Chapter

Introduction to Intelligent Quality Management

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Abstract

Intelligent manufacturing is becoming more and more attractive for industrial societies especially after the introduction of industry 4.0 where most of industrial operations are to be carried by robots equipped with intelligent capabilities. This explicitly implies that the manufacturing systems will entirely be integrated and all manufacturing functions including quality control and management will have to be made as much intelligent as possible in operating with minimum human intervention. This Chapter will present a brief overview of some implications about intelligent quality systems. It intends to provide the readers of the book to understand how the concept of artificial intelligence is to be embedded into quality functions. It is known that the interoperability is the rapid transformation requirement of industry specific operations. This requires the integration of quality functions to other manufacturing functions for sharing the quality related knowledge with other manufacturing functions in order to sustain total intelligent collaboration. Achieving this, on the other hand, ensures the improvement of manufacturing processes for better performance in an integrated manner. Note that, although some general information about intelligent manufacturing systems are given, this chapter is particularly focused on discussing intelligent quality related issues.

Keywords: intelligent quality, intelligent manufacturing, integrated quality, quality management, quality improvements

1. Introduction

Intelligent manufacturing is becoming more and more attractive for industrial societies especially after the emergence of industry 4.0 where most of industrial operations are to be carried by robots equipped with intelligent capabilities. Since digital transformation is increasing every day. The manufacturing societies are enforced not only to increase the development speed of manufacturing systems but also to improve the functionality, flexibility, usability and interoperability of the system developed.

For each manufacturing function, different methods and methodologies are developed to sustain the level of intelligence due to the nature of the operations carried out within the scope. This applies to quality operations as well. Introducing artificial intelligence in quality systems were considered since so many years. Pham and Oztemel (1996) Published a book on intelligent quality systems and took the attention of both research and industrial communities on this issue [1]. They presented real life applications and highlighted possible areas of future developments. Oztemel and Tekez (2008) took this initiative one step ahead and proposed a multi agent quality management system where each quality function is considered to be self-operating and capable of working independently but coordinating with others in a well-designed manufacturing suits [2]. Their approach contributed to the developed a reference model of fully integrated, intelligent manufacturing system so called REMIMS [3]. Application of artificial intelligence techniques and methodologies to quality domain varies. There are vast amount of research and literature available. Here in this Chapter, only a few of them (that are different nature in a wide spectrum) will be mentioned for indicating the importance of this initiatives and the range of applications.

Computer vision technology and artificial intelligence, for example, are well utilized for quality control purpose in many different applications. As the quality of many products in manufacturing is defined by the dimensions and surface features, computer vision technology is utilized for mainly replacing human eyes. This attracted manufacturing community due to cost effectiveness. It is now well proven that together with utilizing statistical analysis methods, automated machine vision systems are capable of analyzing geometric and surface features for deciding about the quality of products [4].

Similarly, Xu et al. (2018) provided an intelligent quality problem solving system capable of performing a comprehensive analysis of data mining process and methods. They run a pilot application in automotive manufacturing company to demonstrate intelligent capabilities of the system proposed [5]. Bihi et al. (2018) designed and intelligent quality management systems which can learn and adapt itself to the requirements of flexible manufacturing systems [6]. The goal of this system is to learn line layout and setup through predefined training cycles. Tseng et al. (2016) presented a remote part tracking and quality control system, so called e-quality control, based on the application of support vector machine (SVM) to predict the output quality [7].

Like some of those mentioned above, a comprehensive literature review will provide huge amount of information on implementing artificial intelligence on quality functions. The information stated above is considered to be sufficient enough for taking the attention of the reader to intelligent quality operations. Note that, the remaining part of this chapter will highlight the importance of intelligent tools for sustaining the quality of systems, processes and products. Also note that, the Chapter will describe a general framework for utilizing intelligent quality systems.

2. Introducing intelligence to manufacturing functions

Success of manufacturing systems in industry 4.0 era will be heavily dependent upon their capability to perform operations with a certain degree of autonomy which can be assured by employing artificial intelligence in designing manufacturing systems to some extent. Oztemel (2010) describes a general framework with possible characteristics of intelligent manufacturing systems [8]. Due to wide variety of products and services requiring very complex operations, manufacturing systems are facing so many challenges. For example, customization is a very demanding properties of the products and services for intended customers. There seems to be several unique requirements like this one for the manufacturing systems to cope with the existing transformation need. Some of these are;

- to be able to adopt new models,
- generating new forms of manufacturing,
- implementing new methodologies for achieving the required level of transformation to smartness in the traditional manufacturing systems.

It is now very obvious that generating a required level of flexibility in manufacturing system is not enough for proper transformation. Whole supply chain is to be involved. Unmanned operations and systems, on the other hand, generates more competitiveness and puts more challenges for those which are having lack of knowledge on generating the required autonomy. Since, artificial intelligence, information technology, and robots with well performing sensors are the technologies to form advanced manufacturing systems which are to be capable of overcoming those challenges, manufacturers should spend a great amount of effort to learn and experiment these in their operations. In other words, the manufacturers may need to follow lean principles together with intelligent equipment. This means, they need to optimize productivity and effectiveness of their manufacturing hardware, reduce possible wastes (scraps, overtimes, costs etc.), reduce cycle times and increase the expected output.

