Doctor of Philosophy

DEVELOPMENT OF AI-BASED MONITORING AND CONTROL SYSTEM FOR THE CYCLIC MANUFACTURING PROCESS

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DEVELOPMENT OF AI-BASED MONITORING AND CONTROL SYSTEM FOR THE CYCLIC MANUFACTURING PROCESS

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DEVELOPMENT OF AI-BASED SMART MONITORING AND CONTROL SYSTEM FOR THE CYCLIC MANUFACTURING PROCESS

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Dedicated to my family and friends who have supported me the whole way.

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Ulsan, December 2021

Saurabh Kumar

Abbreviations

AI: Artificial Intelligence

CBN: Cubic Boron Nitride

DOE: Design of Experiments

ARMA: Auto Regressive Moving Average

RMS: Root Mean Square

NDT: Non Destructive Testing

AE: Acoustic Emission

FFT: Fast Fourier Transform

SAE: Society of Automotive Engineers

ANN: Artificial Neural Network

RSM: Response Surface Methodology

S/N: Sound to Noise

CBR: Case Based Reasoning

PID: Potential Integral Derivative

RBFNN: Radial Basis Function Neural Network

MES: Manufacturing Execution System

RPM: Revolution per Minute

PLC: Programmable Logic Controller

OPC: Open Platform Communications

DAQ: Data Acquisition

UI: User interface

BP: Back Propagation

IMC: Internal Model Control

RELU: Rectified Linear Unit

CAE: Computer Aided Engineering

SQL: Structured Query Language

Abstract

The success of the manufacturing process, which involves grinding as one of the stages, depends solely on the accuracy of the grinding process. The requirement of the desired surface finish at the last stage of the manufacturing makes it the most crucial stage and prone to quality defects, as this process is mainly done to provide the desired surface finish with very high precision. Complexity and importance make the real-time monitoring and control of the grinding process an essential topic for researchers. Quality defects ruin all previous manufacturing stages and incur a substantial economic loss due to product rejection. The presented thesis aims to develop and implement a monitoring system supplemented by an intelligent decision-making system for the detection and compensation of process failures. Conventionally, the quality of the products depends on the machine behavior and the operator's skill, who changes the process parameters from his own experience and expertise.

Monitoring the grinding process has caught the attention of many researchers, but most of the systems are focused on grinding wheel and other machine component conditions. Machine vision, optical sensors, and AI-based process diagnostic tools generally focus on the detection of failure. Over time various models have been proposed to control grinding tasks. However, they are limited only to optimizing the partial aspects of the grinding process. Hence they are able to reach only level three of the diagnostic and control automation. In this thesis, a vibration sensor-based monitoring system and AI-based decision-making system for the grinding process control are introduced. The in-process signals coming from the installed sensors are used for data collection, failure detection, and making intelligent decisions in autonomous way. Four significant essential process parameters were investigated: grinding wheel RPM, workpiece RPM, wheel entry speed, and coolant flow rate. AI model with supervised learning was used to understand their relationship with the real-time vibration signal

coming from the sensors. The model after training and validation was used to make the decisions for the change in the process parameters. The control actions obtained from the AI system are delivered to the machine controller. Software, as well as hardware modules of the developed system, is explained in detail. The functionality of the developed system is also demonstrated through its application into the grinding process of the brake disc. The developed system is installed as an independent software at the industrial PC that can function without any additional CAE or programming tools. The system is a significant contribution towards industry 4. 0 and making the manufacturing facilities autonomous. It has improved the overall productivity of brake disc manufacturing by reducing the occurrence of the quality failure instances and decreasing the dependencies on the operators for the know-how of the process.

This thesis will introduce related literature, followed by the research methodologies involved in the presented piece of research. The influence of critical process parameters on the grinding process is explained. Development of the vibration sensor-based monitoring system follows it. Subsequent sections are developing an intelligent decision-making system, its training, deployment, and implementation at the factory. The final part presents the benefits of this system to the manufacturers.

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Chapter 1 . GENERAL INTRODUCTION

1.1. Motivation

The grinding process is one of the most widely used machining processes to manufacture parts with very high precision. It is a precision operation that uses a higher-speed abrasive grinding wheel to remove softer material, as shown in Figure 1.1. Today it accounts for more than 70% of the total precision machining industry [1–4]. Its wide presence can be seen in all industries, whether automotive, aerospace, marine, medical, or the semiconductor industry [5]. Being the last stage of the manufacturing process, it is of utmost importance. The occurrence of any defect or anomaly in it will affect the quality and performance of the end product and ruin all the previous stages and efforts in the manufacturing of the product.

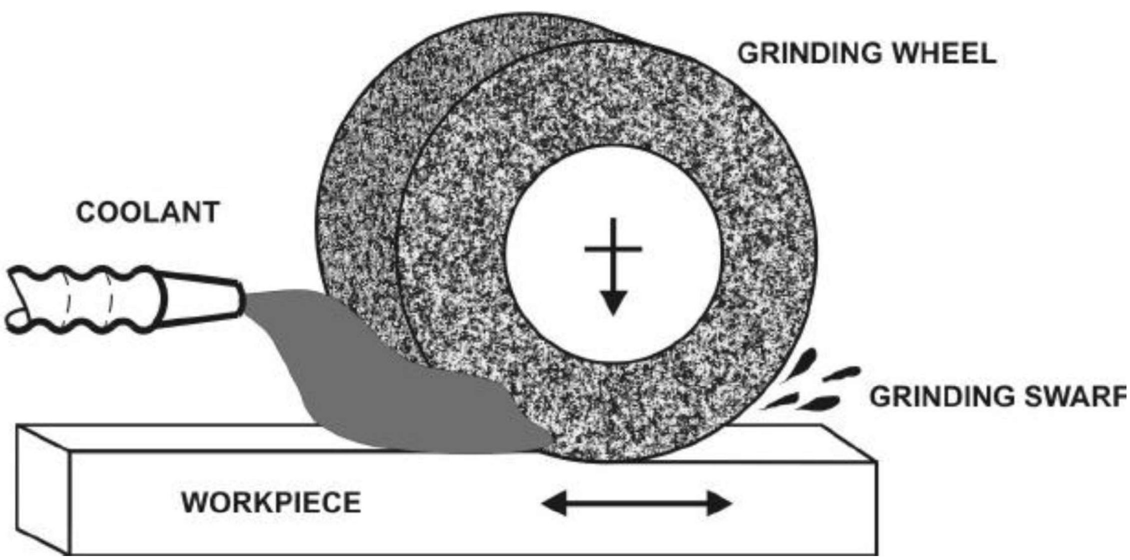


Figure 1.1. Typical grinding process [6].

The process of grinding has been in use since the medieval days. However, for the task of quality check, failure detection, and control actions, there is still a reliance on the operator's skill and knowledge [7]. Until recently, the standard view among many grinding companies has been that the technology is close to its peak and that there is little scope for new or significant technical development [8]. Several researchers have indicated that the failures like burn marks, white chatter layer, and residual stress frequently occur [9]. Quality failures during grinding lead to scrap production that results in a significant economic loss. Rejection costs for a finish-machine gearwheel with a grinding burn can rise to the order of 10,000 euros each as it has been observed that 20-25% of the total cost towards any machining job comes from grinding processes [10]. The conventional approach to dealing with these issues consumes a lot of time and resources. There is a severe need and scope for developing a monitoring and control system for these quality failures. The monitoring of the continuous interaction between the grinding wheel and the workpiece can give important information about the quality failures [11]. Reducing costs by reducing the rejection rate by only 5-10 pieces per year already amortizes costs for data-acquisition hardware for the online process monitoring.

Knowing its importance, researchers have always focused on the know-how of the grinding process. However, monitoring and control of the grinding process is not an easy task. There are certain limitations due to the complexity of the process. Sensor-assisted monitoring combined with an intelligent decision-making system can play a remarkable role in this regard. It has been pointed out that process is the most important among the several quality affecting elements [12]. So, online monitoring of the process parameters and the grinding quality indicators is the need of the hour. There have been many attempts in this regard, but they have been either failure detection using sensors or just the monitoring grinding wheel degradation. Several process parameter optimization techniques have also been used, but they are limited to being applied only in offline mode or in the planning of the process [13].

Therefore, this thesis is oriented towards monitoring the grinding process parameters and vibration and a control system to make changes in the process parameters. In the first section, this thesis gives information about state-of-the-art approaches relating to the sensor-based process monitoring and optimization methods of the process parameters and control systems available. Later the relationship between process parameters and vibration feature will be determined using AI and training model. The final section will present the decision-making system and its validation through the implementation.

1.2. State of the art

1.2.1. Sensor-assisted monitoring systems

In the past, many studies have introduced a force sensor, acoustic sensor, and pressure sensor for monitoring [14]. It was reported that the grinding of thin-walled and honeycombed structured components made up of Hastelloy, undesired burrs are often created: subsequent deburring increases overall manufacturing process time and cost. Subsequent deburring process, like manual deburring with a high-pressure water jet, is required. An electroplated Cubic Boron Nitride (CBN)wheel with a miniature concave and convex surface was developed to develop a high-speed grinding process and grinding strategies to reduce the burr [15–19]. The Design of Experiments (DOE) process parameter was optimized to reduce the occurrence of failures. Monitoring the machining process parameters with a variety of sensors represents a prime setup for reducing poor quality. It hence reduces the cost [11]. The study has researched to correlate the quality of the machined surface after broaching and the output signals obtained from multiple sensors, namely acoustic emission, vibration, and cutting forces. The obtained results indicate that the cutting force signals are sensitive enough to detect the geometrical deviation of the machined profile, burr formation, and to a lesser extent of chatter marks. Time and frequency domain analysis of the output signals can play a crucial role in developing appropriate techniques for qualitative and quantitative evaluation of the machined surface quality. Many research efforts have contributed to monitoring tool conditions of machining processes such as turning, milling, drilling, and broaching [20–28]. The authors give a detailed review of the measurement approaches and sensors for the grinding wheel monitoring [29,30]. A summary of the grinding wheel condition monitoring studies is given in Table 1.1. Although the sensor-based monitoring systems are expensive and limited in implementation, the monitoring of the grinding process with the use of power sensors has also been explored by researchers. Grinding power is recognized as an important indicator for monitoring. The analysis of the grinding process is complicated because the grinding material removing process is full of complexity. No theoretical model can be used to thoroughly explain the grinding process mechanisms nor reveal the correlation between process parameters and the outcome. Works of literature like [31–35] have successfully used a power sensor to characterize the grinding process and the tool performance. Several grinding machine manufacturing companies like Micromatic Inc, India, and others have developed their own power monitoring devices. However, the use of power sensors for monitoring has limitations of only comparing the different power characteristics at different stages of the grinding. The worn-out grits influence the surface finish of the part, necessitating timely dressing. Conventionally the dressing interval is decided either based on the wheel life end criteria.

Authors in [36] have used a combination of Hall effect sensor, dynamometer, and Camera for the grinding wheel redress life estimation. A time-series auto-regressive moving average (ARMA) predictive model was developed to estimate the grinding wheel redress life using the selected root mean square (RMS) feature on a current signal. The developed android application enabled the user to visualize the dressing time based on the RMS value of the spindle motor current signal. It has allowed the operators and machines with sensors to communicate and facilitate real-time traceability, visibility, and control over the dressing action to perform automatic dressing before the wheel reaches its end of life [37–40]. The catch is that they have used it for an elementary part grinding, and the test setup allowed the assembly of such a system. To implement them, the grinding process must be disturbed. Several non-destructive testing (NDT) methods have been so far proposed for the in-process monitoring of grinding burn, such as direct temperature measurement of the grinding chips [41–43]. Andreas et al. used an optical sensor and miniaturized eddy current sensor for the non-destructive detection of grinding burns [44].

Table 1.1. Summary of grinding wheel condition monitoring studies [30]

Reference	Tool state(s)	Grinding conditions	Signal	Signal analysis	Features	Test results
Furutani et al.	Wheel loading and dulling	Fixed	Pressure	FFT	Spectral amplitude	NA
Hosokawa et al.	Wheel wear	Varied dressing feed	Sound	Frequency spectrum	Sound pressure level values	80–100%
Hwang et al.	Wheel wear	Fixed	AE	Power spectral density	RMS of AE signals	NA
Kwak et al.	Wheel loading	Fixed	Force	Wavelet transform	Spectral density	NA
Lezanski	Wheel wear	Three depths of cut	Forces vibration AE	statistical and spectral	8 statistical and spectral features	83.3%
Mokbel et al.	Generated by using different grinding	Fixed	AE	Fast Fourier transform	Spectral amplitude	NA

Since the wear of a grinding wheel directly affects the workpiece vibration, both affect the workpiece quality. Vibration during the cutting phase can be used to monitor the wheel condition. In the monitoring of the grinding process, the automatic detection of surface defects is essential. However, the introduced methods are unable to recognize such failures [45,46]. Several investigations have been carried out to relate the vibration characteristics to the failure's exact process behavior and occurrence. Other sensor-based monitoring has its limitations, but the vibration is produced by cyclic variations in the dynamic components of the grinding machine. Damage control due to process failure is of great importance. However, the above-presented methods have mainly focused on wheel conditions, assuming that the grinding wheel condition affects the product quality most.

Three primary goals of any monitoring system are process monitoring, failure detection, and information sharing to optimize the process [47]. For this purpose, Rodolpho et al. performed the tests on a surface grinding machine, workpiece SAE 1020, and aluminum oxide grinding wheel as the other components. Frequency spectra analysis of obtained signals characterized the phenomenon of burn [48–54]. The ANN model classified the condition of the part as usual and abnormal. Further research is required to monitor the grinding process and failures that occurred during the processing of the work pieces.

1.2.2. Failure prediction and process parameter optimization

With success made in the field of computation power and machine learning, research works have been done to predict the failures during the grinding process. These findings have helped the manufacturers to plan their production setup in a more effective way. Christian et al. Used a machine learning neural network approach to predict grinding burn based on the process parameters to prevent damage [42]. A small dataset of 21 samples was gathered at a specific machine, constantly grinding the same element type with different process parameters, indicating the severity of the grinding burn. As a result of training, the model can predict the severity of grinding burn in multiclass classification, and it turned out that even with little data, the model performed well. In Neto et al., acoustic emission and vibration sensors were used to monitor grinding burn in surface grinding [55]. They trained different models with different frequency bands. It turned out that the best model had two frequency bands for acoustic emission and two frequency bands for vibration signals as input. The work pieces were roughly analyzed through visual inspection, surface roughness and hardness measurements, and metallographic analyses. The root mean square values filtered in the selected bands for both sensors better fit the linear regression, which is highly desirable for setting a threshold to detect burn and implementing it into a monitoring system.

One of the most critical problems in the grinding process is the automatic detection of surface burn in the parts. The burn occurs during the cutting of the part by the grinding wheel when the amount of energy generated in the contact area produces an increase of temperature enough to produce a change of phase in the material. In general, such occurrence can visually be observed by the bluish temper color on the part surface, but more generally, time-consuming tests are required for its after-the-fact determination. Bai et al. compared feed forward neural networks, least squared support vector machines, deep restricted Boltzmann machines, and stack auto encoders to predict quality in a manufacturing process [56]. Deep learning technology has become a hot topic in AI. It has been proven to be effective in many fields. E.g., fault diagnosis, pattern recognition, and forecasting. It has compared two feature learning patterns to investigate their performance in predicting manufacturing quality, including different learning models [57–60].

Authors in [61] conducted an experimental investigation on the wear properties of AI/SiC MMC and built a traditional ANN-based prediction model. Surface finish is a crucial property for determining material quality. Scientists enounce many kinds of prediction modeling methods and identify suitable parameters for surface roughness [62]. The obtained prediction models are beneficial in enhancing the surface quality in the grinding process of MMC materials because the experts in the field would assume the surface roughness without doing any real experiment and determine the input process parameters and the model results. The study [63] investigates some parameters on the surface roughness of some alloys in the end milling machine. Today machine learning methods are successfully utilized for regression, classification, or clustering in material sciences [64,65]. There are several methods for the detection of grinding burn on the machined workpiece. He et al. in beforehand prediction and post-mortem detection methods [66] are the two major ones both beforehand prediction methods and after detection methods are feasible. Beforehand prediction methods are relatively rewarding for grinding burn prediction, but they are not 100 percent effective. Combining both methods can be an excellent approach to deal with the monitoring and control of the machining process to make it defect-free. Researchers have mostly focused on the study of the tool wear for the prediction of failure and its optimization. Vibration features coming from the tool and workpiece interaction can also be an important aspect of failure prediction. A tool condition monitoring system is required to decrease the downtime of the machine and replace the cutting tool at the right time. In tool condition monitoring systems, signals like cutting force, sound, vibration, spindle current, surface roughness, temperature, tool images, AE were employed to examine the tool wear [67–70]. An understanding of the relationship between the process parameters and the vibrations in the grinding process is required to design the optimization techniques. Tao Liu et al. did an experimental analysis of process parameter's effects on vibrations in the high speed-grinding [71]. Two types of vibrations can rise in the high-speed grinding of a camshaft. The first type is forced vibrations that originate from the vibration in the grinding depth and the unbalance of the wheel [72], and the second type, known as "chatter," may rise in grinding due to the regenerative and frictional effects of the machine tool-workpiece system. The capacity to minimize vibrations in grinding by the selection of appropriate process parameters is a significant benefit in the process optimization of cam grinding. It was reported that the vibrations and the surface waviness change with the increase of grinding depth, and an appropriate grinding wheel speed combined with a workpiece speed has, for most grinding conditions, a reducing effect on vibration magnitudes and waviness and waviness. An unstable grinding process occurs due to these self-excited vibrations, and results of grinding wheel wear, unacceptable surface finish, and increased noise would rise [73]. The results demonstrate that the quantization of vibration magnitudes and surface waviness for the different process parameters used in the tests identify the best selection for the process parameters.

Adel et al. presented the effects of process parameters on machining vibration and their optimization [74]. A high vibration leads to poor surface finish and reduced productivity and shortens the tool life; therefore, the parameters should be optimized. The parameters can be optimized using analysis of variance, regression, and optimization techniques to achieve the condition of minimum vibration. Taguchi analysis with L18 orthogonal array was used to optimize the process parameters in consideration of surface roughness and vibration to be minimized [75]. After the collection of the vibration data as an MS Excel file through LabVIEW, the Taguchi method was used to minimize the vibration and chatter, to improve the quality of the product [76]. The authors also showed the effectiveness of the developed in-process portable diagnostic system with case studies. The portability and non-intrusive nature of the diagnostic tool enabled the application of the diagnostic system in different machines and assisted in enhancing the optimum utility of the machine's capability. With consideration of three parameters (Grinding wheel speed, table speed, and depth of cut), a Response surface methodology (RSM) was applied to determine the optimum machining parameters leading to minimum surface roughness and maximum material removal rate [77]. The results showed a match in the experimental values and the predicted values remarkably. The error between experimental and predicted values at the optimal combination of parameter settings for material removal rate and surface roughness came around 4%. An integrated RSM and Taguchi methodology to determine the optimum process parameters for minimum surface roughness and vibration produces promising results [78]. They used the S/N ratio from the Taguchi method to measure the variance of wheel vibration and surface roughness. The statistical analysis demonstrated that the depth of cut and wheel revolution is the dominant parameter among the controllable factors that influence the vibration features coming from the grinding process [79–81].

Irrespective of having promising results in terms of optimization of process parameters in consideration of minimizing the vibration level, these optimization methods can be applied in the offline mode only and can help in getting initial process parameters for the experiment. These methods ignore the fact that the grinding process is a vital factor that incurs the disturbance and results in quality failures.

1.2.3. Process control

The grinding process is transient. Research has not done enough contributed to industrial needs to predict the process behavior. The relationship between input and output parameters in the manufacturing process can fulfill the need for control. Accurate modeling of the grinding process to predict the resulting output quality is extremely difficult considering that abrasive processes are complex non-stationary in nature, and have a large number of parameters [29]. The ultimate goal of the process monitoring is a component that matches the specified quality, machined in a minimal time that characterizes parameters of the process as well as of the component must be checked. The author categorized the decision-making for the control system in two approaches: a) compare the distinctive values of the processed signals to a predetermined threshold in order to identify the status of the process. The database must be prepared in advance. b) another approach for decision making is model-based identification by employing several kinds of physical and empirical models to identify the interrelationships between detected and controllable parameters. A physical model is developed from an understanding of the fundamental physical principles underlying the process, with the specific objective in mind. The different elements of the process monitoring include Sensor, Signal processing, Interpretation, Output, Diagnosis, and Therapy, as shown in Figure 1.2. Sensor application is made at a lower level according to the hierarchy of control loops, and it can still be regarded as an essential part of a so-called intelligent system. Karpuschewski et al. showed the field of sensor application in intelligent grinding systems. It is composed of the application of AI techniques such as knowledge-based systems, neural networks, or fuzzy logic [29]. The measured and processed sensor data are transmitted to succeeding modules such as control modules.

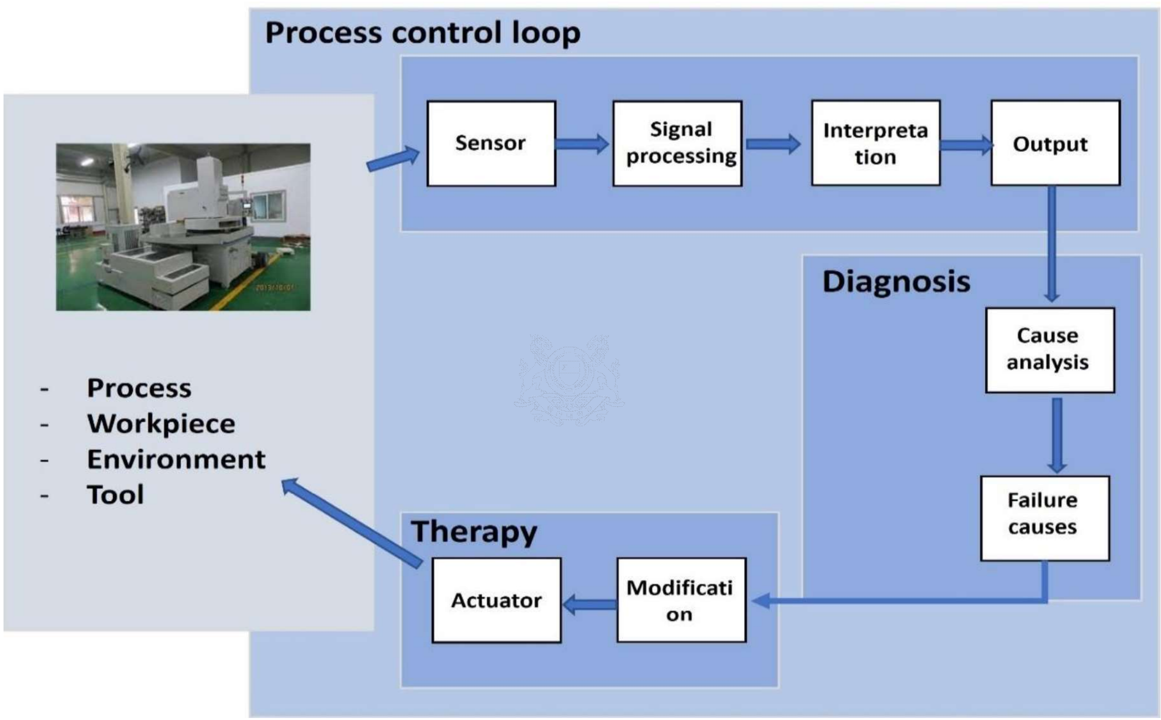


Figure 1.2. Elements of process control loop [82]

Considering the complex production technique and many influencing factors, Jie et al. introduced integrated modeling and intelligent control methods of the grinding process [83]. Case-based reasoning (CBR) and PID decoupling controller can be used to optimize the process simultaneously. Because of the limitations of the industrial field conditions and a lack of mature detectors, the internal parameters of the grinding process is challenging to obtain real-time quality closed-loop control. Scholars have proposed several neural networks and case-based reasoning technology for this purpose [84,85]. Combining the actual working conditions of the grinding classification process, an RBFNN based particle size soft-sensor model is also in use for ore grinding. From the automation and control domain, many model-driven methods have been proposed for automatic set points of the grinding process [86–89]. However, it is hard to achieve these goals at the level of basic feedback and model-based control. To overcome this issue, a data-driven grinding control using reinforcement learning was proposed by Li Guo [90]. Through this, it is not necessary to construct a system process model as it can learn from the historical processes. However, to apply this kind of method, a simulator platform needs to simulate thousands of iterations to reach the optimum process control.

1.2.4. Limitations and research goal

Originally the process monitoring and control was dependent on the operator's gut feel or specialized expertise. However, through research, it has come a long way, and now we can monitor the process using sensors and apply process parameter optimizations. Although several systems using vibration characteristics to detect quality failures have been explored, there is still a lot of scope for further development regarding its reliability and implementation. Most of the available systems collect the data from the process with the help of sensors and later use it for analysis of the process failure and machine component life estimation. These findings are helpful in better planning of the manufacturing, but not in real-time control of the failures to achieve quality consistency. The research findings are either theoretical or have been trying for a very simple part. There is still a lot to do in the direction of implementing a system for real-time monitoring and control of the grinding process.

To overcome the limitations of the introduced research findings, this thesis presents the development of an intelligent grinding process monitoring and control using vibration sensors. The intent is to bring the science of grinding actively for shop floor manufacturing with the help of microscopic interactions taking place during grinding, further integrating it with data analytics. Vibration signals coming from the sensors can be utilized for the monitoring of the grinding process, and from the collected data, a robust AI model can be built that can provide the optimum process parameters to control the process failure. Another goal of this thesis is to make the grinding process more autonomous and smart. For that purpose, all the steps should be programmed using a programming language and should be installed at the manufacturing site. Taking one step from the existing research findings, the system to be developed should be able to control the process parameters in real-time. So the closed-loop connection to the controller will also be introduced. A brief goal of this thesis as the desired system is shown in Figure 1.3.

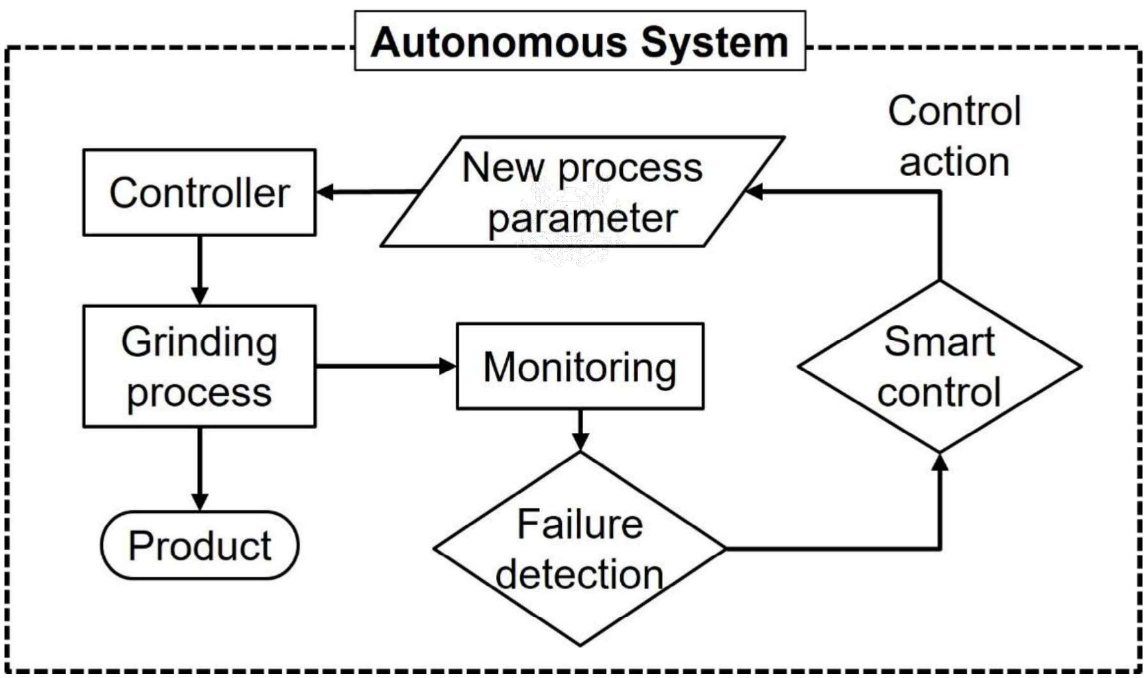


Figure 1.3. Data driven smart monitoring and control system

The machine learning-based AI techniques were used in this research because the focus is on the double-sided grinding process solving the real quality issue faced by the manufacturers. Modeling such a complex process is difficult to find the relationship between its vibration feature and operating process parameters. A double-sided grinding process, in which both the front and back surface of the workpiece is grinded using a pair of grinding stones provided oppositely at both sides of the workpiece, as shown in Figure 1.4.

