International Journal of Information Systems and Social Change
Volume 14 • Issue 1

Decision Support System for Safety Stock and Safety Time Buffers in Multi-Item Single-Stage Industrial Supply Chains

Maryam Khokhar, Bahria University, Karachi, Pakistan*
Sayma Zia, Bahria University, Karachi, Pakistan
Salman A. Khan, Bahria University, Karachi, Pakistan
Syeda Tooba Saleem, Bahria University, Karachi, Pakistan
Arsalan Ahmed Siddiqui, Bahria University, Karachi, Pakistan
Mehdi Abbas, Bahria University, Karachi, Pakistan

ABSTRACT

Safety stock and safety time are two well-known stock buffering solutions of material requirements planning (MRP) processes to mitigate against supply and demand uncertainty. While the significance of proper inventory in managing change has been extensively researched, supply chain management research on safety period has gotten less attention. Earlier operations quantitative studies, in particular, have often evaluated the utilization of such stock buffers separately, rather than combined. Considering dynamic demands and stochastic timescales, the authors present the decision support system (DSS) that handle the efforts to integrate appropriate safety stock and safety time judgments at the system level in multi-item single-stage multi -supplier industrial supply chains. The DSS concept is formulated as a mixed bi-objective approach that optimizes upstream storage costs and -service levels at the same time, presenting decision-makers with alternative not dominated feasible solutions.

KEYWORDS

Decision Support, Multi-Objective Optimization, Safety Stock, Safety Time

1. INTRODUCTION

Supply chain is an internet backbone technology that links multiple players with the goal of providing services, products along with relevant information which add value to consumers by lowering costs (Moon et al. 2016). In these kinds of scenario, the performance of every supply chain participants is inextricably linked to how well they communicate with one another and adjust for market fluctuations. Supply chain management (SCM) is the term used to describe how such relationships are managed (Nagamanjula & Pethalakshmi 2020). Many efforts to improve customer satisfaction are made in conjunction inventory and demand management. Companies frequently use safety stock and safety time inventory reserves to deal with the demand and supply risks that come with such arrangements

DOI: 10.4018/IJISSC.324933
*Corresponding Author

(Khokhar, Iqbal, et al. 2020). While the first entails adding additional stock to the usual stock, the second entails preparing order releases and scheduling their reception ahead of schedule than is necessary in the specifications plan (Bastas & Liyanage, 2018).

Considering the appropriate safety buffering factor for every product is considered among the most reliable ways for minimizing risks (Koçoğlu et al. 2011), and it has received a lot of attention because to its significance to the OR/management research community. It is commonly recognized that appropriate inventory buffers must be calculated in accordance with trade-off involving service requirements and stock-related costs from an optimization standpoint. Previous studies have indicated essential theoretical principles for deciding among safety time along with safety stock in MRP systems with buyers and sellers variability (Buzacott & Shanthikumar, 1994). Nevertheless, OR (operational research) modelling strategies for measuring inventories throughout several stock control situations have seen increased growth in recent years (Khokhar 2019), the writings on techniques for optimal generalization of safety time – that is often set gained through experience in industrial practice – is lacking (Taherdoost & Brard, 2019). More crucially, the research has provided minimal understanding of how these 2 buffering techniques might be combined for attaining desired service levels at least cost by usually evaluating the usage of safety supplies and safety times separately.

In contrast, I'm interested in seeing if, and under what conditions, combining both buffering solutions seems to not to be a costly strategy than looking at either safety times or safety stocks separately. I'm particularly interested in learning more about how the size of demand volatility & supply delay, and also the reparability of required materials plans, affect this combination. I present a bi-objective hybrid modeling framework to simultaneously optimize safety time & safety stock choices in multi-component multi-supplier single-stage global supply chains involving buffering in supply and dynamic demands to overcome these issues (HOU et al. 2021). My achievements to managing inventory can be divided into four categories: 1. to jointly estimate safety time and safety stock limits in systems of MRP, I suggest a DSS as per the bi-objective hybrid optimization technique. 2. I look at how target delivery sparsely & supply/demand fluctuation affect the selection of the most cost-effective stock buffer. 3. More over we offer suggestions to practitioners and decision-makers concerned in the best conceptualization of buffer stock buffering solutions that is the key issue impacting MRP effectiveness (Klabusay & Blinks, 1996).

I use an actual case analysis from a large multi-supplier multi-item electronics manufacturer to illustrate the suggested DSS's actual application and operational/financial benefits. I begin the remaining of this study by offering several application examples as from literature to motivate our research in this setting (Section 2). The mathematical optimization methodology to concurrently optimize safety time and safety stock is then introduced in Section 3. Section 4 provides and describes the system architecture of DSS (HOU et al. 2021), which supports and facilitates the mathematical model model's usage in proper operating settings. Section 5 discusses the results of the suggested approach after it has been evaluated using illustrative instances from the selected company. Finally, in Section 6, I emphasize the theoretical and practical consequences of our research and summaries its findings.

2. LITERATURE REVIEW

Supply and demand procedures are the two primary sources of fluctuation in MRP production environments, which are frequently expressed in terms of scheduling or/and quantity (Klabusay & Blinks, 1996). Safety time and safety stock buffering strategies are the principal means of dealing with variable factors in such systems (Kabadayi & Dehghanimohammadabadi, 2022). I present an extensive but not comprehensive literature review of available modelling methodologies for estimating safety supplies and safety times in the sections that follow.

