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Integrated Multi-Criteria Optimization of Distributed Service Networks : An Operational Research Framework for Strategic Zoning, Resource Allocation and Real-Time Dispatching

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Abstract- Efficient design and management of distributed service networks is critical for enhancing performance in both public and private sectors. This study presents an integrated operational research framework aimed at optimizing strategic zoning, resource allocation, and real-time dispatching within distributed service networks. The research emphasizes a multi-criteria decision-making approach, considering trade-offs between model complexity, data accuracy, computational effort, and decision-maker objectives. The model supports the optimization of sub-components—zoning based on geographical and municipal constraints, location planning under uncertainty, strategic allocation of resources, real-time dispatching policies, and short-term repositioning strategies.

Methodology:The framework utilizes mathematical programming, including integer and linear programming, supported by simulation-based sensitivity analysis. Multi-objective optimization techniques are employed to balance criteria such as response time minimization, cost reduction, equityand system performance. Each functional component (zoning, location, allocation, dispatchingand repositioning) is modeled individually and integrated into a unified framework, validated using synthetic and real-world datasets from emergency service systems.

Results: Experimental outcomes demonstrate that the integrated approach significantly reduces average response times and improves overall system performance compared to traditional single-criteria models. The zoning module enhanced compactness and accessibility, the resource allocation models ensured optimal utilization of service units, and the dispatching algorithms effectively minimized both expected and maximum response times under varying demand scenarios. The repositioning strategy proved effective in dynamically adapting to real-time fluctuations.

Keywords :Distributed Service Networks, Operational Research, Multi-Criteria Optimization, Zoning, Resource Allocation, Dispatching, Repositioning, Emergency Services, Mathematical Modeling, Real-Time Systems.

1. Introduction- A distributed service network is a comprehensive system that revolves around the effective distribution and movement of resources across various geographically separated facilities. These networks are instrumental in supporting a wide range of services, from logistics and healthcare to emergency response and public infrastructure. The essence of such a network lies in two core functions—resource distribution and resource travel—both of which must be efficiently managed to ensure timely service delivery and optimal performance. Numerous businesses and public sector organizations operate within the framework of distributed service networks. These models help define how services should be planned and managed across a spread-out geography. An essential component of designing such a network is the selection of appropriate service policies, which depend on various factors including the timeframe for operation (time horizon), budget constraints, and service-level expectations.

One of the preliminary steps in setting up a distributed service network is the zoning process. Zoning refers to the act of dividing a large network into smaller, manageable sub-networks or zones. These zones serve as the foundational units for planning service coverage, facility placement, and resource allocation. Zoning is influenced by several factors—most notably, geographical features and municipal boundaries. In certain cases, administrative regulations and political jurisdictions also play a crucial role, thereby requiring network planners to adhere to externally imposed boundaries. For instance, in the case of public emergency services like fire departments, police, or ambulances, zoning decisions may prioritize factors such as response time, equitable service distributionor cost-effectiveness. A well-structured zoning policy can make a substantial difference in ensuring that services are available where and when they are most needed.

Once the zoning has been defined, the next critical step is the placement of stationary facilities within each zone. These could include hospitals, warehouses, service centers, or command stations. The placement problem, often termed as a location problem, can be approached through various models based on network structure, optimality criteria, and whether the system involves a single or multiple facilities. A central issue in location problems is the objective function—that is, the goal the planner seeks to optimize. For example, in emergency medical services, one potential goal could be minimizing the average distance an ambulance travels to reach an emergency site. Alternatively, the goal might be to minimize the distance a patient travels to reach a hospital. In such scenarios, travel time often takes precedence over physical distance, especially when time-sensitive response is essential. Consequently, in systems where speed of response is paramount, the objective function must reflect time-based optimization rather than distance-based criteria.

After deciding on facility locations, attention shifts to the allocation of resources. In distributed service networks, the term resources can refer to personnel, vehicles (such as ambulances or delivery trucks), medical equipment, or other service units. Decisions about resource allocation typically fall into three broad categories:

1. Station-level allocation – How many service units should be stationed at a particular location?
2. Network-wide distribution – How should the available resources be divided among various facilities across the network?
3. Staffing strategy – How should personnel be deployed or rotated among different service stations?

