SIMULATION ALGORITHM OF A SUPPLYING PROCESS WITH A VARIABLE TIME STEP

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Abstract
This technique bootraping has been successfully used in various applied statistical problems, although not many applications have been reported in the area of time series. In this paper we present a new application of Bootstrap to time series. A fundamental aspect of supply chain management is accurate demand forecasting. We address the problem of forecasting intermittent (or irregular) demand, i.e. random demand with a large proportion of zero values. Items of spare parts with sporadic consumption can make a significant, up to 60% portion of the value of supplies in service and workshop inventory areas of many industrial segments. An understanding of key features of demand data is important when developing computer systems for forecasting and inventory control.

Keywords: Simulation algorithm, supplying process, simulation modelling variable time step, sporadic demand

1 Introduction

So called driving systems are the most common from advanced approaches in management and optimization of inventory management. They are included into stochastic and dynamic inventory models defined by a random demand. As input random variables are generated data on consumed amount of material gained from a statistical probability distribution. The arithmetic, moving average or a weighted moving means. An exponential averaging of the first and the second degree are used in a trend development of a demand or a linear regression. Auto correlation and identification models are used as well. However arrays of empirical data on a sporadic demand include a random variety of null values with no nulls. It might provide for variable results in defining needed amount in forecast of a mean, a standard deviation or dispersion in a very simple parametric way in mathematical operations [1]. Due to deviousness of input data the distribution of random variable (demand) obviously does not meet standard probability distribution. An applicable option, being used, is a non-parametric method using past data on a sporadic demand called bootstrapping. We classify it among MC simulation statistical methods, based on a stochastic forecast of a future demand from data on a recent demand. Numerous methods of bootstrapping work with random data on demand, from which an experimental pdf, cdf functions of a distribution of random variable (demand) are generated through a computer experiment applicable for assignment of parameters for modelling par a level inventory management [4].

2 Model implements a simulation algorithm of a supplying process with a variable time step

Characteristics of model parameters:
•Lead Time, a number of time units from sending an order until delivery of an item. A delivery time of an order is defined by contract terms. It may be adjusted by a discharge time of the delivery / a logistic delay.
•Provision probability – Service Level, that a demand will not exceed an offer during implementation with a specified probability. Requested provision probability / Service level is specified ranging from 0.95 - 0.99 by an item criticality.
•Level or stock ordering - Reorder Level is specified as an optimal level with respect to a lead time – is specified as an optimal level with respect to a reorder level and service level. It should ensure that a level of stock during a service level will not drop below zero. Optimal reorder level is specified by a bootstrapping in accordance with a demand forecasting during a lead time of a supplier rounded to the nearest higher ordered amount. Fig. 4. In a moment when a reorder level is intersected, the information system generates an order to a supplier marked with a red asterisk. The above mentioned approach allows a setting of a reorder level and a moment for drawing an offer to refill the stocks in accordance with a specified level of logistic provision.

•Safety stock is created due to an unstable demand / or a lead time as a protection against an item shortage. A safety stock is not created in case of a bootstrapping definition of an optimal stock. A safety factor should be taken into consideration by a Service Level. [3]

Sequence of a simulation algorithm:
•It takes the random data over from bootstrapping choices in order to define a demand of a time period from the first part of the model.
•It monitors a decrease of a stock level / a blue colour
•It matches when the stock ordering level reaches a reorder level / green level.
At a moment when a reorder level is reached, or the stock is below the ordering level, it orders an optimal amount of stock, that have been defined in the first part of the model by bootstrapping. Time to draw an order is a random variable.
•It monitors a lead time.
•It carries out a model delivery of an item and it increases a stock level / a red vertical line.
•It collects needed data for computations.
•It computes the costs when a simulation time is shifted.
•It creates graphs of stock and costs courses.
•It repeats a procedure in line with a defined number of time periods in an experiment.

The model allows changing of input values level / delivery time period - LT, number of bootstrapping choices, number of time periods of a demand simulation, a needed level of probability for logistic support, and an initial stock level.
Graphic outputs of a simulation of a short time period are shown in Fig. 1 and Fig. 2.