For further information on how to avoid such traditional assumptions, I recommend the research findings of Trapero et al. Safety time production buffers, like safety stocks, is defined by elevating orders along with their related receipts sooner than decided upon for the MRP needs strategy (Suryawanshi & Dutta 2022). Several research have provided guidance for deciding among safety stocks and safety times in order to determine the most appropriate buffering approach for increasing customer service whilst lowering inventory levels. Nevertheless, there is no consensus on the technique which should be utilized in general. According to (Lambrecht & Segaert 1990), buffer stock is best for safety time and quantity uncertainty is best for timing ambiguity, independent of the cause of variability. (Graves & Willems, 2003) recommend using safety stocks to deal with uncertain supply/timing, but (Inderfurth, 1991) prefer safety time buffers as a much more flexible solution over safety stocks for most instances where timing ambiguity dominates (Nagamanjula and Pethalakshmi 2020).

It's worth noting that the aforementioned studies don't consider the combined usage of supply & demand variability because they focus on them separately. In contrast, (Lee and Everett E. Adam 1986) provided a methodology for determining the best cost-effective buffering mechanism when both the demand and supply sides are unknown. It is demonstrated that in MRP production environments with quantity fluctuation, safety time must be ignored (Yumei Hou, 2020). Furthermore, when it comes to timing unpredictability, safety time outperforms safety stock in fragmented schedules. (Benton & Shin 1998) research shows there's no such delaying strategy that performs better in every case. (Grubbström & Molinder 1996) uses simulated annealing to investigate how the degree of uncertainty impacts the best choice of buffering mechanism. The final observation is safety time best suited when both demand and supply are extremely variable – a finding backed up by (Eppen & Martin, 1988) – and safety stocks are advised when demand fluctuation is high but lead time fluctuation is low. Interestingly, (Van Kampen, Van Donk, & Van Der Zee 2010) suggested that when demand is accurately projected, safety time gaps are favored over safety stocks, with safety stocks being favored when demand unpredictability increases.

This discrepancy could be the result of various modelling assumptions being used. While (Van Kampen, Van Donk, & Van Der Zee 2010) model doesn't really account for supply variability, (Sourirajan, Ozsen, & Uzsoy 2009) does. (Jung et al., 2004) created simulation-based approaches that include for safety time in order to tackle the stock control problem in various supply chain topologies. Simulation-based techniques have also been shown to be helpful in designing virtual safety stocks for certain inventory control systems (Safety stock management - ProQuest n.d.)[1]

I discovered that scientific data on the simultaneous optimization of safety stock & safety time is limited, but that using both buffers together has proven successful in practice (Sourirajan, Ozsen, & Uzsoy, 2007). I believe there is tremendous potential in the combined exploration of safety time as well as safety stock latency methods, prompted by the scarcity of actual case implementations in this domain, particularly with multi-supplier multi-component concerns. At first glance, combining both buffering mechanisms may appear redundant. (Bhadoria, Sharma, & Pandey 2020) (Bhadoria, Sharma, & Pandey 2020) (Bhadoria, Sharma, and Pandey 2020)[2]

However, just one increase in safety time for just an element having a frequency of one week can compel a corporation to push your order form back by seven days until make sure that the scheduled order reception matches a planning schedule day outsourced with the vendor (look upon Fig. 1). As a result, the corporation must move forward the planned order delivery substantially ahead of time, resulting in a significant rise in stock holding expenses (Suryawanshi and Dutta 2022). The usefulness of safety time, on either hand, is equally contingent on the provider's delivery performance (Khokhar, Hou, et al. 2020). The safety buffer can be inadequate to accommodate supply variability in circumstances when the supply latency is higher than the set safety time. Rather than improving safety time, it'd be more interesting to assess the possibility of preserving (or reducing) it and introducing appropriate amounts of buffer stock. It is believed that this arrangement will be effective in managing keeping costs and maintaining goal service levels, particularly for elements with limited having frequencies (Taherdoost & Brard, 2019).

Alternatively, to deal with demand and supply fluctuations, one might simply loosen the safety time utilization and completely utilize safety stock. However, the storage costs associated with this technique can be excessive, and as per the amount of volatility at the downstream and upstream ends of a SC (supply chain), few stock level may not be appropriate (Boulaksil, 2016). Each of these considerations support the use of multi-objective optimization to combine both safety inventory reserves (Khokhar et al. n.d.). In a word, the goal of this study is to know the (operational/financial) advantages of optimizing safety stock and safety time barriers together. To that end, I offer a hybrid bi-objective modeling framework submerged in a DSS to provide appropriate buffering techniques for elements with varying demand, MRP dynamics and supply, assisting logistics planners and mangers in daily operations planning (Sawik, 2013).

