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Deliberative architecture for smart sensors in the filtering operation of a water purification plant

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Abstract. The increase of applications for industrial smart sensors is booming, mainly due to the use of distributed automation architectures, industrial evolution and recent technological advances, which guide the industry to a greater degree of automation, integration and globalization. In this research work, an architecture for deliberative-type intelligent industrial sensors is proposed, based on the BDI (Belief Desire Intentions) model, adaptable to the measurement of different variables of the filtering process of a water purification plant. An intelligent sensor with functions of signal digitalization, self-calibration, alarm generation, communication with PLC, user interface for parameter adjustment, and analysis with data extrapolation have been arranged. For decision making, the use of fuzzy logic techniques has been considered, which allows imprecise parameters to be appropriately represented, simplifying decision problem solving in the industrial environment, generating stable and fast systems with low processing requirements. The proposed architecture has been modelled, simulated and validated using UML language in conjunction with Petri nets, which facilitate the representation of discrete system events, presenting them clearly and precisely. In the implementation and testing of the prototype, C / C ++ language has been used in an 8-bit microcontroller, experimentally corroborating the operation of the device, which allowed evaluating the behavior of a pseudo-intelligent agent based on the requirements of the water treatment plant, and also through comparisons with similar works developed by other researchers.

1. Introduction

Advances in industrial automation, along with computing, digital communications and micro-electronics, are evolving towards a new industrial revolution that promises to lead profound changes in the industrial and manufacturing sectors [1], becoming a priority of many companies [2]. This new approach is based on a deep integration of its components [3], where each manufacturing element interacts with other elements or executes its tasks autonomously[4]. Manufacturing systems are becoming increasingly complex due mainly to the large number of operations in the production chain and its multiple structural characteristics [5]. In this context, smart sensors are one of the key technologies for the future [6], mainly due to their compact design and flexibility, which allows them to be adapted to different types of actuators, interfaces and computer hardware, allowing to respond to many of the problems in current manufacturing systems, based on hierarchical and heterarchical architectures [8-9].

The paradigms of industrial automation are oriented to the distribution of artificial intelligence (AI) among all the components of the factory [7], which have been very useful supports in decision-making, demanding tasks or in case of risks for workers or operators [10], reasons for which they focus on models that adapt to the conditions of an intelligent distributed network [11], Within distributed AI, agents and multi-agent systems represent an ideal solution to design systems based on this paradigm [12-13], supported by the BDI model (Beliefs , Desires and Intentions) allow to systematically describe the behavior of each intelligent agent in the network [14]. This research proposes the design of an architecture for an intelligent sensor based on the BDI model, adapted to the level and flow variables in a water filtering process. The architecture is described using tools based on the Unified Modeling Language (UML) and Petri Nets (PN), to determine its behavior, validate and verify the functions of the



system through the mathematical and graphical analysis of the PN. The smart sensor has been implemented in an ATmega2560 microcontroller using the C / C ++ language. The code and the implementation of the AI has been analyzed prior to the analysis of the variables that intervene in the design of the fuzzy controller.

2. Smart Sensor Architecture

This section analyzes the architectures, both of the sensor and the environment where it will interact, defining the functional requirements and characterizing the industrial automation process.

2.1. General Process Architecture

The sensor architecture is designed to interact with an intelligent distributed control system, therefore, to guarantee distributed intelligence, it is necessary to achieve a modular design with communication networks from the basic sensor level to the supervision level [15-16]. To satisfy the requirement of intelligent field instrumentation, a network based on the MODBUS RTU communication protocol is considered [17]. Figure 1 shows the details of the general architecture of the automation system, made up of compact design controllers that execute intelligent algorithms in the distributed control system [18]. As for the supervisor, it is made up of HMI KINCO panels used to visualize and monitor the dynamic behavior of the filters, the backwash cistern and the washing tank [19]. For the development of advanced automation features, the intelligent supervisory system uses the SCADA CODESYS HMI SL from a PC with wireless connectivity [20].

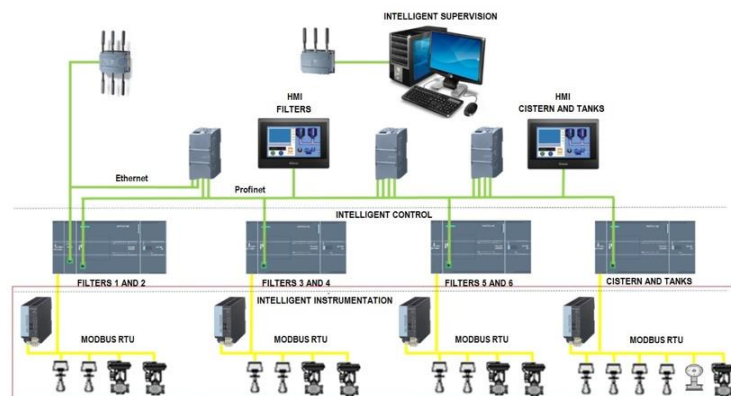


Figure 1. Intelligent instrumentation in the integrated automation architecture.

