ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

PhD THESIS

Atalay Tayfun TÜREDİ

DESIGN OF INTELLIGENT RELIABILITY PREDICTION MODELS FOR INDUSTRIAL AUTOMATION MACHINERY: A ROBOTIC INJECTION MOLDING AUTOMATION CASE STUDY

DEPARTMENT OF MECHANICAL ENGINEERING

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ABSTRACT

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In this thesis study, a Robotic Injection Molding System (RIMS) is taken in the consideration dealing with existing and forecasted equipment and process reliability. Failure Mode and Effect Analysis (FMEA) is used for finding out RIMS most critical cases that effect overall system reliability according to historical 48 months real shop floor performance data. Obtained FMEA results are processed for training and structuring of best performance Artificial Neural Network (ANN) model to predict future performances in terms of equipment Mean Time Between Failure (MTBF). Additionally, 300 cycle (24 Hours production period) process data is used to structure another best performance ANN model to predict future Cycle Time (CT). Consolidated equipment and process reliability prediction results show that the pneumatic gripper of the manipulator is most critical equipment for both system and process reliabilities. In the end of the study preventive and improvement actions that are acquired from FMEA tables are suggested in accordance with forecasted MTBF and CT to eliminate overall potential risk factors to maintain best equipment and process life cycle.

Key Words: Failure Mode and Effect Analysis (FMEA), Artificial Neural Network (ANN), Smart Manufacturing, Intelligent Reliability, Robotic Injection Molding.

ÖZ

DOKTORA TEZİ

ENDÜSTRİYEL OTOMASYON MAKİNELERİ İÇİN AKILLI GÜVENİLİRLİK TAHMİN MODELLERİNİN TASARIMI: BİR ROBOTİK ENJEKSİYON SİSTEMİ ÇALIŞMASI

Atalay Tayfun TÜREDİ

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Bu tez çalışmasında, mevcut ve tahmin edilen ekipman ve proses güvenilirliği ile ilgili bir Robotik Enjeksiyon Kalıplama Sistemi (REKS) ele alınmıştır. Hata Türleri ve Etkileri Analizi (HTEA), geçmiş 48 aylık gerçek işletme performans verilerine göre sistem güvenilirliğini etkileyen en kritik REKS şartlarını bulmak için kullanılmıştır. Elde edilen HTEA sonuçlarının içerdiği ekipman arızaları arasındaki ortalama süre (MTBF), gelecek güvenilirlik tahminde kullanılacak en iyi performansa sahip Yapay Sinir Ağı (YSA) modelinin eğitimi ve yapılandırılması için kullanılmıştır. Ek olarak, gelecekteki Çevrim Süresini (ÇS) tahmini için de başka bir en iyi performanslı YSA modelini oluşturmak için 300 çevrimlik (24 Saat üretim süresi) proses verileri kullanılmıştır. Birlikte değerlendirilen ekipman ve proses güvenilirliği tahmin sonuçları, manipulator robotun pnömatik tutucusunun hem sistem hem de proses güvenilirliği için en kritik ekipman olduğunu göstermektedir. Çalışmanın sonunda, potansiyel risk faktörlerini ortadan kaldırarak elde edilecek en iyi ekipman ömrü ve proses döngüsünü sağlamak için gerekli önleyici ve iyileştirici aksiyonlar, tahmin edilen MTBF, CT verileri ve FMEA tablolarından faydalanılarak önerilmiştir.

Anahtar Kelimeler: Hata Türleri ve Etkileri Analizi (HTEA), Yapay Sinir Ağı (YSA), Akıllı Üretim, Akıllı Güvenilirlik, Robotik Enjeksiyon Kalıplama.

EXTENDED ABSTRACT

In this thesis study, a Robotic Injection Molding System (RIMS) is taken in the consideration dealing with the equipment and process reliability predictions. The studied RIMS is a production cell used for fully automatic thermoplastic injection production of steel-mounted (overmolded) plastic (Polypropylene) support parts in the automotive industry. The RIMS contains equipment such that, a conventional type of hydraulic driven Injection Molding Machine (IMM) with 16-cavity thermoplastic injection mold, a 6-axis manipulator robot, and a steel insert fixture changer system that have communication protocols through an automation.

Proposed RIMS system has been analyzed in terms of equipment and process reliability. The analysis is executed in two steps; one is applied for system reliability by using historical equipment-based performance, another one is applied for production process reliability with respect to realized process performance data. Here, obtained reliability results are assessed, and most proper input and output data characteristics are selected dealing with their criticality and reliability effects on overall system. Identified input and output data has been processing with multilayer Artificial Neural Network (ANN) and the best performance ANN has been decided with the aid of regression tools.

Executed studies about reliability analysis, prediction and intelligent assessment that are done by many precious scientists and industrial professionals based on intelligent reliability analysis and ANN applications on many research areas and industrial fields are researched during the study. Complex industrial equipment based and processes data has been processed to obtain best performance ANN prediction models in different scenarios by Abu-Mahfouz (2007), Turedi and Bircan (2017), Kalem (2008), Chinnam and Mohan (2010), Kumar et al. (2012), Narita et al. (2002), Lee et al. (2018), Yilmaz et al. (2017), Lallot et al. (2010), Mekki et al. (2015), Shen et al. (2007), Popiolek (2016), Dabrowski (2016), Kipli et al. (2012) and Chen et al. (2008). The historical data analyses to determine the most critical cases by using FMEA have been studied by Singh et al. (2012), Degu and Moorthy (2014), Kolich (2014), Turedi and Bircan (2015), Pawar S. and Rathod D. (2013), Turedi et al. (2014), Xie (2013),Yusof et al. (2016) and Cicek et al. (2013). Additionally, as powerful intelligent data processing methodology Industry 4.0 has been explained with case studies by Chukwuekwe et al. (2016), Ma and Liu (2016), Chen and Xing (2015), Anderl (2014), Lee et al. (2017), Zhao et al. (2014), Mantravadia and Møllera (2019) and Kim et al. (2019).

Failure Mode and Effect Analysis (FMEA) is used for finding out RIMS most critical cases according to equipment based historical 48 months real shop floor performance data. The failure data is collected by sensors, Manufacturing Execution System (MES), and operator reports. Here, failures are classified according to their failure mode and effects. Failure's severity, detection, and occurrence criteria are punctuated, and failures occurrence rates are identified in Mean Time Between Failure (MTBF). The results are reflected on the equipment based FMEA table and related Risk Priority Number (RPN)s are reached. The RPNs are transferred to Pareto charts for defining the most critical mechanical and hydraulic equipment. The overall results show that manipulator robot, hydraulic cylinders, toggle clamp and injection unit are most critical in mechanical equipment, hydraulic valves, pump and lines are most critical in hydraulic equipment. Improvement of those equipment reliabilities significantly improve the overall system, since they cover almost 80% of their equipment group performances.

Obtained critical equipment failure modes, effects, and MTBF occurrences are used for ANN training and reliability prediction models. ANN network is structured with a multi-layer feed-forward back-propagation type by using MATLAB ANN Tool. Levenberg Marquardt is used as an algorithm for the training of neural networks. The ANN tool supply design and training networks with graphical support and visual interfaces. In this stage, 10 to 100 hidden layers are implemented on network training to reach the best prediction model. During the training process, hidden and output units are taken with the sigmoidal activation function. The learning process is executed with 200 iterations with different hidden layers. Prediction outputs of each network are compared with realized data and the network performances are evaluated through MAPE, MSE and R^2 statistical and regression values. The comparison table shows that 40 Hidden Layer (HL) network performance is the best among the others. 40 HL prediction results indicate the low MAPE, low MSE and highest R^2. For the determination of future data, logarithmic regression is implemented with the aid of the MS Excel tool and by using 40 HL ANN predicted data. The logarithmic regression equation is calculated for determination of next 12 months forecast MTBF. According to the forecasted results, 8656 minutes or 144 hours MTBF is estimated for 60th month of RIMS service life. FMEA punctuation table is taken for acquiring required occurrence rates and FMEA tables are used to match the forecasted MTBF with experienced and considered occupancies on the analysis tables. On the FMEA punctuation table, 144 hours MTBF indicates a “10” occurrence, and presents that the possibility of “10” rated failures is very high. Failure data on executed FMEA analysis which contains 10 rated occurrences figure out the failure causes and modes. Hydraulic cylinders and robot gripper are found the potential failure sources in forecasted service times. The needed preventive actions to restrain the possible failures and losses are generated according to FMEA contents. By using the structured best performance ANN model, it is possible to make new estimations by running the relevant data processing cycle in system future.

In the other phase of the study, 300 cycle (24 Hours production period) process data is taken in the consideration to structure intelligent process reliability estimation model. All considered process parameters are evaluated for determination of input/output data according to their principles. They are mold closing and opening times, injection pressure and speed, plasticizing time, melt temperature etc. as inputs, cycle time, product temperature, core and cavity temperature as outputs. Here, process Cycle Time (CT) is taken as critical process output for monitoring process reliability. Existing (pressure, time, speed etc.) and required externally measured data is used to reach the most ideal data modelling structure. Determined input and output data is used for training processes of ANN, and regression tools are used for checking the performance ANN to obtain process reliability forecasting as similar with the phase of equipment-based system reliability studies. The reliability of the established ANN model is validated by using regression tools.70 HL prediction results give the low MAPE, low MSE and highest R^2. Logarithmic regression is implemented with the aid of the MS Excel tool and by using 70 HL ANN predicted CT data. The equation is used for the determination of the next 50 realized CT data. Reached data series are evaluated as realized data and fed to 70 HL ANN for the future prediction. 142,5 seconds CT is forecasted at the end of the next 50 production cycles. The structured high-performance ANN model enables making predictions for future process changes that are used in reliability forecasting. Extracted future CTs allow to reach many future production data such as production capacities, energy consumptions, product quality, specifications, inventory and maintenance managements etc. Additionally, preventive actions are suggested to develop continuous improvement implementations and sustain reliable process performances.

Overall results of the study show that the pneumatic gripper of the manipulator is most critical equipment for both system and process reliabilities that can be seen in predicted high RPNs, low MTBF and high CT cases in the results. The results indicate the improvement requirements in gripper connections and components. FMEA-based troubleshooting and preventive actions dealing with the pneumatic gripper supply the solutions against unexpected stoppages and correction needs during the mass production. Proposed improvements and planned preventive actions eliminate production losses such as maintenance costs, labor costs, unexpected breakdowns, reworks, scraps, energy consumption, potential quality issues, and customer complaints due to manual corrections during the process and equipment failures. Structured system and process reliability prediction ANN models execute generating ready-to-use data for cloud interfaces, enabling monitoring of online and historical conditions to intelligent and Industry 4.0 implementations. This approach also eliminates losses, supporting shop floor Lean Manufacturing (LM) applications and allows to improve system reliability, production costs, equipment service life, inventory and maintenance management, environmental health and safety conditions.

The approach of the study also can be effectively used in many industrial systems that contain a lot of measurable and traceable complex/big data, such as robotic assembly lines, high-speed bottling, packaging lines, precise machining cells, critical petroleum refineries, chemical plants, cement plants, nuclear power plants, wind turbines, iron&steel plants, etc. Here, powerful reliability analysis tools must be used such as FMEA to obtain most critical parameters among the big industrial data that effect the overall performance at the highest rates. Additionally, the most suitable intelligent prediction tools and algorithms must be selected to the used data profile and application in order to reach the most accurate future performance predictions.

Accurate data obtained from the relevant data analysis and methods greatly contribute to the acquisition of intelligent dynamic data models about the future of the managed system, to predict bottlenecks and take relevant measures, and to plan continuous improvement studies.

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LIST OF ABBREVIATIONS

AI : Artificial Intelligence
ANN : Artificial Neural Network
BPNN : Back Propagation Neural Network
CFBP : Cascade Forward Back Propagation
CT : Cycle Time
CT : Cycle Time
DCS : Distributed Control System
DFMEA : Design Failure Mode Effect Analysis
ERP : Enterprise Resource Planning
FFBP : Feed Forward Back Propagation
FMEA : Failure Mode and Effect Analysis
FRCA : Failure Root Cause Analysis
FTA : Failure Tree Analysis
GRNN : Generalized Regression Neural Network
HL : Hidden Layer
HMI : Human Machine Interface
IM : Injection Molding
IMM : Injection Molding Machine
IT : Information Technology
LM : Lean Manufacturing
MAPE : Mean Absolute Percentage Error
MES : Manufacturing Execution System
MSE : Mean Squared Error
MTBF : Mean Time Between Failures
MTTF : Mean Time to Failure
MTTR : Mean Time to Repair
NN : Neural Networks

OEE	: Overall Equipment Effectiveness
PLC	: Programmable Logic Controller
RBI	: Risk Based Inspections
RCM	: Reliability Centered Maintenance
RFID	: Radio Frequency Identification Technology
RIMS	: Robotic Injection Molding System
RPN	: Risk Priority Number
SCADA	: Supervisory Control and Data Acquisition
TPM	: Total Productive Maintenance

1. INTRODUCTION

Plastic injection molding is a production method used for the manufacturing of almost all complex shaped polymer-based products. The most common and complex shaped plastic injection molded parts according to industries; handles, bumpers, front panels, air vents, wheel covers, lightings and over molded support parts used in automotive industry, electrical switches, sensor covers, sockets and plugs used in electrical industry, plastic transmission parts, good bodies, brackets, drawers and baskets used in white goods industry, fittings, vanes and filters used in plumbing industry, smart watch bodies, computer covers, memory cases and cell phone covers used in information technology industry.

This method is one of the most widely used robotic automation applications among industrial automation solutions, especially since it requires high production precision, quality ratio, production speeds, equipment reliability, low labor cost and safe working environments. The scopes of robotic automation in plastic injection are to remove the finished material from the mold, place the material into the mold, separate the sprues from the products, attach accessories to the products, label the products, packaging, palletizing, quality control, production, process and equipment monitoring. Since applications which require high speed and precision such as plastic injection robotic automation applications minimize the human factor in the process follow-up, the reliability of the automation system plays a much more critical role. Malfunctions caused by a low-reliability robotic automation system can cause higher-impact damages and compensation can be more expensive and painful. Therefore, design and operation of robotic automation systems must be executed in the manner of reliability centered.

Industrial automation systems include production, maintenance, material stacking and sorting, condition monitoring, process safety, occupational safety, equipment safety, quality control and material handling processes, which are widely used in many branches of industry including critical processes. Industrial automation consists of computer aided systems that are mechanical, hydraulic, pneumatic, electrical and electronic systems. Automation systems provide contributions such as increasing production capacities, equipment reliability, product quality, reducing process costs, production losses, energy consumption, saving labor, improved occupational safety, plant sustainability, process safety and the application of sensitive manufacturing methods. The most widely used automation tools today are Artificial Neural Network (ANN), Distributed Control System (DCS), Human Machine Interface (HMI), Programmable Logic Controller (PLC), Supervisory Control and Data Acquisition (SCADA), Instrumentation, Robotics and Motion Control.

1.1. Reliability of Robotic Automation Systems

Reliability is a feature of the item, which is expressed by the possibility of performing its required function under certain conditions for a given time interval. It is usually indicated by R. The concept of reliability involves both nonrepairable and reparable systems. To be logical, the definition of the required function, working conditions, and duration of operation must accompany a numerical declaration of reliability (eg. R = 0,9. Correlation of 0,9 or 90% indicates a very high correlation and good reliability).

Operating conditions have a significant impact on reliability and therefore be carefully specified. Required functions and working conditions can be time dependent. In these cases, an operation profile must be defined, and all reliability figures will be associated with it.

1.1.1. Robotic Automation System Failures

The failure is a condition that happens in case the item stops performing the required function. Failure-free working time is usually a random variable. It is usually quite long; however, it may be too short, for example, due to a malfunction caused by a temporary event at startup. Malfunctions should be classified by mode, cause, effect, and mechanism.

Mode: Failure mode is the symptom in which a failure is observed such as opens, shorts, or drift for electronic components, brittle rupture, creep, cracking, seizure, fatigue for mechanical components.
Cause: The cause of failure may be internal or external due to defects in design, manufacture or use, weaknesses, and/or wear due to misuse. External causes often lead to systematic failures that are critical and should be considered defects.
Effect: The failure effect is the result of the component or functional state failure on the overall system.
Mechanism: The failure mechanism is the physical, chemical, or other processes that cause failures. Failures can be classified as sudden and gradual. In this case, sudden and complete faults are called catastrophic faults, gradual and partial failures are called degradation failures. The failure rate of a large population of statistically identical and independent substances usually exhibits a typical 3-phase bathtub as shown in Figure 1.1. It shows typical shape for the failure rate of a large population of statistically identical and independent (nonrepairable) items and possible shift dashed line (Birolini, 2013). Here, failure rate demonstrates the failure frequency of a system or component as failures per unit of time. The failure rate of a system depends on the varying rate of the system life cycle.
Early failures: Failure rate (λ (t)) generally decreases rapidly over time; failures at this stage can be associated with randomly distributed weaknesses in the material, component, or manufacturing processes.
Failures with constant (or nearly) failure rate: Failure rate is approximately constant; failures during this period were distributed and often catastrophic.
Wear out failures: Failure rate increases over time; failures in this period include aging, wear, fatigue, etc. (eg. corrosion, electromigration).

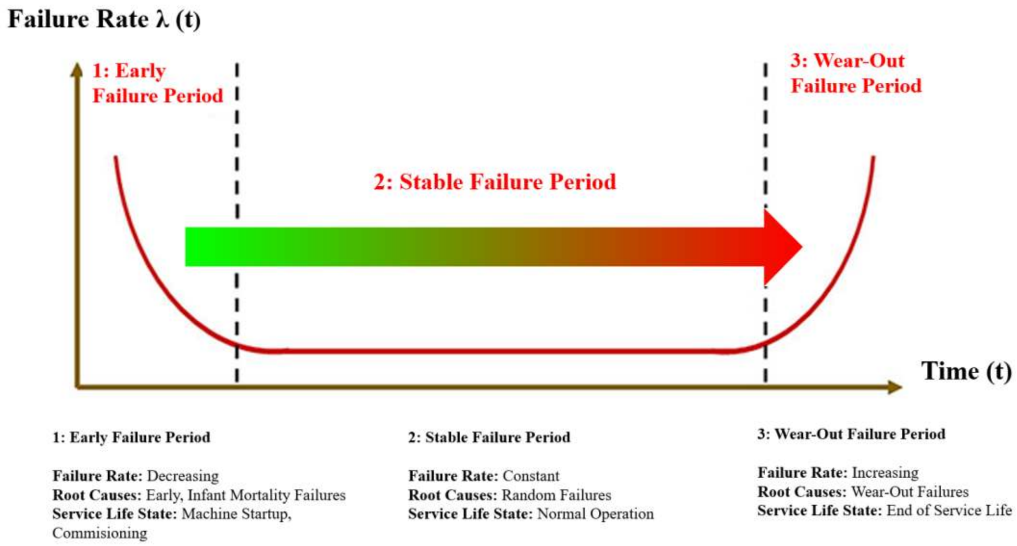


Figure 1.1. Typical Bathtub Curve (Birolini, 2013)

1.1.2. Reliability Centered System Management

Productivity is crucial for any plant, system, or components. Uptime and high equipment reliability and predictability are very important to deliver every product and service. Therefore, just-in-time product delivery is very valuable for all manufacturers where equipment availability is critical. Maintaining controllable equipment reliability assists the minimizing system losses and wastes, provides opportunities for continuous improvements and brings the system to lean manufacturing methodology. Lean Manufacturing (LM) methodology focuses on the eliminations of over production, scrapes, transportation, overtimes, labour and failure losses by using continuous improvement tools and techniques such as 5S, Failure Mode and Effect Analysis (FMEA), Ishikawa Diagram, Total Productive Maintenance (TPM), Poke Yoke, Push-Pull, Kanban etc.

Availability means that physical assets (equipment, plant, system, component, machine etc.) are available and ready to use when they are required. High equipment availability provides more efficient assets.

Availability (A) is measured by dividing the total time that the assets are available by the total time needed for them to run. Availability can be expressed as uptime divided by total time. Uptime is simply total time minus downtime. Downtime for unplanned stoppages is the total time to repair the failures, or Mean Time to Repair (MTTR) multiplied by the number of failures. Reliability takes in to account the number of unplanned downtime incidents suffered. Reliability is, strictly speaking, a probability. A commonly used interpretation is that large values of Mean Time Between Failures (MTBF) indicate highly reliable systems. Generally, plants, components, and systems benefit from greater MTBF because it means fewer disruptions. Reliability management is important in achieving maximum reliability longest MTBF. For most systems, MTBF is long and, typically, MTTR is short. Reducing MTTR requires a high level of maintainability. Adding the two gives the total time that a system could be available if it never broke down. Availability is the portion of this total time that the system is in working order and available to do its job.

Availability can also be written as; A=MTBF/(MTBF+MTTR). Maximizing MTBF and minimizing MTTR increases A. Generally, an operation is better off with fewer downtime incidents. If downtime is seriously threatening the manufacturing process, delivery schedule and overall productivity, preventive actions are needed. Reliability centered management sustain maximized MTBF while keeping MTTR low. The exponential distribution is widely used in complex systems and probabilistic modeling. It is applicable for modeling constant failure-rate phenomena. The unique property of the exponential distribution is presented as:

$$R(t) = e^{-\lambda t} \qquad \text{Eq.1.1}$$

$$\text{MTTF} = \int_0^\infty R(t) = \frac{1}{\lambda} \qquad \text{Eq.1.2}$$

The exponential distribution is widely used for modeling the time-to-failure of automation system components. It is also widely used to model failure at the system level. Component manufacturers usually specify the Mean Time to Failure (MTTF) for their component and can be used to model the overall MTTF of the system. When multiple components are in series and if one fails the whole system shuts down, the MTBF of the overall system uses the following equation:

$$\mathrm{MTBF} = \sum_{i=1}^{n} \frac{1}{\lambda_i} \qquad \text{Eq.1.3}$$

where n is the number of components in the system. Thus, for n components of identical failure rate λ, the expected MTBF=n/ λ (Rhee and Spencer, 2009).

Failure analysis tools and methods have obvious importance to evaluate failure mode, causes, and effects. Results of the analysis methods are come into the reliability management tasks improvements and used to create customized production & maintenance tasks and implementation time schedules. FMEA method is one of the most powerful tools in the failure analysis and system reliability monitoring. Thanks to this method, the equipment, and system failures can be taken into consideration not only as of the failure severity, occurrence, and detection rates but also with identified failure notations. Gathered Risk Priority Number (RPN)'s of failures are the pointers and determinants of operational risks of the system component. Failure Root Cause Analysis (FRCA) methods are the support tools to FMEA methods to examine the failure modes in the subcomponent of the system component (Campbell and Jardine, 2001).

Reliability Centered Maintenance (RCM) is an engineering approach that contains preventive maintenance, reactive maintenance, and proactive maintenance applications to manage and develop the reliability of a machine, system, or component within its design life cycle. RCM follows the functional characteristics, potential failures, consequences of these functional failures and evaluates them to eliminate the probability of failure. Figure 1.2. shows process flow in reliability engineering contains FMEA effect.

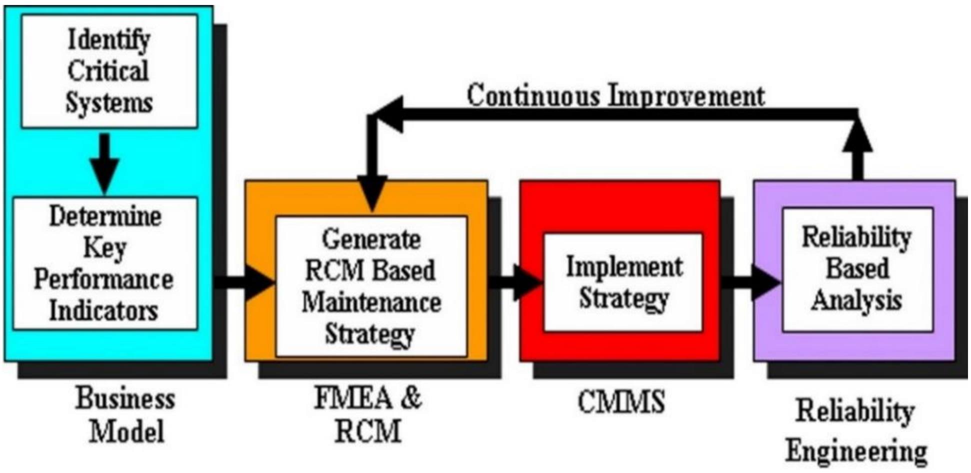


Figure 1.2. RCM Engineering Overview via FMEA (Campbell and Jardine, 2001)

1.2. Intelligent System Management

1.2.1. Industry 4.0 and Smart Manufacturing

Industry and industrial processes are keeping on their evolutions. The requirements for competitive advantages against production and manufacturing challenges have been engineered for the development of advanced and new cost-effective mechanisms. In this purpose, revolutionary technological leaps have been progressed in the distinct times of industrial history. Mechanization and steam engines were the first industrial revolution, the second industrial revolution was using electrical energy and mass production, and the third industrial revolution was founded as an Information Technology (IT) environment and prevalent of digitalization, as shown in Figure 1.3. (Sapre and Tomar, 2016).

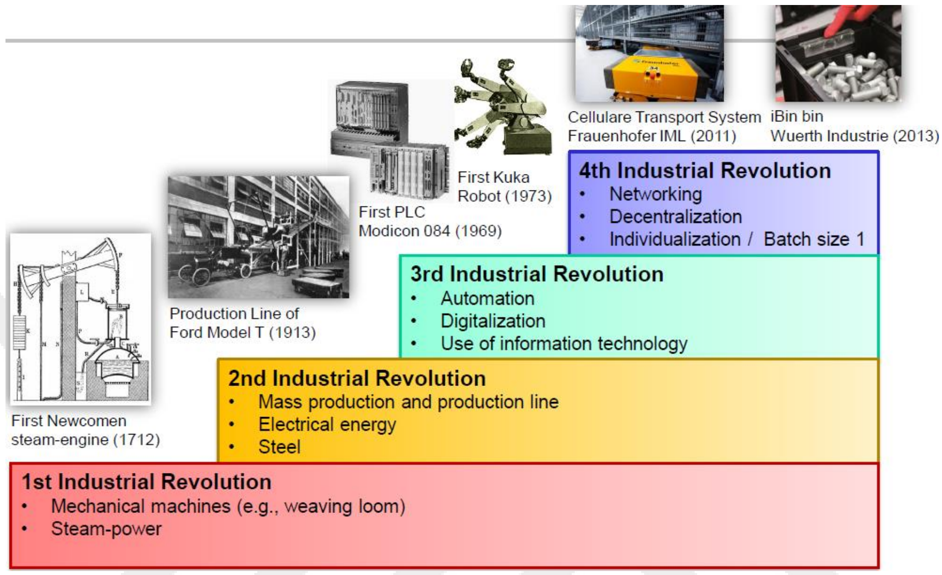


Figure 1.3. Industrial Revolution Steps (Sapre and Tomar, 2016)

The current industrial activity is strict and difficult to replace; innovations can be met with difficulty, lowering raw material prices often reduce quality and can increase process costs, and consequently profit margins are constantly decreasing. There is also a great dependency on the in-hose knowledge base, so when it decreases, improvisation increases, and development times are extended. Although, production systems are strongly automated, they do not have a conscious core to learn and act without constant human interventions (Dopico et. all, 2016).

Especially, process and production monitoring are needed to be smarter and more predictive by using low cost and reliable measurement capability that can be quickly implemented and deployed. Smart factories that are equipped with intelligent monitoring systems enable manufacturing of high-quality products, providing optimum service levels, flexible production background, low response times, low energy consumptions, reliable machines, safer shop floors, more environment-friendly plants, optimum labor hours (minimized human interventions), and more motivated people. Figure 1.4. is a basic demonstration of the essential interconnected implementations through Industry 4.0. Here, monitoring tools and sensors can be taken for data collection and tracing tools from systems. IoT solutions, network structures and industrial apps play important roles to data evaluation. Automations for executing process, safe and high prices quality monitoring environments are most leading features with other components of Industry 4.0 and related intelligent systems.

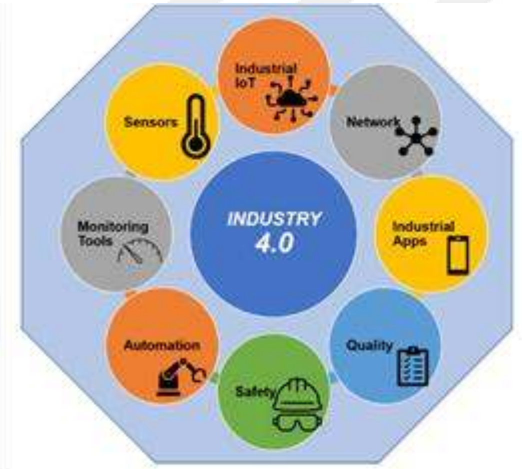


Figure 1.4. Implementation Components of Industry 4.0

Artificial Intelligence (AI) intends to create systems that can perceive their environment and act as a result to increase the chances of success. Therefore, the industrial environment increases the ability to adapt and compete with more flexible industrial intelligent programs. Every step in the industrial process involves information such as energy consumption, speed, pressure, force, temperature, power, weight, volume, precision etc. Therefore, after establishing an advanced digital network that monitoring information at the factories, the next logical step is the combination of internet technologies and "smart" objects to flow of information into an advanced form of production. Here, foreseeing preventive actions and implement it before the case happens would be possible.

1.2.2. Intelligent Reliability Management

Industrial environments are now moving away from static production chains and laying the foundations for a new shift in production and manufacturing processes to a more flexible, individualized, and efficient production idea. The basis of this revolution is in the combination of hardware and software components, towards a smarter, self-conscious, self-configurative, and self-optimizing structure that can predict problems and initiate preventive actions to minimize downtime during production; to understand the entire life cycle of the production process to be ready to respond to new and constantly changing environments. There are many challenges that are energy and resource efficiency, reducing time to market, increasing flexibility towards almost individualized mass production, increasing flexibility for customized mass production, and increasing the existing infrastructure gradually.

The main system tools, which are embedded to the intelligent reliability management system, are cyber-physical systems, the internet of things, big data, and cloud computing with all the infrastructure needed to support and other complementary items such as autonomous robots, simulation and virtualization models, and additive production. Different variables configure embedded systems that affect the new, flexible, standard, decentralized, heterogeneous, innovative form of production, where processes are more customer-oriented and resource-efficient. In the embedded system, the information collected by different sensors and devices are interconnected and communicate with each other to make decentralized decisions for optimization of production, based on the compilation, processing, and analysis of large amount of data by smart objects. The AI can be a perfect niche for it's thrives and implementation for industrial development because its applications can answer different questions and possibilities dealing with Industry 4.0 structure (Dopico et. all, 2016).

1.3. Artificial Intelligence Neural Networks (ANN)

The ANN is a successful tool for analyzing and predicting reliability results in a given equipment life cycle period. Designing an engineering aided intelligent equipment reliability analyzer system is going to create an innovative tool for industrial shop floors. ANN is a kind of mathematical algorithm resulting from simulation of biological neuron networks. The ANN consists of nodes (called neurons) and edges (called synapses). Input data is transmitted to neurons where calculations are processed via weighted synapses and then sent to other neurons or represent output (Sehgal and Meenal, 2016).

ANN also can be applied in many areas such as pattern classification, clustering, function approach, estimation, optimization, and where many areas can solve complex problems with high success. An ANN consists of neuron structure, input element, weight, addition node, activation function, threshold, and output layer as shown in Figure 1.5 (Yılmaz et. all, 2017).

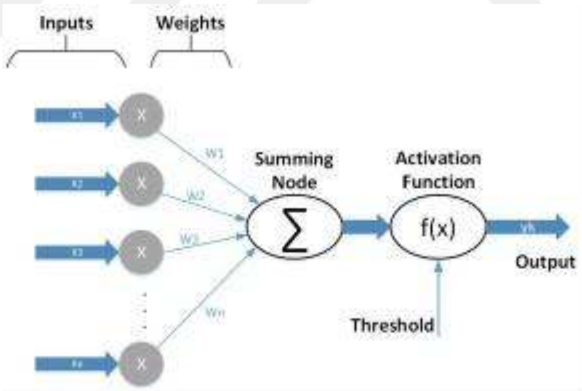


Figure 1.5. Structure of Basic ANN Neuron (Yilmaz et. all, 2017)

The simplest structure is a two-layer NN with an input and an output layer where the number of input neurons is equal to the size of the input vector. The connections between neurons have weights. Each neuron has an activation function. Sigmoid and radial base function is the most common activation function. Two hidden layers and the output layer which shows an example of three output nodes of the ANN as seen in Figure 1.6.

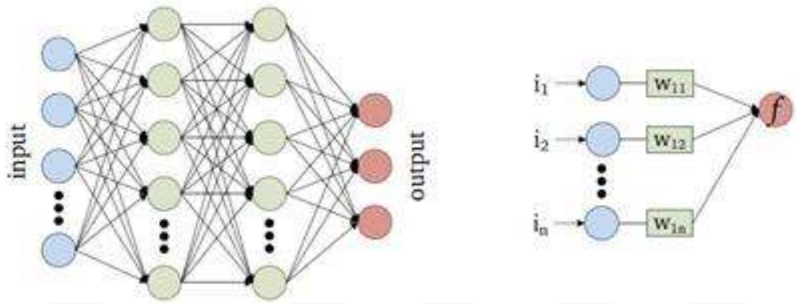


Figure 1.6. Two Hidden Layer ANN and Demonstration of Weights Between Neurons and an Activation Function (Jahnke, 2015).

Neural Networks (NN) can be used to remove patterns and detect trends that are too complex to be noticed by humans or other computer techniques, with their ability to derive meaning from complex or imprecise data. A trained NN can be considered as an "expert" in the category of information provided for analysis. This can provide projections and answer "what if" questions given their new interest. Other advantages include:

- Adaptive Learning: Ability to learn how to perform tasks based on data provided for training or first experience.
- Self-organization: ANN can create its organization or a representation of the information during the learning period.
- Real-Time Operation: ANN calculations can be carried out in parallel, and special hardware devices that use feature are designed and manufactured.
- Fault Tolerance: Partial destruction of a network causes performance to decrease accordingly. However, some networking capabilities can be protected even with major network damage (Sehgal & Meenal, 2016).

1.3.1. Neural Network (NN) Design Process

The workflow for the NN design process basically contains seven major steps. These are definition of input and output parameters, collecting data for feeding it to train and validation, specifying ANN structure, training and validating the network by modifying learning rate, number of layers, number of neurons and activation function, getting and checking the correlation of results and generating the best ANN structure. The data collection step usually takes place outside the relevant software usage framework but is generally discussed in the multilayer NN and back expansion training section. The MATLAB NN Toolbox software uses the network object to store all information that identifies a NN. Once a NN is created, needs to be configured and then trained. Configuration involves arranging the network to be compatible with the problem wanted to solve, as defined by the sample data. After the network is configured, adjustable network parameters, weight and deviation, must be adjusted to optimize network performance. This adjustment process is called network training. Configuration and training require the network to be provided with sample data (Beale et al., 2017).

ANN learning and design flow chart can be seen in Figure 1.7.

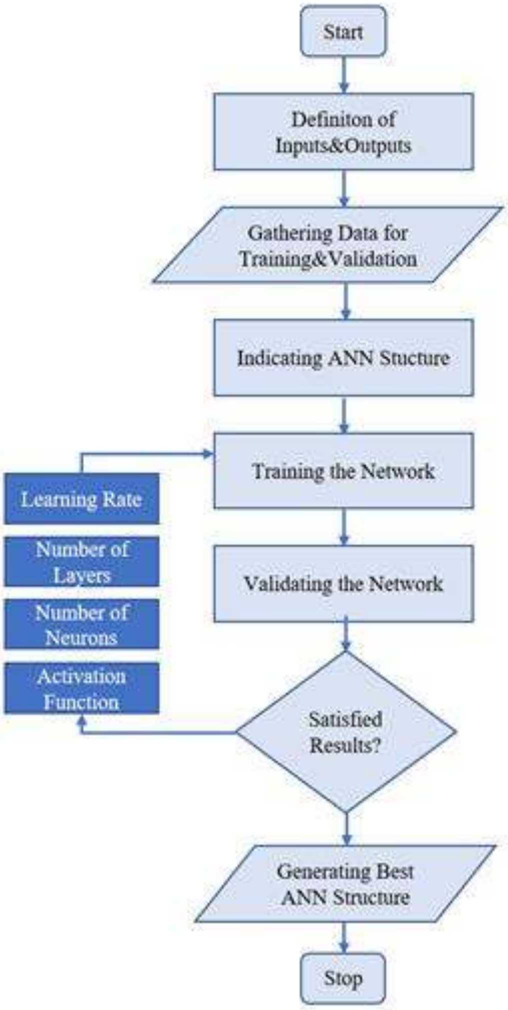


Figure 1.7. Flow Chart of ANN Model

1.4. Plastic Injection Molding and Production Method

1.4.1. Plastic Injection Molding Process and Injection Molding Machine (IMM) Principles

Injection Molding (IM) is the most widely used method to produce products directly from the thermoplastic material through many product markets such as automotive, aviation, packaging, medical, white goods, electronic devices, civil works equipment, etc. IM production cells are commonly assisted with robotic and intelligent automation systems in terms of more productivity.

In the injection moulding process, products are being made by injecting molten polymer into a cooled mould. A thermoplastic material, which is usually available in granules or pellets, enters the cylinder, which is kept at a constant temperature with electrical heating elements. The polymer is molten by heating from the cylinder wall and by shear heat from the screw during plasticizing. When the polymer in the cylinder is sufficiently heated, injected into the cavity of the mould through a narrow gate by the forward-moving screw as shown in Figure 1.8.

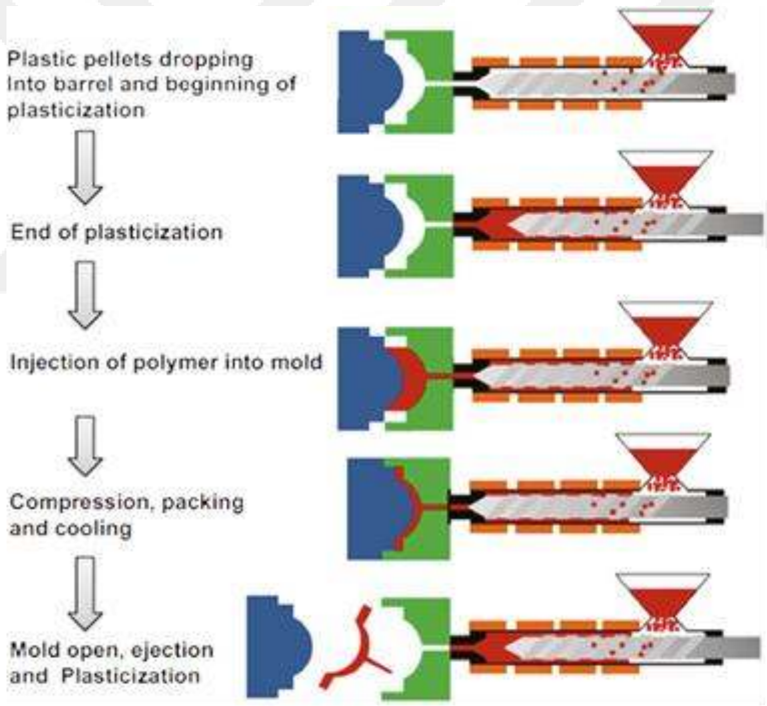


Figure 1.8. IM Cycle (Fang et. all, 2016)

The melted plastic material is kept under pressure in the cavity and cooled down by either water or oil. Once the product is solidified, the mould opens and the product is ejected using ejector pins from the cavity. In the meantime, the screw is in the backward position again and the rotating screw plasticizes new polymer. The two mold halves need to be clamped against each other to prevent the melt from leaking away that is provided by holding pressure. The clamping unit of the IM machine takes care of clamping force. The holding pressure is meant to bring so many polymers into the cavity that it counteracts the thermal shrinkage of the material. During further cooling of the material in the cavity, the screw starts rotating again and plasticize new material for the next shot. Once the product is ejected from the mould, the cycle is repeated, as shown in Figure 1.9.

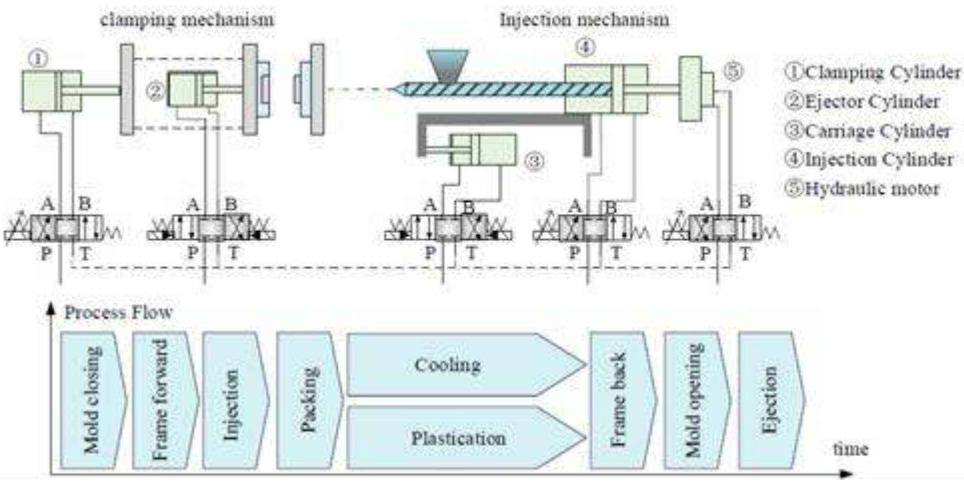


Figure 1.9. Process and Cycle Formation of a Hydraulic IMM (Zhang et. all, 2017)

The mold is a very complicated piece of equipment. It consists of two halves, which are mounted to the platens. One is the stationary platen and the other is the movable. When the shape of the product is complicated or when the flow path is long the injection of the melt into the cavity has to take place at several positions. For the supply of melt to the gate channels are often heated (hot runners). This prevents the melt from being cooled down too much before entering the cavity.

1.4.2. Process Parameters of Plastic Injection Molding

There are enormous process parameters and product-related quality specifications to be controlled. The main causes of the defect in IM can be because of the mold design, process parameters, machine, operator, or material. The details are shown in the Ishikawa diagram as shown in Figure 1.10.