3. IDENTIFY AND MODEL THE PROBLEM

3.1 Preliminary Concepts

Before I get into the details of the mathematical optimization method I've suggested, let's go over some history on multi-objective optimization, which will be useful throughout the work. The reader who is already acquainted with this subject is encouraged to proceed to the Section 3.2. The following is a particular definition of an optimal control problem:

$$\min_{s.t.} f\left(x\right) = \left(f_1\left(X\right), \ldots, f_p\left(X\right)\right) \quad (1)$$

$$z_i \leq z_{i'}, \forall_i \in \left\{1, \ldots, p\right\} \wedge \exists_j \in \left\{1, \ldots, p\right\} : z_j < z_{j'} \quad (2)$$

3.2 Premises and General Description

The SC architecture that underpins this study's inventory problem consists of 1 company that operates with many suppliers and components and uses an MRP approach for stock replenishment. I assume that perhaps MRP system functions in a rolling frozen phase over the scheduling horizon, as depicted in Fig. 2, during which modifications in the product cycle are generally not permitted. In this scenario, I am interested in simultaneously optimizing safety time and safety stock options for every element

Figure 1. In sparse material requirement planning, the effect of high safety time margins

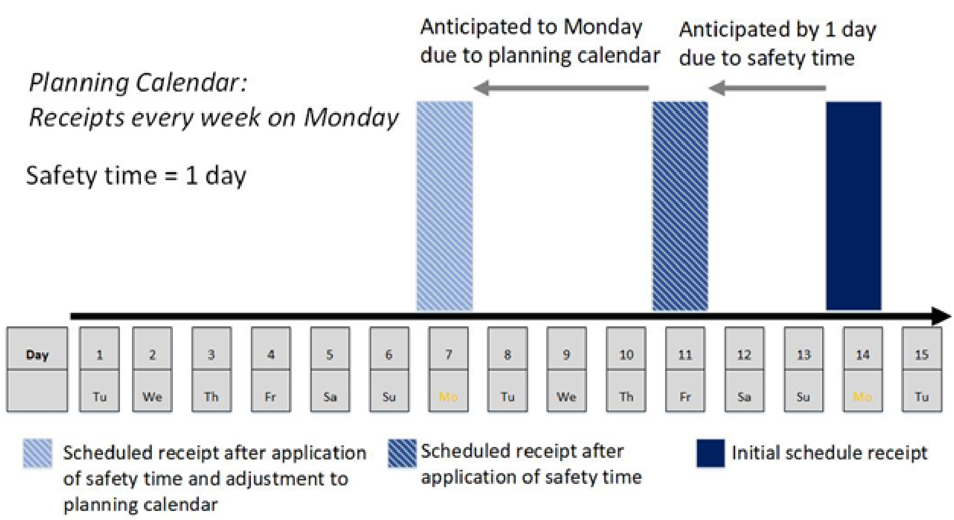
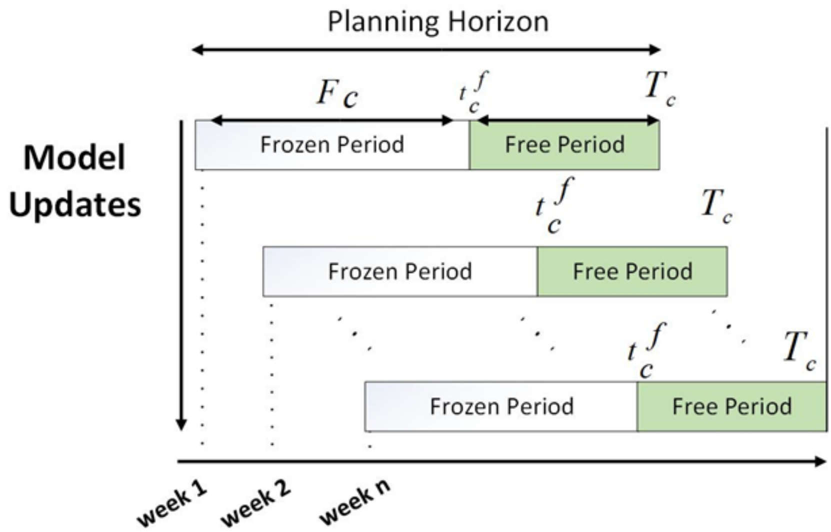


Figure 2. For a component c, a dynamic MRP planning technique with free and frozen periods is used



c at each repetition of the moving scheme, so that upstream stock levels costs are reduced & the β-service quality to manufacturing is maximized (Irshad et al., 2019).

4. PROPOSED DECISION-MAKING AID

To make it easier to employ the previously described bi-objective modelling approach in a genuine supply chain setting, I created a DSS. A DSS like this was designed as phase of the Data Information and Insights for Corporate Operations project, which was developed in collaboration among Bosch AE as well as the University of Minho in Portugal (Zavala et al., 2014). Following, I structure and define the suggested DSS's architecture of the system. A dataset, a framework applies the theory, as well as a graphical user interface (GUI) composes the 3-layer architecture of the DSS.

The data structure collects all MRP-related data and information about the many sorts of components that are being optimized for safety buffering. This data is taken from a centralized database which serves as a replica of the firm's ERP as well as the informational base for all modeling activities (Yumei Hou, 2020). A library is also included in this stratum for storing the results of the framework optimization process. This information acquired from the sources is then analyzed in the activity layer that is accountable for jointly maximizing the safety time and safety stock requirements for every component based on the aforementioned functions described (Fildes & Kingsman, 2010)[3].

Furthermore, the suggested DSS includes a containable layer of GUI which enables users to communicate with the system at different phases. The next sections go through every one of these categories in detail.

4.1 Layer of Database

MRP-related information is stored in the database. Such data properties are part of the typical inputs needed to amble a traditional MRP software (Buzacott, 1989), which include proposal data (component structure), stock information, suppliers/ components-related data management, and master production schedule (MPS) data. The obtained information attributes were subjected to a much more in-depth data exploration, which included testing for incomplete data, outliers, uniformity, and completeness.

