ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

DEVELOPMENT OF QUALITY PREDICTION MODEL AND CONTROL MECHANISM FOR CLINCHING PROCESS

M.Sc. THESIS

Emin Abdullah KAZANCI

Mechatronics Engineering

Mechatronics Engineering Programme

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Emin Abdullah KAZANCI
(518211011)

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Thesis Advisor: Prof. Dr. İlhan KOCAARSLAN

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KENETLEME PROSESİ İÇİN KALİTE TAHMİN MODELİ VE KONTROL MEKANİZMASI GELİŞTİRİLMESİ

YÜKSEK LİSANS TEZİ

Emin Abdullah KAZANCI
(518211011)

Mekatronik Mühendisliği

Mekatronik Mühendisliği Programı

Tez Danışmanı: Prof. Dr. İlhan KOCAARSLAN

TEMMUZ 2024

Emin Abdullah KAZANCI, a M.Sc. student of ITU Graduate School student ID 518211011 successfully defended the thesis entitled “DEVELOPMENT OF QUALITY PREDICTION MODEL AND CONTROL MECHANISM FOR CLINCHING PROCESS”, which he/she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor :	**Prof. Dr. İlhan KOCAARSLAN** Istanbul Technical University	....
Jury Members :	**Prof. Dr. Mustafa BAĞRIYANIK** Istanbul Technical University	....
	Asst. Prof. Mustafa Alparslan ZEHİR Marmara University	....
		....

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To my family,

FOREWORD

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(Specialist Engineer)

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ABBREVIATIONS

FE	: Finite Element
PLC	: Programmable Logic Controller
PC	: Personal Computer
SDM	: Smart Decision Mechanism
SQL	: Structured Query Language
kN	: Kilo Newton
mm	: Milimeter
DAQ	: Data Acquisition
Hz	: Hertz
ms	: Miliseconds
AUC	: Area Under Curve
XGBoost	: Extreme Gradient Boosting
SVM	: Support Vector Machine
SVR	: Support Vector Regression
kNN	: K Nearest Neighbor
R^2	: R-Squared
MAE	: Mean Absolute Error
MSE	: Mean Squared Error
MIN-D	: Minimum Displacement Threshold
MAX-D	: Maximum Displacement Threshold
MIN-F	: Minimum Force Threshold
MAX-F	: Maximum Force Threshold

SYMBOLS

Ω	**:** Ohm
λ	**:** L1 and L2 penalty
$\boldsymbol{y_i}$	**:** Actual values
$\boldsymbol{\hat{y}_i}$	**:** Predicted values

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DEVELOPMENT OF QUALITY PREDICTION MODEL AND CONTROL MECHANISM FOR CLINCHING PROCESS

SUMMARY

Many mass production lines in the industry use the joining technique known as clinching. Reasons for the high demand for the clinching process are the unnecessity of additional binding agent, process speed, waterproofness, eco-friendliness, and ease of implemantation. In the clinching process, metal sheets are formed under mechanical force that is applied by punch and die tools. The tools are designed and produced specifically according to the thickness and material properties of metal sheets. Despite the fact that there are electromechanical or hydro-pneumatic powered, conventional hydraulic powered clinching stations are the most preferred as sources of mechanical force because of their investment cost, process speed, versatility and size advantages. However, hydraulic powered systems bring along some drawbacks such as a lack of precision on the quality of clinched joints, eccentricity between punch and die, power consumption and control difficulty because of the single pump that feeds multi-cylinder systems.

Although there are three major quality indicators of clinched joints, the bottom thickness of the joint is the most used and critical one because it is both the simplest measurement in an production environment and the most related to quality. Nevertheless, inspection of all produced clinched joints is not feasible based on the measurements of a single operator. Therefore, a quality prediction model is developed in this study. The study is conducted with force and displacement data that is collected from 16 different clinching cylinders at a 1200 Hz sampling rate. Linear, ridge, lasso, decision tree, random forest, extreme gradient boosting, support vector machine and k-nearest neighbors machine learning models are experimented with and validated systematically. The random forest regressor is found to be the best validation scored model.

Additionally, a smart decision mechanism (SDM) is developed and implemented based on force and displacement sensor data to overcome major malfunctions that cause a remarkable amount of scrap and production line stoppage.

Moreover, a part-to-part feedback control mechanism is developed and implemented to control clinching quality in the optimum range. The bottom thickness of a clinched joint for 0.4 and 0.5 mm stainless metal sheet joining must be between 0.3 mm and 0.4 mm in order to be evaluated as optimum, while the range of 0.25–0.5 mm is accepted as a proper joint. The control mechanism uses force and displacement sensor data to observe system behavior, and utilizes the prediction model and periodic manual measurements to build reference thresholds.

In conclusion, an application that stores sensor data, runs control algorithms and makes visualization, is developed for two clinching stations that consist of 16 hydraulic

cylinders. In future, the study can be maintained to predict quality more precisely and maintenance dates with regard to the expanding data set and the advanced machine learning algorithms.

KENETLEME PROSESİ İÇİN KALİTE TAHMİN MODELİ VE KONTROL MEKANİZMASI GELİŞTİRİLMESİ

ÖZET

Kenetleme (clinching) olarak bilinen birleştirme prosesi endüstride birçok seri üretim hattında kullanılır. Kenetleme prosesine olan yüksek talebin nedenleri ek birleştirici maddeye gerek duymaması, proses hızı, su geçirmezlik özelliği, çevre dostu olması ve kolay uygulanabilir olmasıdır. Bu özelliklerine ek olarak, kenetleme işlemi farklı kalınlıktaki ve farklı mekanik özelliklere sahip metal çiftlerinin birleştirilmesinde de kullanılabilmektedir.

Kenetleme prosesi temel olarak metal sacların kenet geometrisini almasını sağlayan zımba matris takımı ve onlara doğrusal hareket sağlayan bir aktüatörden meydana gelmektedir. Kenetleme prosesinde metal saclar zımba ve matris takımları arasına yerleştirilir ve uygulanan mekanik kuvvet altında şekil alırlar. Kenet kalitesini etkileyen birçok parametre vardır. Bu parametreler malzeme kaynaklı, takım kaynaklı ve makine kaynaklı olmak üzere üç ana başlıkta incelenir.

Kenet yapılacak metal sacların mekanik özellikleri ve kalınlıklarına göre zımba matris takımları özel olarak tasarlanır ve üretilir. Elektromekanik ve hidropnömatik versiyonları olmasına rağmen, yatırım maliyeti, proses hızı, çok yönlülüğü ve boyut gibi avantajlarından dolayı mekanik kuvvet kaynağı olarak hidrolik, geleneksel kenetleme istasyonlarında en çok tercih edilen aktüatör tipidir. Ancak hidrolik ile çalışan sistemler, kenet birleşimlerinde hassasiyet eksikliği, zımba ve matris arasındaki eksen kaçıklığı, güç tüketimi ve çoklu silindere sahip sistemlerin tek pompadan beslenmesinden kaynaklanan kontrol zorluğu gibi dezavantajları da beraberinde getirir. Hidrolik sistemli kenetleme istasyonlarında yaşanan bu zorluklar kenet noktalarında kalite belirsizliklerine sebebiyet veren önemli etkenlerden bazılarıdır.

Kenet birleşimlerinde geometrik ölçü olarak üç asıl kalite göstergesi olmasına rağmen, birleşimin alt kalınlığı, üretim ortamında kolay ve kenet noktasına zarar vermeden bir komparatör ile ölçülebilir olmasından ve kalite ile doğrudan ilişkisinden dolayı en çok kullanılan ve en kritik olandır. Klasik bir kenetleme prosesi üretim hattında, birleşimin alt kalınlığı bir operatör tarafından kontrol edilir. Belli aralıklarla üretim hattından rastgele seçilen bir üründeki kenet noktalarının kalite kontrolü yapılır. Bundan dolayı, bir üretim hatıında üretilen tüm kenet birleşimlerinin izlenebilirliği tek bir operatörün ölçümleriyle sağlanamamaktadır.

Çalışmanın yürütüldüğü kenetleme istasyonlarında üretimi yapılan tüm kenet operasyonlarında izlenebilirliğin sağlanması için öncelikle istasyonlardaki toplam 16 hidrolik silindire birer adet kuvvet ve deplasman sensörleri yerleştirilmiştir. Kuvvet sensörleri proses sırasında metal sacların yüzeyine uygulanan kuvvetin doğru bir şekilde ölçülebilmesi için matris yapısının altına yerleştirilmiştir. Deplasman

sensörleri ise proses sırasında zımbanın yaptığı sıvama miktarını ölçebilmesi için hidrolik silindirin hareket yoluna yerleştirilmiştir.

İstasyonlara yerleştirilen toplam 32 sensör verisi 2 adet veri toplama cihazı yardımıyla 1200 Hz örnekleme hızı ile toplanmıştır. Gerçek zamanlı toplanan sensör verileri, geliştirlen bir program ile işlenmiş ve her proses için deplasman-kuvvet eğrilerini görselleştiren bir arayüz hazırlanmıştır.

Çalışmanın yürütüldüğü iki kenetleme istasyonunda gerçekleştirilen tüm kenet operasyonlarında izlenebilirliği sağlamak ve kalite çıktılarını tahmin etmek için bir makine öğrenmesi tabanlı tahmin modeli oluşturulmuştur. Öncelikle, tahmin modelinin eğitilebilmesi için toplamda 2400 farklı kenetleme operasyonu, kalite çıktıları olan kenet noktasının alt kalınlıklarının manuel ölçümleriyle etiketlenmişlerdir. Toplanan sensör verilerinin öncül işlemlerinin ardından, kalite çıktısına etkisi olabilecek veri öğeleri çıkartılmıştır. Sekiz farklı makine öğrenmesi regresyon modeli (linear, ridge, lasso, decision tree, random forest, extreme gradient boosting, support vector machine ve k-nearest neighbors) çıkartılan veri öğeleriyle beraber sistemli bir şekilde deneyimlenmiştir. En iyi doğrulama puanlı model olarak random forest regresyon modeli, 10 tekrarlı çapraz doğrulama yöntemi sonucunda bulunmuştur.

Bununla beraber, kayda değer sayıda hurdaya ve montaj hattının durmasına sebep olan büyük arızaları aşmak için kuvvet ve deplasman sensör verilerine bağlı olarak bir akıllı karar mekanizması geliştirilmiş ve uygulanmıştır. Karar mekanizması, proses verisinden çıkarılan deplasman-kuvvet karakteristik eğrisinin tepe noktasının grafikteki konumuna göre çalışmaktadır. Önceden belirlenen sınırlara ve tepe noktasının grafikteki konumuna göre prosesin doğru bir şekilde tamamlandığını veya ilgili hidrolikte bir arıza olduğunu işaret eder. İşaret edilen arızalar sırasıyla kırık zımba veya matris, kenet noktasında beklenmeyen materyal, fazladan uygulanan kuvvet nedeniyle kenet noktasında çatlak riski veya eksik kuvvetten kaynaklı birleşimin tam oluşmama riski şeklinde belirlenmişlerdir. Belirlenen bu arızalar meydana geldiğinde geliştirlen program üretim hattının durmasını sağlar ve operatörü uyarır. Uyarılan operatör programın işaret ettiği hidrolikte gerekli bakım çalışmasını yapar ve böylece, hurda sayısının düşmesini sağlar ve montaj hattının durmasını engeller.

Akıllı karar mekanizmasına ek olarak, kenetleme kalitesini ideal aralıkta kontrol etmek için çevrim bazlı kapalı çevrim kontrol mekanizması geliştirilmiş ve uygulanmıştır. 0.4 ve 0.5 mm paslanmaz metal sac birleşiminde kenet birleşimin alt kalınlığının 0.25-0.5 mm aralığında olması uygun birleşim olarak kabul edilirken, ideal olarak değerlendirilebilmesi için 0.3 ve 0.4 mm arasında olması gerekir. Optimum kalite kontrol mekanizması sistem davranışını gözlemlemek için kuvvet ve deplasman sensör verisini kullanır ve önceden belirlenmiş referans eşiklere göre bir sonraki çevrimdeki proses kalite çıktısını iyileştirebilmek için hattın kontrolcüsüne (PLC) sabit oranlı geri bildirim yapar.

Geliştirilen kontrol algoritmaları önceden belirlenen sınır bölgeleri üzerinden çalıştığından, hatta yapılacak bakım ve onarım çalışmalarının ardından bu sınırların tekrar değerlendirilmesi ve uygun değil ise değiştirilmesi gerekmektedir.

Sonuç olarak, gerçek zamanlı sensör verilerini kaydeden, geliştirilen kontrol algoritmalarını çalıştıran ve hat operatörleri için görselleştirme yapan bir uygulama 16 hidrolik silindirini içeren 2 kenetleme istasyonu için geliştirilmiştir. Gelecekte, çalışma daha hassas kalite tahmini ve bakım dönemlerinin tahmini için genişleyen veri seti ve ileri makine öğrenmesi algoritmalarıyla beraber sürdürülebilir.

1. INTRODUCTION

In modern manufacturing, the pursuit of efficient, cost-effective, and environmentally sustainable joining techniques has become the main objective of facilities that have mass production lines [4]. Within the four industrial revolution periods, numerous joining techniques were developed and improved such as welding, riveting, brazing and adhesive bonding. All the joining techniques have several advantages and disadvantages for different process cases. Among these joining techniques, clinching has emerged as a versatile and promising solution, offering several advantages over conventional joining processes. In fact, the clinching technique was invented in Germany during the 19th century. However, the usage of the clinching process in mass production lines became popular in the late 20th century because of increasing usage of lightweight materials, expanding the variety of materials and advancements in automation [5]. Within years, the clinching process reached a diverse range of industries such as automotive, home appliances, electronics and construction.

The superiority of the clinching process over conventional joining processes is derived from its usage without additional adhesive materials, chemicals or heat, process repeatability, low cost requirements, waterproof joined area, combination of different materials and durability [6].

Despite its widespread adoption, there are challenges and opportunities for further refinement and optimization of the clinching process. Tolerances in material thicknesses, variations in material properties, tool conditions and machine side process parameters influence the quality and performance of clinched joints. Furthermore, the evolution of advanced materials and the demand for ever-lighter, stronger, and more durable products necessitate continuous innovation in joining technologies.

