Incorporating Socio-Economic Factors in Maximizing Two-Dimensional Demand Coverage and Minimizing Distance to Uncovered Demand: A Dual-Objective MCLP Approach for Fire Station Location Selection

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Abstract: In this study, we employ a dual-objective optimization model, utilizing the Implicit Modified Coverage Location Problem (MCLP-Implicit) approach, to determine an appropriate fire station allocation. Our objectives encompass maximizing coverage in areas with a heightened projected demand, based on socioeconomic predictors of building fires, and concurrently minimizing the distance of uncovered demand zones to the closest fire station. The challenges of this model reflect the criticality of strategic placement, aiming for not just swift response times but also the complete coverage of a region with priority given to subregions with a pronounced potential for incidents. The applicability of the proposed approach is demonstrated through a case study in south-east Queensland. Our findings indicate that there is a tangible justification for adopting this model. The broader coverage and wider spread of locations it produces can greatly aid in the dynamic deployment of personnel during surges caused by seasonal fluctuations or unforeseen calamities. By weaving in socioeconomic aspects into demand predictions, our model has also maintained appropriate coverage to socioeconomically disadvantaged communities in the region. Nevertheless, it is paramount to underline the recommendation that further research should account for road connectivity—a pivotal factor when pinpointing these locations in the real world. This research paves the way for enriched insights in long-term urban planning and fire response protocol crafting, especially in regions mirroring similar socioeconomic profiles or risks of natural disasters, not to mention its commercial implications to the relevant industry servicing the fire and rescue authorities.

Keywords: operation research; optimization; location covering problem; fire station; south-east Queensland

MSC: 90B90

1. Introduction

Between 2003 and 2017, Australia witnessed a distressing toll of nearly 900 lives lost due to preventable residential fires, translating to an average of one tragic death each week [1]. Additionally, the economic burden of fire-related incidents reached a substantial 1.3% of Australia’s GDP [2]. As recent as 2020, Queensland alone experienced a staggering 1554 fire incidents, each inflicting personal losses on its residents [3]. The urgency for improvements in fire services, particularly in optimizing fire station placements, becomes evident in the face of such tragedies. Research has shown that proximity to fire stations is associated with reduced unintentional injuries, as exemplified in a study conducted in Dallas [4].

García and Marín [5] categorized location covering models into two primary types: set covering and maximal covering. The former, exemplified by the Location Set Covering Problem (LSCP) and its variants, aims for complete coverage with minimal facilities [6–8].
Conversely, maximal models, such as the Maximal Covering Location Problem (MCLP), strive to cover the majority of demands efficiently [9]. While these models have undergone various refinements, they often rely on three fundamental assumptions that may not always hold true in every real-world scenario. Firstly, they may assume demand coverage to be binary—either fully covered or entirely uncovered. Secondly, some models presume that only a single designated facility serves each demand. Lastly, these models often assume that facilities have circular coverage areas with fixed radii [10].

This paper introduces a proposed modification to the MCLP-Implicit model, situated within the context of the Socioeconomic Facility Location Optimization framework [11]. The foundation of this proposal rests upon a comprehensive case study conducted in the south-east Queensland region. Our research’s primary aim extends beyond presenting these modifications; it involves a critical examination of the revised model’s behaviour. One of the key evaluation criteria centres around the model’s inclination to maximize spatial coverage within the designated study area. Through this rigorous evaluation, we seek to offer profound insights into the potential practicality and utility of the enhanced MCLP-Implicit model in situations where comprehensive coverage is the ultimate objective.

This paper is meticulously structured to facilitate a coherent exploration of the subject matter. Section 2 delves into a literature review, providing a critical examination of the existing modifications to MCLP and identifying gaps that our study aims to fill. Following this foundation, Section 3 delineates the methods employed, detailing the analytical frameworks and the rationale behind their selection. Section 4 is dedicated to presenting the data, focusing on its origins, the parameters of its selection, and its relevance to the study. Following this, Section 5 specifically deals with the findings of the study, systematically presenting the outcomes of the applied methodologies. In Section 6, we delve into a robust discussion, scrutinizing the strengths and weaknesses of the methodologies and providing a reflective evaluation of their efficacy and limitations. The paper culminates in Section 7 with a conclusion that not only synthesizes the key findings and insights from our research but also suggests potential directions for future studies, thereby anchoring the discussion within the broader academic context.

The paper adheres to a standardized set of terms as shown in the nomenclature below, which is used for examining and suggesting models for optimal service location coverage, guaranteeing uniformity in the variables used.

