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APPLICATION OF DEEP NEURAL NETWORK IN INTELLIGENT SYSTEM WITH PRODUCTION DASHBOARD

Juarez da Silva Ramos Junior[1*], Jandecy Cabral Leite[1,2], Marivan Silva Gomes[3], Railma Lima de Paula[4], Michael da Silva Carvalho[5], Ítalo Rodrigo Soares Silva[6], Paulo Oliveira Siqueira Junior[7], Ricardo Silva Parente[8] and Luís Gabryel dos Santos Miranda[9]

[1]Post Graduate Master in Engineering, Process Management, Systems and Environmental (PPG.EPMSE), Institute of Technology and Education Galileo of the Amazon (ITEGAM), Manaus, Amazonas, Brazil. ZIP CODE: 69020-030; [2,6,7,8]Institute of Technology and Education Galileo of the Amazon (ITEGAM), Manaus, Amazonas, Brazil; [3,4,5,9]University of Amazonas State (UEA), Manaus, Amazonas, Brazil. ZIP CODE: 69020-030

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****Corresponding author:***
Juarez da Silva Ramos Junior

ABSTRACT

The Lean Manufacturing process, also known as Lean Manufacturing, is a strategic methodology of action to reduce production waste, obtain product quality, reduce product delivery time to the customer and achieve the lowest number of defects. However, the company, in its electronic meter manufacturing process, does not have technologies that allow the implementation of this methodology, which brings the need for investment in this project, which has as main objective to develop an Intelligent System of Lean Manufacturing based on the requirements of a Manufacturing Execution Systems - MES, which allows or assists the decision-making process regarding Production Control and Management, through technologies such as: Artificial Intelligence, Internet of Things and Embedded Systems, aiming to reduce production costs and product quality. To achieve this objective, the following goals must be performed: Mapping of the requirements of the electronic meter production process, list the parameters of the manufacturing process to analyze and define the requirements for the Intelligent System that uses Artificial Intelligence algorithms, identify the bottlenecks of in such a way that it is possible to make improvements in the electronic meter manufacturing process, develop communication models using Program Application Interfaces - API together with Embedded Systems for data collection, develop the Intelligent System to transform data into real-time information with reports and scenario projections to identify failures or possible improvements with process statistics, validate the Intelligent System requirements to adapt the production control and management module in line with manufacturing and implement the system observing the test period. As an execution method, the PMBOK project management methodology will be used to guarantee deliveries in each phase, observing the incremental cycle for software development, for the development of the Intelligent System, the Django Pyhton framework will be used, in such a way that it meets the need accessibility and portability between different platforms, this framework will use the Front-End and Back-End stack Engines for data communication, three-layer design architecture and MVC pattern, encryption for sending and receiving data, Bootstrap for designing the interaction interfaces, Vue JS to create the interface events and Blade to integrate the models provided by the Back-End to the Front-End in an easy and productive way. The embedded systems for the electronic devices will be developed in C language through the VSCode environment, together with the communication interfaces. Finally, it is expected that the project meets the company's needs, that it improves the manufacturing process of the electronic meter by using the Intelligent System that uses Artificial Intelligence algorithms to generate results that determine viable solutions through previously programmed scenarios, which meet the demand to increase the maturity level of the process as it uses Industry 4.0 methods and technologies.

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INTRODUCTION

The present research presents as a viable solution to the problem of communication, integration and control of the information in the manufacturing process of a model of electronic meter a product that contemplates an Intelligent System, it is intended to improve the level of maturity of the manufacturing production process, based on the ACATECH methodology, where the system will deliver the data in an agile, modular and flexible way, reducing the time of action, for decision making. The research should through functionalities present optimizations or self-corrections of the process or sub-process of transformation of two or more sequential and parallel cells that have influence on each other, use the data, information and knowledge generated throughout the processes and sub-processes of transformation to create, feed back, robust the digital or virtual twin of the sub-processes and transformation processes and use this information and knowledge generated throughout the process to self-correct and self-optimize the entire process and sub-process chain integrated with the supply chain with mechanisms for predicting future demand for inputs, and allow the generation of reports and integration with other systems. The Intelligent System that is a component part of this research will have an architecture divided into three layers: Persistence, Business and Presentation, in such a way that enables the use of the Design Pattern Model, View, Controller (MVC), this design pattern facilitates the process of developing a system that covers distinct functionalities according to the business rule that is worked, besides, separate the activities (functionalities) of the implemented services, in a way to take advantage of the maximum possible of prototypes of functions in a defined requirement space.

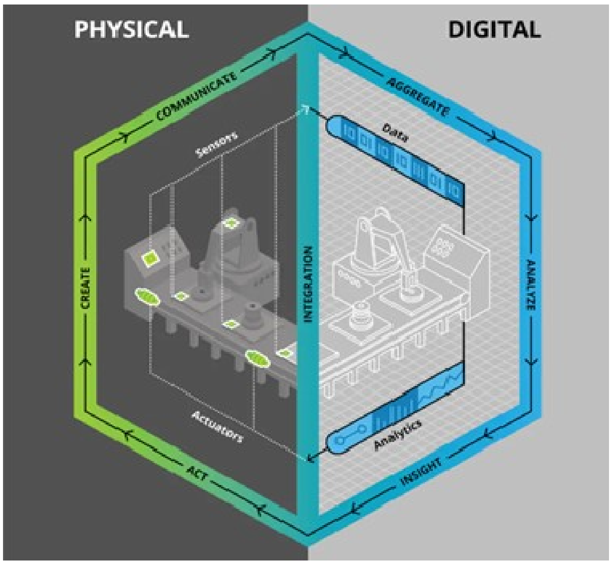
The Expert Systems, which will be embedded in hardware adapted to operate in the workstations, will have as main characteristic to capture the production data in such a way to communicate with the Database and to persist them, these data will later be consulted through the abstracted and separated communication interfaces to provide pre-processed models for the Controller or the Vision, the Models will contain actions, properties and business resources allowing better consultations and maintenance processes. The devices will communicate via hardware, through the module via TCP/IP or similar technology, this way the embedded system together with the electronics, will have the responsibility of pre-processing some data to pass to the software control client via API. The Application Programming Interfaces (API) will play a fundamental role in the data collection process, that is, the sending of data to the DBMS, in this case MySQL. It will be used to determine the integration of the Expert Systems with the Intelligent System, in such a way that both understand each other regardless of the language or platform being used. The main problem that highlights and justifies the development of this research, meets the lack of communication between the various electronic devices, the synchronization of information through a system that allows support for decision making and the need to have this set of data relating to production, process and quality as a requirement for framing the company to the context of Industry 4.0. Considering that the integration of cyber-physical Systems, Intelligent Systems and AI are requirements for the company to increase the maturity of its process according to Ordinance No. 2.091-SEI, of September 17, 2018, it is necessary to develop this research aiming at cost reduction and product quality.

