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Minimizing Material Inventory in Ready Mixed Concrete Plants by Applying a Fuzzy Neural Network Approach Management

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Abstract

In the U.S.A., 70 percent of the manufactured cement and 43 percent of aggregates is used in Ready-Mixed Concrete (RMC) plants. So a material inventory control system is needed to form a consumption pattern for this material to optimize warehousing cost and ordering in RMC plants. Such a material inventory control system of batching plants could be applied as an approach for optimal estimation of the reservoirs required for storage and feeding of material. In this research, a material inventory control system of batching plants has been developed by fuzzy logic (FL) with Economic Order Quantity (EOQ) model of inventory control. 70% and 80% reduction has been obtained in estimation of optimal size of the required reservoirs for aggregate and cement respectively in one of the RMC plants of Tehran in the FL model, which reduced the required land used for the plant and maintenance and manpower expenses.

Keywords: *Batching plant, Ready mixed concrete, Neural network, Fuzzy logic, Material inventory.*

1. Introduction

Concrete is known as one of the main materials in construction projects and the required concrete with a desired quantity and quality is of special importance. About 71 million tons of Portland cement and 2.0 million tons of masonry cement were produced in USA (the output was from 98 plants in 35 States) in 2012. The overall value of sales was about $7.5 billion. Most of the cement was used to make concrete, worth at least $41 billion. About 70% of cement sales went to ready-mixed concrete producers. Construction sand and gravel valued at $6.4 billion was produced by an estimated 4,000 companies and government agencies from about 6,500 operations in 50 States. It is estimated that about 43% of construction sand and gravel was used as concrete aggregates [1].

The above statistics clearly shows the direct effect of sand, gravel and cement on the cost of concrete production. Therefore, an inventory control for this material and planning concrete production can lead to the optimal production of concrete, optimal use of the material, economization of energy in the production of this material, reduction of material loss, increase in sales profit of the produced concrete, saving ordering and warehousing costs of this material.

Considering the size, type and place of the site, one can decide whether the concrete is manufactured in the site or transported from Ready-Mixed Concrete (RMC) plants to the site through a cost-profit analysis. However, it is imperative to create an intelligent system such as an inventory control system of raw materials for the production of concrete in batching plants. A batching plant is a set of equipment which is applied for preparing concrete according to the desired mixture plan and also delivery of the weighed material to the transportation equipment before or after the material in question is mixed. It generally includes the components such as cement silos, aggregates and water reservoirs, material transfer systems, weighing equipment, control equipment and other components such as heaters, chillers which are added if need be. Highly consumed raw material in the RMC plant which constitutes almost total value of the store's inventory includes sand, gravel and cement. The number and size of raw material reservoirs (cement silos, aggregates, water and additive reservoirs) depended on the material and concrete demand in any plants and projects. To estimate the required optimal land used for the storage of this material in batching plants, it is necessary to have the optimal order (demand) of this material in different periods. Analysis of the optimal input and output values of this material requires implementation of an inventory control system of the batching plant.

An inventory is a depot of material and goods which remains fixed at a specified time to respond to the demand under control of the organization. Inventory control is the study and maintenance of a level of inventory which minimizes the inventory system. The goals of inventory control models and formulas are to determine the optimal time and quantity of an order with mathematical models. In inventory models, it is possible to make plans for one or several products simultaneously.

Inventory control is a very important factor which specifies the health level of the supply chain and also the effects of the financial health of the balance sheet. Every organization constantly tries to keep an optimum inventory to fulfill the requirements and prevent over or under inventory which affects the financial figures [2]. Supply chain management pays attention to control of materials and information along the chain from suppliers to producers, distributors, retailers, and customers. Since 1990, supply chain management has been considered by academic researchers and practitioners very much [3].

In fact, one of the major problems in managing construction materials and equipment is tracking them in the supply chain and knowing their location on large job sites. Fortunately, location can now be automatically estimated within metres using emerging technologies [4].

Section two includes the review of the related literature. Proposed Conceptual Model is introduced in section three. Economic Order Quantity and implementation of this model through fuzzy logic and neural network in batching plants are presented in section four and five, respectively. Section six presents the analysis of the results which is followed by the estimation of the optimal reservoirs required by batching plants in section seven. Concluding statements are made in section eight.

2. Literature Review

Classic Economic Order Quantity (EOQ) model was first innovated by Harris, F. W. In this model, order was received immediately and there was no inventory shortage and all parameters were considered certain [5]. Hadley, G. and Whiten, T. M. expanded several certain models and studied permissibility of the inventory shortage in them and improved the primary model of Harris [6]. Darwish, M. A. presented Economic Production Quantity (EPQ) with variable preparation costs and then obtained optimal quantities by deriving from objective functions [7].

