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Editör: Dr.Öğr.Üyesi Serdar KAÇAMER



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**Ağaç İşleri Endüstri Mühendisliği Alanında
Güncel Konular ve Akademik Değerlendirmeler**

Editör

Dr.Öğr.Üyesi Serdar KAÇAMER

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İzham KILINÇ

"Bu kitapta yer alan bölümlerde kullanılan kaynakların, görüşlerin, bulguların, sonuçların, tablo, şekil, resim ve her türlü içeriğin sorumluluğu yazar veya yazarlarına ait olup ulusal ve uluslararası telif haklarına konu olabilecek mali ve hukuki sorumluluk da yazarlara aittir."

THE FURNITURE INDUSTRY UNDER THE VISION OF INDUSTRY 5.0: A COST- EFFECTIVENESS AND SUSTAINABILITY ANALYSIS OF PREDICTIVE MAINTENANCE

İzham KILINÇ¹

1. INTRODUCTION

Increasing global competition, high product variety, and short delivery times are driving manufacturing enterprises toward data-driven maintenance approaches that minimize unplanned downtime and maximize equipment reliability. Predictive maintenance (PdM), supported by the Internet of Things (IoT), cyber-physical systems, and artificial intelligence technologies in the Industry 4.0 ecosystem, is a proactive approach that aims to predict potential failures before they occur by using condition monitoring data (Lee et al., 2014). Unlike traditional methods, this paradigm ensures that maintenance activities are performed just in time and only to the necessary extent.

The production of furniture and industrial wood products involves more heterogeneous failure types compared to general manufacturing, owing to its high-variety/low-batch volume characteristics, the intensive use of multi-purpose and specialized machines (CNC, calibrating, pressing, sizing, edge banding), and complex surface treatment processes. In this context, PdM minimizes downtime by making early anomaly detections in critical sub-components such as spindles and bearings through the continuous monitoring of sensor signals like vibration,

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temperature, pressure, and energy consumption. Recent studies in the field concretely demonstrate the applicability and operational benefits of machine learning-based condition monitoring systems, particularly in CNC woodworking machines and wood-based panel production lines (Wang et al., 2022).

In recent years, the maturity level of PdM has expanded to encompass not only protecting machine health but also energy efficiency and industrial sustainability. While the operation of optimized equipment with lower friction and energy loss prevents energy waste, data-driven intervention timing limits unnecessary part replacements and raw material wastage. This trend directly aligns with the human-centric, resilient, and green transition-oriented vision of Industry 5.0 (European Commission, 2021). Artificial intelligence and autonomous systems are being integrated into a sustainable production philosophy that prioritizes worker well-being and supply chain resilience, rather than merely reducing production costs (Nahavandi, 2019).

On the technological front, digital twin-based PdM architectures support maintenance decisions by providing real-time data analytics through virtual models of production processes and equipment, allowing for performance comparisons of different machine learning algorithms (Tao et al., 2018; Liu et al., 2021). Comprehensive literature reviews emphasize that IoT-supported predictive maintenance systems are becoming increasingly widespread in the manufacturing sectors; however, elements such as data quality, cybersecurity, and system integration are the fundamental keys to success (Liu et al., 2021).

This study examines the effects of predictive maintenance applications in the furniture manufacturing industry on production efficiency, downtime reduction, and cost-effectiveness in light of current literature. The study addresses the systematics of IoT, machine learning, and digital twin integration,

and evaluates implementation challenges such as data security and change management. In this context, by presenting a roadmap that brings together the perspectives of sustainability and Industry 5.0, it aims to develop evidence-based, strategic, and practical recommendations for furniture enterprises with different machine parks.

2. DEFINITION AND CONCEPTUAL FRAMEWORK OF PREDICTIVE MAINTENANCE

Predictive maintenance (PdM) is a data-driven maintenance strategy that aims to predict potential failures before they occur by continuously monitoring the operational status of equipment in production systems. This method enables the detection of micro-level changes in equipment performance by analyzing real-time data obtained from sensors, allowing interventions before these deviations turn into critical failures. Unlike traditional corrective (reactive) or time-based preventive maintenance, PdM relies on a condition-based approach; in other words, the maintenance decision is optimized according to the instantaneous and actual condition of the hardware (Mobley, 2002).

In industrial maintenance strategies, PdM is considered the primary indicator of the transition from reactive approaches to proactive models. At the core of this transformation are data acquisition, data preprocessing, predictive analytical modeling, and decision support systems. The fundamental components of the predictive maintenance process are conceptually presented in Fig. 1.

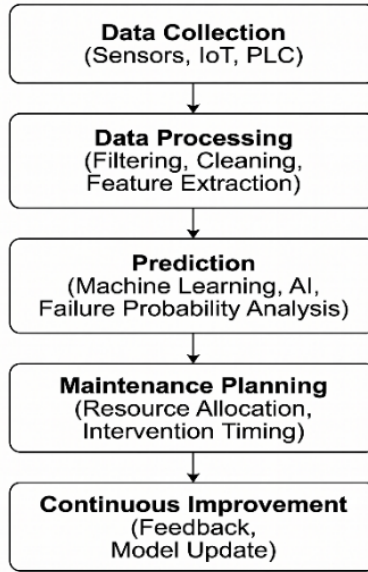


Figure 1. Conceptual Structure of the Predictive Maintenance Process

The data acquisition stage in this process begins with obtaining sensor signals such as temperature, vibration, pressure, energy consumption, acoustic emission, and current density. These obtained data are processed and interpreted through machine learning and artificial intelligence algorithms. In particular, algorithms such as support vector machines (SVM), random forest, and artificial neural networks (ANN) can predict failure probabilities and Remaining Useful Life (RUL) values with high accuracy (Jardine et al., 2006).

