Data-driven Strategies for Affordable Housing: A Hybrid Genetic Algorithm-Machine Learning Optimization Model in the Melbourne Metropolitan Area

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Keywords: Housing Affordability, Multi-Objective Optimization, Machine Learning, XGBoost, Random Forest, Genetic Algorithm

Abstract

The escalating rental crisis in Australia, rooted in demographic dynamics, a scarcity of lands suitable for development and the influence of interest rates and government subsidies, necessitates innovative solutions for housing affordability. One promising approach is to increase the supply of affordable rental housing. Nevertheless, these efforts must be guided by well-informed policies as they are required to cater to the diverse needs of the stakeholders involved. Accordingly, this study aims to prioritize suburbs in the Melbourne Metropolitan area for the construction of apartment/unit buildings, benefiting both builders/investors and renters. Leveraging a hybrid Genetic Algorithm-Machine Learning (GA-ML) framework, multi-objective optimization models are developed to rank 105 suburbs based on key parameters for both builders/investors and renters. The optimization process seeks to maximize economic outlook and rental yields for builders/investors while minimizing rents and commuting distances for renters, in addition to proximity to essential amenities. First, an initial optimization using GA based on six key parameters is performed considering a linear multi-objective function. Subsequently, ML-based objective functions are defined using Random Forest (RF) and extreme Gradient Boosting (XGBoost) models to refine the optimization model for suburb rankings. The evaluation reveals strong correlations between GA and GA-XGB rankings, suggesting the effectiveness of the GA-XGBoost model in prioritizing suburbs. Notably, suburbs consistently prioritized across all models include Brunswick, Coburg, Preston and Reservoir, highlighting their suitability for apartment/unit building construction. By directing attention to specific suburbs aligned with different stakeholders' needs and preferences, this study contributes to a more sustainable and equitable housing landscape.

1. Introduction

Australia is currently experiencing a housing crisis rooted in demographic dynamics, a scarcity of land near jobs and essential services, and an overstated influence of interest rates and government subsidies. This dilemma has resulted in a widening gap between those benefiting from the property market and those grappling with affordability challenges (ANZ-CoreLogic, 2023; PEXA, 2023). Victoria mirrors this nationwide issue, dealing with a persistent shortage of reasonably priced private housing options (Coates and Moloney, 2023).

One particular facet of these housing challenges revolves around the ongoing rental crisis. Australia is facing a severe rental crisis characterized by historically low vacancy rates and increasing rents. This crisis reached a national vacancy rate of 0.9% in September 2022, the lowest level in the past two decades. The shortage of residential dwellings is further compounded by a notable surge in single-person households, contributing to the approximately one million new households formed between 2016 and 2021 (AHURI, 2022), and a substantial increase in the proportion of households (approximately one in four) reliant on the private rental sector for accommodation (Morris, 2023). This crisis underscores the urgent need for effective strategies to address the imbalance between housing supply and the growing demand in the private rental market. Housing experts emphasize building the right kinds of homes in the right places as the major solution (AHURI, 2022). Contributing to such a solution, however, requires a holistic approach that aligns the interests of key stakeholders, including builders/investors and renters.

To contribute meaningfully to the resolution of this housing unaffordability problem, this research focuses on identifying suburbs within the Melbourne Metropolitan area where constructing residential apartment/unit buildings could prove financially advantageous for both builders/investors and renters. The study aims to introduce suburbs where specific factors crucial to builders/investors, such as a positive market outlook and high rental yield, are maximized. Simultaneously, it seeks to minimize factors significant to renters, including rent, commuting distance to work, distance to public transportation and distance to the Central Business District (CBD).

This is a multi-objective optimization task, where objectives often conflict, necessitating the exploration of solutions that satisfy multiple objectives without dominance by any other solution (Konak et al., 2006). Today, data-driven technologies have proven excellent capabilities in handling problems with complex relationships among influential factors. For instance, evolutionary algorithms, such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), have effectively tackled multi-objective optimization tasks. These algorithms explore diverse solutions, allowing for the identification of trade-offs and Pareto-optimal solutions across conflicting objectives, making them applicable to real-world challenges in various domains (Deb, 2011).

