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A Study Regarding the Possibility of Optimizing the Supply Batch using Artificial Neural Networks

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Abstract

This paper presents a study on the possibility of modelling an optimization problem of supply batch using artificial neural networks. The study has a statistical model of inventory management as starting point. Neural network modelling requires knowledge of historical data on supply volume large enough as to provide a good training of the network. There are some situations in which this data is known little, or not at all. In such cases it may be useful to imagine scenarios of the supply's evolution. This paper studies the possibility of modelling a supply activity in the event of such scenarios.

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Keywords: optimize; supply batch; neural network; scenario

1. Introduction

This paper presents a study on the possibility of modelling an optimization problem of a supply batch, using artificial neural networks. In general, in any inventory management systems there are two issues to be resolved, namely: to determine when to issue a new purchase order and the optimal size of the batch. The importance of these two issues is a consequence of the need to provide the raw materials or goods at the right time, and in the right quantity required by a production process or a resale activity, without blocking company resources in oversized inventory compared to demand.

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There are inventory management systems with unknown demand. Several papers present models for such systems. Some of these are statistical models, others rely on neuronal networks or consist on combinations of various methods. Papers [2, 7] develop models based on fuzzy sets. One neural network model in uncertainty conditions of demand and supply is presented in the paper [6]. The paper [8] describes hybrid intelligent systems for demand forecasting. The paper [9] presents a complementary approach of the surrogate data method with neural networks. Also, a combination of extreme learning machine and traditional statistical methods are presented in paper [5].

In statistical batch management systems [4] the historical data regarding consumption can be a starting point that could forecast future consumption, in the context of a stable social and economic environment. However, there are circumstances in which there is either no data concerning the historical consumption, or if there is, it is no longer valid for taking decisions regarding future demand. These circumstances occur in the following cases:

- a company is at the beginning of its activity
- a new inventory item appears
- there occur important changes in the structure of the client portfolio (loss of a significant client)
- the social and economic environment undergoes major changes (such as economic crisis, war, natural disaster, etc.).

When there is little or no statistic data regarding consumption, demand can be forecast using different scenarios of demand evolution. Taking a scenario as a starting point, and transferring the data obtained in a statistical model of batch management can lead to a determination of two important parameters: the order point and the size of the optimum batch. As time passes by, the inventory management system records real, historical data regarding consumption. This data, along with the one forecast based on scenarios is to be used to build a neural model that would stimulate the batch management system.

The study in the current paper is made on a statistical model of inventory management appropriate for situations in which the evolution of supply demand is not known beforehand. This is the case of companies whose main activity is the retail or wholesale of consumer goods or of production ones which do not work on the basis of firm orders. The paper [3] presents the above-mentioned theoretical model in detail. A brief description of it can be found below.

2. Brief description of the statistical model

The following data is considered to be known: the inventory level at any point of time (S_t), statistical data regarding the consumption during a time interval T whose length is considered relevant, the volume of the issued purchase orders and which have not arrived yet (C_d) and the duration of delivery (d). The moment of launching a new purchase order and the optimum batch size must be determined. The order's time of issue coincides with the time at which the inventory level is equal to the consumption needs until the arrival of the next order. This level, denoted by s, is known as the "order point".

The weighted average consumption C_{smed} of the period is calculated considering the interval T divided into the equal subintervals $t_1, t_2, \ldots, t_n$ and the consumption volumes c_i, i=1,…,n, of these intervals:

$$C_{smed} = \frac{\sum_{i=1}^{n} c_i \cdot p_i}{\sum_{i=1}^{n} p_i} \tag{1}$$

where p_i represents the weight associated with the consumption c_i, i=1, …, n.

Furthermore, for a good consumption forecast, the consumption trend, denoted by θ, is calculated taking into account the consumption of the subintervals $t_{n-(k-1)}, t_{n-(k-2)}, \ldots, t_n$, $k>1$, situated at the end of the interval T. A subinterval T_p, $1 \le p < k$, is considered in the interval marked as T_k in fig. 1.

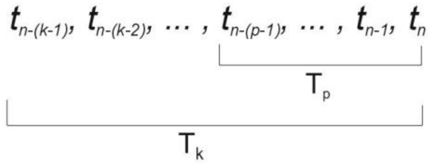

Fig. 1. The intervals used in the trend calculation.