Intelligent equipment should not only be able to utilize artificial intelligence and machine learning technologies, but also be capable of processing big data collected over a certain amount of sensors in different roles for the sake of sustaining proactive management of equipment, processes services as well as products. Generating intelligent systems in this manner requires utilizing advanced information and manufacturing technologies for sustaining intelligence, re-configurability, interoperability, reusability and flexibility. Shen and Norrie (1999) provided a survey pointing out various requirements of especially agent based intelligent manufacturing systems [9]. Note that intelligent manufacturing, requires certain type of technologies for assuring the manufacturing equipment to behave as much intelligent as possible. Internet of Things, Cyber-physical systems, cloud computing, big data analytics, learning events, generating immediate responses to unexpected changes around etc. will be inevitable to sustain required level of smartness. Note that the production life cycle as a whole should be integrated and motivated by AI enriched sensors, decision making systems with big data analytics as well as advanced materials [10]. It seems that the competitiveness of manufacturing systems will heavily be dependent upon the level of intelligence they possess. Especially, utilizing data integration capabilities of information systems, intelligent decision making and reasoning capability (cognitive evaluation) over the data available, representing the results of the cognition process through dashboards and interactive visual analytics, employing smart sensor technologies so on and so forth will be the main focus of manufacturers in the following decade.

For a manufacturing system, being able to process real time data gathered from the machines and performing intelligent analysis over those through implementing AI technologies make it to predict and understand critical events and solve problems immediately before yielding any dangerous and hazardous situation as well as wastes. This capability of manufacturing systems even allows the machine to perform predictive maintenance and generate well operating manufacturing suits.

Current literature is rich enough to provide information regarding intelligent manufacturing as well as various applications. The reader may not have any difficulty in reaching those. For the purpose of this Chapter, it would be beneficial to mention some of the areas where AI technology is heavily utilized in generating intelligent behavior of certain type of quality functions.

3. The need for integrated manufacturing system

Since human intervention is minimized in intelligent operations, the systems should be capable of communicating with one another in order to make sure that the full manufacturing cycle is to operate without and delays and problems. This implies that manufacturing systems should employ knowledge protocols or any other knowledge transfer language [11, 12]. The integrated architecture in this manner ensures the detection of undesired operations and enables generation of immediate responses. This, in turn, improves the quality, minimizes downtime and improves overall equipment efficiency. Through digital operations and simulation technology (empowering digital twins) allow to virtually experiment manufacturing operations and realize possible shortcomings which could be prevented before actual set up.

Smart operations also empower manufacturing systems in terms of optimizing the overall supply chain. Operations like demand forecasting, inventory optimization, supplier monitoring and performance assessments can be made more effective through intelligent methods and internet of things with equipped sensors.

Visual system manipulations, on the other hand, seem to be more and more demanding in manufacturing sites especially after the introduction of 5G. Being able to experiment manufacturing operations in virtual world and generate digital replicates of the manufacturing operations, make the life easy for designers to be able to discover and foresee the effect of new business models, new technology implementations and smart decision making capabilities.

It should be noted that the technological progress and disruptive technologies improve competitive advantage and makes it possible to devices systems which are superior over traditional automation systems. Intelligent manufacturing operations and the capability of real time data processing, on the other hand, allows prediction of possible failures before they actual occur and highlights possible anomalies. This may encourage predictive maintenance and prevent downtime and machine failures. With this respect, the quality management in integrated manufacturing environment is essential in order to sustain competitive manufacturing.

4. A general framework for intelligent quality

Among various other applications, smart systems can be used to assure process and product quality. One of the distinguishing character of intelligent quality in recent years is that, not only the quality of the productions processes is the subject of quality management but also all processes within the production life cycle of the enterprise including the quality of procurement, design, planning, production, distribution and marketing. The applications can therefore be grouped into 3 categories as intelligent quality implementations before, during and after manufacturing operations. To mention some of those, smart manufacturing systems are to be capable of assuring quality through experimental design before production process starts [13]. During the production process some statistical process control (SPC) systems ca be well effectively employed thorough intelligent analysis and implementations [14]. Similarly defect detection after production is subject to intelligent operations. Similarly, visual inspection technology based on computer vision and machine learning is not strange in quality management societies. Wang et al. (2019) presented a computer vision based inspection system by employing deep learning in order to identify and classify defective products without the loss of accuracy [15]. Chesalin et al. (2020) provided an overview of intelligent quality tools that can be utilized for handling quality related issues within a manufacturing suit [16].

Similarly, reviewing respective literature highlights huge amount of areas where intelligent and smart systems are being utilized for the sake of generating a better quality on processes, products and services provided. Some of them can be listed below.

- Sustaining the quality of processes, products and services, ensuring reliability and detecting possible anomalies.
- Generating alerts for process abnormalities and fault detection.
- Predicting the behavior of the machines, devices and respective equipment in terms of expected yield.
- Maintaining machine and condition monitoring for making sure that the machines are healthy enough to operate.
- Assuring the effectiveness of whole supply chain from suppliers to the customers including managing the respective resources as well as customer segmentation.
- Handling inventory and optimizing material management.
- Performing computer vision based inspection through implementing machine learning techniques in order to find out defective products
- Implementing intelligent systems to optimize quality parameters of the process (experimental design)
- Benchmarking which would allow the systems to be compared with their counterparts.