However, traditional multi-objective optimization models may face challenges in handling complex, computationally expensive objective functions and high-dimensional data. In addition, the trade-off exploration process could become computationally burdensome. The integration of surrogate models, powered by Artificial Neural Networks (ANNs) and Machine Learning (ML) techniques, have been developed to mitigate these limitations. Surrogate models provide efficient approximations of the objective function, reducing computational costs and enhancing the optimization process. This approach facilitates a more effective exploration of solution spaces, particularly in scenarios where evaluating the true objective function is resource-intensive or impractical (Miller and Ziemiański, 2023; Rosales-Pérez et al., 2013; Zhang et al., 2022).

Recent advancements in ML have demonstrated the efficiency of ensemble techniques, such as Random Forest (RF) and boosting techniques, in enhancing the performance of surrogate models for multi-objective optimization purposes. These ensemble methods leverage the collective wisdom of multiple trees to capture intricate relationships within the data, thereby further refining the approximations of the objective function and enabling more accurate exploration of solution spaces (Owoyele et al., 2021; Schneider et al., 2023).

Accordingly, this research formulates a multi-objective optimization problem by employing innovative hybrid GA-ML ranking models. These models integrate GA with advanced ML techniques of RF and extreme Gradient Boosting (XGBoost) to prioritize suburbs for the strategic construction of apartment/unit buildings. The synergy of GA and ML can harness the strengths of both approaches, facilitating a nuanced ranking mechanism that balances the complex array of factors crucial to both builders/investors and renters. By leveraging these hybrid models, this research aims to provide a robust and effective strategy for urban planners and policymakers to contribute to addressing the pressing challenges of housing unaffordability in the Melbourne Metropolitan area.

2. Study Area

The Melbourne Metropolitan area, serving as the capital of Victoria, Australia, spans an extensive 10,000 square km and is organized into 31 Local Government Areas (LGAs), each comprising numerous localities or suburbs (Jafary et al., 2024). According to the 2021 Australian national census conducted by the Australian Bureau of Statistics (ABS), the Metropolitan, also referred to as Greater Melbourne, boasted a population of 4,917,750, encompassing 1,299,184 families. The census recorded a total of 2,057,482 private dwellings in the region, with an average household size of 2.6 individuals. Key economic indicators revealed a median weekly household income of $1,901, while median monthly mortgage repayments were $2,000, and median weekly rent stood at $390. Noteworthy trends from the census indicated a 9.6% population increase, an 11.8% rise in family numbers, and a 12.3% surge in the total count of private dwellings since the preceding 2016 census (ABS, 2021).

As reported by Victoria's Department of Transport and Planning (DTP), the 12 months leading up to March 2023 witnessed approximately 63,500 residential building approvals statewide, with a significant allocation to the Melbourne Metropolitan area by the Victorian Building Authority (VBA) (DTP, 2023).

According to a November 2023 report by the REA Group, realestate.com.au, the Melbourne Metropolitan area is facing a severe rental crisis, with only one suburb within 10 kilometers (km) of the CBD deemed affordable for the average tenant. The National Shelter and SGS Economics and Planning's Rental Affordability Index underscores the gravity of the situation, revealing that low-income earners are being priced out of the market. The Index scores suburbs from 1-200 based on the share of a household's income spent on rent, with scores below 50 considered extremely unaffordable and those above 151 deemed affordable (Petty, 2023). Another report published by this institute in January 2024 highlighted that Melbourne's rental landscape experienced a significant surge, with weekly rental prices escalating by approximately 21% throughout the year. PropTrack's latest data revealed a substantial increase in the region's median rental price, soaring from $465 a week in December 2022 to $550 by December 2023. This surge extended to both houses and units, with weekly rent commitments for houses rising by around 15%, from $480 to $550, and for units by approximately 15%, from $450 to $520 over the past year. The tightening rental market was emphasized by a low vacancy rate of 1.2 percent in Melbourne, reflecting the continued challenges tenants face in securing affordable housing (Petty, 2024).

Considering the availability of data on the various factors to be optimized, aligned with the study's objectives (as elaborated in the subsequent section), 105 suburbs within the Melbourne Metropolitan area were selected for analysis, as depicted in Figure 1.

