SIMULATION MODEL OF A SPORADIC DEMAND

Alexej Chovanec[1] – Alena Breznická[2] *

[1]*Ing. Alena Breznická, PhD., Faculty of Special Technology, Alexander Dubcek University of Trencin, Pri parku 19, 911 06 Trencin, Slovakia*

[2]*prof. Ing. Alexej Chovanec, CSc., Faculty of Special Technology, Alexander Dubcek University of Trencin, Pri parku 19, 911 06 Trencin, Slovakia*

*Corresponding author E-mail address: alena.breznicka@tnuni.sk

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 modelling, sporadic demand, bootstrapping, forecasting

1 Introduction

Bootstraping is a method aiming to increase an accuracy value of statistic estimations. The results are dependent only on bootstrapping samples. We do not need to know the basic distribution of a random variable. Bootstraping creates a large amount of random choices from input data of a bootstraping sample and it calculates improved statistics on each of such choice. In addition to numerical characteristics it provides data for statistical characteristics in form of frequency histograms and choices probability histograms. From a data set being reviewed we generate bootstrapping y random choices several thousands times so that we choose with repetition (by a substitution of chosen data) from a data set being reviewed $x = (x_1, x_2, ...,x_n)$, a needed amount of m data $y = (y_1, y_2, ...,y_m)$. The chosen numerical values yi are inter independent and they are chosen for a bootstraping sample with the same probability /uniform distribution/. The samples usually differ from each other and they differ from a base data set being reviewed. As we sample with repetitions, it is possible, that some xi data appear several times in a sample or that we do not choose them ever. In case of a specification of a future demand within a delivery term /a delivery leadtime - LT/ we choose from a bootstrapping sample a number of data corresponding with LT[2].

2 Simulation model of a sporadic demand .

The presented simulation model applies stochastic and dynamic principles of inventories modeling. The simulation model was created based on simple algorithms and MATLAB language commands. It consists of two parts: The first part of a model applies the principle of a bootstrapping aiming to define an optimal stock level for an item with a following sequence:

•Downloading the array and a bootstrapping sample of demand data. Fig. 1.
•Computation of numerical characteristics for a bootstrapping sample of a demand for ani term, number of data, min, max, mean, std.
•Specification of simulation input data – number of bootstrapping choices, number of chosen periods for a delivery time period, specification of a quantile of a demanded logistic support of a delivery.
•Generating a matrix of indices for bootstrapping samples of uniform distribution.
•Transference of indices matrix into a matrix of demand of bootstrapping choices.
•Sum of values in a row of demand matrix of bootstrapping choices.
•Graphic and statistical processing of output data for a definition of a size of an optimal stock.

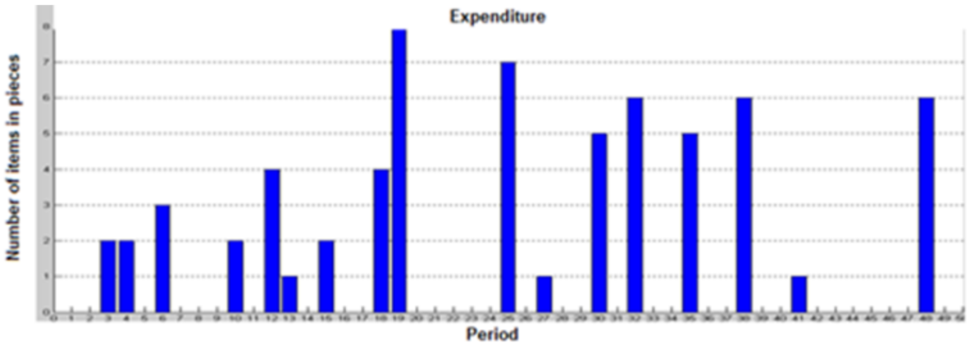


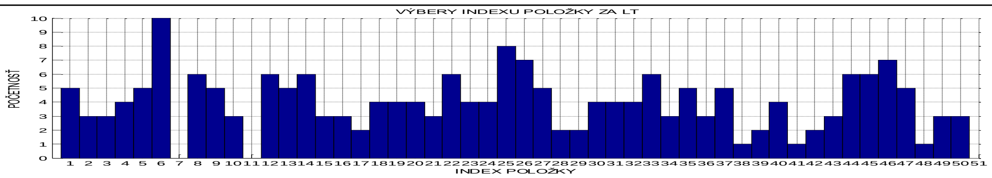
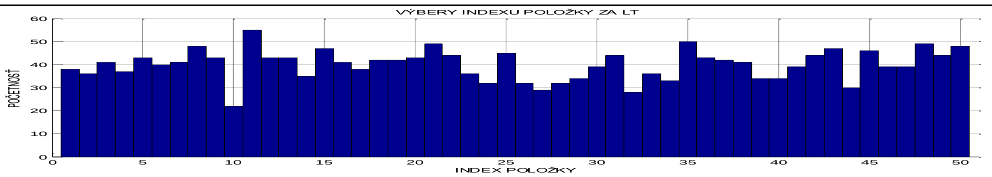
Fig 1 *Sample of demand data for 50 periods*