2.2. Deliberative architecture based on the BDI model

Deliberative architectures explicitly represent the behavior and knowledge of the agents, in the case of the BDI model they represent the mental attitudes: Beliefs, Desires and Intentions [8]. The proposed smart sensor behaves like a sensor node, because, despite being autonomous, it receives instructions and is supervised by a parent node [21], which in this case is a programmable logic controller (PLC). This sensor, due to its architecture, is not an intelligent agent, but it has many of its characteristics, for being considered a pseudo agent, and for this reason, in its projection and design, an intelligent agent methodology is used. The BDI model serves as the basis for designing and proposing the intelligent sensor architecture oriented to industrial environments, where the relationship of the three elements of the BDI model, beliefs and objectives (intentions) is associated with the inputs (sensors) and the outputs of the system. are associated with the plans and intentions corresponding to the output of the actuators from the model [22].

The proposed architecture considers three stages in its design. The first is related to the capture of the signal, which must be flexible to adapt to different types of signals, for which it admits analog and digital signal inputs, through analog to digital conversion channels and the USART [17].

The second stage of the sensor architecture is made up of the elements that make up the BDI architecture, as shown in figure 2. This architecture consists of a belief database that constitutes a set of

parameters stored within the sensor, of which, one group is configurable to adapt to the type of sensor, while the other group is fixed or general. At this stage, the behavior selection and event dispatcher functions have been arranged, which correspond to the wishes or objectives according to the BDI architecture, while the functions of self-calibration, analysis and average of values, extrapolation and data generation, respond to the intentions you have, based on the objectives.

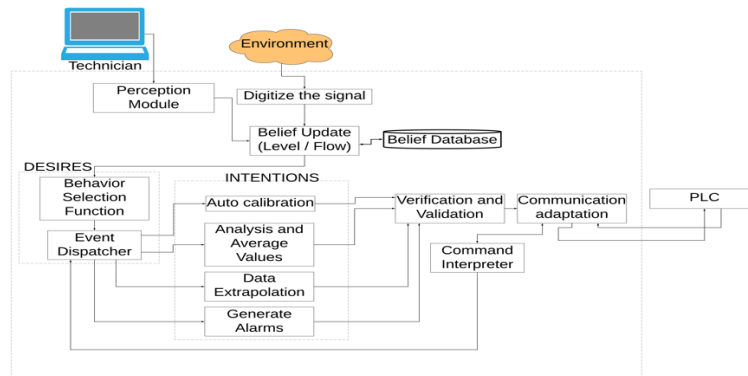


Figure 2. Deliberative smart sensor BDI architecture

The third stage of the architecture is made up of the sensor outputs and communications with the PLC and has a module for verifying and validating the output of the sensor. Additionally, there is a communication adaptation module for the data frame that must be sent to the PLC or actuator; This module is also in charge of generating the required format for the sensor to control an actuator. An additional command interpreter function has also been implemented that allows understanding the commands coming from the PLC so that they are redirected to the corresponding module.

2.3. Smart Sensor Hardware Architecture

Figure 3 shows the hardware architecture with the distribution and interconnection of the different components. Sensor input signals can be digital and analog. The digital signal is captured through the USART arranged for sensors that transmit the signal using the communication channels RS-232, SPI, I2C, ONE WIRE or RS-85. Another type of input is related to analog signals for which analog to digital conversion channels (ADC) are available. Finally, there are digital inputs / outputs (I/O) that come from the ATmega2560 microcontroller. The sensor output to the PLC is done through the MODBUS RTU protocol.

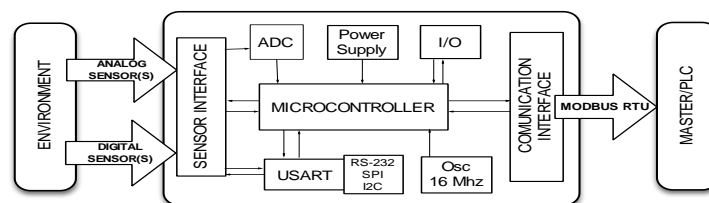


Figure 3. Smart Sensor Hardware Architecture

3. Case Study: Smart Sensor for Water Filtration Process

A case study is analyzed using the HC – SR04 level sensor and the YF-S201 water flow sensor, oriented to a water purification plant [23]. The process begins with the definition of the initial considerations of the smart sensor, then, the modeling and verification of the system is developed using UML and PN and finally the implementation of the level sensor using the fundamentals of fuzzy logic.

