM system has to provide an efficient flow pattern, flow of products, and information (such as assembly costs and time) in an optimal manner to both the producer and the customer based on the demand for the efficient flow of the supply chain. Some existing methods involve applying simple statistical analysis, and these do not apply the optimization method for the analysis. Applied optimization methods such as the GA, PSO, and CPSO methods have low convergence performance, and this affects the overall performance of the method. Some researchers don't consider the trade-off between the supply chain's network efficiency and network connectivity. Many SCM studies do not have the capacity to handle these uncertain parameters, and this affects the efficiency of the model. A multi-echelon supply chain problem is a complex one, and it requires a lot of time and computational power to solve through exact methods. Even the use of metaheuristic methods require a substantial amount of time and resources. Hence, gradient based methods, especially the projected stochastic gradient (PSG) method, is proposed to solve this problem efficiently in terms of time, as well as computational power. The aim of this research work is to improve multi-echelon supply chain network optimization processes through the use of mathematical programming tools by first, developing a model, and finally, by presenting an appropriate methodolgy for solving various scenarios of the demand model, such as expected stochastic, expected non-stochastic, non-stochastic, and non-expected stochastic models, and based on these methods, estimating the profit.

In the convex case, the suggested method has the advantage of a weakly convergent sequence of iterates to a point in the set of minimizers with probability one. With probability one, the presented approach strongly performs sequence convergence to the unique optimum. Generally, gradient based methods require high computational cost; however, with the projected stochastic gradient method the convergence rate is fast, hence requiring relatively lower computational cost. In PSG-based approaches, the gradient is approximated by a single (or few) samples at each iteration, rather than computing the true gradient (which is frequently computationally expensive), as in a standard gradient descent algorithm. PSG converges nearly certainly to a global minimum when the objective function is convex (otherwise, it converges to a local minimum) at a proper learning rate with some regularity constraints, according to stochastic approximation analysis. Hence, this method can be applied to a multifarious supply chain network which has multiple nodes of producers and distributers, since this technique can handle the complexity efficiently.

3. Materials and Methods

Supply chain management (SCM) is the foremost process for many organizations to increase profit. Various optimization methods are applied in SCM to increase the efficiency of SCM. In this research, the PSG method has been proposed to increase the effectiveness of SCM. The presented method has the benefit of a strongly convergent sequence with probability one for the unique optimum. In this paper, we aim to investigate the optimization of a supply chain network with multiple vendors, and warehouses with limited capacity owned by the vendors, so that the minimum amount of stock that will result in the maximum profit is determined. The Bayesian posterior predictive distribution method is applied to predict the SCM model to increase the profit. The block diagram of the proposed PSG and Bayesian posterior predictive distribution method is shown in Figure 1. Figure 1 shows that the dataset is utilized for two purposes, one is to optimize the profit value using the PSG technique, and the other is to predict the demand using the Bayesian posterior predictive distribution method. The objective is to maximize the profit and to predict the demand accurately, considering the uncertainties.

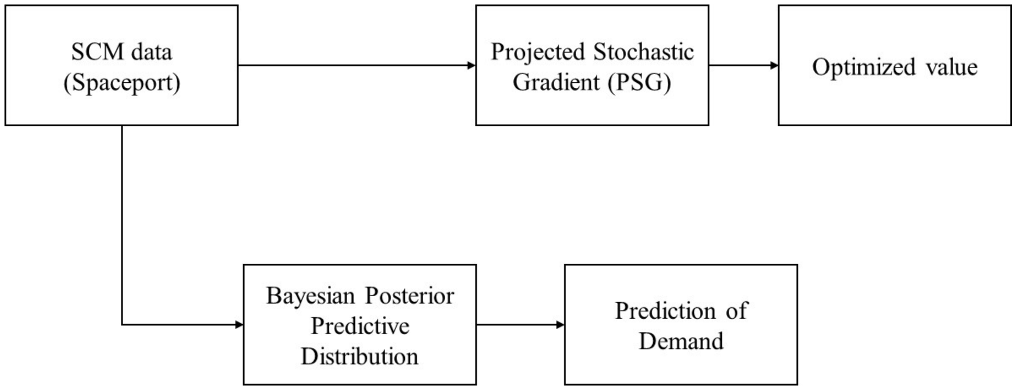

Figure 1. A block diagram of the projected stochastic gradient.

