System of Pressure Detection with IoT for pins in Tail Pinch Test

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Resumen—El Internet de las Cosas (IoT) permite a los objetos conectarse e intercambiar datos de todo tipo usando Internet. Se trata de uno de los componentes de la denominada Industria 4.0, cuyo campo de trabajo son los sistemas ciber-físicos para la automatización de procesos. Pero IoT tiene aplicaciones en muchos otros campos además de la industria, como lo son la investigación y el desarrollo tecnológico en la automatización de laboratorios. Así se creó un sistema que mide y clasifica de manera automática la presión de pinzas usadas en la prueba Tail-Pinch. El objetivo fue crear un sistema que permitiera categorizar instrumentos de experimentación. De tal manera que las variaciones de medición se reduzcan mientras crece la confiabilidad del experimento. Para ello, se empleó una tarjeta Arduino ADK y un sensor resistivo de presión. Se empleó una red WIFI y un servicio de almacenamiento de datos en nube. La aplicación final utilizó 100 medidas de presión y una Red Neuronal Artificial para dar una categoría lingüística de salida a la pinza seleccionada.

Palabras clave— Internet de las cosas, Redes Neuronales Artificiales, Instrumentación Electrónica, Prueba Tail Pinch.

Abstract—Internet of Things (IoT) allows to interconnect and to interchange objects data through Internet. This component is part of a global term denominated Industry 4.0 that involved cyber-physical components for automation in industry. But IoT can be applied to different fields in research and technological developing as laboratory automation. Thus, it was developed a system that measure and classify pins used on Tail Pinch Test automatically. Our objective was to create a system that allow to categorize automatically instruments that are used in experiments. Thus, measurements variations are reduced, and the reliability of experiments grows. The system was based on Arduino ADK and resistive sensor to acquire pressure data. Also, a WIFI network and cloud computing service was used in the system. The application layer processed 100 pressure measurements and classified in linguistic values a pin using an Artificial Neural Network.

Keywords— IoT, Artificial Neural Networks, Electronic Instrumentation, Tail Pinch Test.

I. INTRODUCTION

Industry 4.0 is a consequence of combining Information and Communication Technologies and Artificial Intelligence (AI). This is an industrial revolution based on cyber-physical components [21]. The main task is to automate industrial processes, through technological developing. The consequence is a reduction in costs and an increase on production [14].

In this manner, Industry 4.0 is composed by subfields as: Robotics, additive manufacturing, augmented reality, simulation, big data, cloud computing, security and information, and Internet of thing [16].

Robotics is a field with a great technological developing in the last twenty years. There are two subfields on industrial robotics: Control and Autonomous Robotics [32]. The main task in control robotics is to provide robotics platforms which can be incorporated in serial production., In that way, robots are programmed to solve a repetitive task. Controllers as PLC are used, and robots do not have capabilities to be situated in dynamical conditions. For example, robots in automotive industries are designed to paint and assemble a vehicle. But they must be reprogramed if conditions change.

On the other hand, autonomous robotics is a field in where robots are programed to contend in dynamic environments. It means that robots coexist with humans and robots, also solve different tasks. They have an intelligent system that allow to them to take decisions and to control their skills. In Industry 4.0, autonomous robotics has more importance than control robotics. This is because robots must cooperative and coordinate as a group, which is not easy to achieve with control robotics.

Additive manufacturing is used to create materials and parts in industrial environments [1]. Intelligent optimization process in the main part in this field. It allows to create optimal components for industry, that are chosen by their materials, physical and chemical proprieties.

Augmented reality is a field that combines virtual reality on the real world through artificial vision [5]. There are different applications. For example, it is used in training staff. The objective is decrease risks costs in equipment and training situations. In that way, oil companies train staff for extracting in the deep see using augmented environments without risk for operators.

Simulation is a platform to test different situations and problems. It is combined with augmented reality and additive manufacturing to create computational models of real world [28]. It is possible to simulate industrial processes to kwon potential failures. Also, it is used to identify deficiencies in processes and equipment. In other words, it is a low-cost test platform.

As in industry 4.0 all systems are cyber-physical, it is necessary to create an identity in the web [29]. All of them must to send data about their state all time. This is the reason why it is necessary to have data storage components as cloud computing. These data sets have many instances and are analyzed using big data techniques [31]. Combining Big Data techniques, cloud computing and simulation is possible to know when maintenance must occur. It also possible to know production statics and consumers preferences in real time. Thus, Big Data techniques are used to create optimal strategies inside and outside of companies [10].