Inventory models with multiple demand classes have been extensively studied [8-11] but most of these studies don’t consider a combined backorder and lost sales in multiple demand classes particularly under a (Q; r) policy [12]. However, there are fixed ordering costs and a (Q; r) policy which is widely used in practice. Traditionally, the Economic Order Quantity (EOQ) model considers problems of continuous review inventory given that the demand during the stockout period is either completely backordered or completely lost; the lead time is regarded as a prescribed constant or a random variable which is not controlled [13]. To derive the EOQ/EPQ formulas with/without shortage which reduce the total costs, we find that one good way is to apply the classical optimization techniques [14].

Tarek M. Zayed and Isam Mini Karah planned and allocated resources in batching plants and optimized production in their modeling, considering maximum profit and income. In this regard, they used a linear programming model. Considering the volume of concrete, they estimated the rate of the required critical resources and the optimal number of truck mixers. However, what their study lacked is the fact that raw material inventory control and as a result, production planning should be implemented to optimize the costs of the raw material and the end product (concrete) [15]. Tarek M. Zayed and Ebrahim A. Nosair managed cost in RMC production centers with mathematical random models. This research referred to the effect of delay on concrete unit cost regarding productivity, cost and delay as the most important factors in RMC plants. As for the factor of cost, cost of equipment was also considered for each cubic meter of concrete [16]. Another research studied a new approach in the control and modeling of batching plants based on automation system. In this study, only concrete production processes were simulated to renovate batching plant automation system [17]. One of the other studies related to batching plants was creation of a network-based system to control the quality of ready-mixed concrete which is a new method in the industry. One of its advantages is continuous control of production and saving time [18]. One of the studies related to use of inventory control in civil engineering was Formulation of a pull production system for optimal inventory control of temporary rebar assembly plants; and a methodology is presented that employs Monte Carlo simulation and optimization techniques to identify inventory levels that minimize inventory costs while simulating variability in demand, procurement lead times, and production capacity [19].

No research related to raw material inventory control in batching plants has been conducted particularly to estimate the required reservoirs for storage of materials based on optimal order quantity which necessitated this study. The presence of additional and excessive reservoirs for material increases reservoirs supply costs, repair and maintenance cost, and non-optimal occupation of the plant land space.

3. Proposed Conceptual Model

In this study, a database based on case studies of some plants was used in Economic Order Quantity (EOQ) inventory control model, and then the optimal order quantity and also raw material reordering point of the batching plants were calculated. With optimal order quantity, the optimal number and size of the raw material reservoirs of batching plants can be estimated with a simple computation which was the most important goal of this research. Optimal estimation of the reservoirs of materials could lead to the optimization of the land used, and consequently the required initial capital of the plant is reduced. To implement the EOQ model of the inventory control for batching plants with Artificial Intelligence, fuzzy logic (FL) and artificial neural network (ANN) were used as tools for the prediction of the optimal order quantity and reordering point of the raw material. Another goal of this study was to investigate and compare the application of fuzzy logic and neural network in modeling of an inventory control system in batching plants. The proposed conceptual model of what was explained above is shown in figure 1.

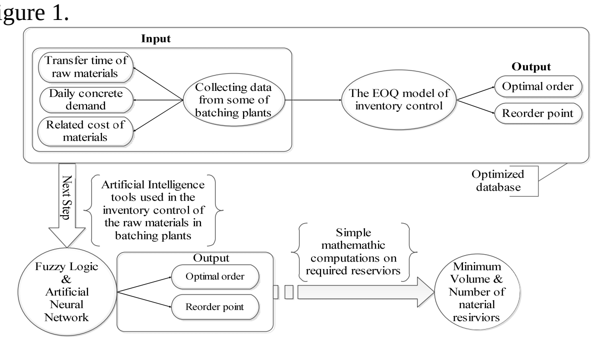

Fig. 1 The sequence of the proposed framework.

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4. Economic Order Quantity Model (EOQ)

This is the simplest and the most common model of an inventory control which determines the optimal order quantity of each material considering with which total inventory costs (holding and ordering) can be minimized.