Considering the complexity and functionality of products and process and the need for handling huge amount of data, sustaining required level of quality is nearly impossible without taking the advantages of information technologies. Enriching those with intelligent capabilities (utilizing artificial intelligence) and data analytics (big data manipulation) definitely improve the performance of quality management activities.

Another aspect of intelligent quality in modern manufacturing systems is to sustain continuous improvement as was deployed by human quality operators and process teams. This definitely require communication of various manufacturing agents designed to exchange required knowledge which can trigger improvement activities.

As above explanations clearly imply, well known artificial intelligence methodologies such as expert systems, machine learning (neural networks), genetic algorithms, fuzzy logic and some others are proven to be good enough for generating solutions to respective quality situations. However, for some situations these methodologies may not generate required responses alone. It may be inevitable to utilize more than one of these. Intelligent agents are capable of utilizing various AI methodologies depending upon the nature of the problem. The studies experimented indicates more effective and solution providers to the manufacturers.

4.1 Requirements for developing intelligent quality management systems

Intelligent quality requires management commitment in order to provide necessary facilities and capabilities for complying with the requirements and continually improve the effectiveness of the quality system. It should allow quality responsible to be able to assess the status of quality objectives. However, not only the quality people be involved but all should take part in developing and running the systems. Everybody in manufacturing chain should aim continuous and sustainable quality level for enterprise wide operations and services. This ensures the required level of integration (quality functions with all others). Meaning of this is to communicate quality problems and protect the other systems to be negatively affected while improving quality culture. Having the commitment of all people also try to enable quality systems to support overall business objectives as set forth by the top management.

Another aspect of intelligent quality is to employ a knowledge driven approach for generating and operating the systems as opposed to traditional data driven one. In order to establish required level of intelligence the system should be equipped with respective operational as well as respective quality knowledge. Traditional data based approaches are not sufficient enough to generate intelligent behavior. There is a need for methods and methodologies to dig out knowledge out of available data (this may be called as knowledge mining) for generating self-behavior of intended quality function. Artificial intelligence and machine learning systems provide various alternatives for locating and utilizing quality knowledge.

Due to the nature of intelligent systems, when they are well defined, they provide quality know-how for those which are having difficulty in setting up quality systems. Since they will be equipped with relate domain and quality knowledge, they would prevent;

- lack of quality in process outputs automatically by taking the attention of the operators or other systems to anomalies and defective outputs. They may also recommend some solutions and remedies.

- lack of quality knowledge as well as related process knowledge to some extent.

- lack of experience in handling quality related issues especially for those who are new in practicing quality operations

- poor system development through highlighting missing parts and required capabilities.

- lack of methods and methodologies to be implemented.

- misleading machine set up and respective inefficiency.

- misleading knowledge and process flow operations.

- inaccurate interfaces between processes and operational units.

Moreover, being able to generate a good quality product and services by intelligent quality practices increase customer trust and loyalty. Since the systems will have to self-operate and make recommendations and remedies for the responsible people, they may also find the system attractive for their success.

With this understanding intelligent quality should aim to satisfy following requirements. These may be called as "the baseline requirements" for intelligent quality management systems. Achieving these, verify, validate and assure the effectiveness of the systems employed.

- Minimizing duplication of work and various types of functionalities.
- Gathering, updating and storing the real time data and making it timely available.
- Generating quality knowledge out of data available and using those for self-decision making.
- Making accurate predictions about the status of manufacturing equipment as well as expected outputs (defect free deployment)
- Assessing supplier automatically and monitoring their performance through on-line tracking systems.
- Generating alerts for the responsible people to take immediate actions where ever the system is not able to do so.
- Measuring and sustaining the reduction of the following by means of digital infrastructure.
    - Customer (both internal and external) complaints
    - Defective products and scrap rates
    - Process anomalies
    - Delayed orders
    - Downtime due to machine unavailability.
- Measuring and sustaining the increase of the following by continuous monitoring systems.
    - Productivity in manufacturing lines
    - Employee satisfaction
    - Customer (both internal and external) satisfaction
    - Supplier satisfaction
- Maintaining quality standards as they evolve and being adaptive to cope with the changes without spending too much effort. That is to adaptively comply with quality regulations.
- Sustaining data security as well as information integrity.

4.2 Framework for intelligent quality systems

Above explanations indicate the importance of intelligent manufacturing in general and intelligent quality in specific. This section provides a general framework for generating an integrated intelligent quality system. As implied above, main requirement behind this framework is to set up knowledge intensive activities for assuring quality and continuous improvement. This, in turn, requires a systematic performance monitoring and assessment. The proposed framework is based on achieving business objectives which in turn needs to be aligned with the objectives of the processes. Note that, intelligent tools can support quality management activities in various ways as listed below.

- Handling quality policies and objectives of any manufacturing system could be supported by intelligent tools in order to set up proper quality plans and standards.