In a mass production environment, ensuring the quality of clinched joints depends on manual measurements of the bottom thickness of the joint. Because manual measurements are not feasible for each product, a lack of inspection for clinched joints occurs. Consequently, in conventional clinching processes, the quality tracing system is primitive, and failures on the clinched joints cause financial and labor losses. This thesis aims to develop a prediction algorithm to track the quality of the clinching process and design control mechanisms based on the prediction model to minimize quality failures in mass production by conducting a thorough review of existing literature and industrial practices.

1.1 Literature Review of Related Research

In this section, related research on clinching processes and automation is analyzed and summarized systematically. First of all, the clinching process and its stages are defined to provide a clear understanding for the next topics. After that, clinching machine and tool types are examined. Their advantages and disadvantages are analyzed in terms of their effects on the clinching process. Then, improved optimization and control mechanisms for the clinching process and the quality of the clinched joints. Finally, developed automation solutions and control mechanisms for the clinching process and other manufacturing processes are shared.

1.1.1 Clinching process

Clinching is a joining technique that uses mechanical force to shape metal sheets into the final geometry that provides the interlock. The clinching process basically includes two tools, which are punch and die. Multiple metal sheets are placed between the centrally aligned punch and die. Then, the metal sheets are compressed by blank holders to avoid possible spaces between the metal sheets and to point the process location. After the localization of the metal sheets on the tools, die or punch starts to move, and metal sheets start to deform due to tool geometry. After the predefined process conditions are provided, the moving tool returns to its starting position. Finally, the clinched joint is released from the die structure. Fig. 1.1 illustrates the essential principle of the clinching process.

The clinching process is a cold-forming operation. One of the characteristic properties of the clinching process is that various combinations of metal sheets can be joined by the process. While metal-metal combinations can be clinched by conventional

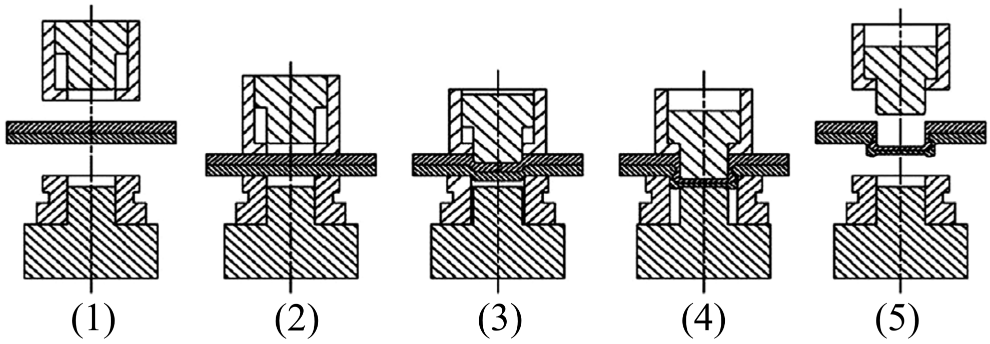

Figure 1.1 : Principle of round clinching [1].

clinching, specific metal-nonmetal combinations can only be joined by special clinching techniques that are modified with additional processes [7]. Moreover, the metal sheets are not required to have equal thickness. However, the thicker or more resistant material sheet is placed on the punch side for best results. In industrial applications, there is up to 12 mm of sheet thickness usage. Punch and die geometries change with material thickness and properties because the required force for deformation on the materials changes.

The clinching process has several advantages when compared with traditional joining methods. The main advantages of clinching include a simple machine structure that consists of only one linear actuator, easy automation options, the ability to connect similar or dissimilar sheets, the ability to join multiple sheets, short processing times, no need for additional materials such as glue or fastener, no need to pre-heat, eco-friendly and waterproof joint area. The disadvantages of the clinching process include limited quality and performance observation for the clinched joint, relatively high force demand to form sheet metals, high energy consumption and unexpected tool breakdowns that cause scrap in mass production [8,9].

1.1.2 Clinching machine and tools

There are wide range of different clinching techniques and machines that are being investigated and subsequently used in the industry. Most of the machines and techniques use at least one linear actuator for movement of the punch. The actuators are being selected according to process conditions or requirements. In production lines, hydraulic actuators are being preferred because of advantages such as less maintenance, cost, speed and heavy load. On the other hand, electromechanical and hydro-pneumatic actuators are mostly being used in specific works that need more precision and accuracy.

Conventional clinching processes mainly have a hydraulic driven punch and a die that is static under the formed sheets. The punch used in conventional clinching processes typically comes in two primary shapes: a circular punch and a square punch. Additionally, when it comes to the dies employed in clinching, they can be categorized as either fixed dies or extensible dies. The fixed die does not incorporate any moving or sliding components. Key parameters for the fixed die are the diameter of the bottom, the depth and radius of the die cavity [10]. The extensible die comprises a stationary die and a set of movable components, allowing for expansion possibilities throughout the forming process. Reducing the die diameter and increasing the punch die diameter or die depth enhances the undercut in extensible die. The volume of the die cavity is primarily influenced by the punch diameter and the ultimate thickness of the joint's bottom head [11].

In addition to the conventional clinching processes, several different clinching techniques were investigated. These improved techniques have pros and cons when compared to the conventional clinching in regard of punch force, mechanical properties of the final clinch, cost and time etc. Flat clinching introduced in the 1990s is one of these improved techniques [12]. In contrast to the conventional clinching process, flat clinching does not have any die structure and furthermore flat clinching involves creating a joint by allowing the sheet material to flow both upwards and radially. Flat clinching is a versatile joining technique that extends beyond metals, as it can also be employed to join materials such as cardboard, wood materials and plastics. This adaptability makes flat clinching a valuable method for creating connections in various applications, including those involving non-metallic materials [13].

Hole clinching is another clinching method that introduces additional tools and machines specifically designed for punching holes in the sheet. This augmentation of equipment primarily involves perforating the brittle material in the lower sheet.

The punch exerts pressure on the ductile material of the upper sheet through the hole, causing it to expand in the bottom die. Hole clinching tools and machines play a crucial role in joining sheets with high strength and low ductility, as well as sheets with diverse material properties [14]. Despite the increased cost associated with these tools, the overall expense of hole clinching remains acceptable due to the elimination of auxiliary components.

Reshaping clinching method have been improved to reduce the protrusion and to increase the strength of conventional clinched joints. In this method, a conventional clinched joint is typically initially created. Subsequently, the formed joint undergoes a reduction with using of various reshaping punches and dies. The selection of reshaping tools plays a critical role in determining the overall effectiveness and quality of the final joint. The reshaping method enhances the material flow and increases the joint mechanical properties however the process is difficult to implement and time-consuming because of having two stages. Another reshaping method uses rivet that is placed in the bottom of the clinched joints to make sure of the material flow. The joints reshaped with rivets exhibit superior performance compared to the method of reshaping clinching without rivet. Conformably, the reshaping a clinched joint without a rivet, this method is both time-consuming and difficult to implement [15].

Rivet clinching is a different clinching method that joins the metal sheets with a specific rivet. A hydraulic power machine propels the flat punch, pressing the rivet to compress the sheets. During the downward movement of the punch, the rivet undergoes gradual reshaping to conform to the shape of the bottom die, enlarging the mechanical interlock through rivet reshaping. The joint is formed when the upper sheet and the rivet align at the same horizontal level.

Rectangular clinching is designed to minimize the joining force and obtain strength clinched joints [16]. The essential difference between the conventional clinching process is the geometrical shape of the punch and die. The sheets tend to fracture during the process which can significantly impact joint quality.

Roller clinching proves to be an effective method for joining metal sheets. This clinching process stands out as a continuous process, facilitated by the incorporation of rotating rollers [17]. The tools employed in the roller clinching process are the punch roller and die roller. During the process, the mold and the punch roller rotate in opposite directions at a specific angular velocity, while the metal sheets continuously pass through the rollers.

There are several hybrid clinching processes which use two or more additional joining techniques in conjunction with clinching; laser shock clinching, hydro-clinching, injection clinching, adhesive clinching, friction-assisted clinching, laser-assisted clinching and ultrasound-assisted clinching.

1.1.3 Clinching quality indicators

The quality of the clinching process depends on the mechanical properties of the final clinched joint. Before the investigation of the mechanical properties of the final clinched joint, probable major failures are analyzed. There are three major failure types in the clinching process (Fig. 1.2). In the first failure mode, the upper metal sheet releases because of crack formation in the clinched joint. The reason for this failure mode might be eccentricity between punch and die structures, improper tool geometries or applied extra force to the clinch point. In the second failure mode, the clinched metal sheets separate, and clinch formation fails. There are two obvious reasons for the second failure mode that are either improper tool geometry or applied insufficient force to the metal sheets [18].

Despite the major failures are detected, all clinched joints produced without major failure do not mean that the joint is produced in standard formation. Because, in addition to these failure modes, there is an additional failure mode that is a combination of the previous modes. In this failure mode, the clinched joint looks like a proper connection despite one side of the joint failing. Consequently, the clinched metal sheets split away without additional force or expected force in time.

The mechanical strength of a clinched joint can be analyzed via three main quality indicators that are neck thickness, undercut and bottom thickness (Fig. 1.3). However, measurement of the neck thickness and undercut is not possible directly, it needs laborious destructive tests to evaluate the clinched joint. Nevertheless, the real

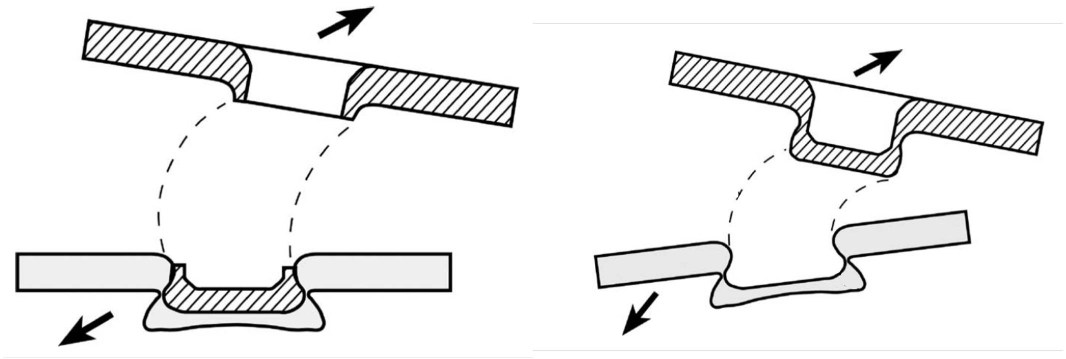

Figure 1.2 : Failure modes in the clinching [2].

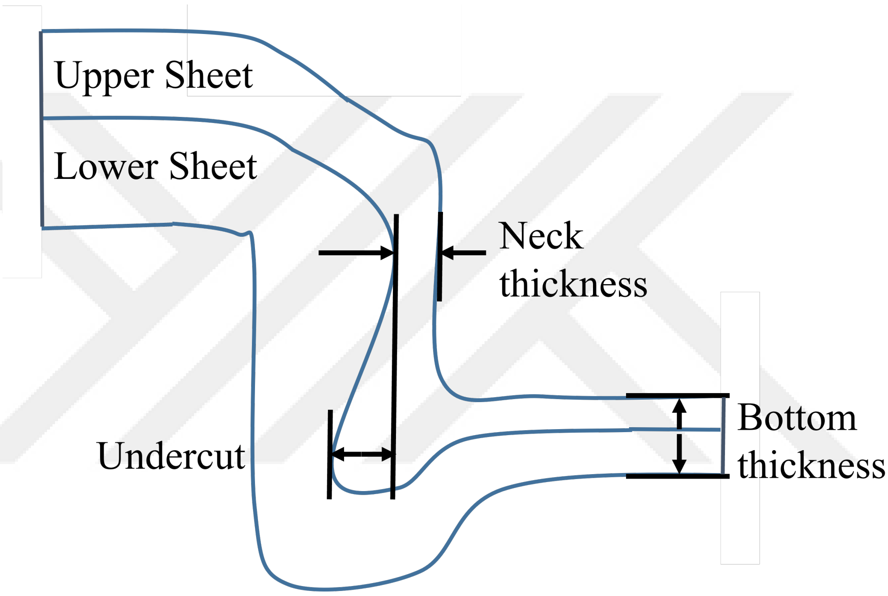

Figure 1.3 : The quality indicators of a clinched joint [3].

mechanical strength of the clinched joint can only be tested via destructive methods. As a result of the tests, shear strength and tensile strength can be analyzed. Because of the inconvenient work on destructive test methods, finite element (FE) analysis methods are being started to use. By utilizing the FE simulations, the design parameters of punch and die tools are being investigated and the design of the tools is optimized.

In addition to neck thickness and undercut measures, there is an additional quality indicator which is the bottom thickness of the clinched joint. Dissimilar to previous indicators, the bottom thickness of a clinched joint is a measurable indicator with nondestructive measurement methods. Along with measurement simplicity, the bottom thickness of a clinched joint can be directly related to the mechanical strength of the joint. Optimum bottom thickness range studies are conducted for different sheet materials and sheet thicknesses by both academia and industrial producers [19].

1.1.4 Clinching process parameters

Clinching quality and performance are affected by a variety of process parameters. These process parameters can be categorized into three main factors: material, tool, and machine. In the following topics, the main factors will be detailed.

1.1.4.1 Material side parameters

In the material side parameters that effect the clinching process, material strength and strength tolerance, material thickness and thickness tolerance, surface condition of the material, formability, pre-hardening or pre-heating, lubrication and additional chemicals can be listed. Material strength and thickness parameters are some of the most effective parameters on clinching process because clinching can be applied to any metal that does not have brittle properties. Therefore, numerous investigations with different materials have been conducted to observe the clinched joint performance and quality. The applied force and tool geometry differ for each combination of material and sheet thickness, since thicker or stronger sheets form more difficultly [20]–[22]. The surface condition of the material is another effective parameter for the clinching process because material flow between punch and die affects the final shape of the clinched joint and interlock structure. Hence, lubrication and additional chemicals are being used to ease material flow and, thereby the clinching process [23]. Formability of the sheet materials is also an effective parameter for the clinching process because the clinching process depends on the plastic deformation of the sheet materials. Therefore, heat treatments such as pre-heating and pre-hardening are applied to the sheets in some cases to achieve proper material flow and formability [24,25].

