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Validating Virtual Safety Stock Effectiveness through Simulation

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Abstract As a means of avoiding stock-outs, safety stocks play an important role in achieving customer satisfaction and retention. However, traditional safety stock theory is based on the assumption of the immediate delivery of the ordered products, which is not a common condition in business-to-business contexts. Virtual safety stock theory was conceived to raise the service level by exploiting the potential time interval in the order-to-delivery process. Nevertheless, its mathematical complexity prevented this technique from being widely adopted in the industrial world. In this paper, we present a simple method to test virtual safety stock effectiveness through simulation in an inventory system using a base stock policy with periodic reviews and backorders. This approach can be useful for researchers as well as practitioners who want to model the behaviour of an inventory system under uncertain conditions and verify the opportunity for setting up a virtual safety stock on top of, or instead of, the traditional physical safety stock.

Keywords Safety Stock, Virtual Safety Stock, Inventory Control, Base Stock Policy, Service Level, Delivery Slack Time

1. Introduction

In managing production systems, the so-called "sandbagging" techniques basically provide three alternatives for protection against uncertainty: reserving productive capacity, extending the lead times when establishing due dates for lots, and reserving a number of product outputs. In 1976 [1], Whybark and Williams described these last two main leverages for managing inventory systems in terms of safety time and safety stocks. Specifically, as a means of avoiding stock-outs, the important role of safety stocks is well-known for achieving customer satisfaction and retention. While the cycle stock size is chosen according to the average values of all the parameters that describe the company's context along with its supply chains or retail networks, the safety stock size depends on the variance of these parameters. Thus, despite the fact that the holding cost of safety stocks may be very high, a part of the safety stocks may, in reality, never be used: a company pursuing a high service level may opt for the expensive solution of keeping high safety stocks and end the year without any stock-outs simply because market behaviour was steady and the supplies always arrived on time. Should the company's management come to the conclusion that they were lucky not to have faced any unexpected events, or unlucky because the expensive investment in safety stock was unnecessary? Investing in safety stocks closely resembles the paradox present in insurance against the risk of accidents: investments are made in the hope of not needing to exploit them. Therefore, any investment in safety stock beyond what is absolutely necessary is wasteful and must be avoided [2]. Traditional safety stock theory [3] is based on the assumption of the immediate delivery of the ordered products. However, this condition is rarely present in practice: when there is an interval between the time that an order is received and the time that the product is actually delivered, the safety stock can be drastically reduced while preserving a high service level. This opportunity can be exploited by implementing a *virtual* safety stock (*VSS*), with which it is possible to increase the service level by exploiting some of the slack time between the time at which an order is received and the time that the ordered item must be sent or delivered directly to the customer.

In 2005 [4], a precise expression of the service level with a combination of *VSS* and traditional safety stock (henceforth the "traditional" safety stock will be renamed '*physical* safety stock' - *PSS* - in order to distinguish it from *VSS*) was formalized in the most general case. Unfortunately, however, this expression could not be solved in a closed form and was just calculated numerically. Hence, this mathematical complexity prevented the *VSS* technique from being widely adopted in the industrial world.

In this paper, we present the structure of a simulation model that can be easily implemented on a common spreadsheet in order to evaluate the opportunity for combining *PSS* and *VSS* in order to reach a target service level in an inventory system. The model simulates a simple base stock policy [5], taking into account stochastic demand and delivery times, and it is validated according to the traditional safety stock theory. Thus, this paper provides the reader with a simple method to test *VSS* effectiveness without the need to resort to the numerical computation of its complex formula. Indeed, we believe that, while waiting for an approximation of the *VSS* expression to be developed, simulation can be an easy and practical method for researchers as well as for practitioners and business managers to find the most convenient trade-off between the expensive storage of physical safety stock and the (hypothetical) negotiation of delivery slack times in order to find the target service level in any supply chain or retail and distribution context.