Another critical element in the success of PdM applications is data integration and coordination with enterprise systems. Integrating heterogeneous sensor data collected from the field with Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) platforms ensures that maintenance decisions are made in full compliance with overall business and production goals (Wang, 2016).

In recent years, PdM architectures have gained significant momentum with the integration of digital twin technology and cloud-based maintenance platforms. Digital twins create high-fidelity virtual replicas of physical equipment, simultaneously reflecting system behavior with real-time data flow and allowing the simulation of various maintenance scenarios (Fuller et al., 2020). This advanced approach not only predicts failures but also provides the opportunity to analyze the multidimensional effects of planned maintenance interventions on production efficiency, downtime costs, and energy consumption (Kritzinger et al., 2018). Table 1 comparatively summarizes the fundamental characteristic features of traditional and modern maintenance approaches and emphasizes the industrial advantages of predictive maintenance.

Table 1. Comparison of Maintenance Approaches

Feature / Approach	Corrective Maintenance	Preventive Maintenance	Predictive Maintenance
Time of Intervention	Post-failure	Time-scheduled	Condition-based (predictive)
Data Utilization	Low	Medium	High (sensor and analytical data)
Cost Impact	High repair cost	Medium	Low in the long term
Downtime	Long	Medium	Minimum
Technology Requirement	Low	Medium	High (IoT, AI, Big Data)
Sustainability Contribution	Low	Medium	High (energy efficiency and waste reduction)

Industrial case studies in the literature demonstrate that PdM applications increase equipment availability by 15–25%, reduce unplanned downtime by 30–40%, and provide savings in total maintenance costs by 20% to 30% (McKinsey & Company, 2017). In the furniture sector, where multi-processing CNC woodworking machines and continuous press lines are

intensively used, these operational and economic gains are of critical importance.

3. APPLICATION AREAS AND BENEFITS OF PREDICTIVE MAINTENANCE IN THE FURNITURE INDUSTRY

The furniture industry has a highly sensitive operational structure in terms of maintenance management due to its high-variety product range, complex production processes, and the simultaneous use of numerous machine types. Equipment in production lines, such as CNC woodworking machines, edge banding machines, presses, drying kilns, and surface coating systems, carry a high risk of failure due to the density of both their mechanical and electronic components (Xu et al., 2021). At this point, predictive maintenance (PdM) makes it possible to detect potential failures before they occur and to plan maintenance activities at the optimum time by continuously monitoring the operational status of these machines.

Recent studies show that PdM in the production of furniture and wood products not only ensures production continuity but also provides strategic contributions in terms of energy efficiency, occupational safety, and sustainable resource utilization (Duflou et al., 2012). Thanks to Internet of Things (IoT)-based sensor networks, the temperature, vibration, current, and pressure data of the machines are monitored in real-time; the predictions obtained from these data are integrated into artificial intelligence-supported software that automates maintenance decisions (Xu et al., 2018). Table 2 below summarizes the machines commonly used in furniture production and the fundamental benefits provided by PdM in this equipment.

Table 2. Predictive Maintenance Application Areas in Furniture Production Equipment

Machine Type	Monitored Parameters	Sensors Used	Benefits Provided
CNC Machines	Vibration, spindle temperature, energy consumption	Accelerometer, thermocouple, current sensor	Early failure warning, tool life tracking, quality stability
Edge Banding Machine	Motor current, adhesive temperature	Current sensor, infrared (IR) temperature sensor	Continuity of bonding quality, downtime reduction
Press Machine	Pressure, stroke count, oil temperature	Pressure sensor, thermistor	Hydraulic failure prevention, energy savings
Drying Kiln	Air flow rate, temperature difference	Humidity and temperature sensor	Energy efficiency, reduction of material deformation
Surface Treatment Line	Fan rotation speed, paint viscosity	Rotation and viscosity sensor	Prevention of coating defects, material savings

These implemented data-driven strategies reduce unplanned downtime in production lines by up to 30% and provide savings of 20–25% in total maintenance costs (Wang et al., 2019). Furthermore, through the integration of PdM with digitalization, production planning systems can perform smart production scheduling by taking maintenance data into account, thereby guaranteeing the uninterrupted operation of the production line (Xu et al., 2021).

However, it is observed that PdM has evolved from being merely an operational tool into a strategic competitive factor in the furniture sector. Shortening customer delivery times, rising energy costs, and global pressures for sustainable production are directing enterprises toward data-driven maintenance management (Xu et al., 2021). This transformation is in full

alignment with the digitalization goals of Industry 4.0 and the emerging paradigms of Industry 5.0, which center on sustainability and human-machine collaboration (Xu et al., 2021). In Fig. 2, the contributions of predictive maintenance to the value chain in furniture production are visualized.

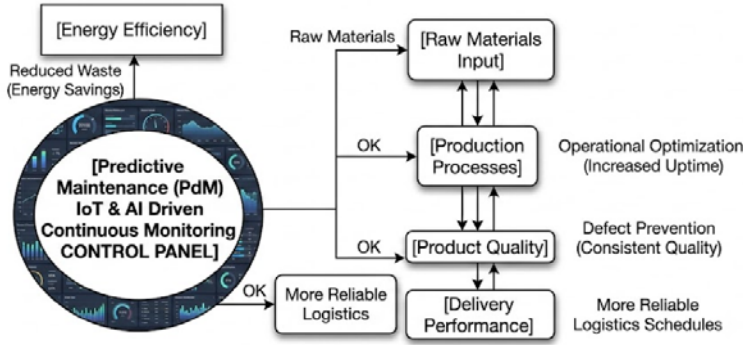


Figure 2. Impact of predictive maintenance on the furniture manufacturing value chain.