1.1.4.2 Tool-side parameters

In the tool-side parameters that affect the clinching process, alignment of the tools, tool geometry and design, coating and surface condition of the tools can be counted. Tool geometry and design are two of the most directly effective factors in clinching quality and performance. Many researchers have studied the influence of different geometry and structure of die and the mechanical strength of the clinched joint to obtain the best quality [26,27]. Alignment and centering of the tools are crucial parameters for the clinching process because in the case of the slightest eccentricity between punch and die, metal sheets wear and the clinched joint is produced with a failure [2]. Alignment problems emerge, especially in mass production environments because of the high vibration levels in the production stations and the high volume of production. Coating and thereby surface condition is another effective parameter for the clinching process. Similar to the surface condition of the metal sheets, the surface quality of the tools is directly related to material flow and formability. A wide range of studies about the surface condition of the clinching tools are conducted.

1.1.4.3 Machine-side parameters

In the machine-side parameters that affect the clinching process, punch force, speed, relation between force and displacement and blankholder force can be listed. Punch force is one of the most related parameters to clinching quality. Punch force is generated by the linear actuator which can be a hydraulic-powered cylinder, a hydro-pneumatic-powered cylinder or an electromechanical motor. Metal sheets between the punch and die are shaped by the punch force. Therefore, the meaning of that applied punch force being less or more than the needed force to shape the sheets is that the quality of the clinched joint might fail, or even one of the major failures might occur [28,29]. Because the clinching process is a highly dynamic process, speed is another effective parameter [30]. The characteristic curve and different stages of the clinching process can be observed using the relationship between force and displacement during the process. The relationship between force and displacement is one of the most commonly used references to interpret forming processes [31]. Blankholder force is another effective parameter for clinching because it is related to material flow into the forming area. In the case of that blackholder force which is greater than normal, material flow is limited and metal sheets are teared. On the contrary, less blankholder force causes blank volume between the sheets [32].

1.2 Clinching Quality Prediction Works

A small number of studies examined the use of data-driven and machine learning techniques in order to achieve a high prediction quality of clinch joint properties for a particular joining job. For example, Oudjene et al. examined the effects of changing tool design parameters on geometric joint qualities including neck thickness and interlock [33].

Because the qualities of the final joint are not solely determined by the clinching process, Roux and Bouchard also included ductile defects in the material behavior as an input parameter [34]. The use of a global optimization approach in this situation produced improved geometric joint properties such as neck thickness and interlock structure. In comparison to an original die and punch design, this allowed the described tool configurations to significantly alter the mechanical strengths of the joints.

An additional investigation looked into the application of artificial neural networks (ANN) to the estimation of joint strengths of an extensible die clinching process [35]. Consequently, five tool parameters distributed over three levels are represented by an intelligent design of the experiment employing a Taguchi L27 orthogonal array. A meaningful ANN made it possible to forecast various joint attributes for various tool combinations after the model was trained and fitted. Then, a genetic algorithm was used to determine the best design parameters for varying the thickness of the blanks.

In order to find an optimal contour of the joining tools, Wang et al. presented a novel technique that involves direct communication between a genetic algorithm and a finite element simulation model [36]. This allows the positioning coordinates of each parameterized shape contour node to be changed individually based on the current genetic algorithm population's results. Ultimately, by simultaneously strengthening the joint's resistance to fractures during the clinching process, an ideal die contour exhibits enhanced clinch joint qualities.

Metamodels were used by Bielak et al. and Martin et al. to explain how preprocessing at the joining area affected geometric properties and load capacity. Validated FE simulation models with different materials and sheet thicknesses were taken into consideration in this situation [25,37]. Xu and Xhao investigated the equations for predicting the maximum failure load by using sheet thickness, the geometry of the tools, the material properties and the direction of the applied force to procure the shear strength and decrease the cost of the performance tests [38].

By contrast, Zirngibl et al. presented a novel approach that uses a deep reinforcement learning algorithm to define optimal clinching tools [39]. To do this, individual clinch joint properties are predicted through the training of an artificial neural network agent, which does not take into account labeled input data. In addition, the implementation of a value-based deep learning algorithm offers the chance to choose the best joining tool design within a multi-dimensional solution space. In another study, Zirngibl et al. looked into the capacity of several machine learning algorithms to use a statistically based feature selection method to obtain a satisfactory estimation accuracy on a restricted amount of input data [40].

1.3 Clinching Automation Solutions

Since clinching technology has become popular, automated clinching stations have been used for joining operations. There are varying industrial clinching applications. Some of the clinching stations use hydraulic-powered multiple cylinders while others use electromechanical motors to have more sensitive clinched joints.

Most of the conventional hydraulic-powered clinching stations include more than one cylinder to clinch multiple regions of the product. However, all the cylinders are fed by a single pump and the clinching process is controlled with the use of a pressure sensor that is placed on the pump output. The pressure threshold is arranged manually according to the quality of the clinched joints produced.

Some of the conventional clinching stations include additional sensors such as pressure, force and displacement and an additional controller to observe the clinching system. Besides, the controller gives binary feedback which means whether a clinching operation succeeded or not, to the main controller of the stations. The feedback information is generated by using the windowing approach or threshold functions on the force and displacement graph. The window technique enables the interpretation of process stages and error cases [31]. However, the constants of the control functions are not responsive to varying material thicknesses and properties. On the other hand, some of the conventional clinching stations do not include a controller or even any additional sensor for monitoring.

In addition to the commercial devices, different quality control aspects such as machine vision can be used for different manufacturing processes [41]. Bruno et al. improved a real-time quality control system for the clinching process by utilizing machine vision technology. The system grades the quality of clinched joints according to a designed mathematical operator. As distinct from clinching quality control, several quality control methodologies for different manufacturing processes such as statistical or machine learning algorithms, are investigated [42,43].

1.4 Research Objectives

The most common problems facing a conventional clinching station can be listed as a lack of quality inspection for the produced parts, scrap parts because of failed clinched joints and the inability to forecast the remaining life cycle of the tools. In this study, a quality prediction model and different control algorithms are developed and implemented into clinching stations to overcome specified pain points in the mass production line.

First of all, 16 pairs of force and displacement sensors are calibrated and placed on the hydraulic cylinders. With the use of two data acquisition devices and an industrial PC, labeled raw process data from the production line has been collected for two months. Then, a quality prediction model is generated using the collected labeled dataset. Thanks to the generated prediction model, 100% quality inspection for the clinching process is achieved.

Secondly, a control mechanism is improved to instantly detect the major malfunctions that cause a high number of scrap parts. After the detection of any malfunction, operators are warned and provided with instructions to take repair action. By virtue of the improved control mechanism, operators are able to find the malfunction type and which cylinder is broken down.

Finally, an additional control mechanism is developed to improve clinching quality. Clinching quality may fluctuate during production because of metal sheet thickness tolerance, material property tolerance or hydraulic behavior. To bring the quality fluctuation under control, a control mechanism based on prediction model outputs is implemented at the clinching stations. The implemented program gives feedback part-to-part to the main controller, which is a programmable logic controller (PLC) to change the turn point of the hydraulic, thereby applying punch force.

1.5 Outline of the Thesis

This thesis contains the development and execution stages of automation solutions to improve clinching quality and minimize production problems because of clinching operations. Chapter 1 presents the introduction to this research, a literature review and the determination of the research objectives.

Chapter 2 defines the prepared system components and system architecture to handle the previously specified pain points during mass production. It starts with sensor selection and placement on the hydraulic cylinders. It expresses the properties and capabilities of the used data acquisition devices. After that, the implemented system architecture is determined with a detailed description of each component. Additionally, monitoring pages for 20 different clinching processes are expressed.

Chapter 3 consists of the construction stages of the prediction model. It starts with detailed problem and system definitions. Then, it continues with regular machine learning steps which are, respectively, data collection, data preprocessing, feature extraction, proper model selection and evaluation results.

Chapter 4 introduces the improved control mechanisms exhaustively. It starts with the windowing approach that the next control mechanisms are based on. After that, the smart decision mechanism (SDM) is detailed with definitions of the major malfunctions detected in mass production. Then, improved optimum quality control is determined and the results of the mechanisms are discussed.

Finally, chapter 5 summarizes the studies done in this thesis, points out significant conclusions and proposes suggestions for future work.

2. METHODOLOGY

2.1 Overview

In the clinching process, quality control is one of the most critical procedures. However tracking each produced clinched joint is unfeasible in a mass production environment. Machine producers placed different kinds of sensors to track the quality of clinched joints. Displacement sensors, force sensors, pressure sensors and strain sensors can be given as examples. Despite sensing possibilities, control of the clinching process is not achieved by the machine producers.

Conventional clinching lines work with hydraulic power. In general, there is one main pump and one main pressure sensor for controlling all hydraulic cylinders at the same time. Various machine producers or measurement system producers implement external data acquisition systems and sensors to classify clinched joint quality in terms of OK or NOK. The classification is executed using displacement and force sensor data. However, these systems do not affect the control mechanisms of the clinching process.

This chapter represents the constructed system and its components in detail. Sensor selection and placement, data acquisition, visualization and data storage will be explained.

2.2 Sensor Selection and Placement

Sensor selection is a critical step because of industrial conditions and the sensitivity of the process. The selection of a displacement sensor is made considering the measuring range and resolution. The measuring range and resolution are selected as 10 mm and 0.01 mm, respectively, when evaluating the summation of the thicknesses of metal sheets and the depth of the die. Lifetime, size and linearity are the points to be taken into consideration. Burster 8712 (Fig. 2.1) 1 kΩ, potentiometric displacement sensor is selected after evaluations. The selection of a force sensor is made considering

Figure 2.1 : Displacement sensor (Burster 8712-10 mm).

the measuring range, accuracy, linearity and dimensional limitations of the clinching station structure. In consideration of the maximum load of the hydraulic cylinder, the measuring range is selected as 100 kN. After evaluation of the other limitations, HBM KMR+ 100 kN (Fig. 2.2) strain-gauge based force sensor is decided to be used. In addition, piezoelectric force sensors are also used in industrial clinching applications. The cables of the sensors are long and delicate. Because of this, protection for the cables should be provided against external damage that is operator or hydraulic motion-based.

The selected displacement sensor is placed on the hydraulic motion line vertically to observe the process clearly (Fig. 2.3). Additional protective plates are added to avoid external damage to the displacement sensor. The placement of the displacement sensor is a compelling stage because the 3 mm forming range must be within the 10 mm measuring range of the sensor. Otherwise, the sensor might be irreversibly damaged, or the process might not be observable in any circumstances. The force sensor is placed under the die structure because hydraulic stroke force must impact the sensor directly (Fig. 2.4). The covering structure of the force sensor is produced properly for sensor size and sensor cable output. In Fig. 2.5, the technical drawing of a hydraulic cylinder from the side shows the placement of displacement and force sensors. In total, there are 16 hydraulic cylinders in 2 clinching stations.

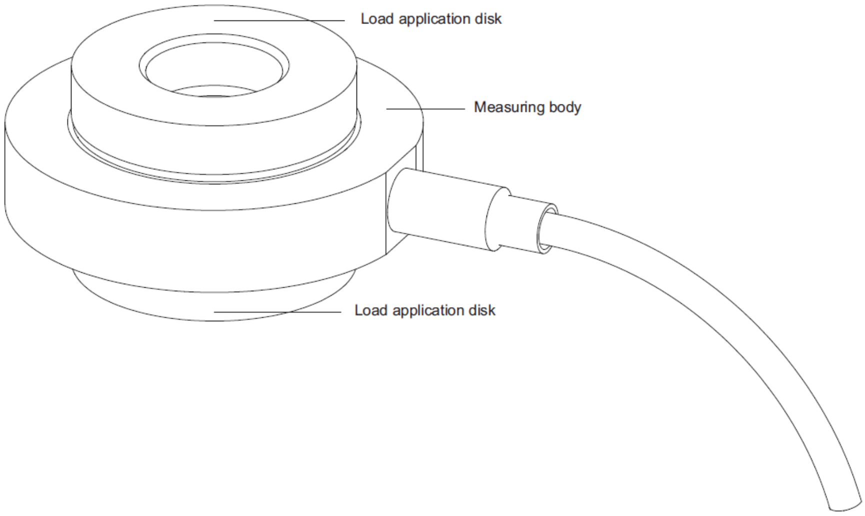

Figure 2.2 : Force sensor (HBM KMR+ 100 kN).

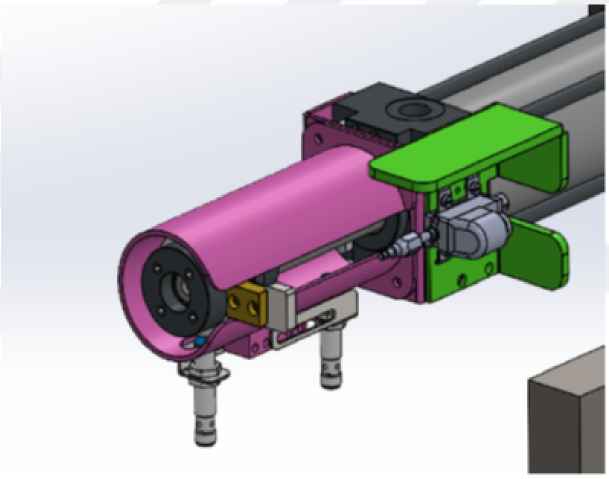

Figure 2.3 : Displacement sensor placement.

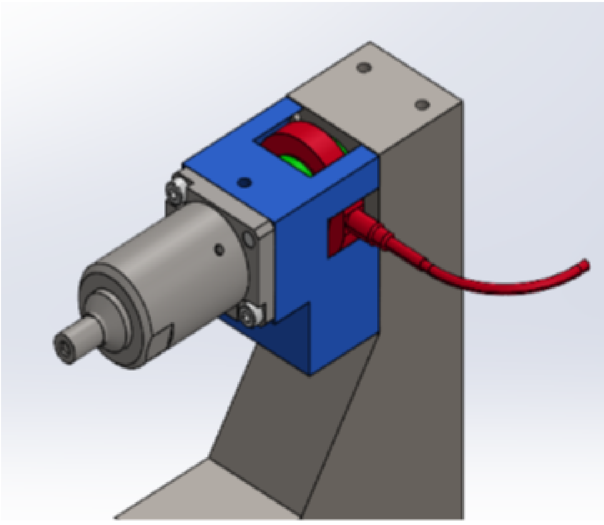

Figure 2.4 : Force sensor placement.