All costs in inventory management include: (1) ordering costs; ordering means purchase or procurement of the required goods of the plant and ordering costs include clerical, administrative, order transportation, information processing, delivery of ordered products and the salary of purchase personnel. Material procurement cost in purchase model is divided into two fixed ordering cost and material purchase cost. Fixed ordering cost means the cost which is charged for ordering material to the inventory system and this cost doesn't depend on the order quantity such as fax, telephone, follow-up etc. Material purchase cost is charged to the inventory system and depends on the quantity of each order and unit price of product. It is necessary to note that transportation costs of the ordered material and inspection costs are regarded as costs of procurement. If these costs are expressed for the unit of product, they will be calculated in the price of the product and are regarded as material purchase costs. Otherwise, they are calculated in ordering costs [20]. (2) Holding cost; it means the cost which is charged due to holding of the inventory to the inventory system. These costs are classified as follows: (a) Store facilities cost which includes the annual rent of store, water, electricity, gas charges etc., (b) Transfer cost such as transportation cost inside store, (c) Cost of loss including decay or breakage of material etc., (d) Insurance and tax costs, (e) Capital stock cost (time cost) which means how much we lost profit opportunity [20-22]. Holding cost is expressed as h=i×C where coefficient i is holding cost rate and is annually between 0.15 and 0.25 and C is the unit price of product. Each organization also can have special policies to estimate holding cost of goods.

Total cost is equal to the sum of ordering and holding costs. The parameters used in EOQ modeling are described in Table 1, and the diagram of total cost, holding cost, ordering cost and optimal point is shown in Figure 2.

Table 1: Parameters used in EOQ modeling

symbol	Description
D	Materials demand during a period
C_o	Fixed cost of each ordering during a period
C_h	Holding cost of a unit of goods during period
i	Holding cost rate during period
N	Number of received orders during period
Q	Order quantity in each order
Q*	Economic (optimal) order quantity
C	Purchase cost of each goods unit
L	Order delivery length
T	Length of each cycle or the time which lasts for the order to reach zero or interval between

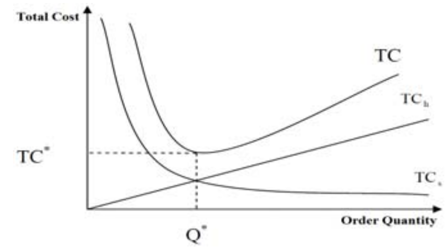

Fig. 2 Diagram of total cost, holding cost, ordering cost and the optimal point.

Relationships in this model are [20-22]:

$$C_h = i.C \ , \quad 0.15 \le i \le 0.25 \quad (1) \quad , \quad t = \frac{Q}{D} \quad (2) \quad , \quad N = \frac{1}{t} \quad (3)$$

$$N = \frac{D}{Q} \quad (4) \quad , \quad Q* = EOQ = \sqrt{\frac{2DCo}{Ch}} \quad (5)$$

Continuous inventory review system: In this policy, the inventory is studied at any time and once the inventory is equal to or below the order point, we order based on the optimal order quantity. In fact, the inventory controlling is continual, the interval between two order points is not necessarily equal but the order quantity is equal [20-22]. EOQ model diagram along with the order quantity during time and also reordering point are shown in Figure 3.

Reordering point in EOQ model: in this model, Reorder Point (ROP) has two states:

$$ROP = \begin{cases} D.L, & L < T \\ D.L - m.Q, & L \ge T \end{cases} \quad , \quad m = \left[\frac{L}{t}\right] \quad (6)$$

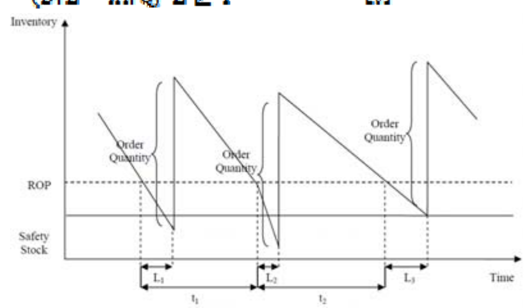

Fig. 3 EOQ model diagram with order quantity during time and also reordering point.

Databases: As mentioned above, highly consumed materials used for the production of concrete are sand, gravel and cement. With the unit price of these materials and also their average holding costs in stores and reservoirs of the plants, EOQ model can be executed. For this purpose, information of the consumable materials of several RMC plants and the batching plants available in the civil projects in Iran was collected. Considering the presence of different strength rankings of the produced concrete, average rates of the sand, gravel and cement were obtained for the production of one cubic meter of concrete from the collected statistics of the selected plants which were 1682, 630 and 232 kg, respectively. Considering that each cubic meter of concrete is averagely 110 dollars, for daily demand of

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concrete with different quantities and also ordering and warehousing costs, information obtained for sand, gravel and cement is given in the following Table 2. The unit price of the material, order cost and daily holding cost of these materials in the RMC plant which were the obtained average statistics are summarized in Table 2.

