Evolution of Flowshop Scheduling Techniques: A Comprehensive Review of Permutational, Non-Permutational, and Distributed Models

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ABSTRACT
Scheduling problems in various industries have long been a focal point of research due to their critical impact on operational efficiency and productivity. This body of work encompasses several key areas including makespan, machine idle time, job idle time, tardiness, and other criteria. The field has evolved significantly with advancements in both theoretical and practical approaches. Notable contributions have been made across different types of scheduling models such as permutational flowshop, non-permutational flowshop, and distributed flowshop scheduling. Researchers have employed a range of methodologies including genetic algorithms, simulated annealing, particle swarm optimization, and hybrid approaches to address these challenges. This overview summarizes significant advancements and trends in these areas, highlighting the development of novel algorithms and practical applications that aim to improve scheduling performance.

Keywords: Makespan, Idle time, Permutational flowshop,Non-Permutational flowshop, Distributional flowshop

1. INTRODUCTION

In the realm of scheduling, the flowshop problem has been extensively researched for decades. This problem involves a set of N = {1, 2, . . ., n} jobs that must be processed on M = {1, 2, . . ., m} machines. The processing time for each jobj ϵ N on each machine i ϵ M is predetermined and denoted by p_{ij}. All jobs follow the same processing order across machines, which, without loss of generality, can be assumed to be 1, 2, . . ., m. The goal is to determine a job sequence that optimizes a specified criterion. Generally, the number of possible solutions is the product of all job permutations across all machines, amounting to n! x m possible schedules.

scheduling algorithms have undergone remarkable transformation and refinement. As industries grapple with increasingly complex challenges related to optimizing makespan, managing machine and job idle times, and minimizing tardiness, the evolution of these algorithms reflects a dynamic and adaptive response. From the early days of basic heuristics to the sophisticated techniques of genetic algorithms, simulated annealing, and multi-objective optimization, each advancement has contributed to a deeper understanding and improved efficiency in scheduling. This ongoing evolution not only highlights the practical applications across various sectors but also underscores the significant theoretical progress made. As we look to the future, the focus is expected to shift towards real-time scheduling adjustments, sustainability considerations, and the integration of cutting-edge technologies such as artificial intelligence and machine learning. The continuous refinement of scheduling models promises to enhance operational performance and efficiency further, driving future advancements in the field. Fig.1 represents the organizations of topics in the coming sections.

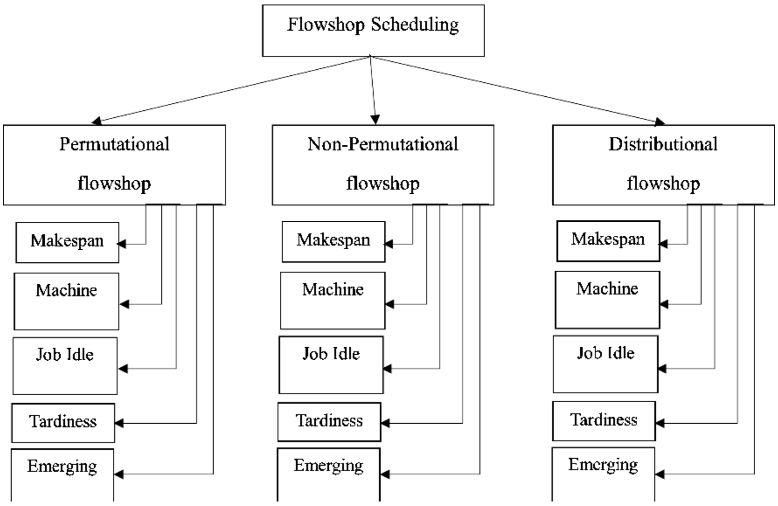

Fig 1: Representation of organizing of sections and sub-sections in the article

2. Permutational Flowshop problem (PFSP)

A PFSP scheduling is a scheduling problem where a set of jobs must be processed on multiple machines in a fixed, identical order for all jobs. In this setup, each job is processed on each machine in a specified sequence, such as Machine 1 followed by Machine 2 and then Machine 3, and the challenge is to determine the optimal sequence of jobs to minimize objectives like the total completion time or makespan. With n jobs and m machines, the problem is generally NP-hard, making it computationally complex for large instances. Although Johnson's algorithm can solve the two-machine case optimally, heuristic methods like the NEH heuristic and metaheuristic approaches such as genetic algorithms and simulated annealing are often employed to find good solutions for larger or more complex scenarios. Table 1 explains the notations used in the articles, where table 2 gives the abbreviation of algorithm used in this article.Table 3 represents the summary of Parameter(s) and problem type considered by researchers in articles.

