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Forecasting, ARIMA, Inventory management, Lot-sizing, Economies-of-scale, Production planning, Heuristic

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JOINT EFFCET OF FORECASTING AND LOT-SIZING METHOD ON COST MINIMIZATION OBJECTIVE OF A MANUFACTURER: A CASE STUDY

Abstract

Forecasting and lot-sizing problems are key for a variety of products manufactured in a plant of finite capacity. The plant manager needs to put special emphasis on the way of selecting the right forecasting methods with a higher level of accuracy and to conduct procurement planning based on specific lot-sizing methods and associated rolling horizon. The study is conducted using real case data form the Fibertex Personal Care, and has evaluated the joint influence of forecasting procedures such as ARIMA, exponential smoothing methods; and deterministic lot-sizing methods such as the Wagner-Whitin method, modified Silver-Meal heuristic to draw insights on the effect of the appropriate method selection on minimization of operational cost. The objective is to explore their joint effect on the cost minimization goal. It is found that a proficient selection process has a considerable impact on performance. The proposed method can help a manager to save substantial operational costs.

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1. INTRODUCTION

In a pragmatic scenario, there exists a natural link between forecasting accuracy and inventory replacement decision. If the demand for a product is at the higher side compared to the expected, i.e. estimated through scientific forecasting tool or educated guessing, a firm can face a stock-out, and when the estimated demand is below the actual level, the firm needs to incur additional holding or operational costs. On the other hand, if a firm makes orders frequently, the policy can reduce holding costs at the expense of higher ordering costs but can face stockout situations. This problem necessitates the integration of the use of robust statistical forecasting methods and lot-sizing decisions. However, many organizations still count on the judgmental adjustment based approach by stock-keeping unit managers for both slow- and fast-moving products (Fildes, Goodwin, Lawrence & Nikolopoulos, 2009). Moreover, researchers and practitioners considered the issue of accurate demand forecasting and inventory lot-sizing decision as two independent decision-making processes, and without the integration of these two-decision processes, it can lead to a suboptimal outcome for a firm (Syntetos, Nikolopoulos & Boylan, 2010). Recently, a project for a Danish-based company Fibertex Personal Care (FPC) was undertaken, which is owned by the Danish conglomerate Schouw & Co. to explore the joint performance of scientific forecasting methods and lot-sizing formulas for time-varying demand (Pedersen et al., 2020).

A single-item, single-level, incapacitated economic lot-size problem with constant cost parameters, time-varying demand rate, and discrete opportunities for replenishment is assumed. Note that the dynamic lot-sizing models under a deterministic environment address the problem of finding an optimal production or replacement planning to minimize total cost that includes fixed setup and holding cost over the time horizon (Silver & Meal, 1973; Van Den Heuvel & Wagelmans, 2005; Saha, Das & Basu, 2010; Grubbström & Tang, 2012; Eriksen & Nielsen, 2016; Moon, Yoo & Saha, 2016; Nilakantan, Li, Tang & Nielsen, 2017, Kian et al., 2020; Ho & Ireland, 2012). A fixed order cost is incurred for each order and holding costs incur for each unused unit stored in each period (Drexl & Kimms, 1997). Although there exist several lot sizing techniques, the Wagner-Whitin (WW) method has been extensively preferred because it can provide optimal outcomes (Heady & Zhu, 1994). When determining the most suitable forecasting performance measures, the product characteristics and inventory management should be taken into consideration, since the objectives of forecasting and inventory control usually are inconsistent. Xi et al. (2012) also study the effect of linkage between forecasting and inventory management, and found that the traditional forecasting performance measures decrease in performance without proper link.

