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MECHANICAL ENGINEERING: SUSTAINABILITY AND INNOVATIVE APPROACHES- I

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CHAPTER 1

SUSTAINABLE BIOMATERIALS DESIGN, PRODUCTION AND APPLICATION PRINCIPLES

Prof. Dr. Kadir Gök[1] & Prof. Dr. Arif Gök[2]

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1. Introduction

Sustainability and biomaterial concepts are among the subjects of study that have recently gained importance. The consumption needs of developing societies are increasing and changing every passing day. In particular, the unabated rise of technology creates disadvantages for the environment and nature, as well as its advantages. The consumption frenzy has prioritized the design, production and application principles of sustainable materials, revealing the importance of the carbon footprint.

Sustainability is defined as the ability to be permanent in the most general sense and emphasizes this ability of the biosphere and civilization in the 21st century. It refers to change in a balanced environment that preserves the potential to meet the needs of both present and future generations, in which resource utilization, investment decisions, technological advancement, and institutional transformations are aligned and coordinated. Sustainability, which is founded on three basic domains of influence: environment, economy and social, also covers cultural, technological and political sub-domains. Sustainable development, on the other hand, entered the literature as defined in the Brundtland Report (1987), it refers to development that satisfies present needs without hindering future generations from fulfilling their own, and while it is the main principle of sustainability for some, it is a contradictory concept for others (Capra, 2015; Ecology; James, 2014; Magee et al., 2013; "Sustainability Primer," ; "What is sustainability?," ; Williams & Millington, 2004).

2. Design Principles

Design is a set of 2 or 3-dimensional shapes that describe the general form and function of an object, product, system, structure, or process, created in a way that suits aesthetics and user needs. Computer-aided design (CAD) involves utilizing a computer to present designs, apply modifications, and compute and visualize the outcomes. It refers to the application of computer systems to support the creation, adjustment, analysis, and enhancement of a design.

Design Types:

- **Industrial Design:** The process of designing the aesthetic and functional aspects of products. Industrial design, or industrial product design, involves creating innovative and contemporary products suitable for mass production by taking into account various factors such as aesthetics, creativity, technical benefits, functionality, ergonomics, material knowledge, marketability, production techniques, and feasibility — all in alignment with consumer needs and challenges ("Endüstriyel tasarım,") (Figure 1).

Figure 1. A 3D designed hair dryer (D. D. A. G. Doç. Dr. Kadir Gök, Mert Tümsek; Kadir Gök, 2018)

- **Interior Design:** Organizing living and working spaces. It includes the processes of designing more comfortable, flexible and useful spaces specifically for the person or need (Figure 2).

Figure 2. An interior design designed with CAD

- **Mold Design:** Advanced modeling techniques should be used to create complex forms for mass production companies. Mold designs for these products are performed in mold design modules of programs with advanced modeling techniques (Figure 3).

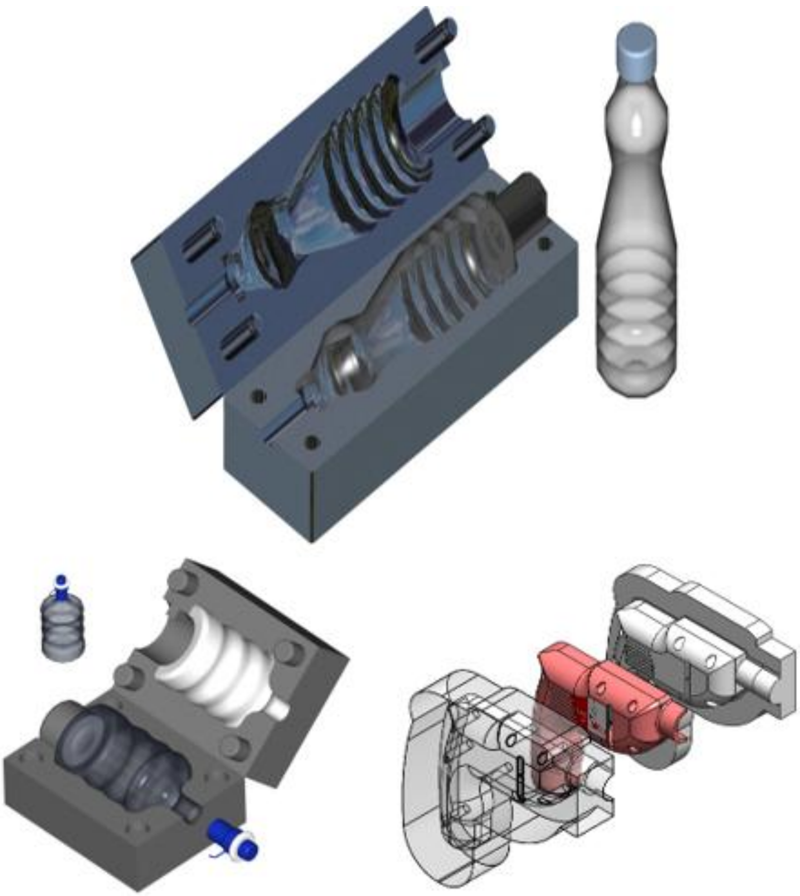

Figure 3. Mold designs designed with CAD

- **Mechanical Part Design:** Monolithic and assembly models and technical drawings of mechanical systems formed by the combination of many components, especially in the automotive industry, are created (Figure 4).

Figure 4. Mechanical assemblies designed with CAD (SOLIDWORKS)

- **Shoe Design:** Using developing modeling techniques, personalized insole and orthopedic shoe designs are gaining importance in terms of both flexibility and comfort (Figure 5).

Figure 5. Shoes and insoles designed with CAD (Blog)

- **Medical Device Design:** Medical device design is the process of developing medical devices, instruments, software and other materials that are used for the diagnosis, prognosis and treatment of diseases. This process encompasses much more than just technical engineering work; it also includes ethical, legal and commercial dimensions (Figure 6).

Figure 6. Ultrasound device (Kadir Gok)

- **Unmanned Aerial Vehicle (UAV) Design:** Today, it is possible to make a 3D design of a UAV optimized for a specific mission using CAD software, perform aerodynamic and structural analyses, and evaluate its suitability for production (Figure 7).

Figure 7. A Drone design designed with CAD (D. D. A. G. Doç. Dr. Kadir Gök, Görkem Karagöz, 2018)

- **Custom Implant and Prosthesis Design:** It is a highly innovative and important field at the intersection of modern medicine, biomedical and biomaterial engineering, as well as additive manufacturing technologies. With advanced design tools, personalized implant and prosthesis designs can be realized today.

Recently, computer aided finite element analyses (FEA) and computational fluid dynamics (CFD) were used to solve processes such as metal turning, bone drilling, bone screwing, water jet process and erosion corrosion processes, fatique behavior of implant materials, simulations of COVID-19 and other infections and optimal configuration of implant materials as seen in Figure 8 (ADA, ERDEM, & GOK, 2021; ERDEM, GOK, GOKCE, & GOK, 2017; A. Gok, Gok, & Bilgin, 2015; Arif Gok, Urtekin, Gok, Ada, & Nalbant, 2023; Kadir Gok; KADIR GOK, 2015; Kadir Gok, Erdem, Kisioglu, Gok, & Tumsek, 2021; Kadir Gok & Gok, 2024; K. Gok & Inal, 2015; Kadir Gok, Inal, Gok, & Pinar, 2017; Kadir Gok, Inal, Urtekin, & Gok, 2019; Gök, Selçuk, & Gök, 2021; Inal, Gok, Gok, Uzumcugil, & Kuyubasi, 2018; Pirhan, Gök, & Gök, 2020; Türkes, Erdem, Gok, & Gok, 2020).

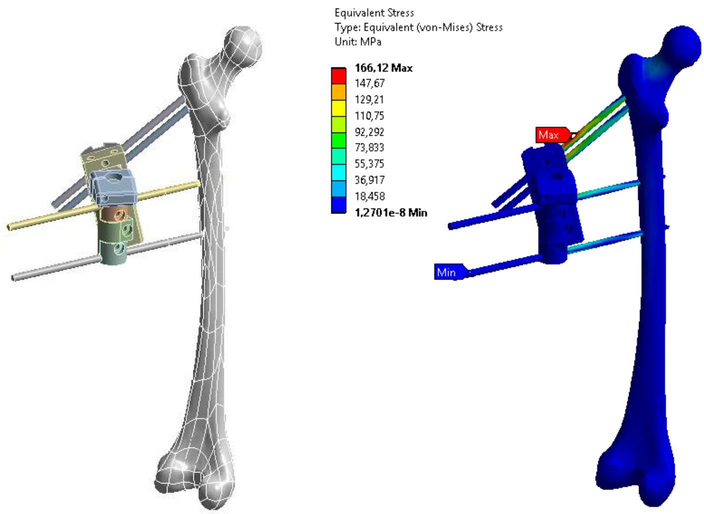

Figure 8. A personalized hip fracture implant

- **Sustainable Design:** After explaining the general design and types above, we can define Sustainable Design, which is the main focus of our department, as follows.

Sustainable design is an approach that takes into account environmental, economic and social impacts; aims to protect the environment and natural resources, and aims to provide maximum benefit with minimum harm throughout the life cycle. In other words, it is a design approach that takes into account the needs of future generations while taking into account today's needs.

Basic Features of Sustainable Design:

1. **Optimal Resource Utilization:** Reducing the consumption of energy, water, and raw materials to a minimum.
2. **Environmentally Friendly Materials:** Preferring recyclable, reusable or nature-friendly materials.
3. **Life Cycle Analysis:** Evaluating the environmental impacts of all stages from product design to manufacturing, from life cycle to disposal.
4. **Reducing Carbon Footprint:** Reducing energy consumption and emissions.
5. **Longevity and Durability:** The ability of products or structures to be used for a long time.

3. Biomaterials

They are natural or synthetic materials that are used to perform or support the functions of living tissues in the human body and that come into contact with body fluids (blood, etc.) continuously or at certain intervals. Generally, "Biomaterials" includes many materials. Metals, ceramics, polymers, glasses, carbons, and composite materials are all included. Besides these types of materials, components such as molded or machined parts, coatings, fibers, films, foams, and fabrics are also utilized (Ratner, Hoffman, Schoen, & Lemons, 2004). Table 1 presents various applications of Synthetic and Modified Natural Materials within the medical field. As illustrated in Table 1, numerous Biomaterials and their diverse applications exist, and this area has evolved into a significant global commercial market. This market encompasses sectors such as the Skeletal System, Cardiovascular System, Dental Implants, Organs, Sensory Systems, Support Devices, and others. Considering the points outlined above, it is clear that Biomaterials science—more so than many other modern technological fields—requires collaboration and open communication among researchers from various disciplines. It is also important to emphasize that this field is inherently interdisciplinary. Figure 9 displays a dental implant manufactured from Ti6Al4V alloy.

Table 1. Example applications of synthetic and modified natural materials (Ratner et al., 2004)

Application	**Material Type**
Skeletal System	
Joint prostheses (hip, knee)	Titanium, Ti – Al – V alloy, stainless steel
Fracture bone plate fixation	Steel, polyethylene
Bone defect repair	Stainless steel, cobalt-chromium alloy
Artificial tendon and ligament	Hydroxyapatite
Dental implant fixation	Teflon, Dacron
	Titanium, alumina, calcium phosphate
Cardiovascular System	
Blood vessel prosthesis	Dacron, Teflon, polyurethane
Heart valve	Processed tissue, stainless steel, carbon
Catheter	Silicone rubber, Teflon, polyurethane
Organs	
Artificial heart	Polyurethane
Skin repair patch	Silicone-collagen composite
Artificial kidney	Cellulose, polyacrylonitrile
Heart-lung machine	Silicone, rubber
Senses	
Intraocular lens	Methyl methacrylate, silicone, rubber, hydrogel
Contact lens	Silicone-acrylate, hydrogel
Corneal bandage	Collagen, hydrogel

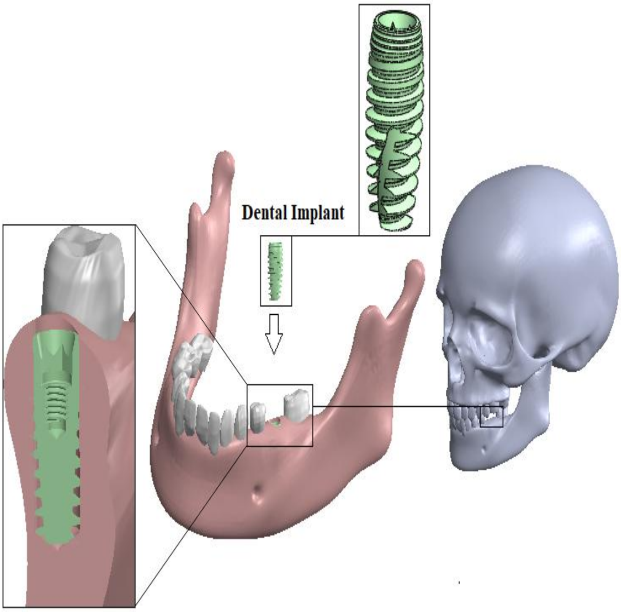

Figure 9. Dental implant made of Ti6Al4V alloy (Kadir Gok)

4. Production Methods and Application Fields

As a solution to today's urgent environmental problems, environmentally friendly materials and production techniques are of great importance; this approach aims to minimize the negative impact on our planet by adopting principles such as energy efficiency, waste reduction and water saving in production processes while encouraging the use of renewable and recycled resources such as bamboo and recycled plastic, thus contributing to the protection of natural resources, reducing pollution and combating climate change, and helping to build a more sustainable future.

In recent years, traditional machining and chipless manufacturing methods and developing additive manufacturing (3D printing) technologies have focused on environmentally friendly approaches. While the use of minimum quantity lubrication (MQL) is among the target points in machining, higher efficiencies are achieved in waste and energy consumption with chip recycling and energy-efficient machines. In parallel, in chipless manufacturing, energy and material optimization come to the fore with high-efficiency molds and waste heat recovery.

Additive manufacturing, which stands out with its features such as providing minimum material waste by nature and enabling the production of complex and lightweight parts, offers a particularly environmentally friendly potential with its ability to use biodegradable materials that can be recycled. These features contribute to a more sustainable future by significantly reducing the industry's carbon footprint.

Three-dimensional Printing (3D Printing) technology has transformed the production of orthopedic implants by allowing the use of patient-specific and personalized designs. The integration of biomaterials such as biodegradable polymers, titanium alloys and composite materials plays a critical role in ensuring biocompatibility and mechanical reliability (Meng et al., 2023; Wu et al., 2023; Zhu et al., 2025). This technology enables the creation of complex geometries and porous structures, increasing osseointegration and extending implant life, which reduces replacement frequency and minimizes medical waste. An example of articular cartilage produced by 3D printing is presented in Figure 10.

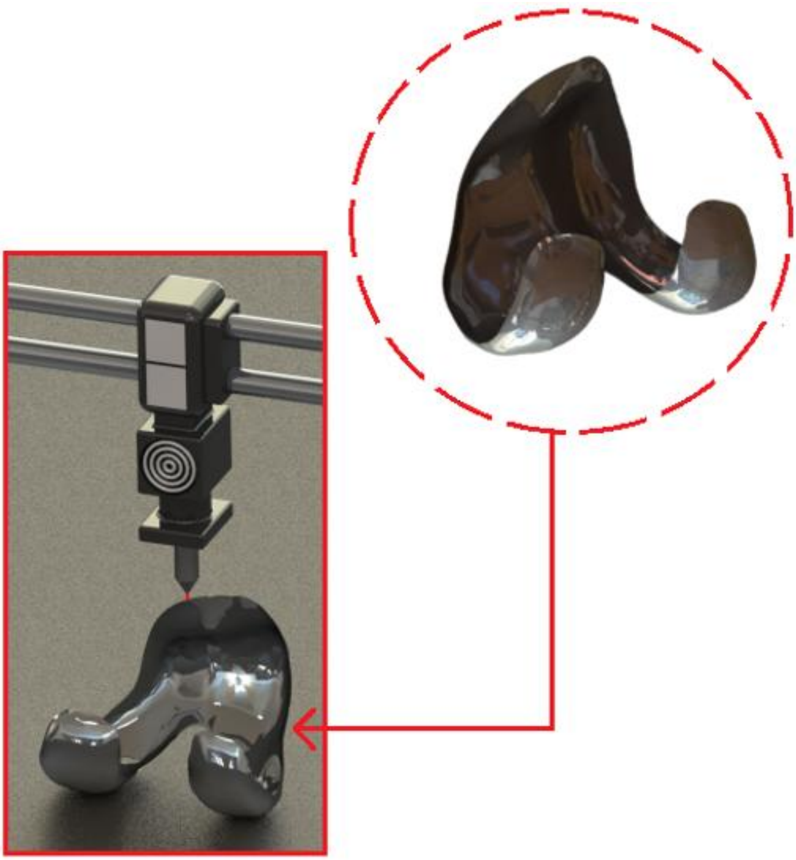

Figure 10. The articular cartilage manufactured by 3D printing (Kadir Gok).

The overall process underscores the implementation of a closed-loop system aimed at minimizing waste generation and optimizing resource efficiency—an approach that aligns with the fundamental tenets of circular economy and sustainability, particularly within the realm of 3D-printed orthopedic implant development. The background imagery appears to depict various natural or bio-based materials, potentially serving to subtly reinforce concepts of environmental sustainability and biological integration. Figure 11 illustrates 3D printable orthopaedic implant's circular economy and sustainability.

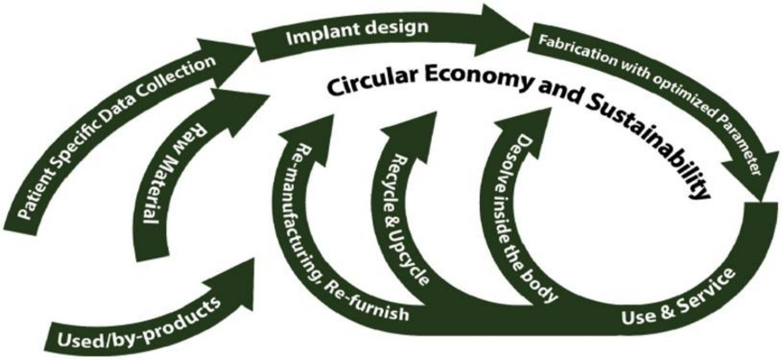

Figure 11. 3D printable orthopaedic implant's circular economy and sustainability (Yadav, Garg, Ahlawat, & Chhabra, 2020)

Biocompatibility is the ability of a material to be compatible with living systems, meaning it does not cause a toxic or harmful reaction in the body; this is especially vital for medical implants and devices. The life cycle of a product or material covers all stages from extraction of raw materials to production, distribution, use and waste management; this comprehensive analysis is used to understand and reduce environmental impacts. Finally, recycling is the process of collecting and converting waste materials into new products, thus conserving natural resources, saving energy and reducing waste. These three concepts together provide a basic framework for fully assessing a product's sustainability potential and environmental footprint.

6. Future Perspective

Today, sustainability has become a global priority, with new technologies being a key driver of developments in this area. Artificial intelligence and machine learning are improving efficiency by optimizing energy use and reducing the carbon footprint of supply chains, while developments such as solar and wind energy storage solutions are accelerating the integration of renewable energy. IoT-enabled smart waste management systems and biotechnology are supporting a circular economy by generating new materials and energy from waste, while technologies such as blockchain are enabling transparency and traceability in sustainable supply chains. These technological advances not only offer environmental benefits, but also open new doors for economic growth, helping us build a greener and more livable future.

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CHAPTER 2

COMPARISON OF STRENGTH, WEIGHT, AND DEFORMATION OF AN AIRCRAFT PART THAT DESIGNED FOR ADDITIVE MANUFACTURING AND CNC MANUFACTURING

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1. Introduction

The aviation and aerospace industry constantly needs lighter yet high-strength components in order to increase fuel efficiency, optimize performance, and reduce operational costs [1] . To meet this need, subtractive manufacturing methods such as Computer Numerical Control (CNC) have traditionally been widely used. CNC technology enables the production of complex parts with high precision and repeatability by removing material from a metal block, but it has disadvantages such as high material waste and certain geometric limitations [2] .

In recent years, additive manufacturing (AM), or more commonly known as 3D printing, has emerged as a revolutionary technology that is changing production paradigms. AM, which creates three-dimensional objects by adding material layer by layer, enables the production of complex and organic geometries that are impossible to produce using traditional methods, especially when integrated with design tools such as topology optimization [3] . This capability offers unique opportunities for achieving weight reduction (lightweighting) goals, which are critical for the aviation industry. Lighter components directly reduce fuel consumption, thereby lowering both environmental impact and operational costs [4] .

One of the most concrete and industry-wide examples of this potential is the aircraft engine bracket design competition organized by General Electric (GE). In this competition, engineers and designers from around the world were asked to redesign an existing titanium engine bracket using additive manufacturing technologies and topology optimization tools.

The use of additive manufacturing in aviation is increasingly widespread in various critical applications such as engine brackets, turbine blades, fuel nozzles, and cabin interior components following such pioneering examples [5] . However, the mechanical properties of parts produced using AM may differ from those of traditional forged or machined counterparts due to potential internal defects such as anisotropy, residual stresses, and porosity inherent to the layered production process [7].

The primary objective of this study is to compare the maximum stress strengths of two different competition designs, which are geometrically optimized to meet the same functional requirements as the original GE motor bracket produced by CNC and are planned to be produced by AM, using the finite element analysis (FEA) method. This study demonstrates that a part designed using EIM can provide significant benefits despite its negligible disadvantages.

2. Materials and Methods

In this section, the selection of geometric models of parts subjected to comparative analysis, the properties of the material used in the analysis, the process of creating the finite element model, the quality of the mesh structure, the boundary conditions applied, and the analysis steps are systematically detailed. This methodology is designed to ensure the repeatability of the study and the reliability of the results.

2.1. Selection and Definition of Geometric Models

As mentioned in the introduction, the geometric models examined in this study were selected from the iconic General Electric (GE) Aircraft Engine Bracket Competition, which showcases the potential of additive manufacturing on an industrial scale. This approach aims to quantitatively highlight the structural performance difference between traditional and AM-focused designs based on a proven case study in the industry rather than theoretical designs. The two models examined are:

• Additive Manufacturing Design: The two additive manufacturing (AM) designs selected for comparison were chosen from among hundreds of innovative designs submitted to and awarded in this competition. This design is the product of topology optimization and generative design algorithms.

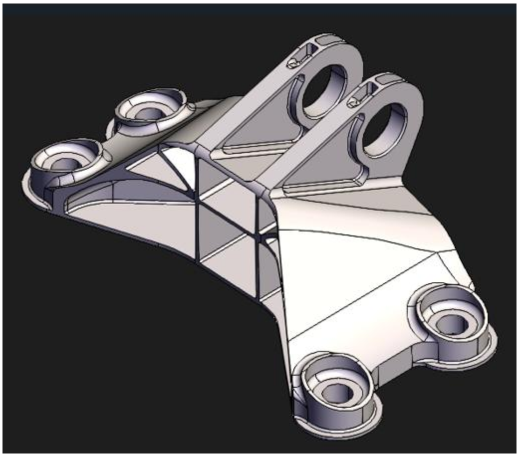

Figure 1: AM Geometry

• CNC Reference Part: This model represents the geometry of the original GE motor bracket, which is the starting point of the competition and is manufactured using traditional machining methods.

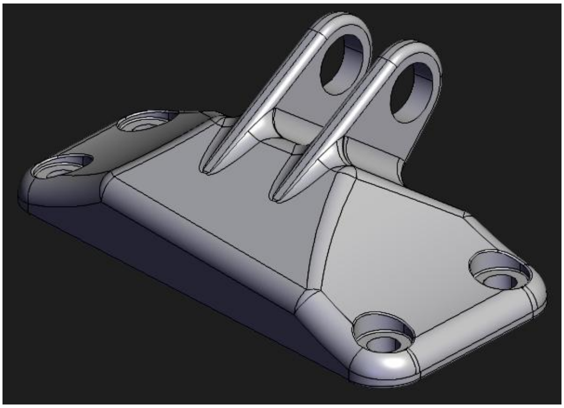

Figure 2: CNC Design

The CAD data of the models used in the analysis were obtained from files publicly available on GrabCAD [7] , an engineering and design community platform. All models were prepared in .STEP format to ensure full compatibility with the analysis software.

2.2. Material Properties and Selection

Although the original GE bracket is made of titanium alloy, in this study, all models were standardized to stainless steel in order to isolate and examine the effect of geometric differences between designs on structural performance. This approach eliminates the material variable, ensuring that the comparison focuses entirely on the topological efficiency and structural superiority of the designs. Since the analyses focus on the material's behavior in the linear elastic region, the material model is assumed to be isotropic and linearly elastic. The basic mechanical properties used in the analysis are presented in Table 1.