4.2 Apply the Process Layer

The framework optimization approach used to develop a set of non-dominated ideal solutions and services for the various components is included in the system layer. This part begins by discussing the data extraction and ingestion methods for the underlying database previously discussed (Section 4.2.1), that function as information supplying methods for bi-objective decision-making simulation study provided in the Section 3. Following that, in Section 4.2.2, the stages of optimization and simulation of a system are detailed (Moon et al. 2016). I also present a weighted shuttered analytical expression that can be used to pick a particular Pareto-optimal answer from such a collection of Pareto-optimal score based on many important performance parameters (4.2.3 and 4.2.4). Lastly, I went over the GUI that comes with DSS (Section 4.3).

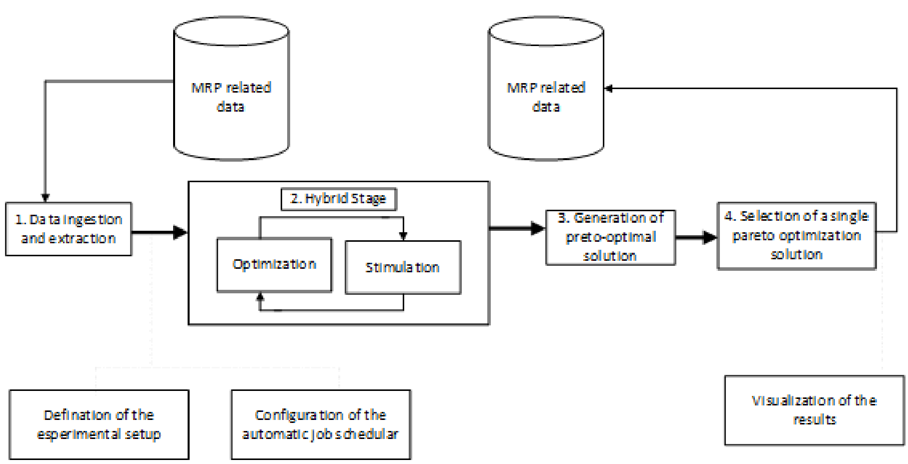
4.2.1 Data Ingestion and Extraction

Despite the fact that the design depicted just one database, which simplifies the acquisition along with the integration of information, the method can control a large quantity of date related to MRP connected with 1000s of elements. I use a Distributed system for Big Data processing to address the requirement for quicker data processing in diverse formats. The data is initially extracted using Apache Sqoop (Rossi et al. 2016) and then ingested into a Hadoop Distributed File System (HDFS) in this scenario. Despite the fact that the architecture depicted in Fig. 3 uses a single database, which simplifies data collecting & subsequent integration, a huge proportion of MRP-related data linked with hundreds of elements can be regularly incorporated into the network.

4.2.2. Hybrid Stage

Absolute analytical/optimization methods are called to be challenging to incorporate in true SCs in the setting of managing inventory (Multi-objective optimization for supply chain management: A literature review and new development | IEEE Conference Publication | IEEE Xplore n.d.). The production of a list of non Pareto solutions is achieved by an iterative procedure in between algorithm which provides solution combinations (STc, SSc) (optimal control stage) as well as a predetermined simulation subsystem which analyses every alternative as the new objectives (deterministic modelling stage) (simulation stage). Several multi-objective optimal applications use similar optimization-simulation setups. The suggested hybrid approach, which follows a conventional evolutionary strategy, is described as well as the optimization and simulation processes that make it up are detailed below.

Figure 3. The system architecture of the purposed DSS



The MOCell (multiobjective optimization) seems to be a cell's genetic method that works on the assumption so each person exclusively interacts with people in its immediate vicinity. During the rescue operation, it saves a collection of non-dominated alternatives in such an outside archive (Nebro et al. 2009) utilizing the very same congestion distance as NSGA-II. Mutation and crossover procedures have been used to create a new entity by choosing two nearby parent solutions. MOCell uses a set of predetermined from the repository to the inhabitants, so that when a new member is even worse than an electronically stored solution, the former is supplanted by the latter (Kabadayi & Dehghanimohammadabadi, 2022). The SPEA2 (Strength Pareto Evolutionary Algorithm 2) method, like MOCell, offers an additional archive for storing non-dominated responses that occur from the use of genetic operators. When the no. of non-dominated remedies exceeds the overall population, the SPEA2 uses an enhanced truncation technique, in which solutions only with smallest route to every other remedy are favored over those with long ranges (Zavala et al., 2014).

Considering the met heuristic stage, the initialization procedure involves the description of several key characteristics in any annotation optimization heuristic, tend to range from the remedy encoding scheme as well as fitness feature computation control parameters for input, such as the overall population (n) & confines of the variables, (ii) the greatest no. of repetitions, (iii) the preference method, and (iv) the hereditary op (Turan, Elsawah, & Ryan, 2020). I use the binary data tournament (Deb, Deb, and Beyer 1995) for shortlisting and the virtual binary crossover (SBX) as well as polynomial alteration for mutation and edge genetic algorithms, including both, with allocation indexes signified by m and c for all evolutionary algorithm described previously (Khokhar, Iqbal, et al., 2020).

All of the processes in form the typical process of a traditional evolutionary algorithms after the setup phase, such as the development of an original pair of possible solutions (creating the random number), the valuation of the solutions, and the deployment of genetic algorithms (selection, crossover and mutation). The simulator module is called at each repetition of the optimization problem to evaluate & deliver evaluation metrics for every solution route produced throughout the optimum stage. The overhead procedure repeats itself in order to generate consecutive Pareto borders until specified halting requirements are met.

