Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Secure Cyber-Physical Robotic Automation for Energy-Efficient Industry 5.0

Abdul Razaque

arazaque@my.bridgeport.edu

Arkansas Technical University https://orcid.org/0000-0003-0409-3526

Zhuldyz Kalpeyeva

Satbayev University

Meenhoon Khan

Arkansas Technical University

Jeffrey Hough

Arkansas Technical University

Dina S. M. Hassan

Princess Nora bint Abdulrahman University: Princess Nourah bint Abdulrahman University

Meer Jaro Khan

International Information Technology University

Aizhan Kassymova

Satbayev University

M.Ajmal Khan

Ohio Northern University

Tolkynay Sadykova

Satbayev University

Research Article

Keywords: Optimized robotic process automation, business process management, energy-efficient automation, secure industrial robotics, intelligent automation

Posted Date: September 18th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-10944757/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Secure Cyber-Physical Robotic Automation for Energy-Efficient Industry 5.0

Abdul Razaque*[1], Zhuldyz Kalpeyeva[2], Meenhoon Khan[1], Jeffrey Hough[1], Dina S. M. Hassan[3], Meer Jaro Khan[4], Aizhan Kassymova[2], M.Ajmal Khan[5], Tolkynay Sadykova[2]

[1]Department of Cyber Security and Information Systems, Arkansas Tech University, Russellville, AR-72802, USA: mkhan4@atu.edu, jhough1@atu.edu
[2]Department of Cyber Security, Information Processing, and Storage, Satbayev University, Almaty, Kazakhstan; z.kalpeyeva@satbayev.university, a.kassymova@satbayev.university, t.sadykova@satbayev.university
[3]Department of Information Technology, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia; dshassan@pnu.edu.sa
[4]Department of Engineering and Information Sciences, International Information Technology University, Almaty, Kazakhstan j.meer@iitu.edu.kz
[5]Department of Electrical Engineering and Computing Science, Ohio Northern University, Ohio, USA; m-khan.2@onu.edu
Corresponding author: Abdul Razaque (e-mail: arazaque@atu.edu).

Abstract: Advanced manufacturing systems increasingly require robotic automation that synchronize production processes, while considering energy consumption and cyber-physical security. This study presents an integrated optimized robotic process automation and business process management (ORPABPM) framework for secure and energy-efficient Industry 5.0 manufacturing. The framework connects business-process modelling and task orchestration with physical robot control, industrial monitoring, adaptive learning, and execution feedback. Its energy-efficient automation for robotics (EEAR) algorithm identifies energy-intensive operations and optimizes task scheduling and resource allocation, while the robotic adversarial threat detection (RATD) algorithm monitors sensory inputs and planning behavior to detect and mitigate blind-spot and planner attacks. The framework was evaluated on a hybrid hardware-in-the-loop manufacturing testbed integrating a programmable logic controller, CNC machinery, an industrial Internet of Things adaptor, Rockwell Automation RSEmulate, SimKit, and MATLAB. Experiments covered workloads of up to 72,000 tasks and assessed execution accuracy, energy consumption, throughput efficiency, and attack-induced error. The complete framework achieved 99.3% task-execution accuracy, completed up to 46,000 tasks while consuming 135 kWh, and maintained approximately 95% throughput efficiency at 40,000 completed tasks. Under blind-spot and planner attacks, the corresponding error rates were limited to 0.035% and 0.053%, respectively. These results indicate that jointly integrating process intelligence, energy-aware scheduling, and adversarial-threat detection can improve the operational efficiency and resilience of cyber-physical robotic manufacturing systems.

Keywords: Optimized robotic process automation; business process management; energy-efficient automation; secure industrial robotics; intelligent automation.

1. INTRODUCTION

Business operations are intricate processes that can significantly benefit from the utilization of specialized management tools [1]. Business process management has emerged as a prominent discipline encompassing methodologies, strategies, and resources for the design, implementation, management, and analysis of business processes [2]. Cost reductions, more flexibility, time efficiency, improved quality, and operational sustainability are among the several advantages associated with BPM [3]. Nevertheless, more robust answers are required due to the challenges presented by the volatility of the global market and the complexities of modern corporate management [4]. Despite the presence of advanced management technologies, their effective utilization often requires a comprehensive understanding of internal processes, which typically involves human involvement [5-6]. Moreover, no singular strategy or technology will guarantee success, compelling firm executives to continually seek and develop improved solutions [7]. Successful business implementation integrates three critical elements: people, process, and technology. BPM effectively integrates these elements by using technology as a supporting tool rather than a transformative force, aligning process design with strategic business objectives, and relying on human participants for implementation [8]. Automation has become imperative for reducing costs and minimizing human errors as industrial improvements influence all facets of daily life [9–12]. In this context, efficient robotic process automation utilizes the existing automation capabilities of BPM [13–14]. Robotic process automation (RPA) facilitates automation without necessitating significant alterations to foundational systems or processes, as it replicates user actions using graphical user interfaces [15-16]. The application of appropriate RPA techniques is essential for optimizing operations and

minimizing company expenses [17]. RPA is effective for tasks characterized by low-skilled labor that are susceptible to human error [18]. Such solutions enhance process accuracy and compliance while conforming to established organizational standards. Additionally, RPA improves the flexibility, scalability, and adaptation of systems, which is essential for workflow optimization. This optimization is crucial as it allows organizations to respond to market fluctuations and operational demands with enhanced agility [19]. Despite the numerous enhancements provided by RPA, its implementation may prove challenging. These factors can undermine the potential benefits of RPA programs, including unrealistic expectations and issues with managerial communication [20]. Therefore, to circumvent these issues and attain the intended enhancements in organizational productivity and process efficiency, these technologies must be implemented with a definitive, strategic approach. Despite advances in robotic process automation and business process management, existing approaches primarily focus on deterministic software bots and structured workflows. Their integration typically supports process modelling, workflow orchestration, compliance, and repetitive interface-level automation but provides limited support for cyber-physical environments involving robots, sensors, programmable logic controllers, industrial machines, and enterprise systems. Consequently, physical robotic control, real-time telemetry, energy-aware task allocation, adaptive policy learning, and adversarial-threat mitigation Consequently, we generally handle physical robotic control, real-time telemetry, energy-aware task allocation, adaptive policy learning, and adversarial-threat mitigation as separate functions. as separate functions. This fragmentation prevents existing approaches from jointly optimizing business objectives, robotic execution, resource utilization, energy consumption, and the integrity of sensory and planning data. Also, most current frameworks don't offer integrated protection against blind-spot and planner attacks that can change how robots see, act, and make decisions.

To address these limitations, this study proposes ORPABPM, a closed-loop cyber-physical framework that integrates BPM-guided process design with robotic control, continuous monitoring, adaptive learning, energy-efficient execution, and adversarial-threat detection. The energy efficient automation for robotics (EEAR) algorithm detects energy intensive processes and optimizes task scheduling and resource allocation. The robotic adversarial threat detection (RATD) algorithm detects and mitigates attacks against sensory inputs and planning decisions. Execution feedback is continually fed back to the learning-adaptation component to update control policies and improve subsequent decisions. Thus, ORPABPM allows coordinated optimization across the business-process and physical-execution layers, jointly accounting for performance, energy and security requirements. Fig. 1 shows the proposed architecture with business-process intelligence, secure and energy-efficient robotic execution, closed-loop feedback, adaptive learning and human supervision.

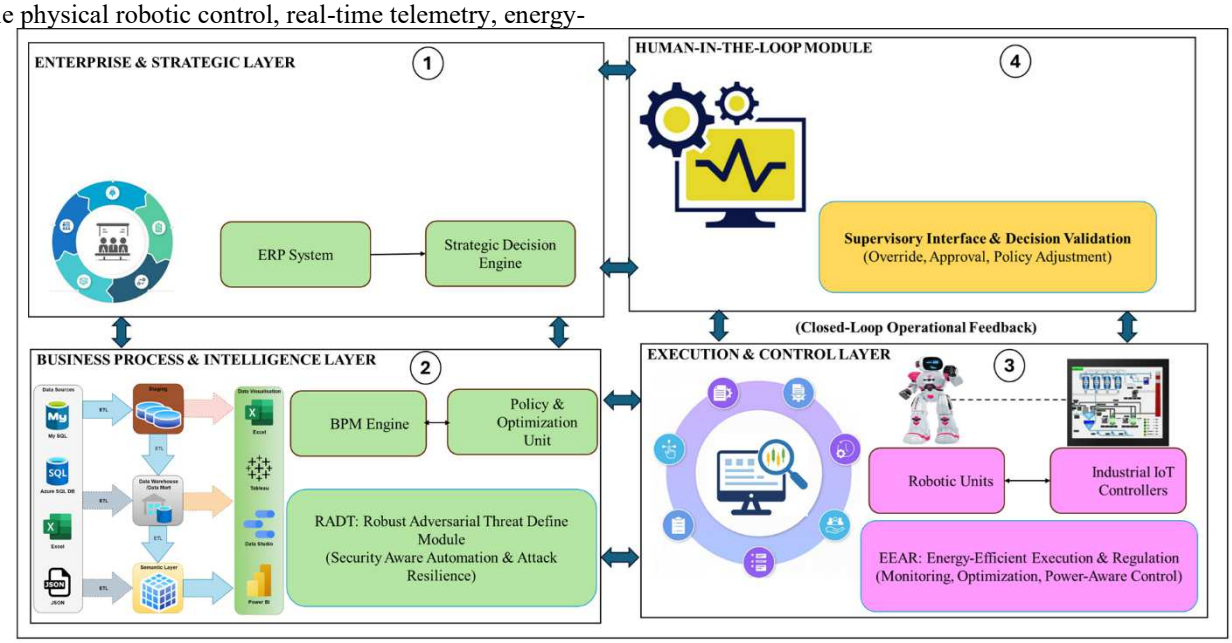


Fig 1. Architecture integrating business process intelligence, security-aware automation, energy-efficient execution, closed-loop feedback, and human-in-the-loop supervision

1.1. PAPER ORGANIZATION

The rest of this paper is organized as follows:

Section-2 highlights the most important aspects of the present contributions in the related work. Section-3 provides the problem formulation for an efficient integration. Section-4 describes the planned integration of BPM and ORPA, as well as the integration methodology. Section-5 shows the results of the experiments. Section-6 covers the benefits and

drawbacks of the proposed work. Finally, section-7 summarizes the entire work.

1.2. RESEARCH CONTRIBUTIONS

Keye contributions of this article are summarized as follows:

- Optimized robotic process automation with business process management is ensured by employing an end-to-end process algorithm that helps in real-time monitoring of the task assignment and task delivery.
- The robotics for business automation is performed using five phases: strategic design, strategic business modelling, robot control, robot monitoring for automation data, and efficient customer experience. These processes ensure business automation and enhance the energy efficiency of robotic automation. As a result, energy is preserved, and the task completion process is optimized across various operational contexts.
- The energy efficiency is confirmed using energy-efficient automation for robotics (EEAR), an algorithm that automates the business tasks. The EEAR involves the following steps: identification of energy-intensive process, analysis of current workflows, design of ORPA solution, ORPA implementation in a live environment, monitoring, and evaluation.
- By integrating ORPA with BPM, our approach significantly reduces management-related expenses and accelerates business operations. The efficacy of this integration is validated by a systematic problem-formation process, which highlights its capacity to revolutionize automatic business process management to ensure enhanced performance, functionality, and cost efficiency.
- The robotic automation process often fails because of two prevalent attacks: planner and blind spot. The RATD algorithm effectively addresses these attacks, enhancing system security by identifying and mitigating them in real time. The RATD algorithm oversees and modifies the robot's sensory inputs and decision-making mechanisms, ensuring maximal efficiency and robustness against adversarial threats. This addition significantly enhances the durability and robustness of robotic automation across diverse applications.

2. RELATED WORK

This section delineates current state-of-the-art methodologies. Sgarbossa et al. [21] demonstrates how one of the typical and challenging management and control issues is the logistics system. The warehouse's rationale is well-explained, and this helps to explain why it uses less time, energy, and money than it needs to. Additionally, the significance of contemporary technologies such as radio-frequency identification (RFID), the Internet-of-Things (IoT), and artificial intelligence (AI) is discussed. However, no implementation of these emerging technologies is provided. Al-Talib et al. [22] introduced IoT-based smart warehouse management systems (ISWMS). This method aids in enhancing the systems' real-time visibility, responsiveness, and efficiency as well as in preventing counterfeiting and inventory shortages. However, the proposed system is limited to the monitoring process. Žunić et al. [23] proposed the application of AI for the warehouse control and management system (AIWCMS). The stock management, initial product allocation, stock-to-choosing zone transfer procedure, order picking, transport, and tracking operations are all supported by the AI-based application for optimal management. However, the proposed application focuses on digitalization management support, but no physical support is provided. Tan et al. [24] improved the effectiveness of the management system, increase production, and save costs, a thorough, in-depth review of current literature is recommended. The present issues with the examined papers' deployment of RFID-IoT in the supply chain are also explored in this work. Four key SCM viewpoints have been used to develop the conceptual framework model: product development, shipping and distribution, inventory, and retail store. Bazza et al. [25] introduced a model-driven architecture method for robotic real-time business intelligence applications | This study presents a Model-Driven Architecture (MDA) methodology to facilitate robotic-based real-time business intelligence. The framework facilitates automation, real-time data integration, and effective decision-making by integrating robotics into business intelligence platforms. The authors illustrate how the proposed method enhances responsiveness, diminishes latency, and facilitates dynamic business operations. Concentrating on the design and implementation of an MDA framework for robotic-driven real-time business intelligence, emphasizing its advantages for automation and decision-making. Patrício et al. created an RPA-AI architecture in 2025 for Industry 5.0, automating rule-based business operations with AI for data analysis and smart decision-making. The platform automates human-machine communication to improve business operations and digital transformation. It automates structured and unstructured data processing and AI decisions. Human-centric automation, operational efficiency, manual labor, and error reduction improve in Industry 5.0. AI-RPA integration may require considerable infrastructure and technological skills. System functionality and framework evaluation require high-quality data and industry validation. A knowledge-intensive adaptive business process management framework for dynamic business processes was presented by Kir and Erdogan (2021) [27]. The framework handles knowledge-driven tasks that require human competency and context for decision-making and process execution. BPM changes knowledge and processes. The framework improves process management by modeling complicated knowledge-based occupations and adapting processes to changing business conditions. Decision-making, process adaptability, and complex, unanticipated task management rise. Conceptual process modeling and adaptive management go beyond industrial experiments and execution. Tsang et al. (2024) explain that RPA has the potential to digitize supply chains and logistics. RPA automates logistics duties that are

based on rules, such as the synchronization of enterprise system data, inventory updates, shipment tracking, and order processing. While supporting corporate infrastructure, logistics information systems, and RPA agents automate data management and process execution. Data entry by software robots expedites supply chains. Efficiency is enhanced through the implementation of supply chain automation. Reduced operational errors, expedited information transfer through the logistics platform, and reduced human interaction. Productivity is enhanced through the implementation of real-time data processing and supply chain coordination. RPA facilitates digital transformation by automating operations without requiring system modifications. Setting up logistics RPA is a challenging task. Complex supply chain frameworks may be impeded by unstructured corporate activities and data types. The implementation process may be impeded by technical updates for legacy system integration. Complex judgment and unstructured decision-making cannot be automated by rules. Research and implementation are necessary to scale RPA and influence large-scale logistics. Ivanov [29] described the Industry 5.0 framework as a combination of resilience, sustainability and human-centricity. The study highlighted the need for next-generation manufacturing systems to find a balance between operational performance and workforce participation, environmental responsibility and resilience to disruptions. This perspective provides an important strategic foundation for sustainable and human-centred industrial automation. However, the framework is primarily conceptual and does not provide an executable architecture that connects business-process management with physical robotic control, energy-aware task allocation, adaptive learning, and adversarial-threat mitigation.

Ataka and Sandiwan [30] developed a robot-navigation method based on deep reinforcement learning. Their approach enabled a mobile robot to learn navigation behaviour through repeated interactions with its environment and reward-based policy improvement. The results demonstrated the ability of reinforcement learning to support adaptive robot control under changing environmental conditions. Nevertheless, the method focuses on robot-level navigation and does not consider enterprise workflows, business-process constraints, industrial energy consumption, cybersecurity threats, or coordination between BPM decisions and robotic task execution. Hosseini and Hahn [31] experimentally investigated the energy consumption of a six-degree-of-freedom UR3e industrial robot during trajectory planning. They showed that the energy consumption of robots depends on the robot's trajectory and movement parameters . The authors also stressed the need for obtaining experimental data on the energy consumption of robots. However, the analysis concentrates on the motion and trajectory of an individual industrial robot. It does not connect energy measurements with business-process selection, multi-stage workflow orchestration, task allocation, operational throughput, attack resilience, or adaptive policy improvement. Alharthi and Brandão [32] examined physical and digital adversarial attacks against grasp-quality networks used in robotic manipulation. Their results showed that adversarial perturbations can change the grasp predictions and compromise the reliability of the learning-based robotic operations. However, it only provides grasp-quality prediction and does no integrated defence mechanism for business-enabled robotic automation.

Schlegel et al. [33] investigated the factors influencing the successful implementation of robotic process automation projects. They identified organizational, technical, managerial and process-related factors influencing RPA adoption and business-process automation results in their analysis. The study is useful in planning and management of software-based automation initiatives. However, it mostly considers software robots and enterprise business processes, and does not consider physical industrial robots, programmable logic controllers, sensor-based control, learning-based adaptation, energy-aware execution, or robotic adversarial attacks. Collectively, existing studies have advanced Industry 5.0, learning-based robotic control, energy-aware robotics, adversarial robotic security, and business-process automation. However, these capabilities are generally investigated independently rather than as interconnected components of an industrial automation system. Existing approaches do not provide unified coordination between enterprise-level business processes and physical robotic execution. They also offer limited support for jointly optimizing task accuracy, energy consumption, operational throughput, and security under a common control framework. Energy management methods concentrate on trajectories of single robots. Learning-based methods optimize behavior of robots without considering business objectives and workflow constraints. Similarly, robotic-security studies generally address specific perception or manipulation attacks without examining their effects on energy efficiency, workflow completion, and operational continuity. Current solutions are mainly designed for software robots and provide insufficient support for physical robots, industrial sensors, programmable logic controllers, adaptive control policies, and real-time attack mitigation. Therefore, a significant research gap remains in developing a closed-loop architecture that integrates business-process modelling, physical robotic control, continuous monitoring, energy-efficient execution, adaptive learning, and adversarial-threat mitigation. The proposed ORPABPM framework addresses this gap by combining BPM-guided robotic automation with EEAR-based energy optimization, RATD-based security, and feedback-driven policy adaptation. The proposed method also provides energy efficiency using five processes (strategic design, strategic business modeling, robot control, robot monitoring for automation data, and efficient customer experience). Table 1 lists the characteristics and limitations of current approaches. processes.