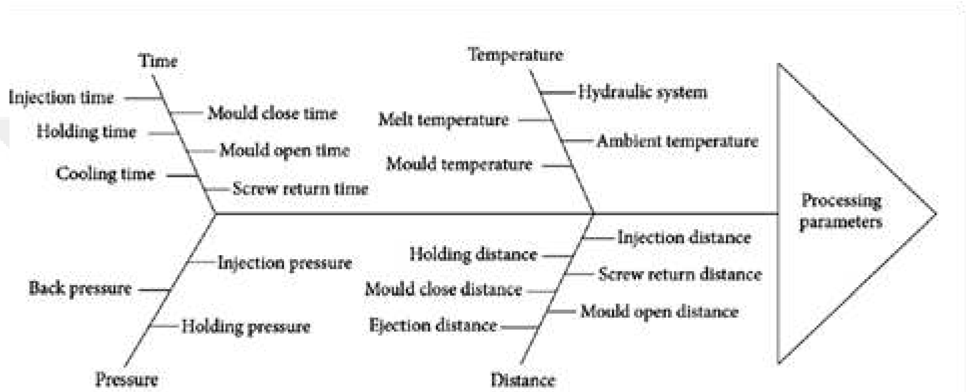


Figure 1.10. Ishikawa Diagram of Process Parameters in IM

The mold and part design are usually determined in the initial stage of product development, which cannot be easily changed. The optimization of the process parameters should be more feasible and reasonable. Quality optimization is the ultimate goal for IM industries, where optimal process settings are determined to meet quality product requirements while saving on materials and energy. Although there are more than 200 recognized parameters that affect the IM process, primary importance can be categorized within four major stages: speed, temperature, pressure, and time.

The IM processes contain strict relationships between process parameters, product specifications, and used automation system type. For each thermoplastic product, production can be separately considered, critical parameters, raw material, and finished product specifications and production capacity needs must be evaluated by choosing the suitable parameters and data formations. According to proposed study, the appropriate factors that affect product quality and productivity can be selected and used to reach the infrastructure of intelligent equipment and process reliability data networks. Thus, exact data sources, types, inputs, outputs, and data collection methods can be decided and examined for determination of optimum data learning algorithms. During the structuring of the IM data evaluation system, the capabilities of used automation systems must be taken into consideration in terms of process and capacity parameters, as well as essential IM parameters.

1.5. Structure of the Study

In this study: reliability analysis and performance prediction of proposed Robotic Injection Molding System (RIMS) has been evaluated using below cascaded steps. The analysis has been executed in two steps; one has been applied for system reliability by using historical equipment-based performance data, another one has been applied for production process reliability with respect to realized process parameters.

In the beginning, historical equipment-based failure data has been identified by sensors, Manufacturing Execution System (MES), and operator reports. Here, failures have been classified with respect to their failure mode and effects. Failure's severity, detection, and occurrence criteria have been punctuated, and occurrence rates items have been selected according to MTBF levels. The results have been reflected on the equipment based FMEA table and reached RPN values that transferred to the Pareto charts for indicating the most critical mechanical and hydraulic equipment. Gathered failure modes, effects, and MTBF have been evaluated for ANN training and reliability prediction. The optimum learning algorithm and best performance multilayer ANN model has been structured. Performance assessment of the ANN has been executed according to regression tools. Realized MTBF data has been evaluated by using its logarithmic trend to figure out the possible future MTBF. This has been fed to the best performance ANN and possible future MTBF has been forecasted in order to find future system reliability and life cycles. In the end, preventive actions have been generated by using predicted MTBF and matching the related data with FMEA results to prepare troubleshooting items against possible failures. Related analysis and intelligent estimation process steps can be seen in Figure 1.11.

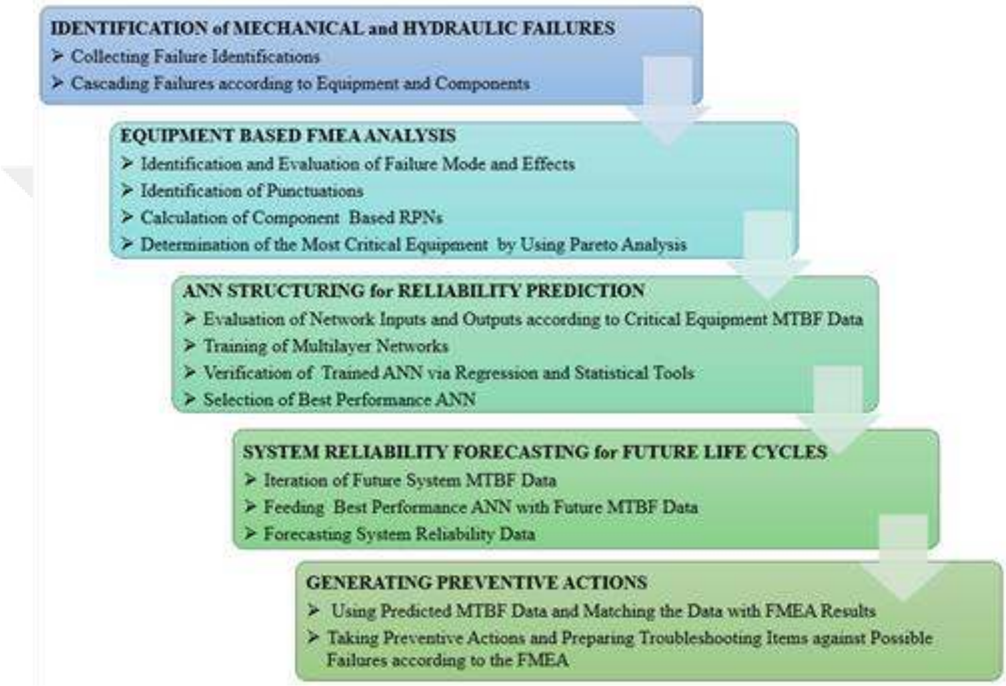


Figure 1.11. Steps of Intelligent System Reliability Analysis of RIMS

In the other phase of the study, used production process parameters have been investigated to reach intelligent process reliability estimation of RIMS. All considered process parameters have been evaluated for determination of input/output data classifications according to their principle and transformation techniques that are mold closing and opening times, injection pressure and speed, plasticizing time, melt temperature etc. as inputs, cycle time, product temperature, core and cavity temperature as outputs. Here, process Cycle Time (CT) has been taken as critical process output for monitoring reliability parameter. Existing (pressure, time, speed etc.) and required externally measured data have been used to reach the most ideal data modelling structure. Determined input and output data have been used for training processes of ANN, and regression tools have been used for checking the performance ANN to reach process reliability forecasting as similar with the phase of system reliability studies. In the end, future CTs have been forecasted according to best performance ANN outputs. Extracted future CTs have been allowed to reach other related future production items such as production capacities, energy consumptions, product quality and specifications. Additionally, preventive actions have been suggested to develop continuous improvement implementations and sustain reliable process performances. The intelligent process reliability estimation process steps are shown in Figure 1.12.

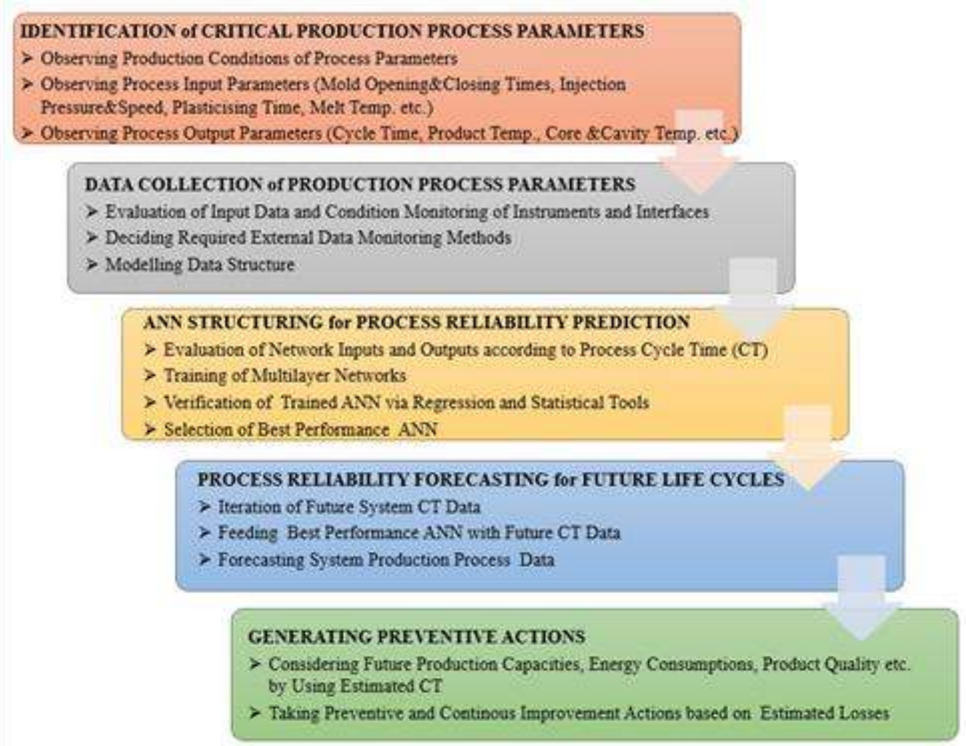


Figure 1.12. Steps of Intelligent Production Process Reliability Analysis of RIMS

2. PREVIOUS STUDIES

Studies about system reliability and intelligent assessment applications have been carried out by many precious scientists and industrial professionals like Birolini (2017), Modarres et al. (2016), Yang (2007), O'Connor and Kleyner (2012), Grinchenko (2020), Bertsche (2011), Mikulak (2008), Bloom (2005), Shanmuganathan et al. (2016), Silva et al. (2017) and Kumar et al. (2019). Among them, FMEA analysis is one of the most used reliability calculations and analysis methods in industrial and other system management.

Singh et al. (2012) examined the reliability analysis of the electrohydraulic automated leveling system of a typical mobile platform. The system can be used for ground drilling machine, mobile antenna system for communication and weapon operation mechanism applications, and other components. Their work limited reliability analysis to hydraulic systems and mechanical components. Failure Tree Analysis (FTA) and FMEA tools were used to reach reliability parameters and to determine the criticality of the components during the design phase.

Degu and Moorthy (2014) applied machinery FMEA in the UPVC pipe production unit of a plastic pipe factory. Here, the failure modes and their causes were examined for each machine, the severity, occurrence, and detection indications were performed with the help of FMEA worksheet. Consequently, the necessary corrective actions were recommended according to results.

Erick et al. (2011) developed a method based on classic system reliability assessment tools of FMEA and FTA and performed the fault analysis of the steering system for LNG carriers. Failure modes of system components were analyzed, and the causes of a steering system failure were identified. A maintenance policy has been proposed for the most critical components. Table 2.1 shows the FMEA result of the axial piston pump.

Table 2.1. FMEA of the Variable Delivery Axial Piston Pump (Erick et al., 2011)

Component	Function	Failure Mode	Failure Causes	Failure Effects
Axial piston pump	Deliver the hydraulic fluid with a particular flow and constant pressure	Pump provides abnormal or unstable flow	Presence of air in the fluid	Absence or slow movement of the hydraulic cylinder (possible stop of steering gear system)
			Very high viscosity of the fluid	
			Cavitation	
			Excessive internal leakage	
			The suction strainer being too small or too dirty	
			Wrong installation of the pump	
		External leakage	Excessive pressure within the pump	
			High temperature of the fluid	Insufficient pressure in the hydraulic cylinders
			Wear on port plate and barrel faces	Incorrect speed of the cylinders hydraulic
			Wear on seal	

Kolich (2014) exerted cost challenges on vehicle manufacturers and discussed more efficient alternatives. He aimed to contribute by using the Design FMEA (DFMEA) technique on the improvement of seating comfort. The study was proposed about teamwork and brainstorming on the definition of seating comfort failure modes, reducing risks, and realizing the designs.

Rakesh et al. (2013) enabled the use of FMEA to increase the reliability of subsystems to ensure productivity, which improved the bottom line of the manufacturing industry. Here, the FMEA technique was applied to an automatic plastic welding machine used for the production of blood bags in a life care company in India. The measures suggested in this study can significantly reduce the loss of production hours in the industry due to machine breakdown.

Turedi and Bircan (2015) studied industrial robotic automation system reliability assessment by using FMEA method with experienced common failures of cartesian type palletizing robots and automation. In this study, the palletizing robot automation system, and its equipment-based failures were used for the evaluation of FMEA structure. Eventually, reliability-centered procedures and troubleshooting items were generated for reliability improvement and preventive cases based on realized downtimes and MTBF.

Fudzin and Majid (2015) studied a robotic assembly and transportation line in an automotive plant. Availability was calculated according to robot failure data which often occurred during operations. Seven years of real-world data were used for the analysis. Combined failure rates and MTBFs were used for the reliability calculation with the presume of the fixed failure rate.

Pawar S. and Rathod D. (2013) conducted the FMEA study of the mixed-model assembly line in the automobile industry. The potential effects of failures were evaluated to reach RPN rates, and the results were used to reduce downtime of the line.

Turedi et al. (2014), used RCM and FMEA methods in industrial hydraulic driven systems reliability of hydraulic vane pumps by monitoring the condition and performance parameters. Techniques such as wear analysis and hydraulic oil analysis played significant roles to generate FMEA analysis tasks and related RCM procedures and preventive action plans. At the end of the study, minimized RPN values of studied systems and conclusive improvement on Overall Equipment Efficiency (OEE) were examined.

High performance data predictions for future forecasting can be executed with powerful neural models like ANN because of their data processing capabilities like human brain. FMEA is one of the most advantageous complex problems or failures of root causes and effects determination tool. It can efficiently generate the most appropriate data to feed ANN input and compare the network with accurate outputs.

Abu-Mahfouz (2007) presented an overview of the three ANN architectures and the results of applying ANNs for the detection and classification of a gearbox operating under steady-state conditions. He examined ANN models using Feed Forward Back Propagation (FFBP). Three artificial defects were defined on gearbox that are loose key, single tooth flank wear, and full tooth breakage (missing tooth). The vibration signals collected from experiments were analyzed using time and frequency domain identifiers used as feature vectors to feed ANNs. Figure 2.1 shows the NN model for transmission failure detection.

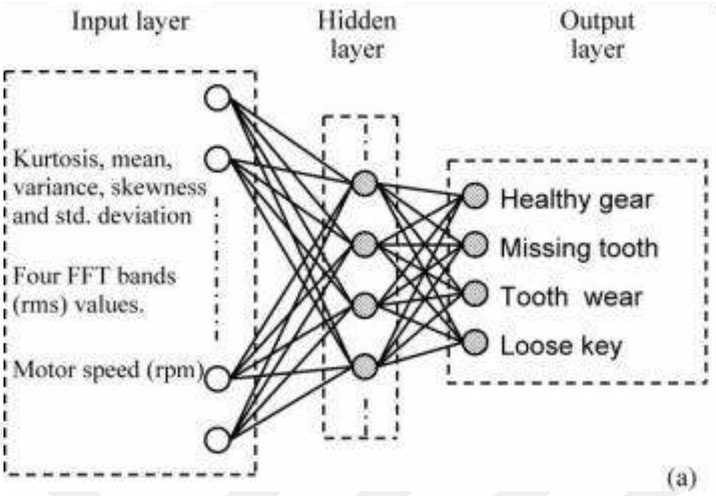


Figure 2.1. NN for Gearbox Fault Detection (Abu Mahfouz, 2007)

Turedi and Bircan (2017) evaluated the cartesian robot reliability prediction model by generating an ANN model with 20 hidden layers. Equipment groups were analyzed and MTBF rates were found out for the ANN matrix. The generated prediction model showed that the model can predict possible failures with a deviation of 2 days for an overall system and 30 days for the equipment (See Figure 2.2 and Figure 2.3).

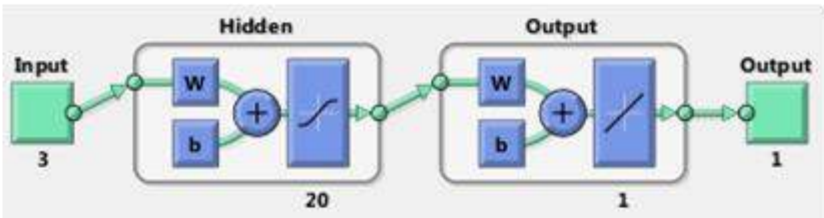


Figure 2.2. ANN Progress and Layer Distribution (Turedi and Bircan, 2017)

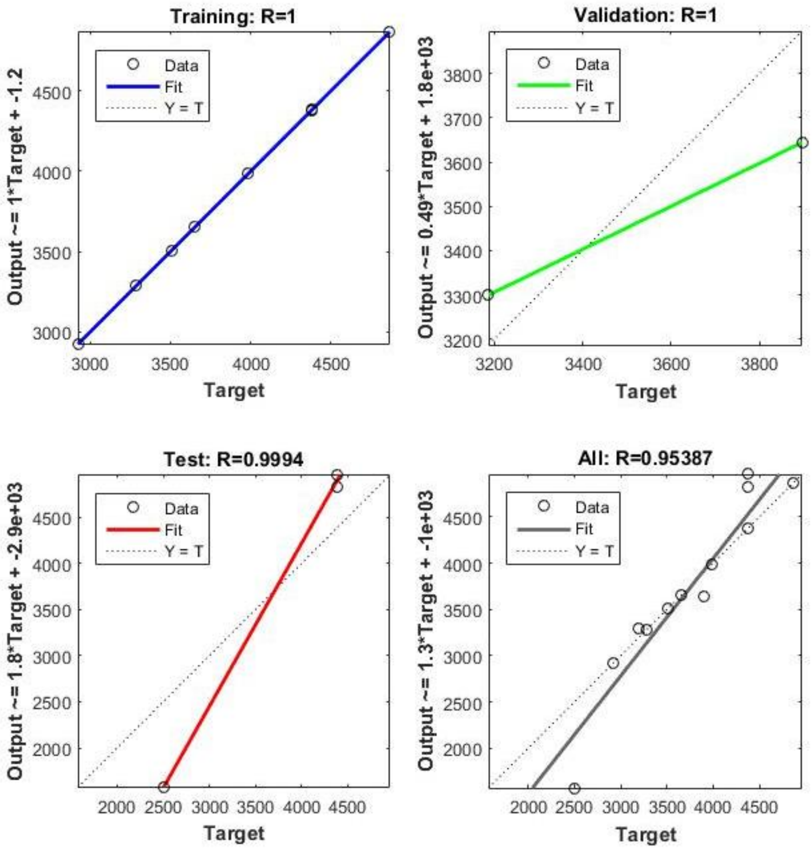


Figure 2.3. ANN Model Training, Verification, Test and Release Processes (Turedi and Bircan, 2017)

Kalem (2008) examined an elevator system with two different speed and bulk capacities, which are vibration parameters on the impulse system. Vibration parameters measured from the engine and reducer with loaded and unloaded were recorded to use in ANN by passing the regulation.

Chinnam and Mohan (2010) proposed the utility of the wavelet transform in preprocessing degradation signals for online reliability estimation. Neural networks were used for forecasting the degradation signals and estimating the likelihood that these signals would exceed a predetermined critical plane representative of unit failure in the immediate future. This leads to an online estimate for individual unit reliability. The proposed method was applied for analyzing degradation signals collected from a vertical CNC drilling machine using drill bits. The degradation signals, force, and torque were collected as the drill bits were destructively tested.

Kumar et al. (2012) used ANN for the performance-based anomaly detection of a small sized gas turbine. The health monitoring data was collected over the entire operational time between two major overhauls and used for ANN. BPNN and Generalized Regression Neural Network (GRNN) models were implemented with MATLAB programming for this work. Both the models appear to well capture the behavior if the output unit loads. The comparison of the test data set collected 17 months after engine overhauling and its ANN based simulation represent an anomalous situation. The difference in the output unit load evaluated as deliberate lower gas pressure adjustments related with seasonal variation in the power requirement.

Opocenska and Hammer (2015) provided basic information about the maintenance stages; refers to the classification of care and analyzes the care systems used in practice. Also, some modern approaches to maintenance have been presented and supported by specific situations selected from engineering practice such as Total Productive Maintenance (TPM), RCM, Risk Based Inspections (RBI).

Chukwuekwe et al. (2016) have reviewed major technological drives (such as big data, cloud computing, cyber-physical systems, Internet of Things, and Internet of Services) up to Industry 4.0 and present the smart factory as its main beneficiary. The study set out general frameworks for a closed loop feedback data driven predictive maintenance system for implementation within an Industry 4.0 environment.

Chen and Xing (2015) discussed Industry 4.0 implementation and the benefits of textile production against cost difficulties. Figure 2.4 shows that the information carrier of production items that are textile material containers, bobbins, warp beam, and fabric. Radio Frequency Identification Technology (RFID) and sensors are used for collecting and storing information of the equipment's operating status and maintenance data. During the data transferring process, the facility quickly and flexibly configured and optimized itself to meet specific production orders. Meanwhile, all information returned to MES and Enterprise Resource Planning (ERP) systems for future management decisions.

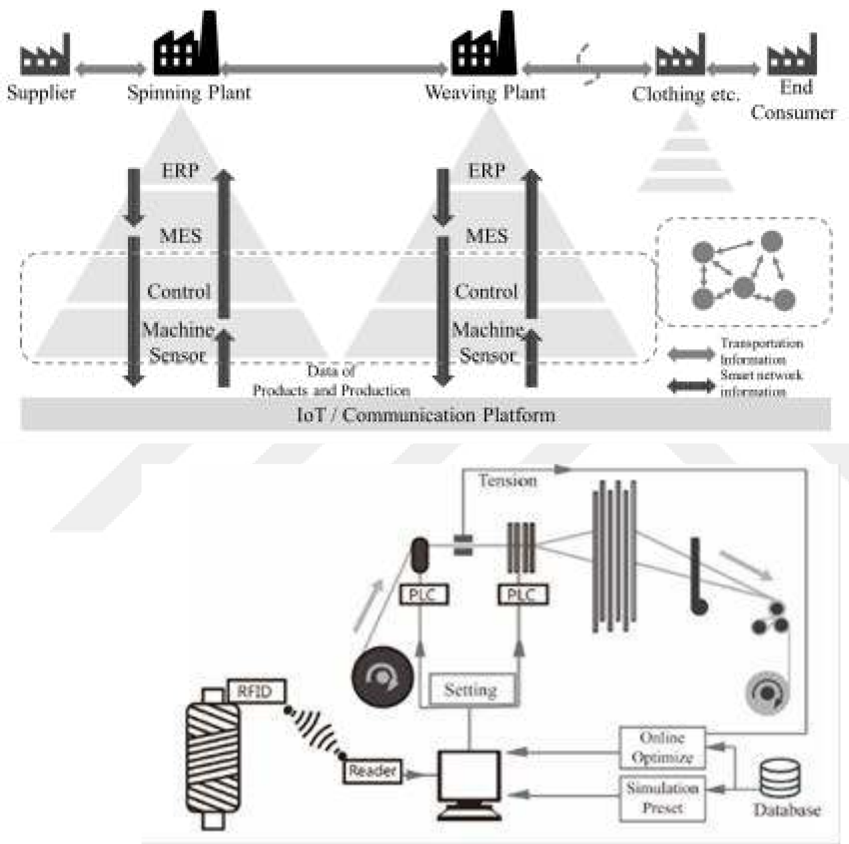


Figure 2.4. Data Transformation and Viewing Process in Textile Plant (Chen and Xing, 2015)

Anderl (2014) proposed smart systems and the Industry 4.0 approach with smart production and product design paradigm by using smart sensors, cyber systems, and smart data mining (Figure 2.5).

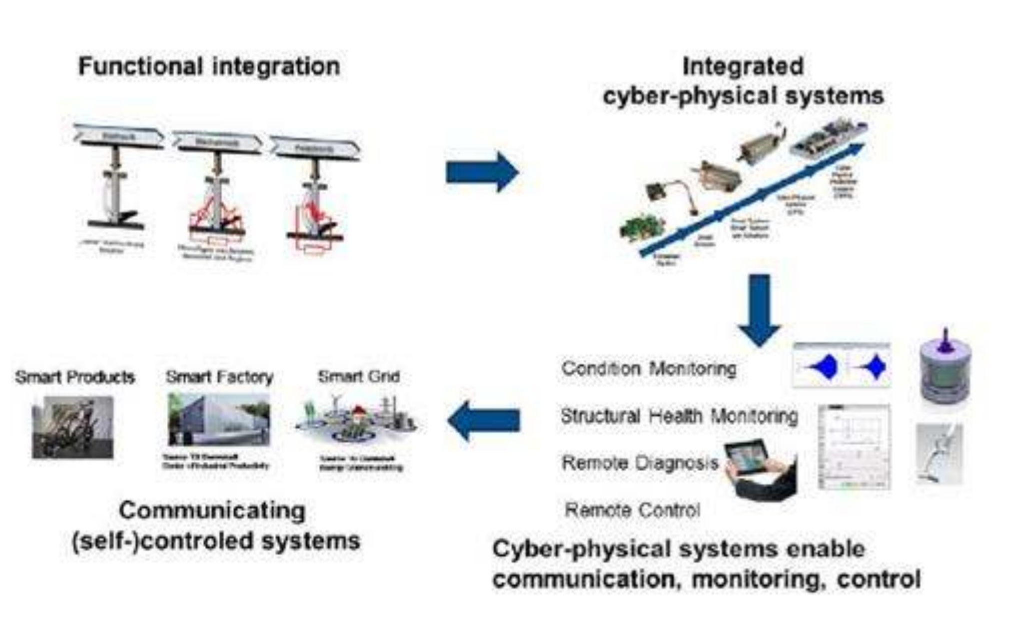


Figure 2.5. The Smart System Approach (Anderl R., 2014)

Here, fundamental approach of Industry 4.0 was considered on individual steps. The steps involve smart sensor equipped components and actuators (integrated cyber physical systems), cyber physical production systems (as a combination of cyber physical systems), condition monitoring or structural health monitoring by using remote control or diagnosis, communicating self-controlled systems and smart products.

Lee et al. (2017) suggested the structure of a smart factory model as an IM system for estimating future failures with the aid of experiences and know-how information. The model involved the communication and data flow of smart sensors, ERP, MES and NN. The main functions of the suggested smart IM system were defined as decision making, process control and analysis. The decision-making function related with real-world data collection by sensors on IM, mold and visual sensors at ejecting point of the system for extracting equipment and quality data in a production cycle time. The process control function was natural language processing, which is shown in Figure 2.6. that control IM machines signals by using the process parameters such as melting temperature, injection pressure and ejection time. Analysis functions consisted of digitalized factory model, abnormality forecaster, process analyst, and decision maker.

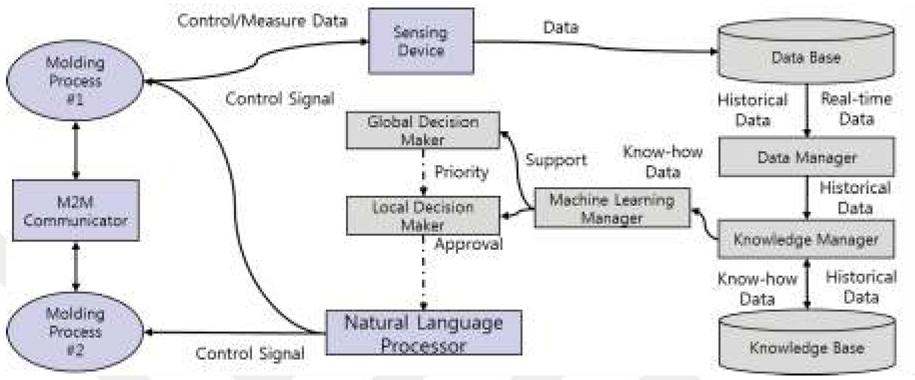


Figure 2.6. Data flow for Process Control (Lee et al., 2017)

Florjanič and Kuzman (2012) studied on the time estimation of manufacturing hours in a mold manufacturing project. Volume of manufacturing hours was taken as critical parameter for estimating manufacturing hours and minimizing underestimation times by using ANN. The structure was developed to obtain data transmission from experienced data to a data-driven network as seen in Figure 2.7. The developed involved 27 inputs and 10 neurons with a sigmoid activation function in the hidden layer, and one neuron with a linear activation function in the output layer. MATLAB was used for modeling software. The results of the ANN performance showed that 95% of all results were in the overestimation interval.

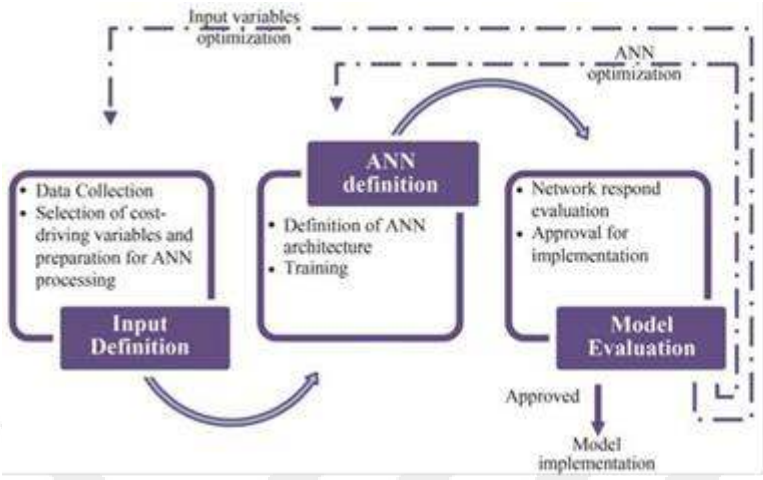


Figure 2.7. Estimation Model Creation (Florjanič and Kuzman, 2012)

Zhao et al. (2014) proposed a non-destructive online method to monitor IM process parameters by collecting and analyzing signals in IM machines. Electrical sensors mounted are used to collect physical signals. The simplified general layout of a method for monitoring is presented in Figure 2.8. Collected sensor data proved that the non-destructive method can continuously monitor the process. The proposed method also can automatically determine the conditions of the IM process stages in real-time environment.

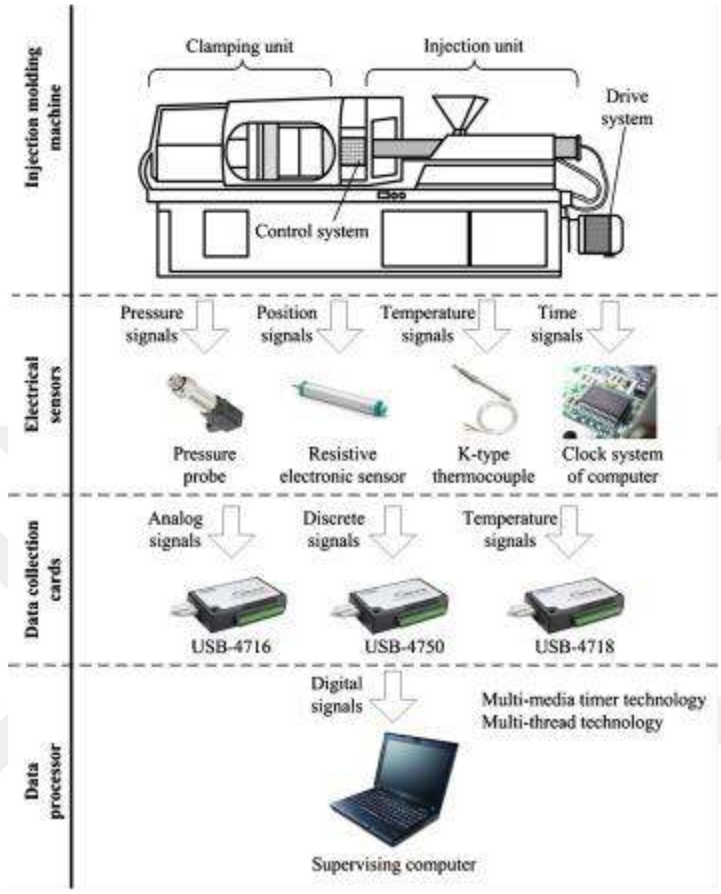


Figure 2.8. A Simplified General Layout of a Method for Monitoring and IM Machine (Zhao et al., 2014)

Lee et al. (2018) suggested a NN structure to optimize real-time IM process parameter that sets optimal process parameters by using mold data, molding machine data, and response data. ANN structure was based on SOM and Back Propagation Neural Network (BPNN) with the aid of shop floor data. SOM was applied to extract the dynamic process parameter characteristics as the network input. The proposed methodology uses a sigmoid function for the BPNN structure. Figure 2.9 is Architecture of the BPNN model. Table 2.2 is input and output variables of the proposed BPNN model.

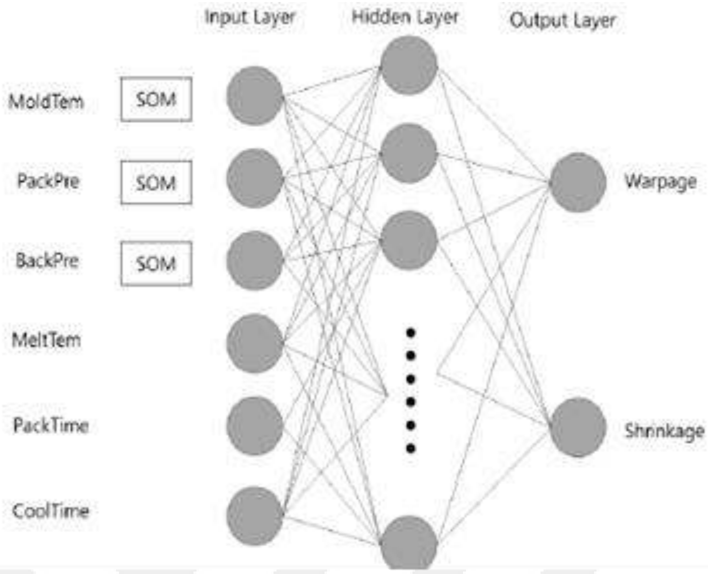


Figure 2.9. The architecture of the Proposed BPNN Model (Lee et. all, 2018)

Table 2.2. Input & Output Variables of the Proposed BPNN Model (Lee et. all, 2018)

	Variables	Setting range	Data feature
Input	Mold temperature (℃)	20 - 80	Continuous
	Packing pressure (MPa)	30 - 175	Continuous
	Back pressure (MPa)	50 – 70	Continuous
	Melt temperature (℃)	180 - 280	Discrete
	Packing time (S)	1 - 18	Discrete
	Cooling time (S)	7 - 25	Discrete
Output	Warpage (mm)	0 – 1	Discrete
	Shrinkage (%)	0 - 3	Discrete

Yilmaz et al. (2017) studied the electrical and maximum power characteristics of Photovoltaic (PV) panel under variable environmental conditions. Two ANN algorithms were used to predict the output parameters. In comparison with FFBP and Cascade Forward Back Propagation (CFBP) algorithms, FFBP gave better results in all training initiatives. LM was found to be successful in the most accurate estimation of output values in the training. Desired results were effectually provided by the FFBP algorithm with the LM training function. The regression results of two different algorithms vs. three different training functions are shown in Table 2.3. Here, the most advantageous mean value can be seen as belonging to the LM algorithm.

Table 2.3. Regression Results of Two Different Algorithms vs. Three Different Training Function (Yilmaz et. all, 2017)

Learning Algorithm	Training function	R Percantage Values for Different Training (%)										
		1st	2nd	3th	4th	5th	6th	7th	8th	9th	10th	Mean Value
Cascade-forward backprop.	Levenberg-Marquardt(LM)	97.505	97.046	96.564	97.617	97.11	97.704	96.004	95.981	99.182	98.47	97,3183
	BFGS quasi-Newton(BFG)	98.338	98.012	96.596	97.801	98.535	98.232	96.697	95.087	96.516	97.257	97.3071
	Gradient Descent(GD)	98.542	97.321	95.71	96.702	98.069	96.701	98.63	97.283	95.879	96.267	97.1104
Feed-forward backprop.	Levenberg-Marquardt(LM)	95.035	98.605	98.597	99.839	98.45	99.842	99.704	99.574	99.684	97.207	**98,6537**
	BFGS quasi-Newton(BFG)	95.536	98.06	98.573	98.569	98.429	98.171	98.243	98.662	97.727	97.795	97,9765
	Gradient Descent(GD)	97.486	96.892	98.185	97.365	97.967	98.121	97.371	97.291	97.624	98.423	97,6725

Mantravadia and Møllera (2019) purposed the evolution of the MES system in the age of digital transformation. Three theoretical case studies were analyzed on MES that are diary, meat processing and electrical equipment manufacturing. The findings provided an overview of MES ready for Industry 4.0 and determined its role in future factories. The study also mapped existing MES research on Industry 4.0 to highlight its importance in digital manufacturing.

Kim et al. (2019) investigated many automated manufacturing companies in Korea and focused on the rolling stock manufacturing industry. Research showed that MES system plays an important role about instant collecting, processing and transferring real-world data its ERP and related resource processor systems as shown is Figure 2.10. Additionally, smart MES system principle has suggested in order increase the effectiveness of MES usage on supply chain management.

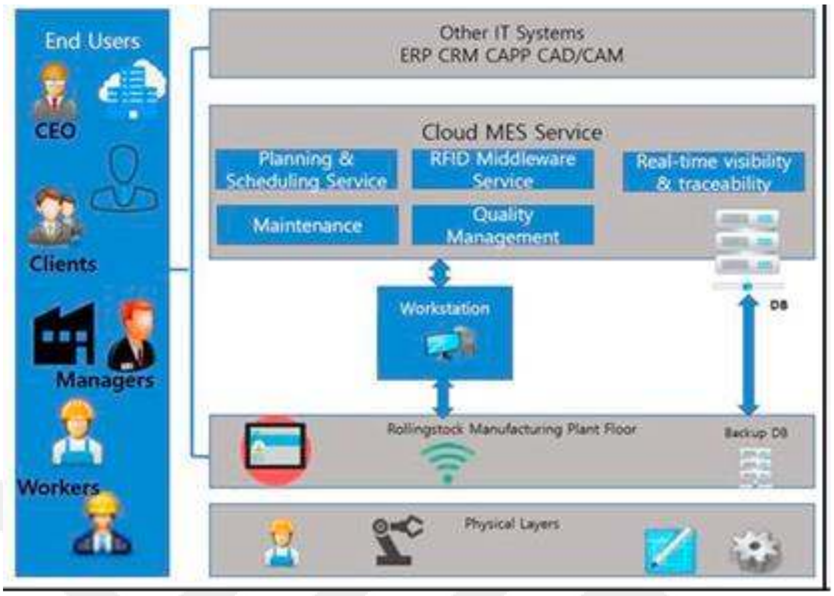


Figure 2.10. Conceptual MES Model for Rolling Stock Manufacturer (Kim et. all, 2019)

A summary table of overviewed previous studies according to their approaches and obtained data can be seen in Table 2.4. The studies showed that deciding on optimum data monitoring, data collecting, and data mapping play significant roles before the structuring of best predictor or reliability assessment models.

Table 2.4. Summary of Overviewed Previous Studies

Author/Year	Case Study	Method/Approach	Obtained Results
Abu-Mahfouz (2007)	Gearbox	ANN	Structuring Failure Detection Model by Using Vibration Signals
Turedi and Bircan (2017)	Cartesian Robot	ANN	Structuring Reliability Predcition Model by Using Realized MTBFs
Kalem (2008)	Elevator System	ANN	Structuring Online Reliability Prediction System by Using Vibration Signals
Chinnam and Mohan (2010)	CNC Drilling	ANN	Structuring Online Reliability Prediction System by Using Realized Process Parameters
Kumar et al. (2012)	Gas Turbine	ANN	Structuring Ejupment Performance Monitoring Network by Using Realized Parameters
Narita et al. (2002)	Machining (Cutting)	ANN	Developing a Real-Time Machining Optimization Network
Florjanič and Kuzman (2012)	Manufacturing Project	ANN	Modelling Estimation of Manufacturing Hours by Comparing with Different Hidden Layers
De La Fuente (2003)	Electrical DC Motor	ANN	Structuring of Motor Condition Predictor Model
Lee et al. (2018)	Injection Molding	ANN	Structuring Product Quality Predictor by Using Realized Process Data
Yilmaz et al. (2017)	Photovoltaic Panel	ANN	Discussing Optimum Training Algorithm for Reaching Best Performance Output Estimation
Elze (2003)	Component Analysis	ANN	Modeling of A Recurrent Neural Network for Principal Component Analysis
Lallot et al. (2010)	Heat Exchangers	ANN	Detection of Fouling in A Cross-Flow Heat Exchanger Using A Neural Network Based Technique
Mekki et al. (2015)	Photovoltaic Generator	ANN	ANN-Based Modeling and Monitoring of Photovoltaic Generator
Shen et al. (2007)	Injection Molding	ANN	Optimization of Injection Molding Process Parameters Using Combination of ANN and GA
Popiolek (2016)	Gearbox	ANN	Diagnosing the Technical Condition of Planetary Gearbox Using the ANN
Dabrowski (2016)	Gearbox	ANN	Condition Monitoring of Planetary Gearbox by Hardware Implementation of ANN
Kipli et al. (2012)	Image Quality Inspection	ANN	Determine the Image Quality by Using LMBNN.
Chen et al. (2008)	Injection Molding	ANN	Structuring Dynamic Product Quality Predictor
Singh et al. (2012)	Automated Leveling System	FMEA	Determination of Critical Equipment
Degu and Moorthy (2014)	UPVC Pipe Prodcution Factory	FMEA	Reaching Corrective Actions
Erick et al. (2011)	Steering System for LNG Carriers	FMEA	Building Maintenance Policy for the Most Critical Equipment
Kolich (2014)	Automative Seating Comfort	FMEA	Reducing Risks and Realizing the Design
Rakesh et al. (2013)	Production Line of Blood Bags	FMEA	Reducing the Production Losses and Machine Breakdowns
Turedi and Bircan (2016)	Automation of Palletizing Robot	FMEA	Generating RCM Procedures and Preventive Actions
Fudzin and Majid (2015)	Automotive Assembly Robots	FMEA	Reliability Calculation according to Realized MTBFs
Pawar S. and Rathod D. (2013)	Automotive Assembly Lines	FMEA	Calculating Equipment RPNs, and Reducing Downtimes
Turedi et al. (2014)	Hydraulic Vane Pumps	FMEA	Calculating Equipment RPN and Improving System OEE
Xie (2013)	Hydrokinetic Turbine	FMEA	FMEA Application in A Hydrokinetic Turbine System
Yusof et al. (2016)	Oil and Gas Industry	FMEA	Analysis of Butterfly Valve in Oil and Gas Industry
Pantazopoulos (2005)	Metal Forming	FMEA	Process Failure Modes and Effects Analysis (PFMEA)
Cicek et al. (2013)	Marine	FMEA	Application of FMEA to Main Engine Crankcase Explosion Failure On-Board Ship
Feili et al. (2013)	Geothermal Power Plant	FMEA	Risk Analysis of Geothermal Power Plants Using FMEA
Chukwuekwe (2016)	Smart Factory Applications	Industry 4.0	Presenting Technological Drives of Industry 4.0
Hozdić (2015)	Smart Factory Applications	Industry 4.0	Presenting Benefits of Flexible and Efficient Production Solutions
Ma and Liu (2016)	Smart Factory Applications	Industry 4.0	Discussing Computing, Automation and Networking Phases of Smart Productions
Chen and Xing (2015)	Textile Production Plant	Industry 4.0	Data Transformation and Viewing Process in Textile Plant by Using MSE and ERP
Anderl (2014)	Cyber Physical Systems	Industry 4.0	Modelling Smart System Applications
Lee et al. (2006)	Production Cases	Industry 4.0	Structuring of Intelligent Maintenance Systems
Lee et al. (2017)	Injection Molding	Industry 4.0	Discussing Data Flow and Process Control in Smart Factory
Zhao et al. (2014)	Injection Molding	Industry 4.0	Structuring Online Condition Monitoring System by Using Sensor Data
Mantravadia and Møllera (2019)	Digital Manufacturing	Industry 4.0	Overviewing Contribution of MES Systems in terms of Digital Manufacturing
Kim et al. (2019)	Automated Manufacturing	Industry 4.0	Discussing of Integration of MES and ERP Systems on Automated Manufacturing
Opocenska and Hammer (2015)	Maintenance Applications	RCM	Classification of RCM Based Maintenance Practices

In this thesis study, FMEA analysis has been used for the reliability processor to reach proper failure and performance data. Real-world data have been monitored, collected and mapped according to intelligent approaches. The results have been evaluated and most proper input and output data characteristics have been selected dealing with their system reliability effects. Identified input and output data has been processing with multilayer ANN and the best performance ANN has been selected with the aid of regression tools.

