JOURNAL OF NANO- AND ELECTRONIC PHYSICS
Vol. 17 No 3, 03020(6pp) (2025)
ЖУРНАЛ НАНО- ТА ЕЛЕКТРОННОЇ ФІЗИКИ
Том 17 № 3, 03020(6cc) (2025)

REGULAR ARTICLE

Quantum Computing Approaches to Autonomous Mobile Robots and Multi-Machine Systems: A Perspective on Design Automation

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(Received 10 April 2025; revised manuscript received 23 June 2025; published online 27 June 2025)

Quantum Annealing (QA), particularly with D-Wave systems, presents a transformative solution for optimizing task allocation in autonomous mobile robots (AMRs) and multi-machine systems within Industry 6.0. Traditional scheduling methods often struggle to efficiently solve NP-hard optimization problems, which results in inefficient resource utilization, increased idle time, and production delays. Quantum Annealing overcomes these limitations by formulating task scheduling as a Quadratic Unconstrained Binary Optimization (QUBO) problem. This allows quantum processors to explore multiple solution paths simultaneously, significantly speeding up the process of identifying near-optimal allocations. By leveraging the principle of quantum tunneling, QA is able to escape local minimum and find globally optimal or near-optimal solutions, ensuring balanced workload distribution among machines and minimizing production bottlenecks. In dynamic industrial environments, where real-time adjustments and adaptive scheduling are crucial, QA offers a significant advantage in continuously optimizing task assignments. This leads to enhanced manufacturing efficiency, reduced energy consumption, and more streamlined production workflows. As quantum hardware continues to evolve, the integration of QA-driven optimization with AI, IoT, and robotics will play a pivotal role in shaping the future of intelligent automation in smart factories, paving the way for higher productivity and cost-efficiency in manufacturing ecosystems.

Keywords: Quantum Annealing, D-Wave systems, Autonomous mobile robots, Task allocation, Optimization, Smart factories.

DOI: 10.21272/jnep.17(3).03020 PACS numbers: 07.05.Tp, 07.07.Tw

1. INTRODUCTION

Industry 6.0 is revolutionizing manufacturing and logistics by integrating Autonomous Mobile Robots (AMRs) and multi-machine systems to optimize production. However, dynamic task allocation remains a challenge, as traditional scheduling methods struggle with scalability, leading to inefficiencies. Task allocation in such environments is NP-hard, requiring advanced techniques for optimal solutions. Quantum Annealing (QA), particularly with D-Wave systems, offers a promising solution by leveraging quantum tunneling to explore multiple solutions simultaneously. By formulating task scheduling as a Quadratic Unconstrained Binary Optimization (QUBO) problem, QA efficiently allocates tasks to AMRs and multi-machine systems, balancing workloads and minimizing delays. Unlike classical methods, QA escapes local minimum, ensuring globally optimal solutions. Key contributions include demonstrating QA's superiority over traditional scheduling, integrating QA with AI-driven systems for real-time adaptability, and developing a quantum-based model to enhance manufacturing efficiency. As Quantum Computing advances, its integration with IoT and robotics will drive intelligent manufacturing, improving productivity, resource utilization, and cost-efficiency in future smart factories. A next-generation smart factory equipped with Autonomous Mobile Robots (AMRs) and multi-machine systems, as depicted in Figure 1. The remaining part of the paper is organized as: The Review of Existing Research in Section 2. In Section 3, Quantum Computing techniques. Autonomous Mobile Robot, Multi machine system are in Section 4 and Section 5 respectively. Quantum Algorithm in Section 6 Computational Analysis in Section 7. Finally, the work is concluded in Section 8.

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Cite this article as: N. Jayasri et al., *J. Nano- Electron. Phys.* 17 No 3, 03020 (2025) https://doi.org/10.21272/jnep.17(3).03020