- Quality management related knowledge could very well be stored in knowledge bases and utilized in making quality decisions. The performance of the system will be depended upon the acquisition and application of relevant knowledge sets.

- Data from various sensors could be gathered and interpreted for the sake of sustaining on-line monitoring of the process in terms of quality requirements.

- Design and operational reliability (ability to perform a specific function) availability (ability to keep a functioning state) maintainability (ability to be timely and easily maintained) and safety (ability not to harm people, the environment, or any assets) analysis (SARM) could be carried out intelligently for assuring engineering characteristics of products or systems. SARM is proven to be good in identifying, analyzing, evaluating, preventing, verifying and correcting the defects and hazards of any system. Intelligent tools could facilitate these analyses more effectively and efficiently for the benefit of the enterprise.

Taking above explanation into account, it would be possible to say that intelligent quality management operations are carried out in 3 different phases of any manufacturing system. These are;

- Phase-1: Operations before running manufacturing processes

- Phase-2: Operations during running manufacturing processes.

- Phase-3: Quality Operations after manufacturing

All of these phases should be supported by intelligent tools in various nature and should be involved within given framework for the sake of integration and completeness of the whole life cycle of quality management activities.

4.2.1 Quality operations before running manufacturing processes

Figure 1 indicates the basic elements of intelligent quality management in the first phase.

There are two aspects of specification analysis like process specification and product specification. These should be compliant with one another. Intelligent systems should be able to align and compare predefined set of requirements (specification match) and intelligently analyze those to generate complete set of specifications which could be used for properly designing the processes to run defined process plans. Fuzzy logic and expert systems could very well be employed for this.

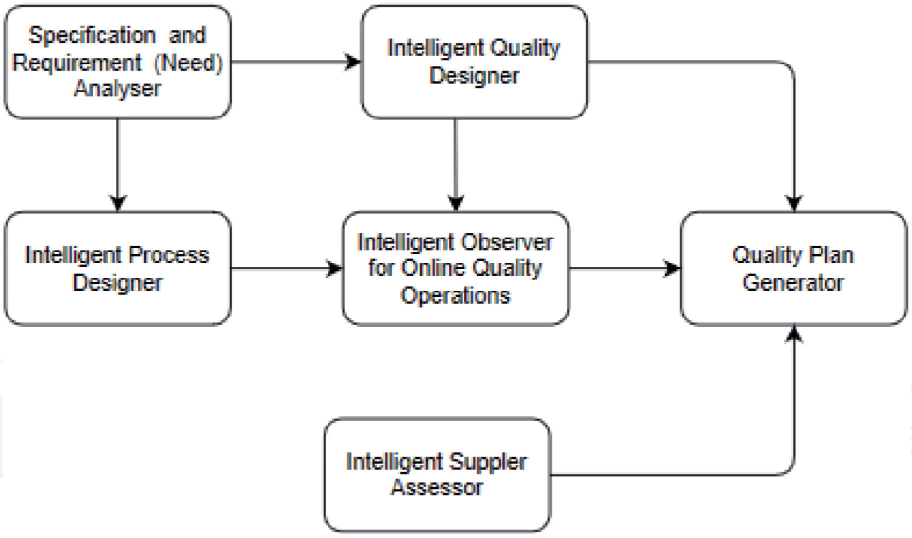

Figure 1.
Intelligent quality operations before manufacturing.

Agents equipped with machine learning systems can also help in refining process and product specifications and generate optimum designs [17].

Designing quality (design of experiment) is another area where machine learning and artificial intelligence can be utilized. Finding out the optimum values of the quality parameters would be possible by learning systems which can learn various parameters and help optimize the quality design [13].

Quality function deployment (QFD) is an effective tool to shape product specifications based on customer requirements. Supporting this function with intelligent tools may enable automatic prediction of product quality with respect to customer expectations [18]. This information would also be used in forming design and manufacturing data. When there is a change in customer demand (which is the case in most of time), the effect of that in manufacturing can be assessed. With this capability intelligent QFD may be used during manufacturing process as well. Adding new requirements, removing an existing one, changing the design attributes would be handled by the support of intelligent tools like fuzzy logic.

Supplier assessment is another area where intelligent systems would be employed. Fuzzy logic theory is heavily involved in selecting best suppliers among alternatives [19]. Similarly, literature shows evolutionary modeling [20], and neural network implementations [21]. This is indirectly related to quality operations as it ensures good quality and timely material with bearable costs to be available.

There are some information systems and software platforms for handling quality standards like ISO 9000 series. The tools which can facilitate especially corrective actions and run validation process over quality implementations. Computer based intelligent decision making along this line may generate effective implementation of quality standards. Enriching these systems with intelligent capabilities may empower quality assurance systems.