3. MATERIAL AND METHOD

3.1. Material

3.1.1. Robotic Injection Molding System (RIMS) Components

The studied RIMS is a production cell used for fully automatic thermoplastic injection production of steel-mounted (overmolded) plastic (Polypropylene) support parts in the automotive industry, similar to the figure below (Figure 3.1).

Figure 3.1. Steel-Mounted (Overmolded) Plastic Support Part Sample

The RIMS contains equipment such that, a 16-cavity water called hot runner injection mold, a 6-axis manipulator robot, and a steel insert fixture changer system, as seen in Figure 3.2. They have communication protocols through a PLC system. Studied IMM in the RIMS is a conventional type of hydraulic driven machine, its clamp unit is specified as a hydromechanical toggle clamp unit that involves four tie bars holding the fixed and movable platens with a toggle hatch. The technical specifications of used IMM are illustrated in Figure 3.2.

Figure 3.2. A View of RIMS

IMM TYPE	Hydraulic Driven	
INJECTION UNIT	*UNIT*	
Screw Diameter	mm	**80**
Screw L/D Rate		**20**
Teoritical Injection Volume	cm3	**1860**
Injection Capacity	g	**1693**
Injection Rate	g/s	**498**
Injection Pressure	Mpa	**158**
Plastification Speed	g/s	**58,7**
Screw RPM	rpm	**0-180**
TOGGLE CLAMP UNIT		
Clamping Capacity	kN	**4500**
Clamp Stroke	mm	**780**
Tie Bar Distance	mm	**820*800**
Max. Mold Thickness	mm	**780**
Min. Mold Thickness	mm	**320**
Ejector Stroke	mm	**200**
Ejector Force	kN	**110**
OTHERS		
Max. Hyd. Pump Pressure	MPa	**16**
Hyd. Pump Power	kW	**55**
Heater Power	kW	**31,5**
Hyd. Oil Tank Capacity	L	**830**

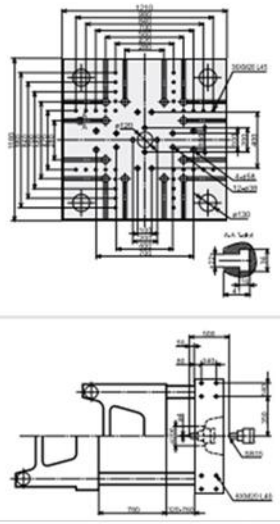


Figure 3.3. Specifications of IMM

In the proposed study, condition monitoring has been executed by using analog and digital outputs on IMM's operator panel for hydraulic oil pressure (manometers and pressure sensors on the hydraulic system), machine positions (position sensors/transducers on IMM), electrical motor amperage (external multimeter) and hydraulic oil temperature (temperature sensors on IMM).

The robot assigned with IMM is a 6-axis manipulator type and its technical specifications are illustrated in Figure 3.4.

MANUPILATOR ROBOT	
Number of Axes	6
Number od Controlled Axes	6
Volume of Working Envolope	41 m3
Pose Repeatability (ISO 9283)	± 0,06
Rated Payload	120 kg
Maximum Reach	2496 mm
Mounitng Position	Floor
Protection Rating	IP65
Axis Data	
Motion Range	
A1	± 185°
A2	-140°/-5°
A3	-120°/-155°
A4	± 350°
A5	± 125°
A6	± 350°
Speed with Rated Payload	
A1	136°/s
A2	130°/s
A3	120°/s
A4	292°/s
A5	258°/s
A6	284°/s

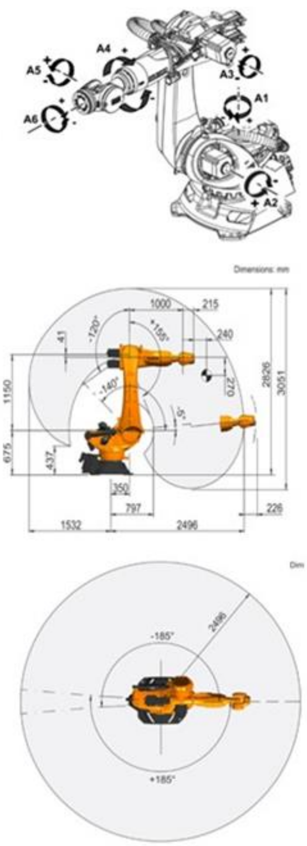


Figure 3.4. Specifications of Manipulator Robot

The robot holds a specially designed gripper holder (screw jointed aluminum structure) carries 16 pneumatic grippers. 3 heat-treated nails (120° angle positioned) are mounted on each gripper for picking and placing operations of steel inserts. Additionally, a compression spring is equipped in the middle of each nail for impact absorption and supporting precise pick and place actions. All actuators and valves on the gripper holder are pneumatic and driven by pressurized air. Figure 3.5. shows an overview of gripper holder details and grippers.

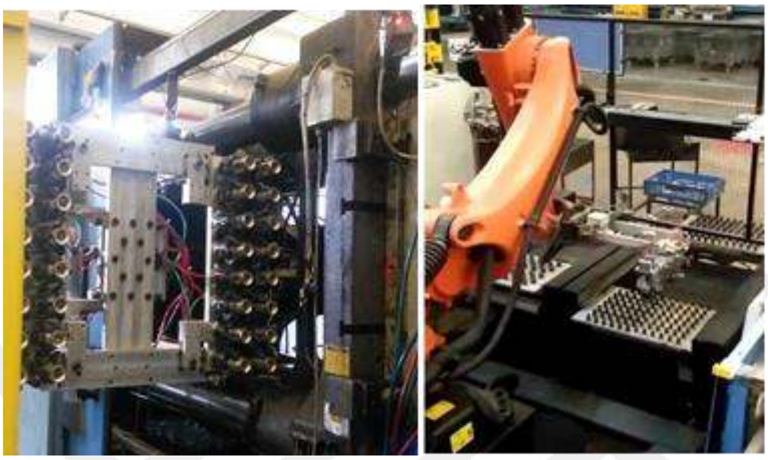


Figure 3.5. Gripper Body with Fixture System

The insert fixture system (Figure 3.4.) that is equipped with two movable pinned table. The inserts are put on the pinned table by operator. Each table can be loaded with 64 inserts (4 cycles) and the robot picks the inserts from these tables.

The tables are composed of linear bearings and driven with servo-controlled motors and timing belts. After each 4 cycles, the main PLC system changes the insert loaded and empty tables for preparation of next cycle. Meanwhile, two cameras are assigned for monitoring the states in the injection mold pairs which is used by the operator for tracing and checking the system.

3.1.2. Production Cycle of RIMS

The production cycle pursues the steps that the robot picks metal steel insert parts from its fixture and places to the 16 cavity injection mold surfaces by using specially designed pneumatic grippers. Then, the robot returns to the fixtures for picking the new ones for the next cycle. At the same time, IMM starts the injection molding cycle during the robot returning trajectory movement, as illustrated in see

Figure 3.6. After injection stage, finished metal inserted plastic support parts are rejected by IMMs open mold and transferred through conveyors to the finished product baskets. Also, Figure 3.7 illustrates the steps of trajectory movement that are executed by the manipulator robot.

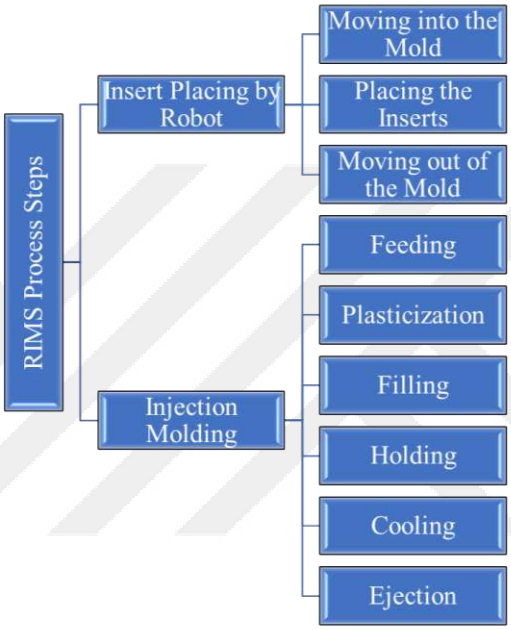


Figure 3.6. Overall Plastic Injection Cycle Contents Included Insert Placing

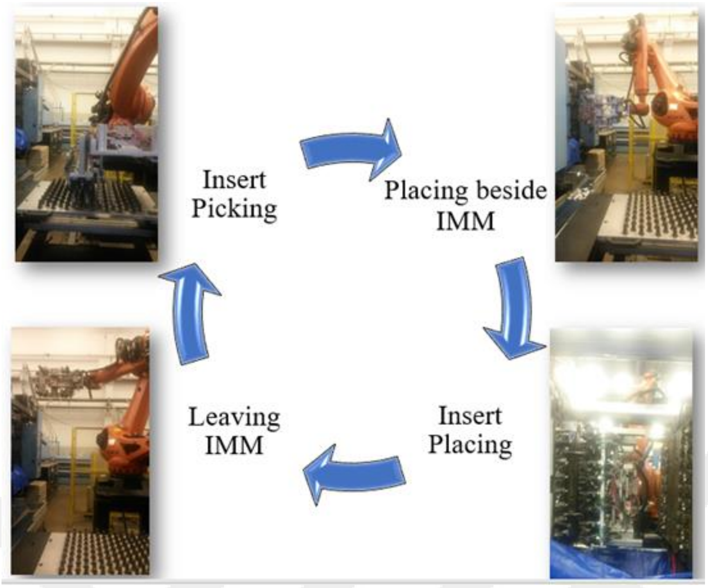


Figure 3.7. Steps of Robots Trajectory Movement

3.1.3. Electrohydraulic Automatic Control of IMM

The hydraulic pump is a critical item for providing efficient hydraulic oil flow, working pressures, maintaining minimized input energy, and heat release. The vane type pumps have high volumetric efficiency and smooth flow. Variable displacement is a useful property that can be minimized by reducing the size of pumping chambers. Maximum system pressure required to move a cylinder is occurred by opening a directional valve until flow demand resumes. The pump outlet gets back the oil into the reservoir tank and brings the system pressure to near zero by a solenoid-operated relief valve when the machine is in idle position. The electrohydraulic proportional-directional, pressure, and flow control valves maintain minimally overlapped controls at final actuator speeds as well as acceleration and deceleration ramps. Otherwise, shock waves cause vibrations during the functional motions of the machine. Linear positioning transducer on the screw plunge cylinder and shaft encoder on the injector screw execute precise motion control that can supply steady and controllable material flow and transmit of material to the mold.

This ensures and supports high-quality processes and products. The logic sensors, transducers, and their generated variable signals are required for proportional valve inputs for a feeding programmable controller to create a fast acted closed-loop controller system as seen in Figure 3.8. The controller also allows processing analog signals with high-resolution conversions and executes adjustable proportional integral derivative error correction to reach accurate loop control. Clamping force is controlled by precisely maintaining hydraulic pressure. The pressure transducer on the hydraulic line that measures the large diameter clamping cylinders pressure sends a signal to the controller. It is used for the clamping cycle for controlling the proportional directional valve to adjust the clamping pressure to give suitable settings until the end of the cycle.

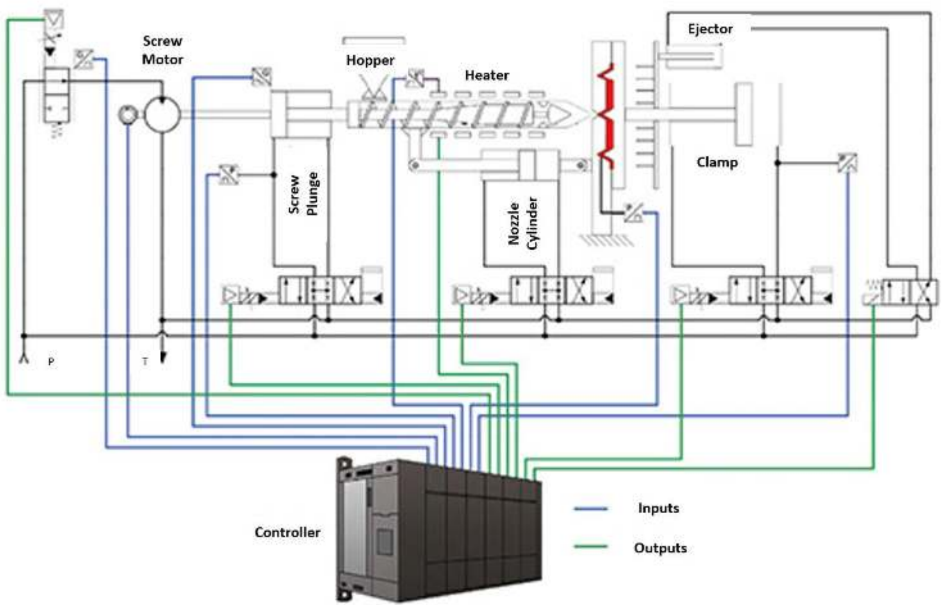


Figure 3.8. Control Circuit with Processor, Transducers, Sensor Inputs, and Valve Outputs

After the injection cycle, hot thermoplastic material in the mold starts to cool, additional material is pushed by a screw with a high pressure against the final products shrinkage and warp formation after release from the mold. This action is operated by a plunger or injection cylinder. This cylinder's pressure is sensed by a pressure transducer, and the cylinder speed is sensed by the linear position transducer. This can provide fine proportional and/or servo valve control to keep pushing the screw forward slowly, holding a suitable pressure, or increasing pressure on a suitable curve for the already cooled plastic product. This phase known as packing which is critical to employ high product quality (Figure 3.9).

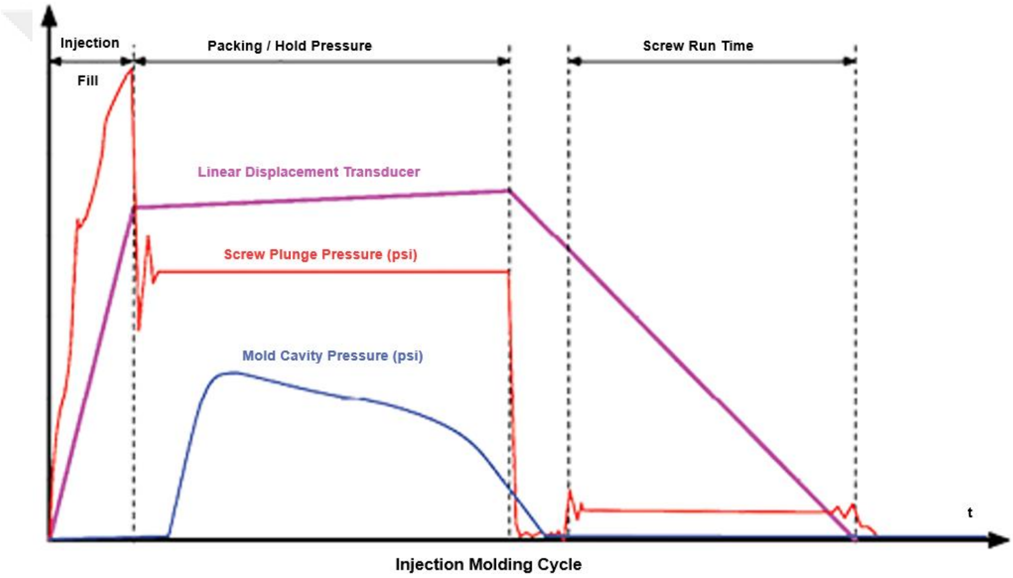


Figure 3.9. Control of Screw Pressure and Its Motion/Speed vs. IM cycle

Accurate hydraulic flow and pressure control become ideal plastic material flow through sprues and gates in the molds and this contribute high quality product and efficient production cycle times. The combined system that is composed of sensors, transducers, programmable controllers, and electrohydraulic valves can regulate the complete process control as seen in the demonstration in Figure 3.10.

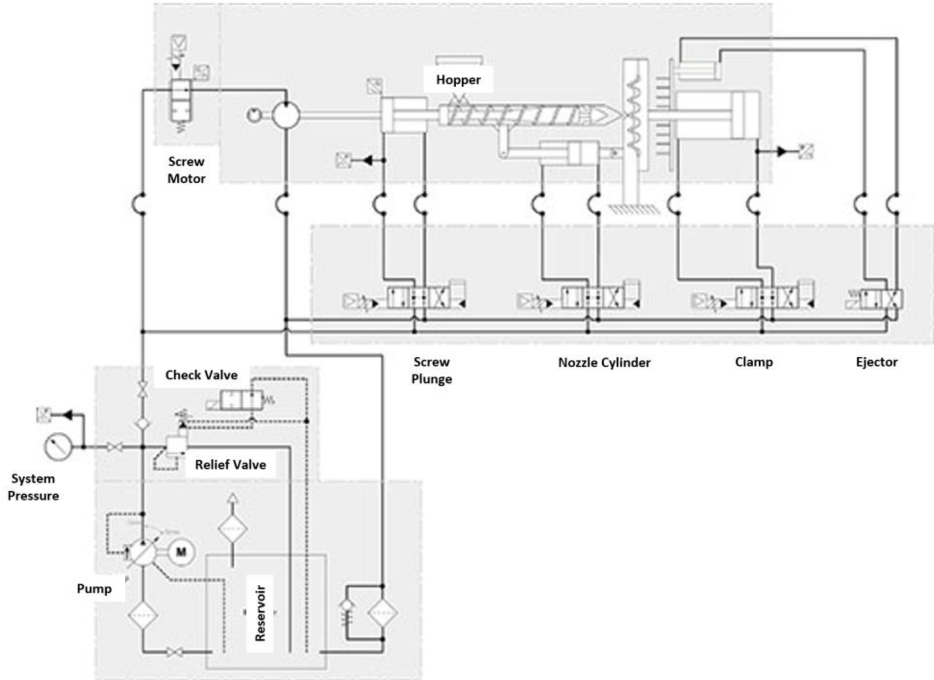


Figure 3.10. Electrohydraulic Motion and Force Control by Using Proportional and Servo Operated Directional Control Valves

3.1.4. Manufacturing Execution System (MES)

MES is a combination of software and hardware system that provide integration and communication between real-world shop floor and Enterprise Resource Planning (ERP) system. There are two essential input resource tools for MES. First tool is the sensors that are dynamic/online input resources in the manner of monitoring the states of machines, the other tool is digital hand terminals that are used for operator-based input data such as failure reasons, production orders, production confirmations (produced and scrap quantities), setup data, scrap reasons, and operator identifications. MES software is embedded into the related server executes the collection of manual and online data and prepare the instant and historical performance output data. The output data, including equipment based MTBF, MTTR, FR, Overall Equipment Efficiency (OEE) performance reports, and production reports, can be monitored from on shop floor, management office, and mobile cells. ERP system triggers the data flow by transferring production orders, include product identification and work scheduling details, to the MES. MES directs orders on terminal devices on work center machines as ready to selection for operators. During the realized production operations, setups, failures, production and scrap quantities are entered by using predetermined reason codes. Production related realized data eventually transfers to the ERP system. MES and ERP system interactions used on studied RIMS can be seen in Figure 3.11.

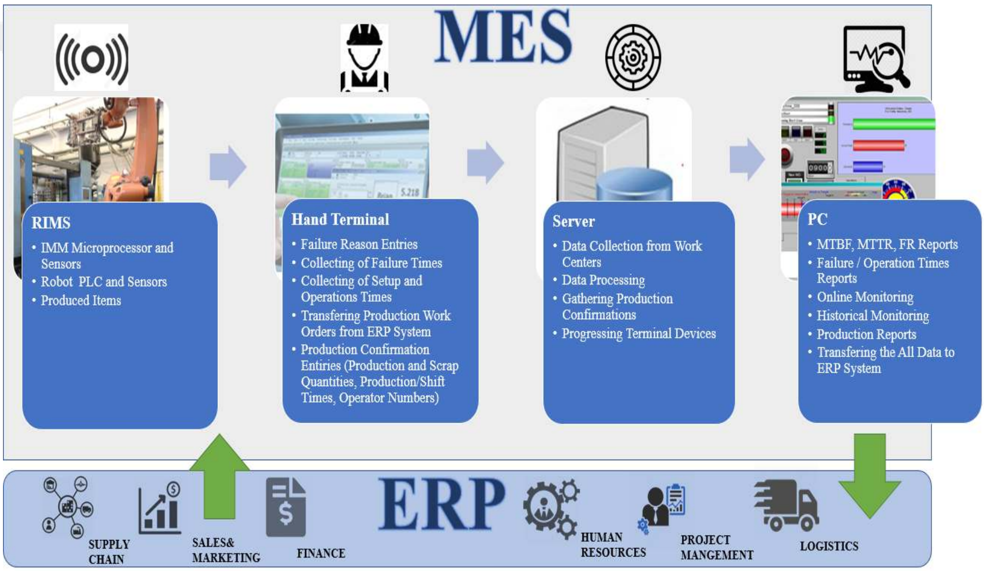


Figure 3.11. RIMS Data Flow between MES and ERP System

3.2. Method

3.2.1. Structure of FMEA

FMEA performs the identification, prioritization, and elimination of potential failures, problems, and errors in the systems, products, or processes before they reach customers. It also provides a systematic method to examine all the possible ways in which failure could occur. Studied FMEA application steps can be seen in Figure 3.12.

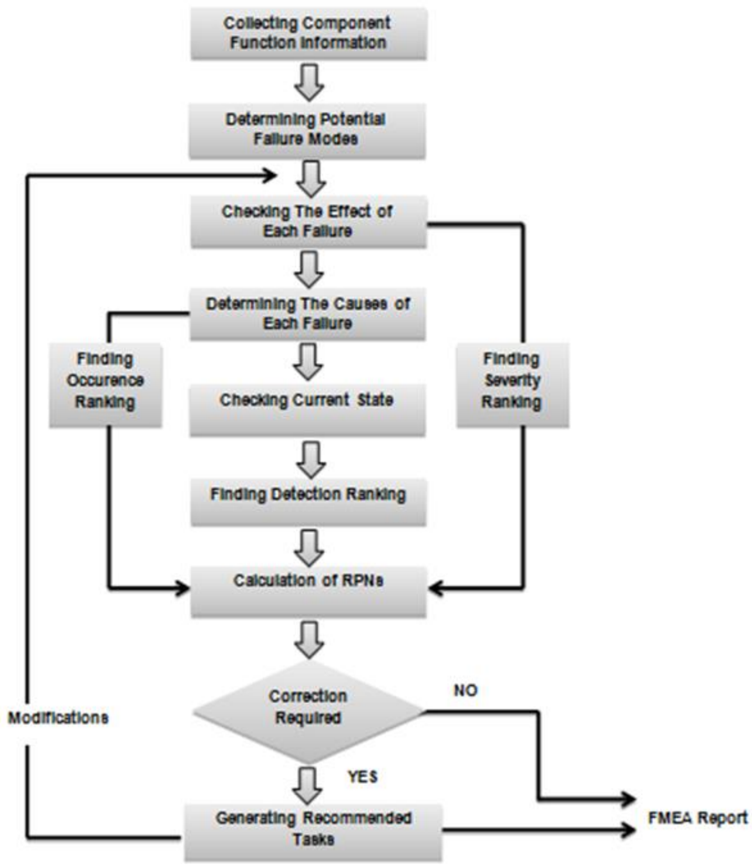


Figure 3.12. FMEA Flow Chart (Turedi, 2013)

FMEA is performed in several steps. The first step is to describe the product or process on which FMEA is conducted. Then, functions of the product or process are defined so that potential failure modes could be identified after all possible failure modes are obtained, the occurrence rating is assigned to the cause of the failure mode about probability of the cause. The degree of severity is assigned to the final effect of the failure mode to reflect the severity of the failure. Finally, detection rating is assigned to the cause of the failure mode to reflect the difficulty of detecting the cause or failure mode. Ratings are measured in integers ranging from 1 to 10 and then multiplied together to obtain the RPNs used to determine the risk priority of a failure mode.

Failure modes with higher RPNs are considered to have a higher risk of malfunction during operation so that corrective actions are taken to reduce the RPNs of these failure modes before others. If RPNs are not reduced as expected, new corrective actions can be designed until the purpose is accomplished (Xie, 2013).

Occurrence: Occurrence is the chance that one of the specific causes are occured. This must be done for every cause listed. Reduction or removal in occurrence rating must not come from any reasoning except for a direct change in the system. The likelihood of occurrence is based on a 1-to-10 scale, with 1 being the least chance of occurrence and 10 being the highest chance of occurrence. In this study, MTBF has been considered dealing with measurement of failure causes.

Severity: Severity is the assessment of the seriousness of the potential failure mode's effect to the next component, sub-system, system, or customer if it occurs. It is important to realize that the severity applies only to the effect of the failure, not the potential failure mode. Reduction in severity rating must not come from any reasoning except for a direct change in the design. Severity should be rated on a 1-to- 10 scales, with a 1 being none and a 10 being the most severe.

Detectability: Detectability is an assessment of the probability that the proposed current process control will detect a potential weakness or subsequent failure mode before the part; component or operation leaves the manufacturing operation, assembly, or service location for process FMEA (Turedi, 2013).

3.2.2. Determination of FMEA Contents

FMEA content must satisfy the following requirements that are identification of known and potential failure modes, causes and effects of each failure modes, prioritizing the identified failure modes via RPN and providing corrective and improvement actions. Composed FMEA table in this study can be seen in Table 3.1 and required input data contents are stated in the table.

Table 3.1. Contents of FMEA Table

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
* Identification of component	* Determination of component functions	* Determination of functional failures	* Determination of failure modes	* Determination of failure causes	* Determination of failure effects	* Determination of severity rate from punctuation table	* Determination of occurance rate from punctuation table as MTBF	* Determination of detection rate from punctuation table	RPN=O*S*D

First step of the FMEA analysis, each system component has been observed, and potential failure mode and effects have been determined. Technical descriptions of the components, their functional principles, technical statements of the failure, and causes have been gathered for FMEA table preparations. The structure and its FMEA outputs must directly support maintenance, equipment, and operations management. Making brainstorming with operators and technical staff during information collections always facilitate an effective analysis structure.

3.2.3. Intelligent Data Processing and ANN

3.2.3.1. Types of Data

Data collection systems need to know the type of data handled. The two most important types of data for failure type detection and predictive actions are collected by sensors and log files.

Sensor Data: Sensors have become smarter, smaller, easier to implement in existing systems, as well as cheaper and more reliable. A sensor converts physical values into electrical values (voltage, current, or resistance). Usually, one measures one mechanical value: for example, the mechanical values of acceleration, pressure, flow, torque, and force. With this mechanical value, one can interpret the vibration data, acoustic data, temperature, humidity, weather, altitude, etc. Data falls into three categories: Value type is the data collection over a given time period where tracking variables have a single value. Waveform type is the data collection where the tracking variables are a series of times commonly called the time waveform. For example, vibration and acoustic data are of the waveform type. Multidimensional type is the data collection over a while where tracking variables are multi-dimensional. The most common multi-dimensional data are infrared thermography, X-ray images, visual images and image data, etc.

Log Files: Events of a system can be recorded in a log file. In this way, the statement of an event is very broad. A changed value could be such an event as it carries out a maintenance action. Log files can only contain fused sensor values. Descriptive log files can be written describing maintenance actions by people, or any malfunction or error detected (Jahnke, 2015).

3.2.3.2. Types of ANNs

There are many other types of NNs. The overall function or functionality achieved is determined by network topology, individual neuron features, learning or education strategy, and training data. Here, some of the most used types of ANNs are Feed-Forward Neural Networks (FFNN), Recurrent Neural Networks (RNN), Radial Basis Function Networks (RBFN), and Self-Organizing Maps (SOM).

FFNN is the first, simplest, and widest used type. Information moves only forward from input nodes or neurons, hidden nodes to output nodes, as shown in Figure 3.13. The universal approximation theorem defines that every continuous function that maps the ranges of real numbers to an output range of real numbers can be arbitrarily zoomed by only one hidden layer by an FFNN. This result is valid only for limited transfer function classes, for example, sigmoidal functions.

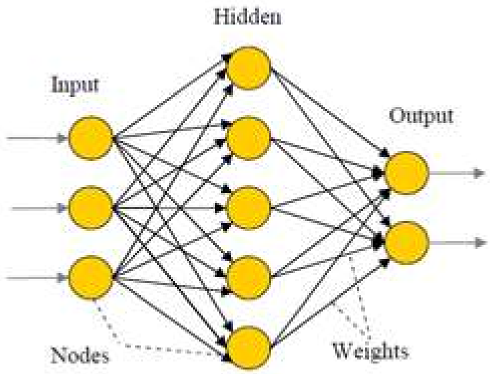


Figure 3.13. Feed-Forward Neural Network (Heng, 2009)

An FFNN with sigmoidal transfer functions is selected for use in the proposed prognostic model. As noted, the universal approximation theorem for NNs states that every continuous function that matches the ranges of real numbers with some output ranges of real numbers can be arbitrarily zoomed by an FFNN with only one hidden layer. This result applies only to classes of limited transfer functions, and sigmoidal functions are one of these classes. RNNs are potentially more powerful than FFNNs, due to their ability to recognize and recall temporal and spatial patterns. However, the behavior of RNNs is much more complex than that of FFNNs. For a given input and an initial network output, the response of an RNN may converge to a stable output. However, it may also oscillate, explode to infinity, or behave chaotically. RBFNs, due to their non-linear approximation properties, can model complex mappings, which normal FFNNs can only model utilizing multiple intermediary layers. However, there is considerable difficulty in deciding the centers and the standard deviations of the RBF activation functions. The vectors in training data need to be manually examined. SOMs are unsupervised learning networks and are more suitable for visualizing high-dimensional data. FFNN, on the other hand, is a supervised learning network.

The capability of supervised learning networks is significantly greater than that of unsupervised learning networks. For failure prognosis, the most important factor is accuracy, and the network must be trained with targets that are as close to the actual values as possible (Heng, 2009).

3.2.3.3. ANN Training

The characteristic of the ANNs that draw the most attention is their learning abilities. ANNs can be trained to perform certain tasks. Training of ANNs consists of two phases that are processing and learning phases.

At the processing phase, an input vector is fed through the input nodes to the hidden nodes. Each hidden node performs a weighted sum of its inputs, applies an activation function to this aggregation, and passes the result to the output layer. Assuming there is l layer in an ANN, with l and l −1 denoting the upper and lower layers respectively, the result or output of a node in layer l is obtained in the following equation.

$$x_i^{(l)} = f\left(\sum_{j=1}^{n} w_{ij} x_j^{(l-1)} + b_j^{(l-1)}\right) \qquad \text{Eq.3.1}$$

where j is the index and n is the number of nodes in layer l −1, with l ≤ j ≤ n, i is the index of nodes in layer l, ij w is the weight connecting a node i in layer l to a node j in layer l −1, (l−1) j x is the activation of node j in layer l −1, (l−1) j b is the bias and f is the transfer function. A transfer function is a mathematical representation of the relationship between a neuron's net output and its actual output. There are many different transfer functions, with the three most commonly used ones being the hard-limit, linear, and log-sigmoid transfer functions.

After the processing phase, learning takes place. The result or output is compared with the target, and the difference or error is propagated back through the preceding layers and the weights are adjusted based on this error. By continuously feeding the training vectors and adjusting the weights, the error can be minimized and a relationship between the inputs and targets can be found. After the error converges, whenever relevant data are inputted to the network, the network can produce an output based on what it has learned (Heng, 2009).

3.2.3.4. Comparison of Multilayer Neural Network Training Algorithm Functions

Training algorithms are chosen according to several factors. Leading factors are the complexity of the problem, number of data, number of weights, and biases in the networks, error goal, and estimation precision. Functional approximation or pattern recognition purposes influence choosing the type of learning algorithm. The following table lists the algorithms that are commonly used in MATLAB analysis software as shown in Table 3.2.

Table 3.2. Most Frequently Used Training Algorithms (Beale et. all, 2017)

Acronym	Algorithm	Description
LM	trainlm	Levenberg-Marquardt
BFG	trainbfg	BFGS Quasi-Newton
RP	trainrp	Resilient Backpropagation
SCG	trainscg	Scaled Conjugate Gradient
CGB	traincgb	Conjugate Gradient with Powell/Beale Restarts
CGF	traincgf	Fletcher-Powell Conjugate Gradient
CGP	traincgp	Polak-Ribiere Conjugate Gradient
OSS	trainoss	One Step Secant
GDX	traingdx	Variable Learning Rate Backpropagation

The LM algorithm has the fastest convergence on function approximation problems for networks up to a few hundred weights, and this is advantageous or accurate training requirements. LM algorithm often releases lower mean square errors than the others. Besides, the performance decreases when the number of weights increases in the network, but relatively poor on pattern recognition problems, and storage requirements are higher than the other algorithms.

Regarding pattern recognition problems the RP algorithm or trainrp function is the fastest algorithm. However, it has poor performance on function approximation. If the error goal is low, the performance degrades. The storage requirements are relatively small compared with the others. The SCG algorithm can perform well for many different problems with a high number of weights. The speed of the SCG is almost the same with the LM on function approximation problems and it can be faster for large networks. Its performance does not decrease as quickly as trainrp performance when the error goal is decreased. The CGB algorithms are required moderate memory sizes. The performance of BFG performs similarly to the LM algorithm. It does not even need the same storage as LM. However, it is required complex computation since the inverse matrix equivalent must be computed at each iteration.

The variable learning rate of the GDX algorithm is usually much slower than the others, and it is required the same storage with RP (Beale et. all, 2017).

The choosing of the training algorithm is determined according to analyzed system specifications, data structure, data size, convergence needs, error goals, and performance speed requirements. All factors can be well-matched with algorithm performances to reach optimum solutions.

3.2.3.5. Levenberg Marquardt Algorithm

The LM algorithm is one of the most widely used algorithms of the second order for the training of neural networks about industrial data processing. Its performance is found to be better than first-order algorithms and some other second-order gradient methods. This algorithm is available in MATLAB as a built-in function and its advantages have been shown by many studies like Sehgal and Meenal, Yılmaz et al. and Kipli et al. (2012). This algorithm is also the fastest method for training moderate-sized feed-forward neural networks, can be up to several hundred weights. Also, the network trainlm can train any network by using derivative functions with weight, net-input, and transfer functions (Kipli et. all, 2012).

3.2.4. ANN Learning Algorithms

3.2.4.1. Data-Driven Models of Machine Learning and Intelligent Data Processing

Statistical and data learning techniques are the essentials for the data-driven models. Learning techniques of machine learning involves developing software that optimizes a performance criterion based on historical data and/or experience. With the increasing number of sensors in the real-world system, the probability of perceiving its behavior and current situation increases. Therefore, most of the approaches to failure detection and predictive actions in recent literature explain data-driven models. The algorithms behind the data-driven models are determined from the given data. There are three different learning techniques: Supervised, Unsupervised, and Reinforcement Learning.

3.2.4.2. Supervised Learning

Supervised learning uses data collected from the real-world system in the past. Since all collected data records cannot be used as learning examples, must be filtered. Each exercise data record is labeled according to the expected result. The resulting dataset is called training data. Since the historical data is used and a real-world system is considered. A supervised learning technique is the most used technique for failure type detection and preventive actions. Real-world historical data improves accuracy in operating of an online system (Figure 3.14).

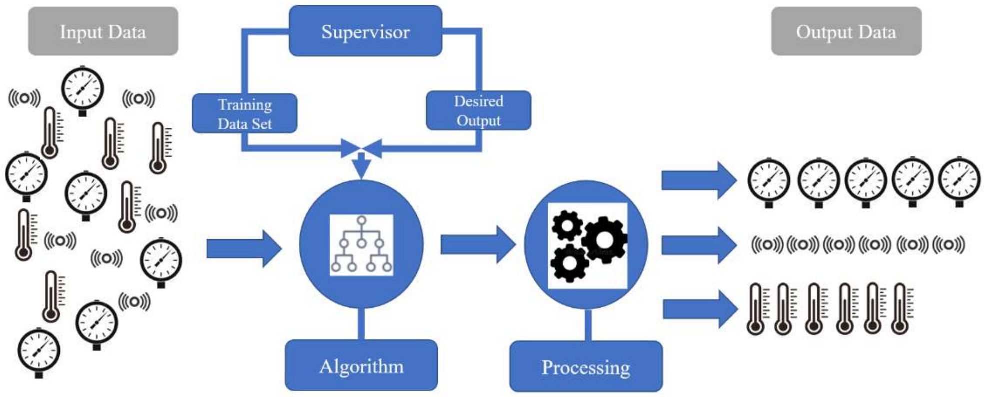


Figure 3.14. Supervised Learning

3.2.4.3. Unsupervised Learning

The scope of unsupervised learning is to find identical or similar sample groups within historical data. This process is called clustering. The unsupervised learning approach may be determined the distribution of data within an input space in a process called density estimation (Figure 3.15). For precise failure type detection and predictive problems, the unsupervised learning technique is unusual because the clustering and density prediction of historical data are not effective (Jahnke, 2015).

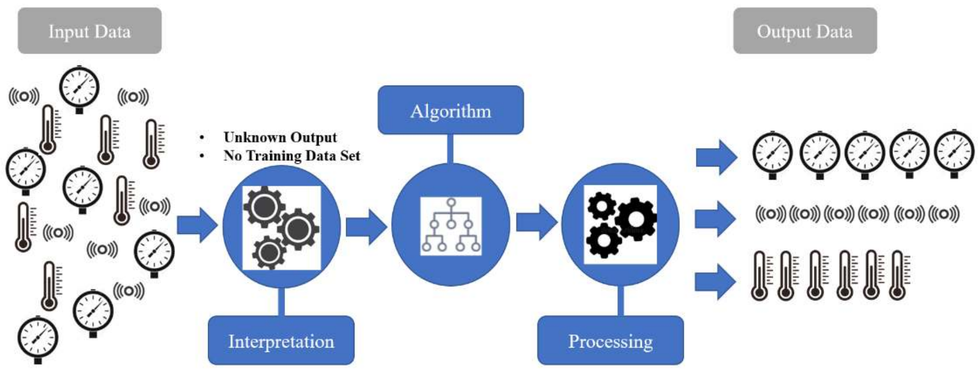


Figure 3.15. Unsupervised Learning

3.2.4.4. Reinforcement Learning

The reinforcement learning technique is used for reaching a suitable result for the given input data. Unlike other learning techniques, it doesn't evaluate historical data. Therefore, the machine learning algorithm is based on a trial-and-error scheme. At the beginning of the learning phase, a machine learning algorithm defines a data-driven model concerning some aspects. Consequently, aspects of the machine learning algorithm that define the data-driven model should also be defined. This model creates a result based on the data available in the real-world system, as shown in Figure 3.16.

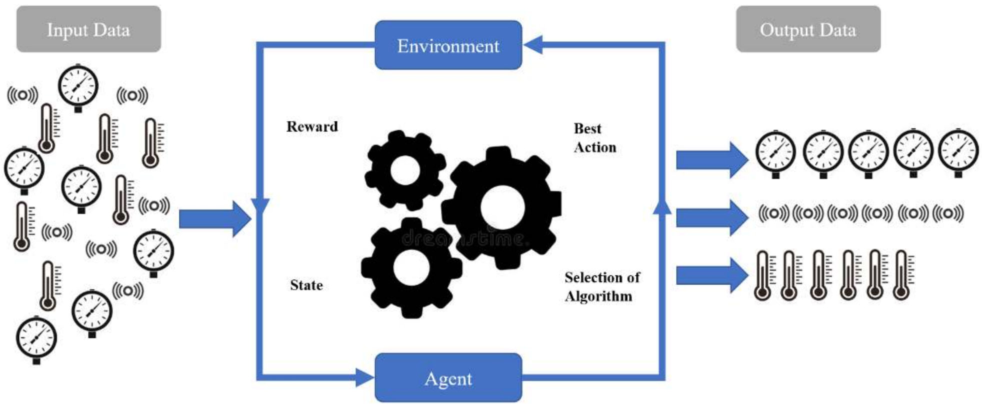


Figure 3.16. Reinforcement Learning

Some applications use combinations of a data-driven model with a supervised learning technique and an expert model. These models attempt to use the field knowledge of an expert model in conjunction with the collected real-world information of data-driven models for achieving better results. A decision tree can help find and select the right model for a specific type of error detection and predictive problems as seen in Figure 3.17 (Jahnke, 2015). Proposed learning model has been taken in the consideration as supervised learning model according to the decision tree that is derived based on historical system and process data.