At present, the quality inspection of the manufactured brake disc is the operator manually, and if there is any defect, then he changes the process parameter accordingly and check if it has solved the quality issues or not. This method requires a lot of expertise and knowledge and is responsible for the loss of time in the experiment and manpower, resulting in the low productivity of the factory. The desirable system where the monitoring is done with the use of sensors and the process is automatically controlled is shown in Figure 1.5.

Figure 1.4. Double sided grinding of the brake disc

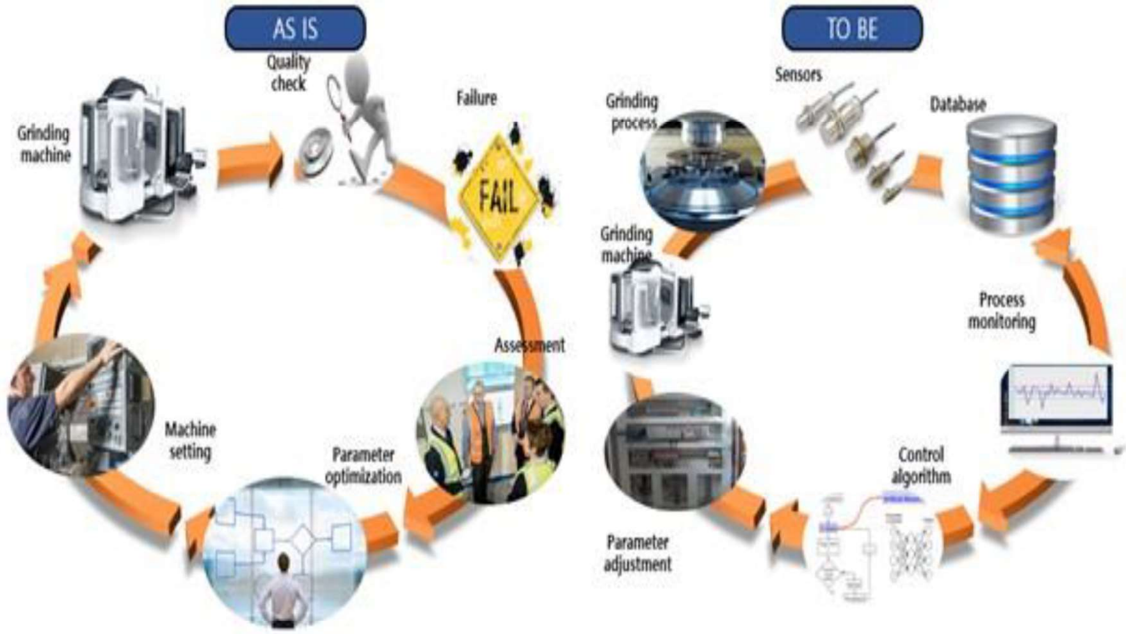


Figure 1.5. Autonomous process monitoring and control system

Chapter 2 . RESEARCH METHODOLOGY

2.1. Research object

As discussed earlier, the goal of this thesis is to develop autonomous monitoring and control of the grinding process. The research object chosen for this study is the manufacturing of the car brake disc with grinding as its last stage. The manufacturing of the brake disc involves several stages, but our focus is on the grinding process, as shown in Figure 2.1.

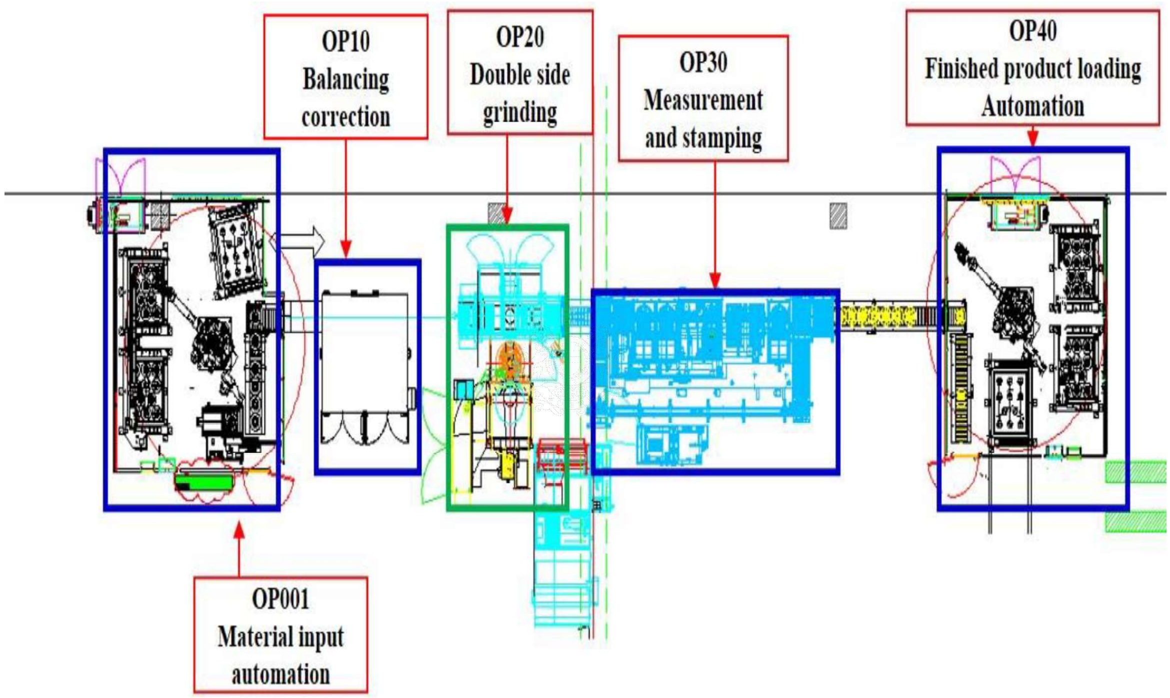


Figure 2.1. Grinding process as the target for the research

Through analysis of the existing manufacturing execution system (MES) in the company suggested that the disturbance that occurred during the machining process is responsible for most of the quality failures in the finished product. The grinding of the automotive brake disc is introduced in Figure 2.2. The complexity of the grinding process involved in attaining the desired surface finish to the brake disc suggests that the monitoring of external sensors along with the process parameters can give better know-how of the process insight. With the combination of hardware and software, we can make the reference models for the process and train the machine brain for failure detection and its control. Through the combination of signal processing and data analytics, rules can be developed to achieve process intelligence. The literature [47] introduced the importance of vibration characteristics being the most suitable option for reciprocating the process conditions. A vibration sensor-based monitoring system along with AI-based control can serve the multiple purposes of fault detection, scrap reduction, process intelligence, and making the conventional factory into the smart one.

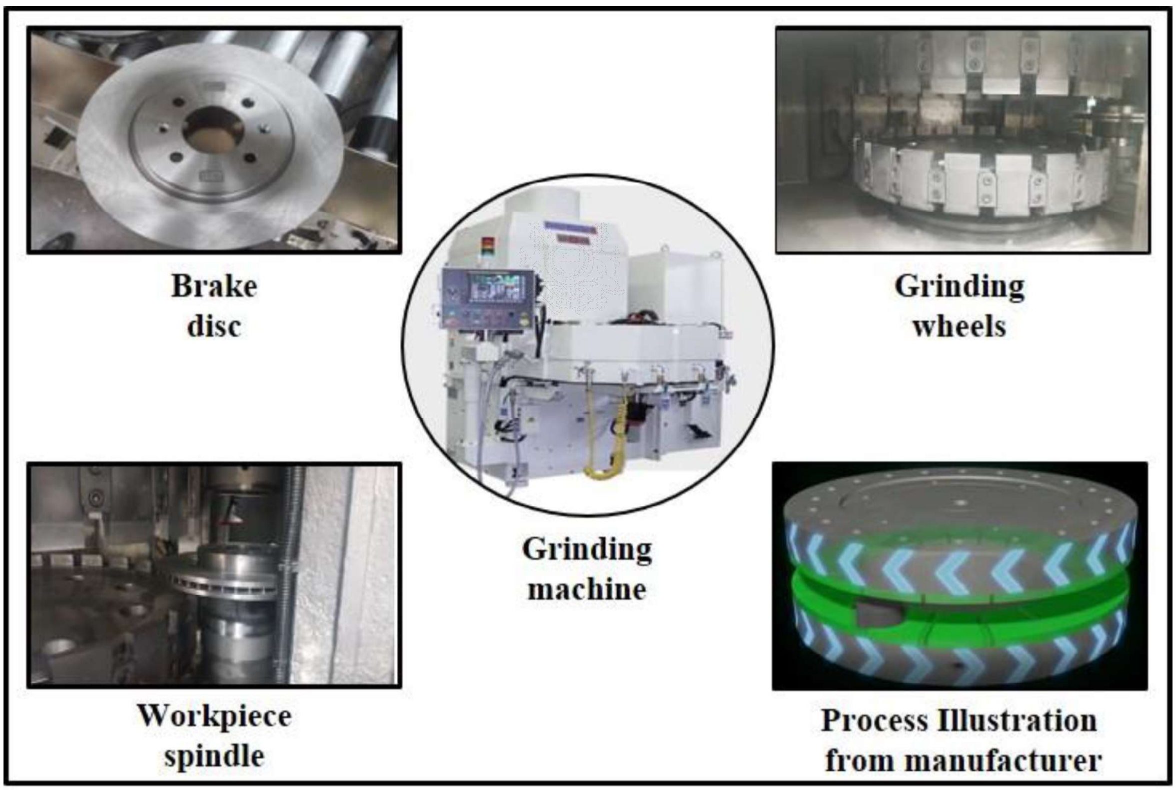


Figure 2.2. Brake disc manufacturing introduction

2.2. Research strategies followed

A comprehensive step-by-step research methodology is given in Figure 2.3. Firstly the real quality defects in the industry are analyzed. The current grinding process, as well as the machine behavior, is analyzed. The continuous interaction between the two grinding wheels and the workpiece sometimes becomes a reason for the process failures. Based on the failure types, influencing factors are selected. Among the materials, machine, operator, and processing, its processing condition, and process parameters affect the quality the most. The influencing process parameters like grinding wheel RPM, workpiece RPM, wheel entry speed, and coolant flow will be monitored throughout the monitoring of the process, as shown in Figure. 2.4.

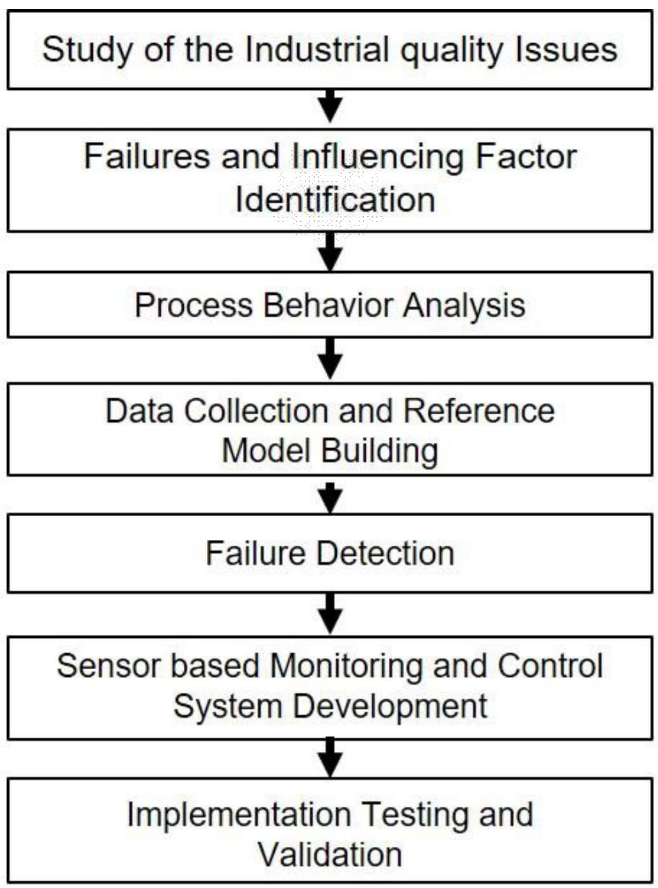


Figure 2.3. Research strategy followed

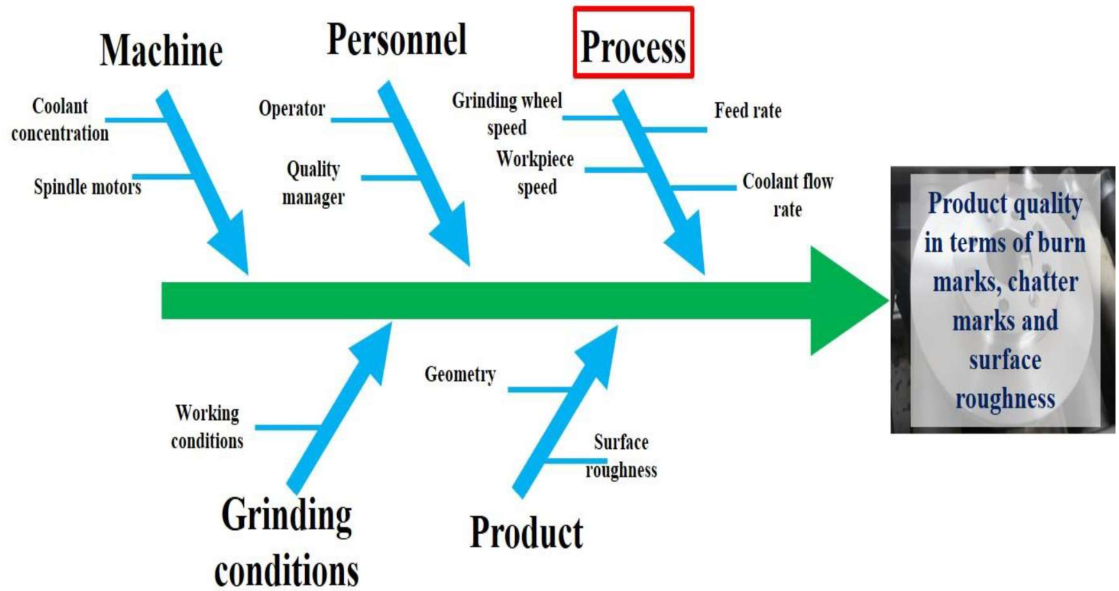


Figure 2.4. Influencing factors in terms of product quality

Data from the vibration sensors as well as machine PLC will be collected in order to build a reference model for the grinding process and for the analysis of the grinding process behavior. The collected data will be used to detect the failure in real-time and also to train the AI model for the prediction and calculation of the process parameters for the control of the grinding process.

2.3. Selection of monitoring and control process parameters

A series of experiments have been conducted to evaluate which grinding factors affect the vibration and workpiece surface roughness. Then a literature survey and brainstorming session helped to identify the grinding factors and their levels of the experiments. Finally, we selected four process parameters that can be associated with vibration and surface roughness. The grinding experiments were carried out on the Daisho Seiki GRV 585 series grinding machines. The grinding parameters include grinding wheel RPM, workpiece RPM, wheel entry speed, and coolant flow rate. There are several types of quality characteristics, such as the lower the better, the higher the better and the nominal the better in the case of vibration and surface roughness that should be a minimum. In this study, therefore, the smaller the better type of the signal to noise (S/N) ratio has been used and is defined as follows:

$$S / N = -10\log[\frac{1}{n}\sum_{i=1}^{n} y_i^2] \tag{2.1}$$

where n is the number of repeated experiments for each combination of control factors, and y_i is the observed response on the ith trial. The negative sign in equation 2.1 is for showing the smaller the better quality characteristics. The response y, in this case, is the wheel vibration and surface roughness, respectively. Response tables of S/N ratio for vibration and surface roughness are given in Table 2.1 along with their experimentally measured values. The S/N ratio for each level of the factor is computed based on the S/N ratio analysis using equation 2.1. A smaller value of vibration and surface roughness is normally required in metal machining. Therefore, the smaller the better methodology of S/N ratio was employed for the aforesaid responses. Regardless of the category of the performance characteristics, the largest S/N ratio corresponds to better performance. Therefore, the optimal level of the process parameter is the level with the greatest S/N ratio. The influence of each control factor on the vibration and the surface roughness has been analyzed with a signal-to-noise ratio response table. They show how the S/N ratio at each level of the control factors and how it changes when the settings of each control factor are changed from one level to another. The influence of each control factor can be more clearly presented with response graphs (see Figure 2.5 and 2.6) respectively. Taguchi L_{27} orthogonal array analysis is done to find the effects of process parameters on surface roughness and vibration characteristics during the process. The analysis of the response table shows that the grinding wheel RPM is the most influencing factor in terms of surface roughness and vibration. Other process parameters like workpiece RPM, wheel entry speed, and the coolant flow rate are also important but their effects o the surface roughness and vibration are not that noticeable.

Table. 2.1. Experiments for selecting most influencing parameter

Exp. No	A Grinding wheel RPM	B Wheel entry speed	C Workpiece RPM	D Coolant flow rate	Vibration (g)	Surface roughness (R_a)	S/N ratio (g)	S/N ratio (R_a)
	Parameter levels							
1.	750	3	170	30	0.8	1.4	1.971	14.1
2.	750	3	170	30	0.3	1.5	2.655	15.3
3.	750	3	170	30	0.6	1.5	1.985	17.7
4.	750	3	170	30	0.3	1.4	2.563	12.8
5.	750	3	170	30	0.4	1.5	1.652	12.2
6.	750	3	170	30	0.3	1.6	2.325	13.2
7.	750	3	170	30	0.8	1.3	1.568	13.0
8.	750	3	170	30	0.3	1.6	0.749	14.1
9.	750	3	170	30	0.4	1.4	1.568	15.3
10.	800	4	200	40	0.9	1.5	3.17	17.7
11.	800	4	200	40	1.0	1.6	1.12	15.3
12.	800	4	200	40	0.3	1.4	2.50	14.5
13.	800	4	200	40	0.4	1.6	3.33	12.5
14.	800	4	200	40	0.8	1.4	2.698	12.4
15.	800	4	200	40	0.6	1.5	2.376	11.3
16.	800	4	200	40	0.5	1.4	2.423	14.8
17.	800	4	200	40	0.9	1.3	1.986	13.1
18.	800	4	200	40	0.9	1.9	1.905	12.0
19.	850	5	230	50	0.5	2.0	3.64	10.7
20.	850	5	230	50	0.3	1.3	2.721	13.9
21.	850	5	230	50	0.8	2.6	2.376	12.8
22.	850	5	230	50	0.6	1.0	3.630	13.2
23.	850	5	230	50	0.7	1.4	2.241	12.4
24.	850	5	230	50	0.3	1.4	1.986	14.4
25.	850	5	230	50	0.4	1.3	2.698	12.4
26.	850	5	230	50	0.5	2.5	3.12	13.9
27.	850	5	230	50	0.9	1.6	2.412	13.2

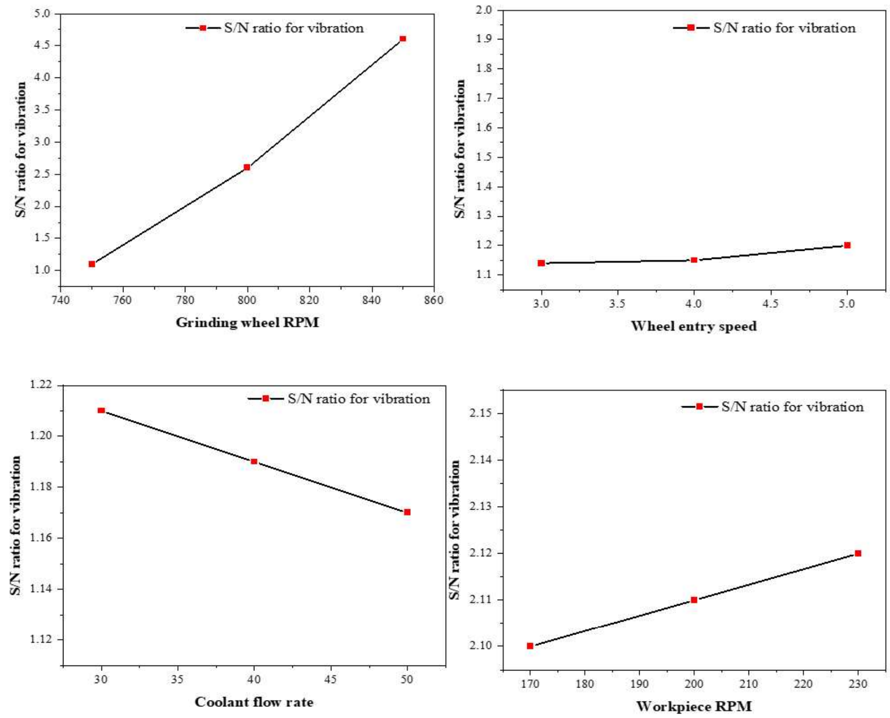


Figure 2.5. Effect plot of process parameters for vibration

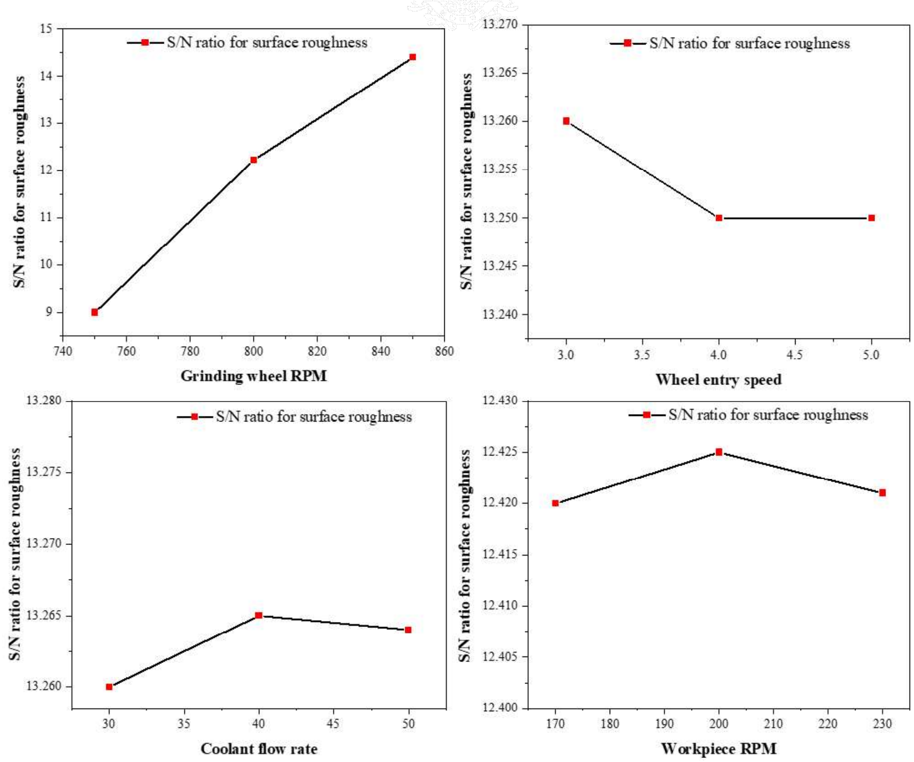


Figure 2.6. Effect plot of process parameters for surface roughness

Based on the analysis of the experimental results and effects of the process parameters, the vibration from the sensor is selected as the most suitable feature for monitoring and grinding wheel RPM is selected for process parameter control.

Chapter 3 . DEVELOPMENT OF THE MONITORING SYSTEM

3.1. Monitoring system flow chart

The monitoring system flow chart covers the flow of the data from sensors to the analysis display and simultaneously to the database, as shown in Figure 3.1. Two single-axis accelerometers are used for the collection of vibration data from the upper grinding wheel as well as the lower grinding wheel. The accelerometers are fixed at the spindle and normal to the grinding wheel direction using magnetic mountings. The collected data from the acquisition module is transmitted to the personal computer (PC).

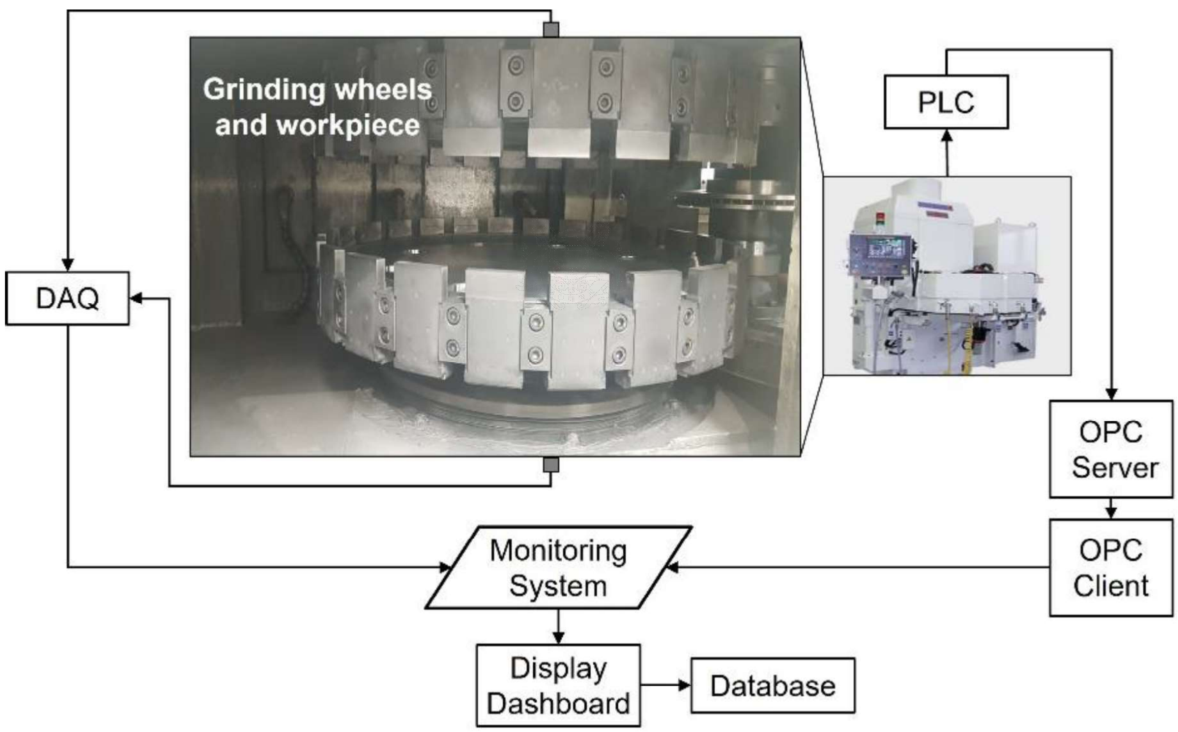


Figure 3.1. Monitoring system flow chart

Real-time process parameters monitoring is also essential for informative insight into the disturbance. For this purpose, the variables from the process are delivered to the monitoring system from the programmable logic controller (PLC) through open platform communications

(OPC) server connection. It plays a significant role in finding the relationship between the process parameters, failure, and the vibration signal coming from the sensor.