TABLE I. Contemporary contributions of existing studies of business process management

Approaches	Study Focus	Core Approach	Application Context	Evaluation Method	Real-Time Automation	Energy-Efficiency Consideration	Security/Reliability	Key Strengths	Limitations/Gaps
Nalgozhina et al. (2022) [2]	Robotics in business processes	Robotics–BPM integration	Enterprise automation	Empirical observations	Partial	Partial; reported efficiency gains	Not addressed	Integrates robotics with BPM and improves process efficiency	Lacks scalable implementation, intelligent adaptation, and integrated security
Sgarbossa et al. (2020) [21]	Logistics-system challenges	Conceptual logistics framework	Logistics and supply-chain management	Conceptual discussion	No	Not addressed	Not addressed	Identifies the need for automation technologies in logistics	No operational implementation or robotic-control validation
Al-Talib et al. (2021) [22]	Smart-warehouse management	IoT-based monitoring	Smart warehouses	System proposal	Partial	Partial	Limited	Improves warehouse visibility and responsiveness	Focuses mainly on monitoring; lacks adaptive robotic execution
Žunić et al. (2020) [23]	AI-supported warehouse control	AI-assisted decision support	Warehouse operations	System-level evaluation	Partial	Not addressed	Limited	Supports stock management, picking, transport, and tracking	No physical robotic integration, security evaluation, or energy optimization
Tan et al. (2019) [24]	RFID–IoT use in supply chains	Literature review and conceptual model	Supply-chain systems	Systematic literature review	No	Not addressed	Limited	Provides comprehensive analysis of RFID–IoT applications in SCM	Does not provide an executable operational framework
Bazza et al. (2020) [25]	Robotic real-time business intelligence	Model-driven architecture	Business intelligence	Framework validation	Yes	Partial	Limited	Enables real-time robotic business intelligence and data integration	Not designed for BPM-wide automation, energy optimization, or robotic security

Patrício et al. (2025) [26]	RPA–AI integration for Industry 5.0	AI-enabled robotic process automation	Intelligent enterprise automation	Framework evaluation	Partial	Not addressed	Limited	Supports intelligent process automation and human–machine collaboration	Requires high-quality data and infrastructure; limited physical-robot and industrial validation
Kir and Erdoğan (2021) [27]	Knowledge-intensive adaptive BPM	Knowledge-based adaptive process management	Dynamic business processes	Conceptual framework	Partial	Not addressed	Not addressed	Supports context-aware decision-making and process adaptation	Does not address physical robotic control, energy efficiency, or adversarial attacks
Tsang et al. (2024) [28]	RPA in logistics and supply-chain digitalization	Rule-based software automation	Logistics and supply chains	Application-oriented analysis	Yes	Partial	Limited	Automates order processing, inventory updates, tracking, and enterprise-data synchronization	Limited handling of unstructured decisions; difficult legacy-system integration and large-scale deployment
Ivanov (2023) [29]	Human-centric, sustainable, and resilient Industry 5.0	Viability-based Industry 5.0 framework	Manufacturing and supply-chain systems	Conceptual and theoretical analysis	No	Sustainability considered at strategic level	Resilience considered conceptually	Integrates human-centricity, sustainability, and resilience	Does not provide an executable robotic-control, BPM, energy-management, or security architecture
Ataka and Sandiwan (2023) [30]	Learning-based robot navigation	Deep reinforcement learning	Mobile-robot navigation	Simulation-based evaluation	Yes	Not addressed	Limited	Enables adaptive navigation through reward-based learning	Does not consider BPM objectives, industrial workflows, energy consumption, or cyberattacks
Hosseini and Hahn (2024) [31]	Industrial-robot energy consumption	Experimental trajectory-energy estimation	UR3e industrial robot	Physical experimental evaluation	Yes	Directly addressed	Not addressed	Provides experimentally measured energy consumption for	Does not integrate energy optimization with BPM, adaptive learning,

								robot trajectories	throughput, or security
Alharthi and Brandão (2024) [32]	Adversarial attacks on robotic grasping	Physical and digital attacks on grasp-quality networks	Robotic manipulation	Physical and digital attack experiments	Yes	Not addressed	Directly evaluates adversarial vulnerability	Demonstrates the effects of adversarial attacks on robotic grasp prediction	Does not provide BPM integration, energy analysis, workflow-level protection, or closed-loop mitigation
Schlegel et al. (2024) [33]	Successful RPA project implementation	Organizational and technical factor analysis	Business-process automation	Empirical analysis	Partial	Not addressed	Organizational reliability considered	Identifies managerial, organizational, process, and technical success factors	Focuses on software robots; lacks physical robotic control, energy optimization, adaptive learning, and adversarial security
Proposed ORPABPM	Secure, adaptive, and energy-efficient business-enabled robotics	Integrated ORPA–BPM, EEAR, RATD, and feedback-driven learning	Industry 5.0 manufacturing	Hybrid hardware-in-the-loop evaluation, ablation study, and statistical analysis	Yes	Directly optimized using EEAR and tasks/kWh	Blind-spot and planner-attack mitigation using RATD	Unifies BPM, physical robotic execution, adaptive learning, energy optimization, real-time monitoring, and security	Requires broader multi-industry and full-scale physical deployment validation

3. Problem Formulation for Efficient Integration

In this section, we delineate the mathematical model employed in designing a class of robots, denoted as R, tasked with the surveillance of extensive populations and the automation of diverse business operations, denoted as O. The model specifies the need for bidirectional capability in these robots, ensuring comprehensive monitoring in a full 360-degree scope. The operational parameters defining R's surveillance and business process automation functions are articulated herein. This includes a set of functions that enable the robot to execute business tasks depicted in Figure 2, which illustrates various applications of robotics in logistics and industrial settings, each demonstrating robots' roles within an enterprise resource planning (ERP) system. The top portion of the figure shows three different robots engaged in transporting tasks within distinct environments: a warehouse (a), a narrow storage aisle (b), and an office (c). Each robot is equipped to handle tasks suitable for its environment, ranging from carrying single large boxes to managing multiple packages on a trolley. To mathematically encapsulate a model that integrates both spatial and functional variables for a robot capable of omnidirectional monitoring and managing automated business activities, we must define a system that includes components for both positional control and task execution capabilities.

Let $x(t)$ be the position vector in a three-dimensional space, representing the robot's special coordinates at time t, and $f(t)$ be a vector of functional states or conditions that represent the robot's operational status or task-specific metrics at time t. This includes variables like operational mode, task completion status, energy levels, etc. The control input vector is $u(t)$which influences both the robot's position and its functional states. This might include translational and rotational velocities for movement and signals or commands for task operations. The dynamics of the robot that integrate spatial and functional variables can be modeled using coupled differential equations that represent the evolution of both types of variables under the influence of the control input

$$x'(t) = Ax(t) + Bx(t) \quad (1)$$

$$f'(t) = Af(t) + Bfu(t) \quad (2)$$

Where $x'(t)$ and $f'(t)$ are the derivatives of the spatial and functional vectors, respectively, representing the rate of change of these variables, Bx and Bf are matrices that define how the control inputs affect the spatial and functional variables.

We can get simultaneous control and monitoring of the robot's position and functional capabilities, providing a comprehensive framework suitable for tasks that require both mobility and specific operational actions. The control inputs $u(t)$can be designed to achieve desired positions and functional outcomes, thus supporting complex tasks like omnidirectional monitoring and automated business management. The coupling between $x(t)$ and $f(t)$ via the control input $u(t)$ emphasizes the integrated approach to managing both spatial and functional aspects, ensuring that the robot can adapt dynamically to the demands of its environment and tasks. The structure of Equation (2) provides a robust theoretical foundation for developing advanced robotic systems capable of versatile operations in complex environments, such as those found in modern business or industrial settings. We may utilize the process that takes into consideration the overall amount of available space as well as the spatial requirements of each robot to determine the maximum number of robots that can be arranged inside a certain area or scope. In settings like manufacturing floors, warehouses, or other places where maximizing space usage is essential, this is very helpful.

Let us assume that A_r be the area required by a single robot. This includes the robot's physical footprint plus any additional space needed for maneuvering or operational safety. The total area required by the robots A_t can be used to distribute. The packing efficiency of the system is η, which accounts for the practical aspects of arranging robots in a given space. This can include the geometry of space, the shape of the robots, and any necessary access lanes or buffer zones between robots. η typically ranges from 0 to 1, where 1 represents perfectly efficient packing. Thus, the maximum number of robots N_{max} that can be placed in the available area can be estimated by the following equation:

$$N_{max} = \frac{\lfloor \eta . A_t \rfloor}{A_r} \quad (3)$$

This equation (3) provides a straightforward method to estimate the maximum number of robots that can be efficiently arranged within a specific area. Adjusting η allows for consideration of less-than-ideal conditions, such as irregular room shapes or additional space needed for robot operations beyond their physical footprint.

Equation (3) is particularly useful in the planning and layout phases of facility management, ensuring that the space is used efficiently while accommodating all necessary robotic equipment. This method can be adapted or refined based on specific operational requirements or constraints, such as varying robot sizes, the inclusion of dynamic spaces for robot movement, or different robot shapes that might affect the packing density. To describe the two-dimensional movement of a robot and to calculate the distance between two robots, we need two sets of equations: one for the kinematic description of the robots' positions over time and another for the Euclidean distance between their positions at any given time. For each robot, assume it moves in a two-dimensional plane described by g and h coordinates. Let's denote the positions of Robot 1 and Robot 2 at time t_1 as $p_1(t) = \{g_1(t), h_1(t)\}$ and $p_2(t) = \{g_2(t), h_2(t)\}$ respectively. Thus, the kinematic equations for robot-1 and robot-2 can be determined as follows:

Robot-1:

$$g^1(t) = g^1, 0 + v_1, g.t + \frac{1}{2a_1}, g.t^2 \;\&\&\; h^1(t) = h^1, 0 + v_1, h.t + \frac{1}{2a_1}, h \quad (4)$$

Robot-2:

$$g^2(t) = g^2,0 + v_2,g.t + \frac{1}{2a_2},g.t^2 \;\&\&\; h^2(t) = h^2,0 + v_2,h.t + \frac{1}{2a_2},h.t^2 \quad (5)$$

Where $g_r,0$ and $h_r,0$ are the initial coordinates of the robot r at the time $t = 0$, v_r,g_r and v_r,h_r and the components of the initial velocity of the robot r, and a_r,g and a_r,h are the acceleration components of the robot r.

The distance between two robots should be calculated. Thus, the distance $d(t)$ between the two robots at any time t can be calculated using the Euclidean distance formula in two dimensions:

$$d(t) = \sqrt{\{g^2(t) - g^1(t)\}^2 + \{h^2(t) - h^1(t)\}^2} \quad (6)$$

The equation (6) calculates the straight-line distance between the two points described by the robots' coordinates at time t. The kinematic equations (4) and (5) describe how each robot moves over time, considering their initial positions, velocities, and accelerations in the plane. The distance equation (6) is crucial for tasks such as collision avoidance, formation control, or coordination between robots, as it provides a dynamic measure of separation between the robots. Thus, monitoring $d(t)$ over time helps in enforcing safety protocols, ensuring optimal spacing for task efficiency, or maintaining formation in tasks involving multiple robots. To formulate an equation that captures the high-dimensional probability P_h used to define a bi-directional robot operating in an environment with multiple people and various objects, we can consider the probability as a function of the robot's capability to interact effectively and safely with both humans and objects in the environment.

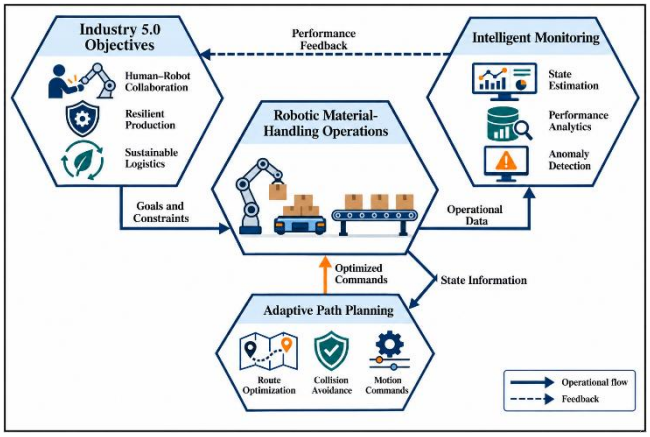


Fig 2. Closed-loop Industry 5.0 framework for intelligent monitoring, adaptive path planning, and robotic material-handling operations

This interaction is bi-directional in the sense that the robot needs to both influence and adapt to the environment based on the actions of the people and the presence of objects. The robot must be capable of both responding to changes in the environment caused by humans and objects and initiating actions that humans and objects must react to. This probability measures the likelihood that the robot can successfully navigate and manipulate within its environment without causing disruptions or accidents, considering the complex and dynamic nature of the environment.

Let us assume the factors that influence the high-dimensional probability P_h of the robot that requires the sensory capabilities of the robot S, which enables it to perceive humans and objects accurately. The cognitive capabilities of the robot C_r is of paramount significance, as it reflects the robot's ability to make decisions based on sensory input. The responsiveness of the robot R_e can improve the ability of the robot to act on cognitive decisions effectively. The environmental complexity E_c plays an important role, which includes the number of people, the density and diversity of objects, and the overall dynamism of the environment. Thus, probability can be modeled as follows:

$$P_h = f(S, R_e, E_c, C_r) \quad (7)$$

where f is a function that combines these factors into a single probability measure. A possible specific form of this function, assuming independence of factors for simplification, could be:

$$P_h = f\left(S\alpha.C_r\beta.R_e\gamma.e^{-E_c\delta}\right) \quad (8)$$

Where $\alpha, \beta, \gamma, \delta$ are coefficients that weigh the relative importance of each factor, $e^{-E_c\delta}$ reflects the impact of environmental complexity, and δ is a parameter that determines how quickly P_h decreases with increasing complexity E_c.

Equation (8) helps in designing and programming robots for environments like factories, warehouses, or public spaces where multiple human-robot interactions and object manipulations occur simultaneously. It also guides the development of AI and machine learning models for robots, emphasizing the enhancement of sensory, cognitive, and responsive capabilities relative to the complexity of the operating environment.

To model a complex and high-dimensional probability for a nonlinear process involving the interaction between a robot and a business environment, we can conceptualize a process that integrates multiple pathways or interactions and breaks them down into sub-intervals for detailed analysis. This can be particularly useful in understanding and optimizing the intricate dynamics of robot-business interactions over time and space.

The high-dimensional probability should be required to measure the likelihood of successful interactions P_{hd} between the robot and various elements of the business environment, factoring in the complex, nonlinear nature of these interactions. The robot needs pathways P_r that represent different interaction routes or operational sequences that the robot can undertake within the business environment. Thus, high-dimensional probability for the likelihood of successful interactions P_{hd} can be modeled as a product of conditional probabilities across all pathways and their respective sub-intervals:

$$P_{hd} = \prod_{i=1}^{n}\left(\prod_{j=1}^{m_i} \mathrm{p}_{ij} \mathrm{ID}_{ij}\right) \quad (9)$$

Equation (9) is particularly useful for simulation and planning in advanced robotics applications, where

interactions with a dynamic business environment are crucial for operational success. It aids in predicting and enhancing the overall effectiveness of robotic systems within complex and variable business settings.

Here, n denotes total pathways under consideration, m_i is the number of sub-interval points in each pathway of the robot, D_{ij} represents dynamics at each sub-interval point j in pathway i, reflecting the interaction complexity and decision requirements, p_{ij} is the probability that the robot successfully navigates the interaction at the sub-interval point j in pathway i, and $\prod_{j=1}^{m_i}$ calculates the joint probability of success across all sub-intervals in a single pathway.

For a robotic system that monitors business activities, the process that captures the dynamic interactions and requirements across multiple nodes, such as distribution and destination points, while accounting for the robot's physical characteristics, should be constructed.

Let us assume there are the two critical nodes N_d and N_s in the system, where N_d is the distribution node, and N_s is the destination node. The physical weight of the robot W_r influences its operational efficiency and capability. Thus, **m**inimal familiarity level F_{min} is required for the ease of operation that the robot achieves when interacting with business activities, particularly when activities are relocated. The link strength $L_{i,j}$ quantifies the strength of connectivity or interaction between the robot positioned at node i and business activity at node j.

To express the system's performance S_P, which depends on these nodes and the robot's characteristics, we can develop a function that integrates these variables:

$$S_P = \sum i,j \in \{d,s\} L_{i,j}.F_{min}(W_r, F_{ij}) \quad (10)$$

where i,j iterate over the nodes d (Distribution) and s (destination), $L_{i,j}$ is the strength of the link between nodes i and j (which could involve data or material transfer, and is influenced by the robot's efficiency at these nodes), F_{ij} is the familiarity level at nodes i and j (which adjusts based on whether business activities are relocated opposite to the robot's position), and $F_{min}(W_r, F_{ij})$ is a function that combines the robot's weight and the familiarity level. This could be defined as $F_{min}(W_r, F_{ij}) = \frac{F_{ij}}{W_r \tau}$ where τ is a parameter that determines how weight impacts performance.

The business monitoring activity enhancement process Ÿ can improve efficiency and can be determined as follows:

$$\ddot{Y} = \frac{1}{1 + e^{-J\mathbb{J}.(P-T)}} \quad (11)$$

Here, $J\mathbb{J}$ is a scaling factor that adjusts the sensitivity of the monitoring response, T is a threshold that defines the expected performance level for adequate monitoring, and $e^{-J\mathbb{J}.(P-T)}$ is an exponential function that models the responsiveness of the system based on the performance score P.

Equation (11) helps in optimizing the placement and operational parameters of robots to enhance monitoring and automation processes in a business environment. This approach is particularly useful in logistics, warehousing, and other sectors where precise and efficient robot deployment is critical to operational success. The variable monitoring time for each robot $t_{r,i}$ based on its weight, data transmission rates, and the complexity of the activities can be determined as follows:

$$t_{r,r} = \frac{C_{activity}.w_r}{R_{send}.R_{recv}, r.F_r^{\mathfrak{g}}} \quad (12)$$

Here, $(t_{r,r})$ variable time allocated for robots to monitor specific business activities, $C_{activity}$ is the measure of the complexity of the business activities being monitored, which influences the monitoring time required, F_r is a parameter that quantifies the range of functions each robot performs, influencing the allocation of monitoring time, and $\mathfrak{g}$ is a scaling factor that adjusts the influence of the robot's functionality on its monitoring time.

We may combine these individual times, adjusted by the data rates, into a system-level monitoring efficiency T_{system} to capture this relationship for all robots in the ORPABPM system:

$$T_{system} = \sum_{i=1}^{T_R} \left(\frac{C_{activity}.w_r}{R_{send}.R_{recv}, r.F_r^{\mathfrak{g}}} \right) \quad (13)$$

where T_R is the number of robots in the system.

If we also consider the efficiency of data handling in the system, which might depend on the collective data throughput and individual robot contributions, we can introduce a data efficiency factor (η):

$$\eta = \frac{1}{1 + e^{-\acute{\omega}\left(\sum_{i=1}^{T_R} R_{send}.R_{recv}, i.F_i^a\right)}} \quad (14)$$

where ώ is a parameter adjusting the sensitivity of the system to deviations in data rates from a threshold.

Combining the monitoring times with the data efficiency factor, the overall system efficiency can be modeled as:

$$\text{System Efficiency} = \eta \cdot \sum_{i=1}^{T_R} \left(\frac{C_{activity}.w_i}{R_{send}.R_{recv}, i.F_i^a} \right) \quad (15)$$

To formulate a detailed process that determines the cost of deploying robots in a business environment, considering the variety of tasks they perform, their weights, and the amount of data they manage, we can consider a comprehensive model that includes several factors affecting costs. The **cost** of installation (R_c, r) includes the cost of the robot itself and the setup cost. The physical weight of the robot (W_r) may affect the cost due to materials and transport. It requires a functionality score (F_r), which quantifies the range and complexity of tasks performed by the robot r. The robot should have data handling capacity D_r that is the amount of data the robot r can process or manage, which affects operational efficiency E_r and maintenance costs M_r. Thus, the cost for each robot can be modeled with a balance that incorporates these variables, reflecting both initial and ongoing costs:

$$R_c, r = \left(C_b + C_w.W_r + C_{func}.F_r + C_{data}.D_r + C_{cop}.E_r + C_{maint}.M_r\right) \quad (16)$$

where C_b is the base cost of the robot, and C_w, C_{func}, C_{data}, C_{op} and C_{maint} are cost-efficient for weight, functionality, data handling, operational efficiency, and maintenance, respectively. K is a scaling factor to adjust the overall cost estimate to current market or economic conditions.

To determine the total cost of installing all the robots required to monitor business operations, we sum the individual costs:

$$R_{C,total} = \sum_{i=1}^{T_R} R_{c,r} \quad (17)$$

Considering volume discounts or efficiency gains from deploying multiple robots, we can introduce a discount factor Ð that reduces the total cost based on the number of robots:

$$R_{C,total} = Ð(n).\sum_{i=1}^{T_R}\{K\left(C_b + C_w.W_r + C_{func}.F_r + C_{data}.D_r + C_{cop}.E_r + C_{maint}.M_r\right)\} \quad (18)$$

where $Ð(n)$ is a function that decreases with increasing nn, reflecting economies of scale.

We can obtain a detailed method for estimating the cost of deploying robots to monitor business operations, considering various factors that affect both initial and ongoing expenses. It allows businesses to plan financially for the deployment of robotic systems, considering the complexities and benefits of such investments. This comprehensive approach ensures that all relevant costs are factored into the decision-making process, optimizing the balance between performance, functionality, and cost.

To synthesize these metrics into a single process that provides a composite measure of expected outcomes Ex_o, we can use a weighted sum approach where each dimension is assigned a weight reflecting its relative importance:

$$Ex_o = W_E.E + W_C.C_s + W_R.R + W_P.P_r + W_D.D_s \quad (19)$$

Where $W_E, W_C, W_R, W_P W_D$ are weights assigned to efficiency, cost savings, reliability, process improvement, and decision support, respectively. These weights should sim 0 to 1 to normalize the outcome measure, and E, C_s, R, P_i, D_s are the normalized scores for each dimension. It provides a comprehensive assessment of the expected outcomes from implementing an ORPABPM system by integrating key performance metrics. It helps stakeholders understand the overall impact of the system in quantifiable terms, guiding decision-making about further investments and operational adjustments in the ORPABPM strategy. This approach allows for flexibility in emphasizing different aspects of performance according to business needs and can be adapted over time as those needs change.

4. Proposed Integration of Secure Robotic Process Automation with Business Process Management

The ORPABPM encourages organizations to view themselves as a collection of highly integrated processes. The ORPABPM comprises architecture and stages for integration of BPM and ORPA.

- ORPABPM architectural Design
- ORPABPM optimization process

4.1. ORPABPM Architectural Design

We present a comprehensive architecture designed to seamlessly integrate ORPA with BPM systems, achieving an optimal operational state for ORPA systems. This architecture serves as the technological bedrock for facilitating connections between ORPA and BPM, simplifying the fusion of ORPA processes into the broader organizational structure. The capability to invoke ORPA functions directly from a BPM platform is a current technological reality, with this integration revealing the particularities of their interaction. Beyond its utility in refining business processes, BPM forms a critical bridge linking organizational goals with customer expectations, managing processes from start to finish with finesse. The architecture unfolds across three distinct but interconnected strata, as illustrated in algorithm 1. The base stratum consists of the technical infrastructure, which not only enables the automated execution of tasks but also equips the system with the necessary IT provisions to support higher-order functionalities. Ascending to the middle stratum, there is a focus on process-level operations with tools for real-time monitoring, ensuring that inputs are received and handled with immediacy. The zenith of this structure is the strategic tier, where behavior analysis transpires, drawing on key performance indicators to refine and guide the overarching business strategy. Collectively, these layers form a robust framework that not only streamlines process execution but also aligns it with strategic business outcomes, thereby enhancing organizational agility and performance.