2. Literature Review

Church and ReVelle [9] initially conceived the Maximal Covering Location Problem (MCLP) as a mean to elevate the most deficient service scenario by curtailing the maximal commuting stretch that users might encounter. The cornerstone of MCLP hinges on its goal to maximize the swath of population within service reach. The pivotal formula within their study (Equation (1)) maximizes the tally of individuals enveloped by the service, while constraint Equations (2) and (3) weave in a binary element signifying the presence of at least a singular facility within a specified subset $O_i$.

$$\max \sum_{i=1}^{I} \eta_i y_i$$  \hspace{1cm} (1)

subject to $\sum_{j \in O_i} x_{ij} \geq y_i, \quad i \in I$  \hspace{1cm} (2)

$$\sum_{j \in J} x_{ij} = |P|, \quad i \in I$$  \hspace{1cm} (3)

Yet, this drive to widen the umbrella of coverage inadvertently swells travel distance due to the inclusion of far-flung dwellings. Constrained to a fixed threshold for response times, the model harboured gaps until Karatas and Yakıcı [12] infused it with the elements of the p-median and p-centre models. This hybrid model aspires to a more egalitarian distribution of services by concurrently minimizing the distance between demand points and their nearest service hub and the most distant travel routes required.
Despite these advancements, the model’s provision for secondary service options in the event of unforeseen circumstances was non-existent. This prompted Dessouky et al. [13] to introduce a layered approach to coverage. They put forth a multi-tiered objective function (Equation (4)), which seeks to minimize the cumulative distances between demand points and their respective facilities, adjusting for the priority level of each layer and the population density at each point. This new approach ensures that facilities closer in proximity are given precedence, with the constraint Equations (5) and (6) capping facility numbers and delineating coverage benchmarks for each tier.

\[
\min \sum_{l \in L} \sum_{i \in I} \sum_{j \in J} h_l \eta_i \pi_{ij} x_{ijl} \tag{4}
\]

subject to \[\sum_{j \in O_i} x_{ijl} \geq \alpha_{il} \tag{5}\]

\[
\sum_{j \in J} x_{ijl} \leq |P| \tag{6}
\]

The problem of demand points excluded by the coverage net due to stringent distance benchmarks and facility caps was next in line, addressed by Yin and Mu [14]. They refashioned the core objective to minimize the sum of distances from these uncovered demand locales to their nearest potential facility, introducing a variable weight (k) to signal the importance of each uncovered demand point (Equation (7)).

\[
\max \sum_{i \in I} \sum_{j \in J} \eta_i \pi_{ij} - k \sum_{l \in L} \sum_{j \in J} \pi_{ij} \eta_i \mu_{ij} \tag{7}
\]

Transitioning from isolated to cooperative dynamics, where facilities and demands interact akin to communication beacons, the Cooperative Maximal Covering Location Problem (CMCLP) came to be. This model represents facilities working in concert, with their service potency diminishing with distance—a concept encapsulated by its constraints (Equations (9) and (10)) and the aggregate signal function. This ensures that multiple facilities contribute to fulfilling demand within a pre-set distance threshold [8].

\[
\max \sum_{i \in N} h_i \tag{8}
\]

subject to \[\sum_{i \in N} h_i \geq \beta H, \tag{9}\]

\[
N = \{ i \in N | \Phi_i(y_p) \geq \beta \} \tag{10}
\]

Murray et al. [15] addressed the limitation of treating demand as pinpoint locations when real-world scenarios often exhibit a two-dimensional object. The MCLP-Implicit model arose from this need, where ‘Implicit’ signifies the abandonment of tracking bi-dimensional coverage combos. Instead, it presents an index (l) to represent distinct coverage layers, each with its own coverage quota (p_l). Ensuring that a minimum facility count (a_l) services each demand point according to the layer-specific threshold, the model sidesteps the binary coverage assumption (Equations (11)–(14)).

\[
\max \sum_{i \in J} \eta_i m_i \tag{11}
\]

subject to \[\sum_{j \in J} x_j \geq a_l m_{il}, \tag{12}\]

\[
\sum_{j \in J} x_j = |P| \tag{13}\]

\[
\sum_{l \in L} m_{il} = m_i \tag{14}
\]

Despite the intricate developments, a glaring omission persisted: the disregard for socioeconomic factors. The discourse hence advances a framework to rectify this blind spot, adopting the MCLP-Implicit model as the scaffold. This choice is especially apt given its compatibility with the two-dimensional nature of socioeconomic data gathered at
the Statistical Area 2 (SA2) level by the Australian Bureau of Statistics (ABS), ready to be dovetailed with the model’s existing structure.

