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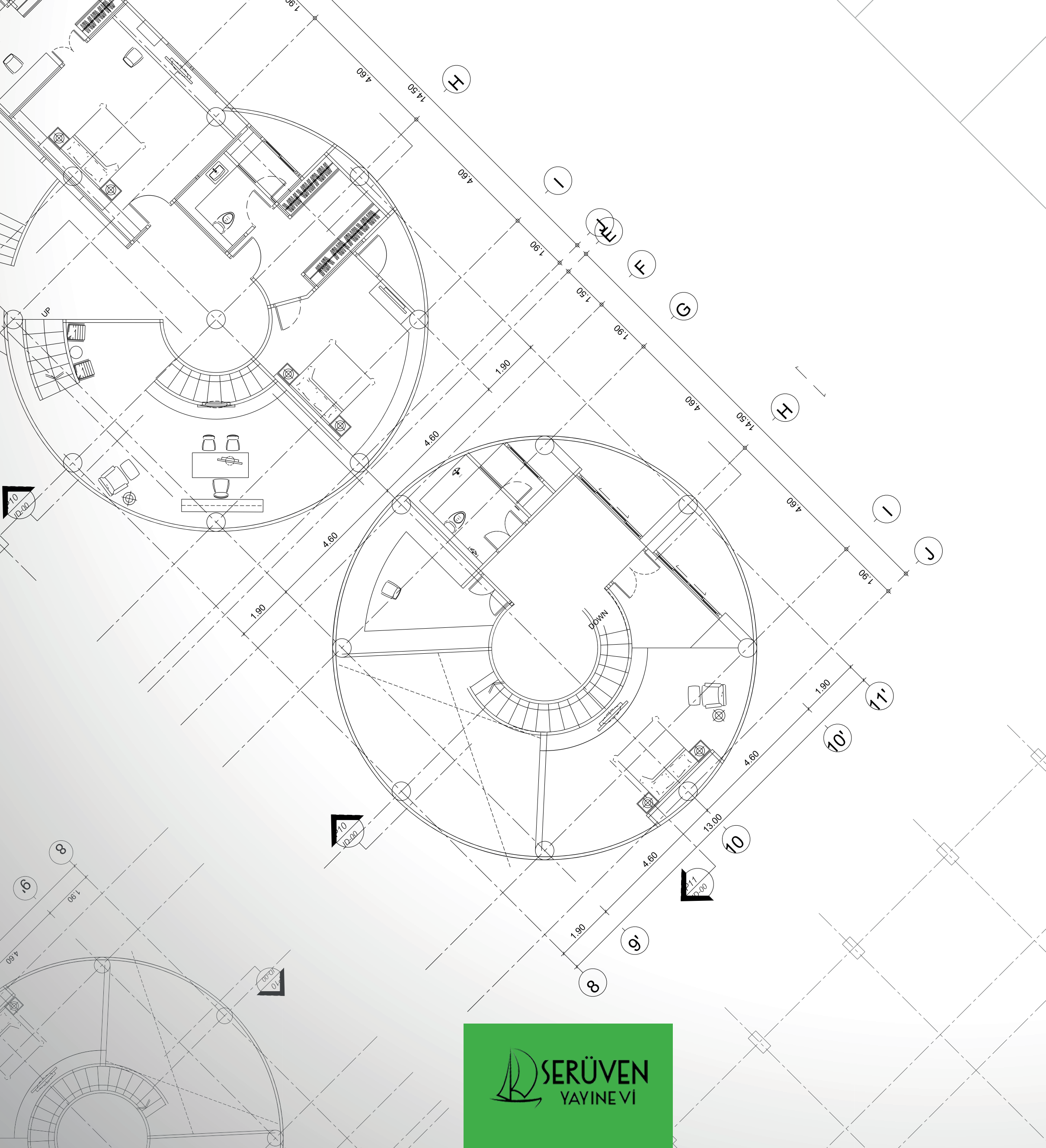

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INTERNATIONAL STUDIES IN ENGINEERING

EDİTÖR **DOÇ. DR. YASİN AKYILDIZ**

SERÜVEN
YAYINEVİ

CONTENTS

Chapter 1

ENTERPRISE ARCHITECTURE GOVERNANCE IN DIGITAL BANKING: A SOCIO-TECHNICAL PERSPECTIVE

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1. Introduction

Enterprise architecture has increasingly been discussed not only as an information systems discipline but also as an architectural design logic guiding organizational structures, digital infrastructures, and governance mechanisms. In complex digital organizations such as banks, enterprise architecture provides a structural framework that coordinates technological systems, organizational processes, and decision-making structures. Enterprise architecture (EA) has become a prominent strategic information systems initiative aimed at coordinating enterprise-wide information technologies, business processes, and decision-making structures in large and complex organizations. Beyond its technical origins, EA is increasingly positioned as a mechanism through which organizations seek to govern digital transformation, manage interdependencies, and enable coordinated strategic action across the enterprise (Ross, Weill, & Robertson, 2006). Despite its widespread adoption, however, empirical evidence on how enterprise architecture generates organizational value remains fragmented and inconclusive within the information systems literature.

Prior research reports mixed findings regarding the performance impact of enterprise architecture initiatives, often referred to as the enterprise architecture value paradox (Tamm et al., 2011; Chan & Reich, 2007). These inconsistencies raise a broader strategic information systems question: why do enterprise-level IS capabilities such as EA frequently fail to translate into observable performance outcomes, despite substantial organizational investment?

A key limitation of existing research lies in the dominant tendency to conceptualize enterprise architecture primarily as a technical or structural artifact. Such perspectives implicitly assume that architectural alignment and completeness translate directly into performance gains, overlooking the organizational and governance mechanisms through which architectural practices are enacted, interpreted, and sustained over time (Hoogervorst, 2004). Strategic IS research, however, has consistently demonstrated that complex organizational capabilities rarely produce immediate performance effects. Instead, their value emerges through governance arrangements, decision-making processes, and accumulated organizational experience that mediate between technological capability and organizational outcomes (Weill & Ross, 2004; Sambamurthy, Bharadwaj, & Grover, 2003).

Building on this insight, the present study reconceptualizes enterprise architecture as a socio-technical governance capability rather than as a static design framework. Drawing on socio-technical systems theory and information systems governance research, we argue that enterprise architecture creates organizational value indirectly by shaping how enterprise-level decisions are coordinated, how architectural knowledge is reused, and how organizations learn over time. From this perspective, architectural maturity and completion do not guarantee efficiency outcomes in isolation; rather, they enable governance mechanisms through which strategic and operational benefits are gradually realized (Leonardi, 2011).

Empirically, the study examines these mechanisms using survey data collected from 397 information technology professionals across 17 banks operating within the Turkish banking system. While the banking sector provides a highly regulated and information-intensive context, the study's theoretical contribution extends beyond this setting by focusing on the governance mechanisms through which enterprise-level IS capabilities influence organizational efficiency. Although the analysis draws on a broader doctoral research project, the present article develops a distinct, theory-driven interpretation centered on mediation, moderation, and socio-technical governance processes.

By examining the mediated and conditional effects of enterprise architecture on organizational efficiency, this chapter makes three contributions to strategic information systems research. First, it explains why enterprise architecture initiatives often produce delayed or uneven performance outcomes, thereby addressing inconsistencies observed in prior empirical studies. Second, it advances IS governance research by positioning enterprise architecture as a socio-technical governance capability embedded in organizational decision-making processes rather than as a purely technical artifact. Third, it highlights the role of human experience as a conditioning mechanism, offering insight into how and under what conditions enterprise-level IS capabilities translate into organizational value (Melville, Kraemer, & Gurbaxani, 2004).

2. Literature Review

2.1 Enterprise Architecture as a Governance and Organizational Capability

Building on these insights, more recent studies have repositioned enterprise architecture as an enterprise governance mechanism that shapes decision rights, coordination, and standardization across organizations (Ross, Weill, & Robertson, 2006; Weill & Ross, 2004). From an enterprise governance perspective, EA contributes not by directly improving performance, but by structuring how strategic and operational decisions are made, coordinated, and enforced across complex organizational environments (Peterson, 2004).

Within this view, enterprise architecture maturity reflects the extent to which architectural principles are institutionalized and routinized across the organization, while enterprise architecture completion captures the degree to which architectural domains are coherently integrated and operationalized (Buckl, Matthes, & Schweda, 2010). Rather than producing immediate efficiency gains, these dimensions support the development of higher-order organizational capabilities such as learning, reuse, and strategic flexibility (Hoogervorst, 2004). Empirical research further suggests that the value of enterprise architecture is realized primarily through its interaction with enterprise governance mechanisms rather than through direct performance effects (Van der Raadt et al., 2010).

Despite this conceptual shift, governance-oriented enterprise architecture research remains underdeveloped in explicating the specific mechanisms through which architectural practices translate into sustained organizational outcomes. While governance is frequently invoked as a key explanatory factor, the socio-technical processes connecting architectural initiatives to organizational efficiency are often left implicit, limiting the explanatory power of existing models (Tamm et al., 2011).

Recent work in IT governance research further underscores the importance of governance process capabilities, particularly decision rights and structured coordination mechanisms, in shaping organizational outcomes. Governance process capability has been shown to influence performance by enhancing an organization's ability to standardize decisions, manage interdependencies, and align governance practices with strategic objectives (Joshi, 2022). This perspective complements the socio-technical governance framing of enterprise architecture by highlighting how formalized decision structures enable architectural capabilities to be enacted consistently across the enterprise.

2.2 Socio-Technical Systems and the Role of Human Mediation

Socio-technical systems theory provides a foundational lens for addressing these limitations by emphasizing the interdependence between technological structures and human actors (Orlikowski, 1992). From a socio-technical perspective, organizational outcomes depend not only on technical design but also on how individuals interpret, enact, and adapt technological arrangements within their organizational contexts (Orlikowski, 2000).

In the context of enterprise architecture, accumulated human experience and institutional knowledge play a critical role in realizing architectural value. Architectural artifacts require interpretation and enactment by organizational actors, which explains why similar frameworks may produce different organizational outcomes.

Despite its importance, human mediation remains underexplored in enterprise architecture research. Many empirical studies treat EA constructs as organization-level variables, implicitly assuming uniform enactment across individuals and units. This assumption obscures important variations in how architectural practices are understood and applied, particularly in large and highly regulated organizational settings (Majchrzak, Markus, & Wareham, 2016).

2.3 Research Gap and Theoretical Positioning

Taken together, the literature reveals two interrelated gaps. First, enterprise architecture research continues to rely heavily on alignment-based explanations that inadequately account for the indirect, processual, and temporally distributed nature of architectural value creation (Chan & Reich, 2007). Second, the human and socio-technical dimensions of enterprise architecture remain insufficiently theorized, despite their central role in governance and decision-making processes (Orlikowski, 2000).

Furthermore, we propose that accumulated human experience moderates these relationships, helping to explain why architectural initiatives often produce uneven or delayed outcomes across organizations.

3. Research Model and Hypotheses Development

3.1 Conceptualizing Enterprise Architecture as a Socio-Technical Governance Capability

Building on the preceding literature, this chapter conceptualizes enterprise architecture not as a static technical blueprint but as a socio-technical governance capability embedded in enterprise-level decision-making and coordination processes. From a strategic information systems perspective, enterprise architecture does not generate organizational value through direct technical alignment alone. Instead, its effects materialize through governance mechanisms that shape how decisions are coordinated, how architectural knowledge is reused, and how organizations learn over time (Weill & Ross, 2004; Orlikowski, 2000).

Prior research demonstrates substantial variation in the outcomes of enterprise architecture initiatives, even among organizations adopting similar architectural frameworks. This variation suggests that architectural value depends less on the formal presence of enterprise architecture and more on the extent to which architectural principles are institutionalized within organizational routines and governance practices (Ross, Weill, & Robertson, 2006; Tamm et al., 2011). Accordingly, this chapter distinguishes between enterprise architecture maturity and enterprise architecture completion as two complementary dimensions of architectural capability.

Enterprise architecture maturity reflects the degree to which architectural thinking is embedded in managerial routines and strategic decision processes, whereas enterprise architecture completion captures the extent to which architectural domains—business, information, application, and technology—are coherently integrated and operationalized across the enterprise (Buckl, Matthes, & Schweda, 2010). Together, these dimensions enable governance processes that influence organizational outcomes indirectly rather than through immediate performance effects.

3.2 Enterprise Architecture Maturity and Governance Effectiveness

Enterprise architecture maturity represents an organization's capability to apply architectural principles consistently across strategic and operational decision contexts. Mature architectural practices support coordination by providing shared representations, common standards, and structured decision frameworks that reduce ambiguity in complex organizational environments (Ross et al., 2006). Through these mechanisms, enterprise architecture maturity enhances governance effectiveness by improving decision transparency, accountability, and consistency (Weill & Ross, 2004).

From a socio-technical perspective, maturity does not imply rigidity. Instead, it enables disciplined flexibility by clarifying which decisions are standardized and which remain subject to managerial discretion (Hoogervorst, 2004). As architectural maturity increases, organizations are better positioned to govern IT-enabled change initiatives through formal governance mechanisms rather than through ad hoc managerial interventions (Sambamurthy, Bharadwaj, & Grover, 2003).

H1: Enterprise architecture maturity positively influences governance effectiveness.

3.3 Enterprise Architecture Completion and Organizational Learning

While architectural maturity reflects institutionalization, enterprise architecture completion captures the operational realization of architectural domains across the enterprise. Completion enables organizations to reuse architectural assets, standardize core processes, and accumulate architectural knowledge over time (Buckl et al., 2010). These outcomes are closely associated with organizational learning and the development of higher-order strategic capabilities (Hoogervorst, 2004).

Architectural completion supports learning by making interdependencies and system relationships explicit. As architectural artifacts become more complete and coherent, organizations are better able to evaluate past decisions, codify lessons learned, and apply this knowledge to future initiatives (Tamm et al., 2011). Through these mechanisms, enterprise architecture completion contributes to governance effectiveness by supporting informed, consistent, and repeatable decision-making practices.

H2: Enterprise architecture completion positively influences organizational learning and reuse capabilities.

3.4 Governance Effectiveness as a Mediating Mechanism

Strategic information systems research consistently demonstrates that architectural and IT-related capabilities rarely exert direct effects on organizational performance. Instead, their influence is mediated through governance processes that structure coordination, accountability, and decision-making (Sambamurthy et al., 2003; Xue, Liang, & Boulton, 2012). Consistent with this view, the present study argues that enterprise architecture affects organizational efficiency indirectly through governance effectiveness.

Governance effectiveness reflects an organization's ability to make timely, informed, and coordinated decisions regarding enterprise systems and processes (Weill & Ross, 2004). By improving decision quality and reducing redundancy, effective governance translates architectural capabilities into operational and strategic efficiency. This mediated relationship provides a theoretical explanation for why prior empirical studies frequently fail to identify direct effects between enterprise architecture constructs and performance outcomes (Tamm et al., 2011).

H3: Governance effectiveness mediates the relationship between enterprise architecture (maturity and completion) and organizational efficiency.

3.5 The Moderating Role of Human Experience

Socio-technical systems theory emphasizes the critical role of human actors in shaping the outcomes of technological and architectural initiatives (Orlikowski, 1992, 2000). In the context of enterprise architecture, accumulated human experience represents a key source of interpretive, cognitive, and practical knowledge. Experienced actors are more likely to understand architectural principles, navigate organizational constraints, and apply architectural guidance effectively within governance processes (Leonardi, 2011).

Accordingly, the impact of enterprise architecture maturity on governance effectiveness is expected to vary depending on the level of accumulated human experience within the organization. In contexts where institutional knowledge is limited, architectural principles may remain symbolic or underutilized. In contrast, higher levels of experience enable organizations to translate architectural maturity into effective governance practices (Majchrzak, Markus, & Wareham, 2016).

H4: Human experience positively moderates the relationship between enterprise architecture maturity and governance effectiveness.

4. Methodology

4.1 Research Design and Empirical Context

This chapter adopts a quantitative research design to examine enterprise architecture as a socio-technical governance capability at the enterprise level. The empirical analysis is based on survey data collected from the Turkish banking sector, an institutional environment characterized by high regulatory intensity, complex information technology infrastructures, and strong governance requirements. These characteristics make the banking sector a theoretically appropriate context for examining how enterprise architecture operates as a governance mechanism rather than as a purely technical framework (Weill & Ross, 2004).

The data employed in this chapter were collected as part of a broader research program examining enterprise architecture practices in the Turkish banking system. While prior work based on this dataset focused on descriptive and operational aspects of enterprise architecture implementation, the present article develops a distinct, theory-driven analysis centered on governance mechanisms, mediation effects, and the role of human experience. The reuse of the dataset is therefore justified by a clearly differentiated research question, theoretical framing, and analytical model, consistent with accepted practices in cumulative and programmatic research (Hair et al., 2019).

4.2 Sample and Data Collection

Data were collected from information technology professionals and managers employed in banks operating within the Turkish banking system. The data collection process involved direct engagement with 17 banks characterized by extensive branch networks and complex enterprise information systems. These organizations represent a substantial portion of the sector in terms of operational scale and technological complexity, making them appropriate units of analysis for examining enterprise architecture as an enterprise-level governance capability.

A total of 524 survey responses were initially obtained using an online data collection instrument. After excluding incomplete and invalid questionnaires, the final sample consisted of 397 usable responses. This sample size exceeds commonly accepted thresholds for structural equation modeling and provides sufficient statistical power for estimating both measurement and structural relationships (Kline, 2016).

Respondents exhibited a high level of professional experience and educational attainment. More than 90 percent held undergraduate or graduate degrees, and the majority reported several years of experience in the banking sector. This profile supports the assumption that respondents possessed adequate familiarity with enterprise architecture concepts and governance practices within their organizations.

4.3 Measurement of Constructs

All constructs were measured using multi-item scales adapted from prior enterprise architecture and IT governance research. The measurement model includes enterprise architecture maturity, enterprise architecture completion, governance effectiveness, organizational efficiency, and accumulated human experience. Enterprise architecture maturity reflects the institutionalization of architectural principles in managerial routines, while architecture completion captures the coherence and integration of architectural domains across the organization. Governance effectiveness represents the organization's capability to coordinate enterprise-level decisions and standardize processes. Organizational efficiency reflects perceived improvements in operational effectiveness, and human experience captures accumulated institutional knowledge and professional expertise within the organization. Reliability analyses indicate strong internal consistency across all constructs, with Cronbach's alpha values exceeding recommended thresholds. Confirmatory factor analysis was conducted to assess construct validity and ensure adequate model fit prior to hypothesis testing, following established guidelines for construct validation (Fornell & Larcker, 1981).

4.4 Analytical Approach

To examine the relationships between enterprise architecture capabilities and governance effectiveness, the chapter employs structural equation modeling based on survey data collected from banking professionals. More importantly, SEM allows for the examination of indirect, mediated, and moderated relationships, which are central to the theoretical argument advanced in this chapter (Kline, 2016).

The analysis was conducted using AMOS software. Model fit was evaluated using multiple fit indices, including comparative fit, goodness-of-fit, and error-based measures, consistent with best practices in SEM-based research (Hair et al., 2019). Mediation analysis was performed to assess whether governance effectiveness explains the relationship between enterprise architecture constructs and organizational efficiency. Moderation analysis was used to examine the conditioning role of human experience on the relationship between enterprise architecture maturity and governance effectiveness.

4.5 Methodological Rigor and Validity Considerations

Several measures were taken to enhance the rigor and validity of the study. First, the inclusion of multiple organizations reduces the likelihood of firm-specific bias. Second, the focus on experienced information technology professionals mitigates concerns regarding respondents' familiarity with enterprise architecture and governance practices. Third, the analytical design explicitly distinguishes between direct and indirect effects, addressing a limitation frequently noted in prior enterprise architecture research.

5. Findings

5.1 Measurement Model Assessment

Prior to testing the structural relationships, the measurement model was assessed to evaluate reliability and construct validity. Confirmatory factor analysis indicated that all constructs demonstrated strong internal consistency, with Cronbach's alpha values exceeding commonly accepted thresholds (Hair et al., 2019). All factor loadings were statistically significant and exceeded recommended minimum levels, supporting convergent validity (Fornell & Larcker, 1981).

Discriminant validity was examined by assessing the relationships among latent constructs. The results indicate that the constructs capture conceptually distinct dimensions of enterprise architecture, governance effectiveness, and organizational outcomes, consistent with the study's socio-technical and governance-oriented theoretical framework. Overall, the measurement model exhibited acceptable fit indices, providing a sound foundation for subsequent structural analysis (Kline, 2016).

5.2 Structural Model Results

The proposed structural model was tested using structural equation modeling to examine the hypothesized relationships depicted in Figure 1. Overall model fit indices indicate a satisfactory fit between the model and the observed data, suggesting that the hypothesized relationships are empirically supported and consistent with recommended criteria for SEM-based research (Hair et al., 2019).