We simulate choices from a demand sample for 50 time periods. For each choice we randomlychoose a number of values corresponding to a lead time. For simplicity LT=2 time periods. Each choice from a sample is represented by a row of a matrix, each column represents a delivery time period. Table1 displays a generating of values of bootstrapping indices matrix on 10 choices with a uniform distribution, transformation of the indices matrix into a matrix of bootstrapping choices demand and a sum of values of the rows from a bootstrapping choices demand matrix.

Table 1 *Generating 10 choices of indices of an item being reviewed and a demand for LT=2*

Choice number	Index 1	Index 2	expenditure1	expenditure2	SUM expenditure
1	26	12	0	4	4
2	31	46	0	0	0
3	45	34	0	0	0
4	7	37	0	0	0
5	15	35	2	5	7
6	4	40	2	0	2
7	8	27	0	1	1
8	4	38	2	6	8
9	10	26	2	0	2
10	39	46	0	0	0

Number of choices – simulations has an impact on a provision of a same probability that an item index will be chosen by which we assign a demand in pieces Fig. 2. A requirement of an uniform distribution does not become evident at a smal number of simulations, amount of choices of indices lines up with an increasing number of simulations and it confirms an algorithm rightness of a procedure for a generator of a uniform distribution from a choice.

Number of choices	For a delivery time period /LT 2 periods
100	
1000	

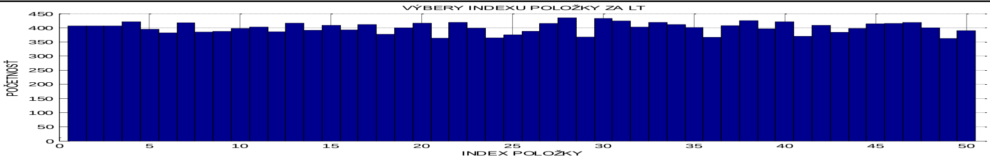
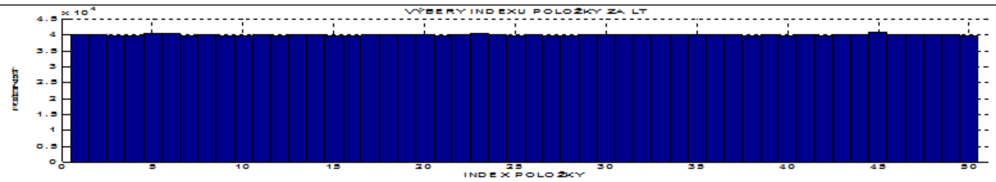
10000	
1000000	

Fig 2 Choice of indices of time periods being modelled and a verification of a uniform distribution

We develop a histogram from a sum of values from the rows of a demand matrix made based on bootstrapping choices. For 100 choices of the delivery time period 2 periods with a probability 0.95, in the Fig. 3, we see that the intervals with a null demand are represented with the greatest frequency. Statistics of the set: min: 0, max: 13, mean: 2.63, median: 1, std: 3.25