2. From Safety Time to Virtual Safety Stock

Several authors in the literature have investigated the "time versus stock" trade-off, either in generic contexts [6] [7] or in specific ones, from the Just-in-Time environment [8] to MRP systems [9] [1] [10] [11] [12] [13] [14] [15]. However, a first introduction of the delivery slack time concept (*DST*) and its influence in effectively reducing safety stocks is analysed in 2002 [16]. Here, the authors presented a technique for evaluating the effect of backlogging and the presence of delivery slack time at the service level. Despite the model working under restrictive hypotheses, the principle of increasing the service level without safety stock and only through the exploitation of time suggested the introduction of the *VSS* concept, which is a complex translation, in product units, of the delivery slack time. It is important to mention that a function may be considered to be "virtual" when the performance of the system does not decrease compared to the traditional physical configuration; in this case, we consider a safety stock to be *virtual* only when the customer does not notice the stock-out when he launches his order, which differs from backorder management.

In order to introduce the simulation model, it is advisable to recall some concepts which stand at the base of the *VSS* technique [4]. For example, let us analyse a typical supplier-retailer situation, where the supplier periodically provides the retailer with a replenishment quantity of *Q* products. This total is planned to be delivered every period *p* and, in the average case, will suffice to satisfy all the customers' orders during the period. The retailer's performances are measured through its service level, defined as the ratio between the number of periods in which a stock-out event is recorded and the total number of analysed periods [3]. According to the traditional theory, given that the customers' demand (*D*) and the supplier's delivery time (*DT*) is uncertain, the retailer keeps the safety stock to secure its service level from two kinds of unexpected events: a delay in the supplier's replenishment delivery or else an increase in the customers' demand. Conventionally, a stock-out event occurs if no products are available when a customer's order is received. However, if a slack time is present in the order-to-delivery process, we shall distinguish two different moments:

- t_r is the moment at which an order is received;
- t_d is the moment at which the ordered product needs to be delivered.

The delivery slack time (*DST*) can be defined as:
$DST = (t_d - t_r)$

Clearly, the physical presence of the ordered products is needed in t_d but not in t_r. Thus, a stock-out occurs if both of the following two conditions are verified:

1. Stock is exhausted within the arrival of the customer's order, i.e., in t_r;
2. No replenishment will arrive within the period for the delivery, i.e., by $t_r + DST$. This second condition

represents the main difference in computing the service level with respect to the traditional safety stock theory.

Unlike backlogging, the delivery slack time may be inexpensive due to the fact that it is intrinsically present in numerous commercial contracts in many industrial contexts, and customers may even be unaware of it. Indeed, in many business relations, the order is often received in advance of the time at which the products need to be delivered. Or, in many other cases, customers may find it normal that deliveries are planned only on certain days of the week. Here, the hypothesis of immediate delivery – on which the traditional safety stock theory is founded – would lead to worse results. For this reason, it is possible to interpret the *DST* as a *virtual* safety stock. Clearly, considering that the *DST* may not suffice to grant the desired service level, a company may opt to store a certain level of physical safety stock (*PSS*) anyway. Indeed, a combination of *PSS* and *VSS* is advisable, but - as it has been said - choosing the most appropriate mix of these parameters is not easy. Now, let us introduce the following stochastic variables:

The demand during period t:

$$D(t) = \mathrm{N}(\mu_d; \sigma_d),\ \text{s.t. } D(t) \geq 0$$

The delivery time for order r:

$$DT(r) = \mathrm{N}(\mu_{dt}; \sigma_{dt}),\ \text{s.t. } DT(r) \geq 0$$

The service level calculated according to the original safety stock theory [3] is:

$$SL(\sigma_d, \mu_d, \sigma_{dt}, \mu_{dt}, PSS) = \frac{1}{\sqrt{2 \cdot \pi}} \cdot \int_{-\infty}^{k} e^{\frac{-z^2}{2}} dz \qquad (1)$$

where:

$$k = \frac{PSS}{\sqrt{\sigma_d^2 \cdot \mu_{dt} + \sigma_{dt}^2 \cdot \mu_d^2}}$$