Inventories are considered to be one of the key assets of an organization, the size of inventory can be determined through different forecasting techniques (Silver, Pyke & Thomas, 2016). Inaccurate forecasts turn out to be expensive for organization operations, in terms of overstocking or stock-outs and lost sales, while the desired service level is not being met (Kourentzes, Trapero & Barrow, 2020). Inventory planning mainly focuses on when to order and how much to order, the lot sizes. Lot-size in the context of this study represents the purchased in a single transaction, while inventory lot-sizing involves determining and scheduling lot sizes, so demand is satisfied in each period of the planning horizon. Optimization of inventory lot-sizing refers to minimizing the total inventory cost, by having a trade-off between large production lots, resulting in low ordering costs, and lot-for-lot ordering resulting in low holding costs. Andriolo et al., (2014) classify lot-sizing into three different models; deterministic, stochastic, and fuzzy models. Several extensions of inventory lot-sizing exists, but it consists of a fixed or variable order quantity together with the periodic or continuous frequency of review. The underlying parameters include: finite or infinite horizon, single or multiple items, deteriorating or not, zero or non-zero fixed or varying lead time, capacitated or incapacitated, deterministic, time-varying or constant, or stochastic demand, single- or multi-echelon, back-ordering or not, fixed or rolling planning horizon, with or without quantity discounts and with constant or fuzzy cost parameters.

Many manufacturing firms feel pressured to cut costs and improve profitability because of increasing competition and globalization (Świć & Gola, 2013). In this regards, business system analytic are designed to facilitate the flow of information and decent planning. However, those systems if not managed carefully, can result in conflict and degrade performance. Researchers pointed out that, a group of organizations are still facing implementation issues; many others fear implementation because of the costs and the pros and cons of implementation (Patalas-Maliszewska, 2012). The most common causes of business system analytic failures are a combination of high software customization combination, poor planning and commitment, relying on legacy systems, lack of clarity about required changes etc. The objective is to explore answer to the following research question: Does there any scope to reduce cost by improving inventory planning and forecasting support systems? Therefore, daily usages data was collected for the 14th month for one product from the FPC, namely Spunbond PP. Several exponential smoothing methods and ARIMA was employed for forecasting requirements. For a lot-sizing decision, the WW method, and its coherent heuristics like Silver-Meal (SM) heuristic (Baker, 1989), modified Silver-Meal (MSM) heuristic, and EOQ heuristic was used. It was found that the company is struggling to achieve desirable outcome through their existing business analytic framework. Compare to existing literature where, forecasting and procurement planning are mainly considered as independent decisions; this study evaluates their joint impact on system wide performance. Therefore, the insights can help them to improve the decision making process. The difference between the problem investigated in this study from those in the existing lot-sizing and forecasting problem is that our focus on the issue of actual implementation in the presence of opportunities to exploit information and scale economies. Our findings suggest that the performance of lot-sizing algorithms appear with different magnitudes and the outcomes leads to a desirable for a short forecast horizon, and which suggest that planning for long period does not necessarily result in a good planning.

2. METHODS

In this section, an overview of forecasting methodology and lot-sizing techniques used in this study is described.

2.1. Forecasting methods

In this study, two classes of forecasting methods was used: (i) exponential smoothing, and (ii) ARIMA model. Forecasting accuracy always key in decision-making process (Bocewicz, Nielsen, Banaszak & Thibbotuwawa, 2018; Nielsen, Jiang, Rytter & Chen, 2014) and the comparative study will help the production managers to explore their impact.

2.1.1. Exponential-smoothing model used in this study

Exponential models used in the study are in of the form presented below:

$$y_t = a_t + b_t t + s(t) + \varepsilon_t, \tag{1}$$

where: a_t, b_t, and $s(t)$ represent the time-varying mean; time-varying slope; and time-varying seasonal component, respectively. In addition, A_t and B_t represent smoothed level that estimates a_t and b_t, respectively. S_{t-j}, $j = 0,..., s-1$ estimates of the $s(t)$. The last components ε_t represent the exogenous random shocks. In addition, it is assumed that α, γ, and δ represent level, trend, and seasonal smoothing weight, respectively. Therefore, larger (small) weights ensure higher (lower) influence to newer observation. Based on the above notation, the methods used in this study is summarized in Table 1.