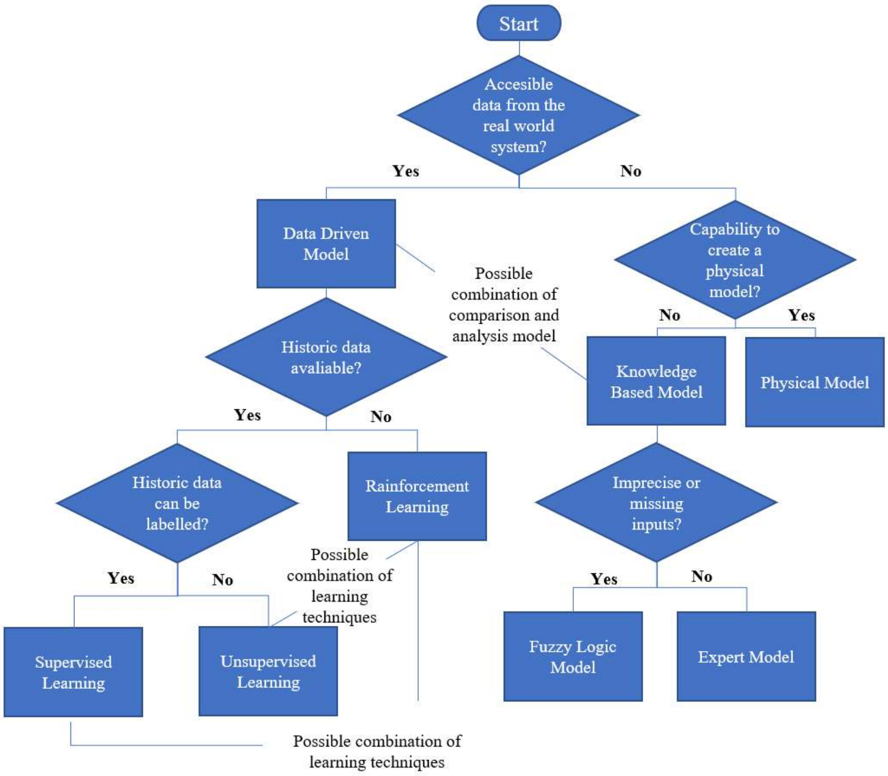


Figure 3.17. Decision Tree for Failure Type Detection and Predictive Actions

4. RESULTS AND DISCUSSIONS

4.1. Reliability Analysis of RIMS

4.1.1. Identification of Equipment Based Failure Sources

Failures of RIMS have been identified in two groups according to the design and process principles of equipment that contain mechanical and hydraulic failures. In this study, human-sourced failure causes have not been considered in RIMS failure root cause and mode effect examinations, so the human factors have been taken as well qualified and the analysis has been only focused on the component failures. The mechanical and hydraulic equipment group, shown in Figure 4.1., FMEA have been considered as toggle clamp unit, injection unit, screw and barrel, hydraulic cylinders, pressure-directional-flow control valves, hydraulic lines, heat exchanger, hydraulic motor, hydraulic pump, conveyor, and six-axis manipulator robot. A manipulator robot has been taken in the mechanical equipment group, since only its mechanical functions and regarding failures have been analyzed dealing with its effects on RIMS performance. Detail of IMM is shown in Figure 4.2 including both hydraulic and mechanical equipment that significantly affect the overall RIMS reliability. Turedi A. (2013) studied hydraulic IMM failures based on mechanical and hydraulic equipment in a detailed Ishikawa Diagram. Here, all main and subcomponents are taken into consideration in the manner of technical principle of hydraulic driven IMM.

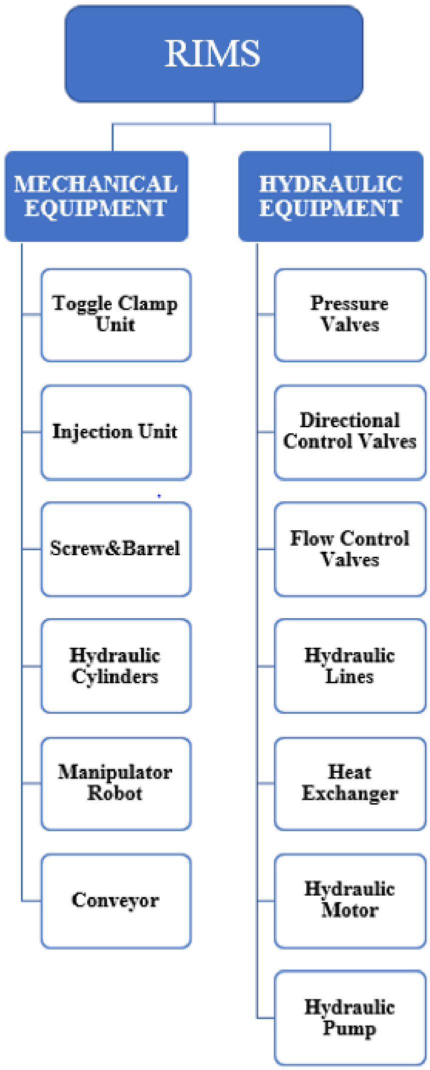


Figure 4.1. Equipment Classification of RIMS

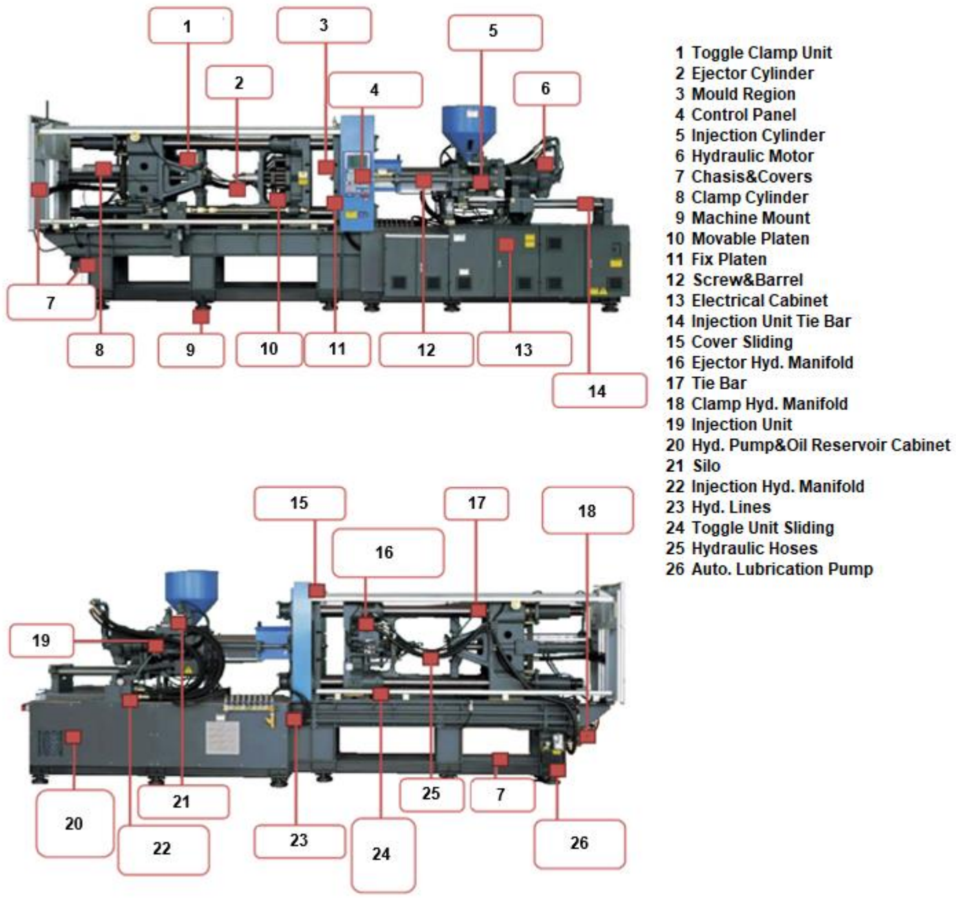


Figure 4.2. Hydraulic and Mechanical Components of IMM

4.1.2. FMEA of RIMS

Each failure mode of equipment has been sequentially numbered and identified in the FMEA structure. These numbers have been used as a failure mode pointer and referenced on the FMEA punctuation form. The failure mode indicators use indices for evaluation of the criticality that each mode represents for the process. The factors for components evaluation consist of a series of criteria used to evaluate the criticality or risk priority. Described failure modes have been numbered with identical and distinct numbers, are used in RPN calculations. Eventually, the analysis results could be easily discussed with these notations. The failure punctuation table, shown in Table 4.1, presents the determined considerations of failure severity, occurrence, and detection values in this study.

Table 4.1. Considered Failure Punctuations

Severity		Occurrence (MTBF in hr)	
1	Very insignificant effect, the failure can be corrected immediately by the production team	**1**	78894<MTBF
2	Insignificant effect, the failure can be corrected immediately by the maintenance team	**2**	61362<MTBF<78894
3	Very insignificant effect, the failure can be corrected immediately by the production team	**3**	43830<MTBF<61362
4	Moderate effect, the component does not properly work, and its maintenance operations does not cause machine stoppage	**4**	26298<MTBF<43830
5	Moderate effect, the component does not properly work, and its maintenance operations cause machine stoppage	**5**	17532<MTBF<26298
6	Moderate effect, the component does not properly work, and its maintenance operations cause machine stoppage for one day or less	**6**	8766<MTBF<17532
7	Critical effect, the component does not properly work, and its maintenance operations cause machine stoppage for more than one day	**7**	4383<MTBF<8766
8	Very critical effect, the component does not properly work and the failure broadly interrupts the all system functions	**8**	2192<MTBF<4383
9	Very critical effect, the failure causes almost collapse of all system	**9**	1096<MTBF<2192
10	Catastrophic effect, the failure can cause damages the properties or accidents	**10**	0<MTBF<1096
Detection			
1	Failure can be notified directly by the instrumentation		
3	Failure can be identified by the production team in daily inspections		
5	Failure can be identified via abnormal vibrations and noises, or indirectly by the instrumentation		
7	Unexpected failure, impossible to be identified by the machine operator		

Severity, Detection and Occurrences have been executed and defined in the manner of MTBF times based on experienced performance rates. Calculated RPN's with the reference of the determined of Severity, Occurrence, and Detection has been evaluated in RPN comparison charts as can be seen in the following sections. These charts indicate the functional relationships between the RPN and failure modes. RPN is calculated by multiplying the severity, occurrence, and detection rankings for each item. The general mechanism of RPN calculation can be seen in Figure 4.3. Besides the RPN calculations, reached concurrency values will be the criteria for discussion of RIMS reliability in the following steps of the study.

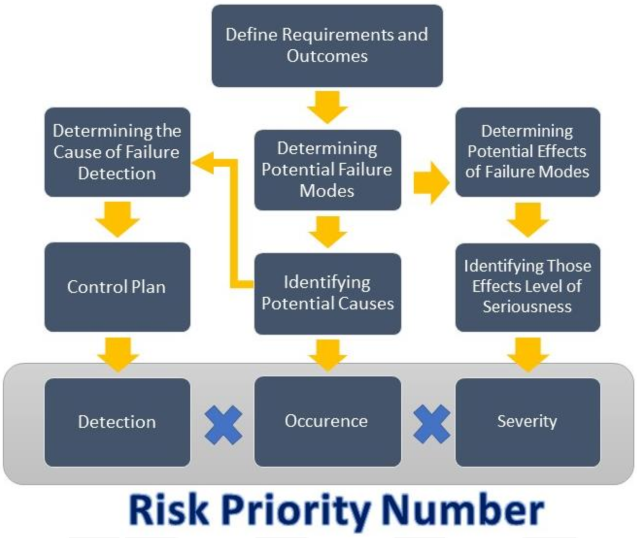


Figure 4.3. RPN Structure

In the following sections, evaluation of related failures, modes, and effects can be found for each equipment with RPN calculations in related FMEA tables. In these tables, mechanical and hydraulic equipment are categorized based on classification discussed in Figure 4.1. FMEA data has been created with all details that involve the duties of equipment in the main system and chain of potential failure modes, causes, and effects by using common technical terminology. The reached FMEA structure and outputs also support the generation of a troubleshooting manual dealing with RIMS and any similar hydraulic-driven industrial systems.

4.1.2.1. FMEA of Mechanical Equipment

FMEA tables, from Table 4.2. to Table 4.7. can be seen as mechanical equipment and its related potential failure modes, causes, and effects.

Table 4.2. FMEA Table of Toggle Clamp Unit

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
1.TOGGLE CLAMP UNIT	Generating Clamping Force	Mold can not be mount on the platen slots	1.1 Platens Surface Cracks	1. Mechanical fatigue 2. Thermal fatigue 3. Operation with unsuitable mold geometry 4. Operation with excessive clamping force 5. Corrosion	Risk that the platen can be out of the service	9	3	5	**135**
		Movable platen can not be reciprocated	1.2 Movable Platen Sliding Way Wear&Cracks	1. (1.1) 2. Material failures 3. Automatic grease lubrication system failures 4. Looseness on the sliding way stoppers 5. (1.5)	Risk that the mechanism can be out of the service	9	3	5	**135**
		Mold can not be mount on the plate holes	1.3 Platens Screw Thread	1. Excessive torsional force application on bolt mounting 2. (1.5)	Risk that the platen can be out of the service	9	3	7	**189**
		The clamp unit mechanism can not be operated	1.4 Toggle Joint Arm Cracks	1. (1.1) 2. (2.2) 3. Manufacturing failures	Risk that the mechanism can be out of the service	10	3	7	**210**
		The clamp unit mechanism can not be operated	1.5 Toggle Joint Rod Cracks&Wears	1. (1.1) 2. (2.2) 3. (4.3) 4. Unsuitable joint lubrication grove design 5. (1.5)	Risk that the mechanism can be out of the service	10	3	7	**210**
		The clamp unit mechanism can not be operated	1.6 Toggle Joint Bush Cracks&Wears	1. (1.1) 2. (2.2) 3. (4.3) 4. unsuitable bush locking design 5. (2.3)	Risk that the mechanism can be out of the service	10	4	7	**280**
		Tie bars can not be efficiently lubricated	1.7 Tie Bars Surface Wear	1. Surface coating materials fatigue 2. (2.3)	Risk that the mechanism can be out of the service	9	4	7	**252**
		Movable platen can not be reciprocated	1.8 Tie Bar Misalignment	1. (1.1) 2. Tie bar tightining nuts looseness 3. Movable platen bush wears&cracks	Risk that the mechanism can be out of the service	9	4	7	**252**
		The clamp unit mechanism lubrication can not be provided	1.9 Automatic Grease Lubrication System Pump Failures	1. Inadequate oil level in the oil tank 2. Suction line blockage 3. Pump electrical motor failues 4. Pump mechanical failures	Risk that the joints bush, sliding ways and rods can not be lubricated	9	4	7	**252**
		The clamp unit mechanism lubrication can not be provided	1.10 Automatic Grease Lubrication System Line Failure	1. Line blockage 2. Line check valves blockage 3. Line check valves spring crack 4. Nozzles blockage 5. Nozzles mechanical cracks&deformations 6. Lines mechanical deformations	Risk that the joints bush, sliding ways and rods can not be lubricated	9	4	7	**252**
		Decrease on the lubrication properties of the grease oil	1.11 Grease Oil Failures	1. Additives failures 2. Oxidation 3. Excessive temperatures 4. Contamination (particle or water)	Risk that the joints bush, sliding ways and rods can not be lubricated	9	3	7	**189**

Table 4.3. FMEA Table of Injection Unit

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
2.INJECTION UNIT	Providing Plasticization & Injection	The screw can not be drived	2.1 Hydraulic Motor Coupling Element Crack	1. Mechanical fatigue 2. Material failures 3. Misalignments after assembling 4. Corrosion	The injection process can not be operated	9	4	7	**252**
		The screw can not be drived	2.2 Hydraulic Motor Thrust&Radial Bearing Set Failures	1. Path interpretations 2. Surface wear (abrasive particle,vibration,inadequate lubrication) 3. Indentation (faulty mounting&overloading,foreign particles) 4. Smearing 5. (1.4) 6. Flaking (misalignment,overloading,compression,rust) 7. Cracks 8. Improper or over lubrication 9. Insufficient lubricant type and viscosity 10. Manuel lubrication system and line failures 11. Grease oil failures 12. Sealing element failures 13. Improper mounting	The injection process can not be operated	9	4	7	**252**
		Tie bars can not be efficiently lubricated	2.3 Unit Tie Bars Wear	1. Surface coating materials wear 2. (2.10)	The unit can not be moved for injection	9	5	3	**135**
		The unit stability can not be proved	2.4 Unit Connection Bolts Crack	1. (1.1) 2. Excessive torsional force application on bolt mounting 3. (1.4)	The unit can be misaligned	9	5	5	**225**
		The inj. unit mechanism lubrication can not be provided	2.5 Auto. Grease Lubrication System Pump Failures	1. Inadequate oil level in the oil tank 2. Suction line blockage 3. Pump mechanical failures	Risk that the bearing set and the unit tie bars can not be lubricated	9	5	5	**225**
		The inj. unit mechanism lubrication can not be provided	2.6 Manuel Grease Lubrication System Line Failure	1. Line blockage 2. Line check valves blockage 3. Line check valves spring crack 4. Nozzles blockage 5. Nozzles mechanical cracks&deformations 6. Lines mechanical deformations	Risk that the bearing set and the unit tie bars can not be lubricated	9	5	5	**225**
		Decrease on the lubrication properties of the grease oil	2.7 Grease Oil Failures	1. Additives failures 2. Oxidation 3. Excessive temperatures 4. Contamination (particle or water)	Risk that the bearing set and the unit tie bars can not be lubricated	9	7	5	**315**

Table 4.4. FMEA Table of Screw& Barrel

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
3.SCREW& BARREL	Feeding the Material to the Mold	The raw material can not be efficiently injected and the finished product quality is low	3.1 Screw Surface Failures	1. Material surface wears & microcracks 2. Untolarable dimentional changes	Performance of the screw can be decreased	9	4	5	**180**
		The raw material can not be efficiently injected and the finished product quality is low	3.2 Screw Body Failures	1. Body branching off 2. Rocket head cracks 3. Rocket head wears 4. Body misalignment 5. Hydraulic motor input shaft spline cracks	Risk that the screw can be out of the service	9	4	5	**180**
		The raw material can not be efficiently injected and the finished product quality is low	3.3 Barrel Inner Surface Wears	1. Material surface wears 2. Untolarable dimentional changes	Performance of the screw can be decreased	9	4	5	**180**
		The raw material can not be efficiently injected and the finished product quality is low	3.4 Barrel Body Failures	1. Nozzle&flange cracks 2. Nozzle&flange screw thread cracks 3. Hydraulic motor connecting screw thread cracks 4. Thermocouple screw thread cracks	Risk that the barrel can be out of the service	9	4	5	**180**

Table 4.5. FMEA Table of Hydraulic Cylinders

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
4.HYDRAULIC CYLINDERS	Converting Hydraulic Power into Linear Mechanical Force	The dynamic functions of the piston can not be operated	4.1 Piston Rod Failures	1. Surface coating materials wear 2. Rod material fatigue 3. Rod material crack 4. Screw thread cracks 5. Screw thread wears 6. Misalignments	Risk that the system functions can be out of the service	9	6	5	**270**
		The dynamic functions of the piston can not be operated	4.2 Piston Head Failures	1. Piston head crack 2. Piston head wear 3. Sealing elements failures 4. Piston road connecting thread cracks 5. Sealing element slot deformations	Risk that the system functions can be out of the service	9	6	5	**270**
		The dynamic functions of the piston can not be operated	4.3 Piston Barrel Failures	1. Inner surface coating materials wear 2. Body cracks 3. Outer surface corrosions	Risk that the system functions can be out of the service	9	10	5	**450**
		The dynamic functions of the piston can not be operated	4.4 Piston Body Failures	1. Piston flanges cracks 2. Piston flanges wears 3. Flange mounting bolts cracks 4. Inlet&outlet ports fittings failures 5. Body misalignment 6. Body cracks 7. Sealing elements failures 8. Corrosion	Risk that the system can be out of the service	9	6	5	**270**
		The lose of the stability of the piston body on the mechansim	4.5 Piston Connecting Elements Failures	1. Bolts&screws cracks 2. Joints cracks 3. Flanges cracks 4. (4.8)	Risk that the system can be out of the service and risk of accidents	9	9	5	**405**

Table 4.6. FMEA Table of Manipulator Robot

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
5. MANUPILATOR ROBOT	Automatic Mounting of the Inserts to the Molds	The dynamic functions of the system can not be controlled on gripper	5.1 Pneumatic Valve Failures	1. Spool mechanism failure 2. Valve body deformation 3. Ports wear 4. Coil failure	Risk that the system functions can be out of the service	5	6	7	**210**
		The dynamic functions of the system can not be controlled on gripper	5.2 Pneumatic Line-Piston Failures	1. Piston head crack 2. Piston road crack 3. Piston body connection failures 4. Sealing element wear 5. Piston barrel inner surface coating wear 6. Piston rod thread crack 7. Gripper nail piston failures 8. Manifold blockage 9. Hose-fittings failures 10. Air preparation unit failures	Risk that the system functions can be out of the service	5	10	7	**350**
		The dynamic functions of the system can not be controlled on gripper	5.3 Pick-Place Mechanism	1. Nail crack 2. Nail piston misalignment 3. Losseness on nail screws and mounting holes 4. Poor nail design 5. Poor insert mounting spring design 6. Wear on spring 7. Poor spring support and alignment design 8. Losseness on spring supports 9. Losseness on screw connections of aluminium gripper body 10. Wears on gripper body	Risk that the system functions can be out of the service	7	10	7	**490**
		The dynamic functions of the system can not be controlled on insert tables	5.4 Servo-Belt Mechanism Failures	1. Servo motor failures 2. Timing belt mechanism failures 3. Table chasis misalignments 4. Table fixing pins failures 5. Position sensor failures 6. Linear guide and bearing wears	Risk that the system functions can be out of the service	9	5	7	**315**
		Axis repeatability inturruptions of robot motion	5.5 Axis Joint Failures	1. Axis servo failures 2. Loosenes on axis gear boxes 3. Wears on axis gear boxes bearings 4. Wears on axis gear boxes	Risk that the system can be out of service and risk of accidents	9	3	7	**189**
		Noise and vibration during axis motions	5.6 Axis Joint Failures	1. (5.4) 2. Wears on axis gear boxes sealing elements 3. Oil pollution on axis gear boxes 4. Cracks on arms 5. Loosenes on robot body supports 6. Unbalance of robot	Risk that the system can be out of service	9	3	7	**189**

Table 4.7. FMEA Table of Conveyor

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
6. CONVEYOR	Transmiting of Products from IMM to Finished Product Container	Misalignement of the body	6.1 Chasis Failures	1. Chasis connection bolts looseness 2. Chasis brakets and supports looseness 3. Guide/diverter metals failures 4. Bearing failures	Risk that the system functions can be out of the service	7	5	1	**35**
		The dynamic functions of the conveyor can not be done	6.2 Belt Failures	1. Belt tear 2. Belt wear 3. Pulling profile deformations 4. Belt connection cracks 5. Belt misalignment 6. Unsufficient belt material 7. Wrong belt assembly	Risk that the system functions can be out of the service	8	6	1	**48**
		The dynamic functions of the conveyor can not be done	6.3 Drive Train Failures	1. Gear box and motor failures 2. Pulley failures 3. Drum failures 4. Wrong drive train assembly 5. Incorrect element selection	Risk that the system functions can be out of the service	8	5	5	**200**

Interruptions or functional loss of gripper and insert tables are the most leading failures of manipulator robot with high occurrence rates. These are among the highest RPN results of all mechanical equipment groups that are involved in the FMEA analysis.

Functional losses and instabilities are critical failures about hydraulic cylinders. Besides the mechanical functions, hydraulic cylinders play critical roles in the hydraulic system performances in the manner of the transformation of hydraulic power to mechanical power. Reliability states of hydraulic cylinders mostly affect the service life and failure causes of the hydraulic members. Defined high occurrence rates of hydraulic cylinder failures are remarkable as can be clearly seen in Table 4.5. FMEA results.

The injection unit covers the process availability of the system due to its plasticizing duty. Screw-driven bearing system, connection losses between the hydraulic motor and bearing case, and grease oil caused failures on the screw-driven system are the most critical failures.

The toggle clamp unit holds the mold pairs and provides the required resistance force against high injection pressure to prevent the opening of mold pairs with complex arm and rod mechanism in the plastic injection stage of the process. Because of complex structure, maintenance and operational reliability of lubrication system by using low viscosity grease create important factor to eliminate wear, crack, and deformation on the links and joints. The critical failures figure out the improper lubrication system or lubricant caused mechanical failures as a whole. Especially, detection of any mechanical deformations on the toggle mechanism is very difficult and cause decrease of clamping precision or completely system losses that can cause high severity rates.

4.1.2.2. FMEA of Hydraulic Equipment

FMEA tables, from Table 4.8. to Table 4.14. can be seen as hydraulic equipment and its related potential failure modes, causes, and effects.

Table 4.8. FMEA Table of Pressure Valves

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
1.PRESSURE VALVES	Adjusting the System Pressure	Noisy valve operations	1.1 Excessive Noises	1. Valve creaking because of dirt on valve seat and worn valve body 2. Insufficient wetting 3. Noisy flow during operation 4. Unsuitable characteristic curve 5. Incorrect design	Risk that the valve breaks	8	7	5	**280**
		Pressure is under the set pressure on the manifold manometer	1.2 Too Low Pressure	1. Too low operating pressure set 2. Internal leakage 3. Dirty valve seat 4. Damaged valve seat 5. Broken valve spring 6. Unsuitable type and set	Disturbance in the system functions	8	7	5	**280**
		System functions are interrupted	1.3 Variations in Pressure and Delivery Flow	1. (1.1) 2. (1.2) 3. Insufficient control line 4. Unsuitable control valve	Disturbance in the system functions	8	7	5	**280**
		System functions are not stable	1.4 No Power Take-off or Too Slowly Turns since Insufficient or No Delivery Flow	1. Too low operating pressure set 2. (2.2) 3. (2.3&2.4) 4. (2.5) 5. (2.6) 6. Worn valve body and too high valve set	Disturbance in the system functions	8	7	5	**280**
		Oil temperature on the control panel display is above 50 C'	1.5 Excessive Operating Temperature	1. Too high delivery flow 2. (2.6) 3. Too high pressure set 4. Too long response time	Risk that the valve breaks	8	7	5	**280**
		Vibration&Noise on the hydraulic lines	1.6 Line Shocks when Switching Takes Place	1. Quick switches 2. Worn or damaged restrictors or orifices	Disturbance in the system functions	8	7	3	**168**
		Valve functions are not stable	1.7 Too Often Pump Switches	1. Worn setting of sequence valve or shut off valve	Disturbance in the system functions	8	6	3	**144**
		Oil is on the system surrounding	1.8 Oil Leakages	1. Worn head valve or opposed head valve 2. Constrained valve piston 3. Insufficient press on the closing of the valve 4. Body deformations 5. Bush&bearing failures 6. Worn or incorrect sealing elements 7. Worn or incorrect hose&fittings	System is under the risk of the out of service and risk of accident	9	7	3	**189**

Table 4.9. FMEA Table of Directional Control Valves

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
2 DIRECTIONAL CONTROL VALVES	Adjusting the System Pressure	Noisy valve operations	2.1 Excessive Noises	1. Valve creaking becuse of defective solenoid, or the voltage is too low 2. Worn valve due to defects anda dirts 3. Excessive flow 4. Variations on pilot pressure 5. Valve damping adjustment doesn't work	Risk that the valve breaks	8	7	5	**280**
		Pressure is under the set pressure on the manifold manometer	2.2 Too Low Pressure	1. Incorrect switched position 2. Defective solenoid 3. Internal leakage 4. Excessive flows 5. Spool jams and sticking	Disturbance in the system functions	8	7	5	**280**
		System functions are interrupted	2.3 Variations in Pressure and Delivery Flow	1. (1.1) 2. (1.2) 3. (1.3) 4. (1.4) 5. (1.5)	Disturbance in the system functions	8	7	5	**280**
		System functions are not stable	2.4 No Power Take-off or Too Slowly Turns since Insufficient or No Delivery Flow	1. (2.1) 2. (2.2) 3. (2.3) 4. (2.4) 5. (2.5) 6. Manually and incorrect operated valves	Disturbance in the system functions	8	7	5	**280**
		Oil temperature on the control panel display is	2.5 Excessive Operating Temperature	1. Too high leakage losses 2. Pressure circulation fails 3. (2.5)	Risk that the valve breaks	8	7	5	**280**
		Vibration&Noise on the hydraulic lines	2.6 Line Shocks when Switching Takes Place	1. Incorrect switching timing 2. Unsuitable type opening crossection changes	Disturbance in the system functions	8	7	5	**280**
		Speed of the cylinder functions are not stable	2.7 Uncontrolled Cylinder Works	1. Too fast switching time set 2. Leakage in valve since defective solenoid 3. Dirty valve	Disturbance in the system functions	8	7	3	**168**
		Oil is on the system surrounding	2.8 Oil Leakages	1. Deformed body 2. Bush&bearing failures 3. Worn or incorrect sealing elements 4. Worn or incorrect hose&fittings	System is under the risk of the out of service and Risk of accident	9	7	3	**189**

Table 4.10. FMEA Table of Flow Control Valves

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
3.FLOW CONTROL VALVES	Adjusting the System Flow Rate	Noisy valve operations	3.1 Excessive Noises	1. Valve vibration 2. Unsuitable valve 3. Operation flow noises 4. Incorrect valve characteristic curve 5. Incorrect design	Risk that the valve breaks	8	7	5	**280**
		System dynamics are not stable	3.2 Insufficient Power and Torque at the Power Take-offs	1. Excessive pressure losses 2. Internal leakage 3. Dirty or damaged valve seat 4. Broken spring 5. Wrong setting	Disturbance in the system functions	8	7	5	**280**
		System functions are interrupted	3.3 Pressure and Delivery Flow	1. (1.1) 2. Dirty valve body	Disturbance in the system functions	8	7	5	**280**
		System functions are not stable	3.4 No Power Take-off or Too Slowly Turns since Insufficient or No Delivery Flow	1. Too low through flow set 2. (1.2) 3. Blocked valve 4. Too high sequence valve setting 5. Valve is defective	Disturbance in the system functions	8	7	5	**280**
		Oil temperature on the control panel display is above 50 C°	3.5 Excessive Operating Temperature	1. Too low through flow set 2. Damaged valve 3. Too high pressure setting 4. Too long response time	Risk that the valve breaks	8	7	5	**280**
		Oil is on the system surrounding	3.6 Oil Leakages	1. Worn body 2. Bush&bearing failures 3. Worn or incorrect sealing elements 4. Worn or incorrect hose&fittings	System is under the risk of the out of service and Risk of accident	8	7	5	**280**

Table 4.11. FMEA Table of Hydraulic Lines

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
4.HYDRAULIC LINES	Transfering the Hydraulic Oil in the System	Noisy line equipment running	4.1 Excessive Noises	1. Blocked or leaking line 2. Worng dimension and desing of suction line 3. Defective pump charge 4. Too low fluid level 5. Loose and missing line mountings 6. Wrong layout of lines 7. Return outlet above fluid level 8. Blocked by pass filter 9. Blocked manifold and valves	Risk that the line equipments breaks	8	8	3	**192**
		Pressure decrease on the system line pressure	4.2 Too Low Pressure	1. Leakages 2. Excessive line resistance 3. Blocked suction filter 4. Blocked by pass filter 5. (1.1) 6. (1.9)	Disturbance in the system functions	8	8	3	**192**
		Fluctuation on the system line pressure	4.3 Variations in Pressure and Delivery Flow	1. 1.1 2. Interrupted flow due to installation 3. (2.2) 4. (1.8) 5. (1.9)	Disturbance in the system functions	8	8	3	**192**
		Interruption on the system line pressure	4.4 No Power Take-off or Too Slowly Turns since Insufficient or No Delivery Flow	1. (2.1) 2. (2.2) 3. (2.3) 4. (2.4) 5. 1.1 6. (1.9)	Disturbance in the system functions	8	8	3	**192**
		Oil temperature on the control panel display is above 50 C'	4.5 Excessive Operating Temperature	1. Frictional resistances due to small line dimensions 2. (2.3) 3. (1.9)	Risk that the line equipments breaks	8	7	3	**168**
		Foam in the oil reservoir	4.6 Hydraulic Fluid Foaming	1. Leakages on suction line 2. (1.4) 3. Incorrect reservoir usage 4. (1.7) 5.Vortex effect due to wrong layout of lines	Disturbance in the system functions	8	7	3	**168**
		Vibrant line equipment running	4.7 Line Shocks due to Switching	1. Looses and missings on lines	Risk that the line equipments breaks	8	6	3	**144**

Table 4.12. FMEA Table of Heat Exchanger

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
5.HEAT EXCHANGER (TUBE TYPE)	Cooling the Hydraulic Oil	Water is on the surrounding of the system	5.1 Water Leakage	1. Fittings looseness on water lines 2. Worn or incorrect gaskets&fittings 3. Deformed water hoses 4. Deformed hose connections 5. Cracked line elements 6. Cracked welded sections 7. Formation of corrosion	Risk that the oil temperature increasing and risk of the electrical system breaks	8	7	3	**168**
		Oil is on the surrounding of the system	5.2 Oil Leakage	1. Looses on hydraulic lines 2. Deformed sealing elements 3. Deformed hoses 4. Incorrect reservoir tank line connections 5. Deformed reservoir tank lines and sealing elements 6. (1.5) 7. (1.6) 8. (1.7)	System is under the risk of the out of service and risk of accident	8	7	3	**168**
		Oil temperature on the control panel display is above 50 C'	5.3 Excessive Operating Temperature	1. Blocked shell and tubes 2. Deformed internal body 3. Insufficient cooling water temperature 4. (1.7)	Risk that the hydraulic equipments breaks	9	8	3	**216**
		Vibrant running of the heat exchanger	5.4 Vibration	1. Looseness on body support and bracket parts 2. Cracked support and bracket parts 3. Incorrect inlet and return line connections	Risk that the heat exchanger is under the risk of the out of service	6	6	3	**108**

Table 4.13. FMEA Table of Hydraulic Motor

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
6.HYDRAULIC MOTOR	Pumping the Hydraulic Oil	Noisy hydraulic motor running	6.1 Excessive Noises	1. Worn moving surfaces 2. Vibration on direction system 3. Blocked inlet&outlet lines 4. Oil sourced failures 5. Output shaft failures	Risk that the motor breaks	8	3	5	**120**
		Running with inefficient operating torq	6.2 Too Low Pressure	1. Internal body leakages 2. Worn internal running surfaces 3. High internal body friction 4. (1.4)	Disturbance in the system functions	8	3	3	**72**
		Hydraulic motor outlet rotation is fluctuated	6.3 Variations in Pressure and Delivery Flow	1. Scratch formations on cylinders inner body surfaces 2. Lower rotational speed than optimum range 3. (1.4)	Disturbance in the system functions	8	3	3	**72**
		Interrupted hydraulic motor running	6.4 No Power Take-off or Too Slowly Turns since Insufficient or	1. (2.1) 2. (1.1) 3. (2.3) 4. Loss of power	Disturbance in the system functions	8	3	3	**72**
		Oil temperature on the control panel display is above 50 C°	6.5 Excessive Operating Temperature	1. Overall body wear and deformations 2. (2.3) 3. (2.1) 4. (1.4)	Risk that the motor breaks	8	3	3	**72**
		The motor functions are	6.6 Line Shocks due to Switching	1. Out of measure forces 2. Lack of breaking	Disturbance in the system functions	8	3	3	**72**
		Oil is on the system surrounding	6.7 Oil Leakages	1. (5.1) 2. Bush&bearing failures 3. Worn or incorrect sealing elements 4. Worn or incorrect hose&fittings	System is under the risk of the out of service and Risk of accident	8	3	3	**72**

Table 4.14. FMEA Table of Hydraulic Pump

COMPONENT	COMPONENT FUNCTION	FUNCTIONAL FAILURE	FAILURE MODE	FAILURE CAUSE	FAILURE EFFECT	Severity	Occurrence	Detection	RPN
7.HYDRAULIC PUMP	Pumping the Hydraulic Oil	Noisy Pump running	7.1 Excessive Noises	1. Too high pump rotation 2. Excessive pump pressure 3. Worn pump charge 4. Worn or incorrect sealing elements on shaft and suction section 5. Overall body wear and deformation 6. Incorrect line connections 7. Vibration on directional system 8. Oil sourced failures 9. Drive shaft failures 10. Catridge failures	Risk that the pump breaks	9	6	5	270
		Pump outlet pressure on the manifold manometer is under the set pressure	7.2 Too Low Pressure	1. Internal body leakages 2. Incorrect pump selection 3. (1.5) 4. Too low pressure set 5. (1.6) 6. (1.8) 7. (1.10) 8. Suction filter failures	Disturbance in the system functions	9	6	5	270
		Pump outlet pressure is fluctuated and system functions are interrupted	7.3 Variations in Pressure and Delivery Flow	1. Pump control system failures 2. (1.5) 3. Other hydraulic system elements and settings 4. Incorrect pilot valve selection 5. (1.8) 6. (1.10)	Disturbance in the system functions	9	6	5	270
		Pump outlet pressure&flow rates are interrupted	7.4 Power Take-off either does not turn at all, or - too Slowly (insufficient or no delivery flow)	1. (2.1) 2. (1.10) 3. (1.6)	Disturbance in the system functions	9	6	5	270
		Oil temperature on the control panel display is above 50 C'	7.5 Excessive Operating Temperature	1. (1.5) 2. (3.1) 3. Excessive rotational speed 4. (1.8) 5. (1.10) 6. (2.8)	Risk that the pump and valves breaks	9	6	5	270
		Foam in the oil reservoir	7.6 Foaming of Hydraulic Fluid	1. (1.4) 2. Return outlet above fluid level 3. (1.8)	Risk that the pump and valves breaks	9	6	5	270
		Pump functions are not stable	7.7 Often Pump Switches	1. (1.5) 2. (1.10)	Risk that the pump breaks	9	6	5	270
		Oil is on the system surrounding	7.8 Oil Leakages	1. (1.5) 2. Worn or incorrect sealing elements 3. Worn or incorrect hose&fittings 4. Bush&bearing failures	System is under the risk of the out of service and risk of accident	10	6	5	300

RPN results of pressure valves of RIMS point out that noisy operation, low pressure, interrupted/unstable system functions, and high hydraulic oil temperature are the most critical and frequent failures, as indicated in Table 4.8. FMEA table. Noisy operation, unstable system pressure and functions, high hydraulic oil temperatures, and vibration on the lines are the most critical experienced failures for directional control valves-based malfunctions. If FMEA results of flow control valves are examined, failures and modes can be seen as similar to pressure, and directional control valves.

Hydraulic lines contain steel pipes, rubber hoses, connection fittings, and parts that create the power transmission circuit of the overall hydraulic system.

Blockages and leakages are most common failures on hydraulic lines, connection and sealing elements on the lines.

Shell and tube heat exchanger, is used in the examined hydraulic system for cooling and stabilizing the oil temperature within the advised clearances to maintain possible long hydraulic oil life, is the most critical equipment. Heat exchanger blockages and fouling are the leading failures that contain high severity levels.

The radial type hydraulic piston motor is used to transform hydraulic power to mechanical power that operates under high hydraulic pressure inputs and high mechanical torque outputs. During the process cycles of the system, fluctuating resistance and impacts generated by driving injection molding screw and changing phases of molten plastic surrounded the screw cause fatigue and wear on the hydraulic motor. The performance of hydraulic piston motor can directly affect the process reliability of plastic injection. Although hydraulic motor failure and fatigue potentials can be considered as high levels, realized data for studied hydraulic systems and FMEA results shows that hydraulic motor is the most reliable and robust equipment in the system.

The vane type hydraulic pump, the heart of hydraulic system, has been investigated from many views of failure and performance losses. Average RPN results of hydraulic pump failures are high, and most of the failures contain high severities about complete loss of system functions and risk of accidents. Moreover, the detection of failure indications is very though and unsure because of the design complexity and many correlated operational factors. Excessive noise, temperature, pressure output fluctuations, and interruptions are often observed failures. Heat exchanger performance and hydraulic service life conditions affect the reliability of hydraulic pumps at high rates relative to other hydraulic equipment.

4.1.3. Comparing RPN Results by Using Pareto Charts

Overall RPN results for analyzed components have been transformed to a summary table, as shown in Table 4.15. Here, average RPN multipliers of each component failure mode have been taken into consideration and component RPNs have been recalculated.

Table 4.15. Overall Component-Based RPN Results

COMPONENT	Severity	Occurrence	Detection	RPN
MECHANICAL EQ.				
1.TOGGLE CLAMP UNIT	9	4	7	**252**
2.INJECTION UNIT	9	5	5	**225**
3.BARREL & SCREW	9	4	5	**180**
4.HYDRAULIC CYLINDERS	9	7	5	**315**
5. MANUPILATOR ROBOT	8	6	7	**336**
6. CONVEYOR	8	5	3	**120**
HYDRAULIC EQ.				
1.PRESSURE VALVES	8	7	5	**280**
2.DIRECTIONAL CONTROL VA	8	7	5	**280**
3.FLOW CONTROL VALVES	8	7	5	**280**
4.HYDRAULIC LINES	8	7	3	**168**
5.HEAT EXCHANGER	8	7	3	**168**
6.HYDRAULIC MOTOR	8	3	3	**72**
7.HYDRAULIC PUMP	9	6	5	**270**

The Pareto Chart is a chart showing the frequency of defects and their cumulative effect. Pareto charts are useful for finding failures to prioritize to observe the biggest overall improvement. The Pareto principle states that 80% of the consequences are determined by 20% of the causes, the failures should be found as 20% of the defect types that cause 80% of all defects. The failure modes are prioritized by ranking in order, from the highest risk priority number to the lowest for mechanical and hydraulic equipment RPN rankings as shown in Figure 4.4 and Figure 4.5.