The aim of the *VSS* research stream is to include the *DST* in a simple and manageable service level formulation. In 2005 [4], a precise expression of service level with *PSS* and *VSS* was formalized as follows:

$$SL(\sigma_d, \mu_d, \sigma_{dt}, \mu_{dt}, PSS, DST) =$$
$$= 1 - \int_0^{\infty} \left[\left(\frac{1}{\sqrt{2 \cdot \pi}} \cdot \int_{\alpha(t)}^{\infty} e^{\frac{-z^2}{2}} dz \right) \cdot \left(-\frac{1}{\sqrt{2 \cdot \pi}} \cdot \int_{\beta(t-\varepsilon)}^{\beta(t+\varepsilon)} e^{\frac{-z^2}{2}} dz \right) \right] dt \qquad (2)$$

where:

$$\alpha(t) = \frac{t - \mu_{dt} + DST}{\sigma_{dt}}$$

$$\beta(t) = (PSS + \mu_d \cdot \mu_{dt} - \mu_d \cdot t) \cdot \frac{\sqrt{\mu_{dt}}}{t \cdot \sigma_d}$$

Unfortunately, this expression cannot be solved in a closed form and should be calculated numerically (indeed, ε represents the time sampling interval; the smaller ε is, the more precise is the numerical computation, e.g., working with weekly deliveries and daily re-orders, ε could represent an hour).

In spite of its complexity, *VSS* is nonetheless extremely effective. However, in order to favour its wide use, a simpler expression to calculate the service level with *PSS* and *VSS* would be desirable. For this reason, while waiting for an approximation of the complex *VSS* formula to be developed, we believe that a simple simulation model on a common spreadsheet can provide a useful aid for academics and businessmen interested in the field.

3. The Simulation Model Structure

Simulation has frequently been used for evaluating the effectiveness of inventory control policies [17] [18] and, in some cases, it has been used for safety stock optimization [9]. However, when simulating inventory models, it is important to pay attention to detail. For instance, Soshko et al. [19] used a Microsoft Excel spread-sheet to reproduce the *s*-*Q* "continuous review" policy; because the *s*-*Q* policy requires a replenishment order to be placed exactly when the inventory level falls below the so-called re-order level threshold [20], this approach is questionable unless the spreadsheet rows (or columns) represent a time interval (e.g., hour) which is sufficiently small compared to the length of the single period (e.g., day, week): the smaller the time interval, the smaller the physiological error (which is inevitably introduced due to the implicit sampling mechanism) will be. This error may easily lead to the underestimation of the service level of the stock policy.

Microsoft Excel is probably the most widespread business computing tool and its flexibility may cause practitioners and - often - academics to use it for complex calculations; however, when using it to simulate continuous events, its limitations may be exposed. Even so, Excel can be used effectively to simulate several discrete inventory [21] or warehousing [22] [23] [24] systems. Specifically, it is suitable for implementing periodic inventory models, such as the *Q*-*p* policy or the "up-to-*S*" base stock policy [25]; the latter was used in this paper. In these cases, the inventory level, the demand and the other key parameters of the model can be easily calculated for the period in the spreadsheet rows.

Here, the simulation of a single-item inventory system adopting the "order-up-to-S" base stock policy with backorders is set up in the following way: for each period t, the system produces a random non-negative demand $D(t)$; thus, for each period a final inventory level is calculated by subtracting this demand from the initial inventory level. In the event that the cycle stock is depleted, the safety stock is used to fulfil the excess of demand; in the event that the safety stock is also depleted, the remaining demand is backlogged.