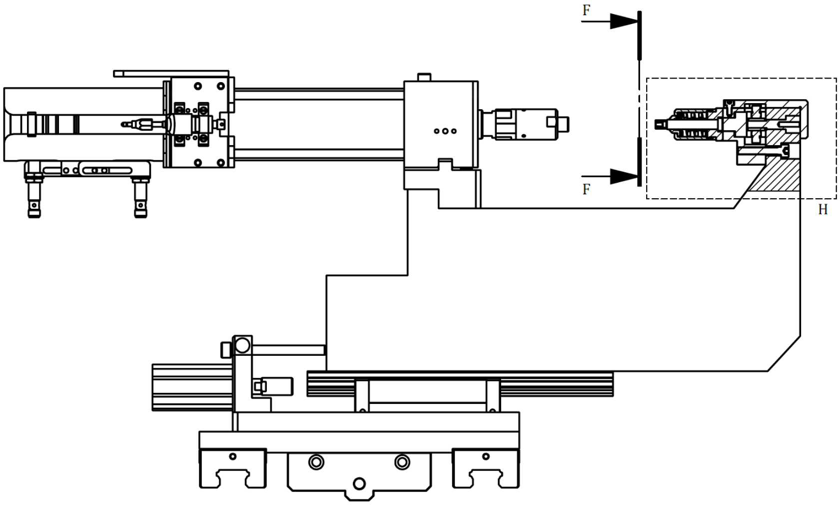

Figure 2.5 : Technical drawing of a clinching hydraulic cylinder.

2.3 Data Acquisition

Displacement and force sensor outputs are relatively weak signals. Moreover, the projected process to observe is extremely fast as the process duration takes 50–100 ms. Therefore, amplification, filtering and digitalization of the signals are conducted by two data acquisition devices named HBM PMX. Each device has 16 analog-to-digital converter channels with a 1200 Hz sampling rate. After the amplification of the analog signal, a bessel filter with a 100 Hz cutoff frequency is applied to the signals to avoid disruption caused by the amplification stage. The filtering stage causes a delay of 2 ms in the signal output. 24-bit digitized sensor data is transmitted to the PLC via a profinet port and the facility network via an ethernet port in real time. One piece of PMX device is placed at each station (Fig. 3.3).

2.4 Visualization

Overall system implementation is represented in Fig. 2.7. As can be seen in the figure, hydraulic cylinders are controlled by a Siemens S7-1500 series PLC with real-time sensor data from data acquisition devices. On the other hand, an industrial computer processes sensor data and controls set values in the PLC for the next cycle. Additionally, the industrial computer generates two different monitoring pages to follow production by operators. One of these pages visualizes characteristic curves for each produced joint (Fig. 2.8). The characteristic curve has crucial information about

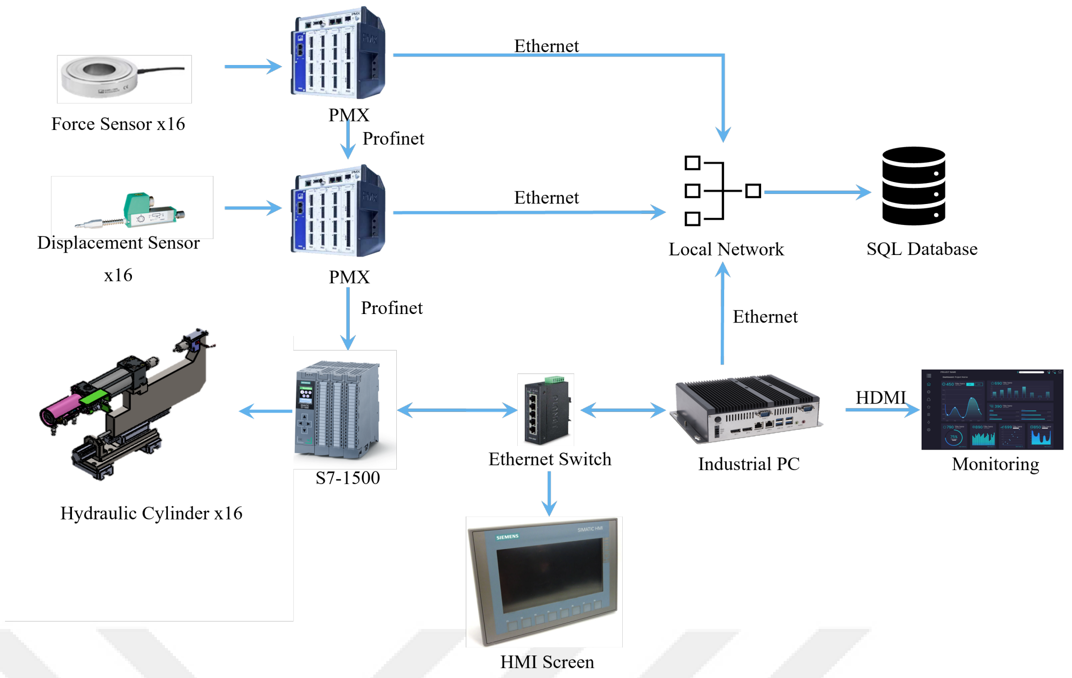

Figure 2.6 : Implemented system diagram.

the clinching process such as drawing, applied force and sensor situation. The second visualization page demonstrates the maximum force and maximum displacement values for the last 50 inner tubes (Fig. 2.9). Maximum force is mostly related to quality indicator which is the bottom thickness of the clinched joint. Maximum displacement is used for tracking the repetability of the process. Moreover, the industrial computer saves processed data into a SQL database and raw data into local computer memory.

2.5 Conclusion

This study is built to enhance the clinching process by using different control methods in an industrial environment. These control methods include informing and warning users, interrupting production, changing set values in the controller and using predictive regression models. The mentioned control strategies will be detailed in further chapters.

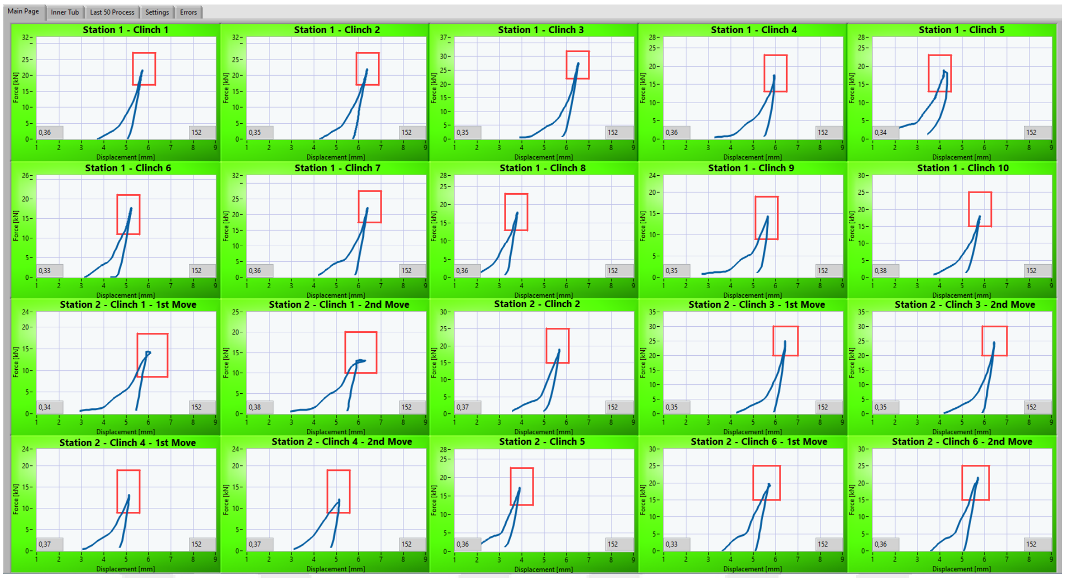

Figure 2.7 : Visualization page that consists of the characteristic curves of last clinching operation.

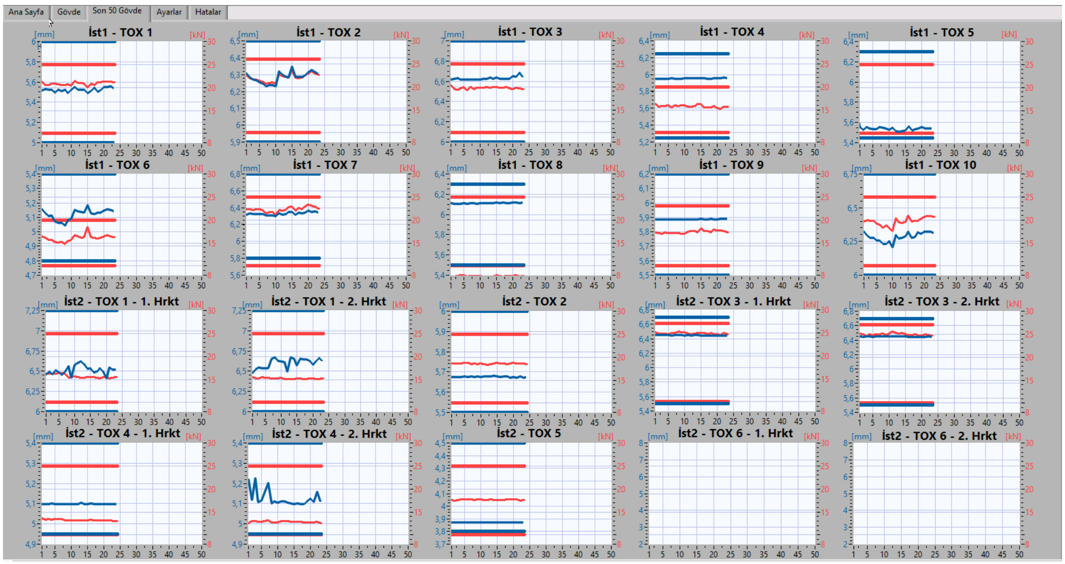

Figure 2.8 : Visualization page that consists of the maximum force and displacement values for last 50 parts.

3. PREDICTION OF QUALITY INDICATOR

3.1 Overview

In clinching technique, there are three main quality indicators as mentioned in previous topics. Nevertheless, there is only one quality indicator that can be measured using the non-destructive method. The bottom thickness of the clinched joint called control X, is the refereed quality indicator. The non-destructive method is crucial because each inner tub has more than 20 clinched joints and even destruction of one of them damages other joints in the same inner tub. On the other hand, destructive methods overspend because of the resultant inconsumable inner tubs. Therefore, measuring bottom thickness is preferred in a mass production industrial environment. Bottom thickness is measured using a comparator tool that has a unique head design for clinched joint measurements (Fig. 3.1).

However, there are two main disadvantages to measuring bottom thicknesses by operator. One of them is the lack of inspection in mass production. The cycle time of the production line is 20 seconds. It is not possible for one operator to measure 22 clinched joint bottom thicknesses within 20 seconds. For this reason, the operator randomly selects an inner tub that is clinched from the production line and measures the 22 clinched joints in the inner tub. This procedure is maintained periodically and approximately one of the 100 inner tubs produced is measured. As a result of a lack of inspection, if a mechanical problem occurs in the clinching stations, it causes a lot of improperly clinched joints and a lot of scraps in the end. Another disadvantage of measurement with a comparator is measurement competence. In consideration of the micron-level measurement range, different operators in different shifts may measure different thickness values. This case may happen even with the same operator's measurements at different time intervals.

In this chapter, a prediction algorithm developed using force and displacement sensor data will be presented and investigated in detail.

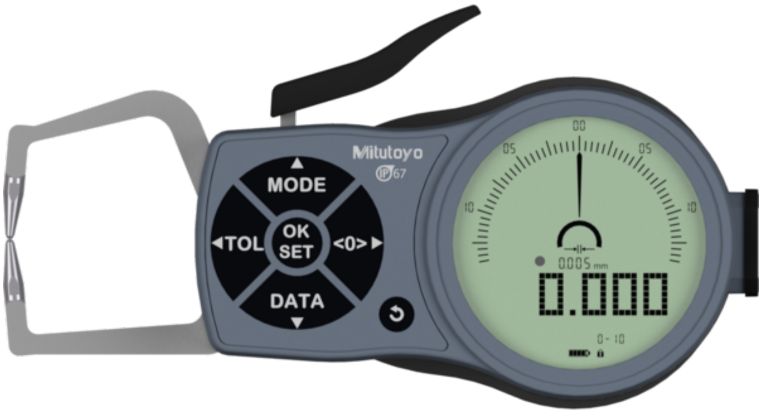

Figure 3.1 : Measurement tool that is used to measure bottom thickness of the clinched joints.

3.2 Data Collection System

The system consists of two clinching stations. One of the stations has 10 hydraulic cylinders, while another has 6. However, some of the 6 cylinders execute second and third clinching operations in the same cycle. Therefore, the total clinching operation number is 22 in a single cycle. All hydraulic cylinders have force and displacement sensor integration (Fig. 3.2).

Production line cycle time is 20 seconds but the actual clinching duration is much shorter. Powered by a single main pump hydraulic cylinders complete the clinching process in the 50–100 ms range. High-frequency data acquisition devices are required to observe the extremely short process time in clinching. Totally, two data acquisition devices are placed and integrated into clinching stations (Fig. 3.3). Data acquisition devices are covered with a distribution board to avoid lubrication and noisy observation in the industrial environment. Each data acquisition device has 16 sensor channels, 2 profinet ports and 1 ethernet port. Process data is collected using a LabVIEW program that was developed with regard to production behavior. The data collection frequency is 1200 Hz. As detailed in the methodology chapter, amplification, filtering, and digitalization stages are conducted on the data acquisition devices. The developed LabVIEW program sorts actual 50–100 ms raw process data from a 20-second data stream. At the end of each cycle, sorted raw data is saved in local computer memory.