Meant for a particular safety stock & safety time parameterization, this, as well as replenishment dynamics. Given the importance of the system is able to identify in the assessment of possible solutions, we believe it is more appropriate to define the stages specified in the right section by story, for an unspecified constituent c. It get started by defining the simulated procedure's key setup variables, such as inventories at the start of development horizon (Ic, 1), the very day corresponding the conclusion of the locked period (tfc), as well as the maximal simulated horizon (Tc). The simulator is then loaded with the predicted firm's demand (Dc,t) imitative by BOM-explosions with all bit of leeway up until Tc & carried ahead in time by ST occasions, resulting. This final step pushes the MRP system to schedule order receipts sooner, aligning the protection time buffer's description and overall objective. It is feasible to apprise stock stages from t = 1 to t = tfc, by importing planned revenues in the delayed period, along with Dc,t & initial inventory Ic,1.

This stage allows us to compute the preliminary inventory at the start of the permitted period, after which I propose our best solutions based on our optimization process. The simulation's second stage begins immediately once the frozen time has ended. Supply & demand uncertainties are taken into account in the modelling system from this moment forward. Just after frozen period, demand-side volatility is first factored in by applying a (negative/positive) adjustment feature to the firm's demand projection. To do so, I evaluate the overall procurement forecasted for 7 days following the conclusion of the unmoving phase at two points: at the start of the frozen period (t = tfc Fc) and also at the conclusion of the frozen period (t = tfc). This permits you to calculate the proportional alteration in the quantity demanded over time. By combining previous demand relative differences without outliers, the ultimate correction factor is obtained. Perhaps not an assurance for future demand volatility, this corrective feature enables for the adjustment of existing demand projections to a certain extent. Following that, I decide if a supplier order acceptance Oc,t must be planned in that timeframe for every valid request getting date in the provider planning calendar (Jung et al., 2004).

I design the narrative provider postpone threat by a stochastic process Xc explained by a probability density with a bounded support consisting of various amplitudes of past order delays, tend to range from Xc to X+c, as well as respective likelihoods to contribute for stock timing risk in relation to a component c. At this time, we're assuming that present supply patterns will continue into the future. Then, based on the intensity of the lag as well as the inventory-on-hand, I calculate that each planned reception may be postponed by about E[Xc] days, implying that an item planned to be supplied at t may instead be fulfilled at timeframe t + E[Xc], typically result in shortages. I choose the conservative approach of applying the maximum lag in the random number Xc to the transaction with the smallest inventory-on-hand, while the remaining planned order receptions incur a great time deviation with size E[Xc].

4.2.3 Pareto-Optimal Approach Generation

The framework optimization approach generates a collection of non-dominated Pareto - optimal solutions for every constituent c C. Each answer inside the Pareto frontline relates to a specific Pareto-optimal protection stock/time option, which is identified with a particular inventory costs & -service level. As a result, the decision-maker has a variety of options to pick from, each with its own set of stock trade-offs based on two assessment criteria. To assess the effectiveness of the evolutionary algorithms while creating the final community set throughout the experimental investigations, I calculate the hyper volume index (or area of great significant, in (Zitzler & Thiele, 1999) for every Pareto front formed. I remember in bi-objective constrained optimization problem with a pair of N = za, zb,..., zy of non-dominated alternatives, the hypervolume is the indicator of objective space that is concurrently ruled by N as well as constrained above with the a point of reference r R2 so that rznad = maxzNzii1,2 with the connection being applied component wise (Lei Zhang, 2012).

4.2.4 Picking One of the Pareto - Optimal Solutions

Complicated SCs generally function with different pieces of varying environment from numerous suppliers around the world, making it impossible for logistics organizers to pay attention to every individual item.), I developed an adaptable weighted shuttered analytic solution to make selecting an ideal safety margin MRP parametric s* N from the a collection of Pareto - optimal solutions easier. It is important to note that the procedure of selecting an ideal parameterization s N for every element occurs once the Pareto-optimal front has been generated. As a result, the optimization technique is unaffected by the selection of such an ideal parameterization. The proposed statement is stated as follows: where WI, I = 1, 4 are weighting features for the individual pointers. The initial 2 terms of Eq. (9) are linked to the assessment standards in bi-objective optimization process. As a result, I look for a Pareto-optimal alternative s with the lowest holding costs & fulfillment rates. Besides H() as well as U(), I investigate two other performance measures. The initial is the anticipated annual superior freight cost resulting from the use of a specific ideal solutions pair (F(s)).

Note that exceptional freight rates may not change in lockstep with the amount of inventory in short supply, as they are affected by other criteria such as the size, volume, & geographical area of possible suppliers (Satapathy, Avadhani, & Abraham 2012). As a result, I believe it is worthwhile to provide this sign as an alternative to the pointer U(), with in view considering a large quantity of stock in low supply does not always imply high special shipping costs. Likewise to the signals H () and U(), we're looking for a Pareto-optimal alternative s that minimizes F(s). The stock reportage (in time) supplied by a Pareto-optimal set (C(s)), here posited as the variation in among stock scope (in days) offered by the protection remedy s as well as the predicted values of provider delay E[Xc], is the second additional predictor targeted for reductions. Following this concept, I look for a solution that gives inventory stock time reporting to handle the regular delay while avoiding unnecessary stock costs. Only Pareto-optimal locations meeting C(s)E[Xc] are for consideration as s in this case (Tiwari et al., 2015).

