EFFECT OF NEGATIVE PARAMETERS IN INVENTORY MODELS PERFORMANCE

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ABSTRACT
This paper presents a comparative study of four inventory models. Three of them are reactive ones, the Order Up to Maximum Inventory Level, Base Stock and Fixed Lot Size models which don't use demand forecasting to quantify the acquisition decisions. One of them, referred as Requirement Planning, operates using demand forecast. The Requirement Planning and Base Stock models operate with minimal purchase order quantity parameter to improve their competitiveness. Reorder Level and Safety Stock parameters are permitted to be negative. Average operation cost per period is the performance measurement considered, restricted to a minimum service level. The analysis uses a search model jointly a simulator to optimize the parameters. The paper analyses the effects, in the relative models performance, of the negative parameters permission and the value of the Purchase Cost and effectuates a sensibility analysis by testing four different Service Levels.

Keywords: inventory, simulation, search methods, forecast

1. INTRODUCTION

The importance of customer satisfaction for business was demonstrated by Japanese success in the last decades. Methods to improve customer service levels with good cost performance were developed by them and now are used worldwide for the same objective.

Just-in time (JIT) is one of these methods. Usually understood like a production system, it is also a concept of ideal materials flow: the production or supply of items in the exact demand moment and quantities, neither before nor after. This ideal flow condition is the most efficient when low inventory quantities and demand satisfaction are the goals of the production system. The system is managed to low inventory quantities and no shortage. But this is not enough to assure cost efficiency. JIT concept often implies a large number of acquisition/production orders, which can result in large operation costs when the purchase/production fixed costs are high. To specify a minimum service level and search a model with the lowest operation cost is a common way of combine these goals.

To attend the JIT concept and keep the purchase cost low are vital to an inventory model achieve good performance in this environment.

Traditional inventory models decide the moment and the quantity to replenish inventory using parameters and inventory level. They "react" to a system condition, justifying the adjective "reactive" that is used here to identify them. Reactive models need safety stocks to face the total demand variability during the time they need to react, and only when demand variability and reaction time are close to zero they attain the JIT condition.

Another class of inventory models can be seen in Material Requirements Planning systems (MRP). They use forecasts to decide when and how much to buy or to produce. Named here Requirements Planning (RP), this "active" model can anticipate the demand, adjusting the quantities and the times close to the moment of use, the JIT condition, reducing the necessity of safety stock needed to face only forecast errors, instead of all demand variability, which the reactive models need to face. This characteristic, combined with good available forecasts, permits, in theory, the model to be close with JIT concept in demand variation environments. In the other hand, it tends to purchase more times than reactive models (Stock Base is an exception), incurring in high operation costs when the inventory system has high purchase cost.

The comparison of inventory models performances in different conditions becomes interesting since each model has weak and strong points.

A comparative cost performance study was performed, using 4 inventory models, 3 reactive and the RP inventory model. Sixteen different combinations of 2 purchase costs, 4 service levels and permission for models parameters assume negative values (important for improve Up to Order Level and Requirements Planning performances) were tested in 160 items with 36 historical demand real data of an mobility products company. Simulation and search methods were used to optimize models parameters to get, for each model in each demand environment, the minimum mean operation cost condition.

2. LITERATURE REVISION

Inventory uses mathematical models since 1913, when F. W. Harris published his famous article about the economic lot size calculation. During the II World War, mathematic formulation of models and parameters calculations were focused, particularly for the reorder point and lot size under particular situations of demand, supplier and costs environments. Several works were important references in the dissemination of this approach, like the articles of Dvoretzky and Kiefer (1952) and Arrow *et al.* (1958), and the books of Hadley and Whitin (1963), Naddor (1966) and Brown (1967).

The inventory models initially presented by this approach, today known as traditional models, allow decide when and how much to reorder without demand forecast. The demand is considered continuous with constant average and explained by a fixed and known probability distribution. Studies about inventory models during the 60s and 70s adopted demand behavior based on static Normal and Poisson distributions, which allowed convenient mathematical treatment. Browne and Zipkin (1991) studied the limits of this traditional approach. Agarwall (1974) is an exception in this period, showing that the environment changes are important and modify the best model for inventory management.

The first reference to forecasting applied to inventory is Brown (1967). This author recommends the use of forecasting to calculate reactive inventory models parameters to achieve better efficiency. In the 70's, Eilon and Elmaleh (1970) continued this approach. At the same time, Just-in-time is discussed in the academy, due to the Japanese success in occidental markets, and the idea of reorder only the necessary material instead of lots starts to be a must.