Tab. 1. Exponential forecasting methods used in this study

Method	Model equation
Simple	$y_t = a_t + \varepsilon_t$ $A_t = \alpha y_t + (1-\alpha)\, A_{t-1}$
Brown	$y_t = a_t + b_t t + \varepsilon_t$ $A_t = \alpha y_t + (1-\alpha)\, A_{t-1}$
Holt	$y_t = a_t + b_t t + \varepsilon_t$ $A_t = \alpha y_t + (1-\alpha)(A_{t-1} + B_{t-1})$ $B_t = \gamma(A_t - A_{t-1}) + (1-\gamma)B_{t-1}$
Seasonal	$y_t = a_t + s(t) + \varepsilon_t$ $A_t = \alpha(y_t - S_{t-s}) + (1-\alpha)A_{t-1}$ $S_t = \delta(y_t - A_{t-s}) + (1-\delta)S_{t-s}$
Winter additive	$y_t = a_t + b_t t + s(t) + \varepsilon_t$ $A_t = \alpha(y_t - S_{t-s}) + (1-\alpha)(A_{t-1} + B_{t-1})$ $B_t = \gamma(A_t - A_{t-1}) + (1-\gamma)B_{t-1}$ $S_t = \delta(y_t - A_{t-s}) + (1-\delta)S_{t-s}$

2.1.2. ARIMA

Time series data frequently experienced both trend and seasonal patterns and might be non-stationary in nature. Therefore, autoregressive integrated moving average (ARIMA(p,d,q)) models are widely used for forecasting (Mills, 2019), where *p*, *q*, and *d* are positive integer numbers, referring to the order of the autoregressive, moving average, and integrated parts of the model, respectively. In an ARIMA model, the future value of a variable is assumed a linear function of several past observations plus random errors. The linear function is based upon three parametric components: auto-regression (AR), integration (I), and moving average (MA). If $d = 0$, then the model reduces to an *ARMA* (*p*,*q*) model. If $p = q = 0$, then it simply converts to the Moving Average (*q*) model. In general, the ARIMA *(p,0,0)* model is formulated as follows:

$$y_t = c + \varphi_1 y_{t-1} + \cdots + \varphi_p y_{t-p} + \varepsilon_t, \tag{2}$$

where y_t and ε_t are the actual value and random error, assumed to be independently and identically distributed with a mean of zero and a constant variance of σ^2; at period t, respectively; *c* is the intercept(constant); φ_p are a finite set of parameters, determined by linear regression. Similarly, the MA (ARIMA *(0,0,q)*) model is formulated as follows:

$$y_t = c_1 - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} + \varepsilon_t, \tag{3}$$

φ_p is a finite set of parameters; and c_1 is the mean of the series. For the detailed discussion on ARIMA, one can see Box et al., (2011), Taneja et al., (2016).

2.1.3. Performance measure for forecasting

In this study, three performance measures is used to evaluate accuracy of forecast as follows:

- Mean absolute error (MAE) $= \frac{1}{n}\sum_{t=1}^{n} |y_t - f_t|$,
- Mean absolute percentage error (MAPE) $= \frac{1}{n}\sum_{t=1}^{n} |\frac{y_t - f_t}{y_t}|$,
- Root mean squared error (RMSE) $= \sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - f_t)^2}$.

Note that f_t represents the forecasted value. For an accurate forecast, the value of MAE, MAPE, and RMSE should be as small as possible.

2.2. Lot-sizing method for time-varying demand

Lot-sizing decision under the time-varying demand is always a subject of importance to planning a robust replenishment decision (De Bodt, Gelders & Van Wassenhove, 1984). A comprehensive study was conducted of the relative performance among WW method (Wagner & Whitin, 1958), EOQ heuristic, SM and MSM heuristics (Silver & Miltenburg, 1984). The cost performance of each method was compared against the WW method by evaluating the percentage deviation from the minimum total cost to holding and ordering cost.

The following assumptions are made to study the impact of the discrete lot-sizing model for the purpose of simplicity:

1. Demand is discrete (weekly basis) and known from forecasting information in advance. Therefore, any considerations of nervousness or stochastic parameters are excluded. The requirements of each week must be available at the beginning of that period.
2. Requisitions are instantaneous; that is lead time is negligible. Shortages are not allowed.
3. The entire procured quantity is delivered at a time and benefits from joint replenishment are ignored.
4. Costs involved are inventory carrying cost and ordering cost. It is assumed that both units carrying cost per period and ordering cost are constant throughout the considered aggregated planning horizon and independent on the replacement quantity.