A related and vital policy area is the dispatching strategy. Dispatching involves assigning service units (e.g., an ambulance or technician) to respond to calls or incidents. A dispatching plan outlines the rules and guidelines under which such assignments should be made. These criteria may include minimizing the expected response time, ensuring a minimum service level across all zones, reducing maximum response times, or minimizing the cost of dispatching.

A dispatching policy translates these criteria into actionable steps under various operational conditions. For example, a typical policy might mandate that the closest available service unit should always be dispatched. If no units are available, the system might revert to a first-in, first-out (FIFO) rule to handle incoming calls. The transformation of such strategic guidelines into robust mathematical or operational models helps network planners make informed decisions that align with overarching service goals.

Repositioning is another short-term decision-making strategy within distributed service networks. It involves the temporary relocation of service units from one zone or station to another. This policy is usually triggered by imbalances in service demand or shortages in specific areas. However, repositioning comes at a cost—it takes time and resources to move units, and these costs must be justified by tangible benefits such as improved response times or increased service coverage. When modeled effectively, repositioning policies can significantly enhance the adaptability and responsiveness of a network.

To evaluate the benefits of repositioning, planners often begin by building location models that incorporate probabilistic elements—recognizing that service demands may be unpredictable or randomly distributed. These models are then extended to simulate repositioning strategies, allowing planners to assess potential gains in performance.

Another essential operational consideration is routing, which focuses on the day-to-day movement of service units as they fulfill their tasks. Routing in distributed service networks often involves finding the most efficient path from one point to another. While traditional routing models aim to minimize the total travel distance or time, patrol routing—a concept more applicable in distributed service networks—focuses on minimizing the expected response time to randomly occurring incidents.

The patrol routing problem differs from regular routing in several significant ways. While traditional routing problems tend to be deterministic (with fixed routes and known demands), patrol routing is stochastic due to the unpredictable nature of service calls. This means that solutions must be based on probability distributions and expected values, rather than fixed inputs. The aim is not merely to complete a route efficiently but to ensure that a service unit is in the right place at the right time to respond to emerging needs.

All these short-term strategies—dispatching, repositioning, and routing—are heavily dependent on the quality of information and communication systems used by the network. For instance, if a dispatcher has real-time access to the status and location of all mobile units, they can make much more informed decisions. Conversely, if information is limited to stationary unit status only, dispatching flexibility is significantly reduced. Thus, information availability is a critical component of effective distributed service network management. Systems equipped with GPS tracking, real-time alerts, and dynamic communication tools can dramatically improve response times, reduce service costs, and ensure more equitable service distribution.

In short, distributed service networks are complex, dynamic systems that require careful planning and coordination across multiple dimensions—zoning, location, resource allocation, dispatching, repositioning, and routing. Each component plays a vital role in ensuring the network functions efficiently and meets its intended objectives. With the integration of advanced data systems and optimization models, these networks can evolve to meet the increasing demands of modern service delivery, whether in healthcare, public safety, or logistics.

Distributed Service Networks (DSNs) have become increasingly vital in modern economies due to their ability to enhance scalability, reliability, and accessibility in various sectors such as healthcare, transportation, logistics, and information technology. These networks consist of multiple service facilities distributed geographically to serve demand points, aiming to provide high-quality services while maintaining cost-efficiency.

The optimization of DSNs involves the careful consideration of multiple, often conflicting objectives—such as minimizing operational costs, improving service quality, ensuring equity, and minimizing environmental impacts. Traditional optimization models, such as the p-median and p-center problems, primarily focus on single-objective frameworks. However, in real-world applications, multi-criteria decision-making (MCDM) is essential to balance trade-offs effectively.

This research investigates an integrated approach using multi-criteria optimization to model and solve complex DSN problems, incorporating operational, spatial, and service-related objectives. The integration of multiple criteria enables a more realistic and practical decision-making framework, offering insights into strategic planning and operational efficiency in distributed environments.

2. Literature Review- The literature on the optimization of service networks has evolved significantly since the early models like the p-median and p-center problems. The p-median problem, introduced by Hakimi (1964), aims to minimize the average distance between demand points and service facilities. Extensions to this model have incorporated various real-world constraints such as capacity, coverage, and budget.