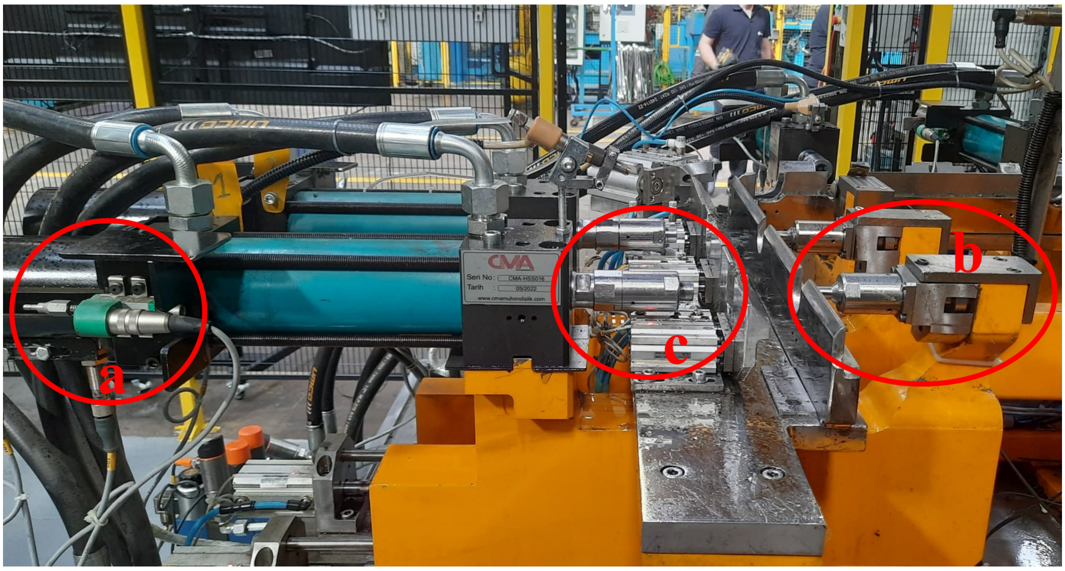

Figure 3.2 : Sensor and tool integration (a) Displacement sensor (b) Force sensor and die structure (c) Punch structure.

The bottom thickness quality indicator prediction model for all hydraulic cylinders is in need of labeled data storage. Therefore, quality indicator data is collected at different time intervals using the same comparator and person measuring to provide measurement competence. Then, the collected data is matched with stored raw process data in computer memory. In total, 2400 labeled clinching process data points are used to build up a prediction model.

3.3 Data Preprocessing and Feature Extraction

In the building prediction model, data preprocessing is a critical stage. In Fig. 3.4, the characteristic curve of a clinching process can be seen. Data preprocessing studies are conducted on the characteristic curve, time-displacement curve and time-force curve (Fig. 3.5). Firstly, all sensor data is scanned and cleaned out of missing or nonsense data. Then, because each displacement sensor settlement in different cylinders has a different process range, all displacement sensor raw data is standardized. Alike, force sensor data is also processed because of zero-point discrepancies that are derived from unstandardized preloads on force sensors.

After the data preprocessing stages, feature extraction is completed using the mentioned curves. In consideration of previous literature studies and production

Figure 3.3 : Data acquisition device (HBM PMX).

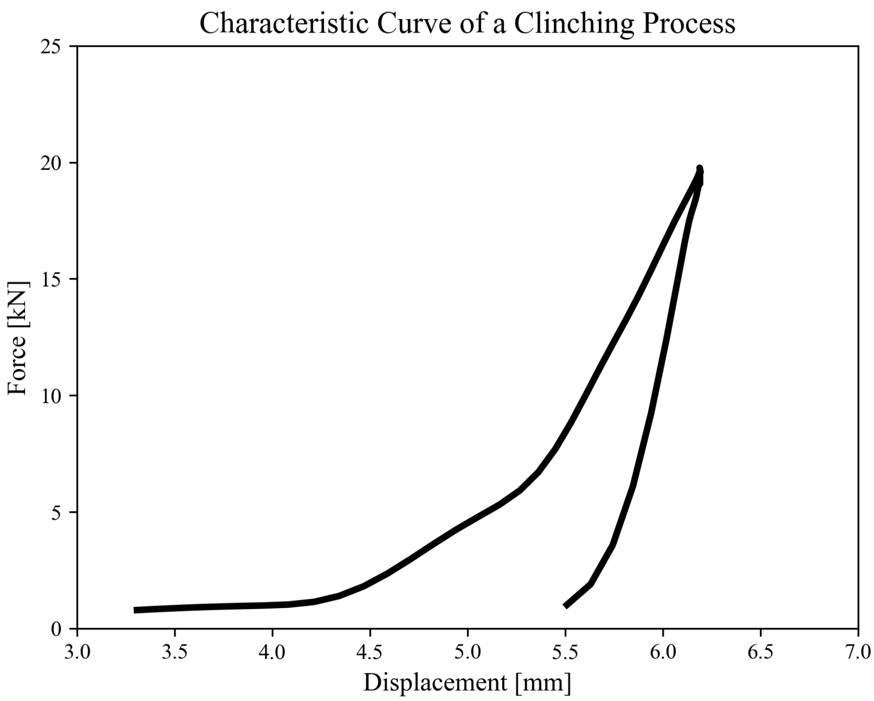

Figure 3.4 : Characteristic curve of a regular clinching process.

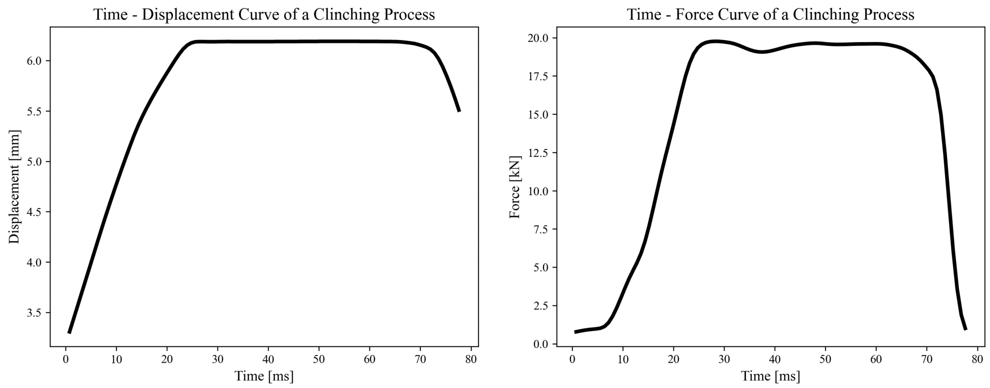

Figure 3.5 : Time-based curves of a regular clinching process (a) Time-displacement (b) Time-force.

Table 3.1 : Extracted features.

Extracted Feature	Unit
Maximum Force	kN
Force at Turn Point	kN
Drawing C	mm
Area Under Curve (AUC)	no unit
Maximum Slope	no unit
Pushing Total Time	mm
Avg. Speed	mm/ms
Total Process Time	ms

observations, 12 features are extracted in total (Table 3.1). Some of the features such as area under curve (AUC) and slope are also applied to time-based curves.

Details of the extracted features are given as follows:

Maximum Force [kN]: Maximum force is the observed maximum force sensor data in a clinching process. Mostly, it is observed at the deepest position of the punch.

Force at Turn Point [kN]: The turn point is the moment of hydraulic valve switching to finish the clinching process. Turn point is controlled by displacement sensor data which is supplied by the data acquisition device in real time. So, the feature represents the force value at the switching moment.

Drawing [mm]: Drawing is the total distance between 2 kN and maximum force values. The first position is selected as 2 kN because deformation of the sheets starts at 2 kN. And deformation continues until it reaches maximum force.

Area Under Curve (AUC): The area under curve formulation is applied to both characteristic curves and time series curves. Integral formulation is applied to the curves for 2 kN and the maximum force interval.

Maximum Slope: Maximum slope is found in the curves until maximum force.

Pushing Total Time [ms]: Pushing total time is the time duration of the forward movement of the punch.

Average Speed [mm/ms]: The average speed of the punch until the turn point is calculated as a proportion of the drawing to the total time during the drawing.

Total Process Time [ms]: Total process time includes the time duration of punch return in addition to pushing total time.

3.4 Prediction Models

In this section, the machine learning prediction models based on labeled and feature-extracted data are detailed. Regression is selected as a supervised learning task to predict the quality indicator. The labeled bottom thickness range is between 0.23 mm and 0.53 mm. Thereafter, eight different prediction models are examined.

3.4.1 Linear regression

Linear regression is one of the most preferred regression models in machine learning algorithms. The reasons for this popularity are simplicity and easy to interpret and train the model. The variable that is desired to predict is named as dependent variable. In addition, the variable which is being used for prediction is named as independent variable. Linear regression model is formed by a linear equation (Eq 3.1). In the equation, y represents the dependent variables, x values represent the independent variables and a values represent the coefficients that are found as a result of the training of the model.

$$y = a_1x_1 + a_2x_2 + ... + a_nx_n + c \tag{3.1}$$

During the training, linear regression model utilizes from least square method to minimize the difference between actual values and predicted values, and to find optimum coefficients (Eq. 3.2). In the equation, L represents the loss function.

$$L = \sum (y - \hat{y})^2 \tag{3.2}$$

However, linear regression model is not penalized for the coefficients found, which can be a reason for overfitting. Therefore, lasso and ridge regression models are improved to overcome the overfitting problem in linear regression [44].

3.4.2 Lasso and ridge regressions

Lasso (Least Absolute Shrinkage and Selection Operator) and ridge regressions are regularized versions of linear regression. The objective of both regressions is to define the variables and model coefficients that provide the prediction error minimization. The generalized lasso regression formula is shared in Eq. 3.3. As can be seen in the equation, the loss function is modified with a penalty section.

In this section, the hyperparameter lambda (λ), known as L1 penalty, penalizes the sum of absolute values of coefficients (a). The meaning of that L1 penalty equals to zero, is turning model into a standard linear regression. L1 regularization operates by driving coefficients towards zero, basically removing corresponding independent variables from the model. The optimal value of (λ) is often found by using cross validation techniques which are iteratively applied.

$$L = \sum (y - \hat{y})^2 + \lambda \sum |a| \tag{3.3}$$

While lasso regression demonstrates superiority over standard methods in some scenarios, it is not an overall solution for tackling overfitting and optimism bias problems. In addition, lasso regression even so requires validation in an external dataset. Generalized ridge regression formula is given in Eq. 3.4. Similar to lasso regression, penalty section is added into loss function. Unlike lasso regression, the hyperparameter lambda (λ), known as L2 penalty, penalizes the sum of squared values of coefficients (a).

Therefore, L2 penalty reduces the coefficients to zero similar to lasso, but the coefficients do not never equal to zero. The optimal value of λ is calculated by using cross validation methods same as lasso regression.

$$L = \sum (y - \hat{y})^2 + \lambda \sum a^2 \tag{3.4}$$

Ridge regression offers high performance in some topics such as overfitting and multicollinearity in linear regression. Both ridge regression and lasso regression reduce the model complexity in different ways. Ridge regression reduces the influence of each independent variable on the output by degrading their coefficients. On the other hand, lasso regression decreases the number of independent variables by shrinking the coefficients to absolute zero [45,46].

3.4.3 Decision tree regression

Decision tree is one of the most functional machine learning algorithms that is non-parametric and supervised. Classification and regression tasks can be handled by decision tree models. As can be seen in Fig 3.6, a decision tree consists of one root node, internal nodes after the root node and leaf nodes as final step of the decision. The objective is to develop a model that forecasts the target class or the closest variable of targeted value by using simple decision rules derived from data features.

For many years, different algorithms of decision tree have been developed for specific learning goals. Decision tree has several advantages. One of the most characteristic advantages is simply interpreting the decision nodes and rules. Being usable for multi-output problems and having both categorical and numerical data are positive properties of decision tree. Nevertheless, there are some weaknesses of decision tree model. Unstability because of insignificant variations in the data, complex trees against big data sets and additional computational load because of complex tree structures can be considered disadvantages of decision tree [47].

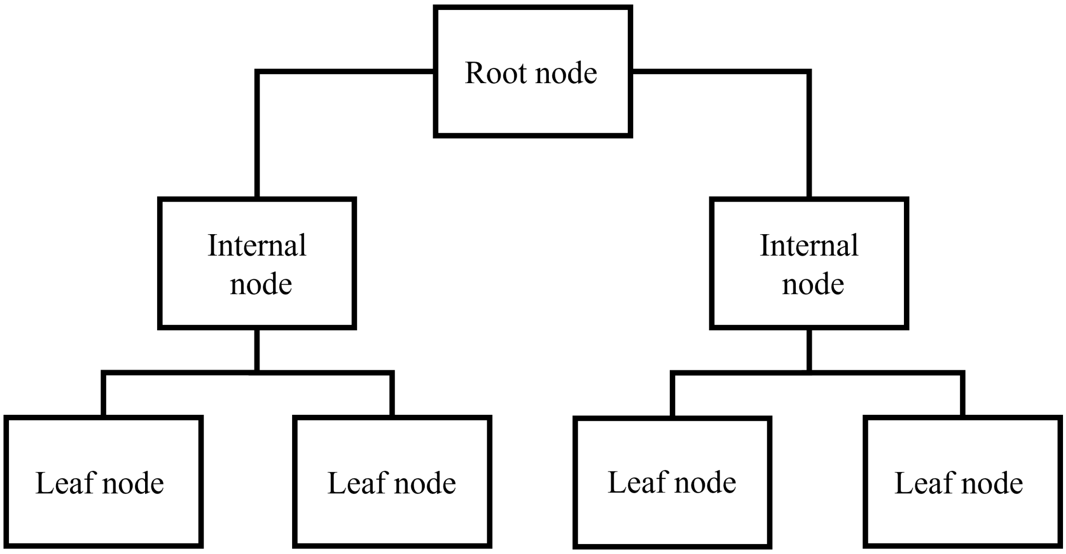

Figure 3.6 : Decision tree structure.

3.4.4 Random forest regression

Random forest is another commonly used machine learning algorithm. Fundamentally, random forest algorithm comprises a multitude of decision trees with a bagging mechanism (Fig. 3.7). Each decision tree operates independently through connective randomization during model formation. Selecting subsets of samples and features can be given as examples of randomly selected node properties. This strategy enhances model performance and facilitates better generalization across diverse data sets.

Likewise, random forest has positive and negative aspects. The risk of overfitting is less than that of a decision tree. Nevertheless, the challenge of overfitting training data remains. In addition, the generalization error consistently decreases even as the number of trees increases. Besides, random forest model can handle both regression and classification tasks with a considerable degree of accuracy and achieve results frequently faster. Negative aspects of the random forest start with the complexity of interpreting especially compared with decision tree. Furthermore, random forest algorithm requires more memory and consumes more time for classification or regression tasks in consideration of larger data sets [48].