The following notation is used to describe lot-sizing methods:

Tab. 2. Notations

N	number of periods(weeks)
i	number of weeks, i ∈ {1⋯ ,N}
T	the number of periods for the planning
D_i	requirement at ith week (forecast)
H	Holding cost
A	Ordering cost

2.2.1. Economic order quaint (EOQ)

When the demand rate is approximately constant, a fixed EOQ model can be applied. However, when demand is a time-varying rate, one can ignore the variability by considering the average demand rate ($D = \frac{\sum_{i=1}^{T} D_i}{T}$) to calculate EOQ, and the EOQ is applied when a requisition is made. Furthermore, $\overline{D}$ can be based on an infrequent estimate of the average demand per period, and therefore, it is not necessary to reevaluate at each replenishment decision. Therefore, first, $EOQ = \sqrt{\frac{2AD}{H}}$ was computed and then at the time of a replenishment, the optimal EOQ is adjusted to exactly satisfy the requirements of a forthcoming integer number of consecutive periods to reduce the inventory holding cost (Silver et al., 2016).

2.2.2. Wagner-Whitin method

The classical WW method was developed to find an optimal ordering policy for deterministic and time-varying demand. The following formulation can be used to present the algorithm:

$$C(t) = min\left\{A + C(t-1), \min_{1 \le i \le t}\left\{A + C(t-1) + \sum_{h=i}^{t-1} \sum_{k=h+1}^{t} H_h D_k\right\}\right\} \quad (4)$$

where $C(0) = 0$, $C(1) = A$, and $C(t)$ represents the minimum cost of ordering and holding inventory for periods 1 to t. Note that a replenishment decision only takes place when the inventory level is zero. There is an upper limit to how far before a period t would be included its requirements (D_t) in a replenishment quantity. Eventually, the carrying costs become so high that it is less expensive to have a replenishment arrive at the start of period j than to include its requirements in a replenishment from earlier periods.

2.2.3. Silver-Meal Heuristic and its modification

The SM heuristic was designed to obtain an easy and effective way to obtain a replenishment strategy under deterministic time-varying demand (Silver and Meal, 1973). As mentioned by the authors, the heuristic is myopic in nature and the goal is to choose a replenishment quantity by minimizing costs per unit time only to the end of the period covered by the replenishment under consideration. Then, the basic idea is to select the lowest period of T by minimizing the following function:

$$C_T = \frac{A + H\sum_{t=1}^{T}(t-1)D_t}{TH}, T = 1,2,3, \ldots, \tag{5}$$

where C_T represents the normalized costs per unit time. Once a value of T is obtained, one needs to move the origin to the end of the period T and repeat the procedure to select the next replenishment interval. To improve the performance of the classical SM heuristic, several modifications are proposed by the researchers. The performance of one such modifications proposed by Silver and Miltenburg (1984) is used to eradicate the truncated horizon problem to some extent and reduce high-cost penalties.

3. CASE STUDY

The project is conducted with the Fibertex Personal Care (FPC) company and a subsidiary of Danish conglomerate Schouw & Co. FPC is one of the largest producers of Spunmelt Nonwovens for the hygiene industry. A regular visit was made to one of their production units at Aalborg, Denmark, to observe how the products are made and acquire detail knowledge about their production procedure (Pedersen et al., 2020). The company currently relies on their forecasting and lot-sizing method for a procurement decision and the regional staff sometimes need to take decision qualitatively, which can increase operational cost. Based on advice from specialists working on the FPC, first, one of their commonly used raw material procured from several suppliers is selected, so that it allowed us to provide a critical focus to explore ways to reduce holding costs and eradicate the possibilities of potential shortages by improving forecasting performance. The objective is to verify how the robust forecasting and lot-sizing methods can help them to eradicate the problem.

4. RESULT ANALYSIS AND DISCUSSION

First, an overview of daily usages of the raw material over the previous 58 weeks is presented. Note that the material is used every day (7 days) and the corresponding sequence plot is presented in Figure 1.