BIBLIOGRAPHIC REVIEW

Industry 4.0 maturity stages: To wit, the Minister of State of Industry, Foreign Trade and Services in the use of the attributions conferred upon him by art. 87, sole paragraph, item II, of the Federal Constitution , having in view the provisions of art. 2, caput, of Law nº 8.387, of December 30, 1991, and considering Decree nº 6. 008, of December 29, 2006, Resolution No. 71, of May 6, 2016, of the Board of Directors of Suframa and Resolution No. 40, of May 10, 2018, of the Board of Directors of Suframa, resolves to approve the methodology adopted for investments in research, development and innovation focused on Industry 4.0 in the Manaus Free Trade Zone and creates the Industry 4.0 Seal (SUFRAMA, 2018). According to (SUFRAMA, 2018) the classification model of the process or sub-process of the stages of Industry 4.0 are important and should be taken into account through methodology and primer of characteristics of the stages, which highlights the main technologies that are covered for that stage, according to Table X. The adoption of Industry 4.0 concepts in the Brazilian production matrix can bring about savings of U$13.77 billion per year, besides generating a production with lower environmental impacts, resulting in more sustainable processes (ABDI, 2017). In this context, companies need to adapt to the new scenario and use the benefits and opportunities that the enabling technologies of Industry 4.0 can bring, in order to remain competitive in the market (SILVA, 2022). One of the sectors that have sought, increasingly, the adoption and incorporation of these new concepts related to Industry 4.0 is the electronic sector. Currently, this sector has been facing an intense process of reorganization of production and work in order to obtain greater flexibility and increase productivity. These processes have been deeply affecting the working class, as it implies several organizational changes, such as in management patterns, in the skills and qualifications required for work as in the composition of the force, in the volume and structure of employment (DURANTE, 2022; VARGAS, 2022). Although technological advances are often considered the major milestones of Industry 4.0, it is not possible to leave aside human factors that are also fundamental to the success of any company that is pursuing the scenario 4.0. It is essential to understand the impacts that Industry 4.0 will cause in the human aspects of organizations (MOURA *et al*., 2022). The new Industrial Revolution will also bring changes in the organizational structure of companies. For De Souza (2022) the organizational structure that best fits the 4.0 scenario is a structure focused on innovation with constant investment in research and development. This structure demands high qualification of workers and skills to deal with the high technical complexity of the work environment. In this scenario, the information exchange will be facilitated, the work will be carried out with multidisciplinary teams organized by process or project, without departments (SIQUEIRA *et al*., 2022).

Digital twin based on data: In light of Industry 4.0, CPPS-supported production systems can do decision making through real-time IIoT (Industrial Internet of Things) communication and cooperation. In this way, companies have new perspectives to effectively improve the challenges arising from the new industrial panorama characterized by a highly globalized, dynamic and heterogeneous market. Thus, for example, on-demand production of highly customized products can be achieved in a cost-effective, sustainable and cost-efficient manner through service-oriented manufacturing activities and the provision of manufacturing resources on cloud platforms (BUENO, 2022; CABRAL, 2022). The digital twin is a step further in the process of developing virtual and digital models of manufacturing processes, instead of just simulating, it is possible to use real signals of the object in question, the more information the more robust is the digital twin (CHATTERJEE, 2021). Most companies still follow the traditional Industry 2.0 and 3.0 model, in which the quality of the process is checked after the components of a part are ready to be tested (KHORASANI, 2021). Among the advantages of the digital twin is the use in processes within factories such as ergonomics, this way it is possible to plan the best position of the employee in a production line or the best way for him to hold an object (MARIOTTONI, 2021). The digital twin allows creating what is possible within the scope of programmed digitalization to test for example how employees can move around within previously defined spaces, safely without compromising the physical environment minimizing possible work accidents (ROSSI FILHO, 2021; AIUB *et al*., 2021). Figure 1 shows a digital twin model in which represents the physical assets and analyzers to optimize the business process in a transparent way.

Production Monitoring Systems: Recently disruptive technologies such as Internet of Things (IoT - Internet of Things), Artificial Intelligence (AI - Artificial Intelligence), Cloud Computing and Big



Source: (DELOITTE, 2017).

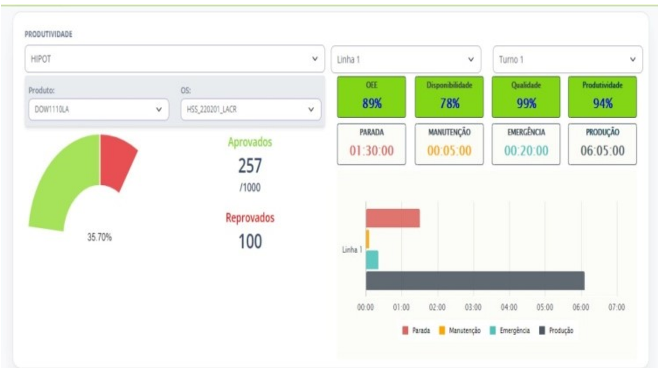
Figure 1. Digital Twin model

Data have erupted from the purposes of Industry 4.0 which is to transform production systems (CABRAL, 2022; ZEBA *et al*., 2021; MITHAS *et al*., 2022). Competitiveness has changed the way industries operate and produce. Real-time production monitoring collaborates to increase the ability to integrate the shop floor with other areas of the industry. Moreover, the real-time production monitoring contributes for all production processes (preparation, quality, traceability and generation of indicators) to become more agile (PINTO, 2022; ANDRADE, 2022).