4. TECHNOLOGIES USED IN PREDICTIVE MAINTENANCE

The effectiveness of predictive maintenance applications is directly related to the accuracy of the technologies used, the level of integration, and data processing capacity. Currently, the Internet of Things (IoT), Machine Learning (ML), Artificial Intelligence (AI), Digital Twins, and Big Data Analytics are the prominent core technologies in this field. The integrated and coordinated use of these components increases the speed and accuracy of maintenance decisions, providing online monitoring and automated decision support on production lines.

4.1. Internet of Things (IoT) and Sensor Technologies

IoT sensors enable real-time data collection from critical equipment used in furniture production, such as CNC machines,

press machines, and surface treatment lines. Multidimensional data, such as vibration, temperature, current, humidity, pressure, and oil viscosity, allow for the early detection of potential failures by instantaneously monitoring the operational status of the equipment. Data collected through these sensors are transferred to data centers or cloud platforms via wireless communication protocols (such as Wi-Fi, LoRaWAN, ZigBee) and integrated with maintenance software (O'Donovan et al., 2015). In the furniture sector, sensor systems based particularly on vibration analysis can predict motor and spindle failures with up to 90% accuracy; furthermore, temperature-based IoT measurements provide early warning of bearing and motor winding failures. Thanks to these proactive monitoring systems, unexpected downtime on the production line is prevented, and maintenance activities are carried out in a planned manner that does not disrupt the production flow.

4.2. Machine Learning and Artificial Intelligence

Machine learning constitutes the core analytical component of predictive maintenance systems. Classification, regression, and clustering algorithms are used to forecast failure probabilities over historical data, calculate the remaining useful life of equipment, and determine anomalies. Recently, deep learning-based models have demonstrated significant success in complex areas such as Time Series Analysis and Failure Type Classification (Ismail Fawaz et al., 2019).

Artificial intelligence plays a critical role in the process of automating maintenance decisions. AI-based systems analyze historical maintenance records and operational data to make predictions based on similar examples for new situations encountered. This approach minimizes human error in maintenance planning and significantly accelerates the decision-making process (Peres et al., 2020).

4.3. Digital Twin Technology

A Digital Twin is the creation of a high-fidelity virtual replica of a physical machine or system and the monitoring of real-time data flow through this copy. This technology provides the opportunity to perform risk analysis of maintenance scenarios by simulating the behavior of production systems (Qi et al., 2021). In the furniture industry, digital twin applications are particularly used in CNC machines and press lines, optimizing the maintenance process and operational efficiency by detecting deviations in machine parameters in advance.

4.4. Big Data Analytics and Cloud-Based Systems

The amount of data generated in PdM applications is quite high due to the high sampling rates of sensors. Big Data Analytics techniques are used to process, store, and interpret these data (O'Donovan et al., 2015). Through platforms such as Hadoop, Spark, and Azure Machine Learning, multidimensional data coming from different machines and facilities can be analyzed holistically and in parallel. Cloud-based maintenance systems, on the other hand, make these analyses and monitoring dashboards accessible remotely. Thus, maintenance engineers can monitor machine status and failure predictions across different production facilities through a single central control panel. This architecture provides significant cost advantages, especially for small and medium-sized furniture enterprises with limited IT infrastructure. Table 3 below summarizes the core technologies used in predictive maintenance, their functions, and the contributions they provide.

Table 3. Core Technologies Used in Predictive Maintenance and Their Functions

Technology	Function	Provided Contribution
IoT Sensors	Real-time data acquisition	Early failure detection, continuous monitoring
Machine Learning	Data analysis and prediction	Failure probability forecasting, maintenance scheduling
Artificial Intelligence	Decision support system	Automated maintenance planning, error reduction
Digital Twin	Virtual modeling and simulation	Process optimization, risk analysis
Big Data Analytics	Multidimensional data processing	Trend analysis, system reliability enhancement
Cloud Systems	Central access and integration	Remote monitoring, cost advantage

5. DATA COLLECTION, ANALYSIS, AND RELIABILITY MANAGEMENT IN THE FURNITURE INDUSTRY

The success of predictive maintenance in the furniture industry depends directly on data quality and analytical accuracy. Data obtained from production lines provide critical information not only on machine performance but also on energy consumption, material quality, and overall process efficiency. Therefore, the data collection process is the most critical step of the predictive maintenance cycle (Zikopoulos et al., 2012).

5.1. Data Collection Process

In furniture production facilities, data collection is generally carried out through a three-tier architecture:

- **Physical Layer (Sensor Level):** Sensor data such as vibration, temperature, current, torque, pressure, and humidity are collected directly from machine components. These data are recorded at high sampling

rates (often per-second), enabling the early detection of potential anomalies.

- **Communication Layer:** The collected data are transmitted to cloud-based data centers via IoT network protocols (e.g., MQTT, OPC-UA, Modbus). At this stage, encryption and authentication mechanisms are utilized to ensure data security.
- **Data Processing Layer:** Raw data are filtered, missing values are imputed, and statistical noise reduction operations are performed.