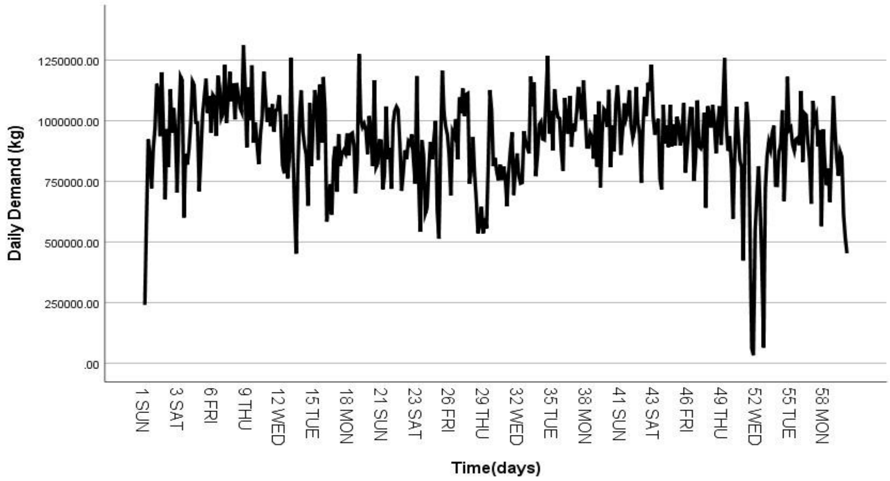

Fig. 1. Sequence plot of daily usage for the raw material

Figure 1 demonstrates that the daily usage almost follows a steady pattern, although the certain drop at week 52 is due to the Christmas Holiday. Based on the actual data, a forecast for the upcoming 14 weeks was made and results are presented below in Table 3.

Note that one cannot conclude about best forecasting methods, preference measures such as RMSE and MAE are higher for ARIMA (2,0,2), but MAPE remains high for ARIMA (0,2,2). Till we use results for ARIMA (2,0,2) for further analysis of determining performance lot-sizing methods. Statistical forecasting techniques have also advanced significantly; however, those have not been used extensively at an operational level mainly due to their complexity (Syntetos, Boylan & Disney, 2009). In our experience, simple exponential forecasting is sometime outperformed by ARIMA, but which might not be practiced while forecasting at the FPC. Next, an overview of lot-sizes based on the forecasted data was computed and presented in Table 4.

Tab. 3. Performance of various forecasting methods

Forecast for weekly requirement of SPUNBOND PP				
Method	Simple	Brown	Holt	Simple Seasonal
Stationary R^2	0.210	0.680	0.687	0.593
RMSE	164391.734	169147.082	164748.279	162363.999
MAPE	23.578	24.080	23.246	22.473
MAE	124825.799	128026.114	125627.671	123059.797
Parameter	α = 0.210	α = 0.106	α = 0.298 γ = 0.00002	α = 0.276 δ = 0.095
Method	ARIMA (1,1,1)	ARIMA (1,1,0)	ARIMA (0,1,1)	ARIMA (1,0,1)
Stationary R^2	0.247	0.075	0.189	0.221
RMSE	159651.828	177013.880	165675.733	160860.753
MAPE	22.065	20.597	23.35	22.476
MAE	122226.078	136575.496	125573.318	121335.635
Parameter	C = -4701.925 MA = 0.364 AR = 0.922	C = -5680.416 AR = -0.274	C = 1073.806 MA = 0.743	C = 907716.15 AR = 0.536 MA = 0.061
Method	ARIMA (2,2,2)	ARIMA (2,2,0)	ARIMA (2,0,2)	ARIMA (0,2,2)
Stationary R^2	0.693	0.417	0.247	0.57
RMSE	163266.4	224298.004	158505.502	192574.644
MAPE	21.823	24.454	22.363	20.233
MAE	125013.8	173679.233	119659.383	151371.789
Parameter	C = -35627.50 AR Lag 1 = 0.233 AR Lag 2 = -0.164 MA Lag 1 = 1.73 MA Lag 2 = -0.73	C = -23150.01 AR Lag 1 = -0.769 AR Lag 2 = -0.407	C = 901727.61 AR Lag 1 = 1.011 AR Lag 2 = -0.070 MA Lag 1 = 0.571 MA Lag 2 = 0.206	C = -19943.330 MA Lag 1 = 0.877 MA Lag 2 = 0.112
Method	ARIMA (2,0,0)	ARIMA (0,2,0)	ARIMA (0,0,2)	Winter Additive
Stationary R^2	0.22	0.01	0.211	0.593
RMSE	160874.79	292270.10	161919	162639.789
MAPE	22.46	29.13	22.83	22.447
MAE	121356.89	227842.62	122334.5	123234.070
Parameter	C = 907446.4 AR Lag 1 = 0.481 AR Lag 2 = 0.019	C = -43233.86	C = 905563.110 MA Lag 1 = -0.478 MA Lag 2 = -0.172	α = 0.281 γ = 0.001 δ = 0.096