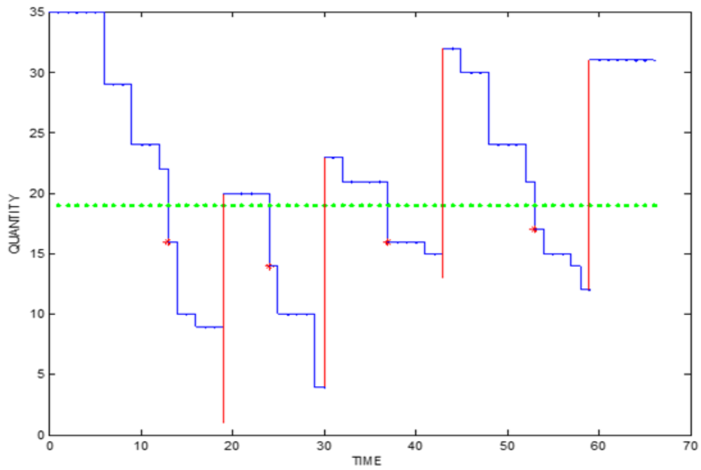


Fig 1 *Course of simulation of stock item movement for 67 time periods at LT=7*

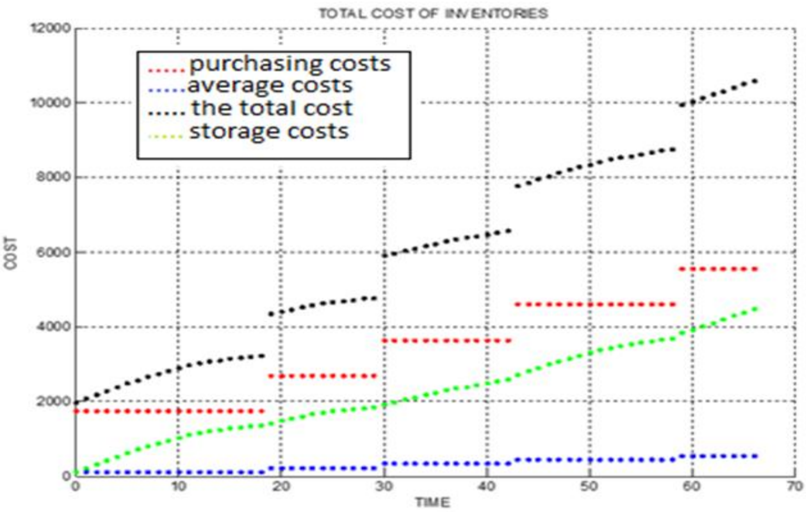
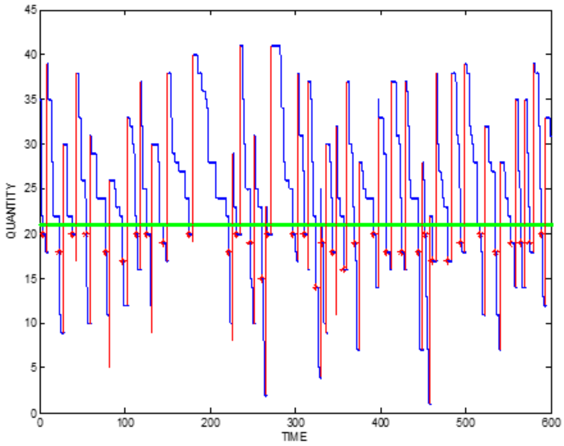


Fig 2 *Course of simulation of stock costs for an item for 67 time periods*

Simulation experiments should prove a validity of a specification of an optimal stock of an item defined by a bootstrapping, depending on a delivery term, on a chosen probability for a provision of an item and on total costs of stocks. Simulation experiments were executed aiming to review an impact of a change in delivery term with the following input data:

- Number of bootstrapping choices = 100000
- Provision probability/Service Level =0.99.
- Number of reviewed simulation time periods = 600.
- Storage costs per a stock unit per day=3
- Transportation costs per a delivery =111
- Purchase costs for a stock unit=50



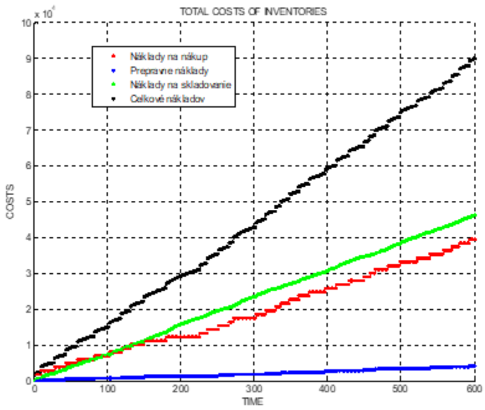


Fig. 3 *The course of stock and cost simulation*

Table 1: *Outputs from simulation experiments for changes in delivery terms LT.*

Output exp./LT	LT=3	LT=4	LT=5	LT=6	LT=7	LT=8
Optimal stock	16	19	21	24	26	28
Lack of periods	5	2	0	5	0	0
Undelivered pieces	16	4	0	7	0	0
Number of deliveries	49	38	36	34	30	25
Costs of a purchase	40950	37850	39550	42550	40750	36750
Transportation Costs	5550	4329	4107	3885	3441	2886
Storage costs	37110	44598	46380	51660	53241	59226
Total costs	83610	86770	90037	98095	97432	98862

Change of a delivery time period influences the costs. The longer delivery time period decreases a number of deliveries for a reviewed period and transportation costs. It increases storage costs and total costs. Therefore it is suitable to **make contracts** with suppliers for shorter delivery terms.

Analysis for changes in probability of an item provision 0,9 0,95,0,99.

- Lead Time=6
- Number of bootstrapping choices = 100000
- Number of simulated periods =600
- Storage costs of a stock unit per day =3
- Transportation costs of a delivery=111
- Purchase costs for a stock unit =50

Table 2: *Results of costs analysis for changes in probability of an item provision 0,9 0,95,0,99*

COSTS / Service Level	0,9	0,95	0,99
Reorder Level /Optimal stock pcs	16	18	24
Costs for a purchase	41750	41650	41350
Transportation costs	5661	4773	3774
Storage costs	26976	35745	49206
TOTAL COSTS	74387	82168	94330

It is obvious from the above mentioned results, that the increased demand for logistic support of an optimum stock / delivery causes an increased level of an optimum stock /Service level and naturally the costs as well. It is interesting, that costs of acquisition are about on the same level, the transportation costs decrease and storage costs increase.

3 Conclusion

For practical problems with finite samples, other estimators may be preferable. Asymptotic theory suggests techniques that often improve the performance of bootstrapped estimators; the bootstrapping of a maximum-likelihood estimator may often be improved using transformations related to pivotal quantities [6]. It is obvious from the above mentioned results, that the increased demand for logistic support of an optimum stock / delivery causes an increased level of an optimum stock /Service level and naturally the costs as well. It is interesting, that costs of acquisition are about on the same level, the transportation costs decrease and storage costs increase.

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