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ARTICLE

Re-engineering process in a food factory: an overview of technologies and approaches for the design of pasta production processes

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ABSTRACT
In this paper are investigated the re-engineering approaches for the optimization of pasta production processes. A preliminary study of technologies and information systems architectures to be applied to the entire pasta supply chain has been carried out. In the first part of the paper is presented an overview concerning Industry 4.0 enabling technologies, besides, in the second part are discussed the engineered processes improving production quality. Concerning simulation process, is designed by means of modelling workflows the wheat storage process, by simulating the automatism of silos controlled and managed by volume sensors. Finally, following Industry 5.0 facilities have been applied image vision and artificial intelligence methodologies suitable for auto-adaptive quality check of pasta. The paper discusses different models about production processes, efficiency, risks, costs and benefits.

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Process; Industry 4.0; food quality monitoring; process re-engineering; process mapping; process workflow simulation; image vision; artificial intelligence; augmented reality; adaptive processes; Industry 5.0

1. Introduction

This study is focused on process design in the pasta industry. Specifically, the research is carried out about useful technologies and monitoring of some production defects, shown at the end of the drying process or directly inside the pasta packaging, which can result from several factors occurred during the manufacturing process or attributed to the raw material (Popper et al., 2006). Generally,these kind of defects do not compromise the healthiness or the organoleptic properties of the food product, but it widely and negatively reflects on the consumers' judgement about the quality of the pasta. Defects can come from different phases, among which the most relevant are (Balasubramanian, 2006, pp. 38–40):

- Processing;
- Drying;
- Packaging.

Nowadays most food companies are oriented to protect consumers. Company staff periodically carry out specific analysis identifying the hazards related to every stage of

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the production, and any potential cause of harm to the consumer health. Starting to the state of the art about technologies enabling Industry 4.0 logic for the case of study, in Section 2 are provided more details about main specifications of these technologies which are of great help in mapping the manufacturing process assuring the achievement of quality. It is important to observe that some important topics of Industry 4.0 (Rubmann et al., 2015, pp. 1–16) are horizontal and vertical system integration, process simulation, Internet of Things – IoT – implementation, cloud computing augmented reality and cybersecurity (Vaidya et al., 2018, pp. 233–238). Different works discussed these topics (Oztemel & Gursev, 2018, pp. 1–56), by analysing different models to apply Industry 4.0 facilities (Basl & Doucek, 2019, pp. 1–13). Scientific innovation in digital manufacturing can be added by artificial intelligence (Skobelev & Borovik, 2017, pp. 207–311), and adaptive process involving predictive maintenance, collaborative robotics and rapid prototyping (OECD, 2017). An innovative system architecture of Industry 4.0 could include artificial intelligence, big data systems and IoT facilities (Özdemir & Hekim, 2018, pp. 65–76). Following the direction provided by the state of the art in this paper is proposed a case of study representing a 'borderline' case involving Industry 4.0 and logics of Industry 5.0.

1.1. Case of study: process workflow of the industry project

In this section is provided a scenario scheme concerning the main processes of the case of study. The main scheme identifies the phases of performed research such as (see Figure 1):

- Identification of the technologies enabling software (sw) and hardware (hw) suitable for the current production process of the company (the proposed sensors are matching with the design of the engineered processes);
- Integration of these technologies in the 'Pasta IOT 4.0' system pertaining to the entire production chain and useful for process management (some of the discussed technologies are suitable for the optimization of production processes, other ones are important for traceability and warehouse management which is part of logistic);
- Technology output (process simulation output and approaches for pasta quality optimization).

The whole system is improved by image vision technique and artificial intelligence tools able to optimize the product quality check (see Figure 1). These facilities are able to provide a feedback system adapting automatically the production on the best production processes. The adaptive system in the specific case provides important information about pasta production defects and predictive maintenance: an image processing based on Watershed approach (Massaro, Vitti, & Galiano, 2018, pp. 1–14) is able to detect some pasta defects and to provide input data for an artificial neural network – ANN – enabling predictive maintenance. The adaptive framework is designed to adapt automatically the production line setting on the best parameters.

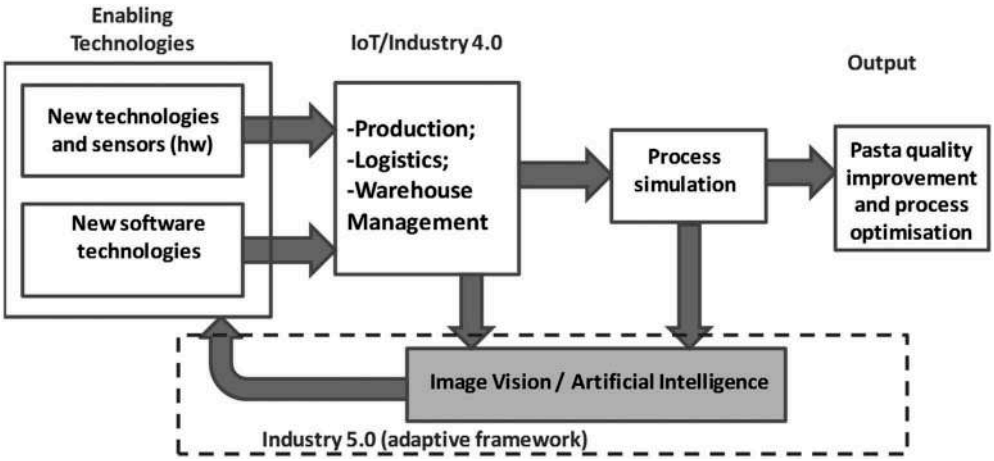

Figure 1. Main architecture of the research project 'PASTA IOT 4.0' and Industry 5.0 research development.

2. State of the art of the Industry 4.0 enabling technologies in food factories

The topics discussed in this section are discussed as follows:

-data acquisition technologies.
-control technologies.
-data management technologies.

2.1. Data acquisition technology: image processing

This technology (Mokhtar et al., 2011) considers the picture as a matrix of square pixels (picture elements) arranged in rows and columns. Pixels are the basic components of the pictures. Many information are included in every pixel (intensity level, color, etc.). The first information is related to the colour difference which could prove the presence of possible defects. Image processing systems are fundamental for the quality check of food products (Takenobu & Shuji, 2013, pp. 1465–1471), and for the control of the moisture during the 'drying process'. They support the food production process control, eliminating the subjectivity belonging to the manual inspections, providing flexibility during their application, and resulting an effective support in the decision process (Mokhtar et al., 2011, pp. 1173–1180). In order to develop an automated system to evaluate food quality, image processing techniques are often integrated into mechanical and instrumental devices. In this way, human manipulative effort is replaced in the execution of a certain process. In such a system, image processing represents the core controlling the machine functioning.

Smart cameras, defined as camera embedding small and powerful computational processors, are generally employed in the same kind of applications where more complex vision systems are used, when it would be uncomfortable to use PC or external computer because of size, costs and reliability reasons.

Typical fields of application are:

-Automatic inspection for quality check (defects detection, lack of components, etc.)
-Contactless measurements
-Product discrimination and orientation
-Code reading and verification (Barcode, data Matrix, alphanumeric characters – OCR or OCV-etc.).
-Continuous material inspection (coils, wires, tubes, extrusion lines) to detect defects of dimensional check.
-Position identification and items' rotation for the automatic picking and the robotic drive.
-Surveillance (intrusion or smoke/flame detection)

2.2. Data acquisition technology: X-rays for the detection of unknown elements in food products

A quality control of pasta is related to the presence of possible contaminants dangerous for human health. One of the main causes of contamination in food products is represented by the presence of unknown elements (i.e. fragments of glass, bones, metal, plastic or pebbles) which accidentally get into the food during the manufacturing process thus potentially generating damages for health. The find of contamination obliges companies to call back a certain number of packages from the supermarket shelves every year due to established danger or precaution. X-ray detection system is based on the principle according to which unknown elements filter radiations in a different manner with respect to other ingredients in food products. Detecting these differences in the density and ray absorption, X-ray systems are able to identify eventual unknown elements inside food.