3.1. Sensor Description

The case study focuses on the development of the level sensor, which, in addition to transmitting the signal value to the PLC, has been assigned functions related to the filtering process; the tasks established,

using fuzzy logic, are the monitoring of the filter level, the generation of alarms and the verification of the transmitted values. The main characteristics of the sensor are:

- Processing with the ATmega2560 microcontroller, 256KM ROM and 8Kb RAM.
- HC - SR04 ultrasonic distance sensor, with a range of 3 to 500 cm.
- YF-S201 flow sensor. The flow range is 1-30 l / min

3.2 Functional Requirements

Considering the environment where the sensor interacts, the following functional requirements were defined:

- Digitization of the analog signal through the digital converter.
- Auto calibration, allows adjusting the ranges of the signals according to their variation.
- Analysis and averaging of signals, allows to improve the stability and precision of the signals
- Generation of alarms in case of sensor failure.
- Data extrapolation, sends average data in case of sensor failure.
- Verification and validation of the information, taking the addresses, frames and communication protocols.

4. Smart Sensor Modeling

UML and PN are used for sensor modeling. UML describes the smart sensor model, specifying the details of the firmware methods and processes. The diagrams used in modeling: use cases, sequence and state. PNs mathematically and graphically represent a discrete event system, such as the smart sensor, allowing the topology and dynamics of its interactions to be described, and through the properties of the network, to verify and validate the operation of the system.

4.1 Use Cases

The use cases are seen in the diagram in figure 4 and are given by him sending measured values of the environment, the pre-processing and averaging of measured values, the self-calibration with the adjustment of the range of values and its precision, the verification of formats and measured values, the generation of alarms, the extrapolation of data, the reception of orders and commands, the configuration of the sensor and the sensing of the environment [4].

4.2 Sequence Diagram

The sequence diagram describes how the sensor initiates its activities and the sequences of interactions with the actors; Figure 5 shows the smart sensor operation sequence.

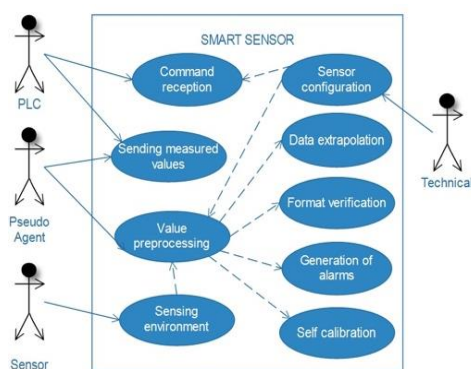


Figure 4. Use Cases Diagram

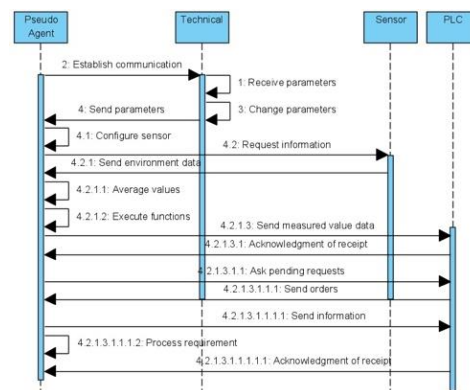


Figure 5. Sequence Diagram

4.3 States Diagram

Figure 6 details the state diagram of the smart sensor, which shows the sequence of the states, and in some cases, the sequence of the tasks available to it. Some of these tasks are rendered concurrently due to the use of microcontroller interrupts.

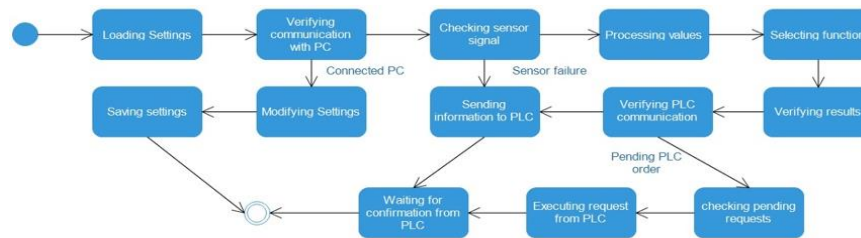


Figure 6. States Diagram

4.4 Petri Nets

Figure 7 shows the PN of the sensor with all the elements involved, as well as their states and live transitions, for which it generates invariants of the system that are shown in equation 1.

