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A comprehensive review of quadratic assignment problem methodologies in healthcare facility layout optimization

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C H R O N I C L E

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A B S T R A C T

The Quadratic Assignment Problem (QAP) is still considered to be one of the most difficult and widely used models in combinatorial optimization. The layout of healthcare facilities has been its most significant application area since the 1970s, representing a crucial field of study for increasing operational efficiency, patient safety, and staff flow. The QAP context has been continually altered and supplemented to cover the particular intricacies of the healthcare sector. After Elshafei's groundbreaking paper in 1977, the QAP framework was reinvented and extended to the point where it gained acceptance in the healthcare facility location planning area. This review offers a synthesis of the existing literature from 1977 to 2025 and classifies the research into ten different methodological streams: Exact Solution Methods, Classical Heuristics, Metaheuristics, Hybrid Approaches, Robust Optimization, Fuzzy QAP, Stochastic Programming, Multi-Objective QAP, Special Structure Exploitation, and Parallel & Dis-tributed Computing. The critical assessment of the transition of solution procedures and how the techniques for handling uncertainty have been developed shows how the research has progressed from modeling with one deterministic objective to a sophisticated data-driven approach where multiple objectives are characterized as well as the inherent uncertainties of the system. The analysis indicates the integration and hybridization trend—in the case of algorithms, objectives, and data sources is quite strong—pointing out the future lines of research in areas such as real-time adaptive layouts, deep learning integration, and pandemic-responsive design.

1. Introduction

The efficient design and optimization of healthcare facilities are not only about architecture but essential for clinical outcomes, operational efficiency, and economic sustainability. The ideal layout design shortens the path for travelling by patients, staff, and materials and it thus leads to a sequence of advantages: it reduces waiting times, decreases staff fatigue, lowers the infection transmission risk, and eventually, the quality of care gets improved. The Quadratic Assignment Problem (QAP) was first formalized by Koopmans and Beckmann (1957) to represent the location of indivisible economic activities and it offers a natural and powerful mathematical framework for this issue. In the standard version, the QAP intends to match `n` facilities (for instance, hospital departments) with `n` locations so that the total cost, which is a quadratic function of the flow between departments and the distance between their assigned spots, is minimized. The application of QAP to hospital layout was first outlined by Elshafei (1977), who showed its power in reflecting the interdependent character of departmental relationships. The main power of the model is found in the possibility of measuring the trade-off of having the very interactive departments, such as the Emergency Room (ER) and Radiology, next to each other. But, on the opposite, the QAP is notorious for its arithmetic complexity; it is in the class NP-hard, meaning that the computational effort to find an optimal solution for realistically sized problems increases exponentially, making exact solution inaccessible for all but the smallest cases (Burkard et al., 1998).

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The natural intricacy involved has initiated over 40 years of vigorous research so that eventually a very rich and varied literature was produced. The scientists have come up with a very large collection of solution methods, which vary from precise algorithms for small problems to very complex and large layouts to very sophisticated heuristics and metaheuristics. Recently, however, the trend has turned from the use of deterministic models to the employment of those that rely on stochastics to cope with the thorough uncertainties and multiple, often antagonistic, objectives characteristic of healthcare settings. This paper sorts this massive volume of research into ten logical categories thus offering a well-defined method of analyzing the path of QAP techniques in medical layout planning.

2. Exact Solution Methods

Exact solution methods are always certain to discover the best solution to a QAP case. These techniques are the cornerstones of the discipline, giving rise to the establishment of the entire set of heuristic and metaheuristic strategies. However, their usage is restricted to a great extent due to the complexity of the problem from the computational point of view.

2.1 Foundational Algorithms and Early Applications

The Koopmans and Beckmann (1957) study, among others, opened up the field of theory, while on the other hand, Burkard et al. (1998) gave a very extensive handbook chapter that continues to be the best reference concerning exact methods, as it explains in detail the techniques such as branch-and-bound (B&B) and cutting planes. In a traditional B&B algorithm for QAP, the initial problem is broken down recursively into increasingly smaller subproblems by fixing which departments are assigned to which locations. Each subproblem's bounds are determined through linear programming (LP) relaxations, frequently using the Gilmore-Lawler bound or other stronger bounds, to eliminate non-optimal branches in the search tree.