3. Materials And Methods

In this section, we outline the methodological framework adopted in this study to rank 105 suburbs of the Melbourne Metropolitan area based on their suitability for residential apartment/unit housing—prioritizing mutual benefits for builders/investors and tenants. The process encompasses several key stages, including data collection and preparation on the parameters pertinent to the optimization objectives, initial multi-objective optimization utilizing GA with a linear objective function, defining RF and XGBoost models using the initial ranking based on GA as the target variable and the six factors as the predictive variables, development of GA-RF and GA-XGB models based on novel objective functions derived from RF and XGBoost, respectively, computation of relevant ranks, and ultimately, evaluation of the outputs to select a final ranking. Figure 2 provides an overview of the applied methodology, which will be further elaborated upon in the subsequent subsections, detailing each step in the process.

3.1 Optimization parameters

This study focuses on optimizing six key parameters to determine the suitability of 105 suburbs in the Melbourne Metropolitan area for residential apartment/unit housing. Two parameters aim to maximize the benefits for builders/investors: the cumulative percentage change in median unit value and rental yield. On the other hand, four parameters, including median rent, distance to CBD, distance to public transportation and commuting distance to work, are targeted for minimization to enhance the benefits for tenants. Table 1 summarises these optimization parameters, indicating their data sources, and outlines the spatial analyses employed for their preparation in the optimization process.

3.2 Initial optimization using GA

In this step, the GA is employed to conduct the initial multi-objective optimization. The process begins with the normalization of the considered six parameters. A linear objective function is then formulated, as shown in Equation (1):