The Material Requirements Planning (MRP) system appeared in sequence. Initially, its focus was the decisions of supply/ production of items with dependent demand which appears in production and assembly structures of items with independent demand. But the need to include trend, seasonality and jumps in demand leaded research to decisions based on forecast. The chronology and relevant aspects of this can be seen in Sipper and Bolfin (1998). Unless the original MRP idea was to buy/produce only the necessary quantities, the high purchase cost in several items leads to several lot forming models applied to MRP systems. Hax (1984) and Orlick (1995) present these models.

Lee and Adam (1986) continued the research of forecasting in inventory. They studied the forecast errors impact in MRP systems, comparing several reactive inventory models performances applied to the dependent items.

Gardner (1990), using real demand historical data of independent items, studied the performance of the inventory system based on the classical Economic Lot Size model.

Defining the lots acquisitions based on forecast demands, generated by four different forecasting models, he calculated "trade off" curves between inventory investment and customer lead-time. Simulation of the system operation during the period of historical demand data was used in the calculations. His main conclusion was the importance of forecasting errors to the amount of inventory investment needed to achieve a specific customer lead-time. The smaller the error, the smaller the investment needed. The study is important, too, due to the adoption of the joint performance measurement of the forecasting and inventory models.

Fildes and Beard (1992) studied the forecasting use in the production and inventory control. They analyzed the typical characteristics of inventory data and several forecasting models, and concluded that researchers neglected the production and inventory control area, the commercial systems had inadequate forecasting models and users experimented unnecessary large errors, inventories and poor demand satisfaction.

The improvement in problems complexity by the use of forecasting in inventory systems asked the use of simulation and search methods for the definition of near- optimal decisions. Examples of it can be seen in Fu and Healy (1997) and Lopez-Garcia and Posada-Bolivar (1999).

2.1. Forecasting Models

All forecasting models selected use the smoothing logic. Table 1 presents the 4 types and the projection equations for forecast calculation.

Table 1: Forecast models and corresponding formulas

Model Curve	Formula
Constant	$Dt = Q + \xi\sigma$
Trend	$D_t = Q_{to} + I.(t-t_o) + \xi\sigma$
Cyclical with constant	$D_t = Q.S_t + \xi\sigma$
Cyclical with trend	$D_t = [Q_{to} + I.(t-t_o)].S_t + \xi\sigma$
to = initial date St = seasonality coefficient of period t Q = constant Dt = demand forecast of period t I = slope t = period	

These models are analyzed in details in Makridakis and Wheelright (1998) and Hanke and Reitsch (1998). Based on them, smoothing methods are used to quantify the Q, I and F parameters, balancing the importance of old and new demand data in the forecasts.

Table 2: Forecast models and corresponding smoothing parameters and projection formulas

Model Curve	Smoothing Method	Projection
Constant	Simple with α	$PD_{t+k} = Q_t$
Trend	Simple with α and β (*Holt*)	$PD_{t+k} = Q_t + k.I_t$
Cyclical with constant	Simple with α and γ (*Winter*)	$PD_{t+k} = Q_t.S_{t+k-nL}$
Cyclical with trend	Simple with α, β and γ (*Winter*)	$(Q_t + k.I_t).S_{t+k-L}$

Table 3: Formulas used in the period-to-period calculations of Q, I and S parameters

Curve	Formula
Constant	$Q_t = \alpha V_t + (1-\alpha) Q_{t-1} = Q_{t-1} + \alpha(V_t - Q_{t-1})$
Trend	$Q_t = \alpha V_t + (1-\alpha)(Q_{t-1} + I_{t-1})$ $I_t = \beta (Q_t - Q_{t-1}) + (1-\beta) I_{t-1}$
Cyclical with constant	$Q_t = \alpha (V_t / S_{t-L}) + (1-\alpha) Q_{t-1}$ (L=cycle in periods) $S_t = \gamma (V_t/Q_t) + (1-\gamma) S_{t-L}$
Cyclical with trend	$Q_t = \alpha (V_t / S_{t-L}) + (1-\alpha)(Q_{t-1} + I_{t-1})$ (L=cycle in periods) $I_t = \beta (Q_t - Q_{t-1}) + (1-\beta) I_{t-1}$ $S_t = \gamma (V_t/Q_t) + (1-\gamma) S_{t-L}$

Table 2 presents the smoothing parameters and projection formula for the models. At each period, Q, I and S are recalculated, using the real demand occurred (V) and Table 3 formulas. The models adjusted to the item demand series allow the selection of the corresponding α, β and γ for each of them, using the search and simulation routine. Again, Makridakis and Wheelright (1998) and Hanke and Reitsch (1998) provide the optimization method, using 12 initial periods to calculate the initial Q, I and S values and the last 24 periods to adjust parameters to the minimum error, measured by mean absolute deviation - MAD.