The trend is calculated by equation (2):

$$\theta = \frac{\frac{k}{p} \cdot \sum_{i=n}^{n-p+1} c_i}{\sum_{i=n}^{n-k-1} c_i} \tag{2}$$

The order point s and the optimum batch size Q are calculated by equations (3), respectively (4):

$$s = \mu \cdot \theta \cdot C_{smed} \cdot d \tag{3}$$

$$Q = \mu \cdot \theta \cdot C_{smed} \cdot (d+1) - (S_t + C_d) \tag{4}$$

where μ represents an adjustment factor.

3. Determining the optimum batch by neural models

As it has been mentioned in the introduction, a good modelling of the batch management system would be possible when the historical consumption throughout a relevant lapse of time, under the circumstances of a stable social and economic environment is known. The fact that these conditions are not always met raises the question of modelling the future evolution starting from the hypothesis of several scenarios. As time passes by, the system records real data, which can constitute, along with the data gathered from the scenario of a future consumption, a wide range of examples of artificial neural network training to model the supply activity.

This modelling activity is to be resumed after a given lapse of time, so that the most recent real data regarding consumption, generated by the system, is taken into account when a new forecast is made.

This raises the question of whether such a model provides a right solution to the problem. In order to answer this question, a first step has been taken by means of the research described in paper [3]. This study examines the possibility of determining the optimum supply batch (Q) as well as the command point (s) for an item in the batch, by means of a neural network simulation, when one knows the historical consumption in a lapse of time close to the calculation. There has been used real data belonging to a company that delivers IT products. Errors obtained in the simulation were in the range of [1.589%, 4.412%]. Since the error is expressed as a percentage by a number of pieces, we consider that the error is small enough. Consequently, it can be stated that in neural model obtained under the circumstances described in paper [3] can be a valid one when a sufficient number of the static consumption is known.

There may be situations in which there are no known statistics on consumption sufficient enough to make a well-founded model. This may be, for example, the situation of companies in an early period of their activity. The importance of consumption forecasts and consequently of the supply needs is easy to understand. A disproportionate supply relative to the needs can lead to a company's financial instability or an inability to meet demand. Imagining scenarios of consumption evolution complete with careful tracking of the real situation and taking the right decisions can be an appropriate solution to the problem of optimizing supply batches.

This paper presents a study on the possibility of batch optimization using neural models for certain scenarios of consumption evolution. A model is created using a three layer perceptron type neural network in all analyzed cases. The network has 4 inputs consisting of the values C_{smed}, θ, S_t and C_d and 2 outputs corresponding to the batch size Q, respectively, the order point s. The values C_{smed} and θ were calculated considering a set of consumption values c_i within consecutive time intervals t_i as the values of some time functions. The values of S_t and C_d belong to intervals chosen so that the scattering is not too high. The network training has been made by using the Levenberg-Marquardt method [1].

Three examples of modeling with neural networks are presented below. The evolution of hypothetical consumption is assumed to be described by different mathematical functions.

Example 1

Let us consider the hypothesis that states that consumption varies according to a law described by a parabola function. Be this

$$c(t) = \frac{8}{90} \cdot t^2 - \frac{16}{3} \cdot t + 160 \tag{5}$$

There are taken into account values of the argument t from the interval [0, 40], where the function of the consumption decreases in the first part of the interval, and then increases, in the last part. Fig. 2(a) shows the evolution of the consumption. The set of the training data is shown in table 1.

The training has been carried out throughout several sessions, and the least mean square error that could be obtained was 0.003624. We mark it as mse.

The results of the validation phase are shown in table 2. The values sR and QR represent the values of the point of order and of the batch, respectively, as recalculated on basis of the model obtained as a result of the training process. By comparing the values of the same variables, s and Q, obtained by means of the mathematical model, one reaches partial errors (s-sR, Q-QR). The mean square error obtained at validation equals 7.5.

Consequently, this large value of the mean square error is explained by the fact that any additional pair of input-output data belonging to the set of test data, taken into account, involves an increased error.

Table 1. Training data set (example 1).