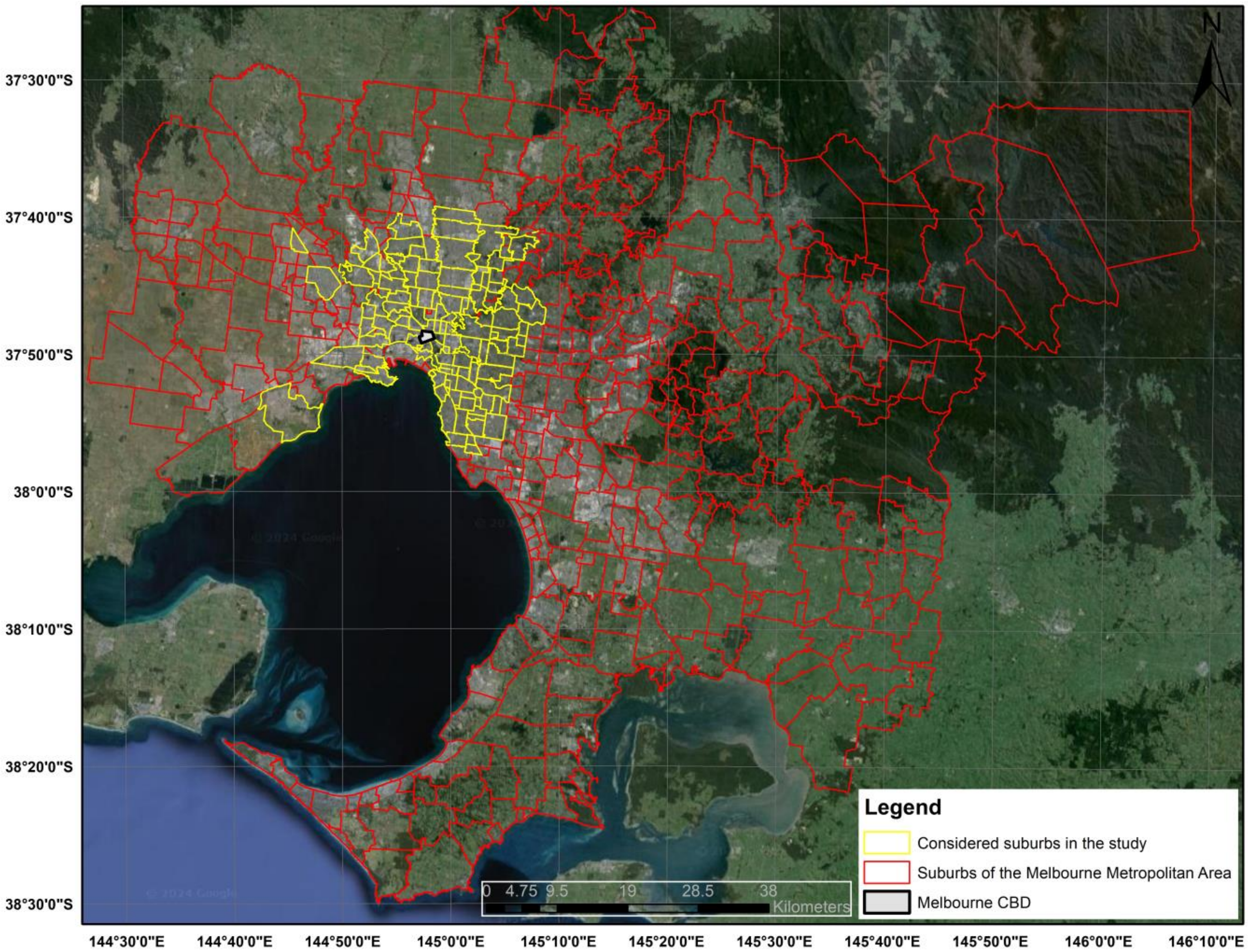

Figure 1. Study area.

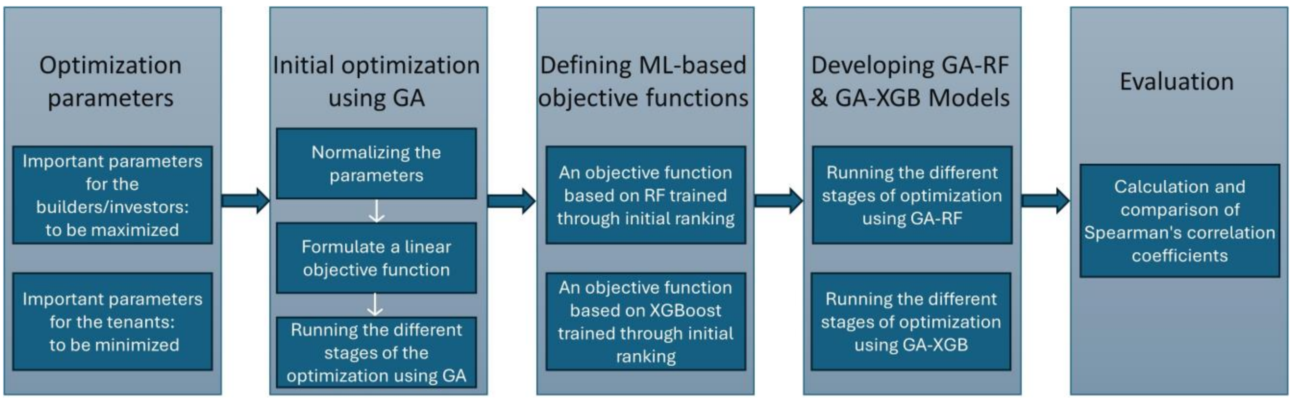

Figure 2. Research method.

$$\sum_{i=1}^{2} w_i X_i - \sum_{j=3}^{6} w_j X_j \qquad (1)$$

where X_i, X_j = Optimization parameters
w_i, w_j = Weights of different parameters

Here, the objective function aims to maximize the cumulative percentage change in median unit value and rental yield (X_1 and X_2) while minimizing median rent, distance to CBD, distance to public transportation and commuting distance to work (X_3 to X_6). The GA optimization process involves a population of potential solutions, where each solution represents a unique combination of weights assigned to the parameters (X_1 to X_6) in the objective function. The optimization proceeds through iterative generations with the following key steps:

- **Initialization**: A diverse population of solutions is generated, each representing a distinct set of weights.
- **Evaluation**: The fitness of each solution is evaluated based on its performance in the objective function, determining its suitability.
- **Selection**: Solutions are selected for reproduction based on their fitness. Those with higher fitness have a greater chance of being chosen.

Parameter	Data source	Preparation process
X_1. Cumulative percentage change in median unit value	The Real Estate Insitute of Victoria (REIV)*: Quarterly median unit prices from Q3 2017 to Q3 2022 for each suburb.	Calculated as the sum of the percentage change in median unit values for each quarter compared to the previous quarter.
X_2. Rental yield	REIV* rental yield data for each suburb.	Calculated as annual rent divided by the value of the property, multiplied by 100
X_3. Median rent	REIV* median weekly rent data for each suburb.	Represents the median monthly rent for residential properties within each suburb.
X_4. Distance to CBD	Department of Environment, Land, Water and Planning (DELWP) layer of the CBD.	Distance of each suburb from the CBD.
X_5. Distance to public transportation	DELWP data on Public Transport Victoria (PTV) stations.	Considered as the total number of tram, bus and train stations in each suburb.
X_6. Commuting distance to work	Australian Bureau of Statistics (ABS) data on commuting distance travelled between a person's Place of Usual Residence and Place of Work at suburb level.	Average commuting distance traveled between a person's Place of Usual Residence and Place of Work.

