AN APPLICATION FOR A PARTICLE BOARD PLANT: WEB-BASED DECISION SUPPORT SYSTEM FOR QUALITY PREDICTION AND DIGITAL TRANSFORMATION

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AN APPLICATION FOR A PARTICLE BOARD PLANT: WEB-BASED DECISION SUPPORT SYSTEM FOR QUALITY PREDICTION AND DIGITAL TRANSFORMATION

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To my precious family, guiding element of my soul...

ABSTRACT

As it is same for most of the production procedures, a certain quality level must be derived in the particle board production. In the particleboard production, a series of samples taken from the production line for the quality analysis of the products produced. These samples are put to the test for analysis and observe whether the quality metrics are satisfying the needs or not. Sampling can be done after a set of production is completed. Laboratory tests samples for at least three hours. If the results of the test are out of acceptable limits, then the facility changes the production parameters, waits for new production output to gain new samples, tests new samples again. While quality testing procedures are running, the products that do not satisfy quality limits, cannot be delivered to customers, which results in crucial capacity loss. In this study a decision support system is developed to measure real-time effects of changes of production parameters on quality metrics by using machine learning based prediction models with live production data collected from production line. Decision support system developed in this study enables to predict three different quality metrics while margin of error is realized around 5%, on the average.

ÖZETÇE

Tüm üretim proseslerinde olduğu gibi yonga levha üretiminde de üretilen ürünlerin belirli kalite değerlerini sağlaması gerekliliği bulunmaktadır. Yonga levha üretiminde, yine birçok üretim sisteminde olduğu gibi, üretilen ürünlere dair kalite değerleri üretim hattından alınan bir dizi numune için laboratuvar testleri sonucunda ölçümlenmekte; istenen değerlere ulaşılıp ulaşılamadığı ise testler sonuçlandıktan sonra anlaşılabilmektedir. Yonga levha prosesinde numunelere dair bu ölçümlerin sonuçları, numune alındıktan en erken üç saat sonra elde edilebilmektedir. Ölçümlerin sonuçlarında kalite değerleri kabul edilebilir limitlerin dışında çıktığında ise işletme üretime dair parametreleri değiştirmekte ve tekrar numune toplanması, laboratuvar testleri sürecine başlan- maktadır. Bu işlemler süresince üretilen ürünler ise kalite değerlerini sağlamadıklarından müşteri talebini karşılamakta kullanılamamakta; sonuç olarak da ciddi bir kapasite kaybı oluşmaktadır. Bu çalışmada, üretim hattından canlı olarak toplanan veriler kullanılarak makina öğrenmesine dayalı tahmin modelleri geliştirilmiş olup; üretim ile ilgili kalite değerlerini canlı olarak tahminleyerek üretim ile ilgili parametrelerdeki anlık değişimlerin kaliteye etkisinin vakit kaybetmeden ölçümlenmesine imkan veren bir karar destek sistemi geliştirilmiştir. Geliştirilen karar destek sistemi dokuz farklı kalite parametresini canlı olarak tahminlerken, tahminlerdeki hata payı ortalamada %5 civarında gerçekleşmiştir.

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CHAPTER I

INTRODUCTION

Digital transformation becomes today's one of the most critical need in manufacturing sectors. Within increasing competitiveness and technological innovations, real-time production tracking and live actions are crucial for sustaining a manufacturing business. Data-driven systems and devices are creating a great opportunity for deploying new ideas in order to develop better production ecosystem. Automated systems makes this possible.

This study discusses a development of data-driven decision support system to ease people who are responsible for producing a good in changeable manufacturing environment with ensuring cost minimization, maximizing production amount and satisfying quality quality requirements. Satisfying the quality becomes critical while trying to minimize the cost and maximize the amount of production, since aiming to achieve minimum cost or maximum capacity ensures non-standard quality results. Eliminating non-standard processes and implementing standardized process at the factories lead to decrease human failures caused by initiatives and increases the efficiency of production processes. Standardization forces to apply predefined production regulation to any level of worker in the production stages.

Standardization is one of the significant requirements to sustain a complex manufacturing business. Standardization needs strict dependence to some predefined regulations, which shall be defined by the producers specific to products. Most of the large scale factories has a lot of experienced workers who are taking initiative to solve instant problems and maintain the process. Standardization is also the key to transfer that experience from master workers to any other operator. In terms of human experience, it is extremely important to spread the knowledge in order to substitute a person with someone else in case of need. To standardize a task regulation tools and decision makers are essential. In this thesis, by using new approaches in the frame of Industry 4.0, a quality prediction based decision support system is designed to ensure quality control is applied in standardized way for company whose quality control processes are still majorly depended on master operators experience. By developing a decision support system (DSS) for machine operators to ensure quality sustains standardize besides satisfying expectations in terms of financial and physical performance.

1.1 History of the Industry

According to the Cambridge Dictionary, meaning of the industry is "The companies and activities involved in the process of producing goods for sale, especially in a factory or special area" [7]. Even though the meaning of the industry is still same for decades, the production applications, products and sectors are changing rapidly.

In the last decade "Industry 4.0" term is revealed as the fourth revolution of industry with the applications and spread of state-of-the-art production methodologies. First revolution is the start of mechanization of the manufacturing procedures. Adoption of steam and water power leads to increase the production amounts by time. Second revolution is revealed by the new transportation networks establishment and expansion of electricity grids. This steered the way of production by letting technology spread around and sharing the ideas faster. On the third revolution, a new era is started by integration of automation systems which enables people to monitor and control the machinery and electronics by computerized systems. Monitoring and controlling ability brings new development concepts and drives current automation system to autonomously initiative taker and self-auditor systems as seen on the Figure 1.

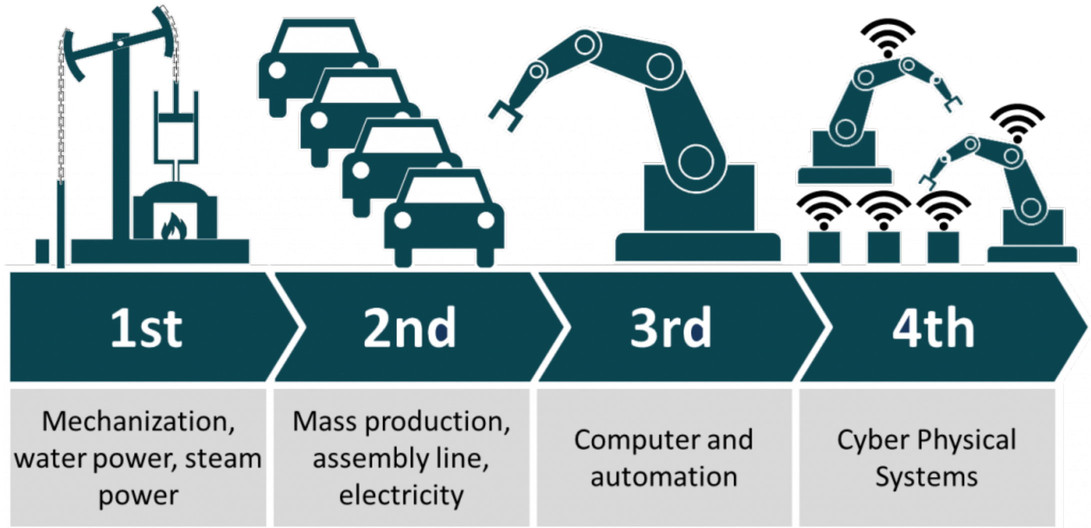


Figure 1: Industrial revolutions [1].

1.2 Fourth Industrial Revolution (Industry 4.0) and Digital Transformation

Fourth Industrial Revolution or Industry 4.0 is about cyber-physical systems that are controlled based on data acquisition, data analysis and decision making processes that mostly rely on data driven models. In today's industry, we can still observe jobs that are completed by manual and conventional methods such as reporting with papers or setting up the production parameters by human experience. By the development of the technology and invention of monitoring and controlling systems, data generation by machinery and devices is very common function at the production facilities. By the time if a monitoring need occurs then a sensor infrastructure can be integrated to system easily within a digitalised ecosystem. Today, to provide competitiveness digital transformation becomes more crucial to production facilities for easy tracking, modifying and analyzing of jobs. Digital transformation applications can be either about tracking a production process from end to end or documentation of a regular office job. Key need of the Industry 4.0 is ensuring a certain level of digital transformation or in another view, providing a digitalised ecosystem.

Big data, cloud computing, internet of things (IoT), industrial IoT (IIoT), cyber-physical systems (CPS), and others are all included in the Industry 4.0, which is defined as the best practice for the integration of business processes with the manufacturing sector [8]. There are a lot of different concepts and application areas in the literature of Industry 4.0. Most common concepts can be seen on the Figure 2.