Fig 1 – Smart factory in Industry 6.0

2. REVIEW OF EXISTING RESEARCH

Distribution centers and warehouses play a crucial role in meeting customer demand efficiently [1]. With the integration of Quantum Computing (QC) in Logistics 4.0, AI and IoT are transforming material flow into smart warehouses [2]. QC enhances Autonomous Mobile Robots (AMRs) and multi-machine systems by optimizing complex tasks such as order picking and batching, improving time management, reducing risks, and enhancing inventory tracking [3-5]. Despite advancements, challenges remain in optimizing path planning and coordinating AMRs [6]. Quantum algorithms, such as A*, Rapidly Exploring Random Trees (RRT), and Fast-Marching Method (FMM) variants, are being adapted for quantum speedup, improving navigation in dynamic environments [7]. Additionally, QC offers potential solutions for NP-hard problems like the Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP) [8-10]. Key research gaps include scalability of quantum algorithms, real-time adaptability, AI-IoT-QC integration, and quantum-based multi-objective optimization. Addressing these challenges will enhance logistics automation, enabling seamless AMR collaboration in smart warehouses. The routing and job assignment problems discussed are illustrated in Figure 2.

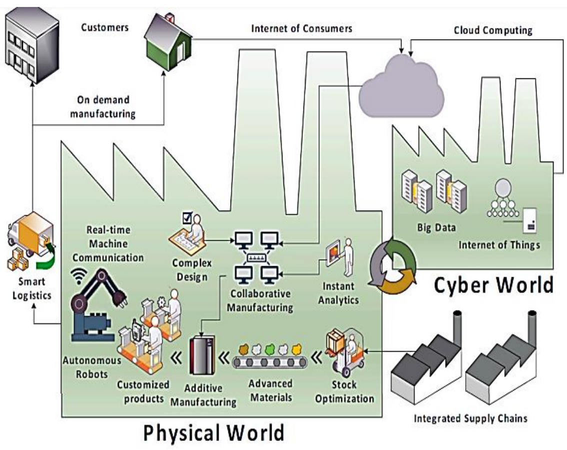

Fig 2 – Routing and job assignment problems in industry

3. QUANTUM COMPUTING

Quantum Computing is set to transform manufacturing by optimizing supply chains, enhancing material discovery, and improving predictive maintenance. It enables real-time data analysis for efficient logistics, reduces waste, and accelerates the development of advanced materials. Quantum simulations enhance product design, minimizing prototyping costs. Additionally, it aids in predictive maintenance by identifying machinery failures in advance, reducing downtime. Key use cases include Volkswagen's quantum-powered traffic flow optimization, which improves logistics efficiency, Boeing's quantum simulations for designing lighter, stronger aircraft materials, and Daimler's quantum research for next-generation EV battery materials. QC is also revolutionizing Autonomous Mobile Robot (AMR) path planning, ensuring optimal navigation in dynamic factory environments, and Multi-Machine System Scheduling, enabling highly efficient production workflows by solving complex scheduling problems faster than classical methods. While challenges like hardware scalability exist, rapid advancements in quantum technology promise significant efficiency gains. These details are included in Figure 3, highlighting QC's transformative impact on manufacturing, making it more cost-effective, sustainable, and innovative.

Fig. 3 – QC in manufacturing industry

4. AUTONOMOUS MOBILE ROBOT

Autonomous mobile robots (AMRs) are revolutionizing smart manufacturing by enhancing automation, flexibility, and efficiency in industrial environments. However, real-time path planning and decision-making in dynamic and complex factory settings pose significant computational challenges. Quantum computing offers a powerful solution by rapidly solving optimization problems that classical computers struggle with, enabling AMRs to navigate efficiently, avoid obstacles, and minimize travel time. Quantum algorithms, such as quantum annealing, can optimize AMR path planning by evaluating multiple routes simultaneously, ensuring the most efficient trajectory with minimal energy consumption [11-12]. This leads to improved material handling, reduced downtime, and enhanced productivity in smart factories. Additionally, quantum computing can optimize multi-robot coordination, preventing bottlenecks and improving workflow synchronization. By integrating quantum computing with AMRs, manufacturers can achieve faster, smarter, and more adaptive automation systems, paving the way for the next generation of industry 6.0, where intelligent robotics and quantum-enhanced decision-making drive unprecedented efficiency and innovation. Autonomous Mobile Robots (AMRs) Integrated with A multi-machine system in the smart manufacturing industry, utilizing quantum computing for enhanced efficiency and optimization, are showed in Figure 4.