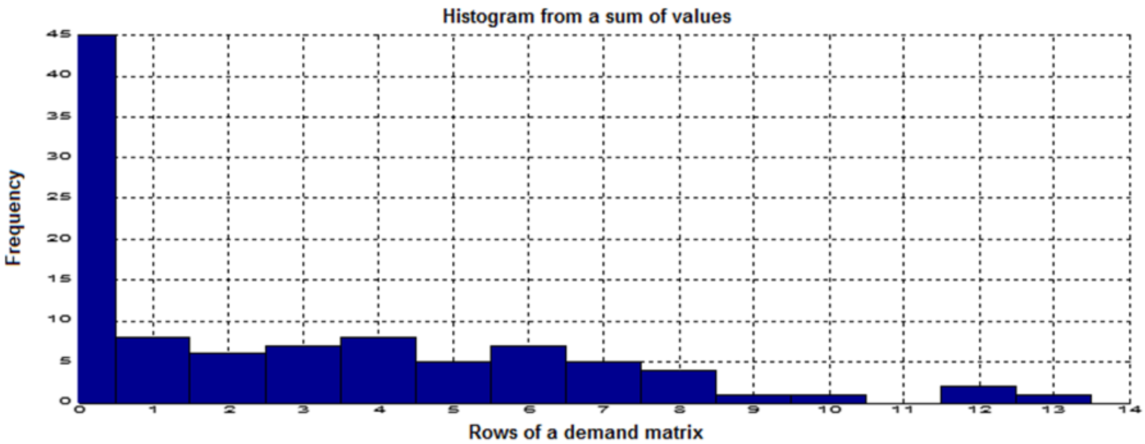
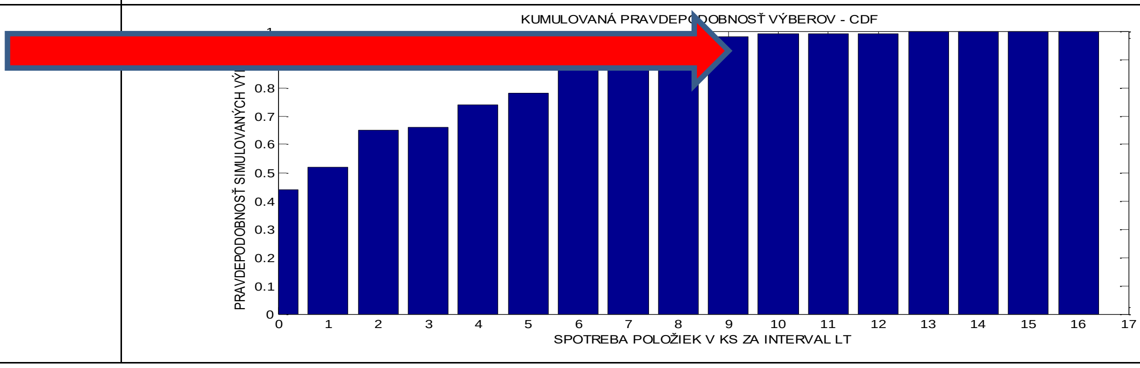


Fig. 3 *Histogram of a sum of choices frequencies*

We also use the data to create a cummulative function of a simulated demand and to define an optimal stock. The greater variance in defining the amount of an item of an optimal stock becomes evident in a smaller number of choices and in a shorter delivery time period. In the Fig.4. Three simulation experiments with a difference in amount of 8-12 pieces

Reorder Level	For a delivery time period/LT 2 periods, 100 choices, probability 0.95
8	

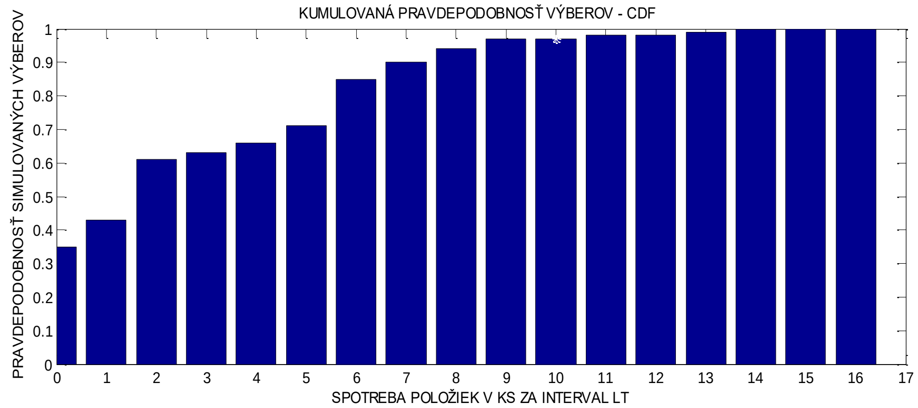
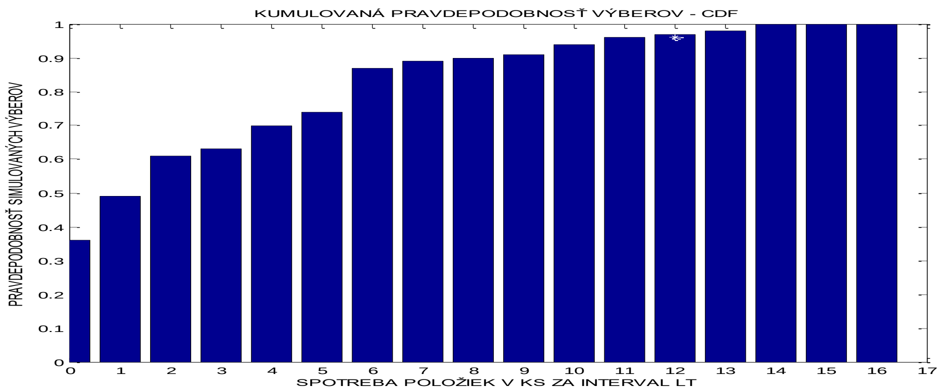
10	
12	

Fig 4 *Cumulative probability of a sum of choices frequency*

We can see in the Fig. 5 that each simulation experiment provides a different course of a cumulative probability of a sum of choices frequency.