In classic inventory models, it is common to assume that excess demand is backordered [26] [5] [27], and this assumption is common in industrial environments [28]. Here, the simulation aims to verify whether it would be possible to exploit the delivery slack time and reduce backorders. Thus, in this simulation all excess demand is satisfied (i.e., there are no lost sales), either through backorders (in which case, the service level decreases) or through delivery slack time (in which case, the service level remains the same).

After each re-order interval p, the initial inventory level is checked and an order is issued for a variable quantity Q. The quantity Q is the difference between a predefined target level S and the initial inventory, taking into account any potential backorders or the need for replenishing the safety stock. The issued order r is received after a random variable delivery time $DT(r)$. When the order is received, the received quantity is first used to fill the backorders (if needed) and replenish the safety stock (again, if needed); the rest is added to the initial inventory. On top of the safety stock level, the level S is determined by calculating the quantity needed, on average, between the time the order is released and the time it is received, i.e., p plus the average delivery time. In this way, a simple base stock inventory system can also be modelled easily using a spreadsheet like Microsoft Excel.

According to the literature, the main sources of variability that should be taken into account when modelling inventory systems are the demand quantity and the order delivery time (see, for instance, Hadley and Whitin [3]). Indeed, when creating a simulation model, these parameters should be randomly generated. When working with spreadsheets, an easy solution is to use a random inverse transformation sampling from an appropriately chosen probability distribution. Poisson [29], Gamma [30], Erlang [31] [32], Log-normal [33], Beta [19] or other asymmetric or skewed probability distributions are frequently used. The theoretical framework in which the first inventory models were originally developed instead used Gaussian-distributed stochastic variables because of their convenient mathematical properties. To comply with the classical theory, in this specific case, this latter distribution was chosen. Clearly, because negative values are unacceptable as a demanded quantity or as a time variable, the Gaussian left negative tail needs to be truncated to zero.

The management-specified service level (SL_{target}) influences the PSS target level, which – in the absence of the DST – is calculated using Hadley and Whitin's formula [3]:

$$PSS_{target} = k \cdot \sqrt{\sigma_d^2 \cdot \mu_{dt} + \sigma_{dt}^2 \cdot \mu_d^2}$$

where k, in accordance with [3], is chosen so that:

$$SL_{target} = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{k} e^{-\frac{z^2}{2}} dz$$

Thus, the S value is defined as:

$$S = \mu_d \cdot (p + \mu_{dt}) + PSS_{target}$$

First of all, the simulation model needed to be validated. For this reason, several scenarios were simulated, randomly choosing the values of different parameters among those most frequently recorded in industrial contexts (e.g., if $t = 1$ day, $p = 7$ means weekly re-orders) and verifying whether the resulting service level was equal or similar to the theoretical value, without considering the VSS. Thus, we assume that a scenario is characterized by the following parameters:

Scenario = $\{\mu_d; \sigma_d, \mu_{dt}; \sigma_{dt}; p; PSS_{target}; DST\}$

The service level is measured as the percentage of the number of re-order intervals in which no backorders are recorded, over the total number of re-order intervals during the whole simulation. A single simulation run consisted of 50,000 periods (e.g., 50,000 days), and 10 runs were performed for each scenario. The resulting service level is calculated as the average value obtained over the 10 runs. The results showed that the simulation reproduced the theoretical behaviour of the inventory systems very well, containing the error (calculated as the absolute distance between each pair of values) below the 0.9% mark.