Algorithm 1: End-to-end process for effective management using BPM

1. Initialization: {T_l:technical level; P_l: Process level; B_l:behavioral level; A_O: Automated operation; R_{tm}: Real-time monitoring, B_a: behavioral analysis; T: Task; $\forall T_t$
2. Input: {T_l, P_l, B_l}
3. Output: {A_O, R_{tm}, B_a}
4. Set T
5. Activate BPM
6. For $T = 0; T \leq \forall T_t; T++$
7. Process $A_O = T_l \Leftarrow T$
8. If $A_O \cong \gamma$ then
9. Process $R_{tm} = P_l \Leftarrow T$
10. End if
11. If $R_{tm} \cong \gamma$ then
12. Process $B_l = B_a \Leftarrow T$
13. End if
14. End for
15. Return T

Algorithm-1 illustrates an efficient end-to-end management method. Step-1 sets the variables that will be utilized by algorithm-1. Steps 2-3 depict the input and output processes. Step 4 demonstrates how to deliver tasks to the model, after which tasks will be assigned. Steps 5-7 depict the activation process of the BPM model, and tasks are passed to the first level of BPM (technical level) to be processed automatically. If an automated operation process is completed, tasks are completed at the process level and real-time monitoring is undertaken, as described in steps 8-10. Steps 11-14 illustrate how the behavioral level process is launched, and activities are processed for behavioral analysis. Finally, at step 15, the tasks are fully accomplished.

The main goal of setting up a software robot for a business is to determine what kinds of workflows should be automated. It implies that the process must be repeatable and determinable using human rules. because it might not harm a company's whole IT solution. For instance, it is simple to switch off the "robot" and adjust the automated steps if the workflow must be changed or a new one is to be established. As a result, the cost of production is significantly falling while operational performance is increasing. Since neither approach can completely replace the other, both are widely employed in digital transformation initiatives and are built for automation. BPM offers a more thorough method by enabling integration with other outside technologies. ORPA, in contrast, is best used for automating repetitive operations because it is not intended for a specific application. BPM is, in a larger sense, the ongoing activity of recording, deciphering, assessing, and enhancing the processes that direct a company's everyday operations. Implementation specifics should be contained in BPM abstractions to prevent a significant amount of development work each time a business wishes to automate an ORPA operation. Therefore, the goal of this part is to present an architecture that enables the methodical integration of ORPA and BPM systems. A system that serves as a link between the BPM and ORPA and domains is specified by the integrated architecture. Without requiring human involvement, the system enables the creation and execution of a robotically automated task within the course of an increased business process. Configured process models should only provide the specification of the process to automate, not the actual implementation. Because of this, process designers simply need to define the inputs and outputs of an activity and need not worry about technological specifics. The system architecture adheres to the following principles assuming that both ORPA and BPM systems are already configured separately and capable of functioning on their own: It is non-invasive since neither of the separate systems' functionality is restricted. Additionally, architecture is not dependent on any one BPM or ORPA provider.

The use of robots with BPM can improve the performance of business processes as depicted in Figure 3, which demonstrates the comprehensive view of how optimized robotic process automation integrates into various stages of a product lifecycle managed by an enterprise resource planning (ERP) system. Robots improve safety and productivity by automating physically hard and precise activities, starting with the extraction of raw materials. The next step of the process is manufacturing, where robots improve quality control and production speed. Robots help with the transportation stage of the manufacturing process, which simplifies distribution and logistics. Robots help in the use and reuse phase of the lifecycle, ensuring that products are maintained and effectively reused, increasing their lifespan. Finally, robots sort and process waste materials during the disposal and recycling stage, maximizing recycling efforts and supporting sustainable practices.

Lemma 1: Integration of robots with business automation makes faster event cycle time for achievable outcomes.

Proof: The simultaneous analysis of robot and business-level performance is possible by merging discrete and continuous models within the integrated business. The process of integration results in a state change and dynamic activity. Before beginning the continuous dynamic simulation, signal conversion from event-based to time-based is required, along with input parameters. The order of actions or programs to be run in each state defines the dynamic robot inputs for industrial equipment.

A robot initiates the event R_e in the discrete model that activates both transitions from t_1 to t_2 and dynamic model instigation (set ϑ=0) concurrently. During the stochastic period Š, the robot event monitoring system (REMS) sends back the transition to the state t_1. The procedure continues until deterministic time ϑΔŠ. Let us assume that the integration of robots with business automation is a single input event R_{ev} resulting in continuous and discrete outputs. The discrete output of the robot R_{do} is a vector ŭ representing the event's cycle time. The time-series vectors of the robot denoted by the matrices ύ$_1$ and ύ$_2$ are the continuous outputs that provide achievable outcomes. Thus, the discrete output of the robot can be calculated as follows:

$$R_{do} = \lceil SR_e \rceil \acute{\upsilon}_1 = \lceil k_{in}(1), \ldots, k_{in}(\vartheta) \rceil \acute{\upsilon}_2 = \lceil k_{sv}(1), \ldots, k_{sv}(\vartheta) \rceil \quad (20)$$

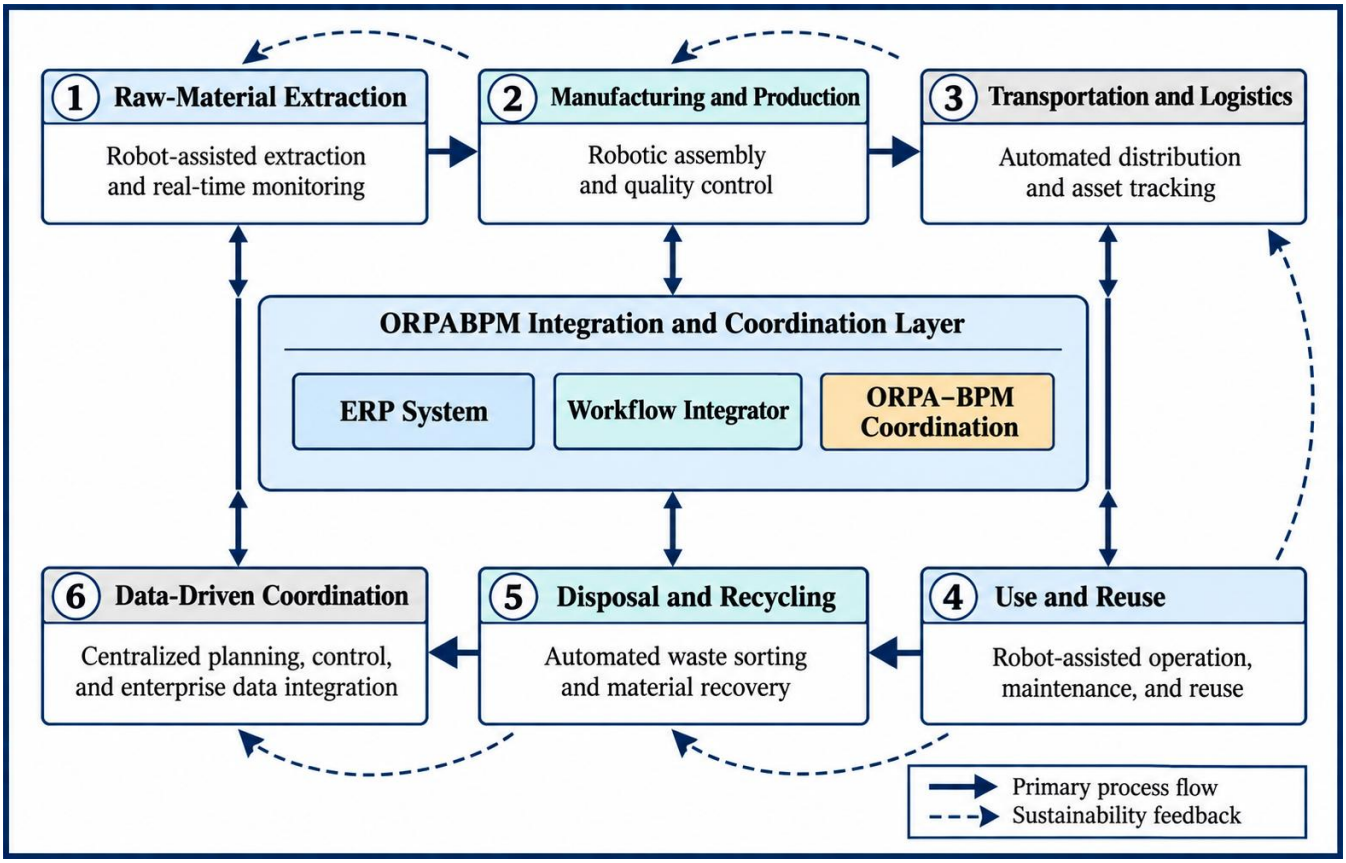


Fig 3. Integrated ORPA–BPM architecture for ERP-centric robotic automation across the closed-loop product

where, SR_e is the number of input events, k_{in} is the constant input vector for business automation, and k_{sv} is the constant state variable vector for the robot

Figure 4 shows an architectural design for incorporating ORPA into BPM. It focuses on the many components and their interactions inside the system. The process is initiated at the top of Figure 4 by the architectural design for ORPA in BPM. The process starts with the design phase, which is overseen by design participants. These individuals are in charge of developing the blueprint for the business processes. The process generator (illustrated on the left) feeds into the vault, which serves as a repository for process definitions. The process engine uses these definitions to carry out business processes. The integrator at the bottom guarantees that various system components along with applications communicate easily via the BPM adaptor. Certain operations inside business processes can be automated by employing the applications invoked that are linked to the processing engine. The ORPA adapter acts as a bridge between the BPM system and ORPA components, allowing for easier communication and data flow. The operator supervises the entire process and ensures that the ORPA system works effectively, which connects with the design participants. To refine and optimize automated operations, the operator and the ORPA process designer collaborate. This designer also uses the ORPA model vault, which stores many ORPA models and templates for subsequent use. The controller is critical in managing deployed robots, guaranteeing that they complete duties correctly and effectively. The ORPA process generator collaborates with the controller to develop new automated processes utilizing specified models and templates. Overall, this architectural design seeks to improve business operations by utilizing ORPA, increasing efficiency, and eliminating manual intervention. The integration of BPM and ORPA components allows for the automation of complicated procedures, resulting in increased productivity and consistency.

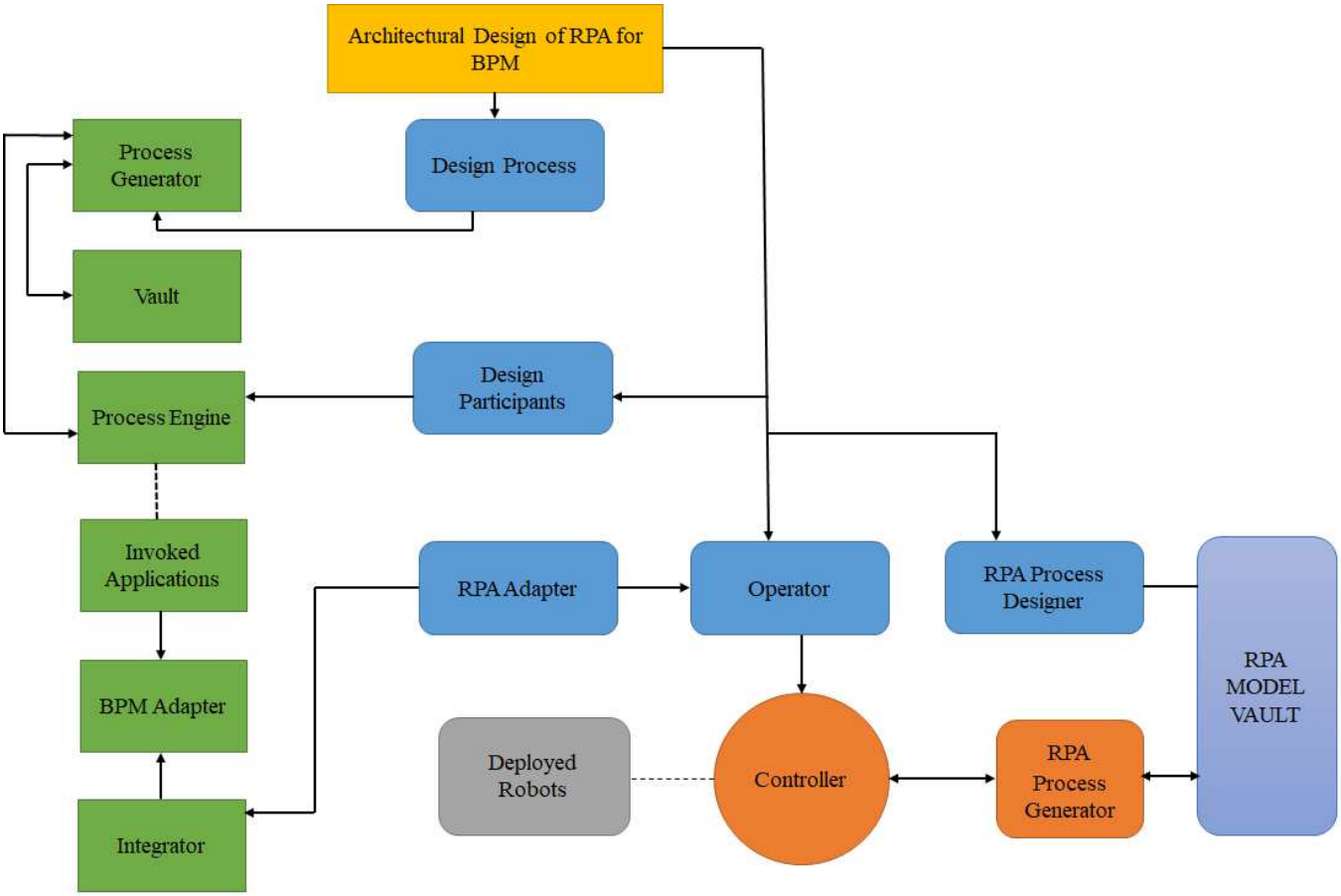


Fig 4. Architectural design for integration of ORPA with BPM

Definition-1: Business process management is investigated in conjunction with its discrete-state representation. In the context of a certain input event, optimized robotic process automation gathers parameters that might aid in speedier performance. A deterministic model is used to investigate state-space variables and outcomes. Business activities may be examined as a system with inputs, outputs, and state variables in their most basic form. The automation of robots can be illustrated by a differential equation given as $\hat{W} = f(v, w, t)$.

where, v is the vector of continuous state variables, w denotes the continuous input vector, and t is the continuous time.

4.2. ORPABPM Optimization Process

Business process design is critical for attaining the objectives of a business, as it involves developing innovative processes from the ground up. This technique is critical for teams to develop scalable and easily replicated workflows that are both efficient and well-defined. This is especially important at the launch phase of new businesses when strategic planning for the production and delivery of goods and services is essential. Business process design is not confined to new organizations; established businesses utilize this methodology when introducing new processes or dramatically restructuring current ones. This redesign can be done formally and systematically. Implicit techniques in business process design include target visualization and proactive planning, which aid in the optimization and refinement of processes without totally modifying current systems. The design step is exceptionally complicated within the contexts of ORPA and BPM when involving four distinct types of designs: product, business, execution, and enterprise. Product design is focused on designing goods that meet consumer needs and standards. Business design is the process of structuring a corporation to successfully support its strategic goals. Execution design is concerned with the operational aspects of successfully implementing business plans. Enterprise design attempts to align each organization's operations with the larger business goals, guaranteeing every process development or innovation contributes to the overall business goals. Each of these design elements is crucial to guarantee that business processes are not only efficient but also linked with an organization's long-term strategic goals, thus improving its overall profitability and stability.

The business process management paradigm increases organizational efficiency by breaking down each level of handling processes into actionable components. This methodical approach allows for the creation of comprehensive lists of criteria and requirements tailored to each specific business case. By dividing the managerial process into several stages. Managers can comprehensively evaluate every facet of

business operations with the use of BPM. Moreover, BPM leverages robotic automation to support several phases of organizational management, such as execution, design, and surveillance. When the ORPA is integrated with BPM, it expedites these procedures while boosting precision and effectiveness. Robots can handle laborious and data-intensive jobs, freeing up human resources for more strategically important tasks that call for human expertise. A robust structure for overseeing and enhancing business operations can be produced with the integration of human supervision and robotic operations. BPM enables a thorough understanding and control over the workflow by offering a clear structure for breaking down and managing business activities. This guarantees that every aspect of the operation is in line with the mission of the organization to achieve common goals. Through a rigorous process, all operational aspects are guaranteed to be optimized, which leads to greater operational outcomes, higher organizational performance, and better resource management. The five phases that make up the BPM lifecycle are modified to create the ORPA-aware lifecycle, as shown in Figure 5.

It provides a comprehensive framework for integrating BPM and ORPA to be capable of performing business automation processes successfully.

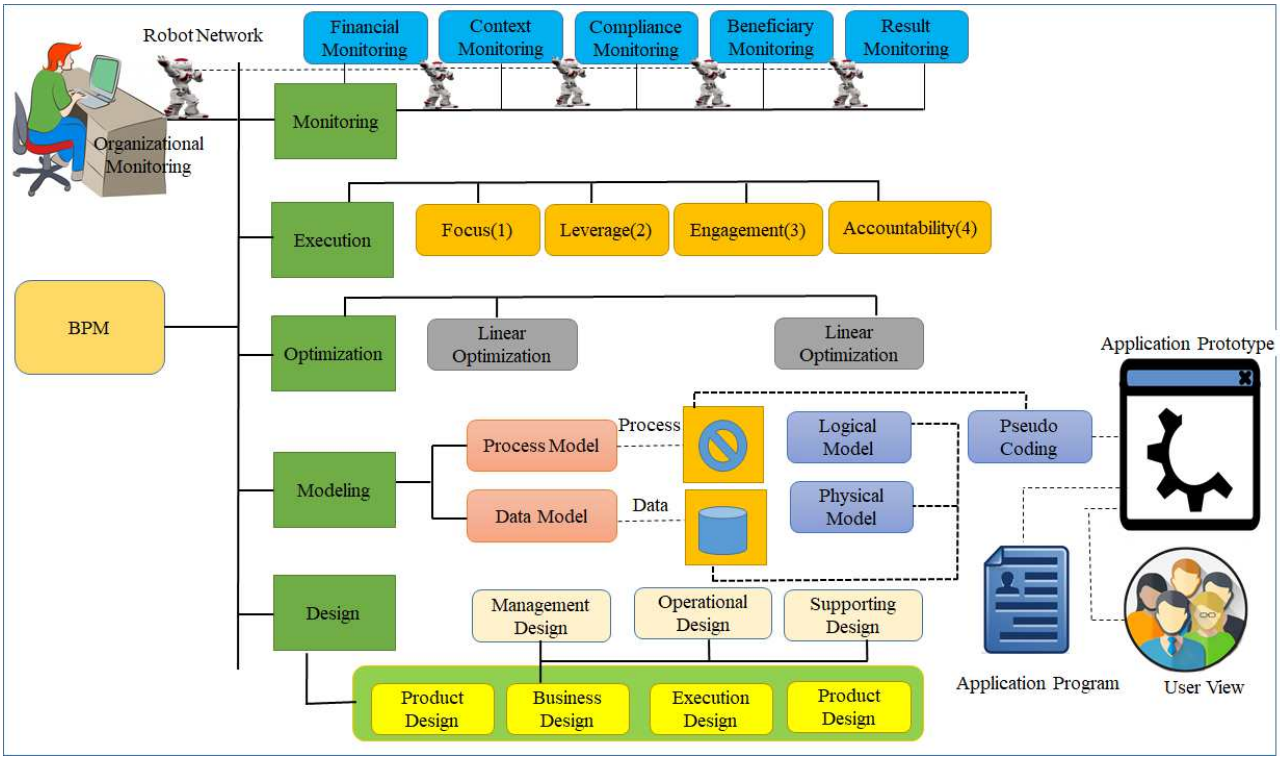


Fig 5. Architectural design features of ORPABPM

The BPM is displayed at the bottom and feeds into a convoluted design process that consists of business, product, execution, and supporting design concepts in addition to operational and management design. Logical and physical models, as well as information from the data and process models, are used in these designs. The modeling, optimization, and execution phases of the BPM are covered in the framework's main sections. Optimization improves execution, which is determined by four important factors: leverage, focus, accountability, and engagement. Optimization is demonstrated to be effective based on linear optimization techniques. A variety of monitoring types are shown above the core BPM processes. These include financial services, context, compliance, beneficiaries, and result monitoring. These types of monitoring contribute to overall organizational monitoring, which may also incorporate inputs from a robot network, thus emphasizing the automation process. Finally, the right side of the figure shows the transition from BPM and monitoring outputs into practical applications, which are proved using algorithm 2, application prototypes, and the user view. Furthermore, it indicates the practical application and visualization of the processes designed and optimized through BPM and ORPA integration. This integration improves a thorough and dynamic approach to organizational process management, emphasizing continuous monitoring and adaptation through technological and procedural innovations. The integration of ORPA with BPM leads to energy efficiency for performing the tasks that are provided in algorithm 2.

