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ОПТИМІЗАЦІЯ РОЗПОДІЛУ РЕСУРСІВ У РЕАЛЬНОМУ ЧАСІ: МЕТОД DRART

Юрій Черненко[1], Наталія Федотова[2], Олена Данченко[3]

[1]К.техн.н., Міжнародний університет бізнесу і права, м. Херсон, Україна, e-mail: yc.gbbio@gmail.com, ORCID: https://orcid.org/0000-0002-7008-7274

[2]Аспірант, ВНЗ «Університет економіки та права «КРОК», м. Київ, Україна, e-mail: FedotovaNO@krok.edu.ua, ORCID: https://orcid.org/0000-0002-9471-8616

[3]Д.техн.н., професор, Черкаський державний технологічний університет, м. Черкаси, Україна, e-mail: o.danchenko@ukr.net, ORCID: https://orcid.org/0000-0001-5657-9144

OPTIMIZING RESOURCE ALLOCATION IN REAL-TIME: THE DRART METHOD

Yuri Chernenko[1], Nataliya Fedotova[2], Olena Danchenko[3]

[1] Candidate of Technical Sciences, International University of Business and Law, Kherson, Ukraine; e-mail: yc.gbbio@gmail.com, ORCID: https://orcid.org/0000-0002-7008-7274

[2]Postgraduate student, «KROK» University, Kyiv, Ukraine, e-mail: FedotovaNO@krok.edu.ua, ORCID: https://orcid.org/0000-0002-9471-8616

[3]Doctor of Technical Sciences, Professor, Cherkasy State Technological University, Cherkasy, Ukraine, e-mail: o.danchenko@ukr.net, ORCID: https://orcid.org/0000-0001-5657-9144

Abstract. *This study aimed to optimize resource allocation and improve project efficiency at Mastergaz, a utility and engineering service provider in Kyiv, by implementing the Dynamic Resource Allocation in Real-Time (DRART) method over a two-year period (2022–2024). A mixed-methods approach was adopted, integrating quantitative data from online surveys with qualitative insights from semi-structured interviews involving 50 professionals in resource management. Twelve engineering projects were examined, including water meter installations and central heating system repairs. Results showed a 25% reduction in average task completion time and a 15% decrease in resource expenditures. The DRART framework, which incorporates resource needs, availability, project priority, and costs, enabled real-time adjustments that led to more efficient allocation. Participants reported improvements in communication, faster decision-making, and streamlined processes. The findings highlight DRART's effectiveness in delivering cost savings and better project outcomes, underscoring its potential for broader application in dynamic resource management environments. By demonstrating both quantitative benefits and qualitative enhancements, the study offers valuable insights for organizations seeking agile strategies to optimize resource utilization. The integration of automated data processing and human oversight facilitates rapid decision-making, mitigating risks tied to project delays or cost overruns. This tilt toward agile decision-making proves especially significant in sectors that face variable budgets, shifting regulations, or seasonally driven workloads. Although these findings emerged from a single organization, they suggest broader applicability for real-time allocation models aimed at boosting project performance in utility management and related fields, particularly when robust data-collection systems are in place. Moreover, DRART's successful deployment at Mastergaz suggests promising directions for further studies examining hybrid solutions that combine DRART with advanced analytics or AI-powered forecasting tools.*

Key words*: dynamic resource allocation, DRART method, real-time data, project efficiency, cost optimization, utility management, engineering projects.*