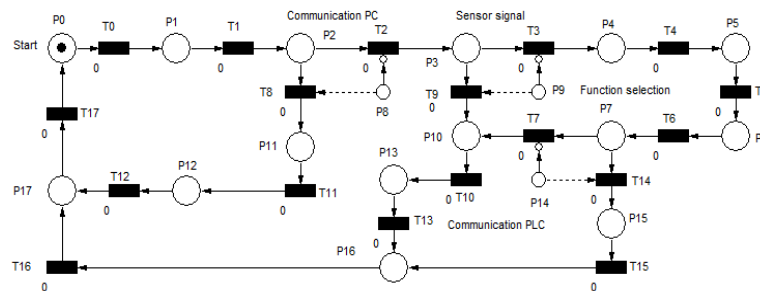


Figure 7. General Petri Net

$$M(P0) + M(P1) + M(P2) + M(P3) + M(P4) + M(P5) + M(P6) + M(P7) + M(P8) + M(P10) + M(P12) + M(P13) + M(P15) + M(P16) + M(P17) = 1 \tag{1}$$

Analyzing equation (1) and figure 7, it is shown that all places are reachable by at least one of the place invariants, so that the PN is well formed and fulfills the reachability property. Furthermore, in the simulation of said network, the repeatability property is fulfilled because the initial state is returned to all paths. All invariants are bounded by a token and the limiting property is fulfilled and, finally, since there are no locks or infinite ties in the operation of the network, the liveness condition is met.

5. Fuzzy controller Design

One of the applications of the level sensor in the water purification process consists in determining the water level in the filters, in which it has been established that if the level exceeds the preset limit of 0.2 m, it will be necessary to proceed to the process of filter washing, operation in which the filtering process is suspended. From the control requirements, a steady state error $\leq \pm 5\%$ of the desired level and a maximum overshoot $\leq 20\%$ above the desired level have been considered.

The input and output variables of the fuzzy set are identified and summarized in Table 1. In the inputs of the fuzzy set, the frequency is associated with the average of the sample number that is taken from the sensor signal. If the error between the average and the samples is low, a smaller number of samples are taken. Figure 8 shows the diagram of the fuzzy set, with its inputs and outputs.

Table 1. Variables input output of the fuzzy set

State variables (System inputs)	
Height	Level in the filter at steady state
Error	Height deviation at steady state
Control variables (System outputs)	
Frequency	Average sensor samples
Filter level	Minimum level $\leq 20\%$

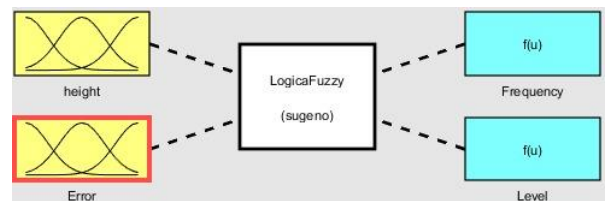


Figure 8. Fuzzy set diagram

Subsequently, we proceed to identify the linguistic terms of the variables and establish the fuzzy sets. Table 2 summarizes the elements for fuzzy inputs and outputs and in Figures 9 and 10 the triangular membership functions for the input of the fuzzy set are observed.

Table 2. Linguistic terms of the fuzzy input and output variables.

Input Variables		Output Variables	
Height	Error	Frequency	Filter level
very low (VL), low (L), normal (N), high (H), very high (VH)	very low (VL), low (L), normal (N), high (H), very high (VH)	low (L) normal (N) high (H)	low (L) normal (N) high (H)

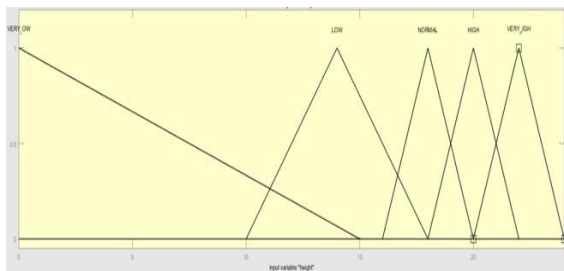


Figure 9: Height membership function

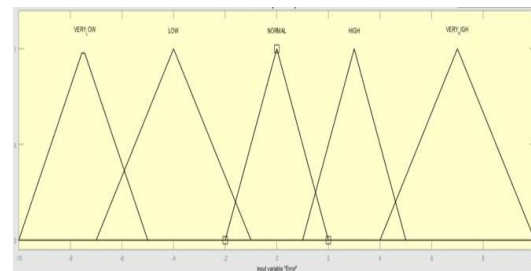


Figure 10: Error membership function

For the two output variables of the fuzzy set, three value labels have been defined called "Normal", "High" and "Very High". The ranges of values of the variables of the fuzzy set are shown in table 3. Figure 11 shows a set of 30 rules entered through MATLAB’s rule editor, using the logical “and” as the minimum between these factors and the Mamdani method for defuzzification using the centroid method.