5.2.1 Effects of Enterprise Architecture Maturity

The results reveal a statistically significant positive relationship between enterprise architecture maturity and governance effectiveness, supporting H1. This finding indicates that higher levels of architectural maturity enhance an organization's capability to coordinate enterprise-level decisions, standardize practices, and manage IT-enabled change through formal governance mechanisms.

Notably, enterprise architecture maturity does not exhibit a significant direct effect on organizational efficiency. Instead, its influence operates through governance effectiveness. This result supports the study's socio-technical perspective, suggesting that architectural maturity functions as an enabling governance capability rather than as an immediate performance driver. In doing so, the finding provides a theoretically grounded explanation for previously mixed empirical results in the enterprise architecture literature (Tamm et al., 2011).

5.2.2 Effects of Enterprise Architecture Completion

Enterprise architecture completion demonstrates a positive and statistically significant relationship with organizational learning and reuse capabilities, supporting H2. Organizations with more complete and coherently integrated architectural domains report higher levels of learning from prior initiatives and greater reuse of architectural assets across enterprise systems.

Similar to architectural maturity, enterprise architecture completion does not exert a strong direct effect on organizational efficiency. Instead, its contribution is realized through governance-related mechanisms that shape how architectural knowledge is mobilized and applied in practice. This finding reinforces the distinction between the formal existence of architectural structures and their effective enactment within enterprise governance processes (Ross, Weill, & Robertson, 2006).

5.3 Governance Effectiveness as a Mediating Mechanism

Consistent with H3, governance effectiveness fully mediates the relationship between enterprise architecture constructs and organizational efficiency. When governance effectiveness is included in the model, the direct effects of enterprise architecture maturity and completion on organizational efficiency become non-significant.

This result provides a process-oriented explanation for why prior studies have reported inconsistent findings regarding the performance impact of enterprise architecture. Rather than producing immediate efficiency gains, enterprise architecture contributes to organizational outcomes indirectly by strengthening governance arrangements, improving decision quality, and enhancing coordination across the enterprise. These findings align closely with strategic information systems research emphasizing mediation and capability transformation mechanisms (Sambamurthy et al., 2003; Van der Raadt et al., 2010).

5.4 Moderating Role of Human Experience

The analysis further indicates that human experience significantly moderates the relationship between enterprise architecture maturity and governance effectiveness, supporting H4. In organizations with higher levels of accumulated institutional experience, the positive effect of architectural maturity on governance effectiveness is significantly stronger.

This finding underscores the socio-technical nature of enterprise architecture. Architectural principles and standards do not operate autonomously; their effectiveness depends on the interpretive capacity, experiential knowledge, and judgment of organizational actors. Where experience is limited, architectural maturity may remain symbolic or weakly enacted. In contrast, experienced actors are better positioned to translate architectural guidance into effective governance practices (Orlikowski, 2000; Leonardi, 2011).

5.5 Summary of Key Findings

Taken together, the findings reveal a coherent and theoretically consistent pattern:

· Enterprise architecture does not directly drive organizational efficiency.

· Architectural value emerges indirectly through governance effectiveness.

· Governance mechanisms translate architectural capabilities into coordinated managerial action.

· Human experience plays a critical role in enabling architectural value realization.

· The absence of direct performance effects reflects the processual and socio-technical nature of enterprise architecture.

Overall, these results empirically support the central argument of this chapter: enterprise architecture functions as a socio-technical governance capability rather than as a purely technical alignment instrument

6. Discussion and Contributions

6.1 Interpreting Enterprise Architecture Beyond Direct Performance Effects

The findings suggest that alignment between business and information technology is a necessary but insufficient condition for achieving organizational efficiency. Enterprise architecture does not generate value through structural alignment alone. Instead, its impact materializes through governance mechanisms that translate architectural principles into coordinated managerial action. From this perspective, enterprise architecture functions as a governance capability that shapes decision-making processes, improves coordination, and enables organizations to manage technological complexity more effectively.

6.2 Enterprise Architecture as a Socio-Technical Governance Capability

The central theoretical contribution of this chapter lies in reconceptualizing enterprise architecture as a socio-technical governance capability. Grounded in socio-technical systems theory, this perspective emphasizes that technological and architectural structures alone are insufficient to generate organizational benefits without complementary human and governance capabilities (Bostrom & Heinen, 1977).

Unlike traditional views that portray enterprise architecture as a technical blueprint or documentation exercise, this approach highlights the interplay between architectural structures, governance arrangements, and human agency (Orlikowski, 1992, 2000). The findings demonstrate that human experience significantly moderates the relationship between architectural maturity and governance effectiveness, underscoring the importance of accumulated institutional knowledge in interpreting and enacting architectural principles.

Architectural artifacts, standards, and models do not govern organizations autonomously; they require experienced actors capable of translating abstract architectural principles into situated managerial decisions (Leonardi, 2011). This socio-technical perspective helps explain why similar architectural frameworks often produce divergent outcomes across organizations and institutional contexts, a phenomenon that has remained under-theorized in prior enterprise architecture research.

6.3 Contributions to Strategic Information Systems Research

This chapter makes three primary contributions to the strategic information systems literature.

First, it advances research on enterprise architecture by clarifying how and through which mechanisms architectural initiatives create organizational value. By identifying governance effectiveness as a mediating mechanism, the study moves beyond outcome-centric evaluations and offers a process-based explanation for architectural impact that resonates with broader IS capability and governance theories (Tamm et al., 2011).

Second, the chapter discusses to IS governance research by empirically linking enterprise architecture to enterprise-level decision-making, coordination, and organizational learning processes. In doing so, it positions enterprise architecture as a foundational governance capability that supports strategic coordination in complex and highly regulated organizational environments (Weill & Ross, 2004; Ross, Weill, & Robertson, 2006).

Third, by incorporating human experience as a moderating factor, the study extends socio-technical systems theory within the context of enterprise architecture and strategic IS. This contribution highlights the need to explicitly account for human mediation when examining large-scale architectural and digital initiatives, particularly in organizational settings characterized by institutional constraints and regulatory complexity (Majchrzak, Markus, & Wareham, 2016).

6.4 Managerial and Practical Implications

For practitioners, the findings suggest that investments in enterprise architecture frameworks alone are unlikely to yield immediate efficiency gains. To realize architectural value, organizations must also invest in governance capabilities and human expertise. Senior managers should therefore focus not only on architectural standards and documentation but also on building institutional knowledge, decision-making competencies, and cross-unit coordination mechanisms.

In highly regulated sectors such as banking, enterprise architecture can serve as a stabilizing governance mechanism that balances standardization with flexibility. However, its effectiveness depends on the organization's ability to embed architectural thinking into everyday decision processes rather than treating enterprise architecture as a compliance-driven or purely IT-centric initiative (Weill & Ross, 2004).

6.5 Limitations and Future Research Directions

While this chapter offers important insights, several limitations should be acknowledged. The use of perceptual measures may introduce subjective bias, and the cross-sectional research design limits causal inference. Future research could address these limitations by employing longitudinal designs to examine how architectural capabilities and governance mechanisms co-evolve over time.

In addition, comparative studies across different institutional and regulatory contexts could further validate the socio-technical governance perspective advanced in this chapter. Future research may also explore how enterprise architecture interacts with emerging digital technologies, platform-based organizational forms, and ecosystem-level governance arrangements, extending the relevance of enterprise architecture research within strategic information systems scholarship

7. Conclusion

This chapter examined how enterprise architecture creates organizational value beyond conventional alignment-based explanations, from a strategic information systems perspective. Drawing on empirical evidence from 397 information technology professionals across large banks, the findings demonstrate that enterprise architecture does not function as a direct driver of organizational efficiency. Instead, architectural value emerges indirectly through architectural maturity, architectural completion, and governance effectiveness, supporting process-oriented and capability-based views of IS value creation.

The results further indicate that enterprise architecture operates as a time-dependent organizational capability. Accumulated experience and sustained architectural practice are more consequential than formal alignment or short-term optimization efforts. As organizations develop architectural maturity and embed architectural thinking into governance routines, their ability to coordinate decisions, learn from prior initiatives, and manage enterprise complexity improves. This path-dependent nature of architectural capabilities helps explain why enterprise architecture initiatives often produce delayed, uneven, or non-linear performance outcomes.

By reframing enterprise architecture as a socio-technical governance capability, this chapter contributes to strategic information systems research in three important ways. First, it clarifies why alignment alone is insufficient to generate efficiency gains without complementary governance mechanisms that translate architectural intent into coordinated managerial action. Second, it positions enterprise architecture as an enterprise-level governance capability rather than an IT-centric documentation or design exercise, thereby extending IS governance and capability-based theories. Third, it highlights the critical role of human experience in mediating the relationship between architectural capability and governance effectiveness, underscoring the importance of socio-technical mechanisms in large-scale IS initiatives.

For practitioners, the findings suggest that investments in enterprise architecture should be evaluated as long-term governance and capability-building initiatives rather than as short-term efficiency programs. Senior managers should focus not only on architectural frameworks and standards but also on governance design, institutional learning, and cross-unit coordination. In highly regulated environments such as banking, enterprise architecture can serve as a stabilizing governance mechanism—provided it is embedded in everyday decision-making processes and supported by experienced organizational actors.

While this chapter is situated in the Turkish banking sector, the proposed socio-technical governance perspective offers a foundation for future strategic IS research across different industries and institutional contexts. Longitudinal and comparative studies could further enhance understanding of how architectural capabilities evolve over time, interact with emerging digital technologies, and shape enterprise-level governance arrangements. Beyond its implications for information systems research, the findings also provide insights for digital architecture design in large organizations. Enterprise architecture should therefore be understood not only as an IT management tool but also as an architectural governance framework that shapes organizational coordination and digital transformation processes.

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Chapter 2

PLM-INTEGRATED DFMA AND MANUFACTURING COST ANALYSIS FOR MISSION-ORIENTED UAV DESIGN

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1. Introduction

Unmanned aerial vehicles (UAVs) are increasingly employed in various civil and industrial applications. Typical use cases include environmental sensing and monitoring, infrastructure inspection, disaster management and surveillance (Gupta et al., 2013; Chen et al., 2025). Due to numerous advances in sensing capabilities, wireless communications, and autonomous control, the capabilities of existing UAV platforms have soared in the recent years, enabling the execution of more sophisticated missions such as collaborative data gathering, real-time monitoring, and distributed sensing (Ore et al., 2015; Rezk et al., 2023). Furthermore, efforts in the domain of autonomous mission planning and group UAV operations have made more prevalent the deployment of UAVs for large-scale surveillance and reconnaissance missions (Gao et al., 2025).

As the complexity of UAV systems increases, the management of product data and system architecture is an even more critical issue. Typical UAV platform architectures often undergo multiple design iterations. They include the addition of new sensors, payloads and subsystems for a specific mission. With these changes, the system architecture might be influenced not only in terms of system functionalities but also the architecture of the overall product. Hence, a product data management and system configuration management in all phases of the product life cycle is required. The PLM (Product Lifecycle Management) system can provide an integrated digital environment to manage product information associated with the entire lifecycle of complex engineering systems (Ameri & Dutta, 2005; Kiritsis, 2011). A PLM environment allows requirements, functional models, product structure and component data to be stored within a single integrated framework. This approach provides traceability between the design decision levels and engineering models. The application of the PLM systems for UAV architecture management and configuration management has also been indicated (Bernabei et al., 2014).

A number of researches identified the support capabilities of PLM environments for UAV mission planning and operational data management. A PLM based framework was proposed to integrate mission plan, sensor data and system components into a multi-domain product information model (Yaman, 2025a). Moreover, PLM-supported monitoring system was studied for UAV structural health monitoring and lifecycle data integration, showing the integration of operational data and product models during the lifecycle of UAV systems (Yaman, 2025b). While these researches focused on mission information and operational data management, the manufacturing aspect of mission directed UAV design change is scantily studied. In particular, the manufacturing consequence of mission-oriented design change was not explicitly reported within the PLM based design environments.

In the case of mission-oriented UAVs, additional sensors, modules, or mechanical components may need to be added to an existing UAV system in order to achieve particular mission objectives. Such design changes may have a considerable impact on the product architecture. New components may need to be added, and additional assembly steps may need to be performed. This may increase the assembly complexity and, consequently, the manufacturing cost. However, in the early stages of design, design considerations may be mainly influenced by the performance of the UAVs in terms of missions, whereas the manufacturing considerations may need to be assessed in the later stages.

Various Design for Manufacturing (DFM) approaches have been developed that offer systematic solutions to the manufacturability issue. Within this context, the following techniques have been used as design evaluation tools. These techniques include Design for Assembly (DFA) techniques and manufacturing cost estimation techniques. Overall, the primary aim of the above techniques is to simplify the product design, improve the assembly performance, and minimize the manufacturing costs. Design for Manual Assembly (DFMA) techniques have been used to estimate the time required for manual assembly and design efficiency. In addition to the above techniques, the manufacturing cost estimation techniques have been used to evaluate the impact of design decisions on the costs. A typical example is the Lucas cost model, which is used to estimate the cost of manufacturing based on material properties, manufacturing processes, and part characteristics.

This chapter is dedicated to the description of the redesign phase in the development of mission-oriented UAVs. The research will examine how Design for Manufacturing techniques can be used in a PLM system to analyze changes in the product's design due to its missions. The main contribution of this chapter is to introduce a new approach to integrating assembly analysis using DFMA techniques with manufacturing cost estimation using Lucas's method in a PLM-supported UAV redesign process. The chapter will introduce a new approach to combining product information modeling in a PLM system with product assembly analysis using DFMA techniques and manufacturing cost estimation using Lucas's method in the Aras Innovator system.

The remainder of this chapter will describe the proposed framework and its implementation in the PLM environment. First, the process of mission-oriented UAV design and redesign will be described along with the PLM-based product modeling process. Then, the DFM framework will be explained along with its integration with DFMA and manufacturing cost calculation methods. Finally, the UAV water rescue module will be used to describe how the evaluation process can be performed for the UAV configuration in the PLM environment.

2. PLM-Supported UAV Mission Redesign Process

Unmanned aerial vehicle platforms are typically configured to be a versatile end platform capable of supporting different mission requirements. As new mission requirements arise for a platform, the UAV baseline platform must often be modified to accommodate the new mission. This may include the addition of components, sensors, or new structural modifications. Similar to conventional designs, design decisions for final production impact more than just system performance. UAV operations are also subject to considerations of manufacturability and production cost, requiring a systematic platform redesign process.

This study is supported by a Product Lifecycle Management (PLM) environment to carry out the redesign process. The mission requirements, the product structures, the engineering evaluations and the manufacturability assessments are merged through the PLM environment. This environment is used to support a more structured redesign process. The overall logical process flow used in this chapter is shown in Figure 1.

This model comprises a number of successive phases to carry through the redesign process. The phases are mission statement, adaptation of UAV architecture, engineering analysis and design-for-manufacturing evaluation. The PLM system is the prime information backbone of this model. It links the mission requirements, product structure, engineering analysis and design-for-manufacturing evaluation results through the whole redesign activities.

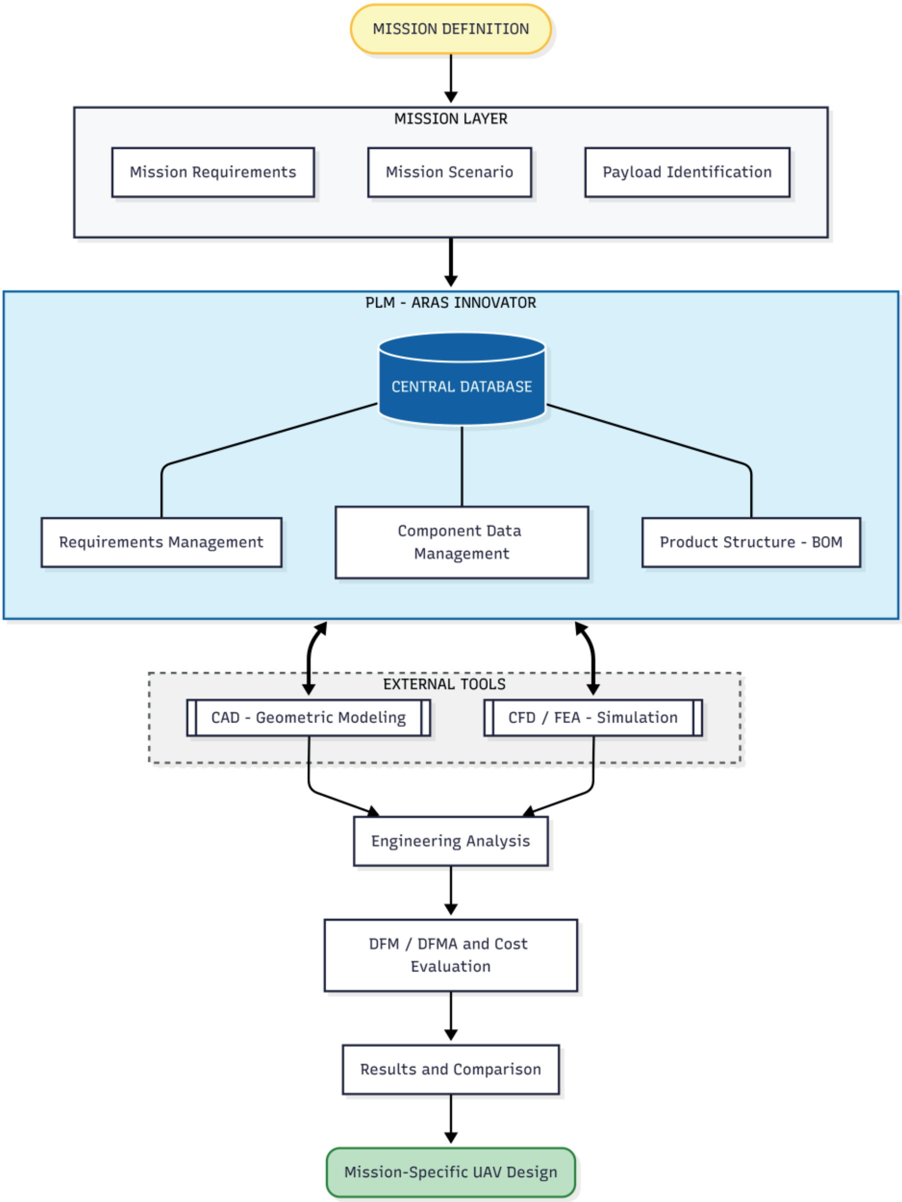


Figure 1. PLM-supported workflow for mission-oriented UAV redesign and manufacturability evaluation.

2.1 Mission Definition and Requirement Identification

The redesign process begins with the definition of mission objectives and operational requirements. For mission-oriented UAV applications, the configuration of the UAV platform is highly dependent on the operational scenario and the sensing needs of the mission.

At this stage, three primary elements are defined:

- mission requirements
- mission scenario
- payload identification

The mission requirement articulates the operational goal that the system is to accomplish. It could be collecting environmental data, performing inspection, or any others. The mission scenario details the environment in which the UAV will be used including terrain, duration of operation, and limitations placed on the flight profile. The payload needed to carry out the mission is then selected from the requirements.

In the PLM context, the particular requirements are addressed in requirements management modules. It is possible to trace the relation between the mission objectives and the design decisions taken in a later point of the redesign process.

2.2 UAV Architecture Adaptation and Component Design

After the mission requirements are defined, the baseline UAV platform is assessed to determine whether or not modifications are needed to accommodate the new mission configuration. Payloads which are mission specific often add new structure, electrical, or integration requirements that the existing platform architecture cannot accommodate.

During this stage, the following design activities are typically performed:

- evaluation of the baseline UAV architecture
- identification of components that require modification or

redesign

- definition of new mission-specific components
- planning of payload integration within the UAV platform

The product structure in the UAV system is managed in the PLM system through the use of the BOM, the Bill of Materials. By using the BOM, the engineers are able to design the hierarchy of the UAV platform, and also create relationships between base level components and new mission only items. All component specifications, geometric models and configuration information will be stored in the PLM database. This means all design data is centrally managed and available for redesign.

2.3 Engineering Analysis and Performance Validation

After the component modifications have been defined, engineering analysis can be performed to examine the feasibility of the proposed modification with respect to performance. External engineering tools are often used at this stage such as CAD modeling tools or some other simulation environments.

CAD tools are utilized to create geometric models of modified parts; simulation tools are used to test their structural properties, mechanical characteristics or suitability for integration. In some cases, these tests take the form of FEA, failure analysis or computational fluid dynamics (CFD) simulations. The results of these tests demonstrate to the engineering team that the modified aircraft configuration will meet all mission requirements and limits.

While the modeling and simulation activities are conducted using third party engineering tools, the results of these analyses are associated to the product data being tracked in the PLM system. This enables engineering analysis results to be tied back to a part or product structure. The traceability and design documentation are thus enhanced in the PLM system.