Data confidentiality and security is an important component of Industry 4.0. Because all devices are cyber-physical, data shared by them have to be safeguarded. Also, all date of products and clients. Theft of industrial data could have a significant increase in the coming decades and techniques to avoid it must improve.

IoT is the perfect medium to provide communication to objects in industry 4.0. The idea is to interconnect all components in industry or grant an identity in the cyber space [30]. This communication system is supported by Internet connection and TCP/IP protocols. If communication uses radiofrequency via, is called Machine to Machine (M2M).

The IoT architecture is hierarchical and divided on four layers: Sensing and identification, Net, Information Processing and Application [6]. Sensing and identification are the name of the first layer and contains all components to create an identity on the net. Also contain sensors that provide information about the object. Embedded devices as Arduino [2] works as main component in this layer and allow devices to connect to Internet.

Net layer determines the type of net that is used to send information. Network scope, reach and transfer rate are variables used to choose net. When applications are connected to local networks, distance between components are lower than in metropolitan applications.

The information processing layer stores data on servers. It is common to use web service model complemented with cloud computing services. There are three possibilities to do this: Software as a Service (SaaS), Platform as a Service (PaaS) and Infrastructure as a Service (IaaS). SaaS systems operates as a storage unity. PaaS stores and processes information. IaaS is the most complete option because stores, processes and connect data. All possibilities are associated to costs to provide services.

The application layer is where data is applicated to some process. For that reason, it is necessary to use Artificial Intelligence techniques to decide new states for objects or systems.

Through IoT, it is possible to create systems that sense internal and external states. Then, data is transmitted using an Internet connection and stored in a cloud computing server. There, data is processed, and decisions are taken using AI techniques. Sensing, transmitting, and decision taking occurs on semi-real time.

Traditional artificial Intelligence methods are not suitable for taking decision in large data bases. Decision trees, metaheuristic classifiers, Bayesian networks are some examples of this. It is because most of them are based on information, that is unbalanced whit large samples. This is the reason that originated the appearance of big data techniques.

However, Artificial Neural Networks (ANN) have special capabilities when process data from electronic devices [22]. One of them is tolerance to errors and noise of data [4].

ANNs are originated as a model of natural neurons. This means that the model tries to represent the way in which our brain works (connectionist paradigm). ANNs are used in classification tasks and work as a discriminating that separate classes [23]. An ANN processes information when input data is mixed with synaptic weights [12]. Mix data travel through each neuron and layer until the output.

In order to obtain ANNs that correctly classifies cases, they have to be optimized. This process is named learning and adjust synaptic weights to obtain a desired output. There are two options to train a net: supervised and not supervised. A supervised process occurs when the exact output is known. When computational learning process kwon an approximate output, learning is named not supervised. One of the most popular algorithms for supervised learning in ANNs is Backpropagation (BP). It works using a random initial point that is adjusted using gradient descent.

However, with large data sets backpropagation is not enough to guide a computational search and adjust ANNs [27]. In that way, Evolutionary Algorithms are a solution. These algorithms work as multi-points search space explorers. IoT is a field in where ANNs can be adjusted using evolutionary algorithms as Genetic Algorithms (GA).

GA are inspired in the Darwin Theory of Evolution [7]. It means that is a representation of evolutionary process in a virtual way. This algorithm uses Evolutionary pressures to adjust and obtain ANNs that achieve the operating objectives. This is because good solutions have more possibilities to keep their genetical information to next generation, than these which do not solve a problem.

Thus, IoT is inspired in service architecture. It is possible to identify producers and consumers. Data is generated by producers through sensing information. Producers send information using Internet connection. Consumers use data to process information and generate decisions.

But IoT is a field that can be applied to other fields besides Industry 4.0. An example is laboratory automation. The idea is increasing the reliability of tests and experiments, reducing human interaction and subjectivity of experiments. In this way, mechanisms as automation and remote processes are used [3].

To get better measures, it is necessary to increase accuracy and precision in instruments. IoT allows to increase the number of measurements, to reduce decision times as a robust calibration process.