Table 1. Optimization parameters.
* Data at the suburb level within the study area is collected from the official website of the REIV.

- **Crossover**: Pairs of selected solutions exchange genetic information, introducing diversity into the population.
- **Mutation**: A random subset of solutions undergoes mutation, altering some of their parameters and adding novel variations.
- **Replacement**: The new generation is formed by combining original and mutated solutions. This process repeats iteratively until convergence.

In the context of this study, the GA optimization navigates through these steps iteratively to find the set of weights that optimizes the specified objectives. The resulting ranking of suburbs reflects an improved balance between the various optimization criteria. This optimized ranking serves as the basis for subsequent ML-based refinement steps.

3.3 Defining ML-based objective functions

Following the initial optimization using GA, the study advances by defining new objective functions grounded in ML techniques. The first ML-based objective function unfolds through the development of an RF model. In this process, the initial ranking generated by GA acts as the target variable, while the six normalized parameters (X_1 to X_6) serve as predictive variables. The RF model undergoes a training phase, where it learns intricate relationships among these variables, capturing complex patterns within the data. The output is an evolved objective function refined through the collective insights of multiple decision trees constituting the RF model. The RF model, a robust ensemble learning technique, consists of an assembly of decision trees. Each tree independently processes the input data, and the final output is determined by the collective decisions of all trees. The randomness injected during tree construction, through random subsets of data and features, enhances the model's generalization capability.

Similarly, the study introduces the XGBoost model as the second ML-based objective function. XGBoost employs a gradient boosting framework, sequentially building a series of weak learners (typically decision trees) to form a strong predictive model collectively. During the boosting process, each subsequent tree corrects the errors of its predecessors, iteratively refining the model's predictions. The resulting XGBoost model encapsulates the complex relationships present in the suburb-ranking data, providing an additional layer of sophistication to the objective function.

3.4 Development of GA-RF and GA-XGB models

At this step, the multi-objective optimization process is repeated two times, with the two objective functions developed based on ML techniques instead of a linear function. The purpose is to harness the predictive capabilities of ML algorithms and enhance the accuracy of the optimization process.

The GA-RF model represents a synergistic amalgamation of GA's optimization prowess and RF's predictive capabilities. Accordingly, GA evolves and fine-tunes the weights assigned to the considered key multi-objective parameters to optimize the RF-based objective function.

Similar to GA-RF, the GA-XGB model employs the GA optimization process but integrates with XGBoost. In both cases, the fusion of GA with ML models aims to synergize the strengths of optimization algorithms and ML techniques, resulting in a more accurate and context-aware objective function for suburb ranking.

3.5 Evaluation

Spearman's rank correlation coefficient, as a measure of the correlation between different optimization approaches, is employed to assess the effectiveness of the optimization models developed in this study. The Spearman correlation coefficients provide insights into the alignment of rankings produced by different optimization strategies. A higher correlation indicates greater agreement between the rankings, while a lower correlation suggests divergence in the prioritization of suburbs.

Different steps of the research methodology are conducted in R programming language using "sf", "rvest", "GA", "randomForest", "xgboost" and "caret" packages.

4. Results and Discussions

Table 2 presents descriptive statistics, including minimum (Min), maximum (Max), mean and standard deviation (SD), for the different factors considered in this study, as described in Table 1. These statistics provide an overview of the distribution and characteristics of the two crucial factors for the builders/investors (X_1: commercial outlook through cumulative percentage change in the property value during the last years and X_2: rental yield) and the four key parameters for the renters (X_3: median rent, X_4: distance to CBD, X_5: access to public transportation and X_6: commuting distance to work).

Parameter	Min	Max	Mean	SD
X_1	-15.68	191.57	30.74	35.26
X_2	0.019	0.048	0.031	0.005
X_3	305	645	426	58
X_4	1.28	23.05	9.22	4.53
X_5	5	316	65	45
X_6	8.45	26.88	13.75	3.25

Table 2. Descriptive statistics of the parameters optimized in this study.