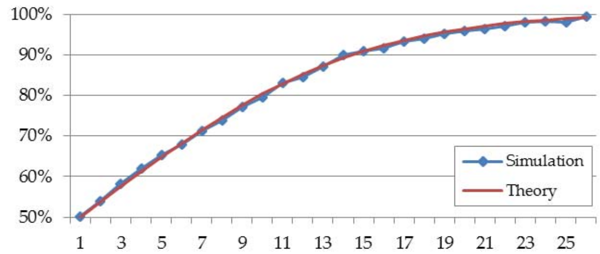

Figure 1. Simulated service level compared to the theoretical values in 26 scenarios, as physical safety stock increases and $DST = 0$

For instance, Figure 1 shows the correspondence of the simulation results with the theoretical service levels for a sequence of 26 scenarios with {10; 1; 3; 1; 7; PSS_{target}; 0}, where the target physical safety stock PSS_{target} varies from 0 to 26 units. Since $DST = 0$ in all scenarios, these tests are performed comparing the simulation examples with the theoretical result of Hadley and Whitin's formula. Once the model is validated, the *DST* can be added in the scenarios and the service level can be recalculated, as is shown in the following section.

4. Simulation Results

Including the *DST* in the simulation involves modifying the method by which customers' orders are managed when the stock level is zero. Indeed, as previously stated, on top of the absence of stock, in order to record a stock-out event a second condition must be verified: no replenishment will arrive within *DST* from the moment in which the order is received. Thus, in the simulation, each new replenishment lot was partially used to fulfil the eventual backorders recorded during the stock-out condition up to the *DST* time in advance. The simulation model was tested in different scenarios with incremental values of the *DST*. The simulation results once again showed an excellent correspondence between the service level values and the numerical calculations of the *VSS* formula given in [4]. For instance,

Figure 2 compares the simulation results with the service levels numerically calculated for three sequences of six scenarios with {10; 1; 3; 1; 7; PSS_{target}; *DST*}, where the target physical safety stock PSS_{target} varies from 0 to 5 units and the *DST* equals 1, 2 or 3 periods. Again, the error value remains below the 1.0% mark.

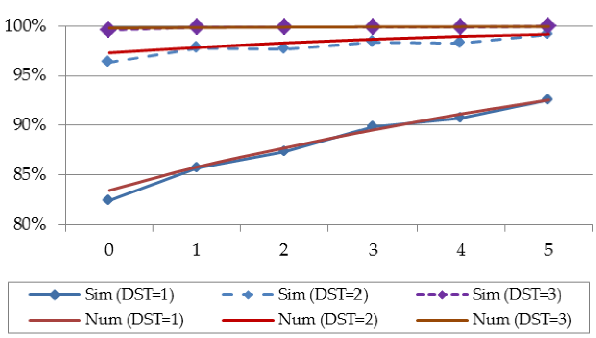

Figure 2. Simulated service levels compared to theoretical values in 3x6 scenarios, as PSS_{target} increases, with $DST = 1; 2; 3$ periods.

In order to prove the adherence of the simulation model to the *VSS* theory, the following figures show the simulated service levels in nine different scenarios where PSS_{target} was always set to zero. Remembering that - according either to the traditional theory or to the previously presented simulation results – in the absence of safety stock, the service level should be 50%, and the *VSS* theory shows that it is possible to reach very high values of service level relying only on delivery slack times. Clearly, the *VSS* effectiveness decreases firstly as σ_{dt} increases (supply unreliability) and, secondly, as σ_d increases (demand variability). For this reason, the following figures represent nine variations of the base-case scenario {10; σ_d; 3; σ_{dt}; 7; 0; *DST*} with different values of σ_d, σ_{dt} and with DST =1; 2; 3 periods. The horizontal axis represents the coefficient of the variation of the demand, i.e., the normalized measure of dispersion of the demand probability distribution, defined as $Cv = \sigma_d / \mu_d$.

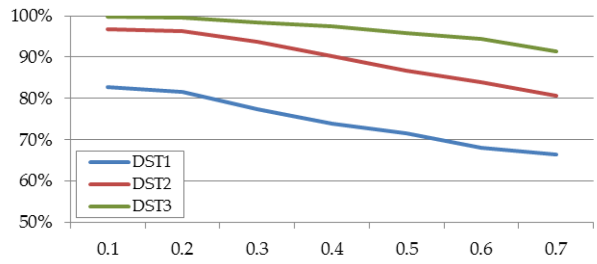

Figure 3. Simulated service level in scenario {10; 1; 3; 1; 7; 0; *DST*}, as *Cv* increases, with $DST = 1; 2; 3$ periods.