In this way, it was developed a system based on IoT to categorize pins used in a Tail Pinch experiment [8] and Wistar rats. This experiment is a model to evaluate analgesic potential using a mechanical stimulus. This stimulus is obtained by a pressure applied to tails. For that reason, it is important to classify pins with high accuracy and determines which one is used in the experimental.

This article is organized as follows. Methodology section gives information about systems and its design and implementation. Results section shows data about System operation. Discussion section contextualizes the system design and its results in IoT and automation context. Finally, conclusion section highlights aspects of the proposed system.

II. METHODOLOGY

The system proposed was composed by four layers (see figure 1). First layer corresponded to physical implementation. Second layer was represented by a WIFI connection. Data was saved in a remote server for cloud computing (Azure Microsoft). Fourth layer was represented by an ANN which received information from pressure measures.

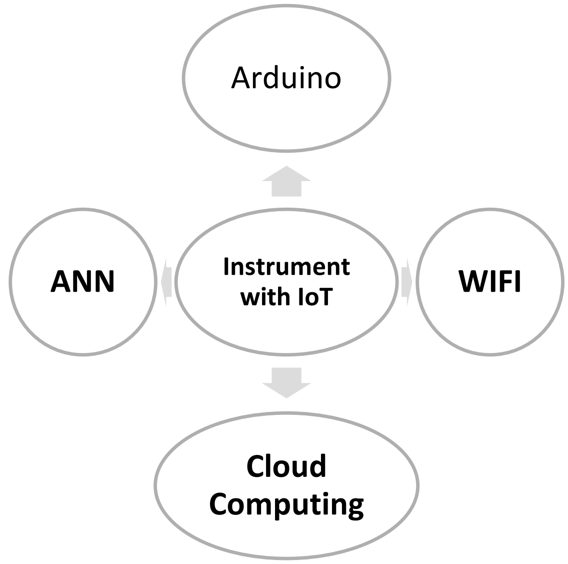

Figure 1. Proposed system.

Pressure of pins was measured using a resistive sensor. It was used a voltage divisor circuit. Thus, the resistive sensor changed the voltage when pressure changed. Minimal pressures produced minimal voltage. An Arduino ADK was used to collect data form sensor through an analogical channel. Signal was transformed to digital value using ADC component of Arduino (1023-max and 0-min). Resistive sensor was linearized using a linear region of resistivity.

In order to obtain an equivalent of pressure value form a digital value, three equations were used. First it was calculated an equivalent to voltage (V_{FR}) acquired by ADC (see eq.1). Then, this voltage (see eq.2) was transformed to resistive equivalent (R_{FR}) using a voltage divisor formula with the voltage supply of Arduino (V_{CC}) and a fixed resistance (R_{DIV} = 3230Ω). Finally, an equivalent strength (F) was obtained (see eq.3) in gr/cm2.

$$V_{FR} = \frac{ADC * Vcc}{1023} \qquad (1)$$

$$R_{FR} = R_{Div} * \left(\frac{Vcc}{V_{FR} - 1.0}\right) \qquad (2)$$

$$F = \frac{\frac{\frac{1.0}{R_{FR}}}{0.00075}}{0.00000032639} \qquad (3)$$

When a signal was acquired and processed, it was sent to cloud computing server. For that, Arduino ADK was complemented with Internet RN-XV, a Wireless extension. Sensorial layer was connected to application layer using a WIFI local area network.

Data was stored in a remote server of cloud computing that represented the third layer. It was used a PaaS service, because processing data occurred in a personal computer. We selected Microsoft Azure because is an open access tool for University of Veracruz.

The application layer was hosted in a personal computer that consumed data from cloud server. An ANN was used to process information and classify pin in four linguistic categories: null-pressure (0-20 gr/cm^2), soft-pressure (20-200 gr/cm^2), medium-pressure (200-500 gr/cm^2) and high-pressure (more than 500 gr/cm^2). Categorization was made using a tail pinch test expert opinion. Also, an average of pin measures was calculated in PC.

Each pin tested was measured 100 times in the sensorial layer measured. The idea was to reduce variability of data and feed a robust model of ANN for categorization. Thus, a three-layered ANN was optimized (see figure 2). The input layer of ANN was formed by 100 neuronal unities, that corresponded to each measurement made. The hidden layer was constituted by 50 neural unities to improve discrimination capabilities. Finally, four neural unities were placed at the output layer, each for category. This neurons at output layer were mutually exclusive, which implies that there was only active. All neurons in the net used tangential sigmoidal transfer function.