2.2. Inventory Models

Following, the inventory models selected for this study are presented.

2.2.1. Periodic Up to Order Level model (UO)

In this model, the lot size is calculated to ensure that the total stock quantity never exceeds a defined quantity, the Order Level (ol) parameter. The decision rule is:

$$poq = (ol - st) \text{ if } st \le rl \quad (1)$$

$$poq = 0 \text{ (zero) if } st > rl \quad (2)$$

where

poq is the Purchase Order Quantity, the lot size to replenish the inventory

ol is the Order Level parameter

st is the current stock at the decision moment, including the purchased lots still arriving

rl is the Reorder Level, the quantity parameter that starts the purchase activity.

The periodic review occurs at the end of each period.

2.2.2. Periodic Base Stock model (BS)

The decision rule for this model is

$$poq = (ol - st) \quad (3)$$

This simple rule implies stock replenishment every time a withdraw occurs. It is a particular case of the precedent model, where the Reorder Level is equal to the Order Level parameter.

Like the other, it is a model with a one-period review.

2.2.3. Periodic Economic Order Quantity model (EQ)

This traditional model has the following decision rule

$$poq = n.ls \quad \text{if } st \le rl \quad (4)$$

$$poq = 0 \text{ (zero) if } st > rl \quad (5)$$

where

ls is the fixed lot size, usually calculated using some economic criteria

n is a number of lots (LS sized) that assure the st>=rl after this purchase

Again, the replenish decision occurs at every 1 period.

2.2.4. Requirements Planning Model (RP)

This active model uses the following decision rule:

$$poq = nr \quad \text{if } nr > 0 \text{ (zero)} \quad (6)$$

$$poq = 0 \text{ (zero) if } nr \le 0 \text{ (zero)} \quad (7)$$

where

nr is the Net Requirements needed to satisfy the forecast demand of the time defined by the Lead Time plus Reviewing Period and also maintains a safety stock.

The general NR formula is:

$$\underline{nr_{t,t+lt}} = \sum_{i=1}^{lt+rp} d_{t,t+i} - \sum_{j=1}^{lt-1} poq_{t+i-lt,t+i} - s_t + ss \quad (8)$$

where

nr is the Net Requirements need to satisfy the demand during the next LT + RP periods

t is the system date when the decision is taken

lt is Lead Time of the item

rp is the Reviewing Period

d is the Demand forecast

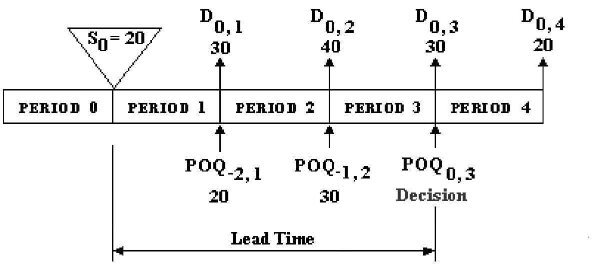
poq is the Purchase Order Quantity

s is the stock of items

ss is the Safety Stock

The first key in the parameters is the date when the system takes the decision, which generates the value parameter. The second key refers to the deadline to that decision.

The following example in Figure 1 helps to understand the model operation (suppose *ss* = 10).



The Net Requirements value in this example is

$$nr = (30 + 40 + 30 + 20) - (20 + 30) - 20 + 10 = 60 \quad (9)$$

The Order decided in the current t = 0 needs to satisfy the next 4 periods, because the lot will only arrive at the end of period 3, to be used in period 4. To order only the necessary quantity, the *poq* decided in the past (and not received) and the current stock is subtracted from the initial sum. Finally, a safety stock is added to prevent shortages due to forecasting errors. Therefore, this model always tries to end the last period with only the Safety Stock in the inventory. Safety Stock is the single parameter for this pure form model.