2.4 Design for Manufacturing Evaluation

Once all the component designs have been assessed for their engineering feasibility, the design will be examined from a manufacturability point of view. Here again, DFM rules are relevant because the component shapes, materials and manufacturing procedures must all be capable of being produced readily.

Typical activities performed during this stage include:

- material selection
- manufacturing process selection
- evaluation of geometric manufacturability

The PLM environment facilitates this evaluation process by storing information such as material properties, process definitions, and component parameters, which are all related to the manufacturing process. The PLM system links the manufacturing considerations with the product structures and the design parameters, thus enabling the engineers to evaluate the manufacturability parameters during the redesign process.

2.5 Manufacturability and Cost Assessment

After the DFM evaluation process, the designed UAV parts are analyzed based on their complexity of assembly and the cost of production. In this case, the emphasis is on the practical implications of the production process of the designed mission-specific parts.

Two complementary evaluation approaches are applied:

- assembly analysis using Design for Assembly (DFMA) principles
- manufacturing cost estimation using the Lucas cost analysis method

The analysis by the DFMA method examines the ease with which the redesigned parts can be assembled within the UAV system. This method can also be used to identify opportunities for simplification within the product structure. The Lucas cost method offers an estimate of the manufacturing costs based on properties such as material properties, geometry, and manufacturing processes.

In this study, these evaluation methods are implemented within the Aras Innovator PLM environment to develop the proposed design evaluation framework. This enables the results obtained by the DFMA method and the Lucas cost method to be related to individual components and the UAV product structure.

2.6 Design Comparison and Mission-Specific UAV Configuration

The last step of redesign process is a performance evaluation, which compares the baseline configuration of the UAV with alternative mission-modified configurations in terms of manufacturability and cost of production. This step assesses the impact of each redesign on ease of manufacture and cost of production.

Key comparison criteria include:

- assembly complexity
- manufacturing cost
- component count and structural modifications

By this evaluation process, the engineers can ascertain whether the mission-specific changes offer an acceptable trade-off in terms of operational capability and manufacturing feasibility. The outcome of this process is the mission-specific UAV configuration whose design, manufacturability, and cost have been systematically evaluated in the PLM environment.

3. PLM-Based Implementation of the DFMA Framework

The proposed manufacturability evaluation framework was implemented in a PLM (Product Lifecycle Management) environment, i.e. the Aras Innovator platform, so as to link product structure management with the DFMA analysis and manufacturing cost estimation. This implementation aims at automating the calculation of manufacturability indices using the product structure and the component-level design parameters stored in the PLM database.

In the PLM environment, every element of the UAV system is encapsulated by a *Part item* with design parameters, configuration information and engineering attributes. The structure of the UAV platform is established by the Bill of Materials (BOM) delineating the relationship between the assembly, sub-assembly, and components.

By widening product data model with parameters concerning manufacturability, the PLM environment facilitates the integration of the DFMA analysis and estimate of manufacturing costs within the product hierarchy. Assembly time, manufacturing costs and design efficiency can be computed automatically with respect to each component and then be propagated to superior assemblies.

Figure 2 shows how the UAV product structure looks like in Aras Innovator PLM environment. Each part representing an element of the UAV platform is a *Part item* in the PLM database. As shown in the figure, a *Part item* is linked to a number of associated structures as defined by *relationship items*, such as BOM and BOM Structure or manufacturability input items such as DFMA Handling Time, DFMA Insertion Time and the DFM Lucas Cost Method.

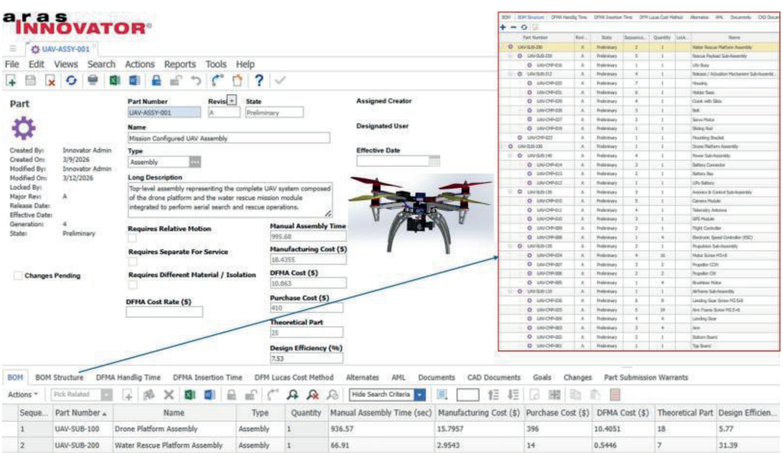


Figure 2. UAV product structure and DFMA evaluation results represented in the Aras Innovator PLM environment.

The component-level items make use of the DFMA Handling Time, DFMA Insertion Time and Lucas manufacturing cost input records to hold the parameters for the assembly time prediction and manufacturing cost assessment. The parameters for each component are found in one of each of these manufacturability input records. The inputs for the handling and insertion inputs provide the data for manual assembly analysis, while the Lucas cost input provides the data for manufacturing cost prediction.

Assembly items utilize the BOM and BOM Structure relationships to describe the stack-up of the UAV platform. Assemblies do not need their own handling, insertion or Lucas cost input record. Assembly-level manufacturability metrics are derived by summing the DFMA results of the assembly's child components up through the BOM structure, with assembly time, manufacturing cost, evaluation metric, etc. computed automatically from component quantities and attributes.

The top-level assembly in the case study is the mission configured UAV system, which includes the main drone platform and the mission specific water rescue payload module. The hierarchies and the manufacturability evaluation results can be visualized and analyzed through the PLM system interface.

3.1 DFMA Data Structure and Input Parameters

To support the manufacturability evaluation within the PLM system, the product data model was extended to incorporate specific DFMA input structures. Three manufacturability input items for each component of the product structure are associated with the related Part item through specific relationships:

- DFMA handling input
- DFMA insertion input
- Lucas manufacturing cost input

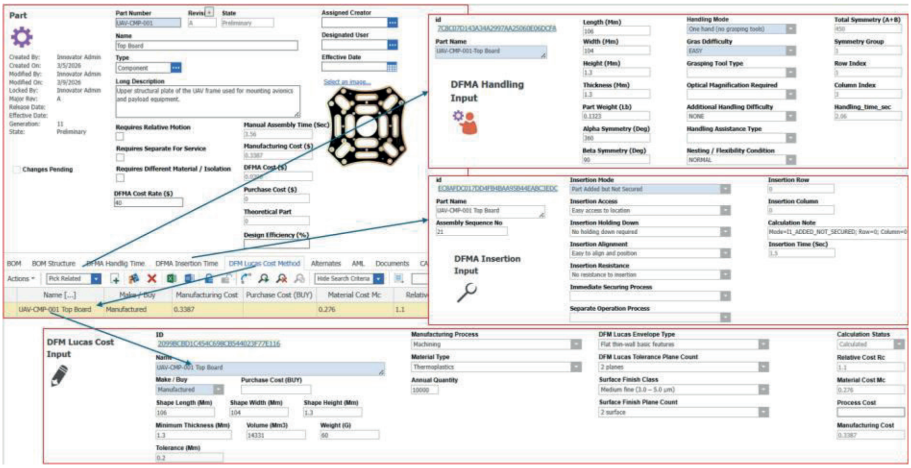


Figure 3. DFMA data structure implemented in the Aras Innovator PLM environment showing the relationships between the Part item and the associated handling, insertion, and Lucas cost input records.

Figure 3 demonstrates the DFMA data structure implemented in the Aras Innovator environment, using the Top Board component as a reference. As shown in the figure, the *Part item* is connected to the three manufacturability input records through relationships, enabling the system to maintain a structured representation of assembly and manufacturing parameters directly linked to the component definition.

The DFMA handling input defines the parameters needed to predict the time required to grasp, orient, and manipulate the component during manual assembly work. These parameters include component size, weight, symmetry features, handling difficulty, and handling aid conditions. Using these parameters, the PLM system selects automatically the required component handling time from the corresponding DFMA evaluation tables.

The DFMA insertion input specifies the insertion parameters for the component. The insertion parameters include insertion mode, insertion access, level of difficult alignment, amount of insertion resistance, and securing operations. Based on the input parameters, insertion index and insertion time are automatically derived for the component.

In addition to assembly analysis, manufacturing cost estimation parameters are defined using the Lucas cost method. These parameters are manufacturing process type, material properties, geometry data, number of production and tolerance specifications. Using these parameters, component manufacturing cost is estimated with Lucas cost evaluation method in the PLM system.

Through the use of the PLM data model these parameters are incorporated into the platform so that the DFMA analysis and manufacturing costing can be linked directly to the component and automatically assessed during the design process.

3.2 DFMA Handling Time Calculation

Handling time for each component is automatically calculated by PLM process based on handling parameters in the *DFMA handling input item*. PLM process is activated whenever a handling input item is created or modified by calling the method *DFMA_Handling_Time_Calculator*.

This approach assesses the handling characteristics of the component in relation to a range of component parameters including its size, weight, symmetry characteristics, ease of grasping, and conditions including handling aids. All are related to the DFMA handling evaluation factors detailed in the literature (Boothroyd et al., 2011; Swift & Brown, 1994).

The method takes the actual handling conditions as input, and finds out the proper handling time value from the corresponding framework, which has been hard-coded based on the DFMA lookup tables, in the PLM environment. The resulted handling time is saved in the attribute of the handling input item, for later use in manual assembly time calculation.

Algorithm 1 summarizes the handling time calculation procedure implemented within the PLM environment.

Algorithm 1. DFMA handling time calculation procedure

Input: Handling parameters of component
Output: Handling time

1 Read component dimensions and weight
2 Determine symmetry parameters (α, β)
3 Identify grasping difficulty and handling mode
4 Determine handling index using the DFMA lookup table
5 Retrieve corresponding handling time from DFMA table
6 Store calculated handling time in PLM database

3.3 DFMA Insertion Time Calculation

Insertion time represents the time required to place and secure a component during manual assembly. PLM environment automatically calculates insertion time in the event the creation or modification of a *DFMA insertion input item.*

The calculation is performed by the *DFMA_Insertion_Time_Calculator* method that measures the operation of insertion with the handle of insertion mode, insertion access, the difficulty of the positioning, the resistance of insertion, the securing process to be used.

These parameters match with the insertion assessment criteria of Design for Manual Assembly procedures. According to the selected circumstances, the procedure finds out the insertion index from the set of pre-calculated DFMA insertion tables, and then retrieves the insertion time.

This estimated insertion time is given as a property of the input item for the insertion and is later added to the handling time to give the total manual assembly time of the part.

Algorithm 2 summarizes the insertion time calculation procedure implemented within the PLM environment.

Algorithm 2. DFMA insertion time calculation procedure

Input: Insertion parameters
Output: Insertion time

1 Read insertion mode and access conditions
2 Evaluate alignment difficulty
3 Evaluate insertion resistance
4 Identify securing operation
5 Retrieve insertion time from DFMA insertion table
6 Store insertion time in PLM database

3.4 Lucas-Based Manufacturing Cost Estimation

Apart from the assembly analysis, the manufacturing cost estimation has been implemented inside the PLM environment, based on the Lucas design for manufacturing methodology. The Lucas technique calculates manufacturing cost according to parts geometry, material properties and manufacturing process parameters (Swift, 1987; Salustri, n.d.).

In the proposed approach, the cost estimation is done inside Aras Innovator PLM system via one dedicated *Lucas cost input item* for each component. It has inputs for cost estimation such as manufacturing process category, material category and basic geometric features of the part.

When a Lucas cost record is created or updated, the PLM system executes the server-side method *DFM_Lucas_Cost_Calculator*. This method retrieves the manufacturing parameters and calculates the manufacturing cost using Lucas cost tables implemented within the PLM environment. The resulting cost value is stored as a property of the component and later used in part-level and assembly-level evaluations.

The framework also supports commercially purchased components by allowing designers to specify a purchase cost value, enabling both manufactured and purchased parts to be evaluated within the same cost structure.

The simplified logic of the Lucas manufacturing cost calculation implemented in the PLM environment is summarized in Algorithm 3

Algorithm 3. Lucas-based manufacturing cost estimation procedure

Input: Component manufacturing parameters Output: Manufacturing cost 1 Read manufacturing process type 2 Read material category and geometric parameters 3 Determine manufacturing envelope and tolerance conditions 4 Retrieve cost coefficient from Lucas cost tables 5 Calculate manufacturing cost 6 Store manufacturing cost in PLM database

3.5 Part-Level DFMA Evaluation

After the calculation of handling time, insertion time, and manufacturing cost parameters, a part-level DFMA evaluation is performed within the PLM environment. This evaluation integrates the results of DFMA assembly analysis and Lucas-based manufacturing cost estimation for each component in the product structure.

In the proposed framework, this evaluation is implemented through an automated PLM method named *DFMA_Update_Part_Summary*. The method retrieves the handling time and insertion time values of the component and calculates the manual assembly time as the sum of these two parameters:

$$T_{ma} = T_h + T_i$$

where T_h represents the handling time and T_i represents the insertion time.

The DFMA assembly cost of the component is then estimated based on the calculated manual assembly time and a predefined DFMA cost rate:

$$C_{DFMA} = T_{ma} \times R_{DFMA}$$

where C_{DFMA} denotes the DFMA cost, T_{ma} is the manual assembly time, and R_{DFMA} represents the DFMA cost rate.

Asides from the method that produces manufacturing cost values calculated with the Lucas method, there are also purchase cost values that define for commercially purchased components.

The method also evaluates if the component meets the theoretical minimum part criteria by DFMA methodology. This is determined using three DFMA questions regarding the relative motion, service requirements and material isolation of the part. The resulting DFMA metrics, which are properties of the component, are stored and used as part of the assembly-level evaluation procedure.

Algorithm 4 summarizes the part-level DFMA evaluation procedure implemented within the PLM environment.

Algorithm 4. Part-level DFMA evaluation procedure

```
Input: Component DFMA and cost data
Output: Part-level DFMA metrics

1 Retrieve handling time
2 Retrieve insertion time
3 Compute manual assembly time and DFMA cost
4 Retrieve manufacturing or purchase cost
5 Evaluate theoretical minimum part criteria
6 Store DFMA metrics in PLM database
```

3.6 Assembly-Level DFMA Evaluation

Once the component level DFMA and cost calculations are obtained for all the components, an assembly level assessment is performed. The assembly level calculation takes into account the DFMA and cost calculations for all the individual components to provides a system-level view of assembly complexity and manufacturing cost.

In the advanced design, the assembly evaluation is performed in the PLM environment with the Automated Method *DFMA_Assembly_Rollup_Calculation*. This method reads the BOM structure of an assembly, and accesses the child components DFMA measurement values.

When this step is performed, the PLM system adds up manual assembly time, manufacturing cost and purchase cost values of all components that are included into the structural assembly, taking into account number of pieces of those components within BOM. Moreover, it calculates the theoretical minimum part number by summing the theoretical part indicators of the components.

Based on these aggregated parameters, the system evaluates the assembly design efficiency using the manual assembly efficiency formulation defined in DFMA methodology:

$$E_{ma} = \frac{N_{min}\, t_a}{t_{ma}}$$

where N_{min} represents the theoretical minimum number of parts, t_a is the theoretical minimum assembly time per part (commonly assumed as approximately 3 seconds in DFMA methodology), and t_{ma} denotes the estimated manual assembly time of the actual product structure.

The resulting metrics are stored as properties of the assembly item within the PLM environment, enabling designers to evaluate assembly complexity and manufacturing cost directly from the product structure.

Algorithm 5 summarizes the assembly-level evaluation procedure implemented in the PLM system.

Algorithm 5. Assembly-level DFMA evaluation procedure

Input: Assembly BOM structure
Output: Assembly DFMA metrics

1 Retrieve child components from BOM
2 Sum manual assembly times of child components
3 Sum manufacturing and purchase costs
4 Sum theoretical minimum part indicators
5 Compute assembly design efficiency
6 Store assembly metrics in PLM database

4. Case Study: Mission-Oriented UAV Rescue Module Design

In order to illustrate the effectiveness of the proposed PLM-supported design and manufacturability assessment framework, a case study on the design of a UAV based water rescue module is presented. The system aims to deliver water rescue payloads (e.g. life buoys) to rescue victims in water rescue situations using a multirotor UAV platform.

Figure 4 shows a functional model of the water-rescue UAV system. The system itself is represented as a black-box at the higher level of system. There are four flight-related inputs in such system including its mission commands, power supply, visual data, and operator control signals. The outputs of the system include video transmission, system status information, and the deployment of the life buoy payload.

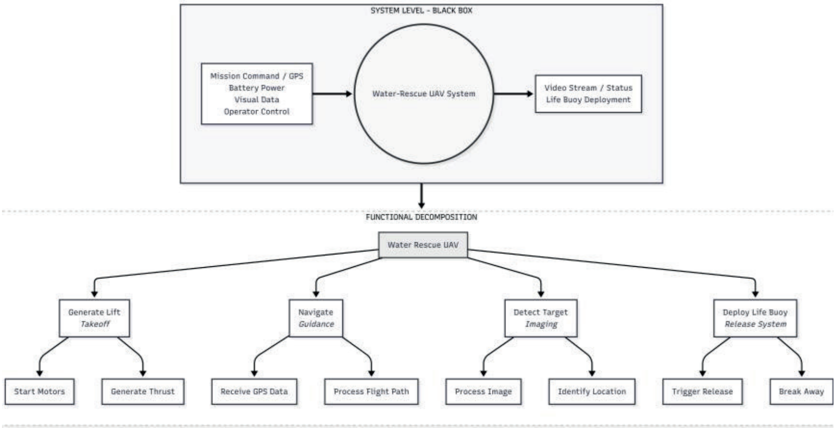


Figure 4. Functional decomposition of the water-rescue UAV system.

Using this abstraction, the system operates in four main functional clusters; lift generation, navigation, target detection, and payload deployment. The first two functions are provided by the baseline UAV platform used in this study. The platform is based on the DJI F450 quadrotor configuration, which provides the propulsion system, flight controller, and basic flight capabilities required for take-off and navigation.

Target detection is done through the implementation of an onboard camera system. This system allows visual observation of the working area and target location detection which helps the operator to decide when and where to release the payload.

The payload deployment for the water rescue operation is a mission-specific capability function. Since this functionality is unavailable to the baseline platform of the UAV, development of a dedicated mechanical release mechanism is undertaken. The release mechanism transforms the rotational input from the servo actuator into a precise mechanical action liberating the life buoy payload.

Consequently, the design effort in this study focuses on the development of the payload release mechanism. Several design alternatives are developed and evaluated in terms of manufacturability and assembly efficiency using the DFMA and Lucas cost estimation methods integrated within the PLM environment.

The following sections present the development of the release mechanism and the evaluation of different design iterations using the proposed PLM-supported framework.

4.1 Initial Release Mechanism Design

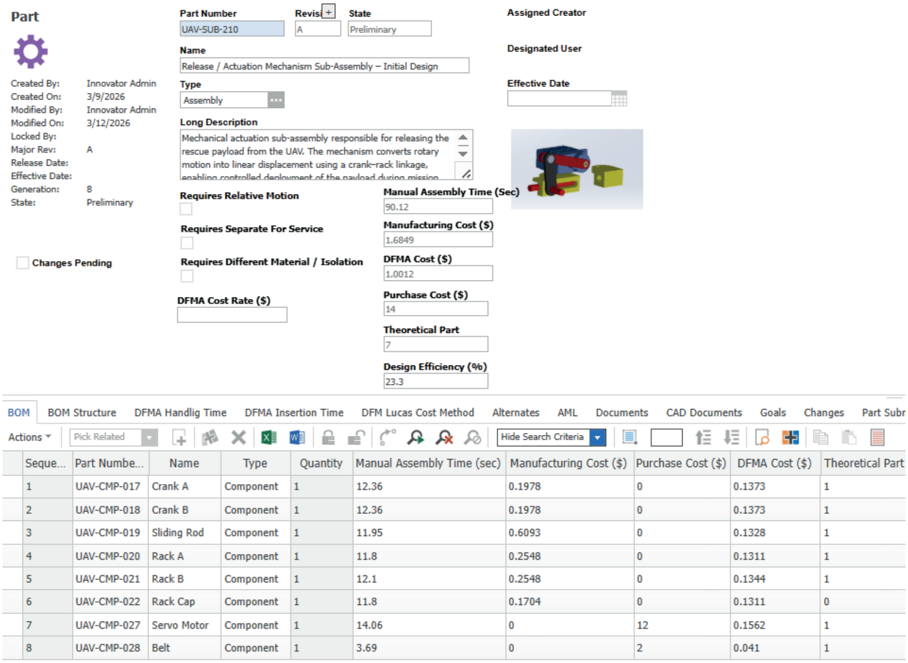
Based on the functional decomposition presented in Figure 4, the payload deployment function requires the design of a dedicated mechanical release mechanism. To fulfill this requirement, an initial actuation mechanism was developed to convert the rotational motion of a servo motor into a linear displacement used to release the life buoy payload.