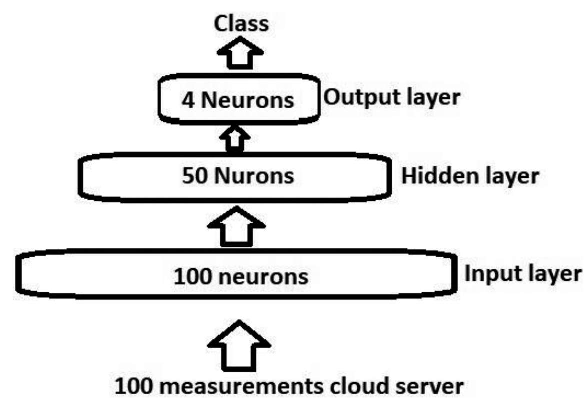

Fig. 2. ANN implemented.

A data set for training neural network was configured. It consisted in 100 random measurements of pressure for 150 pins (SD 1.0). The class of each instance was calculate using an average of measurements and categorized by a human expert.

A generational Genetic Algorithm was used to adjust weights of the ANN.

It was used a free license software named SORNA. To calculate fitness level, classification efficient was measure. The GA was configured with 100 individuals, 100 generations, 2% mutation rate, tournament selection, fixed point crossover, and elitism. Training data base was split in two: 70% (105 instances) for training and 30% (45 instances) for testing. Training process was replicated 60 times and the best ANN was chosen and programmed in a PC in a user interface. The best ANN classified the highest level of training data base.

The best ANN was validated in a real situation. It was measured 13 pins used in Tail-Pinch experiment. The average of measurements for each pin was compared with classification of the best ANN. It was counted the number of hits for the ANN.

III. RESULTS

The system implemented was composed by five components (see figure 3): Pressure measure instrument (data acquisition), Internet connection (WIFI), Cloud storage, ANN and user interface.

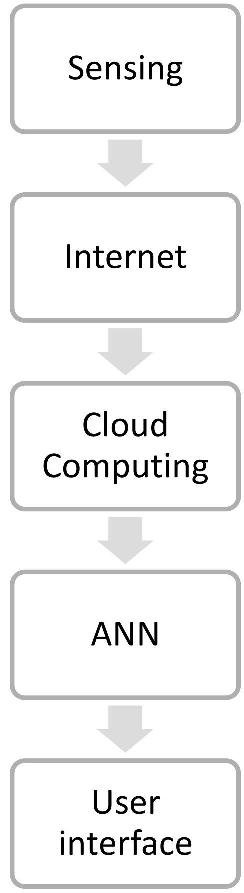

Fig. 3. System implemented

Thus, the GA adjusted a three-layered ANN. Initial fitness was low. But when the evolutionary process advanced, fitness increased (see figure 4). Average fitness in all evolutionary processes at final generation was 95.71 well classified instances of 105 total (91.15% effectivity).

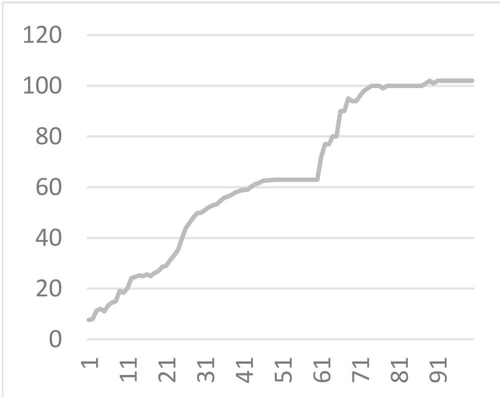

Fig. 4. Fitness landscape of one ANN evolutionary processes (number of generation vs fitness).

Testing stage showed an average of 37.32 well classified examples of 45 total (82.92% effectivity).

The validation stage of the best ANN showed (see table 1) 12 examples correctly classified of 13 total instances (92.3% effectivity).

Table 1. Validation stage data.