Fig. 4 AMR integrated with MMS and QC

5. MULTI MACHINE SYSTEM

In the evolving landscape of smart manufacturing, multi-machine systems, quantum computing, and Autonomous Mobile Robots (AMRs) are at the forefront of innovation. A multi-machine system refers to the integration of several machines working together in a coordinated manner to optimize production processes illustrated in Figure 5. These systems enable seamless automation and data exchange, increasing efficiency and reducing downtime. Quantum computing plays a pivotal role in solving complex optimization problems, such as resource allocation and task scheduling, in real-time, far surpassing the capabilities of classical computing. Finally, AMRs are autonomous units that transport materials and components across the production floor, enhancing flexibility, safety, and productivity. Together, these technologies create a dynamic, self-optimizing manufacturing environment that drives Industry 4.0 advancements.

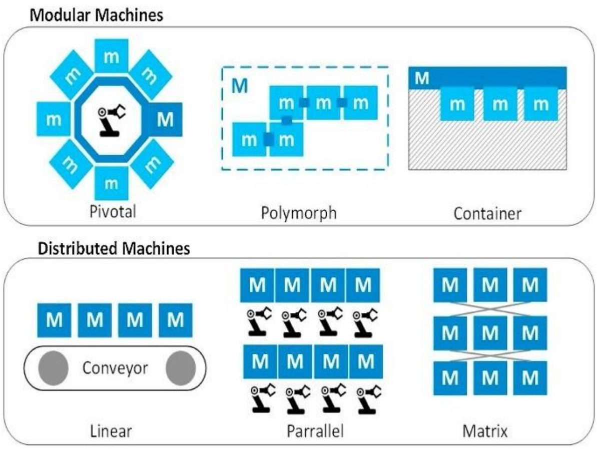

Fig. 5 – Multi machine system in Industry 6.0 [14]

6. QUANTUM ALGORITHM

Quantum algorithms, particularly quantum annealing, offer a powerful approach to optimizing Autonomous Mobile Robot (AMR) path planning. By leveraging quantum superposition and tunneling, these algorithms evaluate multiple possible routes simultaneously, rapidly identifying the most efficient trajectory. This enables AMRs to navigate complex environments while minimizing travel time and energy consumption. Unlike classical methods, which rely on sequential computations and may struggle with high-dimensional optimization, quantum annealing provides near-instantaneous solutions to intricate path-planning problems. As quantum computing advances, integrating such techniques into AMR navigation can significantly enhance efficiency, reduce operational costs, and improve autonomous decision-making in dynamic environments.

6.1 Quantum Annealing

Quantum annealing (QA), pioneered by Kadowaki and Nishimori (1998), optimizes complex problems using quantum tunneling to escape local minima. D-Wave Systems has commercialized QA, enabling efficient AMR path planning by evaluating multiple routes simultaneously. Procedural steps in Quantum Annealing:

1. Problem Formulation – Define the path planning problem as a QUBO or Ising model.
2. Mapping to Quantum System – Represent problem variables as quantum bits (qubits).
3. Initialization – Prepare the system in a superposition state to explore all solutions.
4. Quantum Tunneling and Annealing – Use a Hamiltonian function to transition toward the optimal state.
5. Solution Extraction – Measure the final qubit states to determine the optimal AMR path.

6.2 Implementation of Algorithm

Initial implementation of the algorithm using the QUBO model with two Autonomous Mobile Robots (AMRs) navigating towards four machines (M1 to M4) while optimizing their paths (Figure 6).

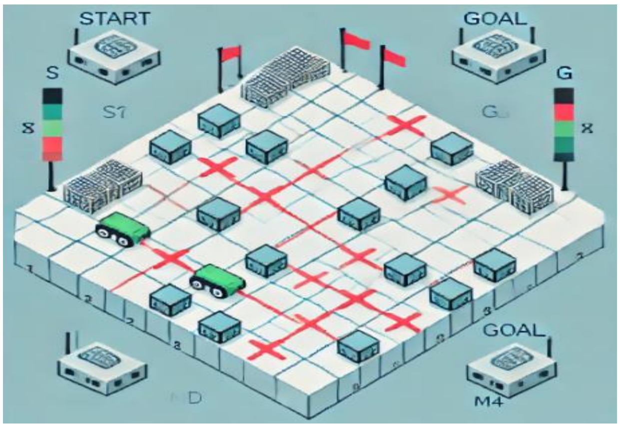

Fig. 6 – QUBO Model with AMRs

Step 1. Objective Function (Minimize Path Length)

$$H_{path} = \sum_{(i,j)\in path} d_{ij}\, x_{ij} \tag{1}$$

Where d_{ij} represents the cost (distance or energy) associated with moving to (i, j).

