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Models using artificial intelligence to optimize the use of wireless network sensors in pharmaceutical depots. I: conception

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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: wireless network sensors, pharmaceutical depots, neural networks.

1. Introduction

In Electrical Engineering, measurements have evolved together with the underlying technology with specific issues and challenges changing dramatically over relatively short periods of time. Data acquisition and processing is closely linked with advanced information technology. In this context, given the evolution of computing power, especially parallelized computing power, and its availability on a large scale and at acceptable cost levels, the field of artificial intelligence is gaining a lot of traction with an important focus on the predictive area. Whether it is genetic algorithms, standard neural nets, or deep learning algorithms, all these models and technologies (which are designed to produce a prediction/inference

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following a learning process and are at the center of today's focus in artificial intelligence) are used more and more in Electrical Engineering.
The analysis of the information with the help of sensor networks is an important research and development subject in the academic environment, with direct use in production applications belonging to the pharmaceutical sector. The objective of this paper is to propose an optimization model of the activities performed on a picking line inside a pharmaceutical depot.

2. Systems model

Currently, the mode of operation for the industrial picking environment is based on an order which is entered into the system, which in turn gets assigned one or more totes that begin to travel on a conveyor belt to the collection stations. The presence of the tote is checked with a suite of sensors placed on the band (proximity optical sensors). Operators store the required landmarks in the order attached to the tote when they arrive at the collection stations, picking up the products on the shelves where they are stored. The totes continue to a check area where they are weighed to check, in a quantitative manner, the presence of all the necessary items. Upon successful completion of this test, they advance to the sealing and delivery area, where they are taken over from the conveyor belt by other operators and shipped to their final destinations (Fig. 1).

Fig. 1. Overview of the picking line
in the analyzed pharmaceutical depot.

The detailed knowledge of the conveyor belt, sensors and electromagnetic transducer elements, as well as the actuators involved, allows for the next phase which involves the design of an information system that controls and acts upon the activities of a pharmaceutical repository. Of course, this design requires a proper modeling of the elements of the pharmaceutical distribution system [1]. In our study, the collection process was simulated using a discreet deterministic model, considering the conveyor belt, the carts, and the workers.
Both electronic hardware components (in particular sensors and border-router units) and software components (Artificial Intelligence modules) are combined in a

holistic approach in the form of an object-oriented infrastructure where elements contain properties, methods, and "neighboring" objects of the same "family" [1]. This approach was chosen to have the possibility of scaling the entire experiment from the validation-test environment to the industrial production environment without the need for additional redesign or implementation iterations. The carts routing was optimized using an HeuristicLab based simulation environment **[**4**]**.

Following the description and analysis of the current architecture, we have established a significant number of deficiencies in the standard industrial systems for order management, from issuing to shipping, such as:

1. The lack of correlation between the operator processing the order and the cart to be processed, making it difficult to follow the occurrence and sequence of errors during processing;
2. The existence of a single method for checking the integrity of a processed order (weighing method);
3. The existence of a single method for tracking the cart along the belt using bar codes and optical readers (which break down).

Considering the above-mentioned issues, our practical proposal consists of using wireless network sensors and Artificial Intelligence models based on Deep Neural Networks (a.k.a Deep Learning – Fig. 2) for the advanced optimization and automation of pharmaceutical distribution centers.