Algorithm 2: Energy-efficient process for automating business tasks using robotics features

1. **Initialization:** { E_{ip} : Energy-intensive processes; B_p : Business processes; E_{cs}: Energy consumption process; B_{pm}: Business process management; pro: Process; $\partial Đ$: Current workflow; $\partial Đ(e)$: Inefficient current workflow; Pro_t: Total processes; Ts: Tasks; R_{pa}: Robot process automation; Ŝ: simulated outcomes; M_{pro} : Monitoring process; M_r : Monitoring reports; E_{eg} : Energy efficiency goals; M_o : Monitoring; Pro_{im}: Improved process}
2. **Input:** $\{T_s; Pro_t;\ pro\}$
3. **Output:** $\{Pro_{im}; E_{eg}\}$

// **Step 1: Identify Energy-Intensive processes

4. **Initiate** E_{ip}
5. **Set** B_p
6. **Assign** $E_{ip} = E_{cs}$

// **Step 2: Analyze current workflows

7. **For** $pro = 0;\ pro \leq E_{ip};\ pro++$
8. **compute** $\partial Đ = B_{pm}$
9. **Identify** $\partial Đ \in \partial Đ(e)$
10. **End for**

// **Step 3: Design ORPA solution

11. **For** $pro = 0;\ pro \leq E_{ip};\ pro++$
12. **Calculate** $Ts \in Pro_t$
13. **Simulate** Ts with B_{pm}
14. **Optimize** R_{pa} with Ŝ
15. **End for**

// **Step 4: Implement ORPA in Live environment

16. **For** $pro = 0;\ pro \leq E_{ip};\ pro++$
17. **Deploy** $R_{pa} = pro$
18. **End for**

// **Step 5: Monitor and evaluate

19. **Perform** $M_r = R \leftarrow M_{pro}[T_s]$
20. **While** $(M_r\ != E_{eg})$
21. **Update** $R_{pa} = M_r + (R_{pa}[Script])$
22. **Show** $M_r \leftarrow M_o$
23. **End while**

// **Step 5: Monitor and evaluate

24. **Repeat** M_r && T_s
25. $Pro_{im} = Im[\ M_r]$
26. **If** $Pro_{im} = Successful$ then // Continue until no further improvements are perceived
27. **Go to step-2**
28. **End if**

Algorithm 2 integrates the features of ORPA and BPM for energy efficiency. The algorithm starts by fetching a list of all business processes explained in step-1. Each process is then analyzed to quantify its energy consumption, and most energy-intensive processes are identified for further analysis and optimization. Step-2 analyzes current workflows for each energy-intensive process, the current workflow is analyzed using BPM tools to identify inefficiencies, such as unnecessary steps, delays, or energy-intensive tasks that might be automated. Step-3 provides a design ORPA solution. The ORPA scripts are developed for tasks within the processes that are repetitive and predictable, which can be automated to save energy. These scripts are first simulated within the BPM model to assess their impact and optimize them for better performance and energy efficiency. Step-4 implements ORPA in Live environment. The optimized ORPA scripts are then deployed to operate in the live environment. This step integrates ORPA into the existing business process managed by the BPM system. Step-5 shows monitoring and evaluation processes. The performance of the integrated system (BPM + ORPA) is continuously monitored. Key metrics to monitor include energy consumption and process efficiency. Based on these reports, ORPA scripts may be adjusted to enhance efficiency further. Step 6 iterates to improve the working process. The algorithm includes a feedback loop to continually assess the results and make iterative improvements. If monitoring reports suggest that improvements are possible, the process cycles back, further analyzing and optimizing workflows. This algorithm systematically integrates ORPA with BPM to enhance energy efficiency in business operations, ensuring that both systems work together to reduce waste and improve performance.

4.2.1. STRATEGIC DESIGN

To accomplish a company's objectives, brand-new procedures must be made from scratch. This assists teams in creating scalable, easily replicable procedures and workflows that are efficient and well-defined. When new businesses begin thinking about how they will create and distribute their goods and services, they participate in business process design at the design stage. When businesses install wholly new processes or restructure current ones, they are also engaging in business process design. Organizations may carry this out subtly or in a more structured and official manner. A goal of visualization and an action plan are only two examples of an implicit method used in business process design. The design of the ORPABPM consists of four types (product design, business design, execution design, and enterprise design). To express the design of a robot using a horizontal projection along the y-axis mathematically, we can define it in terms of coordinates. Typically, horizontal projection in the context of robotics or any object modeling refers to projecting a three-dimensional object onto a two-dimensional plane.

If we consider a 3D point on the robot described by coordinates (x_1, x_2, x_3), the horizontal projection along the y-axis would typically project this point onto the xy-plane. This means the y-coordinate is disregarded in this projection, simplifying each point to $\overline{(x, z)}$

The mathematical representation of this projection for any point on the robot can be written as $P(x_1, x_2) = (x_1, x_3)$

where P is the projection operator that maps (x_1, x_2, x_3), to (x_1, x_3), effectively eliminating the y-component of the point.

Thus, if the robot's design in 3D is defined by a set of points or a function $f(x_1, x_2, x_3)$, the design as viewed from a projection along the y-axis can be described by:

$$f_{proj}(x_1, x_3) = \mathrm{f}(x_1, x_2, x_3), |\ x_2 = 0 \qquad (21)$$

Here, $fproj(x, y)$ represents the 2D function or set of points describing the robot when viewed with a projection that ignores the y-axis values.

When discussing the concept of vertically projecting along the z-axis in a physical or mechanical context, typically, we are concerned with the forces acting along that axis due to gravity. For a robot of mass R_m , the force due to gravity when projected vertically along the z-axis can be quantified using Newton's second law of motion.

If we denote the force due to gravity as F_g , it can be calculated as the product of the mass of the robot R_m and the acceleration due to gravity g. Considering the orientation of our coordinate system where the z-axis is positive upwards, the force of gravity will act in the opposite direction, i.e., downwards. Thus, the gravitational force can be expressed as follows:

$$\vec{F}g = R_m.g.\hat{z} \quad (22)$$

Here, $\hat{z}$ represents the unit vector in the z-direction. This equation explicitly incorporates the direction of the gravitational force, aligning with the conventional representation of vectors in physics where the negative sign indicates that the force is acting opposite to the positive z-axis direction. This downward gravitational force is a fundamental factor to consider in any dynamic calculations involving the robot's movement or stability.

To formulate an equation that determines the resultant torque around the X-axis due to an overhanging distance and tilting angle of a robot, we can use the principle of moments (torques). The moments must balance for static equilibrium, or their sum gives the net torque if dynamics are considered. If we assume the robot's center of mass is located at the overhanging distance d_o from the central pivot (x-axis), the torque due to gravity can be calculated by considering the component of the gravitational force that acts along the line of the overhang when the robot is tilted by an angle θ.

The gravitational force acting downward at the center of mass of the robot is $R_m.g$. The lever arm is effective in causing rotational torque around the X-axis. Given a tilt θ, it is $d_o\ Cos(\theta)$ (because the effective lever arm length reduces as the tilt increases).

Thus, the torque τ around the X-axis due to the gravitational force can be expressed as:

$$\tau = R_m.g.d_o, Cos(\theta) \quad (23)$$

where d_o is the overhanging distance (length of the lever arm beyond the pivot point), d is the distance between the contact points or the effective width of the base around which torques are being calculated, θ is the tilting angle of the robot relative to the vertical axis (assumed to be in radians for simplicity), R_m is the robot's mass, and g is the acceleration due to gravity.

This torque tends to rotate the system further about the X-axis. Under equilibrium conditions—or when calculating the net torque for dynamic analysis—all forces and torques must be considered, including those produced by supports and any additional weights. However, based solely on your query, the equation for the torque caused by the robot's weight due to its geometry and orientation relative to gravity would be as described. To formulate the equation representing the non-slipping condition based on the Coulomb friction law, we consider the relationship between the normal force and the frictional force. The frictional force that prevents slipping is proportional to the normal force exerted by a surface on the robot, multiplied by the friction coefficient. According to the Coulomb friction law, the frictional force that must be overcome to initiate sliding is given by:

$$F_f = F_n \times C_f \quad (24)$$

where F_f denotes the frictional force, C_f is coefficient of friction, and F_n represents normal force.

C_f is the coefficient of friction between the robot and the surface that is the non-slipping condition which implies the tangential force F_t exerted on the robot must not exceed this frictional force F_f. Thus, the equation for the non-slipping condition can be expressed as: $F_t \leq C_f.F_n$. If F_t remains less than or equal to $C_f.F_n$, the robot will not slip.

This ensures that the horizontal forces due to motion or external forces are within the limits set by the frictional interaction between the robot and the surface, thus preventing slipping. This is a critical condition for ensuring stable movement or positioning of robots, especially in environments where traction is a concern.

We use the concepts of static friction as outlined by Coulomb's law to mathematically determine the non-slipping requirement for a robot. The non-slipping criterion guarantees that any lateral forces that may cause the robot to slip are offset by the frictional force generated by the surface. The maximum static friction force F_f that can be exerted by a surface on the robot, preventing it from slipping, is given by the product of the coefficient of static friction μs and the normal force exerted by the robot on the surface. For the robot to maintain a stable position without slipping, the lateral force F_l acting on the robot must not exceed this frictional force that should be $F_l \leq \mu s.F_n$

In the context of a robot, this helps in designing control systems that ensure the robot operates within safe traction limits, especially on surfaces where slipping is a risk, such as on slopes or slick surfaces. To frame an equation for the design of a robot, we must consider various physical and mechanical principles that guide the structural and functional attributes of the robot. However, such an equation can vary widely depending on the specific design goals, such as stability, maneuverability, or efficiency. The stability of a robot, particularly one that needs to maintain balance while performing activities or navigating environments, can be determined by comparing its center of mass to its base of support.

A robot is considered stable if the Stability Index S_I is less than 1. This means that the projection of the center of mass falls within the base area of the robot. The position of the robot aCM_r can be modeled as follows:

$$aCM_r = \frac{(m_r . a_r)}{M} \quad (25)$$

$$bCM_r = \frac{(m_r . b_r)}{M} \quad (26)$$

$$cCM_r = \frac{(m_r . c_r)}{M} \quad (27)$$

where m_r denotes the mass of the robot; a_r, b_r, c_r are coordinates of the center of the mass of the robot; and M_r is the total mass of the robot.

Equations (25-27) help engineers at the design stage by assisting in locating the center of mass so that the robot remains stable whether it is moving or stationary. To maximize stability, modifications might be made to the base dimensions or the mass distribution. This is especially important for designs that require the robot to work on uneven terrain or in different orientations. The functioning of a business management robot might be based on how well it can process tasks, communicate, and interact with others in its operating environment. Let's simplify this into an equation (28) that encompasses these elements:

$$E_r = T_{ps} \times \frac{100}{T_t} \quad (28)$$

Where E_r denotes the efficiency of the robot; T_{ps} is tasks processed successfully; and T_t is total tasks.

Business process integration is important for performance, so the business integration score B_{IS} should be determined.

$$B_{IS} = B_c + B_a + B_s \quad (29)$$

where B_c is business compatibility; B_a is the business adaptability; and B_s is the business scalability.

Hypothesis 1: Integrating Robot Process Automation with Business Process Management can significantly improve the energy efficiency of organizational processes by optimizing resource utilization and minimizing waste. The hypothesis states that the joint implementation of ORPA and BPM reduces the total energy consumption E_{total} in an organization by automating energy-intensive tasks and refining process workflows.

Proof: Let E_{init} be the initial energy consumption of a process before the implementation of ORPA and BPM. After integrating ORPA and BPM into the process, let E_{final} be the new level of energy consumption. The hypothesis can be tested by the equation:

$$\Delta E = E_{init} - E_{final} \quad (30)$$

where ΔE represents the reduction in energy consumption, and a positive value indicates an improvement in energy efficiency. The integration of ORPA automates repetitive and high-volume tasks that were previously manually executed, reducing operational times and the energy used during these periods. Simultaneously, BPM optimizes the process flow, eliminating unnecessary steps and ensuring that energy is only used when and where it is truly needed.

To provide proof, consider the energy usage E in a process as proportional to the time t the process runs and the number of resources Δr it utilizes:

$$E = k.t.\Delta r \quad (31)$$

Here, k is a constant of proportionality that depends on the type of process and equipment used. By introducing ORPA, the time t is reduced due to faster processing speeds and the elimination of human-induced delays. Similarly, BPM may reduce Δr, the number of resources used by improving the process design:

$$t_{new} = t_{old}.(1 - \acute{\omega}), \Delta r_{new} = \Delta r_{old}.(1 - \acute{\alpha}) \quad (32)$$

Here, $\acute{\omega}$ and $\acute{\alpha}$ are the fractions by which time and resource use are reduced, respectively. Thus, the new energy consumption E_{final} becomes:

$$E_{final} = k.t_{new}.\Delta r_{new} = k\big(t_{old}.(1 - \acute{\omega})\big).\Delta r_{old}.(1 - \acute{\alpha}) \quad (33)$$

$$E_{final} = E_{init}.(1 - \acute{\omega}).(1 - \acute{\alpha}) \quad (34)$$

Substituting back into the delta equation:

$$\Delta E = E_{init} - E_{init}.(1 - \acute{\omega}).(1 - \acute{\alpha}) = E_{init}.(\acute{\omega} + \acute{\alpha} - \acute{\omega}\acute{\alpha}) \quad (35)$$

This equation (35) quantifies the reduction in energy consumption attributable to efficiency gains from both ORPA and BPM. The positive values of $\acute{\omega}$ and $\acute{\alpha}$ indicate efficiency improvements should lead to a positive ΔE, validating the hypothesis that ORPA and BPM integration enhances energy efficiency.

4.2.2. UNIFIED ROBOTIC BUSINESS PROCESS

A robust business model is essential for both emerging and established companies, outlining strategies for profitability, estimated costs, and details of products or services offered, alongside the targeted clientele. Within this strategic framework, our research introduces the ORPABPM modeling approach, which integrates two state-of-the-art modeling types: process modeling and data modeling depicted in Figure 6. The first modelling type, Process modeling, is a method of demonstrating the organized execution of work by documenting the relationships between resources, actions, choices, and events. ORPABPM documentation is not merely a record; it is a business strategy that assists in the selection of automation, the organization of tasks, the monitoring of the system, the resolution of exceptions, and the continuous improvement of the system. The method deconstructs each stage into components and illustrates the interconnections between tasks by employing a flowchart-like representation of the process model. This enables organizations to perceive both the existing situation and the optimal workflow.

Process modeling is typically organized into three macro-level layers in ORPABPM. Cost, time, reliability, energy, and conformance are among the organizational objectives that the strategic layer delineates and associates with key performance indicators and policy limitations. Comprehensive protocols, task demarcations, responsibilities, and decision points are each delineated by the process layer. The technical execution layer connects process activities to automation primitives, such as ORPA bots, services, and APIs, and also links these tasks to logging systems, monitors, and sensors. This stratified methodology ensures the stability of process design in the face of changes

in implementation specifics. The model, which is not intricately linked to a particular vendor or toolset, emphasizes input/output expectations and automation objectives, thereby facilitating non-invasive integration. A compilation of fundamental artifacts must be the result of an exhaustive ORPABPM process model. At the macro level, a process map delineates phases from intake to validation, task allocation, execution, monitoring, and closure. An activity model defines the preconditions, triggers, postconditions, service-level requirements, and exception pathways for each activity at the micro level. The responsibilities of human operators, ORPA bots, BPM engines, monitoring subsystems, and security modules are defined by swimlane assignments. In a decision and exception model, failure states are defined as absent data, contradictory approvals, bot malfunctions, blindspot notifications, and noncompliance incidents. Monitoring and audit hooks are responsible for delineating logging parameters, alarm triggers, threshold interpretations, and escalation protocols, thereby guaranteeing operational responsibility and traceability.

A directed labelled graph P= (N, E, G, R) can be used to formalize a process. In this graph, N represents the collection of nodes (events, tasks, gateways), E⊆N×N denotes the set of sequencing edges, G encodes gateway rules (e.g., XOR/AND joins and splits), and R assigns roles/runners (human versus ORPA vs BPM service). Each task node $N_j \in$N can be described as $n_i = \langle I_i, O_i, \tau_i, \pi_i, \sigma_i \rangle$, where I_i represents the input bundle, O_i signifies the output bundle, I_i represents the expected duration distribution or SLA, π_i indicates policy constraints (compliance/security), and σ_i describes the runner binding (human, ORPA bot, or BPM service). This structured framework facilitates automated feasibility assessments, simulations, optimization, and bottleneck identification. The transition from "as-is" to "to-be" must be elucidated by a process-oriented ORPABPM chapter that defines pragmatic guidelines. A task is an ideal candidate for automation if it is consistent in its UI/API interaction patterns, deterministic, and repetitive. Activities that are distinguished by mixed determinism must be divided into deterministic ORPA phases, a human validation phase, and a clearly defined exception pathway. Start logs, completion logs, error logs, and performance indicators should be included in the mandatory monitoring of enrichment for automated segments. Escalation and secure fallback must be incorporated into the workflow from the outset, rather than being appended subsequently, by implementing security-conscious gates at locations where planner or blindspot indicators may arise or where critical actions take place. In order to facilitate objective improvement, process models must be linked to quantifiable key performance indicators (KPIs). Cycle time T_c, cost per case C_c,, error rate E_r,, automation coverage A_c, energy per case E_c, and compliance pass rate C_p are among the most common key performance indicators. These KPIs are transformed into real-time operational indicators upon the execution of the process model through BPM and ORPA integration, which enables closed-loop enhancement that is based on actual performance rather than immutable assumptions. A textual process template that can be reused is defined as follows: a trigger event initiates a case in an ERP or portal, followed by a pre-check to ensure that the data is complete. If the data is incomplete, the system requests the requisite information and enters an await state. A risk/compliance gate enforces policy verifications; noncompliant situations are referred to an operator. The case is directed to an ORPA bot pool through task allocation, with a human failsafe option available. The bot documents all stages while executing activities using the UI/API. Upon the occurrence of a planner or blindspot alarm, exception handling halts the algorithm and isolates activities, subsequently directing the case for human evaluation. Outcome verification validates results and conducts reconciliation assessments. Closure archive audit records, revise KPIs, and refresh the BPM repository or vault to facilitate the monitoring of continuous improvement. The data modelling is the process of defining data, its structure, its interrelations among system components, and its role in decision-making and automation. Process execution, robotic bot administration, operational oversight, security analytics, and closed-loop learning are all included in ORPABPM data modeling. Business data refers to enterprise resource planning records, orders, invoices, shipments, customer information, and inventory, while process data includes case identifiers, activity states, timestamps, roles, gateways, and service level indicators. Bot telemetry includes bot identity, run history, step sequencing, interface interactions, and success or failure outcomes. Utilizing a conceptual entity-relationship framework, this data can be organized into basic entities, including cases, process instances, tasks, bot executions, event records, security alerts, metric snapshots, and policy versions. The entities are hierarchically interconnected, which enables each business case to generate a multitude of process instances. Each instance can encompass multiple tasks, all of which can initiate one or more bot executions. Each bot execution can produce event logs, security notifications, and performance metrics. This company oversees each execution decision and performance outcome in accordance with its business case.

In order to guarantee data integrity and auditability, it is necessary to establish logical constraints. Temporal consistency ensures that the durations of task execution are consistent with the lifecycles of process instances. Until all tasks are either finalized or annulled, closure rules impede the completion of a process. Auditability requires event documentation for each automated execution, while security traceability associates alerts with execution instances and provides verifiable evidence. These constraints improve operational reliability, repeatability, and compliance. Numerous pragmatic considerations are required when implementing the logical data model in physical storage. The segmentation of extensive execution records by temporal intervals is essential for scalable performance. For expedited retrieval, index frequently accessed attributes, including case

identities, execution identifiers, and alert types. In order to maintain audit traces, event logs must be immutable and append-only. Additionally, schema evolution must be meticulously managed to guarantee data consistency with evolving business process models. These design methodologies enable the elimination of analytical constraints and the implementation of scalable monitoring in high-volume automation applications. The data model facilitates closed-loop control and analytics. ORPABPM requires an uninterrupted data stream from execution to monitoring, monitoring to learning, and learning to revised operational policies. As a result, the data structure must enable performance evaluations across policy iterations, comprehensive root cause analysis using execution traces and error logs, correlation of security alerts among bots, processes, and environments, and ongoing enhancement by connecting learning signals to tangible execution results. Process, functional, and kinematic layers are integrated into a coherent, self-sustaining system design through data modeling. The functional modeling defines the enterprise and automation system as input-output functions. Functional modeling has defined the entry and exit sites in ORPABPM, enabling stakeholders to connect strategy with operational conduct by articulating the system's consumption, generation, and guarantee. Functional modeling delineates the system's transformation capabilities and their integration into a comprehensive operational service, while process modeling delineates the sequence of events. Intake and context acquisition (case requests, ERP events, user communications; outputs: normalized case packet and context snapshot), validation, and conformance verification are among the functional decompositions of ORPABPM. Other elements include accepted or flagged case, along with conformance evidence; job planning and allocation, which includes the process model, resources, and constraints; outputs: task plan and runner assignment; and execution orchestration Logs and telemetry inputs, executed actions and execution trail outputs, monitoring and KPI computation outputs (dashboards, alarms, KPI time series), security threat identification and mitigation through RATD (traces and telemetry; alert, isolation, secure fallback), and learning and policy updates. The input-output contract $F: \langle U, D, M, \Pi \rangle \rightarrow \langle Y, \Lambda, K \rangle$ is employed to illustrate the ORPABPM system. U represents user/case inputs, D represents enterprise data (ERP/DB), M denotes monitoring streams (telemetry/logs), and Π represents policies/constraints. The outputs consist of Y for business results (cases and outputs), Λ for audit/security (logs and alarms), and K for KPI vectors (time, cost, energy, error, compliance). This contract aids models in the delineation of the system's commitments, which are not contingent upon implementation specifications, and it verifies requirements through quantifiable outcomes. Functional modeling is rendered practicable by assigning functions to humans, bots, and platform services. Human-in-the-loop incorporates policy overrides, high-risk assessments, exclusions, and approvals. ORPA algorithms execute repetitive tasks, data extraction, and deterministic user interface and application programming interface operations. The functions of a BPM platform include state management, orchestration, routing, and SLA timing. Security and monitoring modules compute metrics, identify anomalies, and supervise incidents. For continuous improvement, the learning module updates versions, modifies policies, and formulates rewards. This allocation facilitates closed-loop feedback on task planning and automation by integrating functional design with governance and operational reliability.