Step 2 The AMR Must Be at Exactly One Position per Step.

$$H_{position} = \sum_t \left(\sum_{(i,j)} x_{i,j,t} - 1\right)^2 \quad (2)$$

Ensure the AMR is at exactly one location at each time step t.

Step 3. The AMR Must Follow a Valid Path.

$$H_{valid} = \sum_t \sum_{(i,j)} (1 - x_{i,j,t})\,(1 - x_{i,j,t+1}) \quad (3)$$

Ensure the AMR moves only to adjacent positions.

Step 4. Final QUBO form

$$H_{total} = \lambda_1 H_{PATH} + \lambda_2 H_{POSITION} + \lambda_3 H_{valid} \quad (4)$$

Where λ_1, λ_2, λ_3 are weight parameters to balance objectives and constraints.

Step 5. Problems variables as quantum bits

$$H_{total} = \lambda_1 H_{PATH} + \lambda_2 H_{POSITION} + \lambda_3 H_{machine} \quad (5)$$

Where $H_{machines}$

$$H_{machines} = \sum_{m \epsilon M} (1 - q_m) \quad (6)$$

Step 6. System in super position state.

Step 7. Hamiltonian function to transition.

During annealing, the system transitions from Hinitial to Hproblem by adjusting the parameter $s(t)$:

$$H(t) = (1 - s) H_{INITIAL} + S H_{problem} \quad (7)$$

As $s \to 1$ quantum fluctuations diminish, and the system collapses into the optimal AMR paths that minimize travel time and energy while satisfying all constraints.

Step 8. Measure the final qubit states to determine the optimal AMR path.

Each position on the grid-based map is assigned a binary qubit:

$$q_{ij} = 1(AMR\ at\ positio\ (i,j)), q_{ij} = 0\ \text{(AMR not at}(i,j)) \quad (8)$$

For two AMRs, separate qubit sets q_{ij}^A and q_{ij}^B track their respective positions.

Example measured state for an AMR path:

$$\{(0,0) \to (1,0) \to (2,0) \to M_1 \to (3,1) \to G\} \quad (9)$$

indicating the AMR moves from start to M1, then to the goal (G) to M4 and the example problem consists of five jobs, each requiring thirteen operations, which must be processed on four machines (M1, M2, M3, and M4). Additionally, two Autonomous Mobile Robots (AMRs) in 4 Smart Manufacturing Environments are responsible for transporting materials between machines and are shown in below Figure 7.

Utilizing the Quantum Annealing algorithm, the total travel time for the AMRs is optimized to 80 units. This setup is based on the example problem presented in Bilge and Ulusoy (1995), as shown in Table 1, demonstrating the effectiveness of quantum-inspired scheduling and path optimization in complex manufacturing environments.

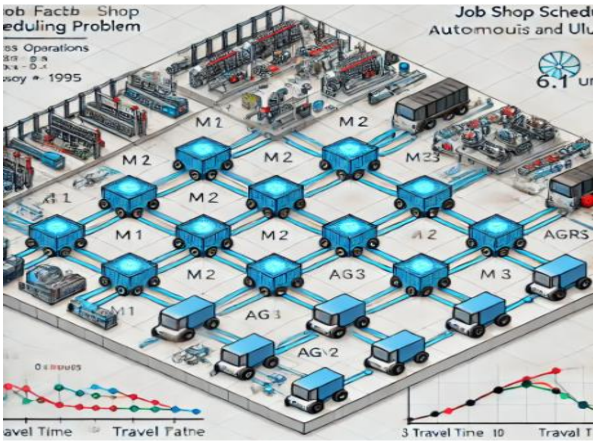

Fig. 7 – Smart manufacturing environment

Table 1 – Optimized AMRs path through QA

O.No	M.No	AMR	PL	VRT	POCT	ET	LT
O_1	1	1	L/U	0	0	0	6
O_10	4	2	L/U	0	0	0	12
O_12	3	1	1	6	0	18	28
O_4	1	2	4	12	0	18	24
O_7	3	1	3	28	0	36	46
O_11	2	2	1	24	18	34	42
O_13	1	1	3	46	31	46	54
O_5	3	2	2	42	42	48	56
O_2	2	1	1	54	12	54	60
O_8	4	2	3	56	55	56	62
O_9	1	2	4	62	65	65	75
O_6	2	1	2	60	62	66	72
O_3	4	1	2	72	72	72	**80**