3. Methods

Drawing from the literature on MCLP, we apply the Socioeconomic Facility Location Optimisation framework [11]. The framework is structured in three sequential parts: Robust Backward Stepwise Regression Modelling, Covering Location Modelling, and Solving Algorithm. Initially, the facility’s demand is analysed using a robust backward stepwise regression, determining key socioeconomic factors and their respective importance. Using these identified variables, the demand is projected and integrated into an adapted MCLP-Implicit model tailored for areas reminiscent of the south-east Queensland, a mix of urban and rural geographic region. Subsequent to the initial formulation, the covering location model is subjected to computational processing via a solving algorithm. While the preliminary proposition suggested the adoption of a metaheuristic algorithm, considering the intricate nature and substantial volume of the spatial data, a random search algorithm is a more suitable choice. This decision is predicated on the need for effective handling of the data’s complexity and ensuring a more efficient optimization process. The subsequent sections delve into each component of our proposed approach in detail.

The crux of this study revolves around devising an optimization model tailored to consider the socioeconomic fabric of populations, pertinent for regions akin to SEQ. Inspired by the foundational MCLP-Implicit model and its subsequent alterations (as cited in Yin and Mu [14]), the proposed adaptation of the MCLP-Implicit model, outlined by Equations (15)–(20) [11].

\[
\begin{align*}
\text{max} & \sum_{i \in I} \hat{\eta}_i m_i - \sum_{i \in I} \text{close}_i \hat{\eta}_i \quad (15) \\
\text{subject to} & \sum_{j \in J} x_j \geq \alpha_i \mu_i, \forall i, l \quad (16) \\
& \sum_{j \in J} x_j = |P| \quad (17) \\
& \text{close}_i = \begin{cases} 
\min(\text{dist}_{ij}), & m_i = 0, \forall i \\
0, & \text{otherwise,} \forall i 
\end{cases} \quad (18) \\
x_j = \{0, 1\}, \forall j \\
m_i = \{0, 1\}, \forall i \quad (19), (20)
\end{align*}
\]

Central to this adaptation (Equation (15)) is the goal to optimize coverage across demand areas (\(\sum_{i} \hat{\eta}_i m_i\)) while concurrently minimizing distances between the centre of the uncovered demand areas and their nearest facilities (\(\sum_{i} \text{close}_i \hat{\eta}_i\)). Constraint (16) links the decision to site a facility at site \(j\) if all \(x_j\) for every \(j\) in \(J\) equals zero (no facility that can cover \(\beta\) of demand area \(i\) has been sited), \(m_i\) will also equal zero. Constraint (17) limits the number of facilities sited. Constraint (18) minimizes the distance for demand areas that has no coverage. It assigns the variable \(\text{close}_i\) a value if and only if demand area \(i\) is uncovered. Constraint (19)–(20) specifies variables are restricted to binary values. One novelty in the MCLP-Implicit modification includes the addition of function (\(\sum_{i} \text{close}_i \hat{\eta}_i\)) in the Objective Function (15), which considers the minimization of uncovered demand areas to their closest facilities. Another novelty is the use of projected rates of building fires \(\hat{\eta}_i\) using socioeconomic variables.

The random search algorithm is adopted to solve the proposed MCLP-Implicit model, due to several compelling reasons that align with the research objectives. Firstly, a random search algorithm serves as an effective baseline in algorithmic research. It offers a point of comparison for more advanced algorithms, allowing future studies to assess whether the increased complexity of these alternatives yields proportionate improvements in performance. Secondly, the flexibility of random search is a significant advantage. This method does not require detailed knowledge of the problem’s structure, making it suitable for scenarios where these characteristics are either unknown or subject to variability. Additionally, the ease of parallelization of random search algorithms stands out, particularly in the
context of large-scale problems. Its ability to being distributed across multiple processors or systems can expedite the search process considerably, a feature not as readily available in more complex algorithms. Finally, the inherent nature of random search to avoid entrapment in local minima is invaluable, especially in problems characterized by complex landscapes. This characteristic enhances the probability of uncovering a global optimum, thereby improving the overall efficacy of the search process [16].