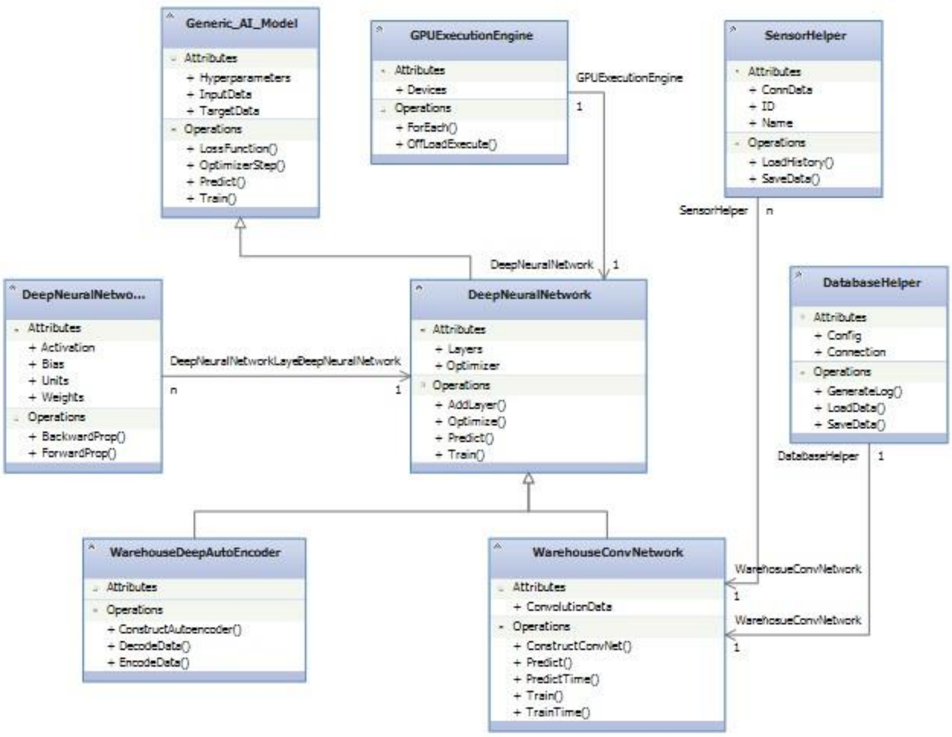

Fig. 2. Object oriented chart of the experiment.

3. The Self-Optimizing System

The whole approach proposed is based on using deep neural networks for the experimental research and development of a model for the type assembly of agents that can solve the following problems through continuous learning and auto-adaptation:
• Determine the optimum time and parameters for an industrial process, based on a set of objective-tasks
• Auto-adapt to the changes in the industrial ecosystem without the need for human intervention
In this context, the proposed sensors (paired, magnetic and optic) solve these problems as follows (Fig. 3):
1. A custom built beacon is placed for the human operator, in the form of a bracelet giving the system information about the position in space and the interaction with the carts;
2. As an option for checking cart integrity, camera modules for visual checks of the cart products are installed (modules based on NVidia Jetson TX1, or TX2, modules capable of autonomous information processing that may support a neural network);
3. Carts are equipped with RFID sensors to ensure multiple methods for tracking the position and interaction with the human operator.

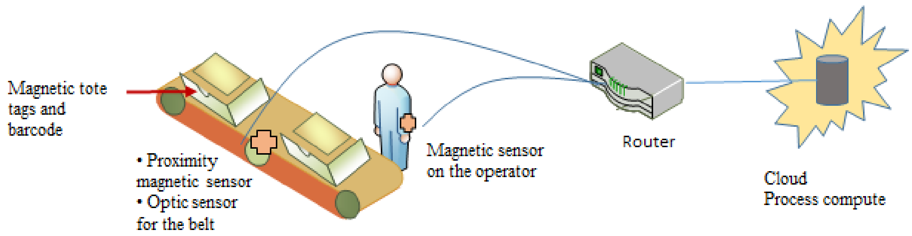

Fig. 3. The proposed architecture.

The newly configured and further analyzed configuration is based on an Industrial Wireless Sensor Network (iWSN) that allows the signal to be retrieved from any point within the depot. The general iWSN layout for designing the experiment is characterized by mesh-network topology, having the advantage that some nodes (sensors) may behave in turn like routers, thus expanding the coverage and offering several channels for communicating the collected information. The infrastructure described in the figure 4 is based on several routers that ensure connectivity to a cloud computing infrastructure. The module ensures connectivity between a classic wired network and a mesh-type sensor network. The communication channel between the sensors and routers uses Zigbee or BLE technology.
The wireless sensors are based on the SensorTag platform, interfacing with the RFID modules described above.

