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# A SIMPLE APPROACH FOR IDENTIFYING AN OPTIMAL SERVICE LEVEL FOR MINIMIZING SCHEDULE NERVOUSNESS UNDER NON-STATIONARY STOCHASTIC DEMAND

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Abstract. *Schedule Nervousness occurs when there is a revision in a planned schedule due to an uncertainty in demand. This is because in reality, a future demand is not a deterministic with a stationary trend, but a non-stationary stochastic demand. A higher inventory service level may lower the probability that actual demand will exceed the inventory, but expected total cost also inclined as the service level increased. So the objective of this paper is to propose a simple approach for identifying an optimal service level between expected total cost and nervousness. First, the cost of operating in a nervousness-free operation was revealed by solving a mixed integer linear programming under static-dynamic uncertainty in a determined set of service levels. The second part provides a proposal of a new simple formulation for identifying an optimal service level between expected total cost and nervousness based on the findings in the first part. Finally, a similar approach was taken for an experiment by using a case study in one of the most nervousness sensitive industries, the airline catering industry. The results were found to be satisfied in both generated data and the case study.*
**Keywords:** Optimal service level, Non-stationary stochastic demand, Schedule nervousness

1. **Introduction.** Schedule nervousness is sometimes referred to as schedule instability, and its definition is defined as "*a term to represent the propagation of changes at the master production schedule (MPS) into instability in the requirement of parts or components at lower levels of product structure*" [1], whereas some papers also defined it as a revision in the original plan, which in turn results in different replenishment decisions in successive planning cycles, e.g., the initial planned schedule is revised according to actual demand in a particular period of time [2]. Law [3] categorized the causes of schedule instability into two groups, which are uncertainty in demand and uncertainty in supply; uncertainty in demand, e.g., an adjustment in the order quantity, whereas uncertainty in supply could be the temporary unavailability of machines, production overrun or delays by the supplier etc. Once occurring, both uncertainties will obstruct actual production from being executed prior to the initial plan and this is where nervousness arises.

The impact of schedule nervousness will lead to a change in personal task scheduling problems, machine utilization and delivery problems or could even incur rescheduling costs [4], while such a revision in an original plan could result in a disruption in the production and distribution system [5]. For some manufacturing industries, a backlogged order from a disruption in production and delivery systems might be negotiable with its customers and a postponement of its delivery due date agreed, but for some others, such disruption will cause a backlog penalty cost, or some might reduce its reliability credit, which is very costly in terms of business.

The consideration of a future demand as a deterministic or stochastic leads to a different impact from demand uncertainty on production stability when solving for a lot sizing problem. According to the assumption of deterministic demand and production, uncertainties like order cancellations or delivery schedule deviations are ignored in the model [6,7]. In the same way as another major assumption on stationary patterns of demand, *stationary demand* assumes that no growth nor seasonality exists, or may occur, but it is only in presumed short term nature [8], whereas *non-stationary demand* has no natural mean and infinite variance [9]. Silver [10] stated that most practical demand patterns are non-stationary, but due to the higher computational complexity compared to a stationary approach, non-stationary inventory policy is not preferred in actual operations planning.

Thus, demand uncertainty, which is a cause of schedule nervousness, is an avoidable challenge when considering a future demand as non-stationary stochastic demand. A number of papers have confirmed that probability of a backlogged order from actual demand exceeded the total inventory declined as service level increases [11,12], whereas a few papers tried to identify the cost of operating at service level with zero instability, also known as nervousness-free [13,14]. Operating in a higher service level will be less exposed to a backlogged opportunity from demand uncertainty, but somehow it will have to trade off with an incline in expected total cost when compared to an operation at lower service levels. So identifying an optimal service level for minimizing total cost and backlogged probability is a challenging topic.

The main objectives of this paper are to propose a simple approach for identifying an optimal service level that can minimize a manufacturer's expected total costs, while the probability of an occurrence of nervousness is at a satisfactory level. The finding of an optimal expected total cost in each service level needs to be revealed in order to see the exact cost that a manufacturer needs to trade off from choosing to operate in a higher service level, which will give them a more stable operation. Then, a framework for identifying optimal service level based on those costs will be proposed. The experiment will be tested on both self-generated demand, and a real demand from the case study company. The first part of this paper will be an experiment by using self-generated data, while the second part will use a case study in a highly nervousness-sensitive industry to make sure that our approach can be implemented by both academicians and practitioners in real world operations. All tests will be solved by using a general-purpose solver, an IBM CPLEX optimization studio.

## 2. **Literature Reviews.**

### 2.1. **Solving a stochastic lot-sizing problem under non-stationary stochastic demand.**

This paper will begin by deciding upon which uncertainty strategy will be used for solving a stochastic lot sizing problem, where demand is considered as a random variable and with known probability distribution function [16-18]. Bookbinder and Tan [15] proposed three different strategies to deal with demand uncertainty under a probabilistic lot sizing problem; dynamic uncertainty, static uncertainty and static-dynamic uncertainty strategy. Hilger [19] explained that *dynamic uncertainty strategy* is the strategy in which decision on production quantity is based on realized demand, so under the $(s_t, S_t)$ policy, the replenishment period and lot size vary upon realized demand, while *static uncertainty strategy* assumed that the value of decision variables are determined at the beginning period of the planning horizon. So replenishment period and lot size quantity are planned in advance of the entire planning horizon, whereas with *static-dynamic* *uncertainty strategy*, the lot size quantity varies upon realized demand, but the replenishment period is determined in advance of the entire horizon. Each strategy has its own advantages and disadvantages, even despite the fact that dynamic uncertainty is a cost optimal strategy, but Smith and Tan [20] summarized from a practical point of view for pros and cons in each strategy; for *dynamic uncertainty programming*, a most cost effective strategy because of varying both replenishment period and lot size quantity is upon actual demand, but it also means an ignorance on its production capacity constraint, because the production capacity as well as supplier and customer due dates are fixed. So the timing of orders and variability of actual lot size will create a schedule nervousness, e.g., in cases of exceeding production capacity or inventory. For *static uncertainty*, both period and quantity are fixed at the beginning of the horizon, and production is executed independently from realized demand. This approach will create no schedule nervousness but will be very costly for manufacturers since it is already absorbed through lot size quantity. Although *static-dynamic uncertainty* may not be a cost effectiveness approach like in *dynamic uncertainty*, it provided less schedule nervousness while causing lower costs than *static uncertainty*. Thus, this paper will use static-dynamic uncertainty strategy since it is a best fit for a current business environment where uncertainty and competitiveness are high.

Then, we need a mathematical model to solve for an optimal solution under *static-dynamic uncertainty* strategy. This is because a previous work has already proved that solving non-stationary demand by using methods for stationary demand is costly and not effective [14], and we will need to use the correct methodology for our paper. There have been attempts to solve for an optimal solution under non-stationary stochastic demand by using *static-dynamic uncertainty* strategy; Tarim and Kingsman's paper [11] was among the most cited paper, they formulated a mixed integer linear programming (MILP) for a multi-period single-item stochastic dynamic lot sizing problem with non-stationary stochastic demand, and the formulation is under static-dynamic uncertainty strategy of Bookbinder and Tan. They included the unit variable cost and services level constraint which was ignored in the original two stage heuristic. The model provided an optimal solution on replenishment period and quantity that will minimize the total cost under the constraint, such that closing inventory numbers in each period will not be negative in each service level. The model is widely cited as a formulation that provides an optimal solution under static-dynamic strategy, and a similar formulation can be found from many papers.

Later, the model was extended into the form of piecewise linear approximation to obtain the nonlinear cost function, and the shortage cost was including in the proposed MILP equivalent model [21]. Later [22] developed it into the new form, a constraint programming, but one still yielding the same solution. After that, an alternative computational approach for solving an original model without the need to use any solver program was proposed [23], the proposed approach is based on relaxation of MILP and equivalent to the shortest path problem, then [24] proposed a linear relaxation of the original model which yielded a better computational performance and the latest being by [25] which developed an MIP model with piecewise linear concave ordering cost based on the original model. However, most of the above papers that have developed an original model into the piecewise linear form have suggested that more line segments provide a better approximation, a different number of line segments will yield a different optimal value, but the optimal numbers of line segment are still reported as a critical question and may vary in each paper.

Since the main objective of this paper is to propose a simple formulation that will enable manufacturers to identify their optimal service level based on a comparison on an obtained optimal expected total cost, with the opportunity cost of order being backlogged, a different number of line segments will result in a different expected total cost even using the same cost parameters, and this will cause an issue on a final optimal service level obtained since the optimal number of line segments is still a question. So, what we want is a simple approach widely acknowledged and accepted within literature on its optimal solution, and which should be in a user-friendly form like MILP, which can be solved by any commercial solver program and practitioner can be practically solved without facing time-consuming complexity over a decision on calculating an optimal number of line segments to use. Thus, we will use the original model of [11].