After running the three multi-objective optimization models of GA, GA-RF and GA-XGB, three rankings were provided to prioritize 105 considered suburbs in the Melbourne Metropolitan area for the construction of apartment/unit buildings that can benefit both renters and builders/investors. The Spearman correlation coefficients between different optimization models are presented in Table 3. Based on the evaluation results:

Model Comparison	Spearman Correlation
GA vs GA-RF	0.448
GA vs GA-XGB	0.739
GA-RF vs GA-XGB	0.449

Table 3. The Spearman correlation coefficients between different optimization models.

- **GA vs. GA-RF**: The positive correlation, equal to 0.448, suggests a moderate positive relationship between the rankings generated by GA and those generated by GA-RF. In other words, the suburbs that are ranked higher by GA tend to be ranked higher by GA-RF, and vice versa.
- **GA vs. GA-XGB**: The higher positive correlation, equal to 0.739, indicates a strong positive relationship between the rankings generated by GA and those generated by GA-XGB.
- **GA-RF vs. GA-XGB**: The positive correlation, equal to 0.449, suggests a moderate positive relationship between the rankings generated by GA-RF and those generated by GA-XGB.

The positive correlations indicate that, in general, the rankings produced by different optimization approaches tend to move in the same direction. The higher correlation between GA and GA-XGB suggests that these two approaches are more aligned in terms of ranking suburbs compared to GA-RF. This might indicate that the XGBoost model captures patterns similar to those of the GA. The Spearman correlation results and the alignment of rankings suggest that the XGBoost model, integrated with the GA, offers a more refined and consistent approach to prioritizing suburbs.

These multi-objective optimization models yielded different rankings for the 105 considered suburbs (Table 4). However, Brunswick, Coburg, Preston and Reservoir were consistently prioritized across all three models (bold ones in the table). Accordingly, this research recommends a targeted focus on these two suburbs, as they have consistently emerged as top priorities across all three optimization models—GA, GA-RF, and GA-XGB. These suburbs exhibit robust performance, making them prime candidates for the construction of apartment/unit buildings that align with the dual objectives of benefiting both builders/investors and tenants.

Suburbs prioritized by GA	Suburbs prioritized by GA-RF	Suburbs Prioritized by GA-XGB
Reservoir	**Reservoir**	**Brunswick**
Preston	Fairfield	Melbourne
Point Cook	Sydenham	Brunswick West
Brunswick West	Lalor	Thornbury
Coburg	Tullamarine	Point Cook
Toorak	**Preston**	St Albans
Murrumbeena	**Coburg**	Doncaster
Northcote	**Brunswick**	Northcote
St Albans	Footscray	Footscray
Melbourne	Malvern East	**Reservoir**
Brunswick	Hawthorn	Glenroy
Essendon	Hadfield	Bundoora
Bundoora	Maidstone	**Preston**
Thornbury	Hawthorn East	**Coburg**
Caulfield	Bentleigh East	Moonee Ponds

Table 4. Suburbs prioritized by each optimization model for the construction of apartment/unit buildings.

Based on the factors considered in this study, the cumulative percentage change in the value of apartments/units (X_1) in Brunswick between quarter 3 2017 and quarter 3 2022 has been significant, at 30.46%. Its rental yield (X_2) has also been 0.036, higher than the median rental yield among the other studied suburbs. These suggest that constructing apartment/unit buildings in this suburb could offer promising financial prospects for builders and investors. Additionally, the median rental yield in Brunswick has been \$415 per week, with a distance of 4.67 km from the CBD, 110 PTV stations in the suburb, and a commuting distance of 13.24 km. Accordingly, all these parameters are more favorable than the mean values of these parameters in different suburbs, as presented in Table 2, indicating a focus on meeting renters' needs.