Pin number	Average	ANN output	Class
1	614.5	High	High
2	484.22	Medium	Medium
3	353.1	Medium	Medium
4	527.25	Medium	Medium
5	698.45	High	High
6	102.85	Soft	Soft
7	367	Medium	Medium
8	229.4	Soft	Medium
9	462.1	Medium	Medium
10	167.5	Soft	Soft
11	458.5	Medium	Medium
12	347.085	Medium	Medium
13	57.855	Soft	Soft

IV. DISCUSSION

Designed system was an example of variety that cyber-physics systems have. Its function was to automate different processes, providing identity on Internet [9]. Industry 4.0 is a technological revolution that incorporates new challenges, and its reach is to be discovered. It is because many components must be interconnected, and coordination system have to emerge [17].

The pressure measure system was based on IoT architecture, composed by four layers [15]: Sensing and identification, Net, Data storage and Application. Thus, IoT provided a platform to connect the system presented. The objective was to create a system that decreased variability of data when a pin is chosen in a Tail-Pinch scenario [25]. This was achieved through the average of 100 measurements of a pin and complemented by a linguistic class provided on ANN. It represented the first step in automatization of Tail-Pinch experiment.

For objects that are not designed for IoT, it is possible to use an embedded system to provide communication and integrate to IoT. Electronical devices as Arduino allow to create complex systems due to modular design. There are many extensions and sensors compatible with Arduino, what it produces multiple solutions to the problems raised. Specially, solutions are cheaper than a microcontroller-based system build for a problem.

An example of this is the resistive sensor used in the system. Voltage divisor is one of the most popular circuits when a change in voltage is sensed. Thus, when a strength in form of pressure was detected by the sensor, voltage changed and was acquired as a voltage change.

In the case of the system presented, sensing was complemented by an extension for Internet connection. Consequently, the embedded card is complemented with modular connections and coordinates each module to produce a global system. So, modular architectures in electronics are an important solution that is incorporated in Industry 4.0 and automation of laboratories. The most important characteristic of modularity in electronics is their capability to represent homogeneous or heterogeneous systems by scalability.

Net layer in IoT presents a future challenge. It is because IP addresses (v4.0) are limited to a finite number [11]. When the number of objects with IoT grows, IP addresses will be insufficient. For that reason, it is necessary to incorporate IP (v6.0) as soon as it is possible. The main characteristic of this version of IP is the highest number of addresses disponible.

Another factor that is significant in Net layer for IoT systems is net latency [24]. This variable represents how fast data is received after its transmitted. In wireless networks, latency is higher because signals are transmitted by air. In this sense, it is necessary to consider special networks for IoT objects. In other words, Internet networks must be duplicated in order to improve latency. Thereby, in the future houses and offices will be equipped with two Internet connections, one for human use and other for IoT use.

Objects equipped with IoT produce a lot of data. Cloud computing have to be prepared for this challenge. Specially, Cloud servers must be ready to refuse attacks and not lose stored information. Attacks of hackers will increase because information of industry will be storage in these servers.

Also, big data bases are an important component for new marketing techniques. For example, a TV producer company equipped with IoT its products. The preferences of users could be monitored, and marketing companies could prepare costume advertising campaigns [26]. In the case of laboratories, all procedures could be monitored by ethical commissions. Also, data bases produced could be used to analyze new variables without respiting the experimental procedures.

In this way, Artificial Intelligence techniques are the special component in application layer. These techniques explore big data sets to find patterns or regularities. IA decision structures must be fast, able to analyze big data sets and learn in real time [20].

ANNs have these characteristics. There are a lot of topologies and models to be explored in IoT applications. Specially, it is important to kwon how these architectures respond to large data bases [13]. The system presented was an example of how ANN can be adapted to large data sets. Input layer received 100 measurements of pressure of a pin. Traditionally, ANN models process less input signals. But the idea was to improve statistically the final linguistic categorization. It implies more measurements to obtain a robust model. ANN also was capable of tolerate failures and noisy of electronical devices. It is due to the model of ANN chosen, that depends on 100 inputs. In that way, ANN selected was robust and handles data variations.

GA adjusted weights of ANN in a good way. It was showed in Results that in validation stage, 12 of 13 pins were well classified. It is an important factor because when an ANN has many weights to adjust, the complexity of search space increases. Thus, traditional learning algorithms like Backpropagation have problems to adjust weights because of complexity of search space [19]. One of the main differences between BP and GA is multipoint search.

It is possible to note that GA used adjusted weights adequately. At the begin of evolutionary process, the initial random produced that solutions (individuals) had a lower fitness function. This strengthless the diversity of potential solution in the search space. Better solutions produced better fitness as they are recombined, and they still in evolutionary process. This is how evolutionary pressures act in GA [18].