The mechanism is based on a crank-rack linkage that transfers the rotational motion of the servo actuator to a sliding component responsible for triggering the payload release. During the initial design stage, the main geometric parameters of the components were determined and appropriate materials and manufacturing processes were selected based on basic manufacturability considerations.

After defining the mechanism geometry, the product structure of the release mechanism was created within the Aras Innovator PLM environment. Each component was defined as a separate part item in the PLM database, where key parameters such as dimensions, material types, and manufacturing processes were recorded. In addition, make-or-buy decisions were specified depending on whether a component was manufactured or purchased.

The components were then organized into a sub-assembly representing the release mechanism. The DFMA and Lucas-based manufacturing cost evaluation methods described in Section 3 were automatically executed using the component parameters and assembly structure stored in the PLM database.

Figure 5 shows the representation of the initial release mechanism within the Aras Innovator environment together with the calculated DFMA and manufacturing cost metrics. The initial design consists of eight components: two crank elements, two rack elements, a sliding rod, a rack cap, a servo motor, and a belt connection element. The DFMA evaluation results indicate a total manual assembly time of 90.12 seconds and a design efficiency of 23.3%. Although the mechanism satisfies the functional requirements of the payload deployment system, the relatively low design efficiency suggests that the product structure can be simplified to improve assembly performance.



Seque...	Part Numbe...	Name	Type	Quantity	Manual Assembly Time (sec)	Manufacturing Cost ($)	Purchase Cost ($)	DFMA Cost ($)	Theoretical Part
1	UAV-CMP-017	Crank A	Component	1	12.36	0.1978	0	0.1373	1
2	UAV-CMP-018	Crank B	Component	1	12.36	0.1978	0	0.1373	1
3	UAV-CMP-019	Sliding Rod	Component	1	11.95	0.6093	0	0.1328	1
4	UAV-CMP-020	Rack A	Component	1	11.8	0.2548	0	0.1311	1
5	UAV-CMP-021	Rack B	Component	1	12.1	0.2548	0	0.1344	1
6	UAV-CMP-022	Rack Cap	Component	1	11.8	0.1704	0	0.1311	0
7	UAV-CMP-027	Servo Motor	Component	1	14.06	0	12	0.1562	1
8	UAV-CMP-028	Belt	Component	1	3.69	0	2	0.041	1

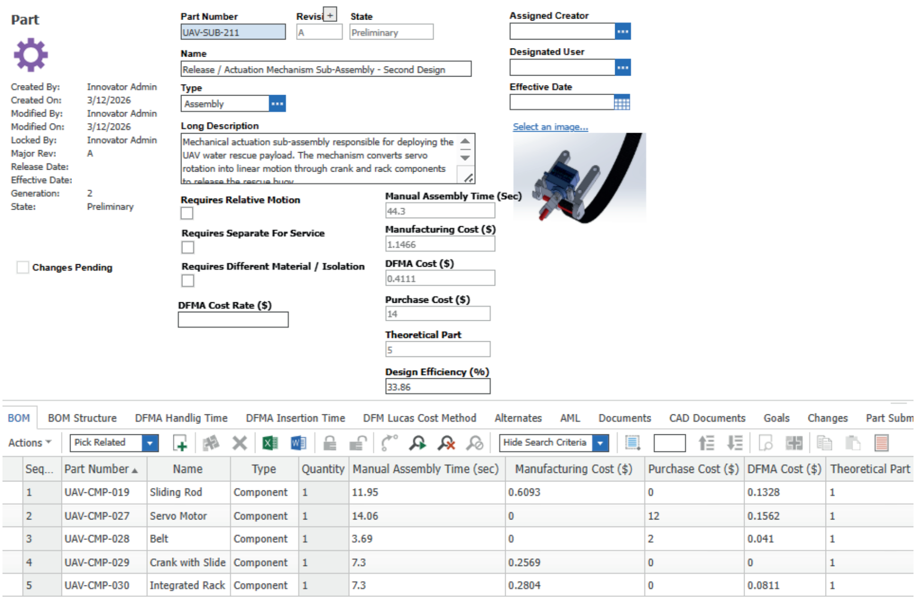
Figure 5. DFMA and manufacturing cost evaluation of the initial payload release mechanism design in the Aras Innovator PLM environment.

4.2 Design Iteration and Structural Simplification

The second design was subsequently derived from the initial design following the evaluation of the first design based on the same criteria. The mechanical analysis of the first configuration revealed that many components provided similar mechanical functionalities and introduced more assembly interfaces.

In the redesigned mechanism, multiple components of the crank-rack structure were integrated in order to reduce the total number of parts. The two crank elements were replaced with a single crank-slide component, while the rack elements were combined into an integrated rack structure. These modifications simplified the mechanical transmission system and reduced the number of assembly operations.

The redesigned parts' information was all entered into the Aras Innovator PLM tool as new part items and classified into a new revision of the sub-assembly. As in the first design iteration, automated DFMA analysis, and Lucas manufacturing cost estimate were automatically calculated based on the product structure stored in the PLM database.



Seq...	Part Number	Name	Type	Quantity	Manual Assembly Time (sec)	Manufacturing Cost ($)	Purchase Cost ($)	DFMA Cost ($)	Theoretical Part
1	UAV-CMP-019	Sliding Rod	Component	1	11.95	0.6093	0	0.1328	1
2	UAV-CMP-027	Servo Motor	Component	1	14.06	0	12	0.1562	1
3	UAV-CMP-028	Belt	Component	1	3.69	0	2	0.041	1
4	UAV-CMP-029	Crank with Slide	Component	1	7.3	0.2569	0	0	1
5	UAV-CMP-030	Integrated Rack	Component	1	7.3	0.2804	0	0.0811	1

Figure 6. DFMA and manufacturing cost evaluation results of the second release mechanism design in the Aras Innovator PLM environment.

Figure 6 presents the representation of the second design iteration within the PLM environment together with the updated DFMA evaluation results. The structural simplification significantly improved the assembly performance. The total manual assembly time decreased from 90.12 seconds in the initial configuration to 44.3 seconds in the second design iteration. In addition, the design efficiency increased from 23.3% to 33.86%, indicating a substantial improvement in assembly efficiency through component integration and structural simplification.

4.2.1 Manufacturability Analysis Using DFMPro

Despite the fact that the second design iteration vastly increased the ease of assembly, a further manufacturability study identified additional issues with manufacturing the part on an injection molding process. To evaluate the manufacturability of the integrated rack component, the geometry was analyzed using the DFMPro manufacturability analysis tool under design for manufacturing constraints of injection molding process.

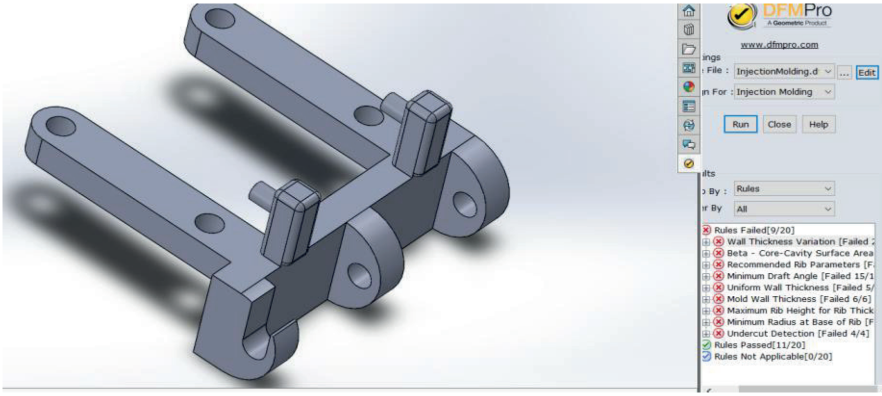


Figure 7. Manufacturability analysis results of the integrated rack component obtained using DFMPro for injection molding.

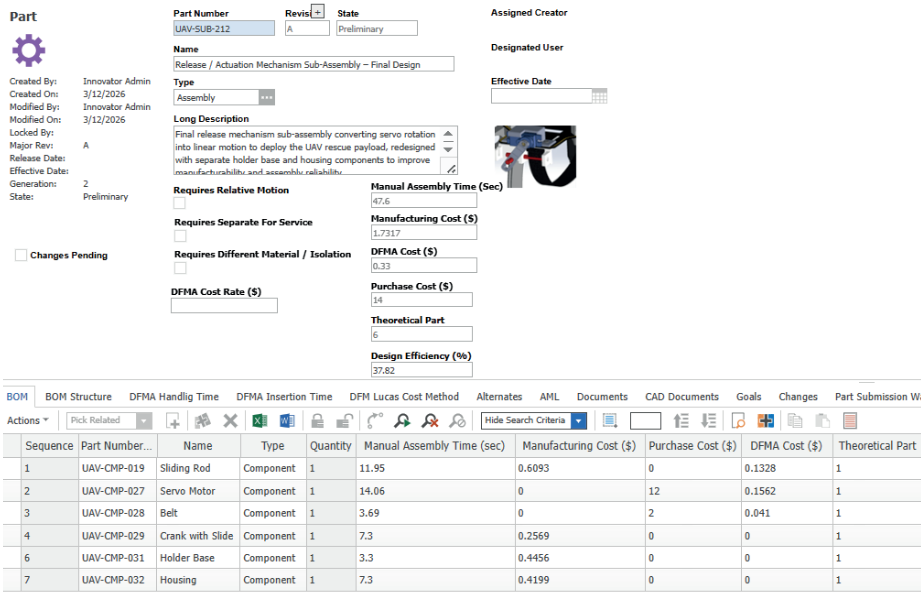
As illustrated in Figure 7, the analysis detected several violations of injection molding design guidelines, including wall thickness variations, insufficient draft angles, and mold wall thickness constraints. These issues indicate that the integrated rack geometry is not well suited for injection molding production without structural modification.

From these results, the combined rack element was modified for manufacture by dismembering it into two components (a holder base and a housing element). This reduces the complexity of the mold geometry and manufacture of the molding, while still maintaining the functional behaviour of the release mechanism.

4.3 Final Design and Manufacturability Improvement

The modified configuration was subsequently deployed into the Aras Innovator PLM. As for the latter editions, the DFMA evaluation and Lucas-type cost estimation were all performed by the PLM managed product structure.

Figure 8 presents the final release mechanism design together with the DFMA and manufacturing cost metrics calculated by the PLM system. The final design results in a total manual assembly time of 47.6 seconds and a design efficiency of 37.82%. Although the assembly time slightly increases compared with the second design iteration, the redesign significantly improves manufacturability for injection molding. This result illustrates the trade-off between assembly efficiency and manufacturing feasibility during the product redesign process.



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Modified By: Innovator Admin
Modified On: 3/12/2026
Locked By:
Major Rev: A
Release Date:
Effective Date:
Generation: 2
State: Preliminary

Changes Pending

Part Number: UAV-SUB-212
Revision: A
State: Preliminary
Name: Release / Actuation Mechanism Sub-Assembly – Final Design
Type: Assembly
Long Description: Final release mechanism sub-assembly converting servo rotation into linear motion to deploy the UAV rescue payload, redesigned with separate holder base and housing components to improve manufacturability and assembly reliability.
Requires Relative Motion
Requires Separate For Service
Requires Different Material / Isolation
DFMA Cost Rate ($)
Manual Assembly Time (Sec): 47.6
Manufacturing Cost ($): 1.7317
DFMA Cost ($): 0.33
Purchase Cost ($): 14
Theoretical Part: 6
Design Efficiency (%): 37.82
Assigned Creator
Designated User
Effective Date

BOM | BOM Structure | DFMA Handlig Time | DFMA Insertion Time | DFM Lucas Cost Method | Alternates | AML | Documents | CAD Documents | Goals | Changes | Part Submission W...

Actions | Pick Related | Hide Search Criteria

Sequence	Part Number...	Name	Type	Quantity	Manual Assembly Time (sec)	Manufacturing Cost ($)	Purchase Cost ($)	DFMA Cost ($)	Theoretical Part
1	UAV-CMP-019	Sliding Rod	Component	1	11.95	0.6093	0	0.1328	1
2	UAV-CMP-027	Servo Motor	Component	1	14.06	0	12	0.1562	1
3	UAV-CMP-028	Belt	Component	1	3.69	0	2	0.041	1
4	UAV-CMP-029	Crank with Slide	Component	1	7.3	0.2569	0	0	1
6	UAV-CMP-031	Holder Base	Component	1	3.3	0.4456	0	0	1
7	UAV-CMP-032	Housing	Component	1	7.3	0.4199	0	0	1

Figure 8. DFMA and manufacturing cost evaluation results of the final release mechanism design in the Aras Innovator PLM environment.

5. Design Comparison and Discussion

In order to quantify the effectiveness of the proposed redesign method, the three mechanism configurations created within this research were evaluated for manufacturability using the metrics generated by the PLM environment. These metrics are manual assembly time, design efficiency, and manufacture cost values as calculated by the DFMA and Lucas based cost evaluation methods outlined in the previous sections. Table 1 presents the evaluation results of the first design, second design that is a simplification of the first design, and the manufacturability-improved final configuration, respectively.

Table 1. Comparison of release mechanism design iterations based on DFMA and Lucas cost evaluation

Design Configuration	Number of Parts	Assembly Time (s)	Design Efficiency (%)	Manufacturing Cost ($)	DFMA Cost ($)
Initial Design	8	90.12	23.3	1.6849	1.0012
Iteration 2 (Simplified Design)	5	44.3	33.86	1.1466	0.4111
Final Design	6	47.6	37.82	1.7317	0.33

The initial design consists of eight components and results in a manual assembly time of 90.12 seconds with a design efficiency of 23.3%. After structural simplification in the second design iteration, the number of components decreases and the assembly time is significantly reduced to 44.3 seconds. As a result, the design efficiency increases to 33.86%, indicating a substantial improvement in assembly performance.

However, manufacturability analysis revealed that the integrated rack structure introduced in the second design iteration created limitations for injection molding production. To address this issue, the final design separates the integrated rack into two components in order to improve manufacturability. Although this modification slightly increases the assembly time to 47.6 seconds, the final configuration achieves the highest design efficiency of 37.82%.

The result above indicates there is a compromise between assembly efficiency and manufacturing feasibility in a product design revision process. Further, the case study reveals that the PLM-supported framework can help designers examine different design options through quantitative manufacturability indices and systematically guide the redesign toward optimized product configuration.

6. Conclusion

This study presented and implemented a PLM-supported framework for evaluating manufacturability and manufacturing cost during mission-oriented UAV redesign. The proposed framework integrates Design for Manufacturing and Assembly (DFMA) analysis and Lucas-based manufacturing cost estimation within the Aras Innovator PLM environment. By linking manufacturability parameters directly to product structure data stored in the PLM system, assembly time, manufacturing cost, and design efficiency can be automatically calculated for both components and assemblies.

Our framework adds a separate set of DFMA handling, insertion, and Lucas cost input structures associated with part items to the existing PLM data model. Automated PLM techniques were developed to determine the handling time, insertion time, part-level DFMA metrics, and assembly-level performance from the product structure stored in the PLM database.

In addition, a case study on the design of a UAV-based water rescue payload release mechanism was conducted to validate the proposed approach. Three design configurations were analyzed, and they included the initial mechanism design, the structurally simplified design, and the final design, which improved manufacturability. The results showed that the structurally simplified design reduced the assembly time and improved design efficiency, and the final design improved compatibility with injection molding manufacturing requirements.

While the DFMA-based assembly time estimation and the Lucas manufacturing cost model may not closely reflect real production data, they can be effective indicators to compare different design configurations and to determine opportunities for product simplification in preliminary design phases. Combining these evaluation techniques within a PLM environment allows engineers to evaluate manufacturability aspects directly from the product structure while preserving traceability between design data, analysis outputs, and engineering decisions.

Future work may extend the framework by incorporating additional manufacturing analysis tools and integrating automated design optimization approaches within the PLM environment.

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Chapter 3

COMPUTER VISION FOR SUSTAINABLE PRODUCTION: CONTEMPORARY DEEP LEARNING APPROACHES TO TOMATO LEAF DISEASE CLASSIFICATION AND FRUIT QUALITY ASSESSMENT

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1. Introduction

1.1. The Role of Tomato Production in Sustainable Agriculture and Food Security

The projection that the global population will reach approximately 10 billion by 2050 places unprecedented pressure on the sustainability of existing food production systems and on food security (Shafik, 2025). In this context, it is essential not only to increase agricultural output but also to optimize production while conserving natural resources and minimizing environmental impacts. Tomato (*Solanum lycopersicum*), one of the most strategic crops in modern agriculture, constitutes a cornerstone of the global nutrition and economic chain through both fresh consumption and industrial processing. Data from the Food and Agriculture Organization (FAO) report that global tomato production reached 370,750 kilotons in 2021; Türkiye, with approximately 32,600 kilotons of production, ranks third worldwide and plays a critical role within this ecosystem (Özel et al., 2025). However, tomato plants are highly susceptible to biotic stress factors, particularly pathogen attacks. Greenhouse conditions—especially those characterized by high plant density and a humid microclimate—facilitate rapid disease spread, leading to annual yield losses of 20% to 40% on a global scale (Wang et al., 2025). In line with the "Zero Hunger" (SDG 2) objective of sustainable agriculture, preventing these losses is not only an economic necessity but also a vital imperative for safeguarding the global food supply.

1.2. Limitations of Traditional Detection Methods

Historically, interventions for agricultural diseases have largely relied on agronomists or farmers periodically inspecting plants in person. However, such traditional visual inspection processes have serious limitations in today's large-scale and intensive production models. Manual monitoring is not only time-consuming and labor-intensive, but it is also highly error-prone due to factors such as fatigue, distraction, and individual subjectivity (Loganathan et al., 2025). In many cases, by the time lesions or discolorations caused by pathogens become detectable to the human eye, the disease has already progressed to an advanced stage and has overcome the plant's defense mechanisms. This often leads farmers to resort to "preventive" or "broad-spectrum" pesticide applications, thereby increasing unnecessary chemical use. Moreover, the early-stage symptomatic characteristics of many tomato diseases (e.g., Early Blight and Late Blight) are highly similar, which can result in misdiagnosis and consequently the implementation of inappropriate treatments—ultimately causing both crop losses and wasted financial resources. These constraints constitute a primary motivation that makes the integration of digitalization and autonomous diagnostic systems in agriculture indispensable.

1.3. The Role of Intelligent Systems in Precision Agriculture

Precision Agriculture (PA) is a management strategy that aims to maximize yield while minimizing input use by leveraging modern technologies. Computer vision and deep learning approaches—among the most powerful tools of this strategy—have initiated a new paradigm in plant health monitoring. Deep learning architectures can detect diseases at the pre-symptomatic stage, when signs are still too subtle to be noticed by the human eye, by analyzing complex textural changes and spectral signatures in plant leaves (Javidan et al., 2024). Early diagnosis enables targeted spraying (spot-spraying), reducing pesticide use by more than 50% and directly contributing to ecological sustainability by preventing the chemical contamination of soil and groundwater (Saxena et al., 2025).

In addition, intelligent systems are not limited to the classification of leaf diseases; they also revolutionize fruit quality assessment and harvesting autonomy. Lightweight deep learning models such as ToRLNet classify the ripeness levels of tomatoes (green, semi-ripe, ripe) in real time, enabling autonomous harvesting robots to perform selective picking (Sun et al., 2025). This translates into reduced food waste and the optimization of logistics processes based on plant health. Today, Visual-Language Transformer (VLM)-based systems—where visual data are integrated with textual explanations—have begun to serve as intelligent assistants that provide farmers not only with diagnosis but also with personalized treatment recommendations (Kaur et al., 2025). This technological evolution is transforming agriculture from a reactive struggle into a proactive management discipline.

2. Datasets, Key Challenges, and Solution Strategies

The success of deep learning models depends largely on the quality, diversity, and representational capacity of the datasets on which they are trained. In tomato leaf disease classification and fruit quality assessment, the field performance of computer vision algorithms is directly related to how accurately training data reflect real-world conditions. However, the collection, annotation, and standardization of agricultural data involve substantial challenges due to complex backgrounds, variable environmental conditions, and biological diversity. This section addresses the evolution of datasets in the tomato disease detection literature, operational bottlenecks, and contemporary strategies developed to overcome these issues.

2.1. Transition from Laboratory Environments to Real-World Field Conditions

Early deep learning studies on tomato leaf diseases were largely based on datasets collected in controlled laboratory environments, such as PlantVillage. PlantVillage consists of high-resolution, clear leaf images captured against homogeneous and sterile backgrounds. Although models trained on this dataset achieve accuracy rates above 99% in laboratory tests, such results are generally considered "overoptimistic" for real agricultural applications (Jelali, 2024). The primary limitation of laboratory-based models is that they do not include the complex visual noise encountered in the field. While the model learns to focus solely on lesions in laboratory settings, it struggles to distinguish elements such as soil, irrigation systems, or other plant parts in real environments.