Some advantages of production monitoring systems can be listed (PINTO, 2022):

- Intercommunication between systems;
- Real time data treatment and processing;
- Monitoring beyond production;
- MES software and the increase of productivity in the industry;
- Historical maintenance;

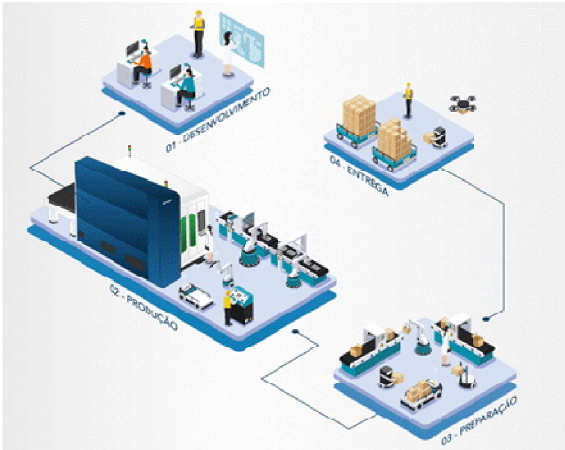
Some systems provide support through quality indicators, production or maintenance, which benefits the decision making by monitoring mechanisms in real time through devices (physical assets) added to the system and deployed in the factory plant, however, the integrity of these systems must be well worked, especially when they have Digital Twin technology, where cyber physical systems become targets for interceptions, for this the team of developers who provide support in the systems must have expertise in information security and work techniques such as Blockchain to ensure data quality (LI, Chunquan *et al*, 2021; YANG *et al*., 2022; FAN *et al*. 2021), Figure 2 shows an example of Dashboard that represents a real-time monitoring system.



Source: (Authors, 2022).

Figure 2. Dashboard Model

Therefore, there is a great importance and investment in increasingly qualified professionals in the field of security with application in manufacturing processes, since the development of programming stacks with computational resources: AI, BI, IoT and IS, adapted to specific scenarios of companies that revolve around complex variables becomes more evident and this requires more commitment from the professional (MORENO, 2021; MADDIKUNTA *et al*., 2022). The IT department becomes an anchor for the company, so that all processes go through the system and the administrators are more applied people with diversified specialties, an IT Manager should not hold such a position if he or she does not have knowledge of DevOps, Fullstack Development, Data Science, Software Multi-Applications and Artificial Intelligence applied to the company's business (MADDIKUNTA *et al*., 2022; EJEH *et al*., 2022). Smart Devices, i.e. sensors and actuators are primordial for data acquisition in a safe, clean and available way, software architects are essential for these technologies and especially IoT and firmware developers with specialties in low and high level programming are also, the understanding of business standards for requirements abstraction becomes a differential in this market, and for a productive process is no different (LV, 2022; GAO *et al*., 2022).



Source: (WELLE, 2020).

Figure 3. Conceptual model of intelligent manufacturing

Well defined processes depend on secure technologies, Blockchain is one of the modern techniques used worldwide, increasingly widespread in the Bitcoin business and its applications such as: financial market, games, intelligent systems, cryptocurrencies and gambling sites. Bringing innovative mechanisms to add security to the physical apparatus of a digital twin or monitoring system that requires availability becomes necessary. Figure 3 shows a conceptual model of connected factory, where physical assets are monitored and capture data in an organized and sectorial way, this is the smart manufacturing model (HAMEED *et al*., 2022; DAS, 2022).

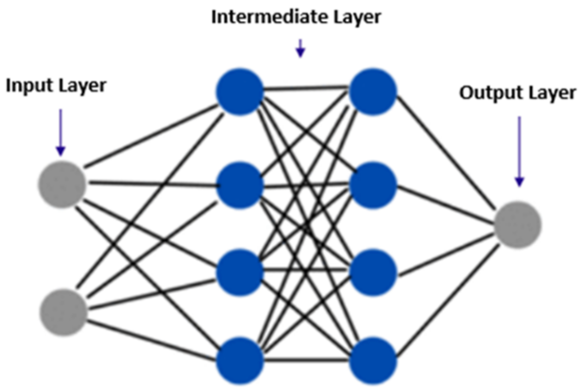
Deep Learning Neural Network: The Deep Learning Neural Network is a computational technique that aims to predict events, recognize or classify patterns, they have architectures and topologies, in addition are inspired by the neural structure of intelligent organisms and with the necessary adjustments in their weights it is possible to acquire knowledge (FERNANDES *et al*., 2021; TELIKANI *et al*., 2021). Its operation is simple each unit is connected by communication channels, the unit is responsible for performing operations on data passed as input (TELIKANI *et al*., 2021; ABD ELAZIZ *et al*., 2021), as a result, neural networks can improve decision processes in several areas such as:

- Credit card and health care fraud detection;
- Logistics optimization for transportation networks;
- Recognition of voice and character patterns;
- Targeted marketing;
- Financial predictions;
- Data classification;
- Computer vision for photo identification.

An ANN uses layers where the weights of its connections are adjusted according to the patterns presented (ABD ELAZIZ *et al*., 2021; PRAMOD, 2021) being classified as follows:

- Input layer: where the patterns are presented to the network;
- Intermediate Layer: where the weights are adjusted and most of the processing takes place considering the training algorithm and mathematical model used;
- Output Layer: where the final result is completed and presented.

Activation Functions are very important devices for a neural net model, since they are responsible for deciding whether a neuron is activated or not, that is, whether the information the neuron is receiving is relevant to the information provided or should be ignored. Such procedures will manifest actions to propagate the data to subsequent layers, provided that the gradients are provided along with the error to update the weights and biases (SILVA *et al*., 2021). A Figure 4 shows an example of a neural network architecture with input, hidden and output layers, where each layer communicates with the next layers by means of its neurons, which carry input values to the hidden layers that have the mission to perform processing of these data and send to the output layer (SILVA *et al*., 2021).



Source: Authors, (2022).

Figure 4. Architecture of an ANN

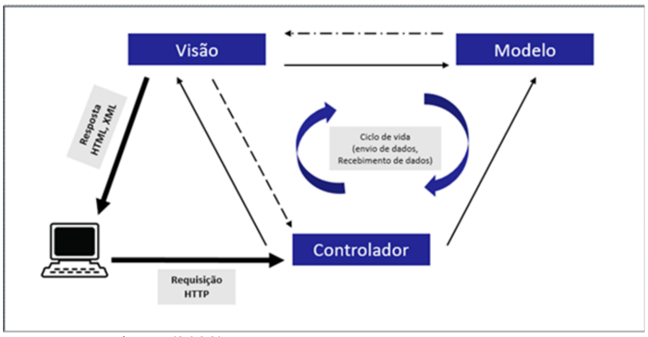
A DNN uses layers of mathematical neurons to process data, understand human speech and recognise objects visually. Information is passed through each layer, with the output of the previous layer providing input to the next layer (BIBB, 2022). The first layer in a network is called the input layer, while the last layer is called the output layer. All layers in between are referred to as hidden layers. Each layer is typically a simple uniform algorithm containing one type of activation function (MÉNDEZ *et al*., 2022). This is a widely used technique for event prediction and computational simulation applied to solutions with Digital Twin (SARKER, 2021; GUPTA, 2021), brings benefits of algorithm customization to meet the business need, so the objective function becomes mutable with the application of different processes for the activation of the neuron.