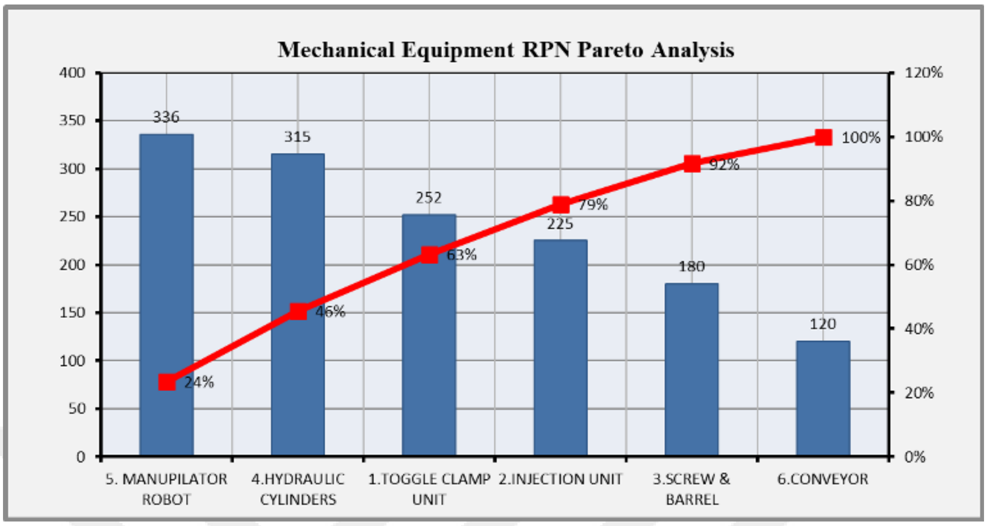


Figure 4.4. Mechanical Equipment RPNs Pareto Chart

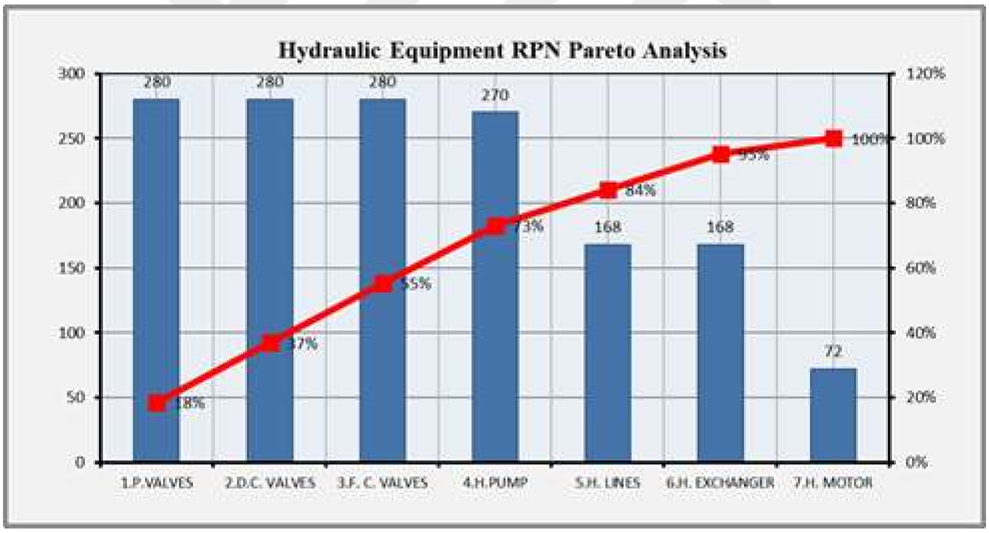


Figure 4.5. Hydraulic Equipment RPNs Pareto Chart

The bars in the charts are presented in descending order (from longest to shortest). The line represents the cumulative percentage of defects. Cumulative percentages indicate what percentage of all defects can be removed if the most important defect types are resolved. In the charts, manipulator robot, hydraulic cylinders, toggle clamp unit and injection unit are most critical in mechanical equipment, hydraulic valves, hydraulic pump and hydraulic lines are most critical in hydraulic equipment. Improvement of those equipment reliabilities will significantly improve the overall system, since they cover almost 80% of their equipment groups.

4.3. Design of ANN for Intelligent Reliability Analysis and Future Forecasts

4.3.1. ANN Structuring for Prediction of RIMS Reliability

4.3.1.1. Definition of System Reliability Data

RIMS failures data have been taken into the consideration according to the processed FMEA results to maintain reliability prediction network. Here, critical equipment and data collection methods have been determined based on failure modes and effects. MTBF based failure data have been collected as an input with realized MTBFs of critical equipment failure that have been obtained by using manual operation and MES systems reports. The MES, an operator-controlled online manufacturing execution system, is used to record and evaluate the failure data to create time-based performance reports by using defined failure reason codes.

Figure 4.6 explains proposed system reliability prediction model. In this system, each colored region (white: FMEA, grey: ANN Training, blue: MTBF Prediction & Forecasting) is dedicated to separate process steps and clarify data processing that is from data collection on analyzed RIMS to build the best performance ANN and forecasted MTBF data.

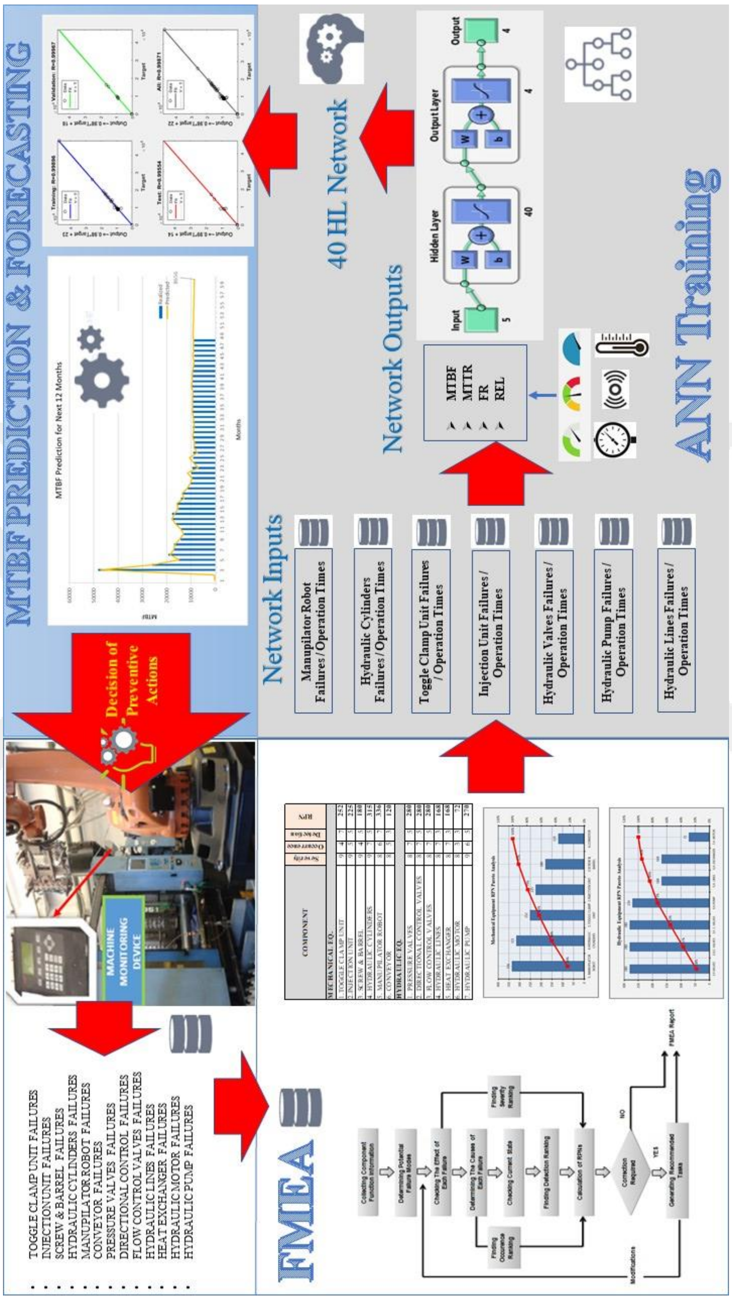


Figure 4.6. Structure of System Reliability Prediction Model

4.3.1.2. ANN Specifications and Network Trainings

ANN network has been structured with a multi-layer feed-forward back-propagation type by using MATLAB ANN Tool. Levenberg Marquardt has been used as an algorithm for the training of neural networks. The ANN tool supply design and training networks with graphical support and visual interfaces. In this study, 10 to 100 hidden layers have been implemented on network training to reach the best prediction model. During the training process, hidden and output units have been taken with the sigmoidal activation function. The learning process has been executed with 200 iterations with different hidden layers. Prediction outputs of each network have been compared with realized data and the network performances have been evaluated through Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) and Coefficient of determination R^2 statistical and regression values. MAPE shows whether a data prediction method is performing well or not. MSE defines the difference between realized data and predicted outputs that are provided by the network; the approximation is better if MSE is smaller (closer to 0). R^2 expresses the correlation between realized data and predicted outputs that are provided by the network as R is closer to 1 as the approximation is better. The lower the MAPE, the better the performance of the data. Equations show the mathematical explanations of the used statistical and regression tools.

$$MAPE = \frac{1}{T}\sum \left|\frac{y_t - \widehat{y_t}}{y_t}\right| x100 \qquad \text{Eq.4.1}$$

$$MSE = \frac{1}{T}\sum_{t=1}^{T}(y_t - \widehat{y_t})^2 \qquad \text{Eq.4.2}$$

$$R^2 = 1 - \left(\frac{\sum_t (y_t - \hat{y}_t)^2}{\sum_t (\hat{y}_t)^2}\right) \quad \text{Eq.4.3}$$

y_t= realized data $\bar{y}_t$= predicted data T= number of predictions

Five input parameters (Failure Time, Failure Qty., Cumulative Failure Time, Cumulative Failure Qty., and Operation Time) and four output parameters (MTBF, MTTR, FR, REL) have been executed in the training of studied multilayered networks. Table 4.16 represents the collected reliability data of the RIMS. Figure 4.7 shows realized MTBF Data for 48 Months that have been considered for network training. Here, it can be seen that after the twenty-fourth month, the MTBF value becomes close to stable, and the fluctuations are minimized via earlier months. The most significant reason of this reliability improvement is the continuous improvement dealing with LM and TPM activities implemented in the proposed shop floor. Also, a similar case study has been taken in the consideration and studied by Turedi A. (2013).

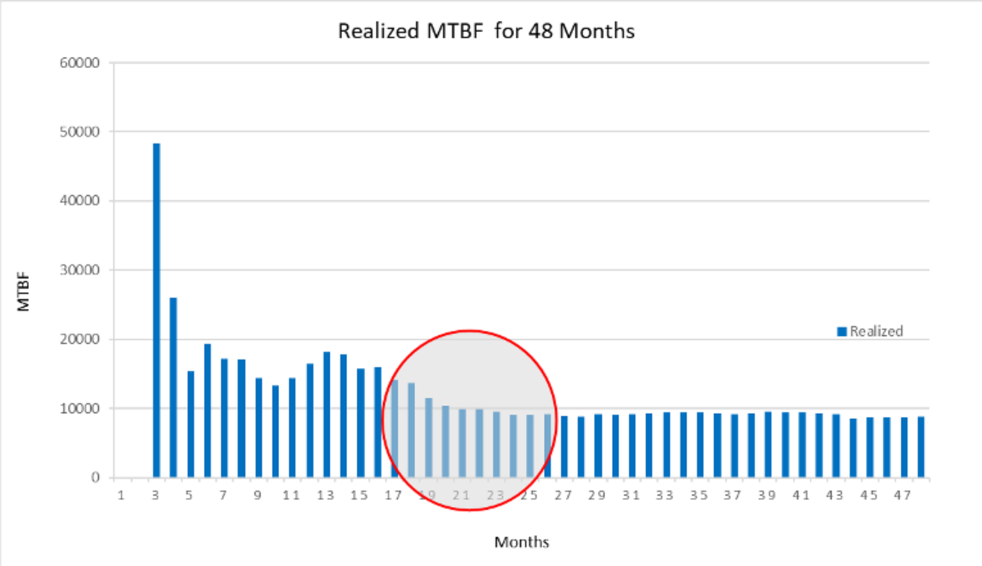


Figure 4.7. Realized MTBF Data for 48 Months

During the training of the networks, randomly 70% input and target data have been used for training, 15% for validation and 15% for a completely independent test of network generalization. Trainings have been respectively executed for 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100 hidden layered networks by recording all outputs and error data of the structured networks. Proposed MATLAB Neural Network Tool interface can be seen in Figure 4.8.

Table 4.16. Collected Reliability Data for Realized Operation of 48 Months

Month	INPUTS					OUTPUTS			
	Failure Time (min)	Failure Qty	Cum. Failure Time (min)	Cum. Failure Qty	Operation Time (min)	MTBF (min)	MTTR (min)	FR (min)	REL
1	0	0	0	0	125,35	0	0	0	1
2	0	0	0	0	8800,15	0	0	0	1
3	526,95	6	526,95	2	96613,75	48306,88	263,475	0,074524	0,135335
4	447,42	5	974,37	6	156386,1	26064,35	162,3944	0,13812	0,002479
5	39,37	3	1013,73	14	214620,75	15330,05	72,40952	0,234833	8,32E-07
6	530,27	4	1544,00	14	271534,5	19395,32	110,2857	0,185612	8,32E-07
7	100,63	2	1644,63	18	308902,15	17161,23	91,36852	0,209775	1,52E-08
8	486,43	5	2131,07	20	340887,15	17044,36	106,5533	0,211214	2,06E-09
9	207,50	3	2338,57	25	359503,9	14380,16	93,54267	0,250345	1,39E-11
10	151,32	2	2489,88	28	371092,65	13253,31	88,9244	0,27163	6,91E-13
11	0,00	0	2489,88	30	432142,05	14404,74	82,99611	0,249918	9,36E-14
12	66,70	1	2556,58	30	492589,3	16419,64	85,21944	0,21925	9,36E-14
13	604,12	5	3160,70	31	562089,95	18131,93	101,9581	0,198545	3,44E-14
14	461,82	6	3622,52	36	639118,05	17753,28	100,6255	0,202779	2,32E-16
15	777,42	9	4399,93	47	740732,05	15760,26	93,6156	0,228423	3,87E-21
16	2408,00	14	6807,93	52	830334,8	15967,98	130,9218	0,225451	2,61E-23
17	967,97	7	7775,90	65	919992,95	14153,74	119,6292	0,25435	5,9E-29
18	2256,05	17	10031,95	74	1008360,6	13626,49	135,5669	0,264191	7,28E-33
19	1933,72	17	11965,67	93	1071580,4	11522,37	128,6631	0,312436	4,08E-41
20	1228,63	11	13194,30	108	1121738,7	10386,47	122,1694	0,346605	1,25E-47
21	624,47	6	13818,77	117	1161160,3	9924,447	118,1091	0,362741	1,54E-51
22	1799,92	12	15618,68	125	1234334,8	9874,678	124,9495	0,364569	5,17E-55
23	1636,72	9	17255,40	137	1300698,7	9494,151	125,9518	0,379181	3,17E-60
24	1533,32	11	18788,72	149	1350283	9062,302	126,0988	0,39725	1,95E-65
25	777,53	7	19566,25	156	1419409,2	9098,777	125,4247	0,395658	1,78E-68
26	1492,60	11	21058,85	164	1495902,3	9121,355	128,4076	0,394678	5,97E-72
27	876,75	11	21935,60	177	1574655,6	8896,359	123,9299	0,40466	1,35E-77
28	246,57	2	22182,17	185	1633359,6	8828,971	119,9036	0,407749	4,52E-81
29	407,22	7	22589,38	189	1722888,5	9115,812	119,5205	0,394918	8,29E-83
30	66,32	1	22655,70	193	1747727,6	9055,583	117,387	0,397545	1,52E-84
31	0,00	0	22655,70	194	1785263,4	9202,389	116,782	0,391203	5,58E-85
32	0,00	0	22655,70	194	1799190,2	9274,176	116,782	0,388175	5,58E-85
33	0,00	0	22655,70	194	1824740,4	9405,878	116,782	0,382739	5,58E-85
34	617,32	10	23273,02	200	1886659,6	9433,298	116,3651	0,381627	1,38E-87
35	303,17	7	23576,18	207	1950161,1	9421,068	113,8946	0,382122	1,26E-90
36	241,82	2	23818,00	211	1970035	9336,659	112,8815	0,385577	2,31E-92
37	1542,03	19	25360,03	224	2050261,4	9152,952	113,2144	0,393316	5,22E-98
38	188,80	3	25548,83	232	2146161	9250,694	110,1243	0,38916	1,8E-101
39	259,02	4	25807,85	236	2255913,8	9558,957	109,3553	0,37661	3,2E-103
40	1408,82	9	27216,67	243	2301771,5	9472,31	112,0027	0,380055	2,9E-106
41	1780,63	8	28997,30	252	2386448,2	9470,032	115,0687	0,380147	3,6E-110
42	2233,35	8	31230,65	260	2420275,4	9308,752	120,1179	0,386733	1,2E-113
43	6921,58	25	38152,23	270	2469351,3	9145,745	141,3046	0,393626	5,5E-118
44	53,22	2	38205,45	290	2501268,9	8625,065	131,7429	0,417388	1,1E-126
45	0,00	0	38205,45	291	2533646	8706,687	131,2902	0,413475	4,2E-127
46	105,80	1	38311,25	291	2536344,1	8715,959	131,6538	0,413035	4,2E-127
47	0,00	0	38311,25	292	2553443,6	8744,67	131,2029	0,411679	1,5E-127
48	0,00	0	38311,25	292	2563738,2	8779,925	131,2029	0,410026	1,5E-127

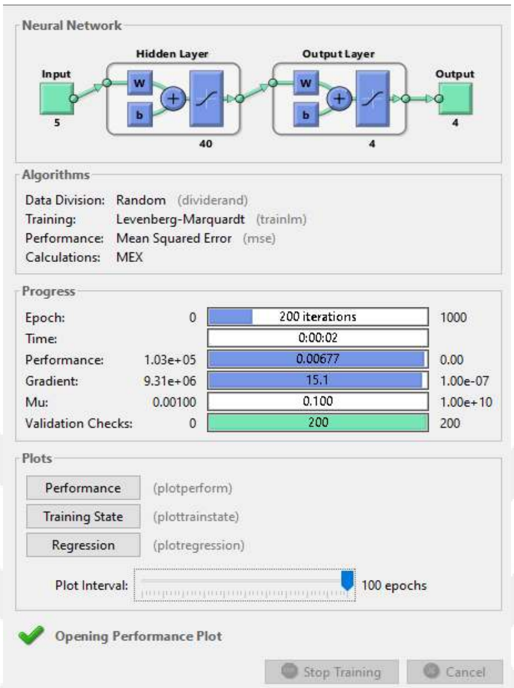


Figure 4.8. ANN Training Interface

4.3.1.3. Discussions of Best Performance Network by Using Regression Results

In order to compare the executed network prediction performances; R^2, MSE, and MAPE statistical and regression tools have been implemented by using realized and predicted MTBF data of trained 10 to 100 layers. Comparison table and graphical demonstrations of realized and predicted MTBF can be seen in Table 4.17, Figure 4.9, Figure 4.10, and Figure 4.11.

From this point of view, the comparison table shows that 40 Hidden Layer (HL) network performance is the best among the others. 40 HL prediction results indicate the low MAPE, low MSE and highest R^2. Additionally, Table 4.17. supports the highest prediction performances of 40 HL with an in-line trend of predicted and realized data.

Table 4.17. MTBF Prediction Outputs of Trained ANNs

Month	Realized	10 HL Training	20 HL Training	30 HL Training	40 HL Training	50 HL Training	60 HL Training	70 HL Training	80 HL Training	90 HL Training	100 HL Training
	MTBF	MTBF	MTBF	MTBF	MTBF	MTBF	MTBF	MTBF	MTBF	MTBF	MTBF
1	0,00	12,97	1509,01	2564,89	342,21	126,65	1514,58	1526,00	3640,57	9,72	2807,07
2	0,00	16,48	1682,32	2657,77	408,60	142,51	1720,35	1664,04	3727,62	12,27	2918,55
3	48306,88	48273,72	43158,43	42606,32	47259,16	42624,88	45175,28	45479,65	41344,20	35589,60	42348,07
4	26064,35	26063,53	26856,41	30262,59	25859,74	26891,30	28174,58	33596,36	29950,60	26064,74	30438,81
5	15330,05	15327,89	12108,16	14698,53	14901,12	13536,93	13046,82	16096,30	15398,25	15330,26	15988,20
6	19395,32	19392,92	18568,94	17127,47	18740,14	17857,82	18543,14	19524,18	17734,27	19395,64	18832,60
7	17161,23	17156,96	16687,43	12822,21	17156,66	14999,79	15821,47	14409,54	13236,43	17161,40	13441,50
8	17044,36	21642,59	18311,68	20990,22	16688,02	12360,74	17444,88	18644,02	20493,59	17044,60	21604,18
9	14380,16	15488,75	15498,24	15321,12	14755,58	12668,69	14914,85	14065,69	14782,62	14380,46	15561,91
10	13253,31	13249,87	15880,01	13403,64	13188,81	11673,97	14037,00	14019,87	13787,25	13253,35	14547,75
11	14404,74	14398,88	16204,03	12265,75	14128,24	12777,53	10195,80	13162,09	14199,53	14404,81	14893,56
12	16419,64	16312,66	19917,76	16972,94	16385,90	22278,73	16562,91	18535,60	17321,95	20181,41	18197,48
13	18131,93	18128,17	20250,98	19311,90	17751,58	16375,08	19208,70	17646,68	18084,16	16166,10	16965,65
14	17753,28	16169,82	18233,70	17903,01	16870,69	16053,22	16688,89	17436,26	18017,41	17753,39	16014,26
15	15760,26	20888,31	15580,99	16016,68	15264,89	15128,32	15924,67	15990,83	18167,77	15760,37	16089,44
16	15967,98	15967,14	17373,16	16316,43	15858,54	16353,73	16128,99	30443,36	18743,50	15968,16	16285,30
17	14153,74	14151,68	13668,48	14473,23	12865,35	14252,79	13952,11	13971,45	13464,48	14153,84	13751,23
18	13626,49	13624,72	13237,92	13418,71	13725,27	13731,10	12017,24	16224,36	16567,39	13626,60	14425,36
19	11522,37	11521,21	11109,01	11705,23	11564,36	10171,26	11471,30	11460,75	11554,78	11522,44	10409,15
20	10386,47	10385,72	10008,80	10794,82	10318,01	10594,22	8420,18	10265,10	10469,25	10386,52	8950,99
21	9924,45	9923,93	9366,49	10011,97	9694,02	9919,44	9922,17	9966,20	10869,71	15835,01	10562,36
22	9874,68	9874,07	10056,09	9508,50	11448,23	9972,69	7350,98	10291,39	9258,15	9874,73	9604,04
23	9494,15	9494,09	10884,93	8746,93	7070,34	9422,25	9557,12	9536,75	9529,40	11477,66	10124,58
24	9062,30	8979,85	9203,78	9103,09	8989,47	10798,34	9151,05	8543,43	9361,08	9062,33	9696,30
25	9098,78	8947,78	9605,87	8748,80	10723,35	8752,57	9027,70	8006,94	8112,17	14897,22	8747,95
26	9121,36	9023,17	8496,62	9512,40	7462,06	9181,55	9007,77	9178,08	8983,95	8338,90	8485,43
27	8896,36	8901,80	10189,68	10558,39	8927,19	8954,03	8028,34	9091,48	9333,77	8896,38	9247,42
28	8828,97	8819,16	7750,34	8618,50	8508,48	8853,70	8903,24	8854,10	8526,78	8828,98	8923,28
29	9115,81	9127,71	9124,54	9386,59	9457,67	8724,64	8870,78	9176,72	9025,21	9115,82	8874,43
30	9055,58	9057,55	8376,43	9575,67	9173,88	9081,05	9089,36	9963,09	8908,50	9055,60	8998,58
31	9202,39	9212,98	9035,26	8873,83	8778,79	9214,88	8846,36	9207,47	9379,45	9028,54	8943,06
32	9274,18	9279,71	9138,10	9081,38	8920,26	9289,18	9225,00	9208,49	9306,44	9159,67	9101,40
33	9405,88	9397,37	9305,08	9456,99	9131,57	9422,10	9922,55	9206,38	9159,40	9405,88	9385,53
34	9433,30	9421,37	9257,34	10045,59	9534,87	9481,35	7939,36	9451,45	9584,19	9433,31	9584,51
35	9421,07	9427,91	9291,46	8408,57	9397,06	9457,92	9473,93	9243,95	9071,59	9421,07	9556,36
36	9336,66	9327,40	9516,97	9801,08	9438,91	9355,98	9667,23	9408,66	9396,17	9336,66	9961,77
37	9152,95	8727,62	9609,58	9126,53	9329,99	9162,24	19729,85	9153,81	9671,32	9152,96	7589,52
38	9250,69	9255,75	8996,83	10124,05	9256,47	9247,14	9216,33	9837,33	9546,10	9250,70	9183,38
39	9558,96	9557,42	8093,69	8719,89	9802,65	9550,04	9755,17	8490,27	8290,03	10487,97	9377,41
40	9472,31	9464,53	9610,10	9918,77	9471,00	9471,18	9506,37	9452,20	9051,06	9472,32	9749,69
41	9470,03	9474,32	9602,39	9016,97	9555,75	10100,99	9956,86	8804,98	9791,54	9470,05	9400,56
42	9308,75	9359,01	9181,42	9741,69	9332,09	10410,47	9331,87	9571,22	11338,33	9308,79	7606,35
43	9145,75	8340,17	9539,51	8828,26	9022,07	8442,93	9101,82	9142,64	9071,52	9145,70	9081,86
44	8625,07	8610,69	8638,79	9454,15	8838,17	8614,86	8792,08	8738,99	7898,18	6203,17	8503,53
45	8706,69	8690,28	8875,77	9187,43	9364,44	8696,85	8775,97	8863,22	9343,69	8649,95	8769,32
46	8715,96	8718,45	8510,09	8372,87	9004,29	8704,35	8510,96	8491,20	8821,50	7230,02	8716,36
47	8744,67	8743,02	8836,24	8747,27	9144,33	8735,48	8792,96	8749,70	9101,91	8744,67	8783,71
48	8779,93	8792,37	8789,02	8581,66	9049,68	8769,11	8920,64	8752,75	8936,55	8779,94	8798,67
	MAPE	96,34	265,57	275,23	169,69	245,84	334,53	289,97	286,12	271,47	271,14
	MSE	2,01	5,53	5,73	3,54	5,12	6,97	6,04	5,96	5,66	5,65
	R^2	0,9792	0,9651	0,9501	0,9917	0,9542	0,9226	0,8879	0,9372	0,8983	0,945

Figure 4.9. Structured ANNs Performances from 10 to 40 HL (Yellow Series: Predicted Data, Blue Series: Realized Data)

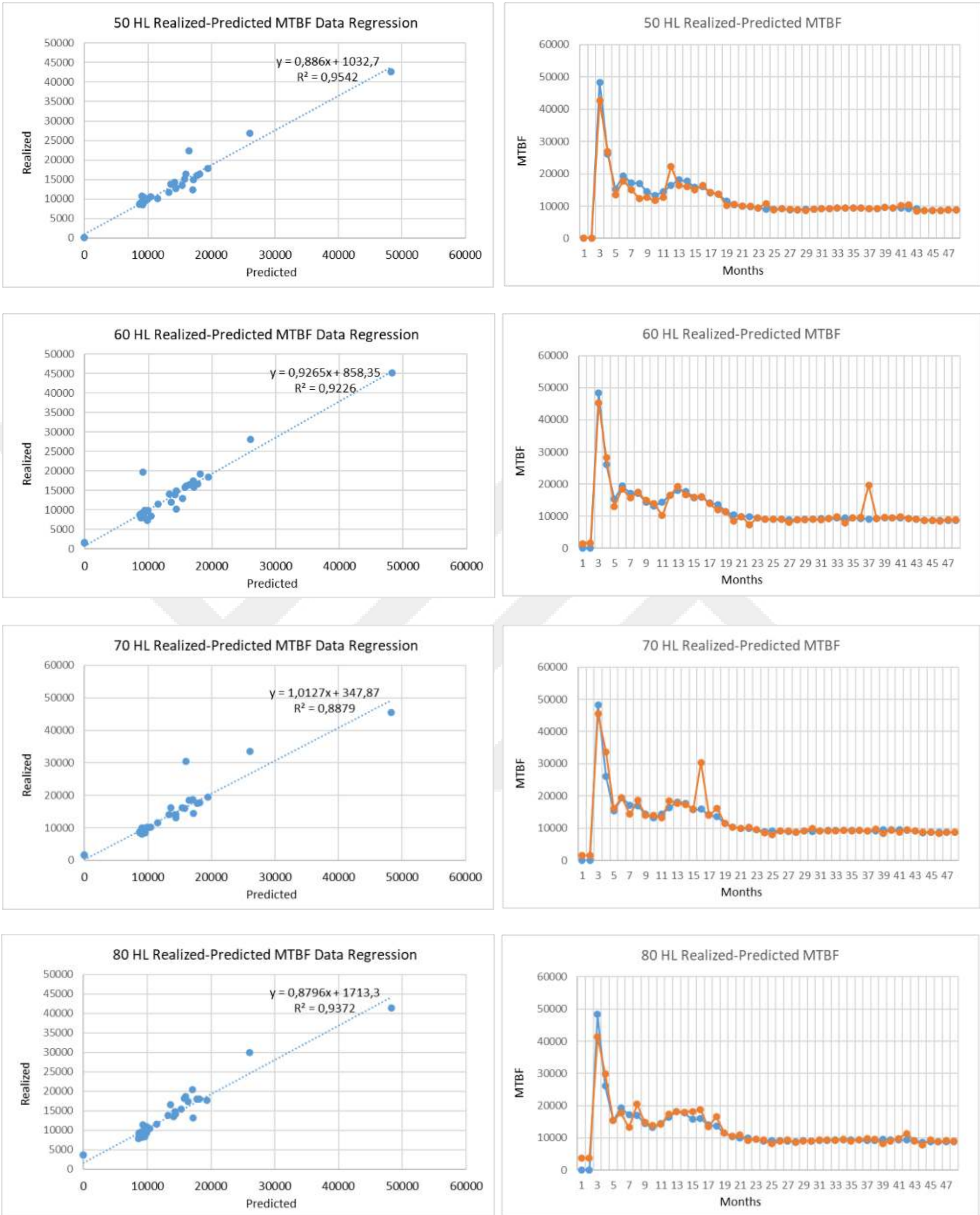


Figure 4.10. Structured ANNs Performances from 50 to 80 HL (Yellow Series: Predicted Data, Blue Series: Realized Data)

Figure 4.11. Structured ANNs Performances from 90 to 100 HL (Yellow Series: Predicted Data, Blue Series: Realized Data)

MTBF prediction errors of 40 HL networks can be sectionally seen in Figure 4.12. In this analysis, stable and near-zero error trends are notable that future predictions can be powerfully maintained by using proposed ANN.

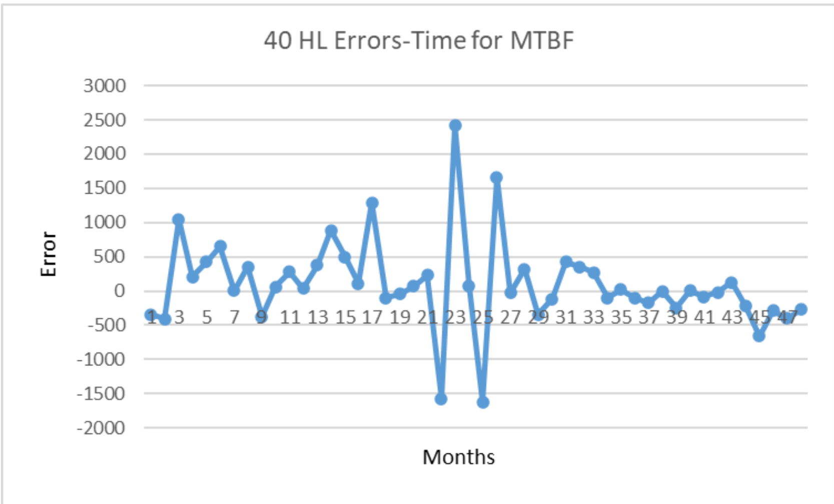


Figure 4.12. MTBF Error Trend of 40 HL Network within Analyzed Time Interval

Figures 4.13 and 4.14 indicate all different HL ANN acts during their training, validation, and testing stages. For 40 HL ANN, all lines of output-target relations can be seen as through-line with x=y lines.

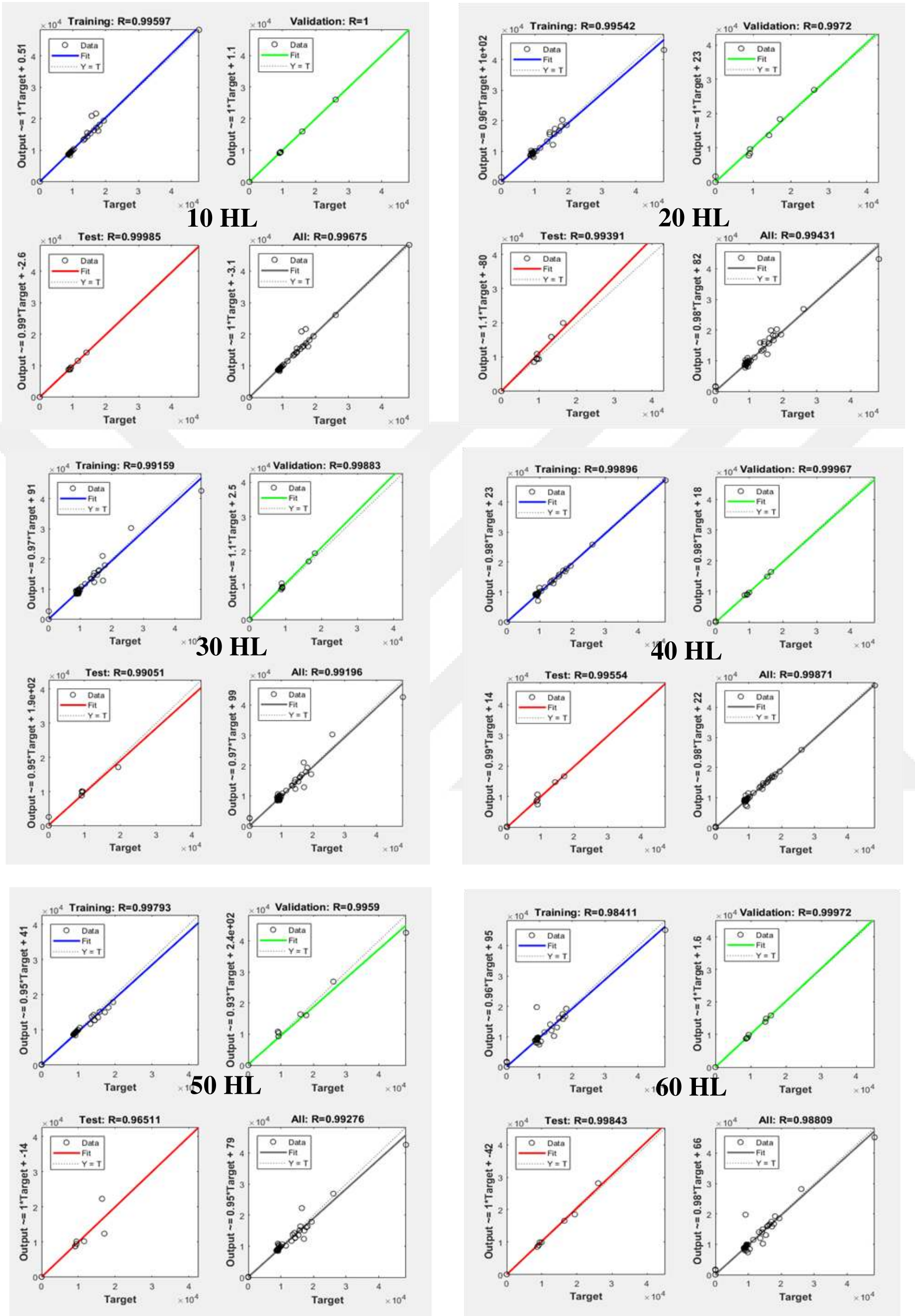


Figure 4.13. Training, Validation, and Test Performances from 10 to 60 HL ANN.

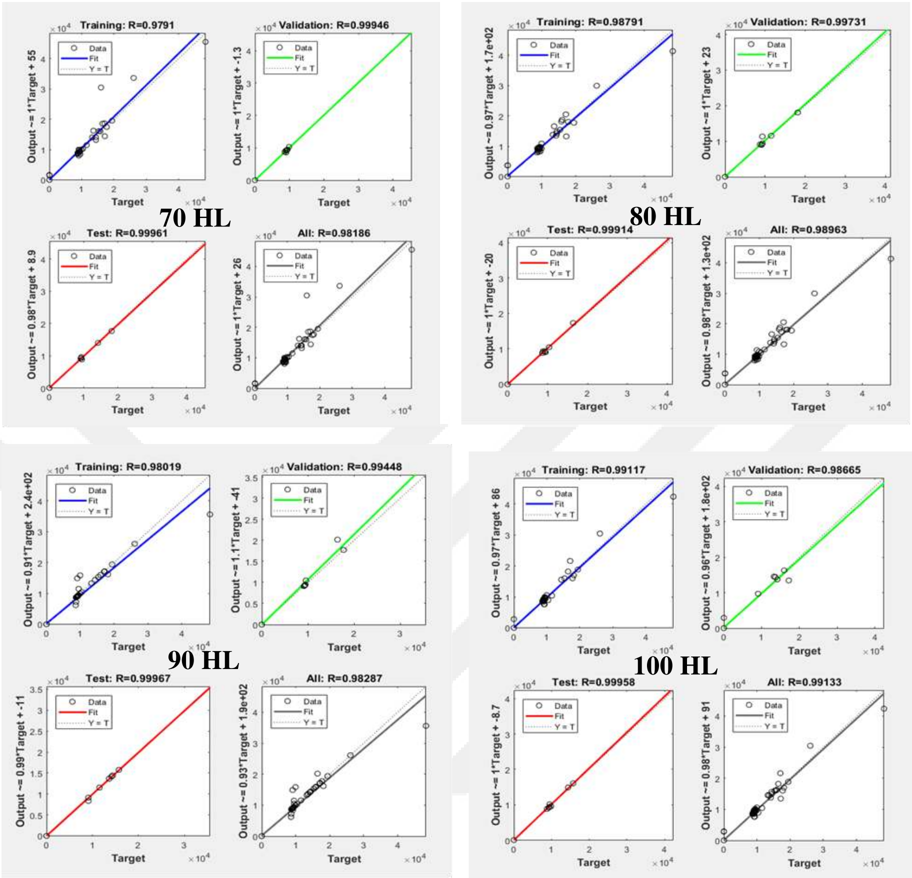


Figure 4.14. Training, Validation, and Test Performances from 70 to 100 HL ANN.

Forecasting future MTBF is the eventual step of the system reliability prediction study. Forecasted future data is one of the most significant tools for directing the industrial systems preventing possible failures, losses, predicting equipment reliability, taking continues improvement actions and executing shop floor management. Therefore, this can only be realized by using intelligent systems that are designed and trained with specific and corrected data.

4.3.1.4. System Reliability Forecasting for Future Life Cycles and Generating Preventive Actions

In the previous steps of the study, we have reached the best performance ANN by processing RIMS for 48 months of failure data. The reliability of the established ANN model has been validated by using regression tools. For the determination of future data, logarithmic regression has been implemented with the aid of the MS Excel tool and by using 40 HL ANN predicted 48 months MTBF data as seen in Table 4.17. The logarithmic regression equation has been calculated as, y = -2889ln(x) + 20477 for determination of next 12 months forecast MTBF data. Forecasted MTBF can be seen in Figure 4.15 with the previously realized 48 months, predicted 40 HL ANN and forecasted 12 months data.

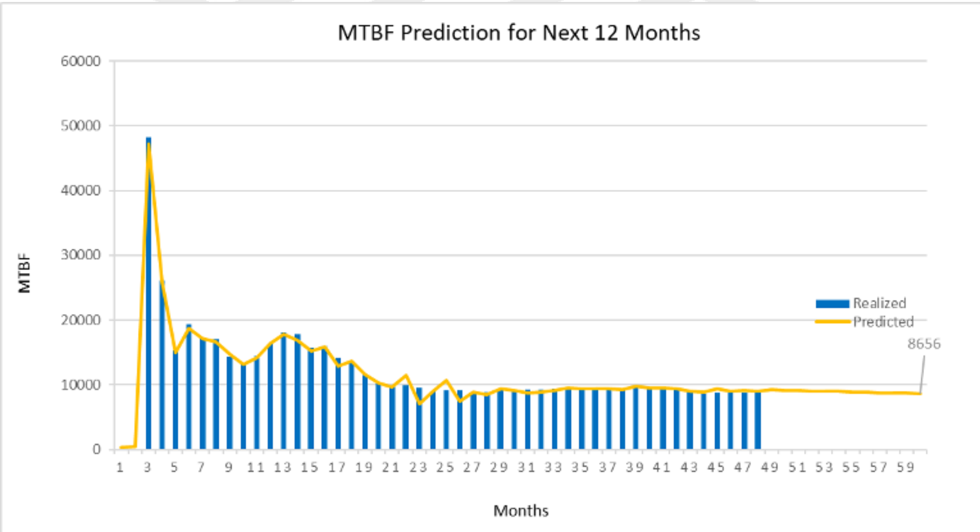


Figure 4.15. MTBF Forecasting for Next 12 Months

According to the forecasted results, as shown in Figure 4.15., 8656 minutes or 144 hours MTBF has been estimated 60th month of RIMS service life. If this value is considered to define preventive actions for the RIMS in the future, FMEA punctuation table can be observed for reaching related occurrence rates and FMEA tables can be searched to match the forecasted MTBF with experienced and considered occupancies on the analysis.

