A digital twin model of a pasteurization system for food beverages: tools and architecture

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***Abstract*—Many enabling technologies of Industry 4.0 (Internet of Things "IoT", Cloud systems, Big Data Analytics) contribute to the creation of what is the Digital Twin or virtual twin of a physical process, that is a mathematical model capable of describing the process, product or service in a precise way in order to carry out analyses and apply strategies. Digital Twin models integrate artificial intelligence, machine learning and analytics software with the data collected from the production plants to create digital simulation models that update when the parameters of the production processes or the working conditions change. This is a self-learning mechanism, which makes use of data collected from various sources (sensors that transmit operating conditions; experts, such as engineers with deep knowledge of the industrial domain; other similar machines or fleets of similar machines) and integrates also historical data relating to the past use of the machine. Starting from the virtual twin vision, simulation plays a key role within the Industry 4.0 transformation. Creating a virtual prototype has become necessary and strategic to raise the safety levels of the operators engaged in the maintenance phases, but above all the integration of the digital model with the IoT has become particularly effective, as the advent of software platforms offers the possibility of integrating real-time data with all the digital information that a company owns on a given process, ensuring the realization of the Digital Twin. In this context, this work aims at developing optimized solutions for application in a beverage pasteurization system using the Digital Twin approach, capable of creating a virtual modelling of the process and preventing high-risk events for operators.**

Keywords— *Digital Twin, Food equipment, Safety, Industry 4.0.*

I. Introduction

In the recent years, the concepts of Industry 4.0 and smart factories have increasingly gained importance in various industry fields. The addressed technologies behind the Industry 4.0 concept offer new market opportunities regarding products and services. These technologies comprise several elements, such as, among others, knowledge management, big data analysis, cyber-security, cyber-physical systems, robotics, computer vision, human-computer interaction, simulation [1]. Driven by the Industry 4.0 vision and the development of big data analytics, faster algorithms, increased computation power, and amount of available data allow for the simulation of real-time control and optimization of products and production lines. The digital representation of the physical twin, which is also known as the digital twin (DT) is one of the crucial aspects of the fourth industrial revolution and is expected to enable the accurate prediction of the future system performance and help in maintaining the process quality effectively by allowing easy visualization and incorporation of cognitive capability in the real system [2]. Achieving this result will be feasible thanks, on the one hand, to the considerable decrease in the calculation time, which has gone from hours to minutes, and, on the other one, to the increased use of sensors and on-line measuring equipment, which enables the usage of simulation models with real context data as input [3], [4].

According to the architecture of DT proposed by Grieves[5], a process model could be represented in several dimensions and could be structured in three different ways:

(i) A digital model, in this case the model is totally disconnected from the physical layer and provide the result of the output parameters at the variation of the input one (e.g. the geometry of the physical plant, or the material property could be modified). This allows the model to be used for similar plants, or for research purposes;

(ii) A digital shadow, well explained by Müller et al. [6], which can be obtained by connecting the input signal sent by the IoT sensor to the digital layer using a dedicated module. A dedicated software processes the data received and stores data in a local database;

(iii) A DT *tout court*: in this case a dedicated module is connected in both ways to the physical plant. The hardware acquires analogic/digital input from the transmitters, the software processes the signal and generates a digital output sent to the PLC in order to control the plant.

DT goes beyond the mere representation of the physical system, as its ultimate aim would be to mimic the behavior of the system and its relationships with operators, components and environment. According to Qi et al. [7], DT models can be classified into three levels (in ranking order), called unit-level, system-level, and system of system (SoS)-level. The unit-level DT is the smallest unit participating in a manufacturing process (e.g. an equipment). The system-level DT reflects the integration of multiple unit-level DTs, connected with each other. The traditional definition of DTs., i.e. physical entities, virtual models and the connections among them, applies to both unit-level and system-level DTs. Multiple unit-level DTs or multiple system-level DTs form the SoS-level DT, which from a practical point of view reflects a complex system. The optimization of any manufacturing process starts obviously from the adjustment of the equipment, and thus from the unit-level DT. For these DTs, the virtual model is typically a very faithful mapping of the physical equipment coupled with its digital description, ranging from the geometric shape, to the function and operating status of equipment [8]. The key attributes of the equipment are transferred to the virtual (simulation) model, for prediction purpose; based on that prediction, the results of the virtual model are used to optimize the functioning of the

2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)