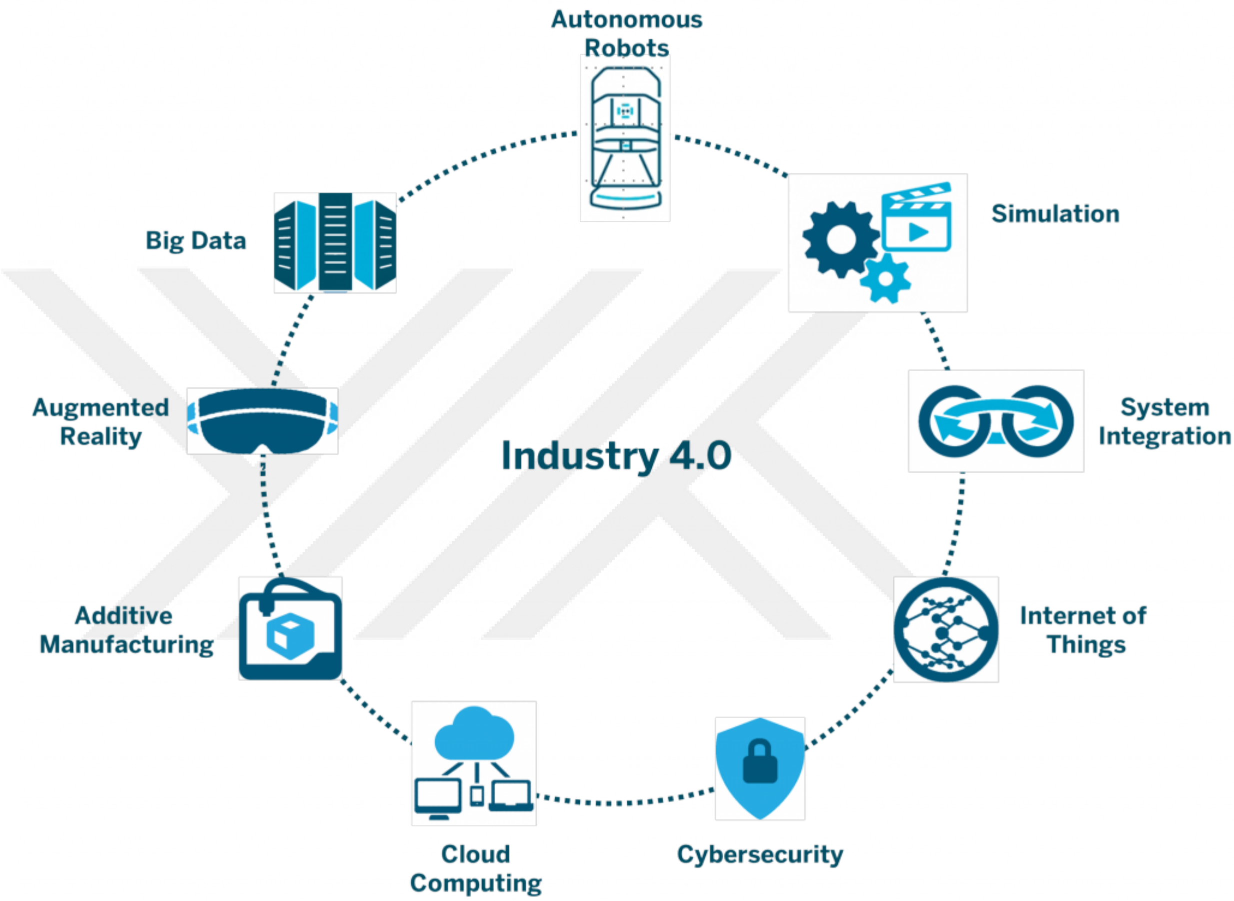


Figure 2: Industry 4.0 Concepts [2].

Industry 4.0 and smart manufacturing are related concepts. A production facility, who integrates the concepts of Industry 4.0 in their production processes with enabling collaboration with workers steers them to transform their systems to smarter environment. Imposing smart manufacturing concepts in a real production facility needs implementation of Industry 4.0 concepts. Smart systems need less real-time manual commands then traditional systems, since it can take many of the needed initiatives to continue the process or let workers take initiatives with the help of DSS depending on predefined frame.

1.3 Smart Manufacturing

According to the definition by The National Institute of Standards and Technology, smart manufacturing is system that consist of full integration and collaborative manufacturing which is able to react the adjustments in environmental properties of the facility and the demands [9]. By using Industry 4.0 elements and creating a smart manufacturing architecture which is reacting to changing the manufacturing design, a certain level of business intelligence is needed. To provide that intelligence and support their decision processes, companies start to employ teams to develop intelligent services or systems. Building smarter and collaborative environments leads to decrease on human failures. As mentioned before, smart manufacturing architecture needs less human intervention.

To ensure intelligent systems decide by themselves, predefined authorizations are need to be assigned. Smart manufacturing system can take actions according to complicated and large scale real-time data which can only be processed by computerized systems. For instance calculating an output (i.e. determining a production parameter) before taking an action can also be done by humans with experience but not in an efficient way which considers thousands of parameters at the same time, but a computer intelligence can do efficiently. In this point, the term of data analytics is involved in smart manufacturing systems. Data analytics provides systems to be capable of think analytically among thousands of parameters and historical data. The difference between humans and computers are the process capability of the data collected from large amount of sources. Computers are capable of processing large scale data and take actions accordingly. For example, predicting an output during the live production by using large amount of process data provides an essential output for decision makers for deciding the possible actions.

In this thesis, a decision support system that assist the decision maker in quality prediction process through state-of-the-art data analytics models is proposed. The prediction model is developed for a leading particleboard manufacturer in the frame of digital transformation and concepts of Industry 4.0 as a case study. The reminder of this thesis is organized as follows: In Section 2 background and literature review is presented. In Section 3 problem description is provided in details and Section 4 presents the case study. Section 5 presents the summary and concluding remarks.

CHAPTER II

BACKGROUND AND LITERATURE REVIEW

With the help of data-driven decision support systems, manufacturers of all sectors and levels have been able to track and standardize their production processes as the technology costs have decreased and digitization has increased [10]. This accelerates the innovations on smart manufacturing technologies. By implementing smart manufacturing designs, sustaining quality, operating with lower costs and producing goods in large amount gets easier.

As Schwab states, the term "Industry 4.0" refers to a notion that unites the physical, digital, and biological worlds that affects all disciplines such as economies and industries [11]. The developed technologies are not only limited to be used in manufacturing. These technologies are started to be used in houses, hospitals, schools and other similar places with minor approach changes and same concepts. For instance the application of tracking and monitoring an industrial machine's health condition with thousands of sensors can be transformed to a smart home application which can tracks a patient's high blood pressure remotely. Since the initial technological developments are occurred in manufacturing areas, spread of the idea of smart applications in another areas is originated from industrial innovations.

The fact that millions of devices' connection to the internet and each other is Industry 4.0's most significant study areas. Smart production has a topology that collects data from several devices. As a consequence, it ensures continuous data transmission between devices through multiple information record systems [12]. This connection also enables other systems apart from manufacturing to communicate with each other and share the information rapidly whether the sector is health, education or finance. In other words, the concept of connected devices are not only used in manufacturing sectors, but still ease the human life.

It is not far wrong to argue that Industry 3.0 began with the computer and internet era. The Third Industrial Revolution in the 1970s was based on the use of electronics and information technologies to automate production by the internet access and connectivity where the speed has become industry's essential specification. Industry 3.0 developed technologies on the manufacturing line that employ programmable logic controllers (PLC) to do human tasks. However, the deployment of computerized and automation technologies in manufacturing areas such as factories to stop the human role in the production line was never sufficient to remove human involvement. Human intervention is a must for next decades, since there are still needs of initiative that can only taken by humans [13].

The concept that is essential for Industry 4.0 idea is Internet of Things (IoT). IoT enables the communication of devices that can operate for different purposes in different sizes and specifications. These purposes can be a home scale smart thermostat or automated guided vehicles used to carry tons of materials on it at mega factories. IoT is other concept that shouldn't be limited with usage at only in the industry. Usage of IoT in industrial scale is named as Industrial IoT (IIoT), but that does not refers that it is only used in industrial areas. Also that does not refers to not having a limitation on using IoT at industry [14]. According to Pflaum A. et al. machines got the capability to handle out missions put on them at the third industrial revolution. With the IoT and the Industry 4.0, centralized philosophy of the decision making processes at many sectors have shifted away from physical items and forwards to data-driven services [15]. This shift also enables new ideas for developing the current systems for moving toward and invent new methods to increase efficiency.

Industry 4.0 aims to establish a flexible manufacturing model with live interactions between humans, assets, devices and systems all across the manufacturing process including procuring raw materials and deliveries to customers. As well as providing interaction Industry 4.0 gives improved levels of automation and business productivity in manufacturing [16]. Flexibility is induced by sub elements of Industry 4.0. These elements are cloud computing, autonomous systems, simulation, horizontal and vertical system integration, internet of things, cyber-security, bid data, augmented reality, and additive manufacturing. Each of these elements provides different level of flexibility depending on the area where they are implemented.