3.2. Data acquisition module

The analysis module for the process behavior monitoring largely depends upon the quality of the data it receives. The data should be reliable and of high quality. Apart from the real-time supply to the system, the acquisition system should also be able to save it in a database. This database can be later used for better manufacturing process planning. The collected data must include the instances of a good product cycle as well as the products incurring failures. A lot of experiments are conducted to build a reference database. It will help in setting threshold limits for the real-time detection of the failures. The data acquisition process for real-time process parameters from the PLC controller of the machine is categorically shown in Figure 3.2. The connection between the PLC and the Microsoft Windows operating system is made through the OPC server and OPC client. When the connection is established, the monitoring tool can receive real-time process parameters for display. The monitored data from the system is also saved in a specified database in comma-separated values (.CSV) format with all the necessary information. Along with the process parameter data, the vibration data is also collected to the database simultaneously. The vibration signal data is collected through the sensor setup and designed tools for the data storage. This data can be recalled at any time for further analysis or reference.

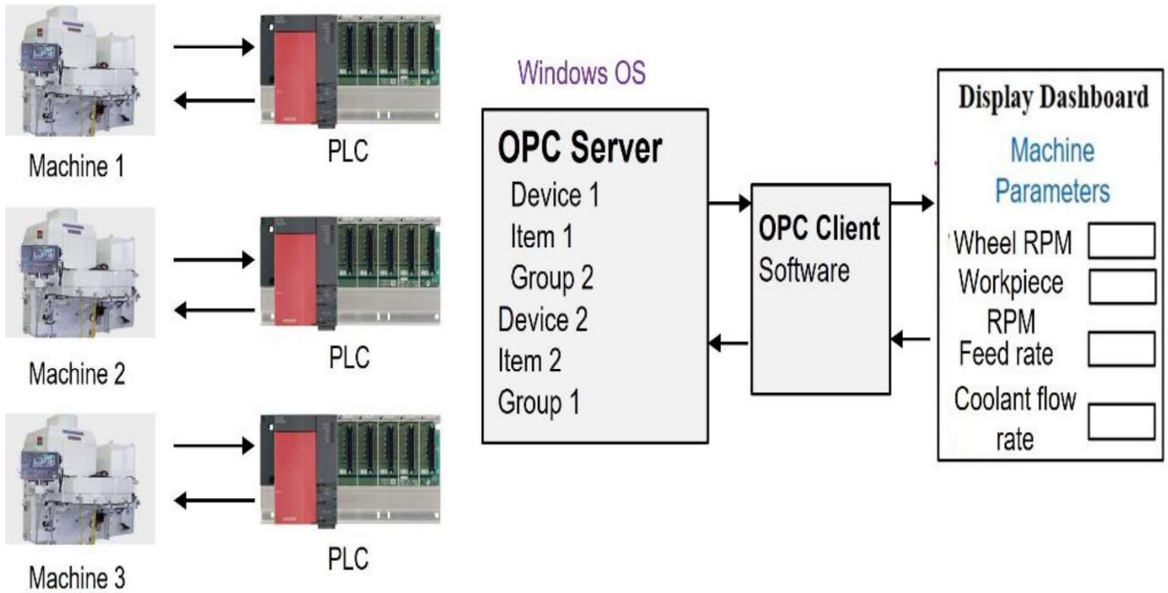


Figure 3.2. Data collection from machine PLC

The vibration data collection system programmed with the LabView software is shown in Figure 3.3.

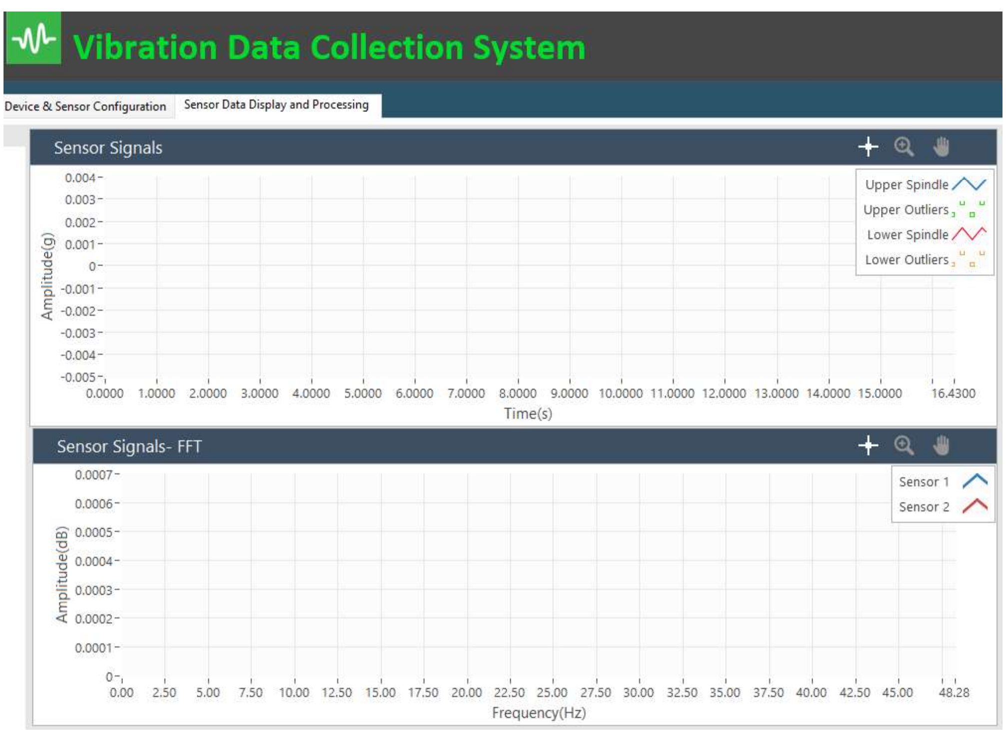


Figure 3.3. Vibration data collection dashboard

3.3. Monitoring threshold setting for failure detection

The Data is the key. It plays an essential role in the determination of threshold limits. Due to the factory production schedule constraints, the data from around 500 product cycles were collected, as shown in Figure 3.4. Machine learning structures are used for the proper training of the system in which the real-time process parameters like grinding wheel RPM, workpiece RPM, feed rate, and the coolant flow rate are given as input, and the g (amplitude) feature for the vibration is selected as the output. Through this, we select a trend or pattern of vibration features for different process conditions. Once the failure setting values is decided, an algorithm is formulated that can detect the occurrence of such instances and trigger an alarm to notify the user about the process failure. For the reliability of the collected data and training system, the quality feedback for each part is also collected. This data is used in offline mode for training the model and finding a pattern in vibration variation related to the change in process parameters. Further research and collection of data from multiple machines will be helpful in building an empirical relation between the process parameter and the vibration signal from the process.

Cycle no	Vibration signal (g)	Wheel RPM	Workpiece RPM	Wheel entry speed	Coolant flow	Product quality standard
Product cycle 1	0.3	850	239	3	30	1
Product cycle 2	0.2	830	230	2	30	1
Product cycle 3	0.3					
Product cycle 18	0.7					
Product cycle 30	0.3					
Product cycle 34	0.9					
Product cycle 56	1					
Product cycle 67	0.3					
Product cycle 80	0.2					
Product cycle 150	0.8					
Product cycle 180	0.2					
Product cycle 200	0.3					

Cycle no	Vibration signal (g)	Wheel RPM	Workpiece RPM	Wheel entry speed	Coolant flow	Product quality standard
Product cycle 200	1	700	230	2.5	30	1
Product cycle 234	0.3	830	140	2.8	30	1
Product cycle 247	0.2	850	220	2.7	30	1
Product cycle 280	0.8	700	230	2.5	30	0
Product cycle 300	0.2	840	170	2.5	30	1
Product cycle 340	0.3	820	200	3	30	0
Product cycle 368	0.4	780	190	2.7	30	0
Product cycle 379	0.6	710	230	3	30	1
Product cycle 390	0.8	700	160	3	30	1
Product cycle 400	0.2	850	150	2.7	30	0
Product cycle 420	0.3	850	230	3	30	1
Product cycle 500	0.8	750	225	3	22	1

Figure 3.4. Collected data for different product qualities

3.4. User interface design for signal display

All the device connections and the software modules are designed and programmed using LabView design software (National Instrument, USA). The developed software has multiple modules and devices. So, state machine architecture in the LabView is used for the programming. It is beneficial in the implementation of complex algorithms and tasks. A block diagram related to the monitoring tool development is shown in Figure 3.5. In the block diagram for the main user interface, there are separate functions for initializing the system, connection to the data acquisition (DAQ), logging the data, and disconnecting the device. The system saves the data simultaneously in a database. Figure 3.6 illustrates the connection of the monitoring system to the DAQ and data acquisition according to the chosen sampling rate. A dedicated user interface (UI) for the process monitoring as a system is also developed, as shown in Figures 3.7 and 3.8. It has separate buttons of ‘start’ and ‘stop’ to control the monitoring behavior. It consists of three different windows of device configuration, sensor signal display, and fast Fourier transform (FFT) display.

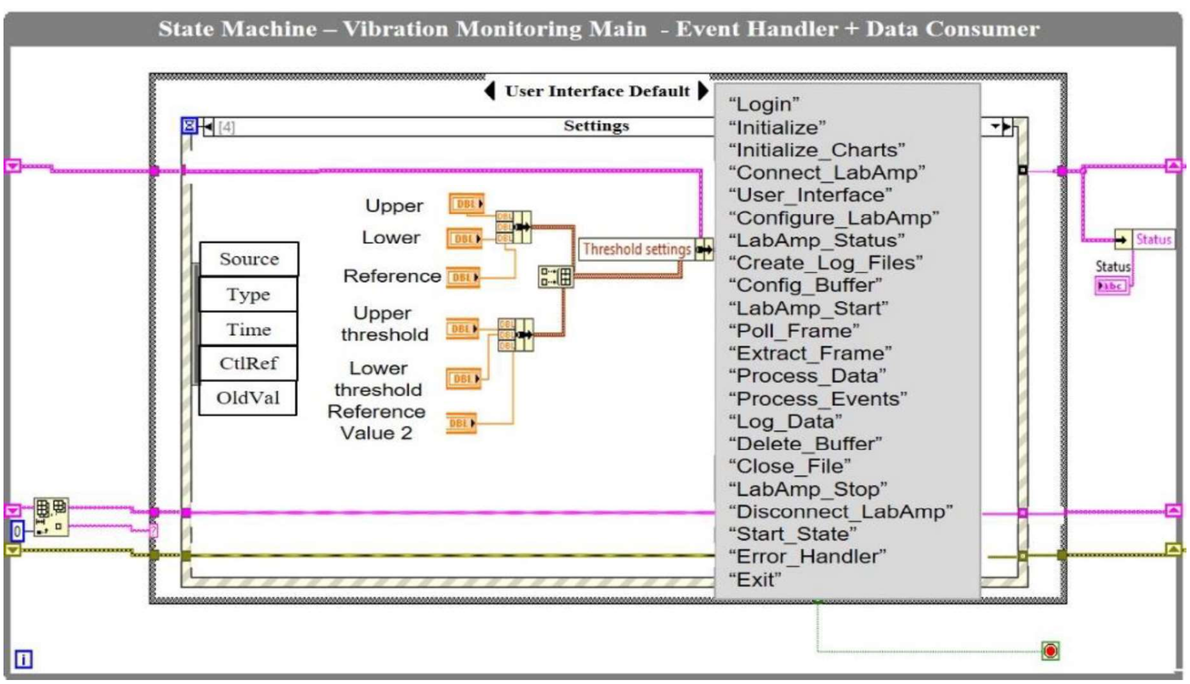


Figure 3.5. Block diagram for main user interface

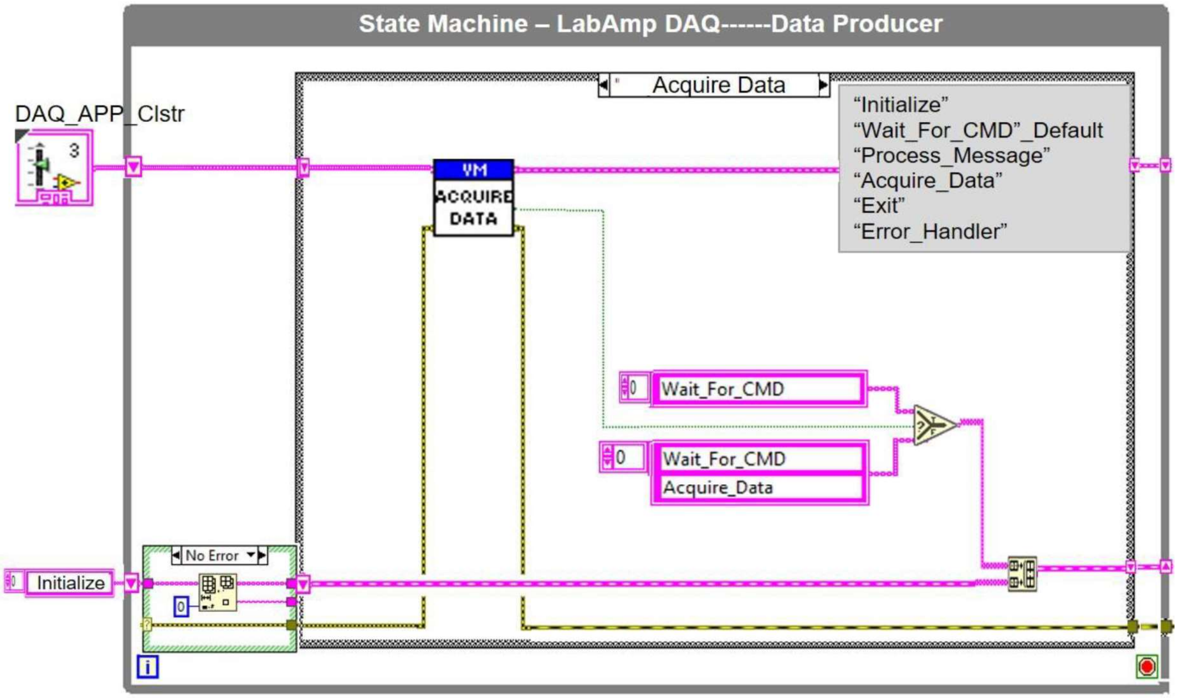


Figure 3.6. Block diagram for data collection from Kistler LabAmp

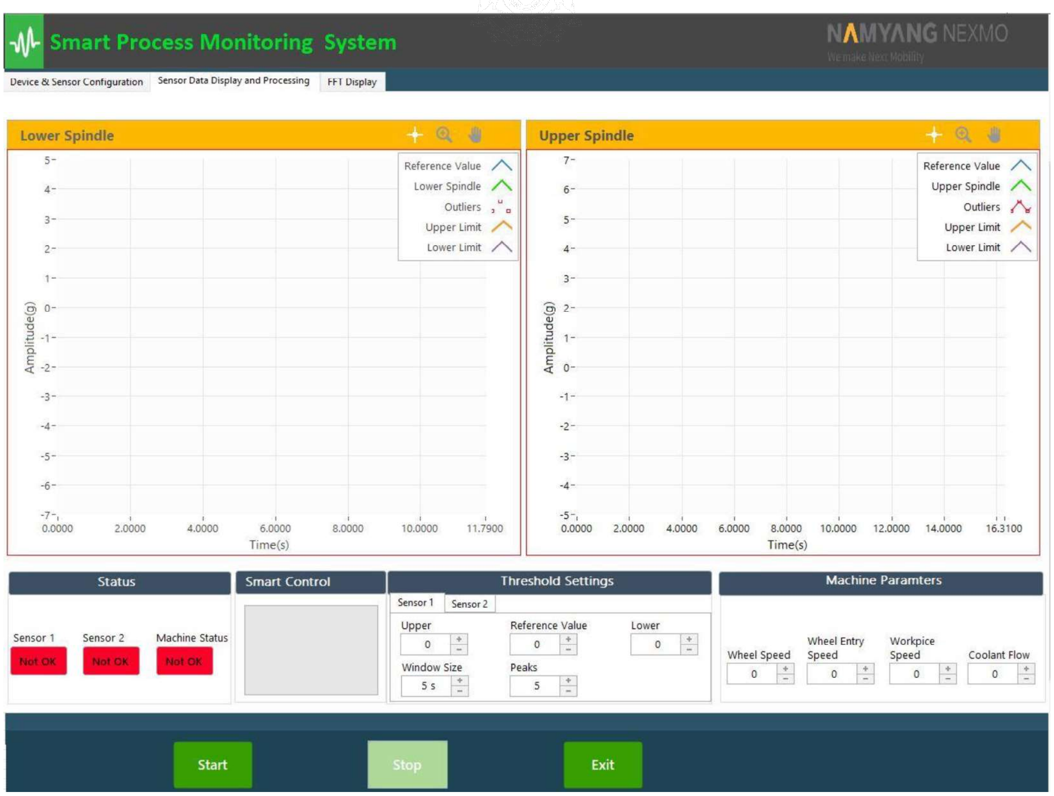


Figure 3.7. Sensor display dashboard

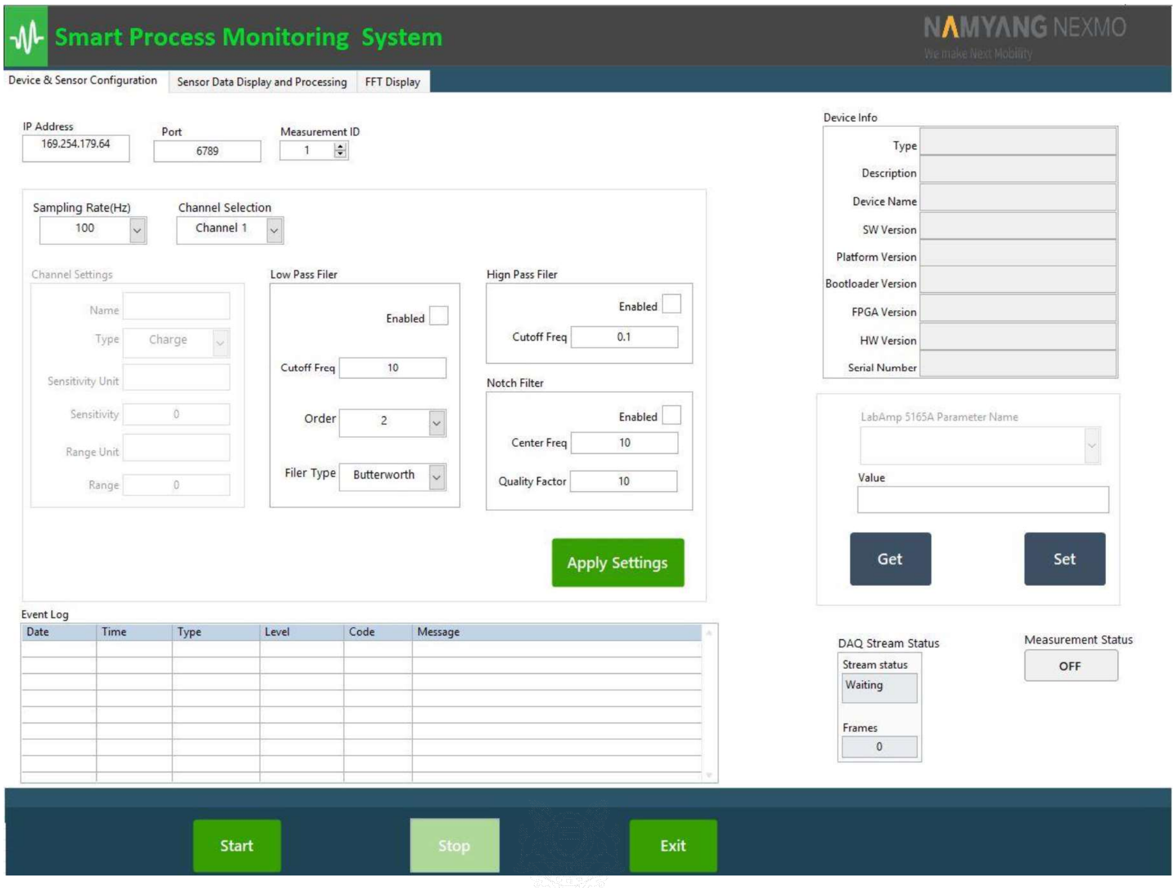


Figure 3.8. User interface for device information

3.5. Hardware setup and architecture

The hardware setup facilitates the propagation of the requisite signal to the software module. For the collection of vibration signals from the process, several sensors were considered. Two accelerometers of type 8703A50M1, having the sensitivity of 100 and range 50, from Kistler Inc. is used for the data collection. The DAQ system of type 5165A with four input channels from the Kistler is used. The connection from the sensor to the DAQ is made with sensor cables, and the DAQ is connected to the PC with an ethernet cable.

3.6. Application of the monitoring system for different purposes

The developed process monitoring system for the grinding can be easily applied to a grinding machine for multiple purposes. It is an externally applied portable system, which can be used for any grinding machine without affecting its grinding controllers or the assembly.

3.6.1. For building the reference model database

With the use of the monitoring tool, real vibration data depicting the process conditions can be acquired and stored in a database (DB). The monitoring system has the functionality of storing the data. CSV (comma-separated values) format to any connected DB system. Based on these various types of data, a reference model can be built and routinely updated with the occurrence of the failures. In that way, the occurrence of any deviation from the standard can be recognized. For a grinding cycle to be in good shape, the processing conditions in the monitoring system must be under the threshold limits. If any deviation occurs, the alarm and notification to the operator will be flagged and simultaneously logged into the database for the attention of the plant manager. A data flow diagram for the developed monitoring system is shown in Figure 3.9. Through OPC server communication, the PLC can broadcast the real-time process parameters. The created DB has information like process parameters, vibration, and alarm occurrence instances. A typical vibration signal plot for different stages of the grinding is plotted in Figure 3.10. During the machining operation, the vibration occurred during the cutting and roughing phases are most important in a total cycle of 25 seconds. To capture the average vibration during this phase, we have used the windowing function. In order to do that, we select a time range that would capture such repetition and calculate the average value of the 'g' i.e., vibration level.

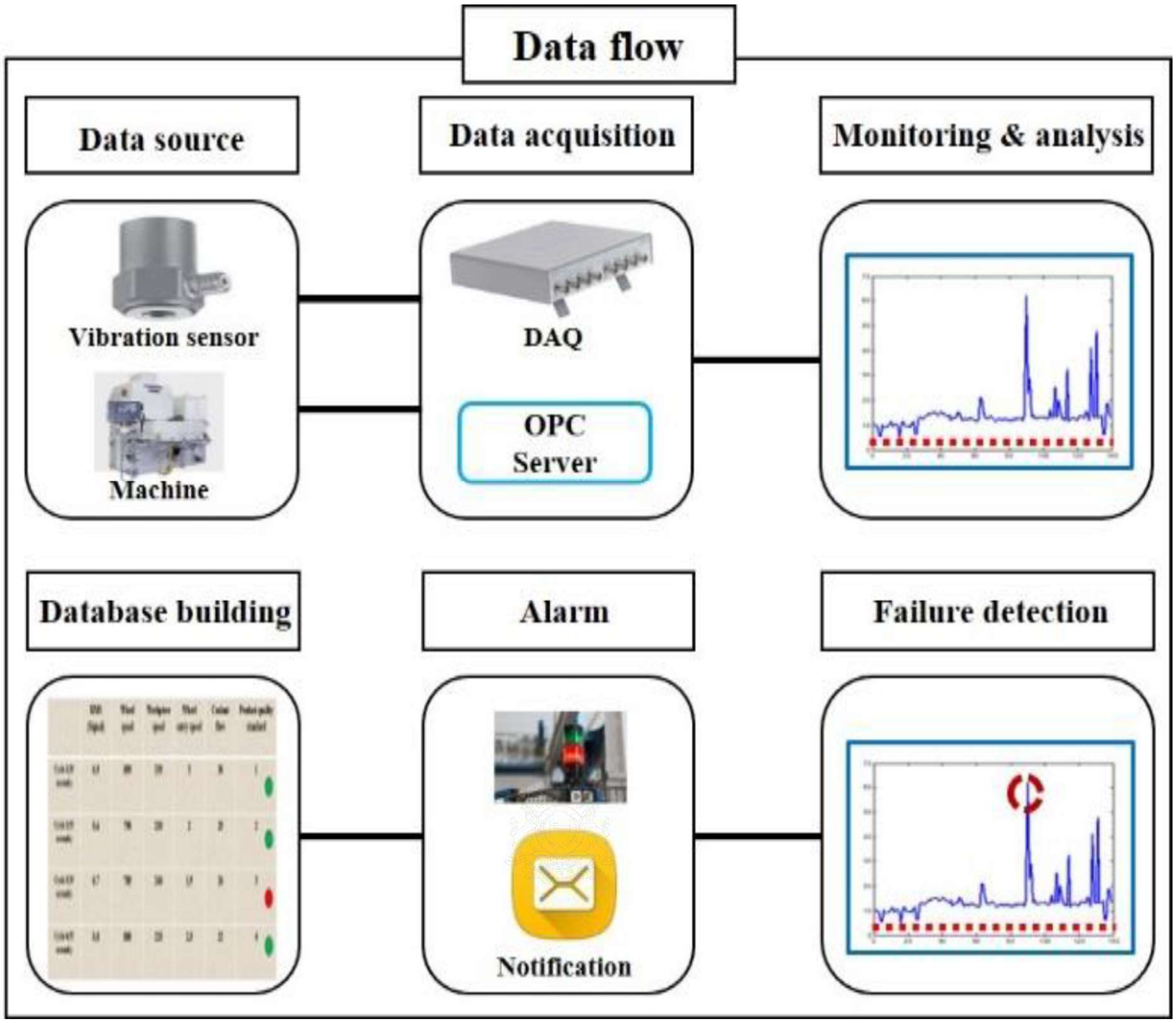


Figure 3.9. Data flow diagram

3.6.2. Process parameter optimization

Further digital signal processing methods and analysis of the sensor signals can give important insight into the interrelationship between the processing conditions and the product quality. Such additional modules can be added to the developed monitoring system. The effects of the important process parameters like grinding wheel speed, workpiece speed, and feed rate can be directly linked with the RMS feature of the vibration signal. The surface-related quality characteristics are directly related to these. With such optimization techniques, cycle time, as well as the cost of the grinding process, can be optimized, and several control algorithms can be derived. Major surface quality failures can be easily detected from the vibration signal coming from the processing spot. It can also be avoided with the use of the latest AI-based control algorithms. If not an in real-time cycle, then at least in the next cycle. In this way, we can reduce the number of scrap parts produced.