Table 2: Unit price of the material in the ready-mixed concrete plants

Material	Co ($)	i (per daily)	Cost ($/unit)
Gravel	3.5	0.005	14
Sand	2.73	0.005	16
Cement	1.14	0.003	28

The collected information was substituted in formulas of EOQ model and the obtained results of the gravel model were given in Table 3 to create databases for the construction of fuzzy logic and Neural Network prediction models. Q* (optimal order quantity) and ROP (reordering point) parameters are results of EOQ model. With the concrete demand rates of the plants, average values of the material mixture plan and also the material delivery time, EOQ model computations were done easily as summarized for the gravel in Table 3.

Table 3: The EOQ model databases for gravel

N.o	Concrete Demand (m3/day)	gravel Demand (ton)	L (hr)	Q* (ton)	Q* (ton)	ROP (ton)	
						L<T	L≥T
1	125	210.3	1	145.0	16.6	8.8	
2	150	252.3	1	158.8	15.1	10.5	
3	150	252.3	6	158.8	15.1	63.1	
4	175	294.4	11	171.6	14.0	134.9	
5	200	336.4	16	183.4	13.1		40.9
6	225	378.5	1	194.5	12.3	15.8	
7	250	420.5	6	205.1	11.7	105.1	
8	275	462.6	11	215.1	11.2	212.0	
9	300	504.6	16	224.6	10.7		111.8
10	325	546.7	1	233.8	10.3	22.8	
11	350	588.7	6	242.6	9.9	147.2	
12	375	630.8	11	251.1	9.6		37.9
13	400	672.8	16	259.4	9.3		189.1
14	425	714.9	1	267.4	9.0	29.8	
15	450	756.9	6	275.1	8.7	189.2	
16	475	799.0	11	282.7	8.5		83.5
17	500	841.0	16	290.0	8.3		270.7
18	525	883.1	1	297.2	8.1	36.8	
19	550	925.1	6	304.2	7.9	231.3	
20	575	967.2	11	311.0	7.7		132.3
21	600	1009.2	16	317.7	7.6		37.4
22	625	1051.3	1	324.2	7.4	43.8	
23	650	1093.3	6	330.7	7.3	273.3	
24	675	1135.4	11	336.9	7.1		183.4
25	700	1177.4	16	343.1	7.0		98.7
26	725	1219.5	1	349.2	6.9	50.8	
27	750	1261.5	6	355.2	6.8	315.4	
28	775	1303.6	11	361.0	6.6		236.4
29	800	1345.6	16	366.8	6.5		163.4
30	825	1387.7	1	372.5	6.4	57.8	
31	850	1429.7	6	378.1	6.3	357.4	
32	875	1471.8	11	383.6	6.3		290.9
33	900	1513.8	16	389.1	6.2		231.0
34	925	1555.9	1	394.4	6.1	64.8	
35	950	1597.9	6	399.7	6.0		399.5
36	975	1640.0	11	405.0	5.9		346.7
37	1000	1682.0	16	410.1	5.9		301.1
38	1025	1724.1	1	415.2	5.8	71.8	
39	1050	1766.1	6	420.2	5.7		21.3
40	1075	1808.2	11	425.2	5.6		403.5
41	1100	1850.2	16	430.1	5.6		373.2
42	1125	1892.3	1	435.0	5.5	78.8	
43	1150	1934.3	6	439.8	5.5		43.8
44	1175	1976.4	11	444.6	5.4		16.7
45	1200	2018.4	16	449.3	5.3		447.1
46	180	302.8	3	174.0	13.8	37.8	
47	265	445.7	7	211.1	11.4	130.0	
48	340	571.9	13	239.1	10.0		70.6
49	560	941.9	8	306.9	7.8		7.1
50	750	1261.5	1	355.2	6.8	52.6	
51	890	1497.0	9	386.9	6.2		174.5
52	955	1606.3	5	400.8	6.0	334.6	
53	1020	1715.6	2	414.2	5.8	143.0	
54	1010	1698.8	10	412.2	5.8		295.7
55	1150	1934.3	12	439.8	5.5		87.5

5. Economic Order Quantity Model (EOQ)

To predict the optimal order quantity in batching plants, and study and compare the performance of fuzzy logic and neural network in modeling of the inventory control of batching plants, neural network and fuzzy logic were used as artificial intelligence tools.