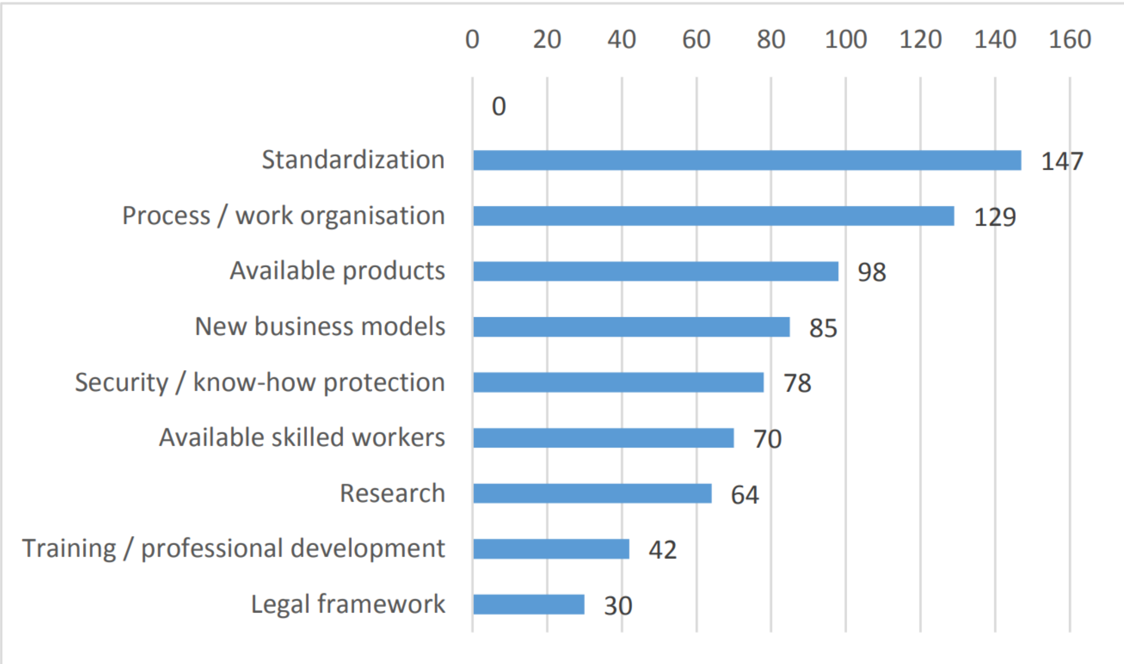


Figure 3: Preconditions for Industry 4.0 [3].

Preconditions for Industry 4.0 can be seen on Figure 3. According to preconditions, standardization is the most important factor while process organization follows as second. The performance level of Industry 4.0 in Turkey is described as most of the small medium enterprises (SMEs) are still using traditional automation systems. Some of the SMEs have awareness, but don't have enough budget for transformation or they lack of knowledge of the benefits of Industry 4.0. Ünlü et al. states that a factor and clustering analysis is done for determining performance levels in terms of Industry 4.0 between Turkey and 28 European Union country, by using ten Industry 4.0 indicator. Factor analysis is done initially and it is observed that Germany is the first country in Industry 4.0 performance while Turkey is 27^{th} and Latvia's performance is the tailender [17].

Industry 4.0 brings new capabilities and skills to systems and humans in terms of getting smarter. Ecosystem that hosts elements of Industry 4.0 provides manufacturing phases that are less affected by environmental disturbances such as lack of experienced workers or sharp changes on manufacturing methods. Smart manufacturing leads to decrease potential failure cases by its rapid adapting and sensing capabilities. These rapid adapting and sensing capabilities are based on data-driven systems.

In factories that smart manufacturing is effectual are managed with new method of production which is governed by smart systems with automatic control that alters its own parameters, evaluates itself, and develops itself [18]. Smart manufacturing enables an organized and performance-oriented production effort that responds to customer needs by utilizing real-time and elevated support systems, optimizing material use and enabling sustainability, efficiency, innovation and economic success [19].

Smart manufacturing consist of technologies such as (IIoT), big data analytic , cloud computing, and CPS and leads to flexible environment at industries [20]. Communication and records of the communication between systems, created a significant knowledge on data. This knowledge steered to use data in order to compose a well-defined and well-presented history. Different kind of branches are available under this knowledge based composition such as big data analytic. Analytic consists of 4 different elements in its framework. These elements are descriptive, diagnostic, predictive and prescriptive as seen on Figure 4.

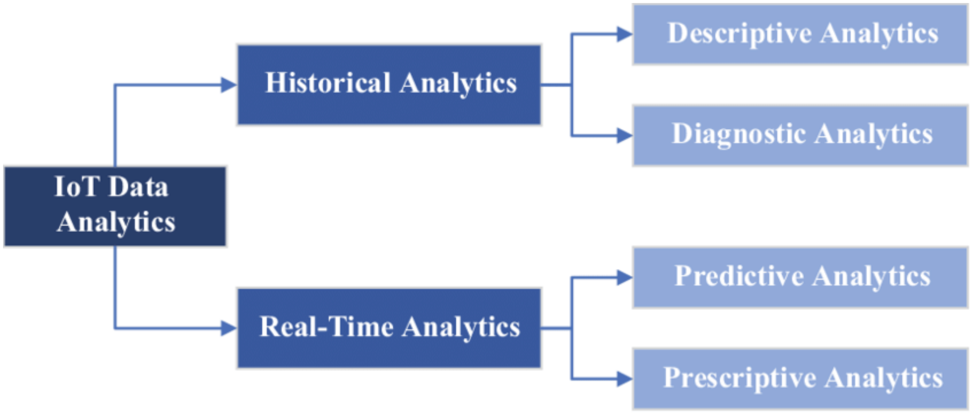


Figure 4: Analytics framework [4].

Starting usage of graphical information reports to deliver the processed feedback according to the conditions and machines triggers new pool of knowledge to be developed. For example, such knowledge can be employed by automated DSS to set predictive maintenance plans by observing the causes of decreased machinery performance and predict product quality to determine failures and defects while defining actions to increase outcome quality [20].

Quality prediction is one of the significant sub-topics in manufacturing analytics under the title of predictive analytics. Quality prediction is a real-time analytic that presents feedback about the quality depending on the process inputs. Being real-time makes operation more complicated in terms of speed of communication and speed of processing the data.

Lieber et al. handles supervised and unsupervised machine learning method for quality prediction study with context of rolling mill operation in steel factory. An in-line quality prediction model is built to predict real-time quality metrics [21]. Bai et al. [22] states that it is very crucial to predict quality in terms of quality management operations. A comparison is made to determine which approaches results better in quality prediction [22].

Building an ecosystem that decreases failure potentials and increases efficiency need to be presented to user in terms of a decision making tool. In traditional facilities decisions are made mostly depending on operators' experiences. DSS concepts lead operators to decide accordingly to a scientifically analysed data. Large scale production facilities have millions of parameters that cannot be easily analyzed and decide on it by human. For this reason development of DSS tools are vital for that kind of facilities.

Wohler et al. examines key performance indicators (KPI) and statistical process control solutions by combined approaches. The statistical process control idea they presented bases on key performance indicators for mechanic and electronic systems. Study statistically evaluates the essential functionalities of the item based on sensor data throughout product control. Ideas are put into practice at a German ATM production facility. Multiple quality targets are monitored using KPI-based quality control models based only on data obtained at product tests [23].

Sauter, 2010, s. 13 mentions that even the Decision Support System (DSS) definition is imposed in different ways by different researchers, most common definition is that DSS is a computer-based system that assists decision makers in observing information and modeling results [24].

John Dutton Conant Little states the DSS is model based procedure set for helping to decision makers to process data and decisions [25]. According to Bonczek, DSS is computer based system that consist of 3 sub elements in interaction. These 3 elements are; user interface that provides communication between user and other mechanisms, database that consist of data and procedures, and lastly problem process system that makes the system capable of manipulating the problem for decision making [26].

As Turban states, DSS is easy to use, interactive, flexible and adaptable information system that enables user to apply their own insights on data in order to support for solving a managerial problem [27]. Aronson et al states that model management consists of two sub factor. These are model directory and integration and command processor for running the model realization operations [28]. Power mentions that decision support systems are classified according to their properties and usage methods. These classifications can be listed as Data-Based, Model-Based, Knowledge-Based, Document-Based, Communication and Group-Based, Intra-Organizational or Inter-Organizational, Task-Specific and General-Purpose, Web-Based [29].

CHAPTER III

PROBLEM DESCRIPTION

The majority of the facilities operate in the forestry industry uses conventional wood production methods. Most of the conventional methods are transformed into machinery-provided processes during the last decades. However, most of the transformation processes do not include all of the critical stages of the wood production. Working with wood still requires a lot of experience and human intervention, since the environmental parameters have no great stability. Tools help to increase stability and standardization become critical at continuously changing external parameters.

3.1 Particleboard and Particleboard Production

Particleboard is one of the growing branches of the forestry sector. Particleboard is used in various areas such as construction, marinership, furniture. They are being sold as large boards, but after the production it can be shaped in desired geometries such as small scaled plates or pieces stuck together to form a new object. Raw material of particleboard is wood and wood's other forms such as thinning cut and sawmill leftovers. These pieces are directly used processed to form wood chips. Mainly heat, pressure, and synthetic resin are used to gather the chips and obtain particleboard [30, 31].

Particleboard production methods are combinations of conventional and modern techniques. As an example of the conventional technique, chipping is done by blades chopping wood pieces, while synthetic resin recipes are made in the laboratory for the best chip-adhesive.