Elshafei's (1977) implementation was a significant turning point in that it presented the abstract hospital layout issue in the form of a rigorous QAP and applied the then-existing exact methods to obtain its solution. The instance size may have been small, but nonetheless, it was a proof of the idea and also a source of optimal solution which was the best for a particular example. So was Montreuil and Ratliff (1989) who set forth a straightforward QAP formulation more than a decade later with an eye for the hospital environment, further pointing out the creation of flow and distance matrices from real-life operational data as the basis of the whole hospital designing process. Their contribution not only made it easier for others, but they also recognized the limitations of exact solvers in the case of hospital design on large-scale.

2.2 Modern Exact Approaches and Limitations

In a thorough review, Anjos and Vieira (2021) have presented modern exact techniques that have expanded the limit of solvable instances. The latter includes the use of symmetry-breaking constraints to reduce the search space, the application of dynamic programming, and the advanced integer programming methods among others. Nevertheless, Li and Zhang (2020) pointed out in their review that pure exact methods are seldom used for layout problems in the healthcare sector these days. The combinatorial explosion associated with the problems of more than 15-20 departments makes them computationally prohibitive for most real-world hospital planning scenarios, which usually consist of 30 or more functional units.

2.3 Role in Contemporary Research

The exact methods' main role today is not direct application but rather validation. Amaral (2008), for example, employs exact solvers for small, simplified versions of his problems or for subproblems within a larger decomposition scheme. The optimal solutions found for these smaller instances are used to calibrate and validate the performance of heuristic algorithms, thereby providing assurance that the heuristics are producing high-quality results, if not provably optimal, for the parts of the problem where optimality can be determined.

3. Classical Heuristics

The classical heuristics are meant to speedily get the QAP's good and feasible solutions, and no optimality guarantee is given. They are usually marked by uncomplicated, easy-to-understand rules and local search methods.

3.1 Constructive and Improvement Heuristics

Constructive heuristics, as the name suggests, develop a whole solution from the very beginning. One typical method, which is the one that Lee and Moore (1973) and later Sahin and Turkay (2009) adapted for healthcare use, is to rank departments according to their total flow and to place the department having the highest flow at the most 'central' location (e.g., the location with the smallest total distance to all others). After this the algorithm takes a greedy approach, placing each next department in the available location where the total cost increase from interactions with already placed departments is the least.

The improvement heuristics commence with a fully developed solution, which is sometimes generated at random, and then gradually make local modifications to it in order to reach a better one. The pairwise exchange or 2-opt heuristic is the most renowned among these. This technique, among others explained in classical references like Dowsland (1993), thoroughly examines the entire set of swaps between two departments' positions. Whenever the swap decreases the total cost, it is ruled in favor. The operation goes on in this manner until there is no swap left that can improve the situation, which is then identified as a local optimum.

3.2 Application and Analysis

The GRASP (Greedy Randomized Adaptive Search Procedure) algorithm applied to QAP and developed by Castillo and Gómez (2009) is a complex classical heuristic that integrates a random constructive and a local search-improvement phase. The initial stage's randomization prevents the method from being stuck in low-quality local optima. Referring to the allocated sources, the final MATLAB code from our earlier conversation, too, employed the local search component which is a direct application of a pairwise exchange improvement heuristic. Its disadvantage is that it is prone to the very local optimum, which may be quite distant from the global optimum; its advantage is that it is simple and guarantees convergence to a local optimum.

Classical heuristics are often regarded as less significant than the more complex metaheuristics but still hold their ground in the problem-solving realm. They are super-fast and can either supply a "good enough" solution for initial planning or function as a highly efficient local search component within a more extensive metaheuristic framework, as has been the case in many hybrid approaches.

4. Metaheuristics

Metaheuristics are large-scale methods that lead basic heuristics to effectively search the solution space, always keeping in mind the trade-off between intensification (extraction of the best regions) and diversification (inquiry of new regions). They are the most productive category in present-day QAP research for health care.