The random search algorithm conducts a set number of iterations where, in each cycle, it randomly generates a specific number of candidate fire station locations within the designated region. The candidates are generated uniformly at random across the spatial extent of the provided areas. In other words, each point within the target area has an equal chance of being selected as a candidate location. The distribution is uniform spatially, so there is no preference or higher probability for any specific region within the target area. For every set of generated points, the algorithm evaluates their efficacy using an objective function that considers both population coverage and the distance to uncovered areas. This score, or widely known as the objective value function, helps determine the best locations among the randomly generated sets. A variable retains the best set of fire station locations and another variable retains the best score across 50 iterations. The number of iterations is chosen considering the complexity of the spatial data and the capacity of the computer used. The number was also chosen based on initial testing, which demonstrated that the objective value function tends to plateau before reaching 50 iterations, indicating convergence. The computation was conducted using the R software at its 2021.09.0 version on a device equipped with AMD Ryzen 5 3450U, Radeon Vega Mobile Gfx 2.10 GHz and 5.89 GB of usable RAM. If an iteration produces an inferior score, the algorithm will ignore the solution to conserve memory space. The random search iterations are illustrated in Figure 1.

![Flowchart](attachment:flowchart.png)

**Figure 1.** Simple random search iteration.

4. Data

The study has adopted socioeconomic modelling of the building fires conducted in Untadi et al. [17]. The socioeconomic data for the model was derived from the 2016 and 2021 Census databases titled ‘2016 Census–Counting Persons, Place of Enumeration’ and
‘2021 Census–Counting Persons, Place of Enumeration’, which can be accessed via the Australian Bureau of Statistics (ABS) TableBuilder tool. These databases present aggregated values for specific Statistical Areas 2 (SA2) in south-east Queensland.

The study set out to create a regression equation that could help us understand the connection between the occurrence of building fires and the socioeconomic makeup of an area. The resulting equation was expected to take the form of Equation (21).

\[
b_i = c_0 + c_1 a_i + \cdots + c_d a_{id},
\]

(21)

where variable \(b_i\) represents the demand for emergency services in area \(i\), \(a_i\) represents various socioeconomic variables specific to area \(i\), \(c_j\) (\(j \in \{1, 2, \cdots, d\}\)) stands for the coefficients associated with these socioeconomic variables and \(c_0\) represents a constant term.

To pinpoint the significant socioeconomic variables, the study used a technique called backward elimination based on the Robust Final Predictor Error (RFPE) criterion. This method helped us identify and eliminate variables that contributed the least to improving RFPE. What is valuable about the RFPE criterion, introduced by Maronna et al. [18], is its robustness against outliers, a weakness in the Akaike’s FPE criterion. We adapted this approach to our data collection and processing method, as previously discussed in Chhetri et al.’s [19] study on building fires in south-east Queensland.

The RFPE equation is presented in Equation (22) as the expected value of the function \(\rho\).

\[
RFPE_C = E\rho\left(\frac{b_0 - b'_{0G} c_G}{\sigma}\right)
\]

(22)

where \(\hat{c} = \arg\min_{c \in \mathbb{R}^d} \sum_{i=1}^{n} \rho\left(\frac{b_i - b'_{iG} c}{\hat{\sigma}}\right)\)

(23)

\[
b_i = \sum_{e=1}^{d} a_{ie} c_e + u_i = x'_i c + u_i
\]

(24)

\[
\rho(r) = r^2
\]

(25)

\[
x_{iG} = \{x_{i1}, \ldots, x_{id}\}
\]

(26)

\[
G \subset \{1, 2, \cdots, d\}
\]

(27)

\[
i = \{1, 2, \cdots, n\}
\]

(28)

where \((a_{ie}, b_i)\) is the dataset consisting of the relevant explanatory variables \(a_{iG}\) and response variable \(b_i\), \((a_0, b_0)\) represents the supplementary data point to measure the sensitivity of the dataset to outliers. \(C\) refers to the set of explanatory variables that are subsets of the index \(\{1, 2, \cdots, d\}\). \(\hat{c}\) and \(\hat{\sigma}\) serve as MM-estimators for parameters and scale, respectively. These estimators, pioneered by Yohai [20], use the Iteratively Reweighted Least Squares (IRWLS) method for optimization. The starting estimators are determined using a strategy proposed by Pena and Yohai [21], which relies on data-driven criteria rather than random selection [22]. The explanatory variables and error term are independent identically distributed (i.i.d.) standard normals. Adapting the estimator for Akaike’s FPE equation, the estimator for the RFPE equation was proposed as follows.

\[
\hat{RFPE} = \frac{1}{n} \sum_{i=1}^{n} \rho\left(\frac{r_{iG}}{\hat{\sigma}}\right) + \frac{q}{n} \hat{\bar{E}}
\]

(29)

where \(\bar{E} = \frac{1}{n} \sum_{i=1}^{n} \psi\left(\frac{r_{iG}}{\hat{\sigma}}\right)^2\)