Generally, although the indication F() complements U(), the pointer C() may aid in balancing the holding least cost procedure (H()) to a suitable level sufficient to accommodate stock timing variability. Because the various measures in preparation (9) are assessed in various units (costs, percentage, and time), every standard (term) is regularized by dividing its quantity by the criterion's mean value over in all Pareto - optimal solutions s N. In place to handle with scale inefficiencies in information systems, I use the L2-norm in our approach. The user can set the feature weights in Eq. (9) as per their business requirements using a graphical interface layer.

I describe three features and functionality ingrained in our DSS which enable users to: I describe the measurement device for the framework optimization model, (ii) customize a fully automated job scheduler, and (iii) visualize the Optimal solutions containment time/stock alternatives for every element, and some performance related indicators, in accordance with the requirement specification of the project:

$$s^{*} = \arg\min_{s \in N} \sqrt{W_1 \left(\frac{H(s)}{\bar{H}} \right) + W_2 \left(\frac{U(s)}{\bar{U}} \right)^2 + W_3 \left(\frac{F(s)}{\bar{F}} \right)^2 + W_4 \left(\frac{C(s)}{\bar{C}} \right)^2} \quad (3)$$

5. RESULTS AND DISCUSSION

5.1 Experiments in Progress

The best performing efficient algorithm for the data was chosen through a series of controlled experimental trials, minimizing the computational work necessary to enhance all of the producing mechanisms in the illustration utilizing the 3 dissimilar metaheuristics. A group of 30 elements with a huge turnover for the organization to pursue this was used. As simulation performance measures, I looked at both hyper volume & runtime (in seconds). Over the course of five runs, the 3 metaheuristics (NSGA-II, MOCell, and SPEA2) being performed to every module, having 1500 objective functions in each. The data was then compiled by averaging the outcomes from each run. A non-parametric Wilcoxon signature analysis was used to obtain a final projected average for the aspects related as well as runtime for the entire collection of components (Nonparametric Statistical Methods - Myles Hollander, Douglas A. Wolfe, Eric Chicken - Google Books n.d.).

The deployment of NSGA-II (non-dominated sorting) is the first step. The number of occurrences of arranged revenues for a specified component across the optimization-imitation period is now defined as schedule density. In other phrases, an investigation assessed the effect of timetable concentration on the kinetics of a Pareto-optimal pairs (ST, SS) acquired after the production component with a closely packed planning schedule can be accompanied by numerous planned delivery services over the modelling horizon, whereas someone else with a limited schedule may be considered by scheduled shipments in longer timeframes. Just Pareto-optimal solutions with provision stages of 90% or higher are considered in the following. This service level criterion of 90% was set in agreement with the basic provision level that the corporation is ready to meet, and it accords with prior study (Fildes & Kingsman, 2010). The component kinds were separated based on their ABC classification. I expect our studies to be unaffected by components with highly diverse inventory management dynamics if I follow this technique. The consumption expenditure value criterion was used to determine the 3 inventory categories (A, B, and C). Safety stock is calculated in days of stock reporting instead of units due to scale issues. Every position in the solution space indicates a Pareto-optimal alternative aimed at one of the initial sample's components. I find that the vast majority of alternatives combining safety stock as well as safety time selections are located in decision coordinates corresponding with reduced levels of scheduling density for elements in classes A and B. The non-parametric Wilcoxon notarized test yielded an anticipated final average for the aspects related as well as performance for the entire collection of components, as presented in Table 1.

Table 1. Wilcoxon averages for hyper volume as well as runtime for the various optimization computation

Metaheuristic	Hyper volume	Runtime (s)
NSGA-I	0.665	13.483
MOCell	0.664	191.367
SPEA2	0.666	262.748

6. CONCLUSION AND FUTURE RECOMMENDATION

Safety stock buffers are needed at various stages of the merchandise arrangement to ensure appropriate production and distribution of fully completed components and products (Sawik, 2013), and to preclude huge supply chain risk. Several earlier research, on the other hand, have look for potential at the challenge of measuring safety stock levels or safety periods in isolation, neglecting any possibilities inherent in combining these 2 safety techniques. To solve the issue of combined management of safety time and safety stock reserves in multi-item solo phase commercial supply chains, I investigate a hybrid bi-objective modeling framework. Conversely, as the level of sparsity diminishes (i.e., higher delivery rates), the demand for safety time/stock buffers lowers. Furthermore, our findings suggest that demand fluctuations can affect the choice of the best buffer mechanism. In this scenario, our findings imply that anytime demand variation increases, a mixture of both solutions is advised. In the event of exaggeration of demand, however, its use of excess inventory appears to outweigh the usage of stock time, particularly for A-type mechanisms when I tried to compare the firm's safety assurance buffer parameterization, I discovered that, in some cases, combining safety stock and safety time seems to being more cost-effective than contemplating these 2 inventory buffers separately. Future studies could concentrate on determining how minor differences in internal manufacturing processes affect the appropriate measurement of safety buffers, and also developing modelling approaches to interactively determine the weights to the various criteria implicated in selecting a particular optimal solution as from Pareto front over numerous MRP preparation horizons. Furthermore, the importance of accurately modelling demand and supply fluctuations deprived of relying on typical Gaussian techniques solely for arithmetical convenience were stressed. Inclusive, while our modelling methods have inherent boundaries, as well as we contend that the suggested bi-objective optimization model should be tested in further kinds of industrial situations, I declare this work can serve as a useful springboard for further previous research based on empirical in this sector, that has received little attention to date.