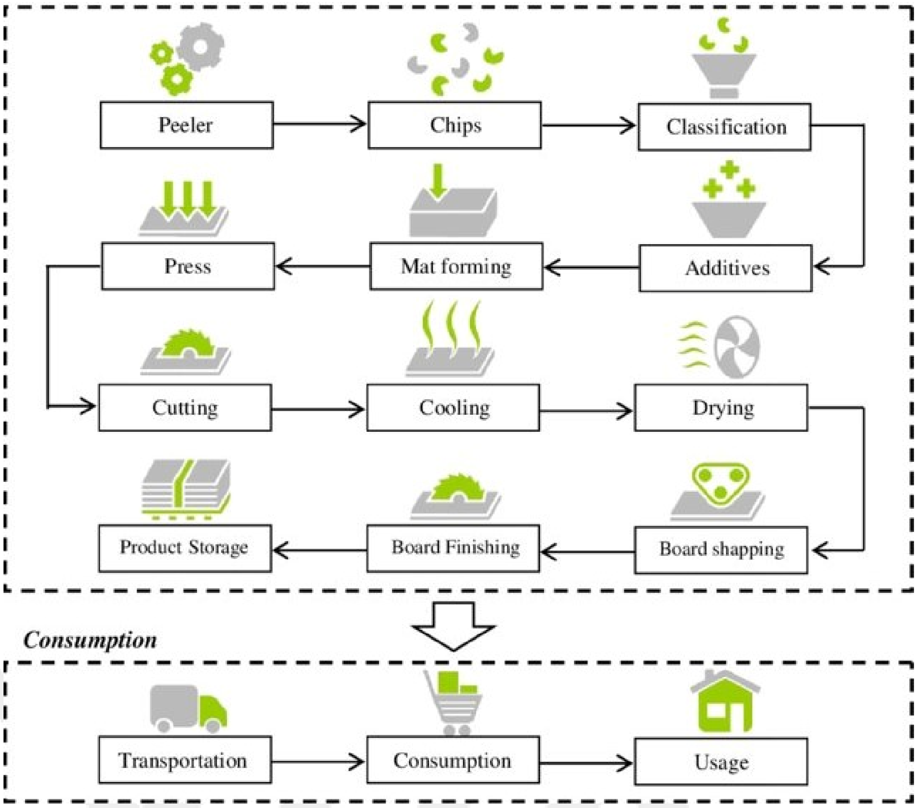


Figure 5: Particleboard production process [5].

The production process of a particleboard is shown in Figure 5. The details of each the main production steps are as follows:

3.1.1 Chipping

Chips are small pieces of wood after crushing, cutting. The shape of the chips is a crucial aspect affecting the quality of the end product. The place where the chips are used in particleboard differentiates depending on how it is obtained. For example, if the crushing method is used, then chips are used in the middle of the boards, but if the cutting method is used, then chips are placed on a surface layer of the particleboard. The cutting method uses sharp blades to obtain fine-edge pieces to fibres, while the crushing method uses hammering machinery [32, 33].

3.1.2 Drying

After chipping the woods, process of drying the chips follows.Moisture is one of the critical quality aspect. If the moisture is not at the desired level,non-tolerated dryness or humidity can lead to production and quality issues. For example, hardening of glue, risk of fire, loss of light chips in the pressing process are potential endings caused by insufficient moisture levels [34]. The moisture level of the chips at the beginning, type of the tree, density of the wood, size, and proportion of the chips, and the machinery used are essential aspects of the procedure [35, 36].

3.1.3 Sorting (Classification)

Obtaining an unvarying size of chips is impossible even if the machinery equipment is very progressive and a classification of the chips is required process to apply following process successfully. Using extremely different-sized chips together as a mixture leads to surface defects such as problem at smoothness and increment of pores. Thick pieces affect the surface, while the thin and dust-like pieces absorb too much synthetic resin and affect the board's resistance. At this point, a sorting procedure needs to be applied to classify different chip sizes. This process needs to be applied after the drying process because the chips are getting stable since the drying affects their volume [37, 38].

3.1.4 Gluing

After the sorting process is completed, one of the significant factors in production is that it highly affects quality, gluing process starts. Adhesive material should be selected carefully for the full functionality since the adherent characteristics may differ among the type of wood. Adhesive material needs to spread on the chips to avoid any quality issues homogeneously. For this reason, the point glue method is used for perfect gluing. This method can be described as spraying the glue mixture on the chips evenly [34]. While spraying the glue on the chips, heavy and light flakes contact with glue in different amounts. For this, centrifugal machinery is used for distributing the glue more evenly [32].

3.1.5 Mat Forming

Mat-forming process start after the gluing process, since the glued chips are ready to be formed by sticking together. After gluing the chips, in this process, homogeneously laid chips are formed as chipboard. Suppose the chipboard is not properly prepared, then the pressing process may not end with a successful result, and the board's center of mass can be obtained differently from how it should be. This may also end with quality value difference between different points on the board. Forming is done by machines that evenly spread the chips in a pattern. This makes the process more standardized and reduces the risk of the center of the mass difference between separate boards [39]. After the mat-forming, a process to ensure the gaps between chips are decreased or removed depending on recipe.

3.1.6 Press

To remove or decrease the air gaps around the chips, high-pressured press is applied. The press machine compresses the semi-formed mat to squeeze the chips for predetermined density. Hot and cold, two types of press can be applied on the chip mat. First, a cold press is applied to re-form the mat. Then hot press is applied to increase the glue effectiveness and decrease the air gaps between glued chips. The increase in temperature provides the stickiness of the chips to each other. This process also makes it easier to achieve a smooth surface [37, 34]. The hot press method is for setting the thickness of the board according. The thickness is a predetermined value according to the recipe of the production. The compression at the mat is essential for the board's resistance. Insufficient pressure, heat, and time increase the risk of rupture [36].

3.1.7 Lab-Cut (Sampling)

Lub-Cut, in other name sampling, process follows the press process. This section will be detailed in the Quality and Laboratory Testing section. Since it is one of the production stages and this section is created to see where the Lab-cut stage occurs.

3.1.8 Climatization

After the pressing process and lab-cut process, the board's surface becomes hot since the press machinery transfers heat to the board. Contact between the outer surface of the board with the press machine makes temperature difference between the surface and the middle parts of the board. For this reason, a humidity difference also occurs. The climatization process converges the different temperatures to exact temperatures. If the temperature difference does not decrease for too long, with high difference may cause contraction inside the board. Depending on the manufacturing recipe, sometimes climatization may not be needed because of not applying too much heat at pressing [36]. Climatization of the board is critical for sustaining and keeping the material characteristics. A wrong applied climatization process will cause non-stable quality.

3.1.9 Sizing (Cutting)

The cooled board at climatization process, continues to sizing station. The sizing process gives the large board a decent shape after the climatization. After the climatization process edges of the rectangular board are not geometrically perfect, and some chips may swell out of the edges. These coarse edges should be tuned. This process can also be applied after the pressing process if the board is not at a high temperature [36].

After these stages are done, products are continues to paint station or directly to warehouse and finished products are shipped to customer directly from warehouse.

3.2 Quality and Laboratory Testing

As mentioned before, testing for quality is a part of the production process. Quality control is a must to ensure production targets comply with the good's actual characteristics. In this part, laboratory process is explained briefly.

Definition of quality control is to ensure a specific level of quality by applying predefined feedback mechanisms to observe product's or service's possible defects [40]. In particleboard production, quality is tested after the pressing process. An operator takes sample boards from the production line and carries them to a quality control laboratory to subject them to different tests, according to their definition of particleboard quality metrics. Total time for testing takes about 3-4 hours. While tests are in progress, the production continues whether the results are in tolerance since it is unknown until this period.

If the test results are acceptable, then the production continues as planned. However, suppose the test results are not acceptable according to tolerance limits. In that case, production may stop completely, products may go to recycle process, or products may be labeled as second-grade quality and sell for lower prices depending on results. If the supervisor decides to send the products to recycle, then products will be carried to the warehouse and wait until recycled to be used in another production setting. If the supervisor decides labeling as a second-grade quality product, the product is carried to the warehouse again without any extra process such as painting or shaping. In all three cases, the significant and common loss is production capacity. Also, in terms of finance, raw material, sub-material, energy, machine maintenance, and employee costs are occurring. For this reason, 3 hours of capacity lost is crucial for the production process. Before this study, the company's production parameters were set within the predetermined recipes, and while the production continued, the supervisor made fine-tuned parameters according to experience-based insights. This method has a dependency on the supervisor's self-experience. The test applied at laboratory are tensile resistance test to determine surface strength, density test in order to measure homogeneity of the board and moisture test to observe moisture level of the board.

A tensile resistance test is used to determine surface strength when the board will not tolerate and start to fraction and break. Surface strength is measured by this test. To start the test, little amount of glue is put on the center of the board. Then a steel plate is placed on the glue point and operator waits until glue is dried.Afterwards, by drilling holes on the steel plate, board is hanged on pulling hanger. Machinery for applying tensile starts to pull the hangers in opposite direction until the fraction starts at board. At that point value of the machine's pulling force is recorded. The formula of calculation of tensile resistance where it represents surface strength test is as follows:

$$SS = \frac{F(max)}{A}$$

Where SS is surface strength of the board, $F(max)$ is maximum force that is applicable on board before fraction and A is surface area of the board. Unit of the SS is N/mm^2

A density test is used to determine the homogeneity of the board. As mentioned in the particleboard production stages, chipping, gluing, mat-forming, and in the pressing process, homogeneous board characteristic is mentioned. Specimens are taken from the board, and variation between the specimen's densities are compared. The formula of the density test as follows:

$$d = \frac{m}{v}$$

Where d is density of the board, m is mass of the board and v is volume of the board. Unit of the d is g/cm^3

A moisture test is used to determine the humidity of the sample. The laboratory operator divides the sample into three even pieces as left, middle, and right pieces. Then the weight is measured to record the initial weight. Afterward, sample pieces are being heated in separate furnaces until the constant value, 103oC. The final humidity level is measured to compare initial weight levels. In this way, change the weight with heating for 6 hours, moisture test ends. The formula of the moisture test is as follows:

$$H = \frac{initial\ weight\ -\ final\ weight}{final\ weight} \times 100$$

Where H is the moisture level, $initial\ weight$ is the board's weight measured at the beginning of the test and $final\,weight$ is board's weight measured at the end of test. Unit of the H is shown in percentage format

After completing the tests, laboratory operators informs the production operators to take action if needed. Actions are depended on the quality requirements of that order. For this reason quality of the product has great importance. If the required quality is not matched then even the production can be stopped.