Formulas: *2; fig.: 0; tabl.: 4; bibl.: 39*

Анотація. *Це дослідження мало на меті оптимізувати розподіл ресурсів і підвищити ефективність проєкту в Мастергазі, постачальника комунальних та інженерних послуг у Києві, шляхом впровадження методу динамічного розподілу ресурсів у реальному часі (DRART) протягом дворічного періоду (2022–2024). Було застосовано змішаний підхід, який об'єднав кількісні дані онлайн-опитувань із якісними даними з напівструктурованих інтерв'ю за участю 50 професіоналів з управління ресурсами. Було вивчено 12 інженерних проєктів, включаючи встановлення лічильників води та ремонт системи центрального опалення. Результати показали скорочення середнього часу виконання завдань на 25%, а скорочення витрат ресурсів – на 15%. Структура DRART, яка включає потреби в ресурсах, доступність, пріоритетність проєкту та витрати, надала можливість здійснювати коригування в режимі реального часу, що призвело до більш ефективного розподілу. Учасники повідомили про покращення комунікації, більш швидке прийняття рішень та оптимізовані процеси. Результати підкреслюють ефективність DRART у забезпеченні економії коштів і кращих результатів проєкту, підкреслюючи його потенціал для більш широкого застосування в динамічних середовищах управління ресурсами. Демонструючи як кількісні переваги, так і якісні покращення, дослідження пропонує цінну інформацію для організацій, які шукають гнучкі стратегії для оптимізації використання ресурсів. Інтеграція* *автоматизованої обробки даних та людського контролю сприяє швидкому прийняттю рішень, знижуючи ризики, пов'язані із затримками проектів або перевитратою коштів. Цей нахил у бік гнучкого прийняття рішень виявляється особливо важливим у секторах, які стикаються зі змінними бюджетами, зміною правил або сезонним робочим навантаженням. Незважаючи на те, що висновки були отримані в одній організації, вони передбачають ширшу застосування моделей розподілу в реальному часі, спрямованих на підвищення ефективності проектів в управлінні комунальними послугами та суміжних областях, особливо за наявності надійних систем збору даних. Крім того, успішне розгортання DRART в Мастергазі пропонує багатообіцяючі напрямки для подальших досліджень із вивчення гібридних рішень, які поєднують DRART із розширеною аналітикою чи інструментами прогнозування на основі ШІ.*

Ключові слова: *динамічний розподіл ресурсів, метод DRART, дані в реальному часі, ефективність проекту, оптимізація витрат, управління комунальними послугами, інженерні проекти.*

Формули: *2; рис.: 0; табл.:4; бібл.: 39*

Introduction. Efficient resource allocation is broadly recognized as a linchpin for enhancing operational performance and ensuring equitable distribution of finite assets (Li et al., 2024). In utility management, the ability to dynamically align resources with rapidly changing project demands, infrastructure conditions, and regulatory landscapes has become paramount. Although many utilities utilize sophisticated frameworks to achieve socio-economic objectives, real-time responsiveness remains a key hurdle (Baynev & Makarevich, 2023).

Analysis of latest research. Classical resource-allocation models—such as linear programming and the Analytic Hierarchy Process (AHP)—offer structured, multi-criteria decision-making frameworks. Nevertheless, they often rely on static assumptions that do not accommodate sudden changes in operational conditions (Osuji, 2024). While certain methods incorporate fairness considerations, their rigidity hinders the quick reallocation demanded by unpredictable environments (Bamel & Bamel, 2018; Momeni & Martinsuo, 2018). These shortcomings become particularly evident in large-scale utility contexts, where project requirements can fluctuate dramatically over short timespans (Chilton, 2022).

Toward Dynamic and Real-Time Frameworks. To address the need for flexibility, researchers have investigated dynamic programming (Forootani et al., 2019) and multiobjective algorithms (Tseng et al., 2018) to iteratively adjust allocations. While such methods enhance adaptability, their computational overhead often hampers real-time performance (Goda et al., 2023). Hybrid approaches—combining classical optimization with live data feeds—further improve responsiveness (Wu et al., 2021), but many still demand substantial historical datasets or specialized infrastructure, limiting their applicability in settings with high variability (Zaher & Eldakhly, 2023). Additionally, cloud-based solutions speed up data processing (Uddin et al., 2023), yet risk misalignment between automated decisions and on-the-ground realities if human validation is minimized (Bertsimas & Stellato, 2022).

Human Oversight, Strategic Flexibility, and Transparency. Recent scholarship emphasizes human oversight and strategic flexibility as catalysts for effective resource management, especially in uncertainty-prone environments. By leveraging knowledge-based resources and expert judgment, organizations can more reliably realign their operational priorities (Bamel & Bamel, 2018; Lemańska-Majdzik & Okręglicka, 2024). Equally important is transparency: when allocation processes are opaque, frameworks risk privileging efficiency over fairness, leading to stakeholder dissatisfaction (Osuji, 2024). Balancing automation with expert review can mitigate these issues, ensuring that resource decisions reflect both algorithmic insights and nuanced contextual constraints (He et al., 2023; Muneeb et al., 2022).

Against this backdrop, the Dynamic Resource Allocation in Real-Time (DRART) method stands out as an agile, data-informed strategy designed to handle real-time fluctuations. Unlike purely static or fully automated approaches, DRART fuses live data inputs with domain expertise to coordinate resource needs, availability, project priorities, and costs—an especially relevant approach for multi-domain operations at utility companies such as Mastergaz.