3.1. Mathematical Model

The mathematical model of the supply chain problem is followed as presented in the research [31]. A novel aspect of the problem is that the integrated supply chain is used to simultaneously determine two types of variables: (i) the locations of the vendors within a specified area of buyers with fixed locations; (ii) the holding quality by vendors based on the demand. In addition, the distance between the buyers and vendors is assumed to be Euclidean. The objective function in problem formulation is to reduce the total purchasing cost (PC), holding cost (HC), and transportation cost (TrC). The objective function is formulated after the estimation of all these cost functions. The Euclidean distance between vendors and buyers is measured for transportation cost, as given in Equation (1).

$$TrC = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{t=1}^{T} Q_{ijkt} w_{ijkt} A_{ijkt} \quad (1)$$

where Euclidean distance between buyer i with coordinate $a_i = (a_{i1}, a_{i2})$ and vendor k coordinate $y_k = (y_{1k}, y_{2k})$.

i = 1, 2, . . . , I is the buyers index
j = 1, 2, . . . , J is the products index
k = 1, 2, . . . , K is the vendors index
t, t = 0, 1, . . . , T is the time periods index
A_{ijkt}: In period t, the ordering cost (transportation cost) per unit of the jth product from vendor k to customer i
Q_{ijkt}: In period t, the ordering quantity of jth product ordered by buyer i from vendor k
w_{ijkt}: If buyer i orders product j from vendor k in period t, this binary variable is set to 1; otherwise, it is set to 0.

The holding cost in the interval $[T, T-1]$, as shown in Equation (2).

$$\int_{T-1}^{T} I(t)dt \quad (2)$$

where *I(t)* inventory condition in the warehouse in period t.

Whole periods are measured in Equation (3).

$$\sum_{t=2}^{T} \int_{t-1}^{t} I(t)dt \quad (3)$$

The total holding cost is measured in Equation (4).

$$HC = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \sum_{t=1}^{T-1} \left(x_{ijkt} + Q_{ijkt} + x_{ijkt} + 1 \right) \times T_{ijkt} h_{ijkt}/2 \quad (4)$$

x_{ijkt}: In period t, the initial (remaining) positive inventory of the jth product purchased by buyer i from vendor k; initially it was set to 0.

T_{ijkt}: Total time elapsed up to and including the tth replenishment cycle of the jth product ordered by the buyer i from vendor k.

h_{ijkt}: In period t, inventory holding cost per unit of jth product in vendor k's warehouse when sold to buyer i.

The products under the all unit discount (AUD) policy, since vendors suggested price-break point, are given in Equation (5).

$$\begin{cases} c_{ijkt1} & e_{ijkt1} \leq Q_{ijkt} < e_{ijkt2} \\ c_{ijkt2} & e_{ijkt2} \leq Q_{ijkt} < e_{ijkt3} \\ & \vdots \\ c_{ijktP} & e_{ijktP} \leq Q_{ijkt} \end{cases} \tag{5}$$

c_{ijkt}: Buyer i pays vendor k at pth price-break point in time t the purchasing cost per unit of jth product.

e_{ijkt}: vendor k proposes pth price-break point to buyer i for purchasing jth product in period t, $e_{ijk1} = 0$.

The AUD policy of total purchasing cost is measured in Equation (6).

$$PC = \sum_{i}^{I} \sum_{j}^{J} \sum_{k}^{K} \sum_{t}^{T-1} \sum_{p}^{P} Q_{ijkt} c_{ijktp} u_{ijktp} \tag{6}$$

u_{ijkt}: If buyer i purchases product j from vendor k at price-break point j in period t, this binary variable is set to 1; otherwise, it is set to 0.

The total cost of the objective function is given in Equation (7).

$$TC = TrC + HC + PC \tag{7}$$

The objective is to minimize the total cost.