2.2.5. Minimum Net Requirements (MNR)

The Base Stock models and the Requirements Planning Model tend to order with low quantities due to their decision rules. This is a great difficulty in environments where the purchase cost is high.

To improve the competitiveness of these 2 models, a second parameter is introduced, the Minimum Net Requirements. It is the smallest quantity the system must order when a quantity different from zero is needed. If a quantity greater than MNR is needed, the model orders this quantity instead of MNR. The new decision rules for Periodic Base Stock and Requirements Planning Model are, respectively:

$$poq = (ol - st) \quad \text{if} \quad (ol - st) \geq mnr \quad (10)$$

$$poq = 0 \quad \text{if} \quad (ol - st) < mnr \quad (11)$$

$$poq = nr \quad \text{if} \quad nr \geq mnr \quad (12)$$

$$poq = mnr \quad \text{if} \quad 0 < nr < mnr \quad (13)$$

$$poq = 0 \text{ (zero)} \quad \text{if} \quad nr \leq 0 \text{ (zero)} \quad (14)$$

These modified rules were used in all simulations of this study.

On a mathematical approach, the parameter reorder level (*ro*) used in UO and RP models would be negative in cases of low minimal service level allowed. In the real word we do not see negative parameters probably by the difficulty of operation with the models.

This work analyses the different performance of the UO and RP models in case of negative parameters allowed.

3. MODELLING

Figure 2 presents the experimental design for models comparison. Actual historical data series of 160 items, each one with 36 periods, are used to compare the inventory models. First, this demand data set was used to select the best between the 4 forecasting models, which provided the demand forecast in the active inventory model. The decision variable was the forecasting error, measured by the Mean Absolute Deviation (MAD), calculated for the last 24 periods of each item. The initial 12 periods were used to calculate the forecast parameters seeds required in the simulation and search routine. Then, the 4 inventory model adjusted to revision period equal to 1 were analysed using the same demand data set.

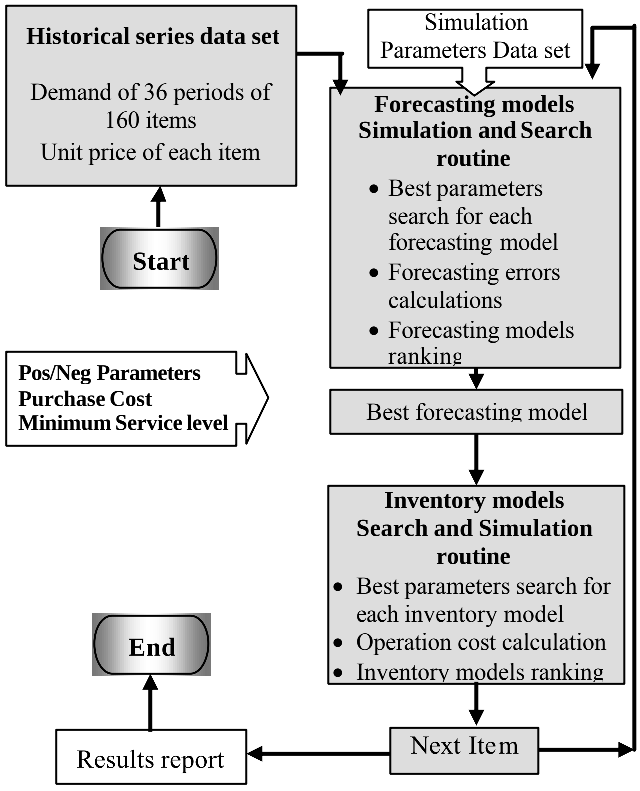


Figure 2: Experimental design for the study

The modeling of the inventory systems uses a multistart neighborhood search. Each search corresponds to a pair of parameters of the inventory model tested. A simulator is used as a function to calculate de search function which, in this case, is a cost function, and a service level restriction is considered. Each simulation runs considering all the 36 months of the planning horizon. The simulator and search routine is fully parameterized with respect to number of restart (5 in this work), search resolution values (3 values of 0.10, 0.05 and 0.02) and termination criteria (3).

The initial seed values of the parameters is obtained by the traditional calculation present in the inventory theory and a routine modify these values founding new feasible seeds with best performance than the originally ones.