4.2.2 Quality operations during execution of manufacturing processes

Figure 2 indicates the basic elements of intelligent quality management in the second phase. As indicated, generating quality standards and quality assurance system is the baseline requirement for setting up intelligent quality operations during execution. This may assure the integration of quality operation for various manufacturing systems. As described by Albers et al. (2016), a comprehensive model can be devised in order to support both digitization process and sustaining

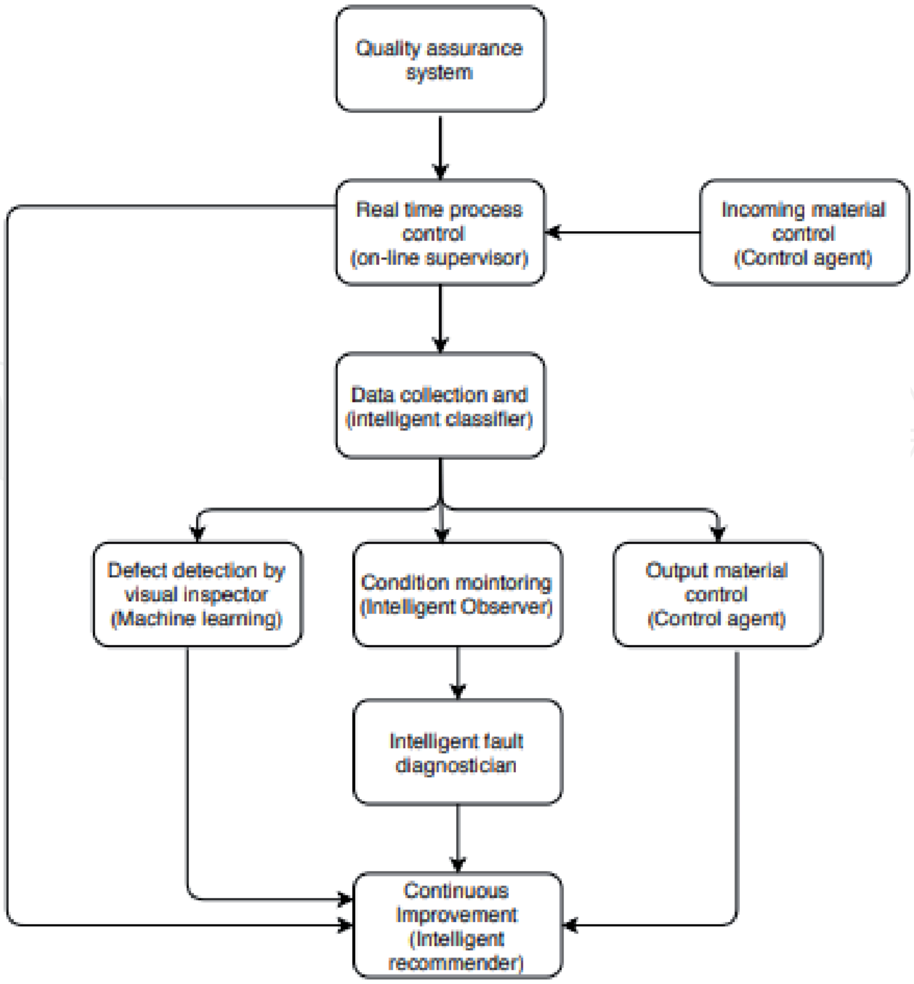

Figure 2.
Intelligent quality operations during manufacturing.

good quality in an integrated manner [22]. Similar studies indicate that, some of the methods and methodologies such visual and constructive inspection of products and processes, intelligent classifier and data acquisition systems, defect detection and fault diagnosis as well as condition monitoring systems are inevitable for real time quality management.

Making the data available through data gathering systems enables analysis and visualization of information which can be effectively used in generating evidences for quality related decision making. By detecting defects as early as possible in manufacturing line not only yields cost reduction but also eliminates causes of failures. This is in fact one of the main requirements for successful quality assurance systems.

Real time intelligent quality assurance may ensure that the smart operations are handle without interruption and sustain continuity of manufacturing operations with the required level of reliability, flexibility, and interoperability. This, in turn, increases productivity and effectiveness as well as to reduce the defects to the minimum level possible.

Real time and online quality operations handled by intelligent tools should support well-known quality tools such as quality function deployment, statistical process control, constructive and visual inspection, failure mode and effect analysis, measurement systems etc. Each of these tools could very well be enriched by self-behaving capability and reconfigured in accordance with the requirements and specification of manufacturing systems.

Statistical process control (SPC) is one of the major area for implementing artificial intelligence for sustaining good quality within a manufacturing process. Pham and Oztemel (1996) are long ago took the attention of the scientific community to this point by introducing an expert system (called XPC) and machine learning system for statistical process control [1]. XPC was able to construct quality control charts and perform process capability analysis in order to make sure that the process is able to comply with customer specifications, collect data on-line, plot those over the chart constructed and interpret the status of the process, perform fault detection and diagnosis, make some recommendation in case of an out of control situation. The system was also able to modify control limits and control chart used in order to embed improved process standards. It was well appreciated as the system was playing the role of a quality engineer and continuously monitoring the process on-line.

When utilizing machines, there is and will be a need for condition monitoring and try to identify possible machine faults before they cause unbearable costs. As described in Zabinski et al. (2019), condition monitoring systems mainly deals with, monitoring and feature extraction, real-time anomaly detection and fault diagnosis [23]. Expert systems and rule based reasoning mechanisms, neural networks and deep learning methods as well as intelligent agents can be extensively used for monitoring the machines and process for possible anomalies and faults. Literature provides huge amount of implementation in these areas. Besides, as condition monitoring is the best way to minimize the probability of failure and therefore maintenance cost, making it intelligent and generating a self-behaving observer can be an important tool for predictive maintenance [24].