No.	C_{smed}	θ	S_t	C_d	s	Q
1	137.393	0.951	87	98	131	76
2	128.741	0.952	82	92	123	71
3	120.800	0.953	76	88	115	66
4	113.570	0.955	71	81	108	65
5	107.052	0.958	68	77	103	60
6	101.244	0.961	66	72	97	57
7	96.148	0.964	62	70	93	53
8	91.763	0.968	60	67	89	51
9	88.089	0.973	57	64	86	50
10	85.126	0.978	56	62	83	49
11	82.874	0.984	54	61	82	48
12	81.333	0.991	54	60	81	47
13	80.504	0.997	52	58	80	51
14	80.385	1.004	53	54	81	54
15	80.978	1.01	55	61	82	48
16	82.281	1.017	57	63	84	47
17	84.296	1.023	60	66	86	46

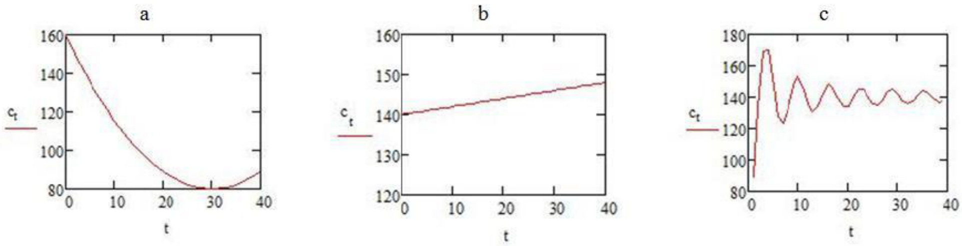

Fig. 2. Consumption variation (a) – parabola; (b) linear function; (c) damp wave function.

Table 2. Validation results (example 1).

No.	C_{smed}	θ	S_t	C_d	s	Q	sR	QR	s-sR	Q-QR
1	132.978	0.952	84	95	127	74	126	74	1	0
2	124.681	0.953	79	89	119	70	119	70	0	0
3	117.096	0.954	76	88	112	59	111	61	1	-2
4	110.222	0.956	71	79	105	61	105	61	0	0
5	104.059	0.959	67	75	100	58	100	58	0	0
6	98.607	0.962	66	72	95	52	94	52	1	0
7	93.867	0.966	60	68	91	53	91	53	0	0
8	89.837	0.971	60	65	87	50	86	51	1	-1
9	86.519	0.976	56	63	84	50	84	49	0	1
10	83.911	0.981	55	62	82	47	82	47	0	0
11	82.015	0.987	54	61	81	47	81	47	0	0
12	80.83	0.994	54	60	80	47	80	47	0	0
13	80.356	1.001	52	58	80	50	80	51	0	-1
14	80.593	1.007	53	54	81	55	81	57	0	-2
15	81.541	1.014	55	62	83	48	83	48	0	0
16	83.2	1.020	57	64	85	49	85	49	0	0

The analysis of the data in table 2 reveals that the simulated values sR and QR of the order point and of the supply batch, simulated on the neural model, show little difference as compared to the results in the mathematical model. The maximum relative error of the order point sR is 1.15%. In the case of the supply batch, it is of 3.67%. If we refer to inexpensive goods (IT products, pieces of clothing, etc) these errors are acceptable.

The true plotting of the differences between the simulated values and the desired ones of the order size and order point is presented in fig. 3.

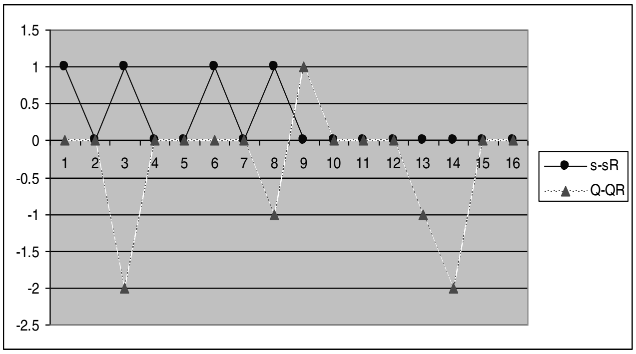

Fig. 3. Differences between the simulated values and the desired ones (example 1).

Example 2:

We consider the situation in which the volume of the consumption follows a linear variation law with a small slope. Be this:

$$c(t) = 0.2 \cdot t + 140 \tag{6}$$

where t∊ [0, 40] (see fig. 2 (b)).

The coefficients of the function have been chosen so that the consumption values are close to the ones used in the training described in example 1.

The neural network has been trained with the input-out pairs of data in table 3, and there was kept the best result, expressed through a mean square error of 0.0006. The validation data are presented in table 4. The mean square error obtained at validation equals 0.13.

Table 3. Training data set (example 2).

