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Models using artificial intelligence to optimize the use of wireless network sensors in pharmaceutical depots. II: Experimental bases and productive use

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Abstract. The automated operations performed in a pharmaceutical depot are determined by a fast, accurate and real-time flow of information through the sensor systems (magnetic, optical, mechanical). Our proposal combines the ability to automate real-time collection and centralization of telemetry data from a sensors network with a learning model based on a deep artificial neural network, incorporating the latest research results in the field of Deep Learning.

Keywords: pharmaceutical depots, network sensors, models based on neural networks.

1. Introduction

In a previous paper [1] we presented a practical proposal for using iWSN (Industrial Wireless Sensor Network) and Artificial Intelligence models based on Deep Neural Networks for the advanced optimization and automation of pharmaceutical distribution centers [2]. The used infrastructure for this experiment is based on routers that ensure connectivity to the cloud (Microsoft Azure) and the Firefly 6lowPAN platform. The communication channel between the sensors and routers uses Zigbee or BLE technology, compatible in terms of the protocol. The wireless sensors are based on the SensorTag platform, interfacing with the RFID modules (fig. 1).

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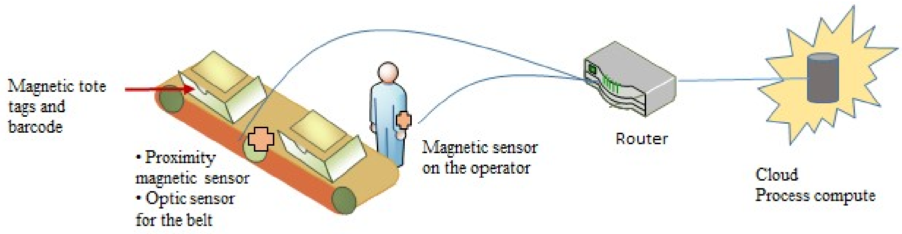

Fig. 1. The experiment architecture.

To improve performance, we used for the cart position identification two types of sensors, magnetic and optic, a design that will significantly reduce the errors rate in the field (especially on the picking line [3], which transports the carts containing the drugs). For the human operator we placed a (custom built) beacon, in the form of a bracelet giving the system information about the position in space and the interaction with the carts. In addition, the carts were equipped with RFID sensors to ensure multiple methods for tracking the position and interaction with the human operator.

The aim of this paper is to analyze the adaptation of deep neural models using data from the database with input data prepared by human operators, and especially from the database with telemetry data generated by mobile electronic devices and by the sensor network installed in the industrial ecosystem [4]. There will be no "programmed" rules in the system, and the system will self-adapt continuously to the operating conditions.

2. The approach for running the Experiment

The experimental execution environment for the proposed innovative system is entirely adapted for processing information and generating decisions in real-time.

<table>
<tr><td colspan="2">SI1: The method of data acquisition from the sensor network and the telemetry of mobile devices</td><td>UI1: The method of data introduction by the user</td></tr>
<tr><td>AI1: The method of predicting processing times</td><td colspan="2">AI2: The method for the inference of optimum process parameters</td></tr>
<tr><td colspan="3">MP1: The method of parallel processing for the real-time execution of tasks from AI1 and AI2</td></tr>
</table>

Fig. 2. The general structure of the system.

The general architecture of the experimental system shown in Figure 2 is based on three categories of main modules [5], as follows:

1) **Acquisition modules** responsible for data collection:

a. The system for the collection of automatic data (sensor network) (SI1)
b. The system for the collection of data from human-operated stations (UI1)
c. The system for the collection of telemetry data from mobile devices (SI1)

2) **Modules based on Artificial Intelligence** which determine inferences and predictions of optimum operations and processing times (AI1), and inferences of optimum process parameters (AI2)
3) **Support modules** for the execution of processes in a massive parallel processing environment – a High Performance Computing system for massive parallel processing using GPU processors for scientific calculation [6]. As for the approach of the entire experiment, we started from the real time operation of the system in a production environment (a Romanian pharmaceutical distributor). The setup of the experiment took into account both the basic system that we started from (based on a classic operation), and the innovations proposed by this study.

The main elements that have been analyzed are closely related to the main purpose for using the proposed optical, magnetic and mechanical assembly, combined with artificial intelligence for the detection and the reduction of the error rate in the order loading/processing process. Thus, the data analyzed came from the following sources:

1) beacon-type operator sensors that identify the operator-picker, both in space and time;
2) optical sensors that interrogate the cart, placed on the belt;
3) magnetic sensors that interrogate the cart, placed both on the belt and on other areas in the industrial space where the cart loading cycle process (order preparation) takes place.