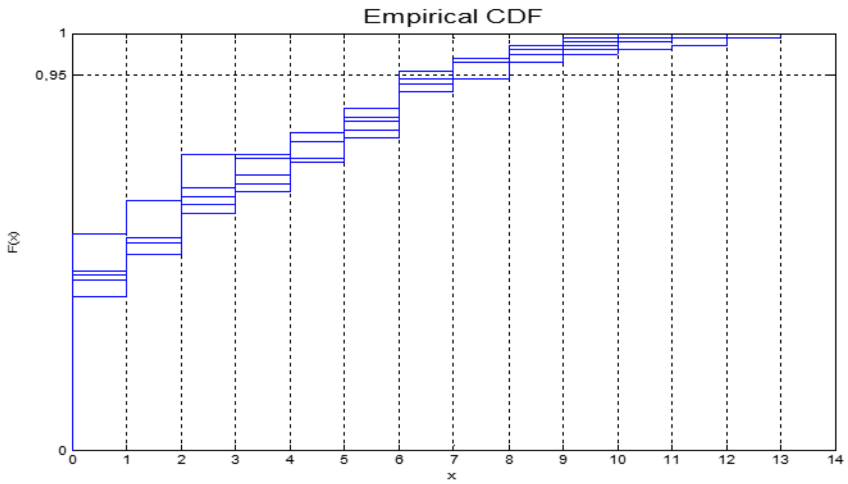


Fig. 5 *Variances of data and course of an empirical CDF for 5 simulations*

3 Conclusion

For evaluation and prediction of the consumption is used arithmetic, moving or weighted moving average. For the trend development of consumption is used exponential equalizing of first and second degree, or linear regression. Auto correlation and identification models are also used. Empirical data arrays of sporadic consumption, however, contain randomly substituting zero values with non-zero. This may, by use of calculations provide variable results for determining the required amount. The bootstrap distribution of a point estimator of a parameter has been used to produce a bootstrapped confidence interval for the parameter's true value, if the parameter can be written as a function of the distribution. Parameters are estimated with many point estimators. A Bayesian point estimator and a maximum-likelihood estimator have good performance when the sample size is infinite, according to asymptotic theory.

References

[1] Efron, B.; Tibshirani, R. An Introduction to the Bootstrap. ISBN 0-412-04231-2., 2003, Boca Raton, FL: Chapman & Hall/CRC..

[2] Rever, M., Wunderink, S., Dekker, K., Schorr, B.: Inventory control based on advanced probability theory, an application, 2005, European Journal of Operational Research, ISBN 0377-2217

[3] DiCiccio TJ, Efron B . Bootstrap confidence intervals, 1996 (with Discussion). Statistical Science 11

[4] Weisstein, E. W. Bootstrap Methods,2015, From MathWorld--A Wolfram Web Resource.http://mathworld.wolfram.com/BootstrapMethods.htm

[5] Raffai, P., Novotný, P., Maršálek, O. Numerical Calculation of Mechanical Losses of the Piston Ring Pack of Internal Combustion Engines. Journal of the Balkan Tribological Association. 2015, no. 4, p. 125–145. ISSN 1310-4772.

[6] Kvačkaj, T. Kráľ, M. Kvačkaj, J. Bidulská, J. Bacsó, L. Némethová, S. Mechanical properties of hot rolled IF steel, In: Hot forming of steels and product properties. Grado, AIM, Milano, CD-ROM (no. 29), 2009, ISBN 88-85298-72-9.

[7] Davison, A. C.; Hinkley, D. V. Bootstrap methods and their application. ISBN 0-521-57391-2, 1997, Cambridge Series in Statistical and Probabilistic Mathematics. Cambridge University Press.

[8] Gershwin, S. Stochastic Modeling of Manufacturing Systems, ISBN: 978-3-540-26579-5,2006, Springer.

[9] Cibulka, V. Riadenie kvality, 1. vyd., Trenčín : TnUAD, 2015, 236 s., ISBN 978-80-8075-681-9.

[10] Rudy V., Lešková A. Modular systems for experimental modelling in the design process of flexible workstations. In: Interdisciplinarity in theory and practice. ISSN 2344-2409

[11] Peško Š., Smieško, J. Stochastické metódy operačnej analýzy, EDIS, ISBN 80-7100-570-3, 2000

[12] Grenčík, J., et al. Manažérstvo údržby, Synergia teórie a praxe, Vydala Slovenská spoločnosť údržby, BEKI design, s. r. o. Košice, 2013, ISBN 978-80-89522-03-3.

[13] Kubiš, J. Procesy podniku a ich modelovanie. Bratislava: Ekonóm 2007, ISBN 978-80-225-2468-1

[14] Cibulka, V.,Počítačové systémy riadenia údržby, 1. vyd., Trenčín, TnUAD, 2017, 112 s., ISBN 978-80- 8075-792.