	A	B	C
1	Property	Value	Unit
2	Material Field Variables	Table	
3	Density	7850	kg m^-3
4	Isotropic Secant Coefficient of Thermal Expansion		
6	Isotropic Elasticity		
7	Derive from	Young's Mo...	
8	Young's Modulus	2E+11	Pa
9	Poisson's Ratio	0,3	
10	Bulk Modulus	1,6667E+11	Pa
11	Shear Modulus	7,6923E+10	Pa
12	Strain-Life Parameters		
20	S-N Curve	Tabular	
24	Tensile Yield Strength	2,5E+08	Pa
25	Compressive Yield Strength	2,5E+08	Pa
26	Tensile Ultimate Strength	4,6E+08	Pa
27	Compressive Ultimate Strength	0	Pa
28	Isotropic Thermal Conductivity	60,5	W m^-1 C^-1
29	Specific Heat Constant Pressure, C_p	434	J kg^-1 C^-1
30	Isotropic Resistivity	1,7E-07	ohm m
31	Isotropic Relative Permeability	10000	

Properties of Outline Row 3: Structural Steel

Table 1. Stainless Steel Material Properties (Source: Ansys)

2.3. Finite Element Analysis (FEA) Methodology

2.3.1. Creation and Validation of the Finite Element Model

The structural performance of the parts was evaluated using the Static Structural module in ANSYS Workbench 2024 R2, an industry-standard software based on the widely accepted finite element methodology for the numerical solution of engineering problems [8] . Mesh refinement was applied locally in critical areas where stress concentration was expected (around holes, in narrow sections).

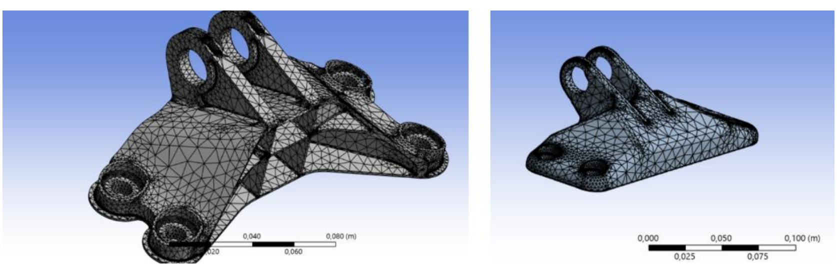

Figure 3: Mesh

2.3.2. Boundary Conditions and Loading

The following boundary conditions have been applied as standard for all three models in order to simulate the actual operating conditions of the part:

- Fixed Support: "Fixed Support" has been applied to the two hole surfaces defined as the mounting surfaces of the part.

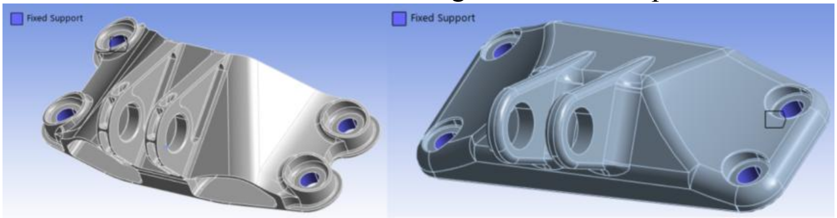

Figure 4: Fixed Support

- Bearing Load: To represent the operational load of the part, a "Bearing Load" of 10,000 N was applied in the +Y direction to the inner surface of the load-bearing pin hole.

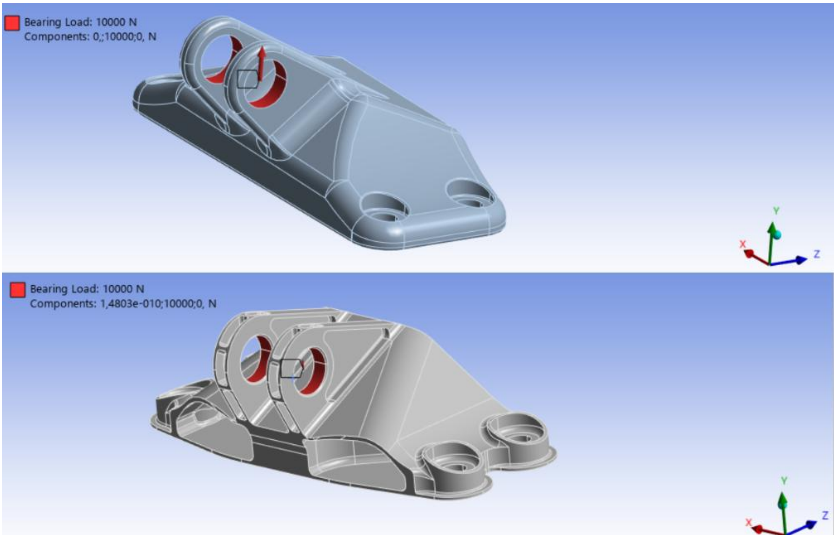

Figure 5: Bearing Load

As a result of the analyses, von Mises equivalent stress was selected as the basic evaluation criterion.

3. Results

As a result of the analyses, the mechanical responses obtained on both parts were evaluated comparatively. The total weight of the part produced by additive manufacturing was measured as 0.60513 kg, while the part produced by CNC weighed 2.2419 kg. This difference demonstrates how additive manufacturing's design flexibility can enhance structural efficiency.

When evaluated in terms of mechanical behavior, the maximum von Mises stress value was 292.76 MPa for the additive manufacturing part and 280.48 MPa for the CNC part. When examining deformation values, the additive manufacturing part exhibited 0.255 mm of deformation, while the CNC part was subjected to 0.108 mm of deformation. Maximum shear stresses were recorded as 165.4 MPa (AM) and 150.88 MPa (CNC), respectively.

These results demonstrate that the additive manufacturing part can operate under similar mechanical loads despite being lighter. Both parts remained within safe stress limits under the specified loading scenario.

The stress distributions obtained from the analysis results are shown in Figures 6 and 7.

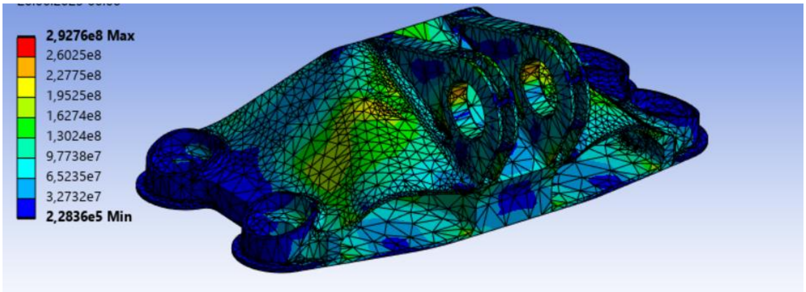

Figure 6: Von Mises Stress Distribution of AM-Design 1

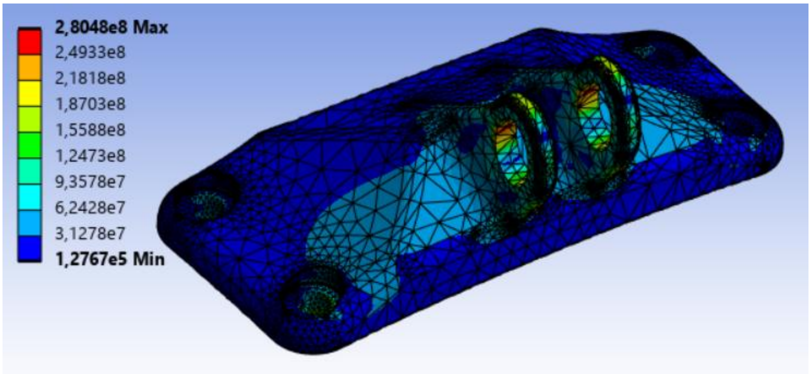

Figure 7: Von-Mises Stress Distribution of CNC Reference Part

4. Conclusion

The analysis results showed that both parts exhibited very similar maximum stress values under similar loads. Despite having a more complex and lightweight geometry, the part produced using additive manufacturing demonstrated similar performance to the CNC-produced part in terms of strength. This supports the potential use of additive manufacturing in high-safety industries such as aviation.

The fact that the part produced using additive manufacturing is approximately 73% lighter clearly demonstrates the possibility of structural weight reduction. This is a significant advantage, particularly in aerospace and space applications, where fuel savings and cost optimization are of great importance. However, this advantage must be carefully evaluated, taking into account the stresses the part will be subjected to, the loading scenario, and post-production processes.

Although the maximum stress and deformation values obtained in this study remained within safe limits, real-world usage conditions can be much more complex. For example, factors such as fatigue resistance, thermal expansion, surface roughness, internal voids, and production defects can significantly affect the behavior of parts produced using additive manufacturing.

Therefore, when choosing between additive manufacturing and CNC, factors such as production tolerances, cost, production time, and quality control must also be considered, not just mechanical strength. Especially for critical structural components, a case-by-case evaluation considering the specific conditions of each application is the most appropriate approach.

Additionally, by combining advanced topology optimization and simulation-supported design processes with additive manufacturing, it is now possible to safely produce geometries that were previously impossible with traditional methods. However, for the reliability of these technologies to be fully ensured, standardization and certification processes must be developed.

In the future, this work can be developed in different directions. First, the evaluations conducted in this study under static loading on a single axis can be expanded to include dynamic loading conditions such as fatigue and impact resistance. Especially in aerospace applications, where parts are often subjected to repetitive loading, fatigue life analyses will be critical.

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CHAPTER 3

COMPARISON OF COAL GASIFICATION TECHNOLOGIES AND SOLUTION SUGGESTIONS TO INCREASE POWER PLANT EFFICIENCY IN ELECTRICITY GENERATION

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1. INTRODUCTION

The rapidly increasing energy demand worldwide necessitates the orientation towards sustainable and efficient technologies in energy production. Acceleration of industrialization, population growth, urbanization and technological developments; While increasing energy demand, they also bring environmental pressures. In this context, countries act with the dual goal of ensuring supply security on the one hand and reducing greenhouse gas emissions on the other. The role of fossil fuels in current energy policies is still quite large; especially coal continues to be a strategic resource that meets nearly 35% of world energy production (IEA, 2022).

Worldwide energy consumption is approximately 620 EJ (exajoule) as of 2023. Approximately 26% of this is provided by coal (Davenport, 2023). In Turkey, nearly 30% of electricity production in 2023 was provided by coal-fired power plants. When this situation is evaluated within the scope of domestic and national energy policies, it reveals that Turkey needs to use its domestic coal resources in a more efficient and environmentally friendly manner. Figure 1 shows the global energy consumption.

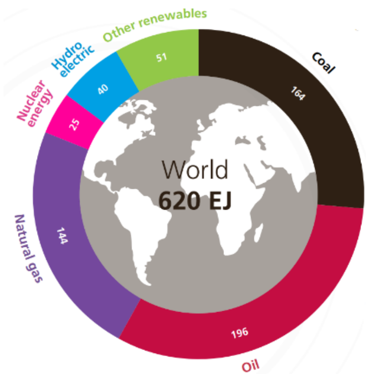

Figure 1. World Energy Consumption Values (Davenport, 2023)

Coal is still used as an important energy source in electricity generation worldwide. Although dependence on fossil resources seems to have decreased, coal has strategic importance for many countries due to energy security, supply continuity and economic factors. In Turkey, coal plays an important role in energy supply, especially thanks to domestic lignite reserves (Ural etc, 2016).

Coal gasification technology is a more environmentally friendly and efficient alternative to traditional coal combustion methods. This technology enables coal to be converted into syngas (H_2 + CO) under controlled conditions. Syngas can be used both in electricity generation and in chemical processes. It also offers advantages in terms of reducing emissions, ease of integration with carbon capture systems and control of by-products (Dong etc., 2018).

Tola et al. (2021) examined the technical and economic performance of the integration of carbon capture and storage (CCS) technologies into coal-fired power plants in their study. Ultra supercritical (USC) systems and integrated gasification combined cycle (IGCC) systems were compared in both CCS and non-CCS configurations. The study determined that USC was more efficient and economical than IGCC without CCS, but the energy losses brought by the CCS system were higher for USC than for IGCC. As a result, it was emphasized that strong incentive policies are needed for CCS technologies to be economically viable in the current market conditions. Feng et al. (2021) examined the environmental impacts of underground gasification combined cycle (UGCC) plants with carbon capture and storage (CCS) technology and separately using the life cycle assessment (LCA) method in their study. UGCC and surface integrated gasification combined cycle (IGCC) plants were compared and it was found that UGCC was more advantageous than IGCC in most environmental impact categories. However, it was determined that the global warming potential was 16.9% higher for UGCC. The study showed that the UGCC-CCS configuration has a lower carbon footprint (249.8 kg CO_2-eq/MWh) and suggested strategies for the use of clean coal. In their comprehensive analysis, Filippov et al. (2021) examined the current status of coal gasification technologies developed worldwide and the demand for these technologies. The study stated that although coal maintains its central role in energy production, the future of gasification technologies is uncertain due to increasing external pressures and carbon emissions. It was emphasized that gasification systems have reached technical maturity and are widely used in the production of chemical products, especially methanol, ammonia and natural gas substitutes. However, the limited number of applications of integrated gasification combined cycle (IGCC) plants indicates that the private sector has little interest in this area. The authors stated that these technologies have high potential for low-carbon energy production, but that this requires the effective disposal of captured CO_2

In their study, Liu et al. (2022) comparatively examined the technical and economic performances of underground coal gasification hydrogen production (UCG-H_2) and surface coal gasification-based hydrogen production (SCG-H_2) systems. As a result of simulation-based analyses, it was determined that the UCG-H_2 system was more advantageous than the SCG-H_2 in terms of both capital investment and product cost. In particular, it was revealed that UCG-H_2 was more resistant to market fluctuations and economic risks. With a carbon capture rate of 80%, it was determined that the product cost of the UCG-H_2 system was still low and the competitive carbon tax threshold was 124 RMB/t CO_2. These results show that the UCG-H_2 technology is promising in terms of economic viability. Harris et al. (2023) examined the potential of coal to be used in the production of high-efficiency electricity, transportation fuels and chemical products through conversion technologies such as gasification and direct liquefaction, beyond its use as a fuel. The study comprehensively covers the current applications of these technologies, the technical and economic barriers encountered, and the main challenges in the field of research. In addition, integrated solutions that offer cost-effective CO_2 capture from coal-based systems and new generation technologies that aim to reduce emissions are also highlighted. Türkiye's shift towards coal gasification technologies is important not only economically, but also environmentally and strategically. Evaluating domestic coal with advanced technologies will contribute to both reducing energy imports and supporting low-emission production policies. This study covers

2. COAL GASIFICATION AND ITS SECTORAL IMPORTANCE

Coal continues to exist as an indispensable resource in energy production due to its large reserves and low cost. Coal is the leader in energy production in countries such as China, India and the USA. As of 2021, China alone accounted for approximately 52% of global coal consumption (BP, 2023). However, it is known that traditional coal combustion methods cause serious environmental problems such as low efficiency and high carbon emissions. Therefore, the need for advanced technologies such as coal gasification to use coal in a cleaner and more efficient way is increasing day by day.

The global coal gasification market is estimated to have reached a valuation of USD 13.87 billion in 2024, with expectations to rise significantly, projecting a growth from USD 14.68 billion in 2025 to USD 22.44 billion by 2032. This growth represents a compound annual growth rate (CAGR) of 6.25% throughout the forecast period. Notably, the Asia Pacific region has established itself as the dominant player in the market, capturing an impressive 73.04% share in 2024. Additionally, the coal gasification sector in the United States is anticipated to expand substantially, with an estimated valuation of USD 1.59 billion expected by 2032.

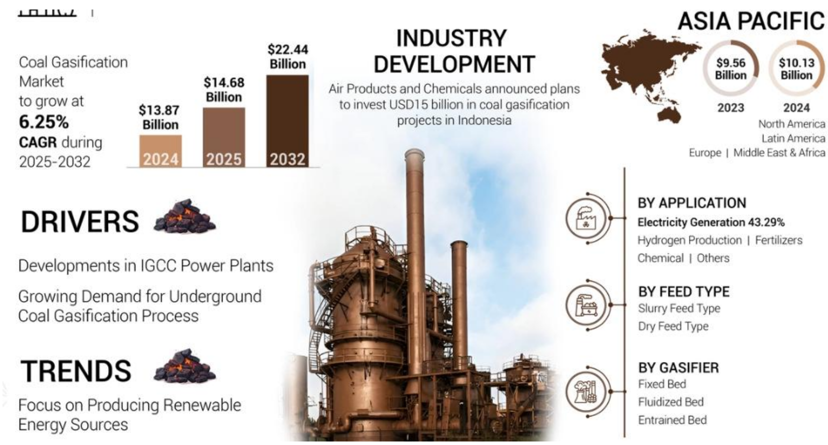

Figure 2. Market Share Status of Coal Gasification Technology (Fortune Business Insights, 2023)

he advancements in coal gasification are significantly enhancing the production capabilities for fertilizers, chemicals, and hydrogen on a global scale, with Asia Pacific taking the lead in the adoption of this technology. The increasing reliance on methanol-infused fuels in sectors such as aviation and hybrid vehicles is anticipated to further propel market expansion in the coming years.

Traditionally, coal has been utilized primarily in conventional coal-fired power plants. However, the gasification process offers a transformative approach, converting solid coal into gaseous forms, electricity, hydrogen, and a variety of other energy products. Coal gasification is a sophisticated thermochemical process where heat and pressure decompose coal into its fundamental chemical components. The end product, known as synthesis gas or syngas, primarily consists of carbon monoxide and hydrogen, along with other possible gaseous compounds.

Syngas serves multiple purposes; it can be harnessed for power generation, utilized in energy-efficient fuel cell technology, or employed as versatile chemical building blocks for a wide array of industrial applications. Additionally, the extraction of hydrogen from syngas is a critical advancement that enhances hydrogen conservation and expands its potential as a clean energy source.

Researchers and industry stakeholders are actively engaged in ongoing improvements and innovations within coal gasification technology, aiming to unlock further potential applications and improve the efficiency of this process. As the demand for cleaner and more sustainable energy solutions continues to grow, coal gasification is positioned to play a crucial role in the energy landscape of the future.

3.COMPARISON OF COAL GASIFICATION TECHNOLOGIES

3.1. Fixed Bed Gasifier

In a fixed bed gasifier, solid coal particles are introduced from the top of the reactor. An air and steam mixture is injected from the bottom, creating a reaction bed that remains fixed in place. As the coal descends, it undergoes a series of oxidation and reduction reactions, facilitating the gasification process. It operates effectively at lower temperatures (typically between 600-800°C) compared to other gasification methods, which can lead to lower energy consumption. The overall investment cost is relatively low because of simpler design and construction requirements. The fixed bed structure requires less complex technology and maintenance, making it suitable for smaller-scale operations (Hobbs etc, 1992).The resulting synthesis gas often contains significant amounts of tar, which can complicate downstream processes and require extensive gas cleaning. The requirement for larger-sized coal particles can limit feedstock options and make the process less versatile. The fixed bed design can lead to difficulties in handling and removing ash residues, potentially affecting efficiency over time (Ryzhiy etc., 2021).

3.2. Fluidized Bed Gasifier

In a fluidized bed gasifier, finely ground coal particles are suspended in a hot fluid medium, typically consisting of sand or ash. The introduction of air or oxygen creates a fluidized state where the solid particles are mixed continuously with the gasifier contents, promoting efficient gasification. The continuous mixing of coal particles in the fluidized state allows for uniform temperature distribution and maximizes combustion efficiency (Xie etc., 2021). This design can accommodate a wide range of coal types and particle sizes, enhancing flexibility in feedstock usage. Operators can easily regulate the bed temperature, leading to better control of the gasification process and improved product quality. Due to the production of particulates and tars, gas produced requires significant cleanup before it can be utilized, which can be resource-intensive. Issues can arise with the transport of solid particles within the gasifier, potentially leading to blockages or uneven flow (Gupta etc., 2022).

3.3. Entrained Flow Gasifier

In an entrained flow gasifier, very finely ground coal, often described as pulverized, is mixed with a high-velocity flow of oxygen and steam. The feed is injected into the reactor at high speeds, allowing gasification to occur at elevated temperatures ranging from 1300 to 1500°C, where the reactions happen extremely efficiently. The high operating temperatures prevent the formation of tar, leading to the generation of high-quality synthesis gas that contains minimal impurities. The resulting syngas possesses a high calorific value and is suitable for subsequent conversion processes into fuels and chemicals (Kong etc., 2021). A comparison of the technical specifications of the gasification processes is given in Table 1.

Table 1. Comparison of Coal Gasification Technologies

Feature	Fixed Bed Gasifier	Fluidized Bed Gasifier	Entrained Flow Gasifier
Operating Temperature (°C)	900 – 1100	800 – 1000	1300 – 1500
Operating Pressure	Atmospheric / Low	Atmospheric / Medium	High
Coal Particle Size	Large (5–50 mm)	Medium (0.5–6 mm)	Very fine (<0.1 mm)
Syngas Quality	Low to Medium	Medium	High (tar-free)
Tar Formation	High	Medium	None
Ash Removal	Difficult	Easy	Easy (as molten slag)
Thermal Efficiency	Medium	High	High
Fuel Flexibility	Low	High	Medium
Capital Cost	Low	Medium	High
Typical Applications	Small to medium-scale plants	Medium-scale plants	Large-scale plants (e.g., IGCC)

The need to maintain high temperatures requires considerable energy input, which can impact overall process efficiency. Higher capital and operational costs are associated with this method due to the extensive processing requirements and specialized equipment needed for high-speed feeding and temperature maintenance. The necessity for very fine grinding of coal adds complexity and further increases operational costs due to the energy required for particle size reduction.

4. CONCLUSION AND RECOMMENDATIONS

Enhancing the efficiency of electricity generation through coal gasification technologies involves several critical technical improvements and system integrations. Central to this advancement is the implementation of integrated gasification combined cycle systems (IGCC). In an IGCC framework, synthesis gas (syngas)—produced from gasifying coal—is first combusted in a gas turbine to generate electricity. The exhaust gases from this process are then directed to a steam turbine, where their heat is utilized to create steam, further driving electricity generation. This dual-turbine approach significantly boosts the overall efficiency of the system, as it effectively harnesses energy that would otherwise be wasted.

Key to maximizing the efficacy of the IGCC system is the recovery of waste heat from the high-temperature gases generated during the gasification process. By utilizing this heat to produce steam, the system enhances its total energy output. Furthermore, the cleaning and enrichment of synthesis gas are paramount. Removing impurities such as tar, carbon dioxide (CO_2), and hydrogen sulfide (H_2S) from the syngas results in a cleaner, high-quality fuel that improves combustion efficiency. Additionally, employing CO-shift reactions can increase the hydrogen content within the syngas, creating a more effective fuel for gas turbines.

Conducting the gasification process under elevated pressure also plays a crucial role in enhancing reaction rates, thereby leading to increased energy production. Implementing preliminary processes—such as reducing the moisture content of coal prior to gasification, along with grinding and homogenizing the coal—makes the gasification system more balanced and effective. These steps ensure that the feedstock is optimized for conversion, leading to improved yields of syngas.

Another vital consideration in the coal gasification process is the capture, utilization, and storage of CO_2 (CCUS systems). Although this has a limited effect on net energy yield, it significantly enhances environmental performance by reducing greenhouse gas emissions, making the process more sustainable.

Finally, merging coal gasification systems with renewable energy sources, such as solar power, enables the development of hybrid energy systems that are both efficient and less reliant on fossil fuels. This integration not only diminishes overall fuel consumption but also lowers the carbon footprint associated with electricity generation. By examining and implementing these collaborative strategies, substantial improvements can be realized in both the energy efficiency and ecological sustainability of coal gasification-based electricity generation systems. Such advancements position coal gasification as a viable player in the transition towards a more sustainable energy landscape.

Coal gasification technologies enable the efficient utilization of Türkiye's low-quality coal while minimizing its environmental impact. Different gasification technologies vary in terms of efficiency, gas composition, installation costs, and environmental profiles. For instance, fixed-bed gasifiers are lower in cost but have limitations regarding gas quality. In contrast, entrained flow systems are more expensive but provide higher efficiency and better gas quality. Coal gasification operates on the principle of converting coal into gas under high temperatures in a limited oxygen environment. The resulting syngas can be used in various chemical processes as well as in electricity generation. When integrated with Integrated Gasification Combined Cycle (IGCC) technology, plant efficiency can exceed 45%, and carbon emissions can be reduced by 25-30% compared to conventional power plants. Additionally, these systems can be combined with carbon capture and storage (CCS) technologies, bringing the concept of "clean coal" closer to reality.