Purpose of the article. This study investigates the Dynamic Resource Allocation in Real-Time (DRART) method to optimize resource allocation at Mastergaz, a Kyiv-based utility and engineering service provider. Over a two-year period (2022–2024), DRART was deployed in 12 engineering projects, blending real-time data analytics (via the Dynamic Resource Allocation Index, DRAI) with expert oversight to facilitate rapid, adaptive decisions. Methodologically, a mixed-methods approach integrated quantitative data (e.g., online surveys, project performance metrics) with qualitative insights (semi-structured interviews involving 50 resource-management professionals), offering both numerical evidence and contextual perspectives on DRART's impact. Specifically, the research addresses two core questions:

1.How does DRART influence resource allocation efficiency in Mastergaz's engineering projects?

2.What comparative advantages does DRART provide relative to less agile, conventional methods?

By emphasizing agile data-driven adjustments, human validation, and continuous adaptation to resource availability and project priority, this study delivers a streamlined yet comprehensive evaluation of DRART's potential benefits within dynamic utility management settings.

The main material of the article. This research takes place at Mastergaz, a major Ukrainian utility management company specializing in engineering services for gas, electricity, heating, water supply, ventilation, and air conditioning. As distributed energy resources expand, organizations like Mastergaz face a growing need for agile resource-allocation mechanisms (Zheng et al., 2018). Sustainability imperatives, reflected in the adoption of hybrid energy systems, further compel utilities to optimize resource usage, reducing both operational costs and environmental impacts (Duan et al., 2018). Despite existing decision-support tools, many operators struggle to recalibrate resources swiftly when faced with unforeseen shifts in project scope or priority.

This study employed a mixed-methods design to develop and validate the Dynamic Resource Allocation in Real-Time (DRART) method in the operational context of Mastergaz, a utility management company in Ukraine. Mixed-methods research is particularly useful for complex issues that benefit from both quantitative and qualitative perspectives (Harris-Lovett et al., 2019), and it enabled a comprehensive assessment of how DRART could enhance project efficiency and resource utilization (Guo et al., 2019). A total of 50 participants, including project managers, resource coordinators, and operational staff, were selected through purposive sampling to ensure that individuals with direct involvement in resource allocation processes were included (Bertsimas & Stellato, 2022). The sample size was designed to balance the need for sufficient statistical power in the quantitative analysis with the richness of qualitative insights, thereby minimizing concerns about representativeness (Pham et al., 2020). Although 50 participants may seem modest, it provided an opportunity to reach data saturation in relation to key operational roles, and further expansion of the sample did not reveal new patterns in preliminary testing.

A survey instrument employing a Likert scale was administered to capture participants' views on resource availability, project prioritization, and cost management, following established approaches for measuring operational performance in multifaceted settings (Wu et al., 2021). Statistical analyses of these survey data, including paired t-tests, were performed to identify significant changes in resource allocation efficiency (Chen et al., 2020). In parallel, 15 participants took part in semi-structured interviews, and their verbatim responses were transcribed and analyzed thematically to uncover deeper insights into DRART's practical implications (Nikjoo et al., 2018). The number of interviews was deemed sufficient for thematic saturation, as new codes and categories ceased to emerge after approximately 12 interviews, and additional sessions merely reinforced existing findings.

Over a two-year period (2022–2024), DRART was integrated into 12 engineering projects at Mastergaz, each with budgets not exceeding 100,000 USD (Tsai et al., 2020). The method was incorporated into the existing BOS CIS platform, which functions as an ERP-BPMS system that automates data collection and processing while also relying on periodic human review and manual verification. Specialists with expertise in finance, engineering, and operational management followed pre-established checklists to verify that inputs such as resource needs and cost estimates were valid, and the system itself flagged potential anomalies, including mismatches in updated project priorities. This reciprocal oversight ensured greater reliability in real-time data usage and allowed both the platform and the personnel to complement each other's monitoring and decision-making processes (Harris-Lovett et al., 2019).

The DRART method is grounded in the Dynamic Resource Allocation Index (DRAI), a metric designed to account for multiple factors in real time.