Figure 3.10. Grinding process vibration signal plot

3.6.3. Grinding wheel and machine component life analysis

The grinding wheel is composed of abrasive grates that go through continuous wear. The changes in the properties of the grain affect the product quality. Its continuous monitoring can also be done by setting the threshold limits for its vibration features and based on that, and the dressing schedule can be fixed for the grinding wheel. Other components going through continuous wear and fatigue may fail to include the workpiece's bearings or the grinding wheel spindle. A detailed study of the collected data can be used to monitor the machine components like bearings. The developed monitoring system can be used for multiple kinds of tasks with slight modifications. Despite its multipurpose use, our advocated piece of work is focused on monitoring real-time behavior of the grinding process and notification to the user when any process failure occurs and storage of the data with the information of such instances.

3.6.4. For process monitoring and control in terms of autonomous beahvior

It's critical to understand that leveraging data is the foundation of a smart factory. Before to the fourth industrial revolution, commonly known as Industry 4.o, manufacturers relied on clipboards and manual methods to collect machine data, perform root-cause analysis or gain insight into their operations. But as the competitive landscape of manufacturing changed, along with advancements in technologies such as the Internet of Things (IoT) and big data, the industry has reached a point where manual processes are no longer efficient. In fact, they cost manufacturers time and money in the form of lost productivity, suboptimal machine output, and product [91]. An organization that has yet to implement IoT technologies either does not have data available or their data is extremely difficult to analyze and turn into insights. There are four levels of autonomous behavior in a smart factory in terms of monitoring and control of the manufacturing processes.

Level One: At the first level of the smart behavior the data connection and information gathering system is designed. It continuously gathers and tracks the production data. With the data in one location and always available, problem-solving becomes almost frictionless. When an issue occurs, operators and engineers can access the data in the system using data visualizations and dashboards. With easy access to all the data, engineers are able to answer questions quickly increasing plant productivity and agility that can weather changing environments. In addition, a connected data infrastructure enables real-time monitoring, as well as monitoring, of the factory floor. There are several state-of-the-art sensor-assisted data collection and monitoring system that satisfies level one of the autonomous behavior as reported in the work of literature [92].

Level Two: Predictive analytics. At this level smart factory shifts manufacturing operations from reactive problem solving to proactive analysis and improvements. Predictive analytics enables operators and engineers to take preventive action to avoid significant downtime or quality failures. By adding machine learning and artificial intelligence, manufacturers can predict and prevent problems on the factory floor. Machine learning technologies typically require three to six months of historical data for accurate predictions. It creates an intelligent system that quickly identifies insights and predicts failures more accurately. Real-time alerts deliver valuable information to the appropriate person allowing them to proactively take action.

Level Three: The third level of autonomous behavior takes production optimization one step further. Instead of predicting when failures might occur, machine learning technologies recommend settings through prescriptive analytics that allows optimization. The optimization recommendations are sent to the engineers who can review the insights and make process changes to maximize throughput without sacrificing product quality. By following the recommended settings, manufacturers can eliminate inefficiencies and waste throughout their production lines as well as increase contribution margins.

Level Four: At this level, AI-based automation deploys the recommendations identified by analyzing manufacturing data. An AI-based model identifies the optimization, then generates and sends the recommended settings in real-time to the machine, where it is automatically executed. In such a closed-loop AI-controlled production line, the time it takes to execute on an insight discovered by the system becomes minimal. Achieving level four requires datasets that are large enough and have enough validated cases to provide the information needed for the system to know the impacts of a production change.

There are several literatures available that have tried to achieve autonomous behavior in the process monitoring and control. Research findings by Voronov et al. [93] created a dynamic mathematical model of the cylindrical grinding process as shown in Figure 3.11.

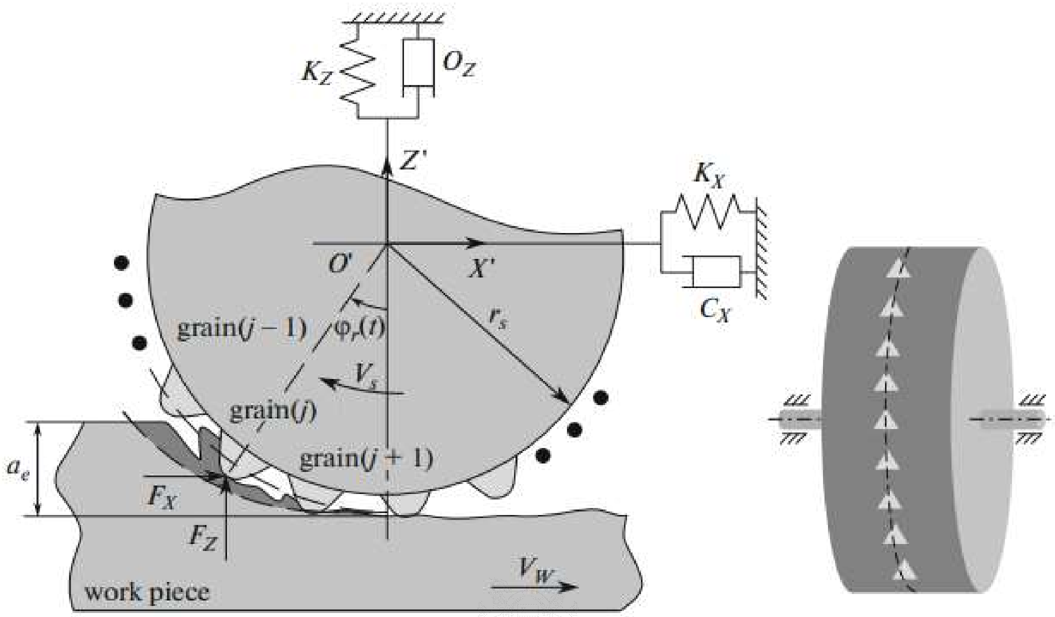


Figure 3.11. Kinematic diagram of flat grinding model

The grinding process is simulated as a dynamic system with two orthogonal degrees of freedom. By doing so, they were able to evaluate the effect of cutting forces and vibrations on the surface to be formed while grinding. It can be very helpful in the design phase of the grinding technological process. Mathematical models, as well as the sensor-assisted monitoring system are able to achieve level two of autonomous behavior. AI-based prediction methods for the recognition of the failures are able to predict the failure and control actions can be taken manually. This makes the available findings being able to achieve level three of the autonomous behavior. Whereas the goal of our research is to not only monitor but the system should be able to deliver the suggested control actions in an autonomous way. Hence the developed system should enable the process behavior to be of level four standard described by the literatures.

Chapter 4 . AUTONOMOUS CONTROL SYSTEM DEVELOPMENT

4.1. Functional design of the autonomous control system

Not many examples of grinding process control devoted to vibration-based process control can be found in the specific literature. The designed control system has two basic functions: the recognition of machining situations and making smart decisions after finding the new process parameters for its compensation. The main aim of the process controller is to improve the performance of a grinding process and the quality of the machined parts, avoiding the limitations caused by the abnormal vibration feature behavior. The autonomous control system feeds indications to the control module to allow a decision-making process and trigger the consequent control actions in terms of cutting parameters or suggested actions. The control module produces both direct commands for the machine to realize an automatic closed-loop process control by process parameters tuning mainly the grinding wheel RPM in a way that is compatible with the machine and the technological constraints. In case when the failure is going to occur can't be controlled, the control system notifies the machine operator of the product being a scrap part [94]. The functional design of the desired autonomous control system is shown in Figure. 4.1.

The vibration error signal coming from the monitoring system is given as input to this control system and it acts autonomously to decide new process parameters. In the past, many predictive controls have been in use. Finding the interrelationship between the process status indicators i.e. vibration signal error and the process parameters to control it is really a difficult task and a core part of the autonomous control system. The complexity of the grinding process of the brake disc by double-sided grinding makes it more challenging to treat it as a model. Finding the interrelationship between indicator and process parameters through pattern recognition can be very helpful to solve this issue. Artificial neural networks can play a key role in finding the process parameters values to give to the machine controller.

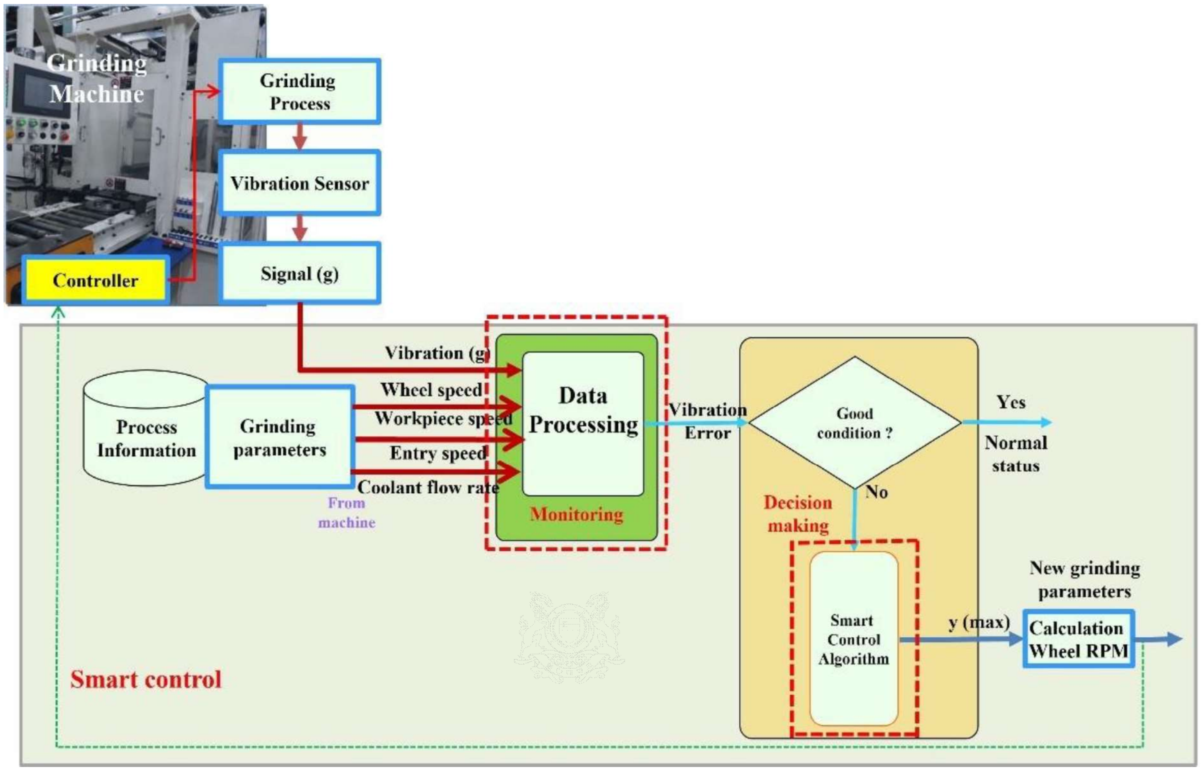


Figure 4.1. Functional design of the autonomous process control system

ANN provides a powerful tool for modeling and controlling nonlinear systems and has been widely used in many fields. Since the 1980s, the application of neural networks in the control field has rapidly developed, and several survey papers appeared in which the neural network predictive control is also a typical example for neural network applications [95]. The applications of neural networks in predictive control include modeling for nonlinear systems and optimization solving using neural networks. In the relevant literature, it is usual to adopt a neural network for modeling and then realize the predictive control in two different ways. One is directly using a neural network to solve the rolling optimization problem. The other is first to identify the dynamic system response by a neural network model and then to solve the online rolling optimization using the parametric optimization method [96].

Assume that the input-output model of a nonlinear system can be represented by

$$y(k) = f((k-1), \ldots, u(k-n_b), y(k-1), \ldots, y(k-n_a)) \tag{4.1}$$

For neural network modeling, this specific representation (4.1) is unknown and only the input and output sample data are available. Consider the commonly used back propagation (BP) network with one layer of hidden nodes layer. It is composed of three layers of nodes, i.e., the input node layer, the hidden node layer, and the output node layer. The nonlinear transformation is considered only in the hidden node layer. Denote the output of the input node as$o_j, j = 1, \ldots, n_a + n_b \triangleq n_t$. They are indeed the variables in the bracket on the right side of (4.1). Denote the input of the hidden node *i* as x_i and its output as $z_i, i = 1, \ldots, m$, z, where *m* is the number of hidden nodes. Denote the output of the output node as$\hat{y}(k)$. According to the working principle of the BP network, it follows that

$$x_i = w_{i0} + \sum_{j=1}^{n_t} w_{ij} o_j, i = 1, \ldots, m$$

$$z_i = \varphi(x_i), i = 1, \ldots m \tag{4.2}$$

$$\hat{y}(k) = w_0 + \sum_{i=1}^{m} w_i z_i$$

Where w_{ij} is the weighting coefficient of connection from the input node *j* to the hidden node *i*, w_{i0} is the input bias of the hidden node *i*, w_i is the weighting coefficient of connection from the hidden node *i* to output node, w_0 is the input bias of the output node, and $\varphi(.)$is the active function of the neuron, usually taken as the Sigmoid function

$$\varphi(x) = \frac{1}{1+e^{-x}} \tag{4.3}$$

The task of neural network modeling is to determine the weighting coefficients and the input biases best matched with the given sample data set, which can be described as the following optimization problem:

$$\min_{w} E = \frac{1}{2}\sum_{l=1}^{N}\left(\hat{y}_l(w) - y_l\right)^2 \tag{4.4}$$

Where N is the number of samples y_l and $\hat{y}_l$ represents, respectively, the system output in the lth group of samples and the neural network output calculated by (4.1) of this sample, and w is a parameter vector containing all the weighting coefficients and input biases.

The weighting coefficients of the BP network can be obtained as follows, Let

$$E_l = \frac{1}{2}(\hat{y}_l(w) - y_l)^2, e_l = \hat{y}_l(w) - y_l, l = 1, \ldots, N$$

$$\delta_i = \frac{\partial E_l}{\partial z_i} = \frac{\partial E_l}{\partial \hat{y}_l}\frac{\partial \hat{y}_l}{\partial z_i} = e_l w_i, i = 1, \ldots, m, l = 1, \ldots, N \tag{4.5}$$

$$\xi_i = \frac{\partial E_l}{\partial x_i} = \frac{\partial E_l}{\partial z_i}\frac{dz_i}{dx_i} = \delta_i \dot{\varphi}(x_i) = \delta_i z_i(1 - z_i), i = 1, \ldots, m$$

Then

$$\frac{\partial E_l}{\partial w_0} = \frac{\partial E_l}{\partial \hat{y}_l}\frac{\partial \hat{y}_l}{\partial w_0} = e_l, \quad \frac{\partial E_l}{\partial w_i} = \frac{\partial E_l}{\partial \hat{y}_l}\frac{\partial \hat{y}_l}{\partial w_i} = e_l z_i$$

$$\frac{\partial E_l}{\partial w_{i0}} = \frac{\partial E_l}{\partial x_i}\frac{\partial x_i}{\partial w_{i0}} = \xi_i, \quad \frac{\partial E_l}{\partial w_{ij}} = \frac{\partial E_l}{\partial x_i}\frac{\partial x_i}{\partial w_{ij}} = \xi_i o_j \tag{4.6}$$

$$l = 1, \ldots, N,, \quad i = 1, \ldots, m,, \quad j = 1, \ldots, n_t$$

After setting the initial parameter vector $\boldsymbol{w}$ for each sample, the network output $\hat{y}_l$ can be calculated by (4.1) for input o_j and compared with the actual output y_l to construct the error e_l; starting from the output side, use the back propagation of error e_l to calculate δ_i, ξ_i using

(4.4) and the partial derivative of E_l to $\boldsymbol{w}$ ($\boldsymbol{w}$ refers to any network parameter in $\boldsymbol{w}$) using (4.5). Then construct

$$\frac{\partial E}{\partial w} = \sum_{l=1}^{N} \frac{\partial E_l}{\partial w} \tag{4.8}$$

Based on which the network parameters are improved by the gradient method

$$w^{new} = w^{old} - \eta \frac{\partial E}{\partial w} \tag{4.9}$$

This process is repeated until the performance index (4.3) reaches the minimum. Then the obtained BP network is the best match to the sample data set. It implicitly established the nonlinear mapping between historical data and the current output, which can be directly used to one-step output prediction when the current control input is given.

However, in predictive control, the above neural network needs to be improved for a multistep prediction. The simplest way is to establish *P* simple BP networks, as above when the prediction horizon is *P*, where the output of the *s*th BP network is the system output $\hat{y}(k + s)$ predicted at$k, s = 1, \dots, P$.

$$\hat{y}(k+s) = G_s(y(k), \dots, y(k-n+1), u(k+s-1), \dots, u(k), \dots, u(k-n+1)) \tag{4.9}$$

Thus, the *s*th BP network should approximate the nonlinear mapping $G_s(.)$from the input/output information available at time *k* and the future control inputs to$\hat{y}(k + s)$. Refer to (4.1) and consider the control horizon *M*<*P*; the *s*th BP network can then be expressed by

$$BP_s:, \quad x_i^s = w_{i0}^w + \sum_{j=1}^{n_1} w_{ij}^s u(k+j-n) + \sum_{l=n_1+1}^{n_2} w_{il}^s y(k+l-n-n_1)$$

$$n_1 = n + min(s, M) - 1, \qquad n_2 = n_1 + n$$

$$z_i^s = \varphi(x_i^s)$$

$$\hat{y}(k+s) = w_0^s + \sum_{i=1}^{m} w_i^s z_i^s , \qquad s = 1,\dots,P \tag{4.10}$$

These BP networks work using the same principle and the whole network outputs can reflect the predicted future outputs at different times over the prediction horizon. Since both the learning process and the real-time prediction of these BP networks can be made in parallel, it is a practical and efficient way for multistep prediction for nonlinear systems.

After establishing the neural network model for the nonlinear system, we now discuss the predictive control method based on that. Predictive control runs in a rolling style, i.e., at each sampling time, the control action is obtained by online solving a nonlinear optimization problem. In addition to output prediction, the neural network model established above can also be used for online optimization, which can be solved by the same gradient optimization process as that in model parameter identification. At the sampling time k, let optimization performance index $j(k)$ have the form

$$min\, j\,(k) = \frac{1}{2}\sum_{s=1}^{P}(\hat{y}(k+s) - y_r(k+s))^2 \tag{4.11}$$

Where $\hat{y}(k+s)(s = 1,\dots,P)$ the outputs of the basic BP prediction models are when future inputs are $u(k+h-1)(h = 1,\dots,M), y_r(k+s)(s = 1,\dots,P)$ the desired outputs. Note that

$$\frac{\partial J(k)}{\partial u(k+h-1)} = \sum_{s=1}^{P}\left\{\frac{\partial J(k)}{\partial \hat{y}(k+s)}\frac{\partial \hat{y}(k+s)}{\partial u(k+h-1)}\right\}$$

And it is known from (4.8) that $\hat{y}(k+s)$ is not related to $u(k+h-1)$ when $h>s$, so the above equation can be rewritten into

$$\frac{\partial J(k)}{\partial u(k+h-1)} = \sum_{s=h}^{P}\frac{\partial J(k)}{\partial \hat{y}(k+s)}\frac{\partial \hat{y}(k+s)}{\partial u(k+h-1)} \tag{4.12}$$

Where

$$\frac{\partial J(k)}{\partial u(k+h-1)} = \sum_{i=1}^{m} \frac{\partial \hat{y}(k+s)}{\partial z_i^s} \frac{dz_i^s}{dx_i^s} \frac{\partial x_i^s}{\partial u(k+h-1)} = \sum_{i=1}^{m} w_i^s z_i^s (1-z_i^s) w_{i,h+n-1}^s$$

Furthermore, according to the performance index (4.10), it follows that

$$\frac{\partial J(k)}{\partial \hat{y}(k+s)} = \hat{y}(k+s) - y_r(k+s), \qquad s = 1, \ldots, P$$

Then the gradient can be given by

$$\frac{\partial J(k)}{\partial u(k+h-1)} = \sum_{s=h}^{P} \left\{ (\hat{y}(k+s) - y_r(k+s)) \sum_{i=1}^{m} w_i^s z_i^s (1-z_i^s) w_{i,h+n-1}^s \right\} \tag{4.13}$$

Therefore, one can initially set a group of controls$u_M(k)$, calculate $\tilde{y}_{PM}(k)$ using the model (4.9), and then substitute it into the performance index (8.40) to calculate $\hat{y} - y_r$ in$J(k)$. Based on that premise, the control can be improved by the gradient method

$$u^{new}(k+h-1) = u^{old}(k+h-1) - \alpha \frac{\partial J(k)}{\partial u(k+h-1)}, \qquad h = 1, \ldots, M \tag{4.14}$$

Where $\alpha$the step length and the gradient is can be calculated by (4.12). This iteration process should be repeated until $J(k)$ it reaches a minimum. Then $u(k)$ as the current optimal control can act for the system for control.

The predictive control algorithm with neural network modeling and online optimization can be described by the internal model control (IMC) structure shown in Figure 4.3, where M_{NN} is the one-step neural network prediction model. It only provides the predicted model output at the next sampling time in terms of current control and (4.9) and constructs the output error using the actual measured output to make a feedback correction. The core part in the figure is the neural network, an online optimization controllerC_{NN}. It uses the neural network prediction model (4.9) and the optimization algorithm (4.13), (4.14) to iteratively calculate the optimal control and then implements the current control, where the weighting coefficients of the model (4.10) have been obtained through off-line learning.

The presented algorithm is only a fundamental one of the neural network based on predictive control algorithms. There are a large variety of methods both for neural network modeling and for predictive control based on the neural network model: for example, using the Hopfield network model, considering a general nonlinear performance index instead of a quadratic one, putting constraints on the system input and output, identifying step response coefficients after establishing the neural network model and then using traditional predictive control algorithm, and so on.

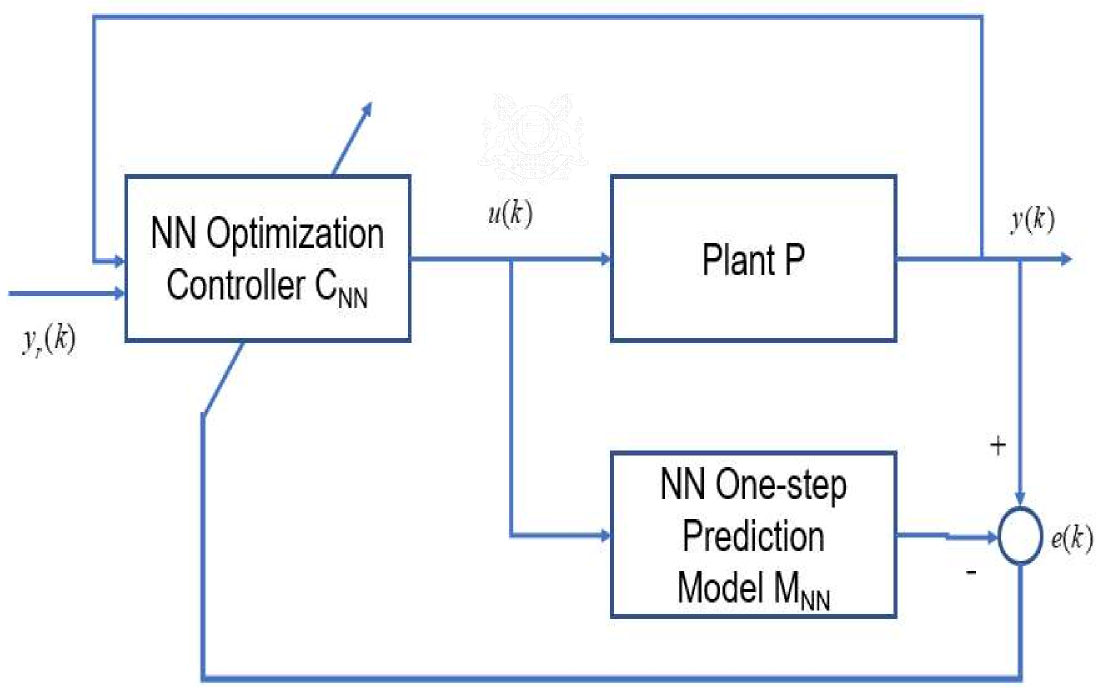


Figure 4.2. Structure of the neural network-based predictive control for nonlinear system

Therefore, we have chosen AI and ANN for our future course of action to solve the problem of autonomous control for the grinding process because it is a way to make machines think and behave intelligently. The grinding machine is controlled by software inside them, so AI has a lot to do with intelligent software programs that control these machines. In the coming parts of this chapter, the basic principle of ANN, the data processing for it, components of ANN, training methodology, testing, validation, and control algorithm generation will be introduced.

4.2. AI model architecture

ANN are computing systems inspired by the biological neural networks that constitute animal brains [97]. An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain, also shown in Figure 4.3. The basic neural network structure is shown in Figure 4.4. It has input neurons, output neurons, and hidden layers.

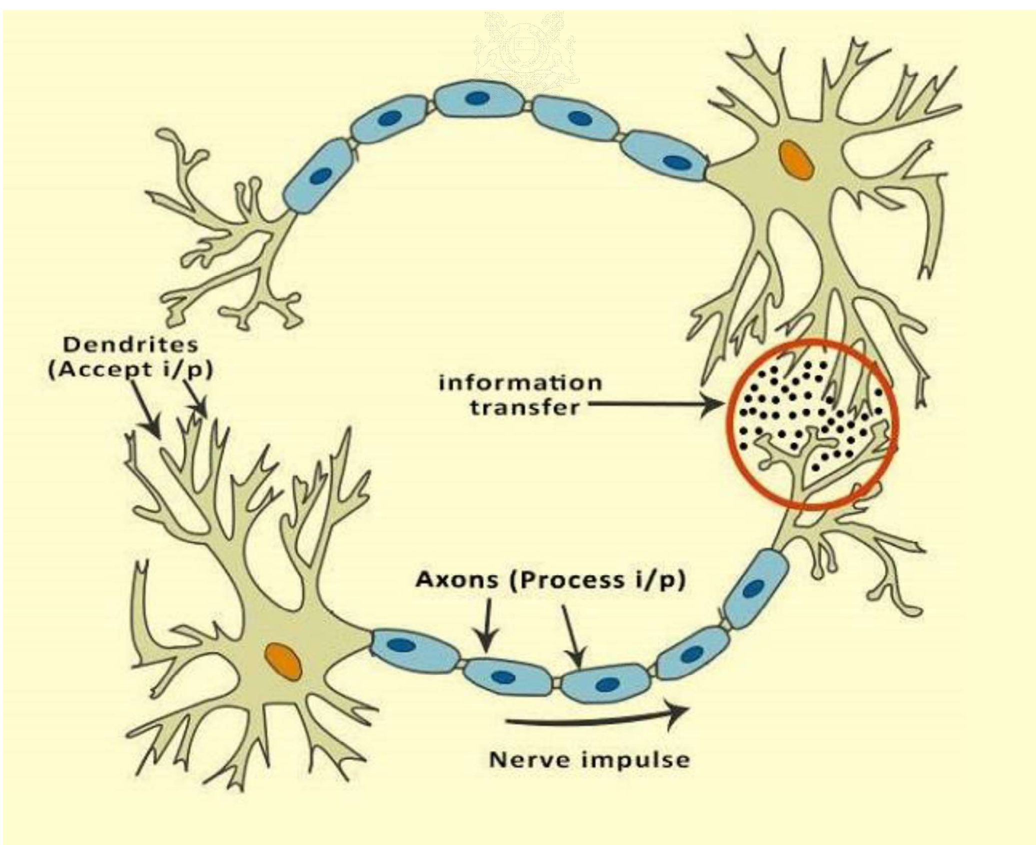


Figure 4.3. Biological brain (*Image source: Data Flair*)

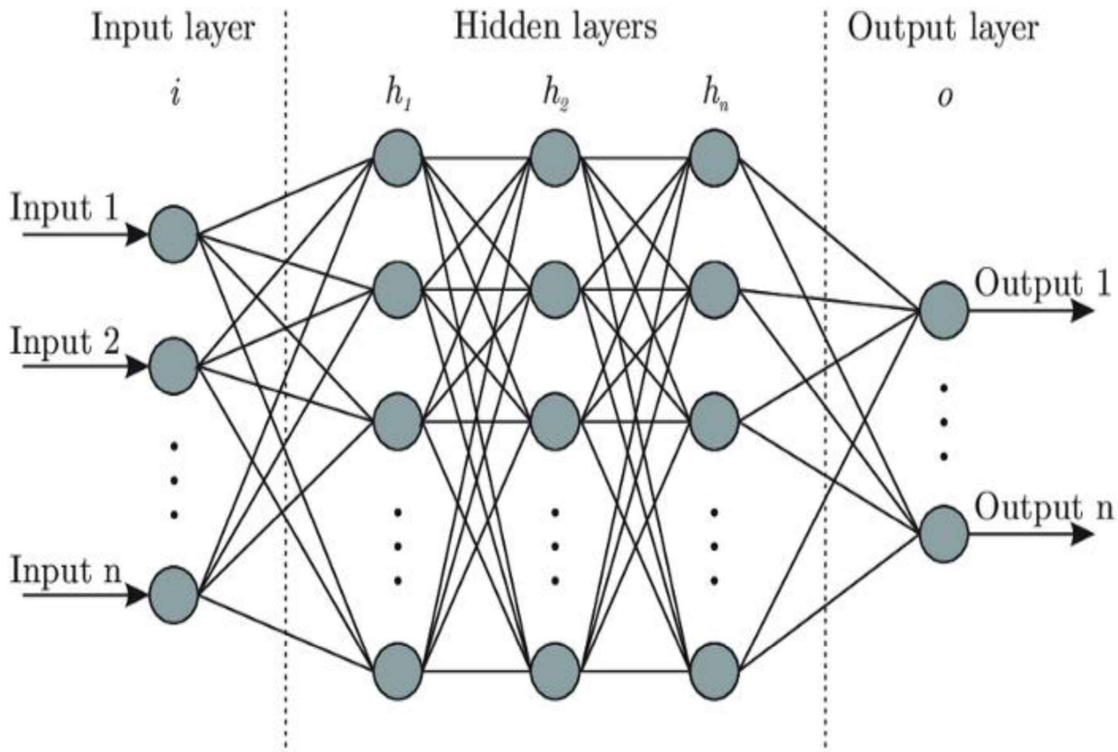


Figure 4.4. Basic neural network structure (*Image source: Towards data science*)

An artificial neuron receives a signal, then processes it and can signal to other neurons. The signal at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connection is called edges. Neurons and edges typically have a weight that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Different layers may perform different transformations on their inputs. Signals travel from the first layer to the last layer (the output layer), possibly after multiple layers traversing.