Tab. 4. **Performance of different lot-sizing methods based on the forecasted data**

Week	Requirement (kg)	EOQ	SM	WH	SMM
1	5444368.49	17298082.39	17298082.39	23438060.67	17298082.39
2	5832505.31				
3	6021208.59				
4	6139978.28	18616491.73	18616491.73		18616491.73
5	6214731.83			18767908.19	
6	6261781.62				
7	6291394.75	18923192.26	18923192.26		25252340.04
8	6310033.23			18960945.29	
9	6321764.28				
10	6329147.78	6329147.78	6329147.78		
Total cost		**6137,18**	**6137,18**	**5850,75**	**5.867,4701**

Note that lot-sizes are determined based on the aggregated weekly requirements. One can easily found that the company can minimize cost through the appropriate selection of lot-sizing methods. According to the results, the efficiency of the heuristics of the WW increased compared to others. To present an overview of cost-saving, sensitivity analysis was conducted, and the results are presented in Figures 2a and 2b.

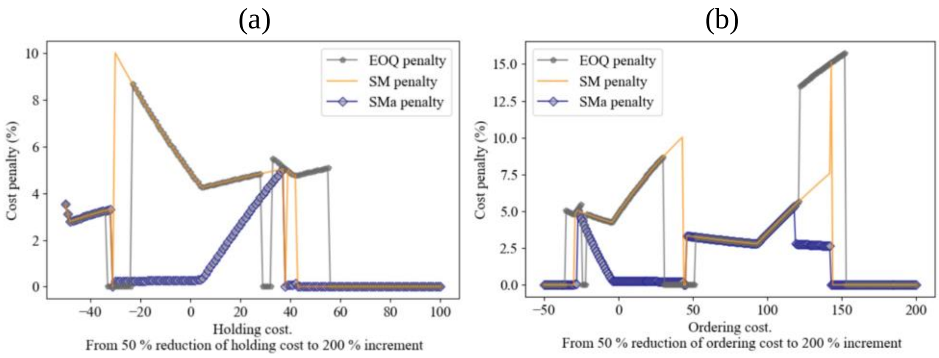

Fig. 2. Total cost comparison among lot-sizing methods EOQ, SM, MSM vs WW (10weeks horizon) from (a) 50% reduction of holding cost to 200% increment and (b) from 50% reduction of ordering cost to 200% increment

Figures 2a and 2b demonstrate that a company can save 0–16% cost through an appropriate replenishment decision. However, as reported by Hopp and Spearman (2011) no commercial MRP package actually uses WW algorithm. Therefore, this remains another dimension of the challenge faced by production managers.

Finally, this study focuses on the impact of aggregated planning horizon selection problem (Pedersen et al., 2020). Note that the factors contributing to the actual lot-sizing calculation and selection of optimization schemes mainly rely on: (1) the ratio between holding and ordering costs, and (2) demand pattern at the end of the horizon. Due to the end-effect, which exists due to the conversion from the T-period model horizon to the truncated n-period horizon, the second factor is important to include when comparing inventory lot-sizing performance (Van Den Heuvel & Wagelmans, 2005; Bach, Bocewicz, Banaszak & Muszyński, 2010). The proportional penalty of truncation is dependent on cost parameter also, even though the existence is a truism since some lot-sizing methods, e.g. SM Heuristic, are designed to cope with the situation of having a demand pattern continuing beyond the planning horizon. This means that "a replenishment is often scheduled unnecessarily close to the end of the horizon" (Silver and Miltenburg, 1984). As illustrated by above figures, the cost penalty of the inventory lot-sizing methods depends on both the holding and ordering cost, since the outcome of one would be the inverse function of the other; it is the ratio between the two costs that is of importance.