One of the limitations in batching plants in this research was parameter L (length of delivery of material in RMC plants) which can be variable or unknown. It all depends on the situation of the plant. As an example, this parameter depends on the location of the stone crushing plant in large civil projects (such as construction of a dam). With the batching plant next to the stone crushing structures, the distance will be very short. A short distance between the plants of raw material seller (stone crushing plant and cement plant) and RMC plants causes faster delivery of material. Another example is when this plant is located inside the city limit. It can be liable to traffic restrictions which means the batching plant management faces time limitation for supply of material. It can be received or ordered in hours out of traffic restrictions which increases parameter L. There is lower limitation in outskirts or out of city, and material is supplied and delivered more easily. Another point considered for holding material in batching plants is necessity of allocation of at least 2 silos to storage of cement. Repair and maintenance and prevention of cement loss in cement silos require the presence of two silos, and also connection of these two silos to each other.
Therefore, limitations like the two cases above should be considered when the inventory control model is used, and the number and size of the required reservoirs of resources are estimated.

Concrete production rate in batching plants is expressed as m3/hr. Generally, raw material is ordered in batching plants considering concrete production rate and also demand of concrete. Considering that demand rate in batching plants is daily and different in weekdays and different seasons of year, time cycle for performing calculations was selected daily in this research. Each of the two methods was created later.

5.1 Neural Network

To create an EOQ-based neural network model, databases shown in Tables 2 and 3 were used, and a neural network model was created for each one of these materials which is described as follows.
To construct this model, four input variables were defined which included: daily concrete demand rate, delivery time, type of material, and ratio of the unit price of the material to the unit price of the concrete. The outputs of the model included two variables namely optimal order quantity (Q*) and reordering point (ROP). To construct this model, the neural network toolbox of MATLAB was used, and a hidden layer with twenty neurons was defined in the structure of the model. In the plan arrangements, 70% of data were selected as education, 15% were selected for validation and 15% were selected for testing the network.

5.2 Fuzzy Logic

To create a fuzzy logic model for the inventory control of the raw material, Mamdani structure was used. For each one of the materials, a separate model was formulated. Only the gravel inventory control model is described due to similarity.
Gravel economic ordering estimation model: This model has three input variables which include the daily concrete demand rate, the ratio of the sand unit price to the concrete unit price and the duration of gravel delivery. The output of the model also has two variables including the optimal order quantity and the reordering point. Membership function of these variables is defined as a rectangle and the membership functions of one of the input and output variables are shown in Figures 4 and 5.

Fuzzy rules: Totally 55 fuzzy rules were written for the gravel inventory control model by the experts of the plants in the case studies. Some of the formulated fuzzy rules for the gravel inventory control model are given in Table 4. Sand and cement stock control models were also formulated like the gravel model, but their results are studied in results analysis section of research.

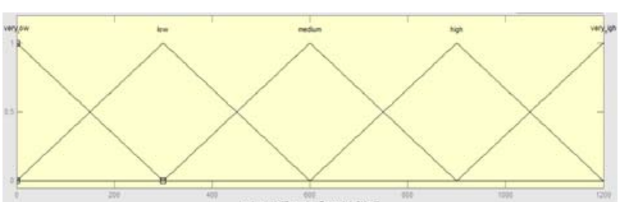

Fig. 4 Membership functions of Concrete demand.

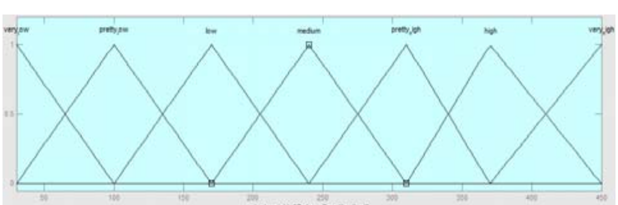

Fig. 5 Membership functions of gravel economic order.

Table 4: Some of the formulated fuzzy rules for the gravel model

	N.O	Concrete Demand	percent Unit Price	Lead Time		Order Quantity	Re order point
	1	very low	low	low		pretty low	very low
	2	low	medium	medium		medium	pretty low
	3	low	medium	high		medium	very low
	4	low	medium	high		medium	medium
	5	low	medium	low		medium	very low
IF	6	medium	medium	low	THEN	pretty high	very low
	7	medium	medium	medium		pretty high	pretty high
	8	medium	medium	high		pretty high	low
	9	medium	medium	high		high	pretty low
	10	high	medium	low		high	pretty low
	11	high	medium	medium		high	high
	12	high	medium	high		very high	very low
	13	high	medium	high		very high	very high

6. Results & Verifications

According to the constructed models of artificial neural network (ANN) and fuzzy logic (FL) for an inventory control of batching plants in the previous section, results of these two models were analyzed. To study the performance of the FL and ANN for the prediction of the optimal order quantity and reordering point of the batching plant material, the results of two models along with the results of EOQ model are summarized in Table 5.