Table 3. Value labels for the output

Frequency: [10 -30] values			
Triangular	Lo	Me	Hi
Normal	10	12	14
High	12	16	20
Very High	18	24	30
Level: [-4 4] cm			
Triangular	Lo	Me	Hi
Normal	-4	-2	1
High	0	1	2
Very High	1	3	4

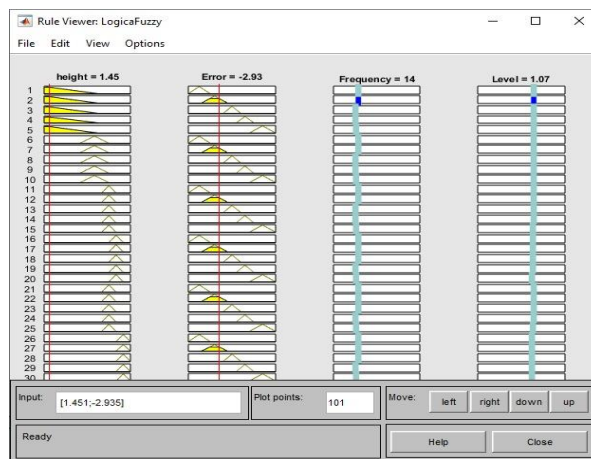


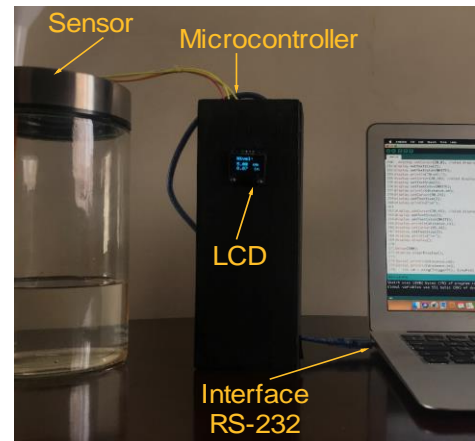
Figure 11. Fuzzy rules in the Matlab editor

6. Experimental Tests

Experimental tests have made it possible to determine the behavior of the smart sensor and compare it with the results of the model, and were carried out with the level sensor (HC-SR04) and the flow sensor (YF-S201). The level test, figure 12, generated output values that remain stable with increasing water level. A 20 cm high reservoir was used to analyze the filter level values; Table 4 shows the values obtained for 10, 15 and 30 samples, the average value and the error percentage are determined. The error values obtained show that the sensor meets the requirements of the plant under study for the different sample values.

Table 4. Level experimental values

Set [cm]	Frec: 30 [cm]	Frec: 15 [cm]	Frec: 10 [cm]
12,00	11,85	11,75	11,65
11,00	10,92	10,83	10,74
10,00	9,95	9,75	9,64
9,00	8,92	8,85	8,81
8,00	7,80	7,73	7,58
7,00	6,91	6,67	6,72
6,00	5,97	5,72	5,72
5,00	4,75	4,68	4,72
4,00	4,10	3,91	3,68
3,00	2,94	2,79	2,75
Error [%]	1.72	3.62	4.68

**Figure 12.** Experimental level test

7. Conclusions

A deliberative architecture based on the BDI model applied to an intelligent sensor oriented to industrial use has been proposed, using a design methodology for intelligent agents, which has been novel and practical in the automation of industrial distributed control systems. Although the sensor cannot be considered an intelligent agent, it has been analyzed as such, since it has inherited many characteristics of multi-agent systems.

In the proposed deliberative architecture, the design is described by means of a hierarchical modular modeling based on UML-PN techniques, which allows detailing the operation of the system in the face of possible situations, from the general conception through use cases to the dynamic detail in the PN. The verification of properties of the PN models is carried out, guaranteeing the good formation of the models and the dynamic validation of the functional requirements through PN simulation.

The contribution of fuzzy logic in smart sensor design greatly facilitates implementation and allows individual sensor behavior to be defined. The beliefs of the network are modeled with fuzzy logic to represent the relationship between the variables of the environment, the user and the PLC, so that the generation of functions proposed in the architecture can associate what the user wants to a set of feasible goals, considering existing beliefs.

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