978-1-7281-7037-4/20/$31.00 ©2020 IEEE

real system [7]. The usage of DTs in the manufacturing industry, leading to the so called "smart manufacturing" industry, is gaining increasing importance. Typically, the main purpose is to leverage the DT model for optimizing the operational procedures of manufacturing, reaching higher level of productivity [2], [7], [8]. Besides this main aim, DT solutions in industry have recently been developed for additional purposes, including reduction of failure rates [9], shorten development cycles [10], and more in general introduction of new business opportunities, such as service optimization [7], [8]. Instead, to date the development of DT models for different purposes, and in particular for safety improvement or maintenance management, is still limited. Nonetheless, these are promising areas for research: compared to traditional approaches, DT models make it possible to apply predictive policies in plant management and maintenance, and allows for a "reactive" approach, on the basis of the data received from the sensors installed on the asset [11]. Developing a DT model to help employees' activities is strategic to increase the safety level of the operators; this is particularly the case for process plants or high risk activities. In line with these considerations, the context in which the present study has been carried out is a research project funded by INAIL (the Italian association for insurance at work); the general aim of the project is to develop solutions for industrial plants using the DT technology, with the purpose of creating a virtual process which will help prevent risk events for the operators. The whole project will cover a two-year time span, from April 2019 to April 2021. This paper describes the first phases of the project, and is organized as follows: the next section details the context of the study, i.e. the food industry, and the usage of DT models in this industry field; then, section III details the architecture of the DT model tailored for this context, while section III A and III B outlines the implementation and testing phase and discusses the main results expected from this stages. Conclusions, limitations and future research directions are proposed in Section IV.

II. DIGITAL TWIN IN THE FOOD INDUSTRY

As far as the application of DT models in the food industry is concerned, some studies have been recently published about their usage in this sector. A study of Wageningen university has identified the current trends in the development of industry 4.0 technologies in the Agrifood sector [12]. As regards to DT the authors ask themselves: "Can virtual models or digital twins, and Big Data replace field experimentation?" and "How do digital twins foster learning and experimentation with new sorts of human- technology-natural environment interactions?". Actually, no answers can be provided to these questions, being the development of the technology relatively young, with not so many real case implementations.

Some applications of DT models in the food sector concern the case of ice cream machines [13]. In this context, a 3D visual representation of the process can be obtained by means of a list of sensors which transfer data to the digital model. This visual representation is available by using VR and AR tools, which can show the evolution of the ice cream production process. The aim of this DT model is to show the evolution of the process in each part of the ice cream machine, without the need for stopping the process or opening the system for physically checking its status. The authors state that many applications in "e-gastronomy" could be further developed in the near future, taking always into account IoT security solutions and advanced artificial intelligence and machine learning algorithms.

Another international research group has developed DT solutions in the field of refrigerated transports and storage [14]. In the case of mango fruit the authors developed a digital systems able to assess and predict the evolution of the temperature inside the fruit in refrigerated situation. This will optimize both the transportation and storage phases, by reducing the environmental issues related to these processes and the quantity of wasted fruit. In addition, the quality of the fruit delivered will increase, thus enhancing the profit of the food industry. As far as the DT model is concerned, in this case a three-dimensional geometric model of the mango fruit was generated and used as input for the computational model. Then, a continuum multi-physics (mass and thermal) model was developed to calculate the heat transport inside this composite fruit and its convective exchange with the environment throughout the cold chain. Finally, to predict the evolution of multiple quality attributes of the mango fruit throughout the cold chain, kinetic rate law models were implemented and implemented in Comsol Multiphysics release 5.3. Several experiments (using physical temperature sensors) were performed to validate the model and to understand the influence of the air around the mango in several conditions (maritime vs. air freight transport). In conclusion, the authors state that in the future, the DT model should also work in real-time, driven by real-time temperature data.

In line with this article, another study of the Swiss authors of the previous research group [15] aimed at developing the mathematical models then used in the previous research. Based on the description of the model, anytime a DT system will be developed, a complex analysis of the boundary conditions and the dynamics of the time temperature evolution should be performed.

All the papers reviewed in this section highlighted that as a development of a DT system requires a plentiful information flow from the real field and a high level of precision and accuracy of the probes and models used. Based on these evidences, the model proposed in this study will consider all the suggestions gathered from the previous authors.

III. DIGITAL TWIN MODEL AND APPLICATION CONTEXT: THE CASE OF A PASTEURIZATION SYSTEM

The DT under development is a parallel environment, which directly mimics the behaviour of the process in the real world. Indeed, the aim of this work is to design, implement and test a model which allows to monitor and control the operations of each machine in various industrial plants by using a software platform that able to simulate the process and compare it with the real scenario in order to prevent future scenarios of high-risk processes for the operators.