Table 5: The results of FL and ANN models for gravel

N.O	Theory results		ANN results		Fuzzy results	
	Q*	ROP	Q*	ROP	Q*	ROP
1	145.0	8.8	160.2	12.6	163	25.5
2	158.8	10.5	168.0	4.4	170	26.3
3	158.8	63.1	170.6	29.4	205	136
4	171.6	134.9	187.9	99.1	205	135
5	183.4	40.9	198.8	52.4	205	135
6	194.5	15.8	192.5	12.7	185	25.5
7	205.1	105.1	204.1	91.5	205	135
8	215.1	212.0	214.2	98.0	205	135
9	224.6	111.8	226.6	107.7	205	135
10	233.8	22.8	226.8	23.6	223	40.6
11	242.6	147.2	239.1	136.1	238	151
12	251.1	37.9	243.9	87.0	222	135
13	259.4	189.1	257.1	136.3	257	164
14	267.4	29.8	261.1	30.0	264	61.9

15	275.1	189.2	273.3	174.9	274	178
16	282.7	83.5	275.4	80.7	243	134
17	290.0	270.7	288.6	135.8	290	173
18	297.2	36.8	293.9	40.0	299	63.8
19	304.2	231.3	304.7	218.6	311	223
20	311.0	132.3	306.3	94.8	282	118
21	317.7	37.4	319.1	124.0	344	169
22	324.2	43.8	324.6	56.1	344	63.8
23	330.7	273.3	332.5	268.5	345	255
24	336.9	183.4	334.8	138.9	332	188
25	343.1	98.7	347.2	127.5	344	203
26	349.2	50.8	351.8	74.5	351	63.8
27	355.2	315.4	356.9	308.0	355	253
28	361.0	236.4	360.0	205.0	348	236
29	366.8	163.4	371.9	164.4	351	227
30	372.5	57.8	374.5	87.1	368	71.2
31	378.1	357.4	378.1	308.6	374	256
32	383.6	290.9	381.7	263.9	368	281
33	389.1	231.0	392.9	231.3	377	255
34	394.4	64.8	392.1	86.2	389	74.2
35	399.7	399.5	396.1	254.8	389	243
36	405.0	346.7	400.0	279.1	381	273
37	410.1	301.1	410.0	307.2	383	281
38	415.2	71.8	405.0	72.9	389	74.2
39	420.2	21.3	411.1	158.8	388	209
40	425.2	403.5	415.7	227.4	392	253
41	430.1	373.2	423.9	373.3	394	291
42	435.0	78.8	414.5	62.0	398	74.2
43	439.8	43.8	423.1	51.1	403	155
44	444.6	16.7	429.7	105.4	411	258
45	449.3	447.1	435.6	417.1	421	384
46	174.0	37.8	172.6	27.3	177	131
47	211.1	130.0	210.3	88.7	205	135
48	239.1	70.6	236.3	131.5	232	148
49	306.9	7.1	303.4	100.2	316	195
50	355.2	52.6	358.0	78.6	355	64.9
51	386.9	174.5	381.1	244.3	381	260
52	400.8	334.6	400.2	264.7	389	239
53	414.2	143.0	409.6	133.9	389	165
54	412.2	295.7	403.6	254.3	384	250
55	439.8	87.5	428.4	165.6	403	245

Absolute error of the results of the FL and ANN models compared with EOQ model for the prediction of optimal order quantity (Q*) and reordering point (ROP) for gravel is given in Table 6. The summarized results of FL and ANN models are presented in table 7. Correlation diagrams of the predicted results of the fuzzy logic and neural network models compared with results of EOQ are presented for optimal order quantity of each material (see figure 6).