3.2. Projected Stochastic Gradient (PSG)

The PSG algorithm is adopted from Geiersbach and Pflug [32] and is adapted for its utilization in the SCM problem. The problem statement is given in Equation (8).

$$\min_{u \in C} \{k(w) = \mathbb{E}[K(w, \xi)]\} \tag{8}$$

where Hilbert space H is non-empty, closed, and the convex subset is denoted as C. A probability space $(\Omega, \mathcal{F}, \mathbb{P})$ is considered for every $\omega, y \to K(w, \xi(\omega))$ as convex on C and k convex as well [33–38]. The L^2-Frechet differentiable is required in K with respect to w, and C neighborhood implies: $k : H \to \mathbb{R}$ is Frechet differentiable, as given in Equation (9).

$$\mathbb{E}[K(w, \xi)] = \int_{\Omega} K(w, \xi(\omega)) d\mathbb{P}(\omega) \tag{9}$$

For each $w \in C$, Equation (9) is finite and well-defined. Unless small and finite $\mathbb{P}$ support, Equation (9) is not traceable. Identically distributed samples $\xi_1, \ldots, \xi_N$ with $\xi_i := \xi(\omega_i)$, and $\omega_i \in \Omega$ is generated by sampling and the random independent common approximation method. The objective function of the sample average approximation (SAA) method is given in Equation (10).

$$\min_{u \in C} \left\{ \hat{K}_N(w) = \frac{1}{N} \sum_{i=1}^{N} K(w, \xi_i) \right\}, \tag{10}$$

Equation (8) solves the objective function. The approximation method is used to solve the randomness of the approximation method, and the SAA method number of samples is defined in priori. The Monte Carlo sampling method is applied for approximation.

The stochastic approximation or stochastic gradient method does not require a priori sample size. The stochastic gradient notion is used for the iterative optimization method, i.e., random function $G(w, \xi)$ such that $\mathbb{E}[G(w, \xi)] \approx \nabla k(w)$. The determination of confidence regions and a stopping criterion are based on information from iteration and advantage in priori rules. The stochastic approximation method is an iteration method that uses the function of estimates to find the function root [39–43].

The stochastic approximation method in partial differential equation (PDE) constrained optimization is unexploited. Hilbert spaces of convex problems of convergence are established in the method and demonstration of problems of particular class application, such as additional convex constraints and PDE constraints of random elliptic in a convex problem. Various methods, such as random fields parametric representation based on noise assumption of finite-dimensional methods, have been applied for investigation.

The induced norm is denoted as $||.|| = \sqrt{\langle ., . \rangle}$, and inner product H is denoted as $\langle ., . \rangle$. The weak convergence in H is denoted as $w_n \to w$. A closed convex set C projection is denoted as $\pi_C : H \to C$ and is defined in a function, as shown in Equation (11).

$$\pi_C(u) = \underset{w \in C}{\operatorname{argmin}} ||w - z|| \tag{11}$$

The major steps of the PSG algorithm [32] applied in this research are shown below (Algorithm 1).

Algorithm 1: Projected Stochastic Gradient (PSG) Algorithm.

1. Initialization: $w_1 \in H$
2. For $w = 1, 2, \ldots$ do
    a. Generate ξ_n, independent from $\xi_1, \ldots, \xi_{n-1}$, and $\tau_n > 0$
    b. $w_{n+1} := \pi_C(w_n - \tau_n G(w_n, \xi_n))$
3. End for

A stochastic gradient is denoted as $G(w, \xi) = \nabla_u K(w, \xi)$ and for some bias, the gradient is selected. Function iterates w_n of history $(\xi_1, \ldots, \xi_{n-1})$ are random. The deterministic gradient-based solver has easy adaptability, and this has low memory requirements such as the current iterate w_n must be stored. The parameter is sensitive to step-size choice, and C projection is given as complex in Equation (8).

The gradient descent of step sizes allows for larger steps in the deterministic case, i.e., ensuring $j(\pi_C[w_n - \tau_n \nabla k(w_n)] \leq k(w_n))$; for Armijo rule projection. The form of exogenous step size in the stochastic case, is given in Equation (12).

$$\tau_n \geq 0, \ \sum_{n=1}^{\infty} \tau_n = \infty, \ \sum_{n=1}^{\infty} \tau_n^2 < \infty \tag{12}$$

The convergence for the common requirement is given in Equation (12). A gradient descent method algorithm is provided for efficient estimates.

The stochastic gradient algorithm convergence is provided in finite-dimension spaces. A Lipschitz continuous gradient (i.e., $C = \mathbb{R}^d$) for unconstrained problems and step sizes is reduced to zero, a finite value converges $\lim_{n \to \infty} k(w_n) = -\infty$ or $k(w_n)$ and set as $\lim_{n \to \infty} \nabla k(w_n) = 0$. The stochastic gradient method projected convergence in the presence of systematic error, and zero-mean noise was handled.