To evaluate the platform potential and identify possible implementation issues, the functionality of the DT has been designed to be applied to a pilot plant. The plant is a highly flexible continuous flow system for the cold sterilization treatment of liquid foods. It consists of:

- A Pulsed Electric Field (PEF) machine which operates a PEF treatment on the liquid food. PEF it is a cold cleaning technology mainly used for high-protein products. Its application is intended for the sterilization of homogeneous liquid foods by the application of short pulses at high voltage, causing the rupture of the membranes of the microbial cells(electroporation), with a minimum increase in the temperature. The machine consists of a titanium co-linear with ceramic insulator treatment chambers, electrically connected to a Marx generator of impulses of electric field of high intensity, with voltage from 10 to 25 kV applied with a pulse repetition in continuous mode from 10 to 200 Hz. It also hosts a series of tools for measuring and recording the flow, the conductivity and temperature of the product, before and after the treatment.

- A pre-heating system that allows the control of the food temperature before it enters the treatment chamber. The pre-warming is obtained through a multiple pipes pasteurization, able of processing viscous liquids containing particles with size up to 10 mm. The machine increases the liquid food temperature by means of a tube-in-tube heat exchanger and can process up to 2500 l/h of product. The machine is equipped with an electromagnetic flowmeter, a differential pressure transducer and a resistance temperature detector.

- An electric heat steam generator operates with a direct exchange and provides the heat steam up to 11.77 bar. The temperature and pressure of the water processed, and the steam, can be controlled on four levels of regulations, by acting on each resistance of the machine (25 kW). The steam generator is also equipped with a level probe.

In addition to the machines, the auxiliary systems supply the electricity, the water at 1.5 bar and the air compressed at 6 bar to each machine.

The process under examination is the pre-heating of food products which involves a pasteurization treatment for a liquid food at the nominal conditions of 75°C and a pressure in the range of 0.1-2 bar, the viscosity of the liquid between 0.1 to 10 Pa*s. The aim is to analyse the state of the system in the real condition and to compare it with the nominal/simulated one, acting on the controllable parameters.

The parameters that define the machine status are the flow of the processed fluid, the pressure and the temperature at the inlet and at the outlet of the multi-tube counter flow heat exchanger. The temperature and the pressure parameters are controlled by dedicated sensors (Table I).

Table I. IoT Sensors

Sensor Model	Description	ID
MUT2400EL	Electromagnetic flowmeter	FE01
PT100	Resistance Temperature Detector (RTD)	TT01
PT100	Resistance Temperature Detector (RTD)	TT02
S-11	Flush pressure transmitter	PT01
S-11	Flush pressure transmitter	PT02

The intelligent system must be able to read the data from each sensor, process the received signals, send alerts and operating instructions to improve the operator's safety, learn from the instructions performed and act directly on the components involved in order to allow/deny certain functions/movements.

The DT environment consists of three main parts: a plant simulation tool for the pilot line, a tool for the anomaly prediction, and a cloud server. The simulation tools can operate online, working together with the anomaly prediction tool as a DT, or off-line acting as a simulation tool in a virtual environment. During the online activity, thanks to the data acquisition module, the DT system creates a database, hosted on a local server, on which the data retrieved from the physical system are stored. These data are used as input variables for the comparison with the simulation model to allow a real-time evaluation of the plant status. Each variation in the controlled parameters corresponds to an analogous variation in the simulation system. The anomaly prediction tool analyses the status of the line in real-time and adjusts the parameters controlled, acting directly on the physical plant, by means of a feedback control mechanism. The database of each measure provided by the sensors is connected to a server on the cloud (fig.1).