MATERIALS AND METHODS

Tools for IS development: For the development of this IS, it will be necessary to use support tools to carry out the scenario projections, technical drawings, simulation models and codification items listed in Table 2.

Technologies for IS development: The technologies that will be used and applied in the research are meeting the needs to supply the technology presented as the scope of the project, Internet of Things (IoT), Intelligent Systems and Artificial Intelligence.

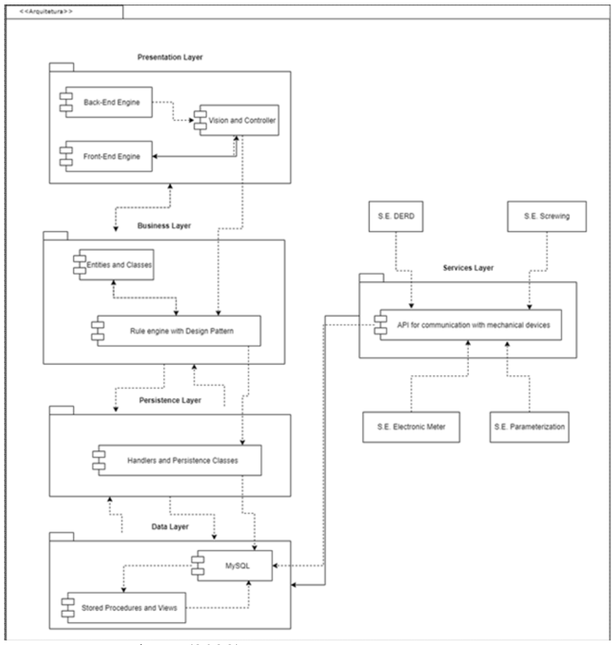
SolutionArchitectureandMethodology: The Intelligent System that is a component part of this research will have an architecture divided into three layers: Persistence, Business and Presentation, in such a way that enables the use of the Design Pattern Model, View, Controller (MVC), this design pattern facilitates the development process of a system that covers distinct functionalities according to the business rule that is worked, in addition to, separate the activities (functionalities) of the implemented services, so as to take advantage of as many function prototypes as possible in a defined requirement space. This methodology allows the decoupling between the actions that will be mapped to the system, greater use of code, ease in the process of maintenance, review and organization, thus the process of scalability becomes possible, once the concept of Front-End and Back-End is deployed, as shown in Figure 4.



Source: Authors, (2022).

Figure 4. MVC Architecture Model

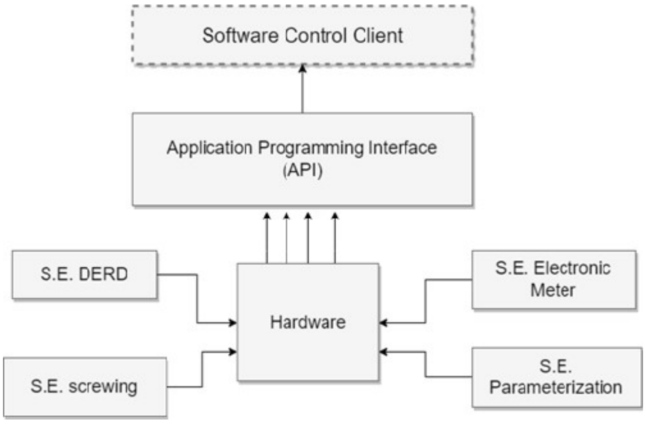
Figure 5 shows the detailing of the general architecture of the scopes foreseen for the research, observing the use of MVC and the separation of responsibilities as discussed.



Source: Authors, (2022).

Figure 5. General SIME Architecture

The devices will communicate via hardware, through the module via TCP/IP or similar technology, in this way the embedded system together with the electronics, will have the responsibility of pre-processing some data to pass to the software control client via API, as illustrated in Figure 6. The Software Requirements Specification (SRS) stage is necessary to demonstrate the requirements, features, objectives and utilities that a system must meet according to the needs of the company and the user. The Requirements Survey, which is an integral part of the ERS, is based on the principle of exploring and searching for these needs in a textual and detailed way so that later the necessary analyses can be performed to abstract the context, which includes defining entities, properties, actions, risks, impediments and necessary resources with other technologies.



Source: Authors, (2022).

Figure 6. API Communication Architecture

This Requirements Survey will be determined through: Meetings with the company's technical team and the project researchers, Prototyping, Questionnaires and Brainstorming. Some of the requirements that can aggregate the Intelligent System as an integral part of the ERS, but, to be defined through the specification strategies, are:

- Importing parameters for production, such as orders and manufacturing priorities (Employee Management);
- Storage of production activities information: operation times (per operator), machine times;
- Metrics and production performance analysis;
- Labor scheduling (quantity produced, production time analysis)

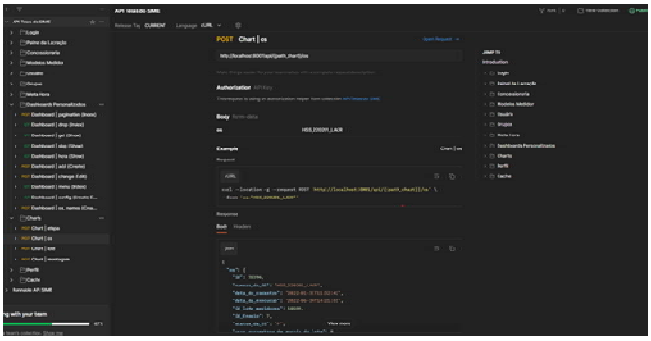
As a result, in the ERS stage, the functional and non-functional requirements will be defined through the strategy of capturing and validating information that meet and aggregate the intelligent system. Furthermore, it will be analyzed which algorithms of Artificial Intelligence (AI) should be used, due to the demand of complexity of the database and the requirements that are intended to achieve to evidence an MES System, will also be defined the mechanisms of integration to SIME and prediction models based on Optimization algorithms for decision making in the process and sub-process, feeding data from the digital twin and to correct and self-optimize the process or sub-process chain, in such a way that characterize the use of AI, this which is one of the pillars of Industry 4. 0. The AI algorithms will play a very important role in SIME, since they will have the ability to feed the digital twin, with qualitative and quantitative data, maintenance and production indicators, will have the ability to analyze processes and sub-processes in chains and will have the perception of a systematic and strategic way to point out improvements and failures based on data, characterizing the digitalization of the process with Machine Learning mechanisms. Meeting the needs of the company's data digitization, communication between devices, data processing and intelligent models of prediction and optimization for decision making, the technique of Computational Intelligence that will be adopted for the development of intelligent analyzers is the Deep Learning Neural Network - DNN, from the TensorFlow library of Django Python. For each vise of methods is contemplated one or more types of techniques that are determined by Algorithms in a computational model, which explicitly depends on the logical data model, where the input variables (independent) have correlation with the output variables (dependent) establishing criteria for designing or simulating scenarios of a lean manufacturing context.