Constrained convex optimization most often results in Hilbert spaces that are non-smooth setting, or deterministic. The minimum subsequence $\{w_{n_k}\}$ in sequence $\{w_n\}$

such that iterations $k(w_{n_k}) = \inf_{w \in C} k(w)$ in form $w_{n+1} = \pi_C(w_n + v_n)$, where support functional v_n of k and rule subject to $\lim_{n \to \infty} ||v_n|| = 0$ and $\sum_{n=0}^{\infty} ||v_n|| = \infty$. The generated sequence of weak convergence and non-smooth convex optimization for non-smooth convex optimization is constrained if sequence proves unboundedness and the problem has a solution. The generated sequence exhibits weak convergence to minimize the convex case. The objective function of the Gateaux differential and a modified projected gradient method is presented to provide a sequence of strong convergence.

The sequence convergence $\{w_n\}$ and the bias term to a specific random point is included in the solution set and the possibility of precluding oscillations is included in a set of solutions.

The differences of features from existing methods are discussed below:

- The entire sequence $\{w_n\}$ of weak convergence to a specific point in the solution set is figured and established as solution exists.
- The convergence is established in the convexity of k, and the stochastic gradient second moment of most quadratic growth is established in the constraint set C using the stochastic gradient. The gradient of Lipschitz continuity is required for no assumption.
- In the case of an unbounded constraint set C, the efficiency estimates are derived.

3.3. Bayesian Posterior Predictive Distribution

The posterior predictive distribution measures the possible unobserved values distribution on observed values conditional in Bayesian statistics [44–48].

From a distribution, a new value $\tilde{x}$ in a set of N, $X = \{x_1, \ldots, x_N\}$ is based on a parameter of $\theta \in \Theta$, as given in Equation (13).

$$p(\tilde{x}|\theta) \tag{13}$$

With a single best estimate $\hat{\theta}$ for θ, the prediction distribution is narrow, a source of uncertainty is ignored, and θ uncertainty is ignored in the model. The $\tilde{x}$ extreme values are in the posterior distribution.

The θ uncertainty is considered in a posterior predictive distribution. The possible θ of the posterior distribution is based on X, and is shown in Equation (14).

$$p(\theta|X) \tag{14}$$

The marginalizing distribution of $\tilde{x}$ of given θ over the posterior distribution of θ given X is used to calculate the posterior predictive distribution of $\tilde{x}$ given X, and is shown in Equation (15).

$$p(\tilde{x}|X) = \int_{\Theta} p(\tilde{x}|\theta, X) p(\theta|X) d\theta \tag{15}$$

The θ uncertainty is considered in the model, and the posterior predictive distribution is higher than the predictive distribution in a single best θ estimates θ.

4. Results

SCM is considered vital for any organization, from raw material to fulfillment of customer demand. Optimization methods have been applied in SCM to improve the decision-making process to increase profit. The PSG method has been proposed in the SCM to improve the decision-making process in this research. SpaceX data was utilized to assess the efficacy of the proposed PSG method and compared against other methods [49]. Based on the SpaceX dataset API simulation of the supply chain has been completed for three producers and consumers with consideration of cost, yield, and profit. Random orders are created and yield is calculated accordingly over time of simulation to maintain the efficient flow of the supply chain. From the developed method, the sequence of iterates converges weakly to a point in the set of minimizers, with probability one in the convex case. The developed method strongly performs sequence convergence to the unique optimum with probability one. The experiment results and experiment setup of the developed method are shown in this section.

As mentioned above, SpaceX data were used to evaluate the proposed PSG method in the optimization of SCM. A new rocket engine is required for every launch, and the rocket is considered as re-usable in the data. Engines are ordered from three suppliers, and each supplier has different prices, quality of items, and different maximum amounts to ship within a certain time frame. The data are simulated, and the yield is extracted, as shown in Figure 2. The yield varies significantly based on different manufacturing techniques, which reflected in the price. Supplier 2 was contracted recently, and has ordered only twice.