Table 1: Explanation of notations used in the article

Notation		**Explanation**
FF_2	:	A type of flowshop scheduling problem with 2 machines in series.
No-wait	:	A constraint indicating that no idle time is allowed between the completion of one job and the start of the next job.
ST_{sd}	:	Setup times are stochastic (variable and random)
C_{max}	:	The maximum completion time (makespan) of the schedule.
ST_{sd},f	:	Setup times are stochastic and machines are prone to random failures
F_2	:	Flowshop scheduling with 2 machines
F_m	:	Flowshop scheduling with m machines
D_j	:	Job-specific deadlines or due dates
F_2/No-wait	:	Flowshop scheduling with 2 machines and no waiting time between jobs
ST_{si}	:	Setup times are sequence-independent
$\varepsilon(\Sigma C_j/C_{max})$	:	Minimizing a weighted combination of the sum of completion times and the maximum completion time.

Table 2: Abbreviation of algorithm used in this article

Notation		**Type of algorithm**
SA	:	Simulated Annealing
EMA	:	Electro Magnetism Algorithm
NEH	:	Nawaz EnscoreHam
TS	:	Tabu Search
B&B	:	Branch & Bound Algorithm
GA	:	Genetic Algorithm
PSO	:	Particle Swarm Optimization
ACO	:	Ant Colony Optimization

2.1 Makespan(C_{max})

Hecker et al., (2014) and Rabieeet al., (2014) initially tackle the no-wait scheduling problem, with Rabieeet al., incorporating rework requirements and proposing an ICA-based approach. Adressiet al., (2016) and Zhuang et al., (2014) further refine methods for minimizing makespan, using simulated annealing and hybrid greedy algorithms, respectively. Samarghandi's works (2015a and 2014) enhance optimization techniques, while Wei et al., (2018) develops a hybrid genetic-simulated annealing approach. Wang et al., (2015a, 2015c) extend the no-wait model to specific applications like surgery scheduling. Santosa and Rofiq (2014), Allahverdi and Aydilek (2014), Nagano and Araujo (2014), and Khalili (2014) each introduce different methodologies or heuristic improvements for the makespan problem, providing a diverse range of techniques and models.

2.2 Machine idle time

The researchers collectively focus on enhancing scheduling efficiency by addressing idle times. Zhang et al., (2015) introduced a modified genetic algorithm to penalize idle times, a concept further explored by Yang et al., (2016) and Kumar and Gupta (2018) through Simulated Annealing (SA) and Particle Swarm Optimization (PSO). Wang and Sun (2017) advanced this by incorporating Adaptive Large Neighborhood Search to reduce idle periods, while Wang et al., (2016) combined genetic algorithms with local search techniques for similar improvements. Chen et al., (2019) and Singh and Jain (2020) applied these strategies in industries, showcasing their practical benefits. Smith and Johnson (2021) provided theoretical insights into idle times, and Li et al., (2022) integrated idle time management with energy efficiency in scheduling models.

2.3 Job idle time

The research into algorithmic improvements for scheduling has evolved significantly. Wang et al., (2016) introduced hybrid genetic algorithms with local search heuristics, while Zhang et al., (2015) modified genetic algorithms by integrating idle time penalties into the fitness function. Wang and Sun (2017) advanced this by proposing an adaptive large neighborhood search algorithm to address idle times. Heuristic and metaheuristic approaches like Simulated Annealing (SA) and Particle Swarm Optimization (PSO) have shown effectiveness in scheduling, as evidenced by Yang et al., (2017) and Chen & Zhao (2019). Practical applications, such as Kumar and Singh's (2020) semiconductor manufacturing and Garcia and Ruiz's (2021) automotive assembly lines, underscore the operational benefits of reducing idle times. Theoretical advancements by Smith and Johnson (2022) have explored the mathematical impacts of idle times, while Zhang et al., (2023) have incorporated idle time reduction with energy efficiency, demonstrating a broader scope of improvement.