X-rays inspection systems, which at first were used to detect the presence of glass fragments in the preserves (contamination due to accidental breakage of bottles and jars along the production line), evolved in machinery able to detect the presence of many further contaminants like metal fragments, bones, pebbles and plastic (Yang et al., 2001, pp. 1195–1200). Radiation technologies currently tend to work making low use of radiation, regardless their speed. Their precision is such that they allow detecting anomalies also in the case of curved packaging. They show a low percentage of false positive thanks to their ability of discriminating among unknown elements, packagingstructure, or food product inhomogeneity. Food such as enveloped mix salad, breakfast cereals, dry fruit and sweets have different levels of density, which determinate a complex x-ray image. This aspect makes the identification of external elements really hard. Material Discrimination X-ray (MDX) technology succeeds in discriminating materials based on the chemical composition (atomic number) and in revealing inorganic contaminants of different density, among which some plastics. Moreover, the MDX technology allows the inspection of food enveloped in non-linear packaging (i.e. folding boards), which can cause difficulties to traditional X-rays.

In order to determine a precise and effective control, the positioning of a machinery at the end of the production line is often not enough. A precise procedure is to be defined based on the risk assessment and the identification of critical control points for a specific company and a specific production cycle.

X-rays inspection systems are thus integral part of a complex management system, starting from the raw material to get to the finished product. Innovative X-rays platforms have been developed to perform a specific check on the raw material, at the beginning of the production line. Other Platforms are located at the end of the production line after the packaging phase.

2.3. Data acquisition technology: thermal imaging

In the food industry, careful check of multiple environmental, process or product parameters is pivotal to assure expected and healthy features to the consumer. In a pasta production company, monitoring of parameters like humidity and temperature during the manufacturing process, drying and moisture owned by the finished food is of utmost importance. This kind of control can be surely performed by thermal cameras as a good alternative for the 'food safety and quality assessment'.

The use of thermal cameras enables automatic contactless measurements of temperature in several applications of food transformation (Huang et al., 2014, pp. 7248–7276). The analogic video output can be displayed on the monitor and the digital temperature data, including the MPEG4 video output, can be addressed to a computer via Ethernet and the processing of the collected data can originate different outputs.

2.4. Data acquisition technology: volumetric sensors

Volumetric sensors (Terzic et al., 2013, pp. 11–35; Bossart, 2015; Morris & Langari, 2015) provide measurements concerned with content of tanks, silos, boilers, basins, cesspools and any other container of liquid and solid material. Fields of application are various, even if a wide diffusion is described in the food industry such as pasta factories and those activities including raw material carriage, dosage and storage. These kind of sensors are well integrated into IOT (Internet of Things) solutions in order to perform an advanced monitoring of raw material level and activate the most suitable signalling devices. Continuous control enables collection and storage of many data, relevant to know all the company processes deeply and design very strong strategies.

- Capacitive level sensors: they measure liquid and solid levels. They are widely used in industry and agriculture, very important for the stock management. It is possible to set different thresholds, using the appropriate number of probes at different heights.
- Radiometric level sensors: they do not come in contact with liquids and are suitable for high temperature and pressure values detection.
- Float level sensor: the detection occurs through a selector embedded in a pole, activated by a magnet generally assembled in the float that freely moves on surface.
- Hydrostatic pressure level sensors. As water pressure increases together with the filling height, these sensors measure the density related to the liquid level, starting from the size of the hydrostatic pressure on the bottom and on the surface of the tank. This kind of sensor is not affected by foams, deposits, conductibility and other liquid properties' change.
- Vibrating level sensors are composed by a probe that, while vibrating at its natural frequency in the air, changes its vibration frequency once a liquid to detect comes

into contact. For example, in case of increasing liquid, vibration (frequency and amplitude) decreases.

Ultrasound level sensors measure the flight time, that is the range between the release of a sound in the tank and the return of the sound wave after its contact with the liquid surface. Flight time is proportional to the distance run and thus to the fluid level. They have several fields of application because they are not affected by the physic and electric properties of the liquid or of the substance.

2.5. Data acquisition technology: NIR spectrometry

Another good method to control moisture in food processing is Near Infrared Spectroscopy (NIR) (Bevilacqua et al., 2013, pp. 726–734; Groß et al., 2011, pp. 1301–1308): a secondary analysis technique which uses the infrared range of the electromagnetic spectrum (from about 800 nm to 2500 nm) to investigate in a non-destructive manner the physical and chemical properties of the samples. Near infrared wavelengths are in the range 1100–2500 nm and have energies corresponding to the vibration energies of the functional group of the organic molecules; they are very useful when we need to analyse the organic substances both qualitatively and quantitatively. According to the quantum theory, every atom or molecule possesses an energy state called 'ground state' where the structure has the lowest energy. If the atom or molecule is hit by radiation, these are absorbed leading to a corresponding increase in the structure energy. The best results are achieved when the NIR spectroscopy is coupled to chemiometric methods and multivariate statistical analysis of the data collected; these techniques, in fact, allow to correlate several NIR spectra belonging to one sample. Next, comparing the outcomes of the previous analysis with online archives a predictive model can be generated. Community is steadily committed to the study of the best application of the NIR spectroscopy in food sector aimed at optimizing a whole production process.

2.6. Control technology: PLC

The Programmable Logic Controller (PLC) is a programmable device to control a process or a system (Bintu, Jayasree, & Sreenivasan, 2013; Song, Tan, & Ding, 2006). The control system receives a series of signals as inputs and activates, based on input signal processing and the current state, command outputs (actuators). Signal processing is carried out based on a software installed on the programme memory area of the PLC.

The PLC acquires all the signals coming from the operating tools, saves on the memory the input information (imagine) defining what the output values are based on the programming logic (software). PLC saves every output values on the memory and can operate the actions derived from the values stored on the output memory.PLC systems can be interconnected to cameras in order to check pasta defects.

In order to ensure the consumer a finished product presenting the highest qualitative standards,should be installed an in-line inspection system recognizing, analysing and classifying defects and embedding a removal tool inside the production plant is without any doubt an advised solution. In this scenario, the image processing could provide information about pasta defects, cracks, crumbles, unevenness in size and stickiness by evaluating different geometrical parameters such as area, aspect ratio, perimeter,

compactness and roundness, surface roughness, edge profile (Mokhtar et al., 2011, pp. 1173–1180).This kind of technology is represented by an artificial viewer, interfaced with the machine PLC that activates a device selecting and separating the defected material.

2.7. Control technology: monitoring of pasta production lines with sensors and cameras connected to PLC systems

Production lines present different critical points often inaccessible which have to be monitored. Semolina level reading is a critical point for the company production. In order to optimize raw material sales and minimize waste a real-time measurement system for the material stored inside the silos is needed. A scheme of a reengineered system using volume sensors connected to a PLC and a monitor displaying the data has been created. Volume measurement has been linked to information processes by specific software and detecting sensors. In Figure 2 is illustrated the Unified Modeling Language (UML) scheme concerning level detection: different volumetric sensors are placed in different silos by a PLC, and all data are plotted in real time on a monitor.

Together with silos, also short and long pasta production aisles are further point to be monitored by high resolution IP cameras' systems. Also, in this case, a specific graph was created. In Figure 3 is illustrated the UML design of the control room connection with IP cameras.