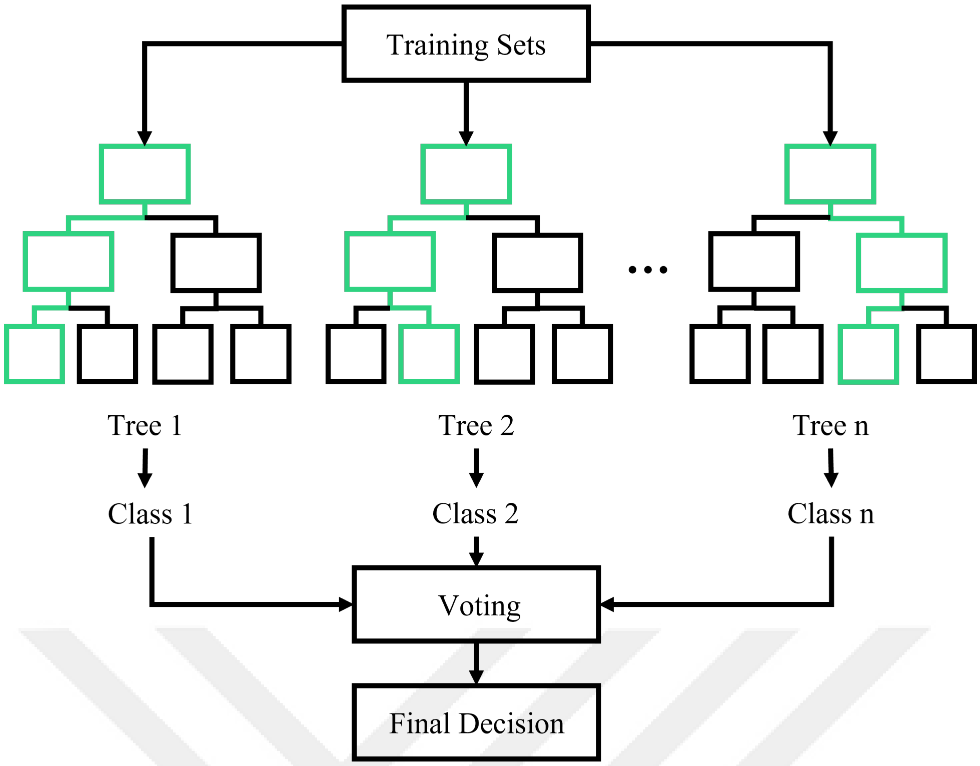

Figure 3.7 : Random forest structure.

3.4.5 Extreme gradient boosting regression

Extreme gradient boosting (XGBoost) algorithm is one of the supervised machine learning algorithms. XGBoost is a combined learning algorithm that is based on decision tree and exploits gradient boosting technique. Boosting mechanism is used to minimize the errors in the foregoing models and help strengthen the impact of high-performing models. The gradient boosting has been improved to achieve more precise forecasting. Nonetheless, implementation of the gradient boosting is restricted because the algorithm needs to produce a decision tree at a moment to minimize errors that were observed in previous trees. With the development of XGBoost, separate decision trees are produced using multiple cores. Instead of selecting majority voting output results in random forest, the predicted output of XGBoost is the sum of all the results (Fig. 3.8). The shortening of the time due to the regularization of the data causes an increase in performance. XGBoost is a powerful and flexible machine learning algorithm that can handle large data sets in both classification and regression tasks. Included regularization mechanisms help to avoid overfitting. Additionally, both high accuracy and speed are the most known properties of the XGBoost algorithm. On

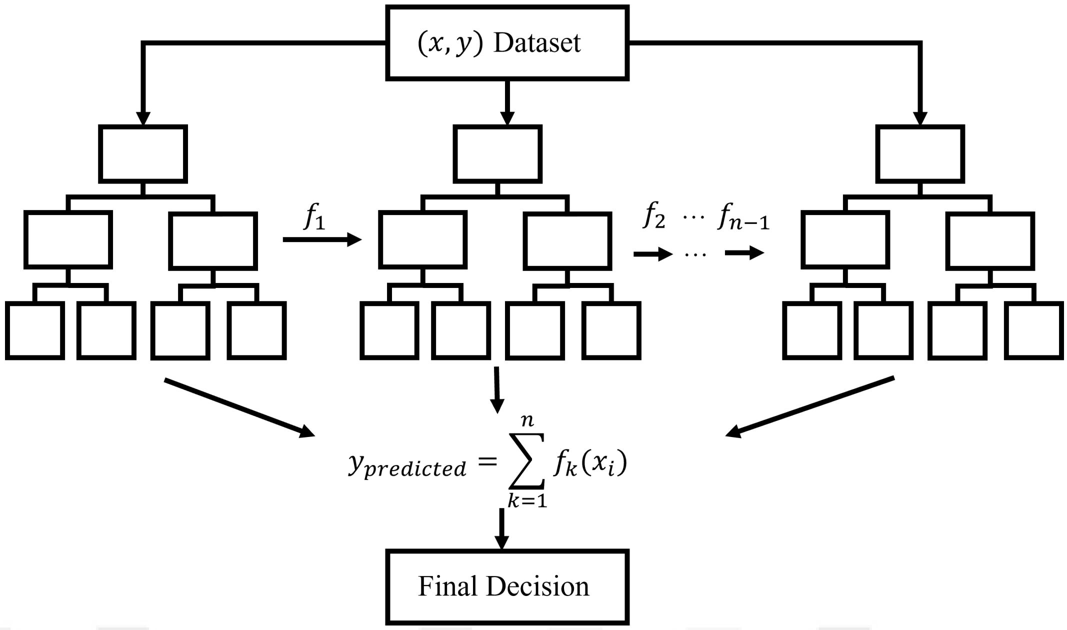

Figure 3.8 : Extreme gradient boosting (XGBoost) structure.

the other hand, the algorithm is difficult to interpret and optimize effectively because of its complexity and lack of transparency [49,50].

3.4.6 Support vector regression

Support vector machine (SVM) is a machine learning algorithm that is utilized for complex classification, detection and regression tasks. The unusual generalization capacity and strong theoretical background make SVMs one of the most frequently used machine learning methods. Support vector regression (SVR) is utilized from SVMs for linear and non-linear regression tasks.

The main objective of the SVM algorithm is to define a hyperplane that explicitly separates the data into different classes (Fig. 3.9). At the same time, the separation gap (margin) between the decision lines is maximized to increase the generalization ability of the model. There is classifiable data using a linear hyperplane in Fig. 3.9. In SVR, the hyperplane demonstrates the predicted regression line. Because the data points do not fit perfectly on the predicted regression line, there is a tolerance gap, known as ε-tube. However, linear SVM falls short when facing non-linear data about real-life problems or scenarios. At this point, kernel functions are utilized to build non-linear

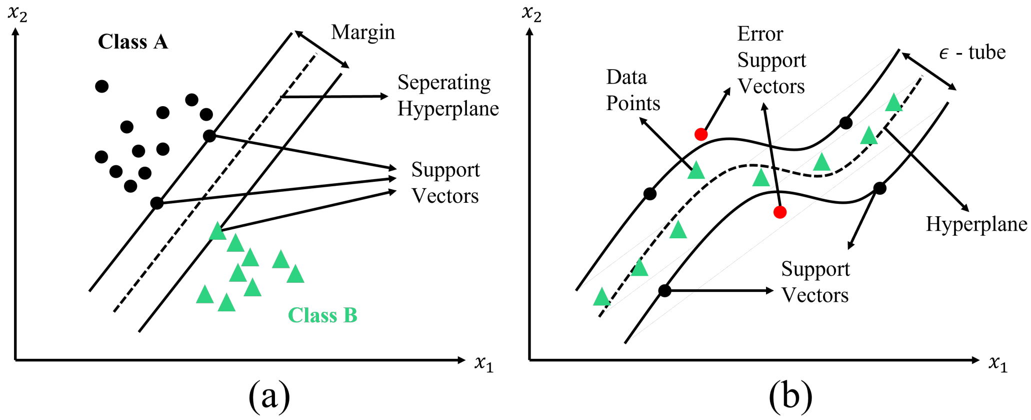

Figure 3.9 : Illustration of (a) linear SVM classifier (b) non-linear SVR.

learning machines. Polynomial, gaussian or sigmoid kernel functions can be given as examples of used in real-life applications.

Despite the generalization capability, efficient memory usage, advanced accuracy performance of the SVM algorithms, they have distinct drawbacks. These drawbacks can be listed as relatively low performance in big and unbalanced data sets, multi-class problems difficulties and algorithmic complexity that increase the computation time of training [47,51].

3.4.7 K nearest neighbor regression

K-nearest neighbor (kNN) is another supervised machine learning method employed to tackle classification and regression tasks. The letter of k represents the number of evaluated nearest neighbors during the prediction.

For instance, k value is accepted as 4 for the new data in Fig. 3.10. Thereby, detection of the nearest neighbors is the first stage for new data classification. After detection of neighbors, the class of the new data is predicted in consideration of similarity and distance metrics based on detected neighbors. In regression tasks, kNN firstly detects k number of neighbors similar to classification. Then, it calculates the average of the detected neighbors numerical values to predict the optimum target value.

Most marked benefit of the kNN algorithm is easy to interpret because of simplicity. kNN is efficient and robust for large and noisy training sets. Otherwise, the computation is very slow in large training sets. Moreover, memory limitations

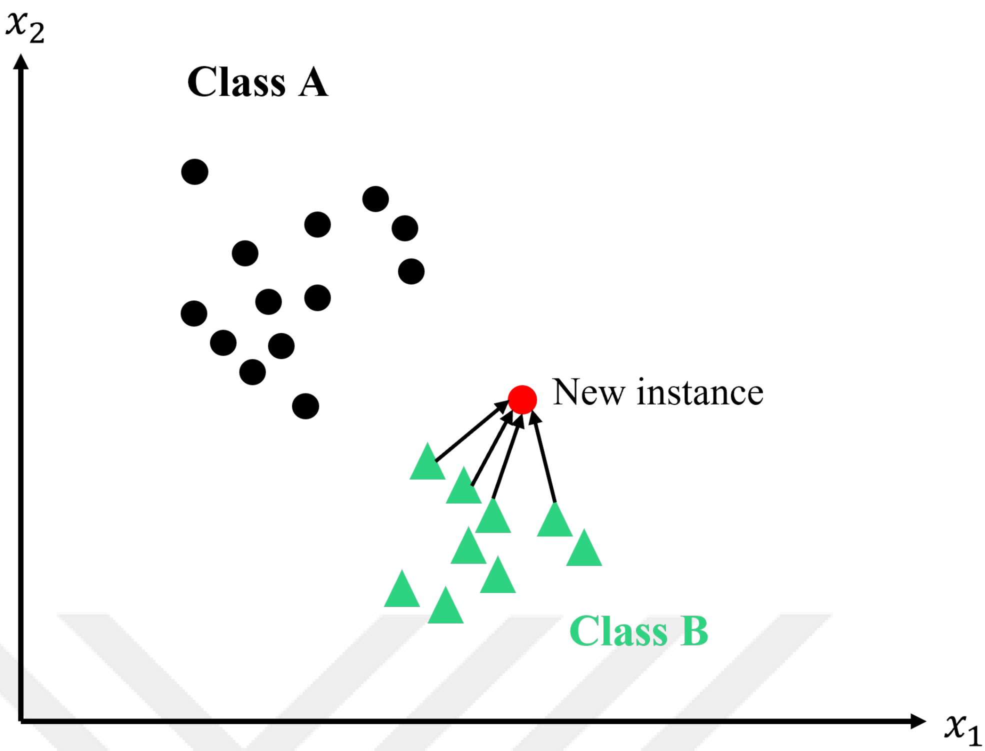

Figure 3.10 : Illustration of the nearest neighbors detection by KNN classifier.

and weakness to irrelevant features can be mentioned as disadvantages of the kNN algorithm [52].

3.5 Evaluation of Prediction Models

There are different metrics to evaluate of classification and regression tasks. In general, any of the metrics gives the best results in all situations. Therefore, R-squared (R^2), mean squared error (MSE) and mean absolute error (MAE) are chosen to evaluate the performance of bottom thickness prediction model.

R^2 is a statistical metric that demonstrates the proportion of the variance for a dependent variable that is explained by an independent variable in a regression model. Calculation of R^2 is given in equation 3.5. In the equation n represents the total prediction number, y_i represents the actual values, $\hat{y}_i$ represents the predicted values and $\bar{y}$ represents the mean value of the all actual values. R^2 scores change between %0 and %100. Meaning of %100 is that the model perfectly predicts the dependent variables while %0 is that the model can not predict the dependent variable whatsoever with using the independent variables. However, R^2 does not represents the prediction model is proper or not singly. Additionally, R^2 measurement is more suitable for linear regression models in comparison to non-linear related data patterns.

$$R^2 = \left(1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}\right).100 \tag{3.5}$$

Another metric that is utilized to evaluate the performance of a regression model, is MSE. Calculation of MSE is given in Eq. 3.6. In the equation n represents the total prediction number, y_i represents the actual values and $\hat{y}_i$ represents the predicted values. As can be seen from the equation, MSE is a basically mean prediction error and it penalizes the errors by squaring the difference between predicted and actual values. Therefore, sensitivity to outliers of MSE is utilized to eliminate larger prediction errors. Smaller MSE score means better performance.

$$MSE = \frac{1}{n}.\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3.6}$$

Last evaluation metric that is used, is MAE. Formula of MAE is given in equation 3.7. In the equation n represents the total prediction number, y_i represents the actual values and $\hat{y}_i$ represents the predicted values. Unlike MSE, MAE measures the mean prediction error by using the absolute value of residuals instead of squaring them. Similar to MSE, smaller MAE score means better performance.

$$MAE = \frac{1}{n}.\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3.7}$$

In consideration of different evaluation metrics, MAE is the most crucial metric for bottom thickness prediction model because of non-linear pattern relations and unexpected outliers. In the outlier cases, additionally developed control mechanism is activated.

3.6 Results

After all, each machine learning algorithms that mentioned above are studiously implemented in proper adjustment to achieve the best results.

Table 3.2 : Validation results of the prediction models.