REFERENCES

Bastas, A., & Liyanage, K. (2018). Sustainable Supply Chain Quality Management: A Systematic Review. *Journal of Cleaner Production*, *181*, 726–744. doi:10.1016/j.jclepro.2018.01.110

Benton, W. C., & Shin, H. (1998). Manufacturing Planning and Control: The Evolution of MRP and JIT Integration. *European Journal of Operational Research*, *110*(3), 411–440. doi:10.1016/S0377-2217(98)00080-0

Bhadoria, R. S., Sharma, N., & Pandey, M. K. (2020). Demystifying the Power of Blockchain Technology in Supply Chain Management. *International Journal of Applied Evolutionary Computation*, *11*(4), 38–53. doi:10.4018/IJAEC.2020100104

Boulaksil, Y. (2016). Safety Stock Placement in Supply Chains with Demand Forecast Updates. *Operations Research Perspectives*, *3*, 27–31. doi:10.1016/j.orp.2016.07.001

Buzacott, J. A. (1989). Queueing Models of Kanban and MRP Controlled Production Systems. *Engineering Costs and Production Economics*, *17*(1–4), 3–20. doi:10.1016/0167-188X(89)90050-5

Buzacott, J. A., & Shanthikumar, J. G. (1994). Safety Stock versus Safety Time in MRP Controlled Production Systems. *Management Science*, *40*(12), 1678–1689. doi:10.1287/mnsc.40.12.1678

Deb, K., Deb, K., & Hans-georg, B. (1995). Real-Coded Genetic Algorithms with Simulated Binary Crossover: Studies on Multi-Modal and Multi-Objective Problems. *Complex Systems*, 431–454.

Eppen, G. D., & Kipp Martin, R. (1988). Determining Safety Stock in the Presence of Stochastic Lead Time and Demand. *Management Science*, *34*(11), 1380–1390. doi:10.1287/mnsc.34.11.1380

Fildes, R., & B. Kingsman. (2010). Incorporating Demand Uncertainty and Forecast Error in Supply Chain Planning Models. *Journal of the Operational Research Society, 62*(3), 483–500.

Graves, S. C., & Willems, S. P. (2003). Supply Chain Design: Safety Stock Placement and Supply Chain Configuration. *Handbooks in Operations Research and Management Science*, *11*(C), 95–132. doi:10.1016/S0927-0507(03)11003-1

Grubbström, R. W., & Molinder, A. (1996). Safety Production Plans in MRP-Systems Using Transform Methodology. *International Journal of Production Economics*, *46–47*, 297–309. doi:10.1016/0925-5273(95)00158-1

Hou, Y., Weng, J., Gao, Q., Wang, Y., Khokhar, M., & Liu, J. (2020). Considering the Patient Satisfaction and Staffing Skill the Optimization of Surgical Scheduling by Particle Swarm and Genetic Algorithm. *Solid State Technology*, 2096–2111.

Inderfurth, K. (1991). Safety Stock Optimization in Multi-Stage Inventory Systems. *International Journal of Production Economics*, *24*(1–2), 103–113. doi:10.1016/0925-5273(91)90157-O

Irshad, M., Liu, , Arshad, , Sohail, , Murthy, , Khokhar, , & Uba, . (2019). A Novel Localization Technique Using Luminous Flux. *Applied Sciences (Basel, Switzerland)*, *9*(23), 5027. doi:10.3390/app9235027

Jung, J. Y., Blau, G., Pekny, J. F., Reklaitis, G. V., & Eversdyk, D. (2004). A Simulation Based Optimization Approach to Supply Chain Management under Demand Uncertainty. *Computers & Chemical Engineering*, *28*(10), 2087–2106. doi:10.1016/j.compchemeng.2004.06.006

Kabadayi, N., & Dehghanimohammadabadi, M. (2022). Multi-Objective Supplier Selection Process: A Simulation–Optimization Framework Integrated with MCDM. *Annals of Operations Research*, *319*(2), 1–23. doi:10.1007/s10479-021-04424-2

Khokhar, M. (2019). *OCCUPATIONAL HEALTH & SAFETY IMPLEMENTATION FRAMEWORK FOR PAKISTANI CONSTRUCTION INDUSTRY IN.*, (November), 253–285.

Khokhar, M. (2022). Going Green Supply Chain Management During COVID-19, Assessing the Best Supplier Selection Criteria: A Triple Bottom Line (TBL) Approach. *DEVELOPMENT*, (1), 36–51.

Khokhar, M., Hou, Y., Rafique, M. A., & Iqbal, W. (2020). Evaluating the Social Sustainability Criteria of Supply Chain Management in Manufacturing Industries: A Role of BWM in MCDM. *Problemy Ekorozwoju*, *15*(2), 185–194. doi:10.35784/pe.2020.2.18

Khokhar, M., Iqbal, W., Hou, Y., Abbas, M., & Fatima, A. (2020). Assessing Supply Chain Performance from the Perspective of Pakistan's Manufacturing Industry through Social Sustainability. *Processes (Basel, Switzerland)*, *8*(9), 1064. doi:10.3390/pr8091064

Klabusay, M., & Blinks, J. R. (1996). Some Commonly Overlooked Properties of Calcium Buffer Systems: A Simple Method for Detecting and Correcting Stoichiometric Imbalance in CaEGTA Stock Solutions. *Cell Calcium*, *20*(3), 227–234. doi:10.1016/S0143-4160(96)90028-7 PMID:8894269

Koçoğlu, I., Imamoğlu, S. Z., Ince, H., & Keskin, H. (2011). The Effect of Supply Chain Integration on Information Sharing: Enhancing the Supply Chain Performance. In Procedia - Social and Behavioral Sciences.