RESULTS AND DISCUSSION

With the development of this research it was possible to obtain an algorithm applied to demand forecasting and production indicator in which generate knowledge and are available in Dashboard and an Intelligent System with integration via API with programming stacks focused on processes of computational optimization using modern technologies and web development frameworks with agile development engines. The research provided significant contributions in the economic context for the company, since when working on process improvements with technologies for data processing, informationmodeling and knowledge for decision making it is possible tooutline strategies for actions that reduce costs in relation to production capacity, loss of raw material, unfinished product and cycle time. The economic impacts will be evident as the action strategies are taken, assuming that the reports and projections generated by the System are of full support to managers and especially with indicators of production and product quality. The research aimed to meet the demand of regional development in the Western Amazon, performing the transformation of the competitive environment with the solution of Lean Manufacturing linked to the technologies of Industry 4.0, adding economic and technological values, according to the following elements:

- Understanding the challenges and the Degree of Maturity of the companies in the region in relation to Industry 4.0;
- Expansion of its contribution to the scientific development of the local CT&I (Science, Technology and Innovation) chain with the development and execution of regional scope projects with multiple participants (IES, ICTs, startups, etc.);
- Increased competitiveness of enterprises through systemic improvement of multiple capacities (innovation, ecology, quality, cost, delivery, flexibility, integration of industrialization and computerization and services) simultaneously;
- Increased capacity of technological services of companies in terms of Industry 4.0 practices;

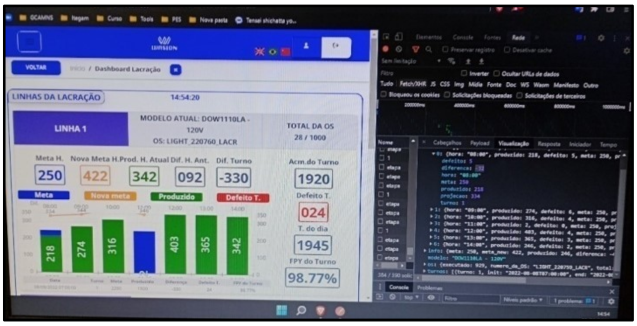
As a result it was possible to develop the API Production applied to the Dashboard for monitoring indicators related to the process of the electronic meter of the company, Figure 7 shows the example of the documentation of the API functions of the system, in which cover the following items: URI, Authorization with Token, Body Parameters (Request and Response).



Source: Authors, (2022).

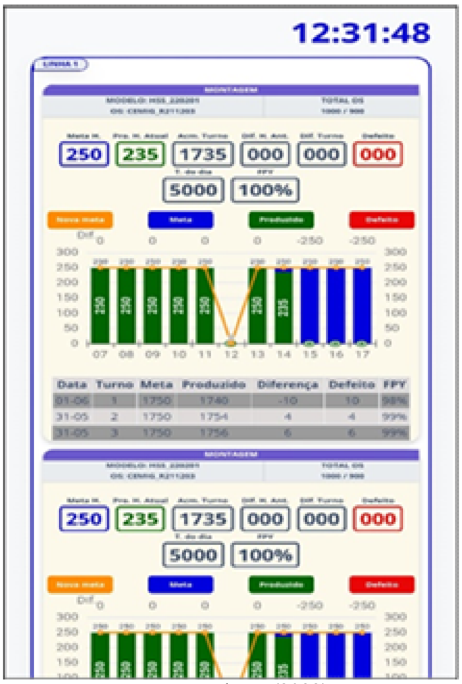
Figure 7. Documentation model in POSTMAN

Several tests were performed in order to ascertain the quality of the system's back-end, among the tests it was possible to analyze flaws and improvements in the Dashboard, among them are: calculation of FPY, counting of approved meters and inclusion of the indicator new goal (projection).After the identification of the flaws and improvements, the development team revalidated the requirements, and reimplemented some functions responsible for treating these data, the API for having this responsibility was the one that suffered the most modifications. Figure 8 shows the process of readapting the Dashboard and the functions with ANN to process the forecast data.Figure 9, shows the mockup of the mobile version of the Production Dashboard, the expectation is that all these data are of great use for managers and operators in the production line, the production control is an important tool for the factory. In the last month of software development, the final API of Production and Quality was consolidated with direct results in the Dashboard, business rules with process restrictions and data processing (inclusion of date filters and real time monitoring) as shown in Figure 10.



Source: Authors, (2022).

Figure 8 - Modified Dashboard



Source: Authors, (2022).

Figure 9. Mockup of the mobile version of the Production Dashboard

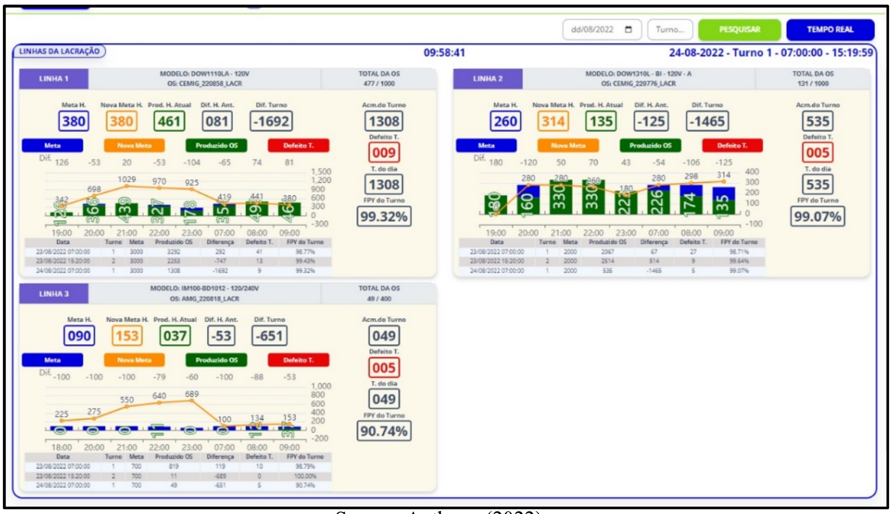
The processes performed in the system interfaces are of paramount importance to feed the digital twin, through computational techniques it is possible to treat, recognize and predict industrial events, this month the technical requirements of database and customer needs were analyzed for acquisition of intelligent mechanisms, among these mechanisms was guided the use of dashboards with indicators of production and quality.