Today's companies are majorly trying to minimize production costs to increase production capacity and gain more profit. With the competitiveness and technological developments increasing in the production sector by integrating digital transformation and smart manufacturing concepts to traditional manufacturing methods, the ways to reduce the costs are also changing. In the scope of competitiveness quality of the goods produced becomes crucial for a company to differentiate itself from the competitors. In the forestry goods sector quality of the goods is a crucial aspect in terms of pricing the end products. As will be mentioned in the following paragraphs, if the quality of the product does not satisfy the company's quality requirements, then the good's price becomes decreased.

The cost of the product may change during the production since the operator decides to make changes on production parameters while the line is running. For instance, if the operator decides to increase the amount of glue to be sprayed on the chips or decrease the heat of the press, then the cost increases directly in terms of glue cost and energy cost. Also, live changes on the recipe effects other facts such as manpower, maintenance needs, energy consumption, raw material amount, and more. All of these facts have a direct effect on the cost.

After observing the production flow, data, and meetings with the company employees, it is determined that the quality of the product is highly dependent on the responsible operator of the production order. It is observed that the quality of the product matches the requirements within a defect rate of 6 out of 1000. The reason behind this quality success is summarized as an excess amount of energy and raw material used. In other words, while having a satisfactory result on quality, the cost of the production is increased. Cost decrements will occur if the correct production parameters are set to obtain the same quality level. Changing the parameters and creating a brand new recipe is one of the options. However, there is no need in this case since the parameters are already optimized. However, the other effects such as the environmental, material, and machinery-based differences take place, and a need for intervention by an operator becomes crucial. Also, the company prefers to make fine-tuning on the production parameter to ensure the production is certainly under control by a human.

At this point, a decision support system becomes a solution. Suppose an operator can keep track of the real-time effects of changing the production parameters on quality metrics and decides whether to change or not or how to change. In that case, this will avoid drastic decisions and behaviors to keep the high production quality. Another result of using a decision support system that reports to the operator about effects than cost term will not only affect the quality but also cost.

Bending resistance, moisture, and density metrics are being used to develop a solution for predicting quality before and while the production continues. Collecting data, storing the data, and pairing the laboratory tests and production parameters are used in the factory in classical machine learning and regressor chain methodologies. An information source for a decision support system is developed using these methodologies.

CHAPTER IV

CASE STUDY

4.1 Quality Prediction Model

Figure 6 depicts the general idea and the data flow model of the proposed quality prediction model. Following sub-sections provides further details of the proposed model.

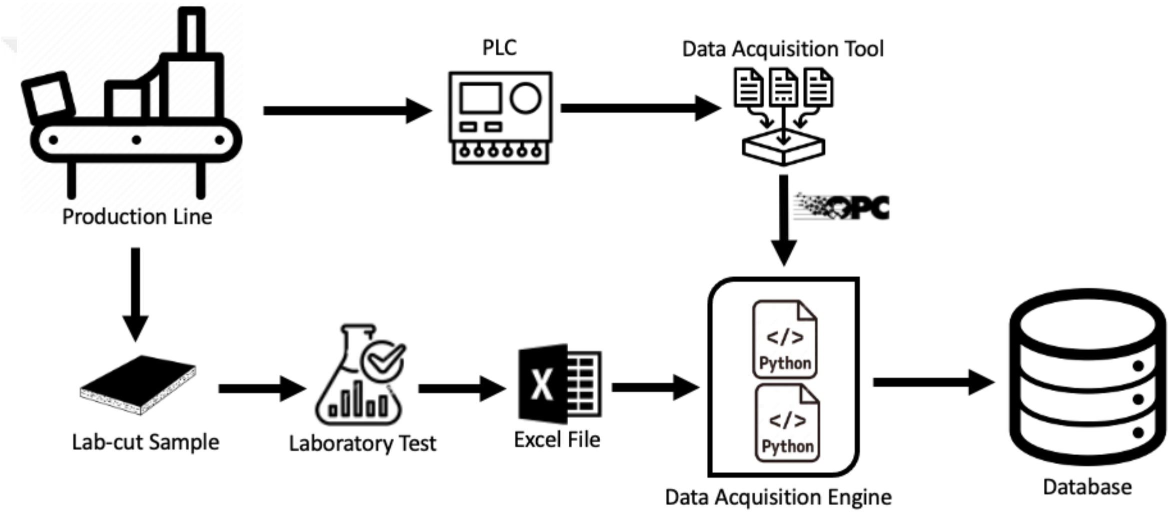


Figure 6: Graphical illustration of production and laboratory data flow.

4.1.1 Data Acquisition and Preparation Strategy

Data acquisition methodology is the first step for developing a predictive model. Since the automation integration at the manufacturing, PLC, and other devices that generates data started to be used widely. Factories are controlling their machinery from their computerized systems. Data transfers provide communication between the machines and computers via PLCs. PLC is an industrial computer device that enables controlling the machines directly by the commands received from PCs or other managerial systems such as servers. The communication between the computers and machines are not in one-direction. Also, the machine sends signals back that are generated from sensors or computers in it. For instance, the server sends a signal to PLC to run a machine and then PLC manages the machine to start running. Afterward, when the machine starts, the machine sends a signal to PLC that represent the machine is on. Then PLC enables the operator to learn the machine is running correctly or not. Otherwise, a worker needs to check the machine manually if it is working or working correctly.

Data can be stored for records if needed while human-to-machine communications are occurring. Storing data acquisition systems do the data in data storage units. Data is collected from different sources such as directly from the sensor, machines, computers, PLCs, or manual entries by humans. In this case, a tool is being used to collect data already in use by the company, called IBA. This tool can connect to different brand and model systems using different TCP/IP, Modbus, or sniffing methods. Also, the tool can record the data to its own managed data storage system in custom frequency, scale, and type. Data collected from the PLCs are recorded to the SQL databases in the frequency of 5 minutes. The data acquisition system uses OPC to transfer data between units. In this environment, data is being gathered on a second basis, and in each 5 minutes, the data batch is recorded to the corresponding database with 300 rows. Each row consists of data created in 1 second by machines and devices. The data table with 300 rows has 50 columns identified as machine and device production signals such as press heat, press speed, motor current, glue spray pressure.

Similarly, manual data entry methodology is being used in this case. As mentioned in the production process of particleboard, the section for quality control procedure at the laboratory, physical tests are being carried out by lab operators. The quality control procedure consists of bending resistance, moisture, and density tests. The results of these manual tests are recorded in a preformed Excel file. Completed excel files are uploaded to a file directory. A Python script reads these Excel files and transfers the laboratory test results to the SQL database used to store the production parameters. Table consisting six months of laboratory test which also equals to 589 test. Each lab test has the output for three different test results identified as target variables: bending resistance, moisture, and density.

Furthermore, the data of production parameters and quality control results needs to be matched to create a cause and effect relation. Timestamps are used to create this relation. If the time when the laboratory procedure ends (t) and the time passed between the laboratory and a production procedure (x) is known, then using the time difference between, the system can automatically search for production parameters recorded and timestamped at $t - x$.

In the light of the above information, the data set consists of a total of 589 rows, for each row indicates a paired lab sample, and there are a total of 78 features, such as press speed. In addition to these, there are three target variables, as mentioned before. Note that details of features cannot be shared due to confidentiality.

A rule-based elimination is made based on operational knowledge. Fifty-six rows have been eliminated because it is considered erroneous for some signals to be above or below specific values. Also, the rows with null values are eliminated.

The correlation matrix of the features is shown in Figure 7.