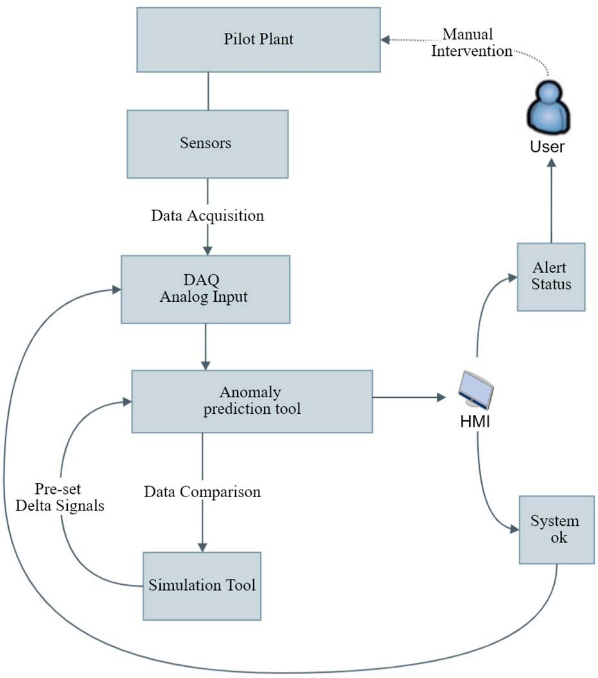

Fig. 1. Architecture of the Digital Twin system.

The development of the DT model requires:

1. *The identification of each component* of the physical system, which allows matching the physical layer and the digital one;
2. *A communication protocol* that fits with the technical properties of each component. It could vary depending on the component (e.g. EPC or UPC or IPv6);
3. *A peer-to-peer network* that allows to share and collect the data stored in the simulation database, with the server on the cloud;
4. *A simulation software* for modelling the real plant. For the case under evaluation, LabVIEW was chosen as the tool to develop the digital model of the plant. The model itself complies with the physical layer and performs the digital simulation. The variation in the controlled parameters of the real plant corresponds to the variation in the digital environment;

5. *A tool of risk prediction*: based on the risk assessment, the model can predict anomalies, by comparing the real data with those obtained by the simulation software and communicate with the server in order to generate a warning;

6. *The cloud server platform*, which is the central architecture of the whole system. This module can communicate with the HMI and the user's devices, by displaying warning alerts and operational procedures useful to restore the anomalies detected on the real plant.

As far as the operating structure is concerned, the system consists of three different levels. As for the DT, this is composed of a digital model uploaded on the simulation tool, and of a communication system which in turn consists in the DAQ module, the anomaly prediction tool and the data storage on cloud. The cloud based platform should be able to query the local server and compare the database filled by the difference of data coming by the simulation tool with those coming from the plant and compare it with pre-set delta signals, which are assumed to depict the normal range of functioning of the system. Once an anomaly is detected (e.g. the real delta signal is higher than the pre-set range), the system will give an alert to the operators and could act for adjusting the controlled parameters *via* PLC; instead, if the problem has been manually solved by the employee, the system will save the new data and update of the pre-set delta signals. Examples of delta signals could be the difference between the pressure or temperature sensors placed at the beginning and at the end of the pre-warming module. As shown later, for each fluid and flow parameters, the system will simulate the pressure drop from the end of the pre-warming to the point at the beginning of the heating module (just after the pump and the flowmeter). If the real pressure drop value obtained from the sensors exceeds the simulated value, an anomaly could occur in the system; for example, some pieces of fruits could be blocked inside one of the tubes of the plant. The same behaviour could be observed using the temperatures sensors: in this case, if the steam generator experiences a failure, the temperature of the water flowing in the external part of the "tube-in-tube" system could be lowered and the fluid could not reach the final expected temperature. Obviously some deviations between the simulated model and the real data are allowed, and this is why a pre-set delta signal is embodied in the anomaly detection tool. All the data recorded are then available for further statistical evaluations.

Besides detecting possible anomalies, the server can also store data about the manual actions carried out by the user during his/her intervention on the real plant. More precisely, restoring actions performed by the user will be saved in the cloud database and used to update the pre-set delta signals, saved on the cloud platform accordingly.

Overall, the system should be able to monitor and control each machine of the pilot plant and generate an alert on the user screen, so as to allow implementing the corrections required for each anomaly. The result is therefore an intelligent environment or system description, that can be used to detect potential risks within the system and undertake corrective actions before the problem is encountered in the real world.

A. The simulation tools system validation

The digital model of the pasteurization system follows the 3D structure proposed by Grieves [5], i.e.: (i) a physical layer constituted by the pilot plant; (ii) a digital layer constituted by the simulation software; and (iii) a linkage for data acquisition and sharing, built with a dedicated hardware architecture between the two layers. The parameters that define the machine status are the flow of the fluid processed, its pressure and the temperature at the inlet and outlet of the multi-tube counter-flow heat exchanger.

For evaluating the consistency of the solution developed, a validation of the digital model of the pre-heating system has been carried out. To this end, the LabVIEW code processes three input parameters that can be varied singularly or simultaneously. By acting on each parameter a different result in terms of temperature and pressure at the outlet or inlet of the pre-heating system can be observed (fig. 2). The front panel shows the user interface in which the machine status and the alert for the output parameters can be read. The flow model is based on the non-Newtonian fluid laws. The rheological properties of the fluid were assumed as constant during each process. The output parameters are evaluated taking into account the real geometry of the heat exchanger, the material properties and the pressure drop.