Thanks to this multi-layered structure, data obtained from production systems become processable with high accuracy. In particular, vibration monitoring and thermal monitoring methods are frequently preferred in CNC and press lines (Wang et al., 2022).

5.2. Data Analysis Approaches

Collected data are processed using descriptive, predictive, and prescriptive analytical approaches. Descriptive analysis focuses on understanding past events and identifying failure patterns. Predictive analysis forecasts potential failures in advance using statistical modeling and machine learning methods. Prescriptive analysis provides an answer to the question "what should be done?" by prioritizing maintenance actions.

The most widely used predictive models in the furniture industry include Random Forest, Support Vector Machines (SVM), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN). For instance, in a study conducted by Wang et al, it was reported that LSTM-based predictive models could detect CNC spindle failures with 93% accuracy (Wang et al., 2022). Table 4 below summarizes the

primary data analysis methods used in the furniture industry and their advantages.

Table 4. Data Analysis Methods Used in Furniture Manufacturing

Analysis Method	Purpose of Use	Advantage
Time Series Analysis	Trend detection from continuous sensor data	Predicting failure time
SVM (Support Vector Machines)	Failure classification	High accuracy, effective on small datasets
Random Forest	Multi-variable analysis	Ability to handle noisy data
LSTM Networks	Prediction on sequential data	Highly suitable for time-dependent data
CNN	Visual and vibration signal analysis	High success rate in recognizing complex patterns

5.3. Data Reliability and Quality Management

Data reliability is one of the determining factors in the success of predictive maintenance systems. Erroneous or missing data can lead to incorrect predictions and unnecessary maintenance interventions. Therefore, a comprehensive Data Quality Management (DQM) process must be implemented.

To enhance data reliability, periodic calibration of sensors must be performed, synchronization errors in the data collection infrastructure must be resolved, and noise filtering and anomaly detection algorithms must be utilized. Furthermore, for data integrity, hash-based verification techniques and cybersecurity protocols (e.g., AES, TLS) should be deployed. In this way, production data are protected from manipulation, and the reliability of artificial intelligence models is significantly increased. Figure 3 illustrates the general flow of the data collection and analysis process in furniture manufacturing.



Figure 3. General flow of the data collection and analysis process in furniture manufacturing.

The diagram illustrates the process starting from the collection of sensor data (IoT/PLC) to the subsequent stages of data transmission, pre-processing, prediction, and decision support. This structure explains how the data flow is processed within predictive maintenance systems and at which specific stages maintenance decisions are generated.

6. COST-EFFECTIVENESS AND SUSTAINABILITY IMPACT OF PREDICTIVE MAINTENANCE IN THE FURNITURE INDUSTRY

Predictive maintenance (PdM) is not only a technical necessity but also a strategic investment in terms of economic and environmental sustainability. While equipment is maintained after a failure or at specific intervals in traditional maintenance approaches, the PdM approach schedules maintenance actions based on real-time data and failure probability predictions. This prevents unnecessary downtime, directly provides cost savings, and increases overall production efficiency.

Field applications in the furniture sector demonstrate that enterprises implementing PdM achieve a 20–30% reduction in maintenance costs and a 35–40% reduction in unplanned downtime. These rates are even more pronounced in high energy-consuming equipment such as CNC machines, edge banding machines, and surface treatment lines.

6.1. Cost-Effectiveness Analysis

The economic impacts of PdM applications are evaluated through direct costs (maintenance, spare parts, labor) and indirect costs (production loss, energy waste, product defects). Table 5 below summarizes the effects of predictive maintenance on these cost elements.

Table 5. Impact of Predictive Maintenance on Cost Elements

Cost Element	Traditional Approach	Predictive Maintenance Approach	Achieved Savings (%)
Maintenance Labor	Planned or post-failure intervention	Condition-based intervention	20–25
Spare Parts Usage	Overstocking or late procurement	Planned procurement prior to failure	15–20
Energy Consumption	Low-efficiency operating cycle	Operation at optimum load	10–18
Production Downtime	Unplanned interruptions	Pre-planned maintenance intervals	30–40
Product Defect Rate	High quality deviations	Process stability is ensured	12–15

This table reveals that PdM provides indirect gains not only by reducing direct repair costs but also by increasing production line stability and product quality. In this context, the Return on Investment (ROI) period is generally realized in the range of 1.5 to 2 years.

6.2. Sustainability Perspective

The furniture sector is a production area with high environmental impacts; elements such as energy consumption, material waste, and chemical emissions directly affect sectoral sustainability performance. PdM systems serve as an important improvement tool at this point:

- Energy efficiency: Machines operating without failure prevent unnecessary energy loss.
- Reduction of material waste: Defective production is minimized through continuous process monitoring.
- Extension of equipment life: Equipment can be used for a longer period under optimal operating conditions.
- Reduction of carbon footprint: The increase in energy efficiency directly contributes to the reduction of CO₂ emissions.

These impacts are also well-aligned with the European Green Deal and Industry 5.0 policies. Particularly in the dimension of environmental sustainability, PdM has become one of the fundamental components of the "smart and green manufacturing" paradigm (European Commission, 2024). The dimensions of PdM's contribution to the sustainability axis in the furniture industry are summarized below.