Deciding the number of neurons in the hidden layers is significant in determining the overall network architecture. Though these layers do not directly interact with the external environment, they greatly influence the final output. Using a too thin network will result in underfitting. It occurs when there are too few neurons in the hidden layers to detect the signal on a complicated data set adequately. Similarly, using a too thick system can result in overfitting. Overfitting happens when the network has too much information processing capacity that the limited amount of information contained on the training set is not enough to train all the neurons in the hidden layers. Moreover, a large network can increase the time to train the network. There are many methods of determining the suitable number of the hidden layers and neurons in the hidden layers. The quantity of neurons in the input layer is equal to the number of features that are the investigating parameters (grinding wheel RPM, workpiece RPM, wheel entry speed, coolant flow rate). The total of neurons in the output layer is equal to the number of analyzed properties that is vibration level error. The number of hidden layers should be set between the size of the input and the size of the output. The number of hidden nodes is calculated by:

$$N_h = \frac{N_s}{\left(\alpha(N_i^+ N_o)\right)} \tag{4.14}$$

Where N_i: number of input neurons; N_o: number of output neurons; N_o: number of samples in training data set; α: an arbitrary scaling factor, usually 2-10. With four input nodes and one output node, the maximum hidden unit should not exceed 50 nodes. These are the theoretical aspects of deciding the number of layers in a neural network. However, in practice, it again has no idea how many nodes to use in the single hidden layer for a given problem nor how to learn or set their weights effectively. Further, many counter-examples have been presented of functions that cannot directly be learned via a single one-hidden layer MLP or require an infinite number of nodes [98–107]. Other aspects of a neural network are explained in further sections, followed by the chosen model and its training.

4.3. Activation functions

It is important for a neural network to learn and map between the features and response variables. Their main purpose is to convert an input or set of input signals of a node in a deep network to an output. The output signal uses input in the next layer in the stack. Particularly, in ANN learning, we do the sum of products of inputs (X) and their corresponding weights (W) and apply an activation function (f(x)) to it to get an output of that layer, and then feed it as an input to the next layer. Without an activation function, the network would become a combination of linear functions and would not be able to learn and model other complicated data. Another important property of an activation function is that it should be differentiable in other to compute the gradient of loss for optimizing network parameters that will be presented in the next section.

The Activation Functions can be divided into 2 types: a) Linear activation function and b) Non-linear activation functions. There are some popular activation functions such as sigmoid, tanh, and ReLU (Rectified Linear Units). The ReLU activation function is shown in Figure 4.5.

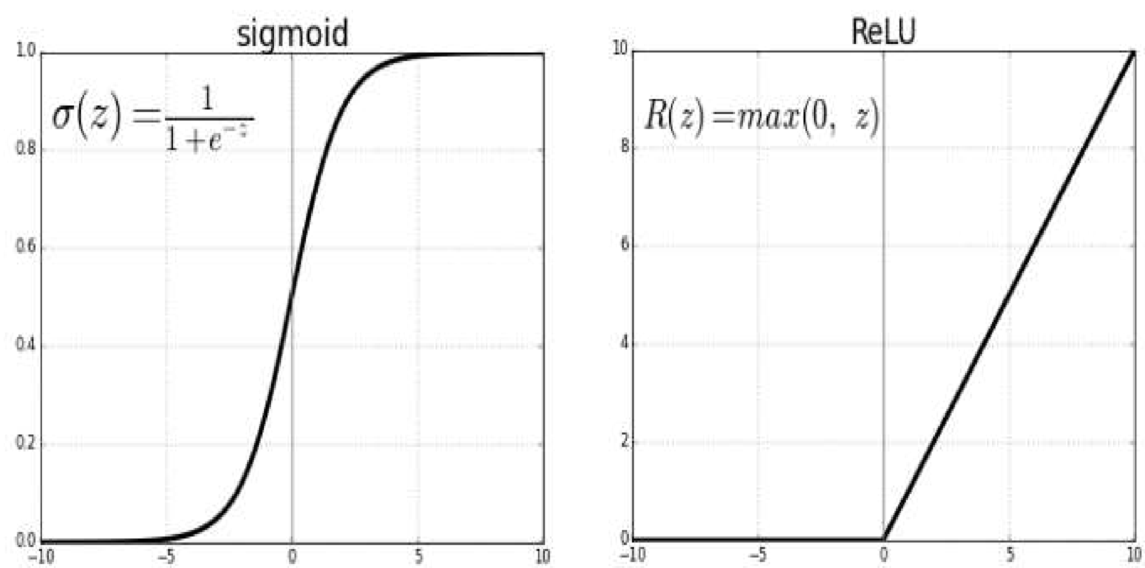


Figure 4.5. ReLU and Logistic sigmoid (*Image source: Towards data science*)

The ReLU function is :

$$f(x) = \max(0, x) \tag{4.15}$$

The derivative of ReLU function is given as 1 for x > 0 or for x < 0. Therefore, the ReLU has a constant zero gradient wherever a unit is inactive. The sigmoid activation function is traditionally a very popular activation function for neural networks. The input to the function is transformed into a value between 0.0 and 1.0. Inputs that are much larger than 1.0 are transformed into the value 1.0. Similarly, values much smaller than 0.0 are snapped to 0.0. The shape of the function for all possible inputs is an S-shape from zero through 0.5 to 1.0 [104,105,107,108]. The sigmoid function was applied in the output layer only. The sigmoid function is:

$$f(x) = \frac{1}{1+e^{-x}} \tag{4.16}$$

4.4. Cost function

While training a neural network, the cost function or the loss function is used. A cost function is the measure of error between what value the model predicts and what the value is, as shown in Figure 4.6. The basic consideration of information on the training process is the evaluation of the loss function. The goal of the training is to find weights and biases that minimize the cost function. In this thesis, for an easier process in the training step that uses a gradient, the cost function uses the mean square error (MSE). For the validation step of the mean absolute error (MAE) is used.

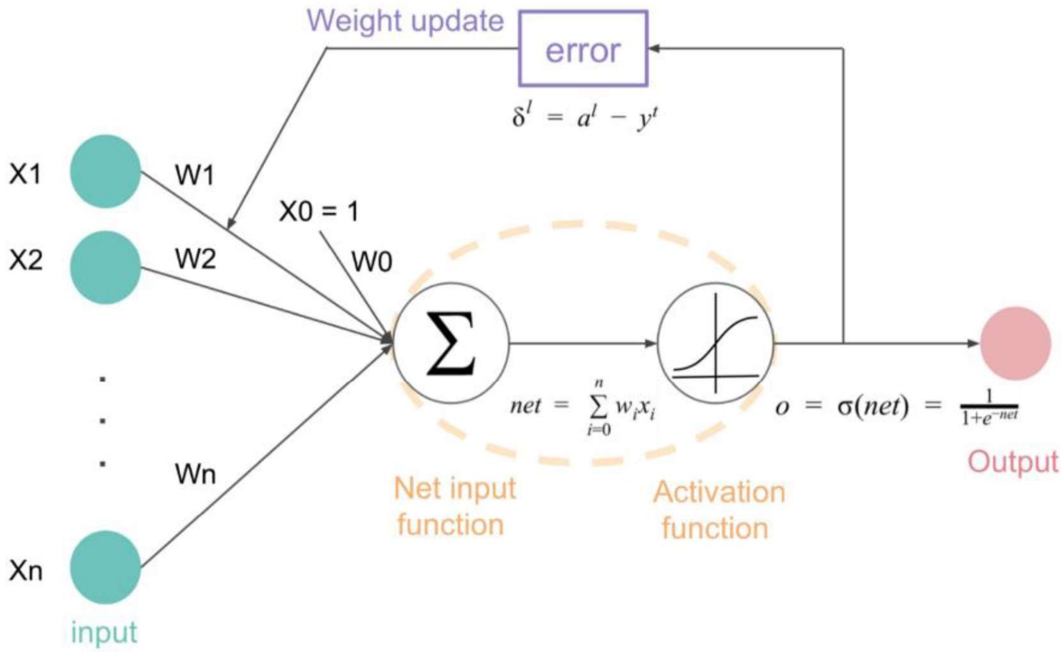


Figure 4.6. Cost function [109]

4.5. Data preprocessing for model

The goal of this thesis as explained earlier, is to predict the change in the process parameter, especially the grinding wheel RPM. Grinding wheel RPM is the most important process parameter that affects the vibration coming from the process, as findings recorded by the authors in different works of literature [110–113]. To control the process parameters, we have also focussed on grinding wheel RPM. To train the model for the grinding wheel RPM, the dataset with grinding wheel RPM, workpiece RPM, wheel entry speed, coolant flow rate, and the vibration error from each cycle has been prepared from the monitoring system collected data. The dataset used for the building and training of the AI model is shown in Table 4.1. Through experiments, we have collected the data for 200 cycles and with the use of oversampling, it has been made the dataset of 500 cycles. The recorded vibration error of more than 1.0 is considered as the cycle during which the failure has happened.

Table. 4.1. Data table for AI model building and training

Cycle No.	Grinding wheel RPM	Workpiece RPM	Wheel entry speed	Coolant flow rate	Vibration error
1	740	200	3	40	1.0
5	800	180	4	30	0.5
9	612	200	3	30	1.35
11	918	230	5	40	1.44
33	850	180	5	50	0.5
55	840	200	4	30	-0.5
67	750	180	3	40	0.9
			....		
200	800	200	3	30	0

4.6. AI modeling and its training

For the autonomous control of the grinding process grinding wheel RPM must be optimized. For that purpose, the ANN model is built as vibration error signal coming from the sensor, workpiece RPM, wheel entry speed, and coolant flow rate as the input and the grinding wheel RPM as the output. The ANN model is used to predict the grinding wheel RPM for the process and then a control action suggests the changes after its comparison with the reference value of the grinding wheel RPM. The selected ANN is a feed-forward neural network. Initially, as per the calculation of the number of hidden nodes stated, we selected three hidden layers with sixteen nodes at each layer.

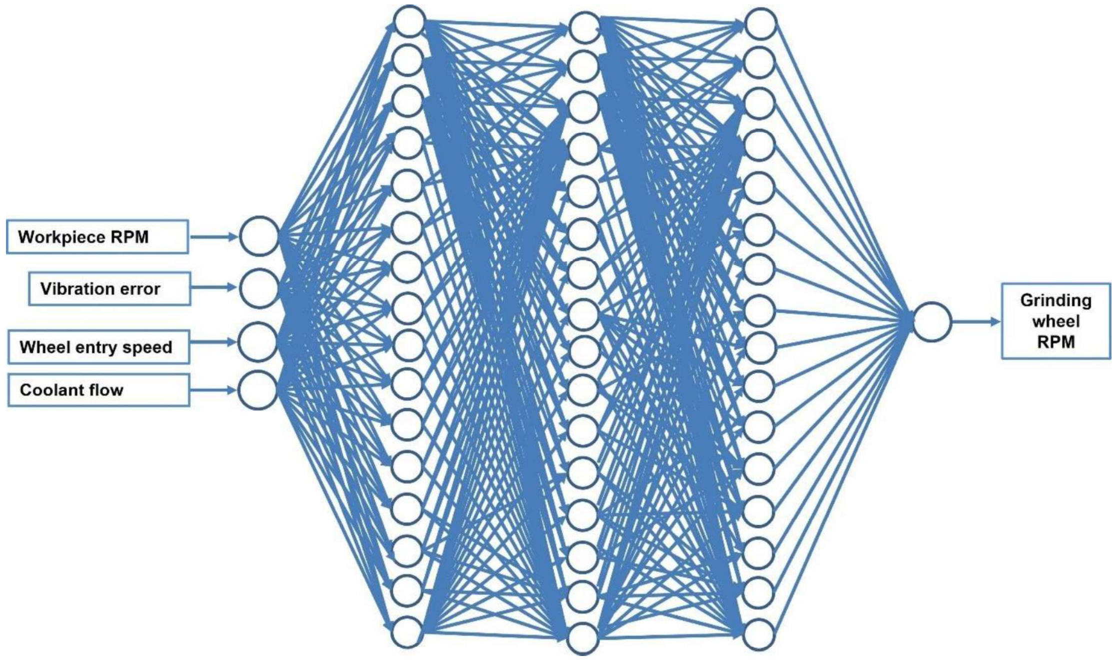


Figure 4.7. Initial AI architecture

The goal of the feedforward neural network is to approximate some function f for a classifier y=f(x). It maps input x to a category y [114]. Output grinding wheel RPM, we have to predict based on other input process parameters. Once we are able to predict the grinding wheel RPM, then we can control it by comparing it with the reference grinding wheel RPM. The AI model for the prediction of the grinding wheel RPM is shown in Figure 4.7. The number of hidden layers is two.

4.6.1. Supervised learning

Supervised machine learning is the machine learning task that maps an input to an output based on example input-output pairs. Training is about minimizing the cost function by changing the value of w, and b parameters. The training process aims to learn a function $f{:}x \rightarrow y$, from a given dataset { Xi, $Y_{i.}$, i = 1, . . N }, where Xi $\in$ X, and $Y_{i.} \in Y$. The process adjusts network parameters by direct comparison between the model output and desired output. It infers a function from labeled training data consisting of set training examples. Supervised machine learning algorithms uncover insights, patterns, and relationships from a labeled training dataset that already contains a known value of the target variable for each record. In industries especially where the practical implementation of the model is required primarily supervised machine learning is used. The backpropagation algorithm is a supervised learning method for multilayer feedforward networks from Artificial Neural Networks.

The principle of the back propagation approach is to model a given function by modifying the internal weightings of input signals to produce an expected output signal. The system is trained using a supervised learning method, where the error between the system's output and a known expected output is presented to the system and used to modify its internal state. The performance of the different layered AI model is shown in Table 4.2.

Table. 4.2. AI model performance with different number of layers and nodes

No. of hidden layers	Hidden layer size (neurons)	Mean absolute error (MAE)	Accuracy
1	4	.432	78 %
2	8-4	0125	82 %
3	8-4-8	.001	98.1 %
3	16-16-16	.278	93.4 %

Technically, the back propagation algorithm is a method for training the weights in a multilayer feed-forward neural network. As such, it requires a network structure to be defined of one or more layers where one layer is fully connected to the next layer. To solve our machine learning problem, we have used the regression model. It is a subfield of supervised learning. It aims to model the relationship between a certain number of features and a continuous target variable [115]. Out of the collected datasets, 80% of the data we are using to train the model and 20% of the data we are using to test the ANN model. The steps for the training of the model with supervised learning are shown in Figure 4.8.

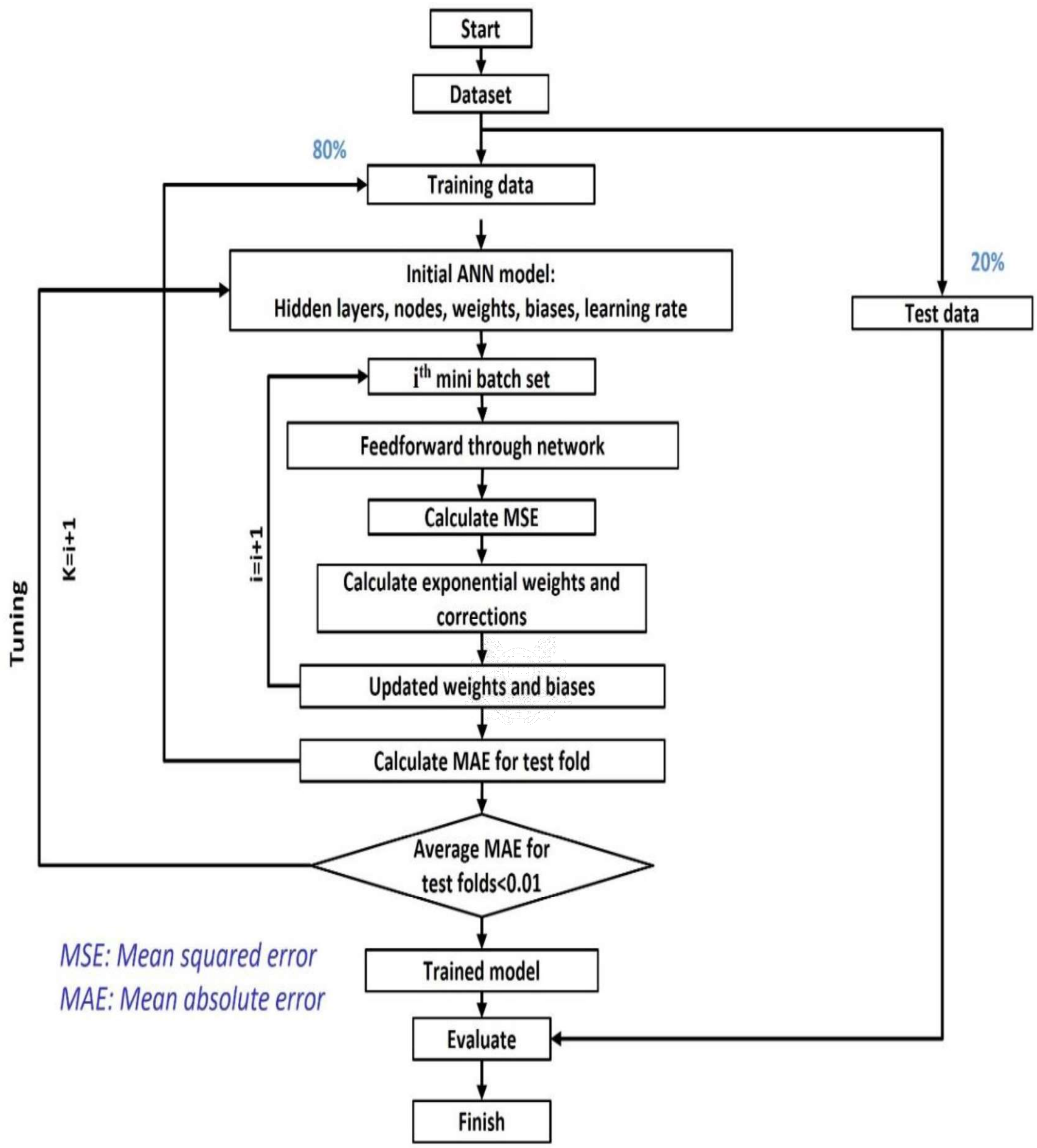


Figure 4.8. AI model training methodology

The ANN model has been implemented using open-source Python programming language available on the internet. The final structure of the ANN model consists of three hidden layers with nodes as 8-4-8 as shown in Figure 4.9. The model validation is shown in Figure 4.10. From the figure, it is clear that the model is good for use, and with more availability of the data, it can be made more suitable for use. The comparative evaluation of the ANN-based training model is done with other supervised learning algorithms like KNN, SVM, and Random forest methods as shown in Table 4.3.

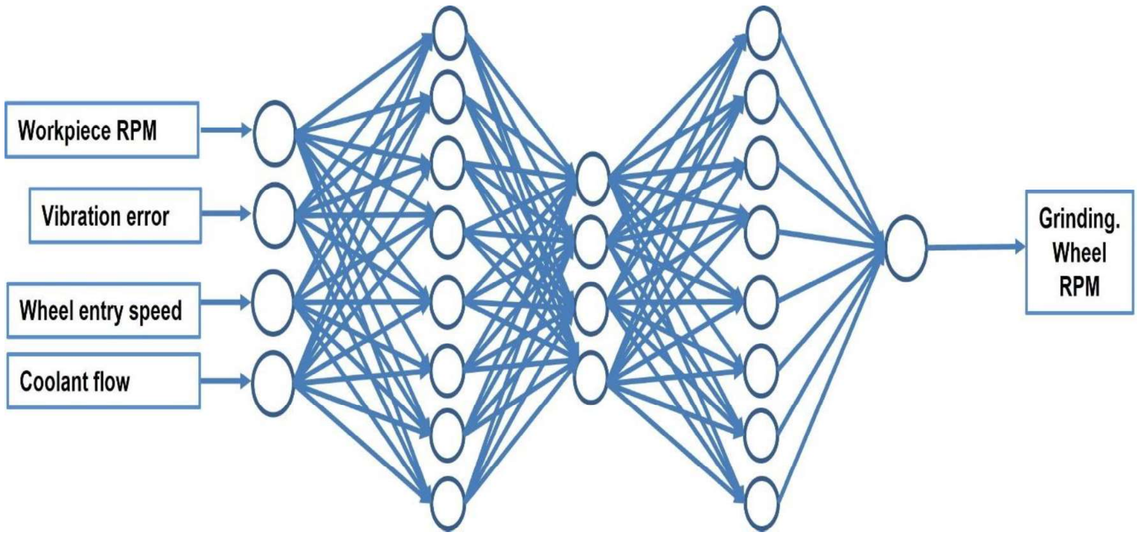


Figure 4.9. Final AI model for grinding wheel RPM prediction

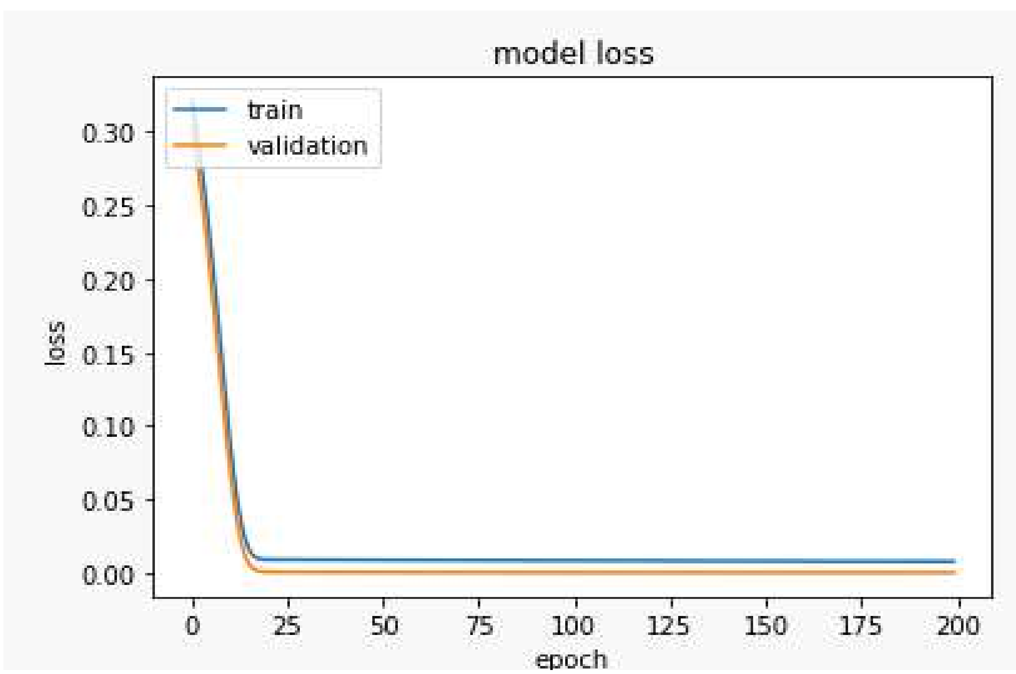


Figure 4.10. Mean absolute error for validation of the model

Table. 4.3. Comparative evaluation with different supervised learning algorithms

Algorithm	Working technique	Accuracy
KNN	Neighbour based	79 %
SVM	Kernel based	73.5 %
Random forest	Ensemble based	82 %
ANN	Neural network	98 %

4.7. Control algorithm for process parameter change

After the prediction of the grinding wheel RPM, the next task of this thesis is to calculate the changed grinding wheel RPM that is causing the failure of the process. The control algorithm with AI trained model is shown in Figure 4.11. It can be seen that the monitoring system for the grinding process delivers the vibration error signal from the monitoring display. The trained AI model takes input with the other three process parameters and predicts the grinding wheel RPM. Then the observer programmed in the system compares the predicted grinding wheel RPM with the reference. The controller compensates for the difference in the reference and the predicted value as shown in equation 4.17.

$$\text{Change in the grinding wheel RPM} = \text{Predicted RPM} - \text{Reference RPM} \tag{4.17}$$

The control action command is propagated to the machine controller through the OPC UA connection.