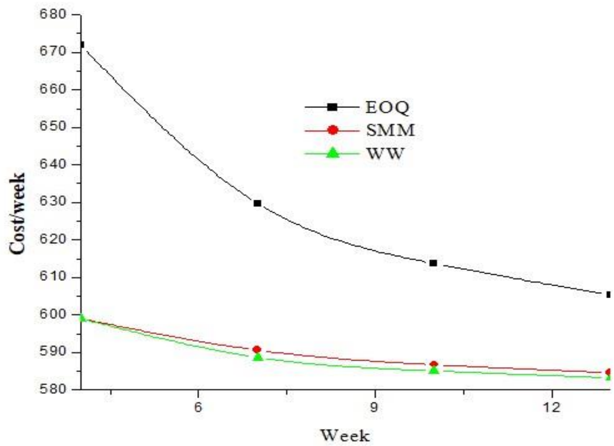

Fig. 3. Effect of lot-sizing methods with an integrated planning horizon

The graphical representation of cost per week when the aggregated planning horizons are considered as 4, 7, 10, and 13 weeks, respectively. Including all variations in the sensitivity analysis, the average penalty for implementation of the lot-sizing formula is nearly 17% , when only including the variations where an effect of the truncated horizon was existent, the average penalty of the SM heuristic was increased. It can be interpreted that the cost penalty in general increases, and becomes more diversified, between the lot sizing methods, as the ratio between ordering cost and holding cost increases when the holding cost decreases. When there is a difference between the penalty of SM heuristic and the

MSM heuristic, it is due to the penalty of the truncated horizon, since the MSM heuristic is performing optimally, underlining the importance of considering the effect. This is consistent with the conclusions of Kazan et al. (2000).

5. CONCLUSIONS

Integrated forecasting and inventory management have received considerable attention over several decades because of their implications for replenishment decision-making at both the strategic level and operational level for organizations. Although this pluralism is healthy from the perspective of knowledge advancement, one of the key issues faced by production managers in practice is how to integrate them? Moreover, the existing MRP or EPR system implementation is precisely defining the lot-sizing policy. Due to its computational complexity, the effect of the robust lot-sizing technique is ignored and a lot-for-lot policy is till practiced (Grubbström, Bogataj & Bogataj, 2010). On the other hand, statistical-forecasting techniques have also advanced significantly; however, they have not been used extensively at an operational level primarily due to their complexity (Syntetos et al., 2009). The dynamic lot-sizing problem behind our problem concerns related to a production plan that minimize total holding and ordering cost. Results demonstrates that the performance of EOQ or SM can deviate by 17% from the minimum cost obtained from the WW method; thus it is clear that WW dominates on both criteria.

Over the last few decades, the business environment of many industries has experienced great changes due to the integration of various frameworks for business analysis such as Collaborative Planning Forecasting and Replenishment (CPFR), Supply Chain Operations Reference-model (SCOR). However, researchers pointed out there are many hurdles both in-house and among the business partners that prevent or slow down business systems integration (Patalas-Maliszewska & Kłos, 2017; Alotaibi, 2016; Bocewicz, Nielsen & Banaszak, 2019). Indeed, approximately 66-70% of ERP implementation projects failed to accomplish their implementation objectives (Zabjek, Kovačič & Štemberger, 2009). In recent empirical research, Ali & Miller, 2017 also found that one of the most problematic and yet unresolved areas of ERP implementation is identifying and agreeing on the industry-standard implementation model. Moreover, as argued by Kourentzes et al. (2020), the inventory gains originate a more difficult optimization problem. In the context of MRP, Li & Disney (2017) also found that MRP systems are not always fully implemented, generate some consistency issues, and are unable to generate accurate data. This study took the initiative in this direction, and reported that although the company is tending towards the integration of modern business analytic, but struggling to achieve desirable performances. This is because the system they are trying to implement needs to be upgraded by introducing robust lot-sizing methods and train their work forces to adopt the process.

The investigation of performance of lot-sizing algorithms is always a classical topic in the production planning (Gola, 2014). This study has several limitations and can be extended in several directions. This study focused on a single-item setting, and purchase cost remains constant, there is no uncertainty in demand, and consequently the effect of safety stock. Therefore, an interesting area of future study is to consider multi-item production planning under demand uncertainty. Implementation of the presented framework for a rolling horizon would make the proposed framework closer to planning in practice, while it would also change the concerns of the truncated horizon effect, and its influence on the comparison between lot-sizing methods.

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