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Project Report

Healthcare Capacity & Location Planning

Abstract

This report presents a prescriptive analytics model designed to address the critical public health challenge of allocating healthcare resources during a pandemic. The project develops a **Mixed-Integer Programming (MIP)** model to determine the optimal placement and capacity of temporary COVID-19 treatment facilities across a network of nine counties. The primary objective is to satisfy all patient demand while minimizing the combined costs of building new facilities and the travel distance for patients. The model was implemented in Python using the Gurobi optimization solver and evaluated under two distinct demand scenarios. In the base scenario, the optimal solution recommends building **three temporary facilities** at a total cost of **\$1.52 million**. In a high-demand scenario (20% increase), the model prescribes building all **nine potential temporary facilities** and adding emergency capacity, highlighting the system's strain and providing a quantitative basis for strategic resource planning and crisis management.

1. Introduction

The COVID-19 pandemic placed unprecedented strain on healthcare systems worldwide, frequently causing hospitals to exceed their treatment capacity. In response, public health officials and healthcare providers were faced with the urgent and complex task of expanding capacity, often through the rapid deployment of temporary facilities. The decision of where to build these facilities and how to allocate patients is a critical logistical problem with significant financial and public health implications. An inefficient allocation can lead to increased costs, longer patient travel times, and, most importantly, unmet medical needs.

This project tackles this problem by creating a **Facility Location Optimization Model**. The goal is to move beyond reactive decision-making and provide a data-driven, prescriptive framework for strategic planning. The model considers a network of nine counties, each with a forecasted number of COVID-19 patients requiring hospitalization. It evaluates a set of existing permanent facilities and a portfolio of potential temporary facility locations to determine the most cost-effective strategy to ensure all patient demand is met.

2. Methodology

The core of this project is a **Mixed-Integer Programming (MIP)** model. This mathematical approach is ideal for facility location problems as it can handle both continuous decisions (how many patients to send from A to B) and discrete, binary decisions (whether or not to build a facility at location C).

Model Components

1. **Sets and Parameters:**
   - **Sets:** The model is defined over sets of Counties (sources of demand) and Facilities (both existing and potential temporary locations).
   - **Parameters:** Real-world data is encoded as model parameters, including the Demand from each county, the Capacity of each facility, the Distance between each county and facility, the fixed Cost of building a temporary facility, and the variable Cost of patient travel.

2. **Decision Variables:** The model's key outputs are represented by three types of decision variables:
   - **y_t (Binary):** A binary variable that equals 1 if a temporary facility is built at location t, and 0 otherwise. This captures the core "go/no-go" decision for each potential site.
   - **x_c,f (Continuous):** A continuous variable representing the number of patients allocated from county c to be treated at facility f.
   - **z_t (Continuous):** A continuous variable representing any emergency "extra capacity" that must be added to a temporary facility if its base capacity is insufficient.

3. **Objective Function:** The model's goal is to **minimize total system-wide costs**. This is formulated as a linear objective function:
   - **Minimize Cost =** (Total Patient Driving Costs) + (Total Fixed Costs of Building Temporary Facilities) + (Total Penalty Costs for Adding Emergency Capacity)
   - A large penalty coefficient (bigM) is applied to the emergency capacity variable (z_t) to ensure the model will only use this option as a last resort when demand cannot be met otherwise.

4. **Constraints:** The operational rules of the healthcare system are defined as linear constraints:
   - **Demand Satisfaction:** Every county's total patient demand must be fully met by the sum of patients allocated to all facilities.
   - **Capacity Limits:** The total number of patients assigned to any facility (both existing and temporary) cannot exceed its available capacity. For temporary facilities, this capacity is only available if the corresponding binary variable y_t is equal to 1.

The model was implemented in Python using the **gurobipy** library and solved to find the optimal values for the decision variables.

3. Results and Inference

The model was run for two scenarios: a base case and a high-demand case.

Base Scenario: Forecasted Demand

In the base scenario, the model found an optimal solution that satisfies all patient demand while minimizing costs.

- **Total Cost:** The minimum possible cost for the system is **\$1,521,653**. This is composed of \$1,500,000 in fixed costs for new facilities and \$21,645 in patient travel costs.
- **Optimal Facility Plan:** To achieve this, the model recommends building **three new temporary facilities** at locations 15, 17, and 18. No extra capacity was needed, indicating the existing and new facilities are sufficient.
- **Patient Allocation Plan:** The solution provides a detailed dispatch plan. For example, facility 7 is allocated 222 patients in total, sourced from three different counties (6 from county 3, 50 from county 5, and 166 from county 6).
- **Inference:** The base scenario shows that the existing facility network is insufficient to handle the forecasted demand, necessitating a \$1.5 million investment in three strategically placed temporary sites. The allocation plan ensures that patients are sent to the nearest available facility, minimizing travel costs and burdens on the community.

Scenario 1: 20% Increase in Demand

This scenario tested the system's resilience against a significant surge in patient numbers.

- **Total Cost:** The total cost dramatically increases to **\$67 billion**. This is not a realistic financial figure but rather an indicator from the model that the system is broken. The cost is composed of \$4,500,000 for facilities, \$25,520 for travel, and the rest is the massive bigM penalty.
- **Optimal Facility Plan:** The model recommends building **all nine available temporary facilities**.
- **Emergency Capacity:** Even with all nine new facilities, the system is still short of capacity. The model is forced to add **40 emergency beds** at facility 15 and **27 emergency beds** at facility 17.
- **Inference:** The huge penalty cost signals a critical system failure. It tells decision-makers that a 20% increase in demand cannot be met even by building every possible temporary facility. This is a powerful insight: it quantifies the demand threshold at which the planned temporary capacity is overwhelmed and highlights an urgent need for a larger-scale contingency plan, such as sourcing capacity from outside the nine-county region or investing in facilities with higher base capacities.

4. Conclusion

This project successfully demonstrates the strategic value of Mixed-Integer Programming for public health logistics and capacity planning. The model provides a clear, optimal, and data-driven solution to a complex resource allocation problem, replacing subjective decision-making with a quantitative framework.

Business & Public Health Value:

- **Cost-Effective Planning:** The model identifies the minimum-cost strategy to meet patient needs, ensuring efficient use of financial resources.
- **Quantitative Decision Support:** It provides concrete answers to "how many" and "where," enabling leaders to make informed decisions about infrastructure investment.
- **Scenario Analysis:** By testing different demand scenarios, the model serves as a powerful tool for risk assessment and contingency planning, highlighting system vulnerabilities before they become critical failures.

The model proves to be a valuable strategic tool, capable of feeding its optimal location and capacity plans into more tactical, real-time dispatching systems for assigning individual patients to facilities.