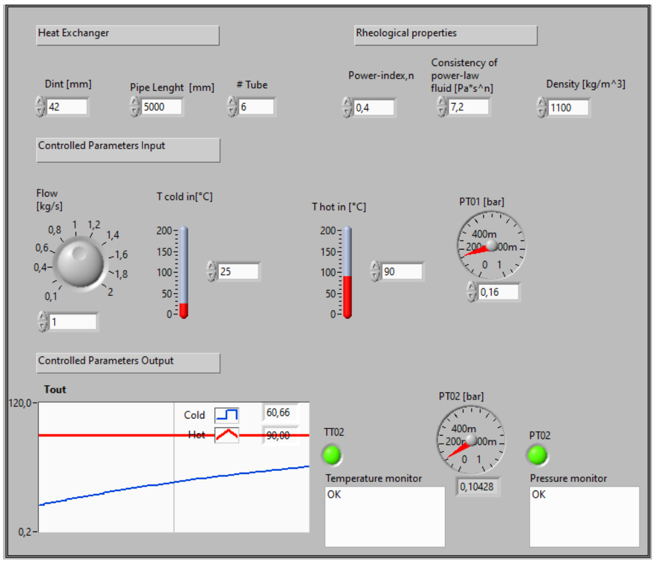

Fig. 2. Front panel of the simulation tool

In order to evaluate the system responsiveness, we ran the simulation model by varying the flow parameter, simulating two different types of liquid foods, with different rheological properties (Table II). *K* in Table II refers to the consistency coefficient of the non-Newtonian fluid, and *n* is the flow behaviour index [16].

Table II: rheological properties of the two considered fluids

Fluid food	*n* [dimensionless]	*K* [Pa s]
Apple juice	0.4	20.2
Apricot juice	0.4	7.2

For the evaluation of the inlet pressure value (P_{in}), we set the pressure at the outlet at the targeted value of 0.1 bar, while the flow can vary from 0.1 kg/s up to 2 kg/s (step 0.5 kg/s). The temperature of the processed fluid at the inlet of the pre-warming system has been kept constant at 25°C. The outcomes describe therefore the system behaviour in the pre-warming phase, in terms of temperature distribution at the section of the heat exchanger, that can be read in the front panel, and monitors the machine status through the message boxes "Temperature monitor" and "Pressure monitor". Fig. 3 shows the variation of the pressure at the inlet section parameter for the flow values considered.

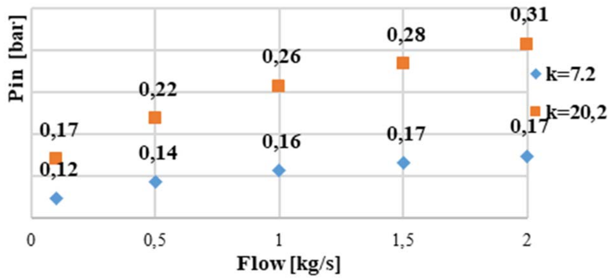

Fig. 3. Trend of the inlet pressure for two liquid foods as a function of the flow variation

B. *The anomaly predicion tool configuration*

As expected, the system provides the machine status for each case considered and shows a message box whenever temperature and pressure values are out of range; on the contrary, if the system works within the correct range of values, the screen message shown displays an "ok" status. Once connected to the real plant, to control the pressure, the system should generate an adequate signal output to act automatically on the plant or display on the screen the instruction for a manual intervention.

The simulation model stores the data collected in a ".tdm" file (Fig.4); these data can be compared with the real ones to return as a result some "delta signals" which can be further compared with pre-set delta signals stored on the server cloud via SQL queries. Hence, the model developed works as a DT by using an adequate hardware for connecting the digital environment to the physical layer. To this end, the LabVIEW Data Acquisition module for Analog Input (DAQ) can be used. We choose a NI-9208 module as DAQ hardware. The sensors are connected to the digital model through the DAQ module capable of reading the 4-20 mA, the analogic signal output of the pressure transmitter, and the 0-5V of the RTD. The hardware modules can operate in both ways, i.e. by acquiring the analogic signal and by generating an output signal that can be sent to the PLC of the plant to adjust the controlled parameter by intervening on the dedicated valves for the hot fluid flow regulation or control the motor-pump by adjusting the inverter frequency required for the fluid flow control. To adjust the setting of the real plant, the software processes the data acquired and generates the proper digital output, using the DAQ module implemented in the LabVIEW environment. This connection between the physical layer and the digital one allows for real-time monitoring of the machine status. The server triggers the database of the simulation tool every 5 seconds; if a deviation is observed, it generates an alert notification and a list of instructions that can be read by the employee on the HMI or on a smart device. Following these instructions, the user can reset the anomaly by physically intervening on the plant or setting the controlled parameters in order to reset the alarm. The anomaly prediction tool records the procedures adopted by the user for each anomaly, elaborates statistical data about the dysfunction causes and operates adjustments on the controlled parameters directly on the real plant.