4.3. Robotic Kinematics

A multi-joint serial manipulator is illustrated in the robotic kinematics diagram appended herewith. The end-effector pose is determined by geometric parameters (H_1, L_1, L_2, W_1) and coupled joint rotations $(\theta_1, \theta_2, \theta_4, \theta_5, \theta_6)$. The end-effector pose $(\boldsymbol{\theta})^s T_b(\boldsymbol{\theta})$ is obtained by combining the homogeneous transformation (DH form) of each joint into the full forward-kinematics product, as defined by the first set of equations. The link offsets depicted in the figure are directly matched by a geometric closed-form position model that expresses $\boldsymbol{\theta}^s p_b(\boldsymbol{\theta})$ with trigonometric coupling, such as $\cos(\theta_2 + \theta_4)$and $\sin(\theta_2 + \theta_4 + \theta_5)$.Orientation is obtained by a chained rotation matrix $\boldsymbol{\theta}^s R_b(\boldsymbol{\theta})$ that captures base yaw and wrist rotations, resulting in the complete 6-DoF pose. The Jacobian J(θ) is used to demonstrate differential kinematics, which maps joint rates $\dot{\theta}$ to end-effector twist. Inverse-kinematics constraints are employed to solve coupled joint angles under reachability constraints using the wrist-centre formulation and cosine-law relations. Collectively, these eight equations establish a formal connection between the physical geometry and coordinate frames of the diagram and mathematically verifiable motion generation and control.

Let $\{s\}$ be the base frame, and intermediate frames $\{1\} \ldots \{5\}$, end-effector $\{b\}$, joint angles $\theta_1, \theta_2, \theta_4, \theta_5, \theta_6$, geometric parameters H_1, L_1, L_2, W_1, and the end-effector axis $\hat{y}_b$.

Use a DH-style chain $\{s\} \rightarrow \{1\} \rightarrow \{2\} \rightarrow \{4\} \rightarrow \{5\} \rightarrow \{b\}$, matching the labeled revolute joints in the figure (θ_1 at base, θ_2 shoulder, θ_4 elbow/wrist, θ_5 wrist pitch, θ_6 wrist roll). The homogeneous transform for each joint using DH parameters is needed.

For link i, the transform from $\{i-1\}$to $\{i\}$is given by:

$$T_i(\theta_i)^{i-1} = \begin{bmatrix} \cos\theta_i & -\sin\theta_i \cos\alpha_i & \sin\theta_i \sin\alpha_i & a_i \cos\theta_i \\ \sin\theta_i & \cos\theta_i \cos\alpha_i & -\cos\theta_i \sin\alpha_i & a_i \sin\theta_i \\ 0 & \sin\alpha_i & \cos\alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (36)$$

The base-to-end-effector forward kinematics should be determined. Let $g_{sb}(0)$be the home pose and $\xi_i$be the screw axis of joint $i$expressed in $\{s\}$. Then:

$$g_{sb}(\theta) = \left(\prod_{i \in \{1,2,4,5,6\}} e^{[\xi_i]\theta_i} \right) g_{sb}(0) \quad (37)$$

where $[\xi_i] \in \mathfrak{se}(3)$is the matrix representation of twist $\xi_i = [\omega_i \quad v_i]$.

A compact position model consistent with the labelled lengths is given by:

$$\begin{aligned} {}^{\theta^s}p_b(\theta) \\ = \begin{bmatrix} \cos\theta_1(L_1\cos\theta_2 + L_2\cos(\theta_2+\theta_4) + W_1\cos(\theta_2+\theta_4+\theta_5)) \\ \sin\theta_1(L_1\cos\theta_2 + L_2\cos(\theta_2+\theta_4) + W_1\cos(\theta_2+\theta_4+\theta_5)) \\ H_1 + L_1\sin\theta_2 + L_2\sin(\theta_2+\theta_4) + W_1\sin(\theta_2+\theta_4+\theta_5) \end{bmatrix} \end{aligned} \quad (38)$$

This directly uses H_1, L_1, L_2, W_1 and coupled angles. A useful closed-form orientation for a yaw–pitch–roll style is determined as follows:

$$^{\theta^s}R_b(\theta) = R_z(\theta_1)\,R_y(\theta_2+\theta_4)\,R_y(\theta_5)\,R_x(\theta_6) \quad (39)$$

with standard axis-rotations:

$$\begin{aligned} R_z(\phi) &= \begin{bmatrix} \cos\phi & -\sin\phi & 0 \\ \sin\phi & \cos\phi & 0 \\ 0 & 0 & 1 \end{bmatrix},\ R_y(\phi) \\ &= \begin{bmatrix} \cos\phi & 0 & \sin\phi \\ 0 & 1 & 0 \\ -\sin\phi & 0 & \cos\phi \end{bmatrix},\ R_x(\phi) \\ &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi & \cos\phi \end{bmatrix} \end{aligned} \quad (40)$$

Full homogeneous transform from base to tool that can be estimated as follows:

$$^{\theta^s}T_b(\theta) = \begin{bmatrix} ^{\theta^s}R_b(\theta) & {}^{\theta^s}p_b(\theta) \\ 0\ 0\ 0 & 1 \end{bmatrix} \quad (41)$$

Let $^{\theta^s}V_b = [\omega_b \quad v_b]$ be the spatial twist, then

$$\begin{aligned} {}^{\theta^s}V_b &= J_s(\theta)\,\dot{\theta}, J_s(\theta) \\ &= [\xi_1 \quad \mathrm{Ad}_{e^{[\xi_1]\theta_1}}\xi_2 \quad \mathrm{Ad}_{e^{[\xi_1]\theta_1 e^{[\xi_2]\theta_2}}}\xi_4 \quad \mathrm{Ad}_{\dots}\xi_5 \quad \mathrm{Ad}_{\dots}\xi_6] \end{aligned} \quad (42)$$

where Ad_g denotes the adjoint operator, capturing how each joint screw axis is transported along the chain.

End-effector linear velocity from differential kinematics position is determined as follows:

$$\begin{aligned} (\partial^s\dot{p}_b\theta) = \frac{\partial^s p_b}{\partial\theta_1}\dot{\theta}_1 + \frac{\partial^s p_b}{\partial\theta_2}\dot{\theta}_2 + \frac{\partial^s p_b}{\partial\theta_4}\dot{\theta}_4 \\ + \frac{\partial^s p_b}{\partial\theta_5}\dot{\theta}_5 \end{aligned} \quad (43)$$

Expanding the θ_1 partial derivative (showing complexity explicitly):

$$\begin{aligned} \frac{\partial^s p_b}{\partial\theta_1} = \begin{bmatrix} -\sin\theta_1\ \Gamma(\theta_2,\theta_4,\theta_5) \\ \cos\theta_1\ \Gamma(\theta_2,\theta_4,\theta_5) \\ 0 \end{bmatrix},\ \Gamma \\ = L_1\cos\theta_2 + L_2\cos(\theta_2+\theta_4) \\ + W_1\cos(\theta_2+\theta_4+\theta_5) \end{aligned} \quad (44)$$

A wrist-centre point p_w be defined by moving back along the tool axis (use $\hat{y}_b$ shown in the figure):

$$\partial^s p_w = \partial^s p_b - d_{wb}\ (\partial^s R_b\,\hat{y}_b) \quad (45)$$

Then, a common IK constraint is given as follows:

$$\begin{aligned} \theta_1 = \mathrm{atan2}\big([p_w]_y, [p_w]_x\big), \| p_w - \begin{bmatrix} 0 \\ 0 \\ H_1 \end{bmatrix} \|^2 \\ = L_1^2 + L_2^2 + 2L_1L_2\cos\theta_4 \end{aligned} \quad (46)$$

It couples geometry and joint space and is typically used to solve θ_4 from a cosine law constraint.

Robot dynamics can be simplified into a single integrator model, which reduces the complexity of the robot's motion equations to a more understandable form. This method usually consists of reducing the state dynamics of the robot to first-order differential equations, in which the derivatives of the state variables (e.g., position or velocity) are directly defined by the control inputs. By limiting the dynamics to direct control over velocities, the single integrator model simplifies robotic control and facilitates control system design and analysis, particularly in automated and autonomous robotics systems.

Corollary 1: Given that the integration of ORPA and BPM leads to improved energy efficiency and operational optimization, it follows that these enhancements can directly contribute to increased profitability for organizations. This can be understood through the reduction in operational costs and the increased productivity and quality of work, which ultimately drive higher profit margins.

Proof: Let C_{int} represent the initial cost of operations, including labor and energy costs, before the integration of ORPA and BPM. After integration, the costs become C_{final}. The reduction in costs due to increased efficiency is given by:

$$\Delta C = C_{int} - C_{final} \quad (47)$$

Simultaneously, let P_{init} represent the initial productivity or output value, and P_{final} represent the productivity after ORPA and BPM integration. The increase in productivity is denoted as:

$$\Delta P = P_{final} - P_{init} \quad (48)$$

Profitability Π' can be modeled as the difference between output value and costs. Initially, profitability is

$$\Pi'_{init} = P_{init} - C_{init} \quad (49)$$

and after improvements,

$$\Pi'_{final} = P_{final} - C_{final} \quad (50)$$

The change in profitability due to ORPA and BPM integration is then:

$$\Delta\Pi' = \Pi'_{final} - \Pi'_{init} = \big(P_{final} - C_{final}\big) - (P_{init} - C_{init}) \quad (51)$$

$$\Delta\Pi' = \Delta P - \Delta C \quad (52)$$

Since both ΔP and ΔC are expected to be positive (indicating an increase in output and a decrease in costs), $\Delta\Pi'$ is also expected to be positive, demonstrating that the integration of ORPA and BPM leads to enhanced profitability. This corollary emphasizes the economic rationale behind the adoption of ORPA and BPM technologies, suggesting that such integrations not only optimize operational efficiencies but also have a tangible positive impact on an organization's financial performance.

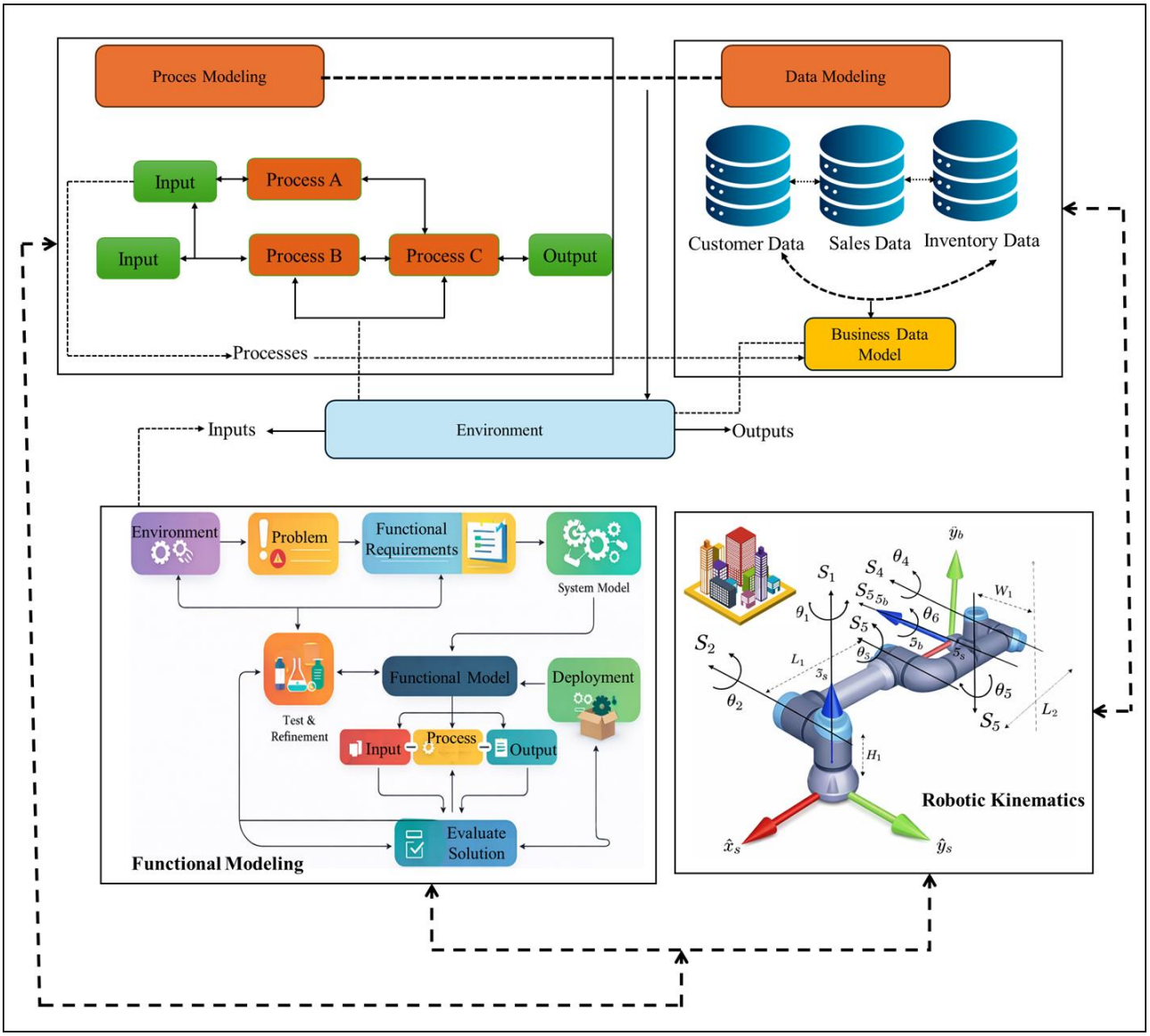


Fig 6. Integrated modeling architecture of the proposed ORPABPM framework

The robot control stage is pivotal in the management process, where the monitoring stage's tracked changes are used to gauge performance. Initial outcomes from this stage allow for the refinement of the developed model, which can subsequently be reintegrated into the operational workflow. System execution procedures are compartmentalized into three distinct but interrelated sections: workflow management, task management, and execution control. These components ensure a structured approach to executing and overseeing business processes. Robot control is depicted in Figure 7, where 6 shows a closed-loop system for controlling robots that has been improved with a learning-based adaptation mechanism. The sensor layer is the first part of the control loop. This is where optical and proprioceptive sensors constantly gather information about the system and the environment. The policy module, which is the layer that makes decisions about what actions to take based on the observed situation, receives this sensor data. The chosen actions are sent to the controller, which uses a traditional PID control structure to turn high-level policy decisions into low-level control commands. The actuator layer carries out these commands, allowing the physical robot to move and do things that are particular to the task at hand. The controller and actuator layers both send system feedback back through special feedback channels. This feedback records how well the task was done, any mistakes made in controlling it, and the results of the task. A learning adaptation module works with the control loop to get this feedback and figure out reward signals that show how well the task is being done, how stable it is, and how much energy it uses. The learning module uses these rewards to change the control strategy in real time, which lets performance keep getting better. The design allows adaptable,

energy-efficient, and robust robotic behavior by having policy optimization and classical control work together in a single feedback loop. This happens through recurrent interaction with the environment. Typically, the execution procedure is driven by two principal streams.

- **Control Flow**: This encompasses the strategic maneuvers, operational directives, and control parameters that transition from task management to workflow coordination, culminating in the actual enactment of tasks. It serves as the backbone of the system execution, guiding the operational dynamics from one phase to the next.
- **Data Flow:** The data stream consists of real-time sensory inputs collected from robots actively engaged in the field. This data travels upstream, from the lower execution tiers to the higher strategic layers, enabling a feedback loop that fosters dynamic and dependable robot control within the system.

An organization then selects an appropriate ORPA system and decides on a robot deployment strategy, which can be executed on either physical or virtual machines. The next step involves translating a semi-formal process description into an executable ORPA process model. This model is then fed into a controller, which is configured and activated. The model's instructions are dispatched to the microcontroller, and the robots are deployed, utilizing the existing infrastructure of BPM (Business Process Management) deployment. Before it goes live, the installed ORPA system must undergo rigorous testing to ensure it operates as intended. Upon successful testing, robot process models are executed, and the ORPA infrastructure becomes fully functional. Experts in the field emphasize the importance of execution in the process selection for ORPA. Tasks performed with regularity are prime candidates for automation, as they enable economies of scale. Consequently, businesses can realize significant cost savings and maximize the benefits of automation. The execution characteristic is quantified in equation (50), which operationalizes it as a measure of a process's ambition for automation. In this equation, the execution measure E is calculated by counting the number of activities ac that are associated with a given process. This comprehensive delineation illustrates the interplay between the operational mechanics and strategic selection in ORPA, highlighting the efficiency gains and process improvements that can be achieved through methodical execution and automation.

Here, P_f is a finite set of processes, A_{ijk} is the stream of different activities, P_c is another component of processes, A_t is an activity type, and i, j, k are processes, cases, and tasks.

$$\boldsymbol{E_{ac}} = \sum_{\boldsymbol{I=0}}^{\boldsymbol{P_f}} \left|\{\boldsymbol{A_{ijk}} \in \boldsymbol{P_c} | \boldsymbol{A_{ijk}} \cong \boldsymbol{A_t}\}\right| \quad (\mathbf{53})$$

Lemma 2: When automation and business management capabilities are combined to create an efficient robot control system, the system's performance $\boldsymbol{S_p}$ can be maximized through task allocation $\boldsymbol{T_{al}}$ and use of resource management $\boldsymbol{R_m}$ using operational data obtained in real-time.

Proof: Let $\boldsymbol{T_{al}}$ be the task allocation for the robot $\boldsymbol{R_i}$ with $\boldsymbol{W_i}$ weight that is the precedence of the task, which has $\boldsymbol{R_{mt}}$ total available resources. Thus, the task allocation can be calculated as follows:

$$\boldsymbol{T_{al}} = \frac{\boldsymbol{W_i}}{\sum_{j=1}^{n} \boldsymbol{W_j}} \times \boldsymbol{R_{mt}} \quad (\mathbf{54})$$

Let $\boldsymbol{S_p}$ be the entire performance of the system requires efficiency $\Delta\boldsymbol{\rho}$ for the robot $\boldsymbol{R_e}$. Thus, the robot has a $\boldsymbol{R_u}$ resource utilization, and weigh factors that reflect the significance of resource utilization and efficiency. Therefore, optimized performance $\boldsymbol{P_{op}}$ can be calculated as follows:

$$\boldsymbol{P_{op}} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \left(\acute{\mathrm{R}}.\, \Delta\boldsymbol{\rho}\right). + \left(\acute{\mathrm{S}}.\, \boldsymbol{R_u}\right) \quad (\mathbf{55})$$

Controlling the robot, the RATD algorithm plays a vital role in ensuring the robustness of the robot. It keeps a check on planning outputs and sensory inputs continuously and identifies irregularities that could be signs of blind spots or planner attacks in real-time. The RATD allows the system to adjust and efficiently reduce potential threats. By taking a proactive stance, the robot is better able to withstand hostile environments and perform reliably and safely. RATD makes a major contribution to preserving the robustness and effectiveness of robotic automation. Algorithm 3 demonstrates how to manage both threats to safeguard the business automation process.

Algorithm 3: Robotic adversarial threat detection for securing the ORPABPM

1. **Initialization:** {S_I: Sensory inputs; P_O: Planning outputs; A_{Bl}: Detection of blindspot attack; A_{PL}: Detection of planner attack; T_{ad}: Threshold for anomaly detection; H_{as}: Historical data for normal sensory inputs; H_{np}: Historical data for normal planning outputs; A_{sc}: Anomaly score; A: Anomaly; C_d: Current data; H_d: Historical data}
2. **Input:** $\{S_I; P_O\}$
3. **Output:** $\{A_{Bl}; A_{PL}\}$
4. **Detect** S_I & H_{as}
5. **Calculate** $A_{sc} \leftarrow S_I$
6. **Calculate** $A_{sc}(A_{Bl}) = S_I + H_{as}$
7. **If** $A_{sc}(A_{Bl}) > T_{ad}$ then
8. Detect $A_{sc}(A_{Bl}) \in A$
9. **Else** $A_{sc}(A_{Bl}) \notin A$
10. **Detect** P_O & H_{np}
11. **Calculate** $A_{sc} \leftarrow P_O$
12. **Calculate** $A_{sc}(A_{PL}) = P_O + H_{np}$
13. **End-Else**
14. **End-If**
15. **If** $A_{sc}(A_{PL}) > T_{ad}$ then
16. **Detect** $A_{sc}(A_{PL}) \in A$
17. **Else** $A_{sc}(A_{PL}) \notin A$
18. **Initiate** $A_{sc}(C_d, H_d)$
19. **End-Else**
20. **End-If**
21. **Calculate** $D = \sqrt{\frac{\sum_{i=1}^{d_p}(C_d - H_d)^2}{d_p - 1}}$ //** calculate deviation

D between Current data C_d and historical data H_d using data point d_p

22. **Normalize** D for obtaining A_{sc}
23. **Perform** $A_{sc} = N(D)$ //** N: Normalize
24. **Found** A_{sc}
25. **Process** (S_I & P_O)
26. **Detect** A_{Bl} (S_I, H_{as})
27. **Detect** A_{PL} (P_O, H_{np})
28. **If** A_{Bl} =($lg + A_{Bl}$) then //** lg: Log
29. **Adjust** S_I to A_m //** A_m: mitigate attack
30. **End-If**
31. **If** A_{PL}==($lg + A_{PL}$) then
32. **Adjust** P_O to A_m
33. **Update** H_{as} with $C(S_I)$//** C: Current
34. **Update** H_{np} with $C(P_O)$
35. **End if**

Algorithm 3 detects malicious threats in a robotic system. The algorithm starts with variable initialization, which comprises planning outputs, sensory inputs, thresholds for detecting anomalies, history data for planning outputs and sensory inputs, anomaly scores, anomalies, current data, and historical data. They also include the detection of blind spots and planned attacks. Planning outputs and sensory inputs make up the input. The outcome is the identification of planner and blinspot attacks. The first step of the procedure is to identify sensory inputs and contrast them with previous sensory data. The sensory inputs are used to calculate an anomaly score. Then, to determine whether this score surpasses the predetermined threshold for anomaly detection, it is coupled with the past sensory data. A blindspot attack may be indicated if the anomaly score for the sensory inputs is higher than the threshold, showing the presence of an abnormality. The algorithm then looks for planning outputs and compares them with previous planning data if it doesn't go above the threshold. The historical planning data is merged with the derived anomaly score for planned outcomes. A discovered anomaly, suggesting a planned attack, is indicated if this anomaly score is greater than the threshold. The algorithm establishes the previous and current data for processing if it falls below the threshold. Using a certain calculation, the difference between the historical and current data is computed. The final anomaly score is then calculated by normalizing this divergence. To find any blind spots or planned attacks, the normalized anomaly score is calculated. To counteract a blindspot attack, the system recognizes the occurrence and modifies the sensory inputs. The system observes the occurrence and modifies the planning outputs to mitigate the planner attack if one is found. The present sensory inputs and planning outputs are updated concerning the past sensory data and planning data. To guarantee ongoing adversarial threat identification and mitigation in the robotic system, this approach is repeated iteratively. To adapt to changing conditions and increase the accuracy of threat detection, the algorithm maintains a process that receives sensory inputs and planning outputs, finds abnormalities, and updates historical data.