2.2. **Identifying the cost of operating at nervousness-free operation.** As mentioned earlier, MILP of [11] included the service level constraint into their model. An operation at the highest service level is often assumed to be a *nervousness-free* operation because of the lowest probability that actual demand will exceed its order-up-to-level (see [2,13,14]). The first existence of this term in literature needs to look back to 2011, where the word "Zero Instability" was used as a term to represent the operations at the level where the possibility of nervousness was the lowest and assumed to have zero instability [13]. At that time, they proposed an approach for measuring the cost of system nervousness under a non-stationary environment by comparing between the dynamic programming model $(s, S)$ policy, which is known as a cost optimal policy but the worst in terms of stability performance, with that of static-dynamic, $(R, S)$ policy, which the authors said was to be zero instability by its definition. The cost of schedule nervousness was then computed by relative cost performance which was by comparing the percentage difference between optimal cost obtained from $(s, S)$ policy and $(R, S)$. Later, authors in [2] were the first who used the term "Nervousness Free" to represent the operations where there is zero instability. The approach for measuring cost of nervousness in their paper was in the same direction with above paper, but they compare between three strategies which are dynamic [26], static [6] and static-dynamic [21]. The cost effectiveness of static and static-dynamic policy was measured by using their expected costs against the expected cost from dynamic policy which is defined as optimal cost policy.

So, we will extend those previous pieces of work on finding the cost of operating at a nervousness-free level, but will be more specific by comparing the optimal expected total cost at nervousness-free level with the base service level, as well as varying test variables to see what costs manufacturers have to pay in order to obtain a nervousness-free level and is it still costing them the same under the different test variables, e.g., demand pattern. This paper will make a new contribution by not comparing an optimal expected total cost against a different strategy as has previously been done, but will be the first comparison between the different service levels under the same uncertainty strategy, which is more practical for the manufacturer to compare its choice of service level under their current uncertainty strategy rather than comparing against another strategy that is not currently in use.

2.3. **Identifying an optimal service level.** Finally, after we have revealed this and manufacturers know their cost of operating at any service level from the lowest one up until a *nervousness-free* level, the most important research question which is also our main research objective, is to identify which service level is an optimal service level for the manufacturer. Because a higher service level will lower the probability of a backlogged order from an uncertainty in demand that might exceed the inventory, numbers of backlogged orders as well as related penalty costs will be lower. However, please let it be noted that at the same time, it will somehow raise the expected total cost up from operating at higher service level where backlogged probability is lower. So, we will propose the formulation for identifying an optimal service level for the manufacturer between an increasing in expected total cost with a declining in opportunity cost of order being backlogged from choosing to operate at a higher service level.

Identifying an optimal service level for inventory under non-stationary stochastic demand under a perspective that demand exceeds the net inventory would lead to backlogged penalty cost did not receive much interest from the researcher compared to an opposite perspective that exceeded demand will result in a lost sale. An approximation procedure to determine an optimal replenishment policy for a periodic review inventory system with a probability of lost sale from exceeded demand under the service level constraint [27], the same as determining optimal safety stock under stochastic demand [28], was developed. Also [29] proposed a model for optimal and near-optimal for lost sale inventory system but under the major constraint that not more than one replenishment order may be outstanding at anytime.

While under the perspective of backlogged cost, [30] proposed a new approach for determining the optimal numerical value of inventory under stochastic demand for obtaining an optimal service level that can minimize total cost while also able to satisfy the customer service level constraint. They first start with proposing a model for finding an optimal numerical value of reorder quantity in the different service levels under the consideration on holding cost, production cost, salvage and backorder cost. Then, they defined backlogged cost in their work as a loss of future profit from lost sales due to exceeded demand over inventory, calculated and confirmed on the quasi-exponential function between backlogged cost and service level, which can be explained by the lower probability of order being backlogged from operating at a higher service level where total replenishment quantity is higher, and vice versa. Finally, they include the backlog cost, which is declining as service level increases together with their solved optimal total cost, which is inclining as service level increases; an optimal service level is where total cost is the lowest.

What we are going to do is to extend the work of [30] by specifically focusing on a static-dynamic uncertainty strategy which is the literature proven to be one of the most effective for hedging against nervousness and widely used by both academicians and practitioners, and then we will find an optimal solution in each service level by using a model of [11] where its solution is widely accepted on its optimality under desired service level. Then, we will propose a new formulation for calculating backlogged cost based on their approach, to be more specific, an opportunity cost from order being backlogged from a larger demand than operating service level, including backlogged cost with solved optimal expected total cost obtained from [11] model, and then the service level as the lowest total cost will be considered as an optimal service level.

## 3. **Methodology.**

*Problem Description*

First, this paper decided to solve a stochastic lot sizing problem with non-stationary demand by using static-dynamic uncertainty strategy, where lot size quantity varies upon realized demand, but where the replenishment period is determined in advance of the entire horizon. The problem will be solved by using mixed integer linear programming proposed by Tarim and Kingsman [11], which is by minimizing the expected total cost under a customer service level constraint. The formulation and its notation are as follows:

$$\min E[TC] = \sum_{t=1}^{n} \left(a\delta_t + hE\{I_t\} + vE\{R_t\} - vE\{I_{t-1}\}\right) \tag{1}$$

subject to

$$E[I_t] = E[R_t] - E[d_t], \quad t = 1, \dots, N \tag{2}$$
$$E[R_t] \geq E[I_{t-1}], \quad t = 1, \dots, N \tag{3}$$
$$E[R_t] - E[I_{t-1}] \leq M\delta_t, \quad t = 1, \dots, N \tag{4}$$
$$E[I_t] \geq \sum_{j=1}^{t} \left( G^{-1}_{d_{t-j+1}+d_{t-j+2}+\ldots+d_t}(\alpha) - \sum_{k=t-j+1}^{t} E[d_k] \right) P_{tj}, \quad t = 1, \dots, N \tag{5}$$
$$\sum_{j=1}^{t} P_{tj} = 1, \quad t = 1, \dots, N \tag{6}$$
$$P_{tj} \geq \delta_{t-j+1} - \sum_{k=t-j+2}^{t} \delta_k, \quad t = 1, \dots, N, \quad j = 1, \dots, t \tag{7}$$
$$E[I_t], E[R_t] \geq 0, \quad \delta_t, P_{tj} \in 0, 1, \quad t = 1, \dots, N, \quad j = 1, \dots, t \tag{8}$$

where

| | |
|---|---|
| $E\{d_t\}$ | Expected demand in period $t$, a random variable with known probability density function. |
| $a$ | The fixed ordering cost. |
| $v$ | The fixed unit variable cost. |
| $h$ | The fixed holding cost. |
| $E\{I_t\}$ | Expected closing inventory at the end of period $t$. |
| $E\{R_t\}$ | Expected replenishment inventory level (order-up-to level). |
| $\delta_t$ | Binary variable, 1 if an order is scheduled in period $t$, 0 otherwise. |
| $P_{jt}$ | Binary variable, 1 if most recent order prior to period $t$ took place in period $t-p+1$, 0 otherwise. |
| $M$ | Some large positive number. |

The model can be explained as follows. The objective function (1) is to minimize the total expected cost from ordering cost, holding cost and unit variable cost over the planning horizon. The model will determine the optimal replenishment schedule, and determine the dynamical value of replenishment quantity when real demand is realized, and thus results in optimal expected total cost. Constraint (2) enforces the inventory conservation by fixing expected inventory at the end of the period with the difference between replenishment level and expected demand in period $t$. Constraints (3) and (4) enforce that the replenishment level must be equal to the closing inventory in period $t-1$ if there is no order received, but will be equal to order-up-to level if there is a review and receipt of order. Constraint (5) represents the constraint on service level, the term $G^{-1}_{d_{t-j+1}+d_{t-j+2}+\ldots+d_t}(\alpha)$ represents the minimum post-replenishment inventory level in period $t-j+1$ that is enough to meet the desired service level in period $t$. This term was calculated offline by using Formula (9).

$$G^{-1}_{d_{t-j+1}+d_{t-j+2}+\ldots+d_t}(\alpha) = \sum_{k=t-j+1}^{t} E\{d_k\} + Z_\alpha C \left( \sum_{k=t-j+1}^{t} E^2\{d_k\} \right)^{1/2} \tag{9}$$

Constraint (6) means if the most recent order prior to period $t$ was in period $t-j+1$. While constraint (7) is to make sure that no order can be placed in between any given period, but should be at the most recent replenishment period.

The above model will be used as the first stage in our proposed approach by revealing an optimal value of replenishment quantity and period the same as the optimal expected total cost in a set of pre-determined service levels. Thus, we will be able to identify an optimal expected total cost from the decision to operate at service level $n$ up until the highest level which is assumed to be nervousness-free level, $N\{n \in N\}$.

$$E[TC]_N - E[TC]_n \quad n \in N \tag{10}$$

Most papers that identify the cost of nervousness-free under non-stationary stochastic demand were a comparison against a different uncertainty strategy, comparing *dynamic* as a cost-effective strategy against *static-dynamic* as a nervousness-free strategy, or *dynamic* and *static-dynamic* against *static* strategy, which is said to be nervousness-free by its definition [2]. However, there was not yet a comparison within the same strategy, so to the best of our knowledge, this is the first paper that enables a manufacturer who has already selected the *static-dynamic* strategy in their planning to identify their operation cost at the nervousness-free level by comparing its optimal expected total cost at desired service level $n$, with a higher service level up until nervousness-free $n+1, \ldots, N$.