Table 6: Absolute errors of the FL and ANN models compared with EOQ model for gravel

N.O	ANN-Absolute Error (%)		FL-Absolute Error (%)	
	Q*	ROP	Q*	ROP
1	9.5	30.5	11.0	65.6
2	5.5	137.8	6.6	60.0
3	6.9	114.7	22.5	53.6
4	8.7	36.1	16.3	0.1
5	7.7	22.1	10.5	69.7
6	1.1	24.5	5.2	38.2
7	0.5	14.9	0.0	22.1
8	0.4	116.4	4.9	57.0
9	0.9	3.8	9.6	17.2
10	3.1	3.3	4.8	43.9
11	1.5	8.2	1.9	2.5
12	3.0	56.4	13.1	71.9
13	0.9	38.8	0.9	15.3
14	2.4	0.8	1.3	51.9
15	0.7	8.2	0.4	6.3
16	2.6	3.5	16.3	37.7
17	0.5	99.4	0.0	56.5
18	1.1	7.9	0.6	42.3
19	0.2	5.8	2.2	3.7
20	1.5	39.5	10.3	12.1
21	0.5	69.8	7.7	77.8
22	0.1	21.9	5.7	31.3
23	0.6	1.8	4.2	7.2
24	0.7	32.1	1.5	2.4
25	1.2	22.6	0.3	51.4
26	0.8	31.8	0.5	20.4
27	0.5	2.4	0.0	24.7
28	0.3	15.3	3.7	0.2

29	1.4	0.6	4.5	28.0
30	0.5	33.6	1.2	18.8
31	0.0	15.8	1.1	39.6
32	0.5	10.2	4.2	3.5
33	1.0	0.1	3.2	9.4
34	0.6	24.8	1.4	12.6
35	0.9	56.8	2.8	64.4
36	1.2	24.2	6.3	27.0
37	0.0	2.0	7.1	7.1
38	2.5	1.5	6.7	3.2
39	2.2	86.6	8.3	89.8
40	2.3	77.4	8.5	59.5
41	1.5	0.0	9.2	28.2
42	4.9	27.2	9.3	6.3
43	3.9	14.4	9.1	71.8
44	3.5	84.2	8.2	93.5
45	3.1	7.2	6.7	16.4
46	0.8	38.4	1.7	71.1
47	0.4	46.6	3.0	3.7
48	1.2	46.3	3.1	52.3
49	1.2	92.9	2.9	96.4
50	0.8	33.1	0.0	19.0
51	1.5	28.6	1.6	32.9
52	0.1	26.4	3.0	40.0
53	1.1	6.8	6.5	13.4
54	2.1	16.3	7.3	18.3
55	2.7	47.1	9.1	64.3

Table 7: Absolute errors of the FL and ANN models compared with EOQ model for gravel

	Gravel Model				Sand Model				Cement Model			
	ANN Error (%)		FL Error (%)		ANN Error (%)		FL Error (%)		ANN Error (%)		FL Error (%)	
	Q*	ROP	Q*	ROP	Q*	ROP	Q*	ROP	Q*	ROP	Q*	ROP
Mean Error	1.9	33.1	5.4	35.2	1.8	95.6	8.9	35.4	6.2	75.2	6.3	38.0
R^2	0.99	_	0.96	35.2	0.99	_	0.94		0.95	_	0.96	_

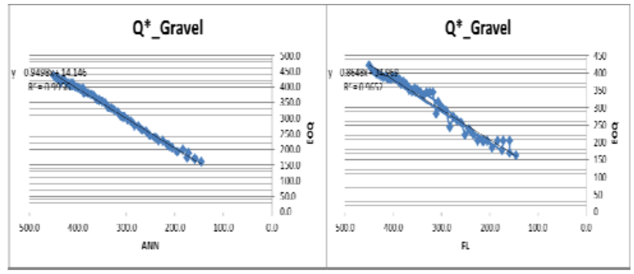

Fig. 6 Correlation of FL and ANN model compared with results of gravel EOQ.

As shown in Table 7, the neural network is more accurate than the fuzzy logic model in the estimation of the Q*. The predicted results for the optimal order quantity of cement are close to each other in both models and have an absolute error of 6.3%. The neural network for gravel has an error below 2% while the fuzzy logic has an error of 5.4%. Prediction results for the optimal order quantity of the neural network in sand with the average error of 1.8% are more accurate than the fuzzy logic model with the average error of 8.9%. None of these two models predicted accurate results for the estimation of ROP, but the error of fuzzy logic in prediction of this variable is much lower than that of neural network.

Observation of the diagrams of the results shows a strong correlation between the results of the neural network and the fuzzy Logic with the results of EOQ to predict the optimal order quantity of batching plant materials. However, the neural network is more accurate in the prediction of Q*.