In the context of Turkey, energy dependence presents a significant challenge. Approximately 70% of the country's energy needs are met by imported resources, leading to economic vulnerability. Conversely, Turkey boasts substantial coal reserves, especially lignite, with total reserves estimated at around 20 billion tons, of which approximately 15 billion tons consist of low-quality lignite. However, because of its low calorific value and high sulfur content, the direct combustion of this coal severely harms the environment.

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CHAPTER 4

CONDITION MONITORING AND ARTIFICIAL INTELLIGENCE-ASSISTED PREDICTIVE MAINTENANCE: TECHNIQUES AND APPLICATIONS

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1. Introduction

CM and PdM have become indispensable elements of modern industrial processes. CM is the process of continuously collecting, processing and analyzing data from various sensors to monitor the health of equipment in real time [1]. These sensors usually measure physical parameters such as vibration, temperature, pressure, oil quality, acoustic signals, electrical currents [2]. For example, increased vibration or temperature in an electric motor can be an indication of an early failure [3]. Similarly, changes in the number of particles or chemical composition through oil analysis can be an indicator of mechanical wear or contamination [4]. This data allows to detect deviations from the normal operating limits of the equipment and to provide immediate notification to maintenance teams

PdM is the analysis of this continuously collected data with the help of artificial intelligence algorithms and statistical models, estimating the remaining life of the equipment before failure and proactively planning the maintenance time [5]. In this way, maintenance is performed not only when the failure occurs, but also before the failure occurs, thus minimizing unplanned downtime, reducing maintenance costs and extending the life of the equipment. Predictive maintenance tries to determine the type of failures and the time of failure, allowing more efficient use of maintenance resources. Condition monitoring and predictive maintenance systems were initially limited to simple threshold value warnings based on a single parameter. However, today, thanks to the Internet of Things (IoT) technology, large data sets can be collected with a large number of sensors and this data is processed with big data analysis techniques on cloud platforms. Thanks to machine learning and deep learning models, complex patterns and anomalies hidden in this big data can be detected more accurately. For example, by processing the features obtained by vibration spectrum analysis and time-frequency transformations with artificial neural networks and convolutional neural networks, different fault types of the equipment can be classified with high accuracy [6].

Models used in predictive maintenance include regression analysis [7], support vector machines [8], random forests [9] and recurrent neural networks (RNN, LSTM etc.) [10]. Especially in time series data, the future state of the equipment is predicted with these models. In addition, anomaly detection methods provide early detection of rare or unknown failure types. These approaches are applied not only for production lines but also for power plants, transportation vehicles, chemical plants and many other critical infrastructures, reducing labor losses and safety risks caused by failures. There are many studies on this subject in the literature. An example of this is the study where instead of periodic maintenance in wind turbines, predictive maintenance is applied to repair turbine blades or generators before they fail. This significantly reduces high maintenance costs and the time the turbine is out of production [11].

In conclusion, condition monitoring and predictive maintenance are critical components of digital transformation in industrial plants. The effectiveness of these methods is directly related to the right selection of sensors, high-quality data collection, development of appropriate AI models and good planning of maintenance strategies.

2. Effects of Condition Monitoring and Predictive Maintenance on Manufacturing Efficiency

Condition monitoring and predictive maintenance have become key strategies for increasing efficiency in modern manufacturing processes. While traditional maintenance methods often result in unplanned downtime and high costs, these new approaches help detect failures in advance. Figure 1 summarizes the effects of condition monitoring and predictive maintenance on production efficiency.

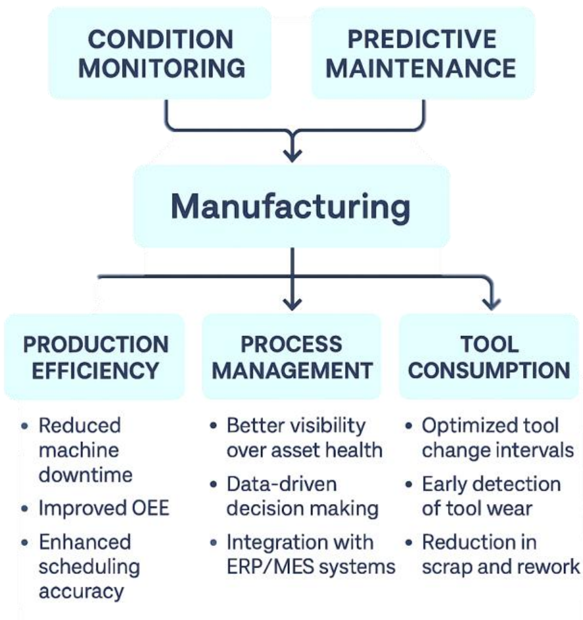

Figure 1. The effect of CM and PM on the manufacturing efficiency

By continuously monitoring the condition of the equipment with sensors and analysis tools, failure risks can be determined at an early stage. This increases production continuity and reduces costs by ensuring that machines are maintained only when needed. Companies gain great advantages by using these methods. For example, machine vibrations and temperatures are continuously monitored in engine assembly lines using condition monitoring systems in production facilities. Thanks to this system, a shaft bearing failure that may occur in a CNC machine processing an engine block can be detected days in advance [12]. In this way, planned maintenance is implemented, the production line continues to operate without stopping and overall efficiency is increased. In another example, large compressors and pumps used in refineries are monitored through condition monitoring [13]. Since production is completely stopped in the event of a failure of critical equipment, this risk is reduced thanks to predictive maintenance. Since failures are fixed before they occur, both efficiency is increased and occupational safety is ensured.

Predictive maintenance applications not only reduce the risk of failure, but also extend the life of the equipment and optimize the use of resources. By preventing unnecessary maintenance operations, both the consumption of spare parts is reduced and the workforce is used more efficiently. In this way, the machines operate at high performance for a longer period of time. In addition, the operation of the equipment under ideal conditions ensures that product quality is maintained, and occupational accidents that may be caused by failures are also prevented. An example of this situation is the reduction of maintenance and emergency response costs for very costly turbine failures used in some sectors. Turbine failures in power plants are very costly. Electricity generation facilities detect critical situations such as overheating and oil pressure changes in advance thanks to the sensors they place in the turbine systems. Thanks to predictive maintenance, unplanned stoppages of turbines are minimized and production continues uninterrupted, while maintenance costs and emergency response costs are reduced. Another example can be given from the cement sector. Sudden failure of heavy machinery such as mills and rotary kilns used in cement production can lead to millions of liras of production loss [14]. Companies constantly monitor these equipment and follow parameters such as bearing temperature, vibration and oil quality. Thanks to this system, maintenance operations are carried out in a planned manner, downtime due to malfunctions is reduced and maintenance and repair costs are reduced accordingly.

Finally, these technologies support data-driven decision-making processes and contribute to the sustainability of production processes. Data collected on equipment performance helps businesses optimize maintenance plans, make more accurate investment decisions, and increase energy efficiency. In this way, condition monitoring and predictive maintenance applications transform not only maintenance processes but also general production strategies, creating a more competitive and resilient production infrastructure. Companies that have adapted technologies such as Industry 4.0 to their production facilities can benefit from the advantages of this method included in data management. In automotive production facilities, data from hundreds of machines and robots are collected on a central digital platform. This data is used not only in maintenance planning but also in investment decisions. System data can be examined for equipment that frequently fails in a production line, and a decision can be made to replace it with a new and more resilient model, and thus production strategies can be optimized based on data [15]. The aviation sector can be given as an example as a different sector. Aircraft manufacturers can analyze the data from the machines that produce aircraft parts in their production processes and determine which processes are more efficient and the potential for failure in the machines. Thanks to these analyses, maintenance programs are reshaped, making not only production but also the entire supply chain more flexible and sustainable [16]. In addition, this data is used in decisions to increase production capacity and optimize stock management, thus contributing to increased efficiency.

3. Condition Monitoring Fundamentals and AI-Assisted Condition Monitoring

Condition Monitoring is a systematic method for assessing the operational performance of industrial equipment in real time. The main purpose of this method is to prevent unplanned downtime by detecting equipment failures at an early stage, reduce maintenance costs and increase production continuity [1]. Condition monitoring processes are generally carried out in three basic stages: sensor-based data collection, analysis of this data and operation of decision support mechanisms based on the results. These basic stages are shown in Figure 2.

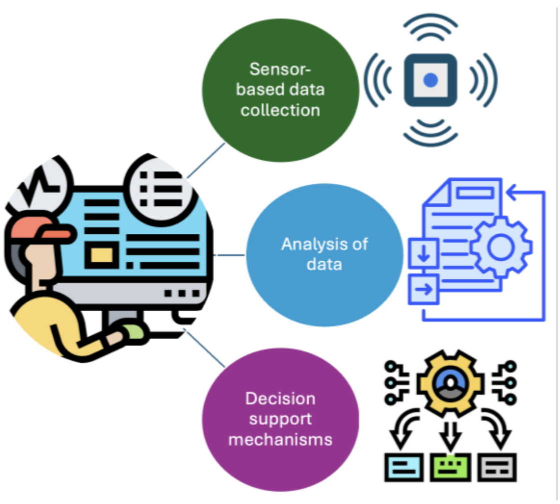

Figure 2. Basic stages of CM

In practice, the data obtained from the equipment includes vibration, temperature, acoustic emission, oil condition, electrical parameters and other physical variables. These data are processed with time/frequency analysis techniques, statistical evaluations and artificial intelligence-based models for anomaly detection and fault diagnosis. The obtained outputs form the basis for the creation of predictive maintenance strategies. Condition monitoring techniques vary depending on the type of equipment being monitored, its operational conditions and possible failure modes.

The most commonly used sensors in the industry during CM are shown in Table 1. This table provides detailed information about sensor types, their usage areas, the parameters they measure, and their intended uses. These sensors form the basis of today's Industry 4.0 and Internet of Things (IoT)-based condition monitoring systems. The collected data is analyzed with artificial intelligence and machine learning algorithms, allowing for the prediction of failures and the implementation of predictive maintenance strategies

Table 1. Sensors used for CM and their features

Sensor	Usage Area and Measured Parameters	Examples of Problems Detected
Vibration Sensors	Measurement of vibration, oscillation, speed and acceleration in rotating machines.	Imbalance, misalignment, bearing damage, mechanical looseness, gear wear.
Temperature Sensors	Measurement of machine parts, fluids and ambient temperature (contact and non-contact).	Overheating, friction, electrical faults, cooling system problems, insulation failures.
Pressure Sensors	Measurement of liquid/gas pressure in hydraulic, pneumatic and fluid systems.	Leaks, blockages, valve failures, overload.
Acoustic Emission Sensors	High-frequency sound waves resulting from micro-level stresses and deformations within the material.	Crack propagation, corrosion, cavitation, premature bear.
Oil Analysis Sensors	Analysis of quality, contamination and wear particles of lubricating and hydraulic fluids	Oil degradation, contamination (water, fuel), wear particles, overheating.
Current and Voltage Sensors	Current draw, voltage fluctuations and power consumption of electric motors and systems.	Motor electrical faults, winding problems, energy inefficiency.
Proximity Sensors	Shaft position, movement, displacement and clearance measurement (non-contact).	Shaft runout, bearing clearances, eccentricity.
Flow Sensors	Measurement of flow rate and volume of liquids or gases in pipes.	Blockages, leaks, pump failures, cooling insufficiency.
Level Sensors	Detection of material (liquid, powder, granule) level in tanks or hoppers.	Overflows, pumps running dry, material supply problems.
Force Sensors	Measurement of mechanical force (tension, compression) (load cells).	Overload, material fatigue, mechanical stress, unbalanced load distribution.
Humidity Sensors	Measurement of humidity in the environment or in the system.	Corrosion, condensation, electrical faults, product quality problems in moisture-sensitive processes.

Complementary techniques used alongside these basic measurement devices significantly increase the accuracy and scope of fault detection. Electrical parameter monitoring is effective in diagnosing electrical anomalies such as short circuits in motor windings, insulation failures and voltage imbalances; while ultrasonic tests are preferred in determining conditions such as sealing problems, valve failures and insufficient lubrication. In addition, current and power analysis techniques allow the analysis of energy efficiency and load behavior of electric motors and performance evaluation. The selection of data collection equipment and techniques to be used greatly affects data collection strategies, data processing and the use of advanced analysis methods. Today, the integration of artificial intelligence and machine learning-based models in this field increases the accuracy of fault prediction and ensures that maintenance plans are placed on a more reliable basis.

The data obtained from such monitoring techniques, although providing limited information in raw form, are transformed into meaningful results through advanced data analysis methods and artificial intelligence-supported models. In some cases, while one sensor data is sufficient, there are applications where multiple sensors are used. Using data from multiple sensors increases the accuracy of the analysis while also increasing the processing load. For this reason, it is necessary to create a balance according to the system being worked on. Thanks to big data infrastructures, data from multiple equipment is processed simultaneously and central maintenance management is supported.

Figure 3 shows the necessary steps for interpreting and processing the data coming from the sensors before proceeding to the decision-making process. After the raw data coming from the sensors are collected, they are subjected to pre-processing processes such as noise reduction, filtering, normalization and missing data completion before the analysis process and during these processes, they are cleaned, organized and prepared using various signal processing techniques. Noise reduction and filtering at this stage are very important to eliminate unwanted signals or random distortions that may hide critical information. Techniques such as low-pass filters or moving averages are widely used here. Normalization or standardization is necessary to ensure comparability between different sensor types and scales. This process scales the data to a consistent range or adjusts it according to statistical properties. In addition, missing data management usually eliminates gaps in the data set by entering values with methods such as carrying forward the last known value or using regression-based estimates. In addition, sensor failures or early signs of failure can be determined by detecting outliers.

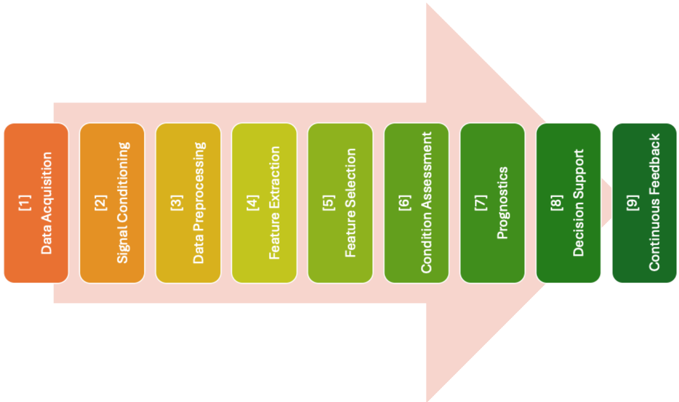

Figure 3. The steps of data processing in CM

The primary objective of data processing in predictive maintenance is to enable informed decision-making and timely action by detecting faults early and planning maintenance to avoid failures. This process begins with pre-processing and feature extraction, where meaningful indicators of equipment health—such as time, frequency, and time-frequency domain features—are derived from raw signals. Analytical techniques like threshold-based monitoring, trend analysis, and statistical process control (SPC) are then used to evaluate equipment condition. Machine learning methods further enhance predictive capabilities: supervised learning classifies conditions or predicts remaining useful life (RUL), unsupervised learning detects anomalies, and deep learning models such as CNNs and RNNs (especially LSTMs) offer automatic feature extraction and improved fault diagnosis with large datasets. Additionally, model-based diagnostics compare sensor data with physical models to identify inconsistencies and faults [17-19].

Another important issue is the increasing importance of multi-technology integration. The combined use of different condition monitoring techniques provides higher accuracy and reliability in fault diagnosis. For example, an anomaly detected in vibration analysis can be verified by supporting it with thermal imaging, while the findings obtained from oil analysis provide complementary information for root cause analysis of mechanical failures. This holistic approach increases the effectiveness of predictive maintenance strategies, while also providing significant gains in critical areas such as reducing unplanned downtime in industrial facilities, reducing maintenance costs, optimizing spare parts usage, increasing human safety and energy efficiency.

As a result, CM techniques have become an indispensable component in industrial facilities to increase system reliability, increase operational efficiency and include maintenance activities in the optimization process. Integrating these techniques with artificial intelligence-based decision support systems plays a critical role in shaping maintenance paradigms of Industry 4.0 and beyond by forming the basic building blocks of intelligent maintenance systems.

4. Adoption of Next-Generation Technologies for AI-Enabled Condition Monitoring

New technological trends are extremely important for condition monitoring and are driving a paradigm shift from reactive or time-based maintenance to highly proactive, predictive, and even prescriptive approaches. One of the prominent technologies in this field is digital twin technology. Digital twin technology enables the creation of virtual copies of physical assets fed with real-time data. Digital twins continuously monitor, analyze, and predict potential failures by creating dynamic, virtual copies of physical assets that process real-time sensor data. They provide advanced fault detection, predictive maintenance, and performance optimization by simulating equipment behavior under various conditions. In this way, maintenance activities are improved, business continuity is increased, and risks are minimized [20]. Through integration with AI and IoT, digital twins make maintenance more accurate, cost-effective, and proactive, paving the way for Industry 4.0 and beyond. Several examples of the use of digital twin technology in industry for CM are provided in Figure 4.

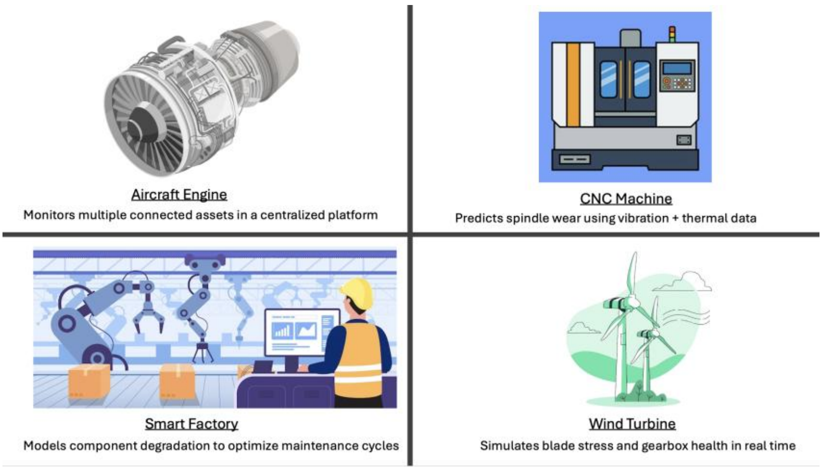

Figure 4. Examples of using digital twin for condition monitoring purposes

Another advanced technology that is increasingly being adopted in CM is Augmented Reality (AR). AR-based Condition Monitoring combines immersive visualization technologies with real-time industrial data to enhance predictive maintenance, asset management, and decision making. It supports field workers' decision-making processes by adding digital information layers to the physical world. Key Applications of AR-based Condition Monitoring include maintenance, training, and remote collaboration. Remote assistance becomes more effective through AR, as experts can guide field workers using visual explanations and live broadcasts. In addition, AR enhances situational awareness and predictive diagnostics by supporting the visualization of digital twins. With the help of this technology, maintenance personnel can view the current status of equipment, access fault codes, and follow step-by-step repair instructions through AR-enabled glasses or tablets. This technology reduces intervention times, lowers error rates, and makes specialized operations more accessible. It also significantly speeds up training and information access processes [21,22].

Blockchain technology provides a distributed registry structure that allows data to be stored transparently, securely, and immutably. CM, which enables the tracking and interpretation of data collected through sensors, plays a critical role in ensuring the reliability of sensor data and in verifying the source. By integrating Blockchain with condition monitoring systems, sensor data from machines is recorded in an immutable ledger. This ensures that historical performance and maintenance records of assets cannot be changed. Blockchain prevents data manipulation while increasing the traceability of the system. In predictive maintenance, this increases trust and accountability by creating a transparent and auditable trail for machine health data and maintenance events. Additionally, combining Blockchain with IoT and AI creates a robust ecosystem where data integrity feeds reliable machine learning models and improves real-time decision making [23].

These technologies make significant contributions to the digitalization process of industrial systems. The visibility and foresight capabilities provided by digital twins, fast and accurate interventions supported by AR, and data integrity guaranteed by Blockchain are becoming the basic building blocks of modern industrial systems. In addition, research continues on the use of new generation technologies for CM purposes and the development of new systems in this direction.

Next-generation systems are moving towards Edge AI and real-time analytics, where data is processed locally on the machine using intelligent algorithms. This reduces latency and reliance on cloud infrastructure, enabling instantaneous fault detection. Furthermore, self-learning and continuously learning systems are emerging; these models adapt over time without retraining from scratch, ensuring that condition monitoring systems maintain accuracy as the machine ages or operating conditions change [24]. Another important trend is the use of multimodal and sensor fusion AI, which combines data from a variety of sensors (such as vibration, acoustic, and thermal) for a more accurate and holistic view of machine health [25].

As trust and transparency become more important, it is driving the adoption of Explainable AI (XAI) to make model decisions understandable to human operators. At the same time, the integration of 5G and Industrial IoT (IIoT) is enabling ultra-fast communication between machines and systems, facilitating real-time condition monitoring at scale [26].

Federated learning and privacy-preserving AI enable models to be trained across multiple sites or machines without sharing sensitive data, while automated machine learning (AutoML) [27] has simplified AI deployment by automating model development for non-experts. Finally, AI-powered root cause analysis (RCA) [28] is transforming fault diagnostics by automatically identifying the source of problems in complex systems, significantly reducing downtime and repair costs.

Collectively, these trends reflect a shift toward smarter, faster, more transparent, and decentralized condition monitoring systems driven by AI. Figure 5 shows these future technologies.

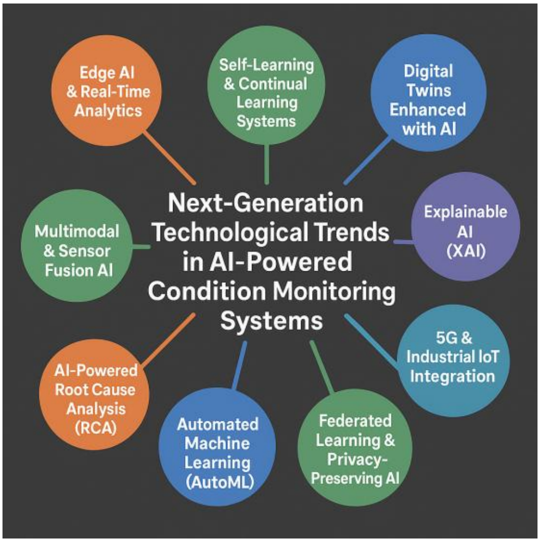

Figure 5. Future trends in AI powered CM systems

AI-supported condition monitoring system architectures can directly affect not only maintenance processes but also production, energy management and supply chain decisions. These systems provide a foundation for Predictive Maintenance strategies; They offer multi-dimensional benefits such as reducing unplanned stops, shortening downtimes, efficient use of maintenance resources and increasing occupational safety.

As a result, it is clear that these AI-supported architectural structures are of strategic importance in the realization of Industry 4.0 and the rising Industry 5.0 visions. In the coming periods, these systems are expected to develop further in the axis of digitalization, sustainability and AI ethics.

5. Artificial Intelligence-Assisted Predictive Maintenance

Predictive Maintenance is an advanced maintenance strategy that aims to monitor industrial assets and systems before they fail and optimize maintenance processes by predicting possible breakdowns [5]. While traditional periodic maintenance practices often bring unnecessary costs and unplanned downtime risks, PdM approaches enable decisions to be made based on real-time data. In order to make the advantages that PdM has shown over traditional maintenance methods applicable, integration with AI has become extremely important today. PdM systems require AI due to the complexity, data volume and speed required to accurately predict equipment failures. While traditional maintenance relies on programmed checks or reacting to failures, PdM aims to predict problems before they occur, and AI is the most important technology that can make this possible at scale and with the necessary precision. Figure 6 shows the intended uses of PdM integration with AI.

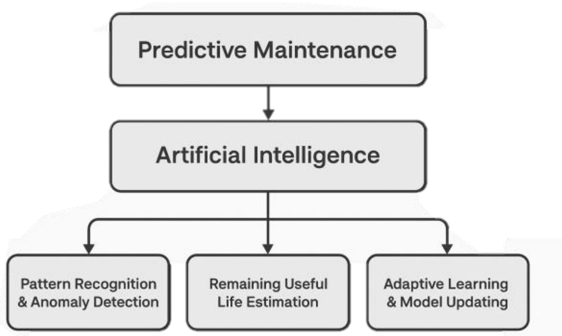

Figure 6. Purposes of using AI integration with PdM

Thanks to the Internet of Things (IoT) and widespread sensor usage, modern industrial equipment generates a tremendous amount of real-time data, such as vibration, temperature, pressure, acoustic signals, current, engine speed, and more. Manually sifting through and interpreting this constant stream of data is time-consuming and labor-intensive. AI algorithms, particularly ML, are specifically designed to efficiently process, analyze, and learn from these massive data sets. AI's ability to drive PdM is based on its advanced capabilities in ML and deep learning (DL). These advanced algorithms empower PdM systems with the ability to not only analyze but also "learn" from vast amounts of historical and real-time equipment data. Through this continuous learning process, AI models are able to identify complex correlations and indicators that precede equipment failures, allowing for highly accurate predictions about when a component is likely to fail.