We propose a mixed infrastructure, where the sensors share the same hardware architecture for processing and communication. If the depot already uses one kind of sensors |(for example, optical) our sensors will be installed as sniffer sensors (they only take over data from the already installed ones, without affecting the current infrastructure) [2].

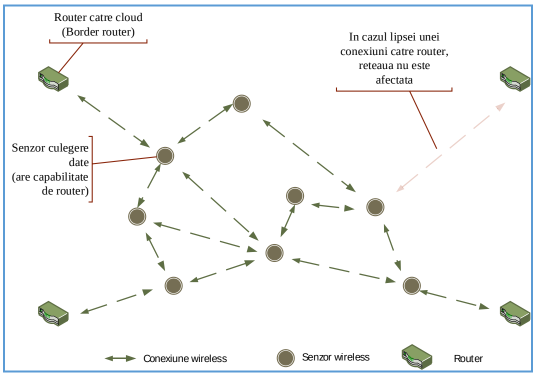

Fig. 4. Architecture of the iWSN sensors network.

For better performance, the use of two types of sensors: magnetic and optic is recommended for the cart position identification, a design that will significantly reduce the errors rate in the field (especially on the picking line, which transports the carts containing the medicines).

4. Management of the depot's activities by an innovative solution

The advanced architecture proposed to automate the collection process relies almost exclusively on the use of a pre-defined collection algorithm.

The suggested model of Artificial Intelligence based on Deep Learning and sensor networks for the management of industrial planning and logistics will address the following main elements:

- The use of deep neural networks in massive parallel processing environments for the analysis of a large volume of data, historical as well as real-time data, without affecting the reaction times and the interaction between users and the system's functions
- The continuous adaptation of deep neural models in the database for input data prepared by human operators (especially in the case of telemetry data generated by mobile electronic devices and by the sensor network installed in the industrial ecosystem). There shall be no "programmed" rules in the system, and the system shall self-adapt continuously to the operating conditions.
- The generation of real-time predictions regarding optimum execution times for processes and the subsequent automatic validation of these times by using the sensor networks and mobile electronic devices.

- The generation of alerts for the situations where the artificial intelligence system detects processes that may contain human errors, including the analysis of input data generated by human operators.

5. The mathematical model used for the system's optimization

The suggested approach is based on the use of state-of-the-art deep neural networks for the experimental research and development of a type of model based on a set of agents with automated learning that can solve the following problems through learning and continuous auto-adaptation:

- Determination of the optimum time for the industrial process based on a set of objective-tasks;
- Determination of the optimum parameters for the industrial process based on a set of objective-tasks;
- Auto-adaptation to the modifications of the industrial ecosystem without the need of human intervention.

According to the previous description, this model will receive data generated by the sensors network, will combine this data with the data entered by human operators, and will perform:
(1) auto-adaptation by means of real-time learning (online learning) to modify operating parameters of the sensors network or of other elements from the production environment (warehouse)
(2) real-time generation of predictions/inferences related to the optimum succession of operations required to achieve a certain goal – in other words, in the case of the automation of a warehouse the following inferences are needed: (a) optimum routes at the level of mobile machinery; (b) optimum sub-routes at the level of the human operator; (c) optimization of the pick-list; (d) selection of the ideal human operator for a certain pick-list structure.
Basically, we can consider that the whole system can be summed up as a single nonlinear function with a very high degree of complexity that looks like the equation (1).

$$f(X_{picklist} \mid \Theta) = \hat{Y} \text{ where } \hat{Y} = (\hat{y}_{operator}, \hat{y}_{operations}, \hat{y}_{time}) \quad (1)$$

$$L(\hat{Y}, Y \mid f(X, \Theta)) = \frac{1}{2m} \sum \left(\hat{y}_{time_i} - y_{time_i}\right)^2, \text{ where:} \quad (2)$$