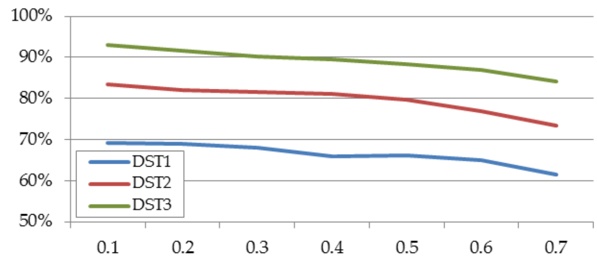

Figure 4. Simulated service level in scenario {10; 1; 3; 2; 7; 0; *DST*}, as *Cv* increases, with $DST = 1; 2; 3$ periods.

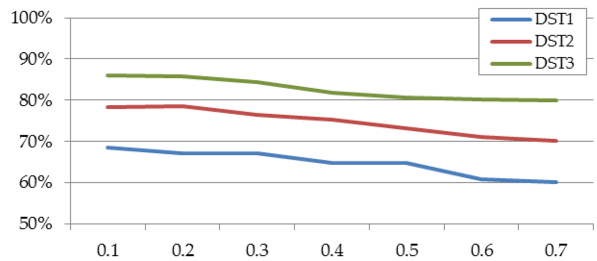

Figure 5. simulated service level in scenario {10;1;3;3;7;0;*DST*} as *Cv* increases, with DST =1;2;3 periods.

In the most complicated scenario, depicted in **Figure 5**, with the extreme unreliability of the supply times ($\sigma_{dt} = \mu_{dt}$) and high demand variability ($\sigma_d = 0.7 \cdot \mu_d$), despite the absence of physical safety stock, it is possible to reach a service level of 60%, 70% and 80%, respectively, by exploiting a delivery slack time of 1, 2 or 3 periods (e.g., days) out of a re-order interval of 7 periods (i.e., weekly re-orders). Obviously, much more promising results are reached in the less unstable scenario ($\sigma_{dt} = 0.33 \cdot \mu_{dt}$, $\sigma_d = 0.1 \cdot \mu_d$) depicted in **Figure 3**, where the service levels reach, respectively, 82.7%, 96.8% and 99.7%. It is important to underline how these service levels are reached without any physical safety stock. On top of demonstrating the effectiveness of the *VSS* approach, these results show that it is possible to easily build a simulation model on a common spreadsheet and calculate the most convenient combination of *PSS* and *VSS* on any desired scenario (e.g., imposing a certain *DST* and a target service level and computing the required *PSS*, without the need to resort to the numerical computation of the *VSS*'s complex formula).

The presented model referred to is a simple base stock policy; thus, the reader interested in applying the *VSS* concept to other inventory management policies should customize the model to the particular case. To this extent, it is important to note that the *VSS* concept - deriving directly from the *PSS* classical theory - lives under the same assumptions and limitations [3] (e.g., it is not suitable to calculate the service level for spare parts, custom products designed for a unique customer, or generic slow movers product). Meanwhile, its best applicability is referred to fast mover items or, in general, to those cases where the product quantities asked by the customers are relatively small with respect to target stock levels.