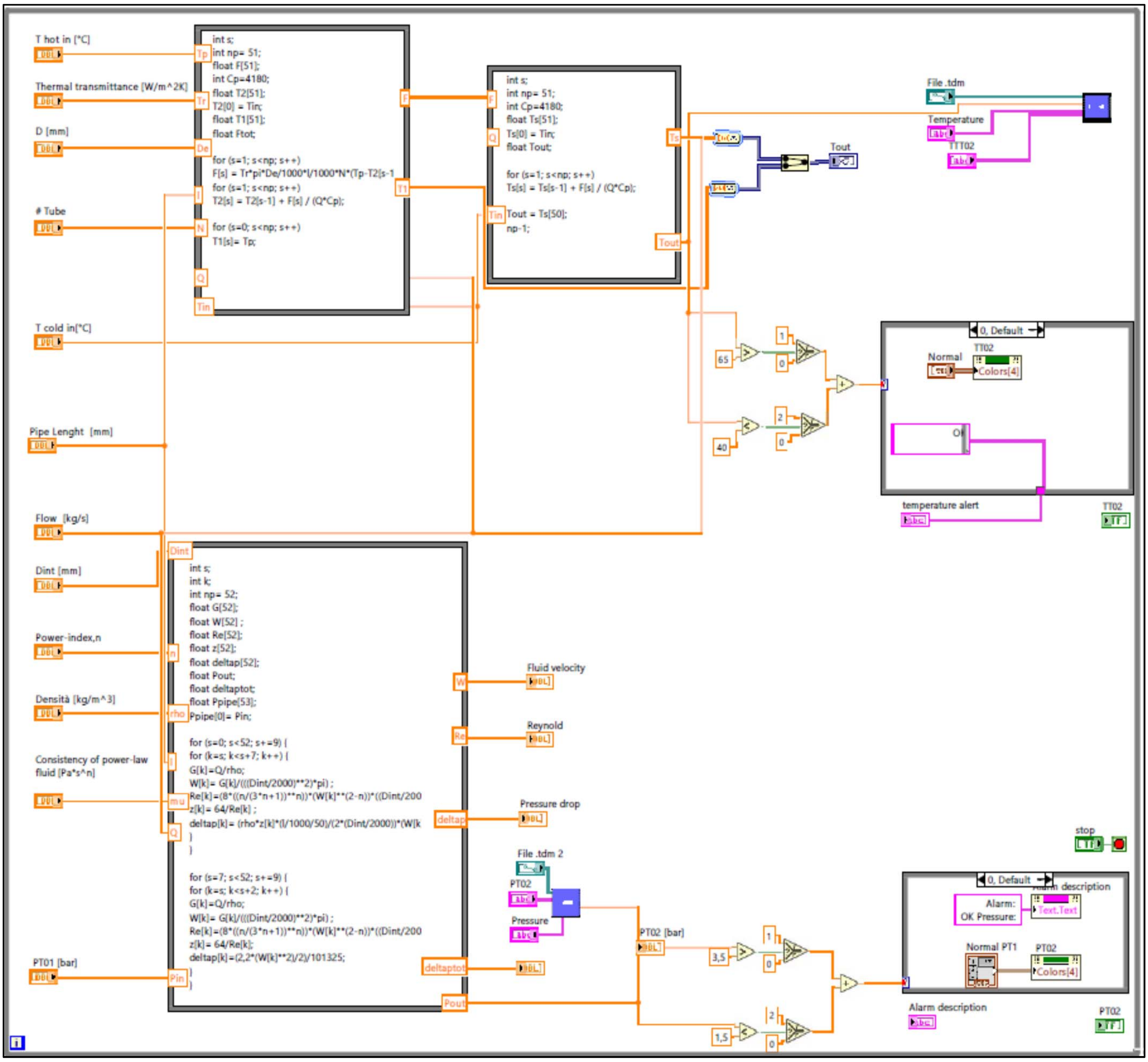

Fig. 4. Block diagram of the anomaly prediction tool in LabVIEW.