By implementing AI techniques to monitor the condition of an equipment, identifying possible faults and observing the trend of the level of deterioration may allow possible actions to be taken at convenient times without interrupting production process. Generating intelligent predictive maintenance system by this way, may prevent major overhauls or increase the time to go into an overhaul. This definitely reduces significant damage that would otherwise be unavoidable. Above all, proper maintenance schedules can be generated in between the demands for having maintaining the equipment if not done automatically. Considering the amount of money spend for keeping spare parts of the machines in stock, intelligent condition monitoring may prevent undesired use of spare parts and avoid unnecessary parts not to be overstocked.

Artificial intelligent methods, especially machine learning techniques remarkably increased the effective utilization of visual inspection system for the sake of improving the quality of products and processes [25]. Note that, quality control through inspection is long being implemented in industry for locating nonconforming products or processes. Main aim is to deliver products and services to the customers in required specification (so called good quality) or defect free.

In earlier times, it was possible to inspect nonconformity by human eyes. Since the complexity and functionality of the systems are increased, it would not be possible to decide about the quality of the inspected items by human eyes. Computer support was inevitable and self-decision making which was assured by artificial intelligence was extremely useful. This is even more important today due to the nature of big data available within manufacturing areas. Two approaches are implemented.

- Taking the video record of the systems and products and then analyzing those off-line for finding if there is any abnormality.

- Real-time data collection and defect detection using image recognition and AI techniques such as neural networks.

Technology enables obtaining high quality video images with certain cameras specifically configured to manufacturing line. Data collected can be cleaned in real time for the sake of locating anomalies and defects such as scratch, dent, crack, dirt, wrong print, foreign objects, undesired bubbles etc. Computer vision system replicates human vision and assessment system.

Inspection systems may require both hardware (camera, gateway, photometer, colorimeter, CPU etc.) and software (video processor, database, reasoning mechanism and learning engine, cloud services etc.). Hardware is mainly used for data collection and processing whereas software is used for recognition and interpretation. In intelligent visual inspection, the learning and interpretation capability indicates the degree of smartness.

Production part approval process (PPAP) can be supported by intelligent tools for providing evidences that all customer demand-based specifications are well understood and proper manufacturing set up is in place. It may ensure that the manufacturing process is running in expected rate and producing well accepted products by the customers. It may also assure the fitness of quality plans, support maintaining design integrity, provide early detection of problems to be sorted, prevent nonconforming parts to be processed etc. Another benefit of intelligent PPAP is to make sure that the suppliers have well understood the engineering design attributes and specifications of the products they are vendoring.

Intelligent failure mode and effect analysis (FMEA) can be very useful for finding and diagnosing process and system faults. The system may handle the information of various failures and analyze and interpret those from multiple point of view. Characteristics of different failures within product and process life cycle can be well managed. As described by Zhao et al. (2004), the system may involve a model base and knowledge base as well as functional models of the products and effect analysis of possible failures [26]. It would be possible to perform various reasoning processes depending upon the type of failure in question. FMEA of very complex system can be carried out with implementing expert knowledge of the domain as well as respective failures. This system may be coupled with Fault Tress Analysis (FTA) which is a hierarchical representation of faults enabling the analysis for the probability of a failure and its consequences. Due to uncertainty, complexity and inexact information, it is not easy to define the probability of a fault to occur. However, intelligent tools such as fuzzy logic and neural network are very capable of handling imprecise knowledge [27]. Generating intelligent FMEA and FTA may allow generating records of failures and recommends some corrective actions for improving the quality of manufacturing systems.

Creating and integrating all of the systems, some of those are listed above, may lead fully automated intelligent quality system within a smart manufacturing environment. Being able to receive data and information from various manufacturing functions and related systems without any interruption enables the designers to device a recommendation system to prevent misleading operations and deterioration from respective manufacturing plans. Recommendation could be provided for;

- Foreseeing possible deteriorations
- Preventing errors and faults over the process or products
- Correcting errors and faults
- Preventing the shift of non-conformed products between processes.
- Preventing the delivery of non-conformed products to customers.

Some of the recommendations would be carried out by intelligent systems capable of self-improving whereas some of them would still be sorted by the human operators.

4.2.3 Quality operations after manufacturing

Upon completing manufacturing, the products, some quality operations need to be carried out in delivery and after sale services. There could be various activities some of those are given in **Figure 3**.

Performing quality predictions before and after manufacturing can be carried out intelligently in order to follow if the predicted quality can be realized or not. Intelligent post production analyzer receives not only the predicted values but also some warranty information to keep track of the products after they delivered to the customers. Products should comply with the specifications and terms of use as promised before order received. The system may define conditions subject to warranty as well.

Comprehensive quality analysis may also be carried out upon receiving some feedback from the customer. Feedback can be received either by satisfaction surveys and information gathered by customer information channels (i.e. on-line support through web page applications). Information provided by the customers may be a good source of updating quality standards and expectations within manufacturing systems.