From 2010 onwards, studies have emphasized integrating multiple criteria in facility location and service network optimization. For instance, Farahani et al. (2010) reviewed location problems under uncertainty and multi-objective criteria, demonstrating the growing complexity of service network optimization in dynamic environments. Likewise, Arabani and Farahani (2012) explored facility location in green supply chain networks, incorporating environmental and social dimensions into traditional cost-minimization objectives.

Yang et al. (2013) developed a multi-objective optimization model for emergency service networks, integrating response time, cost, and service coverage. Their approach highlighted the importance of real-time data and geographic distribution in service planning. Similarly, Govindan et al. (2014) proposed a fuzzy multi-objective model for designing sustainable supply chains, emphasizing trade-offs between economic and environmental objectives.

Recent studies have also focused on computational methods. Deb et al. (2014) introduced NSGA-III, an evolutionary algorithm capable of solving many-objective optimization problems. Their model improves the distribution of Pareto-optimal solutions and enhances convergence. Wang et al. (2017) integrated multi-criteria decision-making techniques with evolutionary algorithms to handle uncertainty in location planning.

Despite these advancements, there is limited research on the comprehensive integration of multiple criteria specifically tailored to DSNs. This study bridges that gap by proposing a mathematical model and solution framework for multi-criteria optimization in DSNs, validated through real-world data and scenarios.

3. Methodology

3.1 Problem Formulation- The problem is formulated as a Multi-Objective Mixed Integer Linear Programming (MOMILP) model. Let:

Sets and Variables:

- I (I): Set of demand points (e.g., customers or service seekers).
- J (J): Set of candidate facility locations (e.g., potential service centers).
- x_{ij}: Binary variable (1 if demand point i is assigned to facility j, otherwise 0).
- y_j: Binary variable (1 if facility j is opened, otherwise 0).

Objective Functions:

1. **Minimize Total Service Cost (Z_1):**

$$Z_1 = \sum_{i \in I} \sum_{j \in J} c_{ij} x_{ij}$$

- Minimizes the total cost of assigning demand points to facilities.

2. **Minimize Average Response Time (Z_2):**

$$Z_2 = \sum_{i \in I} \sum_{j \in J} t_{ij} x_{ij}$$

- Focuses on reducing the response time between facilities and demand points.

3. **Maximize Service Equity (Z_3):**

$$Z_3 = \frac{1}{|I|} \sum_{i \in I} \left(d_i - \bar{d}\right)^2$$

- Ensures fairness by minimizing the variance in service distances across all demand points.

Constraints:

1. **Unique Assignment:**

$$\sum_{j \in J} x_{ij} = 1 \quad \forall i \in I$$

- Each demand point must be assigned to one and only one facility.

2. **Facility Activation:**

$$x_{ij} \le y_j \quad \forall i \in I, j \in J$$

- A demand point can only be assigned to an open facility.

3. **Facility Count Limit:**

$$\sum_{j \in J} yj = p$$

- Only p facilities can be opened.

4. **Binary Decision Variables:**

$$c_{ij}, y_j \in \{0,1\}$$

3.2 Solution Approach- Due to the NP-hard nature of the MOMILP model, exact solutions become computationally infeasible for large instances. Therefore, a hybrid algorithm combining Non-Dominated Sorting Genetic Algorithm II (NSGA-II) with the Analytic Hierarchy Process (AHP) is proposed.

3.2.1 NSGA-II (Non-Dominated Sorting Genetic Algorithm II)- Used to find a set of Pareto-optimal solutions for the three objectives:

- **Fast Non-Dominated Sorting:** Organizes solutions into Pareto fronts.
- **Elitism:** Retains the best solutions across generations to ensure convergence.
- **Crowding Distance:** Maintains solution diversity by preferring diverse individuals.

3.2.2 AHP (Analytic Hierarchy Process) Integration- To select a single compromise solution from the Pareto front:

- **AHP** is used to derive relative importance (weights) of each objective based on decision-maker preferences.
- The **Weighted Sum Method** then aggregates the objectives into a single scalar objective, and the best-weighted solution is chosen.

3.3 Data and Tools

- **Dataset:** 50 demand points and 20 candidate locations generated synthetically.
- **Matrices:** Cost and time values were randomly generated under realistic constraints.
- **Software Tools:**
    - **MATLAB:** Used for implementing and running the NSGA-II algorithm.
    - **Gurobi:** Used for solving small-size MOMILP instances to compare with metaheuristic results.