Since our future demand is considered as a non-stationary stochastic, which can be considered as a random variable $x$, so within the set of determined service level $\{n, \ldots, N\}$, there is a probability that realizes demand will exceed the sum of replenishment quantity from a decision to operate at service level $n\,(P(x > [\sum_t (R_t)]_n))$ which resulted in a backlogged order. Operating in a higher service level can lower the nervousness probability from a higher replenishment quantity; somehow the optimal expected total cost is also inclined as backlog possibilities decrease [12].

So, to identify which service level is an optimal level, we have developed a simple approach based on the findings of several papers (see [12,30]) where an incline of expected total cost as service level increased, was found traded-off with a decline in backlog cost. Thus we will combine an optimal expected total cost in each level together with its possibilities of creating a backlogged order. Our approach can be calculated by using only the optimal values of decision variables which were already solved in the previous part as an input. This is to make sure that our approach is simple and user-friendly enough to be used by the manufacturer in their everyday operations.

$$\beta_m = \sum_{n=m+1}^{M} \beta_{k,n} \tag{11}$$

We have introduced $\beta_m$, the total backlogged opportunities of service level $m$, which can be expressed as a sum of all backlogged possibilities (unit: numbers of replenishment quantities) from choosing to operate at service level $m$, but actual demand exceeds to the level of $n = m+1, \ldots, M$. The variable $\beta_m$ depends on the sum of all possible opportunities of orders being backlogged from operating at $n$ service level, but where realized demand is exceeded at $k$ level, $\beta_{k,n}$.

$$\beta_{k,n} = \left[\sum_t (R_t)\right]_k - \left[\sum_t (R_t)\right]_n \qquad k \in K, \quad n \in N, \quad \widetilde{R}_t | \delta_t = 1 \tag{12}$$

$\beta_{k,n}$ will be expressed from the difference between $[\sum_t (R_t)]_k$, the sum of an entire optimal replenishment quantity in the planning horizon, $t = \{1, \ldots, T\}$, under the service level $k$, and where $[\sum_t (R_t)]_n$ represented the same variable but at the service level $n$. The values of $[\sum_t (R_t)]_k$ and $[\sum_t (R_t)]_n$ were already obtained in the previous part. Note that we will only include the value of $R_t$ under the condition that a value of binary variable $\delta_t = 1$, which represents an optimal replenishment period in the planning horizon as shown in constraints (3) and (4). The next session will be a numerical study by using self-generated demand and followed by the real case study.

4. **Numerical Study.** This part will be an experiment using self-generated data with the aim to reveal the optimal expected total cost for the total of 11 service levels as shown in Table 1, from 90% which is assumed to be an ASIS or based operation until a nervousness-free level at 99.95%. The optimal expected total cost in each service level will be solved by using Tarim and Kingsman's MILP [11].

Table 2 shows the value of self-generated expected demand which will be used for an experiment in this paper. We characterized demand into two patterns: cycle and erratic. The expected demand in each period is assumed to be normally distributed and fixed coefficients of variations over the planning horizon to control the extent of stochasticity of demand (Similar assumptions on fixed coefficient of variations to control the extent of stochasticity under the context of non-stationary stochastic demand can be found in several pieces of research, see [2,13]). The planning horizon is set to be 10 days long while cost parameters and coefficient of variation are shown in Table 3.

Table 3 shows the cost parameter in each demand. We experimented by using the following sets of self-generated parameters with its data: ordering cost $a \in \{10, 100, 500\}$, unit cost $v \in \{10, 100, 500\}$, holding cost $h \in \{1\}$ and coefficient of variation $C \in \{0.1, 0.3\}$. Each pattern will be solving for a five different ordering cost to unit cost ratio under each level of coefficient of variation, this ratio will represent the different types of products or input, e.g., the ratio of 10:1 ($a = 100$, $v = 10$; represent the input or product that the ordering cost is higher than unit cost, e.g., imported inputs. While the ratio of 150

TABLE 1. Set of service level and its $z$ value

| $\alpha =$ | $z_\alpha =$ | $\alpha =$ | $z_\alpha =$ | $\alpha =$ | $z_\alpha =$ |
|---|---|---|---|---|---|
| **0.9000** | 1.285 | **0.9400** | 1.555 | **0.9800** | 2.055 |
| **0.9100** | 1.345 | **0.9500** | 1.645 | **0.9900** | 2.325 |
| **0.9200** | 1.405 | **0.9600** | 1.750 | **0.9995** | 2.575 |
| **0.9300** | 1.475 | **0.9700** | 1.881 | | |

TABLE 2. Generated expected demand value

| **Pattern/Period (day)** | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Cycle** | 300 | 400 | 400 | 500 | 500 | 500 | 400 | 300 | 300 | 200 |
| **Erratic** | 410 | 320 | 710 | 350 | 280 | 800 | 380 | 290 | 450 | 510 |

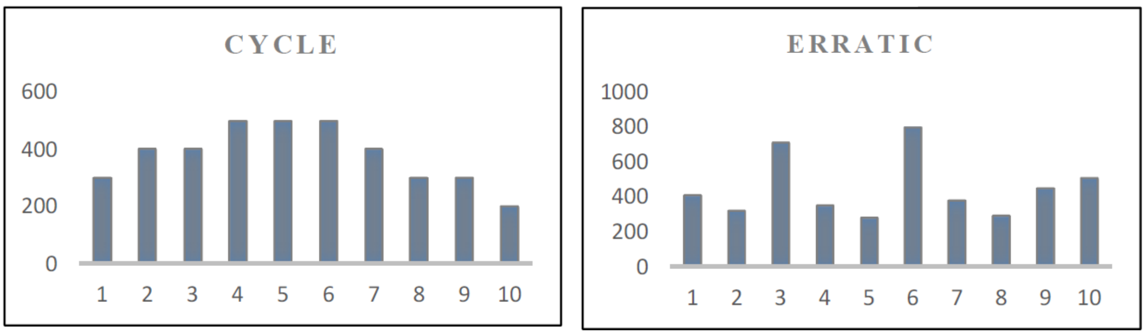



FIGURE 1. Demand patterns

Table 3. Cost parameters

| Pattern | Ordering cost: Unit cost (ratio) | $a$ (ordering cost) | $v$ (unit cost) | $h$ (holding cost) | $C = \sigma_t/\mu_t$ (coefficient of variation) |
|---|---|---|---|---|---|
| **Cycle** | 1:1, 1:10, 1:50, 10:1, 50:1 | 10, 100, 500 | 10, 100, 500 | 1 | 0.1, 0.3 |
| **Erratic** | 1:1, 1:10, 1:50, 10:1, 50:1 | 10, 100, 500 | 10, 100, 500 | 1 | 0.1, 0.3 |

represents a high value input with low ordering cost, e.g., computer or electronic circuits). So, there will be the total of 220 test instances in this part.

All experiments will be performed on PCs equipped with 23GHz Intel core i3, 8192 MB of Ram. The general purpose-solver IBM ILOG CPLEX Optimization studio version 12.6.2 is used with all default settings.

5. **Results.** We will start this part by showing a sample result from solving an objective function (1) with the constraints (2) to (7) in Table 4. The upper part of the table shows the optimal solution from an experiment with erratic demand pattern at 90% service level with coefficient of variation, $C = 0.1$, ordering cost, $a = 10$, unit cost, $v = 10$ and holding cost, $h = 1$. The optimal expected total cost obtained from the model is $E[TC]_{90\%} = 50,740$ with replenishment periods $\{1, 3, 4, 6, 7, 9, 10\}$ with all non-negative expected closing inventory at the end of each period.

In all of our experiments we assumed that 90% service level is current service level, whereas 99.95% is assumed to have zero instability or nervousness-free. We will compare and see the percentage change in the optimal expected total cost in each service level with 90% level. The lower part of the table represents the solution and optimal expected total cost from using the same variables with the upper table but operating in a higher service level at nervousness-free level (99.95%). The optimal expected total cost obtained is $E[TC]_{99.95\%} = 52,883$, or equal to 4.12% higher than $E[TC]_{90\%}$, or we can say that if the manufacturer would like to lower their risk from the schedule nervousness by operating at nervousness-free level under such parameters, they will have to trade off with 4.12% higher in their expected total cost compared to their current operation. The rest of the results are shown in Table 5 and Table 6.