On the FMEA punctuation table (see Table 4.1), 144 hours MTBF indicates a “10” occurrence, and presents that the possibility of “10” rated failures is very high. Failure data on executed FMEA analysis (see Table 4.5 and Table 4.6) which contains 10 rated occurrences can figure out the failure causes, and modes as summarized in Table 4.18. The required preventive actions in the same table to restrain the possible failures and losses have been generated.

Consequently, hydraulic cylinders and robot gripper are the potential failure sources in forecasted service times. Inner surface wear, body deformation, and corrosion effects of hydraulic cylinders must be examined carefully. Required preventive and corrective actions must be taken according to the equipment conditions. Also, overall robot gripper must be investigated in terms of pneumatic piston bodies, lines, and manifolds. Pick and place sections of the gripper that are nails, springs, supports, and bodies must be physically and functionally checked in scheduled periods against unexpected stoppages and losses. Moreover, foreseen critical equipment and interfering component information can facilitate the influential and prospective spare part management.

The obtained high-performance 40 HL ANN plays an important role in making predictions for future system performance changes that have been used in system reliability forecasting structure. In this context, it is going to be possible to make new estimates by running the relevant data processing cycle in Figure 4.6.

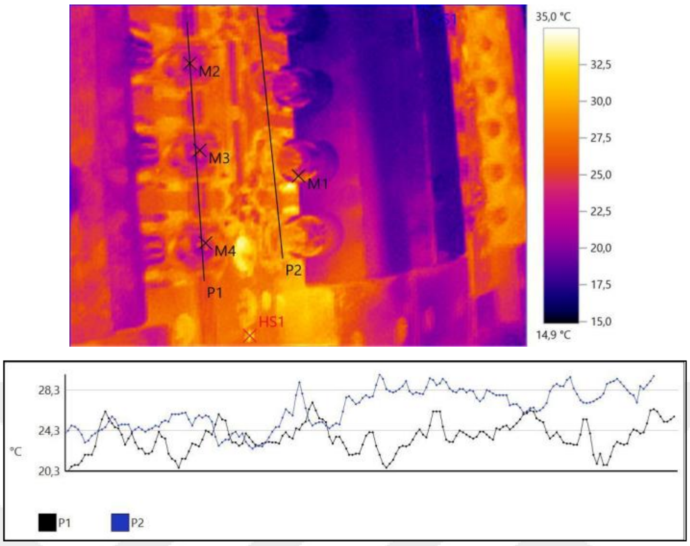
Table 4.18. Forecasted Failures and Suggested Preventive Actions

EQUIPMENT	FAILURE	PREVENTIVE & TROUBLESHOOTING PROCEDURES
HYDRAULIC CYLINDERS	Piston Barrel Failures	1. Check the inner surface coating materials wear
		2. Check body cracks
		3. Check outher surface corrosions
MANUPILATOR ROBOT	Gripper Pneumatic Line-Piston Failures	1. Check piston head crack
		2. Check piston road crack
		3. Check piston body connection failures
		4. Check sealing element wear
		5. Check piston barrel inner surface coating wear
		6. Check piston rod thread crack
		7. Check gripper nail piston failures
		8. Check manifold blockage
		9. Check hose-fittings deformation and leakages
		10. Check air preparation unit functions
	Gripper Pick-Place Mechanism	1. Check nail crack
		2. Check nail piston misalignment
		3. Check losseness on nail screws and mounting holes
		4. Check nail wears
		5. Check poor insert mounting spring
		6. Check wear and deformation on spring
		7. Check poor spring support and alignment
		8. Check losseness on spring supports
		9. Check losseness on screw connections of aluminium gripper body
		10. Check wears on gripper body

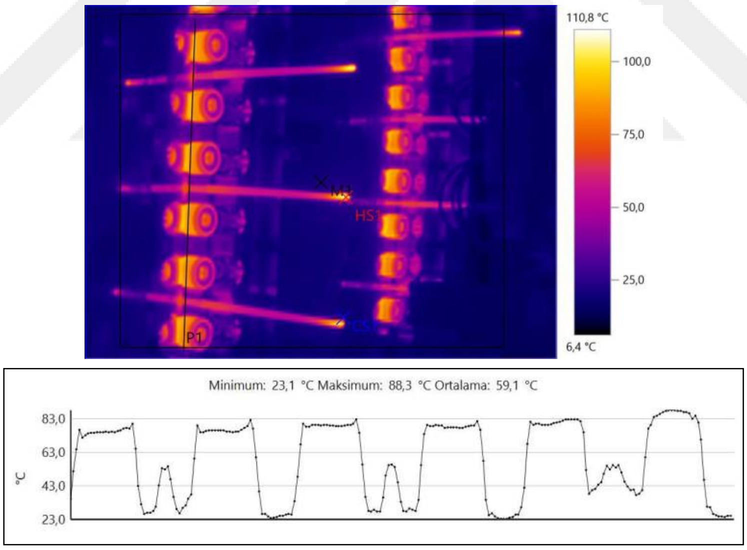
4.3.2. ANN Structuring for Prediction of RIMS Process Reliability

4.3.2.1. Identification and Data Collection of Critical Production Process Parameters

Plastic injection process parameters, robot functions, and product quality data sets have been taken into the consideration to create the structure of the reliability prediction network by investigating 300 cycle (24-Hour production period) for the thermo-plastic support product manufacturing process. Collected process data could be provided by using the IMM and robot operator panels, measured realized data from system panels, thermal camera assisted temperature, digital multimeter assisted amperage and analog manometer measurements. Mold opening time, mold closing time, injection time, injection pressure, injection speed, plasticizing time, mold pair holding position, screw position, mold open position, hydraulic oil temperature, cycle time and melt temperature values have been collected and monitored from IMM system panel. Hydraulic system pressure and back pressure have been collected from analog manometers that are mounted on the hydraulic system of IMM, as shown in Figure 4.17. Robot repeatability has been monitored on the robot pendant which is detailed in previous chapter. System air pressure and cooling water temperature have been collected from shop floor line indicators and manometers. Core, cavity, and product temperatures have been measured with thermal camera. Electrical motor amperage has been measured with multimeter. Final product weights of each cycle shot have been obtained by precision scales. All those regarding data has been provided for each cycle of 300 and recorded on a matrix. Figure 4.16 shows one of the traced cycles that contain mold pair temperature measurement screens by using a thermal camera. Here, product and mold surface temperatures can be precisely measured for each cavity. The diagrams show the realized temperature trends through P1 and P2 trajectories on the mold surfaces.

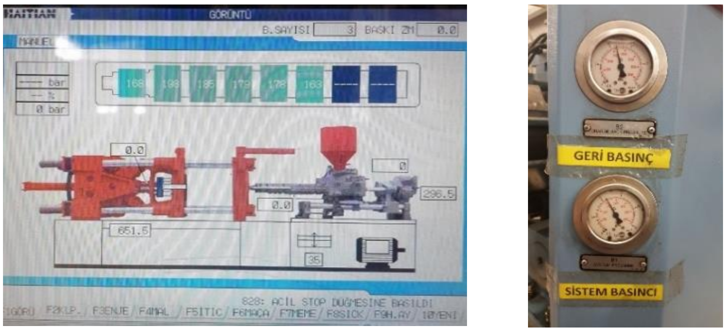


a) Mold Cavity & Core Temperature Measurement

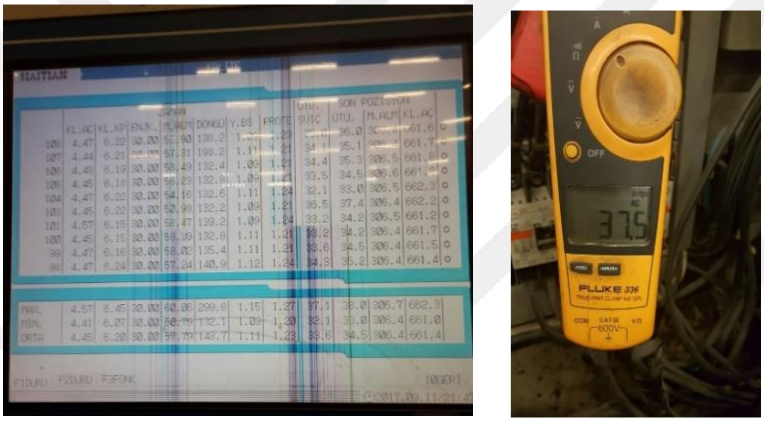


b) Product & Mold Surface Temperature Measurement

Figure 4.16. Data Collection from Thermal Camera Measurements



a) Hydraulic Oil Pressure and Temperature Measurements



b) Process Times, CT, Positions and Electrical Motor Amperage Measurements
Figure 4.17. Data Collection from IMM Operator Panel Displays, Manometer, and Multimeter Measurements

Figure 4.18 explains the proposed process reliability prediction model. In this model, each colored region is dedicated to separate process steps and identify the data processing that start from data collection on analyzed RIMS to create the best performance multilayered ANN and the forecasted Cycle Time (CT) data.

CT is the leading production capacity or plastic injection speed indicator and can be used for building and improving of production planning, raw material management, spare part management, labor hours, energy consumption, waste and rework quantities. Fine-tuned and well-organized CT brings high production and reliability performances.

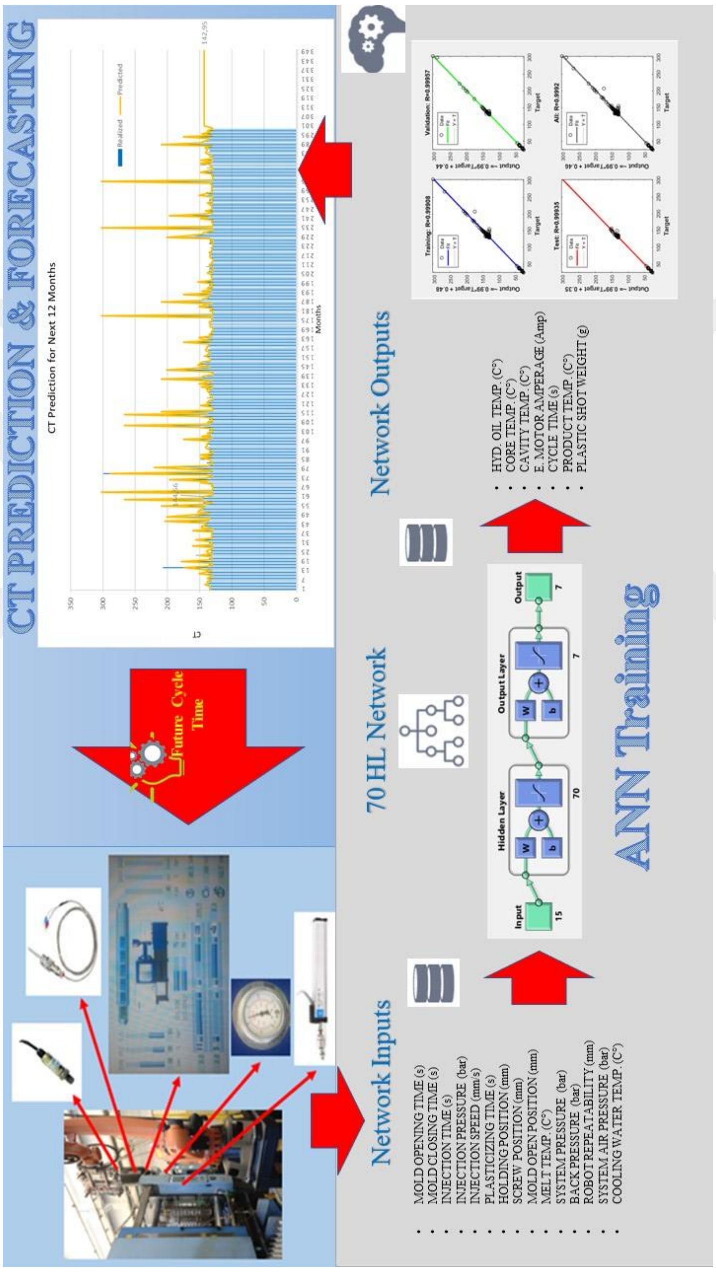


Figure 4.18. Structure of Process Reliability Prediction Model

4.3.2.2. ANN Structuring for Process Reliability Prediction

The process ANN network has been structured with a multi-layer feed-forward back-propagation type by using MATLAB ANN Tool. The creation of the structure contains the same principle with system reliability model that have been implemented from 10 to 100 hidden layers on network training to reach the best prediction model. During the training process, hidden and output units have been used with the sigmoidal activation function. Backpropagation based on Levenberg-Marquardt minimization method has been used as a training algorithm. The learning process has been executed with 200 iterations with different hidden layers. Prediction outputs of each network have been compared with realized data. The network performances have been evaluated through MAPE, MSE and R^2 statistical and regression values.

15 input parameters (Mold Open Time, Mold Close Time, Injection Time, Injection Pressure, Injection Speed, Plasticization Time, Holding Position, Screw Position, Mold Open Position, Melt Temp., System Pressure, Back Pressure, Robot Repeatability, System Air Pressure, Cooling Wat. Temp.) and 7 output parameters (Hyd. Oil Temp., Core Temp., Cavity Temp., E. Motor Amperage, Cycle Time, Product Temp., Plastic Shot Weight) have been executed in the training of studied networks. Realized process data of 300 cycles are demonstrated in Tables 4.19 to 4.24. During the training of the networks, randomly 70% input and target data have been used for training, 15% for validation and 15% for a completely independent test of network generalization. Trainings have been respectively executed for 10, 20, 30, 40, 50, 60, 70, 80, 90, and 100 hidden layered networks by recording all outputs and error data of the structured networks. Proposed MATLAB ANN Tool interface can be seen in Figure 4.19.

Table 4.19. Realized Process Data from Cycles 1 to 50

	INPUTS														OUTPUTS						
Cycle	Mold Open Time (sn)	Mold Close Time (sn)	Injection Time (sn)	Injection Pressure (bar)	Injection Speed (mm/s)	Plasticization Time (s)	Holding Position (mm)	Screw Position (mm)	Mold Open Position (mm)	Melt Temp. (Cº	System Pressure (bar)	Back Pressure (bar)	Robot Repeatability (mm)	System Air Pressure (bar)	Cooling Wat. Temp. (C̊)	Hyd. Oil Temp. (C̊)	Core Temp. (C̊)	Cavity Temp. (C̊)	E.Motor Amperage (Amp)	Cycle Time (s)	Product Temp. (C̊)	Plastic Shot Weight (gr)
1	4,39	6,19	30	115	40	58,83	34,4	306,4	661,2	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	36,6	135,3	44,7	30,81
2	4,41	6,22	30	115	40	58,83	34,1	306,6	661,7	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	37	134,1	44,7	28,86
3	4,41	6,18	30	115	40	58,45	34,7	306,5	661	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	37,5	132,8	44,7	30,89
4	4,41	6,16	30	115	40	58,81	34,5	306,5	661,3	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	37,4	143,4	44,7	27,88
5	4,45	6,13	30	115	40	58,69	34,7	306,5	661,5	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	36,3	137,6	44,7	28,76
6	4,41	6,15	30	115	40	58,63	34,3	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	36,5	138	44,7	28,75
7	4,38	6,15	30	115	40	58,6	34,4	306,5	661,1	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	36,9	133,6	44,7	28,87
8	4,42	6,21	30	115	40	58,8	34,5	306,5	661,4	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	37,4	136,5	44,7	28,65
9	4,41	6,15	30	115	40	58,6	33,9	306,6	661,7	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	36,7	134,6	44,7	29,17
10	4,41	6,15	30	115	40	56,22	35,2	306,5	661,5	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	36,4	134	44,7	27,96
11	4,42	6,25	30	115	40	59,28	34,1	306,4	661,4	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	37,5	151	44,7	27,88
12	4,41	6,21	30	115	40	59,49	33,7	306,4	661,4	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	37,4	141,4	44,7	28,76
13	4,41	6,24	30	115	40	58,33	34,1	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	36,9	140,3	44,7	28,75
14	4,41	6,25	30	115	40	56,74	35,2	306,5	661,6	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	36,6	146,7	44,7	28,86
15	4,45	6,24	30	115	40	58,75	34,1	306,4	661,3	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	37	207,4	44,7	30,79
16	4,41	6,21	30	115	40	59,25	33,9	306,4	661	215	112,6	113,2	0,06	6,1	23	38	24,75	26,72	37,5	142	44,7	29,75
17	4,42	6,22	30	115	40	58,24	34	306,5	661,4	216	112,6	113,2	0,06	6,1	23	38	24,75	26,72	37,4	136,2	44,7	30,89
18	4,44	6,25	30	115	40	57,31	34,5	306,5	661	216	112,6	113,2	0,06	6,1	23	38	24,75	26,72	36,3	150	44,7	27,88
19	4,44	6,19	30	115	40	58,93	34,6	306,4	661,3	216	112,6	113,2	0,06	6,1	23	38	24,75	26,72	36,5	179,7	44,7	28,76
20	4,42	6,21	30	115	40	58,83	34,8	306,4	661,1	216	112,6	113,2	0,06	6,1	23	38	24,75	26,72	36,9	136,1	44,7	29,19
21	4,47	6,24	30	115	40	59,74	33,3	306,6	661,4	216	113,5	112,5	0,06	6,1	23	39	24,75	26,72	37,4	135,5	44,7	27,96
22	4,47	6,25	30	115	40	58,68	34,6	306,5	661,1	216	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,7	132,1	44,7	27,88
23	4,45	6,22	30	115	40	59,71	34	306,5	661,2	216	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,4	155,9	44,7	28,76
24	4,44	6,3	30	115	40	59,86	33,8	306,5	661,4	216	113,5	112,5	0,06	6,1	23	39	24,75	26,72	37,5	133,1	44,7	28,75
25	4,45	6,24	30	115	40	59,98	33,9	306,5	661,1	216	113,5	112,5	0,06	6,1	23	39	24,75	26,72	37,4	132,2	44,7	28,87
26	4,47	6,24	30	115	40	60,07	33,3	306,4	661,1	216	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,9	132,2	44,7	28,75
27	4,45	6,25	30	115	40	59,92	33,7	306,6	661,4	216	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,6	132,3	44,7	28,87
28	4,45	6,27	30	115	40	58,57	34,9	306,6	661,3	216	113,5	112,5	0,06	6,1	23	39	24,75	26,72	37	133,6	44,7	30,78
29	4,47	6,24	30	115	40	59,92	33,9	306,4	661,4	217	113,5	112,5	0,06	6,1	23	39	24,75	26,72	37,5	160,2	44,7	28,8
30	4,44	6,28	30	115	40	59,98	33,9	306,6	660,8	217	113,5	112,5	0,06	6,1	23	39	24,75	26,72	37,4	134,6	44,7	30,89
31	4,47	6,24	30	115	40	59,74	33,3	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,3	135,5	44,7	27,88
32	4,47	6,25	30	115	40	58,68	34,6	306,5	661,1	217	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,5	132,1	44,7	28,76
33	4,45	6,22	30	115	40	59,71	34	306,5	661,2	217	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,9	155,9	44,7	28,75
34	4,44	6,3	30	115	40	59,86	33,8	306,5	661,4	217	113,5	112,5	0,06	6,1	23	39	24,75	26,72	37,4	133,1	44,7	28,84
35	4,45	6,24	30	115	40	59,98	33,9	306,5	661,1	217	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,7	132,2	44,7	30,8
36	4,47	6,24	30	115	40	60,07	33,3	306,4	661,1	217	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,4	132,2	44,7	28,8
37	4,45	6,25	30	115	40	59,92	33,7	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,75	26,72	37,5	132,3	44,7	30,89
38	4,45	6,27	30	115	40	58,57	34,9	306,6	661,3	217	113,5	112,5	0,06	6,1	23	39	24,75	26,72	37,4	133,6	44,7	27,88
39	4,47	6,24	30	115	40	59,92	33,9	306,4	661,4	217	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,9	160,2	44,7	30,79
40	4,44	6,28	30	115	40	59,98	33,9	306,6	661,3	217	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,6	134,6	44,7	28,8
41	4,49	6,3	30	115	40	54,96	34,8	306,4	661,5	216	111	112	0,06	6,1	23	38	24,75	26,72	37	145	44,7	30,89
42	4,51	6,28	30	115	40	54,96	34,9	306,4	661,4	216	111	112	0,06	6,1	23	38	24,75	26,72	37,5	148	44,7	27,88
43	4,45	6,27	30	115	40	54,9	35	306,2	661,3	216	111	112	0,06	6,1	23	38	24,75	26,72	37,4	138	44,7	28,76
44	4,51	6,22	30	115	40	57,25	35,1	306,4	661,4	216	111	112	0,06	6,1	23	38	24,75	26,72	36,3	145	44,7	28,75
45	4,45	6,28	30	115	40	59,34	34	306,5	661,1	216	111	112	0,06	6,1	23	38	24,75	26,72	36,5	204,3	44,7	28,87
46	4,47	6,22	30	115	40	59,98	33	306,6	661,1	216	111	112	0,06	6,1	23	38	24,75	26,72	36,9	143,3	44,7	28,76
47	4,47	6,22	30	115	40	57,28	34,6	306,5	661,2	216	111	112	0,06	6,1	23	38	24,75	26,72	37,4	134,5	44,7	28,75
48	4,42	6,27	30	115	40	58,18	34,5	306,5	661	216	111	112	0,06	6,1	23	38	24,75	26,72	36,7	201,4	44,7	28,88
49	4,44	6,25	30	115	40	60,01	34,2	306,5	661,3	216	111	112	0,06	6,1	23	38	24,75	26,72	36,4	167,2	44,7	28,75
50	4,45	6,19	30	115	40	59,59	34,1	306,6	661,2	216	111	112	0,06	6,1	23	38	24,75	26,72	37,5	133,6	44,7	28,87

Table 4.20. Realized Process Data from 51 to 99 Cycles

	INPUTS															OUTPUTS						
Cycle	Mold Open Time (sn)	Mold Close Time (sn)	Injection Time (sn)	Injection Pressure (bar)	Injection Speed (mm/s)	Plasticization Time (s)	Holding Position (mm)	Screw Position (mm)	Mold Open Position (mm)	Melt Temp. (C?	System Pressure (bar)	Back Pressure (bar)	Robot Repeatability (mm)	System Air Pressure (bar)	Cooling Wat. Temp. (C)	Hyd. Oil Temp. (C)	Core Temp. (C)	Cavity Temp. (C)	E.Motor Amperage (Amp)	Cycle Time (s)	Product Temp. (C)	Plastic Shot Weight (gr)
51	4,47	6,28	30	115	40	59,56	34,4	306,5	661,5	216	110,3	106,8	0,06	6,1	23	39	24,75	26,72	37,4	153	44,7	30,8
52	4,48	6,36	30	115	40	59,68	34,5	306,5	661,3	216	110,3	106,8	0,06	6,1	23	39	24,75	26,72	36,9	150,2	44,7	28,8
53	4,47	6,31	30	115	40	59,41	34,1	306,5	661,5	216	110,3	106,8	0,06	6,1	23	39	24,75	26,72	36,6	146,3	44,7	30,89
54	4,47	6,37	30	115	40	56,11	35,9	306,6	661,5	216	110,3	106,8	0,06	6,1	23	39	24,75	26,72	37	142	44,7	27,88
55	4,48	6,35	30	115	40	56,73	35,3	306,4	661,8	216	110,3	106,8	0,06	6,1	23	39	24,75	26,72	37,5	209,3	44,7	28,76
56	4,47	6,36	30	115	40	55,99	34,3	306,6	661,8	216	110,3	106,8	0,06	6,1	23	39	24,75	26,72	37,4	147	44,7	28,75
57	4,51	6,39	30	115	40	54,57	33,1	306,5	661,7	216	110,3	106,8	0,06	6,1	23	39	24,75	26,72	36,3	144,9	44,7	28,87
58	4,5	6,28	30	115	40	51,93	37,1	306,6	662,1	216	110,3	106,8	0,06	6,1	23	39	24,75	26,72	36,5	145,7	44,7	30,8
59	4,48	6,3	30	115	40	54,96	34,8	306,6	661,5	216	110,3	106,8	0,06	6,1	23	39	24,75	26,72	36,9	267	44,7	28,8
60	4,51	6,28	30	115	40	54,96	34,9	306,4	661,4	216	110,3	106,8	0,06	6,1	23	39	24,75	26,72	37,4	146	44,7	30,89
61	4,12	6,43	30	118	35	56,07	20,1	291,5	660,5	216	113,76	113	0,06	6,1	23	36	24,75	26,72	36,7	144,6	44,7	27,88
62	4,09	6,36	30	118	35	55,75	19,4	291,6	660,9	217	113,76	113	0,06	6,1	23	36	24,75	26,72	36,4	129,3	44,7	28,76
63	4,08	6,4	30	118	35	51,67	22	291,5	660,4	217	113,76	113	0,06	6,1	23	36	24,75	26,72	37,5	129,9	44,7	28,75
64	4,08	6,42	30	118	35	56,59	35,4	291,2	660,3	217	113,76	113	0,06	6,1	23	36	24,75	26,72	37,4	303,8	44,7	28,87
65	4,08	6,39	30	118	35	56,46	34,2	291,5	660,3	217	113,76	113	0,06	6,1	23	36	24,75	26,72	36,9	129,8	44,7	28,68
66	4,15	6,43	30	118	35	56,35	34,1	291,6	660,3	217	113,76	113	0,06	6,1	23	36	24,75	26,72	36,8	129,4	44,7	29,18
67	4,08	6,4	30	118	35	56,5	33,3	291,5	660,4	217	113,76	113	0,06	6,1	23	36	24,75	26,72	37,7	131,5	44,7	27,96
68	4,08	6,39	30	118	35	56,58	35,7	291,5	660,5	217	113,76	113	0,06	6,1	23	36	24,75	26,72	36,6	130,2	44,7	27,88
69	4,08	6,46	30	118	35	55,27	34,2	291,5	660,6	217	113,76	113	0,06	6,1	23	36	24,75	26,72	36,8	130,1	44,7	28,76
70	4,08	6,46	30	118	35	56,83	33,9	291,5	660,5	217	113,76	113	0,06	6,1	23	36	24,75	26,72	36,7	149	44,7	28,79
71	4,45	6,27	30	118	40	57,43	34,5	306,5	661,5	216	113,5	112,5	0,06	6,1	23	37	24,75	26,72	37,5	137,1	44,7	28,87
72	4,42	6,19	30	115	40	59,52	35,6	306,4	661,6	216	113,5	112,5	0,06	6,1	23	37	24,75	26,72	37,4	197,1	44,7	30,8
73	4,44	6,21	30	115	40	59,41	34,4	306,4	661,3	216	113,5	112,5	0,06	6,1	23	37	24,75	26,72	36,9	132,9	44,7	28,8
74	4,47	6,22	30	115	40	59,14	33,3	306,4	661,3	216	113,5	112,5	0,06	6,1	23	37	24,75	26,72	36,6	135,1	44,7	30,89
75	4,44	6,19	30	115	40	55,24	35,7	306,4	661,7	216	113,5	112,5	0,06	6,1	23	37	24,75	26,72	37	141,3	44,7	27,88
76	4,45	6,21	30	115	40	59,97	34,2	306,4	661,2	216	113,5	112,5	0,06	6,1	23	37	24,75	26,72	37,5	299,8	44,7	28,76
77	4,5	6,34	30	115	40	59,14	33,9	306,4	661,4	216	113,5	112,5	0,06	6,1	23	37	24,75	26,72	37,4	136,9	44,7	28,75
78	4,44	6,27	30	115	40	57,91	34,5	306,4	661,7	216	113,5	112,5	0,06	6,1	23	37	24,75	26,72	36,3	155,1	44,7	27,88
79	4,47	6,28	30	115	40	56,76	35,6	306,5	661,4	216	113,5	112,5	0,06	6,1	23	37	24,75	26,72	36,8	181,3	44,7	28,76
80	4,5	6,3	30	115	40	59,34	34,4	306,4	661,3	216	113,5	112,5	0,06	6,1	23	37	24,75	26,72	37,7	221,7	44,7	28,87
81	4,45	6,13	30	115	40	58,3	34,4	306,5	661,3	216	113,5	112,5	0,06	6,1	23	40	24,75	26,72	36,6	136,3	44,7	28,68
82	4,42	6,21	30	115	40	57,94	34,1	306,4	661,1	216	113,5	112,5	0,06	6,1	23	40	24,75	26,72	36,4	132,3	44,7	28,75
83	4,42	6,12	30	115	40	58,14	34	306,4	661,7	216	113,5	112,5	0,06	6,1	23	40	24,75	26,72	37,5	138,7	44,7	28,87
84	4,44	6,13	30	115	40	56,1	34,8	306,4	660,5	216	113,5	112,5	0,06	6,1	23	40	24,75	26,72	37,4	133,6	44,7	28,76
85	4,41	6,13	30	115	40	56,11	35,1	306,4	660,6	216	113,5	112,5	0,06	6,1	23	40	24,75	26,72	36,9	149	44,7	28,75
86	4,42	6,18	30	115	40	57,82	34,1	306,4	660,6	216	113,5	112,5	0,06	6,1	23	40	24,75	26,72	36,6	149	44,7	28,87
87	4,45	6,19	30	115	40	57,72	34,7	306,4	661,1	216	113,5	112,5	0,06	6,1	23	39	24,75	26,72	37	136,9	44,7	28,87
88	4,42	6,21	30	115	40	58,33	34,1	306,5	660,5	216	113,5	112,5	0,06	6,1	23	39	24,75	26,72	37,5	149,2	44,7	28,8
89	4,48	6,24	30	115	40	59,07	33,8	306,5	661,3	216	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,9	132,5	44,7	30,89
90	4,45	6,22	30	115	40	58,32	34,3	306,4	661,4	216	113,5	112,5	0,06	6,1	23	39	24,75	26,72	36,6	135,5	44,7	30,78
91	4,42	6,21	30	115	40	52,51	36,9	306,7	662	215	113,6	112,8	0,06	6,1	23	39	24,75	26,72	36,7	133,7	44,7	30,89
92	4,47	6,1	30	115	40	58,15	34,7	306,4	661,5	215	113,6	112,8	0,06	6,1	23	39	24,75	26,72	37,5	140	44,7	27,88
93	4,47	6,1	30	115	40	58,32	34,5	306,6	661,6	215	113,6	112,8	0,06	6,1	23	39	24,75	26,72	36,3	137	44,7	27,88
94	4,44	6,15	30	115	40	57,9	34,7	306,5	661,5	215	113,6	112,8	0,06	6,1	23	39	24,75	26,72	36,4	134	44,7	27,96
95	4,42	6,13	30	115	40	57,9	34,4	306,5	661,4	215	113,6	112,8	0,06	6,1	23	39	24,75	26,72	36,6	138	44,7	28,86
96	4,42	6,18	30	115	40	58,11	34,1	306,5	661,2	215	113,6	112,8	0,06	6,1	23	39	24,75	26,72	36,3	137	44,7	30,89
97	4,45	6,16	30	115	40	56,55	35,2	306,5	661,5	215	113,6	112,8	0,06	6,1	23	39	24,75	26,72	36,4	135	44,7	28,75
98	4,47	6,16	30	115	40	57,73	34,6	306,5	661,3	215	113,6	112,8	0,06	6,1	23	39	24,75	26,72	36,7	176	44,7	28,8
99	4,42	6,18	30	115	40	57,24	34,5	306,5	661,5	215	113,6	112,8	0,06	6,1	23	39	24,75	26,72	36,6	137	44,7	30,89

Table 4.21. Realized Process Data from 100 to 149 Cycles

	INPUTS															OUTPUTS						
Cycle	Mold Open Time (sn)	Mold Close Time (sn)	Injection Time (sn)	Injection Pressure (bar)	Injection Speed (mm/s)	Plasticization Time (s)	Holding Position (mm)	Screw Position (mm)	Mold Open Position (mm)	Melt Temp. (C⁰	System Pressure (bar)	Back Pressure (bar)	Robot Repeatability (mm)	System Air Pressure (bar)	Cooling Wat. Temp. (C⁰)	Hyd. Oil Temp. (C⁰)	Core Temp. (C⁰)	Cavity Temp. (C⁰)	E.Motor Amperage (Amp)	Cycle Time (s)	Product Temp. (C⁰)	Plastic Shot Weight (gr)
100	4,42	6,1	30	115	40	57,79	34,6	306,4	661,7	215	113,6	112,8	0,06	6,1	23	39	24,75	26,72	37,5	148	44,7	28,88
101	4,41	6,22	30	115	40	58,83	34,1	306,6	661,7	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37	134,1	44,7	28,86
102	4,41	6,15	30	115	40	58,63	34,3	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,5	138	44,7	28,75
103	4,42	6,22	30	115	40	58,24	34	306,5	661,4	216	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37,4	136,2	44,7	30,89
104	4,47	6,24	30	115	40	59,74	33,3	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,7	26,88	36,3	135,5	44,7	27,88
105	4,44	6,28	30	115	40	59,98	33,9	306,6	661,3	217	113,5	112,5	0,06	6,1	23	39	24,7	26,88	36,6	134,6	44,7	28,8
106	4,47	6,28	30	115	40	59,56	34,4	306,5	661,5	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	37,4	153	44,7	30,8
107	4,48	6,3	30	115	40	54,96	34,8	306,6	661,5	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	36,9	267	44,7	28,8
108	4,41	6,22	30	115	40	58,83	34,1	306,6	661,7	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37	134,1	44,7	28,86
109	4,41	6,15	30	115	40	58,63	34,3	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,5	138	44,7	28,75
110	4,42	6,22	30	115	40	58,24	34	306,5	661,4	216	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37,4	136,2	44,7	30,89
111	4,47	6,24	30	115	40	59,74	33,3	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,7	26,88	36,3	135,5	44,7	27,88
112	4,44	6,28	30	115	40	59,98	33,9	306,6	661,3	217	113,5	112,5	0,06	6,1	23	39	24,7	26,88	36,6	134,6	44,7	28,8
113	4,47	6,28	30	115	40	59,56	34,4	306,5	661,5	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	37,4	153	44,7	30,8
114	4,48	6,3	30	115	40	54,96	34,8	306,6	661,5	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	36,9	267	44,7	28,8
115	4,45	6,27	30	115	40	54,9	35	306,2	661,3	216	111	112	0,06	6,1	23	38	24,7	26,88	37,4	138	44,7	28,76
116	4,48	6,35	30	115	40	56,73	35,3	306,4	661,8	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	37,5	209,3	44,7	28,76
117	4,09	6,36	30	118	35	55,75	19,4	291,6	660,9	217	113,76	113	0,06	6,1	23	36	24,7	26,88	36,4	129,3	44,7	28,76
118	4,08	6,39	30	118	35	56,46	34,2	291,5	660,3	217	113,76	113	0,06	6,1	23	36	24,7	26,88	36,9	129,8	44,7	28,68
119	4,08	6,4	30	118	35	56,5	33,3	291,5	660,4	217	113,76	113	0,06	6,1	23	36	24,7	26,88	37,7	131,5	44,7	27,96
120	4,08	6,46	30	118	35	56,83	33,9	291,5	660,5	217	113,76	113	0,06	6,1	23	36	24,7	26,88	36,7	149	44,7	28,79
121	4,42	6,21	30	115	40	52,51	36,9	306,7	662	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,7	133,7	44,7	30,89
122	4,42	6,13	30	115	40	57,9	34,4	306,5	661,4	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,6	138	44,7	28,86
123	4,45	6,16	30	115	40	56,55	35,2	306,5	661,5	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,4	135	44,7	28,75
124	4,42	6,21	30	115	40	57,94	34,1	306,4	661,1	216	113,5	112,5	0,06	6,1	23	40	24,7	26,88	36,4	132,3	44,7	28,75
125	4,42	6,12	30	115	40	58,14	34	306,4	661,7	216	113,5	112,5	0,06	6,1	23	40	24,7	26,88	37,5	138,7	44,7	28,87
126	4,44	6,13	30	115	40	56,1	34,8	306,4	660,5	216	113,5	112,5	0,06	6,1	23	40	24,7	26,88	37,4	133,6	44,7	28,76
127	4,39	6,19	30	115	40	58,83	34,4	306,4	661,2	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,6	135,3	44,7	30,81
128	4,41	6,22	30	115	40	58,83	34,1	306,6	661,7	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37	134,1	44,7	28,86
129	4,45	6,13	30	115	40	58,69	34,7	306,5	661,5	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,3	137,6	44,7	28,76
130	4,41	6,15	30	115	40	58,63	34,3	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,5	138	44,7	28,75
131	4,41	6,24	30	115	40	58,33	34,1	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,9	140,3	44,7	28,75
132	4,41	6,25	30	115	40	56,74	35,2	306,5	661,6	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,6	146,7	44,7	28,86
133	4,41	6,15	30	115	40	56,22	35,2	306,5	661,5	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,4	134	44,7	27,96
134	4,42	6,25	30	115	40	59,28	34,1	306,4	661,4	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37,5	151	44,7	27,88
135	4,41	6,21	30	115	40	59,49	33,7	306,4	661,4	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37,4	141,4	44,7	28,76
136	4,41	6,24	30	115	40	58,33	34,1	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,9	140,3	44,7	28,75
137	4,48	6,35	30	115	40	56,73	35,3	306,4	661,8	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	37,5	209,3	44,7	28,76
138	4,47	6,36	30	115	40	55,99	34,3	306,6	661,8	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	37,4	147	44,7	28,75
139	4,12	6,43	30	118	35	56,07	20,1	291,5	660,5	216	113,76	113	0,06	6,1	23	36	24,7	26,88	36,7	144,6	44,7	27,88
140	4,09	6,36	30	118	35	55,75	19,4	291,6	660,9	217	113,76	113	0,06	6,1	23	36	24,7	26,88	36,4	129,3	44,7	28,76
141	4,08	6,4	30	118	35	51,67	22	291,5	660,4	217	113,76	113	0,06	6,1	23	36	24,7	26,88	37,5	129,9	44,7	28,75
142	4,47	6,22	30	115	40	57,28	34,6	306,5	661,2	216	111	112	0,06	6,1	23	38	24,7	26,88	37,4	134,5	44,7	28,75
143	4,42	6,27	30	115	40	58,18	34,5	306,5	661	216	111	112	0,06	6,1	23	38	24,7	26,88	36,7	201,4	44,7	28,88
144	4,44	6,25	30	115	40	60,01	34,2	306,5	661,3	216	111	112	0,06	6,1	23	38	24,7	26,88	36,4	167,2	44,7	28,75
145	4,45	6,19	30	115	40	59,59	34,1	306,6	661,2	216	111	112	0,06	6,1	23	38	24,7	26,88	37,5	133,6	44,7	28,87
146	4,47	6,28	30	115	40	59,56	34,4	306,5	661,5	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	37,4	153	44,7	30,8
147	4,48	6,36	30	115	40	59,68	34,5	306,5	661,3	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	36,9	150,2	44,7	28,8
148	4,47	6,31	30	115	40	59,41	34,1	306,5	661,5	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	36,6	146,3	44,7	30,89
149	4,39	6,19	30	115	40	58,83	34,4	306,4	661,2	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,6	135,3	44,7	30,81