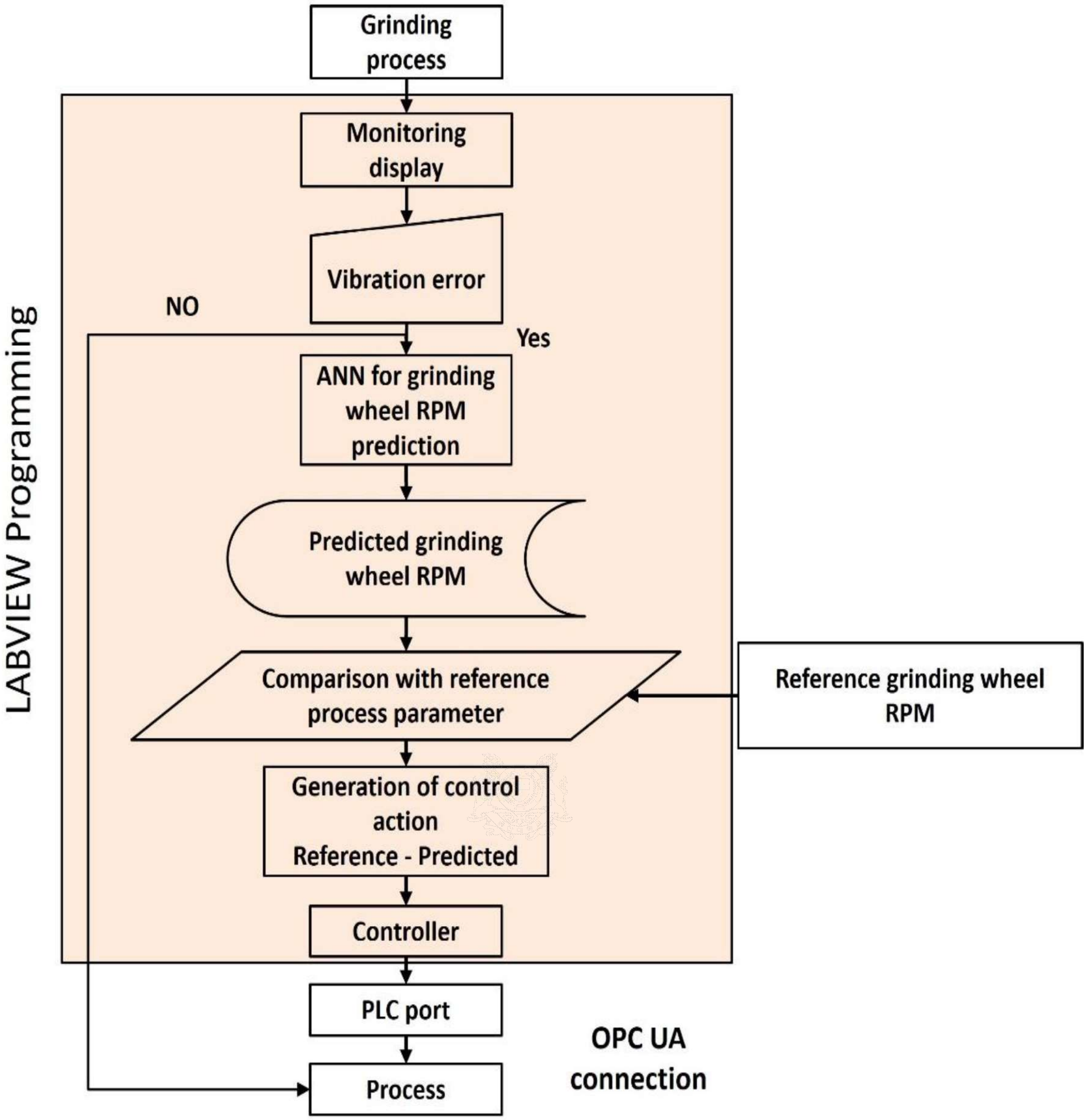


Figure 4.11. Control algorithm

Chapter 5 . RESULTS AND DISCUSSION

5.1. Implementation of the developed system

The developed intelligent monitoring and control system can be easily applied to a grinding machine for multiple purposes. The developed system is applied to the double-sided vertical type surface grinding machine from Daisho, Japan. The machine is used for the grinding of the automotive brake disc. The developed system is portable. It can be easily installed and relocated from machine to machine. The setting values for monitoring can be changed easily. At first, all the components of the smart system are installed at the real machine at Namyang Nexmo, Korea, as seen in Figure 5.1. The manufacturing of the brake disc consists of several stages. However, our focus is on the stage of the grinding process. The sensors are installed at the grinding process location using mountings. Devices like DAQ and sensors are connected to the developed monitoring system using an ethernet cable. The autonomous monitoring and control system is installed into the industrial PC as it can be seen in Figure 5.2. At the industrial PC, the user can visualize the real-time process behavior. The new process parameter is delivered to the machine controller through the industrial PC.

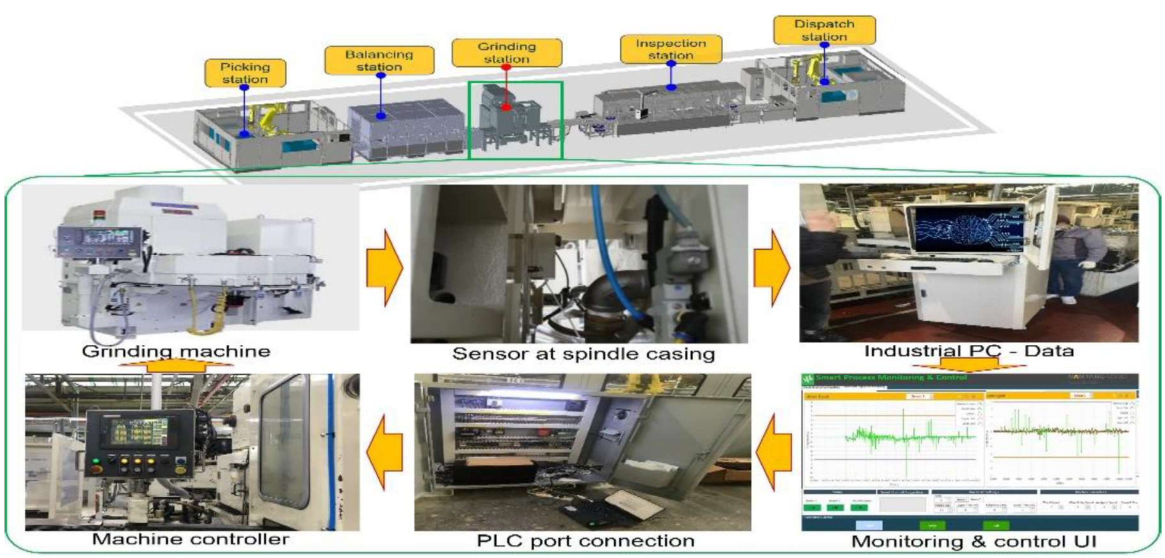


Figure 5.1. Implementation of the system at the site

The LabView delivers a new grinding wheel RPM to the PLC tag in a control action form. Moreover, the controller adjusts the process parameters accordingly.

Figure 5.2. Installation as an independent software with User ID

5.1.2. Integration to the control room

After the successful testing of the implemented system at the industrial PC, it is integrated with the regular control architecture of the company. The industrial PC is connected to the control room PC through transfer communication/Internet protocol (TCP/IP). The plant manager can observe the process behavior just by sitting in the control room. This process monitoring system can be later used for the rotating component remaining life prediction system also. To use the developed system, the user first opens the software like any other application in the windows operating system by double-clicking it. Then the devices are connected to the application. Once connected, the application displays the real-time sensor signal and simultaneously the FFT graph. Based on the company comparison-based study of the scraps produced due to these surface defects, this system is of great help. When entirely operated automatically, it can bring a dramatic change in the overall productivity of the factory.

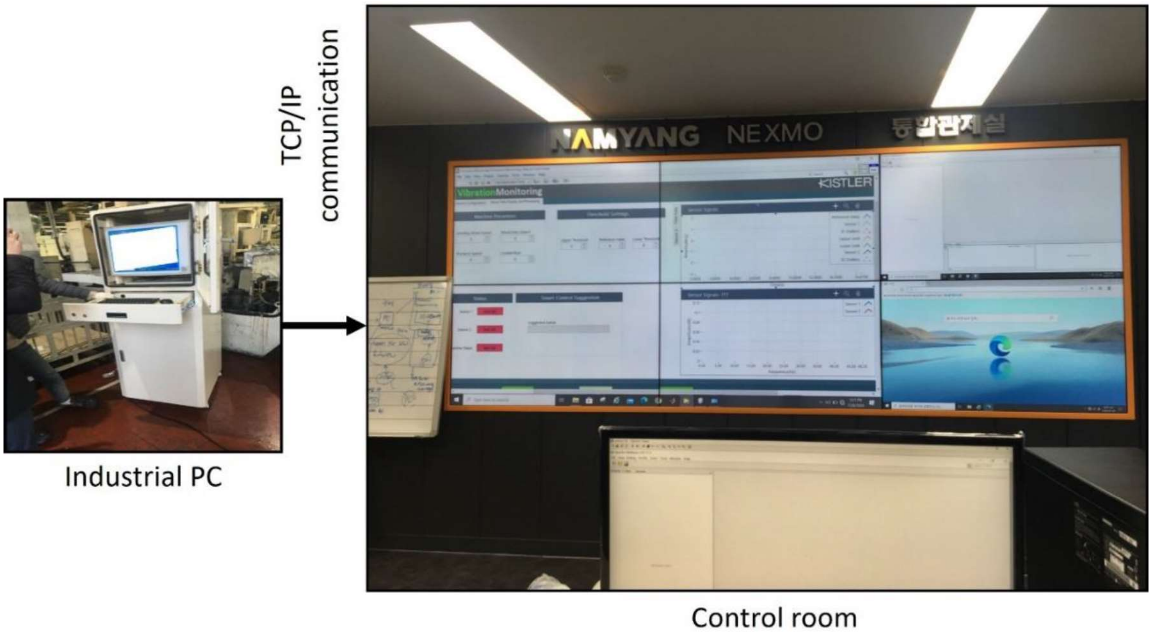


Figure 5.3. Control room display for the plant manager

5.2. Functionality testing of the developed system

5.2.1. Real factory environment testing

The developed software is converted into the application file and installed into the industrial PC at the machine site. The PC does not require to have any external tools like LabView for its functioning. The developed system is tested for the grinding process of the brake disc. The process parameters information for the brake disc is shown in Table 5.1.

Table. 5.1. Process parameter for brake disc grinding

No	Process parameters	Values
1.	Clamp pressure	0.5 ~ 1.5 MPa
2.	Grinding wheel RPM	750 - 850
3.	Workpiece RPM	130 - 250
4.	Feed rate	40/30/20 μm/sec
5.	Spark out time	3.0 sec
6.	Coolant oil concentration	4±2%

When the start button of the system is pressed, the data acquisition from the sensor initiates, and simultaneously the UI window displays the real-time vibration signal behavior. From the collected data and its training, we set the threshold limits for the vibration signal as 0.3. As seen in Figure 5.4, when the vibration amplitude is within the threshold limits, the smart control module does not trigger any alarm or change in process parameters. Demonstration of real-time failure instances at our wish is difficult, so it is demonstrated by altering the threshold limits. In the demonstration scenario, it can be seen that when the vibration amplitude level increases and go beyond threshold limits, the process condition is termed as failure. It is an indication of surface defects like burn marks in the workpiece. Consecutively, the smart control algorithm calculates the difference between the standard and current vibration level and calculates the new process parameters to avoid failure; the new grinding wheel RPM is calculated as 765 and delivered to the machine controller through OPC and PLC connection.

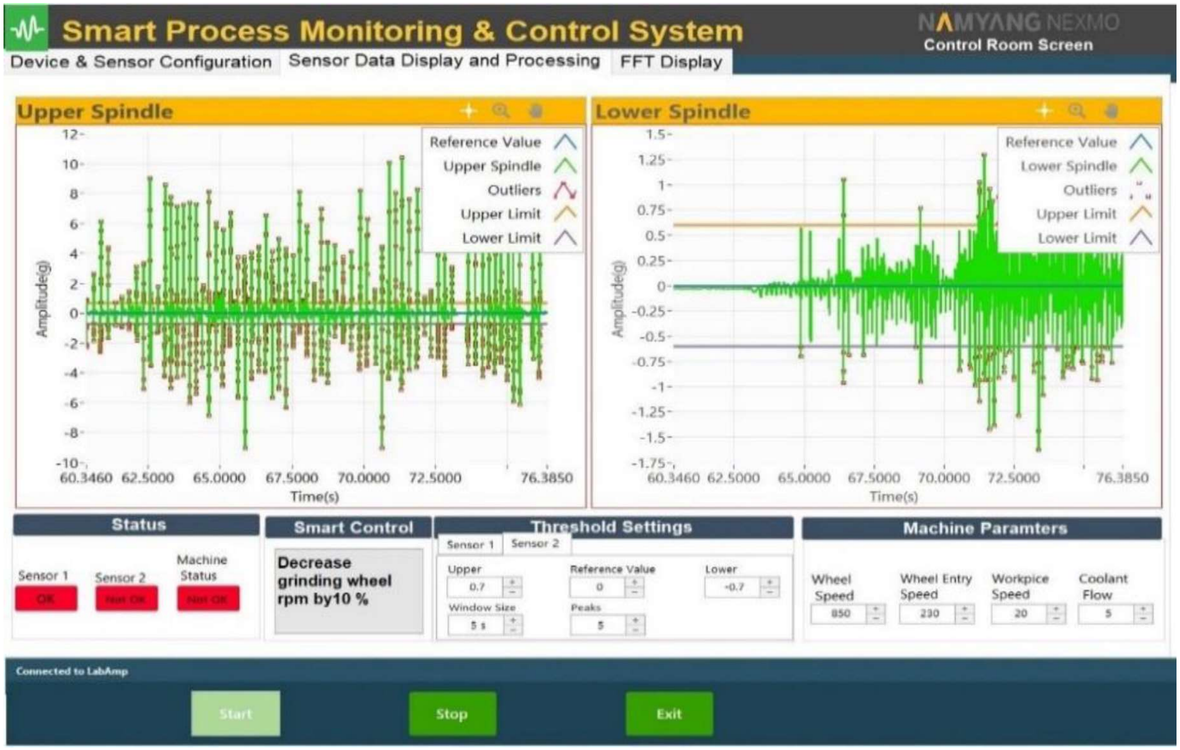


Figure 5.4. Real factory scenario

5.2.2. Benefits to the manufacturer

As seen in Figure 5.5, the new production line of the brake disc manufacturing is integrated with this autonomous process monitoring and control system. This inclusion has helped in shifting the manual product quality evaluation into a more precise and autonomous system. There are several benefits to the manufacturers. The manual quality inspection can be taken care of by the monitoring and control system that can detect and correct the occurring failures. It can successfully reduce the quality failures due to the surface defects that occurred during the grinding process. After consideration of all the involved resources and their application to all available production lines, it can increase productivity by 5 % as stated by the partner company's evaluation.

Figure 5.5. Benefits as before and after scenario

Chapter 6 . AI-BASED MONITORING AND SMART CONTROL OF INJECTION MOLDING PROCESS

6.1. Introduction

Injection molding is the most popular cyclic manufacturing technology and is extensively used to produce a variety of industrial products. With the introduction of modern machinery and computer-aided engineering (CAE), product shapes are becoming increasingly complicated. This complexity can result in surface defects and thermal damages. In a complex manufacturing process, there are various factors like machine conditions, product characteristics, process parameters, raw material, and several disturbances that affect the production plan and the final product quality [116]. To compete effectively in the plastics marketplace, manufacturers and researchers have focused on improving product quality by adopting different methodologies. Among the various responsible factors, cooling is a critical and important stage in the molding process to solidify the product, and it directly affects molding quality [117]. During the molding cycle, cooling consumes most of the time. To improve product quality, enhancing cooling performance appears to be a practical option, and the introduction of three-dimensional (3D) printing presents some promising options, including the use of conformal cooling channels instead of conventional cooling channels [118]. The improved cooling channels manufactured with additive manufacturing technology have increased conventional injection molding [119]. Although uneven cooling is a significant factor in quality defects, previous studies have indicated the choice of process and parameters influences quality to a greater degree than machine or mold design [120]. Major quality defects experienced by manufacturers include short shots, flashes, weld lines, and warpage. To remove surface and thermal failures from molded products, several online and offline optimization methods are in use for a long time [121–125]. These methods can reduce the number of experiments and replace the current hit-or-miss method used by operators to determine the optimal settings for a machine and a product. To minimize warpage failure, the Gaussian regression method is applied [126]. Improved computational power and the introduction of CAE for simulation works have helped reduce costs and improve quality while optimizing process parameters. Most process parameter optimization systems such as genetic algorithms, adaptive neuro-fuzzy inference systems, artificial neural networks, back-propagation neural networks, and hybrid methods work offline. Manufacturers use them to find the optimal processing conditions for a particular product [123].

Conventionally machine operator's assistance is needed to conduct experiments and adjust process parameters based on observed quality feedback. A combination of sensors is introduced to overcome such issues, and a model has been developed to collect cavity and nozzle pressure data. After extracting essential data, the same model is used to diagnose the process conditions [127]. Like other cyclic manufacturing processes, various sensor-assisted monitoring and failure diagnosis systems have been applied to injection molding [128]. These approaches have demonstrated relatively good capability, but sophisticated data acquisition (DAQ) techniques, installation problems, and nonlinear relationships among process parameters have limited their use. In addition to that, many self-energized, wireless, and dual-sensing techniques are in use to monitor the injection molding process [129]. As modern molding machines can generate large data quantities, the literature [126] recently used a big-data management approach to identify faults. A structured query language (SQL) database, stored data from every cycle, and python programming are used to develop a fault-prediction model with an accuracy of 57%. Based on the prediction, control measures can be taken by the operator instantly.

Fault diagnosis is a crucial factor in any industry to detect failure and for scheduling maintenance. Researchers have also developed a DAQ system that employed cavity sensors and analyzed the resulting data for potential faults [130]. Although the performance of the introduced method in terms of injection molding monitoring is reliable, consistent quality in molded products requires more than just a monitoring strategy. The process is still dependent on the skills of the operator and process engineers. The lack of an online feedback system makes it difficult to develop robust monitoring and control techniques. A major portion of the recent research prefers the use of artificial intelligence (AI) technologies to control molding processes as such technologies are better suited to identifying the relationships between measurable and unmeasurable parameters [131]. Park et al. [132] suggested that an AI-based molding process can improve product consistency and quality. Chen et al. [133] assigned injection molding variables to three levels, as shown in Table 6.1.

To reduce level-3variables, a robust monitoring and control model for adaptive control of process parameters is required. Kangalakshmi et al., Schiffers et al. and Wang et al. [134–136] have tried to address quality-related problems by applying model-based proportional-integral-derivative (PID) control, adaptive process control, and phase diagram control, respectively with each achieving some encouraging results. To overcome the complexities of sensor installation, data collection, and difficulties of interrelationship derivation between process parameters and failure, a research object with simple geometry is chosen [137].

Cavity temperature and pressure sensors are used for data collection, and simulations are conducted to validate their models using different tools in all the above-introduced monitoring and control strategy. Although considerable research efforts have been devoted to reducing quality failure rates in injection molding, the application of the developed system is either theoretical or just in simulation models. Furthermore, their practical implementation in industrial applications is still a distant job.

Table 6.1. Summary of grinding wheel condition monitoring studies

Three-Level Variables in Injection Molding
Level 1. Machine variables (independently controllable)
Temperature
Barrel temperature (in several zones)
Nozzle temperature
Coolant temperature
Pressure
Pack/hold pressure
Back (recovery pressure)
Maximum injection pressure
Sequence and Motion
Injection (ram) speed (constant or profiled)
Screw (rotation speed)
Level 2. Process (dependent) variables
Melt temperature (in the nozzle, runner, or mold cavity)
Melt pressure (in the nozzle and cavity)
Melt-front advancement
Maximum shear stress
Rate of heat dissipation and cooling
Level 3. Quality definitions (final response)
Part weight and part thickness
Shrinkage and warpage
Sink marks
Appearance at weld lines
Other aesthetic defects: burn marks, gate blushes, surface texture

The injection-molding process faces quality failures such as sink marks, short shots, warpage, and flashes. Existing solutions such as conformal cooling channels manufactured with 3D printing technology and process parameter optimization systems cannot maintain quality consistency due to variations in process parameters and process instability associated with the various machines and environmental factors. This results in large quantities of scrap parts, reduction of productivity, and wastages of resources. A more efficient molding process is therefore in high demand.

To overcome the difficulties of current methodologies, this paper introduces a data-driven monitoring and smart quality-control model that can reduce quality failures and increase productivity with the application of an improved monitoring system. The primary goal of the presented research is to develop the smart monitoring and control module and validate it with real industrial experiments. Automation of the injection molding quality control is the secondary goal. Major failure considerations for the study are short shot and warpage.

6.2. Methodology

6.2.1. Generating an analysis model for describing real-world process behavior

In earlier works related to cooling performance optimization for a plastic door module, a CAE tool is used to replicate real-world cooling channels [138]. Constraints of machine design and lack of experiments make it impossible to visualize each step of the injection molding process precisely. So, for a detailed description of the process behavior of the manufacturing of car door trim with injection molding, a cyber-engineering analysis model is developed as shown in Figure 6.1. The geometric modeling of the cooling channels, gates, mold, as well as product is precisely identical to the real counterparts. In different phases of the complete molding process, cooling is the most time-intensive. The developed cyber engineering model also helps in reducing the number of required real-world experiments and associated costs. Additive manufacturing technology is used to manufacture the complex conformal cooling channels used for the door trim module [139]. The detailed study of the cyber model, as well as the real industrial experiments, also provides the same influential factors of injection molding as discussed in the earlier section of the paper. The cyber engineering model system is used to grasp the quality criteria and their influencing factors.

6.2.2. Deriving a relationship between quality failure and process parameters

In terms of selected failures for study, the most influential process parameters among all the quality-related factors are flow rate, packing pressure, hold pressure, packing time, melt temperature, and mold temperature. A description of the process parameter selection process is provided in Figure 6.2.

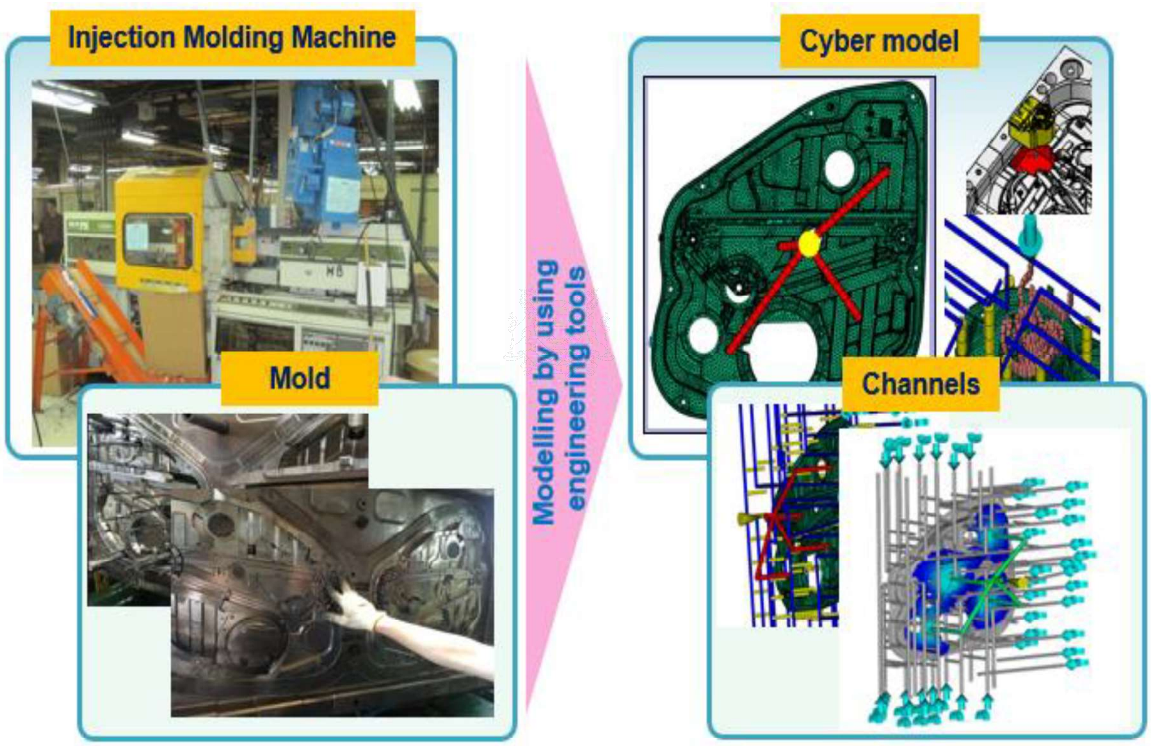


Figure 6.1. A developed cyber engineering model for understanding molding behavior

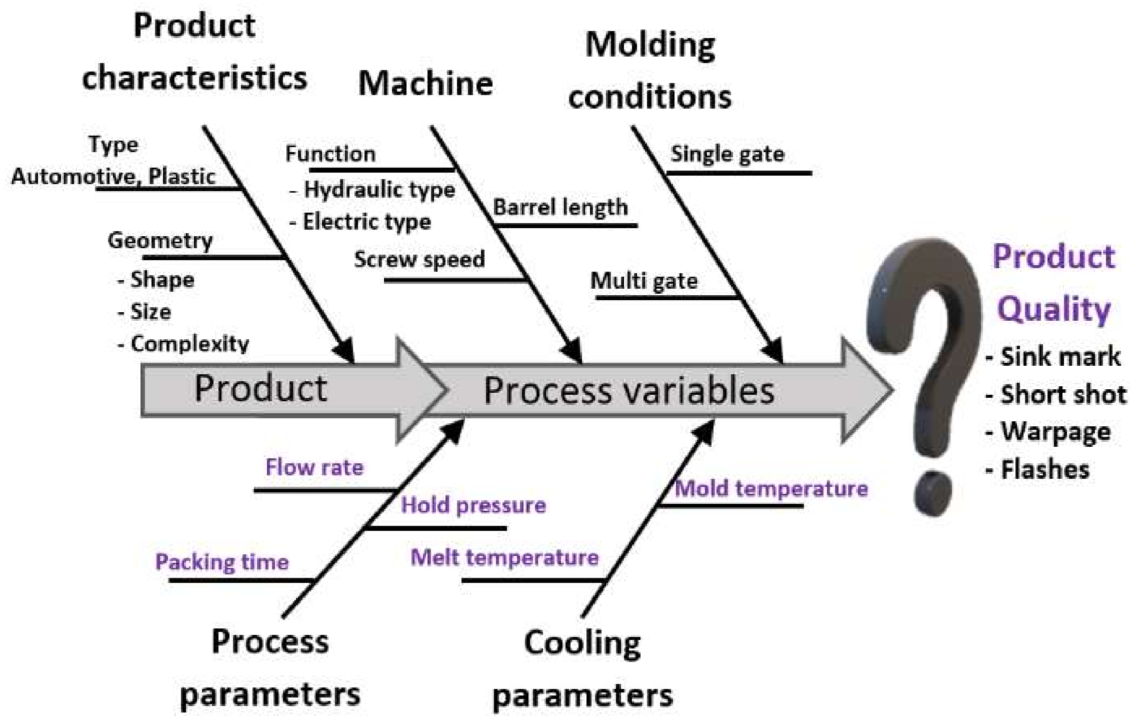


Figure 6.2. Influential process parameter selection in terms of quality

Observable process parameters are nonlinear, and finding an empirical relationship between the parameters and product quality is challenging. Multiple cyber experiments, each with a different set of initial process parameters, are conducted with CAE tools to consider the occurred failures. Additionally, these simulations are supported by factory experiments with the same set of initial parameters and product quality feedback from the operator. Cycles are labeled as good or bad based on the associated quality of the final product. The same approach is then applied to establish a reference model for temperature and pressure profiles. The format for the experiments and related data with the occurrence of the failures are briefly explained in Table 6.2. This detailed study of the tests is designed to develop a process window for the best quality products. The process window depicts the actual conditions of the manufacturing cycle, as discussed previously [140]. A more precise process window after multiple experiments and quality feedback data for the car door trim case is shown in Figure 6.3. During the product molding cycle, deviation from the depicted process window resulted in quality failure, including short shots and warpage.