To enhance the safety of the operators, also an anomaly detection tool has been developed. The majority of the safety issues typically occurs during the pre-warming phase in which the main sensors check the status of the machine. The example below (Fig.5) simulates the data acquisition process on the real plant. To demonstrate the functionality of the tool, Triangle Signal has been used to simulate the signal for temperature acquisition during the pre-warming processes. The signal, acquired by the PT100 sensor, is firstly compared to a temperature threshold that can be set by the user, and triggers an alert in the message box when the current temperature exceeds the setpoint.

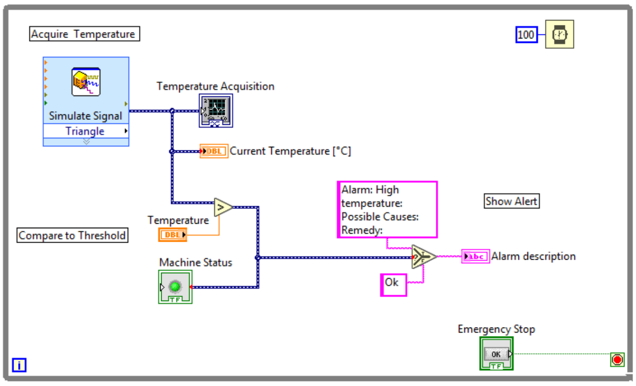

Fig.5. Block diagram of the anomaly detection tool in LabVIEW.

The message box provides the alarm description, the possible causes and a possible remedy to solve the alarm detected. The same structure can be applied when gathering data coming from the pressure and flowmeter sensors. In order to proceed with a statistical study of the data acquired, an additional fuctionality has been developed. The sensors of the real plant can be connected to the LabVIEW User Interface by using the DAQ module. The system below reported (Fig.6) is able to directly acquire the signals from the sensor and gather them in a unique file.

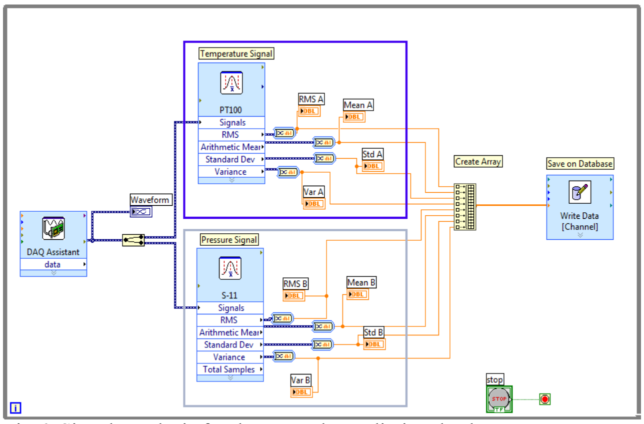

Fig.6. Signals analysis for the anomaly prediction database.

IV. CONCLUSION AND FUTURE RESEARCH

This paper has described the basic architecture of a DT model suitable to be used in a food plant and has discussed the main steps of its implementation in that context. The aim of this model is to predict possible anomalies in the plant functioning, thus preventing safety issues for the employees; this is obtained by comparing the result of a simulated model with the real signals coming from the plant.The development of the DT model is the first part of a research project funded by INAIL (the Italian association for insurance at work), whose general aim is to develop solutions for industrial plants using the DT technology, with the purpose of creating a virtual process which will help prevent risk events for the operators. At the state-of-art, the DT model has been implemented in LabVIEW and will be soon applied to the real plant.

Further developments, which form part of our ongoing research activities, will be required to test the DT performance after its implementation in the real plant. This step of the research will obviously need to access the real plant, set up the testing protocol and scenarios, and evaluate the effectiveness of the solution proposed in predicting the plant functioning. The DT functionalities will obviously be tuned on the basis of the results of the testing phase performed on the operating line. The present study highlights the potential of the DT system as a support for monitoring the plant functioning and enhancing the employee safety .

ACKNOWLEDGMENTS

This research was funded by INAIL (*Istituto Nazionale per l'Assicurazione Contro gli Infortuni sul Lavoro*), the Italian National Institute for Insurance against Accidents at Work, under the project "BRiC 2018" ID 12.