Another important benefit of AI integration is the ability to identify undetectable differences that could lead to equipment failure. Equipment failure often manifests itself with subtle changes in performance metrics long before a failure. These subtle deviations may not trigger traditional threshold-based alarms or be unnoticed by human operators. Through its sophisticated pattern recognition capabilities, AI can detect these tiny anomalies and hidden correlations in data that indicate an impending problem. This impact, which will provide major benefits for many productivity drivers, highlights the importance of using AI. In addition to detecting an anomaly, true predictive maintenance requires an estimate of when equipment is likely to fail. AI models excel at learning temporal dependencies in data. This allows them to analyze historical failure trends and real-time operational data to provide an accurate estimate of a component's remaining lifespan. With this information, organizations can optimize their maintenance programs, ensure interventions are performed exactly when needed, minimize unnecessary downtime, and maximize the operational life of critical assets. This capability provided by AI transforms maintenance from a reactive frenzy into a targeted and efficient operation.

Equipment health is often affected by the complex interaction of multiple parameters. For example, a sudden drop in efficiency may not be related to temperature alone, but rather to a combination of slightly elevated temperature, increased vibration at a certain frequency, and unusual power draw. AI algorithms can automatically identify these complex, nonlinear relationships between different sensor readings and operational parameters and determine their significance. Another positive effect of AI is preventing production disruptions due to false alarms. Traditional alarm systems often have the disadvantage of flagging healthy equipment or missing real problems. This is mainly because they do not consider all possibilities for situations that require alarms, defined by certain fixed criteria. AI models are trained on a variety of datasets representing both healthy and faulty conditions, and can learn to distinguish between normal operational variations and real signs of failure. This leads to more accurate predictions and less unnecessary intervention.

In summary, AI transforms predictive maintenance from a challenging, data-intensive goal into a practical, powerful reality. It enables organizations to use the vast amount of data generated by their assets to make intelligent, proactive decisions that significantly reduce costs, minimize downtime, extend asset life, and increase overall operational efficiency and safety. In this context, AI algorithms form the fundamental building blocks of PdM systems, enabling meaningful inferences to be made. AI not only goes beyond human perception, but also significantly contributes to the process of digitizing maintenance practices by increasing the self-learning, adaptability, and decision-making capabilities of systems

5.1. AI-based Learning Algorithms

In line with the advantages and contributions brought by AI, it is seen that learning with the help of algorithms using the collected and processed data and learning success are the most important factors for all purposes. AI learning algorithms overcome the limitations of traditional methods by equipping predictive maintenance with the ability to "estimation". Thanks to these algorithms, businesses can switch from a failure-focused approach to a data-driven, proactive and optimized asset management strategy. This provides significant benefits not only in terms of cost savings and increased efficiency, but also operational safety and environmental sustainability. Figure 7 shows learning algorithms. Learning algorithms are grouped under 5 main headings.

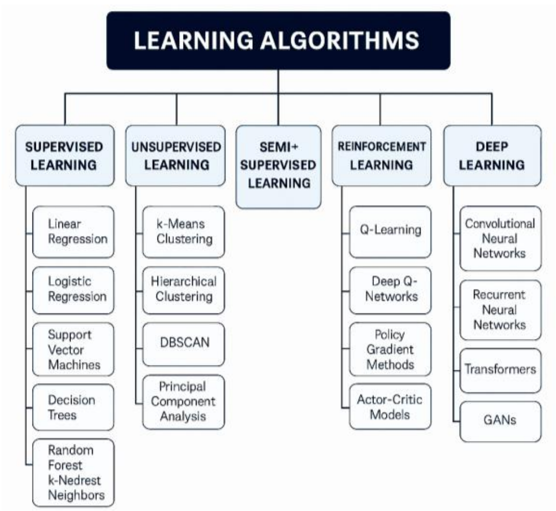

Figure 7. Learning algorithms

Supervised learning, using labeled historical datasets, is widely applied in predictive maintenance (PdM) to predict failure types, maintenance schedules, or remaining useful life (RUL), leveraging algorithms such as Decision Trees, Random Forest, SVM, k-Nearest Neighbor, and regression methods for high prediction accuracy [29, 30]. In contrast, unsupervised learning is effective when labeled data is scarce, employing clustering (e.g., K-Means [31], Hierarchical Clustering [32]) and dimensionality reduction (e.g., PCA [33]) to detect patterns and anomalies in unlabeled data. Semi-supervised learning (SSL) bridges the gap between labeled and unlabeled data, enhancing model performance with limited labeled failure data by using methods like pseudo-labeling [34] and graph-based models [35], enabling scalable and cost-effective PdM. Reinforcement learning (RL), through techniques such as Q-Learning, DQN, and Actor-Critic models, optimizes long-term maintenance strategies by learning through interaction, balancing preventive actions with operational efficiency. Deep learning (DL), increasingly prominent in PdM, excels at processing complex data using architectures like CNNs for image and vibration analysis [36], LSTM and GRU for time series prediction [37, 38], and models like Autoencoders [39] and GANs [40] for anomaly detection and synthetic data generation. Table 2 provides details on these learning algorithms and their usage.

Table 2. The typical use cases of the learning algorithms

Category	Algorithm Name	Typical Use Cases
Supervised Learning	Linear Regression	Predicting continuous values (e.g., temperature, wear rate)
	Logistic Regression	Binary classification (e.g., fault/no-fault)
	Support Vector Machines	Complex classification and regression
	Decision Trees	Interpretable classification and decision support
	Random Forest	Ensemble classification, high accuracy
	k-Nearest Neighbors	Instance-based classification
Unsupervised Learning	k-Means Clustering	Grouping machine states or failure modes
	Hierarchical Clustering	Fault taxonomy and failure mode clustering
	DBSCAN	Anomaly detection in noisy industrial data
	Principal Component Analysis	Dimensionality reduction, sensor fusion
Semi-Supervised Learning	Pseudo-Labeling	Predictive maintenance with limited labeled data
	Graph-based Models	Structure-based pattern recognition
Reinforcement Learning	Q-Learning	Adaptive control systems
	Deep Q-Networks	Real-time scheduling, robot navigation
	Policy Gradient Methods	Dynamic decision policies
	Actor-Critic Models	Energy-efficient control strategies
Deep Learning	Convolutional Neural Networks	Image/spectrogram analysis, visual inspection
	Recurrent Neural Networks	Time-series forecasting (e.g., RUL prediction)
	Transformers	Advanced sequence modeling, anomaly detection

Category	Algorithm Name	Typical Use Cases
	Generative Adversarial Networks	Synthetic data generation for rare faults

As a result, AI algorithms are key components of the analytics and decision support infrastructure of predictive maintenance systems. By providing comprehensive analysis of sensor data, they enable not only early detection of faults but also the development of sustainable and autonomous management strategies for equipment health. With advances in AI, it is anticipated that PdM applications will evolve into more proactive, contextually aware, and continuously learning systems. This transformation will play a critical role in the realization of visions such as digital twins, smart manufacturing, and autonomous system management in Industry 4.0 and beyond.

6. Application Areas of AI-Enabled Predictive Maintenance

As mentioned above, AI-enabled predictive maintenance systems have become one of the fundamental components of digital transformation processes. AI-enabled predictive maintenance technologies are currently being implemented in many sectors, primarily manufacturing, energy, transportation, oil and gas, mining, aviation and defense industries. Each sector customizes and uses AI-based systems in line with its own operational risks, equipment dynamics and maintenance strategies. Figure 8 shows the main application areas of AI-enabled PdM.

Figure 8. Application areas of AI based PdM

As can be seen from the Figure 8, these sectors are among the sectors where productivity should be at the highest level today. The manufacturing sector is one of the areas where artificial intelligence-supported maintenance systems are most widely used. Especially in businesses with continuous lines such as automotive [41], electronics [42] and food production [43], temperature, vibration, sound and electrical signal data from production machines are analyzed with AI algorithms to predict failure probabilities. For example, microscopic vibration changes in joint motors in robotic welding systems are classified as pre-failure symptoms. In this way, unplanned stops are prevented, maintenance time is optimized and the efficiency of the production line is increased.

The Energy Sector is another area where AI-supported PdM systems are of critical importance, especially in renewable energy sources. Thousands of sensor data from wind turbines [44], solar panel inverters [45], hydroelectric power plants [46] and transformer substations [47] are continuously analyzed by machine learning algorithms. Early detection of cracks thanks to aerodynamic vibration analysis of rotor blades in wind turbines is one of the areas of activity of AI-supported architecture. In this way, both energy production continues uninterrupted and maintenance processes are made cost-effective.

In the transportation sector, AI-supported systems are used to monitor brake systems, engines, wheel sets and suspension components in railway systems, maritime transport and road transport vehicles. Especially in railway networks, rail deformations and wheel planes are analyzed using time series data obtained by on-rail sensor systems [48]. Similarly, in aircraft engines, temperature and vibration data can be processed with convolutional neural networks to determine maintenance requirements before the flight [49]. These applications both increase passenger safety and contribute to the on-time operation of flights.

Aviation sector are also one of the most sophisticated areas where AI-supported maintenance technologies are applied. Many components of aircraft, from engines to landing gear, avionics systems to fuel systems, continuously produce data during and after flight. These large data sets can be analyzed by AI-supported systems, and conditions such as wear, temperature increase or pressure changes in critical components can be detected at an early stage [50]. Manufacturers such as Boeing and Airbus track the real-time maintenance status of aircraft using AI-supported digital twin technologies. This not only increases operational continuity but also greatly increases flight safety.

In addition to these sectors, AI-supported PdM has become a frequently used method in the Defense Industry application areas, which always maintains its importance. It requires high-cost and vital equipment to operate safely for a long time. AI-supported PdM systems used in military platforms such as tanks, radar systems, missile launch units, fighter jets and submarines have strategic value in terms of mission continuity and efficiency. Propeller vibration analyses can be performed with data from the engine system in an unmanned aerial vehicle, and preventive intervention can be planned without interrupting the mission in an abnormal situation [51]. At the same time, these PdM systems provide advantages such as optimizing spare part stocks in logistics management and making post-mission maintenance plans more effective.

The success of AI-supported PdM systems depends not only on the power of technology, but also on the organizational capabilities, data management infrastructures, and human resources of companies. It is of great importance for trained personnel to understand AI systems, correctly interpret decision support mechanisms, and ensure that outputs are transferred to practice. For this reason, many leading companies are developing technical training programs and digital transformation strategies in order to adopt a digital maintenance culture at the corporate level. AI-supported maintenance solutions offer integrated benefits not only in terms of fault prevention of industrial operations, but also in terms of cost management, resource planning, and environmental sustainability. In the coming years, these systems will become more intelligent, autonomous, and customizable; It will enable the development of digital maintenance standards across sectors and increase reliability across the industry.

7. Challenges and Solutions in AI-enabled Predictive Maintenance

The effective and sustainable implementation of AI-based PdM systems brings with it many challenges at many levels, from data management to modeling processes, from system integration to organizational change. The success of AI models is directly related to the quality and accessibility of the obtained data to a large extent. In industrial environments, data from sensors can often be noisy, incomplete or inconsistent. The meaningful information carrying capacity of the obtained data decreases due to sensor-related distortions, calibration errors or electromagnetic interference, which limits the learning ability of the models. In addition, communication problems or system outages cause incomplete data; devices from different manufacturers, various data protocols and incompatible formats threaten data integrity. Advanced data preprocessing techniques, statistical interpolation and ML-based data completion methods are used to overcome such problems. In addition, data lakes and ETL processes are put into operation for data integration, and heterogeneous data sources are harmonized in a common schema. Periodic maintenance and calibration of sensors should not be ignored in terms of continuity of data quality, and it is of great importance to obtain accurate data from the field.

Another important difficulty encountered in PdM applications is the process of labeling data. The effective operation of supervised learning algorithms depends on labeled data sets of past failures. However, the fact that failures occur infrequently in industrial systems makes it difficult to collect and label this data. Moreover, the need for technical expertise in this process is high, and human resource and time costs can reach significant dimensions. In this direction, the learning capacity of the model with minimum labeled data is increased with unsupervised and semi-supervised learning approaches, and the labeling process can be optimized by presenting the examples that the model finds uncertain to expert approval with active learning techniques. In addition, artificial failure data is created with physical modeling and simulation-based data generation, and knowledge obtained from similar systems can be transferred to existing models with transfer learning [52].

Another difficulty encountered in the modeling process is the ability of the model to generalize across different operating conditions and equipment types. Models trained with homogeneous and limited data sets can only show high accuracy under certain conditions, but serious performance degradation can occur under different environmental factors or after equipment modifications. Transfer learning strategies and online learning methods are applied to prevent such generalization problems [53, 54]. In these methods, the model gains adaptation ability by updating itself in the light of new incoming data. In order to prevent overfitting, techniques such as regularization, cross-validation, dropout and early stopping are preferred, and context sensitivity is increased by including environmental data as a feature in the model.

Another important issue encountered in the implementation of AI-supported PdM systems is the complexity of integration processes with existing automation infrastructures, control systems and IT infrastructures. The diversity of industrial communication protocols, data incompatibilities and time synchronization problems make this integration difficult.

In addition, while the hardware and software investments required for the implementation of new systems constitute significant cost items, the adaptation of operational personnel to new technologies also stands out as a separate problem. These problems can be overcome with modular and open architectural designs and system preferences that comply with standards. In addition, the establishment of common data platforms and cooperation between IT and operational units are some of the solutions to overcome these problems. In this context, microservice-based structures and API-supported solutions increase the scalability and sustainability of the system.

Along with all this, cybersecurity and data privacy risks also come to the fore in PdM systems. Industrial IoT devices and cloud-based data platforms are vulnerable to threats such as ransomware, DDoS attacks or data manipulation due to their exposure to the internet. In order to prevent these threats, measures such as multi-layered security strategies, encryption algorithms, multi-factor authentication and access controls are implemented. In addition, networks are constantly monitored with attack detection and prevention systems. Companies ensure that security is addressed holistically by providing regular penetration tests, security audits and cyber awareness training for employees.

The human factor and organizational structures also play a major role in the success of AI-supported systems. Lack of technical knowledge, resistance to change, and communication gaps can prevent effective use of systems. In this context, technical and practical training programs, change management strategies that support active participation of employees in the process, and the establishment of open communication channels are of great importance. The support of senior management, the leadership role, and performance-based feedback mechanisms are decisive in the success of such transformation processes.

As a result, the successful and sustainable implementation of AI-supported PdM systems is not limited to technical modeling accuracy alone; it also requires balanced management of data quality, integration, security, and human-management interactions. This multi-dimensional approach emerges as a fundamental requirement for the success of digital transformation processes at both operational and strategic levels.

8. Future Trends in AI-Based Predictive Maintenance

PdM technologies are rapidly advancing alongside the digital transformation of industry, bringing enhanced reliability, efficiency, and sustainability to maintenance processes. These systems leverage artificial intelligence, big data analytics, IoT, edge computing, and digital twins to detect faults in advance, reduce maintenance costs, and improve system performance. While current maintenance decisions still depend heavily on human expertise, emerging autonomous systems are expected to take over these processes. Such systems can monitor equipment in real time, detect anomalies instantly, and autonomously plan and execute maintenance actions—thereby increasing operational efficiency, safety, and cost-effectiveness.

The integration of edge computing and 5G is playing a crucial role in enabling real-time, on-site data processing. This reduces dependence on cloud infrastructure, minimizes latency, and ensures continuous operation even in remote or critical environments such as defense and energy sectors. At the same time, XAI is gaining importance for increasing the transparency and accountability of AI systems. XAI helps users understand how decisions are made, builds trust, supports regulatory compliance, and enables the diagnosis and correction of system errors—key for deploying AI in sensitive industrial environments.

Sustainability is also becoming a central concern in AI-supported PdM. These systems contribute to environmental goals by optimizing energy usage, reducing waste through timely interventions, and extending equipment lifespan. The rise of hybrid models combining human intelligence with AI further enhances these benefits, enabling safer and more informed decision-making. Ultimately, AI-supported PdM is reshaping industrial maintenance into a holistic, strategic function aligned not just with cost-efficiency but also with broader goals like safety, environmental responsibility, transparency, and human-machine collaboration.

Conclusion

Artificial intelligence-supported condition monitoring and predictive maintenance systems offer very important solutions in terms of sustainability, efficiency and reliability in industrial production. In this section, the basic principles of condition monitoring to increase production efficiency are discussed and the integration of artificial intelligence technologies into this field is detailed. Then, the critical role of artificial intelligence-based learning algorithms to perform tasks such as predicting equipment failures and optimizing maintenance schedules more efficiently, as well as artificial intelligence-supported predictive maintenance, is emphasized. The use of artificial intelligence in predictive maintenance offers many important advantages for businesses. These advantages provide significant improvements in operational efficiency, cost savings and overall reliability compared to traditional maintenance methods. Thus, by enabling businesses to switch from a reactive to a proactive maintenance approach, costs are reduced, operational efficiency is increased, equipment reliability and life are extended and overall workplace safety is improved. This provides a competitive advantage and a more sustainable operation in the long term. With the advancement of technology, AI-based CM and PdM processes are also improved. The integration of next-generation technologies such as IoT, digital twins, augmented reality, and blockchain enables these systems to operate more effectively, scalable, and in real time.

Application examples in different sectors clearly demonstrate the prevalence and value of these technologies. However, there are also some technical and operational challenges such as data quality, explainability of algorithms, system integration and security. Solution strategies developed for these problems pave the way for more widespread and effective use of systems. In the future, the role of more autonomous systems, explainable artificial intelligence, edge computing and self-adaptive algorithms will increase in this area. These developments will enable predictive maintenance systems to evolve from tools that only predict failures to decision support systems. As a result, AI-supported condition monitoring and predictive maintenance will become an integral part of the digital transformation process, enabling industrial systems to become more intelligent, flexible and resilient.

As a result, AI transforms condition monitoring and predictive maintenance from mere technological tools into a strategic asset that increases the competitiveness of businesses, reduces costs, improves safety and supports sustainability. In the process of adapting to Industry 4.0 technologies, AI-supported maintenance has become an indispensable part of achieving operational excellence.

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CHAPTER 5

HUMAN-ROBOT INTERACTION AND ROBOTIC SAFETY: CHALLENGES AND SOLUTIONS FOR SUSTAINABLE AUTOMATION

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1. Introduction

The trend towards automation, which means sharing a job between humans and machines, and the demand for industrial robots have increased significantly. From 2015 to 2020, annual installations have increased by an average of 9% each year. The five largest markets for industrial robots are China, Japan, the United States, the Republic of Korea, and Germany. These countries account for 76% of global robot installations. When looking at the sectors where robots are used the most in the industry, the electrical-electronics, automotive, and metal-machinery sectors are at the top [1].

With the increasing use of robots in production, the importance of robot-human interaction, an important concept, is emerging. Human-robot collaboration is a key factor for the development of factories of the future where humans and robots can work together and perform tasks. Robots can make powerful movements that can pose a danger to people around them. Therefore, since the potential danger from robots will also increase significantly, new occupational safety and health issues are on the agenda. Both OSHA and RIA have issued standards on this subject and have introduced regulations for robot production, installation, operation and maintenance. When OSHA records since 1984 are examined, it has been determined that there have been 46 robot accidents in the USA, but these accidents have been more frequent in the last 10 years when the use of robots in industry has increased. Another situation that stands out according to these records is that the death rate in industrial robot accidents is quite high [2,3].

The complexity of tasks performed by robots, the degree of autonomy and self-learning capabilities of robots have been constantly increasing since the creation of the first industrial robot in 1937. Currently, there are three categories of robots: i) industrial robots; ii) professional and personal service robots, and iii) collaborative robots.

The International Organization for Standardization (ISO) defines an industrial robot as “an automatically controlled, reprogrammable, multi-purpose manipulator that can be programmed in three or more axes, fixed in place or mobile, for use in industrial automation applications.” [4]. Figure 1 shows the workspace of an industrial robot.

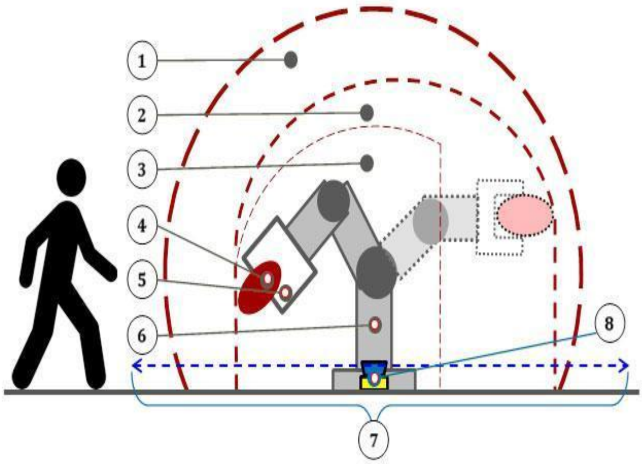

Figure 1. Working space of an industrial robot [5]

This figure shows the regions and components: 1. maximum space, 2. restricted space, 3. operating space, 4. workpiece, 5. end-effector, 6. Manipulator, 7. safeguarded space and 8. protective device or barrier. Industrial robots are characterized by high strength, durability and precision and are widely used for welding, painting, assembly, transportation and testing. These robots can make powerful movements that can be dangerous to people around them. Considering that today, people must cooperate more closely with robots than ever before to ensure production efficiency, quality and continuity, the potential for robots to harm people is also increasing day by day. The most important question we face here is whether these industrial robots, which are widely used in production, can be used collaboratively.

The IFR defines industrial cobots as robots designed for collaboration in industrial environments, typically complying with safety standards such as ISO 10218-1 [6]. Their main advantages include improved safety, increased flexibility and ease of programming, simpler integration, potential cost efficiency, improved productivity and quality, space savings, and assistance in eliminating labor shortages. Despite these benefits, cobots have certain limitations. They generally have lower payload and speed capacities than traditional industrial robots, making them less suitable for very heavy or high-speed tasks. They may also not be ideal for high-precision applications. These disadvantages have a detrimental effect on production efficiency. For this reason, the high operating speeds of industrial robots also necessitate the design of an effective safety system that will increase human-robot interaction.

2. Effect of Robot Safety Application on the Efficiency of Manufacturing

Implementing robot safety applications in production ensures workplace safety while significantly increasing operational efficiency. These systems prevent accidents and injuries, while also positively affecting productivity, reliability and workflow flexibility. Safety measures such as emergency stop systems, collision prevention mechanisms and protective barriers help prevent accidents such as collisions and injuries that can stop production [7].

The development of collaborative robots that include sensors and force-limiting features makes it possible for humans and robots to work side by side safely, reducing the need for physical barriers such as cages, allowing for more flexible workflows and more efficient use of floor space. This allows workers to interact directly with robots, significantly increasing task allocation and the speed of response to changing production needs. In terms of productivity, adaptive safety applications allow robots to adjust their speed and behavior according to human proximity. For example, a robot can work at full speed when there is no human around, but when a person enters the work area, it can automatically change its speed according to the proximity of the human. This dynamic operation helps maintain high productivity levels while keeping safety at the forefront and ensures continuous/efficient work in production.

In addition to increased productivity, another important aspect is the contribution of safety systems to occupational safety. These robot safety systems contribute significantly to reducing injuries that occur as a result of errors made by employees in the robot operating environment. By preventing human presence or predicting and anticipating human movements, potential accidents are prevented and human health is prioritized in the working environment. Although the integration of robot safety applications involves significant initial costs and system complexity, these investments are usually offset by long-term benefits. Increased safety means fewer interruptions, better compliance with safety regulations, and lower overall operational risks, allowing manufacturers to better comply with international safety standards. Finally, since many modern robot safety systems also include monitoring and data collection capabilities, these systems provide valuable information about robot-human interactions, near-miss accidents, and usage habits. Manufacturers can analyze this data to continuously improve processes and conduct studies on safety/performance optimization. Table 1 briefly summarizes the effects of robotic safety systems on production efficiency.

Table 1. The effects of the robot safety system on manufacturing efficiency

Effect	Positive Impact on Efficiency
Accident prevention	Reduces downtime and production halts
Human-robot collaboration	Enables flexible, efficient workflows
Adaptive robot behavior	Balances speed and safety for optimized productivity
Lower injury and error rates	Improves worker availability and task accuracy
Real-time data from safety systems	Improves worker availability and task accuracy

3. Hazards Posed by Industrial Robots

The ANSI Standard recommends that the speed of robots not exceed 250 mm/sec while performing their tasks [8]. It is almost impossible for robots moving at these speeds to stop in time when a person or object enters the work area. Most industrial robots are unaware of their surroundings and can be dangerous to humans. Industrial robots can pose the following types of dangers depending on their type and the tasks they perform [9].