Another important aspect to be highlighted is the way in where training data base was generated. It was used a simulated process to obtain random data and trained the ANN. This process was complemented by expert knowledge, that consisted in classify manually all cases generated (average of measurements).

Training and test stages had different values of classification effectivity. However, this is not a problem. GA produces specialization on ANN, and sometimes produces overfitted models. To counter this effect, is necessary to split the initial data set and reserve a section to do a test process. In that way, specialization is compensated, and the final computational model results robust to solve a problem. In the end, results of validation stage showed that the ANN categorized pins in a good way.

In order to select an ANN, it was used fitness function at the end of evolutionary process and effectivity of neural network in test stage. This guaranteed avoid ANN overfitted.

At the end, validation stage confirmed a well function of the IoT system for pressure measure. As well, that embedded devices sensed and sanded data correctly. This system is used to select the correct pin according to characteristics in a Tail-Pinch experiment. As the decision of what pin is used in this experiment, experimental subjectivity is reduced, and the relatability increases.

V. CONCLUSION

The system developed had a good performance, as it is shown in results. This system measured pressure of pins used in Tail-Pinch experiments. It represents the first stage of automatization of this experiment. Reduces the variability of data and increases the confidence of experiments. Also reduces subjectivity level in experiments. Our system is used as initial stage in real Tail Pinch test. It represents a selection stage, in where experiments chose an appropriate pin.

The ANN trained represents a model for categorization, which is fed using a large number of pressure measurements.

Finally, the system is an example of potentiality on industry 4.0 and cyber-physics elements, that can be applied to automation of process in all areas.

REFERENCES

[1] Almada-Lobo, F. (2016). The Industry 4.0 revolution and the future of Manufacturing Execution Systems (MES). Journal of Innovation Management, 3(4), 16-21.

[2] Bagal, S., Dhobale, J., Sarve, A., Satone, R., Faizan, M., & Pande, S. (2018). Arduino Based Automatic Plant Watering System. International Journal of Engineering Science, 16342.

[3] Brettel, M., Friederichsen, N., Keller, M., & Rosenberg, M. (2014). How virtualization, decentralization and network building change the manufacturing landscape: An Industry 4.0 Perspective. International Journal of Mechanical, Industrial Science and Engineering, 8(1), 37-44.

[4] González-Fernandez, I., Iglesias-Otero, M. A., Esteki, M., Moldes, O. A., Mejuto, J. C., & Simal-Gandara, J. (2018). A critical review on the use of artificial neural networks in olive oil production, characterization and authentication. Critical reviews in food science and nutrition, 1-14.

[5] Gorecky, D., Schmitt, M., Loskyll, M., & Zühlke, D. (2014). Human-machine-interaction in the industry 4.0 era. In Industrial Informatics, 2014 12th IEEE International Conference on(pp. 289-294). Ieee.

[6] Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things (IoT): A vision, architectural elements, and future directions. Future generation computer systems, 29(7), 1645-1660.

[7] Horton, P., Jaboyedoff, M., & Obled, C. (2018). Using genetic algorithms to optimize the analogue method for precipitation prediction in the Swiss Alps. Journal of hydrology, 556, 1220-1231.

[8] Hu, M. H., Bashir, Z., Li, X. F., & O'byrne, K. T. (2016). Posterodorsal Medial Amygdala Mediates Tail-Pinch Induced Food Intake in Female Rats. Journal of neuroendocrinology, 28(5).

[9] Jazdi, N. (2014). Cyber physical systems in the context of Industry 4.0. In Automation, Quality and Testing, Robotics, 2014 IEEE International Conference on (pp. 1-4). IEEE.

[10] Kagermann, H. (2015). Change through digitization—Value creation in the age of Industry 4.0. In Management

of permanent change (pp. 23-45). Springer Gabler, Wiesbaden.

[11] Kelly, S. D. T., Suryadevara, N. K., & Mukhopadhyay, S. C. (2013). Towards the implementation of IoT for environmental condition monitoring in homes. IEEE Sensors Journal, 13(10), 3846-3853.

[12] Khan, G. M. (2018). Evolutionary computation. In Evolution of Artificial Neural Development (pp. 29-37). Springer, Cham.