With the processing of these indicators via API it was possible to investigate processes with Artificial Neural Networks, this procedure will be analyzed in the next topics. The development of the AI module was carried out through the research of computational techniques for testing and validating the queries in the database to adapt a specific dataset for the Dashboard demand, in which it is possible to predict:

- Lots approved as a function of the forecast time;
- Failed batches as a function of the forecast time;
- Approved meters as a function of the forecast time;
- Failed meters according to the forecasting time;

Both possibilities enable the correlation of data with batches quantity, meters quantity and forecast date, filtered by Work Order and period previously specified in the Dashboard.The rna class uses tensorflow as a library that provides part of the computational functions for data processing and algorithms of the biological model, that is, the bio-inspired behaviour of a neural network, from this, the resulting class calls methods from the library, the rna class of the research presents this characteristic and implements other resources that aggregate the business rule of what is being applied, it was configured as follows:

Initialization method with 1000 epochs, an activation layer is added with the function relu, it is a function inspired by the biological model of neuron, the same has the possibility of returning a positive or negative value, in convolutional or recurrent neural networks this function gets satisfactory results in the activation of artificial neurons. The code snippet presents (Figure 11) the signature of the constructor method that also configures the error indicators "mse (Mean Squared Error) ", "mae (Mean Absolute Error)", "mape (Mean Percentage Absolute Error)", "msle (Mean Squared Logarithm Error)" and "accuracy (Accuracy)". The other methods are for data change, network training, prediction, date prediction and performance. This class plays the role of intermediary of the computation process, through the API function, requests are made via POST in which it instantiates this class. AnexampleisshowninFigure 12. A Deep Neural Network (DNN) was used, this model deals well with limitations of matrix factoring, in this model it is possible to apply item features and query features, this facilitates to improve the user experience with pattern based recommendations.As shown above, two layers were used, the first uses an LSTM with 150 neurons and the activation function ReLU, it is a neural network with long short-term memory, widely used in DNN deep neural network applications, this model has feedforward connections, the second uses a densely connected layer with one neuron and no activation function.The tests are still being evaluated, the best model with the best accuracy to be applied in production, however, a test with 200 epochs was performed with a database containing the following fields: month, batch and meters, as presented in Table 7 a summary of the base. Upon this test, the train generator structure was used to plot the temporal results as a function of month and date, Figure 13 shows the behaviour of the prediction.



Source: Authors, (2022).

Figure 10. Dashboard final version

```
def __init__(self, look_back=3, num_epochs=1000, batch_size=20):
self.model = Sequential() self.model.add(
LSTM(150,
            activation='relu', input_shape=(look_back, 1))
      )
self.model.add(Dense(1)) self.model.compile(loss="mse",
optimizer="adam", metrics=["mse", "mae", "mape", "msle", "accuracy"])
self.num_epochs = num_epochs
self.look_back = look_back
self.batch_size = batch_size
```

Source: Authors, (2022).

Figure 11. Constructor method signature

```
from datetime import datetime
reset = data.get('reset',False)
api = cache.get('sime_rna_run')
if api != None and data.get('end'):
   end = data.get('end')
   check = (end.strftime("%Y-%m") >api['mes_predict'][-1].strftime("%Y-%m")) if len(api['mes_predict']) > 0 else True
   if end.strftime("%Y-%m") >api['mes'][-1].strftime("%Y-%m") and check:
      reset = True
if api != None and data.get('init'):
init = data.get('init')
   check = (init.strftime("%Y-%m") >api['mes_predict'][-1].strftime("%Y-%m")) if len(api['mes_predict']) > 0 else True
   if init.strftime("%Y-%m") >api['mes'][-1].strftime("%Y-%m") and check:
      reset = True
if api == None or reset:
api = Api.get('sime_rna_db').run()
   predict = (data.get('end').year - api['mes'][-1].year) * 12 + data.get('end').month - api['mes'][-1].month if data.get('end') else 0
   if predict <= 0:
      predict = (data.get('init').year - api['mes'][-1].year) * 12 + data.get('init').month - api['mes'][-1].month if data.get('init') else 0
api.update({
      'predict': predict if predict > 0 else 0,
'mes_predict': [],
      'lote_predict': [],
      'medidores_predict': [],
'lote_look_back': data.get('lote_look_back'),
      'medidores_look_back': data.get('medidores_look_back'),
      'lote_epochs': data.get('lote_epochs'),
'medidores_epochs': data.get('medidores_epochs'),
'lote_batch_size': data.get('lote_batch_size'),
      'medidores_batch_size': data.get('medidores_batch_size'),
'lote_perf': None,
      'medidores_perf': None,
   })
ifapi['predict'] != 0:
from sime.helper.rna import RNA
rna = RNA(look_back=data.get('lote_look_back'), num_epochs=data.get('lote_epochs'), batch_size=data.get('lote_batch_size'))
rna.setData(api['mes'], api['lote'])
rna.train()
api['lote_predict'] = rna.predict(api['predict'], int)
api['lote_perf'] = rna.perf()
rna = RNA(look_back=data.get('medidores_look_back'), num_epochs=data.get('medidores_epochs'), batch_size=data.get('medidores_batch_size'))
rna.setData(api['mes'], api['medidores'])
rna.train()
api['medidores_predict'] = rna.predict(api['predict'], int)
api['medidores_perf'] = rna.perf()
for i in range(len(api['medidores_predict'])):
lote = api['lote_predict'][i]
         medidores = api['medidores_predict'][i]
api['medidores_perf'] = rna.perf()
for i in range(len(api['medidores_predict'])):
lote = api['lote_predict'][i]
         medidores = api['medidores_predict'][i]
max_medidores = int(lote * 1000)
if medidores >max_medidores:
api['medidores_predict'][i] = max_medidores
api['mes_predict'] = rna.predict_dates(api['predict'])
cache.set('sime_rna_run', api, 345600)
if len(api['mes']) > 0 and (data.get('init') or data.get('end')):
init = data.get('init').strftime("%Y-%m") if data.get('init') else ''
   end = data.get('end').strftime("%Y-%m") if data.get('end') else ''
   for i in range(len(api['mes']),0,-1):
mes = api['mes'][i-1].strftime("%Y-%m")
      check = mes<init and init != ''
check2 = mes> end and end != ''
      if check or check2:
api['mes'].pop(i-1)
api['lote'].pop(i-1)
api['medidores'].pop(i-1)
for i in range(len(api['mes_predict']),0,-1):
mes = api['mes_predict'][i-1].strftime("%Y-%m")
      check = mes<init and init != ''
check2 = mes> end and end != ''
      if check or check2:
api['mes_predict'].pop(i-1)
api['lote_predict'].pop(i-1)
api['medidores_predict'].pop(i-1)
result = api
result.update({
   'init': data.get('init').strftime("%Y-%m") if data.get('init') else '',
   'end': data.get('end').strftime("%Y-%m") if data.get('end') else '',
```