REFERENCES

[1] Tammaro, A., Segura, A., Moreno, A. and Sánchez, J. R. Extending Industrial Digital Twins with Optical Object Tracking. Proceedings of the Spanish Computer Graphics Conference (CEIG), 2017. Available at https://www.vicomtech.org/upload/download/publicaciones/0158687603002d6d596c97be0077d840.pdf

[2] Chhetri, S.R., Faezi, S., Al Faruque, M.A. Digital Twin of Manufacturing Systems. Center for Embedded and Cyber-Physical Systems, University of California, Irvine. Available at http://cecs.uci.edu/files/2018/03/cecs_tech.pdfWang, J.; Ye, L.; Gao, R.X.; Li, C.; Zhang, L. Digital Twin for rotating machinery fault diagnosis in smart manufacturing. Int. J. Prod. Res. 2019, 57, 3920–3934.

[3] Zhong, R.Y., Huang, G.Q., Lan, S., Dai, Q.Y., Chen, X., Zhang, T. A big data approach for logistics trajectory discovery from RFID-enabled production data. International Journal of Production Economics, 165, 260-272, 2015.

[4] Leng, J., Jiang, P. A deep learning approach for relationship extraction from interaction context in social manufacturing paradigm. Knowledge-Based System, 100, 188-199, 2016.

[5] Grieves, M., «Digital twin: manufacturing excellence through virtual factory replication», White paper, 2015.

[6] Müller, R., Vette, M., Hörauf, L., Speicher, C., Burkhard, D. Lean Information and Communication Tool to Connect Shop and Top Floor in Small and Medium-sized Enterprises. Procedia Manufacturing, 11, 1043–1052, 2017.

[7] Qi, Q., Tao, F., Zuo, Y., Zhao, D. Digital Twin Service towards Smart Manufacturing. Proceedings of the 51st CIRP Conference on Manufacturing Systems. Procedia CIRP, 72, 237-242, 2018

[8] Tao, F.; Cheng, J.; Qi, Q.; Zhang, M.; Zhang, H.; Sui, F. Digital twin-driven product design, manufacturing and service with big data. Int. J. Adv. Manuf. Technol. 2018, 94, 3563–3576.

[9] Wang, J.; Ye, L.; Gao, R.X.; Li, C.; Zhang, L. Digital Twin for rotating machinery fault diagnosis in smart manufacturing. Int. J. Prod. Res. 2019, 57, 3920–3934.

[10] Schleich, B.; Anwer, N.; Mathieu, L.; Wartzack, S. Shaping the digital twin for design and production engineering. CIRP Ann. - Manuf. Technol. 2017, 66, 141–144.

[11] Bevilacqua, M.; Bottani, E.; Ciarapica, F.E.; Costantino, F.; Di Donato, L.; Ferraro, A.; Mazzuto, G.; Monteriù, A.; Nardini, G.; Ortenzi, M.; Paroncini, M.; Pirozzi, M.; Prist, M.; Quatrini, E.; Tronci, M.; Vignali, G. Digital Twin Reference Model Development to Prevent Operators' Risk in Process Plants. Sustainability, 12, article no.1088, 2020

[12] Klerkx, L., Jakku, E., Labarthe, P. A review of social science on digital agriculture, smart farming and agriculture 4.0: New contributions and a future research agenda. NJAS - Wageningen Journal of Life Sciences, 2019. 90-91, art. no. 100315, .

[13] Karadeniz, A.M., Arif, İ., Kanak, A., Ergün, S. Digital twin of egastronomic things: A case study for ice cream machines. 2019 Proceedings - IEEE International Symposium on Circuits and Systems, 2019-May, art. no. 8702679, .

[14] Defraeye, T., Tagliavini, G., Wu, W., Prawiranto, K., Schudel, S., Assefa Kerisima, M., Verboven, P., Bühlmann, A. Digital twins probe into food cooling and biochemical quality changes for reducing losses in refrigerated supply chains Resources, Conservation and Recycling, 2019, 149, pp. 778-794.

[15] Tagliavini, G., Defraeye, T., Carmeliet, J. Multiphysics modeling of convective cooling of non-spherical, multi-material fruit to unveil its quality evolution throughout the cold chain. Food and Bioproducts Processing, 2019, 117, pp. 310-320.

[16] Krokida M.K., Maroulis Z. B. & Saravacos G. D. (2001) Rheological properties of fluid fruit and vegetable puree products: compilation of literature data, International Journal of Food Properties, 4:2, 179-200, DOI: 10.1081/JFP-100105186