- Mechanical hazards, such as those resulting from unintended and unexpected movements or release of tools
- Electrical hazards, such as contact with live parts and connections or exposure to arc flash
- Thermal hazards such as hot surfaces or exposure to extreme temperatures
- noise hazards
- other hazards such as vibration, radiation and chemicals

Due to all these dangers, an effective robotic safety system is needed that will also regulate the cooperation of humans and robots. Otherwise, the robot may not notice a human entering the work area and may cause injury or death. On the other hand, if the robot stops after detecting a human entering the work area, it will reduce production efficiency and increase production costs in the time it takes to work again. An effective robotic safety system must take all these situations into account and provide the most active and efficient safety according to certain criteria. The right choice of a robotic safety system should be based on the hazard analysis of the operation involving a particular robot.

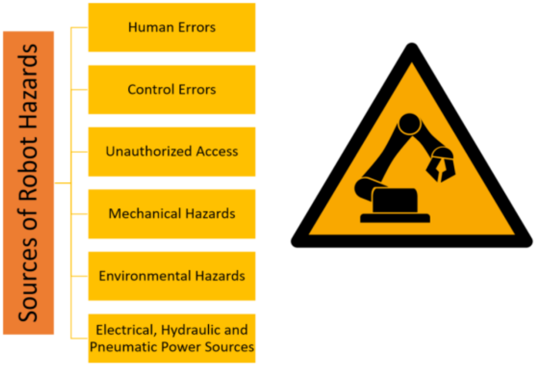

Figure 2. Robot danger sources

Figure 2 shows common sources of danger associated with industrial robots. Human errors, such as misunderstandings about the direction of motion or incorrect activation of controls during integration and programming, are major concerns. Control errors resulting from software errors, electromagnetic effects, or problems with the robot's hydraulic, pneumatic, or electrical sub-controls can also lead to dangerous unexpected actions. Furthermore, unauthorized access to restricted robot areas poses risks due to lack of familiarity with hazards and safety precautions. Additional critical hazard sources include cumulative wear that is not addressed, time pressures leading to ignored safety procedures, and mechanical failures due to adverse environmental conditions such as exposure to water, heat, or flammable atmospheres. Power system failures or failures in pneumatic, hydraulic, or electrical components can disrupt robot operation and create risks of fire or electric shock. Finally, improper assembly and installation that do not comply with safety codes and standards can create inherent hazards within the design and layout of the robot application. Therefore, proactively addressing these potential hazards throughout the robot's life cycle is crucial to ensuring a safe work environment [5,10].

There are two main categories of worker injuries that result from working around robots: engineering errors and human errors, as shown in Figure 3.

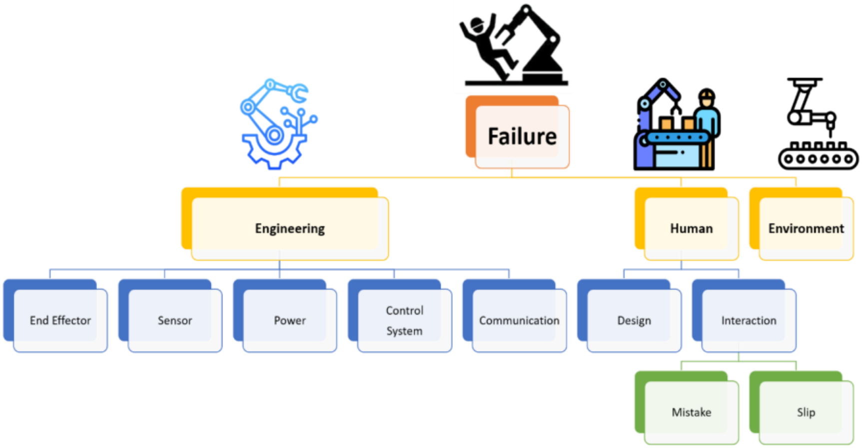

Figure 3. Sources of worker injuries in robot-human interaction

Engineering errors include errors in the robot's mechanics and errors made by the controller. For example, robots may not stop, or a robot arm may produce high, uncontrolled speeds, sudden movements, or accelerations. Programming errors include errors such as failure to communicate between interfaces and failure to successfully interpret data from sensors used for human detection. These errors can result in unpredictable movements or actions by the robot that could result in personnel injury or equipment failure.

4. Industrial Robot - Human Interaction and Safety

Human-robot interaction (HRI) is an interdisciplinary field of study in which humans communicate and collaborate directly or indirectly with robots. This interaction must be designed to enable robots to work safely, efficiently and effectively with humans. HRI is directly related not only to the technical characteristics of the robot but also to human psychology, perception capacity and social behavior.

4.1. Human Robot Interaction Principles

The basic principles of HRI consist of five main points. Figure 4 shows these main principles [11].

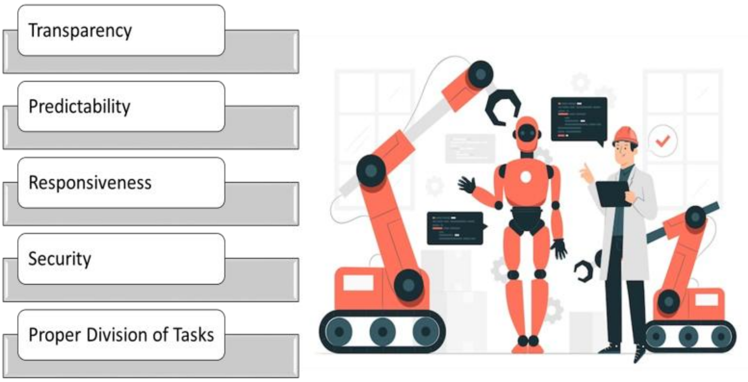

Figure 4. Five basic principles of robot-human interaction

The definition, applications and benefits of these principles are summarized in Table 2.

Table 2. Basic principles of human-robot interaction

Principle	Definition	Technical Application	Benefits
Transparency	Providing information to the user about what the robot is doing and why it is doing it	Status indicators, audio/visual notifications, explainable AI	Trust formation, user awareness, ease of control
Predictability	Consistency and predictability of robot behavior	Fixed timing, repetitive movements, advance warning signs	Ease of coordination, error reduction, security
Responsiveness	The robot responds quickly and appropriately to environmental and user inputs	Real-time sensors, voice command recognition, fast response algorithms	Efficiency, user satisfaction, intervention safety
Security	Design approach that provides protection from physical and cognitive hazards	Force-limiting systems, collision avoidance devices, emergency stop buttons	Reducing accidents, legal compliance, user safety
Proper Division of Tasks	Sharing of human and robot tasks according to capabilities	Dynamic task assignment, hybrid decision systems, competency-based distribution	Collaboration efficiency, load balancing, system flexibility

5.2. Human Robot Interaction Models

HRI can be defined by various models according to the nature of the interaction, the level of decision sharing and the task structure. These models help designers and developers to make systems more understandable, safe and efficient. HRI models facilitate decision making in the design, evaluation and implementation processes of human-robot systems. The choice of model type depends on the application context, task type, user profile and security requirements. HRI models are shown in Figure 5.

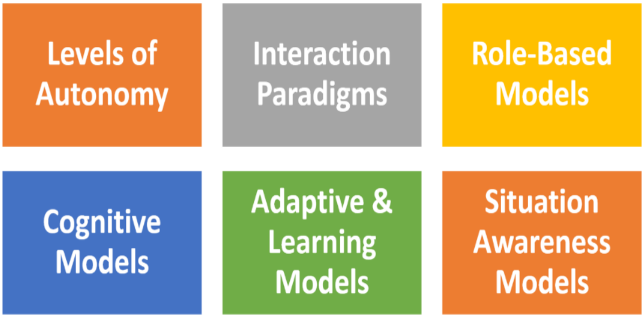

Figure 5. Models of HRI

5.2.1. Levels of Autonomy

The robot's decision-making capacity and control level are classified according to their autonomy levels. This model is used especially when making critical decisions in terms of work safety, system complexity and user experience [12]. This classification and usage areas are given in Figure 6.

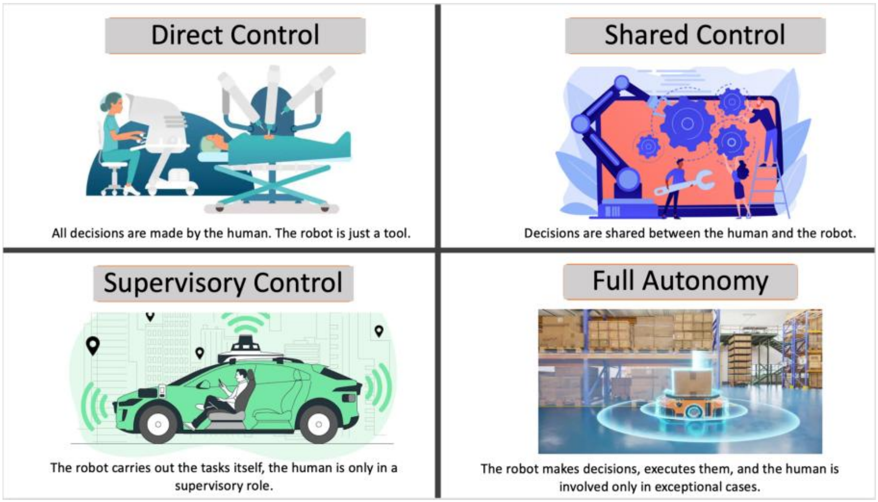

Figure 6. Levels of Autonomy

5.2.2. Interaction Paradigms

This model, classified according to the structure of the interaction, defines the relationship between the human and the robot on the task. This model is important in terms of defining the role of the robot and the user expectations [13]. Table 3 also provides the contents and application areas of these relationship types.

Table 3. Interaction Paradigms Model Features and Applications

Paradigm	Definition	Application Areas
Teleoperation [14]	The human controls the robot in real time.	Medical robots, military robots
Task Based Interaction [15]	The human gives the goal, the robot determines the appropriate steps.	Logistics robots, cleaning robots
Cooperative Cooperation [16]	Human and robot perform the same task together, physically or cognitively.	Assembly line cobots
Social Interaction [17]	The robot responds to the human in a socially appropriate manner.	Social assistant robots, service robots

5.2.3. Role-Based Models

In this approach, the roles of the human and the robot within the task are clearly defined. These roles can be variable and reassigned according to the context. In the Supervisor model, the human controls the entire process and the robot implements the given tasks. In the Teammate model, the human and the robot share the work equally in the process being worked on and the work is carried out with a 50% partnership. In another model, the Assistant model, the human is involved in the process and performs the tasks. The robot acts as an assistant supporting the human. In the Trainer/Student model, the roles are shared as trainer and learner [18,19]. One of the robots or humans helps the other learn tasks and supports the learning process in this process. Role-based models are used in contextual areas such as education, health and rehabilitation.

5.2.4. Cognitive Models

Cognitive models developed in the field of HRI allow the robot to better predict human behavior by taking into account important psychological factors such as decision making, attention allocation, and trust. Trust Models allow the robot to perform its function by adjusting its behavior according to the user's trust level [20]. Cognitive Load Models [21], which monitor the mental load on the human and enable the robot to take more responsibility according to the situation, and Intention Prediction Models [22], which enable the robot to take supportive actions by predicting what the human wants to do, are among the most frequently used cognitive models. Such cognitive approaches contribute greatly to making the interaction between humans and robots more fluid, efficient and personalized, especially in artificial intelligence-based HRI systems.

5.2.5. Adaptive and Learning Models

Adaptability and learning, a critical dimension for HRI, involves robot systems optimizing their behavior by learning according to user habits, environmental conditions, or task characteristics. In this context, Reinforcement Learning-Based Interaction approaches stand out, which enable the robot to learn from experience and collaborate better with humans [23]. Additionally, models such as User Profile-Based Adaptation [24], which allows the robot to optimize its response patterns according to different user types, and Human-Error Compensatory Systems [25], which detect and automatically correct human errors, are also being developed. Such adaptive and learning models form the basis for human-centered and personalized interactions.

5.2.6. Situation Awareness Models

For operating HRI systems reliably and effectively, it is a basic requirement that the robot accurately perceives and understands environmental conditions, human movements and contextual information, and acts accordingly [26]. This critical capability is often addressed through a staged model: The first level is Perception, which involves the robot using sensor data to recognize and locate objects, people, and their key features in its environment. The second level, Understanding, involves taking this perceived information and interpreting the meaning of the current situation, establishing relationships between events, and figuring out the context of the interaction; that is, not just seeing what happened, but understanding why or how it happened. Finally, the third level, Prediction, aims to predict what might happen in the future, specifically the human's next move, intention, or potential problem, based on the current level of perception and understanding. The robot's ability to use this perception, understanding, and prediction capabilities in an integrated manner is of great importance for the stability, safety, and smooth interaction of HRI systems, especially in environments where variable and complex multitasking is performed [27].

6. Robotic Safety

Since robots can make high-energy and fast movements beyond their size, the serious dangers they can create were given in the previous section. Even small changes in the working environment can affect the behavior of the robot. In addition, maintenance workers, operators or programmers may have to work in narrow spaces with systems under energy. This increases the risk of injury from physical contact, pinching or flying objects. Although robots are usually equipped with safety monitoring systems, software or hardware failures can also lead to unexpected dangerous situations. For this reason, robots must constantly monitor the people in the environment and adapt their behavior according to many variables.

Robotic Safety refers to systems, standards, and practices designed to ensure that robotic systems operate without harming people, equipment, or the environment [28]. As robots become increasingly autonomous and integrated into human environments, security has become multidimensional. Robot security is generally divided into three main types: ethical security, physical security, and functional security. Ethical (Socio-Technical) Security, a critical aspect of robotic security that is becoming increasingly evident and goes beyond mere technical dimensions, addresses the broad moral, legal, and social implications of robot behavior. The main goal of this type of security is to ensure that robots' actions, especially in autonomous decision-making processes, are consistent with human values, existing laws, and established ethical norms. This area covers basics such as ensuring that robot decisions are transparent and explainable in a way that can be understood by humans, avoiding harmful outcomes such as manipulating humans, and protecting individuals' privacy and data. Areas that interact directly with humans, such as healthcare robots, social and service robots, and potentially sensitive applications such as autonomous weapons and surveillance systems, are common areas where ethical security is of the utmost importance [29].

Physical Safety focuses on the mechanical design of the robot and the spatial configuration of the workspace to minimize the risk of injury that may arise from physical interaction between humans and robots. This type of safety primarily emphasizes hardware-level measures. It can be provided by measures taken within the robot itself (e.g. mechanical restraints or software-implemented force/torque limits) and is reinforced by strategies that regulate the robot's environment. These strategies include creating protective barriers and cages that prevent humans from entering the robot's dangerous movement area. Also, using cooperative modes such as Force and Force Limitation in situations where humans and robots share the same space is part of physical security [30]. The process of determining and implementing all these physical security measures begins with risk assessment and hazard identification studies in line with standards such as ISO 12100 and can be supported by technologies such as work area monitoring systems.

Functional Safety focuses on ensuring that the robot's control systems and software behave safely even in the event of malfunctions or unexpected situations. The main purpose of this approach is to prevent dangerous situations that may arise from system malfunctions, software errors or control system irregularities. The sub-components of this approach include emergency stop functions that can be activated at any time, redundant sensors and actuators, safe motion control mechanisms that keep the robot's speed, force and motion trajectory within safe limits, and controlled stop functions defined according to standards [31].

6.1. Standards

In order for robotic systems to work safely in their workplaces, it has become necessary to take into account certain standards from production to application. For this purpose, standards have been regulated at both international and national levels. Three of the most widely known and complementary standards are ISO 10218, ISO/TS 15066 and ANSI/RIA R15.06. The ISO 10218 standard is the primary international safety framework for industrial robot systems and focuses on traditional separate workspace safety. ISO/TS 15066 is a supplementary guide to ISO 10218-2 that provides more detailed requirements for collaborative robot applications that ensure the safety of humans and robots in shared or shared workspaces. ANSI/RIA R15.06 is the US equivalent of ISO 10218. The basic safety principles are the same but include details specific to US laws and practices. When designing and integrating a collaborative robot system, the basic safety requirements of ISO 10218 (ANSI/RIA R15.06) must first be met and then the additional guidelines and requirements in ISO/TS 15066 for collaborative features must be applied. Table 4 compares these standards with each other.

Table 4. Comparison of the international and national standards.

Property	ISO 10218 [6]	ISO/TS 15066 [32]	ANSI/RIA R15.06 [33]
Primary Focus / Scope	Basic safety requirements of industrial robots and robot systems. Addresses common hazards.	Additional requirements and guidelines specifically for collaborative robots (cobots) and collaborative applications	Safety requirements for industrial robots and robot systems in the USA. Essentially the same scope as ISO 10218.
Basic Concepts and Requirements	Risk assessment (basic), safety functions (safety-rated stops, speed limits), protective measures (fences, light curtains), layout requirements, testing, documentation. Focuses on traditional industrial robot safety (zone separation).	Based on risk assessment in ISO 10218. Detailed requirements specific to types of collaborative work, including power and force limitation (PFL) details, pain threshold limits for different body parts (informative appendix), safety-rated supervised stance, speed/distance monitoring and hand guidance.	It covers largely the same concepts as ISO 10218. Risk assessment, safety functions, system layout, etc. There may be some minor differences or references specific to US practices or regulations (e.g. OSHA).
HRI Emphasis	Focuses on separating humans from hazardous robot movements with physical barriers or safety functions. Limited focus on direct human-robot interaction during operation.	Very high emphasis. Details the safety of collaborative work types where humans can safely share the same workspace with robots and even physically interact with them under controlled conditions.	Focuses on traditional separation methods, similar to ISO 10218. For collaborative HRI, reference is usually made to the relevant parts of ISO/TS 15066 or its US adaptations.

6.2. Modes of Collaborative Operations

Four basic collaborative operation modes have been defined by international standards: Safety-Rated Monitored Stop (SMS), Hand Guiding (HG), Speed and Separation Monitoring (SSM), and Power and Force Limiting (PFL). These modes have been developed to ensure safe human-robot interaction, and each includes different safety approaches. These modes directly affect the safety and efficiency of collaborative applications and, depending on the application context, a single mode or a combination of them can be preferred. A comprehensive risk assessment during the design and commissioning of collaborative robot systems is essential to ensure the correct and safe implementation of these modes.

SMS mode is the most basic collaborative mode. When a human operator enters the collaborative work area, the robot is safely stopped by the safety system and this stop is constantly monitored. The robot does not move until the human leaves the area or safety conditions are met. This mode is used when people work separately from the robot but occasionally need to enter the robot's work area [6,32].

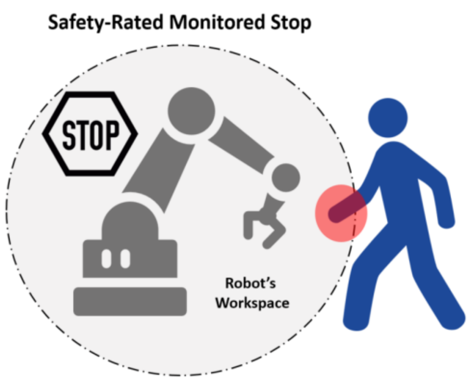

Figure 7. Level 1: Safety-rated monitored stop

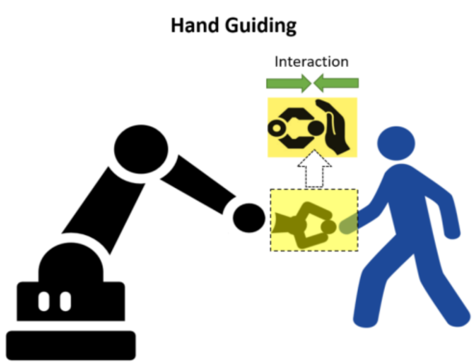

Figure 8. Level 2: Hand Guiding

In HG mode, the operator moves the robot directly by hand or using a hand-guided device. It is typically used for teaching or precise positioning tasks. Safety is ensured by limiting the robot’s speed to a certain degree while it is being guided by a human, and by triggering a rapid safety stop in the event of an emergency (e.g. releasing the hand-guided button, applying excessive force) [6,32].

SSM mode is a mode that increases productivity for production. In this mode, the robot's speed is dynamically adjusted according to the distance between the human and the robot. The robot constantly monitors the human's position and speed. The robot slows down as the human approaches and automatically switches to SMS mode when the minimum safe distance defined in the safety standard is exceeded. This mode is suitable for applications where humans and robots work in the same area but without physical contact [6,32].

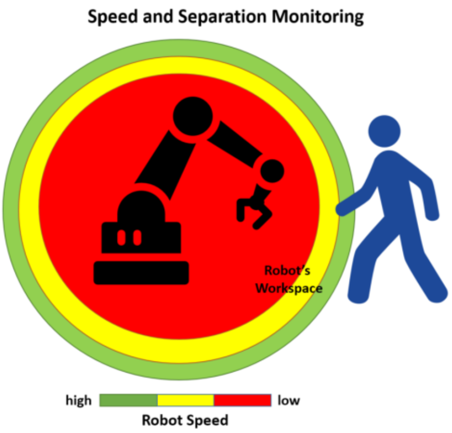

Figure 9. Level 3: Speed and seperation monitoring

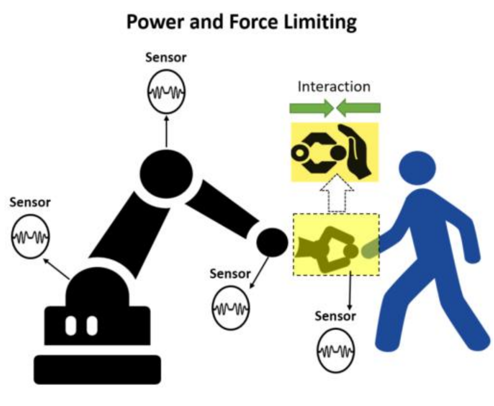

Figure 10. Level 4: Power and force limiting

The PFL mode is designed for applications where physical contact between humans and robots is expected or occurs in a controlled manner. Safety is ensured by limiting the robot's power and the forces it can apply in a way that will not harm the human or exceed pain thresholds in the event of a collision. The ISO/TS 15066 standard provides detailed guidelines on the force and pressure limits that can be applied to different body parts for this mode. This mode is used in scenarios where the robot works in direct contact with humans and requires the highest level of risk assessment sensitivity [6,32]. The comparisons of these modes are given in the table below.

Table 5. The comparison of the four forms of collaboration

Mode	Description	Physical Contact	Sensor Requirements	Advantages	Limitations	Typical Application
SMS	Robot stops when a human enters the shared workspace; resumes when the human leaves	No	Area scanners, safety sensors	Simple setup, compatible with conventional robots	Process stops during human interaction	CNC loading, packaging
HG	Human directly guides or positions the robot by hand	Yes (controlled)	Force-sensing end-effector	No programming needed, user-friendly	Limited to teaching/programming phases	Training, positioning
SSM	Robot slows or stops as a human approach; no physical contact occurs	No	Cameras, LIDAR, radar, etc.	High productivity, contact-free collaboration	Requires complex sensing infrastructure	Palletizing, material handling
PFL	Robot stops automatically upon contact; force and speed are limited to ensure safe interaction	Yes	Force/Torque sensors	Safe physical interaction, direct collaboration	Limited payload and speed	Assembly, test lines

6.3. Basic Components of Robotic Safety Systems

Robotic safety design elements are important components that ensure the safe operation of robots, especially when robots interact with humans or operate in environments where errors/failures can lead to accidents. The main approach to industrial robot safety is to maintain a safe distance between human workers and working robots by creating “protected areas.” Workers entering a safe protected area will require the robot to be shut down. Shutting down a robot for safety reasons on a robot assembly line can significantly reduce productivity. In addition, it has been observed that fencing in the robot work area reduces the space utilization efficiency of the factory. This measure is impossible to use when robots work collaboratively with humans. This reduces both the layout efficiency and the production efficiency.

For this reason, new proactive solutions have been developed for security measures with the developing technology. These more technological security elements include sensors, locks and emergency stops. These components play critical roles in protecting both humans and machines from hazards. Integrating these security elements is very important to protect workers, optimize human-robot collaboration and maintain system reliability. Table 6 provides brief descriptions of these components, their basic features and main examples in robot systems.