Prediction Models	MAE (mm)	$R^2 (\%)$	MSE (mm^2) ($x10^{-4}$)
Linear Regression	0.0194	79.19	5.568
Lasso Regression	0.0184	85.35	4.904
Ridge Regression	0.0185	83.52	4.799
Random Forest	0.0174	85.34	4.529
XGBoost	0.0206	74.72	6.071
SVR	0.0199	81.87	5.558
Decision Tree	0.0189	82.80	5.123
kNN	0.0198	80.33	5.678

In the implementation and evaluation periods, the number of feature is reduced to dispose of unnecessary computational load on the controller. Conducted feature importance works shows that there are 5 critical features that are the most related with the bottom thickness of the clinched joint. They are maximum force, turn point force, drawing, and area under curve values of force time and characteristic curves. Remained features are nearly irrelevant with the quality indicator. Thereby, machine learning algorithm implementations and evaluations are processed within the 5 critical features.

The results of the quality indicator prediction algorithms are presented in Table 3.2.

R^2, mean absolute error and mean squared error ratios are the results of cross validation studies that computes the score 10 consecutive times. As can be seen from the table, random forest prediction algorithm has the best performance in consideration of MAE and MSE. In what follows, ridge regression and lasso regression algorithms have best prediction performances after random forest. Conspicuously, extreme gradient boosting model has the lowest prediction performance for each evaluation metric.

MAE is the most significant metric for bottom thickness model because less sensitivity to outliers which are not expected in the process. Therefore, random forest prediction model is used to forecast the quality indicator because of MAE and R^2 scores.

3.7 Conclusion

In conclusion, a quality indicator prediction model is developed based on force and displacement sensors for clinching processes that use hydraulic-powered cylinders.

The developed prediction model shows that production and quality tracking can be provided using machine learning algorithms. In the meantime, research on the prediction methods is pursued within the large data set based on production.

4. CONTROL MECHANISM

4.1 Overview

In the conventional clinching process, there are two kinds of quality failures. One of the failures is that metal sheets are punctured because of redundant force, broken tools or eccentricity between punch and die structures. The other failure is the improper joint because less than necessary force is applied to the metal sheets. While the puncture of clinched joints causes water leakage in the dishwasher, improper joints induce a lack of mechanical strength in the machine.

In the case of failures, the production line stops until detection of the root cause malfunction and fixing it. In addition to the lost because of production line stoppage, all inner tubs that are clinched until the failure detection, are scrapped.

Except of the detailed above major failures, there is likewise a probability of quality degradation during the production. There is a clinching process of joints of 0.4 mm and 0.5 mm stainless steel metal sheets in 2 clinching stations that were previously detailed. The optimum bottom thickness range of the joint is between 0.3 and 0.4 mm, according to conducted quality studies. Bottom thickness values that are below 0.3 mm increase the probability of a punctured, clinched joint. On the other hand, values that are over 0.4 mm increase the probability of an improper joint and reduce the structural strength of the inner tub. The main reasons for the quality degradation are the thickness variety of the metal sheets, the eccentricity between the punch and die, tool wear or lubrication problems.

Respectively, the windowing approach, rule-based control of major malfunctions and optimum quality control will be detailed in this chapter.

4.2 Windowing Approach

The windowing approach has been used in the clinching operations by the machine producers for several years. Developed visualization and data acquisition devices are being sold with the sensors. Window thresholds are adjusted in the first implementation of the line. After that, rearrangement of the thresholds or replacement of the sensors are needed in the case of any change in the clinching stations. The windowing functions of the commercial devices are being used to only define whether the clinching process is OK or NOK. Otherwise, any other information about the process or the quality of the joint is not given to the main controllers or the users. Details of the windowing approach as an alternative to similar commercial products and the developed control mechanisms that are based on the window will be given next.

A window is constituted on the characteristic curve of the clinching process (Fig. 4.1). Essentially, a window consists of four thresholds; two of them are based on force while the last two are based on displacement values. These thresholds are used to check the position of the peak point of the clinching curve. If the peak point is within the window borders, the process is completed properly. On the contrary, positioning the peak point out of the window means that the process had a major malfunction or that the bottom thickness values are out of range. Thresholds are determined in regard to the preset rules that are conducted on the developed LabVIEW program periodically. The preset rules are shared below:

Minimum displacement threshold (MIN-D) is determined according to the turn point value of the hydraulic in the programmable logic controller (PLC) of the stations.

Maximum displacement threshold (MAX-D) is assigned according to the drawing value of the cylinder and the minimum displacement threshold.

Minimum force threshold (MIN-F) and maximum force threshold (MAX-F) are generated from both the quality indicator prediction model and operator measurements. The maximum (peak) force value is both the easiest to calculate and one of the most related to the quality indicator feature. Additionally, minimum and maximum force thresholds cannot be respectively below 10 kN and over 35 kN, according to the experimental results on production.

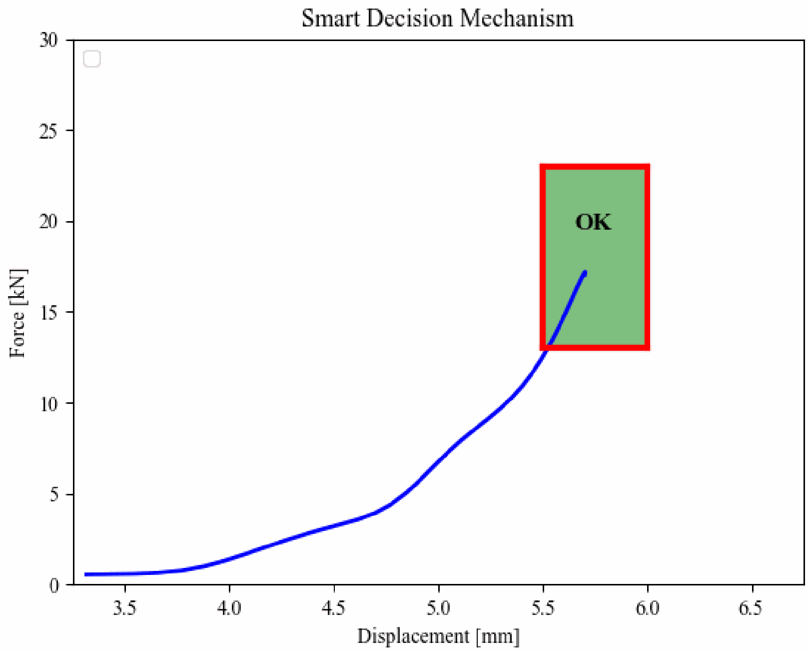

Figure 4.1 : Windowing approach at the peak point of the process.

The developed control mechanisms that are based on the window will be detailed below.

4.3 Smart Decision Mechanism

Smart decision mechanism (SDM) is developed to avoid scrap production after undetected major malfunctions in the clinching stations. There are four different major malfunction and clinch failure patterns that are classified based on the peak point of the process. Classified malfunctions and clinching failures are broken tool, external material, improper joint and smaller bottom thickness (Fig. 4.2).

In the case of any malfunction occurs, the developed SDM immediately stops production by sending a stop command to the PLC. After the production stoppage, operators make adjustments to the cylinder that is pointed by the SDM. After the adjustments of the operators, SDM assumes the clinching quality of the adjusted cylinder as acceptable. With the entry of the first quality measurements after the adjustment, the SDM arranges the thresholds according to the prediction model and measurement results.

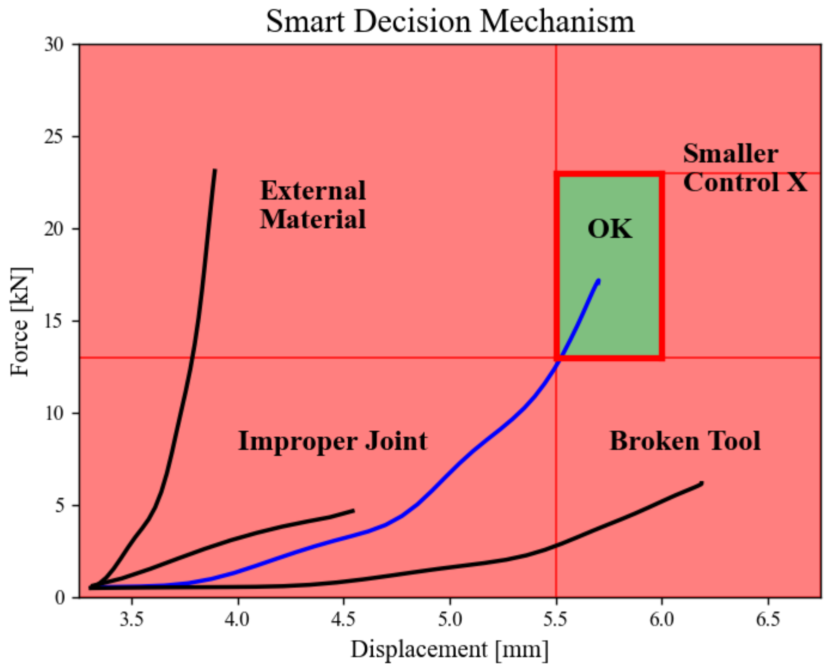

Figure 4.2 : The areas of classified major malfunctions and clinching failures.

4.3.1 Broken tool

Die and punch pairs are being specially designed and produced with regard to the thickness and material properties of the metal sheets. However, these tools have a working life. After completing their working lives, tools abruptly break or wear over time. The process behavior of the broken tools is investigated in the experimental studies. Broken tools that are taken from production are used in these studies (Fig. 4.3). As a result of the experiments that are conducted on the broken tools, displacement increases peculiarly while the maximum force remains under 10 kN. The broken tool decision area in the characteristic graph is determined as shown in Fig 4.2 with the test results. The area can be described as the intersection of upper MIN-D and lower MIN-F.

4.3.2 External material

External materials can be jammed in the clinching process although this is rare. These materials mostly belong to previous operations in the production line (Fig. 4.4). Besides, the probability of tool breakage is higher than in normal conditions in the case of external material jamming. Similar external materials are jammed into the

Figure 4.3 : Broken tool instance.

tools to observe the process behavior. As a result of the simulated experiments, force increases while displacement remains under MIN-D. Therefore, the external material decision area in the characteristic graph is determined as shown in Fig. 4.2. The area can be defined as the intersection of upper MIN-F and lower MIN-D.

4.3.3 Improper joint and smaller bottom thickness

An improper joint means that neither displacement nor force conditions are met. In the case of an improper joint, expected displacement and force values are incomplete for clinching. In the characteristic graph, the improper joint decision area is determined as shown in Fig. 4.2. The area can be defined as the intersection of lower MIN-F and lower MIN-D.

On the contrary, smaller control X area means that metal sheets are formed under extreme force. Consequently, the bottom thickness of the joint is under 0.25 mm and the probability of crack formation in the joint increases. In the characteristic graph, smaller control X area is determined as shown in Fig. 4.2. The area can be defined as the intersection of upper MIN-F, upper MIN-D and except for the acceptable green area.

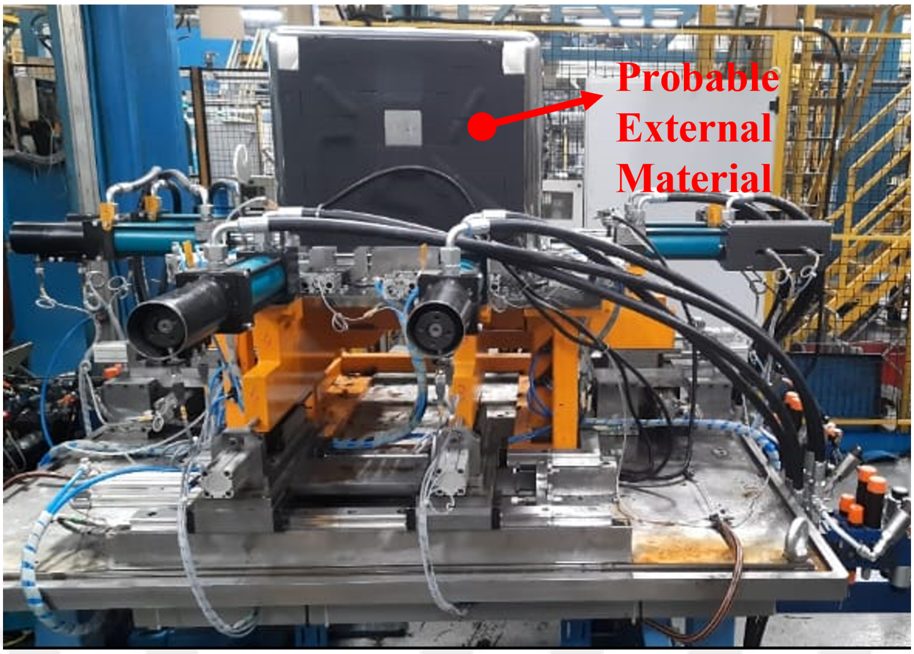

Figure 4.4 : Probable external material on the inner tub.

4.4 Optimum Quality Control

As mentioned previously, the optimum bottom thickness range is 0.3–0.4 mm for the joint of 0.4 mm and 0.5 mm stainless steel metal sheets. However, acceptable window thresholds are set to ensure the bottom thickness is between 0.25 mm and 0.5 mm. In the range of 0.25 mm and 0.5 mm, the clinched joint provides the minimum mechanical conditions. Although the minimum conditions are satisfied, the optimum bottom thickness range of the joint of 0.4 mm and 0.5 mm is 0.3–0.4 mm.

Therefore, an additional part-to-part control mechanism in the window is implemented in SDM to provide optimum quality (Fig. 4.5). This mechanism steps in only in cases where the peak point is positioned in the window. The target of this mechanism is to keep the peak point of the curve in the optimum range of quality output. The feedback decision is transmitted to the main controller of the line which is a programmable logic controller (PLC). The feedback to the cylinder is given gradually with respect to the distance between the peak point and the optimum quality range.