(30)

\[
r_{iG} = b_i - a'_{iG} c_G
\]

(31)

\[
q = |G|
\]

(32)

\[
\psi(r) = 2(r)
\]

(33)
In our study, we adopted a backward stepwise regression modelling approach, starting with the inclusion of all potential variables to avoid initial biases and ensure comprehensive coverage in the exploratory stages. This methodology systematically eliminates variables that show minimal contribution to the model’s predictive power, thereby enhancing efficiency and reducing the risk of overfitting. In simpler terms, we are essentially using these equations and methods to analyse the relationship between socioeconomic factors and building fires while taking outlier data into account. The resulting model is detailed in Table 1. Nine variables have been eliminated from the variables used to calculate the Index of Relative Socioeconomic Advantage and Disadvantage (IRSAD) [23], leaving ten variables in the final model that are further explained in Appendix A.

Table 1. Socioeconomic Modelling of Building Fires in south-east Queensland by Untadi, Li, Li, and Dodd [17].

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient Est.</th>
<th>Variables</th>
<th>Coefficient Est.</th>
</tr>
</thead>
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Conversely, the building fire rate in south-east Queensland was identified as the study’s response variable. Derived from the Queensland Fire and Emergency Services (QFES) incident classifications 111, 112, 113, and 119 for the years 2015–2017 and 2021 (as mentioned in Australasian Fire and Emergency Service Authorities Council 2013), this rate was computed by aggregating incidents over the said years, scaling by 1000, and normalizing using the 2011 Census count for each SA2 region. This led to a triennial building fire rate per 1000 individuals. This information is publicly available via the Queensland Government Open Data Portal, and the time frame was selected to ensure the 2016 Census data remain relevant throughout.

For the purposes of spatial optimization, geographic data pertaining to south-east Queensland is sourced from the ABS in the Shapefile format [23]. Consequently, the analysis adheres to the geographical boundaries delineated by the ABS.

5. Results

In this section, we present the findings from the location optimization model for two distinct service radius $r$ scenarios: 7.5 km and 10 km. Initial testings found that a radius over 10 km did not yield meaningful insights. Specifically, every random search within this range achieved one hundred percent coverage, rendering it an ineffective metric for differentiation. Solutions in both scenarios must adhere to a pre-set threshold $\beta$ of 50 percent for an area to be considered appropriately covered. The optimal locations derived from the model are visualized through detailed maps for each scenario, providing clear insight into the spatial coverage provided by the fire stations. The number of fire stations assessed in this analysis is 244 stations ($|P| = 244$), the current number of stations in south-east Queensland [24,25]. Additionally, we evaluate the extent of area coverage in terms of percentages to offer a comprehensive understanding of the model’s efficiency for each radius.

Upon implementing the model with a service radius of 7.5 km in 50 iterations of randomly generated candidate facility locations, the optimal locations for fire stations were determined which obtained a maximum objective function value of 2461.61551 (Table 2). The value is the highest result of Equation (15) based on the candidate locations generated.
at the fourth iteration. The solution provided in the iteration is visualized in Figure 2, in comparison to the current locations of fire stations in south-east Queensland.

Table 2. Objective Value Functions (Scores) at Every Iteration for 10 km service radius.

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<th>Score at T</th>
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</table>

Max 2461.61551
Min 1530.50203
Average 2153.52444
Median 2152.80647
Standard Deviation 188.2331376

As visualized in Figure 2b, the locations are distributed evenly across the region. With this configuration, the model achieved a coverage of 82.57082 percent, compared to the current locations’ coverage of 73.55848 percent (Table 3). This means that 82.57082 percent of the total area in our study region is within a 7.5 km radius of an optimal fire station location, a 9.01234 percent higher proportion than the current locations of QFES stations.

After executing the model over 50 iterations, using a service range of 10 km and random potential facility sites, we identified the prime positions for fire stations, achieving a peak objective function score of 2770.62506 (refer to Table 4). This figure represents the most favourable outcome from Equation (15), derived from the candidate sites established during the fourteenth run. The proposed locations from this run are depicted in Figure 3, alongside the existing fire stations in south-east Queensland for comparison.
Table 3. Comparison of the Proportions of Land Covered for 7.5 km service radius.

<table>
<thead>
<tr>
<th>Facility Locations</th>
<th>Percentage of Land Covered</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current</td>
<td>73.55848</td>
</tr>
<tr>
<td>Optimized</td>
<td>82.57082</td>
</tr>
</tbody>
</table>

Figure 2. (a) Current locations of QFES stations in south-east Queensland with a 7.5 km coverage radius; (b) optimal locations of QFES stations in south-east Queensland at a 7.5 km coverage radius based on proposed model.