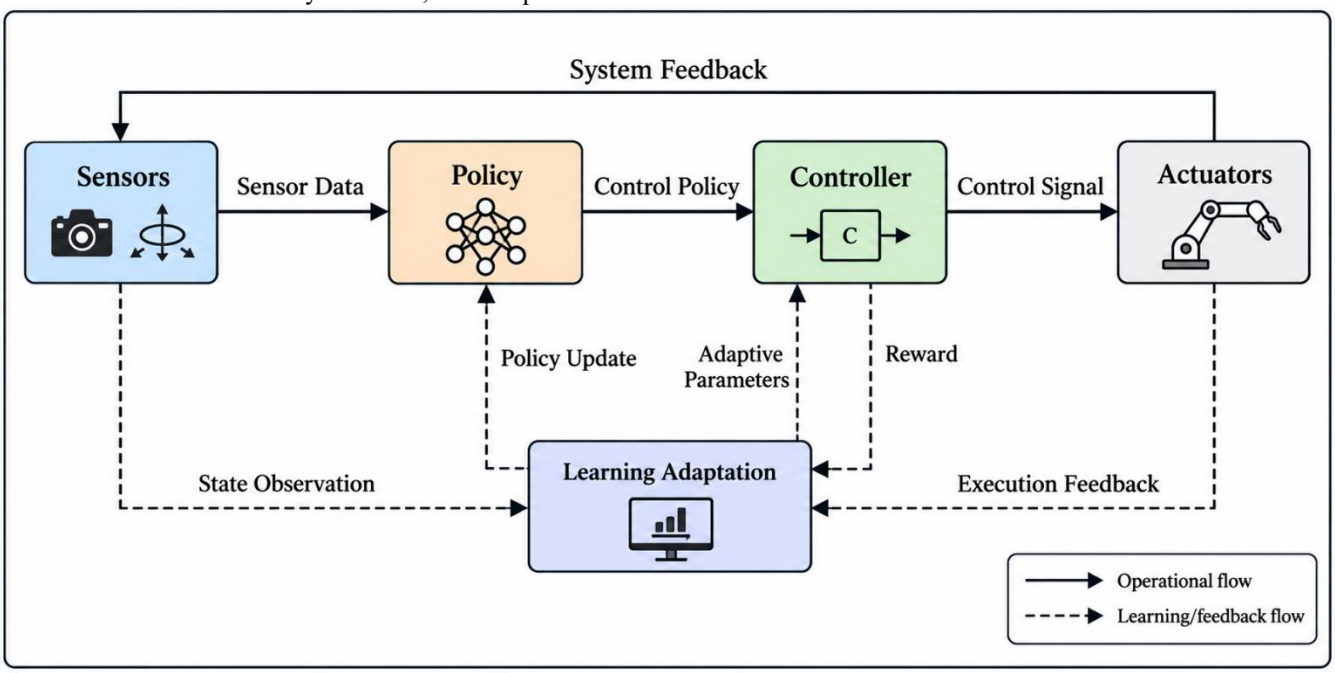


Fig 7. Closed-loop learning-based control architecture integrating sensing, policy adaptation, and actuator feedback

4.3.1. ROBOT MONITORING FOR AUTOMATION DATA

One of the major challenges in business monitoring is managing the vast amount of data generated daily by robots. It is crucial to not only access the precise data needed but also ensure it is readily available when required. The specific type of business information necessary can vary depending on the observer. For instance, a mechatronics engineer might need to investigate issues such as why a robot occasionally loses

balance, shuts down unexpectedly, or fails to grasp certain objects. Identifying these data points is essential for pinpointing potential areas of improvement within the broader business automation process. To address this challenge, robots can offer customizable monitoring options. Users can tailor their monitoring interface by adding or removing widgets that display specific telemetry streams. This customization is facilitated using HTML, JavaScript, and CSS, which are employed to create intuitive visualizations. Such configurations ensure that all essential information is not only visible at a glance but also organized in a manner that highlights the most relevant data according to user needs. This method significantly enhances data management capabilities, ensuring that vital insights are always accessible, which is crucial for quick decision-making and ongoing process optimization. In this system, we monitor the residuals for both continuous and discrete variables associated with every task performed by robots under Business Process Management (BPM), considering a series of input events (E_{input}). We diligently track the time series of both the input tasks $(\nabla u, \nabla \mho)$ and outputs $(O, \hat{O})$ that robots generate for BPM. This rigorous tracking facilitates effective monitoring, which, in turn, leads to measurable energy savings in robotic $M_{ef}(r)$ operations. These savings can be quantified using the following mathematical expression:

$$\boldsymbol{M_{ef}(r)} = \sum_{i=1}^{E_{input}} \sum_{k=1}^{T_t} \left(\left(\nabla u_{i,k}(T_t) - \nabla \mho_{i,k}(T_{tk}) \right) + \left(O_{i,k}(T_t) - \hat{O}_{i,k}(T_{tk}) \right) \right)^2 \quad (56)$$

where $\boldsymbol{T_{tk}}$ denotes the total number of tasks performed by the robot during each event, and $(\boldsymbol{E_{input}}')$ indicates the number of erroneous input events. Equation (56) allows us to effectively measure the precision and energy efficiency of the robotic tasks, highlighting the difference between expected and actual outputs, thereby aiding in the continuous improvement of energy management within the robotic processes.

4.3.2. EFFICIENT CUSTOMER EXPERIENCE

When considering technological investments, firms prioritize enhancing customer experience and boosting productivity. Intelligent automation emerges as a pivotal solution, capable of addressing critical bottlenecks in business processes and reinventing current operational frameworks. Key benefits include:

- Businesses can significantly cut costs by automating mundane tasks traditionally assigned to personnel, such as data entry and management. This shift not only saves money but also reallocates human resources to more strategic initiatives.
- By automating routine office procedures, such as paper filing, companies can free up valuable resources and time. This efficiency gain allows staff to focus on more critical projects, enhancing overall productivity and job satisfaction.
- Over half of businesses recognize that BPA substantially reduces workflow errors. By minimizing the risk of human mistakes, companies enhance reliability and improve operational quality.
- Intelligent automation facilitates faster processing of service information, enabling businesses to respond to customer needs more promptly and effectively. This improvement in service delivery can significantly enhance customer experience, fostering loyalty and satisfaction. Intelligent automation not only streamlines operations but also supports businesses in achieving a competitive advantage by enhancing efficiency and customer interaction. For the given statement about intelligent automation enhancing service delivery and customer experience, we can mathematically model the impact of automation on service efficiency and customer satisfaction. The reduction in processing time due to intelligent automation can be given by the equation:

$$\Delta T = T_{init}\left(1 - 1/\check{G}\right) \quad (57)$$

Improvement in customer satisfaction due to decreased processing times is:

$$\Delta S = pr_r.\Delta T = pr_r.T_{init}\left(1 - 1/\check{G}\right) \quad (58)$$

The final customer satisfaction can be described as:

$$S_{final} = S_{init} + \Delta S \quad (59)$$

Now, integrating these into a single equation also accounts for a competitive advantage C_A, we get:

$$sC_A = C_{ist}(S_{init} + pr_r.T_{init})(1 - 1/\check{G})) + e_{pr}.T_{init}(1/\check{G}) \quad (60)$$

where T_{init} is the initial average processing time for service requests, S_{init} is the initial customer satisfaction index, $\check{G}$ denotes the factor by which processing speed is enhanced due to automation, pr_r represents a coefficient representing the impact of reduced processing time on customer satisfaction, C_{ist} is a parameter that quantifies the direct impact of improved customer satisfaction on competitive advantage, and e_{pr} is a parameter that quantifies the impact of reduced processing time on overall efficiency, influencing competitive advantage. The equation (60) models competitive advantage C_A as a function of initial customer satisfaction S_{init}, enhanced by the product of a satisfaction impact constant pr_r and the reduction in processing time, plus a factor e_{pr} times the inverse of the processing time improvement, which represents efficiency gains. This formulation not only accounts for the direct benefits of automation on service delivery speed and customer satisfaction but also reflects how these improvements contribute to a broader competitive advantage by enhancing business efficiency and interaction quality. This model effectively combines several dimensions of business improvements due to intelligent automation into a single, quantifiable expression.

5. EXPERIMENTAL RESULTS

In this study, we developed a hybrid model that integrates both discrete and continuous characteristics to assess manufacturing system productivity and machine operations in real-time. We utilized deterministic systems with continuous dynamics to model robot operations, as detailed in reference [40]. This deterministic model was expanded to include the interactions of various components such as processors and buffers, allowing for a comprehensive examination of system-level behavior. We developed a strong data-collecting strategy utilizing Internet of Things (IoT) technology to enable real-time hybrid simulation, which is an inventive method for tracking and assessing industrial performance. Data was captured from an actual manufacturing testbed, specifically within the textiles industry, employing an IoT adaptor connected to a programmable logic controller (PLC). This setup enabled the temporary storage of performance monitoring variables on tags within the PLC. Data acquisition was structured around the PLC scan rates, which determined the key timing steps, capturing data in discrete intervals. We simulated PLC activities using Rockwell Automation's RSEmulate, with the interface configured via SimKit software. In our MATLAB-based simulation, both discrete and continuous signals were retrieved from the PLC through a Rockwell Automation IoT adaptor, illustrating the seamless integration of these technologies. Further enhancing our model, PLC logic was adapted to monitor and control the operations of Computerized Numerical Control (CNC) machinery. This included managing transitions within the CNC through a binary signal initiated by the PLC, which started the machining task and the turnover device (TOD). Upon completion of the machining operation, the CNC sent a binary signal back to the PLC, prompting the TOD to cease operation. This experimental setup not only demonstrates the practical application of integrating IoT and PLC technologies in a real-world manufacturing environment but also highlights the potential of hybrid models in improving the efficiency and precision of industrial operations. Table 2 organizes complex information about the experimental setup and methodologies used in the study, highlighting the integration of various technologies and approaches to improve industrial efficiency and productivity.

Table2. Summary of modeling parameters, technologies, and purposes used in the proposed manufacturing system framework

Parameters	Description	Technology/Method Used	Purpose
Model Type	Hybrid model integrating discrete and continuous characteristics	Deterministic systems, MATLAB	To assess manufacturing productivity and machine operations in real-time
System Components	Robots, processors, and buffers	Deterministic continuous dynamics	To model operations and interactions within the manufacturing system
Simulation Technology	Real-time hybrid simulation	IoT, PLC, RSEmulate, SimKit	For monitoring and evaluating manufacturing performance
Data Collection Strategy	Utilized IoT technology for robust data acquisition	IoT adaptor, PLC	To capture real-time data from manufacturing processes
Industry Focus	Textiles industry	Actual manufacturing testbed	Contextual implementation of the model
Data Storage	Temporary storage of performance monitoring variables	PLC tags	To facilitate intermediate data handling
Data Acquisition Timing	Structured around PLC scan rates	PLC	To determine the timing for capturing data in discrete intervals
Interface Configuration	Configured to integrate with the manufacturing system	RSEmulate, SimKit	To simulate PLC activities effectively

Signal Integration	Both discrete and continuous signals retrieved	Rockwell Automation IoT adaptor	To integrate data retrieval seamlessly
Control Operations	PLC logic adapted to monitor and control CNC machinery operations	PLC, CNC	
Machine Operation Management	Managing transitions within the CNC through binary signals	Binary Signals, PLC	To start and stop CNC tasks effectively
Task and Turnover Device	Transition management for machining tasks and turnover device (TOD)	PLC, Binary signal	To coordinate operations between CNC and TOD
Experimental Setup	Demonstrates practical application of IoT and PLC integration in a real-world manufacturing environment	IoT, PLC, CNC	To demonstrate the effectiveness of hybrid models in industrial operations

5.1. PERFORMANCE EVALUATION

Univariate and multivariate analysis of several performance variables is conducted to use as the foundation for the proposed approach, ORPABPM. We tracked cycle times for CNC, or the amount of time the machine is processing a part when in the "Busy" state. Robots' monitoring time is observed while completing pick-and-place tasks. SimMechanics is used to model machine dynamics. The 6-DoF robotics has been developed. The trajectory criteria for a certain activity are also carefully observed using MATLAB Robotics Toolbox. A PLC function is used for control purposes to manage an automated manufacturing process by coordinating tasks based on input/output signals. In a memory region called "tags," data from sensors and devices can be temporarily preserved. Furthermore, the binary or numeric values needed for performance analysis can be stored in tags. Based on the results, the state-of-the-art parameters have been evaluated (accuracy, energy efficiency, error rate, and throughput efficiency).

5.1.1. ACCURACY

The degree to which robots execute activities accurately and precisely by predetermined norms and expectations is referred to as accuracy when performing business tasks. It includes the proportion of jobs successfully finished without errors or requiring human assistance, the frequency of errors or variations from the intended results, and the performance consistency over time. It also entails following company rules, quality standards, and industry-specific laws to guarantee the accuracy and dependability of any data processed, saved, or sent by robots. It's critical to execute activities precisely, particularly those involving fine motor skills or delicate manipulations, and to do them within the allotted time range without sacrificing quality or precision. The accuracy of five distinct methods: (RFIDTS, ISWMS, AIWCMS, RPABPM, and ORPABPM) across a range of completed jobs, from 0 to 30,000, is shown in Figure 8A. The number of tasks completed is represented by the x-axis, and the accuracy percentage, which ranges from 98.0% to 100%, is represented by the y-axis. All methods demonstrate an increase in accuracy as the number of tasks rises. RFIDTS eventually increases to about 99.5% after starting with about 98.4%. Starting at almost 98.5%, AIWCMS increases to over 99.7%. ISWMS rises to roughly 99.3% from a starting point of about 98.6%. RPABPM exhibits a greater early accuracy, peaking at 99.9% after beginning at 99.1%. Our proposed ORPABPM method regularly performs better than the others. As the number of tasks increases, it steadily rises from a starting point of 99.95% to a stable 100%. This steady high accuracy is evidence of the precision and robustness of the approach. The accuracy of a variety of completed tasks, from 0 to 70,000, is displayed in Figure 8B. The accuracy percentage, which ranges from 96.0% to 100%, is shown on the y-axis, while the x-axis indicates the number of tasks completed. All approaches show varied degrees of accuracy improvement as the number of tasks grows. RFIDTS eventually rises to about 98.5% from a starting point of about 96.4%. AIWCMS starts at roughly 96.6% and rises to over 98.7%. ISWMS rises to roughly 98.9% from a starting point of about 96.8%. RPABPM exhibits a higher early accuracy, peaking at 99.3% after beginning at 97.0%.

Our proposed ORPABPM method consistently achieves the best accuracy across the board for all activities. It begins at 99.9% and stays steady at 100% even though the number of tasks gets closer to 70,000. The ORPABPM approach's resilience and reliability are demonstrated by its consistently high accuracy. There are other reasons behind ORPABPM's higher accuracy. It probably incorporates precise error detection and correction systems, guaranteeing that jobs are finished with the fewest possible mistakes. The strategy might

include real-time feedback and monitoring technologies that provide quick corrections and ongoing learning, improving the accuracy of task execution. Furthermore, ORPABPM may make use of optimized task processing methods, like effective resource allocation and data management, which lower error rates while preserving high precision. Collectively, these cutting-edge capabilities provide ORPABPM an advantage over other approaches in achieving and maintaining near-perfect accuracy. The accuracy of the robot A_r after planner/blind spot attacks can be determined as follows:

$$A_r = A_r(i) - (A_{ra}.A_n) \quad (61)$$

where $A_r(i)$ denotes the initial accuracy when no attacks are launched, A_{ra} is the rate of accuracy decay per attack, and A_n is the number of blindspot/planner attacks.

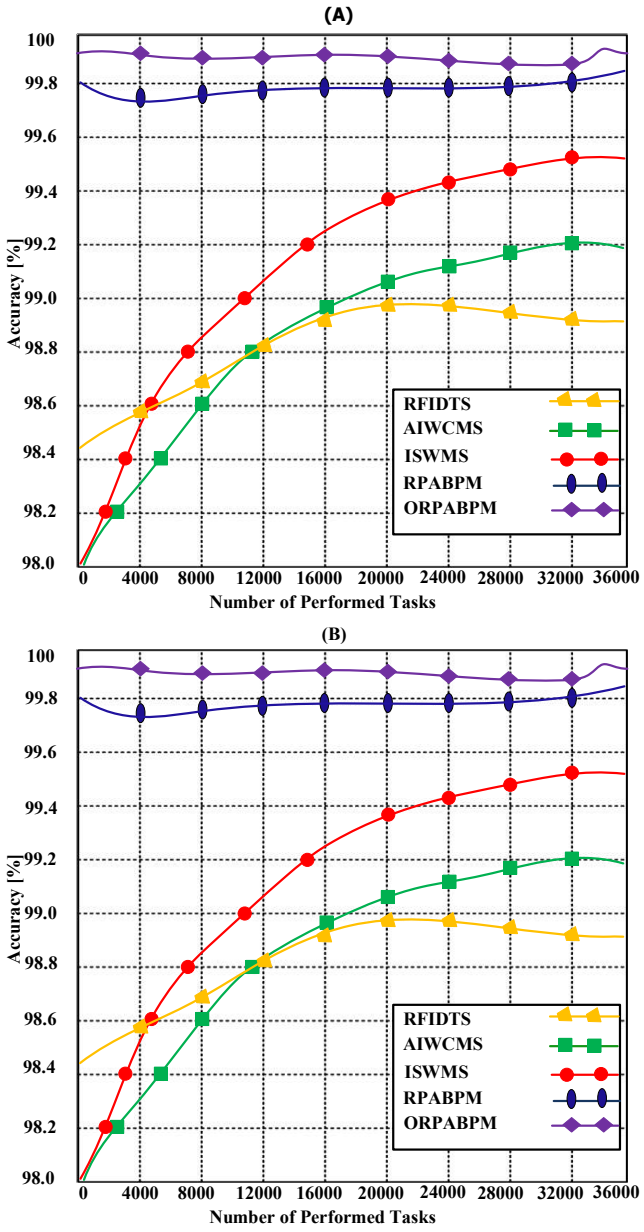


Fig 8A. Accuracy of the proposed ORPABPM and competing methods RFIDTS, ISWMS, AIWCMS, and RPABPM with a maximum of 36000 performed tasks, **B.** Accuracy of the proposed ORPABPM and competing methods RFIDTS, ISWMS, AIWCMS, and RPABPM with a maximum of 72000 performed tasks

5.1.2. ENERGY EFFICIENCY

The energy efficiency of robots during task execution is determined by the ratio of the number of tasks finished to the energy used. This metric shows how well a robot uses energy to carry out its tasks. A robot with high energy efficiency can carry out a lot of activities with little energy consumption, which reflects outstanding efficiency and resource management. The robot's task execution algorithms, resource management strategies, real-time monitoring, and adaptive modifications are some of the factors that affect energy efficiency. Robots that are efficient use less energy and complete tasks faster, which leads to more economical and sustainable operations. The correlation between power consumption (measured in kilowatt-hours, KWH) and the number of tasks completed by robots utilizing various methodologies, including RPABPM, ORPABPM, RFIDTS, AIWCMS, and ISWMS, is depicted in Figure 9A. Power usage is represented by the x-axis, which ranges from 0 to 117 KWH, and the number of jobs completed is represented by the y-axis, which ranges from 0 to 40,000. With a maximum workday of two hours and an hourly power usage of 0.14 kW, each robot can consume up to 0.84 KWH of power every day. Figure 9B illustrates how, for all methodologies, the number of jobs completed rises in tandem with power consumption.
Methods differ in terms of efficiency when it comes to the number of tasks completed per unit of power used. Starting lower on the curve, RFIDTS progressively rises to a peak of 20,000 tasks at 117 KWH. The rise in AIWCMS is more pronounced, reaching about 25,000 tasks at 117 KWH. At 117 KWH, ISWMS shows a moderate improvement, completing about 28,000 tasks. RPABPM has improved significantly, achieving around 32,000 jobs at 117 KWH. Our proposed ORPABPM method has the best efficiency, completing roughly 38,000 jobs at 117 KWH. The correlation between energy efficiency (measured in kilowatt-hours, KWH) and the number of activities completed by robots utilizing various methodologies, including RFIDTS, ISWMS, AIWCMS, RPABPM, and ORPABPM, is depicted in Figure 8(b). Power usage is indicated by the x-axis, which ranges from 0 to 135 KWH, and the number of jobs completed is represented by the y-axis, which ranges from 0 to 47,000. With a maximum workday of six hours and an hourly rate of 0.14 kW, each robot can consume up to 0.84 KWH of power every day.
For all approaches, the number of activities completed rises with power usage, although their efficiency differs: Starting at a lower point on the curve, RFIDTS performs around 19,000 tasks at 135 KWH. The rise in AIWCMS is more pronounced, reaching about 25,000 tasks at 135 KWH. The ISWMS has

shown some improvement, completing about 28,000 tasks at 135 KWH. RPABPM has improved significantly, hitting around 33,000 jobs at 135 KWH. Our proposed method, ORPABPM, has the best efficiency, completing roughly 41,000 jobs at 135 KWH. Multiple components contribute to ORPABPM's high energy efficiency performance. It probably incorporates cutting-edge algorithms that maximize task performance and lower the amount of energy needed for each activity. The strategy may also make use of effective resource management strategies, guaranteeing that energy usage is kept to a minimum while job throughput is maximized. Furthermore, as tasks become more complicated, ORPABPM may include adaptive modifications and real-time monitoring to maintain high accuracy and efficiency.