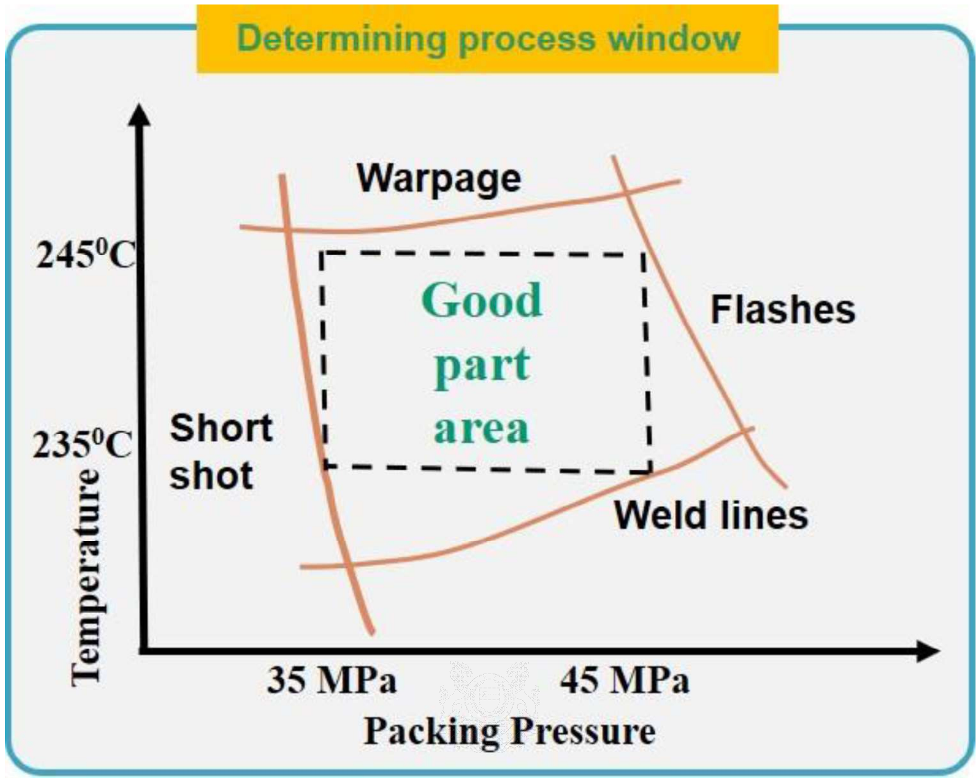


Figure 6.3. Obtained process window for a good quality product

Initial optimal settings for the car door trim, based on the physical experiments, virtual model, and the obtained process window, are provided in Table 6.3.

6.2.3. Data collection and monitoring technology

Cyber and real experiments are performed to visualize defects such as warpage and short shots. It is assumed that if we can control the process and the process window is followed every cycle, the product quality will be good. Based on this assumption, there is no need to define each failure. If the temperature and pressure profiles are optimized, then the chances of quality failures are small. Virtual temperature and pressure sensors are assumed in the cyber molding experiments. In addition to the virtual model analysis real data is also collected for its relative validation. The data obtained from cavity sensors are in the form of a time series and imported to a database in the company server as well as a local laptop as comma-separated files. The data collection infrastructure for this research is shown in Figure 6.4. Different sensor setups are used to simulate all possible molding processes. Because of the time-series data, if used directly, it makes process monitoring difficult.

Features like peak, average, maximum, and minimum are extracted from the raw data for the temperature and pressure, respectively. These features reciprocate the process condition of the current and previous cycle.

6.2.4. Threshold value setting for collected sensor signals

In factories, an operator sets the initial process parameters and, during the production, adjusts them according to the quality of the molded part to get a product with the best quality. Instead, the collected datasets are used to determine optimal pressure and temperature profiles for the mold cavity. Based on analysis results and after validation with references, selected threshold limits are chosen as shown in Table 6.4.

Further development of the monitoring system is based on the threshold limits of the features extracted from the raw signal.

Table 6.2. Collected data from different cyber experiments

Cycle	Flow rate (cm^3/s)	Coolant temperature	Melt temperature	Packing pressure	Packing time	Deflection	Part weight	Remarks
1	400	15	230	40	3	4.6	814.6	Short shot
2	400	15	240	50	5	4.3	824.4	
3	400	20	230	50	5	3.7	831	
4	400	20	250	40	3	5	810	Short shot
5	450	15	250	40	7	5.6	816.9	Short shot
6	450	20	240	40	5	4.3	813.6	Short shot
7	450	25	230	40	5	4.3	814.2	Short shot
8	450	25	230	50	3	4.5	820.9	
9	450	20	240	40	5	4.4	826	
				……..				
				……..				
103	500	25	240	40	5	5.9	824.8	

Table 6.3. Process parameter for the injection molding of the car door

Parameters	Setting values
Injection rate	450 g/cm^3
Packing pressure	50% of injection pressure
Packing time	5 sec
Melt temperature	240 ^{0}C
Coolant temperature	20 ^{0}C

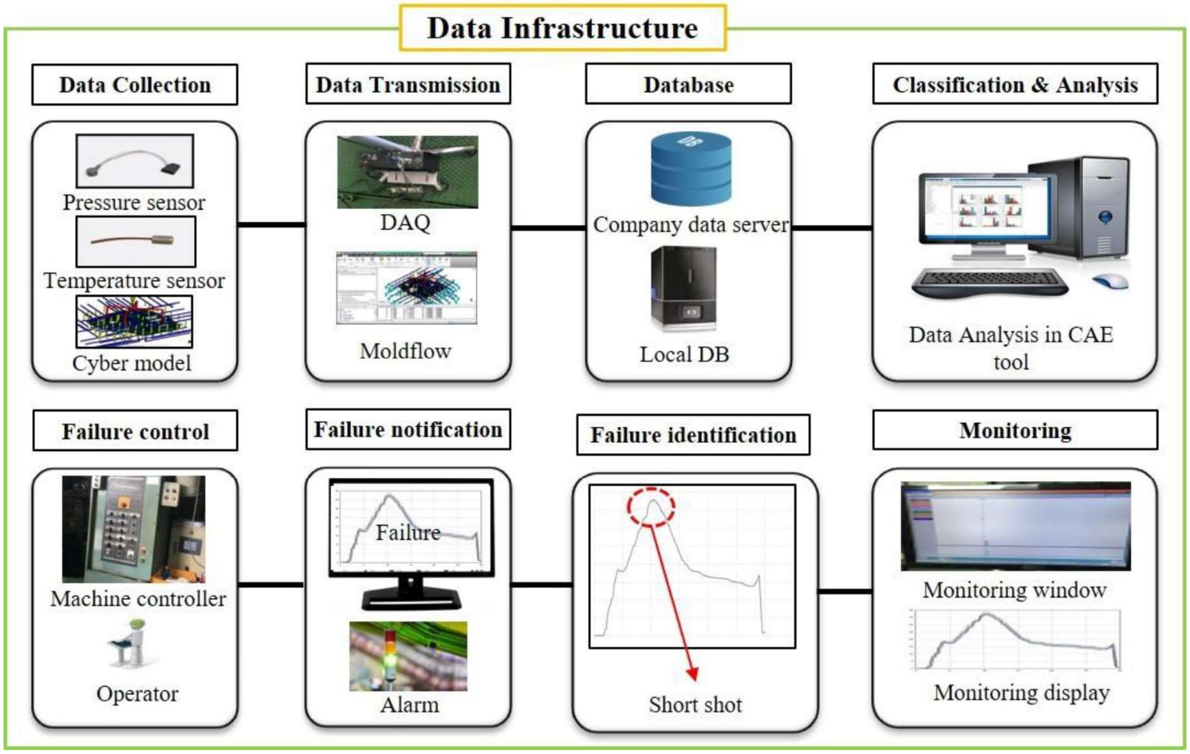


Figure 6.4. Data collection and processing infrastructure

Table 6.4. Threshold limits

Profile	Feature	Min	Max
Pressure profile	Peak value of pressure (MPa)	35	40
	Packing pressure (MPa)	26	30
	Packing time (s)	5.5	7
	Average pressure (MPa)	23	25
Temperature profile	Peak temperature	238	242
	Average temperature	92	96

6.3. Development of a smart control system for quality consistency

In previous sections, the primary focus has been on developing the monitoring system for injection molding. However, monitoring without a control strategy is not a viable method of maintaining quality in the mass production of car door trim modules. Although it is possible to derive a statistical relationship between process parameters and sensor signals, our research is oriented towards solving real problems and their implementation. A case-based control strategy derived from the engineering analysis model and real data is explained in this section of the paper.

6.3.1. Failure recognition and control algorithm development

The monitoring of sensor signal profiles provides a detailed explanation of the occurred failure and corresponding process parameters. A control algorithm to recognize deviations from the process parameters and the standard threshold limit is illustrated in Figure 6.5. It also facilitates the changes in the process parameters to compensate for the occurring failures.

The molding process is first run with the initial settings. Data of peak value of pressure, packing pressure, packing time, average pressure, peak temperature, and the average temperature is extracted from the temperature and pressure profiles. These extracted values are then compared with their threshold limits to detect the cases of failure. After searching the database for the best solution, the new adjusted process parameter is delivered as the output of the system, and the same is delivered to the controller. The controller then adjusts the process parameters according to the algorithm output.

6.3.2. System architecture for a smart quality control system

To implement the smart quality control module, a system architecture is introduced. The architecture includes a data collection module from sensors, a failure recognition module after the comparison with threshold limits, and a decision-making module that follows a predefined set of rules. This is connected to the database through a developed user interface. The most important part of this module is the numerical control module that adjusts the process parameters based on the recommendations from the control algorithm. Architecture is detailed in Figure 6.6.

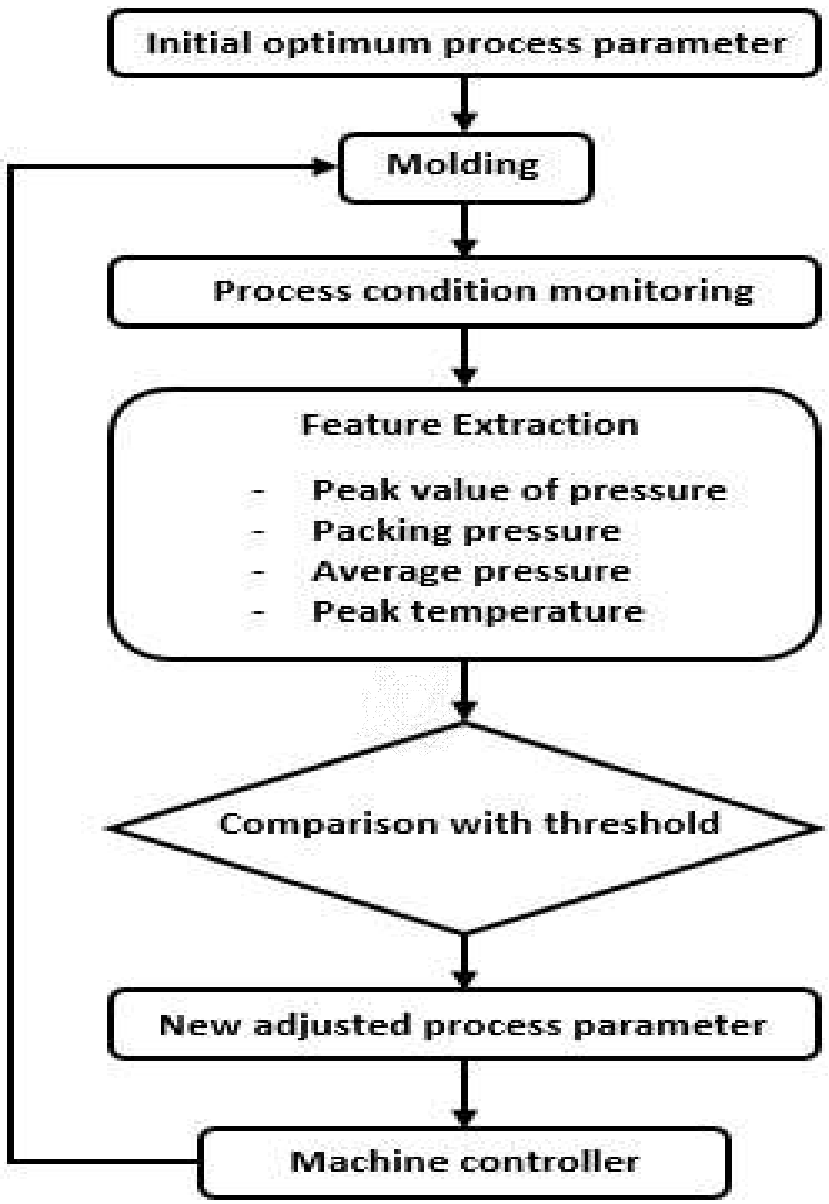


Figure 6.5. Control algorithm

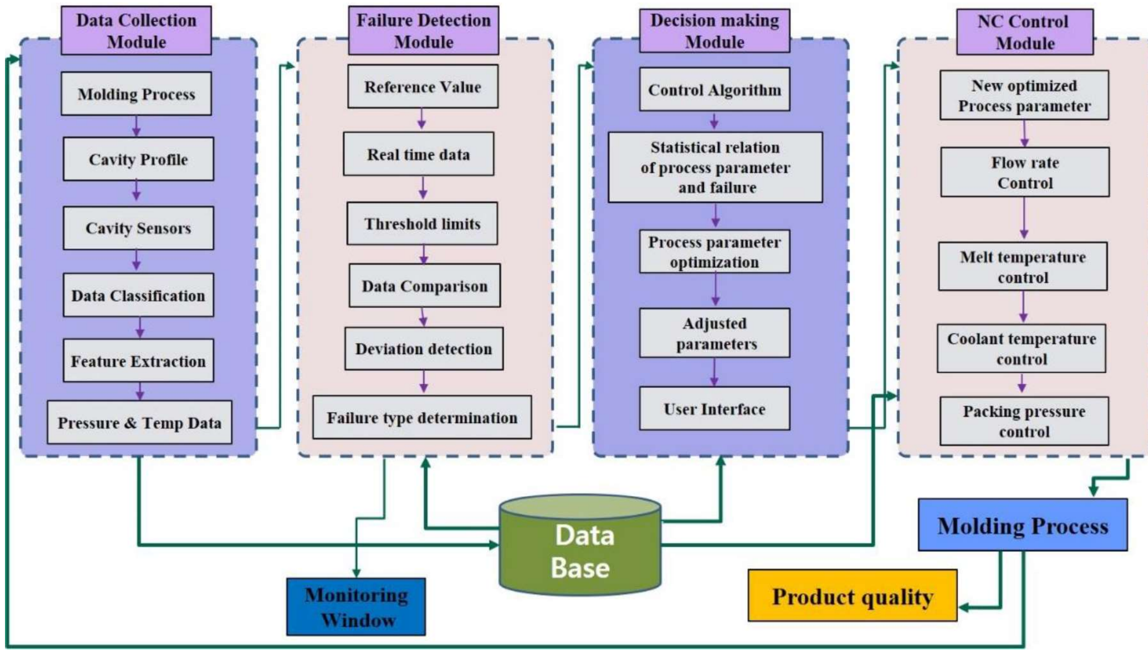


Figure 6.6. System architecture

6.4. Results & discussion

Based on the results of several experiments and consultation with manufacturing experts, an applicable rule-based algorithm for choosing the new process parameter is introduced.

6.4.1. Algorithm for adjusting parameters based on if-then case-based rules

The defined rules are integrated into MATLAB programming and executed directly from it. Some of the cases are described below:

- If average peak values of 5 molding cycles are larger than the upper value, then decrease flow rate by 2 cm^3/s; else Do Nothing.
- If packing pressure is greater than the upper value, then decrease packing pressure by 1%; else Do Nothing.
- If the packing time is longer than the upper value, then decrease the packing time by 0.25 s and decrease packing pressure by 0.5%; else Do Nothing.

- If the average of the maximum values for mold cavity temperature in 5 continuous cycles is greater than the upper value, then decrease the melt temperature by 1^0C; else Do Nothing.
- If the average mold cavity temperature in a molding cycle (obtained by integration) is greater than the upper value, decrease the coolant temperature by 1^0C; else, Do Nothing.

6.4.2. Control strategy to avoid failures

Based on the case-based rules described in the previous section, a few examples are introduced to validate the control mechanism. As shown in Figure 6.7, in cases of warpage and short shot failure in the cyber model, changes are recommended for the process parameters. The occurrence of the failure is recognized from the extracted feature behavior of the sensor signals.

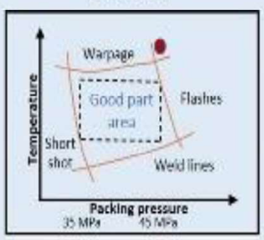
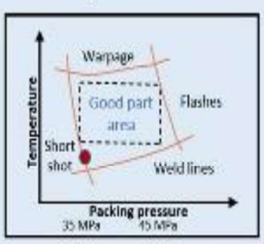
Case	Failure type	Control action
Higher cavity temperature & pressure 	Warpage	Change in machine initial control parameters ➢ Decrease injection rate by 2 % and make it $441 g/cm^3$ ➢ Melt temperature also decrease by 5 % and make it 232^0C ➢ Other parameters, keep same ➢ Else do nothing
Lower cavity temperature & pressure 	Short shot	Increase the melt temperature and injection pressure ➢ Increase injection rate by 3 % ➢ Increase packing time by 40 % - additional 2 seconds ➢ Increase melt temperature by 2.5% 238^0C ➢ Coolant temperature set to 20^0C

Figure 6.7. Control strategy to reduce warpage and short shot

6.4.3. Implementation of a sensor assisted monitoring system in a real factory environment

After the successful realization of the developed model in the cyber system, the model is tested in a real-world setting, using a Toshiba 2500 Ton injection-molding machine for manufacturing car-door trim in an automotive manufacturing factory. The information flow of the monitoring system starts with the molding process and then propagates through cavity sensors. Sensors collect temperature and pressure profiles and send this signal to a DAQ device. After converting the analog signal into digital data, the raw sensor data is classified, and features illustrating the quality are extracted. The programmed display tool then displays the current cycle's process parameter signal, as shown in Figure 6.10.

6.4.4. Installation of cavity sensors in a molding machine

After an extensive study of mold geometry, the complexity of the plastic car-door trim, and monitoring requirements, three temperature and three pressure sensors are installed through holes made in the mold cavity. The specification of sensors for pressure and temperature measurement are MCSG-B-127-2000 and TS-PF03-K, respectively. Sensor connection hardware, including wires, amplifiers, connecting devices, and DAQ equipment, were provided by RJG Inc. USA. The locations for the sensors are slightly different from the cyber model because sensors can only be installed by making holes inside the mold. Sensors are placed near the gates and to the location where defects are most reported. The sensors, DAQ equipment, connectors, and their assembly is shown in Figure 6.8 and 6.9.

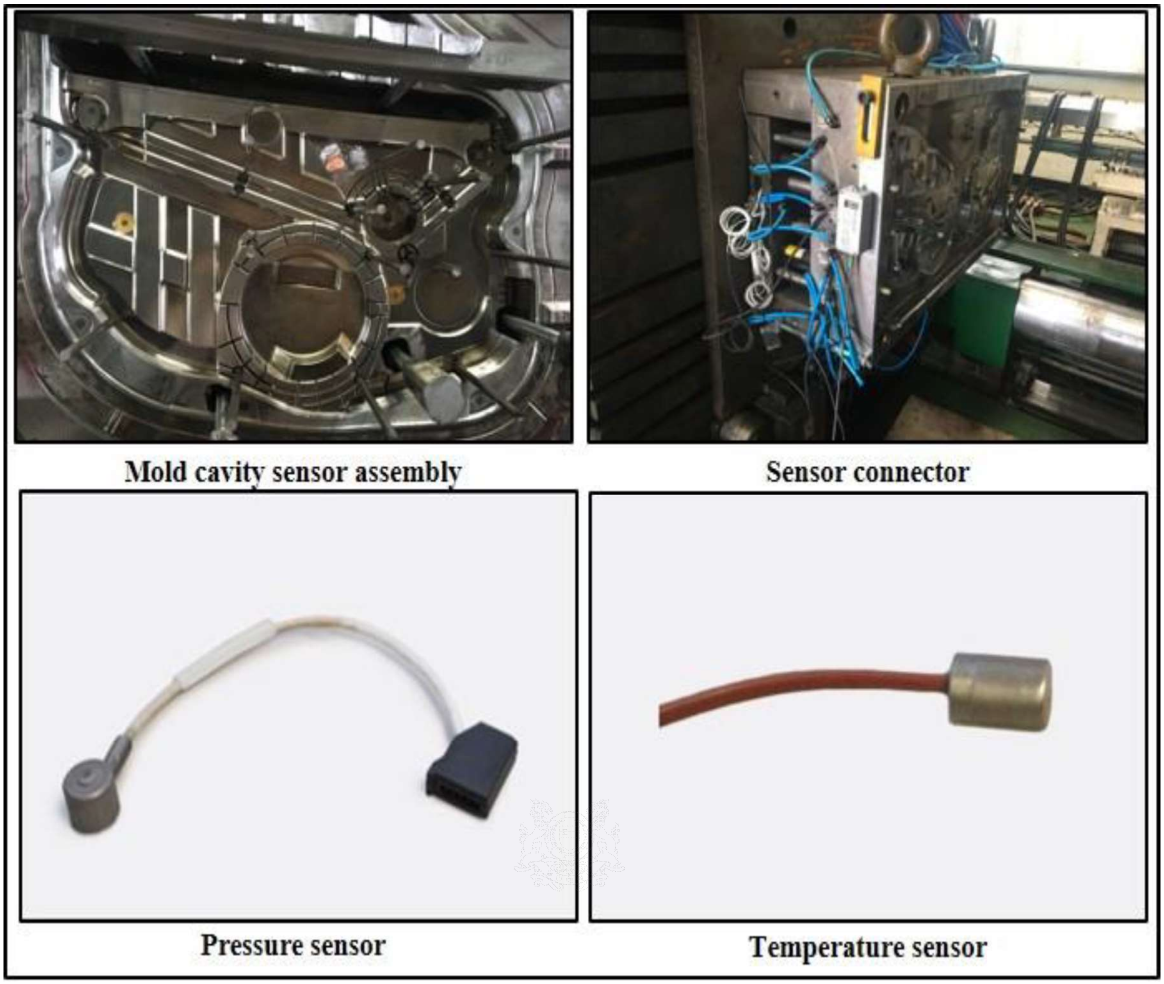


Figure 6.8. Sensors and its mold assembly

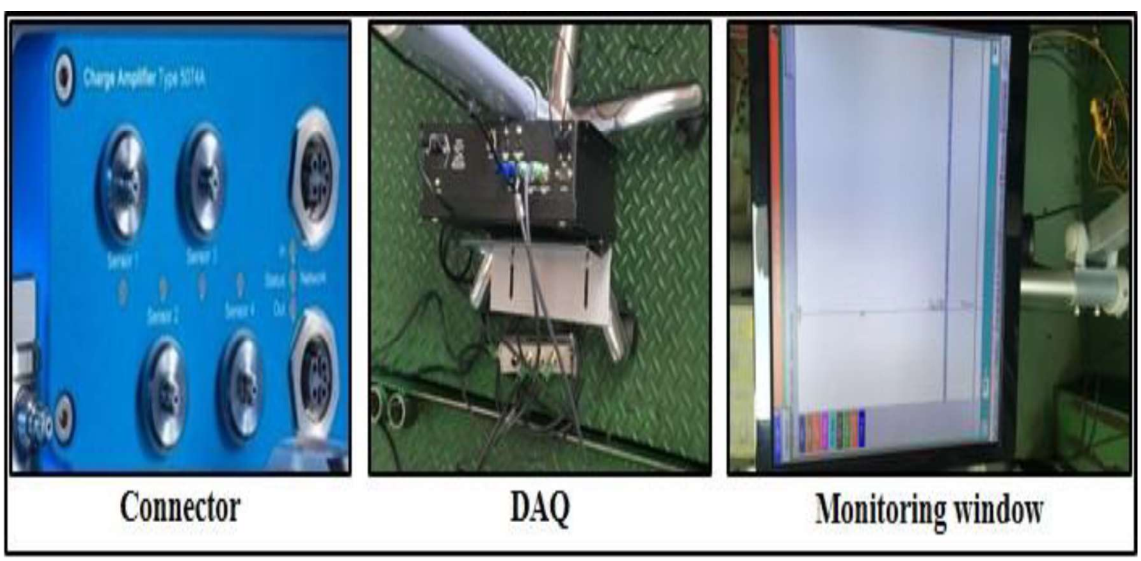


Figure 6.9. DAQ and connectors

6.4.5. Development of interface for data monitoring and quality consistency control module

To connect the system components and provide quality control after analysis of raw signals, an integrated control system is programmed using the commercial tool. Data collected from the simulation, as well as real-world factory data, is used to identify threshold values for cavity temperature and pressure. Data is extracted automatically from the sensor signals. When any deviation is observed, the system alerts the operator and generates adjusted process parameters to return the monitored features within threshold limits. Due to difficulty in inducing sudden changes in temperatures of the molten material and the mold, the developed module required several cycles to achieve desired changes in the process parameters. The graphical user interface for the quality control system is shown in Figure 6.10. The initial parameters for injection molding are chosen as optimal conditions. Variations in the machine environment and plastic material properties increase the possibility of deviation in process parameters. The system visualizes real-time cavity pressure and temperature signals coming from the cyber and physical model and is displayed in separate dashboards. The temperature from the real machine is mold temperature, where the sensors are installed due to the design constraints. The display on the left side is from the cyber model, and on the right side, the data from the mold sensors are displayed. When a real-time signal exceeds the set threshold limit, the display interface triggers an alarm relayed to the machine operator, and simultaneously the process parameter is changed. The system has a dedicated smart button, which triggers the smart behavior when it is turned on.