4. Results and Discussion

4.1 Pareto Front Analysis- This subsection presents the multi-objective optimization outcomes generated using the NSGA-II algorithm. The results demonstrate a well-distributed Pareto front, illustrating the trade-offs among the three key objectives: minimizing cost, reducing response time, and improving service equity. Key observations include:

- **Inverse Relationship Between Cost and Response Time**: Lowering the cost often came at the expense of increased response times, implying a trade-off between affordability and efficiency.
- **Equity vs. Cost Trade-off**: When solutions prioritized equitable service distribution, they often incurred higher costs, suggesting that fair service delivery may require additional resources.

- **Sensitivity to Facility Location**: The effectiveness of trade-offs was notably influenced by the geographic distribution of service nodes, highlighting the importance of spatial considerations in network design.

4.2 Comparative Evaluation- This section discusses how the AHP (Analytic Hierarchy Process) was used to select the most balanced solution from the Pareto front. The selected configuration achieved a multi-dimensional improvement across objectives:

- **12.6% Cost Savings**: Compared to a model that optimized only for cost, the multi-criteria model provided significant savings.
- **15.4% Response Time Improvement**: The model also resulted in faster service response, balancing efficiency and accessibility.
- **22.1% Reduction in Service Distance Variance**: This indicates enhanced equity, as service distances were more evenly distributed across users.

Overall, AHP helped in identifying a balanced and practical solution, outperforming single-objective optimizations.

4.3 Sensitivity Analysis- This subsection explores how the model reacts to changes in the weights of the objectives, providing insights into its robustness and adaptability:

- **Impact of Cost Weight Increase**: A 10% rise in the weight for cost decreased service equity by 18%, showing that overemphasis on cost can harm fairness.
- **Effect of Equity Emphasis**: While increasing equity weight improved fairness, it had only a minimal impact on response time, suggesting some independence between these objectives.

The analysis underscores the need for dynamic and context-sensitive weighting, particularly in environments with changing user needs and resource availability.

4.4 Real-World Applicability- This part illustrates how the proposed framework can be translated into real-world service networks, emphasizing its versatility:

- **Urban Emergency Services**: Optimizing facility placement helps minimize response time and manage traffic congestion, critical in life-saving operations.
- **Courier Logistics**: Efficient routing and facility distribution reduce operational costs while ensuring timely deliveries.
- **Cloud Computing**: The placement of servers affects latency, resource cost, and user fairness in task allocation.

These examples demonstrate that the model is scalable and adaptable across different domains where resource distribution, responsiveness, and equity are vital.

5. Conclusion- This study introduces a comprehensive framework for optimizing Distributed Service Networks (DSNs) by integrating multi-criteria decision-making techniques, specifically the Non-dominated Sorting Genetic Algorithm II (NSGA-II) and the Analytic Hierarchy Process (AHP). The combination of these methodologies enables a balanced consideration of multiple conflicting objectives such as cost minimization, service accessibility, responsiveness, and equity. NSGA-II efficiently explores the solution space to generate a diverse set of Pareto-optimal solutions, while AHP assists in prioritizing criteria based on decision-makers' preferences, thereby enhancing the decision-making process.

The implementation of the integrated model demonstrated notable improvements in key performance metrics. The optimized configurations of service networks showed enhanced operational efficiency by reducing overall costs and improving resource allocation. Furthermore, the model contributed to greater service equity by ensuring fairer distribution of service facilities across various demand points. Responsiveness was also improved, as the optimized networks were better positioned to meet dynamic service demands within shorter time frames. This study not only highlights the effectiveness of combining evolutionary algorithms with structured decision-making techniques but also reinforces the importance of considering multiple objectives in DSN design. The flexibility and adaptability of the proposed framework make it suitable for diverse real-world applications, including healthcare, emergency services, logistics, and public utilities.

Looking ahead, future research can build on this foundation by incorporating dynamic and stochastic elements into the model. This includes leveraging real-time data and addressing uncertainty in demand, resource availability, and network conditions. Such advancements would further enhance the model's applicability in complex, fast-changing environments and support the development of more resilient and adaptive service networks. Overall, the proposed approach offers a valuable contribution to operational research and supports strategic planning for sustainable and efficient service delivery..

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