To address this "domain shift" problem, more heterogeneous datasets such as PlantDoc and Tomato-Village have been developed. The PlantDoc dataset includes images collected from the internet that reflect real field conditions, featuring noisy backgrounds and diverse capture angles (Jelali, 2024). Comparative analyses have shown that a model achieving 99% accuracy on PlantVillage may experience a 30% to 40% performance drop when applied to real field data such as PlantDoc. This demonstrates that, for a sustainable agricultural AI system, training data must incorporate factors such as variable lighting, shadows, and plant density typical of greenhouse environments. Recent research has therefore adopted a two-stage strategy: pre-training on laboratory data and subsequently fine-tuning with a limited amount of real field data to improve generalization (Hu et al., 2026).

2.2. Class Imbalance and the Limited Data Problem

Deep learning algorithms learn most effectively when there is an equal or sufficient number of samples for each class. However, in agricultural practice, while thousands of images may exist for prevalent diseases such as Early Blight or Late Blight, it is often difficult to obtain visual data for tomato spotted wilt virus or certain rare bacterial infections. This situation creates a problem known in the literature as "class imbalance," which causes the model to bias toward majority classes and misclassify rare diseases (Hu et al., 2026).

The limited data problem constitutes a major barrier, particularly for diagnosing newly emerging pathogens or region-specific diseases. When sufficient data cannot be collected for rare diseases, the model's recall decreases for these classes, rendering the diagnostic process unsustainable. To address this challenge, approaches such as few-shot learning and zero-shot learning have become prominent. These methods aim to enable the model to extract core attributes from a small number of images or to visually match an unseen disease based on textual descriptions (Hu et al., 2026). Another strategy to mitigate class imbalance involves assigning higher weights to minority classes during training or artificially balancing the dataset using re-sampling techniques.

2.3. Occlusion, Illumination Variability, and Noise

Images captured in uncontrolled environments such as greenhouses and open fields are exposed to numerous environmental factors that complicate object separation. Chief among these is occlusion. Due to the dense foliage structure of tomato plants, a diseased leaf may remain behind healthy leaves or fruits, or overlapping leaves may reveal only part of pathological patterns (Wang & Liu, 2021). Occlusion can lead object detection models to draw inaccurate bounding boxes or to miss small lesions entirely.

Illumination variability can dramatically change the color and contrast of images depending on sun angle, cloud cover, or artificial lighting in greenhouses. Overexposure may cause fine textures on leaves to disappear, whereas dense shadows may lead healthy regions to be perceived as diseased (Liu et al., 2025). In addition, noise factors such as dust on the camera lens or fogging caused by greenhouse humidity degrade image quality and disrupt feature extraction. To cope with these challenges, occlusion-resistant architectures such as YOLO-Dense have been proposed, leveraging dense connectivity layers to preserve feature flow even in overlapped regions (Wang & Liu, 2021).

2.4. Data Augmentation and Enhancement Techniques

To improve the quality of limited and noisy datasets, two main approaches have been adopted in the contemporary literature: traditional data augmentation and synthetic data generation. Traditional methods include rotating and scaling images, modifying color space, and applying random cropping. These techniques help prevent overfitting by enabling the model to recognize objects from different perspectives (Mamatha & Raju, 2025). However, they do not add genuinely "new" information to the dataset; rather, they transform the form of existing information.

For true data enrichment, synthetic data generation technologies such as Generative Adversarial Networks (GANs) are employed. Architectures like DoubleGAN can generate realistic yet entirely artificial images based on existing diseased leaf images, thereby alleviating data scarcity in rare classes. In addition, Transfer Learning enables the reuse of weights pre-trained on large-scale datasets such as ImageNet or agriculture-specific datasets such as AgriNet, allowing strong performance even with small datasets. One study reported that AgriNet-based models achieved 18.6% higher accuracy in agricultural classification tasks compared to general-purpose models (Thakur et al., 2025).

Finally, segmentation-based filtering methods play a critical role in the data enhancement process. In recent models such as TLDVLM, algorithms including GroundingDINO and SAM-2 remove complex backgrounds, enabling the model to focus exclusively on relevant plant tissue and thereby minimizing the adverse impact of environmental noise (Kaur et al., 2025). Such preprocessing and data enrichment strategies form the basis for establishing a sustainable and reliable diagnostic mechanism in tomato production.

In summary, quantitative and qualitative dataset limitations remain among the most significant bottlenecks for deep learning in agricultural applications. Nevertheless, field-oriented data collection, synthetic data generation, and the hybrid use of advanced augmentation techniques are bridging the gap between laboratory and field settings. The early-diagnosis capability required for sustainable production will be achievable only through the effective integration of these technological strategies.

3. Contemporary Deep Learning Architectures for Tomato Leaf Disease Classification

Rapid advances in computer vision have shifted agricultural disease diagnosis from traditional image-processing methods to deep learning architectures that automatically extract and hierarchically process features. The complex disease patterns, textural variations, and irregular lesion structures observed on tomato leaves can be analyzed with high accuracy thanks to the strong representational capacity of these architectures. This section reviews state-of-the-art deep learning solutions, ranging from classification tasks to object detection, attention mechanisms, and hybrid approaches.

3.1. Core Convolutional Neural Network (CNN) Applications

Convolutional Neural Networks (CNNs) form the foundation of the plant disease detection literature. In early studies, AlexNet and its modified variants achieved high accuracy rates (approximately 98%) in classifying tomato leaf diseases (e.g., Early Blight, Late Blight, Leaf Mold) (Chen et al., 2022). AlexNet's success stems largely from its ability to deliver strong performance with relatively low computational cost, particularly on mobile platforms. However, for more complex datasets, deeper architectures such as VGG16, ResNet50, and MobileNetV2 have become more prominent.

In a comparative analysis by Mamatha and Raju (2025), ResNet50 and VGG16 were shown to produce more consistent feature maps than classical architectures for difficult-to-detect classes such as mosaic virus and spider mites. In particular, the ResNet architecture addresses the vanishing gradient problem in deep networks through residual connections, playing a critical role in distinguishing micro-scale lesions on leaves. When combined with transfer learning techniques, these systems developed for sustainable agriculture demonstrate strong generalization even on relatively small datasets (approximately 1,000–1,100 images) (Mamatha & Raju, 2025).

3.2. Real-Time Object Detection: YOLO-Based Approaches

Disease detection requires not only identifying what is present in an image but also determining the exact location of lesions on the leaf (localization). In this context, the YOLO (You Only Look Once) family of algorithms has become a standard for agricultural monitoring systems due to its balance between speed and accuracy. Research indicates that the YOLOv8 architecture provides 98% accuracy and higher precision values in detecting tomato fruit and leaf diseases compared with its predecessor YOLOv5 (Özel et al., 2025). The anchor-free detection mechanism offered by YOLOv8 enables more accurate bounding boxes around irregularly shaped disease spots.

The most recent development in the literature is the integration of the YOLOv11 architecture into agricultural applications. Lightweight variants such as YOLOv11n are optimized for deployment on edge devices and provide real-time analysis capability in dynamic environments such as greenhouses (Peng et al., 2026). YOLOv11n-based enhanced frameworks strengthen multi-scale feature extraction through modules such as EfficientMSF, substantially improving mAP values, particularly for challenging classes with complex backgrounds such as Leaf Mold (Meng et al., 2025).

3.3. Attention Mechanisms and Hybrid Models

Attention mechanisms constitute a critical innovation that enables deep learning models to focus on relevant disease regions while suppressing complex greenhouse backgrounds. Modules such as CBAM (Convolutional Block Attention Module) integrate both channel and spatial attention processes, thereby increasing the model's sensitivity to diseased tissues. For instance, hybrid systems combining a CNN architecture with CBAM and an SVM (Support Vector Machine) classifier can classify nine different tomato diseases with 97.2% accuracy (Altalak et al., 2022). In these approaches, the CNN functions as a feature extractor, while the SVM's decision mechanism maximizes the margin between classes, reducing classification error.

In recent years, Vision Transformer (ViT)-based models have begun to replace CNNs or to be combined with them due to their ability to capture long-range dependencies. Visual-Language Transformer-based models such as TLDVLM incorporate the BLIP-2 architecture into the image-processing pipeline, blending visual data with semantic information (Kaur et al., 2025). Moreover, integrating parameter-free attention mechanisms such as SimAM into models like YOLOv8 improves sensitivity by filtering out irrelevant background noise (Chen et al., 2025). These advanced architectures not only improve diagnostic accuracy but also constitute the backbone of rapid, reliable, and autonomous decision-support systems required for sustainable agriculture.

In conclusion, the technological trajectory that began with core CNN architectures has now reached a new level through the real-time speed of YOLOv11 and the semantic depth of Transformers. This architectural diversity is a key driving force in the digitalization of disease management strategies and the achievement of resource efficiency in tomato production.

4. Fruit Quality Assessment and Autonomous Harvesting Systems

The ultimate goal of sustainable agricultural production is not only to protect plant health but also to ensure that high-value, standards-compliant products are harvested with minimal losses. Computer vision systems have become a critical component that extends beyond leaf-level disease diagnosis to directly analyze fruit quality and orchestrate autonomous harvesting processes. This section reviews contemporary algorithms for detecting fruit ripeness levels, analyzing surface defects, and optimizing perception for harvesting robots.

4.1. Detecting Fruit Ripeness Levels

Accurate harvest timing is strategically important for tomato shelf life, nutritional value, and logistics planning. Traditional manual evaluations based on color scales have increasingly been replaced by deep learning-based RGB image analysis. One of the most notable studies in this area, ToRLNet (Tomato Ripeness Lightweight Network), is a lightweight model designed to classify tomatoes into three main stages: unripe (green), color-turning (semi-ripe), and fully ripe (red) (Sun et al., 2025). Even under complex greenhouse backgrounds, ToRLNet can detect ripeness stages with mAP values above 90% and can transmit, in real time, whether the fruit is ready for harvesting to autonomous systems (Sun et al., 2025). In addition, tracking fruit growth processes with networks such as YOLO-Deepsort provides up to 95% accuracy for yield estimation and harvest planning (Ge et al., 2022).

4.2. Fruit Diseases and Surface Defects

Pathological and physiological disorders that directly affect the fruit can entirely eliminate commercial value. In a comparative analysis by Özel et al. (2025), YOLOv8 demonstrated superior performance over YOLOv5 for detecting fruit diseases, achieving 98.0% accuracy. In particular, defects such as galleries created on the fruit surface by *Tuta absoluta* (tomato leafminer), blossom-end rot, and sunscald are encoded by deep learning models as characteristic textural changes (Özel et al., 2025). Densely connected architectures such as YOLO-Dense can localize these surface anomalies with high precision even when fruits occlude one another or remain partially hidden among branches (Wang & Liu, 2021). Autonomous defect detection accelerates quality control processes in post-harvest packaging facilities, thereby minimizing food waste.

4.3. Algorithm Development for Harvesting Robots

For harvesting robots to operate efficiently under greenhouse conditions, both high accuracy and low latency are required. These systems are typically deployed on edge devices with limited computational capacity, such as NVIDIA Jetson Nano or Raspberry Pi. Thakur et al. (2025) reported that AgriNet models provide 18.6% higher accuracy for tomato ripeness classification compared with general-purpose ImageNet models and noted that these models are well suited for visual guidance of robotic picking arms. Lightweight architectures such as YOLOv11n, developed for harvesting robots, can process more than 30 frames per second and determine fruit coordinates with millimetric precision (Peng et al., 2026). Optimizing models through quantization and pruning techniques reduces energy consumption while increasing battery life and the operational sustainability of autonomous harvesting systems in the field (Saxena et al., 2025).

In conclusion, fruit-focused computer vision approaches support the economic efficiency objectives of sustainable agriculture by digitalizing the "harvest and quality control" stage of the tomato production chain.

5. Advanced Technologies: Multimodal Data and Edge AI

Deep learning models developed to ensure sustainability in tomato production have, in recent years, evolved beyond image classification toward more complex and interactive architectures. Increasing data diversity and moving computational capability to edge devices in the field have enabled a shift in disease management from a reactive approach to a proactive management model.

5.1. Fusion of RGB and Hyperspectral Imaging

Although conventional RGB cameras are effective for detecting necrosis and lesions on leaves, by the time these symptoms emerge, pathogens have often already inflicted irreversible damage on the plant. For sustainable protection strategies, diagnosing diseases at the pre-symptomatic stage is critical. Hyperspectral imaging (HSI) can capture biochemical changes in plant reflectance spectra (400–2500 nm), enabling the detection of early signals such as chlorophyll loss or water stress. Javidan et al. (2024) demonstrated that multimodal fusion strategies combining RGB data with spectral signatures provide substantially higher sensitivity than visual analysis alone for the early detection of fungal diseases such as *Alternaria solani* and *Fusarium oxysporum*. Fusion frameworks such as PSNet blend the depth of spectral data with the spatial resolution of RGB, offering the potential to halt disease spread before it becomes established in the field (Javidan et al., 2024).

5.2. Vision–Language Models (VLMs) and Intelligent Assistants

Another advanced step for artificial intelligence in agriculture is enabling models not only to state what they "see" but also to explain what should be done. Vision–Language Models (VLMs) associate plant images with semantic text and can interact with farmers in natural language. For example, systems such as TLDVLM (Tomato Leaf Disease Visual Language Model), built on the BLIP-2 architecture, not only diagnose disease using advanced segmentation tools such as GroundingDINO and SAM-2, but also provide detailed reports on disease stage and recommended biocontrol measures (Kaur et al., 2025). By democratizing access to expert knowledge for small-scale producers, these intelligent assistants play a strategic role in preventing incorrect pesticide use and protecting ecological sustainability.

5.3. Deployment on Edge Devices and the Internet of Things (IoT)

Reliance on cloud-based systems for these computationally heavy architectures can cause operational delays in rural areas where internet access is limited. To overcome this limitation, Edge AI approaches aim to run models directly on hardware such as Android smartphones, Raspberry Pi, or NVIDIA Jetson Nano. Saxena et al. (2025) developed an intelligent greenhouse platform that integrates data collected by ESP32-based wireless sensors (soil moisture, temperature, air quality) with outputs from a YOLOv8 model running on Raspberry Pi. Monitored via cloud dashboards such as ThingsBoard, these systems can correlate climatic data with visual disease risk and make autonomous ventilation and irrigation decisions. Gunasekaran et al. (2026) further reported that optimizing lightweight models through techniques such as quantization and pruning minimizes energy consumption while increasing on-site diagnostic speed by 35%.

In summary, spectral data fusion, interactive language models, and edge computing integration are transforming tomato production into a digital ecosystem and expanding the technological frontier of sustainable agriculture.

6. Conclusion and Future Perspectives

The integration of deep learning-based computer vision systems into tomato production represents a turning point in the digitalization of agricultural processes. This technological transformation is not merely an efficiency-driven advancement, but also a strategic step toward enhancing the resilience of global food systems.

6.1. Economic and Ecological Impacts

Within the framework of sustainable crop protection strategies, precision disease detection enabled by deep learning models promises a dramatic reduction in agricultural input costs. Replacing broad-spectrum spraying practices with localized interventions targeted at detected hotspots can reduce pesticide use by up to 50% (Shafik, 2025). This both supports economic sustainability by lowering chemical costs for farmers and protects ecological balance by preventing chemical accumulation in soil and groundwater. Minimizing yield losses contributes directly to the United Nations "Zero Hunger" (SDG 2) goal and strengthens food supply security (Özel et al., 2025).

6.2. Explainable Artificial Intelligence (XAI)

Transparency and trust are central to the widespread adoption of AI models in agricultural practice. Making the decision-making processes of complex deep learning architectures understandable to humans facilitates agronomists' and farmers' acceptance of these systems as supportive assistants. Explainable AI (XAI) techniques such as Grad-CAM, EigenCAM, and LIME visualize which lesions or textural changes on the leaf the model focuses on when generating a diagnosis (Gunasekaran et al., 2026). Such visual evidence demonstrates that the system is not merely a prediction machine, but a scientific tool that accurately analyzes biological symptoms, thereby strengthening societal trust in the technology.

6.3. Open Problems and Future Research Directions

Despite current achievements, the "domain shift" problem remains relevant when transferring high accuracy attained in laboratory environments to variable greenhouse and field conditions (Jelali, 2024). Future research is expected to place greater emphasis on few-shot learning and synthetic data generation (GANs) to improve the detection of rare diseases (Hu et al., 2026). In addition, Federated Learning approaches—which enable model training without centralizing data from different locations—will facilitate global collaboration while preserving data privacy (Thakur et al., 2025). Ultimately, the full integration of visual data with climate sensors and multimodal language models (VLMs) is likely to transform tomato production into a fully autonomous and self-improving intelligent ecosystem.

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Chapter 4

METAHEURISTIC OPTIMIZATION OF PI CONTROLLER PARAMETERS FOR DC MOTOR SPEED CONTROL: COMPARATIVE EVALUATION OF APO AND GMO ALGORITHMS

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1.INTRODUCTION

The regulation of DC motor speed is a critical concern in industrial drives, robotic systems, and automation applications, owing to the favorable torque-speed characteristics of DC motors, their uncomplicated design, and their extensive application in processes necessitating precise speed control. Extensive review studies and experimental research in the literature demonstrate that PI and PID control methods have become the predominant control strategies for DC motor systems. The main aim of these control structures is to attain a rapid transient response, minimal overshoot, and robust steady-state performance in the face of disturbances such load changes (Sultan et al., 2021; Xie et al., 2019).

In this regard, computational methods that can autonomously modify controller gains based on fluctuating operating conditions have garnered significant interest. These strategies offer the possibility for enhanced performance relative to conventional tuning guidelines. While conventional tuning methods like Ziegler-Nichols, Cohen-Coon, and the root locus technique have certain practical benefits, they frequently result in inadequate or unstable performance when utilized for the nonlinear dynamics of DC motor systems. These inadequacies become increasingly evident under changes in system parameters, frictional influences, and variable load situations. Consequently, these constraints require the use of surrogate optimization methods to ascertain suitable PI or PID controller gains that meet established time domain and/or frequency domain performance standards (Borin et al., 2019).

Conversely, Particle Swarm Optimization (PSO) and analogous metaheuristic optimization techniques have been extensively utilized for the calibration of PI and PID controller parameters in dynamic systems. The broad popularity of these methodologies is primarily due to their proficiency in managing nonlinear system dynamics, non-differentiable fitness functions, and various performance criteria (Abdulhussein et al., 2021; Ahmad et al., 2022; Tang & Chen, 2013; Wubu et al., 2024).

This study seeks to optimize the settings of a proportional-integral (PI) controller for speed regulation of direct current (DC) motors using metaheuristic optimization techniques. The proportional (Kp) and integral (Ki) parameters of the PI controller are ascertained through two distinct optimization techniques. This study employs the recently introduced Artificial Protozoa Optimizer (APO) and Geometric Mean Optimizer (GMO) algorithms to optimize the parameters of the PI controller. The findings are assessed by juxtaposing them with the traditional PI controller parameters based on system performance error metrics, including the Integral of Squared Error (ISE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The impact of several metaheuristic optimization techniques on the speed control efficacy of DC motors is examined comparably.

2.MATERIAL AND METHODS

This study conducts a simulation-based analysis to evaluate the speed control performance of direct current (DC) motors. The MATLAB/Simulink software environment is used to implement the DC motor model and to apply the metaheuristic optimization algorithms considered in this study. The DC motor model used in the study is based on an example linear electric actuator model provided publicly on the official MATLAB website (The Mathworks, 2026) and included in the Simscape Electrical library. The model represents an actuator structure in which a DC motor drives a mechanical transmission system that converts rotational motion into linear motion. The model has multiple subsystems, including the DC motor unit, a sensor structure for speed measurement, a motor driver circuit, a gear transmission mechanism, and a load model. This structure concurrently considers the electrical and mechanical dynamics of the motor, facilitating a realistic assessment of the system's speed control performance. To ascertain the proportional (Kp) and integral (Ki) parameters of the PI controller employed for motor speed regulation, two distinct metaheuristic optimization strategies are utilized. The Artificial Protozoa Optimizer (APO) and Geometric Mean Optimizer (GMO) algorithms are utilized to optimize the parameters of the PI controller. The fundamental framework of the DC motor model employed in this research is illustrated in Figure 1 (The MathWorks, 2026).