Figure 3. (a) Current locations of QFES stations in south-east Queensland with a 10 km coverage radius; (b) optimal locations of QFES stations in south-east Queensland at a 10 km coverage radius based on proposed model.

Shifting the service radius to 10 km, the model’s optimal fire station locations were found to be slightly more dispersed compared to the 7.5 km scenario and significantly more dispersed than the current location of QFES stations. The visual representation of these locations can be seen in Figure 3b, highlighting the model’s tendency to place stations at a broader span across suburban zones. The expanded radius resulted in a higher coverage, capturing 95.865998 percent of the total area, compared to 82.89955 percent with the current location (Table 5). This indicates that the larger service radius has effectively covered a
greater portion of the region. However, it is important to note that the coverage of areas is not the sole factor in determining optimality. The result is discussed further, including highlighting the potential limitations and areas of caution within the adopted methodology in Section 5.

Table 4. Objective Value Functions (Scores) at Every Iteration for \( r = 10 \) km.

<table>
<thead>
<tr>
<th>Iteration (T)</th>
<th>Score at T</th>
<th>Max Score at T</th>
<th>Iteration (T)</th>
<th>Score at T</th>
<th>Max Score at T - 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2639.97522</td>
<td>2639.97522</td>
<td>6</td>
<td>2524.91474</td>
<td>2770.62506</td>
</tr>
<tr>
<td>2</td>
<td>2521.15581</td>
<td>2639.97522</td>
<td>7</td>
<td>2656.28111</td>
<td>2770.62506</td>
</tr>
<tr>
<td>3</td>
<td>2690.44802</td>
<td>2690.44802</td>
<td>8</td>
<td>2443.36868</td>
<td>2770.62506</td>
</tr>
<tr>
<td>4</td>
<td>1968.87096</td>
<td>2690.44802</td>
<td>9</td>
<td>2592.67651</td>
<td>2770.62506</td>
</tr>
<tr>
<td>5</td>
<td>2644.47204</td>
<td>2690.44802</td>
<td>10</td>
<td>2693.19797</td>
<td>2770.62506</td>
</tr>
<tr>
<td>6</td>
<td>2519.97558</td>
<td>2690.44802</td>
<td>11</td>
<td>2600.78525</td>
<td>2770.62506</td>
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<tr>
<td>7</td>
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<td>2690.44802</td>
<td>12</td>
<td>2661.16803</td>
<td>2770.62506</td>
</tr>
<tr>
<td>8</td>
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<td>2690.44802</td>
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<tr>
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<tr>
<td>11</td>
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<td>2700.25903</td>
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<td>2634.30519</td>
<td>2770.62506</td>
</tr>
<tr>
<td>12</td>
<td>2700.25903</td>
<td>2700.25903</td>
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<td>2736.04875</td>
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</tr>
<tr>
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<td>2469.55156</td>
<td>2700.25903</td>
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<td>2770.62506</td>
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<tr>
<td>14</td>
<td>2469.55156</td>
<td>2700.25903</td>
<td>19</td>
<td>2633.84819</td>
<td>2770.62506</td>
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<tr>
<td>15</td>
<td>2770.62506</td>
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<td>16</td>
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<td>2770.62506</td>
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<tr>
<td>20</td>
<td>2454.46084</td>
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<td>25</td>
<td>2552.26337</td>
<td>2770.62506</td>
</tr>
</tbody>
</table>


Table 5. Comparison of the Proportions of Land Covered for \( r = 10 \) km.

<table>
<thead>
<tr>
<th>Facility Locations</th>
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</tr>
</tbody>
</table>

6. Discussions

6.1. Demonstrated Advantages

As demonstrated by the case study in south-east Queensland, the model produces a spread that strives to provide coverage to every area at a pre-set threshold \( \beta \) of 50 percent. For areas that do not receive the threshold coverage, the model pulls the nearest facility
closer to the geographic centre of the area as the variable close in Equation (15) measures the distance between the centroid of the SA2 area to the closest facility as seen more evidently in Figure 2a for \( r = 7.5 \) km. It means that the station can have the higher probability to reach every end of the area subject to the road connectivity that will be discussed in Section 6.2. This feature is useful for working area and function that are similar to the Queensland Fire and Emergency Service (QFES). The QFES functions include a multifaceted role, addressing a spectrum of challenges beyond just urban structural fires. While urban working areas, with their dense populations and potential hazards, naturally attract significant attention, the QFES’s remit encompasses a wider scope. Bushfires, for instance, predominantly manifest in rural or sparsely populated areas. These fires can quickly escalate, imperilling not just their immediate vicinity but also neighbouring urban centres. The QFES’s strategy is not limited to urban response; it extends to providing timely interventions in these areas, crucial for averting potential catastrophes. Road accidents further exemplify the QFES’s diverse mandate. These emergencies can arise anywhere, demanding swift rescue and first aid. A delayed response, potentially due to a remote fire station location, can be disastrous. Hence, the model ensures coverage even in less dense areas, substantially reducing emergency response times.