Table 4. Solved decision variables

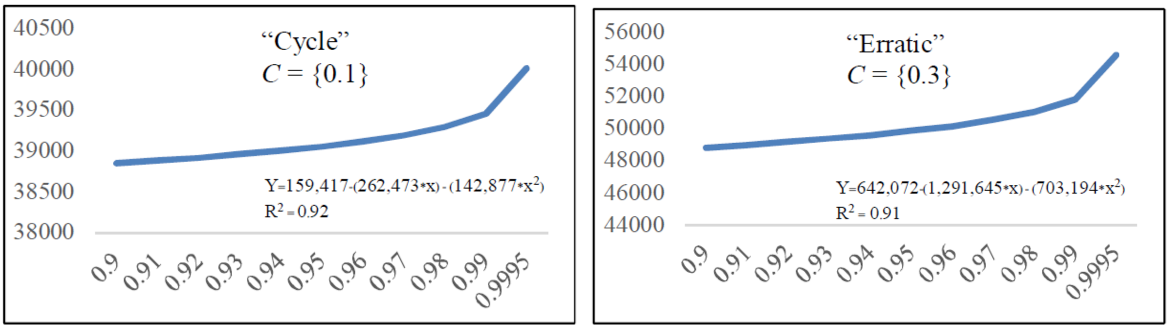
| **Erratic Demand**, $a = 500$, $v = 10$, $h = 1$ | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| $\alpha = 0.9000$ (50:1) Period ($t$) | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
| Order-up-to-level ($E\{R_t\}_{\delta_t=1}$) | 797 | – | 801 | 688 | – | 903 | 731 | – | 508 | 576 |
| Expected opening inventory ($E\{R_t\}$) | 797 | 387 | 801 | 688 | 338 | 903 | 731 | 351 | 508 | 576 |
| Expected closing inventory ($E\{I_t\}$) | 387 | 67 | 91 | 338 | 58 | 103 | 351 | 61 | 58 | 66 |
| Expected total cost ($E[TC]_{90\%}$) | 50,740 | | | | | | | | | |
| **Erratic Demand**, $a = 500$, $v = 10$, $h = 1$ | | | | | | | | | | |
| $\alpha = 0.9995$ (50:1) Period ($t$) | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
| Order-up-to level ($E\{R_t\}_{\delta_t=1}$) | 901 | – | 944 | 777 | – | 827 | 827 | – | 827 | 901 |
| Expected opening inventory ($E\{R_t\}$) | 901 | 491 | 944 | 777 | 427 | 827 | 827 | 827 | 827 | 901 |
| Expected closing inventory ($E\{I_t\}$) | 491 | 171 | 234 | 427 | 147 | 157 | 157 | 157 | 157 | 157 |
| Expected total cost ($E[TC]_{99.95\%}$) | 52,883 | | | | | | | | | |

TABLE 5. Optimal expected total cost (unit: $)

| **Service Level** | **Optimal Expected Total Cost** | | | |
|---|---|---|---|---|
| | **Cycle** | | **Erratic** | |
| | $C = \{0.1\}$ | $C = \{0.3\}$ | $C = \{0.1\}$ | $C = \{0.3\}$ |
| | 1:1 | 1:1 | 1:1 | 1:1 |
| 0.9000 | 38,848 | 40,336 | 46,339 | 48,804 |
| 0.9100 | 38,880 | 40,433 | 46,396 | 48,975 |
| 0.9200 | 38,912 | 40,542 | 46,452 | 49,147 |
| 0.9300 | 38,961 | 40,672 | 46,513 | 49,351 |
| 0.9400 | 39,002 | 40,803 | 46,589 | 49,578 |
| 0.9500 | 39,054 | 40,965 | 46,682 | 49,841 |
| 0.9600 | 39,118 | 41,148 | 46,778 | 50,143 |
| 0.9700 | 39,193 | 41,374 | 46,907 | 50,520 |
| 0.9800 | 39,292 | 41,673 | 47,075 | 51,014 |
| 0.9900 | 39,454 | 42,151 | 47,335 | 51,798 |
| 0.9995 | 40,014 | 43,822 | 48,260 | 54,571 |

TABLE 6. The difference in optimal expected total cost compared with base level at 90% (unit: %)

| **Service Level** | **Cycle** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $C = \{0.1\}$ | | | | | $C = \{0.3\}$ | | | | |
| | **1:1** | **1:10** | **1:50** | **50:1** | **10:1** | **1:1** | **1:10** | **1:50** | **50:1** | **10:1** |
| 0.9000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.9100 | 0.08 | 0.03 | 0.03 | 0.11 | 0.08 | 0.24 | 0.12 | 0.11 | 0.25 | 0.26 |
| 0.9200 | 0.16 | 0.06 | 0.05 | 0.21 | 0.16 | 0.51 | 0.21 | 0.19 | 0.48 | 0.50 |
| 0.9300 | 0.29 | 0.12 | 0.11 | 0.34 | 0.28 | 0.83 | 0.36 | 0.32 | 0.78 | 0.81 |
| 0.9400 | 0.40 | 0.16 | 0.14 | 0.45 | 0.39 | 1.16 | 0.49 | 0.43 | 1.08 | 1.13 |
| 0.9500 | 0.53 | 0.22 | 0.19 | 0.59 | 0.52 | 1.56 | 0.67 | 0.59 | 1.45 | 1.53 |
| 0.9600 | 0.70 | 0.28 | 0.24 | 0.75 | 0.68 | 2.01 | 0.86 | 0.75 | 1.87 | 1.97 |
| 0.9700 | 0.89 | 0.37 | 0.33 | 0.96 | 0.87 | 2.57 | 1.10 | 0.96 | 2.40 | 2.52 |
| 0.9800 | 1.14 | 0.47 | 0.41 | 1.22 | 1.12 | 3.31 | 1.41 | 1.23 | 3.09 | 3.24 |
| 0.9900 | 1.56 | 0.65 | 0.57 | 1.65 | 1.52 | 4.50 | 1.92 | 1.68 | 4.19 | 4.40 |
| 0.9995 | 3.00 | 1.24 | 1.09 | 3.09 | 2.93 | 8.64 | 3.67 | 3.21 | 7.95 | 8.45 |
| **Service Level** | **Erratic** | | | | | | | | | |
| | $C = \{0.1\}$ | | | | | $C = \{0.3\}$ | | | | |
| | **1:1** | **1:10** | **1:50** | **50:1** | **10:1** | **1:1** | **1:10** | **1:50** | **50:1** | **10:1** |
| 0.9000 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0.9100 | 0.12 | 0.07 | 0.07 | 0.12 | 0.12 | 0.35 | 0.21 | 0.19 | 0.35 | 0.34 |
| 0.9200 | 0.24 | 0.14 | 0.13 | 0.24 | 0.24 | 0.70 | 0.42 | 0.39 | 0.70 | 0.69 |
| 0.9300 | 0.38 | 0.22 | 0.20 | 0.38 | 0.37 | 1.12 | 0.67 | 0.63 | 1.12 | 1.10 |
| 0.9400 | 0.54 | 0.31 | 0.29 | 0.54 | 0.53 | 1.59 | 0.95 | 0.89 | 1.58 | 1.56 |
| 0.9500 | 0.74 | 0.43 | 0.40 | 0.74 | 0.73 | 2.12 | 1.27 | 1.19 | 2.12 | 2.09 |
| 0.9600 | 0.95 | 0.55 | 0.51 | 0.94 | 0.93 | 2.74 | 1.64 | 1.54 | 2.73 | 2.69 |
| 0.9700 | 1.23 | 0.71 | 0.67 | 1.22 | 1.20 | 3.52 | 2.10 | 1.97 | 3.50 | 3.45 |
| 0.9800 | 1.59 | 0.93 | 0.96 | 1.58 | 1.56 | 4.53 | 2.70 | 2.53 | 4.49 | 4.45 |
| 0.9900 | 2.15 | 1.26 | 1.18 | 2.14 | 2.11 | 6.13 | 3.67 | 3.44 | 6.04 | 6.02 |
| 0.9995 | 4.15 | 2.43 | 2.27 | 4.12 | 4.07 | 11.82 | 7.06 | 6.62 | 11.31 | 11.60 |




(a) (b)

FIGURE 2. Curve fitting with quadratic function between expected total cost and service level

Table 5 found optimal expected total cost in all experiments were inclined as the service level increased. This is a confirmation that lower nervousness operations need to be traded off with higher expected total cost. We have also conducted a curve-fitting to see its relationship and found it to be the best fit with quadratic function shown in Figure 2.

Figure 2 showed the results from fitting the solved optimal expected total cost in Table 5 with quadratic function; the results show that tradeoff cost for obtaining less instability by operating at a higher service level in all instance found the best fit with quadratic function (with $R^2 \geq 0.90$). This is in the same direction with Nakashima et al. [30] who found that a relationship between service level and optimal expected total cost is not a linear relationship.

5.1. **Revealing the cost of nervousness free operations.** To keep our approach as simplest as possible, an expected total cost in each service level in each instance which was obtained by solving TK model representing an optimal solution under static-dynamic strategy, we will make it simple by seeing it as a percentage difference in expected total cost in each service level.