As for the measurements for the experiment, the following data were analyzed (starting from the primary data and ending with the variation of the experiment indicators) [7]:

a) Entry data generated by individual sensors;
b) Prediction data generated by the proposed system;
c) Primary results obtained during the experiment (real vs. forecast data);
d) Components of the confusion matrix.

3. Experiment and results

In order to define more clearly the experiment we will present in the following section the relational structure of the data processed within the system using a subset for purposes of concrete experimental analysis. The first analyzed data set is the one generated by the sensors placed in the complete process of the warehouse conveyor belt:

Table 1. The time measurement of the industrial conveyor belt process.

ID	SensorID	Time	TimeDelta	CartID	Picker
1	4393724	2016-02-10 07:33:28.363	0	32004210	4081
2	4393731	2016-02-10 07:34:29.657	01:01.294	32004210	9692
3	4393747	2016-02-10 07:36:48.987	02:19.330	32004210	9593
4	4393761	2016-02-10 07:38:05.470	01:16.483	32004210	9593
5	4393767	2016-02-10 07:38:22.397	00:16.927	32004210	10239
6	4393788	2016-02-10 07:39:51.060	01:28.663	32004210	9768
7	4393795	2016-02-10 07:41:15.897	01:24.837	32004210	10239
8	4393805	2016-02-10 07:42:32.853	01:16.956	32004210	10456
9	4393809	2016-02-10 07:42:57.777	00:24.924	32004210	12682
10	4393871	2016-02-10 07:51:08.607	08:10.830	32004210	11967
11	4393920	2016-02-10 07:56:39.540	05:30.933	32004210	12050
12	4393930	2016-02-10 07:57:08.663	00:29.123	32004210	12682
13	4393935	2016-02-10 07:57:47.233	00:38.570	32004210	7338
14	4394145	2016-02-10 08:20:23.300	22:36.067	32004210	10239
15	4394756	2016-02-10 09:35:21.270	14:57.970	32004210	10239

The information in Table 1 is divided into the following vectors:
• **ID**: measurement (observation) identifier; • **SensorID**: the identifier of the sensor that generated the information for the identification of the tracked cart; • **Time**: time stamp generated by the sensor; • **TimeDelta**: time variation from the stamp generated previously by the previous sensor in the sensor sequence (time needed for completing the industrial conveyor belt segment); • **CartID**: cart identifier; • **Picker**: the human picker responsible for the respective cart on the given segment of the industrial conveyor belt.

In terms of the interpretation, the data set above [3] represents the cart "check-in" in front of each (optical or magnetic) sensor during a pre-established route containing 15 sensors. In terms of the systems (regarding the log presented in Table 1), no extra information from the respective sensors is necessary, other than the proper identification of the sensor (SensorID) the time stamp generated by the sensor when the cart passes/is identified.

The need to use a dual optical-magnetic network of sensors. As discussed in the architecture section, the cart contains both the visual identifier (bar code) required by optical sensors and the tag required by magnetic sensors. By this double-check system we ensure a maximum degree of tolerance for errors in tracking the cart in the industrial process of loading it onto the picking belt. Practically, should a particular type of tag be damaged (bar code or the RFID tag), redundancy ensures that the cart tracking is done in optimum conditions and implicitly the error prediction and analysis system generates inferences with a maximum degree of accuracy. Also, in terms of the physical content that must be loaded in the cart, the information is structured and presented in Table 2, which contains the information available regarding the content loaded in the cart whose route was covered according to Table 1.