4.1 Simulated Annealing (SA) and Tabu Search (TS)

Simulated Annealing, as the name suggests, is a method that takes its inspiration from the annealing process in metallurgy and gives the opportunity to the system to make occasional "uphill" moves in order to get out of local optima. The acceptance probability of a worse solution is set to shrink gradually with respect to the predefined cooling schedule. Bandy-opadhyay and Saha (2022) employed SA in redesigning hospital layouts and they were able to present a superior solution when compared to the simple local search strategy due to their tactical accepting of temporary worsening. Dowsland (1993) is the one who laid down the very basic principles that such applications are grounded upon.

The algorithm of Tabu Search implements memory structures as a means to prevent itself from cycling back to the most recently visited solutions. A list of "tabu" holds the recent swaps done, which are then banned for a specific number of iterations. In their paper, Mohammadi and Khosravi (2022) on hybrid genetic and tabu search algorithms, reported the combination of the two algorithms in the product of the powerful TS's intensification capabilities. The GA is used to explore broadly and then the TS is employed to search deeply for promising solutions in the neighborhoods, a combination which turned out to be very effective for the layouts of complex hospitals.

4.2 Evolutionary and Swarm Intelligence Algorithms

Genetic Algorithms (GAs), which imitate nature's way of selecting the fittest, are one of the most widely used metaheuristics for QAP. They keep evolving a population of solutions (chromosomes) that are subjected to selection, combination (recombination), and variations. Miç, Gülsün, and Edalı (2021) as well as Mohammadi and Khosravi (2022) both apply GAs to multi-objective hospital layout problems, thus taking advantage of the methods' versatility to cater for multiple criteria and to yield a range of Pareto-optimal solutions.

Another strong method is Particle Swarm Optimization (PSO), which draws its inspiration from the social pattern of birds moving together. Ahmed and Rahman (2021) used PSO in a particularly innovative way for hospital layout; they considered the potential solutions as particles that move around the solution space, changing their paths according to their own experience and that of their neighbors. The outcome was that PSO for some problem configurations could find high-quality solutions faster than some traditional GAs.

Ant Colony Optimization (ACO), which imitates the foraging behavior of ants, has, in addition, been successfully applied. ACO was introduced by Wang and Liu (2021) for hospital layout planning in a completely new way, where "artificial ants" build solutions with probabilities determined by both "pheromone trails" laid on the good tasks and the heuristic desirability. This indirect communication via pheromone trails fully supports the population to efficiently find out remarkable solutions.

5. Hybrid Approaches

Hybrid methodologies that combine two or more approaches to AI in order to take advantage of their strengths and reduce their weaknesses are the current trend in the algorithm development for QAP in healthcare. This type represents the leading edge of algorithmic development for healthcare QAP.

5.1 Metaheuristic-Metaheuristic Hybrids

The fusion of a population-based method along with a trajectory-based one is a well-known and strong pattern. Mohammadi and Khosravi (2022) give a recognizable instance with their combined Genetic and Tabu Search algorithm. The GA presents diversity in exploring the solution space and TS does the best with a rigorous local search. By incorporating a TS routine as a local search step inside the GA, they end up with an algorithm that is majorly an explorer and minorly a digger which is also the case with the use of either algorithm alone.

5.2 Matheuristics and Simulation-Optimization

Matheuristics represent a combination of mathematical programming and heuristics. A classic example of simulation-optimization is given by Ahmadi-Javid, Jalali, and Klassen (2017). An optimization model (a linearized version of QAP) is used to generate the layout candidates with the most potential. However, instead of a simple cost function, these candidates are assessed through a comprehensive discrete-event simulation model that can depict dynamic and stochastic factors such as patient arrival patterns, service times, and queuing. The layout optimization is guided by the simulation feedback resulting in layouts that are not only statically efficient but also dynamically robust.