For example, in Table 5, solving "cycle demand" with $C = 0.1$, $a = 10$, $v = 10$, $h = 1$ (ordering cost to unit cost ratio = 1:1) at 90% service level will provide an optimal expected total cost equal to 38,848, then solving again at 95% and 99.95% will equal to 39,054 and 40,014 respectively. This can be interpreted as, if the manufacturer would like to lower its probability that actual demand (random variable $x$) will exceed its order-up-to-level ($E\{R_t\}_{\delta_t=1}$) from 10% (operating at 90% service level) to 5% (operating at 95% service level), they have to trade off with 0.53% higher expected total cost (Percentage difference between the expected total cost at 90% service level and 95% service level), whereas, it will cost them 3% higher than their current level if they choose to operate at nervousness-free level where probability that actual demand will exceed its inventory is the lowest. The rest of the results are shown in Table 6.

Table 6 represents a first major finding in this paper, the cost of operating at nervousness-free level (compared with the base service level) was found to be different among each test instances. The difference in demand pattern was found to be a cause that makes the difference in cost of operating at nervousness-free level. For example, on 1:1 ratio ($a = 10$, $v = 10$) with $C = 0.3$ under the "cycle demand", it costs a manufacturer 8.64% more than their base service level for operating at nervousness-free level, whereas 11.82% for "erratic demand".

We also found that a different ordering cost to unit cost ratio causes a different nervousness-free operations cost. For example, under erratic demand with $C = 0.1$, it costs the manufacturer 4.15%, 2.43%, 2.27%, 4.12%, 4.07% for the ratios of 1:1, 1:50, 1:500, 500:1 and 100:1 respectively for operating at nervousness-free level.

In addition to demand pattern and ordering cost to unit cost ratio, we found that a different coefficient of variation ($C$) causes a different cost for operating at nervousness-free level in each demand pattern and ratio. For example, the cost for "erratic demand" with 1:10 ratio and $C = 0.1$ to operate at nervousness-free level is 2.43% higher than base level, whereas those costs increased to 7.06% when the coefficient of variation increased to $C = 0.3$.

This lead to a first conclusion that the different types of product (Considered from a difference in demand pattern, cost parameters, ratio between ordering to unit cost, and coefficient of variations in demand) should not apply the same inventory policy for hedging against nervousness. For example, it costs the manufacturer 3% more than its base service level for operating at nervousness-free under "Cycle demand" with $C = 0.1$, $a = 10$, $v = 10$, $h = 1$. However, it will cost them 8.64% more when $C$ is increased from 0.1 to 0.3 while other parameters remain unchanged. So using the optimal value, e.g., replenishment quantity, which was obtained from solving $C = 0.3$ on $C = 0.1$, will result in excess total replenishment quantity and vice versa.

5.2. **Identifying an optimal service level.** Table 7 represents a calculation on optimal service level of erratic demand with 1:1 ratio and $C = 0.3$ by the use of the proposed formulation. The constraint (12) $\beta_{k,n} = [\sum_t (R_t)]_k - [\sum_t (R)]_n$ represents the opportunity cost (unit: quantity of product produced) from a decision to operate in service level $n$ but actual demand is exceeded to the $k$ service level. For example, $\beta_{0.910,0.900}$ means the opportunity cost of operating at 90% service level, but actual demand was found exceeded to the 91% service level. Firstly, we need to find $\sum_{t=1}^{T} R_{t\delta_t}$ of 90% service level ($n$ service level, a decided operating level), which is the sum of replenishment quantity in the whole planning horizon ($t = \{1, \ldots, 10\}$), this value can be obtained from solving TK model for $R_t$ and sum it under the service level constraint of 90% which is equal to 6,234 units. Then, finding $\sum_{t=1}^{T} R_{t\delta_t}$ of 91% ($k$ service level, a service level that is sufficient with exceeded actual demand, in this case is 91%) which equals 6,315. So the value of $\beta_{0.910,0.900} = [\sum_t (R_t)]_k - [\sum_t (R_t)]_n$ is equal to $\beta_{0.910,0.900} = 6,315 - 6,234 = 81$ units that should not be backlogged if it is decided to operate at 91% service level instead of 90%.

The above sample is only an opportunity cost from operating at 90% but where actual demand exceeded the 91% level, but in this paper we have determined the set of service

Table 7. Calculating a proposed framework for choosing optimal service level (Erratic, $C = 0.3$, $a = 10$, $v = 10$, $h = 1$)

| **Service Level** | $\sum_t (R_t)$ | $\beta_m$ | | | | | | | | | | | **Back -logged Cost** | **Solved Optimal Cost** | **Total Cost** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **0.9000** | **0.9100** | **0.9200** | **0.9300** | **0.9400** | **0.9500** | **0.9600** | **0.9700** | **0.9800** | **0.9900** | **0.9995** | | | |
| 0.9000 | 6234 | ***7938*** | | | | | | | | | | | 3,969 | 48,804 | 52,773 |
| 0.9100 | 6315 | 81 | ***7128*** | | | | | | | | | | 3,564 | 48,975 | 52,539 |
| 0.9200 | 6397 | 163 | 82 | ***6390*** | | | | | | | | | 3,195 | 49,147 | 52,342 |
| 0.9300 | 6491 | 257 | 176 | 94 | ***5638*** | | | | | | | | 2,819 | 49,351 | 52,170 |
| 0.9400 | 6598 | 364 | 283 | 201 | 107 | ***4889*** | | | | | | | 2,444 | 49,578 | 52,023 |
| 0.9500 | 6721 | 487 | 406 | 324 | 230 | 123 | ***4151*** | | | | | | 2,075 | 49,841 | 51,917 |
| 0.9600 | 6863 | 629 | 548 | 466 | 372 | 265 | 142 | ***3441*** | | | | | 1,720 | 50,143 | *51,864** |
| 0.9700 | 7040 | 806 | 725 | 643 | 549 | 442 | 319 | 177 | ***2733*** | | | | 1,366 | 50,520 | 51,887 |
| 0.9800 | 7274 | 1040 | 959 | 877 | 783 | 676 | 553 | 411 | 234 | ***2031*** | | | 1,015 | 51,014 | 52,030 |
| 0.9900 | 7638 | 1404 | 1323 | 1241 | 1147 | 1040 | 917 | 775 | 598 | 364 | ***1303*** | | 651 | 51,798 | 52,450 |
| 0.9995 | 8941 | 2707 | 2626 | 2544 | 2450 | 2343 | 2220 | 2078 | 1901 | 1667 | 1303 | ***0*** | 0 | 54,571 | 54,571 |

*Optimal service level (lowest total cost)

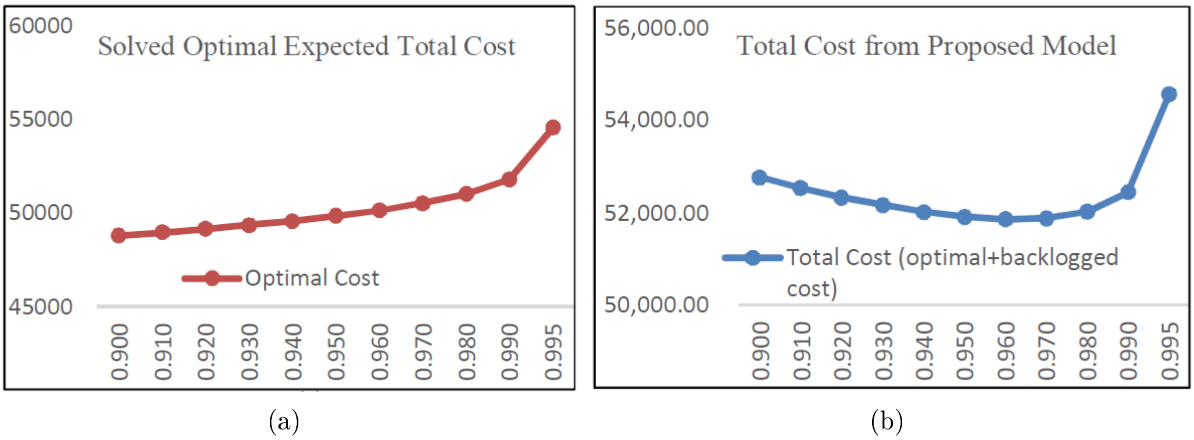



FIGURE 3. Optimal service level of erratic demand at 1:1 ratio and $C = 0.3$

level $(n, \ldots, N)$ for the total of 11 service levels (Table 1) which means there will be the total of 10 situations that actual demand could possibly exceed the decided operating service level at 90%. So the value of $\beta_{m=0.900}$ can be calculate by $\beta_{0.900} = \sum_{m+1}^{0.9995} \beta_{k,n}$ or the total opportunity cost from deciding to operate at 90% service level, which is the sum of every opportunity that actual demand could possibly exceed 90%, $(m \le n < k)$. Thus, $\beta_{0.900} = \beta_{0.910,0.900} + \ldots + \beta_{0.9995,0.900}$ which is equal to $81 + 163 + 257 + 364 + 487 + 629 + 806 + 1040 + 1404 + 2707 = 7,938$ units that have an opportunity to be backlogged from higher actual demand than the decided service level at 90%. Whereas operating in a higher service level like 98% can lower the backlogged opportunity, says $\beta_{0.980} = \beta_{0.990,0.980} + \beta_{0.9995,0.980} = 364 + 1667 = 2031$ units, and if it is decided to operate at nervousness-free level where we assumed zero instability or no chance of exceeded demand, $\beta_{0.9995} = 0$.