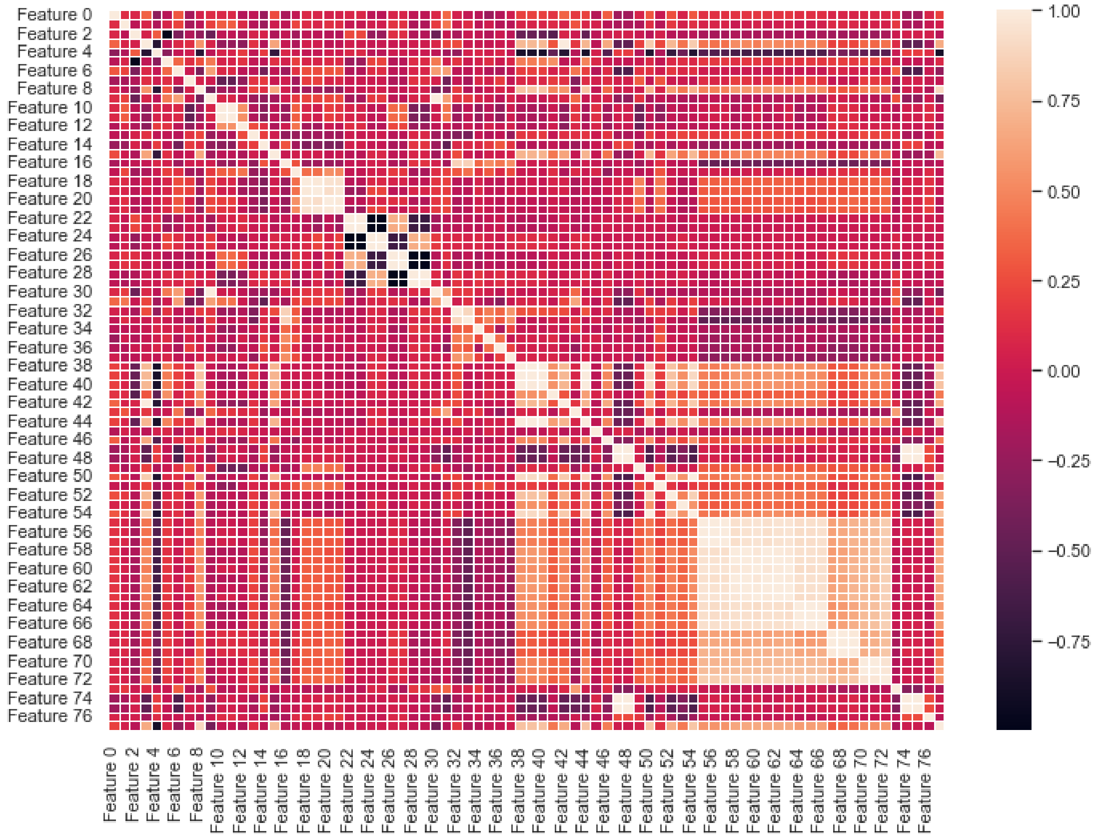


Figure 7: Correlation Matrix of the features.

As shown in Figure 7, Features 18-21, Features 38-41, Features 54-65, and Features 66-69 take similar values in each. Using the operation knowledge, it is shown that these are sensor information that reads values from different parts of the board. For this reason, these features have been aggregated. When the data set is examined, it is determined that at least one of these values was zero or invalid with 3% and 2%, respectively. Therefore, median values are used instead of average when aggregating these values.

At the end, the data set has 67 features with 433 samples. After the data cleaning and aggregation process, the feature selection has been implemented. Firstly, correlation matrix is constructed. One of the feature of the features with correlation higher than 0.9 or less than -0.9 with operational knowledge.

In addition, a p-value based selection of features is constructed. It is assumed that the null hypothesis is "The selected combination of dependent variables does not affect the independent variable." Then, a small RM is constructed for calculating the p-values. If the p-values are higher than the threshold (0.05), that combination of features is discarded. After the feature selection phase, the data set contains 28 features.

4.1.2 Model Building Methodology

After collecting the data and analyzing it, two different approaches are created to develop quality prediction models. The first approach is a conventional machine learning approach, where the model are developed for each quality metric. This approach is designed in a flow where data is divided into two parts: train and test. Then, following steps are executed: i) get fit on the train data, ii) get predictions for test data by the fitted model, and iii) make the performance tests. Note that the same process has to be done for each dependent variable (quality metric) since there is same model with different parameters. This flow is shown in Figure 8.

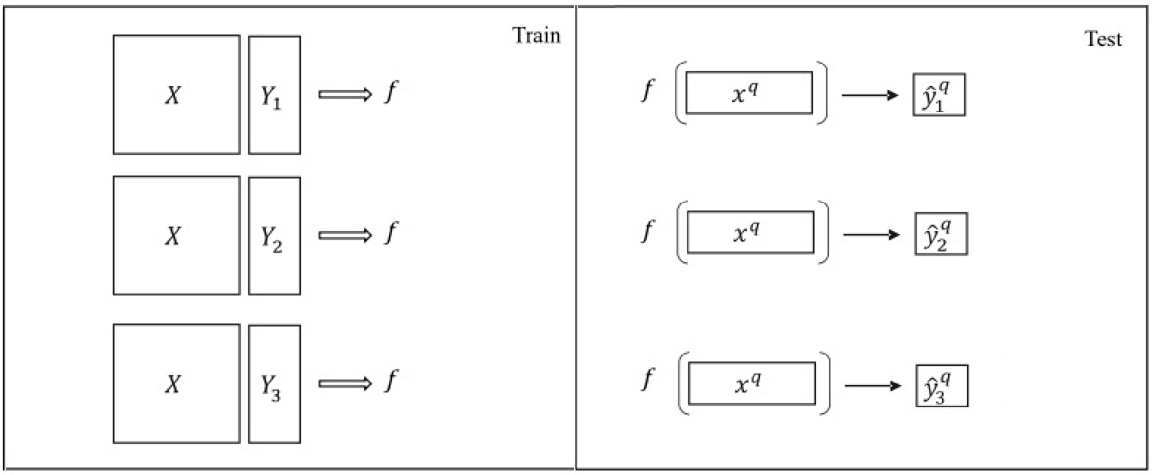


Figure 8: Graphical illustration of single target models.

In the second approach, Ensemble of Regression Chain methodology is used which is a branch of Multi Target Regressor (MTR) approach. As mentioned before, there are multiple target variables in the problem. For this reason, it is possible to construct a predictive model for a target variable; in which the other target variables are used as inputs. In the literature, this is known as the regressor chain [41]. The regressor chain prediction model flow is shown in Figure 9.

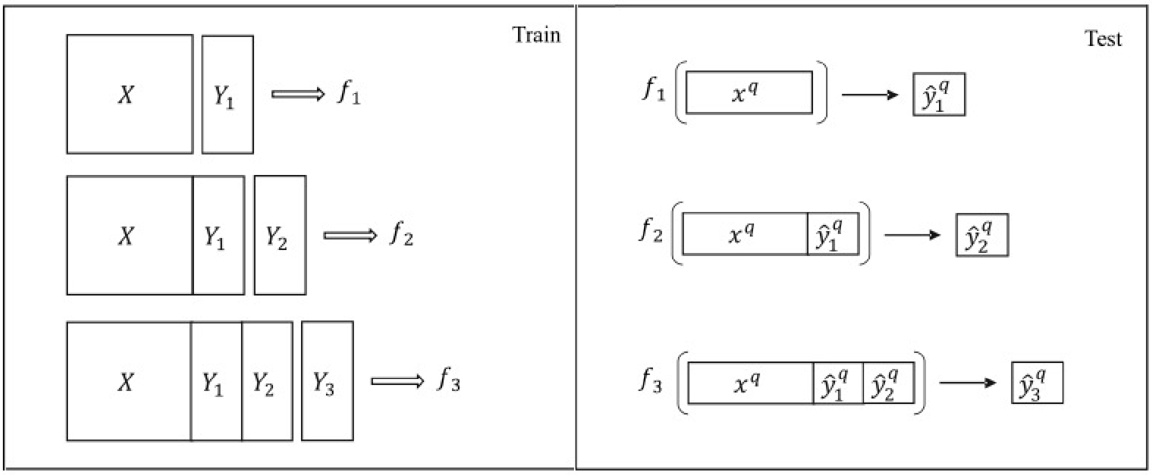


Figure 9: Graphical illustration of RC [6].

When creating a predictive model with a regressor chain, there are different ensemble methods. Most commonly used approach in the literature is constructing chains with each sequential combination of target variables, getting mean of prediction of each chain as final prediction and determining a single chain sequence according to a predetermined rule. This method introduces a complexity if the number of target variables in the prediction model is large. However, as mentioned in the literature, there is no problem in using this approach for five or fewer variables. Another method is based on information from the single-target model, with a performance-based ranking. The first member of the chain is the variable that produces the best performance, whereas the last member performs the worst [41].

The core concept of RC is the chaining of single-target models. RC is constructed based on regression models (RM) for each target variable by training the targets progressively in a randomly defined chain sequence. The RM is trained independently of the other target variables for the first target variable chosen within the given chain. The predicted target values are put to the training set as a new input vector for predicting the following target variable. The RM for the new target variable in the chain sequence is trained using the augmented input matrix. The procedure is repeated for all consecutive targets in the chain [6].

Random Forrest Regressor (RFR) is used as the main model for our approaches. RFR is used to obtain more robust predictions by utilizing multiple Decision Tree Regressor (DTR) approach. Basically, DTR model constructing process is as follows: The data set is separated into subsets, and these associated subsets create a tree form layout. If a node has two or more branches for each attribute test, then it is a decision node. If it is a leaf node, then it is defined as a numerical target decision. The main algorithm used in the decision tree is a top-down, greedy algorithm without backtracking [42]. True or false nodes continue until reaching the leaf node. So the prediction at the end becomes the average value of the dependent variable at that specific node [43]. By using RFR instead of DTR, the over-fitting possibility is eliminated. Moreover, the RF algorithm is also faster and more robust [44].

4.1.3 Performance Comparison Methodology

For the performance comparison of the approaches, Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE), and paired t-test, are used. For the sake of completeness, the details of each performance metric are described as follows:

MAPE is a percentage calculation is made of the absolute value of dividing differences between actual and predicted results by actual result. This method cannot be used when there is a value of zero in the actual results since the denominator of a fraction cannot be zero. MAPE is used for comparing results of regression chain models and time series with actual data. A percentage calculation is made of the absolute value of dividing differences between actual and predicted results by actual result. This method cannot be used when there is a value of zero in the actual results since the denominator of a fraction cannot be zero. MAPE is calculated by the following equation:

$$MAPE = \frac{1}{n} \sum_i \frac{|\hat{y}_i - y_i|}{|y_i|}, \tag{1}$$

where y_i is actual laboratory value of sample i and $\hat{y}_i$ is prediction of sample i.