Table 2. The proposed content of a cart based on a given order

pId	L	W	H	M	bQty	Qt	Batch	BL	BW	BH	BM
4913	56	56	141	306.4	24	5	491101A2	370	250	160	7818
5167	62	54	116	229.2	60	5	FH1922	310	225	360	14022
18206	43	43	66	22.5	80	10	213133	350	220	145	1969
27843	67	54	186	251.12	36	5	F1610	420	340	200	9355
36853	61	55	142	222.83	32	16	3931115	550	235	155	7430
183	92	22	71	32.2	120	2	528031	380	250	260	4211
958	132	33	35	46.5	100	20	922T	355	335	150	4942
1396	127	23	85	52.9	160	21	35001779	517	267	356	8857
8809	85	18	76	31.5	100	30	5ZR4288A	391	195	193	3356
14873	51	40	77	61	168	20	3079	390	260	340	10769
18206	43	43	66	22.5	80	10	213133	350	220	145	1969
1396	127	23	85	52.9	160	29	35001779	517	267	356	8857
1766	69	36	125	65.8	80	4	15F1775	375	290	280	5770
3755	138	14	49	14.6	336	20	1203093	500	365	320	7560
16838	106	24	76	71.4	40	4	170715	320	145	125	1522
19136	53	42	92	54.8	168	3	K21189	445	330	295	9702
36861	55	55	150	281.76	12	6	32252	240	180	150	3476.5
39811	85	40	145	246.04	12	4	15036	270	190	155	3056.5
18313	72	41	199	372.12	24	2	F1103	300	265	215	7521
19136	53	42	92	54.8	168	37	K21189	445	330	295	9702
29693	105	60	60	67.63	36	18	93514505	355	360	235	4000.5
32324	47	47	178	181.79	16	1	L003	210	215	225	3152
34172	60	60	140	305	80	1	40315	60	60	140	305
2322	94	19	66	12.8	180	6	194925	410	310	210	2807
2822	82	36	52	29.7	252	5	338276	390	265	345	7975.5
3397	49	49	132	217.4	40	5	94677	260	215	285	8924
14160	36	28	152	60.9	126	10	AV790	420	340	165	8055
16765	56	56	29	35.08	100	31	43	340	275	125	3809
19507	32	32	72	20.2	200	5	3154657	335	335	160	4312

pId	L	W	H	M	bQty	Qt	Batch	BL	BW	BH	BM
25625	73	73	173	547.3	12	6	23651	225	155	180	3392.5

The information refers to product characteristics:
• **pId**: product identifier; • **L**: length of the product in cm – needed to calculate the volume necessary/taken up in the cart; • **W**: length of the product in cm – needed to calculate the volume necessary/taken up in the cart; • **H**: height of the product in cm – needed to calculate the volume necessary/taken up in the cart; • **M**: product weight – needed to check the content of a cart using the weight sensor (scales); • **bQty**: the quantity in a box; • **Qt**: the quantity that must be loaded into a cart; • **Batch**: product batch; • **BL, BW, BH, BM**: sizes (length, width, height, weight) for the standard box of the respective product.
The basic purpose of the method proposed is the data inference (prediction) in Table 1 based on the data in Table 2 or more exactly the prediction of the times when the cart passes.
The primary data resulting from the experiment and the acceptable prediction error starting from the RMSE (root mean square error) are as follows:

$$H(X) = \textit{inference (prediction) function} \tag{1}$$

$$F(X) = \textit{observation function (real measurement)} \tag{2}$$

$$\hat{Y} = H(X) = \textit{milisec predicted} \tag{3}$$

$$Y = F(X) = \textit{milisec measured} \tag{4}$$

$$E_{RMSE} = \sqrt{\frac{\sum_{i=1\ldots m}\left(\hat{Y} - Y\right)^2}{m}} \tag{5}$$

$$E = R^2 = E_{RMSE}^2 \tag{6}$$

According to (6), the square of the root mean square can be considered as the reference error in the analysis of the experiment results.
The collected data are present in Table 3 with the following information:
• **ID**: observation identifier (the same as in Table 1); • **SensorID:** sole identifier of the sensor generating the observation (the same as in Table 1); • **Predicted Time:** time in seconds (with 3 decimals) predicted by the system for completing the respective segment of the industrial belt; • **Real Time:** real completion time (the same as in Table 1); • **Squared error**: the mean squared error between the predicted and the observed time during a particular segment (for a certain observation); • **Root Mean Squared Error**: the root of the square of the difference between the predicted and the observed time. Thus, according to the collected data we have the following total error:

$$E = (E_{RMSE})^2 = \left(\sqrt{\frac{\sum_{i=1\ldots m} (\hat{Y} - Y)^2}{m}} \right)^2 \quad (7)$$

$$E_{RMSE} = 169.896\,; \quad E = 28864.701\,.$$

Hence, we will consider the acceptable error:

$$E_T = Y \cdot 0.1; \quad E_T = 48.753 \quad (8)$$

By interpreting this primary data one can notice that in all observed cases the root mean squared error is the **0-20% of the real observed value range for the time** required to complete a segment of the industrial belt (time generated by the sensor network for the respective section).

Table 3. Predictions *vs* Real Times.