Source: Authors, (2022).

Figure 12. Network training, prediction, date prediction and performance - API

Table 1. Process maturity stage identification

MaturityStage 4.0 (ACATECH)	**Classification: Identification of the initial stage**	**YES**	**NO**
1	Is there a digital record of the process or sub-process?		
	Supporting questions: Does your company use computers for any function in the production or transformation process, such as: (a) notes and tracks production data / parameters? b) Record and track production data (quantity, volume, etc.)? c) Notes and tracks production quality data? d) Record and track input material data? e) Record and track any pertinent data related to machine maintenance? f) Record and follow-up on any data related to the relationship between employees and the operation executed? g) Record and follow-up data on the distribution and sale of products?		
2	Digital information is automatically transmitted throughout the process?		
	Supporting questions: (a) Can the data noted on a particular computer allocated in production be observed on any other computer in the company? b) Can the data / operating parameters of the machines and the process noted on any computer, be observed on any other computer at another location in the plant? c) Can data from any point in the transformation/production process noted on any computer be monitored on any other computer in the transformation process, either at the front or back of the production line?		
3	Is there an interface (connection) of the process or sub-process with any process or sub-process management system in real time in which it is possible to monitor any key performance indicator?		
	a) Is the data recorded and stored in any computer of the production line and/or transformation process used elsewhere for any type of decision-making? b) Can the data / parameters of machine operation and of the transformation process noted in any computer be used in any other computer and by any computer program in another location of the factory for some decision making? Example: machine maintenance, time to buy more raw material, time to reduce the production speed, etc.? c) Are the data/parameters of machine operation and of the transformation process noted in a computer transformed into graphs for production follow-up? d) Is there any type of real-time sensor monitoring of the process? e) Can you observe the phenomena of the transformation process through sensors?		
4	Is the process or sub-process and its control, monitoring and action system capable of generating some type of cause and effect relationship of the variables involved with the quality and productivity of the product or goods/services being produced?		
	Supporting questions; a) Does your system / subsystem of your transformation process check or inspect the output quality of each sub-process? b) Is the evolution and trend of the quality level of each sub-process output monitored and controlled? c) Can you by sensing observe the phenomena and evaluate the quality of the output of the transformation process? d) The system / subsystem of the transformation process by the existing sensing can relate the quality of the output of the process with the variables of the transformation process or sub-process? e) Is the sensing system able to interpret and translate the data of the process or sub-process in some information for decision making?		

Continue

5	Are cause and effect relationships used to generate or simulate future scenarios in real time?		
	Supporting questions: (a) Is the data from the quality inspection process of the output of your sub-process interpreted by any computer program? b) Is the process data of speed monitoring of the output of the sub-process interpreted by any computer program? c) Are the input and output data of the process or subprocess crossed and analyzed by a computer program? d) Based on the input and output data, is the control system of the process / subprocess capable of relating the defects to their causes? e) Based on the input and output data, the process or sub-process control system is capable of informing the operator how to proceed, that is, which parameters must be altered so that the output returns to the predefined quality levels?		
6	Is the process or sub-process and its control, monitoring and action system capable of correcting or optimising the production process according to the simulated scenarios?		
	a) Based on the input and output data, is the process or sub-process control system capable of relating the defects to their causes and is it capable of acting on the equipment controls of the transformation process or sub-process, correcting the output quality of the process/sub-process autonomously? b) Based on the input and output data, is the process or sub-process control system capable of relating the defects to their causes and is it capable of acting on the controls of the equipment of the transformation process/sub-process by autonomously correcting the output speed of the process/sub-process? c) Based on the input and output data, the control system of the process or sub-process is capable of relating the defects to their causes and is capable of acting on the controls of the equipment of the transformation process or sub-process, correcting the process input variables/parameters autonomously? d) The process or sub-process is capable of operating without any operator, and correcting in real time all oscillations of the production?		
Iftheanswerto:			
a) 1 is YES and for 2 is NO: initial maturity stage is 1;			
b) 1 and 2 are YES and 3 is NO: early maturity stage is 2;			
c) 1, 2 and 3 are YES and 4 is NO: early maturity stage is 3;			
d) 1, 2, 3 and 4 are YES and 5 is NO: initial maturity stage is 4;			
e) 1, 2, 3, 4 and 5 are YES and 6 is NO: early maturity stage is 5; and			
f) 1, 2, 3, 4, 5 and 6 are YES: initial maturity stage is 6.			

Source: (SUFRAMA, 2018).