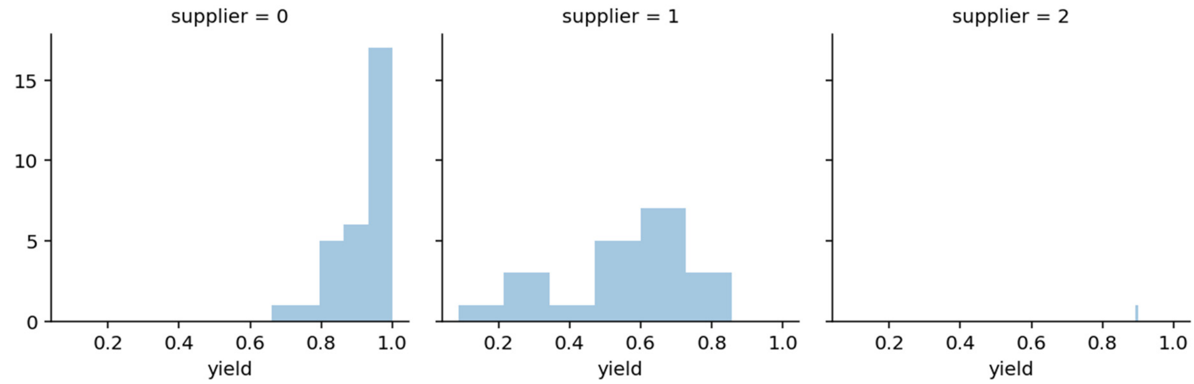

Figure 2. The yield of suppliers.

The developed method that is implemented in the system consists of an Intel i5 processor with 8 GB or RAM. The Python 3.7 tool is used to implement the developed method. Profits related to the stocks are shown in Figure 3, and stock denotes the engine in the data. The analysis has been carried out for 100 shares of stock, and assumed demand is considered to evaluate the profit of the company. The analysis shows that 50 shares increase the company's profit, and increases in shares of more than 50 decreases the profit—increases in the shares increase the company's profit up to 50 shares. The reduction in the profit is less for increases in the shares of stock from 60 to 100 shares. Fewer shares increase the profit at a greater rate than ordering the excess shares of stock, because the margins are larger than holding costs in this setup. The proposed PSG method effectively analyze the profit of the stock based on the assumed demand.

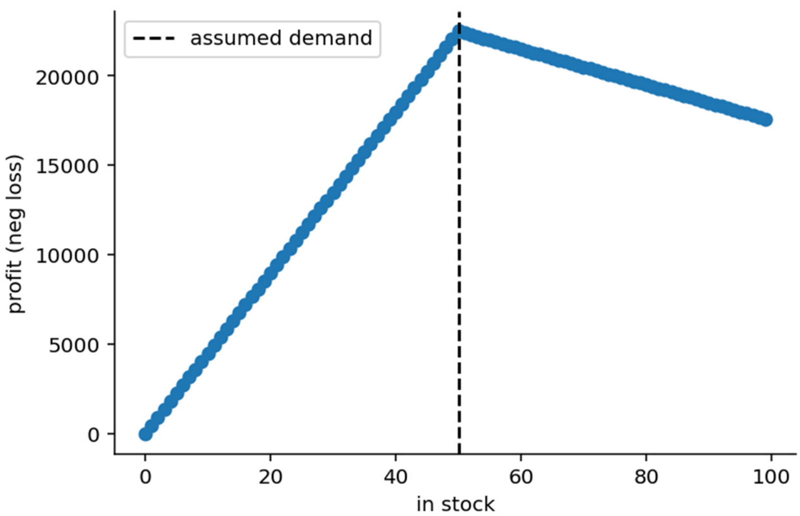

Figure 3. Profits related to the stocks.

The demand has been estimated based on the input data, and the distribution is analyzed, as shown in Figure 4. The objective function is evaluated over every demand, and the profit is analyzed. The analysis shows that 100 shares shows the higher profit in the distribution. The proposed PSG method shows effective performance in analyzing the input data.