The original formula is

$$r_t = \frac{\sum_{i=1}^{n} (u_i \, a_i \, p_i)}{\sum_{j=1}^{m} (c_j + 1)} \quad (1)$$

where r_t represents total resource allocation at time t,

u_i denotes the project's resource needs,

a_i indicates resource availability,

p_i reflects the project priority, and

c_j represents costs.

To refine the method and achieve greater accuracy, weighted parameters for u_i, a_i, p_i, and c_j were introduced in line with research on multi-objective frameworks (Ghasemi et al., 2022; Chang et al., 2021).

The modified formula is

$$r_t = \frac{\sum_{i=1}^{n} (w_u u_i + w_a a_i + w_p p_i)}{\sum_{j=1}^{m} (w_c c_j + 1)} \quad (2)$$

where w_u, w_a, w_p, and w_c are weights for resource needs, availability, project priority, and costs, respectively (He et al., 2023). A sensitivity analysis was performed internally to confirm that small deviations in w_u, w_a, w_p, or w_c would not drastically alter final resource allocation decisions. Through this combination of automated calculations and human input, the DRART approach retained the agility needed for real-time responsiveness while ensuring that domain experts validated the parameters on a regular basis.

Validation involved comparing task completion times and resource expenditures before and after DRART's implementation, with paired t-tests employed to assess whether observed changes in allocation efficiency were statistically significant (Asghariniya et al., 2019). Baseline metrics were compared to post-implementation data covering multiple phases of the projects, thereby allowing a longitudinal view of the impact (Boikov & Kropotova, 2018). The study adhered to ethical standards through informed consent, data protection measures, and explicit acknowledgments of potential constraints that arose from focusing on a single organization (Li et al., 2018). The combination of an automated ERP-BPMS platform and human checkpoints facilitated transparent data gathering throughout the two-year period and supported reproducibility of the findings, given that the procedures and verification steps were systematically documented.

The two-year application of the Dynamic Resource Allocation in Real-Time (DRART) method at Mastergaz, spanning 2022 to 2024, led to substantial improvements in resource allocation and project outcomes across 12 engineering initiatives, which included water meter installations, central heating system repairs, and ventilation unit maintenance, each with budgets capped at 100,000 USD. To capture the breadth of these enhancements, indicators such as average task completion time and resource expenditures were evaluated before and after DRART's implementation. Prior to DRART, the average task completion time stood at 40 days, whereas post-implementation data showed a decrease to 30 days, reflecting a 25% reduction (Table 1).

Table 1

Average Task Completion Time Before and After DRART Implementation.

Metric	Before DRART Implementation	After DRART Implementation	Improvement (%)
Average Task Completion Time (days)	40	30	25

Source: calculated by the authors based on Mastergaz data (2022-2024)

In parallel, the mean cost per project decreased from 80,000 USD to 68,000 USD, which represents a 15% reduction in resource expenditures (Table 2).

The results of paired t-tests demonstrated that these observed reductions in both task completion time and expenditures were statistically significant at $p < 0.05$ [9].

Table 2

Average Resource Expenditures Before and After DRART Implementation.

Metric	Before DRART Implementation	After DRART Implementation	Improvement (%)
Average Resource Expenditures ($)	80	68	15

Source: calculated by the authors based on Mastergaz data (2022-2024)

Qualitative feedback from semi-structured interviews reinforced this pattern of improvement, with participants noting that DRART's capacity for real-time reallocation not only accelerated key decisions but also made the distribution of labor and materials more targeted. During water meter installations, a more dynamic approach to shifting both human and material resources was credited with producing a 20% decline in overall resource wastage relative to prior methods, which aligns with the broader literature on real-time adjustments for efficient resource management (Wu et al., 2021).

In order to illustrate these benefits more concretely, two representative engineering projects were examined in detail. The first project focused on installing new water meters in three high-rise residential buildings, covering a total of 150 apartments. Prior to DRART, tasks were scheduled weekly, often leading to either underutilized technicians or unexpected delays if additional materials were required mid-way. By contrast, once DRART was implemented, BOS CIS automatically analyzed real-time data on meter availability, technician proximity, and customer schedules. The result was a drop-in completion time from 35 days to 25 days, along with an 18% reduction in unused or damaged parts. This more responsive scheduling also allowed technicians to respond to urgent service requests (such as leaks or pressure issues) without disrupting the overall project flow (Table 3).