[13] Ki, Y. K., Heo, N. W., Choi, J. W., Ahn, G. H., & Park, K. S. (2018). An incident detection algorithm using artificial neural networks and traffic information. In Cybernetics & Informatics, 2018 (pp. 1-5). IEEE.

[14] Lasi, H., Fettke, P., Kemper, H. G., Feld, T., & Hoffmann, M. (2014). Industry 4.0. Business & Information Systems Engineering, 6(4), 239-242.

[15] Lee, I., & Lee, K. (2015). The Internet of Things (IoT): Applications, investments, and challenges for enterprises. Business Horizons, 58(4), 431-440.

[16] Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for industry 4.0-based manufacturing systems. Manufacturing Letters, 3, 18-23.

[17] Lee, J., Kao, H. A., & Yang, S. (2014). Service innovation and smart analytics for industry 4.0 and big data environment. Procedia Cirp, 16, 3-8.

[18] Montes-González, F., & Aldana-Franco, F. (2011). The Evolution of Signal Communication for the e-puck Robot. In Mexican International Conference on Artificial Intelligence (pp. 466-477). Springer, Berlin, Heidelberg.

[19] Montes-González, F., Palacios-Leyva, R., Aldana-Franco, F., & Cruz-Alvarez, V. (2011). The Coevolution of Behavior and Motivated Action Selection. In On Biomimetics. InTech.

[20] Negrete, J. C., Kriuskova, E. R., Canteñs, G. D. J. L., Avila, C. I. Z., & Hernandez, G. L. (2018). Arduino Board in the Automation of Agriculture in Mexico, a Review. International Journal of Horticulture, 8.

[21] Oesterreich, T. D., & Teuteberg, F. (2016). Understanding the implications of digitisation and automation in the context of Industry 4.0: A triangulation approach and elements of a research agenda for the construction industry. Computers in Industry, 83, 121-139.

[22] Pagliuca, P., Milano, N., & Nolfi, S. (2018). Maximizing adaptive power in neuroevolution. PloS one, 13(7), e0198788.

[23] Palacios-Leyva, R., Aldana-Franco, F., Lara-Guzmán, B., & Montes-González, F. (2017). The impact of population composition for cooperation

emergence in evolutionary robotics. International Journal of Combinatorial Optimization Problems and Informatics, 8(3), 20-32.

[24] Pérez, M. S., & Carrera, E. (2015). Time synchronization in Arduino-based wireless sensor networks. IEEE Latin America Transactions, 13(2), 455-461.

[25] Rabiei, Z., Naderi, S., & Rafieian-Kopaei, M. (2017). Study of antidepressant effects of grape seed oil in male mice using tail suspension and forced swim tests. Bangladesh Journal of Pharmacology, 12(4), 397-402.

[26] Rüßmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., Engel, P., & Harnisch, M. (2015). Industry 4.0: The future of productivity and growth in manufacturing industries. Boston Consulting Group, 9.

[27] Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural networks, 61, 85-117.

[28] Schmidt, R., Möhring, M., Härting, R. C., Reichstein, C., Neumaier, P., & Jozinović, P. (2015). Industry 4.0-potentials for creating smart products: empirical research results. In International Conference on Business Information Systems(pp. 16-27). Springer, Cham.

[29] Shrouf, F., Ordieres, J., & Miragliotta, G. (2014). Smart factories in Industry 4.0: A review of the concept and of energy management approached in production based on the Internet of Things paradigm. In Industrial Engineering and Engineering Management (IEEM), 2014 IEEE International Conference on (pp. 697-701). IEEE.

[30] Wan, J., Tang, S., Shu, Z., Li, D., Wang, S., Imran, M., & Vasilakos, A. V. (2016). Software-defined industrial internet of things in the context of industry 4.0. IEEE Sensors Journal, 16(20), 7373-7380.

[31] Wollschlaeger, M., Sauter, T., & Jasperneite, J. (2017). The future of industrial communication: Automation networks in the era of the internet of things and industry 4.0. IEEE Industrial Electronics Magazine, 11(1), 17-27.

[32] Zhou, K., Liu, T., & Zhou, L. (2015). Industry 4.0: Towards future industrial opportunities and challenges. In Fuzzy Systems and Knowledge Discovery (FSKD), 2015 12th International Conference on (pp. 2147-2152). IEEE.