Analyzing the quality costs may provide some useful information for quality related operations and their effectiveness. Cost benefit analysis could direct improvements over the quality management process. Deterioration and sampling costs as well as the cost of inspection and control systems for specific products with specific attributes/specifications. Intelligent cost analyzer may collect cost data and may establish true costing and pricing strategies which would not compromise from the quality but increase the attractiveness of the products and services. Analyzer may generate some recommendations for quality improvements.

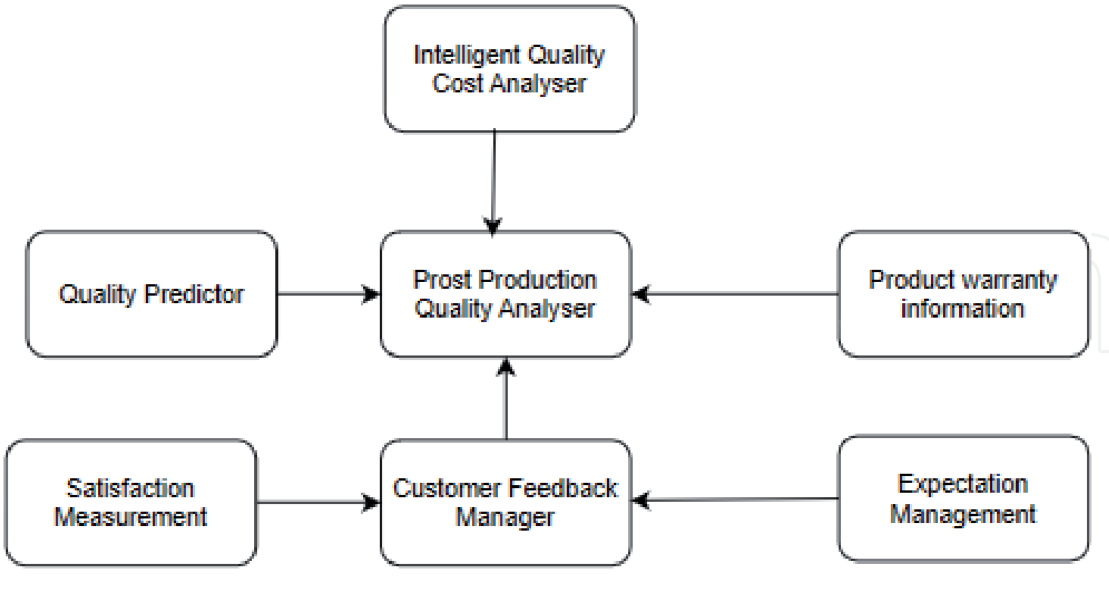

Figure 3.
Intelligent quality operations after manufacturing.

5. Conclusion

Intelligent quality management is attracting the attention of manufacturing society as it provides much opportunities to improve quality of both products and services. Agent based systems, knowledge based system, computer vision and intelligent inspection systems are proven to be capable of sustaining the quality of manufacturing systems as well as the quality of respective outputs.

As outlined in this Chapter, artificial intelligence and intelligent tools can be utilized for quality operations before, during and after manufacturing. Since each manufacturing proses is unique in terms of attributes, characteristics, and qualities products and processes. Special attention is to be given in developing intelligent quality systems. Relevant expertise and domain knowledge need to be acquired and presented to the computer for generating reasoning about the respective quality function.

Developing real-time monitoring and failure prediction systems, real time observation through visual inspection, data analysis and visualization of information which drives the evidence-based decision making and integration of the manufacturing systems throughout the whole supply chain and manufacturing life cycle could very well handled with the support of intelligent system generation technologies. This in turn supports continuous improvement of manufacturing systems in terms of reaching better quality.

The examples from the literature clearly indicates successful implementations. Sustainable quality can be better ensured with the support of intelligent tools. The manufacturers may have so many opportunities for generating fully automated quality systems with certain degree of autonomy. This definitely encourages transformation of traditional quality system to smart production system, especially when digitization process is recognized as one of the major strategic objectives.

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References

[1] Pham D.T., Oztemel E. Intelligent Quality Systems. London: Springer Verlag; 1996 London, ISBN: 3-540-76045-8

[2] Oztemel E., Tekez E. "multi-agent based integrated quality systems. In: 4th I*PROMS Virtual International Conference, 1-14 July 2008

[3] Oztemel E, Tekez Kurt E. A general framework of a reference model for intelligent integrated manufacturing systems (REMIMS). Engineering Applications of Artificial Intelligence. 2009;**22**(6):855-864. DOI: 10.1016/j.engappai.2008.10.013

[4] Rusenov B, Taneva A, Ganchev I, Petrov M. Machine Vision Systems for Intelligent Quality Control of Manufacturing Processes. In: International Scientific Conference on Engineering, Technologies and Systems (TECHSYS'17). 18 – 20 May 2017; Sofia. Bulgaria

[5] Z X, Yang D, Munro P. Knowledge-driven intelligent quality problem-solving system in the automotive industry. Advanced Engineering Informatics. 2018;**38**:441-457. DOI: 10.1016/j.aei.2018.08.013

[6] Bihi T, Luwes N, Kusakana K. Innovative Quality Management System for Flexible Manufacturing Systems. In: Open Innovations Conference (OI), 3-5 Oct. 2018, Johannesburg, South Africa. DOI: 10.1109/OI.2018.8535610.