2.8. Control technology: bar code

Identification techniques finding wide application inside the food traceability sector are bar codes. These have been the first to be introduced and consequently, the most diffused; their functioning principle is based on an optical reader recognizing black bars and the white spaces between. Bar code's success was determined by its affordable cost, its high speed, precision and reliability. The coding is based on the binary

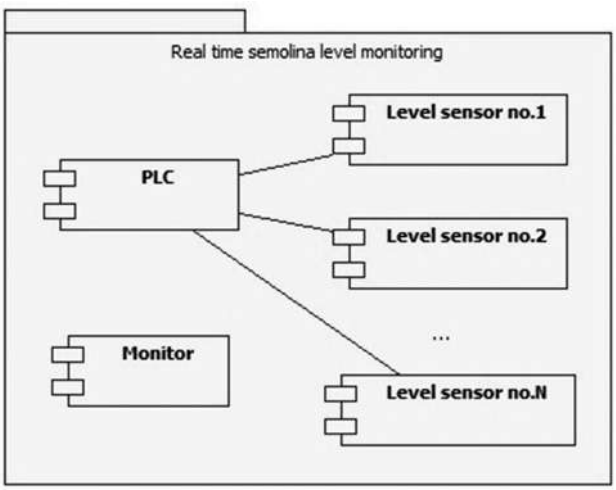

Figure 2. UML design of the real time semolina level monitoring.

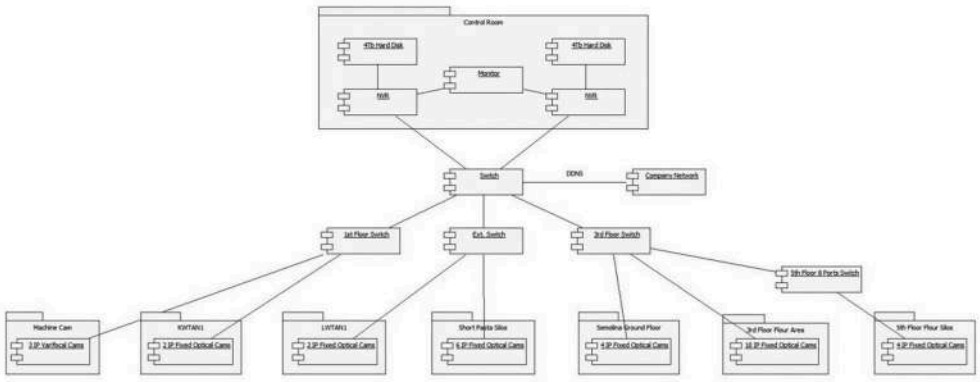

Figure 3. UML design of the control room connectivity of the case of study.

representation of the information, close to the calculator language. This feature encouraged the rapid establishment of bar code as recognition tool easily and fastly integrable in computers.

2.9. Control technology: RFID

Radiofrequency identification systems (RFID) represent a novel technology (Lotlikar et al., 2013, pp. 817–821) rapidly diffusing in food companies. They are made up of a transceiver (reader) and a further device allowing the electronic identification called TAG or transponder (transmitter/responder). They are able to communicate each other using ether as transmitting means, and irradiating a radiofrequency modulated signal through appropriate antennas. Transponder can be equipped with its own power supply, defining itself 'active' and 'passive'. The active version is equipped with Li interchangeable internal battery or is powered by an external source. The passive version, not equipped with battery, gets the needed power to function by the field generated by the transceiver. Passive transponders are lighter, more compact and cheap than the active ones, offering a lifetime potentially unlimited. On the other hand, the active TAGs are typically employed where writing operations are needed and allow great distance attainment keeping a good noise insulation and a higher modulation speed.

2.10. Data management technology: design and industry process mapping

Company operating context nowadays is radically changed. Innovative measures are always required to stay competitive on the market . Global markets ask for maximum efficiency of the different sectors inside the companies, to be achieved through a constant improvement and optimization of the services and the complete knowledge of the elements in the system (personnel, infrastructures, means, etc.). A deep knowledge of the elements belonging to the company system leads to analyze strengths and aspects to be improved. Relationships among the active elements can be described in a process;

process design and planning is a strategic step towards the improvement and innovation of the entire organization in the company, and becomes the operative reference for the human resources involved. Here lies the importance of effective design and process mapping, the graphic representation of company processes.

Two relevant aspects for the optimal functioning of the whole company system in the Industry 4.0 scenario as well as in food factories are related to the network connecting the several operating devices and the energy management for assuring the continuity of all the processes. This is the reason why we assessed the consequences of the application of new enabling technologies in the production line layout designing the following UML graphs (Rumbaugh et al., 2005).

2.11. Data management technology: ethernet connection system for control devices in a pasta production line

A first stage of deep analysis was performed with the scope to study current processes, identifying the control systems in use and the process information available for operators and other company actors. It was addressed to all production departments and to the responsible persons involved in the different company roles. Then, with the use of the UML language, an exhaustive diagram was depicted that is reported as follows. In Figure 4 is shown the design of the whole information communication system of the case of study. Big Data systems can be interconnected to the Ethernet line in order to collect all data of pasta production lines. Big Data analytics performed by artificial intelligence algorithms could improve all the processes management by providing a decision support system (DSS).

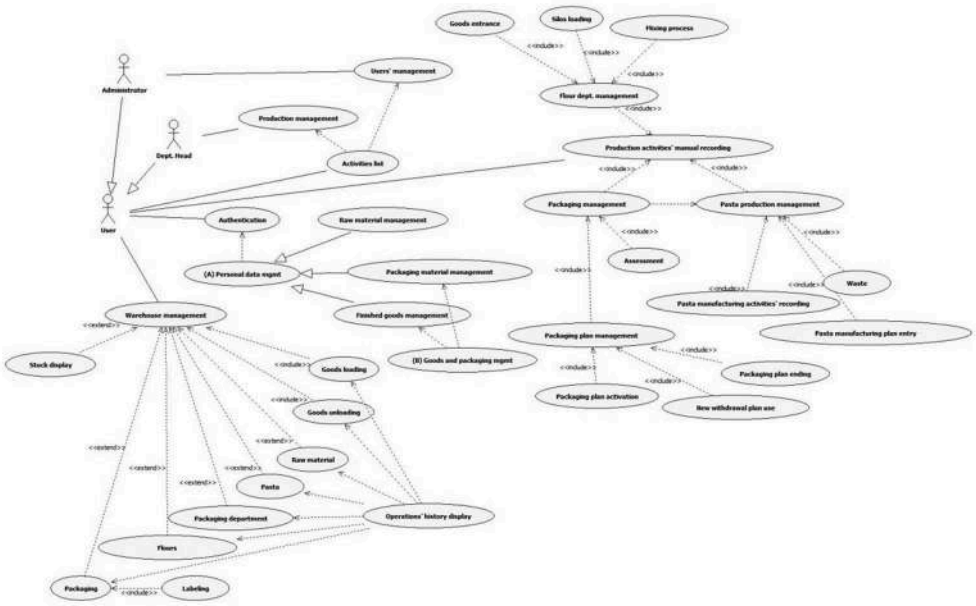

Figure 4. UML design of the information communication system of the pasta industry.

2.12. Data management technology: primary energy consumption monitoring

In the whole of the industrial processes another essential aspect to be considered is the continuity of the production and so, the vital parameters of all the machines. Monitoring primary energy consumption and absorption of the main users in the line represents one of the aspects to improve strengthening the control of the machineries in real time to analyse, assess and revise the affected energy parameters. Another UML graph was created to display the design of an energy monitoring system useful to supervise the energy indicators of all the pasta production plant thanks to the following features:

- Energy monitoring, both electrical and thermal
- Instant consumption and totalizations
- Statistics and energy report creation
- Data storage on server
- Remote analysis of data through graphical pages.

In Figure 5 is illustrated the UML design of the energy consumption monitoring information system.