$\hat{y}_{time}$ = time predicted by the hypothetical function $f(X_{picklist} \mid \Theta)$

y_{time} = time waiting (ideally)

m = number of elements of analyzed data

$$\theta^* = \underset{\theta}{\operatorname{argmin}}\, L(\hat{Y}, Y \mid f(X, \Theta)) \quad (3)$$

The whole approach is reduced to determining a set of parameters Θ of the hypothesis-function $f(X_{picklist} \mid \Theta)$ which determines a minimum process time

y_{timp} (continuous real value) through a deep neural network for regression (figure 5) as well as other parameters such as $y_{operator}$, $y_{package}$, y_{cart} etc., but this time using a deep network for classification (figure 5). As was previously mentioned, to determine the continuous real values, we will use the regression method, an established method of automated learning applicable both through state-of-the-art methods and through classic linear methods [2].

To get the parameters for the neural networks, we will determine an error computing function (equation (2), for the neural regression network) which can be minimized according to the equation (3). For the optimum parameters, we will apply a search algorithm in the parameter vector space by applying the method of "descending" through sequential gradients, the ideal method for online and real-time work environments according to (4) and (5).

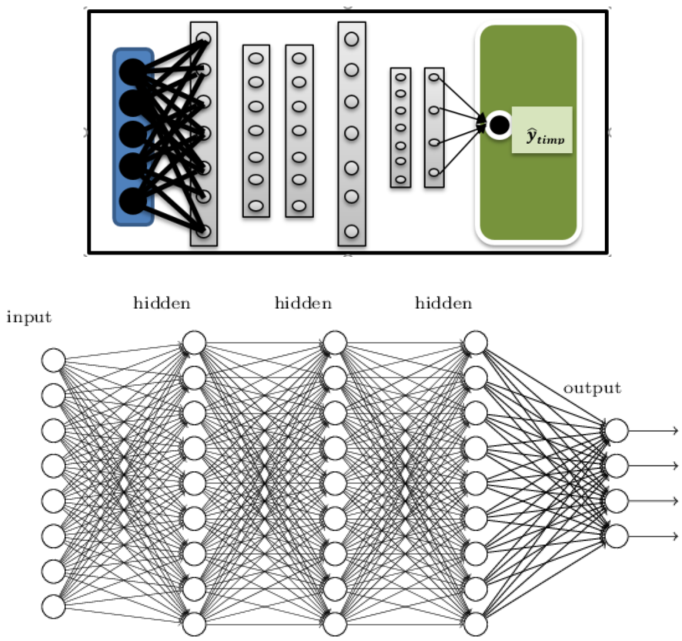

Fig. 5. Deep neural network for classification.

$$\theta_{grad} = \nabla L(\hat{Y}, Y \mid f(X, \Theta)) = \frac{\partial f}{\partial \theta} \quad (4)$$

$$\theta_{new} = \theta_{old} - \alpha * \theta_{grad} \quad (5)$$

Coming back to the nonlinear hypothesis-function, the focus point of the suggested mathematical model – the function will be defined by a deep neural network whose generic structure is described in the figure [5] where the first level (the input generated both by the sensor network and by human operators) colored with blue, receives input data from the sensor network. The following levels colored with grey contain the hidden units of the deep neural network and the last level (green) contains the output data of the deep neural network. For graphical presentation reasons, in this figure the correct number of hidden levels, the individual units from each level, and the connection between the different levels of the deep neural network were omitted (the only connections presented are the connections between the input level and the first hidden level). For one of the architecture cases suggested, we have to deal with the following model structure: 8 network inputs, 3 hidden levels completely connected that use ReLU neural activators, and a level of input data classification with 4 Softmax outputs according to the equation.

The model for the propagation of information through the regression neural network is mainly based on the use of units with linear rectification (ReLU) [3] that have the property of being stable in numeric computing processes required to drive the deep network. Thus, the ReLU function described in detail in the equation (6) shall "activate" the results obtained at the previous level of the deep neural network after they have been multiplied with the parameters of the current level.