For Coburg, the values of X_1, as the cumulative percentage change in the value, and X_2, as the rental yield, are 25.06 and 0.031, respectively. Although these values are still high, they are lower than Brunswick's. However, Coburg's weekly rent and commuting distance are lower than Brunswick's, equaling \$400 and 12.31 km, respectively. In addition, it has a higher number of PTV stations, at 135. These indicate the importance of meeting renters' needs when selecting this suburb using different models. The situation regarding Preston is very similar to Coburg, with X_1 and X_2 values of 22.29 and 0.032, respectively, which are high but less than Brunswick's, and having lower rent (\$400), higher PTV stations (205) and less commuting distance (12.4 km) compared to Brunswick. Finally, regarding the Reservoir, the values for the different parameters are 13.85% cumulative percentage change in the value of apartments/units, 0.03 rental

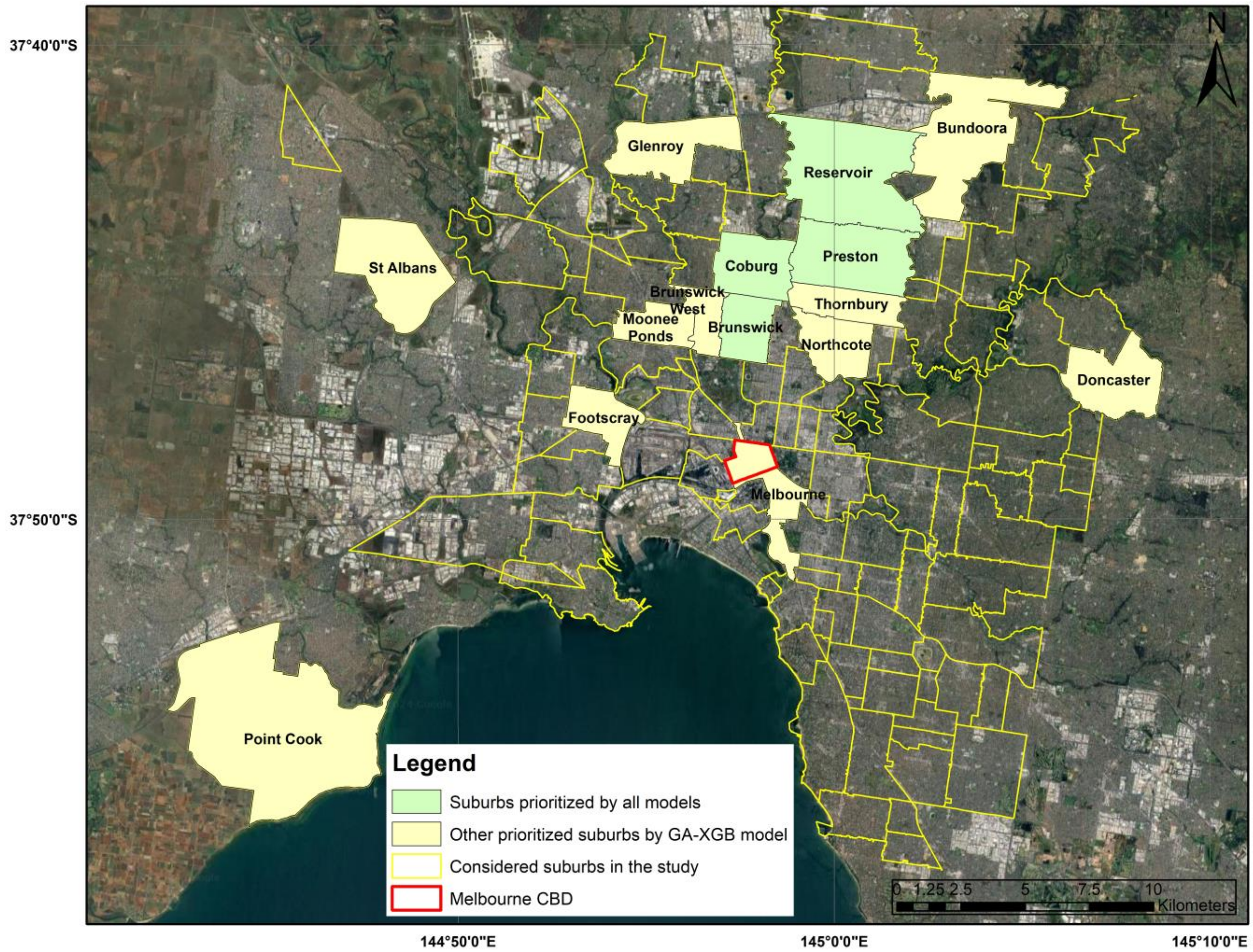

Figure 3. Suburbs prioritized for the construction of apartment/unit buildings in the study area.

yield, $380 median weekly rent, 11.03 km distance from the CBD, 316 PTV stations, and 13.75 km commuting distance. In this suburb, while the factors necessary for builders and investors show positive aspects, more attention has been given to meeting the needs of renters through the different optimization models, particularly concerning median weekly rent and access to public transportation.