2.13. Data management technology: process re-engineering

Design and mapping of production processes are methods related to business process reeingineering of manufacturing companies. They are practical approach to assist

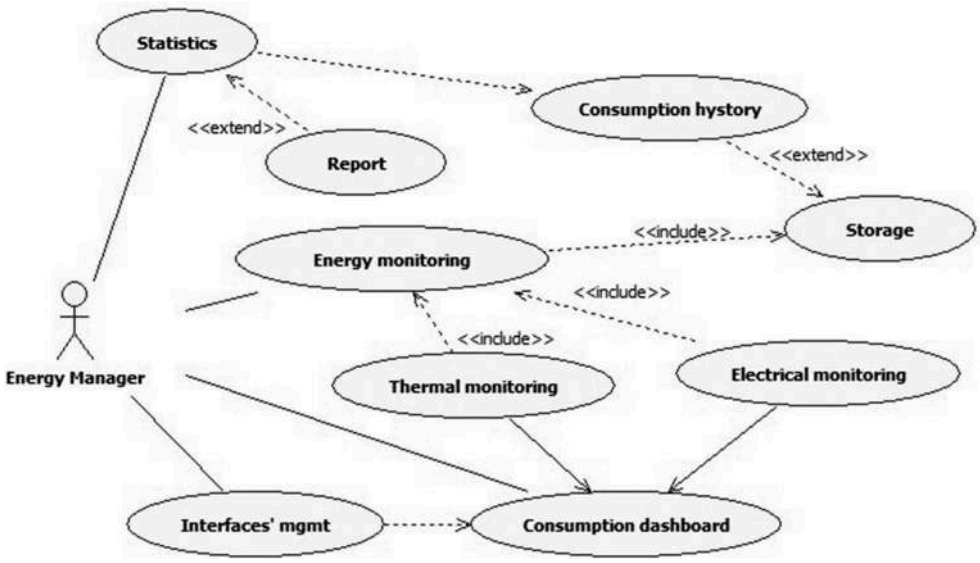

Figure 5. UML design of the energy monitoring communication system.

companies that want to make the monitoring of their manufacturing processes a competitive advantage in meeting future market and customer demands. The mapping of processes in pasta industry is important to understand production mechanisms (Balasubramanian, 2006, pp. 38–40), and to improve Industry 4.0 logics involving data digitalization processes and machine control (Balasubramanian, 2006, pp. 38–40; Rubmann et al., 2015; Hozdić, 2015, pp. 28–35; Crnjac et al., 2017, pp. 21–30). In this work we focused on three monitoring systems in a pasta factory using sensors, cameras and optical devices to achieve excellence in managing the most relevant manufacturing operations.

2.14. Data management technology:traceability process management

In a food factory, the transportation of the finished products outside the production area represents another critical aspect. It can be monitored by different technologies that were evaluated and integrated into a complete monitoring platform which is depicted as follows. In Figure 6 are shown the facilities concerning the traceability process management of the case of study.

3. Simulation results: pasta storage case

Simulations can be performed to all the supply chain processes which have been mapped. In this section is simulated the automated process of the engineered process related to the

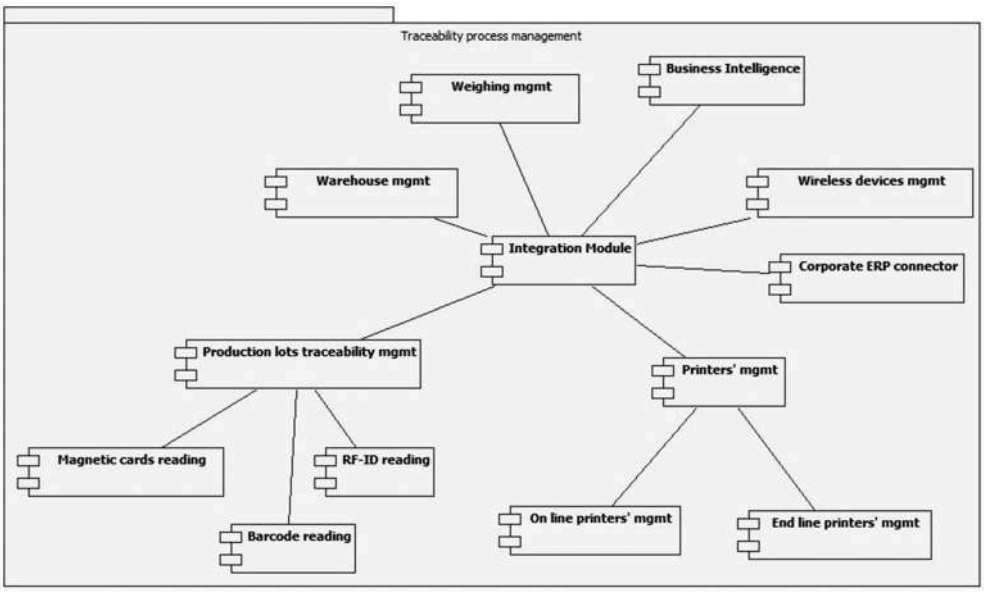

Figure 6. UML design of the traceability process management (*mgmt*.: management).

pasta (raw material) storage process. In order to simulate the wheat storage process, it is mapped the alarm condition of the following case:

- different silos are connected in cascade configuration with sensors detecting the volume level of each one;
- alarm condition is detected when the volume level is low if compared with a threshold level;
- when an alarm is detected, automatically is activated the wheat withdrawal from the next silos, thus ensuring the continuity of the production process.

This process is simulated by the Bonita Studio (Marcos et al., 2014) workflow of Figure 7: this model represents the process that it is activated when the alarm condition is detected from the silos *n*; the model simulates the verification of volume conditions of the last three silos.

The process mapped in Figure 7 is implemented by the KNIME (Konstanz Information Miner) (Wimmer & Powell, 2015, Al-Khoder & Harmouch, 2015, pp. 13–23) workflow of Figure 8 described as follows:

- Node 1 (python source node): this node allows to read volume sensor values (a python script allows to read from sensor volume data of silos);
- Node 2, Node 3 and Node 5 ('If Switch' logic condition nodes): these nodes verify the condition that if the volume is enough then allowing the production else verify the volume of the next silos;
- Node 4 (Python Script node): this node allows to continue the production process;
- Node 6 (Python Script node): the script embedded in this node allows to continue the production and to update the silos volume data after the new filling;
- Node 7 (Python Script node): this node takes into account the last alarm condition blocking the storage process (the production is stopped).

The KNIME workflow approach of Figure 8 can be generalized for the digitalized information of all processes of the supply chain.

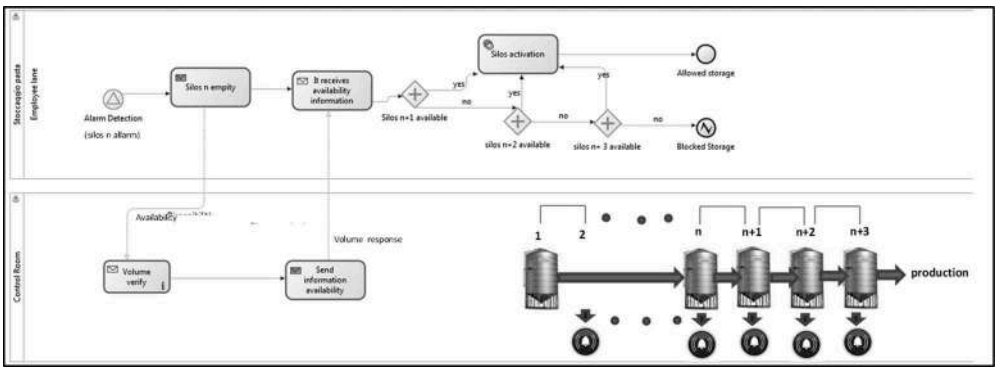

Figure 7. Bonita studio: control of the wheat storage process.