Table 4.22. Realized Process Data from 150 to 199 Cycles

	INPUTS															OUTPUTS						
Cycle	Mold Open Time (sn)	Mold Close Time (sn)	Injection Time (sn)	Injection Pressure (bar)	Injection Speed (mm/s)	Plasticization Time (s)	Holding Position (mm)	Screw Position (mm)	Mold Open Position (mm)	Melt Temp. (C°	System Pressure (bar)	Back Pressure (bar)	Robot Repeatability (mm)	System Air Pressure (bar)	Cooling Wat. Temp. (C°)	Hyd. Oil Temp. (C°)	Core Temp. (C°)	Cavity Temp. (C°)	E.Motor Amperage (Amp)	Cycle Time (s)	Product Temp. (C°)	Plastic Shot Weight (gr)
150	4,41	6,22	30	115	40	58,83	34,1	306,6	661,7	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37	134,1	44,7	28,86
151	4,41	6,18	30	115	40	58,45	34,7	306,5	661	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37,5	132,8	44,7	30,89
152	4,41	6,16	30	115	40	58,81	34,5	306,5	661,3	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37,4	143,4	44,7	27,88
153	4,45	6,13	30	115	40	58,69	34,7	306,5	661,5	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,3	137,6	44,7	28,76
154	4,42	6,21	30	115	40	52,51	36,9	306,7	662	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,7	133,7	44,7	30,89
155	4,47	6,1	30	115	40	58,15	34,7	306,4	661,5	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	37,5	140	44,7	27,88
156	4,47	6,1	30	115	40	58,32	34,5	306,6	661,6	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,3	137	44,7	27,88
157	4,44	6,15	30	115	40	57,9	34,7	306,5	661,5	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,4	134	44,7	27,96
158	4,42	6,13	30	115	40	57,9	34,4	306,5	661,4	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,6	138	44,7	28,86
159	4,42	6,18	30	115	40	58,11	34,1	306,5	661,2	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,3	137	44,7	30,89
160	4,45	6,16	30	115	40	56,55	35,2	306,5	661,5	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,4	135	44,7	28,75
161	4,47	6,16	30	115	40	57,73	34,6	306,5	661,3	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,7	176	44,7	28,8
162	4,42	6,18	30	115	40	57,24	34,5	306,5	661,5	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,6	137	44,7	30,89
163	4,42	6,1	30	115	40	57,79	34,6	306,4	661,7	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	37,5	148	44,7	28,88
164	4,42	6,25	30	115	40	59,28	34,1	306,4	661,4	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37,5	151	44,7	27,88
165	4,41	6,24	30	115	40	58,33	34,1	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,9	140,3	44,7	28,75
166	4,42	6,21	30	115	40	58,83	34,8	306,4	661,1	216	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,9	136,1	44,7	29,19
167	4,47	6,25	30	115	40	58,68	34,6	306,5	661,1	216	113,5	112,5	0,06	6,1	23	39	24,7	26,88	36,7	132,1	44,7	27,88
168	4,45	6,25	30	115	40	59,92	33,7	306,6	661,4	216	113,5	112,5	0,06	6,1	23	39	24,7	26,88	36,6	132,3	44,7	28,87
169	4,09	6,36	30	118	35	55,75	19,4	291,6	660,9	217	113,76	113	0,06	6,1	23	36	24,7	26,88	36,4	129,3	44,7	28,76
170	4,08	6,4	30	118	35	51,67	22	291,5	660,4	217	113,76	113	0,06	6,1	23	36	24,7	26,88	37,5	129,9	44,7	28,75
171	4,47	6,22	30	115	40	57,28	34,6	306,5	661,2	216	111	112	0,06	6,1	23	38	24,7	26,88	37,4	134,5	44,7	28,75
172	4,39	6,19	30	115	40	58,83	34,4	306,4	661,2	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,6	135,3	44,7	30,81
173	4,41	6,22	30	115	40	58,83	34,1	306,6	661,7	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37	134,1	44,7	28,86
174	4,41	6,18	30	115	40	58,45	34,7	306,5	661	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37,5	132,8	44,7	30,89
175	4,47	6,24	30	115	40	60,07	33,3	306,4	661,1	217	113,5	112,5	0,06	6,1	23	39	24,7	26,88	36,4	132,2	44,7	28,8
176	4,45	6,25	30	115	40	59,92	33,7	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,7	26,88	37,5	132,3	44,7	30,89
177	4,45	6,27	30	115	40	58,57	34,9	306,6	661,3	217	113,5	112,5	0,06	6,1	23	39	24,7	26,88	37,4	133,6	44,7	27,88
178	4,08	6,42	30	118	35	56,59	35,4	291,2	660,3	217	113,76	113	0,06	6,1	23	36	24,7	26,88	37,4	303,8	44,7	28,87
179	4,08	6,39	30	118	35	56,46	34,2	291,5	660,3	217	113,76	113	0,06	6,1	23	36	24,7	26,88	36,9	129,8	44,7	28,68
180	4,15	6,43	30	118	35	56,35	34,1	291,6	660,3	217	113,76	113	0,06	6,1	23	36	24,7	26,88	36,8	129,4	44,7	29,18
181	4,45	6,22	30	115	40	58,32	34,3	306,4	661,4	216	113,5	112,5	0,06	6,1	23	39	24,7	26,88	36,6	135,5	44,7	30,78
182	4,42	6,21	30	115	40	52,51	36,9	306,7	662	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,7	133,7	44,7	30,89
183	4,41	6,15	30	115	40	56,22	35,2	306,5	661,5	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,4	134	44,7	27,96
184	4,42	6,25	30	115	40	59,28	34,1	306,4	661,4	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37,5	151	44,7	27,88
185	4,41	6,21	30	115	40	59,49	33,7	306,4	661,4	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37,4	141,4	44,7	28,76
186	4,41	6,24	30	115	40	58,33	34,1	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,9	140,3	44,7	28,75
187	4,48	6,35	30	115	40	56,73	35,3	306,4	661,8	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	37,5	209,3	44,7	28,76
188	4,47	6,36	30	115	40	55,99	34,3	306,6	661,8	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	37,4	147	44,7	28,75
189	4,12	6,43	30	118	35	56,07	20,1	291,5	660,5	216	113,76	113	0,06	6,1	23	36	24,7	26,88	36,7	144,6	44,7	27,88
190	4,42	6,18	30	115	40	58,11	34,1	306,5	661,2	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,3	137	44,7	30,89
191	4,45	6,16	30	115	40	56,55	35,2	306,5	661,5	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,4	135	44,7	28,75
192	4,47	6,16	30	115	40	57,73	34,6	306,5	661,3	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,7	176	44,7	28,8
193	4,42	6,18	30	115	40	57,24	34,5	306,5	661,5	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	36,6	137	44,7	30,89
194	4,42	6,1	30	115	40	57,79	34,6	306,4	661,7	215	113,6	112,8	0,06	6,1	23	39	24,7	26,88	37,5	148	44,7	28,88
195	4,41	6,22	30	115	40	58,83	34,1	306,6	661,7	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37	134,1	44,7	28,86
196	4,41	6,15	30	115	40	58,63	34,3	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,7	26,88	36,5	138	44,7	28,75
197	4,42	6,22	30	115	40	58,24	34	306,5	661,4	216	112,6	113,2	0,06	6,1	23	38	24,7	26,88	37,4	136,2	44,7	30,89
198	4,47	6,24	30	115	40	59,74	33,3	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,7	26,88	36,3	135,5	44,7	27,88
199	4,44	6,28	30	115	40	59,98	33,9	306,6	661,3	217	113,5	112,5	0,06	6,1	23	39	24,7	26,88	36,6	134,6	44,7	28,8

Table 4.23. Realized Process Data from 200 to 249 Cycles

	INPUTS															OUTPUTS						
Cycle	Mold Open Time (sn)	Mold Close Time (sn)	Injection Time (sn)	Injection Pressure (bar)	Injection Speed (mm/s)	Plasticization Time (s)	Holding Position (mm)	Screw Position (mm)	Mold Open Position (mm)	Melt Temp. (C°	System Pressure (bar)	Back Pressure (bar)	Robot Repeatability (mm)	System Air Pressure (bar)	Cooling Wat. Temp. (C°)	Hyd. Oil Temp. (C°)	Core Temp. (C°)	Cavity Temp. (C°)	E.Motor Amperage (Amp)	Cycle Time (s)	Product Temp. (C°)	Plastic Shot Weight (gr)
200	4,47	6,28	30	115	40	59,56	34,4	306,5	661,5	216	110,3	106,8	0,06	6,1	23	39	24,7	26,88	37,4	153	44,7	30,8
201	4,44	6,3	30	115	40	59,86	33,8	306,5	661,4	217	113,5	112,5	0,06	6,1	23	39	24,7	26,88	37,4	133,1	44,7	28,84
202	4,45	6,24	30	115	40	59,98	33,9	306,5	661,1	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,7	132,2	44,7	30,8
203	4,47	6,24	30	115	40	60,07	33,3	306,4	661,1	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,4	132,2	44,7	28,8
204	4,45	6,25	30	115	40	59,92	33,7	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	37,5	132,3	44,7	30,89
205	4,41	6,22	30	115	40	58,83	34,1	306,6	661,7	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	37	134,1	44,7	28,86
206	4,41	6,15	30	115	40	58,63	34,3	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	36,5	138	44,7	28,75
207	4,42	6,22	30	115	40	58,24	34	306,5	661,4	216	112,6	113,2	0,06	6,1	23	38	24,88	26,5	37,4	136,2	44,7	30,89
208	4,47	6,24	30	115	40	59,74	33,3	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,3	135,5	44,7	27,88
209	4,44	6,28	30	115	40	59,98	33,9	306,6	661,3	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,6	134,6	44,7	28,8
210	4,41	6,24	30	115	40	58,33	34,1	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	36,9	140,3	44,7	28,75
211	4,42	6,21	30	115	40	58,83	34,8	306,4	661,1	216	112,6	113,2	0,06	6,1	23	38	24,88	26,5	36,9	136,1	44,7	29,19
212	4,47	6,25	30	115	40	58,68	34,6	306,5	661,1	216	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,7	132,1	44,7	27,88
213	4,45	6,25	30	115	40	59,92	33,7	306,6	661,4	216	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,6	132,3	44,7	28,87
214	4,09	6,36	30	118	35	55,75	19,4	291,6	660,9	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,4	129,3	44,7	28,76
215	4,08	6,4	30	118	35	51,67	22	291,5	660,4	217	113,76	113	0,06	6,1	23	36	24,88	26,5	37,5	129,9	44,7	28,75
216	4,47	6,22	30	115	40	57,28	34,6	306,5	661,2	216	111	112	0,06	6,1	23	38	24,88	26,5	37,4	134,5	44,7	28,75
217	4,39	6,19	30	115	40	58,83	34,4	306,4	661,2	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	36,6	135,3	44,7	30,81
218	4,41	6,22	30	115	40	58,83	34,1	306,6	661,7	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	37	134,1	44,7	28,86
219	4,41	6,18	30	115	40	58,45	34,7	306,5	661	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	37,5	132,8	44,7	30,89
220	4,47	6,24	30	115	40	60,07	33,3	306,4	661,1	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,4	132,2	44,7	28,8
221	4,45	6,25	30	115	40	59,92	33,7	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	37,5	132,3	44,7	30,89
222	4,45	6,27	30	115	40	58,57	34,9	306,6	661,3	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	37,4	133,6	44,7	27,88
223	4,08	6,39	30	118	35	56,46	34,2	291,5	660,3	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,9	129,8	44,7	28,68
224	4,15	6,43	30	118	35	56,35	34,1	291,6	660,3	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,8	129,4	44,7	29,18
225	4,45	6,22	30	115	40	58,32	34,3	306,4	661,4	216	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,6	135,5	44,7	30,78
226	4,42	6,21	30	115	40	52,51	36,9	306,7	662	215	113,6	112,8	0,06	6,1	23	39	24,88	26,5	36,7	133,7	44,7	30,89
227	4,41	6,15	30	115	40	56,22	35,2	306,5	661,5	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	36,4	134	44,7	27,96
228	4,47	6,22	30	115	40	57,28	34,6	306,5	661,2	216	111	112	0,06	6,1	23	38	24,88	26,5	37,4	134,5	44,7	28,75
229	4,42	6,27	30	115	40	58,18	34,5	306,5	661	216	111	112	0,06	6,1	23	38	24,88	26,5	36,7	201,4	44,7	28,88
230	4,44	6,25	30	115	40	60,01	34,2	306,5	661,3	216	111	112	0,06	6,1	23	38	24,88	26,5	36,4	167,2	44,7	28,75
231	4,51	6,28	30	115	40	54,96	34,9	306,4	661,4	216	110,3	106,8	0,06	6,1	23	39	24,88	26,5	37,4	146	44,7	30,89
232	4,12	6,43	30	118	35	56,07	20,1	291,5	660,5	216	113,76	113	0,06	6,1	23	36	24,88	26,5	36,7	144,6	44,7	27,88
233	4,09	6,36	30	118	35	55,75	19,4	291,6	660,9	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,4	129,3	44,7	28,76
234	4,08	6,4	30	118	35	51,67	22	291,5	660,4	217	113,76	113	0,06	6,1	23	36	24,88	26,5	37,5	129,9	44,7	28,75
235	4,08	6,42	30	118	35	56,59	35,4	291,2	660,3	217	113,76	113	0,06	6,1	23	36	24,88	26,5	37,4	303,8	44,7	28,87
236	4,08	6,39	30	118	35	56,46	34,2	291,5	660,3	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,9	129,8	44,7	28,68
237	4,15	6,43	30	118	35	56,35	34,1	291,6	660,3	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,8	129,4	44,7	29,18
238	4,08	6,4	30	118	35	56,5	33,3	291,5	660,4	217	113,76	113	0,06	6,1	23	36	24,88	26,5	37,7	131,5	44,7	27,96
239	4,08	6,39	30	118	35	56,58	35,7	291,5	660,5	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,6	130,2	44,7	27,88
240	4,08	6,46	30	118	35	55,27	34,2	291,5	660,6	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,8	130,1	44,7	28,76
241	4,08	6,46	30	118	35	56,83	33,9	291,5	660,5	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,7	149	44,7	28,79
242	4,45	6,27	30	118	40	57,43	34,5	306,5	661,5	216	113,5	112,5	0,06	6,1	23	37	24,88	26,5	37,5	137,1	44,7	28,87
243	4,42	6,19	30	115	40	59,52	35,6	306,4	661,6	216	113,5	112,5	0,06	6,1	23	37	24,88	26,5	37,4	197,1	44,7	30,8
244	4,44	6,21	30	115	40	59,41	34,4	306,4	661,3	216	113,5	112,5	0,06	6,1	23	37	24,88	26,5	36,9	132,9	44,7	28,8
245	4,47	6,22	30	115	40	59,14	33,3	306,4	661,3	216	113,5	112,5	0,06	6,1	23	37	24,88	26,5	36,6	135,1	44,7	30,89
246	4,44	6,19	30	115	40	55,24	35,7	306,4	661,7	216	113,5	112,5	0,06	6,1	23	37	24,88	26,5	37	141,3	44,7	27,88
247	4,45	6,24	30	115	40	59,98	33,9	306,5	661,1	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,7	132,2	44,7	30,8
248	4,47	6,24	30	115	40	60,07	33,3	306,4	661,1	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,4	132,2	44,7	28,8
249	4,45	6,25	30	115	40	59,92	33,7	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	37,5	132,3	44,7	30,89

Table 4.24. Realized Process Data from 250 to 300 Cycles

	INPUTS															OUTPUTS						
Cycle	Mold Open Time (sn)	Mold Close Time (sn)	Injection Time (sn)	Injection Pressure (bar)	Injection Speed (mm/s)	Plasticization Time (s)	Holding Position (mm)	Screw Position (mm)	Mold Open Position (mm)	Melt Temp. (C°	System Pressure (bar)	Back Pressure (bar)	Robot Repeatability (mm)	System Air Pressure (bar)	Cooling Wat. Temp. (C)	Hyd. Oil Temp. (C)	Core Temp. (C)	Cavity Temp. (C)	E.Motor Amperage (Amp)	Cycle Time (s)	Product Temp. (C)	Plastic Shot Weight (gr)
250	4,41	6,22	30	115	40	58,83	34,1	306,6	661,7	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	37	134,1	44,7	28,86
251	4,41	6,15	30	115	40	58,63	34,3	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	36,5	138	44,7	28,75
252	4,42	6,22	30	115	40	58,24	34	306,5	661,4	216	112,6	113,2	0,06	6,1	23	38	24,88	26,5	37,4	136,2	44,7	30,89
253	4,47	6,24	30	115	40	59,74	33,3	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,3	135,5	44,7	27,88
254	4,44	6,28	30	115	40	59,98	33,9	306,6	661,3	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,6	134,6	44,7	28,8
255	4,41	6,15	30	115	40	56,22	35,2	306,5	661,5	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	36,4	134	44,7	27,96
256	4,42	6,25	30	115	40	59,28	34,1	306,4	661,4	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	37,5	151	44,7	27,88
257	4,41	6,21	30	115	40	59,49	33,7	306,4	661,4	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	37,4	141,4	44,7	28,76
258	4,41	6,24	30	115	40	58,33	34,1	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	36,9	140,3	44,7	28,75
259	4,44	6,3	30	115	40	59,86	33,8	306,5	661,4	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	37,4	133,1	44,7	28,84
260	4,45	6,24	30	115	40	59,98	33,9	306,5	661,1	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,7	132,2	44,7	30,8
261	4,47	6,24	30	115	40	60,07	33,3	306,4	661,1	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,4	132,2	44,7	28,8
262	4,45	6,25	30	115	40	59,92	33,7	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	37,5	132,3	44,7	30,89
263	4,45	6,27	30	115	40	58,57	34,9	306,6	661,3	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	37,4	133,6	44,7	27,88
264	4,45	6,19	30	115	40	59,59	34,1	306,6	661,2	216	111	112	0,06	6,1	23	38	24,88	26,5	37,5	133,6	44,7	28,87
265	4,08	6,42	30	118	35	56,59	35,4	291,2	660,3	217	113,76	113	0,06	6,1	23	36	24,88	26,5	37,4	303,8	44,7	28,87
266	4,08	6,39	30	118	35	56,46	34,2	291,5	660,3	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,9	129,8	44,7	28,68
267	4,15	6,43	30	118	35	56,35	34,1	291,6	660,3	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,8	129,4	44,7	29,18
268	4,08	6,4	30	118	35	56,5	33,3	291,5	660,4	217	113,76	113	0,06	6,1	23	36	24,88	26,5	37,7	131,5	44,7	27,96
269	4,08	6,39	30	118	35	56,58	35,7	291,5	660,5	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,6	130,2	44,7	27,88
270	4,08	6,46	30	118	35	55,27	34,2	291,5	660,6	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,8	130,1	44,7	28,76
271	4,08	6,46	30	118	35	56,83	33,9	291,5	660,5	217	113,76	113	0,06	6,1	23	36	24,88	26,5	36,7	149	44,7	28,79
272	4,45	6,27	30	118	40	57,43	34,5	306,5	661,5	216	113,5	112,5	0,06	6,1	23	37	24,88	26,5	37,5	137,1	44,7	28,87
273	4,42	6,21	30	115	40	57,94	34,1	306,4	661,1	216	113,5	112,5	0,06	6,1	23	40	24,88	26,5	36,4	132,3	44,7	28,75
274	4,42	6,12	30	115	40	58,14	34	306,4	661,7	216	113,5	112,5	0,06	6,1	23	40	24,88	26,5	37,5	138,7	44,7	28,87
275	4,44	6,13	30	115	40	56,1	34,8	306,4	660,5	216	113,5	112,5	0,06	6,1	23	40	24,88	26,5	37,4	133,6	44,7	28,76
276	4,41	6,13	30	115	40	56,11	35,1	306,4	660,6	216	113,5	112,5	0,06	6,1	23	40	24,88	26,5	36,9	149	44,7	28,75
277	4,42	6,18	30	115	40	57,82	34,1	306,4	660,6	216	113,5	112,5	0,06	6,1	23	40	24,88	26,5	36,6	149	44,7	28,87
278	4,45	6,19	30	115	40	57,72	34,7	306,4	661,1	216	113,5	112,5	0,06	6,1	23	39	24,88	26,5	37	136,9	44,7	28,87
279	4,42	6,21	30	115	40	58,33	34,1	306,5	660,5	216	113,5	112,5	0,06	6,1	23	39	24,88	26,5	37,5	149,2	44,7	28,8
280	4,48	6,24	30	115	40	59,07	33,8	306,5	661,3	216	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,9	132,5	44,7	30,89
281	4,45	6,22	30	115	40	58,32	34,3	306,4	661,4	216	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,6	135,5	44,7	30,78
282	4,42	6,21	30	115	40	52,51	36,9	306,7	662	215	113,6	112,8	0,06	6,1	23	39	24,88	26,5	36,7	133,7	44,7	30,89
283	4,47	6,1	30	115	40	58,15	34,7	306,4	661,5	215	113,6	112,8	0,06	6,1	23	39	24,88	26,5	37,5	140	44,7	27,88
284	4,47	6,1	30	115	40	58,32	34,5	306,6	661,6	215	113,6	112,8	0,06	6,1	23	39	24,88	26,5	36,3	137	44,7	27,88
285	4,44	6,15	30	115	40	57,9	34,7	306,5	661,5	215	113,6	112,8	0,06	6,1	23	39	24,88	26,5	36,4	134	44,7	27,96
286	4,42	6,13	30	115	40	57,9	34,4	306,5	661,4	215	113,6	112,8	0,06	6,1	23	39	24,88	26,5	36,6	138	44,7	28,86
287	4,41	6,21	30	115	40	59,49	33,7	306,4	661,4	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	37,4	141,4	44,7	28,76
288	4,41	6,24	30	115	40	58,33	34,1	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	36,9	140,3	44,7	28,75
289	4,48	6,35	30	115	40	56,73	35,3	306,4	661,8	216	110,3	106,8	0,06	6,1	23	39	24,88	26,5	37,5	209,3	44,7	28,76
290	4,47	6,36	30	115	40	55,99	34,3	306,6	661,8	216	110,3	106,8	0,06	6,1	23	39	24,88	26,5	37,4	147	44,7	28,75
291	4,12	6,43	30	118	35	56,07	20,1	291,5	660,5	216	113,76	113	0,06	6,1	23	36	24,88	26,5	36,7	144,6	44,7	27,88
292	4,42	6,18	30	115	40	58,11	34,1	306,5	661,2	215	113,6	112,8	0,06	6,1	23	39	24,88	26,5	36,3	137	44,7	30,89
293	4,45	6,16	30	115	40	56,55	35,2	306,5	661,5	215	113,6	112,8	0,06	6,1	23	39	24,88	26,5	36,4	135	44,7	28,75
294	4,47	6,16	30	115	40	57,73	34,6	306,5	661,3	215	113,6	112,8	0,06	6,1	23	39	24,88	26,5	36,7	176	44,7	28,8
295	4,42	6,18	30	115	40	57,24	34,5	306,5	661,5	215	113,6	112,8	0,06	6,1	23	39	24,88	26,5	36,6	137	44,7	30,89
296	4,42	6,1	30	115	40	57,79	34,6	306,4	661,7	215	113,6	112,8	0,06	6,1	23	39	24,88	26,5	37,5	148	44,7	28,88
297	4,41	6,22	30	115	40	58,83	34,1	306,6	661,7	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	37	134,1	44,7	28,86
298	4,41	6,15	30	115	40	58,63	34,3	306,6	661,6	215	112,6	113,2	0,06	6,1	23	38	24,88	26,5	36,5	138	44,7	28,75
299	4,42	6,22	30	115	40	58,24	34	306,5	661,4	216	112,6	113,2	0,06	6,1	23	38	24,88	26,5	37,4	136,2	44,7	30,89
300	4,47	6,24	30	115	40	59,74	33,3	306,6	661,4	217	113,5	112,5	0,06	6,1	23	39	24,88	26,5	36,3	135,5	44,7	27,88

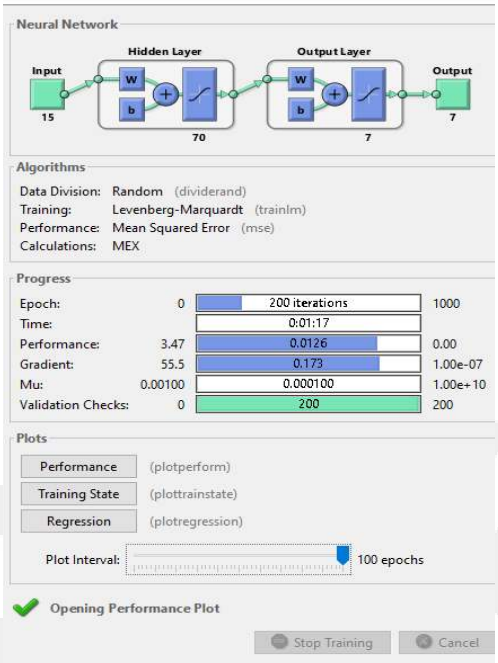


Figure 4.19. ANN Training Interface

4.3.2.3. Discussions of Best Performance Network by Using Regression Results

In order to compare the executed network prediction performances, MAPE, MSE and R^2 statistical and regression tools have been implemented by using realized and predicted CT data of trained 10 to 100 layers. Comparison table and graphical demonstrations of realized and predicted CT data can be seen in Tables 4.25-4.27, and Figures 4.20-4.22. The comparison table shows that 70 Hidden Layer (HL) network performance is the best among the others. 70 HL prediction results indicate the low MAPE, low MSE and highest R^2. Additionally, Figure 4.22. supports the highest prediction performances of 70 HL with an in-line trend of predicted and realized data.

Table 4.25. CT Prediction Outputs of Trained ANNs from 1 to 100 Cycles

Cycle	Realized	10 HL Training	20 HL Training	30 HL Training	40 HL Training	50 HL Training	60 HL Training	70 HL Training	80 HL Training	90 HL Training	100 HL Training
	CT	CT	CT	CT	CT	CT	CT	CT	CT	CT	CT
1	135,30	135,54	135,30	135,12	135,07	135,58	135,28	133,62	135,52	135,30	136,17
2	134,10	134,15	134,11	134,06	134,04	134,19	134,09	133,74	134,22	134,10	137,78
3	132,80	132,81	132,80	132,68	132,41	133,00	132,82	135,14	133,36	132,80	137,75
4	143,40	143,34	143,41	143,55	142,83	143,95	143,40	141,17	143,81	143,40	142,61
5	137,60	137,60	137,61	137,39	137,51	137,74	137,60	137,49	137,63	137,59	139,01
6	138,00	138,01	138,00	137,84	138,01	138,06	137,99	138,37	138,52	137,99	139,99
7	133,60	130,34	130,09	138,36	134,53	133,45	133,76	131,80	132,98	133,58	135,07
8	136,50	213,29	136,51	136,47	137,52	136,44	137,67	138,34	135,81	138,44	148,93
9	134,60	132,42	134,60	135,11	134,59	134,70	129,73	135,31	134,01	134,62	143,27
10	134,00	134,02	134,01	133,93	134,00	134,26	134,01	129,67	134,10	134,00	134,68
11	151,00	150,98	150,99	150,79	150,99	151,57	150,94	151,50	151,16	151,00	151,53
12	141,40	141,39	141,38	141,31	141,43	141,71	141,36	141,73	141,61	141,39	142,83
13	140,30	140,31	140,29	140,23	140,29	140,49	140,30	130,58	140,65	140,30	141,40
14	146,70	130,14	146,69	146,47	146,66	147,20	146,68	147,66	147,48	170,79	147,78
15	207,40	207,37	207,35	238,09	207,33	210,56	207,30	174,46	147,62	207,40	216,30
16	142,00	142,01	142,01	141,86	142,24	142,38	141,97	139,29	142,40	142,00	143,46
17	136,20	136,19	136,20	136,15	136,21	136,14	136,20	129,30	129,33	136,20	131,57
18	150,00	150,06	150,01	150,04	150,04	149,82	136,76	129,32	138,36	150,00	150,92
19	179,70	179,71	179,71	179,73	179,71	179,94	179,64	177,67	180,34	144,22	188,05
20	136,10	136,08	136,10	136,08	136,01	135,94	136,04	135,61	138,16	136,10	146,80
21	135,50	131,80	147,44	140,80	135,85	132,18	129,65	130,60	129,36	135,46	132,32
22	132,10	132,15	132,03	129,58	131,52	131,75	132,06	131,67	132,33	132,07	134,71
23	155,90	155,89	155,94	155,46	136,22	155,34	155,71	150,57	143,72	155,90	163,94
24	133,10	133,15	133,13	133,04	132,96	133,31	132,03	129,32	129,31	134,98	129,39
25	132,20	132,37	132,09	145,72	131,44	133,24	178,29	138,32	133,07	275,06	151,85
26	132,20	132,06	132,25	132,95	132,67	132,30	132,21	139,51	134,33	302,87	158,43
27	132,30	132,30	132,26	132,20	131,17	130,67	132,35	130,17	129,32	132,30	131,06
28	133,60	133,35	133,59	134,12	134,17	133,01	133,56	129,57	129,33	133,53	130,04
29	160,20	160,20	160,24	160,13	160,28	159,98	129,30	161,21	159,62	160,22	160,44
30	134,60	134,95	134,59	129,31	130,75	129,30	134,54	129,31	129,33	134,61	129,32
31	135,50	135,49	135,52	135,47	135,44	135,46	129,30	131,98	135,08	135,51	133,18
32	132,10	132,16	132,12	130,89	130,56	132,21	132,08	134,40	150,95	132,11	129,47
33	155,90	283,04	133,94	155,92	155,94	156,13	129,30	156,46	154,14	155,90	151,73
34	133,10	132,80	133,03	133,04	133,43	132,88	133,06	129,32	133,78	133,10	129,41
35	132,20	131,98	132,24	132,08	132,16	132,13	132,17	132,15	133,19	132,32	133,26
36	132,20	132,41	132,19	132,28	132,18	132,26	129,30	131,11	131,57	132,18	131,25
37	132,30	132,26	132,29	132,28	132,64	132,52	129,30	131,39	132,80	132,42	134,99
38	133,60	133,59	133,61	133,56	133,57	133,51	133,59	130,30	134,13	133,61	129,41
39	160,20	160,20	160,24	160,13	160,28	159,98	129,30	161,21	159,62	160,22	160,44
40	134,60	134,69	134,61	134,64	134,51	134,40	134,54	129,38	133,57	134,58	129,59
41	145,00	144,97	168,10	145,06	145,06	156,71	144,99	147,16	145,09	130,39	148,89
42	148,00	148,02	148,05	147,86	155,21	148,04	148,03	145,72	136,02	134,17	136,00
43	138,00	138,02	129,31	138,01	138,01	138,03	137,98	137,58	138,67	138,00	141,12
44	145,00	153,52	131,14	144,93	145,00	190,97	144,98	145,23	145,95	145,00	147,59
45	204,30	300,87	204,31	204,47	204,32	203,38	129,30	204,22	205,30	204,29	205,19
46	143,30	143,29	143,31	143,28	143,32	143,52	129,30	135,42	149,07	163,04	140,19
47	134,50	134,49	134,49	134,55	134,60	134,43	134,49	134,53	134,75	134,50	135,57
48	201,40	201,40	201,41	201,62	201,39	200,52	129,30	201,35	201,08	201,40	203,92
49	167,20	167,20	167,21	167,27	167,20	166,66	129,30	167,22	168,52	167,21	166,02
50	133,60	133,62	133,62	133,51	133,61	133,60	133,60	133,96	133,73	133,60	134,98
51	153,00	153,04	153,00	153,28	152,89	152,65	152,99	152,90	153,61	153,00	151,51
52	150,20	150,24	150,19	150,65	150,16	149,66	150,20	150,20	150,93	150,20	147,01
53	146,30	146,31	146,29	146,38	146,22	146,07	132,36	147,45	146,88	146,30	148,09
54	142,00	142,01	130,04	301,46	129,30	142,26	142,00	141,76	142,35	303,64	143,33
55	209,30	209,30	209,30	209,42	129,30	209,57	209,30	209,35	211,05	209,31	209,89
56	147,00	147,02	147,00	147,05	129,30	147,27	147,00	146,95	147,63	147,00	148,22
57	144,90	129,84	144,91	144,92	129,30	129,33	144,90	130,38	145,10	144,90	129,53
58	145,70	154,14	145,71	129,30	129,30	146,38	145,69	145,85	145,67	141,89	302,78
59	267,00	266,99	267,00	266,98	129,30	266,35	267,00	267,05	267,66	266,99	266,33
60	146,00	146,01	146,02	145,98	129,30	145,49	146,00	145,99	146,31	146,00	148,26
61	144,60	129,30	144,61	129,30	144,47	144,26	144,59	144,56	129,30	144,59	129,30
62	129,30	129,30	129,31	129,30	129,30	129,30	129,30	129,30	129,30	129,30	129,30
63	129,90	129,91	129,89	129,30	129,30	129,30	129,90	129,30	129,30	129,30	129,30
64	303,80	303,62	303,71	303,43	303,60	303,32	303,78	302,33	303,26	303,68	298,22
65	129,80	129,80	129,79	129,85	129,86	129,86	129,82	130,88	129,83	129,83	133,30
66	129,40	129,30	129,43	129,53	129,30	129,45	129,39	130,15	129,67	129,44	130,26
67	131,50	131,51	129,31	129,30	129,30	129,30	131,50	129,31	129,30	129,30	129,40
68	130,20	130,23	130,23	129,32	130,17	130,20	130,20	131,73	130,52	130,19	132,37
69	130,10	130,09	130,12	130,02	129,30	129,93	130,08	129,61	129,30	129,30	129,31
70	149,00	149,00	149,00	148,78	149,03	147,94	149,00	148,92	148,87	149,00	148,70
71	137,10	137,10	137,13	137,04	129,30	136,86	129,30	137,14	129,30	137,10	129,30
72	197,10	197,09	197,75	196,69	196,50	197,82	196,93	196,93	197,28	197,09	206,18
73	132,90	133,20	132,94	134,75	133,54	135,05	173,54	141,91	134,78	132,89	153,79
74	135,10	134,78	135,12	135,24	134,72	134,67	135,21	129,73	129,34	135,09	132,17
75	141,30	141,36	141,32	141,01	141,29	141,29	129,31	141,57	140,83	141,28	129,33
76	299,80	299,84	209,08	211,50	299,45	300,25	153,38	289,00	297,12	238,30	274,56
77	136,90	136,92	136,90	299,00	134,49	294,66	151,98	138,92	191,61	136,89	189,61
78	155,10	155,07	155,13	154,89	155,14	154,82	155,01	129,52	129,31	155,09	129,41
79	181,30	129,30	181,30	189,83	181,41	180,53	181,23	181,30	159,52	181,29	135,50
80	221,70	131,85	221,72	221,76	221,86	221,33	220,84	220,88	225,76	221,70	231,17
81	136,30	139,12	131,29	136,07	136,27	266,49	136,26	138,11	274,92	158,46	148,35
82	132,30	132,08	132,30	132,39	131,75	132,47	132,26	129,31	129,30	132,26	129,40
83	138,70	129,43	138,72	138,62	138,72	138,69	138,67	130,45	138,40	138,70	131,16
84	133,60	133,58	133,60	133,58	133,61	133,41	133,60	133,73	134,11	133,60	141,31
85	149,00	148,99	149,01	149,01	148,96	148,73	149,02	133,13	150,05	132,20	159,42
86	149,00	149,00	149,03	149,18	149,04	148,50	148,95	148,95	149,75	148,98	154,47
87	136,90	136,86	136,91	136,96	137,03	136,89	148,07	130,51	137,79	136,90	130,67
88	149,20	149,18	149,24	133,00	150,13	149,13	149,13	149,14	150,22	149,18	145,33
89	132,50	134,27	132,52	133,20	133,50	134,74	132,29	130,40	129,49	132,54	134,72
90	135,50	135,88	135,51	135,12	135,31	134,89	135,45	129,37	129,30	135,51	129,64
91	133,70	133,70	133,70	133,63	133,72	133,63	129,30	133,62	133,75	133,70	133,48
92	140,00	139,97	140,04	139,71	139,82	146,52	129,30	138,25	139,45	139,98	146,45
93	137,00	136,99	137,02	136,81	137,02	136,99	129,30	141,29	137,66	136,99	141,35
94	134,00	133,99	133,99	133,85	134,02	134,06	133,97	138,43	134,97	133,97	143,98
95	138,00	138,03	138,02	137,82	137,96	138,14	137,98	138,91	138,36	138,00	140,13
96	137,00	136,97	136,99	137,03	136,98	137,13	136,97	136,19	137,28	136,99	140,05
97	135,00	134,98	135,01	134,87	135,12	134,82	134,99	135,97	135,47	135,00	138,24
98	176,00	176,00	176,06	175,30	175,88	176,62	175,93	175,48	176,42	175,98	179,76
99	137,00	136,99	137,00	136,79	136,88	137,33	137,00	130,55	130,69	137,00	138,27
100	148,00	147,99	148,03	147,61	147,98	147,63	129,30	146,77	148,02	147,97	147,13

Table 4.26. CT Prediction Outputs of Trained ANNs from 100 to 200 Cycles

Cycle	Realized	10 HL Training	20 HL Training	30 HL Training	40 HL Training	50 HL Training	60 HL Training	70 HL Training	80 HL Training	90 HL Training	100 HL Training
	CT	CT	CT	CT	CT	CT	CT	CT	CT	CT	CT
101	134,10	134,15	134,11	134,06	134,04	134,19	134,09	133,74	134,22	134,10	137,78
102	138,00	138,01	138,00	137,84	138,01	138,06	137,99	138,37	138,52	137,99	139,99
103	136,20	136,19	136,20	136,15	136,21	136,14	136,20	129,30	129,33	136,20	131,57
104	135,50	135,49	135,52	135,47	135,44	135,46	129,30	131,98	135,08	135,51	133,18
105	134,60	134,69	134,61	134,64	134,51	134,40	134,54	129,38	133,57	134,58	129,59
106	153,00	153,04	153,00	153,28	152,89	152,65	152,99	152,90	153,61	153,00	151,51
107	267,00	266,99	267,00	266,98	129,30	266,35	267,00	267,05	267,66	266,99	266,33
108	134,10	134,15	134,11	134,06	134,04	134,19	134,09	133,74	134,22	134,10	137,78
109	138,00	138,01	138,00	137,84	138,01	138,06	137,99	138,37	138,52	137,99	139,99
110	136,20	136,19	136,20	136,15	136,21	136,14	136,20	129,30	129,33	136,20	131,57
111	135,50	135,49	135,52	135,47	135,44	135,46	129,30	131,98	135,08	135,51	133,18
112	134,60	134,69	134,61	134,64	134,51	134,40	134,54	129,38	133,57	134,58	129,59
113	153,00	153,04	153,00	153,28	152,89	152,65	152,99	152,90	153,61	153,00	151,51
114	267,00	266,99	267,00	266,98	129,30	266,35	267,00	267,05	267,66	266,99	266,33
115	138,00	138,02	129,31	138,01	138,01	138,03	137,98	137,58	138,67	138,00	141,12
116	209,30	209,30	209,30	209,42	129,30	209,57	209,30	209,35	211,05	209,31	209,89
117	129,30	129,30	129,31	129,30	129,30	129,30	129,30	129,30	129,30	129,30	129,30
118	129,80	129,80	129,79	129,85	129,86	129,86	129,82	130,88	129,83	129,83	133,30
119	131,50	131,51	129,31	129,30	129,30	129,30	131,50	129,31	129,30	129,30	129,40
120	149,00	149,00	149,00	148,78	149,03	147,94	149,00	148,92	148,87	149,00	148,70
121	133,70	133,70	133,70	133,63	133,72	133,63	129,30	133,62	133,75	133,70	133,48
122	138,00	138,03	138,02	137,82	137,96	138,14	137,98	138,91	138,36	138,00	140,13
123	135,00	134,98	135,01	134,87	135,12	134,82	134,99	135,97	135,47	135,00	138,24
124	132,30	132,08	132,30	132,39	131,75	132,47	132,26	129,31	129,30	132,26	129,40
125	138,70	129,43	138,72	138,62	138,72	138,69	138,67	130,45	138,40	138,70	131,16
126	133,60	133,58	133,60	133,58	133,61	133,41	133,60	133,73	134,11	133,60	141,31
127	135,30	135,54	135,30	135,12	135,07	135,58	135,28	133,62	135,52	135,30	136,17
128	134,10	134,15	134,11	134,06	134,04	134,19	134,09	133,74	134,22	134,10	137,78
129	137,60	137,60	137,61	137,39	137,51	137,74	137,60	137,49	137,63	137,59	139,01
130	138,00	138,01	138,00	137,84	138,01	138,06	137,99	138,37	138,52	137,99	139,99
131	140,30	140,31	140,29	140,23	140,29	140,49	140,30	130,58	140,65	140,30	141,40
132	146,70	130,14	146,69	146,47	146,66	147,20	146,68	147,66	147,48	170,79	147,78
133	134,00	134,02	134,01	133,93	134,00	134,26	134,01	129,67	134,10	134,00	134,68
134	151,00	150,98	150,99	150,79	150,99	151,57	150,94	151,50	151,16	151,00	151,53
135	141,40	141,39	141,38	141,31	141,43	141,71	141,36	141,73	141,61	141,39	142,83
136	140,30	140,31	140,29	140,23	140,29	140,49	140,30	130,58	140,65	140,30	141,40
137	209,30	209,30	209,30	209,42	129,30	209,57	209,30	209,35	211,05	209,31	209,89
138	147,00	147,02	147,00	147,05	129,30	147,27	147,00	146,95	147,63	147,00	148,22
139	144,60	129,30	144,61	129,30	144,47	144,26	144,59	144,56	129,30	144,59	129,30
140	129,30	129,30	129,31	129,30	129,30	129,30	129,30	129,30	129,30	129,30	129,30
141	129,90	129,91	129,89	129,30	129,30	129,30	129,90	129,30	129,30	129,30	129,30
142	134,50	134,49	134,49	134,55	134,60	134,43	134,49	134,53	134,75	134,50	135,57
143	201,40	201,40	201,41	201,62	201,39	200,52	129,30	201,35	201,08	201,40	203,92
144	167,20	167,20	167,21	167,27	167,20	166,66	129,30	167,22	168,52	167,21	166,02
145	133,60	133,62	133,62	133,51	133,61	133,60	133,60	133,96	133,73	133,60	134,98
146	153,00	153,04	153,00	153,28	152,89	152,65	152,99	152,90	153,61	153,00	151,51
147	150,20	150,24	150,19	150,65	150,16	149,66	150,20	150,20	150,93	150,20	147,01
148	146,30	146,31	146,29	146,38	146,22	146,07	132,36	147,45	146,88	146,30	148,09
149	135,30	135,54	135,30	135,12	135,07	135,58	135,28	133,62	135,52	135,30	136,17
150	134,10	134,15	134,11	134,06	134,04	134,19	134,09	133,74	134,22	134,10	137,78
151	132,80	132,81	132,80	132,68	132,41	133,00	132,82	135,14	133,36	132,80	137,75
152	143,40	143,34	143,41	143,55	142,83	143,95	143,40	141,17	143,81	143,40	142,61
153	137,60	137,60	137,61	137,39	137,51	137,74	137,60	137,49	137,63	137,59	139,01
154	133,70	133,70	133,70	133,63	133,72	133,63	129,30	133,62	133,75	133,70	133,48
155	140,00	139,97	140,04	139,71	139,82	146,52	129,30	138,25	139,45	139,98	146,45
156	137,00	136,99	137,02	136,81	137,02	136,99	129,30	141,29	137,66	136,99	141,35
157	134,00	133,99	133,99	133,85	134,02	134,06	133,97	138,43	134,97	133,97	143,98
158	138,00	138,03	138,02	137,82	137,96	138,14	137,98	138,91	138,36	138,00	140,13
159	137,00	136,97	136,99	137,03	136,98	137,13	136,97	136,19	137,28	136,99	140,05
160	135,00	134,98	135,01	134,87	135,12	134,82	134,99	135,97	135,47	135,00	138,24
161	176,00	176,00	176,06	175,30	175,88	176,62	175,93	175,48	176,42	175,98	179,76
162	137,00	136,99	137,00	136,79	136,88	137,33	137,00	130,55	130,69	137,00	138,27
163	148,00	147,99	148,03	147,61	147,98	147,63	129,30	146,77	148,02	147,97	147,13
164	151,00	150,98	150,99	150,79	150,99	151,57	150,94	151,50	151,16	151,00	151,53
165	140,30	140,31	140,29	140,23	140,29	140,49	140,30	130,58	140,65	140,30	141,40
166	136,10	136,08	136,10	136,08	136,01	135,94	136,04	135,61	138,16	136,10	146,80
167	132,10	132,15	132,03	129,58	131,52	131,75	132,06	131,67	132,33	132,07	134,71
168	132,30	132,30	132,26	132,20	131,17	130,67	132,35	130,17	129,32	132,30	131,06
169	129,30	129,30	129,31	129,30	129,30	129,30	129,30	129,30	129,30	129,30	129,30
170	129,90	129,91	129,89	129,30	129,30	129,30	129,90	129,30	129,30	129,30	129,30
171	134,50	134,49	134,49	134,55	134,60	134,43	134,49	134,53	134,75	134,50	135,57
172	135,30	135,54	135,30	135,12	135,07	135,58	135,28	133,62	135,52	135,30	136,17
173	134,10	134,15	134,11	134,06	134,04	134,19	134,09	133,74	134,22	134,10	137,78
174	132,80	132,81	132,80	132,68	132,41	133,00	132,82	135,14	133,36	132,80	137,75
175	132,20	132,41	132,19	132,28	132,18	132,26	129,30	131,11	131,57	132,18	131,25
176	132,30	132,26	132,29	132,28	132,64	132,52	129,30	131,39	132,80	132,42	134,99
177	133,60	133,59	133,61	133,56	133,57	133,51	133,59	130,30	134,13	133,61	129,41
178	303,80	303,62	303,71	303,43	303,60	303,32	303,78	302,33	303,26	303,68	298,22
179	129,80	129,80	129,79	129,85	129,86	129,86	129,82	130,88	129,83	129,83	133,30
180	129,40	129,30	129,43	129,53	129,30	129,45	129,39	130,15	129,67	129,44	130,26
181	135,50	135,88	135,51	135,12	135,31	134,89	135,45	129,37	129,30	135,51	129,64
182	133,70	133,70	133,70	133,63	133,72	133,63	129,30	133,62	133,75	133,70	133,48
183	134,00	134,02	134,01	133,93	134,00	134,26	134,01	129,67	134,10	134,00	134,68
184	151,00	150,98	150,99	150,79	150,99	151,57	150,94	151,50	151,16	151,00	151,53
185	141,40	141,39	141,38	141,31	141,43	141,71	141,36	141,73	141,61	141,39	142,83
186	140,30	140,31	140,29	140,23	140,29	140,49	140,30	130,58	140,65	140,30	141,40
187	209,30	209,30	209,30	209,42	129,30	209,57	209,30	209,35	211,05	209,31	209,89
188	147,00	147,02	147,00	147,05	129,30	147,27	147,00	146,95	147,63	147,00	148,22
189	144,60	129,30	144,61	129,30	144,47	144,26	144,59	144,56	129,30	144,59	129,30
190	137,00	136,97	136,99	137,03	136,98	137,13	136,97	136,19	137,28	136,99	140,05
191	135,00	134,98	135,01	134,87	135,12	134,82	134,99	135,97	135,47	135,00	138,24
192	176,00	176,00	176,06	175,30	175,88	176,62	175,93	175,48	176,42	175,98	179,76
193	137,00	136,99	137,00	136,79	136,88	137,33	137,00	130,55	130,69	137,00	138,27
194	148,00	147,99	148,03	147,61	147,98	147,63	129,30	146,77	148,02	147,97	147,13
195	134,10	134,15	134,11	134,06	134,04	134,19	134,09	133,74	134,22	134,10	137,78
196	138,00	138,01	138,00	137,84	138,01	138,06	137,99	138,37	138,52	137,99	139,99
197	136,20	136,19	136,20	136,15	136,21	136,14	136,20	129,30	129,33	136,20	131,57
198	135,50	135,49	135,52	135,47	135,44	135,46	129,30	131,98	135,08	135,51	133,18
199	134,60	134,69	134,61	134,64	134,51	134,40	134,54	129,38	133,57	134,58	129,59