To make it easier and more practical, we will turn the above opportunity cost which is currently in the unit of quantity of product produced, into the backlogged penalty cost for every unit backlogged (unit: \$). Firstly, let us determine that penalty cost for a unit being backlogged is equal to 5% of its unit cost. Hence, Table 7 represents the 1:1 ratio in which unit cost $(v) = 10$. So backlogged penalty cost will be equal to \$0.5 per unit. The backlogged cost will be a downward sloping curve from the peak at 90% service level and will reach its lowest (\$0) at nervousness-free level prior to an increase in service level. Finally, we will add this backlogged cost to the solved optimal expected total cost in Figure 3(a), which is an upward sloping curve, for example, solved optimal expected total cost at 90% is \$48,804 (as shown in Table 8) whereas the backlogged cost from operating in this service level is 7,938 units with the penalty cost of 5% or \$0.5 per each backlogged order, which is equal to \$3,969 and which will result in a new total cost, $48,804 + 3,969 = \$52,773$ (Figure 3(b)). The optimal service level for this case in Table 6 is found to be at 96% since it provides a lowest total cost of \$51,864. The rest of the optimal service level in other test instances are summarized in Table 8.

The value of $\beta_m$ at 90% is equal to 7,938 backlogged units or equal to \$3,969, whereas $\beta_m$ at 99.95% or nervousness-free level is equal to 0 backlogged units and cost \$0, this can be explained together with the solved expected total cost in Table 6 (as percentage different) that, if the manufacturer would like to lower the opportunity cost of an order being backlogged from 7,938 units (\$3,969 of penalty) to 0 unit (\$0 of penalty), they will have to trade off with 11.82% of their total cost higher than the decided operating level 90%). When we sum the new backlogged cost with an obtained optimal expected total

TABLE 8. Results in optimal service level in all instances

| Optimal service level | Cycle ($C = 0.1$) | | | | | Cycle ($C = 0.3$) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **1:1** | **1:10** | **1:50** | **50:1** | **10:1** | **1:1** | **1:10** | **1:50** | **50:1** | **10:1** |
| | 98% | 99% | 99% | 96% | 98% | 97% | 99% | 99% | 97% | 97% |

(a)

| Optimal Service Level | Erratic ($C = 0.1$) | | | | | Erratic ($C = 0.3$) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **1:1** | **1:10** | **1:50** | **50:1** | **10:1** | **1:1** | **1:10** | **1:50** | **50:1** | **10:1** |
| | 96% | 97% | 99% | 95% | 96% | 96% | 98% | 98% | 95% | 96% |

(b)

cost, we will get the new total cost as shown in Table 8. The optimal service level is a service level with the lowest total cost. The rest of the findings on optimal service level in all instances are shown in Table 8.

Table 8 shows the results from calculating a proposed framework for finding optimal service level in every test instance. The major finding from Table 8 is that a different type of demand pattern ("cycle" and "erratic") should not apply the same inventory policy for reducing nervousness, this is because we have already proved that a different demand pattern was found to cause a different cost for operating at nervousness-free level (based on a comparison against its ASIS operations service level). And we also proved that optimal service level was found to be different among the different demand patterns, as well as the different types of product nature (e.g., different coefficients of variation, ordering cost to unit cost ratio) that were also found to have a different optimal service level even under the same type of demand pattern.

The above findings suggest that if a manufacturer planned production by solving static-dynamic uncertainty strategy for an optimal value of replenishment periods and quantity, and identified its optimal service level by using our approach, then they should not apply those exact values for every product, but rather solve and gather those optimal values specifically for each product. Although their cost parameters or demand size may not be quite different, this paper has already proved that while the rest of the parameters are exactly the same, only a single different parameter, e.g., $C = 0.1$ and $C = 0.3$, will yield a different optimal service level (Table 8).

We have achieved almost every objective and answered the research questions, starting from revealing the cost of operating at every service level from 90% until nervousness-free service level; an incline in obtained optimal expected total cost from 90% to 99.95% service level was found to be the best fitted with a quadratic function. Then we proposed a framework for finding an optimal service level based on opportunity cost of order being backlogged from the opportunity that actual demand will exceed net inventory from a decision to operate at a desired service level. Finally, we found that optimal service level for each test instance was in the same direction with our first part, which says different demand and different testing parameters were found to have a different optimal service level.

What we have not yet achieved is to test whether our approach on finding the cost of nervousness-free and choosing its optimal service level (which was based on self-generated demand numbers) can be used in real operations by using real demand numbers or not. So, the next part will be a case study of an airline catering company, a highly nervousness sensitive industry that is faced with non-stationary stochastic demand every production day.

6. **Case Study.** When air-transport shifted into the mass passenger travel era, a greater number of routes became available and cheaper so that more people could afford to use them. The number of passengers reported by the World Bank has increased year by year from 10,213 million passengers in 1999 to 19,122 million passengers in 2013. More passengers flying, obviously means that more in-flight meals will be needed. Most caterers are faced with the same challenges of unavailability of information on the exact numbers of meals until just minutes prior to departure time [31]. The production is executed following the planned MPS, which was planned based on the forecasted meal numbers. As mentioned earlier, revision in the initial plan, known as schedule nervousness which leads to the disruption of the system, could occur.

Disruption in the production or delivery system may lead to a situation where there are not enough meals for the cabin crew to serve all passengers on board, and in the worst case scenario could result in a flight being delayed until the exact number of in-flight meals are loaded, one of the most sensitive situations for any airline. On the other hand, caterers will only get paid for the exact number of meals they have loaded onto the aircraft, the excess produced as a buffer stock will not be paid for and will result in a big burden for them since many caterers like LSG Skychefs in Qingdao, China. As same as SATS (Singapore Airport Terminal Services), providing in-house catering for Singapore Airlines is now capable of producing more than 80,000 meals daily.

Although airline catering is very sensitive to schedule nervousness and its production planning needs to be carefully planned in order to minimize the risk of making a flight delay, there are only a limited number of papers that study schedule nervousness specifically in this industry. [33] confirmed an existence of schedule nervousness in the operations of the airline catering industry by observed on the total of 5,572 orders from actual operations of an airline catering company based in Thailand, and found that buffer stock worked as instability absorption for caterers.

Later, [32] extended the previous paper and found around 80 percent of the total changes in initial planned schedule were caused from customers, explained by the operations process of the airline catering industry (Figure 4), a first confirmed order prior to the booking number (not finalized yet) will be available within 12-24 hours, whereas a final confirmed order can only be finalized 0-12 hours (according to the finalized number

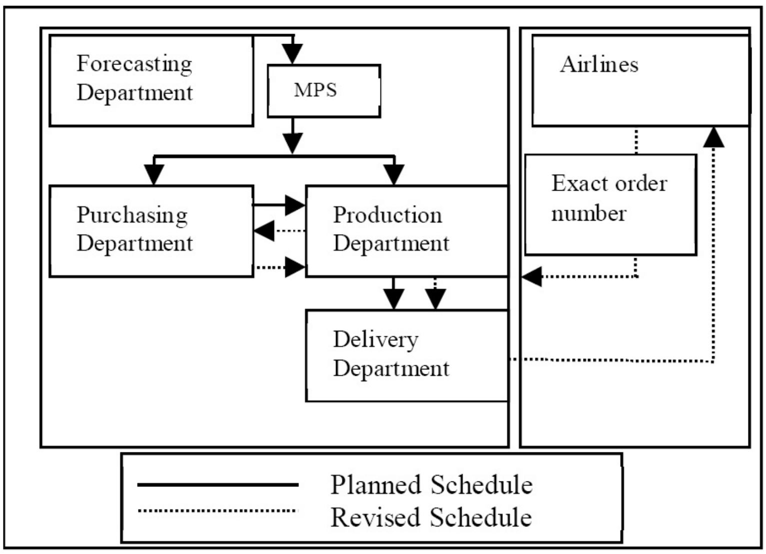



FIGURE 4. Operations process of airline caterer (Source: Hasachoo and Masuchun [34])

of passengers checked-in at the check-in counter) prior to departure time. However, international regulators, e.g., International Flight Services Association (IFSA), International Flight Catering Association (IFCA) regulated some production processes, e.g., rapid cooling procedures of heat-treated food [34], which required food to be cooled from 60°C to 21°C within 2 hours, and 21°C to 5°C within 4 hours. Only by this procedure, it already extended the production time by 4-6 hours. Thus, it is very difficult for caterers to wait for a confirmed finalized order, but inevitably they need to operate in advance by producing each order following the forecasting of numbers. Since demand for inflight meals is a derived demand, to be more specific, the amount of inflight meals depends on the numbers of passengers on each flight and their preferences, e.g., special requests and pre-ordered meals. So demand for inflight meals should not be considered as deterministic, but rather a random variable with known probability distribution or *probabilistic*. At the same time, [35] reports *"forecasting inflight meals is much more complex than it might seem, as there is no direct link between the number of passengers and the meals they consume"*, so it is rational to say demand for inflight meals is rather *non-stationary* than *stationary*.