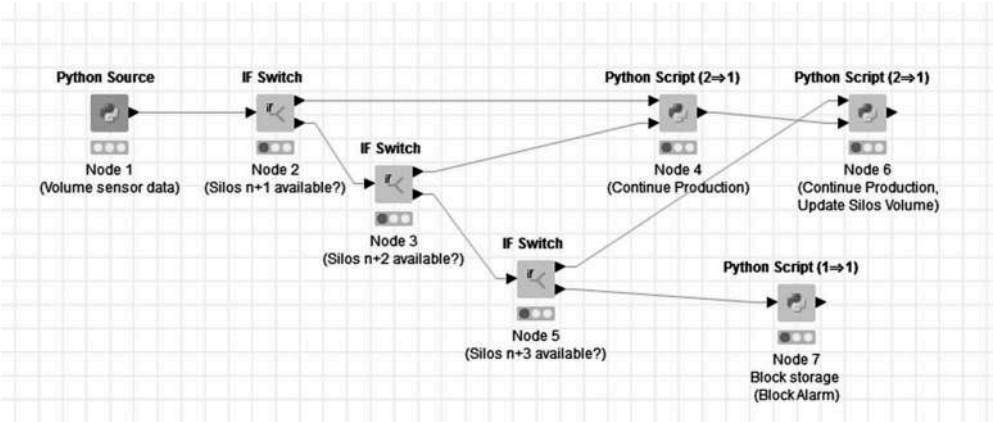

Figure 8. KNIME workflow simulating the automated process of.Figure 7.

4. Other scientific approaches useful to control workflows and for Industry 5.0 developments

Other tools which can be adopted for the control of workflows are learning systems based on artificial neural network ANN (Du & Sun, 2006, pp. 39–55) processing pasta images and supporting defect classification. The ANN algorithms are suitable also for the prediction of predictive maintenance (Massaro et al., 2018, pp. 1–17, Zhang et al., 2015, pp. 6996–7015) of machines of the whole pasta production lines. Other methodologies able to map production process are the 4 M maps (Favi et al., 2017, pp. 1510–1518; Arsovski et al., 2011, pp. 309–316), the Deming cycle PDCA (Plan Do Check Act) (Chakraborty, 2016, pp. 14–18), and Xm-R charts (Fouad & Mukattash, 2010, pp. 694–700).

4.1. Image processing and pasta quality check suitable for feedback systems

The process mapping can be performed also for quality check. In an automated system, image processing technique could facilitate the quality check thus allowing to adjust machine parameter setting by a feedback control. For the specific case of study has been applied to the Watershed image segmentation approach (Massaro et al., 2018, pp. 1–14), by detecting white spots defects of pasta. Pasta processing is the process in which wheat semolina or flour is mixed with water extruding the composite into a specific shape which is dried and packaged.

The pasta defects which the image processing algorithm can classify are:

- white Spots.
- dark Spots.
- misshaped Pasta.
- stickiness.
- cracking.

By focusing the attention on white spots, possible causes are:

- presence of whitish particles in the flour difficult to hydrate.

- irregular granulometry in the flour with large diameter particles present alongside fine particles.
- uneven kneading, too dry or not enough kneaded, or unevenly moistened.

By applying the ImageJ tool it is possible to classify white spots defects by extracting geometrical features. In Figure 9(a) is illustrated a zoomed part of a pasta region containing white spot defects. The defects are extracted by filtering the white spots (see Figure 9(b)) and by extracting geometrical features as ellipses enclosing filtered regions (see Figure 9(c)). The features extraction is automatized by setting properly the threshold color as shown in Figure 9(d). The output of the image processing algorithm is illustrated in Figure 9(e), indicating elliptical areas of the extracted defects expressed in pixels^2. By defining a threshold limit as in Figure 9(e) it is possible to classify the defects as follows: the areas under the defined limits are acceptable, while the other ones are abnormal.

The feedback system can work following the scheme of Figure 1: during the time are acquired inline different photos of pasta sample by calculating the number of areas over the threshold limits; then is predicted by a ANN algorithm the number of abnormal

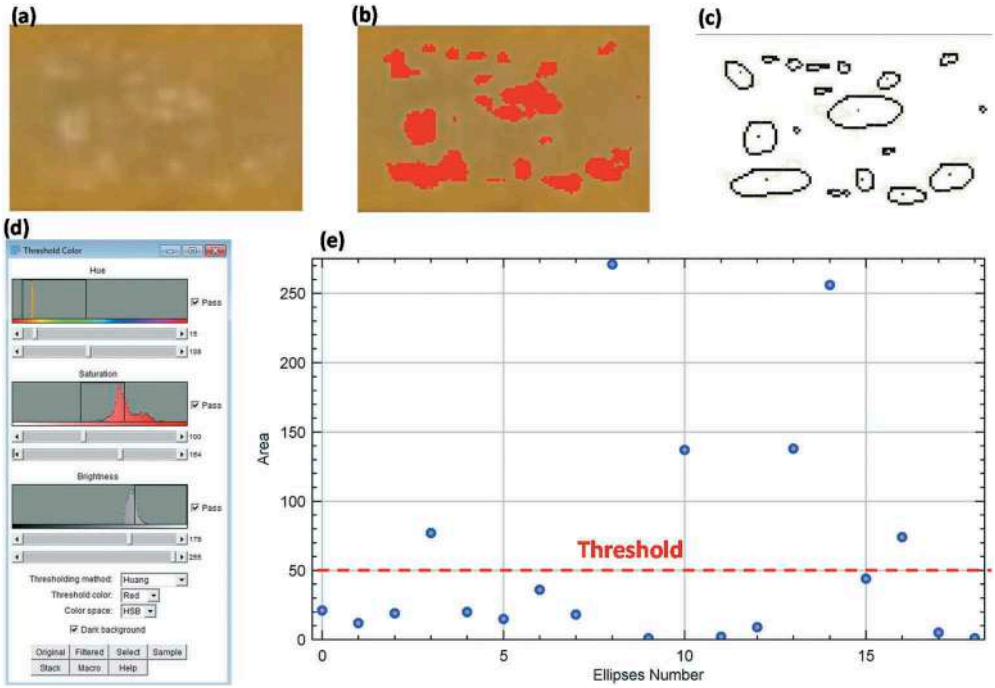

Figure 9. ImageJ image processing: (a) zoomed part of pasta with white spots defects; (b) image segmentation by Watershed approach; (c) extraction of geometrical features of the white spots defects; (d) color threshold setting; (e) defects classification by a threshold limit.

defects (process simulation by predicting quality); if the prediction indicates alerts, will be changed automatically the production process parameters in order to 'adjust' the production quality as in dynamic adaptive process.

4.2. ANN algorithm enabling process simulation and automated setting of the machines

Data mining is an important tool for predictive maintenance of production machines (Bastos et al., 2014, pp. 933–940). A model which can be adopted is based on a decision support system (DSS) enabling different alerting levels (Bastos et al., 2014, pp. 933–940) including warning signals (level 1), corrective and preventive actions (level 2), and predictive actions (level3). Other researchers have applied the same predictive maintenance multilayer concept on other applications using ANN as data mining algorithm for the DSS (Massaro et al., 2018, pp. 1–20).