No.	C_{smed}	θ	S_t	C_d	s	Q
1	141	1.0019	87	98	141	98
2	142	1.002	82	92	142	111
3	142	1.002	76	88	142	121
4	143	1.002	71	81	143	135
5	143	1.002	68	77	143	142
6	143	1.002	66	72	143	149
7	144	1.002	62	70	144	157
8	144	1.002	60	67	144	162
9	145	1.002	57	64	145	170
10	145	1.002	56	62	145	173
11	145	1.002	54	61	145	176
12	146	1.002	54	60	146	179
13	146	1.002	52	58	146	183
14	147	1.002	53	54	147	188
15	147	1.002	55	61	147	179
16	147	1.002	57	63	147	175
17	148	1.002	60	66	148	171

The differences between the simulated values and the desired ones, express by the partial errors, are shown in fig. 4.

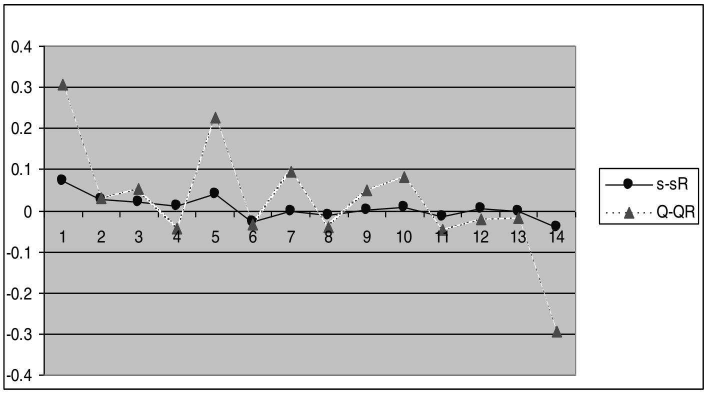

Fig. 4. Differences between the simulated values and the desired ones (example 2).

Table 4. Validation results (example 2).

No.	C_{smed}	θ	S_t	C_d	s	Q	sR	QR	s-sR	Q-QR
1	142	1.002	79	89	142	117	142	117	0	0
2	142	1.002	76	88	142	121	142	121	0	0
3	143	1.002	71	79	143	137	143	137	0	0
4	143	1.002	67	75	143	145	143	145	0	0
5	144	1.002	66	72	144	151	144	151	0	0
6	144	1.002	60	68	144	161	143	161	-1	0
7	144	1.002	60	65	144	164	143	164	-1	0
8	145	1.002	56	63	145	172	144	172	-1	0
9	146	1.002	54	61	146	178	146	178	0	0
10	146	1.002	54	60	146	179	146	179	0	0
11	146	1.002	52	58	146	183	145	183	-1	0
12	147	1.002	53	54	147	188	147	188	0	0
13	147	1.002	55	62	147	178	146	178	-1	0
14	148	1.002	57	64	148	176	147	176	-1	0

Analysing the data in table 4, one notices reduced relative simulation errors for the order point s—0.69%. In the case of the supply batch, the error is of 0%. These errors are acceptable.

Example 3:

Let us consider the hypothesis in which consumption varies according to a law described by a damp wave function. Be this

$$c(t) = e^{-\frac{1}{t}\cdot \sin t}, \quad t > 0 \tag{7}$$

Consumption has positive and negative variations from one stage to another, and it shows a tendency to settle down in time, as the segment on the market is taking shape. The graphic of consumption is shown in fig. 2 (c).

The network has been trained with the data shown in table 5. The mean square error obtained was 0.881.

Table 5. Training data set (example 3).

No.	C_{smed}	θ	S_t	C_d	s	Q
1	137	0.852	87	98	117	48
2	141	1.036	82	92	146	118
3	143	1.063	76	88	152	140
4	140	0.932	71	81	130	109
5	140	1.004	68	77	141	136
6	142	1.049	66	72	149	160
7	140	0.961	62	70	135	137
8	140	0.990	60	67	139	150
9	142	1.039	57	64	148	174
10	141	0.978	56	62	138	158
11	140	0.984	54	61	138	161
12	141	1.032	54	60	146	177
13	141	0.990	52	58	140	169
14	140	0.980	53	54	137	167
15	141	1.025	55	61	145	173
16	141	0.998	57	63	141	161
17	140	0.980	60	66	137	148

The model obtained has been tested, and the results are shown in table 6. The mean square error equals 65.21.

Table 6. Validation results (example 3).