Since the cost function in this routine is the average operation cost of the planning horizon, a set of unit costs was supplied to the software:

- Purchase cost – cost incurred each time a purchase order is decided - 2 values were used in the experiment: 9 (high level), and 3 (low level) for all items;
- Holding cost – cost incurred in holding one unit of the item during 1 period – this cost was equal to 1% of the item acquisition price, informed to the system in the simulation parameters data set. The current items prices are used in this study.

Once a minimum service level is considered, the shortage cost can be disconsidered. The average operation cost was the sum of average purchase and holding costs, considering only the periods the model was running on phase.

Table 4 presents the 16 combinations of range of the parameters: positive/negative parameters allowed, purchase costs, and service levels, resulting in 16 comparative simulation runs.

Table 4: Parameters values used in the simulation runs

	Positive		Purchase		Service Level			
Run	Y	N	9	3	78	84	90	96
1	o		o		o			
2	o		o			o		
3	o		o				o	
4	o		o					o
5	o			o	o			
6	o			o		o		
7	o			o			o	
8	o			o				o
9		o	o		o			
10		o	o			o		
11		o	o				o	
12		o	o					o
13		o		o	o			
14		o		o		o		
15		o		o			o	
16		o		o				o

A sensibility analysis was made considering the 4 different Service Levels: 78 %, 84%, 90% and 96%. Combination of all tested parameters conditions permits a good analysis of the system efficiency and stability.

Visual Basic Applications software and Excel worksheets were the basic tools used for all routines.

4. EXPERIMENTAL RESULTS

The 16 experimental runs were conducted in an Intel Core 2 Duo 1.8 GHz, 2 Gb RAM computer. Each run took approximately 3 minutes. The main results were the inventory models ranking for each item in each run. The model with the lowest Average Operation Cost was ranked in the first place, the model with the next lowest Average Operation Cost was ranked in the second place, and so on.

At the end of each run, 160 first places were obtained. Then, a percentage of first places for each inventory model at each run were calculated. These percentages are presented in tables 5 to 9, grouped by parameters values to permit better analysis. The greatest percentage in each run is shaded to identify the best performance model.

Table 5 shows the results of runs where only positive values are permitted for parameters *ro* and *ss*. Clearly, the EQ model has the best performance for lower service levels, losing its advantage when the service level grows. RP model takes the first position at the highest service level value, and this happens in both Purchase Cost levels tested, but with more emphasis in the lower PC level. The other 2 simulated models show similar EQ behaviour when service level grows.

Table 5: Percentage of First Places with Positive Parameters Only

Positive Parameters Only						
Run	**PC**	**SL**	**UO**	**BS**	**EQ**	**RP**
1	**9**	**78**	**18.8%**	**23.8%**	**41.3%**	**16.3%**
2	**9**	**84**	**20.0%**	**18.1%**	**42.5%**	**19.4%**
3	**9**	**90**	**20.0%**	**11.3%**	**41.9%**	**26.9%**
4	**9**	**96**	**13.8%**	**17.5%**	**33.1%**	**35.6%**
5	**3**	**78**	**20.0%**	**20.6%**	**36.3%**	**23.1%**
6	**3**	**84**	**15.6%**	**13.1%**	**38.8%**	**32.5%**
7	**3**	**90**	**10.0%**	**10.0%**	**40.6%**	**39.4%**
8	**3**	**96**	**11.3%**	**10.6%**	**28.1%**	**50.0%**

Table 6: Percentage of First Places with Positive and Negative Parameters

Positive and Negative Parameters						
Run	**PC**	**SL**	**UO**	**BS**	**EQ**	**RP**
9	**9**	**78**	**16.9%**	**18.1%**	**26.9%**	**38.1%**
10	**9**	**84**	**13.8%**	**12.5%**	**32.5%**	**41.3%**
11	**9**	**90**	**15.0%**	**9.4%**	**30.0%**	**45.6%**
12	**9**	**96**	**11.3%**	**12.5%**	**24.4%**	**51.9%**
13	**3**	**78**	**16.9%**	**16.3%**	**24.4%**	**42.5%**
14	**3**	**84**	**14.4%**	**10.6%**	**25.0%**	**50.0%**
15	**3**	**90**	**10.6%**	**8.1%**	**27.5%**	**53.8%**
16	**3**	**96**	**8.8%**	**8.8%**	**25.0%**	**57.5%**

The permission for negative *ro* and *ss* values generates the runs presented in Table 6. RP model has the best performance in all runs, improving the first places percentage with the SL growth. The negative values empowered the RP, but not UO and EQ models. Analysis of differences between 8 and 16 runs in RP model, for example, show 5,2% operation cost reduction in 54 items with negative *ss*.