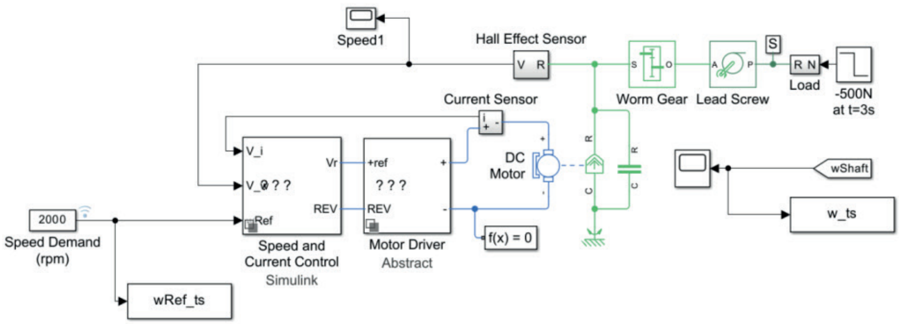

Fig. 1. System Architecture

The initial method utilized in this study is the APO, a recently introduced population-based metaheuristic optimization algorithm inspired by the survival strategies of protozoa, specifically Euglena, found in nature. The program conducts a search within the solution space by mathematically simulating the eating, dormancy, and reproductive actions of microorganisms. The eating habit is classified into autotrophic and heterotrophic systems. The autotrophic feeding and dormancy behaviors enhance the global exploration capability of the algorithm across the search space, whereas the heterotrophic feeding and reproduction behaviors promote intensive exploitation around potentially optimal solutions. APO requires only two specific control parameters, which provides a relatively low computational complexity while maintaining a well-balanced tradeoff between the exploration and exploitation phases of the optimization process. Owing to its flexible structure, the algorithm can be effectively applied to both continuous and discrete optimization problems (Wang et al., 2024).

In the literature, APO has been successfully applied to various constrained engineering design problems such as pressure vessel design, welded beam design, speed reducer design, and spring design in order to obtain optimal solutions in terms of cost and weight. In addition, the algorithm has also been used in multilevel image segmentation tasks based on minimum cross entropy for color image processing problems. Scientific comparisons performed using the CEC2022 benchmark test suite demonstrate that the APO algorithm achieves faster convergence and produces superior optimization results compared with 32 different modern metaheuristic algorithms (Wang et al., 2024).

The second method utilized in this work is the GMO, a recently introduced population-based metaheuristic optimization algorithm inspired by the characteristics of the geometric mean operator in mathematics. The primary innovation of the algorithm is the use of a singular metric known as the Dual-Fitness Index (DFI), which concurrently assesses the fitness and diversity conditions of the search agents throughout the optimization procedure. The index is computed by deriving the pseudo-geometric average of the normalized objective function values of the elite agents. The GMO algorithm adeptly sustains equilibrium between the exploration and exploitation stages of the optimization process, thus alleviating the issue of premature convergence, a significant drawback of most metaheuristic algorithms (Rezaei et al., 2023).

A notable advantage of genetic algorithms over other prevalent optimization techniques is their lack of necessity for user-defined control parameters, rendering the algorithm comparatively stable and dependable. Moreover, rather than directing the entire population towards a singular optimal solution, GMO designates an individual guide for each search agent by the application of Gaussian mutation, hence diminishing the likelihood of convergence to local optima. The method has been evaluated on 52 standard benchmark functions and nine hard engineering design issues. The reported results demonstrate that GMO achieves superior optimization performance and high convergence accuracy, particularly in high dimensional, complex, and highly constrained real-world optimization problems (Rezaei et al., 2023).

Since both the APO and GMO algorithms used in this study for determining the proportional (Kp) and integral (Ki) parameters of the PI controller are population-based metaheuristic optimization, potential solutions in the search space are represented by a population of search agents. In the optimization process considered in this study, the population size is set to 12 individuals, and the search process of the algorithms is carried out for 15 iterations.

In the formulated optimization problem, the decision variables are defined as the proportional (Kp) and integral (Ki) coefficients of the PI controller. Therefore, the optimization problem is performed within a two-dimensional solution space. The search ranges of the parameters are selected to ensure stable operation of the control system. Accordingly, the search interval of the Kp parameter is defined as [0–5], whereas the Ki parameter is limited to the range of [0–50].

In each iteration, the potential solutions generated by the optimization algorithms are evaluated using the DC motor speed control model developed in the MATLAB/Simulink environment. The effectiveness of the solutions offered is assessed based on error metrics obtained from the difference between the reference speed signal and the system output. The performance metrics employed are the Integral of Squared Error (ISE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The objective of the optimization strategies is to determine the PI controller values that minimize these error criteria.

The mathematical expressions for the performance indices utilized in the optimization process are shown in Equations (1)–(3). The Integral of Squared Error (ISE) quantifies the cumulative squared tracking error throughout the simulation time, as delineated in Equation 1. Here, $e(t)$ signifies the error signal, which is the disparity between the reference speed and the actual motor speed, while T specifies the complete duration of the simulation.

$$ISE = \int_0^T e^2(t)dt \quad \ldots(1)$$

The Root Mean Square Error (RMSE) evaluates the average magnitude of the error signal by considering the square root of the mean squared error and is expressed as Equation 2. Where Nrepresents the total number of sampled data points during the simulation.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} e^2(i)} \quad \ldots(2)$$

The Mean Absolute Error (MAE) calculates the average absolute value of the error signal and is defined as Equation 3.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |e(i)| \quad \ldots(3)$$

These performance indices are commonly used in control system analysis to evaluate the tracking accuracy and overall control performance of the system. During the optimization process, the algorithms aim to minimize these error metrics by determining the optimal values of the PI controller parameters.

3.SIMULATION RESULTS

Table 1 presents the PI controller parameters obtained using different optimization methods together with the corresponding performance metrics. As shown in the table, the proportional and integral coefficients of the classical PI controller are selected as $K_p = 1$and $K_i = 2$, respectively. Under these parameter settings, the error criteria calculated to evaluate the system performance indicate that the Integral of Squared Error (ISE) is 3.38×10^5, the Root Mean Square Error (RMSE) is 436.07, and the Mean Absolute Error (MAE) is 129.43.

Table 1. PI Controller Parameter Results

PI_Controller	K_p	K_i	ISE	RMSE	MAE
PI_Default	1	2	3.38×10^5	436.07	129.43
PI_APO	1.2912	2.1405	3.02×10^5	308.73	80.883
PI_GMO	1.2904	1.5956	2.9551×10^5	300.58	139.02

Upon executing the optimization with the APO algorithm, the parameters of the PI controller are established as Kp = 1.2912 and Ki = 2.1405. A notable enhancement in system performance is evident with these options. The ISE value specifically diminishes to 3.02×10^-5, indicating an enhancement of around 10.65%. The RMSE number diminishes from 436.07 to 308.73, indicating an enhancement of roughly 29.20%. The MAE value decreased from 129.43 to 80.883, reflecting an enhancement of around 37.51%.

When the optimization is carried out using the GMO algorithm, the PI controller parameters are obtained as $K_p = 1.2904$and $K_i = 1.5956$. Under these parameter values, the ISE decreases to 2.9551×10^5, which corresponds to an improvement of approximately 12.56% compared with the classical PI controller and represents the lowest ISE value obtained in this study. Furthermore, the RMSE value is calculated as 300.58, indicating a reduction of approximately 31.06% relative to the classical PI controller. However, the MAE value is calculated as 139.02, which is approximately 7.41% higher than the value obtained using the classical PI controller. Overall, the results demonstrate that both metaheuristic optimization algorithms significantly improve the system performance compared with the classical PI controller tuning. While the best performance in terms of the ISE criterion is achieved using the GMO algorithm, the APO algorithm produces better results in terms of the MAE criterion.

Figure 2 shows the tracking error responses obtained using the classical PI controller and the PI controller optimized using the APO algorithm. As observed in the figure, a large transient error occurs at the initial stage in both methods due to the application of the reference speed signal. However, compared with the classical PI controller, the APO optimized PI controller suppresses the error more rapidly and reaches values close to zero in a shorter time.

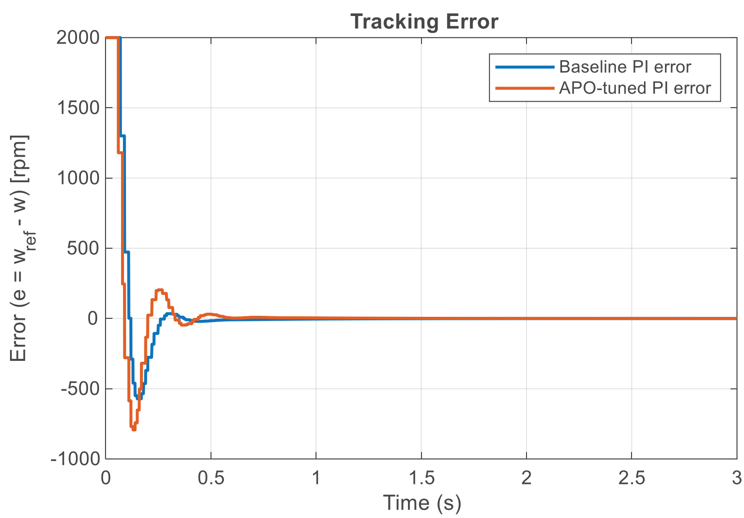

Fig. 2. PI Controller Tracking Error-I

Figure 3 shows the tracking error responses obtained using the classical PI controller and the PI controller optimized using the GMO algorithm. As observed in the figure, transient errors occur at the initial stage in both methods due to the application of the reference speed signal. However, the PI controller optimized using the GMO algorithm suppresses the error more rapidly and allows the system to reach the steady state in a shorter time compared with the classical PI controller.

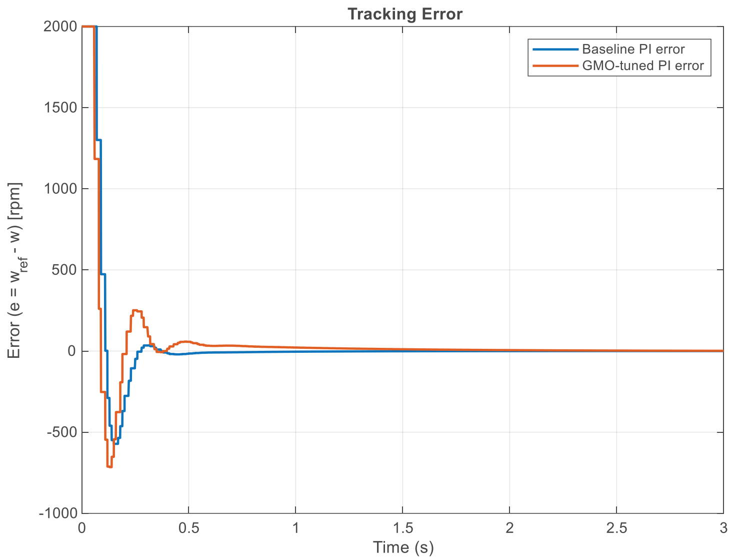

Fig. 3. PI Controller Tracking Error-II

Figure 4 shows the speed tracking performance obtained using the classical PI controller and the PI controller optimized using the APO algorithm. As observed in the figure, both methods can track the reference speed value. However, the PI controller optimized using the APO algorithm settles faster and suppresses the oscillations occurring during the transient response in a shorter time.

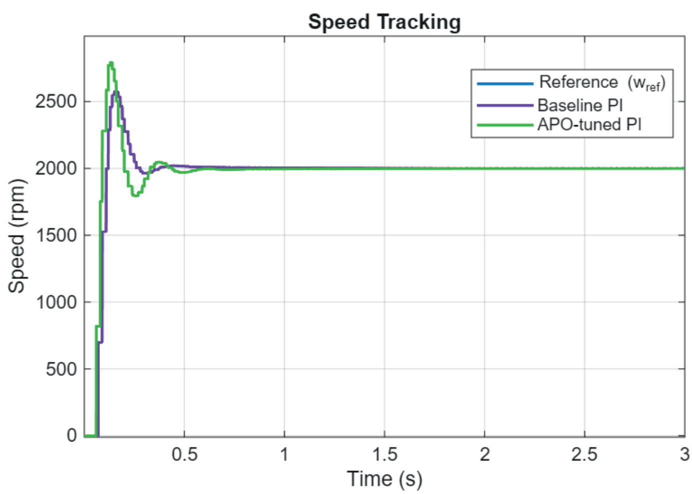

Fig. 4. PI Controller Speed Tracking-I

Figure 5 shows the speed tracking performance obtained using the classical PI controller and the PI controller optimized using the GMO algorithm. As observed in the figure, both methods successfully track the reference speed signal. However, the PI controller optimized using the GMO algorithm suppresses the oscillations occurring during the transient response more rapidly and allows the system to reach the steady state in a shorter time.

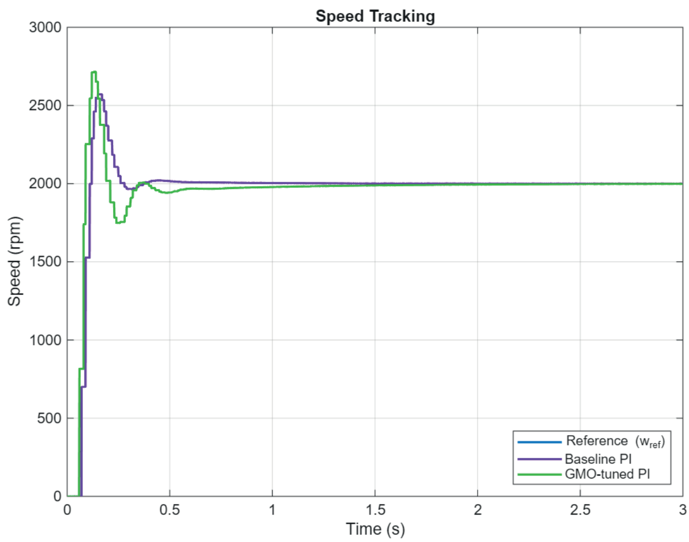

Fig. 5. PI Controller Speed Tracking-II

4.CONCLUSION

In this study, the PI controller parameters were determined using two different metaheuristic optimization algorithms in order to improve the speed control performance of direct current (DC) motors. In this context, the proportional (Kp) and integral (Ki) coefficients of the PI controller were optimized using the Artificial Protozoa Optimizer (APO) and Geometric Mean Optimizer (GMO) algorithms. The DC motor model used in the study was developed in the MATLAB Simulink environment, and the controller parameters obtained during the optimization process were tested on this model.

The optimization results demonstrate that both APO and GMO algorithms significantly improve the system performance compared with the classical PI controller tuning. When the performance metrics used for evaluation, namely ISE, RMSE, and MAE, are examined, it is observed that both optimization methods reduce the system error and provide a more effective control performance. In particular, the lowest error values in terms of the ISE and RMSE criteria are obtained using the GMO algorithm, whereas the APO algorithm produces better results in terms of the MAE criterion.

The tracking errors obtained and speed tracking graphs also support these findings. The PI controllers tuned using the optimization algorithms to improve the transient response performance of the system, suppress the error more rapidly, and allow the system to reach the steady state in a shorter time. These results indicate that metaheuristic optimization methods provide an effective approach for determining controller parameters in control systems.

In conclusion, this study demonstrates that metaheuristic optimization algorithms are effective and applicable methods for determining PI controller parameters in DC motor speed control problems. In future studies, different optimization algorithms can be compared, different performance criteria can be used, and the proposed approach can be applied to different control systems.

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Chapter 5

MACHINABILITY OF COMPOSITE MATERIALS IN MACHINING: CURRENT APPROACHES TO RF/GFR BLENDS

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INTRODUCTION

Composite materials have become the preferred engineering materials across a wide range of applications from aerospace to automotive, defence to biomedical, thanks to their advantages such as high specific strength, low weight, corrosion resistance and design flexibility (Phiri, Mavinkere Rangappa, Siengchin, Oladijo, Ozbakkaloglu, 2024; Dipen Kumar Rajak, Pagar, Kumar, Pruncu, 2019). The widespread use of fibre-reinforced composites and synthetic reinforcements such as glass fibre. Driven by clean environment policies and sustainable production processes the use of natural fibre-reinforced composites in industry has been rising year on year while glass fibre-reinforced composites still hold an important place in applications requiring higher mechanical performance (R. Kumar, Ul Haq, Raina, Anand, 2019). In parallel with these developments hybrid RF/GFR composites which combine the properties of rattan fibre reinforced (RF) and glass fibre reinforced (GFR) composites have become a new focus of research in recent years. The low density and environmental compatibility provided by the natural structure of rattan fibre when combined with the high strength and stiffness properties of glass fibre results in hybrid materials with more balanced mechanical properties compared to traditional composites (Lokesh et al., 2024). The ability to obtain a wide range of customisation by altering the ratio and sequence of the fibres enables these hybrids to be used in engineering applications tailored to different design requirements. Although hybrid composites offer advantages in terms of mechanical performance the behaviour of these materials in machining processes is quite complex and remains an insufficiently understood area of research (Kurien et al., 2025). Chip formation in composite materials does not proceed with homogeneous deformation as it does in metal materials. Fibre orientation, matrix elasticity, interface conditions and errors in the production process cause extremely heterogeneous deformation during cutting. This situation leads to numerous problems particularly in chip removal operations such as turning and milling, including fibre pull-out, delamination, matrix fracture, fibre fracture, surface integrity damage, and accelerated tool wear (Cepero-Mejías, Phadnis, Kerrigan, Curiel-Sosa, 2021). In hybrid composites the level and nature of these problems become even more complex due to the presence of both natural and synthetic fibres. The heterogeneity of the fibre-matrix interface is one of the main machinability difficulties encountered in RF/GFR hybrid composites. Rattan fibres are inherently irregular and hygroscopic in structure. This structure can cause weak areas to form at the interface with the matrix during cutting. However, in GFR composites the high rigidity of glass fibre causes intense abrasive wear on the cutting tool (Sun et al., 2024). When these two structures are combined it is normal to observe both brittle fracture and ductile deformation occurring simultaneously in the cutting zone. Therefore, predicting the behaviour of hybrid composites in machining is more difficult and depends on more parameters than composites containing a single type of fibre (Zan, Liao, Robles-Linares, Garcia Luna, Axinte, 2023). This complexity necessitates the careful evaluation of performance indicators such as surface roughness, cutting forces, tool wear, energy consumption and chip morphology. For this reason it is crucial to systematically investigate the machining parameters of RF/GFR composites and develop effective solutions to production problems in this field. Furthermore the machinability of hybrid composites is not solely dependent on cutting parameters. In addition to cutting parameters it is influenced by numerous factors such as layer sequence, fibre content, production method, curing conditions, moisture content and the microstructural integrity of the composite (Gao et al., 2022). This multifaceted structure has led to limited comprehensive modelling studies in the literature in this area. Investigating the machinability of composite materials particularly those with a hybrid structure is critical for sustainable and high-precision production processes (K. N. Kumar, Babu, 2024).

The aim of this book chapter is to examine in detail the machinability behaviour of RF/GFR hybrid composites in machining within the framework of modern approaches to systematically evaluate findings in the literature and to shed light on production processes with conclusions supported by applied research. The section will address both fibre and matrix behaviour as well as tool wear, surface quality, forces, chip formation and optimisation approaches. Furthermore machinability problems specific to hybrid composites and proposed solutions will be evaluated as far as possible.

Within this framework the main objectives of the study are listed below:

- To reveal the microstructural properties and mechanical behaviour of RF, GFR and hybrid RF/GFR composites,

- Explain the damage modes that occur during machining and the mechanisms of chip formation,

- Conduct comprehensive assessments of critical performance outputs such as tool wear and surface integrity,

- Presenting modern optimisation and modelling approaches for the processability of hybrid composites,

- Develop guiding recommendations for future research areas.

Consequently this section aims both to compile the existing body of knowledge in the academic literature and to provide researchers, practitioners and engineers working in the field of production technologies with a comprehensive resource on the processability of hybrid composites.

STRUCTURE OF COMPOSITE MATERIALS AND HYBRID RF/GFR COMPOSITES

Composite materials are new materials obtained by physically mixing at least two chemically different materials together. These materials generally consist of two main components: the matrix phase and the reinforcement element. The matrix phase is responsible for providing load transfer protection against environmental effects (corrosion) and maintaining structural integrity. Reinforcement elements on the other hand are the fundamental components that determine the mechanical strength rigidity and wear resistance of composite materials. Fibre-reinforced polymer composite materials constitute the most widely used composite material group today due to their high specific strength and design flexibility (Dipen K Rajak, Pagar, Menezes, Linul, 2019).

Classification of Fibre-Reinforced Composites

Fibre-reinforced composites are classified into three main groups based on the type of fibre used: natural fibre-reinforced, synthetic fibre-reinforced, and hybrid composites. Synthetic fibres such as glass, carbon and aramid exhibit high mechanical strength and stiffness. Natural fibres such as flax, jute, sisal and rattan, on the other hand, offer advantages such as low density, biodegradability and environmental sustainability. However, due to the irregular microstructure and moisture sensitivity of natural fibres, some inconsistencies in mechanical performance may occur. Therefore hybrid composites, which combine natural and synthetic fibres, stand out as a balanced solution that brings together the advantages of both fibre types (Mohd Bakhori et al., 2022).