A second project addressed the scheduled maintenance of 200 central heating units in multiple residential blocks. Before DRART, maintenance tasks were queued by static work orders that did not adapt to sudden issues or uneven workloads, resulting in a completion time of about 45 days.

Table 3

Example of Water Meter Installation Project Before and After DRART.

Metric	Before DRART (Baseline)	After DRART (New Approach)	% Improvement
Completion Time (days)	35	25	29
Material Wastage (%)	12	10	18
Technician Overtime (hours)	120	80	33
Customer Complaints (count)	8	3	63

Source: compiled by the authors based on BOS CIS platform analysis (2022-2024)

After DRART was introduced, data from technicians' smartphones regarding heating units needing extra parts or more specialized work were immediately processed in the ERP-BPMS system, prompting a real-time recalibration of staff schedules and material stock. Maintenance time fell to 32 days, while overall resource expenditures declined by 15%. Staff utilization improved in parallel, as fewer idle hours were observed and urgent requests were integrated into the revised schedule without necessitating costly overtime or re-routing (Table 4).

Table 4

Example of Central Heating Unit Maintenance Project Before and After DRART.

Metric	Before DRART (Baseline)	After DRART (New Approach)	% Improvement
Completion Time (days)	45	32	29
Resource Expenditures (USD)	75	63,75	15
Technician Idle Time (hours/month)	45	28	38
Urgent Requests Handled on Schedule (%)	65	85	+20 p.p.

Source: compiled by the authors based on BOS CIS platform analysis (2022-2024)

Additional descriptive and inferential analyses offered further insight into DRART's positive impact. Regression modeling assessed the relationship between DRART adoption and subsequent reductions in completion times and costs. Modeled as $y = b0 + b1x1 + b2x2 + \varepsilon$, where y denotes either time or cost metrics, the coefficients linked to DRART emerged as positive predictors of performance improvement. This finding is consistent with best practices in performance measurement, where longitudinal data analysis and formal statistical testing reliably establish causal links between managerial innovations and enhanced project outcomes (Boikov & Kropotova, 2018; Asghariniya et al., 2019). The overall trend confirms that DRART fosters more adaptive allocation processes, enabling both cost-effectiveness and timely delivery in the context of large-scale utility management.

These results also reflect the systematic checks performed by qualified specialists and the BOS CIS platform, which worked in tandem to verify data inputs, flag potential anomalies, and update project priorities. Managers noted that real-time oversight prevented bottlenecks and facilitated a faster response to contingencies, such as unexpected equipment failures or last-minute customer cancellations. This reciprocal approach—combining automated calculations with human validation—helped maintain accurate performance metrics and ensured that the documented improvements in time, cost, and resource utilization were both consistent and reproducible. By highlighting case-specific outcomes in meter installations and heating unit maintenance, the data confirm that DRART can be readily adapted to projects of varying complexity across Mastergaz's broad operational scope, thereby enhancing the firm's capacity to serve over 750,000 apartment owners and to process 200–300 service requests daily.

The findings from Mastergaz illustrate how a real-time and adaptable resource allocation system can address the challenges posed by dynamic environments. The Dynamic Resource Allocation in Real-Time (DRART) method builds upon the idea that timely adjustments to resource availability and project priorities can greatly enhance operational effectiveness. Compared to conventional static strategies, DRART's reliance on current data allows resources to be rapidly redirected to where they are most needed, thus overcoming the rigidity of approaches that struggle to accommodate sudden shifts in project demands (Abedallah & Almajed, 2019). Its Dynamic Resource

Allocation Index (DRAI) further streamlines the prioritization process, offering a more straightforward method of balancing multiple factors than Fuzzy TOPSIS-based frameworks, which can suffer from high computational overhead (Momeni & Martinsuo, 2018).

This study confirms that DRART can outperform heuristic and machine learning-based approaches in scenarios where historical datasets are sparse or of limited relevance. While machine learning models can predict resource shortfalls, they generally require extensive historical inputs (Zaher & Eldakhly, 2023). DRART, by contrast, uses fewer historical data points, placing greater emphasis on real-time updates for efficiency gains in multi-project settings. The simplicity of DRART also provides an edge over dynamic programming, where computational complexity may complicate quick recalibrations (Goda et al., 2023). In addition, DRART helps mitigate operational inefficiencies, such as the cascading delays associated with conventional resource leveling (Chilton, 2022), because it integrates project priorities, availability, and costs into a single, coherent decision-making framework.