The abnormal defect areas are calculated by the ANN algorithm implemented by the KNIME workflow of Figure 10(a). The algorithm is structured as follows:

- Node 1: input node able to load the output of the image processing algorithm shown in Figure 9;
- Node 2: a normalizer operator scaling all the area value in a range between 0 and 1 (the data normalization is useful in order to optimize the computational error);
- Node 3: the partitioning operator split the input dataset into a training dataset which is the input of the learner block (Node 4) and into a testing dataset which will be processed by the ANN predictor operator (Node 5);
- Node 4: the 20% of the input dataset is adopted to learn the model by the Probabilistic Neural Network – PNN – based on the Dynamic Decay Adjustment – DDA – algorithm;
- Node 5: the remaining part of the dataset is used for the ANN model testing performed by the PNN Predictor block;
- Node 6: the results reporting of Figure 10(b) are achieved by the Line Plot block.

In the analysed case of Figure 10(b) is observed that the predicted areas are always under the threshold limit thus ensuring pasta quality. In the case of predicted areas overcoming the threshold, will be adjusted automatically the machine parameters, for example, of the drying process. Experimental observations are important in order to learn automatically the predictive model which will save all the programs to execute in the case of production failure conditions. The analysis of historical data is useful also for the predictive maintenance of the production line.

5. Discussion about costs, benefits and efficiencies of the innovative technologies

All the proposed technologies are oriented to avoid production risks. A business plan can be formulated in order to provide a scenario about costs and benefits linked to the production efficiency. The introduction of the Industry 4.0/5.0 introduces the following estimated main benefits (see Figure 11):

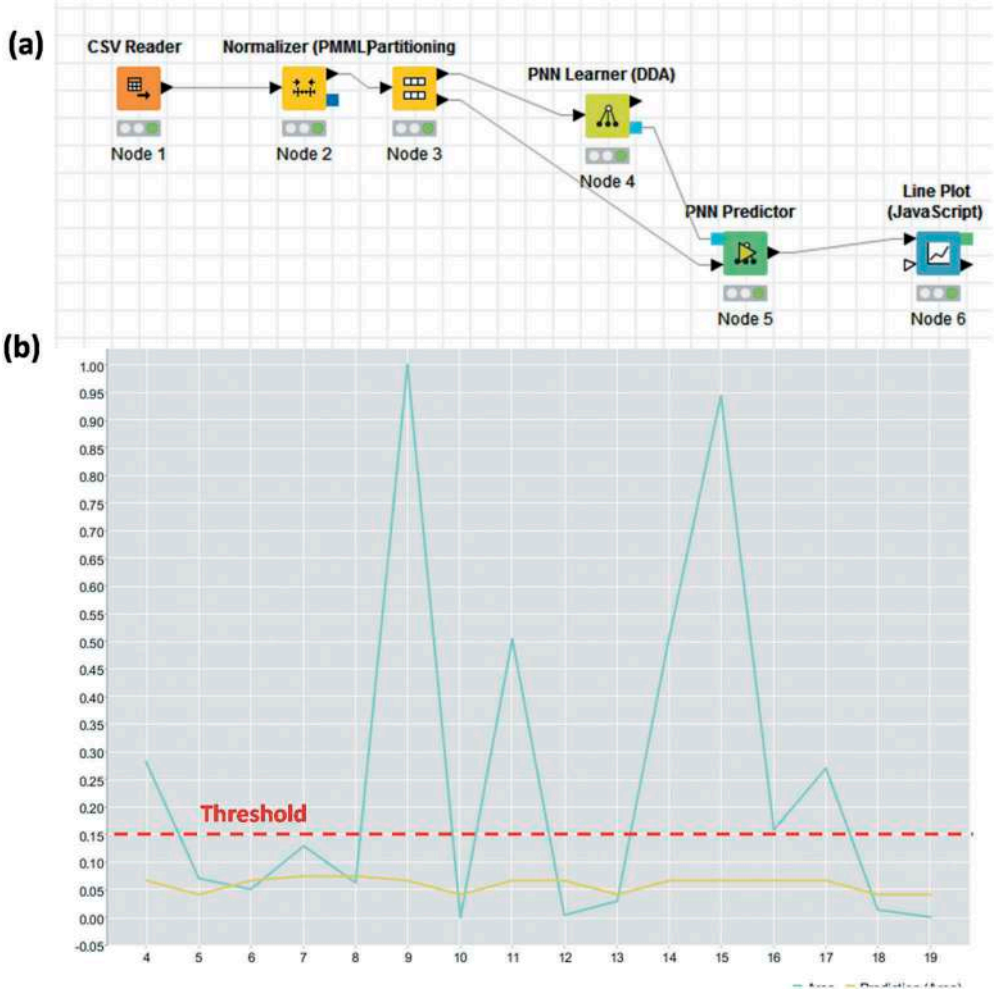

Figure 10. (a) ANN workflow implemented by KNIME. (b) Some real defects are measurements and predicted areas (area expressed in normalized arbitrary units versus the dataset record number).

Costs and Benefits analysis and VAN and TIR indicators.

	Year Activity	1	2	3	4	5	Total Values
Costs	*Number of Industry 4.0/5.0 Tools*	0	20	100	500	2500	3.120,00 €
	Tools values	0,00 €	200,00 €	1.000,00 €	5.000,00 €	25.000,00 €	31.200,00 €
	Project Cost (Hypotetic R & D Cost)		500.000,00 €				
	Maintenance Costs of Tools	0,00 €	40,00 €	200,00 €	1.000,00 €	5.000,00 €	6.240,00 €
	Total Costs	0,00 €	500.240,00 €	1.200,00 €	6.000,00 €	30.000,00 €	537.440,00 €
Benefits	*Tools Proceeds*			4.000,00 €	20.000,00 €	100.000,00 €	124.000,00 €
	Tools Maintenance Proceeds			1.700,00 €	8.500,00 €	42.500,00 €	52.700,00 €
	Benefits following traceability services			960,00 €	4.800,00 €	27.000,00 €	32.760,00 €
	Benefits following predictive maintenance services			200.000,00 €	1.000.000,00 €	5.000.000,00 €	6.200.000,00 €
	Total Benefits	0,00 €	0,00 €	206.660,00 €	1.033.300,00 €	5.169.500,00 €	6.409.460,00 €
	Benefits-Costs	0,00 €	-500.240,00 €	205.460,00 €	1.027.300,00 €	5.139.500,00 €	5.872.020,00 €
Discount factor	*(1+i)^n****	2,06	4,24	8,74	18,01	37,10	
	VAN	0,00	-117881,04	23503,13	57046,42	138543,06	101211,56
	TIR						1,65

** The cost of each tool is estimated in 10,00 euro*
*** The price for the customer is 40,00 euro for a tool*
**** The interest rate that is applied as a discount factor equal to 1.06 (i is the rate at which the European Central Bank lends money to the banks). The exercise number is indicated with n.*

Figure 11. Business plan model related to Industry 4.0/5.0 tools production.

-A production increase of the 20% due to the prediction of machine failures, thus ensuring the production continuity.
-A decrease of 40% of waste raw materials used for pasta production.
-A decrease of the 80% of costs related the machine maintenance.
-A decrease of the 90% of all the risks associated with the production malfunctions.
-An increase of the 60% of pasta quality due to the quick and inline detection of pasta defects.

The industry could obtain other benefits in the additional production of Industry 4.0/5.0 tools to adopt in general in food industry improving traceability services. The tools are related to software or hardware (IoT) products. In order to quantify these supporting benefits, is simulated the following business plan, providing a numerical model of costs/benefits estimated in a period of 5 years where the first two are related to the research development.

The simulation model is designed also to estimate TIR and VAN financial indicators.

6. Risk model: risks estimation

In order to control risks during the production can be adopted the following adapted model (Saponaro, 2018), where the risks factors are estimates as R = P*E*V, being:

-P the probability of event occurrence (value between 1 and 4).
-E the risk exposure (distribution of elements exposed to risk).
-V the vulnerability (damage function that indicates how much each element is likely to suffer damage or not, and is also a function of the level of security).