5. New Business Opportunities from the Virtual Safety Stock Exploitation

As has been mentioned, *VSS* can be extremely effective in raising the service level without the need for the immobilization of capital in *PSS*. Moreover, a delivery slack time is present in any case in which the delivery is not as immediate, such as when the order is received, which is a frequent condition. For example, in 2009, an application of the *VSS* to the retailing of large household appliances in a hypermarket [34] proved not only its effectiveness in real cases but also its applicability in business-to-consumer contexts. There, a positive delivery slack time was indeed present because customers who buy washing machines, dishwashers, fridges and other heavy electrical appliances in a metropolitan hypermarket rarely decide to take the product they purchased home with them immediately; more frequently, a house delivery is requested and planned over the following five or six days. Thus, in that context it was easy to exploit this slack time to increase the service level by constituting a *VSS*. In [4], the authors distinguished three cases:

- The *DST* can be totally inside the retailer's order-to-delivery process: for instance, it is known - and accepted by customers - that the retailer arranges the deliveries only on Friday morning; thus, if an order is received on Monday evening, the retailer can rely on three working days for the *DST*. If on Monday the retailer has no stock, he should not refuse the order because he may receive the product by Friday, and the customer will never know that his order found the retailer in a stock-out condition;
- The *DST* can be partly inside and partly outside the retailer's order-to-delivery process: for instance, the order is received on Monday as a preliminary agreement that the delivery will be on Friday. Despite this, the retailer negotiates another two days of backlog. In this way, the total *DST* will be five days;
- The *DST* can be totally outside the retailer's order-to-delivery process: for instance, a customer orders a product and expects an immediate delivery; the retailer negotiates a delayed delivery (backlog) of three days, offering an economical compensation to the customer. In this case, he will have a *DST* of three days as well, although the customer will notice that the retailer was in a stock-out condition when he made the order.

In the first and second cases (in part), the *DST* is inexpensive, and thus not exploiting its significant positive influence on the service level seems unwise. In the third case, there is still the opportunity of finding a more convenient agreement with the customer, with respect to the classical supply contract with a unique service level: indeed, managing an inventory point with both the *VSS* and the *PSS* leads to the possibility of outlining a more complex supply contract, in which two service levels are defined: a first service level (e.g., 70%) is granted thanks to the presence of the *PSS*, that can thus be calculated with the traditional formula (1); on top of this, an extra stake of the service level (e.g., 25%, in order to reach a total of 95%) is granted with the *VSS*. In other words, this would mean that orders are granted with immediate delivery in 70% of cases, while they are delivered within the *DST* in a residual 25% of cases. This kind of contract is much more convenient, in terms of lowering safety stock levels, with respect to a traditional 95% service-level contract. Supplier and customer may negotiate a mutually convenient *DST* while also knowing that the delivery will rarely experience a delay, because the *VSS* is exploited only when the *PSS* is finished. With these presuppositions, the possibility of computing the most appropriate combination of the *PSS* and *VSS* with a simple simulation model on Microsoft Excel - instead of numerically solving a nested integral expression – seems useful in practice.

6. Conclusions

In most industrial contexts, as well as in some specific business-to-consumer situations, it is not appropriate to calculate safety stocks with the hypothesis of immediate delivery. Indeed, the delivery slack time – which is the positive interval between the time at which an order is received and the time at which the product is shipped – can be extremely effective in raising the service level. In

2003, this concept led to the definition of *virtual safety stock* (*VSS*). However, its mathematical complexity made it difficult to develop successfully in the business world. In this paper, we described how to build a simple simulation model on a common Excel spreadsheet, in order to test the effectiveness of combining a *VSS* and a *PSS* for any desired scenario; the presented approach is extremely helpful for those academics and practitioners who want to compute the safety stock level while avoiding the complexity of the *VSS* formula, or else who want to easily verify whether a delivery slack time can be effectively exploited in order to raise their company's service level or reduce the stockholding cost. The paper describes the structure of the simulation model along with its validation on an inventory system working with an "order-up-to-S" base stock policy with backorders, subject to uncertainty in both the demand quantity and the order's delivery time: the simulation results showed that, in the absence of any physical safety stock, a *VSS* may help raise the service level from 10% to almost 50%, depending upon the different scenario characteristics. These results confirm the effectiveness of *VSS* and they illustrate a simple method to evaluate its applicability, while waiting for an approximation of the complex mathematical expressions to be developed for *VSS*.

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