Traditional fire station placements, typically concentrated in populous zones, can sometimes result in overlapping services. By expanding its reach, the proposed model aims for a balanced resource distribution, equitably addressing both urban fires and emergencies in sparse areas. Importantly, while striving for this comprehensive coverage, the model does not compromise urban areas’ needs. It calibrates its priorities based on a projected rate of building fires in each SA2 area in south-east Queensland. Therefore, densely populated regions, inherently having higher fire probability, continue to receive the attention and resources they warrant.

6.2. Avenues for Improvements

One caution in adopting the model is the inability to consider road connectivity. Road connectivity is also a fundamental aspect of the effectiveness and efficiency of any emergency response service, especially for the QFES. The strategic positioning of fire stations is only part of the equation. Even if a fire station is placed optimally based on coverage metrics, it might not serve its primary purpose if there are inadequate or inefficient road networks connecting it to the areas it serves. For instance, a fire station might be geographically close to a call-out location, but if there is no direct or accessible road linking them, the response time increases, nullifying the advantage of proximity. Consideration of road connectivity ensures that once a call-out is received, the QFES can navigate swiftly without undue obstructions. Areas prone to congestion, roads that are frequently closed for maintenance, or regions that lack necessary infrastructural development can hamper rapid movement. Emergency response services do not have the luxury of time, and every second counts. Moreover, road connectivity is not just about speed; it is also about accessibility. There might be regions that, while close, are inaccessible due to the absence of roads. This is especially pertinent in rural or hilly terrains where direct routes might not exist. Furthermore, in cases of natural disasters or bushfires, certain routes can become blocked, and having a well-connected road network ensures that there are alternative routes available.

In essence, while the model’s current approach to optimizing fire station locations based on coverage is commendable, it must be complemented with a thorough analysis of road networks. The synergy of socioeconomic data and road connectivity will truly maximize the efficiency of the QFES’s response times and ensure that they can reach any call-out location, irrespective of its terrain or challenges.

7. Conclusions

This research has successfully demonstrated the efficacy and behaviour of the modified Implicit Coverage Location Problem (MCLP-Implicit) approach in optimal fire station
location, particularly in the context of the south-east Queensland region. It is important to note that the resulting locations is primarily aimed to measure the performance of the current fire station locations. It does not necessarily recommend the fire stations to be moved to the optimal locations determined in this study. Novelty in the MCLP-Implicit modification includes the consideration to minimize distances of uncovered demand areas to their closest facilities and the use of projected rates of building fires using socioeconomic variables. By integrating socioeconomic factors into demand projections, the model prioritizes socioeconomically disadvantaged areas and expansive coverage strategy. This approach also ensures readiness in sparser regions, thereby supporting dynamic personnel deployment in unforeseen emergencies or seasonal disasters.

However, every model has room for improvement. Future research should include road connectivity as a pivotal factor in determining optimal locations. While our current model gives priority to coverage based on anticipated demand, it is crucial to acknowledge that accessibility and travel times are essential for practical application. Integrating these factors would enhance the model’s accuracy, as it would account for real-world challenges that affect the speed and ease of reaching emergency sites, particularly considering road layouts and traffic conditions. A sophisticated analysis of the road network to pinpoint potential bottlenecks or hard-to-access areas would also bolster the resilience of fire and emergency services.

Moreover, it is important to recognize that the cost of constructing fire stations plays a significant role in their optimal placement. High construction costs necessitate concurrent planning that optimizes coverage while also keeping expenses in check. Strategically situated fire stations can efficiently serve larger areas, thus reducing the requirement for multiple costly facilities. Conversely, if construction costs are lower, it might be viable to build more stations, yielding faster response times and better coverage, especially in densely populated or high-risk zones. The key lies in striking a balance between cost and coverage, aiming to provide sufficient emergency services across the region without overwhelming financial burdens. This calls for a thorough analysis of geographic, demographic, and financial factors.