Another critical procedure for result comparison is MSE which is described as the average of the square of the difference between actual and predicted values. According to this definition, actual results are the quality metrics obtained from laboratory tests, and estimated values are predictions for quality metrics. MSE shows how close are the results obtained from two different sources. If MSE has a lower value, predicted results are very similar to actualized quality values. MSE is calculated by the following equation:

$$MSE = \frac{1}{n} \sum_i (\hat{y}_i - y_i)^2, \tag{2}$$

where y_i is actual laboratory value of sample i and $\hat{y}_i$ is prediction of sample i.

In paired t-test two data sets' means are compared. To apply paired t-test, the observations in one of the data sets should be able to paired with other data set's observations. In other words if both of the data sets are depended, then paired t-test can be used. For instance it can be used on data sets of outputs where two different approaches are applied for same case. Paired t-test compares the mean's identicality of two data sets.

4.1.4 Results

Before starting the running approaches, the data set is randomly split into train and test sets to represent all data points. The ratio of test set is 20%.

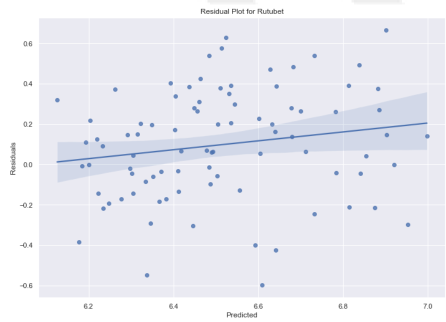
In the first approach, the RFR models are constructed for each quality metric with the train set. These models are called single-target models. For each single-target model, hyper-parameter tuning is constructed. The main problem of hyper-parameter tuning is over-fitting. The K-Fold cross-validation (CV) setting is implemented to handle this problem. A grid of hyper-parameter ranges for each parameter of the models are defined, and K-Fold CV is performed with each combination of the values.

After hyper-parameter tuning, the models fitted on a train set for each quality metric. The test and train MAPE and MSE are given in Table 1. As can be seen in the Table 1, Density shows the minimum error based on MAPE, while other metrics are seen that there is a possibility of improvement. Note that, MSE error of Density is highest since the numerical values of density are greater than others. Also, the residuals for each quality metric are shown in Figure 10.

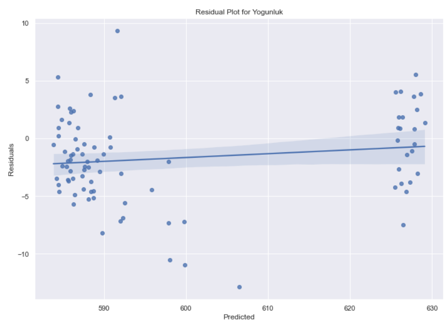
Table 1: MAPE and MSE results for the single target models.

	TrainMAPE		TestMAPE	
Target	**MAPE**	**MSE**	**MAPE**	**MSE**
Surface strength	0.049	0.002	0.060	0.006
Moisture	0.032	0.071	0.035	0.082
Density	0.006	8.23	0.006	17.62

(a) Surface strength



(b) Moisture



(c) Density

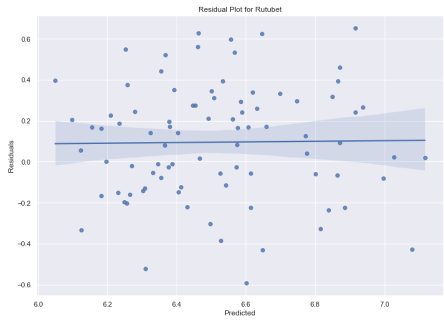
Figure 10: Residual Plots for single target models.

As mentioned before, the ensemble of regression chain methodology is used for the second approach. It is possible to increase the predictive performance by considering other target variables and the inputs with the ERC approach. Since there are three target variables, RFR models are trained for all combination chain sequences using ERC methodology. At the end, the final predictions for each quality metric are obtained from the mean of predicted values from each model. The performance of the ERC is shown in Table 2. Also, the residuals for each quality metric are shown in Figure 11.

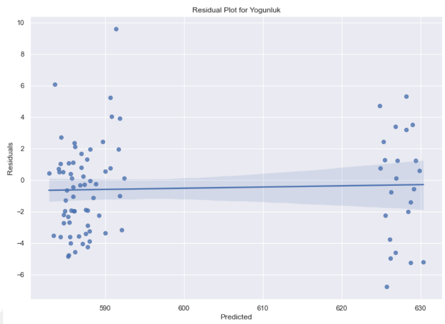
Table 2: MAPE and MSE results for the ERC models.

	TrainMAPE		TestMAPE	
Target	**MAPE**	**MSE**	**MAPE**	**MSE**
Surface Strength	0.028	<0.001	0.046	0.006
Moisture	0.014	0.003	0.029	0.086
Density	0.002	4.72	0.005	9.098

(a) Surface Strength



(b) Moisture



(c) Density

Figure 11: Residual Plots for regressor chain models.

Table 3: Residuals of ERC and single target t-test Comparison for test set.

Residuals	p-Value
$\vec{R}_{ERC}^{\,1} - \vec{R}_{ST}^{\,1}$	0.055
$\vec{R}_{ERC}^{\,2} - \vec{R}_{ST}^{\,2}$	0.025
$\vec{R}_{ERC}^{\,3} - \vec{R}_{ST}^{\,3}$	0.682

The paired-t-test comparison for the residuals of ERC and single target approaches is shown in Table 3. It is seen that prediction performance ERC approach is significantly better ST approach for surface strength and moisture at 0.05 significance level, since there is no indication for density. Note that $\vec{R_i}^{\,j}$ represents residual vector of approach i for metric j where $j = \{$1:Surface Strength, 2: Moisture, 3: Density$\}$.

4.2 Decision Support System

4.2.1 Design

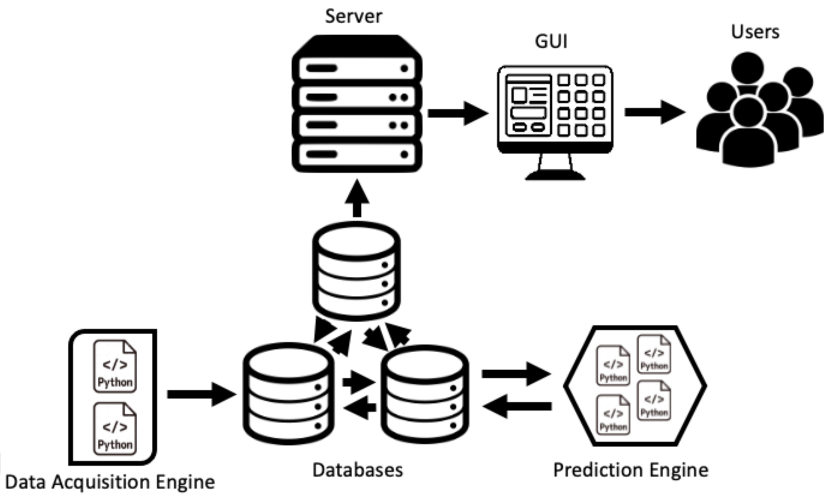


Figure 12: Graphical illustration of DSS data flow [6].

A decision support system is built and developed to present the results obtained from the quality prediction module as seen in Figure 12. DSS is a tool to help decision-makers to decide, as mentioned before. For this reason, the outputs need to be understandable by any level of the user. DSS in this study ensures the whole architecture management. DSS framework is consists of two parts, online and offline, as seen in Figure 13.

In the online framework of DSS, the data acquisition from the production line is recorded in the database for process in the prediction engine that runs the quality prediction module. Data batch from the database is sent to the prediction engine, and within 5-minutes frequencies, the engine returns real-time predicted quality results to the database. The company determines time-frequency according to their needs. After the prediction engine runs and returns the outputs, the central server requests for outputs. The server stores the outputs temporally just for converting outputs to graphical data. Graphical User Interface in website format publishes the graphical data in a predetermined format. Published outputs are accessible for different users but within access limitations. Production operators can access real-time production inputs and quality prediction outputs, while executive-level users can access all data recorded in the system, including past production history.

In the offline framework of DSS, if provoking model update is needed, then historical production data kept in the historical database is processed. The processed data to be used in future predictions are transferred to the prediction engine and updated the prediction model. This process is repeated twice a year depending on the need of the company.

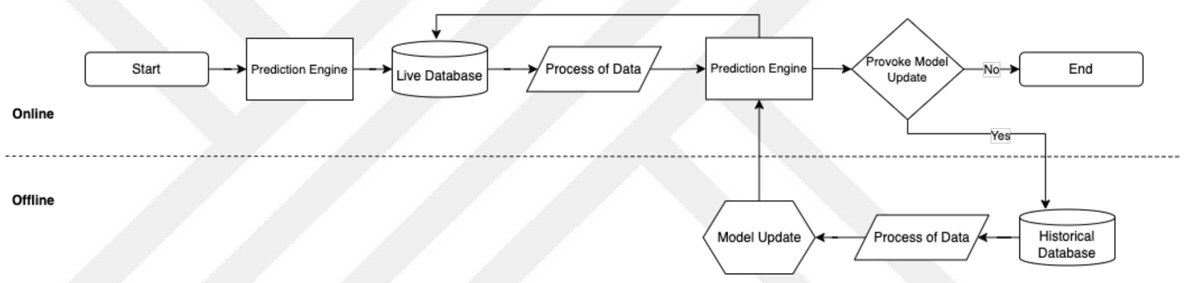


Figure 13: Flowchart of DSS Framework.