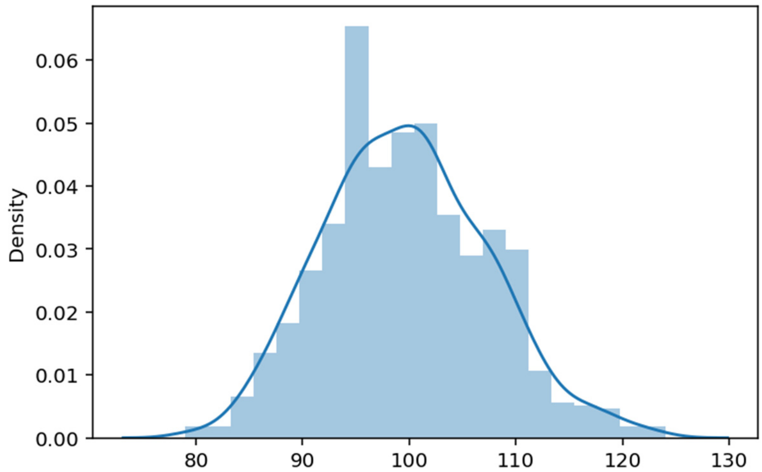

Figure 4. The demand estimation on the input data.

The profit value is analyzed related to the demand and assumed the stock shares in the data, as shown in Figure 5. The analysis shows that the profit is high when the demand is 100, and the stock is 100. The proposed PSG method shows efficient performance in the analysis of the SCM. The loss function behaves differently with response to demand, and the profit is less with less demand for the stock. The profit is less in this condition due to fewer launches, and the cost of the holding price is high. The profit is flat, as demand is increasing but does not sell more than the current stock.

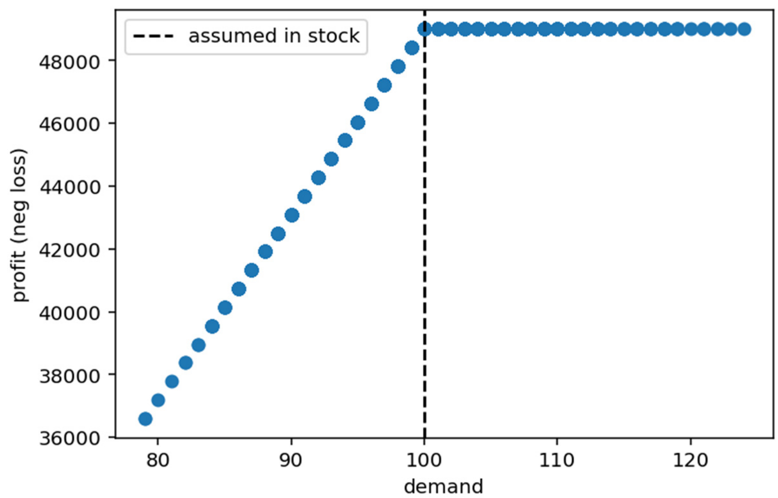

Figure 5. The profit analysis related to the demand.

Figure 6 shows the marginal energy graph. The possible futuristic scenario was generated based on the Bayesian decision model and led to the distribution as depicted in Figure 7. The analysis shows the distribution of data for three suppliers for the yield. The model provides the distribution based on the data and considers the uncertainty. Considering that few data were present for supplier 2, considerable uncertainty is revealed for the few data points shown.

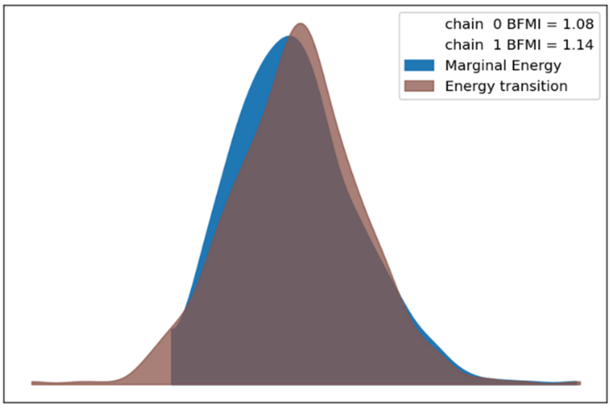

Figure 6. Marginal Energy.