7. The estimation of material storages

To estimate the size and number of the reservoirs for storage and feeding of batching plant materials based on the results of the prediction of the optimal order quantity, the batching plant of a construction project was studied in Tehran, the capital of Iran. The mentioned project was executed inside Tehran city which was liable to traffic restrictions, and entry of trucks in the city limit was permitted between 10 P.M and 6 A.M. Therefore, it faced time limitation. Delay rate in arrival of sand, gravel and cement for this project was 12 hours. The batching plant of this project was of a dragline type, and the production capacity of its mixer, which was a pan type, was 35 m^3/hr. In this plant, there were three silos with capacities of 80, 80 and 170 tons. Capacity of its sand and gravel reservoirs was totally 1000 cubic meters. Daily average demand rate of the plant for supply of the required concrete was 450 m^3 /hr. The optimal order quantity and reordering point were obtained by implementing specifications of the plant in the neural network and the fuzzy logic models. With these two parameters, the near optimal number and size of these reservoirs could also be estimated.

Due to probability of failure, need for repair and maintenance or any other reason in material reservoirs, it is necessary to have more than one reservoir particularly for cement silos. About aggregates, the number of sand and gravel hoppers can be enhanced, too. In dragline system, only the size of reservoirs can be enhanced and these systems are designed to be excessively large. To estimate the required space for the reservoirs of this material, the desired response can be achieved considering specific weight and also the effect of an incremental coefficient (for example between 1.2 and 1.3) for assurance and simple calculations. With the desired quantity of the reservoirs, and considering length, width and height limitations, total dimensions and structure of the reservoirs can easily be designed. Results of executing the fuzzy logic model for the batching plant are given in Table 8 and 9. In this Table, calculations relating to the estimation of the reservoir size are shown as comparable to the condition of this plant.

Table 8: Case study to comparison of exist material storages

Concrete Demand (m3/day)	Material	L (hr)	Q* (ton)	ROP (ton)	w (ton/m^3)	V_t=1.3(Q*/W) (m^3)
450	Gravel	12	270	156	1.9	175
	Sand	12	232	74.2	1.7	94
	Cement	12	30	29.8	1.15	59

Table 9: Comparison the Reservoirs

Material	Proposed Reservoirs (m^3)		Exist Reservoirs (m^3)		
	V_1	V_2	V_1	V_2	V_3
aggregate	270	-	1000	-	-
Cement	30	30	80	80	170

The size of the sand and gravel reservoirs predicted by the fuzzy model is 30% of the available reservoirs, and the predicted size of cement reservoirs is 20% of the available reservoirs. These figures show non-optimal use of reservoirs and their over-design in this batching plant which increase required initial capital, cost of repair and maintenance, manpower, and space.

8. Conclusion

Considering the high inventory value of the raw material and products of the plants and the fact that inventory control models are advised to increase productivity, and to reduce warehousing and ordering costs in these plants, Economic Order Quantity (EOQ) was used for the analysis of an inventory control model in Ready-Mixed Concrete (RMC) plants. Output of this inventory control model included the optimal order quantity and reordering point (ROP). With the fuzzy logic (FL) and neural network artificial (ANN) toolbox of the MATLAB 7.1 package, the Economic Order Quantity model for the material of a batching plant was formulated based on the database of RMC plants. To create fuzzy logic and neural network models considering the daily required concrete (demand) of a plant, and to reduce ordering and warehousing costs in these centers, and also to reduce additional occupancy area level by the material reservoirs, required optimal order and reordering quantity were regarded as the outputs of the model. Analysis of the results and diagrams showed that the neural network had higher accuracy in the prediction of the optimal order quantity compared with the fuzzy logic. Average errors of the fuzzy logic model in prediction of gravel, sand and cement economic order quantities were found to be 1.9%, 1.8% and 6.2%, respectively. To predict the material reordering point, both fuzzy logic and neural network models had high estimation errors but the error of the fuzzy model was lower than that of the neural network.

With the optimal order quantity of material and simple computations, the number and size of the required reservoir for a batching plant can be estimated which was another goal of this study. There was 70% and 80% reduction in the estimation of the optimal size of the required reservoirs for aggregate and cement by implementing specifications of material order in one of the ready-mixed concrete plants of Tehran in the fuzzy logic model, which reduced the required land used for the plant and maintenance and manpower expenses.

Therefore, the inventory control models can be used in concrete manufacturing workshops, civil projects and also ready-mixed concrete centers. Fuzzy logic and neural network are the tools which can be used as methods of Artificial Intelligence for implementation of an inventory control system for the material of a batching plant.

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