An architecture with 8 inputs is proposed for the theoretical analysis model. In the experimental phase, a number of inputs shall be generated equal to:

$$N_{in} = N_{sensors} + N_{PDA} + N_{operator} \tag{6}$$

- $N_{sensors}$ is the number of input signals from the sensor network;
- N_{PDA} is the number of telemetry signals from personal mobile devices;
- $N_{operator}$ is the number of parameters entered by human operators.

6. Experimentation environment

The experimental execution environment for the proposed system is fully adapted for processing information and generating decisions in real-time. The general architecture of the experimental system shown in figure (4) is based on 3 categories of modules 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 for the inference 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.

The predictive self-regulating system has four major components:

• The dual sensor system that collects the data regarding the tote measured on the picking line (position on the conveyor belt and tote identification), the data for the operator performing the operation of picking the drugs, and the date related to checking the accuracy of the picking operation and the conveyor belt speed.

• The prediction system, based on the deep neural network, whose role is to optimize the operation of the processes in the picking area, significantly reduce errors in the system concerning drug picking, ensure the visibility of the potential to serve customers, and anticipate the execution and delivery times .

• The volumetric algorithm (ERP, Warehouse Management System module), optimizes the arrangement of totes on the conveyor belt and the selection of the tote type (big/small) based on the volume of drugs corresponding to the shipment order to be processed.

• The actuating system, comprising Schafer PLCs and actuators that drive the conveyor belt motor.

According to an approach previously proposed [1], both the electronic hardware components (especially sensors and border-router units) as well as software components (Artificial Intelligence modules) are combined in a holistic approach under the form of an object-oriented infrastructure, where each element contains properties and methods, as well as “neighboring” objects or objects belonging to the same “family” [5].

The system is self-regulating and is defined by the entry and reference size (r), the exit size (y) and perturbation factors [Fig. 6]. The role of the prediction algorithm is to ensure a value as close as possible between the predicted size and the exit size, the prediction percentage error being of maximum 5%.

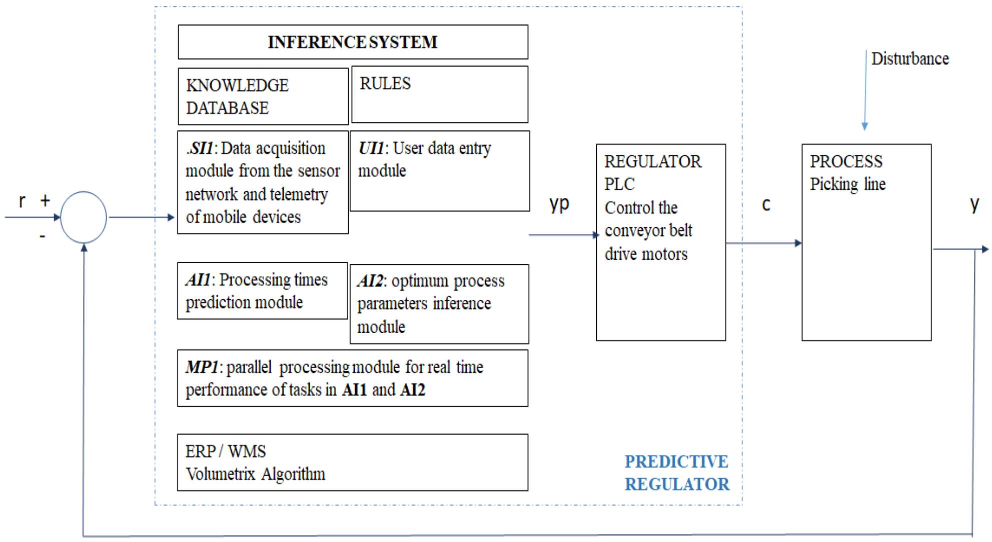

Fig. 6. The structure of the automatic predictive self-regulating system;
r – reference size; *c* – order; *y* – exit; *yp* – predicted exit.