Tables 7 and 8 present the same data of the precedent tables, arranged by Purchase Cost level. RP and EQ models present similar performance in both levels, with the expected better RP performance in the low Purchase Cost level. Again, the permission for negative values and the growth in the minimum Service Level give big advantage to the RP model.

Table 7: First Places Percentages - Purchase Cost = 9

Purchase Cost = 9						
Run	**PPO**	**SL**	**UO**	**BS**	**EQ**	**RP**
1	**Y**	**78**	**18.8%**	**23.8%**	**41.3%**	**16.3%**
2	**Y**	**84**	**20.0%**	**18.1%**	**42.5%**	**19.4%**
3	**Y**	**90**	**20.0%**	**11.3%**	**41.9%**	**26.9%**
4	**Y**	**96**	**13.8%**	**17.5%**	**33.1%**	**35.6%**
9	**N**	**78**	**16.9%**	**18.1%**	**26.9%**	**38.1%**
10	**N**	**84**	**13.8%**	**12.5%**	**32.5%**	**41.3%**
11	**N**	**90**	**15.0%**	**9.4%**	**30.0%**	**45.6%**
12	**N**	**96**	**11.3%**	**12.5%**	**24.4%**	**51.9%**

Table 8: First Places Percentages - Purchase Cost = 3

Purchase Cost = 3						
Run	**PPO**	**SL**	**UO**	**BS**	**EQ**	**RP**
5	**Y**	**78**	**20.0%**	**20.6%**	**36.3%**	**23.1%**
6	**Y**	**84**	**15.6%**	**13.1%**	**38.8%**	**32.5%**
7	**Y**	**90**	**10.0%**	**10.0%**	**40.6%**	**39.4%**
8	**Y**	**96**	**11.3%**	**10.6%**	**28.1%**	**50.0%**
13	**N**	**78**	**16.9%**	**16.3%**	**24.4%**	**42.5%**
14	**N**	**84**	**14.4%**	**10.6%**	**25.0%**	**50.0%**
15	**N**	**90**	**10.6%**	**9.4%**	**27.5%**	**53.8%**
16	**N**	**96**	**9.4%**	**9.4%**	**25.0%**	**57.5%**

Table 9: Percentage of First Places with different Service Levels

Run	PPO	PC	SL	UO	BS	EQ	RP
1	Y	9	78	18.8%	23.8%	41.3%	16.3%
5	Y	3	78	20.0%	20.6%	36.3%	23.1%
9	N	9	78	16.9%	18.1%	26.9%	38.1%
13	N	3	78	16.9%	16.3%	24.4%	42.5%
2	Y	9	84	20.0%	18.1%	42.5%	19.4%
6	Y	3	84	15.6%	13.1%	38.8%	32.5%
10	N	9	84	13.8%	12.5%	32.5%	41.3%
14	N	3	84	14.4%	10.6%	25.0%	50.0%
3	Y	9	90	20.0%	11.3%	41.9%	26.9%
7	Y	3	90	10.0%	10.0%	40.6%	39.4%
11	N	9	90	15.0%	9.4%	30.0%	45.6%
15	N	3	90	10.6%	9.4%	27.5%	53.8%
4	Y	9	96	13.8%	17.5%	33.1%	35.6%
8	Y	3	96	11.3%	10.6%	28.1%	50.0%
12	N	9	96	11.3%	12.5%	24.4%	51.9%
16	N	3	96	9.4%	9.4%	25.0%	57.5%

Finally, table 9 shows the data arranged by Service Level. The same pattern (EQ better when negative values aren't permitted and RP when it is possible) is present in all levels except in the highest 96% SL value, where RP model wins in all combinations.

5. CONCLUSION

The results indicate the best overall performance of the Periodic Economic Order Quantity (EQ) and Requirements Planning (RP) models. The EQ prevails when low minimum Service Levels (SL) and positive values are used. Its advantage decreases with the minimum Service Level growth and disappears when the RP Safety Stock parameter (*ss*) is free to receive negative values. The same flexibility in the UO and EQ Reorder Point parameter (*ro*) results in no performance improvements.

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