Comparison of Structural Properties of Rattan Fibre Reinforced (RF) and Glass Fibre Reinforced (GFR) Composites

Rattan fibre reinforced (RF) and glass fibre reinforced (GFR) composites exhibit distinctly different mechanical and microstructural properties due to their different fibre structures. Table 1 provides a comparison of the basic structural and processability properties of rattan fibre reinforced (RF) and glass fibre reinforced (GFR) composites. Rattan fibres have a natural, irregular diameter distribution and a cellular structure. This structure provides advantages in terms of low density and environmental sustainability. In contrast glass fibres possess a more homogeneous morphology high tensile strength and high rigidity due to their synthetic structure. These structural differences directly affect not only mechanical performance but also the matrix–fibre interface behaviour and post-production processability characteristics (Ahmed, Hosseinpourpia, Brischke, Adamopoulos, 2022; Wang et al., 2022). The variability of the fibre-matrix interface bonding in RF composites and the moisture sensitivity of natural fibres create significant limitations, while the high hardness and abrasive character of GFR composites can cause intense wear on cutting tools. Therefore these complementary properties of RF and GFR composites in terms of structure and machinability form the fundamental rationale for the development of hybrid RF/GFR composites (Chaudhary, Bajpai, Maheshwari, 2020).

Table 1. Comparison of the Fundamental Structural and Processability Properties of RF and GFR

Property	RF Composites	GFR Composites
Density	Low	Moderate
Mechanical strength	Moderate	High
Stiffness	Moderate	High
Fiber–matrix interface behavior	Variable, moisture-sensitive	More stable
Environmental impact	High environmental compatibility	Limited environmental compatibility
Typical machining-related issues	Fiber pull-out, delamination	Abrasive tool wear
Effect on tool life	Relatively longer	Relatively shorter

Effects of RF and GFR Composites on Machining Behaviour

The behaviour of rattan fibre reinforced (RF) and glass fibre reinforced (GFR) composites during machining exhibits distinct differences due to the mechanical properties of the fibres and the matrix-fibre interface character (Irawan et al., 2022). In RF composites the irregular structure of natural fibres and their moisture sensitivity may cause weak areas to form at the fibre-matrix interface during cutting. This situation leads to damage mechanisms such as fibre pulling, matrix separation and local delamination, particularly during turning and milling operations. In contrast the high stiffness and abrasive nature of glass fibres in GFR composites cause intense abrasive effects in the cutting tool-workpiece contact area. Subsequently the cutting tool life is reduced. When evaluated in terms of chip formation mechanism, a more ductile deformation behaviour is observed in RF composites during the cutting process while in GFR composites, chip formation is predominantly brittle fracture (Masoud, Sapuan, Mohd Ariffin, Nukman, Bayraktar, 2020). The cutting forces, surface integrity and tool life that occur in machinability are shaped by these differences. RF composites exhibit a more sensitive structure in terms of surface quality, fibre orientation, and cutting parameters. In contrast, surface roughness in GFR composites is generally related to tool wear and cutting edge wear. In this context, the different damage mechanisms and machinability tendencies exhibited by RF and GFR composites during machining result in certain limitations when using either material group alone. Hybrid RF/GFR composites which combine natural and synthetic fibres, emerge as an important alternative solution to reduce these limitations and achieve balanced machinability performance (Suriani, Rapi, Ilyas, Petrů, Sapuan, 2021). As schematically illustrated in Figure 1 RF and GFR composites exhibit fundamentally different machining-related damage mechanisms due to their distinct fibre characteristics.

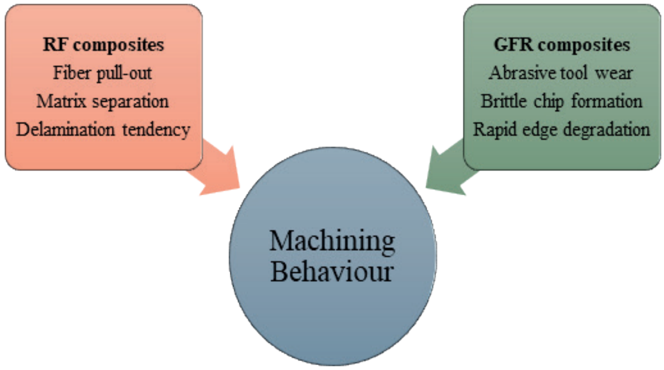

Figure 1. Relationship-based SmartArt representation of dominant machining-related damage mechanisms observed in RF and GFR composites.

Machining Behaviour of Hybrid RF/GFR Composites

The processability of hybrid RF/GFR composites is more complex than that of single-fibre reinforced composites due to the coexistence of natural and synthetic fibres within the same structure; however, they exhibit a more balanced character. The machinability limitations observed separately in RF and GFR composites can be balanced to a certain extent in hybrid structures through fibre ratio and layer arrangement (Yazman, Gemi, Morkavuk, Köklü, 2024). This enables hybrid composites to offer more controlled performance in terms of both surface quality and tool life in machining. The chip formation mechanism in hybrid RF/GFR composites is characterised by the simultaneous display of different deformation behaviours of natural and synthetic fibres in the cutting zone. The more ductile and irregular structure of rattan fibres can lead to fibre pulling and local matrix separation during cutting. The high stiffness and brittle structure of glass fibres cause chip breakage and abrasive interactions to dominate. The occurrence of these two different behaviours in the same cutting zone leads to a heterogeneous chip morphology in hybrid structures. However the negative effects of this heterogeneity can be significantly reduced with appropriate cutting parameters and fibre placement (Abena et al., 2023).

When evaluated in terms of cutting tool wear the behaviour of hybrid RF/GFR composites exhibits a transitional character between RF and GFR composites. Although the abrasive wear caused by glass fibres is still effective on the cutting tool in hybrid structures the presence of rattan fibres can partially reduce the severity of this effect. It has been reported that in hybrid structures where glass fibres are positioned in the outer layers and rattan fibres in the inner layers the tool-workpiece interaction becomes more balanced and tool life can be extended (Baharvand, Teuwen, Shankar Verma, 2025; Calabrese, Badagliacco, Sanfilippo, Fiore, 2023; Karthick et al., 2022). Furthermore if the fibre ratio and arrangement are not designed appropriately both fibre pull-out and abrasive wear mechanisms can occur simultaneously. In terms of surface integrity hybrid RF/GFR composites can offer a more consistent surface quality compared to uniform fibre-reinforced structures under the right processing conditions. When rattan fibres are concentrated in areas close to the surface fibre protrusions and surface defects increase while in layer arrangements where glass fibres dominate the surface roughness is observed to be more related to tool wear. Therefore surface quality in the machining of hybrid composites is not solely dependent on cutting parameters. It is also directly related to the hybrid structure design.

Consequently the machining behaviour of hybrid RF/GFR composites is significant in terms of balancing the disadvantages exhibited by natural and synthetic fibres alone. However for this situation to be effectively evaluated, cutting parameters, tool characteristics and hybrid structure design must be considered together. In this context when hybrid composites are properly designed they stand out as engineering materials that can provide more sustainable and predictable performance in machining processes.

MACHINABILITY AND DAMAGE MECHANISMS OF HYBRID RF/GFR COMPOSITES

Chip Formation Mechanisms

The machinability behaviour of hybrid RF/GFR composites during machining exhibits a more complex structure compared to single-fibre reinforced composites due to the coexistence of natural and synthetic fibres within the same structure (Jesthi, Nayak, 2020). In the cutting zone the simultaneous interaction of rattan fibres, glass fibres and the polymer matrix leads to non-homogeneous stress distribution and an irregular material removal mechanism. The machinability performance of hybrid composites, particularly chip formation, depends on multiple factors which explains this situation.

The continuous chip formation observed in metal materials during machinability is not seen in hybrid RF/GFR composites. This occurs in these composites during chip removal or cutting processes due to the simultaneous occurrence of mechanisms such as fibre breakage and fibre pulling. During the cutting of rattan fibres which have a more ductile and irregular structure, fibre pulling and local matrix separation may become easier (Geier et al., 2023). However the high stiffness and brittle structure of glass fibres bring fibre breakage and segmented chip formation to the fore. The simultaneous occurrence of these two different behaviours in the same cutting zone leads to the formation of heterogeneous chip morphology in hybrid structures. However it is possible to reduce these negative effects to a certain extent with appropriate cutting parameters and fibre placement.

Damage Mechanisms and Surface Integrity

The damage mechanisms observed in hybrid RF/GFR composites during processing are directly related to the mechanical properties of the fibre types and the matrix-fibre interface behaviour. The natural and irregular structure of rattan fibres causes local variability in the bonding quality at the fibre-matrix interface. This situation leads to the emergence of damage types such as fibre pull-out, matrix separation and surface roughness. In contrast the high rigidity and abrasive structure of glass fibres increase fibre breakage and the formation of surface microcracks during cutting (Qian et al., 2025). In hybrid composites these damage mechanisms are often observed together and cause the surface integrity to exhibit a more complex structure compared to uniform fibre-reinforced structures. When evaluated in terms of tool life and tool wear the behaviour of hybrid RF/GFR composites shows a transitional structure between RF and GFR composites. Abrasive wear is typically a type of wear observed in the machinability of glass fibres. The use of rattan fibres allows this type of wear to be partially reduced. This indicates that the contact formed at the chip-cutting tool interface is at a more acceptable level under hybrid conditions. Thus a longer tool life can be achieved. Furthermore if the fibre ratio and layer arrangement are not designed appropriately both fibre pull-out and abrasive wear mechanisms can be active simultaneously. As schematically illustrated in Figure 2 the dominant damage mechanisms observed during the machining of hybrid RF/GFR composites include fibre pull-out, delamination and matrix cracking.

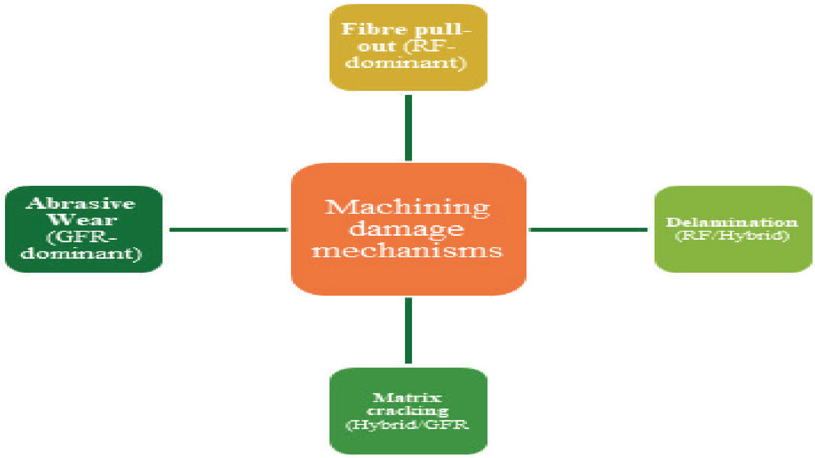

Figure 2. SmartArt-based conceptual illustration of dominant damage mechanisms observed during the machining of hybrid RF/GFR composites.

Tool Wear and Its Effects on Machinability

Surface roughness in particular surface integrity emerges as a critical parameter in assessing the machinability of hybrid RF/GFR composites. The surface quality obtained after machining is closely related to the fibre type and cutting tool wear condition (Kulkarni, Siddeshkumar, Prasad, Shankar, Suresh, 2023). In structures where rattan fibres are concentrated near the surface fibre protrusions and surface irregularities may increase. However in hybrid designs where glass fibres are effective on the surface surface roughness can be said to be more related to cutting tool wear. Therefore in the machining of hybrid composites surface integrity is not only determined by cutting parameters but is also directly related to the hybrid structure design.

In general hybrid RF/GFR composites have the potential to balance the machinability limitations that arise from the use of natural and synthetic fibres alone. The accurate identification of damage mechanisms and the controlled execution of the machining process are directly related to the effective utilisation of this potential. This necessitates a detailed examination of the effects of cutting parameters on the machinability of hybrid composites under a separate heading. The dominant machining-related damage modes observed in hybrid RF/GFR composites and their effects on surface integrity and tool behaviour are summarised in Table 2.

Table 2. Hybrid RF/GFR Composites: Machining Damage Modes and Their Effects

Damage mechanism	Dominant fibre type	Primary cause	Effect on surface integrity
Fibre pull-out	RF	Weak fibre–matrix bonding	Surface roughness increase
Delamination	RF / Hybrid	Interlaminar stress	Edge damage
Matrix cracking	Hybrid	Stress concentration	Micro-surface defects
Abrasive wear	GFR	High fibre hardness	Tool degradation

Therefore a detailed evaluation of machining parameters and process conditions is required to better control the machinability behaviour of hybrid RF/GFR composites.

EFFECT OF MACHINING PARAMETERS AND PROCESS CONDITIONS

The machinability behaviour and damage mechanisms observed in hybrid RF/GFR composites are strongly influenced by machining parameters and process conditions. Cutting speed, feed rate and depth of cut play a critical role in controlling chip formation surface integrity and tool wear during machining operations. Due to the heterogeneous nature of hybrid composites variations in these parameters may lead to significantly different responses compared to single-fibre-reinforced composites. Therefore understanding the influence of machining parameters is essential for achieving stable and controlled machining performance in hybrid RF/GFR composite materials (Zou, Gao, Xi, 2024).

The Effect of Cutting Speed

Cutting speed is one of the fundamental cutting parameters that directly affects the chip removal mechanism in the machinability of hybrid RF/GFR composites. When the cutting speed is set low damage mechanisms such as fibre pulling and local matrix separation may occur particularly due to the ductile and irregular structure of rattan fibres (Gao et al., 2022). This can lead to a deterioration in surface integrity and an increase in surface roughness. As the cutting speed increases the temperature in the cutting zone rises. This increase in temperature can alter the viscoelastic behaviour of the polymer matrix. The most significant effect of abrasive wear in hybrid structures containing glass fibres is related to the increase in cutting speed. With increased abrasive wear the cutting tool enters the wear tendency very early. This faster wear directly affects machinability costs. To optimise this cost and the machinability process the cutting speed must be determined correctly. Preliminary experiments can be conducted to ensure this determination is carried out properly. This creates a balanced operating range and minimises machinability costs.

The Effect of the Amount of Progress

The feed rate plays a significant role in the machinability of hybrid composites as it does in other machining processes. The feed rate which is generally preferred at low levels in hybrid composites, directly affects many factors primarily surface roughness. As a traditional approach a low feed rate is attributed to good surface roughness. However at very low feed rates the increased tool-workpiece contact time can accelerate tool wear particularly in areas containing glass fibres. Conversely when the feed rate is high cutting forces inevitably increase as in other machining processes (Saghir, ur Rehman Shah, Kamran Afaq, Ahmed, Song, 2023). Along with the increase in cutting forces the formation process of damage mechanisms such as fibre breakage, fibre pulling and delamination may accelerate. As the subject is hybrid composites the damage mechanisms formed due to the different deformation behaviours of natural and synthetic fibres exhibit a more complex structure. For example in areas containing rattan fibres high feed rate values may cause the fibres to be pulled rather than cut. Similarly in areas containing glass fibres, fibre breakage and surface microcracks may become more dominant. Therefore the accurate determination of the feed rate is crucial in terms of production efficiency, indirect processability costs and surface integrity. Determining the optimal conditions based on the cutting and cut material plays a significant role in the positive contribution of the feed rate.

The Effect of Cutting Depth

Cutting depth is generally considered a secondary parameter in the machinability of hybrid composites. As such it has a significant effect particularly in hybrid structures with a multi-layered structure. It is a commonplace observation that an increase in cutting depth leads to an increase in cutting forces. Here an increase in cutting depth simultaneously causes more fibres to enter the cutting zone (Chegdani, Mansori, 2018). Along with the increased cutting force the risk of damage also increases. This situation especially with the increase in interlayer stresses paves the way for damage mechanisms such as delamination and matrix cracking. When evaluating the effect of cutting depth in hybrid composites the fibre ratio and layer arrangement should be taken into account. In structures where glass fibres are close to the surface large cutting depths can accelerate tool wear. In areas where rattan fibres are predominant, surface roughness and fibre protrusions can become more pronounced. Therefore when determining the cutting depth it must be set in accordance with the cutting speed and feed rate.

Consequently, cutting speed, feed rate and cutting depth are parameters that must be evaluated together not individually in the machinability of hybrid RF/GFR composites. The compatibility of these parameters has a positive/

negative effect on machinability indicators. This compatibility plays a decisive role particularly in chip formation the effect of damage mechanisms and tool wear behaviour. Naturally hybrid materials with a heterogeneous structure may not exhibit the same performance as the parameter combinations suitable for uniform fibre-reinforced composites. Therefore cutting parameters must be addressed holistically to achieve machinability performance within tolerance in the machining of hybrid RF/GFR composites. Appropriate parameter selection contributes to both maintaining surface integrity and extending tool life thereby increasing the usability of hybrid composites in industrial applications. The interaction between machining parameters dominant damage mechanisms and key machinability indicators in hybrid RF/GFR composites is schematically illustrated in Figure 3.

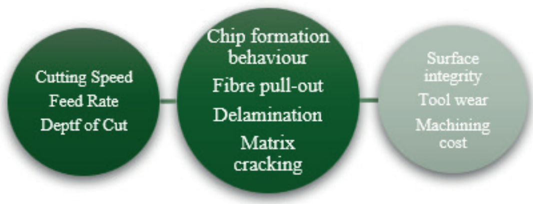

Figure 3. Schematic illustration of the relationship between machining parameters, dominant damage mechanisms and machinability indicators in hybrid RF/GFR composites.

INDUSTRIAL APPLICATIONS AND CASE PERSPECTIVE

Academic studies on the machinability of RF/GFR and hybrid composites are mostly conducted under controlled laboratory conditions (Attia et al., 2024; Nikam et al., 2023). However when the real value of these materials is the main issue the most appropriate approach is to consider their capacity to cope with the problems encountered in industrial production environments. Based on this the machinability behaviour of such materials should be evaluated in terms of how it reflects on industrial applications the effect of cutting parameters on production efficiency and their impact on part quality. The primary objectives in the machining of RF/GFR and hybrid composites on an industrial scale can be summarised as reducing delamination, preserving surface integrity, improving tool life and reducing production costs. As these objectives often involve conflicting parameters machining strategies must be addressed with a holistic approach.

Aviation and Space Industry Applications

The aerospace industry is among the sectors where RF/GFR and hybrid composites are most widely used. High specific strength and low weight are fundamental design criteria for critical components such as wing panels, fuselage parts and equipment, internal structural components and fasteners (Zhu, Li, Childs, 2018). The most common processing problems encountered in these sectors are listed below:

- Delamination due to thrust force during drilling operations
- Surface tears due to fibre alignment
- Damage differences between layers in multi-layered structures

The methods provided in bullet points can be applied to resolve the issues mentioned:

- Optimising the advancement rate through preliminary experiments (e.g. selecting a low advancement rate)
- Implementation of step drilling strategies
- Use specially shaped composite drill bits

preferable. Of course the use of these methods can also increase production time and production costs. Therefore the adaptability of the optimum cutting parameters recommended in academic studies to mass production is a critical research topic.

Processing of RF/GFR and Hybrid Composites in the Automotive Industry

RF/GFR and hybrid composites are also frequently used products in the automotive industry. They are widely and safely used particularly in structural reinforcements, bodywork elements and interior trim components (Mohammadi et al., 2023). The primary priority in this field is to achieve a long service life and an acceptable level of quality at a lower cost compared to aerospace applications. The variables that are paramount in mass production lines are listed below.

- High travel speeds
- Automatic tool changes
- Minimum dwell time

This approach therefore brings with it damage parameters that are more controllable in terms of workability but where repeatability is more critical. In the processing of RF/GFR and hybrid composites for automotive applications:

- The effect of cutting tool wear on production continuity
- The surface roughness is at the desired values
- Assembly compatibility in hole tolerances

these are quite important criteria. Consequently the low-damage processing strategies proposed in the literature are mostly applied in the automotive industry with optimised medium-level parameters.

Energy and Defence Industry Applications

RF/GFR and hybrid composites used in energy and defence industry applications are generally preferred for components requiring high reliability and long service life (Simões, 2024). Examples include wind turbine blades radar enclosures and ballistic protective structures. In terms of workability the main issues in this area can be summarised as the long-term performance impact of microstructural damage. Thermal effects that alter the material's properties and residual stresses generated during processing are also key parameters affecting machinability. When determining machining parameters in the energy and defence industries the ability of the component to perform its function over an extended period in its intended application must be considered.

The Industrial Implications of Academic Findings

There are some fundamental challenges in transferring the results and findings obtained in the field of processability in academic studies to industrial applications. Some of these challenges are listed below.

- Differences between production line and laboratory scale conditions
- Maintenance requirements and cutting tool cost
- Operator and machine variability

Despite these issues understanding the damage mechanisms defined in the literature and proposing solutions contribute positively to industrial processes. In particular, optimising production in industrial processes offers significant gains in practical areas such as clarifying the role of fibre-matrix interaction in processing behaviour in RF/GFR and hybrid composites.