The risk model can be estimated by structuring the following table

In the scheme of Figure 12 is sketched the proposed model which can be applied to the use of the Industry 4.0/5.0 facilities.

In order to reduce the risks, the expected solutions must ensure that the acceptable risk level remains at average-low and low levels. In Table 1 and Figure 12 are illustrated the attributes and the risk levels of the model, respectively.

7. Logistic aspects and innovation technologies

Table 1. Table layout implementing the risk model where the risk level is: 1 (none risk), 2 (average-low risk), 3 (average risk), 4 (average-high risk), 5 (high risk).

Risk parameters	Qualitative	Quantitative	Risk level	Expected solutions
Risk type	x	f(P,E,V)	1	Expected solution to avoid the specific risk
…	…	…	…	…

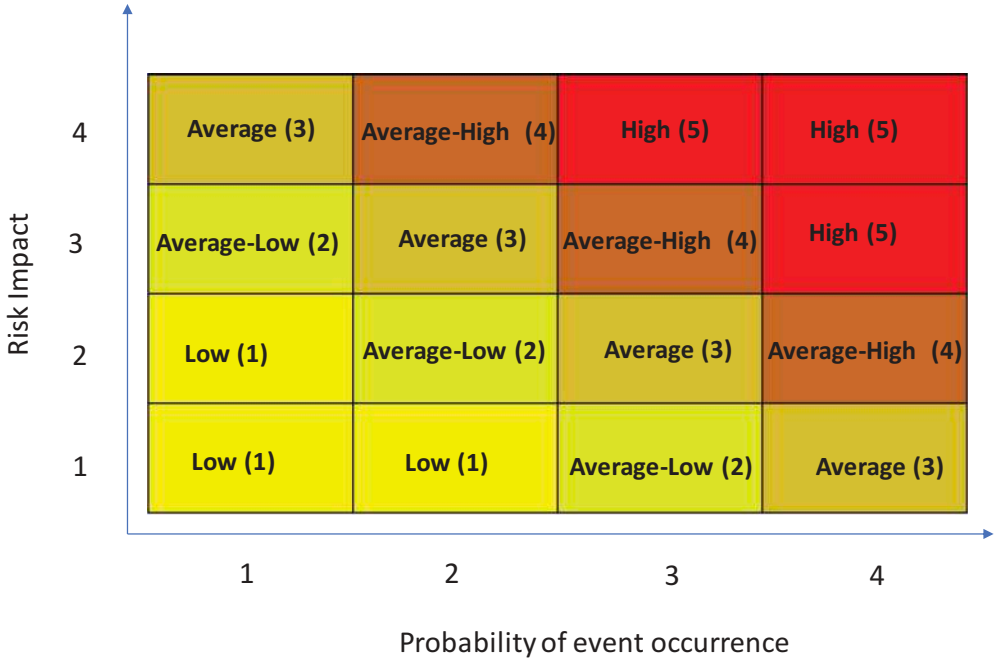

Figure 12. Risk modelling.

Logistics aspects are very important for business intelligence and for product traceability. In this direction, in order to optimize logistics patterns can be adopted different algorithms such as (Massaro et al., 2019):

- Dijkstra's algorithm.
- Eulerian Cycle algorithm.
- Ford-Fulkerson algorithm.
- Greedy algorithm.
- Hungarian method.
- Nearest Neighbor.
- Savings algorithm.
- Floyd–Warshall algorithm.
- Vogel's Approximation Method.
- Lavesdk.

Furthermore, logistics aspects are fundamental also for pasta quality improvement by tracing the raw material geolocalization and storage processes. In this direction, the blockchain technology plays an important role in sustainable logistics, helping digitally trace and authenticating food products from an ecosystem of suppliers to store shelves and ultimately to end customers (Tijan et al., 2019). Logistics is an important component for the whole supply chain integrating model concerning Industry 4.0 and lean management (Sony, 2018), and can be improved by artificial intelligence algorithms (Kowalski et al., 2012).

8. Conclusion

The proposed work analyses the possible technologies and approaches compatible with pasta industry mapping processes and indicates solutions for a case of study for the pasta industry. The tailored production processes have been formulated by UMLdesign improving industry connectivity, the traceability, the energy consumption optimization, and the monitoring processes by sensor and cameras. Finally, the case of wheat storage process is discussed by simulating the automated process by workflows. All the proposed sections indicate an overview of technologies suitable for the application of Industry 4.0 facilities. In particular, the last section enhances how it is possible to apply the simulation process to a particular pasta storage process, and the upgrading of the information system for Industry 5.0. The information system upgrade is performed by image processing for inline detection system, and by artificial neural network predicting pasta defects. The image processing is applied in order to check automatically the pasta quality according to the standard UNI EN ISO 9001:2015 introducing the plan do check act (PDCA) procedure oriented on the optimization of control points for quality improvement. The paper discusses other important aspects about possible costs and benefits introduced by the Industry 4.0 facilities, risk model for the use of the proposed new technologies, and intelligent logistics.

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References

Al-Khoder, A., & Harmouch, H. (2015, February – March).Evaluating four of the most popular open source and free data mining tools. *IJASR International Journal of Academic Scientific Research*, *3*(1), 13–23.

Arsovski, S., Đokić, I., & Đokić, S. P. (2011). Quality in World class manufacturing. *International Journal for Quality Research UDK - 005:658.56, Short Scientific Paper (1.03)*, *5*(4), 309–316.

Balasubramanian, S. (2006). Pasta: Process mechanism and its production technology. *Beverage & Food World*, *33*(8), 38–40. https://www.researchgate.net/publication/278686004_Pasta_process_mechanism_and_its_production_technology

Basl, J., & Doucek, P. (2019). A metamodel for evaluating enterprise readiness in the context of Industry 4.0. *Information*, *10*(89), 1–13. https://doi.org/10.3390/info10030089

Bastos, P., Lopes, I., & Pires, L. (2014). Application of data mining in a maintenance system for failure prediction. In R. Steenbergen, P. H. A. J. M. Van Gelder, S. Miraglia, & T. Vrouwenvelder (Eds.), *Safety, reliability and risk analysis: Beyond the horizon* (pp. 933–940). Taylor &Francis Group.

Bevilacqua, M., Bucci, R., Materazzi, S., & Marini, F. (2013). Application of Near Infrared (NIR) spectroscopy coupled to chemometrics for fried egg-pasta characterization and egg content quantification. *Food Chemistry*, *140*(4), 726–734. https://doi.org/10.1016/j.foodchem.2012.11.018

Bindu, K. P., Jayasree, N. R., & Sreenivasan, E. (2013, July). Control, automation and monitoring of hardboard production process using PLCSCADA system. *International Journal of Advanced Research in Electrical, Electronics and instrumentation Engineering*, *2*(7), 3281–3286. https://www.ijareeie.com/upload/2013/july/54_Control.pdf

Bossart, E. (2015). Fundamentals of hydrostatic level measurement. *Sensors and Measurement*, *1* (1),1–6.

Chakraborty, A. (2016). Importance of PDCA cycle for SMEs. *SSRG International Journal of Mechanical Engineering (SSRG-IJME)*, *3*(5), 14–18. doi:10.14445/23488360/IJME-V3I5P105

Crnjac, M., Veža, I., & Banduka, N. (2017). From concept to the introduction of Industry 4.0. *International Journal of Industrial Engineering and Management (IJIEM)*, *8*(1), 21–30. https://bib.irb.hr/datoteka/894382.IJIEM_24.pdf

Du, C.-J., & Sun, D.-W. (2006). Learning techniques used in computer vision for food quality evaluation: A review. *Journal of Food Engineering*, *72*(1), 39–55. https://doi.org/10.1016/j.jfoodeng.2004.11.017

Favi, C., Germani, M., & Marconi, M. (2017, June 27-30). A 4M approach for a comprehensive analysis and improvement of manual assembly lines. In *27th International conference on flexible automation and intelligentmanufacturing, FAIM2017* (Vol. 11, pp. 1510–1518). Modena, Italy, ProcediaManufacturing.