No.	C_{smed}	θ	S_t	C_d	s	Q	sR	QR	s-sR	Q-QR
1	139	0.918	84	95	128	76	132	72	4	-4
2	143	1.097	79	89	157	146	155	147	-2	1
3	141	0.983	76	88	139	113	135	116	-4	3
4	139	0.945	71	79	131	113	132	111	1	-2
5	141	1.052	67	75	148	155	145	157	-3	2
6	142	1.004	66	72	143	147	139	149	-4	2
7	139	0.956	60	68	133	138	133	138	0	0
8	141	1.030	60	65	145	165	148	163	3	-2
9	142	1.013	56	63	144	169	143	169	-1	0
10	140	0.965	55	62	135	153	134	154	-1	1
11	140	1.016	54	61	142	169	143	169	1	0
12	141	1.018	54	60	144	173	145	172	1	-1
13	140	0.972	52	58	136	162	135	163	-1	1
14	140	1.006	53	54	141	175	142	174	1	-1
15	141	1.020	55	62	144	171	144	171	0	0
16	140	0.979	57	64	137	153	134	155	-3	2

The approximation of the order point has been made with a maximum relative error of 3.13%, and that of the batch, with one of 5.26%. One can notice an even more significant difference between the values calculated by using the mathematical model and the ones simulated on the neural one. This can be explained by the alternate positive and negative variations of the consumption, as well as by the scarce number of learning examples. Research completed and described in other paper have revealed that the results of the simulation on neural networks can be improved substantially by considering a larger number of learning examples in the stage of network training. This can be achieved by considering a thinner division $t_1, t_2, \ldots, t_n$ of the lapse of time T for which the modelling is made.

The simulation errors charts are illustrated in fig. 5.

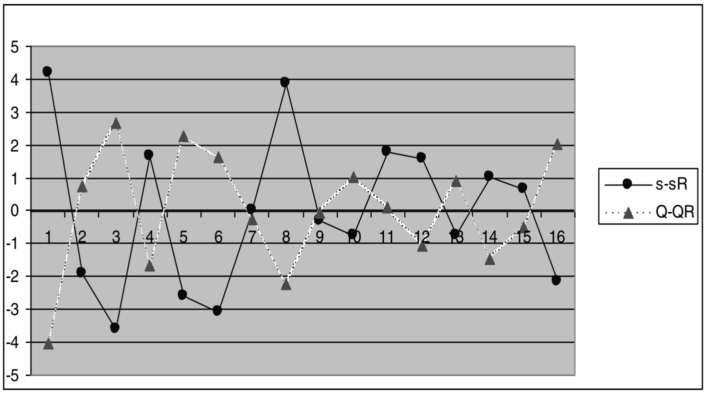

Fig. 5. Differences between the simulated values and the desired ones (example 3).

4. Conclusion

A major problem of small-size companies consists in the estimation of the necessary supply when there is no certain data regarding demand. There are no few cases when the suppliers of such companies are located far away. The probability that a supply command made by a supplier be met in a short time is very low. In such case, it is important to estimate the needed supply as accurately as possible. Under these circumstances, conceiving possible evolution scenarios of the supply needed might prove useful.

The author of this article aims at finding a way of forecasting demand and, implicitly, the needed supply, when no certain facts are known. The goal is to make a software product conceived as an instrument of forecasting demand that is to be based on neural networks. This program will be made so that

- when there is no historical data regarding consumption, or when the existing data can not serve as ground for the decision-making, it would simulate future demand based on scenarios expresses through values of mathematical functions
- as the company records real data regarding statistic consumption and the factors which influence demand are defined by certain stability (constant), this data will be complemented with the results from a certain scenario of a future evolution.
- the set obtained this way will become the training basis of the neural network that will be used in the forecast of the next demand.

The research in paper [3] has shown that, starting from statistic consumption, one can create a neural model to simulate the next demand. The research described in this paper proves the fact that the simulation of the next demand, in the case of the hypothesis of some “mathematical” scenarios, using the same means, is feasible. Regarding the latter aspect, one can highlight the following conclusions:

- the quality of these models, expressed by the simulating error, depends on more factors;
- the number of the examples used in the network training process is one of these;
- another factor is represented by the characteristics of the function which express the consumption evolution scenario; the neural model is better in case of a monotone function (examples 1 and 2) in comparison with the damp wave one;
- better results can be obtained in this case, and in the others, by creating training sets that contain more examples.

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