ID	SensorID	Predicted Time (s)	Real Time (s)	Squared error (E)	Root Mean Squared Error
1	4393724	0.000	0.000	0.0	0.000
2	4393731	63.746	61.294	6.0	2.452
3	4393747	147.690	139.330	69.9	8.360
4	4393761	78.013	76.483	2.3	1.530
5	4393767	16.927	16.927	0.0	0.000
6	4393788	95.756	88.663	50.3	7.093
7	4393795	96.714	84.837	141.1	11.877
8	4393805	69.260	76.956	59.2	7.696
9	4393809	26.419	24.924	2.2	1.495
10	4393871	490.830	490.830	0.0	0.000
11	4393920	337.552	330.933	43.8	6.619
12	4393930	26.211	29.123	8.5	2.912
13	4393935	37.027	38.570	2.4	1.543
14	4394145	1545.916	1356.067	36042.8	189.849
15	4394756	5127.686	4497.970	396542.0	629.716

Finally, for the experimental data set we will have the following result structure:
In Table 4 below, we also entered, in addition to the information proposed in Table 3, the next and final level for interpreting the results, consisting of the following elements:

- **Value of the acceptable error**: represented by 10% of the value of the observed time (E_T) for a particular segment of the industrial belt

- **Prediction error percentage**: represented by the ratio between the root mean squared error and the observed time for the respective segment:

$$E_p = \frac{\sqrt{\left(\hat{Y} - Y\right)^2}}{Y} \tag{9}$$

- **Prediction acceptance indicator**: in the end we defined the A variable as being the acceptable prediction according to the formula: $A = \{1 \text{ IF } E \leq E_T; \text{ELSE } 0\}$. This variable-indicator constitutes the final element in the assessment of the proposed system. The Boolean value {0.1} of the indicator is the most direct method of measuring the validity of the prediction obtained for the times required for the *cart* to complete each of the segments of the industrial belt.

Interpretation of the indicators and accuracy rates

In this section we discuss the production simulation experiment and especially the analysis of the experimental results. Starting from the results presented previously we continue the analysis with the help of a series of indicators defined as follows:

$$T = \textit{Number of observations with } E \leq E_T = 12 \tag{10}$$

$$F = \textit{Number of observations with } E \geq E_T = 3 \tag{11}$$

$$TR = \frac{T}{T+F} = \frac{12}{12+3} = 0.8 = 80\% \text{ (system accuracy)} \tag{12}$$

An accurate prediction rate of 80% was obtained where, for 20% of the observed cases in tables (1), (2), (3), (4), an error percentage (root mean squared error) of approximatively 14.0%, meaning 4.0% over the accepted threshold of 10%, was obtained. If the tolerance of the accepted error threshold E_T is incrcredased from 10% to 15%, according to the (13) formula and Table 5, an accuracy *TR = 100%* will be obtained.

$$E_T = Y \cdot 0.15; \quad E_T = 73.12 \tag{13}$$

Table 4. Analysis of the system performance.

ID	SensorID	Predicted Time (s)	Real Time (s)	Squared error	Root Mean Squared Error	Accept. error (10%)	Prediction error percent. ( )	Accept. prediction (*A*)
	4393724	0.000	0.000	0.0	0.000	0.000	0.0%	1
	4393731	63.746	61.294	6.0	2.452	6.129	4.0%	1
	4393747	147.690	139.330	69.9	8.360	13.933	6.0%	1
	4393761	78.013	76.483	2.3	1.530	7.648	2.0%	1

ID	SensorID	Predicted Time (s)	Real Time (s)	Squared error	Root Mean Squared Error	Accept. error (10%)	Prediction error percent. ( )	Accept. prediction (*A*)
	4393767	16.927	16.927	0.0	0.000	1.693	0.0%	1
	4393788	95.756	88.663	50.3	7.093	8.866	8.0%	1
	4393795	96.714	84.837	141.1	11.877	8.484	14.0%	0
	4393805	69.260	76.956	59.2	7.696	7.696	10.0%	1
	4393809	26.419	24.924	2.2	1.495	2.492	6.0%	1
	4393871	490.830	490.830	0.0	0.000	49.083	0.0%	1
	4393920	337.552	330.933	43.8	6.619	33.093	2.0%	1
	4393930	26.211	29.123	8.5	2.912	2.912	10.0%	1
	4393935	37.027	38.570	2.4	1.543	3.857	4.0%	1
	4394145	1545.916	1356.067	36042.8	189.849	135.607	14.0%	0
	4394756	5127.686	4497.970	396542.0	629.716	449.797	14.0%	0

Table 5. Increasing the error threshold from 10% to 15%.