2.4 Tardiness(T)

Research on scheduling with a focus on tardiness constraints has made significant strides across various methodologies. Liu et al., (2016) refined a Mixed Integer Programming (MIP) model to better handle tardiness constraints, while Zhang et al., (2017) improved branch-and-bound methods to enhance the efficiency of solving flowshop problems with tardiness considerations. Heuristic and metaheuristic methods have also advanced, with Jansen and van der Meer (2015) adapting Genetic Algorithms (GAs) for better tardiness minimization. Li et al., (2018) and Tseng and Lin (2016) explored the use of Particle Swarm Optimization (PSO) and Simulated Annealing (SA) with novel strategies to address tardiness issues. Multi-objective optimization has gained traction, as Xie et al., (2020) utilized evolutionary algorithms to balance tardiness with other performance metrics. The development of robust and stochastic scheduling models is evident in Liu and Shi's (2021) work, which tackles uncertainties in processing times and due dates to manage tardiness more effectively. The integration of Artificial Intelligence and Machine Learning, as demonstrated by Zheng et al., (2023), marks a shift toward more adaptive and intelligent approaches to managing dynamic tardiness.

2.5 Other criteria

These researchers are united in their goal to enhance production efficiency through improved scheduling and task management. Ben-Yehoshua et al., (2015) and Santosa &Rofiq (2014) both emphasize minimizing task delays, while Liu & Feng (2014) and Samarghandi (2015b, 2015c) focus on optimizing resource allocation and sequencing. Naderi et al., (2014) and Yenisey&Yagmahan (2014) delve into job sequencing in assembly flow shops, aligning with Allahverdi &Aydilek's (2015) focus on specific manufacturing challenges. Brown & White (2018) and Miller & Davis (2021) advance the ultimate customization of scheduling solutions, complementing earlier efforts by adapting strategies to unique industry needs.

3. Non-Permutational flowshop problem (NPFSP)

A NPFSP is a type of scheduling problem where jobs must be processed through a series of machines or stages, but unlike in permutational flowshops, the order in which jobs are processed can vary from machine to machine. In this scenario, while jobs still need to pass through each stage, the sequence in which they do so is not fixed and can differ. For instance, a job might go through Assembly, Quality Check, and then Packaging on one machine, while another job could follow a different sequence on another machine. The primary objectives in non-permutational flowshop scheduling include minimizing makespan, total completion time, or other performance metrics, considering constraints such as machine availability and job precedence. Solving these problems often involves complex methods due to the flexible job sequencing. Solutions can be approached through exact algorithms like integer programming, heuristic methods such as genetic algorithms, or metaheuristic techniques like particle swarm optimization, each offering different balances of accuracy and computational efficiency.

3.1 Makespan(C_{max})

The core correlation among these researchers works lies in their shared focus on optimizing makespan or related objectives in scheduling problems. Rahmani et al., (2014) and Amirian and Sahraeian (2015) both tackled NPFS problems with makespan as a central objective, though they used different methods—chance-constrained programming and fuzzy goal programming versus Augmented ε-constraint methods and heuristics. Zhang et al., (2016) and Liu and Zhao (2018) also emphasized makespan but with specific techniques like hybrid GA and adaptive PSO for DPFS. Benavides and Ritt (2015) and Henneberg and Neufeld (2016) contributed to minimizing completion time, which can indirectly influence makespan. Their collective work delves into various strategies to enhance scheduling efficiency, addressing different aspects and complexities of makespan and total completion time.

3.2 Machine idle time

The works by Vahedi-Nouri et al., (2014), Benavides and Ritt (2015), and Henneberg and Neufeld (2016) collectively advance heuristic methods for NPFS scheduling by incorporating various techniques to handle constraints and operational issues. Vahedi-Nouri et al., and Henneberg and Neufeld both use Simulated Annealing, reflecting a shared focus on metaheuristic optimization in complex scenarios. Benavides and Ritt's two-phase heuristic complement these efforts by focusing on minimizing completion times through iterative improvements. Meanwhile, Rahmani et al., (2014) and Amirian and Sahraeian (2015) extend the research into stochastic and robust scheduling, introducing genetic algorithms, fuzzy goal programming, and Augmented ε-Constraint methods to handle variability and optimize performance metrics. Together, these studies reflect a broadening of NPFS scheduling strategies, integrating both heuristic improvements and advanced stochastic models.