In addition to Brunswick, Coburg, Preston and Reservoir, GA-XGB, the selected model for its refined and consistent approach, highlights eight more suburbs for consideration: Melbourne, Brunswick West, Thornbury, Point Cook, St Albans, Doncaster, Northcote, Footscray, Glenroy, Bundoora and Moonee Ponds. These suburbs, prioritized based on the GA-XGB model, present promising opportunities for strategic development efforts. Figure 3 illustrates the spatial distribution of these 15 prioritized suburbs across the 105 considered suburbs in the study.

The integration of GA with ML models aligns with contemporary data-driven decision-making paradigms, leveraging data patterns to inform optimized rankings. This contrasts with conventional GIS approaches that may rely more on predefined rules or heuristics. These models excel in capturing complex relationships and patterns in the data, allowing for a nuanced analysis of suburb rankings. The ML approach offers advantages over traditional GIS methods by efficiently handling non-linear relationships and optimizing multi-criteria objective functions, thereby providing a more refined and accurate prioritization of suburbs.

Factors considered in this study benefitting the builders/investors, including cumulative percentage change in median unit value and rental yield, as well as those advantageous for the renters, including median rent, distance to CBD, transportation accessibility and commuting patterns, are not limited to Melbourne or even Australia. These parameters influence both sides of the rental market in urban areas worldwide. Therefore, similar studies could be conducted in other locations if the required data is available. The applicability of our ML-based multi-objective optimization approach hinges on the availability of high-quality, granular data across these variables. Additionally, the integration of further influential factors, such as construction costs, land values and regulatory frameworks, would enhance the robustness of future studies. The proposed approach's flexibility allows for customization to suit specific urban dynamics, but it necessitates thorough preliminary data analysis to identify the most pertinent variables. By doing so, the methodology can provide tailored recommendations for urban planning and housing policy, contributing to resolving housing affordability challenges globally.

5. Conclusions

In this study, we prioritized specific suburbs for the construction of apartment/unit buildings in the Melbourne Metropolitan area, aiming to address the escalating rental crisis and housing affordability challenges in the region. We employed a hybrid approach combining GA and ML techniques of RF and XGBoost to conduct a multi-objective optimization for ranking suburbs. We considered six key parameters related to builders/investors'

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benefits, such as cumulative percentage change in median unit value and rental yield, and factors affecting renters' preferences, including median rent, distance to CBD, distance to public transportation, and commuting distance to work.

By ranking and recommending specific suburbs in the study area for the construction of apartment/unit buildings, this research offers a strategic approach that can be beneficial for both builders/investors and renters. Suburbs prioritized through the applied hybrid GA-ML multi-objective optimization models not only promise economic viability and attractive rental yields for builders/investors but also align with the needs and preferences of renters. By focusing on constructing residential apartments/units in the suburbs with minimized rents and distance to places of work, public transportation and the CBD, it is possible to contribute to alleviating the affordability challenges faced by renters in the current housing market. Additionally, by providing more accessible and affordable housing options in these identified suburbs, this initiative can potentially ease the burden on government resources and housing programs.

Considering the current escalating rental crisis in the Melbourne Metropolitan area, the findings of this study can hold direct implications to address the pressing housing affordability challenges. Accordingly, this study offers a proactive solution to the pressing rental crisis, fostering a more sustainable and equitable housing landscape for residents of the Melbourne Metropolitan area. However, it is essential to acknowledge certain limitations in the study. Due to constraints in accessing data for all relevant parameters, our analysis was limited to 105 suburbs within the study area.

Future research could benefit from broader data availability, allowing for a more comprehensive evaluation of suburbs and their suitability for apartment/unit building construction. Furthermore, to enhance the efficacy of our optimization models and rankings, future studies could consider integrating additional influential factors. Factors such as construction cost, land value and construction regulations play crucial roles in the feasibility and success of apartment/unit building projects. Incorporating these factors into the optimization process can provide a more holistic and accurate assessment, leading to more informed decisions for builders/investors and improved outcomes for renters.

Acknowledgements

This research is supported by Building 4.0 CRC. The support of the Commonwealth of Australia through the Cooperative Research Centre Programme is acknowledged.

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