Ghasemi and Pourmohammadi (2021) elaborate on this simulation-based QAP model, showing that it is able to reflect, in a much better way, the actual operational dynamics which get dissipated in static QAP formulation. Moreover, Chatterjee and Dey (2023) join the same crowd, mixing a QAP core with extra constraints and employing heuristic solution methods to tackle the intricate patient movement patterns thereby facilitating smoother flow of patients.

6. Robust Optimization

Classic QAP frameworks hold that flow and distance parameters are precisely known, which is seldom the case in the hospital's erratic atmosphere. Robust optimization confronts this by discovering solutions that yield good results over a wide variety of input scenarios.

6.1 Foundational Concepts and Models

In the opinion of Ben-Tal and Nemirovski, robust optimization categorically models uncertainties via the imposition of bounded uncertainty sets instead of using probability distributions. The calculation is often based on the minimization of the worst-case cost or the maximum regret incurred, depending on the specific case. In their 2022 paper, Rezaei and Tavakkoli-Moghaddam proposed a robust optimization method that is suitable for hospital layout planning, where patient flows are uncertain and confined to a given polyhedral uncertainty set. The model determines a layout that is protected from the worst-case scenario of these flows, thus giving a vital safety net for the planning of facilities over the long term.

Sadeghi and Tavakkoli-Moghaddam (2023) have gone even further with the idea by combining strong QAP with particular healthcare risks, such as the demand for different medical services varying and changes in staff levels. According to their research, a layout designed for certainty can perform very badly in real-world uncertain conditions, but at the same time, a strong layout can give up a little of its nominal efficiency in return for a large gain in reliability and resilience.

6.2 Application in Crisis Situations

The worth of robust optimization became vividly noticed in the course of the COVID-19 crisis. Pourmohammadi and Ghasemi (2024), in their research on hospital layout considering pandemic restrictions, tend to apply a robust method implicitly. They create layouts that should be able to work properly in the usual situation as well as in the extreme pressure and changed flow patterns of a pandemic, for instance, the demand for tight division of infected and non-infected areas. This is an actual example of designing for the worst-case scenario among the uncertainty set of possible states of hospital operations.

7. Category 6: Fuzzy QAP

Fuzzy set theory comes up with a different approach for dealing with uncertainty, especially when the uncertainty is due to factors like imprecision, vagueness or no hard data which are often expressed in linguistic terms.

7.1 Modeling Imprecise Parameters

Often in the case of hospital planning, the exact flow data may be either completely unavailable or the cost of collecting it would be prohibitively high. In this respect, experts may give rough estimates such as "there's a lot of movement between the ER and the ICU." Fuzzy QAP models that have been presented by Ghasemi and Shafahi (2021) are very efficient in depicting this type of situation by assigning fuzzy numbers to the flow matrix 'F' and sometimes also to the distance matrix 'D'. For example, a tri-angular fuzzy number can be characterized by three values: a pessimistic one, a most likely one, and an optimistic one, thus expressing the uncertainty of the expert opinion.

Jafari and Khalili-Damghani (2023) developed a multi-objective fuzzy QAP model as a further step in this direction. With their method, it is possible for directors not only to eliminate the expenses, lower the infection risk, and amplify customer satisfaction, but also to do all these things simultaneously under the given fuzzy input parameters. Instead of just one layout, a choice of layouts that are non-dominated is provided, thus giving the planners a variety of options that show the best possible compromises under uncertainty.

7.2 Solution Techniques and Defuzzification

Fuzzy QAPs are usually solved by creating a crisp model that is equivalent to the fuzzy model, which is a procedure called defuzzification. Kumar and Singh (2022) propose a hybrid method that merges QAP with fuzzy logic, with the aid of fuzzy rules to assess the qualitative dimensions of a layout that are not easily represented in a pure cost function. The obtained models reflect human reasoning more and thus are very useful in the initial, conceptual phases of design where little data is available and expert opinion is the most decisive factor.

8. Stochastic Programming

Robust optimization confronts the scenario where the uncertainty is in the form of bounds, and fuzzy logic is employed where the uncertainty has to do with the lack of knowledge, while stochastic programming takes care of the aleatoric uncertainty—the kind of uncertainty that can be represented by the known (or estimated) probability distributions.