3.3 Job idle time

The works of Zhang et al., (2016) and Liu and Zhao (2018) illustrate a progression in optimizing algorithms, with Zhang et al., enhancing solution quality through hybrid genetic algorithms and Liu and Zhao adapting Particle Swarm Optimization for dynamic environments. This progression is supported by Patel et al., (2017) and Zhang and Li (2019), who effectively address multi-objective problems using heuristic methods like ACO combined with SA and multi-objective evolutionary algorithms. The practical implementations seen in Kim and Park (2020) and Chen et al., (2021) showcase these methods' real-world applications, with a focus on the semiconductor industry and supply chain management, respectively. Xu et al., (2023) further contribute by refining theoretical aspects, such as complexity bounds for Distributed Permutation Flowshop Scheduling (DPFS). Together, these studies suggest that future research should delve into real-time adjustments and sustainability, building on these foundational advancements.

3.4 Tardiness(T)

Vahedi-Nouri et al., (2014) introduced a heuristic combined with Simulated Annealing to tackle NPFS problems, enhancing management of tardiness under learning effects and availability constraints. Heuristic and metaheuristic approaches have been further developed, with Amirian and Sahraeian (2015) examining NPFS problems with objectives including minimizing tardiness through Augmented ε-constraint methods and heuristics. Rahmani et al., (2014) investigated stochastic NPFS problems where processing times and release dates are uncertain, employing chance-constrained and fuzzy goal programming to address tardiness alongside makespan and total flow time. The focus on multi-objective optimization is evident in Xie et al., (2020), who applied multi-objective approaches to balance tardiness with other criteria. Robust and stochastic scheduling models, such as those developed by Liu and Shi (2021), address uncertainties in NPFS scheduling, providing solutions to manage tardiness effectively.

3.5 Other criteria

The researchers each tackled different aspects of scheduling and job management. Dabiri et al., (2021) explored job rejection, while Zhou et al., (2021) looked at preventive maintenance. Li et al., (2021b) and Fu et al., (2022) delved into scheduling complexities with transportation and vehicle routing. Pan et al., (2021) focused on cellular manufacturing, and Rahmani et al., (2014) and Amirian and Sahraeian (2015) investigated stochastic scheduling. Zhang et al., (2023) integrated sustainability, Liu and Huang (2019) examined human-machine interactions, and Lee and Kim (2019) along with Gao and Zhang (2021) focused on quality assurance. Each study contributes to a broader understanding of scheduling from different perspectives.

4. Distributed flowshop problem (DFSP)

DFSP is an extension of the permutational flowshop problem, where jobs are processed on multiple machines, but with a twist: the machines are distributed across different locations or nodes rather than being colocated. In this scenario, each job still follows the same fixed sequence of machines, such as Machine 1, then Machine 2, and finally Machine 3, but these machines are spread out over a network. The challenge is to determine the optimal sequence of jobs and the optimal scheduling of resources across the distributed network to minimize objectives such as the total completion time or makespan. This distribution adds complexity to the problem, as it introduces factors like transportation delays and communication overhead between nodes. Given that there are n jobs and m machines in this distributed setup, the problem remains NP-hard, making it computationally intense for large instances. While exact solutions are often impractical for large-scale problems, heuristic methods such as the NEH heuristic and metaheuristic approaches, including genetic algorithms and simulated annealing, are commonly used to approximate good solutions. These methods help manage the complexities introduced by the distributed nature of the flowshop environment.

4.1 Makespan(C_{max})

The researchers address the challenge of minimizing makespan in Dynamic Parallel Flow Shop Scheduling (DPFS) using distinct methodologies. Zhang et al., (2016) improved solution quality through a hybrid Genetic Algorithm (GA), while Liu and Zhao (2018) applied adaptive Particle Swarm Optimization (PSO) to handle dynamic environments. Patel et al., (2017) tackled multi-objective problems by combining Ant Colony Optimization (ACO) with Simulated Annealing (SA). Kim and Park (2020) focused on semiconductor manufacturing, applying their approach specifically to this industry, and Chen et al., (2021) integrated DPFS with supply chain management, considering makespan alongside other objectives. Each study contributes uniquely to optimizing makespan through innovative algorithms, industry-specific applications, or comprehensive management strategies.