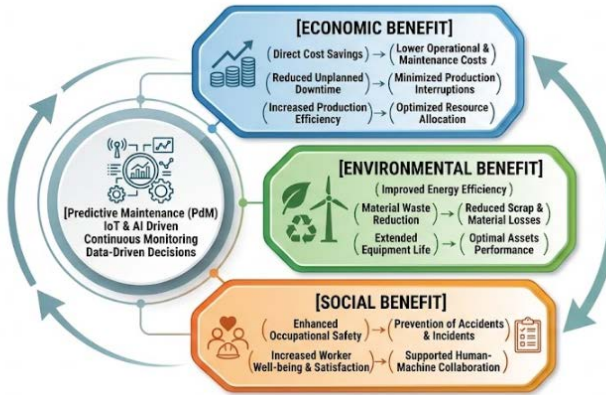


Figure 4. Sustainability dimensions of predictive maintenance.

7. IMPLEMENTATION CHALLENGES AND FUTURE TRENDS OF PREDICTIVE MAINTENANCE IN THE FURNITURE INDUSTRY

The applicability of predictive maintenance (PdM) in the furniture industry is closely linked to both the adequacy of technical infrastructure and the capacity for organizational transformation. Although PdM offers significant advantages in terms of production continuity and cost-effectiveness, various challenges and limitations exist in practice.

7.1. Implementation Challenges

- **Data Quality and Lack of Standards:** Machines used in furniture manufacturing often belong to different manufacturers, leading to incompatibility among sensor protocols, data formats, and communication standards. This situation weakens data integrity and complicates analysis processes.
- **High Initial Investment Cost:** The deployment of IoT sensors, data collection infrastructure, and AI-supported software requires a substantial investment, particularly for small and medium-sized enterprises (SMEs). Although it provides cost advantages in the long term, it creates capital pressure in the short term.
- **Scarcity of Skilled Human Resources:** The shortage of personnel specialized in data science, artificial intelligence, and industrial analytics hinders the sustainability of PdM projects. In the majority of furniture SMEs in Turkey and Europe, maintenance personnel still operate using traditional methods.
- **Integration Difficulties:** The integration of PdM systems with existing ERP, MES, and SCADA

architectures is a technically complex and time-consuming process. This necessitates a comprehensive restructuring of the information technology infrastructure.

- **Cultural and Managerial Resistance:** The prevalence of a "reactive maintenance" (post-failure intervention) mindset within corporate culture can create resistance to transitioning to predictive maintenance practices. Therefore, management support and change management strategies are of critical importance.

7.2. Future Trends

Technological advancements in the field of PdM are shaping the vision of smart, autonomous, and sustainable maintenance systems in the furniture sector.

- **AI-Powered Self-Learning Systems:** Next-generation artificial intelligence algorithms are gaining the ability to learn continuously from machine data and dynamically optimize maintenance scheduling. These approaches enable the production line to achieve a self-regulating structure.
- **Widespread Use of Digital Twins:** Digital twin technology enables the real-time simulation of all equipment by creating virtual replicas of production facilities. Consequently, maintenance scenarios can be pre-tested in terms of cost and risk factors.
- **Sustainability-Oriented Smart Maintenance:** In alignment with the Industry 5.0 paradigm, PdM is becoming compatible not only with efficiency but also with environmental sustainability and human-centric manufacturing goals. Energy efficiency, waste management, and carbon footprint reduction have

begun to feature among the key performance indicators of maintenance strategies (European Commission, 2024).

- **Integration of Cloud and Edge Computing:** Cloud-based data storage and edge computing technologies enhance real-time analysis speed and minimize network latency. This architecture allows IoT devices in furniture factories to perform local data processing without continuous dependence on a central server.
- **Standardization and Open Data Platforms:** In the future, open-source industrial data protocols (e.g., OPC UA, MQTT, DDS) will become more prevalent to facilitate seamless data sharing in PdM applications. This will significantly enhance interoperability among machines originating from diverse manufacturers.

8. CONCLUSION

This study demonstrates that predictive maintenance (PdM) offers multidimensional benefits to the furniture industry, moving beyond mere cost reduction to enhance production quality, energy efficiency, and environmental sustainability. Given the high precision required in furniture manufacturing—where mechanical, thermal, and chemical processes intersect—the integrated use of IoT, AI, and digital twins is critical for proactive failure prediction and production continuity.

Economically, PdM accelerates the return on investment (ROI) by reducing maintenance costs by 20–30% and unplanned downtime by 35–40%. Environmentally and socially, it minimizes material waste, lowers the carbon footprint, and mitigates occupational safety risks, perfectly aligning with the green manufacturing paradigm.

To integrate PdM systems within the Industry 5.0 vision of human-machine collaboration and sustainability, the following actions are recommended:

- Modular, low-cost sensor solutions should be developed for SMEs.
- University-industry collaborations must be promoted to localize AI-based maintenance algorithms.
- Data literacy and digital competency training should be expanded for employees.
- PdM systems must be aligned with environmental performance reporting and carbon reduction policies.

Ultimately, PdM is not merely a technical upgrade but a strategic necessity for the furniture sector, shaping future manufacturing paradigms through its combined economic, environmental, and social advantages.

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KUSURDAN İŞLEVE: 4B BASKI VE PROGRAMLANABİLİR YAPILARDA AHŞABIN HIGROMORFİK DAVRANIŞINDAN YARARLANILMASI

İzham KILINÇ¹

1. GİRİŞ

Doğal ve yenilenebilir bir mühendislik malzemesi olan ahşap, hücre duvarını oluşturan selüloz, hemiselüloz ve lignin polimerlerinin hidroksil gruplarından ötürü çevresindeki bağıl nem değişimlerine karşı yüksek du-yarlılık gösterir ve bünyesine su alıp verirken radyal, teğet ve boyuna ek-senlerde birbirinden farklı oranlarda genişir ya da daralır. Geleneksel ahşap işleme endüstrisinde bu anizotropik davranış; çarpılma, dönme ve çatlama gibi boyutsal kararsızlıklara yol açtığı için bir kusur olarak kabul edilmiş, bu kusuru gidermek amacıyla yüzey kaplamaları, termal modifikasyon ve emp-renye işlemleri geliştirilmiştir (Yang ve Liu, 2020; Holmberg vd., 1999).