Table 2. Tools for IS development

Tool	**Concept**	**Researchapplication**
Proteus VSM	Software that allows the creation of circuits, simulate and elaborate layouts of analog and digital applications, including microcontrollers.	It will be applied to the development of boards and electronic connections.
Solid Works	Software for the creation of three-dimensional virtual mechanical prototypes. It is also possible to simulate the operation of parts, assemblies, movements, among others.	In the research, the software will be used to model mechanical parts and devices. From three-dimensional prototypes, 2D drawings will be generated and forwarded for machining process.
PMBOK Guide	It is a set of practices in project management organized by the PMI institute and is considered the knowledge base on project management by professionals in the area.	It will be used to manage the project from the initial stage to closure.
Visual Studio Code	Source code editor developed by Microsoft for Windows, Linux and macOS. It includes debugging support, built-in Git versioning control, syntax highlighting, smart code completion.	Developmentenvironment
MySQL Workbench	Client for SQL queries execution, system administration and database modeller, creator and maintainer through an integrated environment.	Development environment for queries, data structures and logical models.
AstahComunity	Class Diagrammer, Use Cases, Sequence, Communication, State Machine, Activity, Components, Deployment and Composite Structure Diagram. Used in Software Engineering.	Diagrammer of Class projects and Requirements diagrams.
Draw io	Online graphic editor in which it is possible to develop drawings, graphics and others without the need to use expensive and heavy software. It provides resources for creating any type of design and has a part dedicated to information architecture.	Diagrammer of architectural designs and flowcharts.
Trello	Collaboration tool that organises projects into boards. At a glance, Trello tells you what is being worked on, who is working on what, and where something is in a process.	Activity Manager
Github Desktop	Application that allows you to interact with GitHub using a GUI instead of the command line or a web browser, with it you can upload, extract and clone remote repositories.	CodeVerifier
Prototipador UX - Jutinmind	Justinmind is a prototyping tool for websites, software applications and mobile apps that can work with Windows and Mac, or iOS and Android. There is a free version that you can work with very well.	Interface Design Prototyper
Barcode scanner for meter tracking	Industrial scanner for 1D, 2D barcode reading from 15cm to 15m	It will be necessary to track the item by station and identify through data where the product is, if it was rejected or not, in addition to adding to the body of the block the information of the stage completed according to the layout of the line.

Source: Authors, (2022).

Table 3. Technologies for IS development

Technology	Concept	Researchapplication
C language	It is a general purpose, structured, imperative, procedural, compiled programming language.	In this research, it will be used for the development of the firmware and system module.
Internet ofThings	It refers to the integration of physical and virtual objects in networks connected to the internet, allowing objects to collect, exchange and store data that will be processed and analysed, generating large-scale information and services.	The implementation of the internet of things in this project, is to collect data in real time, sensor status data, productivity, alerts, errors. Situations that occur in the equipment will be informed to the operator through a monitor.
Framework Laravel	Free and open source PHP framework used in the development of web systems. Some of its main features are to allow writing simpler and more readable code, and support for advanced features that speed up the development process	Applied to the Back-end and Communication Modules via API.
PHP	Free interpreted language, originally used only for the development of server-side applications capable of generating dynamic content on the World Wide Web.	Applied to Back-End
Bootstrap	Open source web framework for developing front-end and interface components for websites and web applications using HTML, CSS and JavaScript, based on design templates for typography, enhancing the user experience in a friendly and responsive website	Applied toFront-End
CSS	Mechanism to style code created by languages such as HTML, XML or XHTML, for example. In practical terms, it works as a layer of personalization to the visible content	Applied toFront-End
Javascript	Structured, high-level scripting interpreted programming language with weak dynamic typing and multi-paradigm. Along with HTML and CSS, JavaScript is one of the three core technologies of the World Wide Web.	Applied toFront-End
Blade	Laravel framework's template engine that enables code reuse and simplifies the insertion of PHP snippets into HTML pages with a cleaner syntax	Applied toFront-End
MySQL	Open source relational database management system used in most free applications to manage their databases	Applied toBack-End
Git	distributed version control system, used mainly in software development, but can be used to record the history of edits to any type of file	Applied andstacks

Source: Authors, (2022).

Upon this test, the train_generator structure was used to plot the temporal results as a function of month and date, Figure 14 shows the behavior of the prediction: Among the challenges, it is possible to point out the application of the neural network for the reality of the company, because of not having worked with this type of technology before, the adaptation of scientific graphs was a challenge, so the development of the Dashboard with simpler graphs containing results provided by the ANN became the solution, the model is executed in a way not to overload the server, saving data in cache. As a result, a neural network was applied to predict the indicator of approved batch, approved meters, predicted batches and predicted meters for a future demand. A graph of Figure15 was developed to perform the measurements and tests, later this graph will serve as a basis as well as the source code to adapt other applications in the research. The use of these computational models enables the use of digital twins, besides validating mathematical mechanisms for predicting industrial events and consolidates the increase of the maturity stage to a level 4, where the company can understand the processes, errors and events before they happen. The company has exhaustive processes regarding meter tests, so the importance of each stage becomes greater, the reality is to optimize the corrective maintenance and increase the preventive maintenance, where the system alerts and points out these scenarios based on data. The final documentation that was delivered is relative to the information of technologies used in the system and software architecture, therefore, one of the initial premises of the research was to develop a system with access via API which characterizes the integration of systems and enables load balancing in data processing, since they are worked on different services. Because of this, a document was prepared with the technologies and flows of the life cycle of requests on the back-end and front-end, Figure 16 presents the main layers of access for acquisition of information and procedures performed at the communication level.

CONCLUSION

The software research was successful in what was proposed and especially with regard to information processing and generation of useful knowledge for company managers when using a system with decision making and real-time monitoring of production with production and quality indicators. The research concluded the objectives of mapping the requirements of the production process with research flowcharts and conceptual maps. Identify the parameters of the manufacturing process of the electronic meter that is the object of study of the intelligent system and with the application of computational intelligence techniques. It also meets the goal of identifying possible bottlenecks and performs optimizations based on data with reports refined in real time with graphs and indicators of production and quality using AI and BI in order to provide subsidies for process improvement and cost reduction. It presents a viable solution for the objective of developing communication models using API with normalisation and pre-processing of data in real time and guaranteed test quality through agile and automated tools of the mechanical devices in such a way as to transform and digitalise the process. It also meets the objective of developing an intelligent monitoring system with transformation of data into knowledge through a digital twin capable of feedback decision making processes with real-time data capture and processing devices with well-defined connectivity and security protocols. The research also enabled well-defined and validated requirements to ensure the quality of the functionalities implemented in the system that throughout the development period underwent changes due to customer requirements and process adaptations to suit the final need. The implementation of the system in the productive process made possible the scientific investigation of these computational processes, it was possible to identify several points of improvement and prospection of new software projects, considering that Industry 4.0 with its pillars is very rich in technologies which can be explored in an exploratory way in manufacturing environments with well diversified development teams. Finally, the company became eligible for evaluation for maturity stage 4 of the Ordinance 2.091 that establishes the principles and characteristics of the manufacturing process 4.0.

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