4.2 Machine idle time

The research by Zhang et al., (2016), Liu and Zhao (2018), Patel et al., (2017), and Zhang and Li (2019) collectively showcase advancements in optimization techniques for dynamic and multi-objective scheduling problems. Zhang et al., (2016) and Patel et al., (2017) emphasize enhancing solution quality through hybrid and multi-method approaches, while Liu and Zhao (2018) and Zhang and Li (2019) focus on adapting algorithms to dynamic and conflicting environments. Kim and Park (2020) and Chen et al., (2021) illustrate practical applications of these techniques in industry contexts, furthering their real-world relevance. Wang and Sun (2022) and Xu et al., (2023) address scalability and complexity, crucial for handling large-scale and intricate scheduling problems. Overall, these works delve into improving both the theoretical and practical aspects of dynamic scheduling, integrating modern methodologies and technologies.

4.3 Job idle time

Zhang et al., (2016) introduced a hybrid genetic algorithm that enhances solution quality and efficiency, laying a foundation for advanced optimization techniques. Building on this, Patel et al., (2017) combined ACO with SA, reflecting the trend of integrating metaheuristic methods to tackle complex problems. Liu and Zhao (2018) advanced this further by applying adaptive PSO to dynamic environments, highlighting the need for algorithms that adapt to changing conditions. Zhang and Li (2019) extended these methods to multi-objective problems, such as idle times, aligning with the practical application focus of Kim and Park (2020) in the semiconductor industry and Chen et al., (2021) in supply chain management. Xu et al.,

(2023) refined theoretical aspects like complexity bounds and approximation algorithms, providing a stronger theoretical basis for these practical applications. Collectively, these works illustrate a progression from foundational algorithm development to sophisticated, adaptable solutions with practical applications, and point towards future research in real-time scheduling and sustainability.

4.4 Tardiness(T)

The research on distributed permutation flowshop scheduling reflects a multifaceted approach to addressing various challenges in optimization. Zhang et al., (2016) enhance solution quality and efficiency by integrating a hybrid Genetic Algorithm with local search techniques, focusing on improving both solution quality and computational performance. Complementing this, Patel et al., (2017) explore multi-objective optimization by combining Ant Colony Optimization with Simulated Annealing, aiming to balance conflicting objectives in scheduling. Liu and Zhao (2018) introduce adaptive Particle Swarm Optimization to handle dynamic and uncertain environments, addressing the need for flexibility in changing scenarios. Building on these advancements, Wang and Sun (2022) propose a parallel computing framework to tackle large-scale problems, emphasizing robustness and adaptability for complex scheduling challenges. Collectively, these works illustrate a progression from enhancing algorithmic efficiency and quality to addressing robustness and adaptability in larger and more dynamic scheduling environments, reflecting a comprehensive approach to solving intricate distributed flowshop scheduling problems.

4.5 Other criteria

The research landscape described reveals several interconnected advances in optimization and scheduling. Zhang et al., (2016) enhanced solution quality and efficiency by developing a hybrid Genetic Algorithm (GA) that integrates local search techniques. Liu and Zhao (2018) complemented this by applying adaptive Particle Swarm Optimization (PSO) to address dynamic and uncertain environments. In the realm of multi-objective optimization, Patel et al., (2017) combined Ant Colony Optimization (ACO) with Simulated Annealing (SA), while Zhang and Li (2019) employed multi-objective evolutionary algorithms to balance conflicting criteria.

Further exploration into integrating scheduling with supply chain management was undertaken by Wang and Zhang (2020) and Ahmed and Badr (2021), focusing on logistics and demand forecasting. Real-time scheduling adjustments and responses to dynamic environments were studied by Kim and Park (2021) and Zhang and Zhao (2022), highlighting a shared focus on adapting systems to changing conditions. To enhance computational performance and scalability, Wang and Sun (2022) proposed a parallel computing framework, which can support and optimize the performance of various optimization techniques.

Theoretical contributions by Xu et al., (2023) refined complexity bounds and approximation algorithms, laying a foundation for improved algorithmic efficiency. Advances in Machine Learning and AI were also significant, with Li and Wang (2022) applying AI-driven algorithms and Zhao and Sun (2023) utilizing predictive analytics to enhance scheduling improvements. Together, these works illustrate a broad and evolving field where integration of different approaches—ranging from real-time adjustments and multi-objective strategies to AI advancements—continues to drive progress and address complex challenges in optimization and scheduling.