Since production is executed in advance of finalized meals numbers, and demand was proved to be non-stationary stochastic, combining the results found in the previous part of this paper, we will find at what cost do airline caterers have to trade off in order to obtain an operation with less instability. Also applying the proposed framework for finding optimal service level would enable us to identify an optimal service level in the real case study company. This will also achieve our objective that the proposed model must be able to be applied in reality for both academics and practitioners.

This part will use the case study of an airline catering company in Thailand. This company is involved with servicing customers for both domestic and international airlines at Suvanabhumi airport, Bangkok, with food and non-food items (e.g., towels and newspapers). Their operations start from the flight landing until departure from the airport: firstly, producing inflight meals, then assembling both food and non-food products, and finally, loading and unloading from the aircraft. This research will only focus on the operation of the hot kitchen, which produced eight types of food, e.g., through boiling, frying and grilling. We collected the forecasting demand quantity of 6 menus in one planning horizon with 7-day length as well as its corresponding cost parameters which are needed for solving by using TK model shown in Table 9.

Each menu in the table has different cost parameters according to its nature, as for example menu A and menu B that are menus for economy class passengers. The nature of the product in this group is a low unit cost ($v = 20$) and low ordering cost ($a = 10$) with the same coefficient of variations ($c = 0.1$) which implies the demand for both menus is quite stable. The main difference between these two is demand size. Menu A represents

TABLE 9. Demand and cost parameters

| **Class/Product** | | **Expected value of period demands** Periods $k$ | | | | | | | $C = \sigma_t/\mu_t$ | $v$ | $h$ | $a$ | ***Back-logged Cost*** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | | | | | |
| **Economy** | Menu: A | 1000 | 1057 | 950 | 1000 | 988 | 921 | 928 | 0.1 | 20 | 1 | 10 | 5% of $v$ |
| | Menu: B | 500 | 460 | 520 | 600 | 400 | 350 | 390 | 0.1 | 20 | 1 | 10 | |
| | Menu: C | 570 | 400 | 480 | 540 | 770 | 870 | 450 | 0.2 | 20 | 1 | 10 | |
| **First Class** | Menu: D | 61 | 53 | 65 | 61 | 52 | 54 | 54 | 0.2 | 100 | 1 | 100 | 10% of $v$ |
| | Menu: E | 60 | 55 | 62 | 74 | 80 | 62 | 55 | 0.3 | 100 | 1 | 100 | |
| | Menu: F | 50 | 38 | 45 | 69 | 69 | 45 | 35 | 0.3 | 200 | 1 | 100 | |

a general menu using a low cost of production, which is needed by most flights, e.g., steamed rice, and fried rice. While menu B has a reduced demand size since it is not a general menu that is required by all flights, e.g., omelette or noodles. Another menu in this economy class of service is menu C, a menu with lower demand stability ($c = 0.2$) representing a more specific menu which will only be served on board upon a special request, e.g., vegetarian meal with non dairy product (VGML) or baby meal (BBML).

Whereas menus D, E and F represented a menu servicing first class passengers. They are higher in cost parameters and smaller in demand quantity compared to the economy class (according to the ticket price and numbers of seats available). Due to the ability of passengers in being able to select a menu, menu D is the menu that the majority of passengers often select, e.g., salad with some imported topping, and imported beef steak (that is why the unit cost and ordering cost are higher than menus in economy class). However, as mentioned, it is somehow dependent on the numbers of passenger and their preferences on each flight (which is only a few seats compared to the economy class), so its $C = 0.2$. Menus E and F represent menus for first class passengers with less tendency of being ordered ($c = 0.3$). The major difference between these two menus is unit cost, $v = 100$ for menu E, and $v = 200$ for menu F. For example, oven roasted rack of lamb for menu E, whereas menu F which is higher in unit cost and could be an exclusive menu like lobster, scallop or imported salmon sashimi.

To summarize, menus A and B will give us an answer as to whether the menus under the same class of service and same cost parameters, but different demand sizes, will cost the caterer the same tradeoff cost for operating at nervousness-free service level and whether will they share the same optimal service level or not. For menu C, which is a special request menu and represented by a higher coefficient of variation than A and B, it will allow us to explore another finding on whether this type of special menu costs a manufacturer the same for operating at nervousness-free as menus A and B cost, and should manufacturers use the same inventory policy on service levels between lower class and superior class of service?

We also collected the penalty cost from orders being backlogged from the case company, which is a very important parameter for finding optimal service levels. We were told from a production manager that an exact penalty cost for each order being backlogged is quite complicated to calculate, unlike in another industry, the worst case scenario from orders being backlogged in the airline catering industry is that a pilot will not take-off at the scheduled time since there are not enough meals for the passengers yet. So finding the exact cost of flight time being delayed due to a disruption in production and distribution system of the airline catering company is an interesting topic and will be elaborated upon in the discussion part. The closest thing to penalty cost that a company can identify is an opportunity cost for each menu from being backlogged, 5% of unit variable cost ($v$) for menus A, B and C, whereas 10% for menus D, E and F is their estimation for the backlogged cost of each order ($1 per unit for menus A, B and C and $10 for menus D and E, and $20 for F). This number came from an estimation of extra cost that the company has to spend for intervening in a planned scheduling. For example, when menu A is found to be backlogged by 50 units from flight A, which will depart in the next hour, the company will intervene in the production of flight B (which will be scheduled for departure in the next 10 hours) and bring those 50 units to flight A. Since the production plan of flight B was messed up, an extra 50 units of menu A need to be produced with decreased production time. The same approach will be done for an extra input needed; an overtime payment for extra manpower will also be needed to cover pay. Menus like D, E and F will cause more cost (10%) compared to menus A, B and C (5%) since their production requires a more complicated process.

TABLE 10. Percentage change in expected total cost and its optimal service level of the case study

| **Service Level** | **Percentage change in expected total cost (%)** | | | | | |
|---|---|---|---|---|---|---|
| | **Economy Class** | | | **First Class** | | |
| | **Menu A** | **Menu B** | **Menu C** | **Menu D** | **Menu E** | **Menu F** |
| **0.9000** | 0 | 0 | 0 | 0 | 0 | 0 |
| **0.9100** | 0.12 | 0.09 | 0.01 | 0.25 | 0.24 | 0.28 |
| **0.9200** | 0.22 | 0.21 | 0.02 | 0.27 | 0.47 | 0.57 |
| **0.9300** | 0.35 | 0.34 | 0.04 | 0.52 | 0.71 | 0.58 |
| **0.9400** | 0.49 | 0.47 | 0.06 | 0.78 | 1.15 | 0.87 |
| **0.9500** | 0.66 | 0.60 | 0.07 | 1.04 | 1.40 | 1.16 |
| **0.9600** | 0.84 | 0.78 | 0.09 | 1.30 | 1.85 | 1.45 |
| **0.9700** | 1.09 | 0.99 | 0.12 | 1.58 | 2.32 | 2.02 |
| **0.9800** | 1.40 | 1.29 | 0.16 | 2.10 | 3.00 | 2.60 |
| **0.9900** | 1.89 | 1.75 | 0.21 | 2.88 | 3.93 | 3.19 |
| **0.9995** | 3.63 | 3.35 | 0.41 | 5.74 | 7.57 | 6.36 |
| **Optimal service level** | 0.970 | 0.970 | 0.980 | 0.980 | 0.990 | 0.990 |

The production manager also claimed that they are now operating at 90% of inventory service level which means only 10% chance that actual demand will be exceeded than what they produced is allowed in each planning horizon (7-day length). Thus, each menu will be solved for the total of 11 service levels from their current service level to nervousness-free level $\{0.900, 0.910, 0.920, 0.930, 0.940, 0.950, 0.960, 0.970, 0.980, 0.990, 0.9995\}$. The results are shown in Table 10.

Table 10 shows the results of solved optimal total expected cost (as a percentage change) from the case study company's current service level (90%) until nervousness-free level (99.95%), as well as the optimal service level for each menu by using the proposed formulation in the previous part. The results were found to be in the same direction with the self-generated demand in the previous part in which products with higher coefficient of variations like menus D, E and F were found to be more costly for the company to reduce nervousness by operating at nervousness-free level than those products with more stable demand like menus A and B, which compared to their current service level, will cost them 3.63% and 3.35% more for operating at nervousness-free operation for products A and B, but 7.57% and 6.36% for menus E and F respectively.