[7] Tseng T, Aleti KR, Hu Z, Kwon Y. E-quality control: A support vector machines approach. Journal of Computational Design and Engineering. 2016;**3**:91-101

[8] Oztemel E. Intelligent manufacturing systems. In: Benyoucef L, Grabot B, editors. Artificial Intelligence Techniques for Networked Manufacturing Enterprises Management. London: Springer Verlag; 2010. pp. 1-41

[9] Shen WM, Norrie DH. Agent-based systems for intelligent manufacturing: A state-of-the-art survey. Knowledge and Information Systems. 1999;**1**(2):129-156

[10] Li B, Hou B, Yu W, Lu X, Yang C. Applications of artificial intelligence in intelligent manufacturing: A review. Frontiers of Information Technology and Electronics Engineering. 2017;**18**(1):86-96

[11] Oztemel E, Tekez E. Knowledge Protocols. In: Cunha M M, Olivera E F, Tavares A J, Ferreira L G, editors. Handbook of Research on Social Dimensions of Semantic Technologies and Web Services. IGI Global. 2009;304-324. ISBN: 978-1- 60566-650-1,

[12] Soon GK, On CK, Anthony P, Hamdan AR. A review on agent communication language. In: Alfred R., Lim Y., Ibrahim a., Anthony P. editors. Computational science and technology. Lecture notes in electrical engineering. 2019;481. Singapore: Springer Verlag. . DOI: 10.1007/978-981-13-2622-6_47

[13] Rowlands H, Packianather MS, Oztemel E. Using artificial neural networks for experimental design and off-line quality control. Journal of Systems Engineering. 1996;**6**:46-59

[14] Pham D T, Oztemel E.TEMPEX: An expert system for temperature control in an injection moulding process. Quality and Reliability Engineering International. 1992;8;1;9-15-DOI: 10.1002/qre.4680080104

[15] Wang J, Fu P, Gao RX. Machine vision intelligence for product defect inspection based on deep learning

and Hough transform. Journal of Manufacturing System. 2019;**51**:52-60. DOI: 10.1016/j.jmsy.2019.03.002

[16] Chesalin AN, Grodzenskiy SY, Nilovand MY. Tu P V. intelligent quality management tools for digital production and knowledge management system for their application. IOP Conference Series: Materials Science and Engineering. 2020;**862**. DOI: 10.1088/1757-899X/862/4/0420321

[17] Shen W, Norrie D H, Barthes J-P. Multi-Agent Systems for Concurrent Intelligent Design and Manufacturing. CRC Press; 2001. ISBN 9780748408825.

[18] Hossein IS, Hamid R. Intelligent QFD; a new approach for improving customer satisfaction. Lambert Academic Publishing. 2014 978-3659649356

[19] Bevilacqua. M, Ciarapica F F, Giacchetta G. A fuzzy-QFD approach to supplier selection. Journal of Purchasing and Supply Management. 2006;12;1;14-27

[20] Simić D, Svirčević V, Simić S. A hybrid evolutionary model for supplier assessment and selection in inbound logistics. Journal of Applied Logic. 2015;**13;2**:138-147

[21] Kuo. R J, Wang Y C, Tien F C. Integration of artificial neural network and MADA methods for green supplier selection. Journal of Cleaner Production. 2010;18;12;1161-1170 – DOI:10.1016/j.jclepro.2010.03.020

[22] Albers A, Gladysz B, Pinner T, Butenko V, Stürmlinger T. Procedure for defining the system of objectives in the initial phase of an industry 4.0 project focusing on intelligent quality control systems. Procedia CIRP. 2016;**52**:262-267. DOI: 10.1016/j.procir.2016.07.067

[23] Zabinski T, Mączka T, Kluska J, Madera M, Sęp J. Condition monitoring in industry 4.0 production systems - the idea of computational intelligence methods application. Procedia CIRP. 2019;**79**:63-67. DOI: 10.1016/j.procir.2019.02.012

[24] Yam RCM, Tse PW, Li L, Tu P. Intelligent predictive decision support system for condition-based maintenance. International Journal of Advanced Manufacturing Technology. 2001;**17**:383-391

[25] Nagata F, Tokuno K, Otsuka A, Ikeda T, Ochi H, Watanabe K, et al. Design tool of deep convolutional neural network for intelligent visual inspection. IOP Conference Series: Material Science and Engineering. 2018;**423**:012073

[26] Zhao T, Tiejun S, Xiao H, Linling S. Intelligent FMEA based on model FIORN. In: Annual Reliability and Maintainability Symposium (RAMS'04); 2004, Los Angeles; DOI:10.1109/RAMS.2004.1285480, pp:386-390

[27] Guimarees ACF, Ebecken NFF. FuzzyFTA: A fuzzy fault tree system for uncertainty analysis. Annals of Nuclear Energy. 1999;**26;6**:523-532. DOI: 10.1016/S0306-4549(98)00070-X