Table 6. The comparison of the four forms of collaboration

Element	Description	Key Function	Example
Sensors	Detect environmental conditions and robot behavior	Enable safe interaction, collision avoidance	Proximity sensors, vision systems, force sensors
Interlocks	Safety mechanisms that prevent unsafe robot actions	Prevent robot operation in unsafe conditions	Physical interlocks (gates), software interlocks (limits), electrical interlocks
Emergency Stops	Immediate manual or automatic stop of robot operations	Provide a fail-safe mechanism to halt operations	Emergency stop buttons, automatic stops via sensors

6.4. Technological Solutions and Innovations on Robotic Safety

In HRI environments where humans interact directly with robots, human safety is at the forefront. Technology areas aimed at improving robot safety include advanced sensing systems, AI-supported intent recognition and behavior prediction, real-time safety monitoring and safety mechanisms, and the use of simulation and digital twins for safety testing and verification using wearable and environmental sensors that detect human presence. These technologies positively affect both human safety and production efficiency by focusing on preventing accidents, reducing hazards, and increasing productivity through smarter and safer systems [34]. A robot's ability to perceive its environment enables navigation, obstacle avoidance, and informed decision making for safe operation [35].

Table 7. Comparison of Advanced Perception Sensor Modalities for Robotic Safety [36,37]

	Key Strengths	Key Weaknesses	Primary Safety App.
Lidar	• High accuracy distance measurement; • 3D mapping; • Good resolution; • Verifiable geometric algorithms	• Adverse weather sensitivity; • Poor detection of transparent/reflective objects; • Cost; • Potential speed/accuracy trade-off	• SLAM; • Obstacle avoidance; • Navigation; • Safety zone monitoring; • Distance measurement
Vision	• Rich semantic/color/texture info; • Object recognition; • Relatively low cost (cameras)	• Lighting/weather dependent; • Occlusion sensitive; • High computational cost; • Verifiability issues; • Privacy concerns	• Human detection/tracking; • Gesture/Action recognition; • Object identification; • SLAM; • Grasping validation
Radar	• Robust in adverse weather; • Direct velocity measurement; • Good range	• Lower resolution; • Poor detection of static objects; • Limited semantic info	• Collision avoidance; • Velocity estimation; • Long-range detection
Proximity	• Detects transparent/reflective objects (Ultrasonic); • Contact/Force sensing (Tactile); • Low cost; • Occlusion-free (Skins)	• Limited range; • Environmental sensitivity; • Lower accuracy /resolution; • Limited detection scope	• Close-range obstacle avoidance; • Physical contact detection; • Proximity alerts; • Tactile interaction

As mentioned above, data from LIDAR, camera, radar and proximity sensors can be processed together or alone to create a large amount of data for an effective security system. In addition to many studies where data from these sensors are used alone, sensor fusion techniques are also frequently used in the literature to use and interpret data from these sensors together for more advanced and high-perception systems. Because there are certain advantages and disadvantages in using these sensors alone. A comparison of these sensors is given in Table 7.

Given that individual sensors have inherent limitations, sensor fusion is a key requirement to achieve robust and reliable perception in complex and dynamic environments. This approach overcomes the shortcomings of a single sensor, offering significant benefits such as higher accuracy, improved reliability against sensor failures or adverse conditions, and the ability to perform more complex perception tasks required for safety [38]. However, sensor fusion brings its own challenges. System complexity increases significantly, and accurate data synchronization and temporal alignment across different sensors can be challenging. Additionally, processing multiple data streams and running fusion algorithms can be computationally expensive. Precise calibration across different sensor coordinate frames is essential, and it is necessary to design optimal strategies that effectively combine information from multiple sources [39]. Although advanced artificial intelligence techniques provide high detection performance, the difficulty of formal verifiability in terms of security limits the use of these techniques in critical applications. Therefore, hybrid architectures such as the Simplex model and layered security systems are gaining importance [40]. With future developments, more transparent artificial intelligence models and secure system designs integrating components with different verification levels will also help increase security levels.

Artificial intelligence (AI) is moving beyond reactive obstacle avoidance to enable proactive systems that can understand human intentions and predict future behaviors. This capability is critical to achieving safe and smooth HRI. AI-powered predictive capabilities significantly increase robot safety by enabling proactive and adaptive behaviors. This allows robots to predict human trajectories to avoid collisions, adjust their movements accordingly, and synchronize tasks more efficiently by understanding human intent. Additionally, robots can adapt their behavior to human states, such as fatigue or focus, and use tools such as augmented reality to structure workspaces that guide human movement and increase predictability. Despite these advances, several challenges prevent the full realization of AI-powered safety in robotics [41]. Predictive models are inherently probabilistic, which can compromise security if not handled properly. Real-time performance is limited by computational demands, especially on limited hardware. Furthermore, human trust in predictive robots should also be questioned, as both mistrust and overconfidence can pose risks. Trust in the awareness of robot systems to correctly interpret human actions is difficult to achieve. Finally, it raises ethical concerns around privacy, potential misuse of predictive systems, and questions of accountability in AI-driven decisions.

To address these concerns, robotic systems must meet certain design principles. Real-time monitoring of system status (Safety monitors etc.) is crucial to ensure a safe condition in the event of component failures, incorrect predictions or violation of safety restrictions [42]. The fail-safe design principle ensures that the system switches to a safe mode in the event of a failure, and Runtime Assurance architectures offer hybrid control systems where verified safe controllers replace potentially unsafe high-performance controllers [43,44]. Various software frameworks support the implementation of these security policies. Robot Operating System (ROS)-based systems allow for the automatic creation of monitoring nodes with tools such as FRET and Copilot [45,46]. RTA frameworks such as SOTER [47] provide modular and verifiable control structures. Layered architectures and programmable controllers (PLCs) enable safety-critical functions to override higher-level commands. Digital twins provide continuous monitoring by comparing real-time behavior of robots with virtual models [48].

Another technology is to ensure human safety through wearable technologies. Wearable sensors are worn by human operators and provide direct information about the operators' status, position or actions. Common examples include IMUs, EMG sensors, ECG/EEG, UWB or RF tags, capacitive vests, smart textiles and gloves containing various sensors, and AR headsets with embedded sensors for location tracking [34]. This wearable technology provides direct, potentially highly accurate measurements of user state and movement. However, it also has its drawbacks. It requires active participation and compliance from users, and raises issues of comfort, intrusiveness, and acceptance. Disadvantages include limited battery life, potential sensor drift, signal noise, cost, and setup/calibration time [49].

Digital Twins (DTs) are used for the design, testing, validation and optimization of robotic systems and safety features [50]. Virtual environments offer comprehensive methods for safety testing and verification of robot systems. Simulation-based testing enables testing of both software and hardware components by evaluating robot controllers and system behaviors in virtual environments with tools such as Gazebo, Pybullet or Unreal Engin [51]. Digital twins provide bidirectional data flow between both virtual and physical systems by synchronizing with real-time data from physical robots. These structures enable the safe testing of various operational scenarios, verification of virtual security zones and sensor placements, and control of security systems before they are deployed [50].

In addition, by integrating digital human models into simulations, ergonomic risks can be analyzed and safety protocols can be tested in tasks involving HRI. AI algorithms can be trained and tested safely in these virtual environments to prevent accidents that may occur in the real world; this is especially critical for complex systems such as reinforcement learning and perception models. In addition, DTs can be integrated into optimization processes to find ideal system parameters in terms of both safety and efficiency [52].

Table 8. Comparison of advanced perception sensor modalities for robotic safety

Benefit	Description
Cost and Time Efficiency	Reduces the need for physical prototypes and real-world trials, speeding up design, validation, and deployment processes.
Enhanced Safety during Development	Enables testing of hazardous scenarios without risking human safety or equipment; supports proactive risk management.
Improved Analysis and Optimization	Offers a platform for detailed performance assessments, layout/trajectory optimization, and predictive maintenance planning.
Data Generation	Produces large, labeled synthetic datasets essential for training AI models, especially in data-scarce environments.
Thoroughness and Repeatability	Allows exhaustive testing under diverse conditions with high repeatability, unlike variable real-world testing environments.

All these technological solutions and innovations pave the way for robots to collaborate safely and efficiently with humans in industrial and service environments, thus increasing both occupational safety and significantly increasing operational efficiency.

7. Future Outlook and Research Directions

In the future, robot security systems will gain great importance in an environment where robots work more closely with humans, their autonomy levels increase, and decision-making mechanisms become more complex. In this direction, physical security systems will be equipped with more advanced perception and response capabilities. Thanks to lidar, radar, depth cameras, and artificial intelligence-supported sensors, robots will be able to perceive people, objects, and potential dangers around them much more precisely. These perception systems, combined with collision prevention algorithms, will enable robots to operate safely without harming their surroundings.

As robots become smarter and integrate with AI, future systems will rely heavily on seamless human-AI collaboration. The focus in the future will be on developing frameworks that define how humans and AI systems can interact more effectively toward a specific goal. These frameworks will aim to optimize task allocation, decision-making, and real-time adaptation, and to ensure that AI complements rather than replaces human capabilities. Effective human-robot-AI collaboration will become essential in high-risk environments such as healthcare, defense, and disaster response. As robot systems and multi-human and multi-robot environments increasingly increase the efficiency of work, ensuring robot safety is becoming significantly more complex. It is anticipated that there will be an increasing need for scalable security architectures that can manage dynamic interactions between robots and humans, such as evaluating data from multiple sensors and integrating security systems with technologies such as AI. This includes decentralized coordination, predictive collision prevention, and robust fail-safe mechanisms that operate in real time. Such systems should also be flexible enough to accommodate unpredictable human behaviors and heterogeneous robotic platforms. In addition, the fact that robots will operate more networked and data-driven in the future will also bring cybersecurity risks to the forefront. Strong authentication systems, end-to-end data encryption, and secure communication protocols will ensure that robots are protected against both external threats and internal threats.

To build trust and accountability in automated systems, robots must be able to explain their decisions and actions in terms that humans can understand. Future research will focus on developing intuitive interfaces and visualization tools that help users understand robotic reasoning, allowing for better control and faster resolution of errors or unexpected actions. The development of Explainable Artificial Intelligence (XAI) techniques and the ability to provide customized explanations to different user groups is also an important subfield. XAI describes the ability of humans to understand how AI systems work so that they can trust them [53]. Therefore, explainability is not only a technical requirement but also a legal and social imperative.

8. Conclusion

In this section, the basics of robot-human interaction and its effects on productivity are examined in general. In this context, robot hazards, human-robot interaction principles and modes determined by standards are emphasized. Afterwards, robot safety systems, components and more technological solutions offered for safety systems are mentioned. When all these are considered, it is seen that robotic safety systems are very important in terms of both productivity and work safety.

In terms of work safety, these systems minimize potential hazards by preventing or stopping human entry into the robots' work areas. Thanks to equipment such as emergency stop buttons, safety sensors and laser scanners, the risk of injury to personnel working with robots is significantly reduced. This both protects the health of employees and reduces costs (medical expenses, compensation, loss of production, etc.) resulting from work accidents.

In terms of production efficiency, robot safety systems reduce malfunctions and downtime, ensuring the uninterrupted operation of the production line. A safe working environment leads to more motivated and focused employees, which reduces errors and the need for rework. In addition, the ability of robots to work faster and more safely increases production capacity and shortens delivery times. As a result, robot safety systems both protect human life and fulfill social responsibility, while also providing a competitive advantage by helping businesses achieve operational excellence.

Robot security systems are expected to become much more effective as technology advances with AI, digital twins, advanced equipment and software. The future of these systems will be shaped by a holistic approach that focuses not only on physical security but also cybersecurity, ethical principles and legal compliance. These developments will enable robots to work more closely and safely with humans, while also contributing to the creation of systems that are more resilient to new risks brought about by technology.

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CHAPTER 6

WIND FARMS AND SUSTAINABILITY: ECOSYSTEM, ENVIRONMENTAL AND SOCIAL IMPACTS

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The 21st century is a period in which humanity faces a major dilemma: the climate crisis, biodiversity loss, and the collapse of ecosystems caused by fossil fuel dependence have made the pursuit of a sustainable future imperative (Hansen et al., 2013). Climate change manifests itself through rising global temperatures, sea level rise, and extreme weather events. The primary cause of this phenomenon—fossil fuel consumption—has elevated greenhouse gas concentrations in the atmosphere to critical levels (IPCC, 2021). In this context, renewable energy sources are not merely an alternative; they have become the key to preserving the ecological balance of our planet (Jacobson et al., 2017). Global issues such as biodiversity loss and ecosystem collapse highlight the urgent need for action (Díaz et al., 2019). Particularly, deforestation, industrial activities, and fossil fuel consumption exert severe pressure on ecosystems and threaten biodiversity (WWF, 2020; Almond & Petersen, 2020). The world order established through industrialization has not only endangered the future of our own species but has also evolved into a scenario that threatens the entire living ecosystem on Earth. This reality reminds us that, at least in the near future, we have no other home to live in, prompting the need to first slow down the unsustainable systems we have created and then define processes to transform them into sustainable structures. The undeniable central theme of these processes is the concept of sustainability.

Our home, which we call Earth, is surrounded by a layer of air known as the atmosphere. Due to the energy coming from the Sun, different pressure zones form within the atmosphere. These varying pressure regions cause the air to move, giving rise to the wind phenomenon—one of the most familiar natural events in our daily lives. The use of kinetic energy within air masses is an idea that dates back almost as far as human history itself. Today, modern wind turbines are classified as mature industrial products. According to the Global Wind Energy Council (GWEC, 2023), wind energy accounted for 7% of global electricity generation in 2023, making it one of the most dynamic components of the renewable energy portfolio. Wind farms have taken a central role in achieving the Sustainable Development Goals (SDGs) with their potential to reduce carbon emissions, ensure energy security, and support economic growth (GWEC, 2023). Wind energy can significantly reduce carbon emissions by replacing fossil fuels and can play a key role in combating climate change (Luderer et al., 2017). Moreover, wind farms enhance energy security by reducing fossil fuel dependency and contribute to local economic development (Sovacool, 2017). The United Nations (UN, 2019) emphasizes that wind energy plays a vital role in achieving the Sustainable Development Goals, particularly in terms of clean energy access and climate action.

In current energy and environmental discussions, global warming and the negative impacts of fossil fuels have come to the forefront. Fossil fuel consumption, the primary driving force behind climate change, increases the concentration of carbon dioxide (CO_2) in the atmosphere, leading to global temperature rises (Change, 2023). Fossil fuels—especially coal, oil, and natural gas—account for a significant portion of global carbon emissions, accelerating the climate crisis (Friedlingstein et al., 2022). In addition to fossil fuels, deforestation and industrial activities also contribute to greenhouse gas emissions, placing severe pressure on ecosystems. In this context, the transition to renewable energy sources has become not only an environmental necessity but also an economic and social imperative for sustainability.

Wind energy is one of the most important components of this transition process. It has been proven that wind energy can significantly reduce carbon emissions by replacing fossil fuels and play a key role in combating climate change (Jacobson et al., 2017). Moreover, the International Renewable Energy Agency (IRENA, 2021) states that, with decreasing costs, wind energy has become a more cost-effective and environmentally friendly alternative compared to fossil fuels. Wind farms not only provide environmental benefits but also support local economic growth and enhance energy security (Sovacool, 2017). Therefore, wind farms are considered an indispensable tool both in addressing the climate crisis and in building a sustainable future.

Evaluation of Wind Energy in Terms of Sustainability

Wind energy offers distinct advantages over other renewable energy sources in terms of reducing carbon emissions and improving economic outcomes (Mubarak, Rezaee, & Wood, 2024). These advantages are particularly evident in studies where environmental benefits are quantitatively assessed. For instance, it has been reported that wind energy can reach very low emission levels, such as 3.0 g CO_2 kWh^{-1}, which corresponds to only 4% of emissions from coal-based energy production (Rule, Worth, & Boyle, 2009). Moreover, its emission profile is 10–20% lower compared to gas turbines, making wind energy environmentally superior to fossil fuel alternatives. This demonstrates that wind energy can play a significant role in combating climate change. Life cycle analyses show that wind energy generally has low or minimal environmental impact. However, in some cases, photovoltaic systems may exhibit a more favorable profile during their production and recycling phases (Osman et al., 2022). These comparisons indicate that the environmental impacts of wind energy can vary depending on context and technological developments.

Figure 1. Modern Wind Turbines Located in A Wind Farm

In terms of economic advantages, wind energy holds significant potential. From 2010 to 2021, the cost of wind energy dropped by 68%, with the levelized cost of electricity decreasing from \$0.08 to \$0.03 per kilowatt-hour (Mubarak, Rezaee, & Wood, 2024). This cost reduction can be attributed primarily to technological innovations and economies of scale. Advances in turbine technology have enabled the production of more efficient and durable equipment, while improvements in mass production and installation processes have further reduced costs. Additionally, the wind energy sector has had a notable positive impact on the labor market. For instance, the creation of 117,000 new jobs in the United States demonstrates the tangible role of wind energy in driving economic development (Mubarak, Rezaee, & Wood, 2024). These employment opportunities extend not only to the installation and maintenance of turbines but also significantly affect supporting industries.

Figure 2. Technician Working on Wind Turbine Installation

The impact of wind energy on economic development is not limited to job creation. Its potential use as an efficient energy source in innovative applications such as hydrogen production indicates that wind energy could play a strategic role in future energy systems. One of the major disadvantages of wind energy lies in the intermittent nature of the wind resource. Air movements in the atmosphere do not consider the patterns of daily electricity demand. To address this issue, research on energy storage systems has gained momentum. In particular, green hydrogen production stands out as a promising solution to balance the intermittent nature of wind energy. However, several challenges must be overcome for this potential to be fully realized. Chief among these are grid integration problems and the inadequacy of current energy storage technologies, which pose significant barriers due to the variability of wind energy (Zhao et al., 2021). Since wind energy production varies with wind speed, the development of effective energy storage systems remains one of the most critical needs in this field.

Regional factors and local economic conditions significantly shape the effectiveness of wind energy. For example, in regions with high wind potential but weak infrastructure, the installation and maintenance costs of turbines may increase, or the distribution of energy may remain limited (Zhao et al., 2021). In such areas, expanding transmission lines and improving grid infrastructure are vital to fully harness the potential of wind energy. In contrast, well-developed grid systems in Europe and North America facilitate the integration of wind energy, contributing to greater success in these regions. In these areas, innovative solutions such as energy storage technologies and smart grid systems enable more efficient utilization of wind energy.

In conclusion, wind energy stands out as an indispensable option in terms of both environmental and economic sustainability. Its potential to reduce carbon emissions, low costs, and capacity to create employment place wind energy at the center of the global energy transition. However, to fully realize this potential, challenges such as grid integration, energy storage, and infrastructure investments must be addressed. Overcoming these challenges will allow wind energy to play an even more significant role in future energy systems.

Effects on Ecosystems

Wind turbines have significant ecological impacts, particularly on birds and marine life. Birds of prey may exhibit avoidance behavior near wind farms, leading to reduced populations in these areas. Large soaring species are especially at risk of turbine collisions due to their wingspan and flight altitude (Estellés-Domingo & López-López, 2024). Additionally, the barrier effect may force migratory birds to alter their traditional routes, resulting in longer, more energy-consuming paths that threaten the long-term resilience of their populations (Drewitt & Langston, 2006). This poses a serious problem, especially for migratory species that rely on specific routes to conserve energy during migration.

Floating turbines present unique challenges, such as the risk of marine animals becoming entangled in mooring lines and the displacement of seabirds from their natural habitats (Maxwell et al., 2022). Marine mammals (e.g., whales, dolphins) and deep-sea fish face entanglement risks with the mooring lines of turbines, which can lead to physical injuries or fatalities. Additionally, seabed excavation during turbine installation disrupts the habitats of benthic organisms and negatively impacts the marine food chain. Seabirds (e.g., cormorants, gulls) may abandon nesting areas due to turbine noise and artificial lighting, leading to declines in local populations.

Figure 3. Floating Wind Turbines Installed Offshore

Wind farms can lead to bird fatalities, noise pollution, visual disturbance, deforestation, and soil erosion (Nazir et al., 2020). The primary impacts on birds include collisions, displacement, barrier effects, and habitat loss (Drewitt & Langston, 2006). In particular, deforestation and soil erosion result from land clearing activities carried out during turbine construction. These activities can degrade local ecosystems and reduce biodiversity. To mitigate these adverse effects, several strategies have been proposed, such as curtailment on demand, deterrent measures, smart siting, and micrositing (Estellés-Domingo & López-López, 2024; Maxwell et al., 2022). Curtailment on demand involves temporarily shutting down turbines during peak migration periods when bird activity is high. Deterrent measures use auditory or visual signals to keep birds away from turbines. Smart siting and micrositing aim to position turbines away from bird migration routes and critical habitats, thereby reducing the risk of collisions.

Standardized policies, careful environmental assessments, and post-construction monitoring are vital for minimizing adverse impacts (Nazir et al., 2020; Drewitt & Langston, 2006). Environmental assessments require a detailed analysis of the biodiversity and ecosystem dynamics of the proposed turbine installation sites. Post-construction monitoring ensures the continuous observation of the environmental impacts during the operational phase of the turbines and enables the implementation of necessary mitigation measures.

Further research is needed to develop effective mitigation strategies and ensure sustainable wind energy production. In particular, a better understanding of the long-term effects of turbines on birds and marine life, the development of innovative technologies to reduce these impacts, and the collection of comprehensive data to guide policymakers are essential. These efforts will help minimize the environmental costs of wind energy while enabling the achievement of global renewable energy goals.

Environmental Impacts

Wind energy offers significant environmental benefits by reducing greenhouse gas emissions and air pollution associated with fossil fuel-based energy sources (Jaber, 2013; Adeyeye et al., 2020). By the year 2020, it was estimated that wind energy could reduce carbon dioxide emissions in the energy sector by approximately 4.5% (Council, 2007). Wind power requires virtually no water and generates near-zero pollutant emissions, contributing to improved air quality (Ledec et al., 2011). Due to its renewable nature and potential to reduce mining activities, the environmental benefits of wind energy are generally viewed positively (Jaber, 2013). However, wind energy projects can have some adverse effects on biodiversity, posing threats particularly to birds, bats, and natural habitats (Ledec et al., 2011). Despite these challenges, wind energy is regarded as a key component of a low-carbon energy future with high environmental sustainability, thanks to its economic competitiveness and environmentally favorable characteristics (Ledec et al., 2011; Adeyeye et al., 2020).

Although wind energy is considered a green alternative to fossil fuels, it has potential adverse environmental impacts. These include visual pollution, noise disturbance, electromagnetic interference, and effects on land use (Nazir et al., 2020; Zamot et al., 2005). Wind farms can have significant impacts on local ecosystems and natural landscapes, with larger installations producing more substantial effects than individual turbines (Ma, 2008). Bird mortality is a particular concern, especially in forested areas and natural habitats (Nazir et al., 2020; Zamot et al., 2005). The effects on birds and bats have been extensively studied, especially in Europe and North America. However, many of these impacts are case-specific, and more generalizable research is needed (Sander et al., 2024). Stakeholders must collaborate to standardize policies that promote sustainable wind energy development while minimizing environmental impacts (Nazir et al., 2020).

While wind energy plays a critical role in sustainable development and climate goals, it also presents environmental challenges that require careful management.

The main impacts include noise pollution, visual disturbance, and particularly, effects on flying animals (Sebestyén, 2021; Kondili, 2021). Technological advancements such as larger turbine designs and floating wind turbines have increased efficiency and reduced costs, making wind energy more competitive with fossil fuels (Uzondu & Lele, 2024). To address environmental concerns, comprehensive impact assessments and mitigation measures are essential (Kondili, 2021). These measures may include noise control techniques, visual impact reduction strategies, and wildlife protection efforts. Public acceptance is crucial for the successful implementation of wind projects (Uzondu & Lele, 2024). Especially with the growth in size and capacity of wind farms, an integrated life cycle approach is recommended to address the complexity of environmental impacts (Kondili, 2021).

Social Impacts

Although wind energy projects are widely supported by the general public, they often face resistance at the local level. While this resistance has traditionally been explained by the NIMBYism (Not In My Backyard) approach (Petrova, 2013), recent research reveals that opposition is rooted in far more complex and multidimensional reasons. Local communities express deep concerns about the environmental and social impacts of these projects. In particular, negative changes to the landscape can degrade natural beauty, reduce quality of life, and lead to significant declines in property values. Furthermore, feelings of exclusion from decision-making processes among local residents can intensify this resistance (Wright, 2012). This issue is often linked to the failure to adequately consider community opinions during the planning phase or to ensure a transparent process. Such shortcomings undermine trust in the projects and may lead to long-term conflicts. To address these concerns, it is crucial to ensure the active participation of local communities in the planning and implementation phases of wind energy projects (Wright, 2012; Akerboom, 2018). Involving local residents not only increases the acceptability of projects but also allows for the development of solutions that better align with the needs and expectations of the community. In this context, approaches such as the ENUF framework (Engage – Don't Use the Term NIMBY – Understand – Facilitate) offer an effective way to understand and address the concerns of local communities (Petrova, 2013). This framework encourages project developers to communicate more effectively with residents and to produce solutions that take their concerns into account. Moreover, the establishment of legal and administrative regulations that balance global energy needs with local interests plays a critical role in the successful implementation of wind energy projects (Olsen, 2010; Wright, 2012). Such regulations help minimize both environmental and social impacts, thereby enabling progress toward global energy targets while preserving local quality of life.