A flowchart diagram that consists of previously detailed control mechanisms is represented in Fig. 4.6. As shown in the figure, the control loop is executed for each cycle repetitively. The control sequence starts with verification of the thresholds to

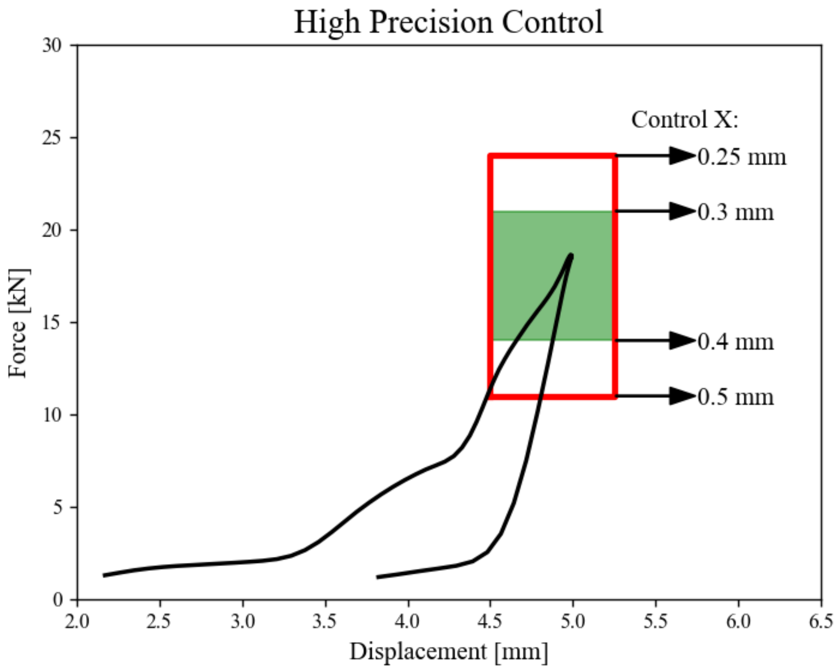

Figure 4.5 : Predicted bottom thickness values on the characteristic graph.

ensure that there are no modifications to the cylinders. After the verification of the thresholds, SDM and the optimum range controller check the peak point positioning of the last produced clinched joint. Decisions are executed sequentially, as shown in the flowchart. Decisions influence the next cycle, which is continued iteratively.

4.5 Results

Results show that SDM detects the malfunction successfully using force and displacement sensor data. After detection of the major malfunctions, SDM stops production and prevents the loss. However, reference values, robustness, and stabilization of the SDM must be checked by the professionals periodically because production stoppage is a crucial decision.

On the other hand, an example execution of the optimum quality control mechanism is represented in Fig. 4.7. The represented illustration of a clinching hydraulic cylinder belongs to real production data. As can be seen in the figure, the clinched joint of the first curve is in the acceptable quality range, but it is not in the optimum quality range. With the becoming involved of the control mechanism, peak point of the curve is being pulled into the optimum range gradually automatically. The control mechanism

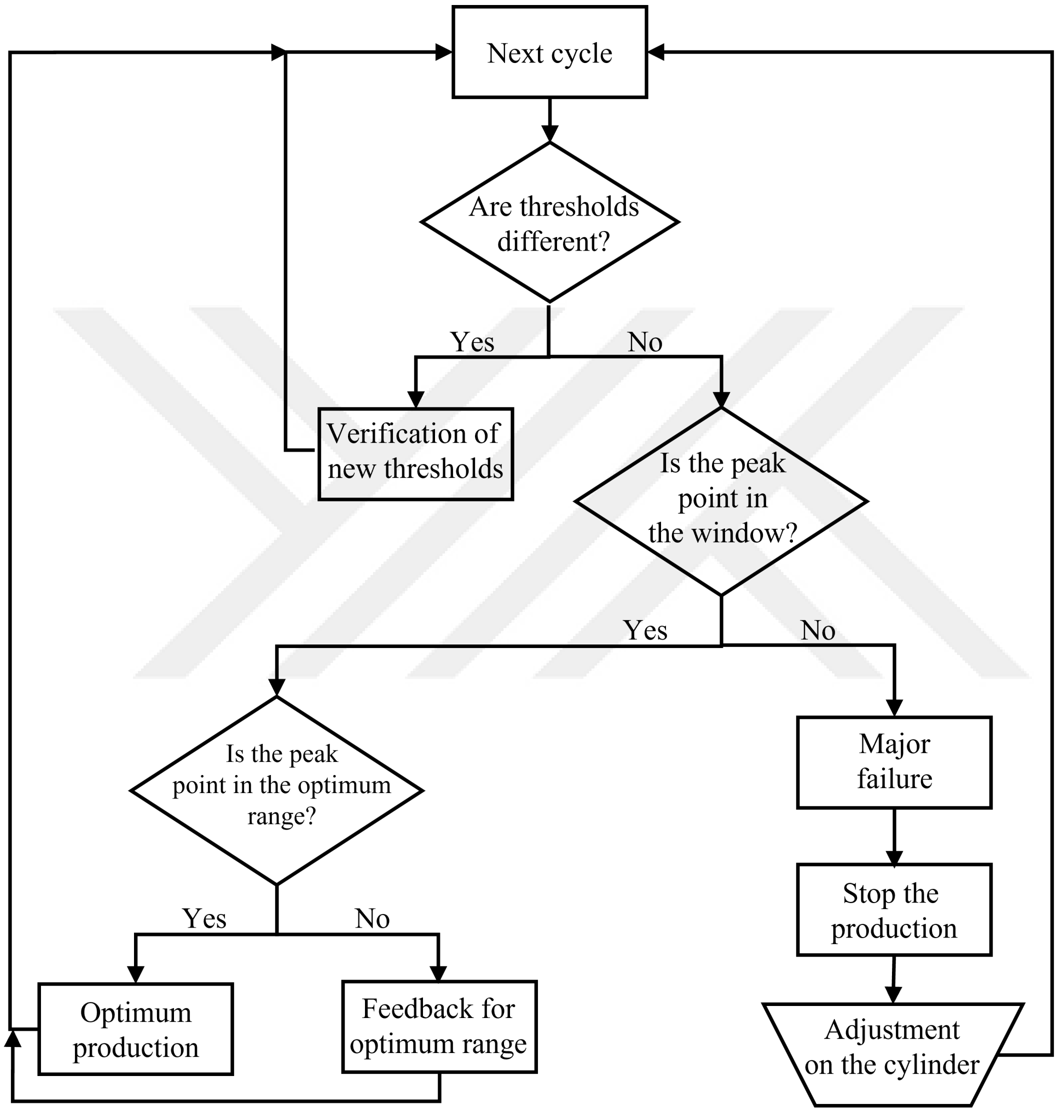

Figure 4.6 : Flowchart diagram of the control mechanisms.

changes the turn point of the hydraulic stroke for each cycle to achieve the optimum quality range. Keeping the quality output of the clinching process in the optimum range is provided by the developed control mechanism.

Similarly, sensor calibrations, robustness and stabilization of the controllers must be checked by professionals periodically.

4.6 Conclusion

In conclusion, developed control mechanisms are implemented into production to improve the quality output of the clinching process. SDM detects malfunctions that cause production losses when they happen. In addition to SDM, the feedback control mechanism ensures that the quality output of the clinching is in the optimum range.

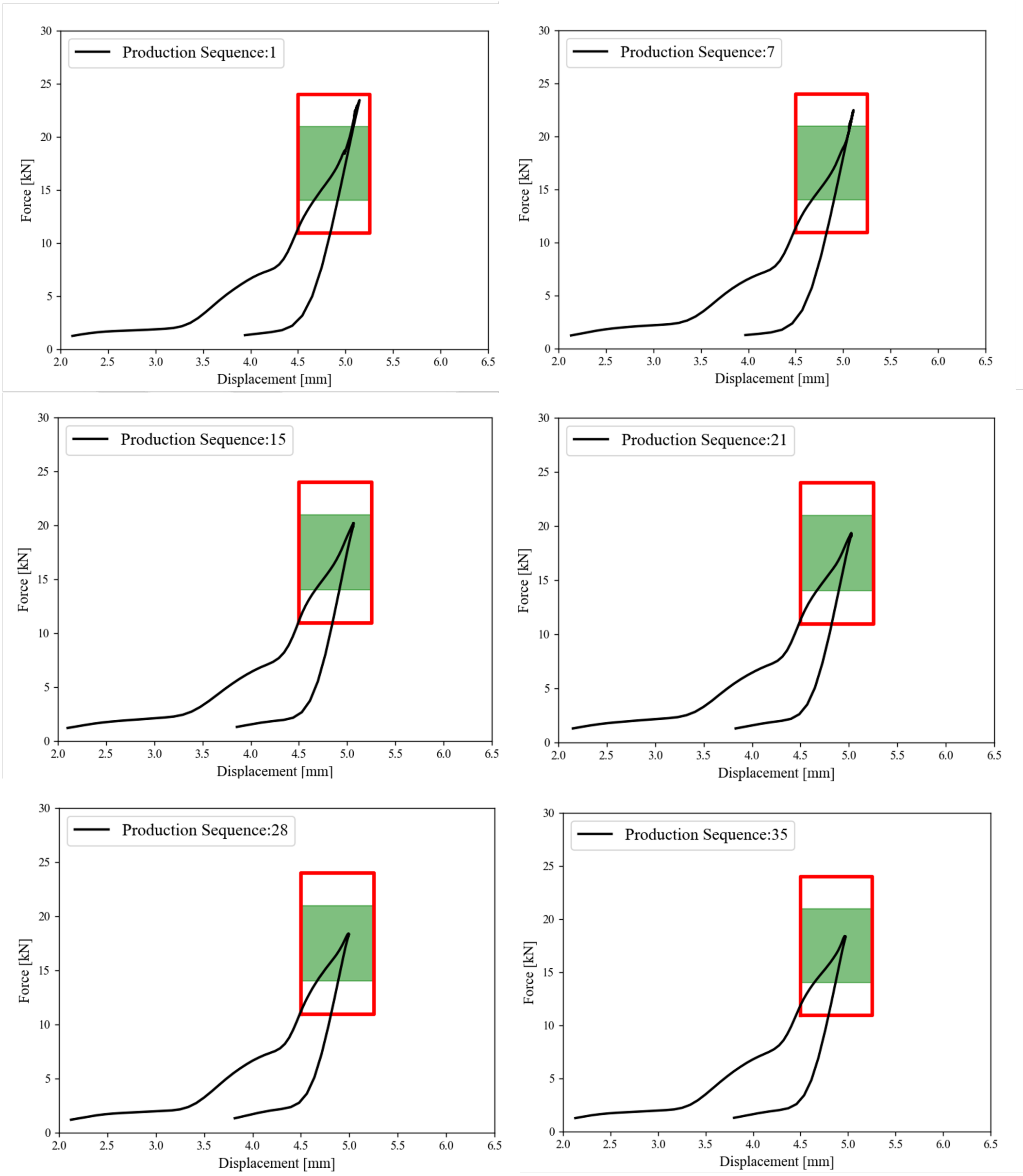

Figure 4.7 : Influence of the feedback system to the clinching process.

5. CONCLUSION

Clinching is a joining technique that utilizes mechanical force to shape the metal sheets into a special geometry. The final geometry of the clinched joints is formed by the punch and die pairs that are designed and produced specially for the clinching process. Besides, the total process time is momentary because of the hydraulic-powered stroke movement. Despite the extreme conditions of the clinching process, a prediction model for the most critical quality indicator and two essential control mechanisms are developed and implemented in this study.

As a result of the literature studies, it has been deduced that force and displacement sensors are the most essential and useful sensors to observe the clinching process clearly. The characteristic curve of a clinching process is composed of force and displacement sensor data. Hence, in regard to the extreme process conditions, attentively selected force and displacement sensors are placed in the clinching structure. In addition, two high-frequency data acquisition devices are located in the clinching stations.

After the digitalization stage of the clinching stations, a LabVIEW application that is responsible for raw data storage in local industrial PC, processed data storage in SQL database, visualization and the running of control mechanisms tasks, is developed and implemented.

The bottom thickness of the clinched joint is the most critical quality indicator. It was tracked with operator measurements that were not repeated enough. Because of the lack of inspection, the quality indicator prediction model is investigated. Eight different machine learning algorithms are experienced and validated systematically. Random forest regression model is selected due to its high performance against other algorithms. With the use of the prediction model, it is provided to track the clinching process online automatically. Despite the necessity of manual measurements by operators for prediction model calibration, dependency on operators has substantially disappeared.

Moreover, two different control mechanisms are developed and implemented in production. In the case of major malfunctions in the clinching stations, production is conducted until detection of the clinch failure. The amount of the facility lost changes according to early or late detection of the failure. Smart decision mechanism is developed to avoid late failure detection. The mechanism stops the line when a malfunction occurs. In addition to the smart decision mechanism, a part-to-part feedback control mechanism is developed to ensure that the bottom thickness of the clinched joint is in the optimum range. This mechanism gives feedback to the programmable logic controller to change the hydraulic cylinder turn point. With a change in the turn point, the force that is applied to the metal sheets can be adjusted. As a result of the force adjustment, the bottom thickness is controlled within the range of optimum quality.

In the future work, it is observed that there are some points that are needed to advance. The aggressiveness of the feedback is being assigned as a function of the distance between the target and peak positions on the characteristic curve. It must be more robust, stabilized and independent from the different cylinder behaviors. Additionally, the quality prediction models can be considered regularly according to the newly developed algorithms and expanding data sets. Finally, predictive maintenance (PdM) algorithms can be studied to detect probable tool-side or machine-side malfunctions. Long-term labeled data will be needed to build a predictive maintenance model for clinching operations.

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CURRICULUM VITAE

Emin Abdullah KAZANCI:

EDUCATION:

- **B.Sc.:** 2020, Yıldız Technical University, Faculty of Mechanical Engineering, Department of Mechatronics Engineering
- **M.Sc.(Canditate):** 2024, Istanbul Technical University, Graduate School, Mechatronics Engineering Programme

PROFESSIONAL EXPERIENCE AND REWARDS:

- 2020 1st project in Health and First Aid category of TEKNOFEST 2020
- 2020 2nd project in Health category of TÜBİTAK 2242 Undergraduates Graduation Projects Competition
- 2021 R&D Engineer at Orhun Makine
- 2021 R&D Engineer at Eximious Medical Devices
- 2022-Now Specialist Engineer at Arçelik A.Ş.

PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

- Yürükaslan G.B., **Kazancı E.A.**, Yasin O., Kerimoğlu V., Kocaarslan, İ., Solak N. (2023). Optimum Process Parameters Determination and Developing Combined Control Algorithm for Clinched Stainless Steel Metal Sheets. *International Graduate Research Symposium-IGRS*, 2023 İstanbul, Turkey.

OTHER PUBLICATIONS, PRESENTATIONS AND PATENTS:

- Karadeniz F., Aydoğan, Ö. E., **Kazancı E.A.**, Akdoğan, E. (2020). Design of a 4-DOF grounded exoskeletal robot for shoulder and elbow rehabilitation. *Sustainable Engineering and Innovation.* Vol. 2. pp. 41-65.