7. COMPUTATIONAL ANALYSIS

The FMS job shop scenario considered in this study is derived from Bilge and Ulusoy [1995][15]. The 40 test problems outlined in their work have been addressed using the QA approach. The results obtained, including the travel time (TT) of AMRs and the operational completion time (OCT) of 10 jobs across four smart manufacturing environments, are presented in Table 2. These results are compared with the Fuzzy Heuristic Algorithm proposed by Kanakavalli et al. [13], referred to as Fuzzy. The operational completion times for different layouts using Quantum Annealing (QA) and Fuzzy methods reveal significant energy savings when employing QA. For Layout-1, the operational completion time with QA is 1284, while with Fuzzy, it is 2196, leading to an energy saving of 41.54%. Similarly, Layout-2 has a QA time of 1057 and a Fuzzy time of 1899, resulting in an energy saving of 44.33 %. In Layout-3, the QA method achieves completion in 1122 compared to 1920 with Fuzzy, yielding a 41.56 % energy saving. Finally, Layout-4 demonstrates the highest energy saving at 44.84 %, with QA completing operations in 1403, whereas Fuzzy takes 2543. Overall, the energy saving across all layouts is calculated to be 43.21 %, indicating that QA significantly enhances energy efficiency compared to the Fuzzy method. These findings highlight the effectiveness of QA in reducing both operational time and energy consumption, making it a superior approach for optimization. The travel times for different layouts using Quantum Annealing (QA) and Fuzzy methods also demonstrate notable energy savings when utilizing QA. For Layout-1, the travel time with QA is 1206, while with Fuzzy, it is 2196, leading to an energy saving of 45.09 %. Similarly, Layout-2 has a QA time of 948 and a Fuzzy time of 1786, resulting in an energy saving of 46.94 %. In Layout-3, the QA method achieves completion in 1017 compared to 1808 with Fuzzy, yielding a 43.75 % energy saving. Finally, Layout-4 demonstrates the highest energy saving at 46.60 %, with QA completing travel in 1298, whereas Fuzzy takes 2430. The overall energy saving across all layouts is calculated to be approximately 45.10 %, reflecting the substantial efficiency gains of the QA method in reducing travel time and energy consumption. These findings reinforce the effectiveness of QA in enhancing performance and optimizing energy use for Autonomous Mobile Robots (AMRs) across different layout configurations.

Table 2 – Optimized AMRs path through QA

J.No	Travel Time			Operational Completion Time		
	FUZZY	QA	% Devi	FUZZY	QA	% Devi
4_2	226	86	162.79	232	94	146.81
9_2	242	96	152.08	249	105	137.14
4_3	228	91	150.55	234	99	136.36
1_2	170	68	150.00	188	82	129.27
1_1	190	78	143.59	208	96	116.67
9_3	244	101	141.58	251	107	134.58
9_4	288	120	140.00	295	126	134.13
9_1	266	111	139.64	273	117	133.33
1_4	210	90	133.33	228	108	111.11
1_3	172	74	132.43	190	86	120.93
5_2	141	61	131.15	156	73	113.70
4_4	293	127	130.71	299	135	121.48
5_3	141	67	110.45	156	76	105.26
3_2	168	81	107.41	178	97	83.51
5_1	159	77	106.49	174	89	95.51
3_3	166	81	104.94	176	102	72.55
5_4	178	87	104.60	193	97	98.97
10_4	338	175	93.14	353	184	91.85
3_1	201	105	91.43	211	120	75.83
10_1	300	158	89.87	315	171	84.21
3_4	215	115	86.96	225	130	73.08
10_2	259	139	86.33	274	152	80.26
4_1	262	144	81.94	268	122	119.67
10_3	265	146	81.51	280	157	78.34
6_1	220	128	71.88	233	137	70.07
6_4	230	138	66.67	243	148	64.19
2_4	178	112	58.93	190	124	53.23
2_2	115	74	55.41	127	86	47.67
2_1	158	102	54.90	170	114	49.12
6_2	162	106	52.83	175	114	53.51
7_4	224	148	51.35	232	156	48.72
7_2	131	87	50.57	139	95	46.32
8_4	276	186	48.39	285	195	46.15
7_1	188	127	48.03	196	133	47.37
6_3	164	112	46.43	177	121	46.28
8_1	252	176	43.18	261	185	41.08
2_3	121	88	37.50	133	100	33.00
7_3	133	97	37.11	141	105	34.29
8_2	172	150	14.67	181	159	13.84
8_3	174	160	8.75	183	169	8.28