Buna karşılık doğa, higromorfik davranışı bir kusurdan ziyade harici enerji gerektirmeyen pasif bir hareket mekanizması olarak değerlendirir. Çam kozalaklarının düşük bağıl nemde ayırık bir mekanik eklem yapısına gereksinim duymaksızın açılarak tohumlarını saçması, hücre duvarındaki mikrofibril yöneliminin tetiklediği adaptif bir bükülme hareketidir ve bitki biyomekaniği literatüründe biyoesinli aktüasyon sistemlerinin başlıca modellerinden biri olarak kabul edilir (Burgert ve Fratzl, 2009). Eklemeli İmalat (3B baskı) teknolojilerinin üretim sürecine

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"zaman" ve "uyarana tepki" değişkenlerini dahil etmesiyle Dört Boyutlu (4B) Baskı kavramı ortaya çıkmıştır; bu kavrama göre üretilen bir parça, nem, ısı veya ışık gibi çevre-sel uyaranlara maruz kaldığında önceden tasarlanmış bir geometriye doğru form değiştirebilir (Tibbits, 2014). Ahşap ve polimer matrislerin bu ilkeyle birleştirilmesi, ahşabın higroskopik şişme ve büzülme eğilimini yapısal bir dezavantajdan akıllı kompozit malzemeler için programlanabilir bir avantaja dönüştürmüştür (Correa vd., 2015). Alandaki güncel derlemeler de higro-morfik 4B baskı sistemlerinin malzeme seçimi, üretim yöntemi ve aktüasyon performansı bakımından hâlâ hızla gelişen, disiplinlerarası bir araştırma alanı olduğunu vurgulamaktadır (de Kergariou vd., 2023). Bu bölümde, ahşap-polimer kompozitlerin 4B baskı süreçlerindeki higromorfik programlanabilirliği; malzeme formülasyonları, üretim parametreleri, biyomimetik tasarım stratejileri, şekil değiştirme davranışının hesaplamalı modellenmesi ve iç mekan/mimari uygulamalar başlıkları altında bütüncül bir şekilde ele alınmaktadır.

2. AHŞABIN HİGROMORFİK MEKANİZMALARI VE ANİZOTROPİ

Ahşabın su ile etkileşimi ve buna bağlı boyutsal değişimleri, malzemenin kimyasal bileşimi ve hücresel ultrastrüktürü ile doğrudan ilişkilidir. Hücre duvarını oluşturan selüloz, hemiselüloz ve lignin polimerleri, içerdikleri hidroksil (-OH) grupları nedeniyle su molekülleriyle hidrojen bağı kurma eğilimindedir; bu da nem alımı sırasında hücre duvarı katmanlarının farklı yönlerde genişmesine yol açar.

2.1. Hücre Duvarı Ultrastrüktürü ve Mikrofibril Açısı

Higromorfik tepkinin şiddeti ve yönü, hücre duvarının kalın S2 taba-kasındaki selüloz mikrofibrillerinin uzunlamasına

eksenle yaptığı açıya, yani mikrofibril açısına bağlıdır (Xaiver vd., 2025; Burgert ve Fratzl, 2009). Nem emilimi sırasında su molekülleri mikrofibriller arasına girerek ağ yapı-sını genişletir; mikrofibril açısının düşük olduğu durumlarda eksenel uzama sınırlı kalırken enine (teğet ve radyal) genişleme belirgin biçimde artar (Song vd., 2024). 4B baskı uygulamalarında malzeme yığma (toolpath) yönü, doğal odundaki mikrofibril açısına benzer şekilde yapay bir anizotropi oluşturarak kompozit malzemenin hangi yönde şişip büzüleceğini belirle-yen temel mekanizma olarak kullanılmaktadır (Le Duigou vd., 2016).

2.2. Sürdürülebilirlik Bağlamında Ahşabın Rolü

Ahşabın yenilenebilir olması, düşük gömülü enerjiye sahip olması ve büyüme sürecinde atmosferik karbonu depolaması, malzemeyi sürdürülebilir yapı bileşenleri literatüründe öne çıkarmaktadır; ahşap esaslı yapı ele-manlarının yaşam döngüsü değerlendirmeleri, bu malzemenin gömülü sera gazı emisyonlarının muhasebeleştirilmesinde konvansiyonel malzemelere kıyasla belirgin avantajlar sunduğunu göstermektedir (Andersen vd., 2021). Küçük ölçekli, kompakt yaşam birimleri (tiny house) üzerine yürütülen yaşam döngüsü analizleri de, ahşap ve diğer doğal esaslı yapı sistemlerinin çevresel performans açısından endüstriyel alternatiflere kıyasla olumlu so-nuçlar verdiğini ortaya koymaktadır (Dipasquale vd., 2025). Bu bulgular, ahşabın higromorfik davranışının işlevselleştirilmesinin yalnızca malzeme bilimi açısından değil, sürdürülebilir mimari tasarım hedefleri açısından da anlamlı olduğunu göstermektedir.