ID	SensorID	Predicted Time (s)	Real Time (s)	Squared error	Root Mean Squared Error	Accept. error (10%)	Prediction error percent. ( )	Accept. predicti-on (*A*)
1	4393724	0.000	0.000	0.0	0.000	0.000	0.0%	1
2	4393731	63.746	61.294	6.0	2.452	9.194	4.0%	1
3	4393747	147.690	139.330	69.9	8.360	20.899	6.0%	1
4	4393761	78.013	76.483	2.3	1.530	11.472	2.0%	1
5	4393767	16.927	16.927	0.0	0.000	2.539	0.0%	1
6	4393788	95.756	88.663	50.3	7.093	13.299	8.0%	1
7	4393795	96.714	84.837	141.1	11.877	12.726	14.0%	1
8	4393805	69.260	76.956	59.2	7.696	11.543	10.0%	1
9	4393809	26.419	24.924	2.2	1.495	3.739	6.0%	1
10	4393871	490.830	490.830	0.0	0.000	73.625	0.0%	1
11	4393920	337.552	330.933	43.8	6.619	49.640	2.0%	1
12	4393930	26.211	29.123	8.5	2.912	4.368	10.0%	1
13	4393935	37.027	38.570	2.4	1.543	5.785	4.0%	1
14	4394145	1545.916	1356.067	36042.8	189.849	203.410	14.0%	1
15	4394756	5127.686	4497.970	396542.0	629.716	674.696	14.0%	1

4. Graphical interpretation of the main experiment indicators

In this section we discuss the production simulation experiment. The main element analyzed is the histogram of the “trust” in the system proposed, consisting of the observed values of the prediction error percentage (simple deviation from the observed value). As one can notice (Fig. 2) the proposed system generates an acceptable error distribution, with a considerable quantity of inferences in the 0-5% range.

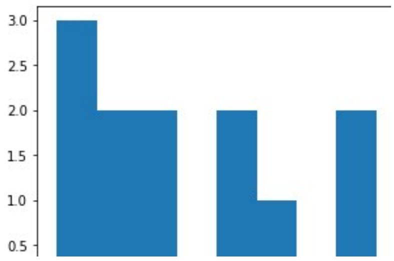

Fig. 2. Histogram of error percentages

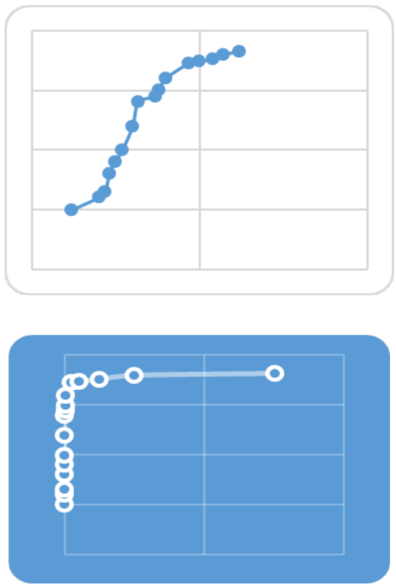

Fig. 3. Evolution of the accuracy according to the number of observed observations, using the linear (left) or logarithmic (right) scale.

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Starting from the example above with 15 observations and 15 predictions respectively and passing to a large volume of data we are going to analyze the behavior of the E_{RMSE} error and of the error.

As one can see in the chart above, the inference error percentage (A) has an asymptotic evolution towards an approximate maximum value of 94% for the inference error. In conclusion, the system reaches an optimum efficiency when it completes a minimum of 10^4 observations generated by the dual sensor network in the industrial belt.

Table 6. Increasing the error threshold from 10% to 15%

Test	Number of observations	Inference error percentage (A)
1	15	80%
2	100	81%
3	150	82%
4	200	83%
5	300	84%
6	500	85%
7	1000	87%
8	1500	89%
9	5000	90%
10	6000	90%
11	10000	91%
12	50000	92%
13	100000	92%
14	250000	93%
15	500000	93%
16	1500000	93%

5. Conclusions

The design of an iWSN network allows the signal to be taken from any point within the warehouse and to centralize telemetry data, automatically and in real-time. This mesh configuration has a low error rate compared to a classical star topology (with a single router and sensors without routing capabilities). The scope of coverage is expanded, providing more modular ways of communicating accumulated information (increased redundancy).

The experiment proved that the improvement consists of the continuous "self-adaptation" of the system to unforeseen or "rare" factors occurring within the industrial process. We note the prediction rate of over 90% of the proposed system under conditions of assuming a tolerance of maximum 5-10%. Following this number of analyzed observations (10^4 – 10^6) the system enters a plateau with relatively small improvement.
This research of a deep learning model and sensor networks (iWSN) for industrial planning and logistics management brings a new approach to deep warehouse management based on an advanced self-evolving system with constant adaptation to the ever-changing environment. Practical applicability is immediate in the case of complex pharmaceutical stores with special features: product traceability, expiration date, emergency delivery, international distribution standards, high volumes on many distinct products.

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