8.1 Two-Stage and Chance-Constrained Models

The stochastic programming models for QAP usually have the two-stage form. The layout assignment that the uncertain parameters (for instance, future patient flows) have not yet been realized. The operational costs after the uncertainty is resolved are incurred in the second stage. The goal is to reduce the first-stage cost together with the expected second-stage cost. The pioneering work of Slyke and Wets (1969) on Lagrange multipliers for stochastic programming is the basis for these techniques.

Even though no reference mentioned or labelled the model as a two-stage stochastic QAP, the work of Ahmadi-Javid et al. (2017) on simulation-optimization can still be considered as the first step of a sampling-based approach for solving a stochastic program. The simulation conducted by them calculates the expected operational cost of the layout (i.e. the second-stage cost) very efficiently by taking the average over numerous random scenarios of patient arrivals and service times.

8.2 Scenario-Based Approaches

An efficient strategy that is often utilized for dealing with stochastic QAPs is the application of a discrete collection of scenarios, to each of which a probability is allocated. The anticipated performance is then optimized by the model over these scenarios. This method is very much suited for the simulation-optimization framework where every simulation run is equivalent to one scenario. The idea is advancing the domain towards data-driven stochastic optimization, in which the probability distributions are not fixed but rather inferred from large volumes of electronic health record (EHR) and sensor data.

9. Multi-Objective QAP

A hospital's aim is not solely to shorten the distance of travel. It operates as a complex system with several conflicting aims. MO-QAP is an exact model of that situation.

9.1 Pareto Optimization and Evolutionary Algorithms

A MO-QAP does not only yield one optimal layout but rather a collection of Pareto-optimal layouts. To be more precise, a layout is said to be Pareto-optimal when there is no alternative layout that can enhance one objective without deteriorating another. Evolutionary algorithms, and among them especially NSGA-II (Non-dominated Sorting Genetic Algorithm II), can be considered as the most suitable candidates for this purpose since they already work with a population of solutions. On the other hand, Rahimi and Zandieh (2021) utilized NSGA-II for the hospital layout case where simultaneously total travel distance was minimized, construction cost reduced, and flexibility increased.

Jafari and Khalili-Damghani (2023) and Miç et al. (2021) also make contributions to the same line of research, showing how planners can find their way around the trade-offs among cost, clinical efficiency, safety, and patient privacy. The output of these models makes it easier for the decision-makers by illustrating the Pareto front, giving them the opportunity to choose a final layout according to institutional priorities that may be hard to measure.

9.2 Integrating Soft Objectives

One of the main difficulties that in MO-QAP is expressing in numbers the "soft" objectives like staff satisfaction or patient experience. Newer and newer research works blend quantitative models with qualitative evaluations using techniques such as the Analytical Hierarchy Process (AHP) to assign different weights to the objectives according to the opinions of the stakeholders. The combination of human judgment and mathematical optimization is indispensable in the production of layouts that are not only efficient but also humane and functional.

10. Special Structure Exploitation and Emerging Paradigms

Under appropriate circumstance it takes an energy to work on specific problem characteristics or open up an entirely different window.

10.1 Exploiting Spatial and Digital Structures

Al-Hussein and Nassar (2020) optimize the physical arrangement of hospitals through the combination of Building Information Modeling (BIM) and Quadratic Assignment Problem (QAP) methods. The use of BIM results in a highly detailed digital portrayal of the building which is data-rich, enabling the precise and automatic computation of the distance matrix "D" that consists of actual walking paths and not only Euclidean distances. The combination of QAP with digital twin technology delivers a substantial improvement in model accuracy.

Nourian and Sariyildiz (2022) as well as Sari and Jabi (2023) are examples of the same trend, graph-based algorithms and spatial analysis being primarily applied to the layout problem pre-processing or the generation of a solution space that is in accord with architectural and regulatory constraints. The latter one is then inputted into a QAP optimizer. Besbes et al. (2020) are also part of this scenario with their methodology that combines GA and A* search to deal with physical barriers in the facility, a common situation that pure QAP models have a tendency to overlook, explicitly in a way that is very similar to QAP-based optimization methods.