3. 4B BASKI İÇİN AHŞAP-POLİMER KOMPOZİT FORMÜLASYONLARI

4B baskı uygulamalarında en sık kullanılan yöntemlerden biri olan Eriyik Yığma Modellemesi (FDM), termoplastik

matrisler ile ahşap bazlı dolgu maddelerinin entegrasyonuna imkân tanımaktadır. Polilaktik Asit (PLA) gibi biyobozunur polimerler, ahşap unu partikülleriyle birleştirilerek nem değişimine duyarlı, higroskopik olarak aktif filamentler üretilmektedir (Kariz vd., 2018a). Bu filamentlerden üretilen 3B baskı numunelerinin farklı bağıl nem koşullarında kondisyonlanması, wood oranı arttıkça nem alımının, boyutsal şişmenin arttığını ve eğilme elastikiyet modülünün azaldığını göstermiştir (Kariz vd., 2018b). Tamamen ahşap bileşenlerinden oluşun, sentetik reçine gerektirmeyen mürekkep sistemleri üzerine yapılan çalışmalar ise baskı yolunun (toolpath) ve akış hızının kontrolüyle kurutma sonrası çarpılma davranışının önceden tasarlanabildiğini, düz baskılanan nesnelerin eyer, kubbe veya sarmal geometrilere dönüşebildiğini ortaya koymuştur (Kam vd., 2022).

3.1. Partikül Boyutu ve Dolgu Optimizasyonu

Eklemeli imalat süreçlerinde nozül tıkanmalarını önlemek, arayüzey yapışmasını artırmak ve homojen bir higroskopik tepki elde etmek için partikül boyutu ve dolgu türü kritik parametrelerdir. Atık kaynaklı biyokömürün (bio-char) ahşap-polimer kompozitlere katkı maddesi olarak eklenmesinin, kompozitin mekanik ve nem alım özelliklerini iyileştirdiği ve organik atıkların değerlendirilmesi açısından sürdürülebilir bir yaklaşım sunduğu bildirilmiştir (Das ve Bhattacharyya, 2015). Benzer şekilde, dolgu oranının ve fiber içeriğinin artırılması kompozitin su emme kapasitesini ve dolayısıyla higromorfik hareket kabiliyetini artırırken, aşırı dolgu oranlarının malzemenin gözenekliliğini ve kırılma dayanımını artırabildiği, bu nedenle formülasyonun mekanik dayanım ile aktüasyon performansı arasında bir denge gözetilerek optimize edilmesi gerektiği vurgulanmaktadır (Le Duigou vd., 2016).

4. PROGRAMLANABİLİR YAPILAR VE BİYOMİMETİK TASARIM STRATEJİLERİ

Geleneksel imalatla malzemenin nihai formu kalıplama veya talaşlı imalat ile verilirken, 4B baskıda form, malzemenin çevresel bir uyarana (neme) verdiği tepkiyle özerk biçimde ortaya çıkar. Bu durum, geometrinin sabit bir sonuç olarak değil, zamana ve nem koşullarına bağlı dinamik bir fonksiyon olarak tasarlanmasını gerektirir.

4.1. Baskı Yöneliminin Şekil Programlamaya Etkisi

4B baskı ile higromorfik programlamanın temel ilkesi, baskı yolları-nın yönelimini kontrol ederek kompozit parça içinde kasti bir anizotropi oluşturmaktır. Doğal ahşaptaki radyal-teğetsel farklara benzer biçimde, FDM ile ekstrüde edilen katmanlar kendi eksenleri doğrultusunda yüksek sertlik ve düşük şişme gösterirken, katmanlara dik yönde belirgin bir genleşme sergilemektedir (Correa, Papadopoulou, Guberan, Jhaveri, Reichert, Menges ve Tibbits, 2015). Bilgisayar destekli tasarım araçlarıyla çok katmanlı yapıların her bir katmanındaki serim açısı ayrı ayrı programlanabilir; örneğin 0°/90° yönelimli iki katmanlı bir yapı, neme maruz kaldığında belirgin bir eksende bükülme veya kıvrılma hareketi sergileyebilir (Menges ve Reichert, 2012). Bu tasarım mantığı, giyilebilir sistemlerden mimari kabuklara kadar geniş bir ölçek aralığında, malzeme uyumluluğunun hesaplamalı olarak programlanabilmesine temel oluşturmaktadır (Cheng vd., 2021).

5. ŞEKİL DEĞİŞTİRME DAVRANIŞININ MAKİNE ÖĞRENMESİ İLE MODELLENMESİ

Higromorfik deformasyonların, polimer-ahşap arayüzey etkileşimleri-nin ve nem difüzyon kinetiklerinin doğrusal olmayan ve çok değişkenli doğası, geleneksel analitik modellerle