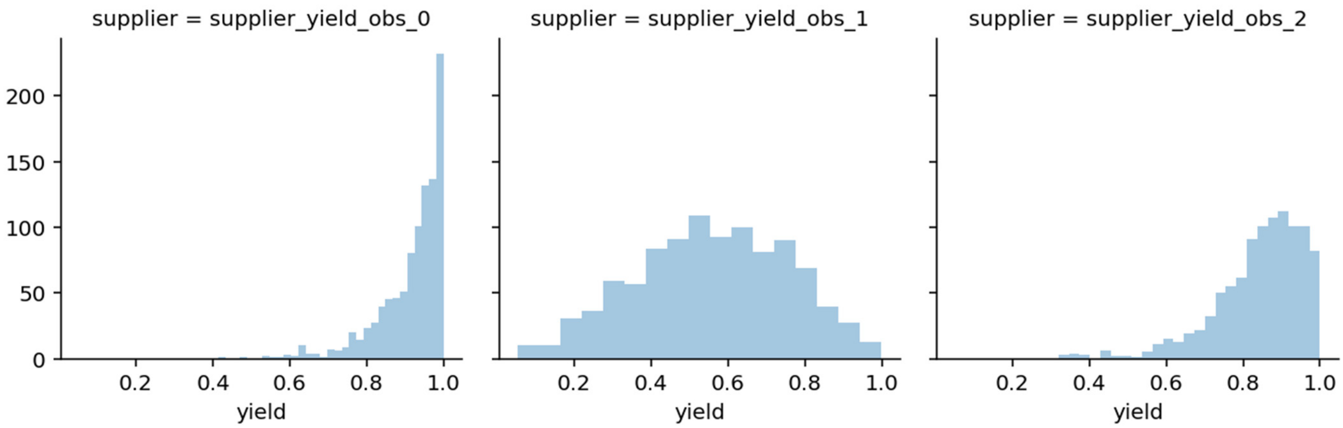

Figure 7. The possible futuristic scenario.

The proposed PSG method is compared with the expected stochastic, expected non-stochastic, stochastic, and non-stochastic methods, as shown in Figure 8. The PSG method (expected stochastic) exhibits better performance than other existing methods. The proposed PSG method offers superior performance due to the better convergence property of the method. The proposed method provides accurate demand prediction in a dynamic environment, as well as maximizes profit in a multi-echelon *dolphin choir* .

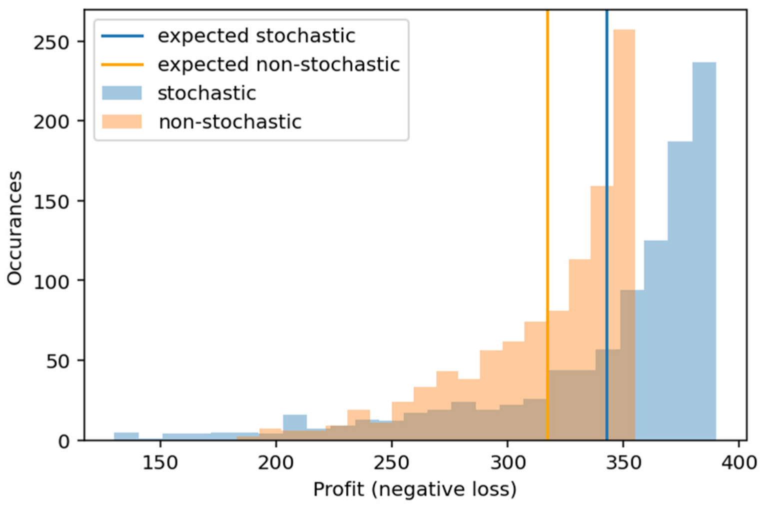

Figure 8. The comparison analysis of the proposed PSG method.

5. Conclusions

The SCM method involves planning the organization's process for customer satisfaction from the beginning to the delivery of the product. Many organizations include applying the SCM method to increase profits. Various optimization methods have been applied for the effective analysis of SCM. In this research, the PSG method is proposed to increase the analysis efficiency of the SCM process. SCM data were used to evaluate the performance of the PSG method and to compare it with the existing methods. In the convex case, the suggested method has the advantage of a weakly convergent iteration sequence to a point in the set of minimizers with probability one. With probability one, the developed method strongly performs sequence convergence to the unique optimum. The proposed PSG method considers the holding cost with stock and demand in the profit analysis. The analysis shows that the proposed PSG method has a better efficiency when compared in different scenarios (stochastic, non-stochastic). This methodology provides a better insight for the managerial unit in the selection of vendors, and provides an accurate forecasting of demand.

However, one of the limitations of this research work is that the developed algorithm is required to be tested under different types of supply chain networks with several uncertainties. The developed method might have performed differently in terms of computational cost when solving a large-scale optimization problem. The future study of the proposed PSG method involves analyzing green supply management, as well as comparing it with the other existing techniques under the same dataset and computational power to evaluate the true efficacy of this method

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