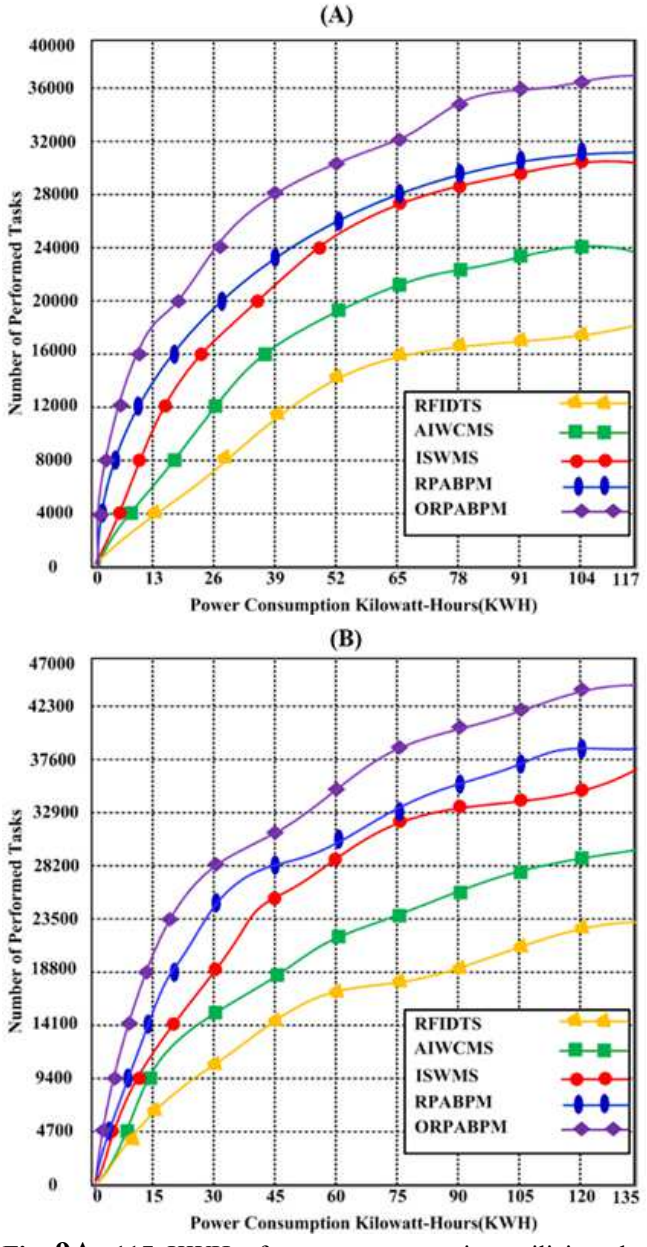


Fig 9A. 117 KWH of power consumption utilizing the proposed ORPABPM and competing approaches: RFIDTS, ISWMS, AIWCMS, and RPABPM for a maximum of 40000 completed tasks, **B.** 135 KWH of power consumption utilizing the proposed ORPABPM and competing approaches: RFIDTS, ISWMS, AIWCMS, and RPABPM for a maximum of 47000 completed tasks

When compared to the other approaches, ORPABPM can do a notably greater number of tasks per unit of energy consumed because of these properties together. The energy efficiency R_{ee} can be calculated as follows:

$$R_{ee} = \frac{R_{tp}}{R_{ce}} \tag{62}$$

where R_{tp} denotes the energy efficiency of the robot when performing tasks, and R_{ce} is the energy consumed in kilowatt-hours (KWH)

5.1.3. ERROR RATE

Figure 10A shows the error rate as an indicator of the number of attacks that are launched through a blind spot. RFIDTS, RPABPM, AIWCMS, ORPABPM, and ISWMS demonstrate different error rates. Each line illustrates how the error rate rises with the number of attacks, demonstrating the robustness and efficiency of any approach against blind spot attacks. When it comes to blind spot attacks, the proposed ORPABPM outperforms the other approaches with the lowest error rate across all attack rates. Both RPABPM and ISWMS exhibit moderate increases in error rates; however, RPABPM exhibits a marginally greater error rate than ISWMS. RFIDTS has the highest error rate among the approaches under consideration, indicating that it is the most vulnerable to blind spot attacks. A critical study of these results indicates that ORPABPM is the most effective defense approach against blind spot attacks, consistently achieving the lowest mistake rates. AIWCMS also works well, however, it is less robust than ORPABPM. ISWMS and RPABPM are reasonably effective, but their efficacy degrades faster as the number of attacks grows. RFIDTS exhibits the least resilience, with an instant rise in error rate, indicating great vulnerability to blind spot attacks. The efficiency of these defense systems appears to be heavily reliant on their capacity to manage and mitigate the specific risks provided by blind spot attacks, with ORPABPM emerging as the most dependable strategy. Figure 10B depicts the error rate as a percentage of the total number of planner attacks launched for the approaches (ORPABPM, AIWCMS, ISWMS, RPABPM, and RFIDTS).

The error rate for all approaches increases as more planner attacks are executed. The error rates for 200 attacks are approximately 0.015% for ORPABPM, 0.02% for AIWCMS, 0.025 for ISWMS, 0.03% for RPABPM, and 0.035% for RFIDTS. For 600 attacks, RPABPM has an error rate of about 0.04%, RFIDTS about 0.05%, AIWCMS about 0.03%, ISWMS about 0.035, and ORPABPM about 0.02%. The error rates for ORPABPM, AIWCMS, ISWMS, RPABPM, and RFIDTS are approximately 0.03%, 0.045%, 0.05%, and 0.065%, respectively, for 1000 attacks. The error rate for 1400 attacks is roughly 0.035% for ORPABPM, 0.055% for AIWCMS, 0.06% for ISWMS, 0.065% for RPABPM, and 0.075% for RFIDTS. The approximate error rates for

ORPABPM, AIWCMS, ISWMS, RPABPM, and RFIDTS for 1800 attacks are 0.04%, 0.065%, 0.07%, and 0.09%, respectively. These statistical findings show that ORPABPM is more resilient than other planner attacks, continuously maintaining the lowest error rates under escalating planner attacks. Following with moderate error rates, AIWCMS performs better than RFIDTS, RPABPM, and ISWMS. The error rates of ISWMS and RPABPM are comparable, with ISWMS outperforming it by a small margin. The largest error rates are observed in RFIDTS, demonstrating a high degree of vulnerability to planner attacks.

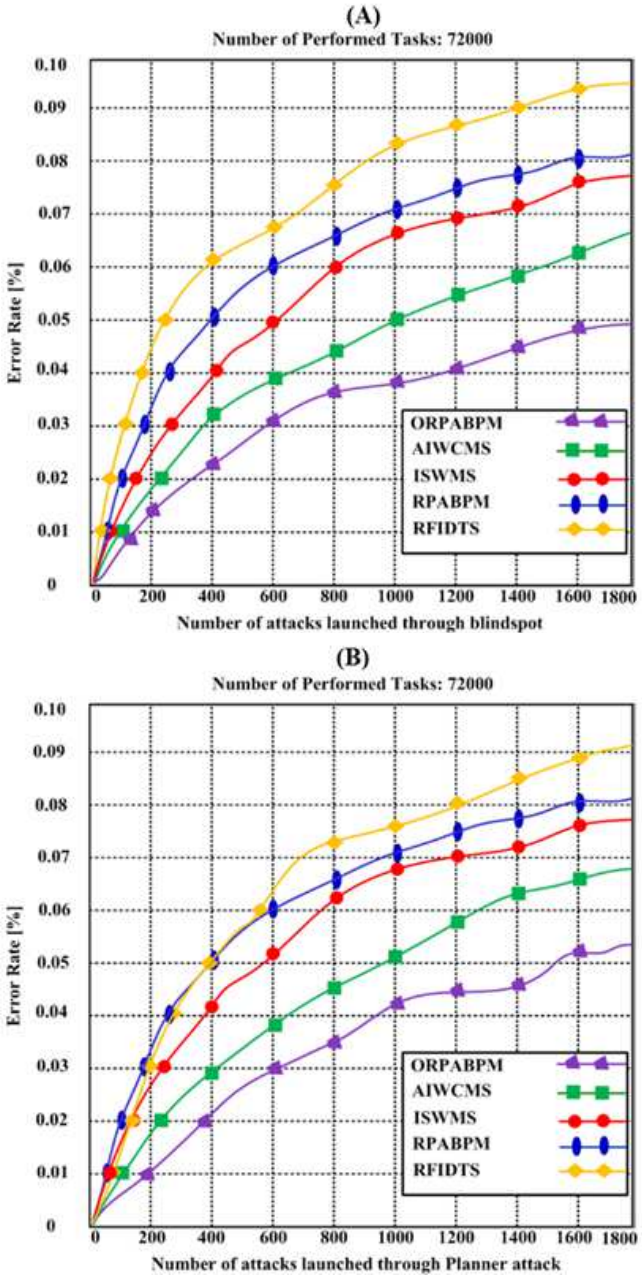


Fig 10A. Error rate of proposed ORPABPM and competing approaches: RFIDTS, ISWMS, AIWCMS, and RPABPM using blindspot attack, **B.** Error rate of proposed ORPABPM and competing approaches: RFIDTS, ISWMS, AIWCMS, and RPABPM using planner attack

The different levels of robustness among the various approaches are highlighted by the steady increase in error rates with the number of attacks, where ORPABPM is the most effective and RFIDTS is the least effective. Error rate E_r can be calculated as follows:

$$E_r = E_{ri} + \tau . A_n \tag{63}$$

where E_{ri} is the initial error rate when no attacks are launched, and τ denotes the rate of increase in the error rate per attack.

5.1.4. THROUGHPUT EFFICIENCY

Figure 11A illustrates the efficacy of the proposed ORPABPM technique. It commences at 100% throughput efficiency with zero jobs completed and progressively declines to approximately 95% after 40,000 tasks. This signifies that ORPABPM sustains superior efficiency relative to alternative protocols, even with escalating workloads. Figure 11B depicts the RPABPM protocol. Commencing at approximately 97% throughput efficiency, its performance progressively diminishes to roughly 88% following 40,000 tasks. The decline is more pronounced than ORPABPM. Figure 11C illustrates the RFIDTS protocol. It commences with a throughput efficiency of 95% and diminishes to roughly 85% following 40,000 tasks. This persistent decline suggests that, although initially robust, RFIDTS diminishes in efficiency more rapidly than ORPABPM and RPABPM as task volume escalates. Figure 11D illustrates the ISWMS procedure. It commences at 94% efficiency and declines to approximately 83% upon the completion of 40,000 tasks. This indicates a greater efficiency loss relative to the other protocols, implying diminished scalability under substantial workloads. Figure 11E illustrates the AIWCMS protocol. Commencing at 96% efficiency, it diminishes to approximately 86% following 40,000 tasks. The performance is situated between RFIDTS and RPABPM, signifying intermediate efficiency preservation under substantial load. Figure 11F amalgamates all five methods for direct comparison. ORPABPM routinely surpasses its competitors, maintaining a performance level over 95% even under extreme workload conditions. RPABPM, RFIDTS, ISWMS, and AIWCMS all exhibit a more pronounced drop, with ISWMS demonstrating the lowest efficiency at approximately 83%. This integrated perspective emphasizes the enhanced throughput efficiency and resilience of the proposed ORPABPM protocol.

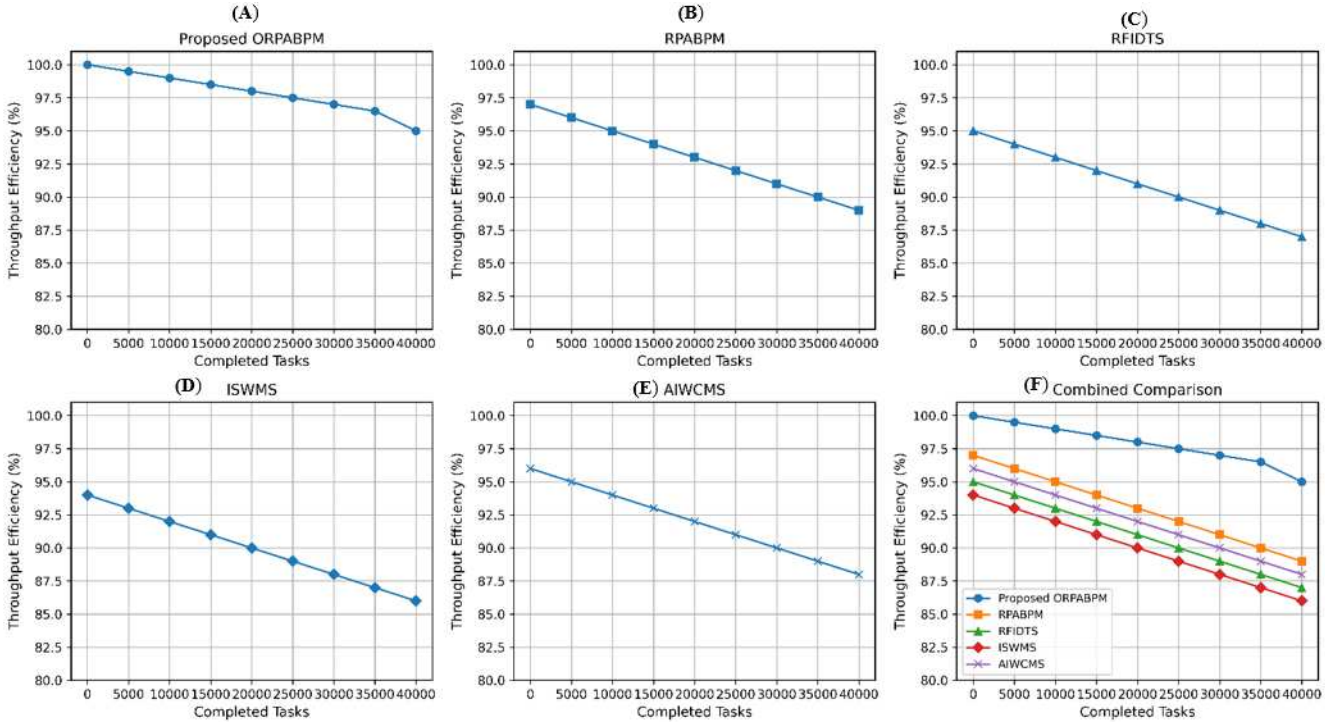


Fig 11A-F. Throughput efficiency across ORPABPM, RPABPM, RFIDTS, ISWMS, and AIWCMS protocols for 0–40,000 completed tasks. The proposed ORPABPM demonstrates the highest performance, sustaining efficiency from 100% to 95%, while RPABPM, RFIDTS, AIWCMS, and ISWMS exhibit sharp declines to 88%, 85%, 86%, and 83%, respectively

5.1.5. STATISTICAL VALIDATION AND ABLATION STUDY

Figure 12 presents the ablation and statistical evaluation of the complete ORPABPM framework and three reduced variants over 10 independent runs. As can be seen in Fig. 12 (a), the full ORPABPM achieves the highest accuracy of 99.24%, which is higher than 98.00% without EEAR, 98.40% without RATD, and 98.24% without adaptive learning. The narrow 95% confidence intervals indicate that the performance was stable over the independent runs. The Bonferroni-adjusted comparisons indicate that all differences are statistically significant ($p < 0.001$). Figure 12 (b) shows that the complete framework provides the highest energy efficiency of 340.4 tasks/kWh. The largest reduction is obtained by removing EEAR, where energy efficiency drops to 273.9 tasks/kWh. The variants without RATD and adaptive learning get 315.5 and 300.9 tasks/kWh, respectively. These results confirm EEAR is the main contributor to energy-aware robotic operation, but RATD and adaptive learning also contribute to efficiency improvements. In Fig. 12 (c), complete ORPABPM achieves a throughput efficiency of 95.1%. This value decreases to 89.5% without EEAR, 92.0% without RATD, and 90.7% without adaptive learning. Therefore, all three components contribute to efficient task processing, with EEAR and adaptive learning producing the largest improvements in throughput under the evaluated workload. Figure 12(d) evaluates resilience against blind-spot and planner attacks. Complete ORPABPM achieves 96.6% attack resilience, whereas removing RATD reduces resilience to 87.5%, representing the largest security-related degradation. The framework without EEAR achieves 93.9%, while the variant without adaptive learning obtains 91.5%. These results indicate that RATD is necessary for attack detection and mitigation and adaptive learning improves the framework's ability to respond to changing adversarial environments. The heatmap in Fig. 12(e) provides a component-level interpretation of the performance losses. Without EEAR, the largest energy-efficiency loss is 19.0%, and the throughput reduction is 5.9%. The largest loss of attack-resilience is due to the removal of RATD, at 8.9%, while the removal of adaptive learning results in reductions in energy efficiency, throughput and resilience of 11.7%, 4.5% and 5.1% respectively. Thus, each component has its unique functional contribution: EEAR mainly enhances energy utilization; RATD offers security protection; adaptive learning facilitates performance optimization and operational adaptation. Finally, Fig. 12 (f) reports Cohen's d effect sizes between each ablation variant and complete ORPABPM. All effect sizes exceed the conventional large-effect threshold of $d = 0.8$ and range from 2.7 to 8.7. The largest effects are observed for removing EEAR from the energy-efficiency evaluation ($d = 8.7$) and removing RATD from the attack-resilience evaluation ($d = 8.2$). Together with the adjusted significance results, these large effect sizes demonstrate that the improvements produced by the complete framework are statistically significant and practically substantial.