önceden kestirilmesini güçleştirmek-tedir. Bu nedenle son yıllarda yapay sinir ağları (YSA) ve diğer makine öğrenmesi yöntemleri, ahşap esaslı kompozit malzemelerin üretim parametrelerine bağlı mekanik ve higroskopik özelliklerinin modellenmesinde yaygın biçimde kullanılmaya başlanmıştır. Ahşap kompozitlerinin üretim ko-şullarına bağlı özelliklerini kestirmek amacıyla geliştirilen YSA tabanlı modellerin, yüksek belirleme katsayısı (R^2) değerleriyle güvenilir tahminler üretebildiği gösterilmiştir (Bardak vd., 2016). Bu yaklaşım, doğrudan 3B baskı ile üretilen PLA-ahşap kompozitlerine de uyarlanmış; baskı hızı, kat-man kalınlığı, tarama açısı, dolgu oranı ve nozül sıcaklığı gibi parametrele-rin çekme ve basma dayanımı üzerindeki etkisini modelleyen yapay sinir ağı ve bulanık mantık tabanlı modellerin, deneysel değerlere çok yakın tahminler ürettiği raporlanmıştır (Ulkir vd., 2025). Farklı makine öğrenmesi algoritmalarının karşılaştırıldığı çalışmalarda ise, kısıtlı veri setleriyle çalışıldığında dahi topluluk (ensemble) yöntemlerinin ahşap-PLA kompozitler-inin mekanik davranışını yüksek doğrulukla kestirebildiği bulunmuştur (Anerao vd., 2024). 4B baskı alanında daha genel ölçeğe, aktif kompozit levhaların voksel düzeyinde malzeme dağılımına bağlı şekil değişimini önceden kestiren ve bu kestirimi tasarım sürecine geri besleyen makine öğ-renmesi tabanlı yaklaşımlar da geliştirilmiştir; bu çalışmalar, hedeflenen bir geometriye ulaşmak için gerekli malzeme dağılımının tasarım aşamasında optimize edilebileceğini göstermektedir (Sun vd., 2024). Ahşap-polimer sistemlerine özgü, higromorfik kıvrılma yarıçapı ve tepki süresi gibi çıktıları doğrudan kestiren, geniş ölçekli veri setlerine dayanan modellerin sayısı literatürde henüz sınırlı olmakla birlikte, yukarıda özetlenen çalışmalar bu yönde hızla gelişen bir araştırma eğilimine işaret etmektedir.

6. İÇ MEKAN TASARIMI VE MİMARİ UYGULAMALAR

Kusurdan işleve geçiş konsepti, özellikle akıllı mimari kabuklar ve in-teraktif iç mekân mobilyaları alanında somut uygulama örnekleri üretmek-tedir. Menges ve Reichert (2012) tarafından ortaya konan gömülü duyarlılık (embedded responsiveness) yaklaşımı, ahşabın doğal higromorfik yapısından yararlanılarak ortamdaki nem oranına göre kendiliğinden açılıp kapana-bilen, enerji gerektirmeyen gölgelendirme panellerinin tasarım ilkesini oluş-turmuştur. Bu ilke, güncel çalışmalarda gerçek ölçekli bir bina cephesine uygulanmış; biyoesinli, selüloz esaslı çift katmanlı 4B baskı elemanlarından oluşan bir gölgelendirme sisteminin, bir yıl boyunca gerçek hava koşulla-rında test edilerek enerji açısından özerk ve mimari ölçekte uygulanabilir olduğu gösterilmiştir (Cheng vd., 2024). İç mekân mobilyası ölçeğinde ise, düz paketlenip nakliyesi kolaylaştırılan ancak nihai kullanım ortamındaki nem koşullarıyla kendiliğinden istenen forma bürünen ahşap esaslı mobilya prototipleri geliştirilmiştir; bu tür kendiliğinden şekillenen (self-shaping) tasarımlar, baskı yolunun ve kurutma koşullarının önceden programlanma-sıyla montaj gerektirmeyen, bağlantı elemanı kullanmayan mobilya sistem-leri için yeni bir üretim paradigması önermektedir (Kam vd., 2022). Bu örnekler, higromorfik 4B baskının yalnızca laboratuvar ölçeğinde bir merak konusu olmaktan çıkıp, sürdürülebilir ve uyarlanabilir iç mekân çözümleri için uygulanabilir bir teknoloji hâline geldiğini göstermektedir.

7. SONUÇ

Geleneksel ahşap bilimi literatüründe uzun süre boyunca mekanik ve boyutsal bir kusur olarak değerlendirilen higroskopik genleşme davranışı, günümüz 4B baskı teknolojileri ve gelişmiş

polimer kompozit formülasyon-larıyla işlevsel bir tasarım ilkesine dönüşmüştür. Optimize edilmiş partikül boyutu ve dolgu oranlarıyla üretilen ahşap-polimer filamentler, hücresel düzeydeki biyomimetik hareketliliği makro ölçeğe taşıyabilmektedir. Baskı yöneliminin kontrolüyle oluşturulan kasti anizotropi stratejileri sayesinde bu malzemeler, harici bir enerji kaynağına ihtiyaç duymadan çevresel neme tepki verebilmektedir. Bu karmaşık şekil değiştirme dinamiklerinin yapay sinir ağları ve diğer makine öğrenmesi yöntemleriyle önceden modellenen-bilmesi, tasarımcılara ve mühendislere öngörülebilir akıllı yapılar geliştirme imkânı sunmaktadır. Cephe gölgelendirme sistemlerinden kendiliğinden şekillenen mobilyalara uzanan uygulama örnekleri, bu yaklaşımın yalnızca kavramsal değil, mimari ölçekte test edilmiş, uygulanabilir bir teknoloji olduğunu göstermektedir. Sonuç olarak, doğanın yüzyıllardır işlettiği hig-romorfik mekanizmaların eklemeli imalat ve veri odaklı modelleme yöntemleriyle birleşmesi, sürdürülebilir, adaptif ve düşük enerjili iç mekân ve mimari çözümler için güçlü bir teknolojik zemin oluşturmaktadır.

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**AĞAÇ İŞLERİ ENDÜSTRİ MÜHENDİSLİĞİ ALANINDA
GÜNCEL KONULAR VE
AKADEMİK DEĞERLENDİRMELER**

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