7. Conclusions

In terms of the experiments metrics, the following data were analyzed, starting from the primary data and ending with the variation of the experiment indicators:

a) The entry data generated by individual sensors (both magnetic and optical, according to the dual nature of the sensor network proposed).

b) The prediction data generated by the system proposed.

c) The primary results obtained in the experiment (real data vs. predicted data).

The experiment performed was made up of **two sub-experiments** carried out on two different structures of industrial belts.

a) The first sub-experiment used only optical sensors and introduced disturbances in the operation of the belt (the tote barcode label was damaged).

b) In the second sub-experiment we used the same industrial belt structure, to which we added magnetic sensors and implicitly the readings they obtained, keeping of course the damage to the barcode label at a certain point in the process.

As for interpretation, the checking of the tote was performed in front of each sensor (optical or magnetic) for a predefined route containing 15 sensors. We take the square of the root, mean square to be the reference error *E* in the results analysis of the data prediction experiment.

Following the two sub-experiments, the variation of the system's accuracy over time, given by the error *E* depends on the data volume processed by the system. The graphical representation from Fig. 7, using linear or logarithmic scale, highlights that **over time and after observing an ever-rising quantity of data, the percentage error decreases more and more and the interval for reliability becomes narrower.**

As can be observed, the percentage error for inferences (*A*) has an asymptotic evolution towards a maximum value of 94% for the percentage error for inferences**.** **The system reaches optimum efficiency when a minimum number of** *104* **observations generated by the dual sensor network of the industrial conveyor belt** are processed. After this set of analyzed data (104 - 105), the system stabilizes in an area with relatively small improvements.

The experiment has proven that the improvements made contribute decisively to the continuous self-adaptation of the system to unforeseen or "rare" factors arising during the industrial process.

Our research of a deep learning model and sensor network (iWSN) combination for industrial planning and logistics management brings a new approach to complex 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.

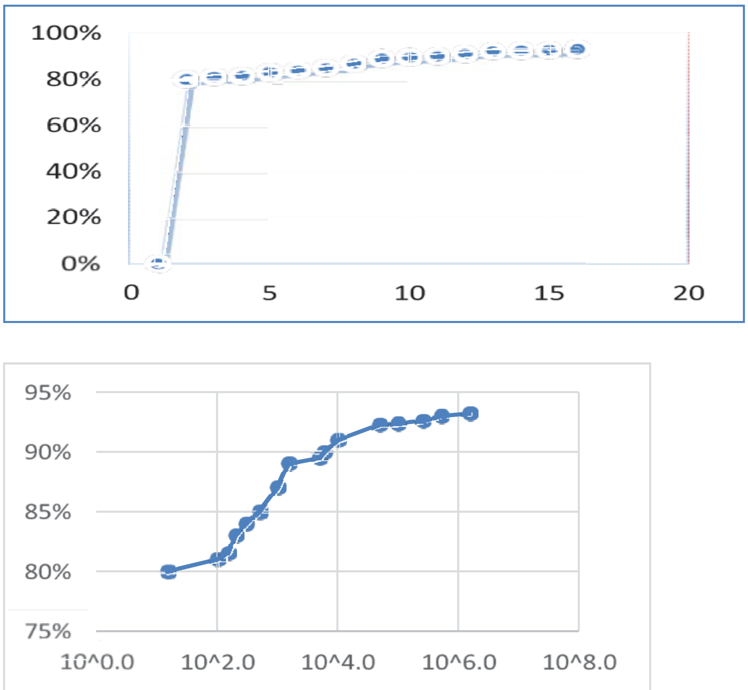

Fig. 7. Evolution of accuracy depending on the number of processed observations, using the linear scale (left) or the logarithmic scale (right).

The prediction system, based on the basic neural network and used to optimize the warehouse processes, proves significant reduction of system and drug picking errors, while ensuring visibility of the potential to serve customers and anticipating the execution and delivery times.

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