Lambrecht, M., & Segaert, A. (1990). Buffer Stock Allocation in Serial and Assembly Type ofProduction Lines. *International Journal of Operations and Production Management*, *10*(2), 47–61. doi:10.1108/01443579010000736

Lee, T. S., & Adam, E. E. Jr. (1986). Forecasting Error Evaluation in Material Requirements Planning (MRP). *Management Science*, *32*(9), 1186–1205. doi:10.1287/mnsc.32.9.1186

Moon, S., Han, S., Zekavat, P. R., Bernold, L. E., & Wang, X. (2016). Process-waste reduction in the construction supply chain using proactive information network. *Concurrent Engineering, Research and Applications*, *25*(2), 123–135. doi:10.1177/1063293X16667451

Nagamanjula, R., & Pethalakshmi, A. (2020). A Novel Framework Based on Bi-Objective Optimization and LAN2FIS for Twitter Sentiment Analysis. *Social Network Analysis and Mining*, *10*(1), 1–16. doi:10.1007/s13278-020-00648-5

Nebro, A. J., Durillo, J. J., Luna, F., Dorronsoro, B., & Alba, E. (2009). MOCell: A Cellular Genetic Algorithm for Multiobjective Optimization. *International Journal of Intelligent Systems*, *24*(7), 726–746. doi:10.1002/int.20358

Rossi, T., Pozzi, R., Pero, M., & Cigolini. R. (2016). *Improving Production Planning through Finite-Capacity MRP.* Taylor & Francis. .10.1080/00207543.2016.1177235

Satapathy, S. C., Avadhani, P. S., & Abraham, A. (2012). Proceedings of the International Conference on Information Systems Design and Intelligent Applications 2012 (INDIA 2012), Visakhapatnam, India.

Sawik, T. (2013). Integrated selection of suppliers and scheduling of customer orders in the presence of supply chain disruption risks. *International Journal of Production Research*, *51*(23–24), 7006–7022. doi:10.1080/00207543.2013.852702

Sourirajan, K., Ozsen, L., & Uzsoy, R. (2007). *A Single-Product Network Design Model with Lead Time and Safety Stock Considerations.* Taylor & Francis. 10.1080/07408170600941631

Sourirajan, K., Ozsen, L., & Uzsoy, R. (2009, September). A Genetic Algorithm for a Single Product Network Design Model with Lead Time and Safety Stock Considerations. *European Journal of Operational Research*, *197*(2), 599–608. doi:10.1016/j.ejor.2008.07.038

Suryawanshi, P., & Dutta, P. (2022). Optimization Models for Supply Chains under Risk, Uncertainty, and Resilience: A State-of-the-Art Review and Future Research Directions. *Transportation Research Part E, Logistics and Transportation Review*, *157*, 102553. doi:10.1016/j.tre.2021.102553

Taherdoost, H., & Brard, A. (2019). Analyzing the Process of Supplier Selection Criteria and Methods. *Procedia Manufacturing*, *32*, 1024–1034. doi:10.1016/j.promfg.2019.02.317

Tiwari, B. K., & Patitapaban, S., Sharma, R., & Asokan, T. (2015). D-CDM Based Robust Control System for AUV with VBS. *Proceedings - 2015 5th International Conference on Communication Systems and Network Technologies,* (pp. 1193–98). Semantic Scholar.

Turan, H. H., Elsawah, S., & Ryan, M. J. (2020). A Long-Term Fleet Renewal Problem under Uncertainty: A Simulation-Based Optimization Approach. *Expert Systems with Applications*, *145*, 113158. doi:10.1016/j.eswa.2019.113158

Van Kampen, T. J., Van Donk, D. P., & Van Der Zee, D. J. (2010). Safety Stock or Safety Lead Time. *International Journal of Production Research*, *48*(24), 7463–7481. doi:10.1080/00207540903348346

Yumei, H. (2021). Put Safety First. *SAGE Open*, *11*(3), 215824402110321. doi:10.1177/21582440211032173

Zavala, G. R., Nebro, A. J., Luna, F., & Coello Coello, C. A. (2014). A Survey of Multi-Objective Metaheuristics Applied to Structural Optimization. *Structural and Multidisciplinary Optimization*, *49*(4), 537–558. doi:10.1007/s00158-013-0996-4

Zhang, L., & Tian, F. (2012). A Novel Chaotic Sequence Optimization Neural Network for Concentration Estimation of Formaldehyde by an Electronic Nose. *2012 Fourth International Conference on Computational Intelligence and Communication Networks*, (pp. 856–59).

Zitzler, E., & Thiele, L. (1999). Multiobjective Evolutionary Algorithms: A Comparative Case Study and the Strength Pareto Approach. *IEEE Transactions on Evolutionary Computation*, *3*(4), 257–271. doi:10.1109/4235.797969

Sayma Zia is a social scientist, consultant, counselor, and Head of Business School. Her research interests include management, marketing, gender, social issues, and education.