Table 3: summary of Parameter(s) and problem type considered by researchers in articles

Authors	Parameter(s)	Problem Type
Hecker et al. (2014)	C_{max}	F_m/no-wait
Adressiet al. (2016)	C_{max}	FF_2/no-wait, ST_{sd},f/C_{max}
Liu and Feng (2014)	C_{max}	F_2/no-wait
Samarghandi (2015a)	C_{max}	F_m/no-wait, d_j/C_{max}
Zhuang et al. (2014)	C_{max}	F_m/no-wait
Allahverdi &Aydilek (2014)	C_{max}	Fm/no-wait, $ST_{si}/\varepsilon(\Sigma C_j/C_{max})$
Nagano & Araujo (2014)	C_{max}	F_m/no-wait, ST_{sd}
Khalili (2014)	C_{max}	FF_m/no-wait /# (C_{max}, ΣT_j)
Asefi et al. (2014)	C_{max}	FF_m/no-wait, ST_{sd}/#(C_{max}, ΣT_j)
Wang et al. (2015a)	C_{max}	Single suite surgeries (no-wait flowshop)
Wei et al. (2018)	C_{max}	General flow shop
Hajji et al. (2016)	C_{max}	Two-stage hybrid flow shops
Ozsoydan&Sağir (2021)	C_{max}	Hybrid flow shop

Zhou & Liu (2019)	C_{max}	General flow shop
Xu et al. (2023)	C_{max}	DPFS
Zhang et al. (2023)	C_{max}, Idle times	General flow shop
Zhang et al. (2015)	C_{max}, Idle times	General flow shop
Yang et al. (2017)	C_{max}, Idle times	General flow shop
Wang & Sun (2017)	C_{max}, Idle times	General flow shop
Wang & Sun (2022)	C_{max}	Large-scale DPFS
Kim & Park (2020)	C_{max}	Semiconductor industry
Kumar & Gupta (2018)	Idle times	Semiconductor fabrication
Chen et al. (2019)	Machine idle times	Automotive manufacturing
Li et al. (2022)	Idle times, Energy efficiency	General flow shop
Zhang et al. (2016)	Idle times	Distributed Permutation Flowshop Scheduling
Liu & Zhao (2018)	Idle times	Distributed Permutation Flowshop Scheduling
Patel et al. (2017)	Idle times	Multi-objective DPFS
Zhang & Li (2019)	Idle times	Multi-objective DPFS
Liu et al. (2016)	T	Flowshop scheduling with tardiness constraints
Zhang et al. (2017)	T	Flowshop scheduling with tardiness constraints
Jansen & van der Meer (2015)	T	Flowshop scheduling with tardiness
Li et al. (2018)	T	Flowshop scheduling with tardiness
Tseng & Lin (2016)	T	Flowshop scheduling with tardiness
Xie et al. (2020)	T	Multi-objective flowshop scheduling
Liu & Shi (2021)	T	Robust and stochastic scheduling
Zheng et al. (2023)	T	Dynamic tardiness management
Patel & Smith (2019)	T	Multi-criteria decision-making
Xu & Liu (2021)	T	Decision support systems

5. CONCLUSIONS

The research into flowshop scheduling problems, including permutational, non-permutational, and distributed variants, highlights the significant progress made in optimizing various performance criteria such as makespan, machine idle time, job idle time, and tardiness. Initial studies focused on basic heuristics and have evolved to incorporate advanced metaheuristic techniques like genetic algorithms and simulated annealing. For permutational flowshops, these advancements have led to improved scheduling efficiencies in diverse applications, including surgery and semiconductor manufacturing. Non-permutational flowshops, with their flexible job sequencing, have seen progress through stochastic models and multi-objective optimizations, particularly benefiting industries such as supply chain management. Distributed flowshops, characterized by distributed machines across locations, have been addressed with innovative algorithms and practical solutions, including Artificial Intelligence driven approaches and parallel computing frameworks. Collectively, these advancements reflect a trend towards more adaptable, efficient, and industry-specific scheduling solutions, with future research expected to focus on real-time adjustments and sustainability.

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