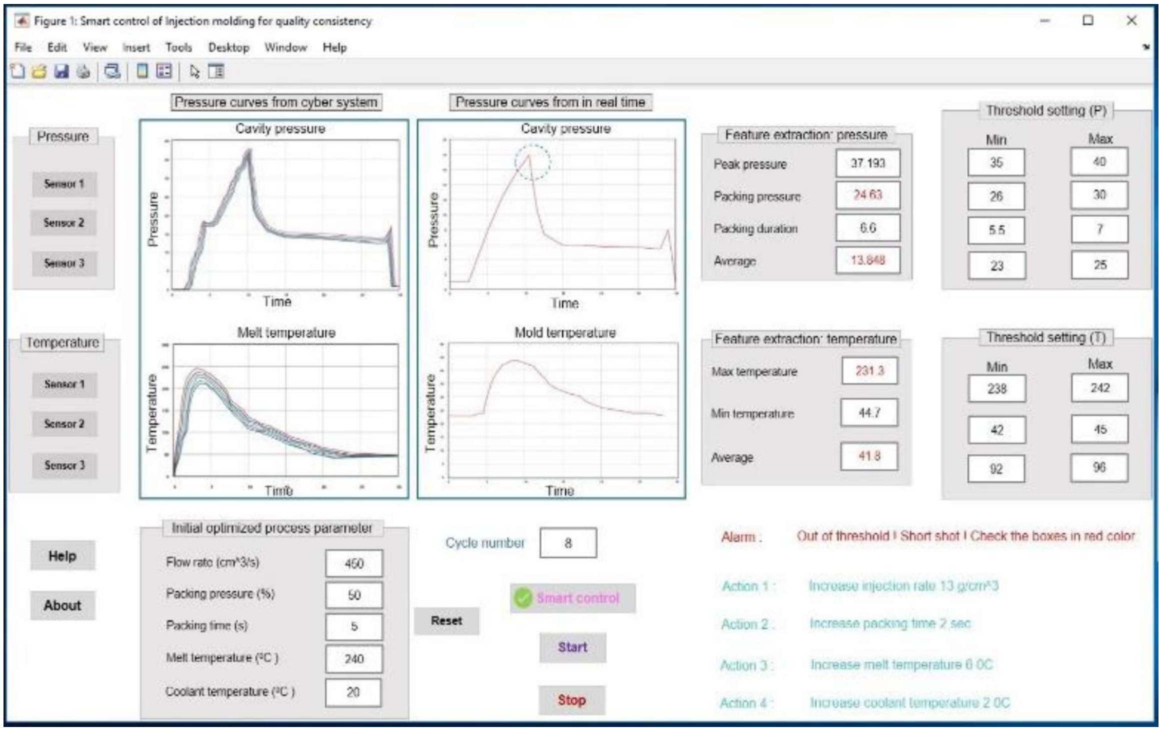


Figure 6.10. Interface display for the quality control system

6.5. Implementation and functionality testing of the developed system

The chosen research object specifications are shown in Table 6.5.

Table 6.5. Product specifications

Product name	Car door
Material	PP
Volume	831 cm^3
Max thickness	7.6 mm
Min thickness	1.8 mm
Failure type	Warpage

A picture illustration of the machine and the product is given in Figure 6.11. The data-driven-smart quality control system is installed at a manufacturing factory. Cavity sensors installed in the mold cavity are connected to the monitoring system through DAQ and amplifier. With a software tool, signals are displayed. Failure detection from the monitoring system quickly notified the operator with alarm, and adapted process parameters like flow rate, packing time, hold pressure, melt temperature, or coolant temperature are also delivered to the controller. Implementation of the integrated monitoring and quality control system is followed by its validation by solving failure scenarios in its demonstration. Implementation plan and factory setup pictures from the factory are provided in Figures 6.12 and 6.13. In the case of short shot failure detection, the smart quality control gives the adjustment process parameters to the controller for increasing the injection rate by $13 g/cm^3$, packing time by 2 seconds, melt temperature by 6^0 C, and coolant temperature by 2^0 C. However, the suggested increase in the process parameters cannot be achieved instantly, especially the melt temperature. So, it is achieved in successive cycles. Due to the aged condition of the machine controller, the target changes are done with the operator's help. Further work is being in progress to make it autonomous.

Figure 6.11. Molding machine and the car door trim module

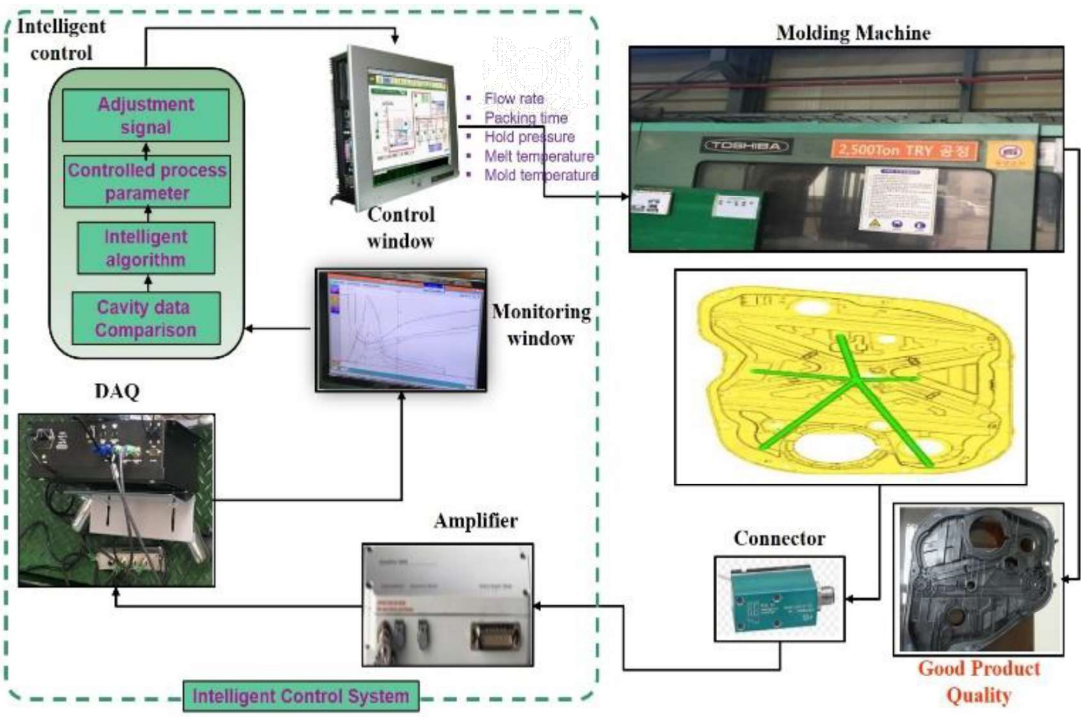


Figure 6.12. Implementation of the quality consistency control system

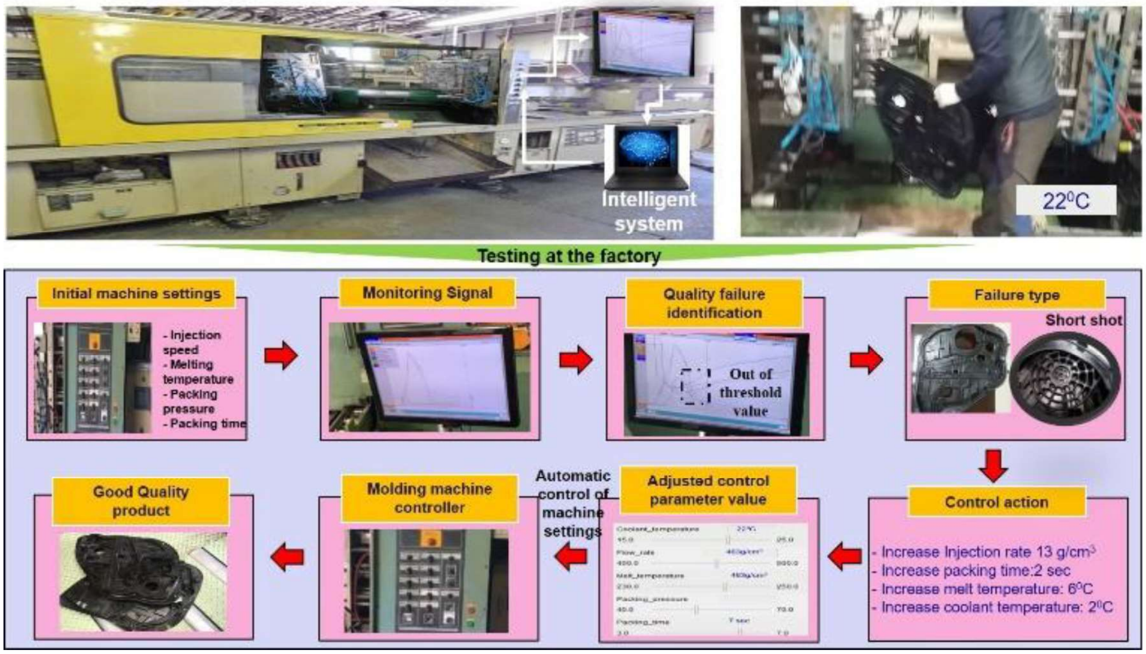


Figure 6.13. Testing the functionality of the system

6.6. Conclusion and future works

This work presented an engineering analysis model to analyze the process behavior in a cyber-way because a fully experimental approach is a lengthy, costly, and impractical option. Conventionally this understanding is entirely dependent on the operator's feedback. The analysis of the collected data from the cyber model and real factory experiments resulted in the design of the process control boundary as a process window. A graphical user interface created in MATLAB provides smart AI-based quality control. A rule-based intelligent algorithm based entirely on the experience and knowledge gained through the proposed study is derived. A data-driven monitoring and smart quality control system for injection molding is developed and implemented in a real manufacturing factory. And with the application of this robust system, existing quality problems have been addressed. The developed system's performance achieved its target of solving a real-world industrial problem and reduced the number of scrap parts as well as the operating cost of the process. This system will surely benefit society with more reliable product quality, job opportunities, and energy saving. Future research for this topic is oriented towards making the whole process automated and, after the data collection applying it to mass production and to the different injection molding machines and products.

Chapter 7 . CONCLUSION AND FUTURE WORKS

7.1. Conclusion

The presented thesis has presented a novel approach and methodology for monitoring and controlling the cyclic manufacturing process. In the case of the injection molding process, pressure and temperature with installed cavity sensors are monitored, and process abnormality is detected. The rule-based control algorithm is used to control the injection molding process. A vibration-based system is used to monitor the double-sided grinding process in the manufacturing of the brake disc. Based on the vibration characteristics of process behavior, a software module is developed which facilitates the real-time monitoring of the grinding process. The developed system comprises of vibration sensor, data acquisition device, monitoring window as the hardware components. The developed system has modules like signal acquisition, feature extraction, threshold limiting, failure detection, alarm, and data storage. It can be used further for training as well as better manufacturing planning and hence reducing the occurrence of quality failures. Conventionally these monitoring systems are not implemented at the production site. However, we have tried to solve the real quality issues faced by the grinding manufacturer. The monitoring system detects the process failure through the real-time monitoring of the vibration signal from the process.

It also includes the development and implementation of an autonomous control system for the manufacturing of the brake disc by the process of grinding. The smart decision-making or the control module suggests the change of the process parameters in order to bring the process behavior within threshold limits. AI-based process parameter prediction system is designed and implemented. The trained model predicts the grinding wheel RPM from the vibration error delivered from the monitoring system. Moreover, the smart control algorithm compares the predicted grinding wheel RPM and the reference grinding wheel RPM. The difference of the process parameter is delivered to the machine controller for the adjustment. The change in process parameters is delivered to the machine controller through PLC and developed module connection. The whole setup is installed at the factory using a vibration sensor, mounting, sensor cables, DAQ, monitoring window, OPC server, and industrial PC as its required hardware components. After the installation, its functioning is demonstrated with the grinding process of the brake disc. Earlier, the factory personnel used to check the finished product physically and then modify the process parameters repeatedly to get the product with the best quality. However, the development and implementation of such an intelligent system made all the tasks autonomous. Results and feedback from the manufacturers about the system are pretty encouraging. The system is very convenient, easy to use, and helpful to the manufacturers in reducing surface defect failures and increasing the factory's overall productivity by 5 % after its complete installation. It has helped transform a conventional manufacturing factory into a smart factory along with the benefits in terms of economy. It is also going to help society by reducing the work hazard to the operator due to the prolonged quality checking hours and creating lots of new job opportunities in terms of intelligent and autonomous technology. Making the whole process more autonomous and including the predictive maintenance system for machinery components will make this system more robust and versatile.

7.2. Limitations

The advocated work is taking a step towards making the conventional factory into the smart factory. However, the sensor installation and data collection have been a significant concern, especially for the failure products. The model is trained on a particular machine, and the same model cannot be used for other machines. The logic is valid for only the machine from which the data is collected and trained.

7.3. Future works

To solve the limitations of the presented work, the future cope of this involves designing a digital twin-based model for the grinding process, which can reciprocate the actual grinding behavior. Once we can get such a simulator model to test our control algorithm with virtual PLC, we can use reinforcement learning to train the model using open source AI brain for decision-making like Bonsai from Microsoft. The limitation of deriving the interrelationship between the monitored and controlled parameters can be easily solved.

Curriculum Vitae

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Publications

❑ **Journal**

[1] **<u>Kumar, S[1].</u>**; Park, H. S[2].; Nedelcu, D[3]**.**, "**Development of Real-time Grinding Process Monitoring and Analysis System**", ***International Journal of Precision Engineering and Manufacturing***., 2021, *22*, 1345-1355, DOI: <u>10.1007/s12541-021-00539-5</u>

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❑ **Book Chapter**

[1] Park, H. S[1].; **Kumar, S[2].**; Qi, B[3]., "**Study on the Development of a Deformation Prediction System for 3D Printed Parts in Additive Manufacturing**", ***Recent Trends in Chemical and Material Sciences, Book Pi International***., 2021, *4*, ISBN: 978-93-5547-208-3

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❑ **Program Registration**

[1] Title: "**Grinding Spindle Bearing Remaining Useful Life Prediction System**", Registration No. C-2021-035496

[2] Title: **"Smart Monitoring and Control of Grinding Process using Vibration Sensors**", Registration No. C-2021-023374

[3] Title: "**Vibration Data Collection System for Grinding Process Monitoring**", Registration No. C-2021-019475

[4] Title: "**Control Simulation Program for Injection Molding Process Intelligence**", (Submitted)

❑ **Patent**

[1] Title: "**Digital Twin Based Grinding Process Control of Brake Disc Manufacturing**", (Submitted)

- ❑ **Award**

[1] Park, H. S.; **Kumar, S**., **Best Paper Award** at an Academic Conference, "**Smart Monitoring and Control System for Quality Consistency of Injection Molding**" KSPE 2019 Conference.

- ❑ **Conférences and Meetings**

[1] Park, H. S[1].; **Kumar, S[2]**; Qi, B[3]., "**Brake-disc Manufacturing Process Control based on Digital Twin**", KSAE 2021

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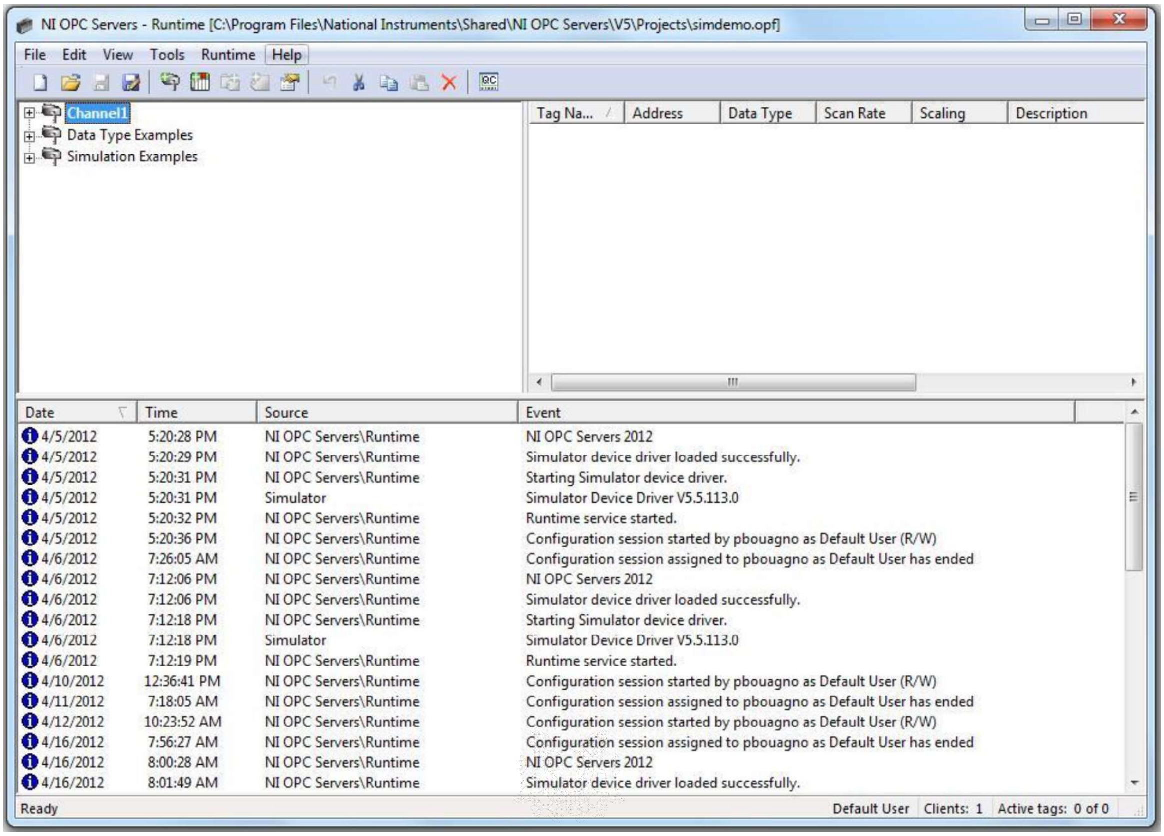
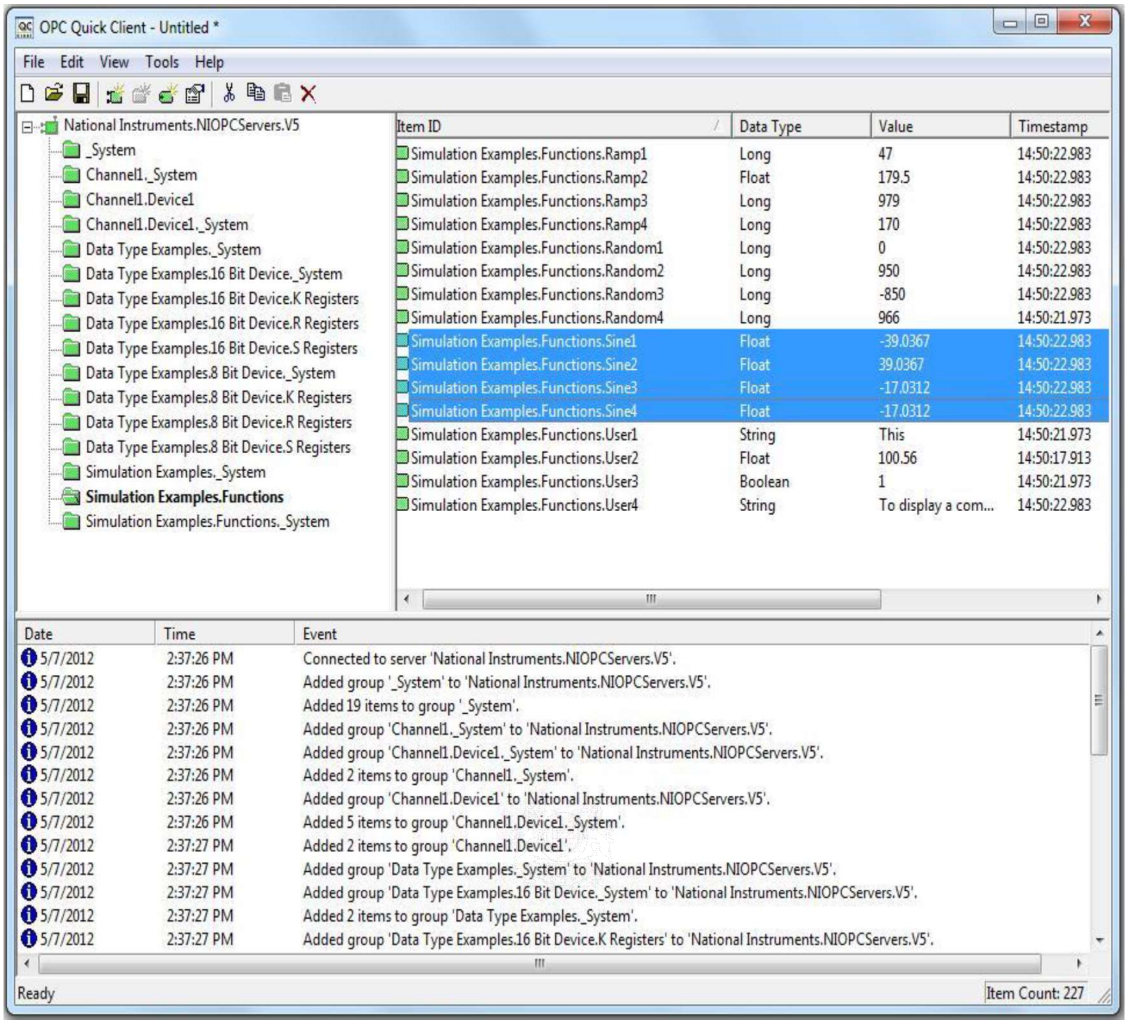
Appendix : Control design and simulation module in LabView

Connecting LabView to PLC using OPC

NI LabVIEW software can communicate with a programmable logic controller (PLC) in a number of ways. OLE for Process Control (OPC) defines a standard for communicating real-time plant data between a control unit and a Human Machine Interface (HMI). The OPC server can be used with almost any PLC and programmable automation controller (PAC). In this tutorial, you will learn how to use LabVIEW to communicate with a networked PLC using OPC. The LabVIEW Data Logging and Supervisory Control (DSC) module is used in this tutorial. This module includes tools for logging data to a networked historical database, real-time and historical trends, alarm and event management, networking LabVIEW Real-Time targets and OPC devices into one complete system, and adding security to your user interface. . These features make LabVIEW a powerful HMI/SCADA package for industrial control applications.



NI OPC Server 2012



OPC Quick Client - Untitled *
File Edit View Tools Help
National Instruments.NIOPCServers.V5
_System
Channel1._System
Channel1.Device1
Channel1.Device1._System
Data Type Examples._System
Data Type Examples.16 Bit Device._System
Data Type Examples.16 Bit Device.K Registers
Data Type Examples.16 Bit Device.R Registers
Data Type Examples.16 Bit Device.S Registers
Data Type Examples.8 Bit Device._System
Data Type Examples.8 Bit Device.K Registers
Data Type Examples.8 Bit Device.R Registers
Data Type Examples.8 Bit Device.S Registers
Simulation Examples._System
Simulation Examples.Functions
Simulation Examples.Functions._System
Item ID
Data Type
Value
Timestamp
Simulation Examples.Functions.Ramp1 Long 47 14:50:22.983
Simulation Examples.Functions.Ramp2 Float 179.5 14:50:22.983
Simulation Examples.Functions.Ramp3 Long 979 14:50:22.983
Simulation Examples.Functions.Ramp4 Long 170 14:50:22.983
Simulation Examples.Functions.Random1 Long 0 14:50:22.983
Simulation Examples.Functions.Random2 Long 950 14:50:22.983
Simulation Examples.Functions.Random3 Long -850 14:50:22.983
Simulation Examples.Functions.Random4 Long 966 14:50:21.973
Simulation Examples.Functions.Sine1 Float -39.0367 14:50:22.983
Simulation Examples.Functions.Sine2 Float 39.0367 14:50:22.983
Simulation Examples.Functions.Sine3 Float -17.0312 14:50:22.983
Simulation Examples.Functions.Sine4 Float -17.0312 14:50:22.983
Simulation Examples.Functions.User1 String This 14:50:21.973
Simulation Examples.Functions.User2 Float 100.56 14:50:17.913
Simulation Examples.Functions.User3 Boolean 1 14:50:21.973
Simulation Examples.Functions.User4 String To display a com... 14:50:22.983
Date
Time
Event
5/7/2012 2:37:26 PM Connected to server 'National Instruments.NIOPCServers.V5'.
5/7/2012 2:37:26 PM Added group '_System' to 'National Instruments.NIOPCServers.V5'.
5/7/2012 2:37:26 PM Added 19 items to group '_System'.
5/7/2012 2:37:26 PM Added group 'Channel1._System' to 'National Instruments.NIOPCServers.V5'.
5/7/2012 2:37:26 PM Added group 'Channel1.Device1._System' to 'National Instruments.NIOPCServers.V5'.
5/7/2012 2:37:26 PM Added 2 items to group 'Channel1._System'.
5/7/2012 2:37:26 PM Added group 'Channel1.Device1' to 'National Instruments.NIOPCServers.V5'.
5/7/2012 2:37:26 PM Added 5 items to group 'Channel1.Device1._System'.
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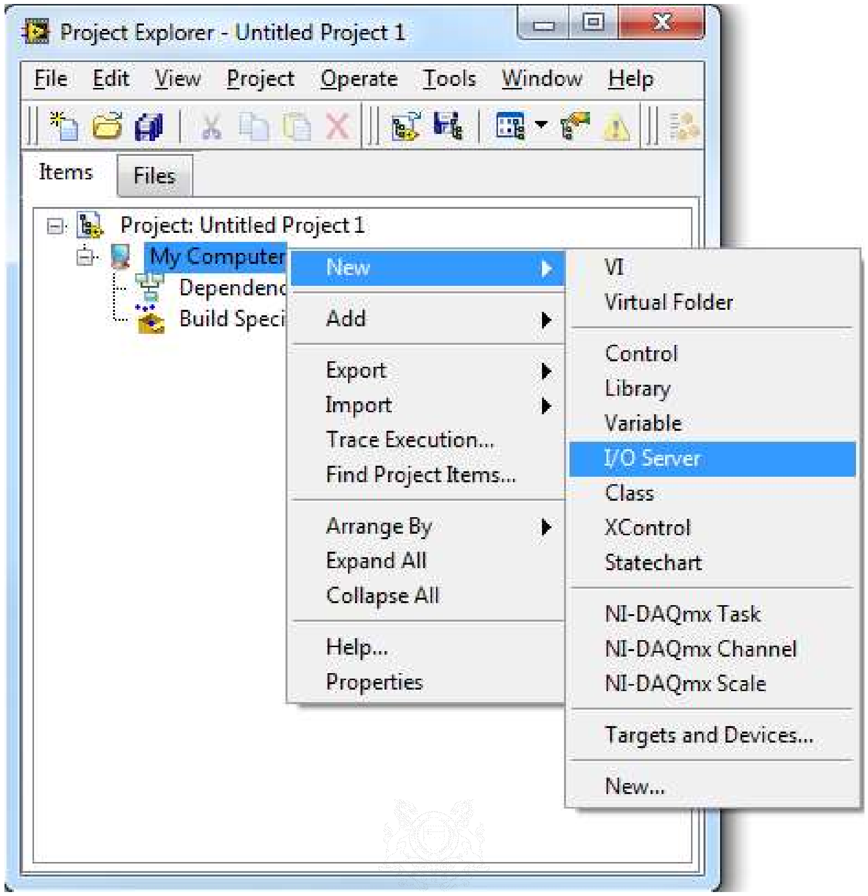
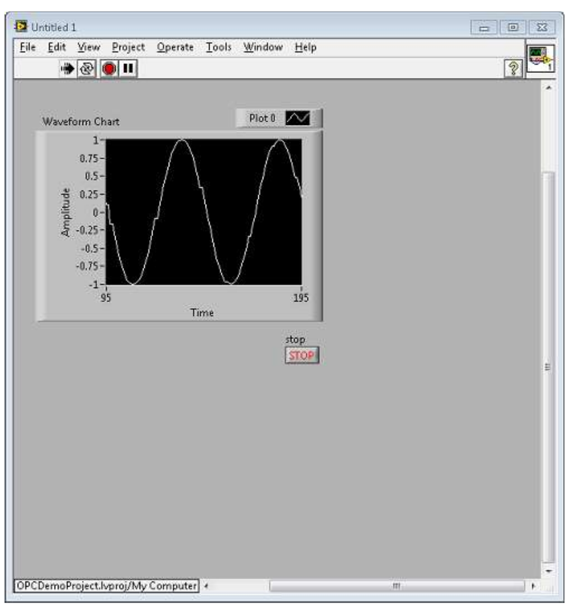
Ready
Item Count: 227

OPC Tag data



I/O server



PLC data in waveform