The comparison of travel time between Fuzzy and Quantum Annealing (QA) methods reveals significant differences in optimization efficiency. For five test cases with maximum deviation, QA consistently outperforms Fuzzy by reducing travel time and ensuring better path optimization. Conversely, for five cases with minimum deviation, both methods exhibit comparable performance, though QA maintains a slight advantage in consistency. These results highlight QA's effectiveness in handling complex path-planning scenarios with higher deviations while maintaining efficiency in stable conditions. The detailed comparison is illustrated in Figure 8.

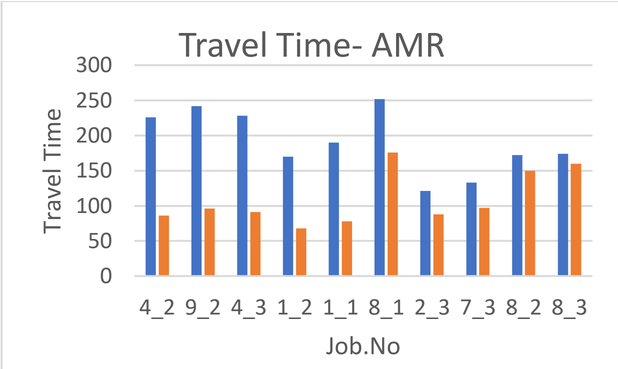

Fig. 8 – Comparision of travel time maximum and minimum

8. CONCLUSIONS

Results clearly highlight the significant advantages of using Quantum Annealing (QA) over the Fuzzy method in both operational completion and travel times for Autonomous Mobile Robots (AMRs). Across all layouts, QA consistently provides substantial energy savings, ranging from 41.54 % to 46.94 %. The overall energy saving across all layouts is approximately 43.21 % for operational completion times and 45.10 % for travel times. These findings underscore the potential of QA to improve both time efficiency and energy optimization, making it a superior approach for enhancing the performance and sustainability of AMRs in various operational environments.

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Підходи квантових обчислень до автономних мобільних роботів та багатомашинних систем: погляд на автоматизацію проектування

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Квантовий відпал (QA), особливо з системами D-Wave, пропонує трансформаційне рішення для оптимізації розподілу завдань в автономних мобільних роботах (AMR) та багатомашинних системах в рамках Індустрії 6.0. Традиційні методи планування часто мають труднощі з ефективним вирішенням NP-складних задач оптимізації, що призводить до неефективного використання ресурсів, збільшення часу простою та затримок виробництва. Квантовий відпал долає ці обмеження, формулюючи планування завдань як задачу квадратичної безобмеженої бінарної оптимізації (QUBO). Це дозволяє квантовим процесорам одночасно досліджувати кілька шляхів рішення, значно пришвидшуючи процес визначення майже оптимальних розподілів. Використовуючи принцип квантового тунелювання, QA здатний уникнути локального мінімуму та знайти глобально оптимальні або майже оптимальні рішення, забезпечуючи збалансований розподіл робочого навантаження між машинами та мінімізуючи вузькі місця у виробництві. У динамічних промислових середовищах, де коригування в режимі реального часу та адаптивне планування є критично важливими, QA пропонує значну перевагу в постійній оптимізації розподілу завдань. Це призводить до підвищення ефективності виробництва, зниження споживання енергії та більш оптимізованих робочих процесів виробництва. Оскільки квантове обладнання продовжує розвиватися, інтеграція оптимізації на основі контролю якості зі штучним інтелектом, Інтернетом речей та робототехнікою відіграватиме ключову роль у формуванні майбутнього інтелектуальної автоматизації на розумних фабриках, прокладаючи шлях до підвищення продуктивності та економічної ефективності у виробничих екосистемах.

Ключові слова: Квантовий відпал, D-хвильові системи, Автономні мобільні роботи, Розподіл завдань, Оптимізація, Розумні фабрики.