Figure 4. Rural Life Integrated with Renewable Energy Sources

Wind energy projects have significant impacts on local and regional economies. While these projects create employment opportunities at the local level, they can also cause certain disruptions within communities (Brown, 2011). For example, although temporary jobs may be provided during the construction phase of projects, there can be uncertainties regarding the sustainability of this employment in the long term. Nevertheless, at the regional level, wind energy projects offer considerable economic benefits, such as increases in per capita GDP, income, and property values (Brunner & Schwegman, 2022). Additionally, these projects promote regional economic diversification by shifting employment from agricultural sectors to non-agricultural ones, particularly construction and manufacturing. To maximize these benefits and reduce negative impacts, project developers should focus on delivering greater value to local communities and minimizing disruptions (Brown, 2011). Furthermore, policymakers can implement supportive policies and provide technical assistance to promote the wind energy sector and foster sustainable economic development (Dinh et al., 2024).

Effective strategies for public participation and communication in wind energy projects are crucial for increasing community engagement and support. The early and systematic involvement of local communities is necessary to reduce negative reactions and project delays (Dütschke et al., 2017). In this process, key factors such as procedural justice—which offers opportunities for public participation in planning, site selection, and approval stages—and distributive justice—which ensures the fair distribution of costs and benefits—should be taken into account. Procedural justice enables local communities to actively participate in decision-making processes, while distributive justice guarantees that the benefits and burdens of projects are shared equitably. Furthermore, financial participation of local communities can enhance project acceptance (Luca et al., 2020). For instance, allowing local residents to receive a share of the revenues generated by the projects or involving them in project management can strengthen community support. Cooperation with local governments and stakeholders is also essential for successful project implementation and public support (Horbaty et al., 2012). Such collaboration ensures that projects are designed and executed in line with local needs and expectations, thereby supporting both environmental and social sustainability.

Technological and Planning Approaches

Recent advancements in wind turbine technology play a critical role in achieving the efficiency and sustainability goals of the renewable energy sector. Research focusing particularly on turbine blade design and maintenance strategies aims to both increase energy production capacity and minimize environmental impacts. Today, researchers are testing active and passive flow control devices (e.g., micro surface protrusions, wingtip devices) and biomimetic designs (e.g., structures inspired by dolphin fins or owl wings) to improve aerodynamic performance and reduce noise levels. These adaptations help optimize energy production even at low wind speeds while enhancing aeroacoustic performance, thereby reducing negative impacts on local ecosystems (Krishnan et al., 2023). In addition, the use of advanced composite materials such as carbon fiber and graphene-reinforced polymers allows for lighter blades with increased fatigue resistance, thus extending the operational lifespan of turbines.

In the context of performance optimization, parameters such as annual energy yield and power coefficient are dynamically analyzed to enable turbines to adapt to varying wind profiles. For instance, reducing blade mass allows turbines to generate energy even at low cut-in speeds, which ensures a stable energy output even in regions with irregular wind patterns (Rehman et al., 2018). At the same time, condition-based maintenance strategies supported by smart sensor technologies and machine learning algorithms enable real-time monitoring of turbine components, preventing unexpected failures and reducing maintenance costs. In particular, advanced vibration analysis and thermal imaging techniques allow for the early detection of issues such as blade cracks or gearbox wear, enabling proactive intervention (Besnard & Bertling, 2010).

The integration of these technologies into large-scale projects offers important insights for the future of the sector. For example, the Hornsea Project One (United Kingdom), with a capacity of 1.2 GW, stands as the world's largest offshore wind farm and demonstrates resilience to high wave and saline water conditions thanks to adaptive blade angles and hydrodynamic foundation designs. Similarly, China's Gansu Wind Farm project, with a capacity of 20 GW, has enhanced abrasion resistance by using specially developed composite blade coatings designed to withstand sandstorms. These projects have proven that the synergy between dynamic aerodynamic optimization and materials engineering can extend turbine lifespan (Firoozi et al., 2024).

On a global scale, these technological advancements are being supported in alignment with regulatory frameworks such as the European Union's Green Deal objectives and the Paris Agreement. In particular, decarbonization policies and renewable energy incentives are compelling companies to develop more efficient and environmentally friendly turbine designs. As a result, the wind energy sector maintains its potential to be a key player in achieving the net-zero emissions targets by 2050 through technological innovation and policy-driven investments.

Case Studies and Examples

Wind energy has demonstrated significant potential and growth worldwide. Turkey, in particular, offers considerable resources in both wind and wave energy. Studies have shown that Turkey's theoretical wind energy potential is approximately 88,000 MW annually, with successful implementations already in place (Ozgener et al., 2004). This potential is especially concentrated in the Aegean, Marmara, and Mediterranean regions, which are considered ideal for wind energy production due to high wind speeds and favorable topographic conditions. Furthermore, Turkey's geographical location provides a strategic advantage for integration into both European and Asian energy markets. This makes Turkey a strong candidate to become a regional hub in the field of renewable energy. However, challenges such as political and market-related factors, site selection issues, environmental conflicts, and social acceptance continue to pose obstacles to the development of wind energy (Gartman et al., 2014). In particular, site selection processes require careful planning due to the environmental and social impacts associated with turbine placement. Moreover, resistance from local communities can hinder social acceptance, potentially delaying project implementation and increasing costs. Environmental conflicts, especially those related to protected areas and wildlife, also represent a significant barrier.

The European Union has made significant progress in wind energy, surpassing previous targets and recognizing its reliability and cost-effectiveness in reducing CO_2 emissions (Kaygusuz, 2006). EU countries have made substantial investments in wind energy to achieve their renewable energy targets and have become global leaders in this field. Offshore wind farms, in particular, hold a significant share in the EU’s energy portfolio. This success has been made possible through both technological innovation and effective policies and regulations. The EU's experience serves as an important example for other countries such as Turkey.

Case studies such as Istanbul’s Çatalca district demonstrate the feasibility of wind energy projects in Turkey, with annual average wind power densities ranging between 400.31 and 611.02 W/m² at various altitudes (Wadi et al., 2019). These data indicate that Çatalca is a suitable region for wind energy production. Moreover, the successful implementation of such projects contributes to the local economy and creates employment opportunities. However, for these projects to be scaled up, local community participation and the minimization of environmental impacts are of great importance. Addressing challenges through adaptive management and innovative solutions can improve the future of wind energy applications (Gartman et al., 2014). In particular, including local communities in projects and carefully assessing environmental impacts can enhance social acceptance. In addition, technological innovations and smart grid systems can help balance the intermittent nature of wind energy and address energy storage issues. Such solutions could enable the wider deployment of wind energy and contribute to the global energy transition. In conclusion, wind energy is a significant renewable energy source for both Turkey and the world. However, realizing its full potential requires overcoming political, environmental, and social challenges. In this process, innovative solutions and effective policy implementation will shape the future of wind energy.

Conclusion and Evaluation

This comprehensive review of the ecosystemic, environmental, and social impacts of wind energy projects reveals the complex dynamics of the renewable energy transition. The main findings indicate that, in addition to global benefits such as reducing carbon emissions and promoting energy independence, wind farms pose significant ecological risks—particularly to bird populations and marine ecosystems. For instance, the increased collision rates among raptors and the habitat loss for marine species highlight the necessity of making these projects compatible with wildlife (Estellés-Domingo & López-López, 2024; Maxwell et al., 2022). On the social side, local resistance to projects is linked not only to the

NIMBY (Not In My Backyard) syndrome, but also to structural issues such as the lack of involvement in decision-making processes and the unequal distribution of economic benefits (Wright, 2012; Petrova, 2013). From an economic perspective, while wind energy positively influences regional GDP and employment (Brunner & Schwegman, 2022), it also brings technical challenges such as infrastructure costs and grid integration—necessitating a careful balancing act.

While wind farms play an indispensable role in sustainable energy production, the effectiveness of this role depends on minimizing environmental and social costs. Among the benefits achieved are tangible economic gains such as cost reductions between 2010 and 2021 (Mubarak, Rezaee, & Wood, 2024) and the creation of 117,000 jobs in the United States. However, alongside these successes, the long-term impacts of projects on ecosystems (e.g., disruption of bird migration routes) and the lack of communication with local communities have been identified as critical barriers to sustainability. The successes achieved by the European Union in offshore wind farms (Kaygusuz, 2006) demonstrate the importance of transparent policies and participatory planning. In the case of Turkey, the high wind potential in regions such as Çatalca (Wadi et al., 2019), if evaluated using similar strategies, could enhance the country's energy diversification.

Future Emphasis and Recommendations

The principal conclusion derived from this study is that the success of wind energy deployment is contingent not only upon technological innovation but also on a comprehensive sensitivity to social and ecological dimensions. Accordingly, the following rec ommendations are proposed for future applications:

1. **Technological Adaptation:** Bird-friendly turbine designs (e.g., biomimetic blades) and floating platforms that protect marine ecosystems should be developed. Condition-based maintenance systems equipped with smart sensors can enhance turbine efficiency.

2. **Policy and Governance**: Globally standardized environmental assessment protocols should be established. Models such as the ENUF framework should ensure the integration of local communities into wind energy projects.

3. **Community Engagement:** Financial participation of local residents (e.g., through energy cooperatives) should be encouraged in project development processes. This will both enhance social acceptance and help reduce economic inequalities.

4. **Research and Collaboration:** Long-term field studies should be supported to monitor ecosystem impacts. Interdisciplinary research must build bridges between engineering and ecology.

In conclusion, wind energy retains its potential as a critical tool in the fight against the climate crisis. However, the realization of this potential depends on establishing a balanced dialogue between humanity and nature. The joint efforts of science, policy, and society can transform the power of the wind not only into energy but also into a sustainable future.

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CHAPTER 7

CONCEPTS AND DESIGNS OF VIBRATION-BASED PIEZOELECTRIC ENERGY HARVESTING SYSTEMS FOR EFFICIENT SUSTAINABILITY

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1. Introduction

In recent years, piezoelectric materials, called smart materials, have become popular especially in the field of engineering. When it comes to industrial use; it comes to the forefront in sensor and actuator applications. The reason for this is that piezoelectric materials have the ability to harvest energy by converting mechanical energy into electrical energy or vice versa. The basis of this feature is based on the formation of an electric charge as a result of the induction of ions within the material when a mechanical force is applied to the material. Harvesting energy is an important feature that allows the development of self-powered devices that do not require a power source by capturing renewable energy in the environment and converting it into electrical energy. nergy harvesting is possible from sources such as vibration, electromagnetic waves, wind, running water, sun or human movement. In particular, providing the power requirements of autonomous electronic devices through vibration energy harvesting (VEH) stands out as an important option. Different power sources have emerged with the importance of small-sized, low-power, easily portable and remotely controlled devices in recent years. For example, batteries are not sufficient in such applications due to their limited lifespan, need for frequent charging and limited energy storage capacity, and the search for alternative power sources has emerged [1]. At this point, the concept of collecting energy from ambient sources to eliminate the need for batteries or extend the life of the battery has become the focus of researchers. Collecting energy from the environment or energy harvesting is an important technique that provides advantages especially in biomedical devices that are difficult to access, need to be controlled remotely, and have expensive maintenance [2,3] and in tracking devices integrated into the human body. In addition, limited energy providers are shown as a significant challenge for wireless sensor network technologies. The development of efficient and high-performance energy harvesting systems to overcome this limitation is investigated in the literature [4,5,6]. Vibration energy harvesting systems are taking a step forward in areas where battery replacement is difficult, such as structural health monitoring [7], biomedical applications [8], environmental monitoring [9] and wireless sensor networks [10].

Despite significant advances in piezoelectric energy harvesting, many energy harvesting systems fail to provide energy conversion efficiency in real system applications. One of the biggest challenges in these applications is known as frequency sensitivity. Namely, most vibration energy harvesters obtain maximum power output at the resonance frequency and are therefore designed to operate at or very close to that frequency. However, due to the nature of the work, the vibration frequency of the surrounding vibration sources is often variable and unpredictable. This environmental frequency is rarely likely to coincide with the resonance frequency of the system. Therefore, even small deviations from the designed operating frequency can cause significant reductions in the harvested energy, limiting the overall efficiency and applicability of the system [11].

Studies on vibration energy harvesting systems are progressing on different topics. These can be stated as material properties, structural designs and system-level application strategies. Thanks to the numerous theoretical and experimental studies conducted under these headings, significant progress has been made. However, certain limits are still mentioned in the literature on some issues at present. Therefore, future research focuses on the integration of smart materials, adaptable structures and intelligent control algorithms to develop robust, efficient and sustainable energy harvesting systems that can operate reliably even in different and unpredictable environmental conditions. Such systems are expected to not only increase current energy efficiency but also make resource use more efficient by minimizing environmental impacts. Piezoelectric energy harvesting is the most intensively studied method due to its many advantages. These advantages include; easy applicability, ability to produce high voltage output without voltage increase or external source use, high energy density and availability of suitable manufacturing techniques for device production at different geometric scales. However, alternative methods such as electromagnetic induction and electrostatic conversion also offer their own advantages.

The purpose of this study is to examine energy harvesting systems; especially the latest developments in piezoelectric energy harvesting systems, the materials used and the properties of these materials, system design principles and application areas. The second section includes details of the piezoelectric energy harvesting technique, the third section discusses system configurations, the fourth section evaluates energy harvesting systems in terms of sustainability, and the fifth section focuses on practical application areas.

2. Fundamental Mechanisms for Vibration Energy Harvesting

Harvesting vibration energy offers a sustainable and autonomous energy solution for microelectronic systems, especially when batteries or wired power sources are insufficient or when wired systems are difficult to install. The kinetic energy obtained from human motion, the energy obtained from mechanical vibrations and the mechanical vibrations coming from the surrounding industrial equipment are a type of waste energy with a significant potential to be converted into electrical energy. The conversion of this waste mechanical energy can be achieved with piezoelectric, electromagnetic, electrostatic or hybrid approaches. Each conversion mechanism has its own advantages and disadvantages. Studies in the literature show that they are preferred according to their application areas, working principles and the amount of energy they harvest. The topics on which the conversion performance of VEH systems depends can be summarized as follows; resonance frequency of the system, bandwidth of the system, amount of energy absorption of the system, volume of the system and system cost.

Piezoelectric materials such as quartz, Rochelle salt, tourmaline and barium titanate have a special property that they can produce an electrical charge as a result of the mechanical stress applied to them. This phenomenon is called the direct piezoelectric effect. Conversely, when an electric field is applied to these crystalline structures, they undergo mechanical deformation; This is known as the “converse piezoelectric effect”. The direct effect is generally used in sensing (sensor) and energy conversion applications, while the reverse effect is used in actuator systems. This bidirectional electromechanical behavior of piezoelectric materials can be mathematically modeled by two basic linearized correlation equations [17]. The first of the equations given below represents the direct piezoelectric effect, and the second represents the reverse piezoelectric effect,

$$D_i = e_{ij}E_j + d_{im}\sigma_m \qquad (1)$$

$$\varepsilon_k = d_{jk}E_j + S_{km}\sigma_m \qquad (2)$$

where $D_i$is the dielectric displacement (N/mV or C/m^2), e_{ij} is the dielectric permittivity (N/ V^2 or F/m), vector E_j is the applied electric field (V/m), d_{im} and d_{jk} are the piezoelectric constants (m/V or C/N), σ_m is stress vector, ε_k is strain vector (N/m^2), S_{km} is eleastic compliance matrix (m^2/N).

2.1 Piezoelectric Mechanisms

The conversion of inert mechanical energy into electrical energy using piezoelectric materials is called piezoelectric energy harvesting (PEH) in the literature. Considering the studies conducted so far, it has been stated that a small amount of energy is collected in the microwatt to milliwatt range with this method and is suitable for electronic devices with low power requirements. On the other hand, energy conversion systems such as solar, wind, and geothermal from renewable energy sources can produce power in the range of hundreds of watts. Although it seems disadvantageous when compared from this perspective, it has advantages depending on where it is used and is preferred in applications. For example, ambient vibrations occurring in an environment where machines are constantly operating can be converted with PEH systems, and in such environments, neither wind nor solar sources can be mentioned. In other words, PEH systems allow for the acquisition of extra energy, albeit in small amounts. Since such an energy source is not exposed to natural events, it is relatively stable and less sensitive to environmental changes over time. In other words, piezoelectric harvesting systems can work efficiently in places where there is no renewable energy that provides high power conversion; this is an important advantage for embedded systems and remote monitoring applications. In short, PEH systems are widely used to power embedded systems, implantable biomedical devices, wireless sensor nodes, and portable electronic devices. Piezoelectric energy harvesting systems can provide an autonomous system and significantly reduce the costs associated with battery replacement compared to traditional energy sources such as batteries. In addition, self-powered energy sources allow electronic devices to be integrated into structural components or deployed in remote areas. In recent years, the increasing use of low-power electronics such as wireless sensors and microelectronic devices has led to a significant increase in interest in piezoelectric energy harvesting research.

As mentioned above that material properties are one of the main topic of development of PEH systems. In this context, especially after the discovery of ferroelectric materials such as Barium titanate ($BaTiO_3$) and lead zirconate titanate (PZT), piezoelectric properties have been provided to many synthetic materials. Researchers in this field continue their studies to develop new materials with different electromechanical, mechanical and thermal properties [12]. Materials with piezoelectric properties can be classified into four main groups according to their components: piezoelectric ceramics, piezoelectric polymers, piezoelectric single crystals and piezoelectric composites. Piezoelectric materials with these different material properties are preferred in different application areas depending on their physical and electrical properties.

Piezoelectric ceramics are the most widely used among piezoelectric material groups. Among these groups, PZT (Lead Zirconate Titanate) attracts particular attention with its high piezoelectric coefficient and structural stability. However, it has a brittle structure and since its lead content is harmful to the environment and human health, this poses a problem for some studies. PNN-PZT, a more advanced type, was developed later by obtaining a much higher coupling coefficient compared to traditional PZT ceramics [13]. Such modified ceramics are widely used in sensors and sensitive energy harvesting systems. However, their price remains higher.

Piezoelectric polymers are another group used in energy harvesting research; they are ideal for applications requiring flexibility and lightness. The most important example in this group is PVDF (Polyvinylidene Fluoride), which has advantages such as low density, corrosion resistance and easy formability. Although it has lower piezoelectric performance compared to ceramics, the coupling coefficient is significantly improved by increasing the β-phase content. Recent studies in the field of PVDF have focused on improving the performance of this material through the use of processing techniques, piezoelectric additives and various filler materials, and these new developments have significantly improved the output performance of energy harvesting devices [14].

The piezoelectric single crystals group exhibits good piezoelectric performance due to their highly ordered atomic structure. An example of this group is the piezoelectric material PMN-PT (Lead Magnesium Niobate - Lead Titanate). PMN-PT has a much higher binding coefficient compared to PZT. Such materials are especially used in applications requiring high sensitivity such as medical imaging, ultrasonic transducers and advanced energy harvesting systems. However, their high cost and brittle structure limit the wider use of these materials [15].

Finally, piezoelectric composites are hybrid materials formed by combining ceramics and polymers. These materials offer a balanced solution in terms of both functionality and durability by combining the high piezoelectric performance of ceramics and the mechanical flexibility of polymers. PVDF-based nanocomposites can exhibit superior performance compared to other piezoelectric structures due to the superior physicochemical properties developed by the addition of nanofiller with high surface-to-volume ratio [16].

3. Piezoelectric Based Energy Harvester Structural Configurations

Piezoelectric Energy Harvesting (PEH) systems convert mechanical stress into alternating current (AC) voltage through piezoelectric materials. This AC output is used after being converted to direct current, i.e. DC current, to power low-energy devices. The amount of energy harvested, i.e. the efficiency of energy conversion, depends on constants that represent various material properties such as elasticity, thermal stability and dielectric constant. Piezoelectric Energy Harvesters (PEH) can be classified according to both their structural design and the configuration of the piezoelectric material used. This classification is structurally categorized as cantilever beam, membrane type, shell structures and multi-beam systems.

The cantilever beam type is the most commonly used configuration due to its fixed-end and free-end structure and offers high efficiency under low-frequency ambient vibrations. Membrane-type structures are generally widely used in MEMS applications and can exhibit multi-directional deformations. Thanks to their thin, flexible structures and high sensitivity, piezoelectric membranes are also used in a wide variety of applications such as biomedical sensing systems and structural health monitoring applications [21, 22]. In the context of energy harvesting, these membranes serve as efficient converters that convert mechanical energy into electrical energy for autonomous microsystems, especially in low-frequency vibration environments such as human motion, environmental mechanical vibrations, and acoustic energy. A schematic representation of a membrane-type piezoelectric energy harvester is shown in Figure 1b.

PEH systems using shell structures are also available in the literature. For example, a system that harvests energy from wind energy was investigated in one study. A cylindrical shell structure was used and a newly developed flow breaker integrated into the system was found to significantly improve the aeroelastic behavior. In the use of this shell structure, the interaction between the shell and wind-induced vibrations was optimized and the efficiency of converting mechanical energy into electrical energy was also increased. This clearly demonstrates the critical role of shell structures in wind energy harvesting applications [22]. Figure 1a shows a cross-sectional view of a typical piezoelectric shell structure.

When we look at the studies conducted on PEH system structures, the most common structures are unimorph and bimorph system designs. According to the arrangement of the piezoelectric material, they are classified as single-form and double-form. Single-form structures consist of a single piezoelectric layer bonded to an elastic layer. The simple architecture of these structures makes them easy and cost-effective to manufacture; however, their output power is relatively low. In contrast, double-form structures consist of two piezoelectric layers arranged symmetrically. This configuration provides higher output voltage than single-forms; however, it requires a more complex manufacturing process and more material usage. The most commonly used structures in the design and modeling processes of piezoelectric energy harvesters are cantilever-type unimorph and bimorph systems. The unimorph structure is formed by bonding a piezoelectric layer to an elastic layer, while the bimorph structure is formed by placing an elastic layer between two piezoelectric layers. There are many studies in the literature on unimorph and bimorph piezoelectric energy harvesting systems, and their electromechanical interactions have been modeled in detail [18]. These studies have been carried out both theoretically and experimentally and have made significant contributions to the development of piezoelectric energy harvesting at the millimeter scale. In these studies, models have been developed to describe the electromechanical interactions of unimorph and bimorph systems under base excitation. Figure 1c presents a schematic representation of a unimorph piezoelectric energy harvester with a mass at its tip, while Figure 1d presents a schematic representation of an asymmetric bimorph piezoelectric energy harvester with a mass at its tip.

In addition, various theories have been used in the mathematical modeling of piezoelectric energy harvesters. These theories include the Euler-Bernoulli, Rayleigh and Timoshenko models, which address different levels of deformation and inertia effects. Since mathematical models of PEH systems are a separate and comprehensive topic, they will not be discussed in detail in this study.