The optimal service level found in the above table was based on the given penalty cost or opportunity cost of an order being backlogged from the case study company: 5% of unit cost ($v$) or $1 per each order backlogged for menus A, B and C, 10% or $10 per each backlogged order for menus D and E, and $20 for menu F. The optimal service level of menus A and B was found to be the same at 0.970, while a menu for first class services which is higher in both cost parameters and coefficient of variation was found to be different at 0.980 for menu D, whereas 0.990 for E and F. Lastly, menu C which is a special request menu like a vegetarian meal, was found to be optimal at the level of 0.980.

7. **Discussion and Conclusion.** This paper has tried to identify an optimal service level with the goal of lowering the risk of schedule nervousness, which is a change in planned schedule caused by an uncertainty in demand. This is because in reality, a future demand is not deterministic but should be considered as a random variable with known probability distribution function as well as no such stationary trend existed, but rather a

non-stationary trend by using *static-dynamic uncertainty strategy*. The first major contribution of this paper is that we are among the first that are able to identify the cost of operating at zero-instability operations, otherwise known as *nervousness-free* operations, by comparing an optimal expected total cost within the *static-dynamic* uncertainty strategy. We have also proved and confirmed that the cost of lowering schedule nervousness is found to vary depending upon the different product nature, and thus, this leads to the conclusion that the manufacturer should not use the identical inventory policy for all products when hedging against nervousness.

The second major contribution is the proposal of a simple formulation for identifying optimal service level between nervousness and expected total cost based on that fact of calculating an opportunity cost of orders being backlogged at every level of a predetermined set of service levels.

Finally, in addition to an experiment on our self-generated demand and cost parameters, we have also selected an airline catering company in Thailand to be our case study. So, we are the first to point out that airline catering is a nervousness-sensitive industry since its finalized order can only be confirmed minutes prior to departure time, any disruption in production or distribution system from nervousness may lead to one of the most unacceptable situations, flights being delayed. We have used our case study to test whether our approach is still effective when applied by a practitioner in the real world or not. The findings of an optimal service level in a total of 6 products in two classes of service were found to be satisfied by our case study company and thus, confirmed that our proposed framework is simple and effective to be used by both academics and practitioners. The findings in this paper also lead to one of the interesting research questions in calculating the cost of a flight being delayed from a nervousness in production operations of an airline caterer. As well as an exact penalty cost or tradeoff cost that the caterer needs to pay when a backlogged order occurred due to nervousness.

## REFERENCES


[1] I. N. Pujawan, Schedule nervousness in a manufacturing: A case study, *Production Planning and Control*, vol.15, no.5, pp.515-524, 2004.

[2] H. Tunc, O. A. Kilic, A. S. Tarim and B. Eskioglu, A simple approach for assessing the cost of system nervousness, *International Journal of Production Economics*, vol.141, pp.619-625, 2013.

[3] K. M. Y. Law, Airline catering service operation, schedule nervousness and collective efficacy on performance: Hong Kong evidence, *The Service Industries Journal*, vol.31, no.6, pp.959-973, 2011.

[4] R. R. Inman and D. J. Gonsalvez, The causes of schedule instability in an automotive supply chain, *Production and Inventory Management Journal*, vol.38, no.2, pp.26-32, 1997.

[5] C. J. Carlson, J. V. Jucker and D. H. Kropp, Less nervousness MRP systems: A dynamic economic lot sizing approach, *Management Science*, vol.25, no.8, pp.754-761, 1979.

[6] H. M. Wagner and T. M. Whitin, Dynamic version of the economic lot size model, *Management Science*, pp.89-96, 1958.

[7] W. Hopp and M. Spearman, *Factory Physics*, 2nd Edition, McGrawHill, New York, 2000.

[8] C. D. Lewis, *Demand Forecasting and Inventory Control. A Computer Aided Learning Approach*, Woodhead Publishing Ltd., England, 1997.

[9] S. M. Disney and M. R. Lambrecht, On replenishment rules, forecasting, and the bullwhip effect in supply chains, *Foundation and Trends in Technology, Information and Operations Management*, vol.2, no.1, 2007.

[10] E. A. Silver, Inventory management: An overview, Canadian publications, practical applications and suggestions for future research, *INFOR 2008*, vol.46, pp.15-28, 2008.

[11] S. A. Tarim and B. G. Kingsman, The stochastic dynamic production inventory lot sizing problem with service level constraints, *International Journal of Production Economics*, vol.88, pp.105-119, 2004.

[12] N. Hasachoo and R. Masuchun, Reducing schedule nervousness in production and operations under non-stationary stochastic demand: The case of an airline catering company, *Proc. of IEEE*

*International Conference on Industrial Engineering and Engineering Management*, Bali, Indonesia, 2016.

[13] O. A. Kilic and A. S. Tarim, An investigation of setup instability in non-stationary stochastic inventory systems, *International Journal of Production Economics*, vol.133, pp.286-292, 2011.

[14] H. Tunc, O. A. Kilic, S. A. Tarim and B. Eksioglu, The cost of using stationary inventory policies when demand is non-stationary, *OMEGA*, vol.39, no.4, pp.410-415, 2011.

[15] J. H. Bookbinder and J. Y. Tan, Strategies for the probabilistic lotsizing problem with service level constraints, *Management Science*, vol.34, pp.1096-1108, 1988.

[16] J. ChristianLang, *Productions and Inventory Management with Substitutions*, Springer, Berlin, 2010.

[17] E. A. Silver, Inventory control under a probabilistic time varying demand pattern, *AIIE Transactions*, vol.10, pp.371-379, 1978.

[18] R. G. Askin, A procedure for production lot-sizing with probabilistic dynamic demand, *AIIE Transactions*, vol.13, pp.132-137, 1981.

[19] T. J. Hilger, Stochastic dynamic lot-sizing in supply chains, *BoD-Books on Demand*, Norderstedt, Cologne., 2015.

[20] J. M. Smith and B. Tan, *Handbook of Stochastic Models and Analysis of Manufacturing System Operations*, Springer, New York, 2013.

[21] S. A. Tarim and B. Kingsman, Modelling and computing $(\mathrm{R}'', \mathrm{S}'')$ policies for inventory systems with non-stationary stochastic demands, *European Journal of Operations Research*, vol.174, pp.581-599, 2006.

[22] S. A. Tarim and B. M. Smith, Constraint programming for computing non-stationary $(\mathrm{R}, \mathrm{S})$ inventory policies, *European Journal of Operational Research*, vol.189, pp.1004-1021, 2008.

[23] S. A. Tarim, M. K. Dogru, U. Ozen and R. Rossi, An efficient computational method for non-stationary $(\mathrm{R}, \mathrm{S})$ inventory policy with service level constraints, *European Journal of Operational Research*, vol.215, pp.563-571, 2011.

[24] H. Tunc, O. A. Kilic, S. A. Tarim and B. Eksioglu, A reformulation for the stochastic lot sizing problem with service level constraints, *Operations Research Letters*, vol.42, no.2, pp.161-165, 2014.

[25] H. Tunc, O. A. Kilic, S. A. Tarim and B. Eksioglu, The stochastic lot sizing problem with piecewise linear concave ordering costs, *Computers & Operations Research*, vol.65, pp.104-110, 2016.

[26] S. Bollapragada and T. Morton, A simple heuristic for computing non-stationary $(s, S)$ policies, *Operations Research*, vol.47, no.4, pp.576-584, 1999.

[27] M. Bijvank and I. F. A. Vis, Lostsales inventory systems with a service level criterion, *European Journal of Operational Research*, vol.220, pp.610-618, 2012.

[28] K. H. van Donselaar and R. A. C. M. Broekmeulen, Determination of safety stocks in a lost sales inventory system with periodic review, positive lead-time, lot-sizing and a target fill rate, *International Journal of Production Economics*, vol.143, no.2, 2013.

[29] R. M. Hill and S. G. Johansen, Optimal and near-optimal policies for lost sales inventory models with at most one replenishment order outstanding, *European Journal of Operational Research*, vol.169, no.1, pp.111-132, 2006.

[30] K. Nakashima, S. Thitima, E. Hans and G. Yachi, Stochastic inventory control systems with consideration for the cost factors based on EBIT, *International Journal of Supply Chain Management*, vol.3, no.3, pp.68-74, 2014.

[31] P. Jones, *Flight Catering*, 2nd Edition, Elsevier Butterworth Heinemann, 2004.

[32] N. Hasachoo and R. Masuchun, Schedule nervousness in production operations of an airline catering company: The challenge of an effective demand response program, *Proc. of IEOM International Conference on Industrial Engineering and Operations Management*, Malaysia, 2016.

[33] N. Hasachoo and R. Masuchun, Factors affecting schedule nervousness in the production operations of airline catering industry, *Proc. of IEEE International Conference on Industrial Engineering and Engineering Management*, Singapore, 2015.

[34] IATA, Catering quality assurance programme: Food processing safety standards, *IATA Catering Assurance Programme in Collaboration with Medina Quality Assurance Services*, Copyright 2002-2010, Medina Food Inc., 2010.

[35] N. Johan and P. Jones, Forecasting the demand for airline meals, *Quarterly Market Intelligent Report*, 2007.