Fouad, R. H., & Mukattash, A. (2010). Statistical process control tools: A practical guide for Jordanian Industrial Organizations. *Jordan Journal of Mechanical and Industrial Engineering*, *4* (6), 694–700. http://jjmie.hu.edu.jo/files/v4n6/4.pdf

Groß, F., Benning, R., Bindrich, U., Franke, K., Heinz, V., & Delgado, A. (2011). Optical online measurement technique used for process control of the drying step during pasta production. *Procedia Food Science*, *1*(2011), 1301–1308. https://doi.org/10.1016/j.profoo.2011.09.193

Hozdić, E. (2015). Smart factory for Industry 4.0: A review. *International Journal of Modern Manufacturing Technologies*, *7*(1), 28–35. https://www.researchgate.net/publication/282791888_Smart_factory_for_industry_40_A_review

Huang, H., Liu, L., & Ngadi, M. O. (2014). Recent developments in hyperspectral imaging for assessment of food quality and safety. *Sensors*, *14*(4), 7248–7276. https://doi.org/10.3390/s140407248

Kowalski, M., Zelewski, S., Bergenrodt, D., & Klupfel, H. (2012). Application of new techniques of artificial intelligence il logistics: an ontology-driven case- based reasoning approach. In *Proceeding of the European modelling and simulation conference, Essen, Germany*.

Lotlikar, T., Kankapurkar, R., Parekar, A., & Mohite, A. (2013). Comparative study of barcode, QR-code and RFID system. *International Journal of Computer Technology and Applications*, *4*(5), 817–821. http://journaldatabase.info/articles/comparative_study_barcode_qr-code_rfid.html

Marcos, A., Chiarello, M. C., Emer, F. P., & Neto, A. G. S. S. (2014, February). An approach of software requirements elicitation based on the model and notation business process (BPMN). *Lecture Notes on Software Engineering*, *2*(1), 65–70. doi:10.7763/LNSE.2014.V2.96

Massaro, A., Maritati, V., Galiano, A., Birardi, V., & Pellicani, L. (2018, May). ESB platform integrating KNIME data mining tool oriented on Industry 4.0 based on artificial neural network predictive maintenance. *International Journal of Artificial Intelligence and Applications (IJAIA)*, *9*(3), 1–17.

Massaro, A., Maritati, V., Savino, N., Galiano, A., Convertini, D., De Fonte, E., & Di Muro, M. (2018). A study of a health resources management platform integrating neural networks and DSS telemedicine for homecare assistance. *Information*, *9*(176), 1–20. https://doi.org/10.3390/info9070176

Massaro, A., Vitti, V., & Galiano, A. (2018). Automatic image processing engine oriented on quality control of electronic boards. *Signal & Image Processing: An International Journal (SIPIJ)*, *9*(2), 1–14. doi:10.5121/sipij.2018.9201

Massaro, A., Vitti, V., Galiano, A., & Morelli, A. (2019). Business intelligence improved by data mining algorithms and big data systems: an overview of different tools applied in industrial research. *Computer Science and Information Technology*, *7*(1), 1–21. https://doi.org/10.13189/csit.2019.070101

Mokhtar, A., Becker, T., & Hussein, M. A. (2011). Monitoring pasta production line using automated imaging. *Procedia Food Science*, *1*(2011), 1173–1180. https://doi.org/10.1016/j.profoo.2011.09.175

Morris, A. S., & Langari, R. (2015). *Measurement and instrumentation: Theory and application* (2nd ed.). Elsevier.

OECD. (2017). *The next production revolution: Implications for governments and business*.

Özdemir, V., & Hekim, N. (2018). Birth of Industry 5.0: Making sense of big data with artificial intelligence, 'The Internet of Things" and Next-Generation Technology Policy'. *OMICS: A Journal of Integrative Biology*, *22*(1), 65–76. https://doi.org/10.1089/omi.2017.0194

Oztemel, E., & Gursev, S. (2018). Literature review of Industry 4.0 and related technologies. *Journal of Intelligent Manufacturing 31*(1), 127–182. https://doi.org/10.1007/s10845-018-1433-8.

Popper, L., Schäfer, W., & Freund, W. (2006). *A compendium of flour improvement*. Verlag Agrimedia.

Rubmann, M., Lorenz, M., Gerbert, P., Waldner, M., Justus, J., & Harnish, M. (2015). *Industry 4.0: The future of productivity and growth in manufacturing industries* (The Boston Consulting Group Report). https://www.zvw.de/media.media.72e472fb-1698-4a15-8858-344351c8902f.original.pdf

Rumbaugh, J., Jacobson, I., & Booch, G. (2005). *The unified modeling language reference Manua* (2nd ed.). Addison-Wesley.

Saponaro, A. (2018). *Cross-border risk assessment of earthquake-induced landslides in Central Asia* [PhD thesis]. Technischen Universität Berlin: https://depositonce.tu-berlin.de/bitstream/11303/7412/4/saponaro_annamaria.pdf

Skobelev, P. O., & Borovik, S. Y. (2017). On the way from Industry 4.0 to Industry 5.0: From digital manufacturing to digital society. *International Scientific Journal "Industry 4.0*, *2*(6), 207–311. https://stumejournals.com/journals/i4/2017/6/307.full.pdf

Song, X., Tan, S., & Ding, J. (2006, June 15–17). A monitoring system for plcControlledmanufacturing system based on fieldbus. In *Knowledge enterprise: IntelligentStrategies in Product design, manufacturing, and management proceedings ofPROLAMAT 2006, IFIP TC5 international conference*, Shanghai, China.

Sony, M. (2018). Industry 4.0 and lean management: a proposed integration model and research propositions. *Production & Manufacturing Research*, *6*(1), 416–432. https://doi.org/10.1080/21693277.2018.1540949

Takenobu, O., & Shuji, A. (2013). Measurement of moisture profiles in pasta during rehydration. *Food and Bioprocess Technology*, *7*(5), 1465–1471. http://dx.doi.org/10.1007/s11947-013-1156-y.

Terzic, J., Terzic, E., Nagarajah, R., & Alamgir, M. (2013). Ultrasonic sensing technology. In Terzic, J., Terzic, E., Nagarajah, R., Alamgir, M (Eds.), *Dynamic vehicular applications* chapter 2 (pp. 11–35). Springer. https://doi.org/http://dx.doi.10.1007/978-3-319-00633-8_2

Tijan, E., Aksentijevic, S., Ivanic, K., & Jardas, M. (2019). Blockchain technology implementation in logistics. *Sustainability*, *11*(1185), 1–13. https://doi.org/10.3390/su11041185

Vaidya, S., Ambad, P., & Bhosle, S. (2018). Industry 4.0 –A Glimpse. *Procedia Manufacturing*, *20* (1), 233–238. https://doi.org/10.1016/j.promfg.2018.02.034

Wimmer, H., & Powell, L. M. (2015). In A comparison of open source tools for data science. *Proceedings of the conference on information systems applied research Wilmington*, North Carolina USA.

Yang, T., Chen, X., & Chen, Z. (2001). Multiresolution local contrast enhancement of x-ray images for poultry meat inspection. *Applied Optics*, *40*(8), 1195–1200. https://doi.org/10.1364/AO.40.001195

Zhang, X., Lei, X., & Kan, J. (2015). Degradation prediction model based on a neural network with dynamic windows. *Sensors*, *15*(3), 6996–7015. https://doi.org/10.3390/s150306996