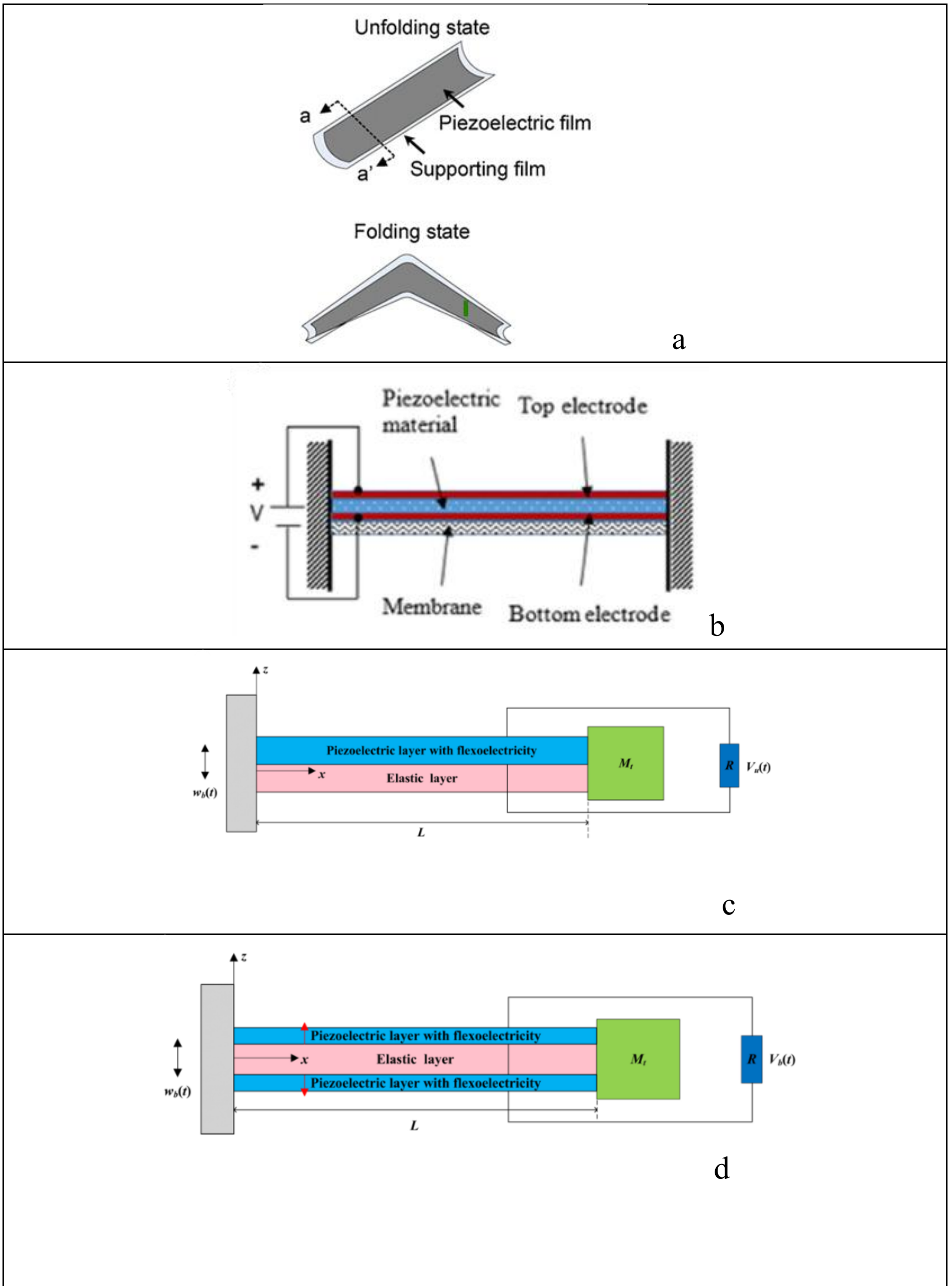

Figure 1. Different PEH system design; a) Shell structure [24] b) Membrane type [23] c) Unimorph type [19] d) Bimorph type [19]

4. Sustainability-Oriented Approaches in Piezoelectric Energy Harvesting Systems: Material and Structural Perspectives

The conversion of mechanical energy to electrical energy using piezoelectric materials has been investigated for many years. The ability to harvest inert mechanical energy such as fluid-plate interactions [36], human movements (such as knee, ankle, heel movement) or ambient vibrations stands out. The energy it harvests is used to meet the energy needs of low-power electronic devices, sensors and biological implants in a sustainable way. However, from a sustainability perspective, not only the energy efficiency of these systems but also the environmental friendliness of the materials used, minimum toxicity and high recyclability should be taken into account. The most commonly used piezoelectric ceramics are usually based on lead-containing compounds (e.g., PZT - lead zirconate titanate) and these can pose environmental risks due to their toxic components [25]. On the other hand, lead-free material alternatives such as barium titanate ($BaTiO_3$) and potassium sodium niobate (KNN) can be preferred as a clean option due to their environmental friendliness, together with bio-based polymeric materials such as PVDF derivatives and cellulose-based nanocomposites. In recent years, demand for these environmentally friendly alternatives has increased over lead-based piezoelectric materials. Lead-free piezoelectric materials also have some disadvantages, exemplified by their relatively low piezoelectric responses. Studies have attempted to improve the performance of these environmentally friendly materials using both experimental and numerical methods.

Considering the entire life cycle of the energy harvesting system, from production to use and recycling, is essential for sustainability. Life Cycle Assessment (LCA) tools can be used to measure the carbon footprint and overall environmental impact of these systems and can guide the development of not only efficient but also ecologically responsible energy solutions [26].

In other words, with ongoing studies, when piezoelectric energy harvesting systems integrated with sustainable design principles are successfully achieved, it will be in an environmentally friendly position not only in terms of technological innovation but also in the development of future energy solutions.

5. Practical Applications of Vibration Energy Harvesting

5.1 Industrial Monitoring

Many industrial machines and equipment constantly produce vibration. If we consider these vibrations as unused idle energy, the idea of generating electrical energy from them is the main idea of VEH systems. If vibration energy harvesting is done using piezoelectric materials, these systems are called PEH systems. These systems provide power to wireless condition monitoring systems, both reducing costs by reducing the need for cables and preventing efficiency loss by helping continuity of maintenance [27].

PEH systems are also used by being mounted on rotating equipment such as pumps and motors in order to provide energy to sensors used in predictive maintenance systems.

Thus, early detection of faults such as bearing wear, imbalance or misalignment in the equipment is provided.

There are many studies in the literature where piezoelectric energy harvesting is applied in industrial automation, and it has been shown by these studies that PZT-based systems can reliably power low-power elements by taking vibration from the environment and converting it into electrical energy [28].

In addition, PEH systems have been studied as autonomous sensor solutions designed for instantaneous data collection in harsh industrial environments with high temperatures, high humidity, and vibrations [29].

Another study has shown the successful integration of a piezoelectric collector into an industrial HVAC fan motor to power IoT sensors that collect temperature and vibration data [30].

The progress of PEH systems in the field of industrial monitoring continues, and research is being conducted on converting even low-frequency vibrations into electrical energy with adaptive resonance tuning techniques. Of course, the development of materials science and the development of hybrid energy harvester structures are also paving the way for advances in this field. It is possible to say that these developments support the development of smarter, energy-independent, and sustainable industrial monitoring systems in the context of Industry 4.0.

5.2 Structural Health Monitoring

Structural Health Monitoring (SHM) is an important method developed for early detection of possible damage in various engineering structures.

In recent years, there has been increasing interest in technologies that can continuously monitor the integrity and current status of systems and structures in many engineering disciplines.

Autonomous monitoring systems have enabled the development of self-sufficient SHM systems by integrating sensors, data acquisition units, wireless communication modules and energy harvesting technologies.

In some research, energy has been obtained from energy sources in the environment such as vibration, thermal gradients, solar radiation, wind and pressure. In structures under dynamic loading, it is even possible to collect the necessary energy directly from the main structure itself. In this context, PEH systems have led to the widespread use of piezoelectric materials in the construction field or in the field of railway systems through the ability of piezoelectric materials to convert mechanical stress into electrical energy. In SHM applications, piezoelectric elements are strategically placed at points where vibrations or mechanical loads cause stress, and thus electricity is harvested. This harvested energy is then used to power low-consumption sensors and wireless communication units, enabling the realization of fully self-powered SHM systems.

Integrating such technologies into SHM not only increases the energy independence of the systems, but also reduces maintenance requirements over time, providing a more sustainable and efficient structural monitoring approach [31].

Another area of focus is the aviation sector.

In this field, the availability of renewable energy sources such as solar, wind and mechanical vibrations and the possibility of harvesting energy from them have recently attracted attention. Harvesting energy from ambient sources has become important to ensure the uninterrupted operation of wireless sensors, especially in situations where battery maintenance is costly or practically impossible.

As a result, smart structures that can self-generate electricity from environmental energy are of interest. These structures are suitable not only for powering wireless sensors, but also for powering micro and nano electronic devices. At the same time, advanced structural health monitoring ring (SHM) methods based on guided wave propagation are being developed to detect early-stage micro defects in engineered structures. Compared to traditional non-destructive testing (NDT) techniques, these SHM approaches offer more efficient and reliable solutions, especially for aerospace applications [32, 33].

5.3 IoT and Wireless Sensor Nodes

With the rapid advancement of Internet of Things (IoT) technologies, interest in autonomous sensor networks is also increasing [34]. There are many examples of piezoelectric energy harvesting (PEH) systems that convert ambient energy sources into usable electrical power in IoT technologies and more are coming.

For example, mechanical vibrations are constantly present in many industrial and structural environments and can be converted into a reliable and accessible energy source to power wireless sensor nodes without requiring frequent maintenance. Thus, sensor networks are enabled to operate without maintenance in the long term. As a result, as the energy conversion efficiency is increased with the developing material technology and PEH system designs, a directly proportional development will be achieved in IoT technologies.

In addition to energy harvesting, research in this area also focuses on minimizing the power consumption of wireless sensor nodes. This dual approach increases the overall efficiency of Wireless Sensor Networks (WSNs) and supports their deployment in long-term, uninterrupted monitoring applications [35].

5.4 Biomedical Devices

In the development of biomedical and implantable devices, the advancement of self-powered systems and smart material technologies plays a very important role.

Among these technologies, piezoelectric materials are important due to their ability to generate electrical energy in response to applied mechanical stress or strain.

Piezoelectric energy harvesters (PEHs) stand out from other technologies such as triboelectric and electromagnetic systems by effectively converting ambient mechanical energy into electrical power.

The efficiency of the piezoelectric effect largely depends on the positive properties of these materials, such as high electromechanical coupling coefficient, thermal stability, and resistance to changing environmental conditions. Current studies and ongoing research in this regard are also leading to advances in biomedical applications.

The variety of available piezoelectric biomaterials and different device designs increase their performance and adaptability in various biomedical environments.

Natural human movements and dynamic behavior of internal organs serve as consistent and applicable mechanical energy sources that enable PEHs to generate electricity from physiological activities such as heartbeat, respiration, and muscle contractions. With this feature, PEH systems stand out as energy providers for wireless biomedical sensors and devices.

The applications of PEHs cover a wide range of biomedical fields, including real-time health monitoring, cellular and neural stimulation, brain interface systems, and tissue engineering.

Recent studies have increasingly focused on improving material properties, optimizing device architecture, and ensuring biocompatibility; all of these are critical for the sustainable integration of PEHs into biomedical systems. With ongoing research and development, piezoelectric energy harvesters are expected to become a reliable and sustainable energy source for future healthcare technologies and implantable medical devices [2].

6. Conclusion

In this section, the design principles, structural configurations, application areas and sustainability features of vibration-based piezoelectric energy harvesting systems are investigated. The focus is on piezoelectric mechanisms to convert mechanical vibration into electrical energy and harvester designs for improved performance. In PEH systems, all relevant aspects are considered from the materials used, energy conversion efficiency, factors affecting this efficiency and studies to improve their compatibility with the environment. In real world implementations, prominent applications include industrial condition monitoring, structural health monitoring, wireless sensor networks with IoT integration and biomedical implants. In general, piezoelectric energy harvesting technology still needs innovative structural designs and advancements in materials to increase efficiency. The development of these topics is important in ensuring functionality and sustainability in practical engineering applications. Ongoing studies in the field of piezoelectric energy harvesting systems play an important role in terms of technological development and widening application domains . Future work will likely focus on systems that can operate over a wider frequency range and materials that have high piezoelectric coefficients and mechanical strength to improve energy conversion efficiency. Furthermore, developing scalable, low-cost, and industry-compatible manufacturing technologies is essential. Much work needs to be done to bring compact and fully integrated piezoelectric energy harvesters to IoT devices, biomedical sensors, and smart infrastructure systems. Overcoming limitations such as low output voltage and narrow bandwidth operation requires interdisciplinary collaboration. Therefore, collaboration between scientists working in materials, electronics, and mechanical engineering is essential.

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CHAPTER 8

THE EFFECT OF USING BOREHOLE HEAT EXCHANGER IN GEOTHERMAL ENERGY SYSTEMS ON THERMAL EFFECTIVENESS

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1. INTRODUCTION

The increasing world population and technological advances are increasing countries' energy consumption. Due to the decrease in traditional energy fuels, the difficulty of accessing fossil resources, and the negative effects of conventional energy fuels on the environment, countries have had to start new searches for energy (Arat and Arslan 2017b). Fossil fuels are used in a large part of the heating systems in our country. With the recent developments, it has become a policy for countries to end the use of fossil fuels that are harmful to the environment and use more efficient and cleaner alternative energies. Countries need to diversify their energy production sources and increase the ratio of renewable energy sources in total production.

Geothermal energy is a continuous and clean energy source that is not dependent on environmental conditions and is relatively less affected by environmental conditions among renewable energy sources (Arat and Arslan 2017a). Geothermal energy is defined as ground heat, but in general, it is defined as thermal energy accumulated in the Earth's crust and containing various minerals. This thermal energy is obtained from natural fluids in rocks underground and in the cracks and pores of these rocks (US Department of Energy 2025). Certain conditions must be met in order for geothermal energy to be used. The first requirement, being accessibility, occurs through natural transport processes such as heat transfer in porous and/or fractured formations or heat transfer in the rock itself. A geothermal system has three main elements; heat source, fluid carrying the energy, and storage reservoir (Haklidir and Haklidir 2010).

Technologies that use geothermal energy at this level are currently being developed, and current technology can reach 10,000 meters down into the Earth's crust. A geothermal gradient is the temperature behavior linked to increasing depth in the Earth's crust. This term is used in studies on the Earth's crust and geothermal fluids. The increase in geothermal gradient is approximately 3°C for every 100 meters from the Earth's surface (Dincer and Ozturk 2021). The Earth's crust has a temperature of about 14 degrees Celsius on its surface, but the temperature inside the crust ranges from 1000 to 3500 degrees Celsius, according to studies (Earle 2025). The reason for the increase in temperature with depth is the heat source at the center of the Earth. The heat source at the Earth's center provides temperatures of approximately 5000 C, despite less energy being needed from this source than from the Sun (National Geographic 2025). Even though this energy source at the Earth's center cannot be directly observed, numerous models have been used to explain it. Because it is a necessary and useful energy source for the entire world, this energy source, situated in the planet's heart, is a significant source of heat (Dickson and Fanelli 2013).

Geothermal energy, which was used only for health purposes in the early ages, is now widely used in applications such as electricity generation, direct heating and hybrid systems. The reason for the variety of application areas is that geothermal resources have different enthalpy values due to different temperatures. The modified Lindal diagram showing the areas of use of geothermal fluid according to temperature values is given in Figure 1 (Fridleifsson 1998). When the Lindal diagram, named after Baldur Lindal, an Icelandic engineer, is examined, it is seen that conventional electricity generation is carried out between 140ºC and 180ºC, while electricity generation with dual fluid can be done at lower temperatures. While resources between 30ºC and 50ºC are preferred for health applications such as swimming pools and spas, geothermal resources with higher temperatures are used for direct heating, cooling and drying operations.

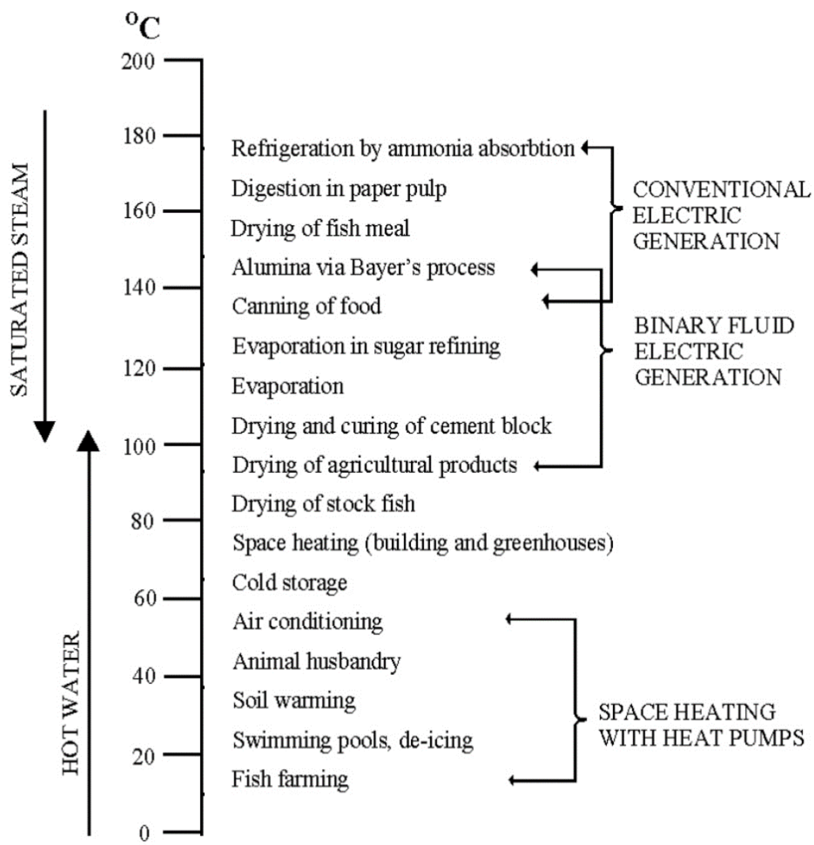

Figure 1. Modified Lindal diagram (Fridleifsson 1998).

Geothermal energy is independent of environmental conditions because it is obtained from the Earth's crust. Compared to other renewable energy systems, it is a more reliable and highly usable energy source because it provides stable and continuous energy. It is an environmentally friendly energy type because it does not require storage and transportation and does not release harmful gases like fossil fuels (Arat and Arslan 2017b).

The heat source, reservoir, and heat-carrying fluid are the three primary components of the geothermal system. The main use of high-temperature geothermal resources (>150 °C) is the production of electricity. Geothermal resources with low and medium temperatures (less than 150 °C) have a variety of uses (DiPippo 2015). Heat pumps are used to heat and cool using geothermal resources below 20 °C (Fridleifsson 1998).

Geothermal fluids having a reservoir temperature of 200°C or higher are used to generate electricity. However, geothermal waters with reservoir temperatures as low as 150°C can also be used to generate energy, according to new technologies that are being developed every day (Fridleifsson 1998). Additionally, research has recently been conducted to use water temperatures between 70 and 900 °C to produce energy using gasses with low evaporation points (Cruz et al. 2021).

2. GEOTHERMAL BOREHOLE HEAT EXCHANGER

The costs of the exploration and drilling phases, with the geothermal drilling stage accounting for about half of the entire cost, are the primary barriers to expanding the geothermal industry. Despite the concerns of corrosion and scale, deep borehole heat exchangers are employed to lower this expense (Alimonti, Conti, and Soldo 2021). When looking at the studies in the literature, the heat of the geothermal source is drawn from the source by the borehole heat exchanger and given to the system. This borehole heat exchanger is released into the geothermal water in a compact form, as shown in Figure 2, and the heat transfer process in the exchanger occurs inside the geothermal water.

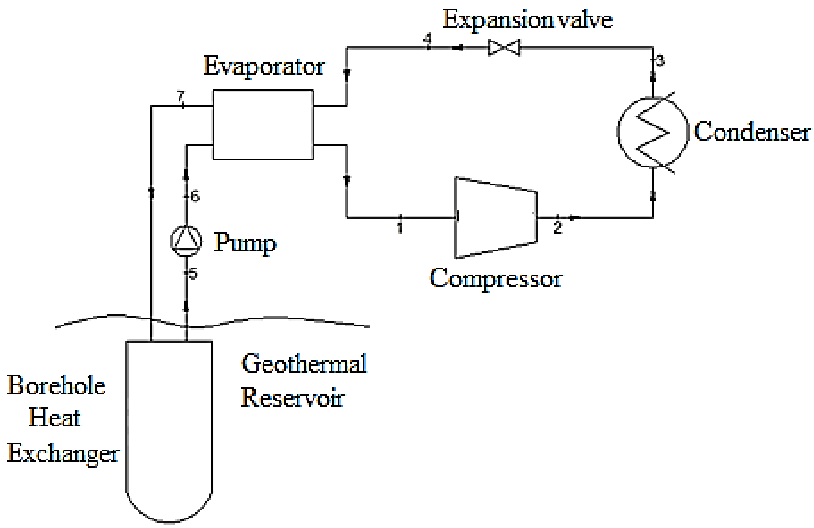

Figure 2. A system using a borehole heat exchanger.

When looking at the studies in the literature, L. Lamarche et al. conducted a study evaluating the thermal borehole resistance formed between the fluid and the borehole and the internal resistances with different approaches. Borehole resistance is significant for the sizing of the heat exchanger used in underground heat pumps and is also an important parameter used in estimating the required drilling depth. The study presented a new method that allows the evaluation of borehole resistance and internal resistances with the temperature information at the bottom of the U-pipe. This method has the advantage of considering the flow rate and the equivalent borehole resistance depth. This study was conducted only for single U-pipes (Lamarche, Kajl, and Beauchamp 2010). S. Focaccia and F. Tinti brought an innovative design to the borehole heat exchanger in their study. They compressed the rods inside the borehole with filling material and immersed them in the artificial (brine) fluid. This new system paved the way for the increase of heat transfer inside the borehole because it paved the way for the heat transfer to start with natural conduction between the vertical rods and the protected system. Moreover, this new system increased the reliability and environmental protection since it allowed controlling the rods at all times during operation and reduced the risk of rod breakage (Focaccia and Tinti 2013).

C.K. Lee and H.N. Lam performed computer simulations of borehole heat exchangers used in geothermal heat pumps using a three-dimensional finite-difference method with rectangular coordinates. As a result of the study, they found that the temperature and loading were not constant throughout the borehole heat exchanger. They determined that the results obtained from a single connected borehole would not be sufficient to evaluate the performance in the borehole region. They stated that the best way to separate the entire borehole region is to simulate all borehole exchangers simultaneously using the rectangular coordinate system (Lee and Lam 2008). A. Casasso and R. Sethi analyzed the most important parameters affecting the performance of ground source heat pumps and estimated the energy consumption of the heat pump in each variation. Most of these parameters were analyzed in other studies, but not all were considered together in the same framework. As a result of the simulation analysis, it was revealed that the most critical design parameter is the length of the borehole heat exchanger. The optimum borehole heat exchanger length that minimizes the total operating cost should be determined by considering the fluctuation in the unit electricity price. It was revealed that the heat-carrying fluid, the location, and the distance of the pipes in the borehole are also critical parameters to be considered (Casasso and Sethi 2014). R. Al-Khoury et al. presented a finite element technique for a double U-tube borehole heat exchanger surrounded by soil mass. They stated that this computer solution method made significant contributions to the calculation of heat transfer in the borehole heat exchanger in a shorter time and in an efficient manner (Al-Khoury, Kölbel, and Schramedei 2010).

L. Jun et al. analyzed the effects of seven different factors -operation time, body area, borehole depth, pipe velocity, grout thermal conductivity, inlet temperature and soil type- on the thermal resistance and heat transfer rate with different methods and compared the results. The total thermal resistance and heat transfer rate along the depth changed depending on the operation time; the thermal resistance of the soil accounted for 68.4% of the total thermal resistance of the ground source heat exchanger. A larger body area showed better thermal performance. While the drilling costs increased with the increase in borehole depth, the heat transfer rate per depth decreased slightly. The increase in fluid velocity did not reduce the thermal resistance much, but significantly increased the heat transfer rate per depth. They concluded that the soil type significantly affected the heat transfer performance of the heat pump (Jun et al. 2009).

Using a 2D coupled heat conduction-advection model, J. Chan Choi et al. examined how the direction and soil water flow rate affected the performance of several kinds of borehole heat exchanger arrays. By using three different arrays, the heating processes were simulated over 15 years. The results showed that the performance of L-type and single-line type arrays was significantly affected by the flow rate and the soil water flow direction. When the characteristic length of the Peclet number is considered a unit value on the system performance was negligible regardless of the array type and flow rate. The comparison of annual heat capacity showed that the difference could be up to 13% depending on the flow direction. When designing the best BHE arrays, both direction and soil water flow rate may be crucial, particularly for non-square rectangular arrays (Choi, Park, and Lee 2013).

3. CONCLUSION AND RECOMMENDATIONS

Recent developments have made it a national policy to cease using environmentally damaging fossil fuels and switch to cleaner, more efficient alternative energy sources. Countries must raise the proportion of renewable energy sources in their overall production and diversify their sources of energy production. Among renewable energy sources, geothermal energy is a clean, continuous energy source that is not reliant on environmental conditions and is comparatively less impacted by them.

In the past, geothermal energy was mainly utilized for medical purposes. It is widely used in direct heating, hybrid systems, and electricity generation. Because it produces steady and continuous energy, it is a more dependable and highly usable energy source than other renewable energy systems. It is an environmentally beneficial energy source because it doesn't need to be stored or transported, and because it doesn't emit any hazardous gases like fossil fuels do.

The main obstacles to the growth of the geothermal sector are the expenses of the exploration and drilling stages, with the geothermal drilling stage costing around half of the total. Deep borehole heat exchangers are used to reduce this cost despite corrosion and scale issues.

By using a borehole heat exchanger, the installation costs can be decreased, and less energy is utilized. Therefore, the countries have performed well on the zero-carbon emissions target.

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