10.2 Machine and Deep Learning Integration

The latest and most advanced methods are those that fuse the quadratic assignment problem (QAP) with machine learning (ML). Sadeghi and Zandieh (2023) and Zhang and Zhou (2022) investigate the application of ML for anticipating the performance of a layout or, mefurthermore, for the discovery of a heuristic that would be good for producing solutions. One example is Zhang and Zhou's (2022) deep learning scheme, which can be trained on a massive collection of solved QAP instances to discover a relationship between the problem characteristics (flow and distance matrices) and the allocation with good quality, thus making it possible to get near-optimal solutions in a few milliseconds.

10.3 Reinforcement Learning

Focusing on the future, Zhang and Wang (2023, 2025) use Reinforcement Learning (RL) for hospital layout planning. Their entire procedure includes an RL agent learning to assign departments one after the other and getting rewarded for the assignments that result in low total costs. This is a total break from classic optimization and shows the reliance on AI for design. The agent develops a policy that is able to be applied to new, unknown layout challenges, possibly even real-time adjusting to the newly changing operational needs.

11. Synthesis and Comparative Analysis

In healthcare layout, several major trends have influenced the evolution of QAP methodologies.

From Exact to Approximate to Intelligent: Initially, the difficulty of exact solution methods was so small that the field never considered it as a focus of research. The metaheuristics were then introduced and the field's attention shifted to the efficient finding of good solutions for large instances. Now, it is the time for learning-based methods to take over and the field will be characterized by "intelligent" optimization. From Deterministic to Uncertain: The acceptance that healthcare is a naturally stochastic and data-poor sector has resulted in the creation of strong, fuzzy, and stochastic models, thus leading the attention from pure effectiveness to resilience and reliability. The shift in perspective from single-objective to multi-objective has resulted in the adoption of Pareto-based methods that facilitate intricate decision-making involving multiple parties. This change in view recognizes that the cost is merely one among various factors. Isolated to Integrated: The dominant contemporary techniques are hybrid, intermixing optimization with simulation, BIM, and machine learning, thus developing high-fidelity, usable decision-support tools.

From the illustration that has been made of the references, it is clear that hybrid metaheuristics like GA-TS (Mohammadi & Khosravi, 2022) are currently providing the best solution quality in terms of computational time and vice versa for standard, deterministic problems. In situations of uncertainty, the choice to use robust (Rezaei & Tavakkoli-Moghaddam, 2022) or fuzzy (Ghasemi & Shafahi, 2021) models depends on the type of uncertainty—whether it is bounded variability or linguistic imprecision. For the most complex, dynamic problems, simulation-optimization (Ahmadi-Javid et al., 2017) still is the gold standard. Table 1 summarizes the literature review of this paper.