Qualitative insights at Mastergaz confirmed that DRART supports a collaborative, adaptable approach to problem-solving, aligning with the literature on hybrid resource allocation (Momeni & Martinsuo, 2018). Real-time recalibration proved especially beneficial for multi-phase engineering assignments, resulting in shorter completion times and cost reductions. These outcomes corroborate previous work suggesting that DRART surpasses various methods, including dynamic programming and machine learning-based models, by delivering faster project completion when conditions are uncertain (Forootani et al., 2019). In the management of ventilation systems, DRART made use of both historical maintenance records and immediate operational data to reduce expenses, exemplifying its capacity to combine predictive elements with live resource allocation (Zheng et al., 2024; Shanmugam et al., 2023). Its ability to function with minimal computational overhead distinguishes it from AI-driven optimization frameworks that often carry significant requirements, such as edge computing's latency constraints or high processing power (Islam, 2024; Tseng et al., 2018; Kumar et al., 2023).

These findings speak directly to the research questions. First, they demonstrate that deploying the DRART method at Mastergaz yields measurable gains in resource allocation efficiency, thereby validating the real-time adjustment mechanism as a catalyst for more rapid project execution and lower expenditures. Second, they show that DRART holds a competitive edge over classical approaches, owing to its responsiveness and reduced reliance on comprehensive historical datasets, reinforcing the principle that simpler, real-time methods can be equally or more effective than computationally heavy alternatives.

Despite DRART's effectiveness under rapidly evolving conditions, the study was limited to a single organization whose data infrastructure is relatively mature. This reliance on robust data systems contrasts with generalized machine learning frameworks that can adapt to different contexts if large volumes of historical data are available (Abishek et al., 2023). DRART's streamlined structure also has inherent constraints; in very high-dimensional contexts, such as multi-user cloud networks, more sophisticated algorithms may account for interactions that DRART cannot fully capture (Lin et al., 2020). Future work may explore hybrid configurations that blend DRART's real-time recalibration capabilities with advanced AI-based methods, including reinforcement learning and neural networks, in order to expand scalability and adaptability (Lyu et al., 2024; Gupta et al., 2024). Such endeavors would help determine whether the method's key strengths extend to a wider variety of organizational environments and whether incorporating more computational elements could refine DRART's decision-making processes without jeopardizing its capacity for rapid, flexible responses.

Conclusion. The results achieved at Mastergaz confirm that the Dynamic Resource Allocation in Real-Time (DRART) method provides an effective and adaptable strategy for optimizing resource allocation amid constantly shifting conditions. Over the two-year implementation period, DRART's emphasis on real-time data and flexibility led to a 25% decrease in average task completion times and a 15% reduction in overall expenditures. These quantitative improvements were supported by qualitative observations that indicated enhanced communication, accelerated decision-making, and more transparent allocation mechanisms. By integrating variables for resource needs, availability, project priority, and costs into the Dynamic Resource Allocation Index, DRART enabled Mastergaz to respond more precisely to immediate operational requirements. Although these findings emerged from a single organization, they suggest broader applicability for real-time allocation models aimed at boosting project performance in utility management and related fields, particularly when robust data-collection systems are in place.

DRART has demonstrated that continuous monitoring and flexible resource distribution yield tangible benefits for managers by minimizing inefficiencies and bridging information gaps. The integration of automated data processing and human oversight facilitates rapid decision-making, mitigating risks tied to project delays or cost overruns. Managers can also leverage DRART's quick recalibration capabilities to foster a proactive communication culture, wherein cross-functional teams regularly align resource usage with evolving operational demands. This tilt toward agile decision-making proves especially significant in sectors that face variable budgets, shifting regulations, or seasonally driven workloads.

From a theoretical perspective, DRART advances the literature on dynamic resource allocation by showing how real-time indices can be designed to incorporate multiple decision variables without imposing prohibitive computational burdens. Its integrated structure, encompassing resource needs (u_i), availability (a_i), project priority (p_i), and costs (c_j), refines existing allocation approaches that often rely on static optimization techniques or historical data. Moreover, DRART's successful deployment at Mastergaz suggests promising directions for further studies examining hybrid solutions that combine DRART with advanced analytics or AI-powered forecasting tools. Such inquiries could illuminate how real-time adaptability might be refined in multidimensional or large-scale contexts, thereby contributing to ongoing discussions of resource optimization in project management.

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