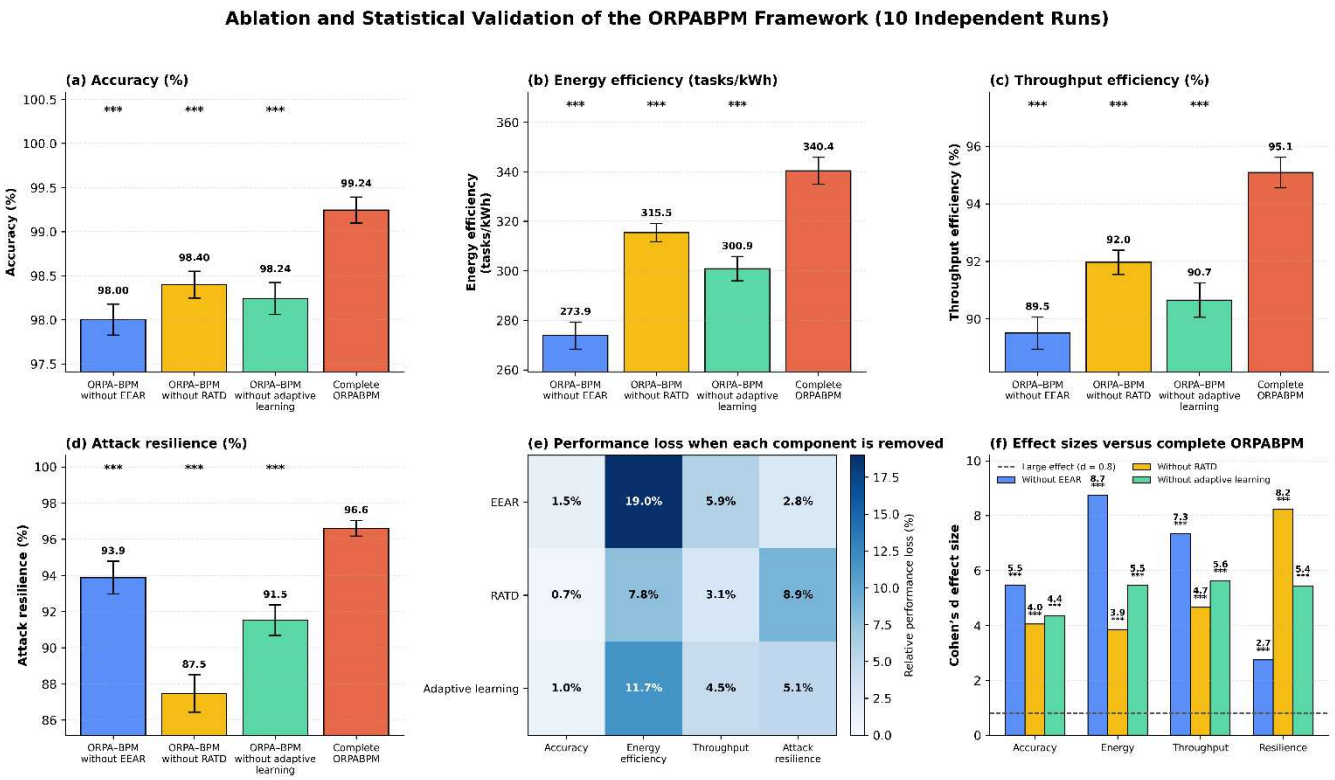


Figure 12. Ablation and statistical validation of the proposed ORPABPM framework over 10 independent runs: **(a)** task-execution accuracy, **(b)** energy efficiency, **(c)** throughput efficiency, **(d)** resilience against adversarial attacks, (e) relative performance degradation caused by removing individual components, and **(f)** Cohen's d effect sizes for comparisons with the complete ORPABPM framework. Bars represent mean values with 95% confidence intervals. Statistical significance was determined using Bonferroni-adjusted comparisons ($p < 0.05$, $*p < 0.01$, and $p < 0.001$

6. Discussion of Results

The primary advantage of the ORPABPM architecture that has been suggested is its pragmatic approach to incorporating ORPA into BPM systems. This strategy makes it easier for ORPA to be adopted and implemented in companies with pre-existing BPM infrastructures and expertise. In contrast to ad hoc approaches, which necessitate customized development, businesses can make use of and build upon the structured ORPABPM lifecycle, improving scalability and lowering the risk of project failures by utilizing tried-and-true BPM processes and technologies. By utilizing the comprehensive process information generated throughout the BPM lifecycle, the integration of ORPA with BPM not only makes the most of already existing BPM assets but also solves major drawbacks of independent ORPA systems. This integration allows for the management of various ORPA processes, enhancing scalability and operational efficiency. The information generated in the analysis and enactment phases of BPM is crucial for identifying opportunities to develop new ORPA applications or refine existing ones. BPM's established documentation and standards further support process optimization and consistency across non-ORPA-controlled processes. Using established BPM methodologies and technologies, which have been rigorously tested and proven, greatly reduces the risk of project failures. BPM's scalability allows for effective management across multiple processes, and its full integration with ORPA ensures that various ORPA tasks can be scaled accordingly. The ORPA-aware lifecycle not only addresses some traditional limitations of ORPA by utilizing the detailed process information generated during the BPM lifecycle but also provides a foundation for identifying and refining ORPA processes. Furthermore, the ORPA-aware lifecycle considerably lessens typical ORPA difficulties. By standardizing answers to business exceptions, BPM's strong exception-handling capabilities, for example, lessen the load on employees. Furthermore, RPA process faults can be identified and fixed more quickly thanks to BPM's technological tools, which promote more dependable and error-free operations. Notwithstanding these advantages, it is important to pay attention to a few

ORPABPM approach drawbacks. The framework falls short in addressing essential organizational culture modifications including role reorganizations and staff training. Incorporating ORPA into BPM successfully necessitates not just technological integration but also making sure that staff members are ready and receptive of the change. The ability for ORPABPM to reach its maximum efficacy may be hampered if these human variables are not taken into consideration. Although the ORPABPM paradigm automates processes to improve overall process management, it does not provide solutions tailored to ORPA needs. Not enough attention is paid to issues like specific testing settings for ORPA processes. This may have an impact on the ORPA systems' resilience and flexibility to changing operating environments. There are currently no sophisticated tools in the lifecycle that are designed to handle exceptions and errors unique to ORPA procedures. This mistake can make it more difficult for the system to deal with unforeseen problems unique to ORPA. When it comes to laying out clear expectations and getting the system ready for smooth integration and operation, the ORPABPM approach falls short in the pre-implementation stages. In summary, the comparison results in Table 3 demonstrate that the ORPABPM framework is a considerable improvement over current techniques; however, resolving these limitations could improve the framework's applicability and efficacy in a variety of business situations. Subsequent improvements ought to concentrate on incorporating all-encompassing strategies for managing organizational transformation, creating solutions tailored specifically for ORPA, and improving specificity and documentation across the whole lifecycle.

Table 3. Comparative performance of the proposed ORPABPM and contending approaches

Approaches	Accuracy with 36000 tasks	Accuracy with Max: 72000 tasks	Error Rate with Blindspot Attack	Error Rate with Planner Attack	Completed Tasks with Max: 117 (KWH) Power Consumption	Completed Tasks with Max: 135 (KWH) Power Consumption
ORPABPM	99.7%	99.3%	0.035%	0.053%	35,000	46,000
AIWCMS	99.5%	96.8%	0.06%	0.068%	28,000	36,000
ISWMS	99.3%	96.1%	0.07%	0.078%	24,000	33,000
RPABPM	99.6%	97.0%	0.08%	0.081%	22,000	30,000
RFIDTS	98.7%	95.4%	0.09%	0.091%	14,000	18,000

7. Conclusion and Research Implications

This section highlights the suggested approach's overall outcome as well as its implications.

A. Conclusion

This study has shown how ORPA and BPM may work together with a complete solution that includes five essential stages: strategic design, strategic business modeling, robot control, robot monitoring for automation data, and efficient customer experience. For business processes to successfully automate and achieve energy efficiency, several stages are essential. Using synergies that improve the technology and methodology of BPM tools, our strategy integrates ORPA into the larger BPM framework. We have verified the technological viability of smoothly incorporating ORPA activities into current BPM systems with the least amount of disturbance, preserving the integrity of business process management principles, using real-time testbed simulations. The proposed ORPABPM model not only facilitates more efficient automation but also significantly reduces energy consumption compared to other state-of-the-art methods: (RPABPM, ISWMS, AIWCMS, and RFIDTS). The EEAR algorithm automates business tasks and verifies increased energy efficiency. (Identifying energy-intensive processes, assessing present workflows, designing an ORPA solution, implementing ORPA in a real environment, monitoring, and evaluation) are the phases included in the EEAR. Better performance, enhanced functionality, and lower costs are ensured by employing a methodical problem-formation process to test the optimum integration of ORPA with BPM. Furthermore, two typical attacks that often cause the robotic automation process to fail (planner and blindspot) are addressed by employing the RATD algorithm. The RATD effectively detects these attacks in real-time to enhance system security. The robot's sensory inputs and decision-making processes are continuously monitored and adjusted by the RATD algorithm, which ensures maximum effectiveness and protection against both attacks. The robustness and resilience of robotic automation are significantly increased by this contribution in a range of applications. The findings emphasize the potential of ORPABPM and prove that the proposed ORPABPM outperforms other state-of-the-art contending approaches in terms of accuracy, energy efficiency, and error rate. The

results provide more sustainable and efficient business practices. This study sets a foundation for future research in the integration of process automation technologies within industry settings, aiming at continuous improvement and innovation in process management.

B. Practical and Research Implications

Research and practical implications When integrating existing technologies and directing future advancements, ORPA and BPM are important factors to take into account. This is how the landscape might be shaped by these implications.

i. Practical Implications

The ORPABPM paradigm can be implemented by organizations to optimize their processes in a variety of areas. Businesses can lower operational expenses dramatically by implementing the five steps of design, modeling, execution, monitoring, and optimization. This approach not only increases efficiency but also yields significant energy savings. The testbed simulations show how ORPA can be successfully integrated into current BPM frameworks, and this can serve as a model for companies who want to improve their process automation without having to completely rebuild their systems. This concept provides a workable approach to smoothly and minimally disrupting the integration of advanced automation technology. The ORPABPM model's notable energy consumption decrease is consistent with companies' increasing need to adopt sustainable practices. Businesses can use this model to increase operational efficiency and make a positive impact on the environment. Organizations that use the ORPABPM paradigm can outperform those that stick with less integrated ORPA solutions or traditional BPM. Faster processing times, fewer errors, and cheaper operating expenses are examples of this benefit.

ii. Research Implications

The current study lays the groundwork for future investigations to test and improve the ORPABPM model in a range of sectors and organizational sizes. Future studies could examine the model's flexibility and scalability in various contexts. More advanced error management techniques and diagnostic tools that are tailored for combined ORPA-BPM systems are required. The improvement of automation systems' resilience and dependability could be the main goal of this field's research. Subsequent research endeavors ought to investigate the potential integration of nascent technologies, such as artificial intelligence and machine learning, with the ORPABPM framework. The creation of self-optimizing systems that dynamically adjust to shifting business contexts may result from this integration. The socio-technical effects of incorporating ORPA into BPM, particularly as they relate to workforce roles, skill needs, and organizational structure, should also be taken into account in research. Designing more effective transition strategies for technology adoption can be aided by an understanding of these shifts. To determine the precise advantages of the ORPABPM model over other cutting-edge technologies, such as the AI warehouse control and management system and the integrated solid waste management system, more comparative research is necessary. These kinds of studies may be useful in identifying the special qualities and situational benefits of the ORPABPM methodology.

C. Future Work

The incorporation of ORPA into BPM offers auspicious prospects for augmenting organizational functions. Future studies ought to concentrate on examining the integration's wider effects, especially as they relate to corporate workforce development and process enhancement. It is critical to comprehend how ORPA affects worker responsibilities, skill advancement, and organizational structure. Examining these relationships might help businesses better educate their personnel for the rapidly changing technology environment. Furthermore, even though ORPA greatly increases process dependability and efficiency, there is still cause for concern regarding the mistake rates in ORPA workflow executions. Subsequent research endeavors ought to explore the creation of specialized testing methodologies specifically designed for ORPA systems. Enhancing the resilience and dependability of ORPA installations, these strategies should seek to better identify, reduce, and manage failures. To predict and prevent problems before they impact workflow, research should be done on developing sophisticated diagnostic tools and procedures. In addition, as ORPA develops further, it will be important to look at how it works with newer technologies like machine learning and artificial intelligence. Further reduction of the amount of manual labor needed for process management and oversight could result from this investigation into intelligent ORPA solutions that can learn and adapt to new processes dynamically. Future research in these areas will push the frontiers of automation technology in business environments and help to better understand and develop ORPA implementations. Ensuring that ORPA implementations optimize operational savings and increase strategic results across sectors is contingent upon this trend.

Acknowledgement: This research has been funded by the Committee of Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan under Grant No. BR24993051, under the thematic focus: 'Development of an Intelligent city system based on IoT and data analysis, and the authors would like to thank the support of Princess Nourah bint Abdulrahman University Researchers Supporting Project number (PNURSP2026R751), Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia.

Funding: This research has received funding from the Committee of Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan under Grant No. BR24993051.

Availability of Data and Materials: The datasets and experimental configurations used to support the findings of this study are available from the corresponding author upon reasonable request. Simulation environments used in this work include Rockwell Automation RSEmulate and MATLAB platforms, which were employed to validate the proposed ORPABPM framework.

Conflicts of Interest: The authors declare no conflict of interest regarding the publication of this article. The research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Ethics Approval: This study does not involve human participants, animals, or personal data. Therefore, ethical approval was not required for this research. All experiments were conducted using simulation environments and computational models.

REFERENCES

[1] Park A, Jung SY, Yune I, Lee HY. Applying robotic process automation to monitor business processes in hospital information systems: Mixed method approach. *JMIR Med Inform*. 2025;13:e59801. DOI: https://doi.org/10.2196/59801

[2] Nalgozhina N, Razaque A, Uskenbayeva R, Yoo J. Developing robotic process automation to efficiently integrate long-term business process management. *Technologies*. 2023;11(6):164. OI: https://doi.org/10.3390/technologies11060164

[3] Shah R, Doss ASA, Lakshmaiya N. Advancements in AI-enhanced collaborative robotics: Towards safer, smarter, and human-centric industrial automation. *Results Eng*. 2025;105704. DOI: https://doi.org/10.1016/j.rineng.2025.105704

Chu CH, Weng CY. Experimental analysis of augmented reality interfaces for robot programming by demonstration in manufacturing. *J Manuf Syst*. 2024;74:463–476. DOI: https://doi.org/10.1016/j.jmsy.2024.05.012

[4] Shah IA, Jhanjhi NZ, Amsaad F, Razaque A. The role of cutting-edge technologies in Industry 4.0. In: *Cyber Security Applications for Industry 4.0*. Boca Raton: CRC Press; 2022. p.97–109.

[5] Obosu M, Frimpong S. Advances in automation and robotics: The state of the emerging future mining industry. *J Saf Sustain*. 2025.
DOI: https://doi.org/10.1016/j.jss.2025.100012

[6] Shamsuzzoha A, Pelkonen S. A robotic process automation model for order-handling optimization in supply chain management. *Supply Chain Anal*. 2025;9:100102. DOI: https://doi.org/10.1016/j.sca.2024.100102

[7] Cheng X, Zhou J, Zhou Z, Zhao X, Gao J, Qiao T. An Improved RRT-Connect path planning algorithm of robotic arm for automatic sampling in Industry 4.0. *J Ind Inf Integr*. 2023;33:100436. DOI: https://doi.org/10.1016/j.jii.2023.100436

[8] Wang L, Liu S, Liu H, Wang XV. Overview of human-robot collaboration in manufacturing. In: *Industry 4.0: Managing the Digital Transformation*. Springer; 2020.

Li C, Zheng P, Yin Y, Wang B, Wang L. Deep reinforcement learning in smart manufacturing: A review and prospects. *CIRP J Manuf Sci Technol*. 2023;40:75–101. DOI: https://doi.org/10.1016/j.cirpj.2022.11.003

[9] Hong Y, He X, Xu J, Yuan R, Lin K, Chang B. AF-FTTSNet: End-to-end convolutional neural network for robotic welding quality monitoring. *J Manuf Syst*. 2024;74:422–434. DOI: https://doi.org/10.1016/j.jmsy.2024.04.006

[10] Wewerka J, Reichert M. Robotic process automation: A systematic mapping study and classification framework. *Enterp Inf Syst*. 2021.
DOI: https://doi.org/10.1080/17517575.2021.1882181

[11] González M, Rodríguez A, López-Saratxaga U, Pereira O, López de Lacalle LN. Adaptive edge finishing through robot-assisted computer vision. *J Manuf Syst*. 2024;74:41–54. DOI: https://doi.org/10.1016/j.jmsy.2024.02.003

[12] Bu S, Jeong UA, Koh J. Robotic process automation: A new enabler for digital transformation and operational excellence. *Bus Commun Res Pract*. 2022;5(1):29–35. DOI: https://doi.org/10.22682/bcrp.2022.5.1.29

[13] Mehta R, Chaher R. Implementation of robotic process automation in digital marketing. In: *Proc. Int Conf Emerging Technol (INCET)*; 2022.
DOI: https:/ 10.1109/INCET54531.2022.9824263

[14] Kirchmer M, Franz P. Value-driven robotic process automation: A process-led approach to fast results at minimal risk. In: *Business Modeling and Software Design*. Springer; 2019. DOI: https://doi.org/10.1007/978-3-030-52306-0_3

[15] Syed R, Suriadi S, Adams M, Bandara W, Leemans SJJ, Ouyang C. Robotic process automation: Contemporary themes and challenges. *Comput Ind*. 2020;115:103162. DOI: https://doi.org/10.1016/j.compind.2019.103162

[16] König M, Bein L, Nikaj A, Weske M. Integrating robotic process automation into business process management. In: *Business Process Management Forum*. Springer; 2020. DOI: https://doi.org/10.1007/978-3-030-58666-9_9

[17] Sobczak A. Robotic process automation as a digital transformation tool for increasing organizational resilience. *Sustainability*. 2022;14(3):1333. DOI: https://doi.org/10.3390/su14031333

[18] Mendling J, Decker G, Hull R, Reijers HA, Weber I. Machine learning, robotic process automation, and blockchain in business process management. *Commun Assoc Inf Syst*. 2018;43:19. DOI: 10.17705/1CAIS.04319

Sgarbossa F, Grosse EH, Neumann WP, Battini D, Glock CH. Human factors in production and logistics systems of the future. *Annu Rev Control*. 2020;49:295–305. DOI: https://doi.org/10.1016/j.arcontrol.2020.04.002

Al-Talib M, Melhem WY, Anosike AI, Garza Reyes JA, Nadeem SP. Achieving resilience in supply chains using IoT technology. *Procedia CIRP*. 2020;91:752–757. DOI: https://doi.org/10.1016/j.procir.2020.02.231

[19] Žunić E, Delalić S, Hodžić K, Beširević A, Hindija H. Smart warehouse management system concept with implementation. In: *Proc Int Symp Neural Netw Appl (NEUREL)*; 2018. DOI: 10.1109/NEUREL.2018.8587004

[20] Tan WC, Sidhu MS. Review of RFID and IoT integration in supply chain management. *Oper Res Perspect*. 2022;100229. DOI: https://doi.org/10.1016/j.orp.2022.100229

Bazza H, Bimonte S, Gourti Z, Rizzi S, Badir H. Model-driven architecture for robotic real-time business intelligence applications. *Data Knowl Eng*. 2025;157:102418. DOI: https://doi.org/10.1016/j.datak.2024.102418

[21] Patrício, Leonel, Leonilde Varela, Zilda Silveira, Carlos Felgueiras, and Filipe Pereira. "A framework for integrating robotic process automation with artificial intelligence applied to industry 5.0." Applied Sciences 15, no. 13 (2025): 7402. DOI: https://doi.org/10.3390/app15137402

[22] Kir H, Erdogan N. Knowledge-intensive adaptive business process management framework. *Inf Syst*. 2021;95:101639. DOI: https://doi.org/10.1016/j.is.2020.101639

[23] Tsang, Yung Po, Valerie Tang, C. H. Wu, and Fuqing Li. "Unlocking the potential of robotic process automation for digital transformation in logistics and supply chain management." *Journal of Global*

Information Management (JGIM) 32, no. 1 (2024): 1-24.DOI: 10.4018/JGIM.361710

[24] Ivanov, D. The Industry 5.0 framework: Viability-based integration of the resilience, sustainability, and human-centricity perspectives. *Int. J. Prod. Res.* 2023**,** *61***,** 1683–1695. https://doi.org/10.1080/00207543.2022.2118892.

[25] Ataka, A.; Sandiwan, A.P. Growing robot navigation based on deep reinforcement learning. In *Proceedings of the 2023 9th International Conference on Control, Automation and Robotics (ICCAR)***,** Beijing, China, 21–23 April 2023; pp. 115–120. https://doi.org/10.1109/ICCAR57134.2023.10151740.

[26] Hosseini, S.; Hahn, I. On experimental energy consumption estimation of a 6-DoF industrial UR3e robot arm manipulator in trajectory planning. In *Proceedings of the 2024 33rd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)***,** Pasadena, CA, USA, 26–30 August 2024; pp. 1430–1435. https://doi.org/10.1109/RO-MAN60168.2024.10731263.

[27] Alharthi, N.W.; Brandão, M. Physical and digital adversarial attacks on grasp quality networks. In *Proceedings of the 2024 IEEE International Conference on Robotics and Automation (ICRA)***,** Yokohama, Japan, 13–17 May 2024; pp. 1907–1912. https://doi.org/10.1109/ICRA57147.2024.10610886.

[28] Schlegel, D.; Rosenberg, B.; Fundanovic, O.; Kraus, P. How to conduct successful business process automation projects? An analysis of key factors in the context of robotic process automation. *Bus. Process Manag. J.* 2024**,** *30*, 99–119. https://doi.org/10.1108/BPMJ-06-2023-0465.

[29] Ivanov, D. The Industry 5.0 framework: Viability-based integration of the resilience, sustainability, and human-centricity perspectives. *Int. J. Prod. Res.* 2023**,** *61***,** 1683–1695. https://doi.org/10.1080/00207543.2022.2118892.

[30] Ataka, A.; Sandiwan, A.P. Growing robot navigation based on deep reinforcement learning. In *Proceedings of the 2023 9th International Conference on Control, Automation and Robotics (ICCAR)***,** Beijing, China, 21–23 April 2023; pp. 115–120. https://doi.org/10.1109/ICCAR57134.2023.10151740.

[31] Hosseini, S.; Hahn, I. On experimental energy consumption estimation of a 6-DoF industrial UR3e robot arm manipulator in trajectory planning. In *Proceedings of the 2024 33rd IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)***,** Pasadena, CA, USA, 26–30 August 2024; pp. 1430–1435. https://doi.org/10.1109/RO-MAN60168.2024.10731263.

[32] Alharthi, N.W.; Brandão, M. Physical and digital adversarial attacks on grasp quality networks. In *Proceedings of the 2024 IEEE International Conference on Robotics and Automation (ICRA)***,** Yokohama, Japan, 13–17 May 2024; pp. 1907–1912. https://doi.org/10.1109/ICRA57147.2024.10610886.

[33] Schlegel, D.; Rosenberg, B.; Fundanovic, O.; Kraus, P. How to conduct successful business process automation projects? An analysis of key factors in the context of robotic process automation. *Bus. Process Manag. J.* 2024**,** *30*, 99–119. https://doi.org/10.1108/BPMJ-06-2023-0465.