4.2.2 Graphical User Interface

Three different pages are developed for GUI. These are for live quality prediction monitor, comparison between laboratory results and predicted results, and report page.

The "Live Quality Prediction" page enables the operators to monitor real-time quality predictions on current production parameters. As seen in Figure 14 histogram graph for three quality metrics are available. Suppose the predicted quality value is above or below the required threshold. In that case, red-colored bars appear and show the user that quality metrics of current production are out of required quality value boundaries.

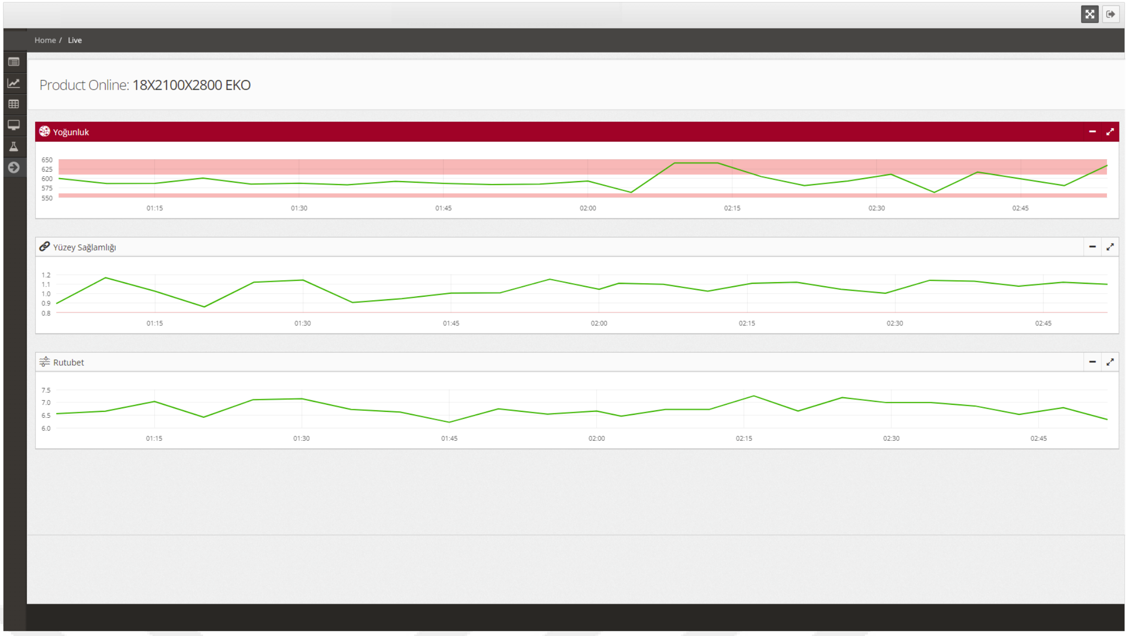


Figure 14: Live prediction web-page screenshot of DSS GUI.

In the "Laboratory Results and Predicted Results Comparison" page, as seen on Figure 15, users can access historical data of actual laboratory results while predicted results are also seen for comparison in box-plot format. Blue boxes represent the measured and actualized quality results in laboratory tests. If the cross mark in the box-plot graph is green-colored, it represents the predicted result in the actual laboratory result interval. In contrast, the red-colored cross mark represents predicted value is not actualized. Time interval and product name for comparison graphs are selected by entering date to observe comparison in specific time interval and product.

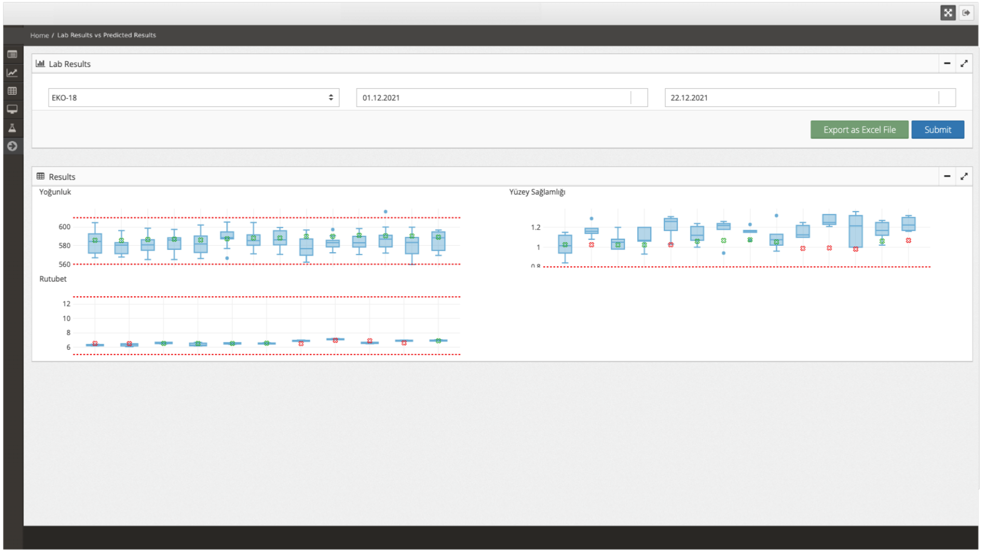


Figure 15: Laboratory results versus prediction results web-page screenshot of DSS GUI.

As seen in Figure 16, historical data about a product and its quality history is accessible on the “Prediction Report” page. After choosing the product name and time interval from the menu, users observe past quality histogram.

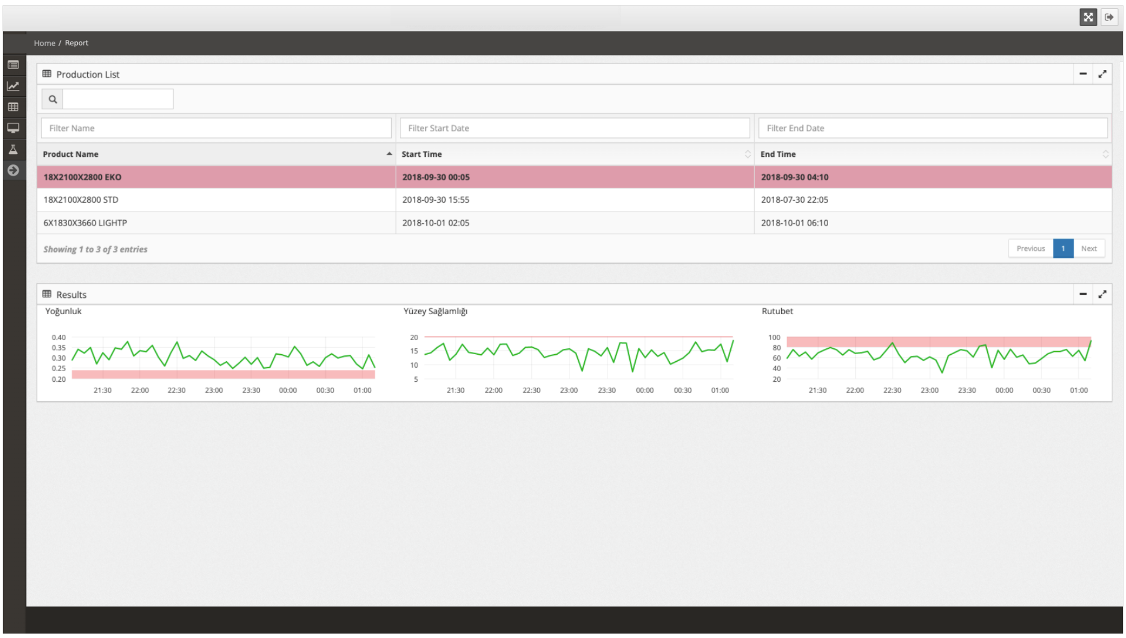


Figure 16: Reports web-page screenshot of DSS GUI.

4.2.3 Tools

While developing the GUI, .NET framework [45], Cascading Style Sheets (CSS) [46] and HyperText Markup Language (HTML) [47] are used since they are very common and easy to modify frameworks. The need for modification of the GUI can be occurred in future developments in order to embed new functions or fix possible bugs. These common tools were used so that the company itself could make improvements. Moreover, for the database, Microsoft Structured Query Language (MSSQL) [48] is used since the current database structure is already built with MSSQL.

CHAPTER V

SUMMARY AND CONCLUSION

In this study, a web-based decision support system is developed for the real-time prediction of quality metrics of particleboard in the frame of Industry 4.0. The system enables to obtain predictions of the quality of products before about three hours lasting physical laboratory tests in order to avoid production capacity loss. The study was carried out in two different approaches: i) developing models for each quality metric and ii) developing models based on regressor chain methodology. In the first approach, models performs with error percentage of 0.06%, 0.035%, 0.006% for surface strength, moisture and density respectively. In the second approach, ensemble regressor chain, the prediction performance improved by approximately 20% on the average.

In addition to this, the company shared a feedback report about the system. The report indicates 5% saving has occurred on the cost of glue while the accuracy ratio was calculated as above 95%. In detail, the glue amount is decreased from 6.5kg to 6.2kg per 100kg dried particleboard with the help of the system.

As future works, an optimization model can be used to find the optimal production parameters under the restriction of quality metric values based on predictive models while maximizing the throughput or minimizing the cost. This will enable the to obtain a production recipe for specific quality level. Also, in terms of standardization, production becomes more stable and avoids from possible human failures.

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