Table 1
The summary of the literature review

Reference	Exact Methods	Classical Heuristics	Metaheuristics	Hybrid Approaches	Robust Optimization	Fuzzy QAP	Stochastic Programming	Multi-Objective QAP	Special Structure Exploitation	Parallel & Distributed Computing
Ahmadi-Javid et al. (2017)		✓		✓			✓		✓	
Ahmed & Rahman (2021)			✓							
Al-Hussein & Nassar (2020)									✓	
Amaral (2008)	✓									
Anjos & Vieira (2021)	✓	✓	✓	✓						
Bandyopadhyay & Saha (2022)			✓							
Besbes et al. (2020)			✓	✓					✓	
Burkard et al. (1998)	✓	✓								
Castillo & Gómez (2009)		✓								
Chatterjee & Dey (2023)				✓					✓	
Dowsland (1993)		✓	✓							
Drezner (2005)	✓	✓								
Elshafei (1977)	✓									
Farahani & Hekmatfar (2009)	✓	✓								
Ghasemi & Shafahi (2021)						✓		✓		
Ghasemi & Pourmohammadi (2021)				✓			✓		✓	
Ghosh & De (2023)		✓	✓	✓						
Heragu & Kusiak (1991)	✓	✓								
Jafari & Khalili-Damghani (2023) - MCDA								✓		
Jafari & Khalili-Damghani (2023) - Fuzzy						✓		✓		
Kumar & Singh (2022)				✓		✓				
Kusiak & Heragu (1987)	✓	✓								
Lee & Moore (1973)		✓								
Li & Chen (2020)	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Li & Zhang (2020)	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Meller & Gau (1996)	✓	✓	✓							
Miç et al. (2021)			✓					✓		
Mohammadi & Khosravi (2022) - Hybrid			✓	✓						
Mohammadi & Khosravi (2022) - ESWA				✓						
Montreuil & Ratliff (1989)	✓									
Nourian & Sariyildiz (2022)									✓	
Patel & Mehta (2024)		✓	✓							
Pitsoulis & Pardalos (2009)	✓	✓	✓							
Pourmohammadi & Ghasemi (2024) - HCMS				✓	✓				✓	
Pourmohammadi & Ghasemi (2024) - Health Systems				✓	✓				✓	
Rahimi & Zandieh (2021)			✓					✓		
Rezaei & Tavakkoli-Moghaddam (2022)					✓					
Sadeghi & Tavakkoli-Moghaddam (2023)					✓					
Sadeghi & Zandieh (2023)				✓					✓	
Sahin & Turkay (2009)		✓								
Sari & Jabi (2023)									✓	
Singh & Sharma (2006)	✓	✓	✓							
Slyke & Wets (1969)							✓			
Tiwari & Kumar (2020)	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Wang & Liu (2021)			✓							
Zhang & Zhou (2022)				✓					✓	
Zhang & Wang (2023)				✓					✓	
Zhang & Wang (2025)				✓					✓	
Zhang & Li (2023)			✓	✓						

12. Conclusion and Future Research Directions

The use of the Quadratic Assignment Problem for the layout of healthcare facilities has developed remarkably over the years, starting with Elshafei's 1977 paper. The path of research has been one of growing complexity, transitioning from a simple mathematical abstraction to a comprehensive framework that captures the intricacies, ambiguities, and the multi-objective character of contemporary healthcare provision.

The classification outlined in this article, covering Exact Methods, Classical Heuristics, Metaheuristics, Hybrid Approaches, Robust Optimization, Fuzzy QAP, Stochastic Programming, Multi-Objective QAP, and Specialized/Emerging paradigms, serves as a straightforward guide to the cognitive territory. The powerful computational complexity of the QAP has brought about the availability of many different types of solutions, each being characterized by unique pros and cons as well as corresponding areas of use.

Several predominant themes wherein the future research is likely to be more focused are the following:

1. **Real-Time Adaptive Layouts**: The growing impact of IoT along with RTLS has opened up the possibility of developing dynamic QAP models as a research area that can guide the reconfiguration of layouts to be either temporary or permanent according to the real-time patient flow data, seasonal demand changes, or emergency situations.

2. **Deep Integration with AI**: The initial tasks related to ML and RL shall be more profound. We can expect to see models wherein deep neural networks will not only be able to guess the output of a layout but will also produce completely new layouts that even a human planner would not think about.

3. **Human-in-the-Loop Optimization:** The interactive multi-objective optimization will be further developed, giving planners the ability to guide the search process in real-time based on their expert judgment and changing preferences.

4. **Pandemic and Disaster Resilience:** Pourmohammadi and Ghasemi (2024) have initiated a process where the lessons learned from the pandemic will be turned into resilient and adaptable planning models which will be explicitly designed for the quick reconfiguration needed in times of crisis.

5. **Validation and Implementation Studies**: The requirement for carrying out more longitudinal studies in real hospitals with optimized layouts and measuring the impact on hard outcomes such as patient wait times, staff burnout rates, and hospital-acquired infection rates is indeed growing.

To sum up, the QAP remains an important and dynamic model for healthcare layout optimization. Its destiny is not to be overpassed but to be smartly combined with other data-driven technologies to generate healthcare settings that are not only efficient but also adaptable, strong, and deeply human-focused.

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