Additionally, exploring the use of evolutionary algorithms could also push the solution closer to a global optimum, although this would necessitate more advanced computing resources. Lastly, while this study concentrated on the placement of fixed fire stations, future research could enhance the model by incorporating optimal strategies for dynamic allocation of personnel and resources, taking into account the temporal variations in demand. Such advancements would further refine the model, ensuring a more comprehensive and adaptive fire safety infrastructure.


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**Data Availability Statement:** Restrictions apply to the availability of these data. The building fire data in south-east Queensland was derived from Queensland Fire and Emergency Services (QFES) incident data that are publicly available via the Queensland Government Open Data Portal. The geographic data pertaining to south-east Queensland is sourced from the Australian Bureau of Statistics (ABS) in the Shapefile format [22].

**Conflicts of Interest:** The authors declare no conflict of interest.
Nomenclature

- $i \in I$: index for demand points/demand areas
- $j \in J$: index for potential facility sites
- $l \in L$: index for coverage level
- $p \in P$: index for facility to be cited
- $e \in E$: index for socioeconomic variable
- $h_l$: weight attached to coverage level $l$
- $\Phi_i$: aggregate signal function
- $I_{il}$: set of facility sites covering demand point $i$ at least $\beta_l$
- $O_{ij}$: set of eligible site to cover demand point $i$
- $b_l$: rates of building fires at demand area $i$ per 1000 residents
- $close_i$: distance between the centroid of ‘uncovered’ demand area $i$ to its closest facility
- $dist_{ij}$: distance between the centroid of demand area $i$ to site $j$
- $h_i$: weight attached to demand point $i$
- $h_l$: weight attached to coverage level $l$
- $m_i$: binary variable indicating if demand area $i$ is covered
- $m_{il}$: binary variable indicating if demand point/area $i$ is covered at coverage level $l$
- $x_{ijl}$: binary variable to indicate if site $j$ is covering demand point $i$ at coverage level $l$
- $x_i$: binary variable indicating if a facility is sited at site $j$
- $y_i$: binary variable indicating if a facility is sited within $S$ distance of demand point $i$
- $y_p$: set of location vector for facility $p$
- $a_{il}$: minimum number of facilities for complete coverage for demand point $i$ at level $l$
- $a_l$: minimum number of facilities for complete coverage at level $l$
- $\beta$: universal coverage proportion threshold
- $\beta_l$: coverage proportion threshold for coverage level $l$
- $\eta_i$: number of people/volume of demand at demand point $i$
- $\mu_{ij}$: proportion of demand at demand point $i$ covered by facility at site $j$
- $\tau_{ij}$: distance from demand point $i$ to site $j$
- $H$: summation of weight attached to demand point $i$
- $k$: weight to minimize distance of uncovered demand points
- $N$: set of demand points covered
- $T$: $T$th iteration

Appendix A

Table A1. Explanation of Notations Utilized. Adapted from Australian Bureau of Statistics [23].

<table>
<thead>
<tr>
<th>Variable (Proportion)</th>
<th>ABS Notation</th>
</tr>
</thead>
<tbody>
<tr>
<td>People aged 15 years and over whose highest level of educational attainment is a Certificate Level III or IV qualification</td>
<td>CERTIFICATE</td>
</tr>
<tr>
<td>People aged 15 years and over who have no educational attainment</td>
<td>NOEDU</td>
</tr>
<tr>
<td>Employed people classified as Machinery Operators and Drivers</td>
<td>OCC_DRIVERS</td>
</tr>
<tr>
<td>Employed people classified as Labourers</td>
<td>OCC_LABOUR</td>
</tr>
<tr>
<td>Employed people classified as Managers</td>
<td>OCC_MANAGER</td>
</tr>
<tr>
<td>Employed people classified as Low-Skill Community and Personal Service Workers</td>
<td>OCC_SERVICE_L</td>
</tr>
<tr>
<td>Occupied private dwellings with four or more bedrooms</td>
<td>HIGHBED</td>
</tr>
<tr>
<td>Occupied private dwellings with no cars</td>
<td>NOCAR</td>
</tr>
<tr>
<td>Families with children under 15 years of age and jobless parents</td>
<td>CHILDJOBLESS</td>
</tr>
<tr>
<td>People aged under 70 who need assistance with core activities due to a long-term health condition, disability or old age</td>
<td>DISABILITYU70</td>
</tr>
</tbody>
</table>
References


2. Ashe, B.; McAneney, K.J.; Pitman, A.J. Total cost of fire in Australia. J. Risk Res. 2009, 12, 121–136. [CrossRef]


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