Table 4.27. CT Prediction Outputs of Trained ANNs from 200 to 300 Cycles

Cycle	Realized	10 HL Training	20 HL Training	30 HL Training	40 HL Training	50 HL Training	60 HL Training	70 HL Training	80 HL Training	90 HL Training	100 HL Training
	CT	CT	CT	CT	CT	CT	CT	CT	CT	CT	CT
200	153,00	153,04	153,00	153,28	152,89	152,65	152,99	152,90	153,61	153,00	151,51
201	133,10	132,80	133,03	133,04	133,43	132,88	133,06	129,32	133,78	133,10	129,41
202	132,20	131,98	132,24	132,08	132,16	132,13	132,17	132,15	133,19	132,32	133,26
203	132,20	132,41	132,19	132,28	132,18	132,26	129,30	131,11	131,57	132,18	131,25
204	132,30	132,26	132,29	132,28	132,64	132,52	129,30	131,39	132,80	132,42	134,99
205	134,10	134,15	134,11	134,06	134,04	134,19	134,09	133,74	134,22	134,10	137,78
206	138,00	138,01	138,00	137,84	138,01	138,06	137,99	138,37	138,52	137,99	139,99
207	136,20	136,19	136,20	136,15	136,21	136,14	136,20	129,30	129,33	136,20	131,57
208	135,50	135,49	135,52	135,47	135,44	135,46	129,30	131,98	135,08	135,51	133,18
209	134,60	134,69	134,61	134,64	134,51	134,40	134,54	129,38	133,57	134,58	129,59
210	140,30	140,31	140,29	140,23	140,29	140,49	140,30	130,58	140,65	140,30	141,40
211	136,10	136,08	136,10	136,08	136,01	135,94	136,04	135,61	138,16	136,10	146,80
212	132,10	132,15	132,03	129,58	131,52	131,75	132,06	131,67	132,33	132,07	134,71
213	132,30	132,30	132,26	132,20	131,17	130,67	132,35	130,17	129,32	132,30	131,06
214	129,30	129,30	129,31	129,30	129,30	129,30	129,30	129,30	129,30	129,30	129,30
215	129,90	129,91	129,89	129,30	129,30	129,30	129,90	129,30	129,30	129,30	129,30
216	134,50	134,49	134,49	134,55	134,60	134,43	134,49	134,53	134,75	134,50	135,57
217	135,30	135,54	135,30	135,12	135,07	135,58	135,28	133,62	135,52	135,30	136,17
218	134,10	134,15	134,11	134,06	134,04	134,19	134,09	133,74	134,22	134,10	137,78
219	132,80	132,81	132,80	132,68	132,41	133,00	132,82	135,14	133,36	132,80	137,75
220	132,20	132,41	132,19	132,28	132,18	132,26	129,30	131,11	131,57	132,18	131,25
221	132,30	132,26	132,29	132,28	132,64	132,52	129,30	131,39	132,80	132,42	134,99
222	133,60	133,59	133,61	133,56	133,57	133,51	133,59	130,30	134,13	133,61	129,41
223	129,80	129,80	129,79	129,85	129,86	129,86	129,82	130,88	129,83	129,83	133,30
224	129,40	129,30	129,43	129,53	129,30	129,45	129,39	130,15	129,67	129,44	130,26
225	135,50	135,88	135,51	135,12	135,31	134,89	135,45	129,37	129,30	135,51	129,64
226	133,70	133,70	133,70	133,63	133,72	133,63	129,30	133,62	133,75	133,70	133,48
227	134,00	134,02	134,01	133,93	134,00	134,26	134,01	129,67	134,10	134,00	134,68
228	134,50	134,49	134,49	134,55	134,60	134,43	134,49	134,53	134,75	134,50	135,57
229	201,40	201,40	201,41	201,62	201,39	200,52	129,30	201,35	201,08	201,40	203,92
230	167,20	167,20	167,21	167,27	167,20	166,66	129,30	167,22	168,52	167,21	166,02
231	146,00	146,01	146,02	145,98	129,30	145,49	146,00	145,99	146,31	146,00	148,26
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242	137,10	137,10	137,13	137,04	129,30	136,86	129,30	137,14	129,30	137,10	129,30
243	197,10	197,09	197,75	196,69	196,50	197,82	196,93	196,93	197,28	197,09	206,18
244	132,90	133,20	132,94	134,75	133,54	135,05	173,54	141,91	134,78	132,89	153,79
245	135,10	134,78	135,12	135,24	134,72	134,67	135,21	129,73	129,34	135,09	132,17
246	141,30	141,36	141,32	141,01	141,29	141,29	129,31	141,57	140,83	141,28	129,33
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248	132,20	132,41	132,19	132,28	132,18	132,26	129,30	131,11	131,57	132,18	131,25
249	132,30	132,26	132,29	132,28	132,64	132,52	129,30	131,39	132,80	132,42	134,99
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262	132,30	132,26	132,29	132,28	132,64	132,52	129,30	131,39	132,80	132,42	134,99
263	133,60	133,59	133,61	133,56	133,57	133,51	133,59	130,30	134,13	133,61	129,41
264	133,60	133,62	133,62	133,51	133,61	133,60	133,60	133,96	133,73	133,60	134,98
265	303,80	303,62	303,71	303,43	303,60	303,32	303,78	302,33	303,26	303,68	298,22
266	129,80	129,80	129,79	129,85	129,86	129,86	129,82	130,88	129,83	129,83	133,30
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268	131,50	131,51	129,31	129,30	129,30	129,30	131,50	129,31	129,30	129,30	129,40
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270	130,10	130,09	130,12	130,02	129,30	129,93	130,08	129,61	129,30	129,30	129,31
271	149,00	149,00	149,00	148,78	149,03	147,94	149,00	148,92	148,87	149,00	148,70
272	137,10	137,10	137,13	137,04	129,30	136,86	129,30	137,14	129,30	137,10	129,30
273	132,30	132,08	132,30	132,39	131,75	132,47	132,26	129,31	129,30	132,26	129,40
274	138,70	129,43	138,72	138,62	138,72	138,69	138,67	130,45	138,40	138,70	131,16
275	133,60	133,58	133,60	133,58	133,61	133,41	133,60	133,73	134,11	133,60	141,31
276	149,00	148,99	149,01	149,01	148,96	148,73	149,02	133,13	150,05	132,20	159,42
277	149,00	149,00	149,03	149,18	149,04	148,50	148,95	148,95	149,75	148,98	154,47
278	136,90	136,86	136,91	136,96	137,03	136,89	148,07	130,51	137,79	136,90	130,67
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280	132,50	134,27	132,52	133,20	133,50	134,74	132,29	130,40	129,49	132,54	134,72
281	135,50	135,88	135,51	135,12	135,31	134,89	135,45	129,37	129,30	135,51	129,64
282	133,70	133,70	133,70	133,63	133,72	133,63	129,30	133,62	133,75	133,70	133,48
283	140,00	139,97	140,04	139,71	139,82	146,52	129,30	138,25	139,45	139,98	146,45
284	137,00	136,99	137,02	136,81	137,02	136,99	129,30	141,29	137,66	136,99	141,35
285	134,00	133,99	133,99	133,85	134,02	134,06	133,97	138,43	134,97	133,97	143,98
286	138,00	138,03	138,02	137,82	137,96	138,14	137,98	138,91	138,36	138,00	140,13
287	141,40	141,39	141,38	141,31	141,43	141,71	141,36	141,73	141,61	141,39	142,83
288	140,30	140,31	140,29	140,23	140,29	140,49	140,30	130,58	140,65	140,30	141,40
289	209,30	209,30	209,30	209,42	129,30	209,57	209,30	209,35	211,05	209,31	209,89
290	147,00	147,02	147,00	147,05	129,30	147,27	147,00	146,95	147,63	147,00	148,22
291	144,60	129,30	144,61	129,30	144,47	144,26	144,59	144,56	129,30	144,59	129,30
292	137,00	136,97	136,99	137,03	136,98	137,13	136,97	136,19	137,28	136,99	140,05
293	135,00	134,98	135,01	134,87	135,12	134,82	134,99	135,97	135,47	135,00	138,24
294	176,00	176,00	176,06	175,30	175,88	176,62	175,93	175,48	176,42	175,98	179,76
295	137,00	136,99	137,00	136,79	136,88	137,33	137,00	130,55	130,69	137,00	138,27
296	148,00	147,99	148,03	147,61	147,98	147,63	129,30	146,77	148,02	147,97	147,13
297	134,10	134,15	134,11	134,06	134,04	134,19	134,09	133,74	134,22	134,10	137,78
298	138,00	138,01	138,00	137,84	138,01	138,06	137,99	138,37	138,52	137,99	139,99
299	136,20	136,19	136,20	136,15	136,21	136,14	136,20	129,30	129,33	136,20	131,57
300	135,50	135,49	135,52	135,47	135,44	135,46	129,30	131,98	135,08	135,51	133,18
	MAPE	393,68	116,44	432,07	525,63	346,12	694,58	499,46	519,45	515,16	929,94
	MSE	1,31	0,39	1,44	1,75	1,15	2,32	1,66	1,73	1,72	3,10
	R^2	0,85	0,96	0,79	0,65	0,85	0,78	0,98	0,89	0,73	0,86

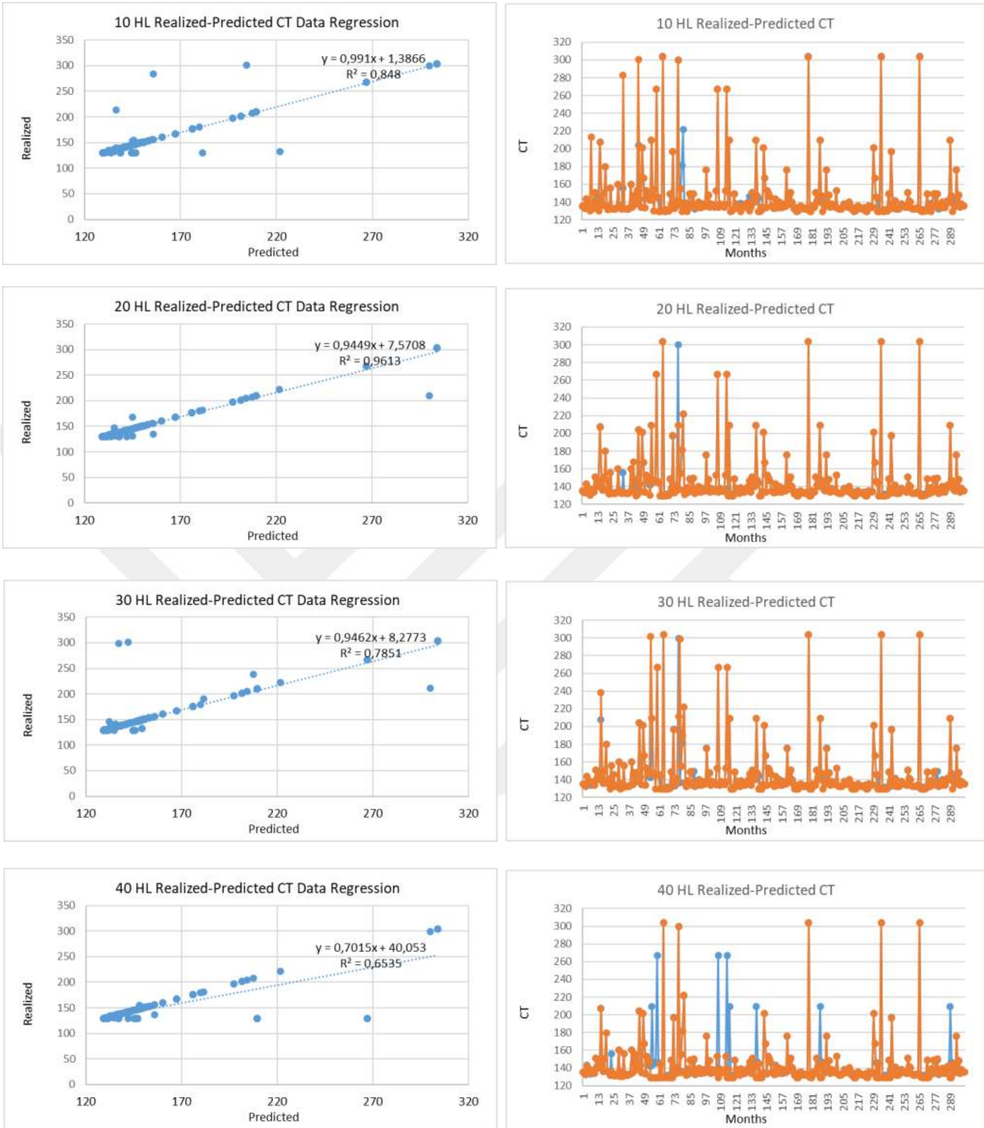

Figure 4.20. Structured ANNs Performances from 10 to 40 HL (Yellow Series: Predicted Data, Blue Series: Realized Data)

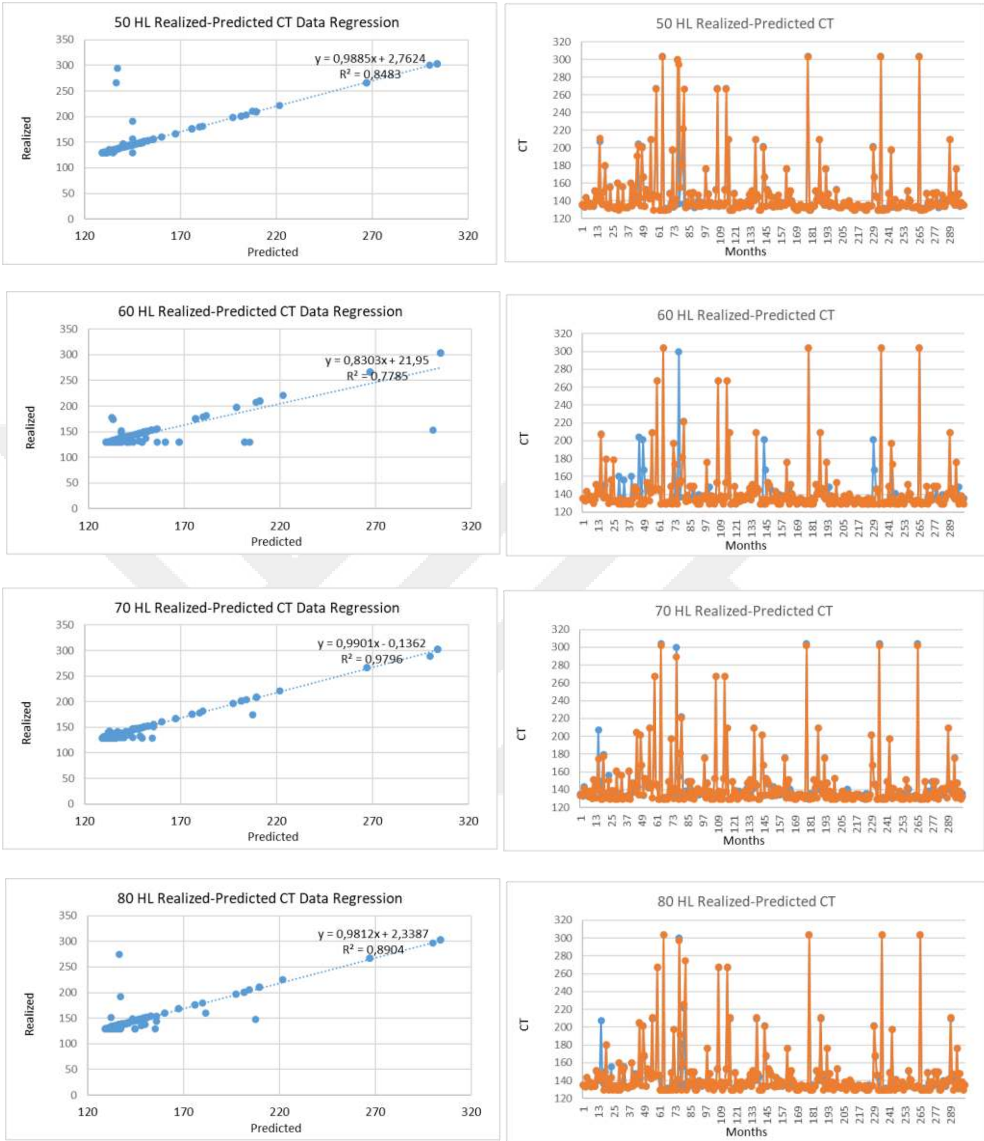

Figure 4.21. Structured ANNs Performances from 50 to 80 HL (Yellow Series: Predicted Data, Blue Series: Realized Data)

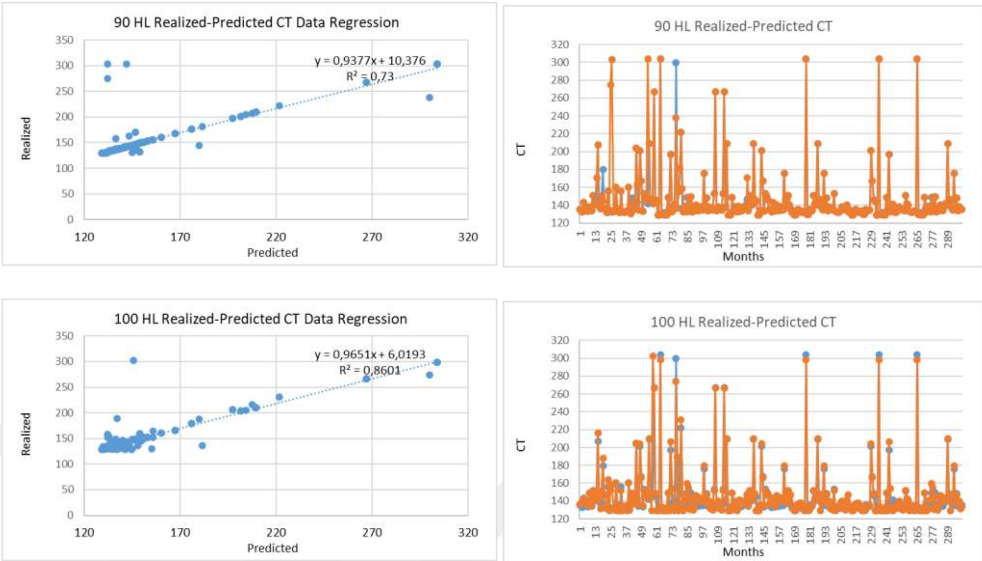

Figure 4.22. Structured ANNs Performances from 90 to 100 HL (Yellow Series: Predicted Data, Blue Series: Realized Data)

CT prediction errors of 70 HL networks can be sectionally seen in Figure 4.23. In this analysis, stable and near-zero error trends are notable which means future prediction can be powerfully maintained by using this ANN.

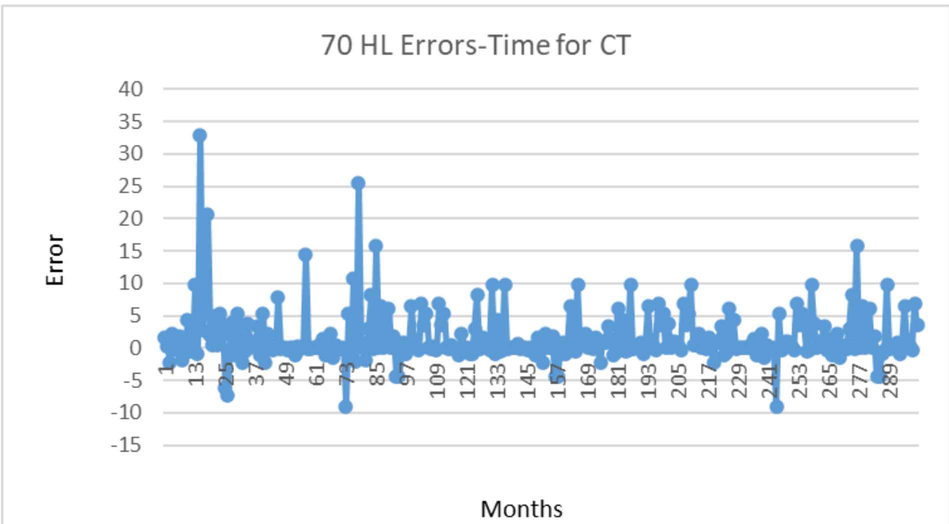

Figure 4.23. CT Error Trend of 40 HL Network within Analyzed Time Interval

Figure 4.24 and Figure 4.25 indicate all different HL ANN acts during their training, validation, and testing stages. For 70 HL ANN, all lines of output-target relations can be seen as through-line with x=y lines.

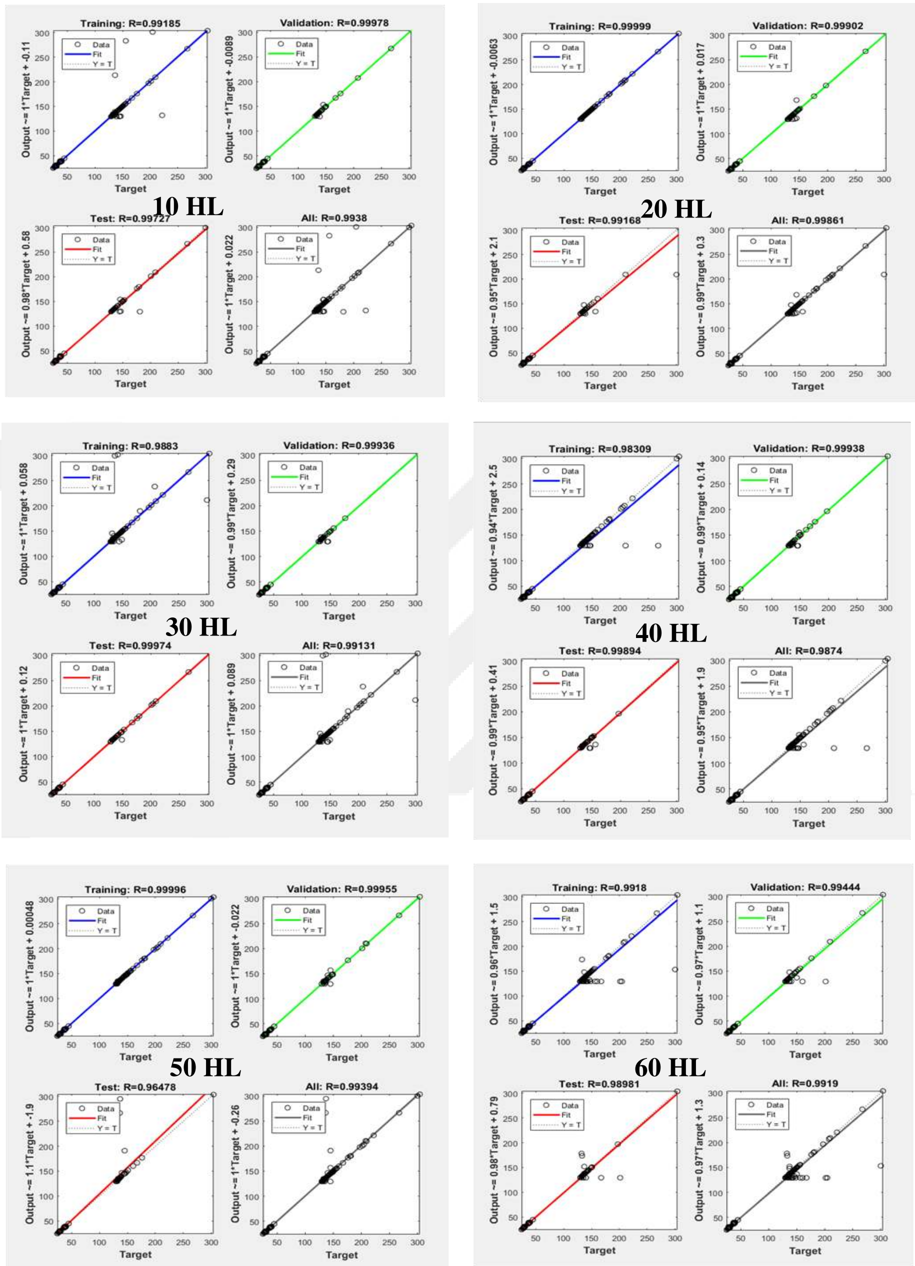

Figure 4.24. Training, Validation, and Test Performances from 10 to 60 HL ANN.

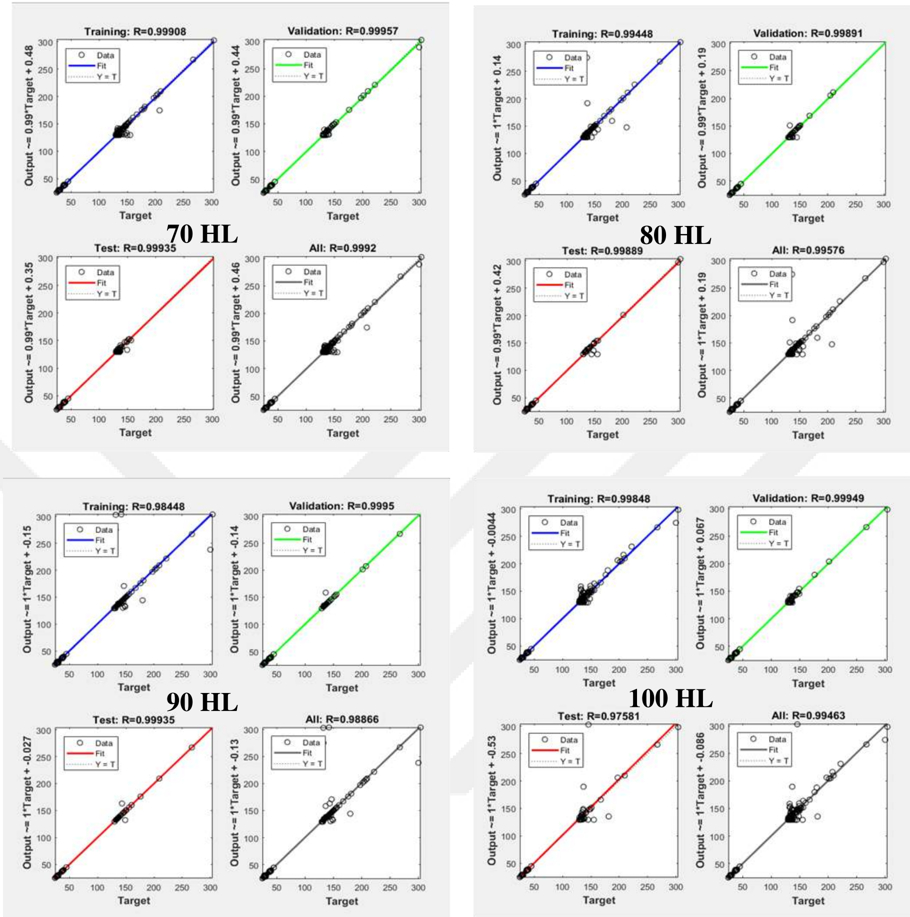

Figure 4.25. Training, Validation, and Test Performances from 70 to 100 HL ANN.

4.3.2.4. Process Reliability Forecasting for Future Life Cycles and Generating Preventive Actions

The best performance ANN has been obtained by using 300 cycle process data in RIMS for 24-hour production period. The reliability of the established ANN model has been validated by using regression tools. From this point of view, logarithmic regression has been implemented with the aid of the MS Excel tool and by using 70 HL ANN predicted CT data as shown in Tables 4.25- 4.27, the regression equation has been calculated as, y = -0,0984ln(x) + 150,28. The equation has been used for the determination of the next 50 realized CT data. Reached data series have been evaluated as realized data and fed to 70 HL ANN for the future prediction. Forecasted CT can be seen in Figure 4.26 with the previously realized 300 cycles, and 70 HL ANN predicted data. 142,5 seconds CT has been forecasted at the end of the next 50 production cycles of RIMS. The obtained high-performance 70 HL ANN plays an important role in making predictions for future process changes that have been used in system reliability forecasting structure. In this context, it is going to be possible to make new estimates by running the relevant data processing cycle in Figure 4.18.

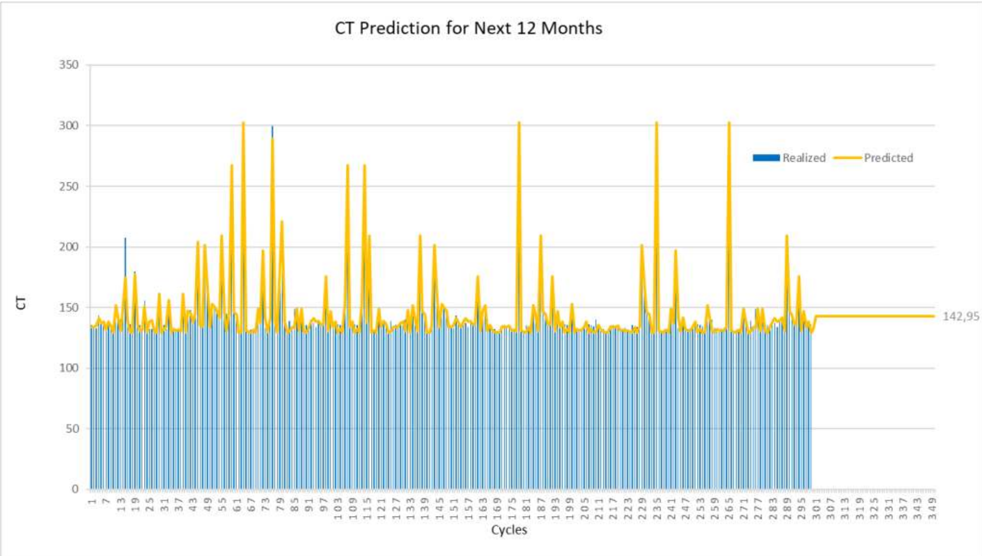

Figure 4.26. CT Forecasting for Next 50 Cycles

If the overall results of the proposed study are discussed based on the determination of the most critical items that affect both system and process reliabilities, the pneumatic gripper of the manipulator robot significantly outstands. Since the grippers present highest RPN and predicted MTBF rates indicate the gripper failures as most potential ones, as discussed in 4.1.2.1 and 4.2.1. Additionally, despite all collected process data is almost close to each other in the data matrix, CT independently fluctuates for many cycles ± 10 % via mean CT as seen in Table 4.25-4.27. Hence, shop floor investigations show that pneumatic gripper performance causes uncontrollable CT, because of the needed correction on gripper connections and components as can be seen in realized data Figure 4.26. Also, accomplished FMEA support this situation and the results indicate inefficiencies and potential failure modes. Therefore, in the following time period, FMEA based generated troubleshooting and preventive actions about pneumatic gripper could be a solution against unexpected stoppages and correction necessities (See section 4.3.1.4). Related preventive actions could establish a reliable process and capacity management system. In addition to the preventive actions, gripper nail, compression spring, and spring support part designs should be re-engineered and improved for a more robust and lean design.

Suggested improvements, preventive and correction actions are going to eliminate manual correction caused by production stoppages, high maintenance costs, high labor costs, high rework quantities, high scrap quantities, high energy consumptions and possible customer claims. The designed high-performance ANN makes predictions for updated system performances and conditions using the reliability prediction structure and data processing cycle. The intelligent and future data processing algorithm provides monitoring online and historical conditions, eliminate big losses (setups-adjustments, equipment failures, idling-minor stoppages, speed losses, process defects, production capacity loses), answer future questions, improve the environment-health and safety conditions. Also, it sustains reliability-centered maintenance strategies, increase the overall system reliability, provide effective asset service life management, maintain intelligent machine and process safety controls, create ready-to-use data for cloud interfaces, and allow machine learning and Industry 4.0 structuring.

5. CONCLUSION AND FUTURE STUDIES

5.1. Conclusion

In this thesis, RIMS and production cycles are examined in a real shop floor environment. The investigated RIMS is a robotic automation system consisting of a hydraulic-driven toggle clamp IMM and a six-axis manipulator robot. The RIMS system executes the production of thermo-plastic parts with metal thread using manipulator robots that insert them. This production automation system is not only one of the most common production systems, but also a case study suitable for other robotic automation applications such as machining cells, logistic centers, automotive assembly, white goods assembly, packaging, bottling, food processing, medicine lines and any other high speed and precise applications. Robotic automation systems advance to be a fundamental factor in high-performance, smart, intelligent, and safe production applications through Industry 4.0 methodologies.

ANNs provide powerful data processing algorithms and predictive networks. In particular, they play an important role in the design of intelligent interfaces that enable complex industrial data processing applications. Multilayer FFBP networks with LM training algorithms are used, which prove their high-performance prediction and processing capabilities by feeding and testing with different data types. FMEA is also the most powerful reliability analysis tool that combines and processes historical data effectively.

In this study, the FMEA method was applied to establish the reliability modes of the equipment-based system since the efficiency of data and the decision of monitoring methods directly affect the prediction performance of the designed ANN. In addition, the generated FMEA tables were used at every stage of the forecast design as an equipment-based reliability guide to correlate outputs between equipment and process reliability results and to generate preventive solutions.

The study has been examined two aspects of RIMS including the design of prediction models for both system and process reliability. For the system reliability prediction, the previous 4 years' failure data has been evaluated by considering two main equipment groups that involve mechanical and hydraulic components. The manipulator robot has been considered as mechanical equipment since it has been analyzed dealing with its mechanical performances. 48 months of overall system failure data have been analyzed by using equipment MTBF in FMEA. System failure data for 48 months has been analyzed in FMEA using collected equipment failure MTBF as the occurrence values. Calculated equipment RPNs in FMEA have been filtered by using Pareto Charts to reach critical equipment in the system. According to the analysis, manipulator robot, hydraulic cylinders, toggle clamp unit, and injection unit in the mechanical equipment group, hydraulic valves, hydraulic pump, and hydraulic lines in the hydraulic equipment group were determined as critical. Historical failure data consolidated with FMEA results have been used for structuring ANN. 10 to 100 multilayer hidden layer network training results showed that 40 HL ANN gives the best performance reliability prediction model. Comparative results that have been gained from low MAPE, low MSE, and highest R^2 regression tools confirmed the 40 HL ANN's best performance. In addition, the MTBF result for the next 12 months has been predicted and potential critical failures on the most critical equipment has been reached on FMEA tables. During this period, the most critical equipment in the estimated time interval was obtained by converting the estimated MTBF to the corresponding formations in the punctuation table and searching the FMEA tables for the equipment in which these occurrences were seen. The obtained data has showed that pneumatic gripper of the manipulator robot and the hydraulic cylinders of the IMM are the most critical equipment components that affect the overall system reliability in considered future time. Required preventive actions have been suggested in the troubleshooting table to prevent high potential failures by using cause and effect information on FMEA.

For the process reliability prediction model, the process parameters of 300 cycle production (24-hour production period) have been examined in the real shop floor. The process parameters affecting CT, collected from IMM and robot automation panels, were mold opening/closing time, injection time, injection pressure, injection speed, plasticizing time, holding position, screw position, mold open position, melting temperature, system pressure, back pressure, and robot repeatability. In addition, system air pressure and cooling water were collected using external measurement methods. Collected data has been used as input for the training of ANNs. Hydraulic oil temperature and cycle time from IMM automation panel, mold core temperature, mold cavity temperature, electrical motor amperage, final product temperature, and plastic shot weight collected by using proper measurement devices were entered as output in the ANN training.

70 HL ANN has been defined as the best performance prediction tool for process output data by using MAPE, MSE and R^2 regression tools. Since CT is one of the most leading outputs for determining production capacity and process reliability of plastic injection, CT has been taken in consideration to predict future production capacity and reliability. Best performance prediction results of CT have been generated by using 70 HL ANN.

The overall results of the study show that the pneumatic gripper of the manipulator robot plays an important role as critical equipment for both system and process reliabilities. The highest RPN values and predicted low MTBF rates from FMEA tables support this result. Uncontrollable CT and system FMEA result also indicate the need for improvement in gripper connections and components. Therefore, FMEA-based troubleshooting and preventive actions related to the pneumatic gripper can be the solution to unexpected stoppages and correction needs. Proposed improvements and planned preventive actions eliminate production losses, maintenance costs, labor costs, rework amounts, scrap quantities, energy consumption, and potential quality issues, and customer complaints due to manual correction and experienced failures. High-performance system and process reliability ANNs provide reliability prediction structure and data processing cycle with intelligent and future-proof data processing. This intelligent and Industry 4.0 based methodology produces ready-to-use data for cloud interfaces, enabling online and historical status monitoring. It also eliminates losses and allows to improve system reliability, production costs, service life and maintenance management, environmental health, and safety conditions.

This proposed study can be effectively applied in industrial systems that contain a lot of measurable and traceable complex/big data, such as robotic assembly lines, high-speed bottling, packaging lines, precise machining cells, critical petroleum refineries, chemical plants, cement plants, nuclear power plants, wind turbines, iron steel plants, etc. To determine the most effective data inside the big industrial data, effective reliability and prediction methods must be used like FMEA and ANN. Establishing significant solutions about bottlenecks can be obtained by analyzing only the correctly selected data.

5.2. Future Remarks

In the near future, the considered data evaluation method could be used to configure online, cloud-based intelligent prediction networks of robotic injection cells and similar automated industrial systems. In robotic injection molding, more measurable system and process data can be incorporated into data matrices to create more precise and detailed reliability prediction models. Such as online cavity pressure monitoring, strain measurements of IMM tie bars, online quality control via image processors, position controls of manipulator robot, detection of grippers insert placing performance by using image processors, vibration, and online current data of electrical motor, shock trends of hydraulic pump and online vibration of robot arms. From this point of view, the entire system is not only analyzed separately, but also effective estimation methods can be designed by examining the most critical system, process and product quality situations.

This study draws attention to the importance of smart shop floor data processing using predictive ANN. The best practice is to create an intelligent system that collects, routes, and monitors all MES and online smart sensor data in embedded software, based on the outputs of the study. It should process live data and combine it with production data according to structured and tested multi-layer ANNs.

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CURRICULUM VITAE

Atalay Tayfun TÜREDİ, he had admission to Department of Mechanical Engineering at Çukurova University and graduated as Mechanical Engineer in 2007. In 2013, He had received master's degree in the same department.

In 2007, he started to work in Altunorak Mold&Machinery Ltd. Co. as Project and R&D Engineer in Mersin. He carried on this position as coordinator of the biggest Turkish Glass Manufacturing Company Şişecam's foreign plant investment projects and managed the collective machinery and production line manufacturing projects with foreign suppliers till 2008.

In 2009, he finished his military service and he started to work in Wavin TR Plastic Inc. Co. as Mechanical Maintenance Engineer in Adana. The company is one of the members of Wavin-Orbia Group, which group is the biggest manufacturer of agriculture, building and infrastructure, fluorinated solutions, polymer solutions and data communication systems in the World. He worked in this position till 2012, and took respectively Production Engineer, Production Chief Engineer positions till 2017. He has been working as Injection Molding Production Manager since 2017 as responsible and leader of production and maintenance operations of injection molding shop floors and mold workshop.

Atalay Tayfun TÜREDİ is married with Huriye TÜREDİ and has a six-year-old son Atamer Mert TÜREDİ. His wife is working as Turkish Teacher in Turkish Ministry of Education.