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

This book chapter addresses the machinability of RF/GFR and hybrid composite materials. The introductory section defines the general properties of composite materials and machinability issues. Subsequently a comparative assessment of RF and GFR composites is presented. Damage mechanisms and the effects of cutting parameters are discussed in detail specifically for hybrid composite structures.

Evaluations for industrial applications have revealed the challenges and opportunities encountered in transferring academic findings to machinability processes. Based on this the machining of RF/GFR and hybrid composites:

- Delamination
- Fibre breakage
- Matrix cracking

It has been observed that the cutting parameters and tool geometry are directly related to damage types such as these. The main conclusions drawn from this study are listed below:

In industrial applications it is critically important to adapt the academically recommended workability conditions and optimum parameters to production conditions.

- Compared to homogeneous composites hybrid composites have a more complex structure but exhibit more controllable processability behaviour.

- Optimising cutting parameters directly affects not only surface integrity but also tool life and energy efficiency.

In future studies supporting data-driven modelling approaches for the workability of RF/GFR and hybrid composites with artificial intelligence and machine learning techniques stands out as an important area of research. Furthermore incorporating energy consumption and environmental impacts into workability processes from a sustainable production perspective will broaden the scope of studies in this field.

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Chapter 6

MACHINE LEARNING BASED WEATHER FORECASTING

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INTRODUCTION

Weather forecasting has long been regarded as one of the most critical domains within environmental science, primarily because atmospheric conditions exert a profound influence on virtually every facet of human activity. In the agricultural sector, reliable forecasts enable farmers to make informed decisions regarding irrigation schedules and harvest timing (Chen et al., 2021). In the aviation industry, accurate meteorological predictions are essential for ensuring flight safety and mitigating costly operational delays (Thiagarajan et al., 2017). Similarly, municipal governments depend on weather forecasts to implement preparedness measures against floods, storms, and heavy snowfall events (Kumar et al., 2023). Inaccurate predictions may lead to substantial economic losses, transportation disruptions, and inadequate community preparedness for natural hazards (Kameswari et al., 2023).

Since the 17th century, the systematic measurement of meteorological variables has constituted a central concern in the atmospheric sciences. The development of early meteorological instruments left the groundwork for progressively improving forecast accuracy. Over subsequent centuries, mathematical and statistical methods have been extensively applied to atmospheric modeling, the majority of which are inherently nonlinear. In the contemporary era, climatic conditions are undergoing substantial changes driven by a multitude of factors. For instance, increasing concentrations of atmospheric pollutants contribute significantly to climate change, thereby posing serious threats to global ecosystems (Singh and Yadav, 2021). Consequently, the precise measurement of meteorological variables has become increasingly important, as the data collected from meteorological stations are indispensable for monitoring long-term global climate trends (Karl et al., 1995).

Climate may be defined as the aggregate of meteorological phenomena that interact in a complex, interdependent manner; a perturbation in one variable frequently induces variations in others. The weather at any given moment is characterized by variables such as wind speed, temperature, and humidity, which are governed by radiative fluxes and surface heat exchange processes. Local climate, by contrast, is conventionally described as the mean atmospheric state averaged over a 20–30 year period for a given region and season (Giorgi et al., 2004). Computational, statistical, and numerical methods are widely employed to model these variables, and the majority of such models are nonlinear in nature (Steppeler et al., 2003). Nevertheless, accurate forecasting remains a considerable challenge owing to the inherent variability of the climate system, which further complicates the management of renewable energy resources (Meenal et al., 2022).

The early 21st century, characterized by the emergence of large-scale data, high-performance computing with Graphics Processing Units (GPUs), and growing scientific interest in novel methodologies, has represented a pivotal period in the evolution of machine learning (Madiajagan and Raj, 2019). Although many of the fundamental techniques were introduced as early as the 1960s, the recent exponential growth in data availability and computational capacity has been widely referred to as the golden era of artificial intelligence and machine learning. Comprehensive reviews of machine learning algorithms, recognized as a significant subfield of artificial intelligence, have proliferated in the atmospheric sciences (Singh et al., 2022). When labeled data are available, supervised learning methods can establish mappings from inputs to outputs and subsequently be applied to unseen datasets for classification or regression tasks. Notable examples include ensemble methods such as Random Forest (Liu et al., 2012) and XGBoost (Chen et al., 2015), as well as Artificial Neural Networks (Yegnanarayana, 2009), Deep Learning architectures (LeCun et al., 2015), and Support Vector Machines (Hearst et al., 1998).

Unsupervised learning, in contrast, operates on unlabeled data and is primarily concerned with clustering and dimensionality reduction. Prominent techniques within this paradigm include K-means clustering (Na et al., 2010) and Principal Component Analysis (Howley et al., 2005). Both supervised and unsupervised approaches have been increasingly applied to atmospheric science, weather forecasting, and climate analysis in recent years.

The objective of the present study is to develop and evaluate a Random Forest–based classification pipeline for weather prediction. This research contributes to the growing body of literature on the application of machine learning to meteorology and climatology. The intent is not to supplant physics-based models but rather to complement them with data-driven approaches. Specifically, this study investigates whether the Random Forest algorithm can achieve satisfactory accuracy in classifying daily weather conditions. Simultaneously, attention is devoted to identifying which meteorological variables contribute most substantially to the predictions and to assessing the stability of the model in discriminating among the four target categories: sunny, cloudy, rainy, and snowy.

METHODS

Dataset

This study employed a publicly available dataset (Narayan, n.d.) comprising 13,200 daily weather observations, each described by 11 attributes. The predictor variables included temperature (°C), humidity (%), wind speed (m/s), precipitation (%), cloud cover, atmospheric pressure (hPa), UV index, season, visibility (km), and location, with the target variable being the weather type. The weather conditions were uniformly distributed across four categories: sunny, cloudy, rainy, and snowy. This balanced class distribution provided an optimal foundation for supervised learning by mitigating potential bias toward any particular weather category. Prior to model construction, the dataset underwent preprocessing procedures that included the removal of inconsistencies, encoding of categorical variables such as season and location, and normalization of numerical features to ensure scale uniformity. By integrating both continuous and categorical predictors, the dataset offered a comprehensive representation of atmospheric conditions, rendering it particularly suitable for classification tasks employing ensemble-based methods such as Random Forest.

Procedure

The model development process comprised three principal stages: data preparation, model construction, and performance evaluation. During the data preparation phase, the raw dataset was cleaned by eliminating duplicate entries and imputing missing values. Continuous features such as temperature and humidity were standardized to a common scale, while categorical variables including season and location were transformed into numerical representations through one-hot encoding.

Subsequently, the Random Forest algorithm was selected as the classification model. Rather than relying on a single decision tree, this ensemble method constructs a large number of trees in this case, 400 each of which contributes a vote toward the final classification decision. Each constituent tree was trained on a distinct bootstrap sample of the data, a procedure that reduces the propensity of individual models to overfit and enhances the overall predictive stability. The final stage involved model evaluation: the dataset was partitioned into training (80%) and testing (20%) subsets using stratified sampling to preserve the class distribution. Accuracy and F1 scores (both macro-averaged and weighted) were subsequently employed to provide a comprehensive assessment of the model's classification performance across all categories.

Implementation in Python

The entire analytical pipeline was implemented in Python, owing to its extensive ecosystem of libraries for data analysis and machine learning. The Pandas and NumPy libraries were utilized for data manipulation and numerical computation, respectively. For modeling purposes, Scikit-learn provided the requisite tools for feature scaling, missing value imputation, and categorical feature encoding. These preprocessing steps were integrated through a ColumnTransformer to ensure consistent handling of heterogeneous variable types. The RandomForestClassifier served as the core classification algorithm, and the joblib library was employed to serialize the trained model for subsequent reproducibility without requiring retraining.

Model Development

For model training, the dataset was divided into a training subset and a held-out test subset. Stratified sampling was applied during this partitioning to maintain a balanced representation of sunny, cloudy, rainy, and snowy observations across both subsets. The Random Forest algorithm relies on bootstrap aggregation (bagging), whereby each constituent decision tree is trained on a randomly resampled subset of the training data. This diversity among individual trees serves to mitigate overfitting and enhance the model's generalization capacity. Following training, predictions were generated on the held-out test set. The results indicated that the model achieved high classification accuracy and demonstrated robust generalization to previously unseen observations.

RESULTS AND DISCUSSIONS

Table 1 presents a summary of the Random Forest model's performance metrics, indicating strong classification performance across all weather categories. The overall accuracy was approximately 91.2%, and both the macro-averaged and weighted F1 scores corroborated that this performance was not attributable to any single dominant class but was distributed relatively uniformly across all categories. The sunny and snowy categories exhibited the highest classification reliability, with precision and recall values ranging between 0.91 and 0.95. The cloudy and rainy categories proved comparatively more challenging, with scores typically ranging from 0.87 to 0.92. This reduction in performance is not unexpected, as cloudy and rainy weather conditions frequently share overlapping meteorological characteristics, rendering their discrimination more difficult even for experienced human forecasters.

Table 1: *Summary of Random Forest classification metrics*

Class and Metrics	Precision	Recall	F1-Score
Accuracy	0.912	–	–
F1-Macro	0.912	–	–
F1-Weighted	0.912	–	–
Sunny	0.94	0.91	0.93
Snowy	0.95	0.91	0.93
Cloudy	0.87	0.92	0.9
Rainy	0.89	0.91	0.9

The confusion matrix corroborates the overall performance trends, as illustrated in Figure 1. An examination of the raw classification counts reveals that the majority of misclassifications occurred between the cloudy and rainy categories. Of all cloudy days, 607 were correctly classified, whereas 38 were erroneously assigned to the rainy category, 7 to snowy, and 8 to sunny. For the rainy class, the model yielded 600 correct predictions, with 35 instances mislabeled as cloudy, 13 as snowy, and 12 as sunny. Snowy days were predicted with comparatively higher reliability: 598 instances were correctly classified, while only 27 were misassigned as cloudy, 19 as rainy, and 16 as sunny. Similarly, the sunny category recorded 603 correct predictions, with relatively few misclassifications 27 as cloudy, 18 as rainy, and 12 as snowy.

This distribution of errors indicates that the model's principal limitation resides in discriminating between cloudy and rainy conditions, which share numerous overlapping meteorological features. Conversely, the model demonstrates considerably higher certainty when classifying the more meteorologically distinct extremes, namely sunny and snowy weather. The pronounced diagonal dominance in the confusion matrix confirms that the Random Forest classifier effectively captured the defining characteristics of each class, while the balanced row totals indicate that no class was disproportionately disadvantaged.

The normalized confusion matrix further reinforces this interpretation (Figure 2). The preponderance of errors originated from the mutual misclassification between cloudy and rainy days. In contrast, predictions for sunny and snowy conditions were considerably more precise, with the model placing these observations almost entirely on the correct diagonal of the matrix. Following normalization, each category maintained approximately 91% correct classification, suggesting that the model treated all classes equitably and did not exhibit discernible bias toward any particular weather type.

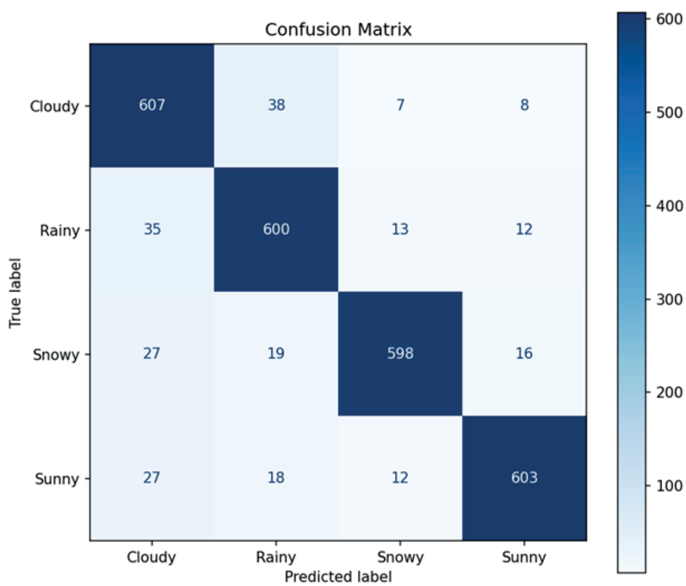

Figure 1: *Confusion matrix (Not Normalized)*

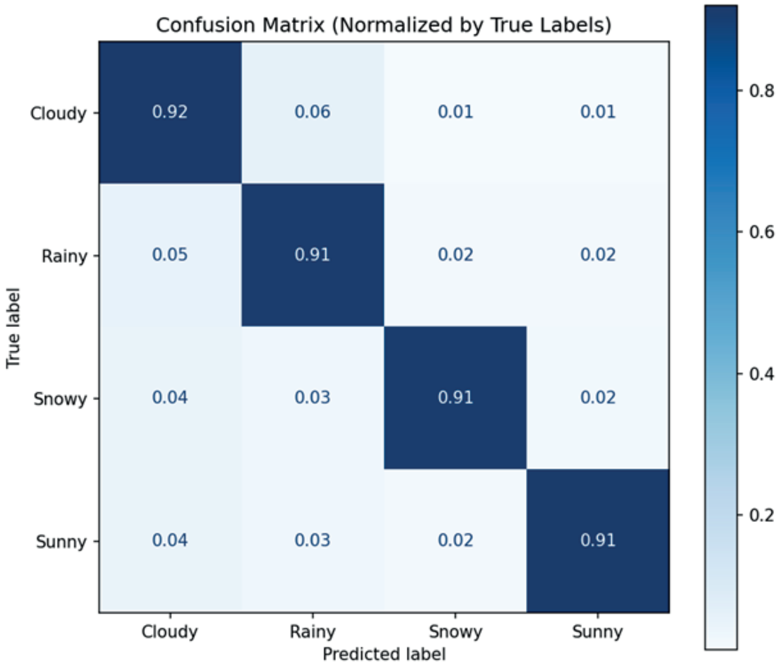

***Figure 2:** Confusion matrix (Normalized)*

The Receiver Operating Characteristic (ROC) curve analysis provided additional confirmation of the model's discriminative capability (Figure 3). For all four classes, the area under the curve (AUC) was notably high, approaching 0.99. This indicates that the classifier maintained a robust capacity to distinguish among classes even under varying decision threshold settings. The macro-averaged AUC was computed at 0.994, a value that underscores the overall balance and reliability of the classification system. Notably, even the more challenging categories cloudy and rainy exhibited AUC values in close proximity to this level, suggesting that the model was capable of detecting subtle discriminative features between these overlapping conditions.

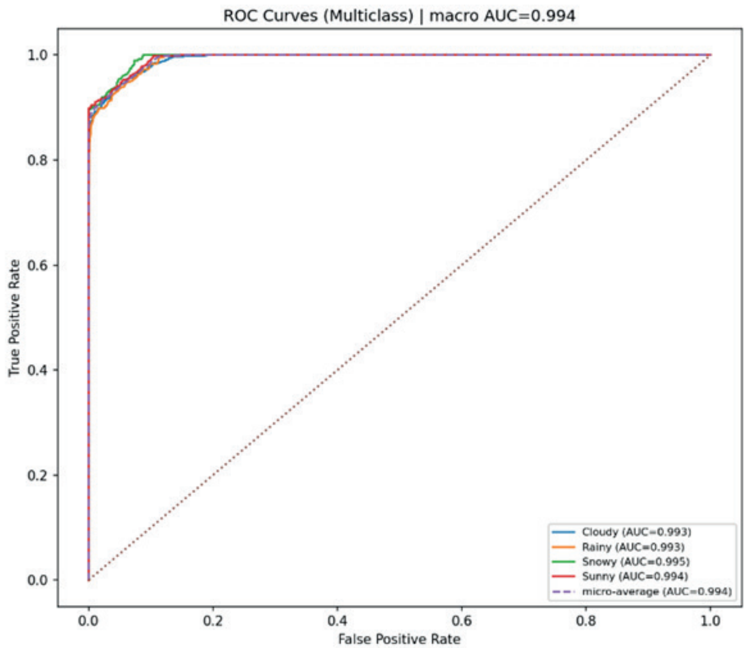

Figure 3: *The ROC-AUC curve*

The feature importance analysis derived from the Random Forest model, as depicted in Figure 4, revealed that temperature constituted the most influential predictor, accounting for approximately 19.5% of the total feature importance. This finding is consistent with established meteorological principles, as temperature variations fundamentally determine whether a given day is characterized by sunny or snowy conditions and also modulate the probability of precipitation. Visibility emerged as the second most important feature, contributing approximately 15% of the total importance. Reduced visibility is frequently associated with heavy precipitation or dense cloud cover, rendering it an effective discriminator between cloudy and rainy conditions. Precipitation followed closely at approximately 13.4%, which is anticipated given that rainfall constitutes the most direct indicator of wet weather conditions. The UV Index (12.7%) also demonstrated considerable predictive value, principally because elevated UV levels are characteristic of clear-sky conditions and thus facilitate the identification of sunny weather. Atmospheric pressure contributed approximately 11.5%, reflecting its well-established role in synoptic-scale weather systems; fluctuations in pressure frequently herald transitions from stable to more unsettled meteorological conditions. Cloud cover (clear) accounted for 7.6%, underscoring the fact that the absence of cloud cover is a strong characteristic of sunny conditions. Humidity, although contributing a comparatively modest 5.7%, nonetheless influenced the classification, particularly in discriminating between rainy and snowy conditions, where elevated humidity levels are typically observed. Among seasonal indicators, Winter (4.3%) exhibited the greatest significance relative to Summer, Spring, and Autumn (each approximately 0.5–0.6%), consistent with the pronounced seasonality of snowfall events. Wind speed (3.3%) exerted a moderate influence, as elevated wind velocities are frequently associated with storm systems or cold frontal passages. Additional cloud-related features, including Overcast (1.9%), Partly Cloudy (1.0%), and Cloudy (0.6%), played minor yet discernible roles in resolving the ambiguity between cloudy and precipitating conditions. Geographic variables coastal (1.3%), inland (0.3%), and mountainous (0.3%) received the lowest importance rankings. Although these variables reflect broad climatological tendencies, they are less consequential for daily weather classification than direct meteorological measurements.

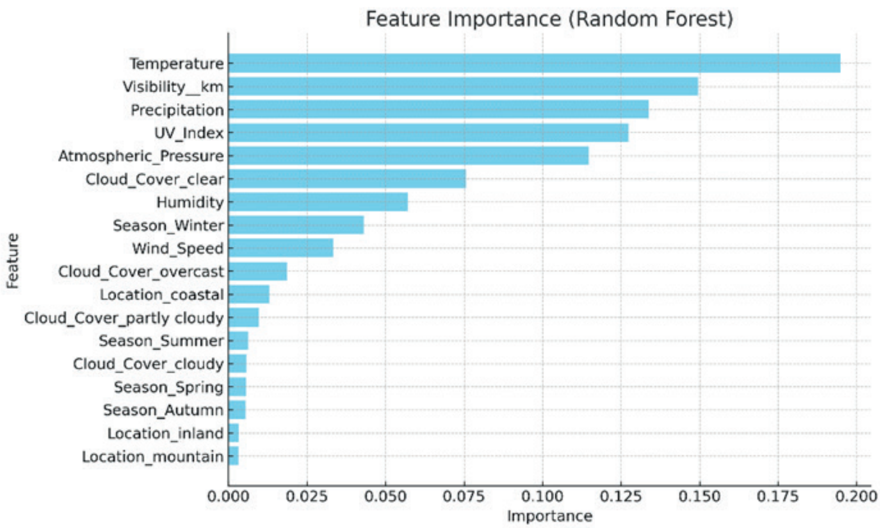

Figure 4: *Feature importance in model training*

CONCLUSION

This study demonstrated that the Random Forest algorithm can effectively classify daily weather conditions into the categories of sunny, cloudy, rainy, and snowy with robust overall accuracy. The model exhibited consistent performance across all four classes and did not display preferential bias toward any particular weather type. The majority of misclassifications occurred between cloudy and rainy conditions, an outcome that is attributable to the substantial meteorological similarity between these two categories. The feature importance analysis revealed that temperature, visibility, precipitation, UV index, atmospheric pressure, and cloud cover constituted the principal predictive drivers. These variables are well established in the meteorological literature, and their prominence in the model's predictions corroborates that the classifier operates in a manner consistent with established atmospheric science principles.

In summary, the findings of this study indicate that machine learning approaches, particularly the Random Forest algorithm, represent viable tools for short-term weather classification. Beyond achieving high predictive accuracy, such models also afford valuable insights into the relative importance of individual environmental variables. Owing to this balance of predictive precision and interpretability, the proposed methodology holds promise for practical applications in domains such as agriculture, transportation, and urban planning, where reliable meteorological information is essential for informed decision-making.

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